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# Process System Engineering in Wastewater Treatment Process

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**Abstract**−This paper reviews the research and development of process system engineering (PSE) in the wastewater treatment process (WWTP). A diverse range of PSE applications have evolved in the wastewater treatment process, such as modeling, control, estimation, expert system, fault detection and monitoring system. This article describes several types of PSE that have proven to be effective in WWTP. The merits and shortcoming of PSE and its detailed applications are presented. Since its development is the forefront in WWTP, a reasonable review of the research progress in this field is addressed.

Key words: Control, Estimation, Expert System, Modeling, Monitoring and Diagnosis, Process System Engineering, Wastewater Treatment Process (WWTP)

## INTRODUCTION

The effluent requirements in WWTP have become increasingly stringent and loads on the existing plants have increased. These require more efficient treatment methodology for wastewater. One way to improve process efficiency is by building a new and large treatment plant, which is normally expensive and often impossible since the required land or foundation is not available. Another way is to introduce advanced techniques. This may reduce large volumes, improve the effluent water quality, decrease the use of chemical, and save energy and operating cost. Sustainable solutions to the problems of wastewater treatment will require the development of an adequate information system for control and supervision of the process.

The introduction of PSE such as control, estimation, expert system, modeling, optimization, monitoring and diagnostic techniques in WWTP has been slow due to the lack of reliable instrumentation and the harsh environment in which the computer and automation devices are housed and operated. However, this situation is rapidly changing due to advances in sensor technology and the introduction of smart sensors capable of self-cleaning, self-calibration and self-reconfiguration. Now, there is a trend for an integrated process system engineering starting from the sources of wastewater treatment to the receiving water and sludge disposal.

We first describe and explain the wastewater treatment plant, then review the applications of modeling, advanced process control, parameter estimation, expert system, monitoring and diagnosis in WWTP reported in the literature and used in practice.

## DESCRIPTION OF WASTEWATER TREATMENT PROCESS

Wastewater treatment processes aim at removal of pollutants in the wastewater by transformation and separation processes. Depending on the characteristics of the wastewater, the desired effluent quality, and other environmental or social factors, this can be achieved in many different ways.. Traditionally, WWTP is divided into mechanical, physical, chemical and biological treatment, which has been utilized with many different combinations. Fig. 1 shows the principal layout of a typical plant with physical, biological and chemical treatment. Physical treatment involves, for instance, screens, sedimentation, flotation, filters and membrane techniques. Chemical treatment involves coagulation and flocculation of colloidal and finely suspended matter as well as precipitation of some dissolved matter.

Biological processes are based on biological cultures that consist of bacteria, uni-cellular life forms and even some multi-cellular life forms. The organic pollutants in the wastewater serve as food and energy sources for the microbiological culture as it grows. The microbiological culture can either grow suspended in the water phase or in a fixed position on surfaces such as a bio-film. Suspended growth is used in so-called activated sludge (AS) reactors, while the fixed growth is used in fixed bed reactors. Biological treatment aims at a certain amount of microbiological culture in the process. In AS reactors, this is achieved by separating the sludge from the water phase in a separation unit and then returning the sludge into the biological reactor. The excess sludge created in the process is removed and treated in sludge treatment processes, which stabilize and dewater the sludge. Stabilization of sludge makes it biologically safe and often usable as a fertilizer. The reduction of organic matter in a biological treatment plant can be 90% or more.

## MODELING

In wastewater treatment, the goals of a treatment plant are to achieve an average reduction in nutrient concentrations and good effluent quality in spite of the many disturbances. Modeling and simulations are key tools in the achievement of these goals.

### 1. Mechanistic Model

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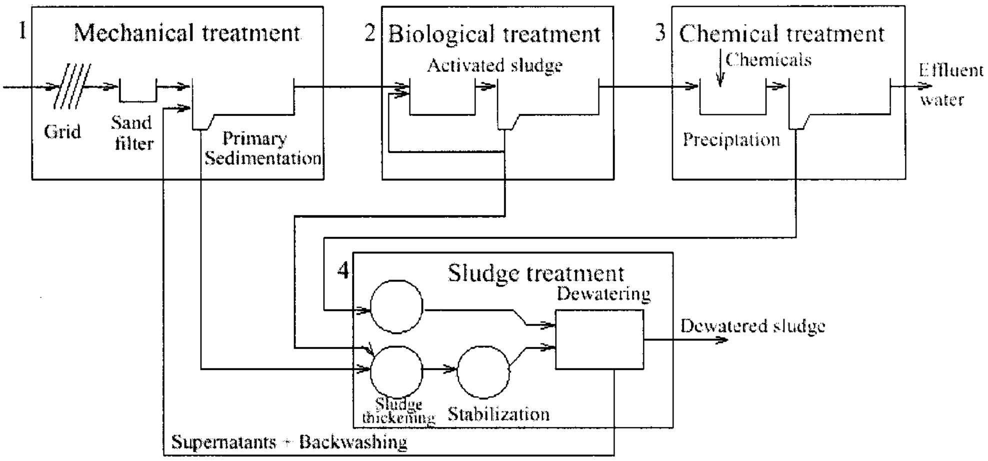


**Fig. 1. A common layout of a wastewater treatment plant.**

A mechanistic model is based on the actual or believed physics, chemistry and microbiology that govern the system. Mechanistic models of wastewater treatment process aim at describing all biological reactions and important mass balances of the system in such a way that the volumes and the flow rates of the system can be designed adequately. In order to faithfully describe a biological WWTP, a large number of phenomena also have to be taken into consideration, such as characterization of the influent, hydraulics of each tank, hydrolysis of different substrates of the influent, removal mechanisms of organic materials and sludge clarification-thickening mechanisms.

1-1. Aerator Model

In 1983, the International Association on Water Quality (IAWQ) formed a task group to develop a practical model for the design and operation of a biological wastewater treatment facility. The first goal was to review the existing models and the second was to reach an agreement concerning the simple mathematical model having the capability of predicting the performance of single-sludge systems carrying out carbon oxidation, nitrification and denitrification. As a result, in 1987, the "Activated Sludge Model (ASM) No. 1" was presented [Henze et al., 1987a, b]. Though the model has been modified and extended, it is still used widely because of its detailed description of biomass growth and removal of organic compounds.

This model divided organic and inorganic materials related with wastewater treatment into 13 components and used their mass balances. All components in the model are expressed in the matrix form. The meaning of components, stoichiometric parameters, chemical reaction equation etc. are described in detail in the matrix. Components are largely classified into carbonaceous compounds and nitrogenous compounds, and each is divided again into readily biodegradable and slowly biodegradable. ASM No. 1 has four important reactions: the growth of biomass (implies oxidation of carbon compounds and nitrification/denitrification), decay of biomass, and ammonification of organic nitrogen and hydrolysis of particulate or-

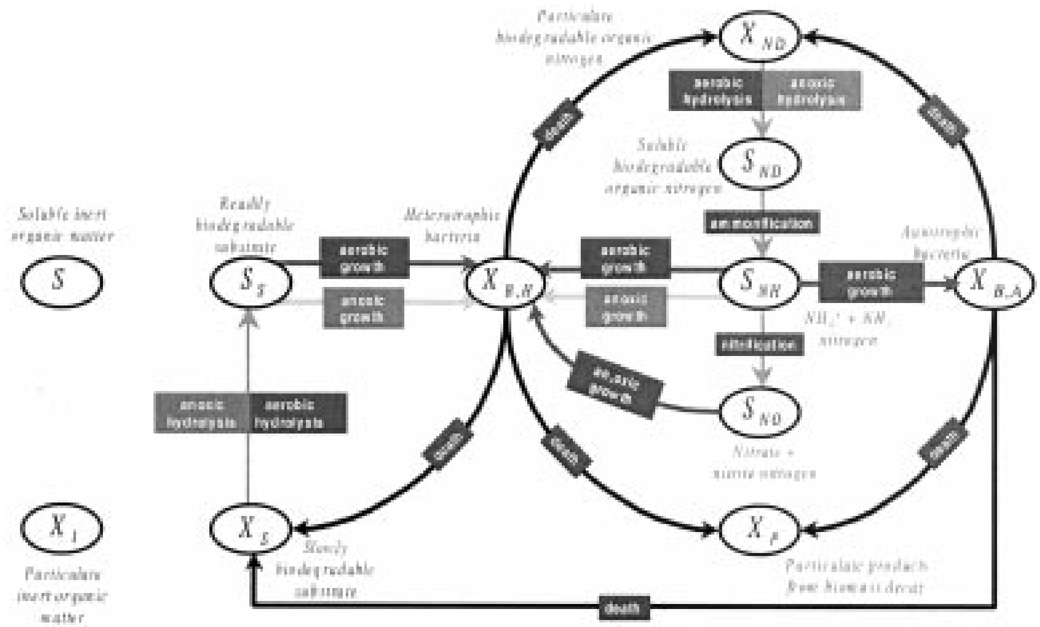


**Fig. 2. Schematic diagram of IAWQ ASM No. 1.**

ganic matter. The main emphasis of the model is the biological reactor, while the settler dynamics is treated comparatively superficially. Main reactions and inter-relationship of components are illustrated in Fig. 2.

Recently, several papers reporting research on biological nutrient removal (BNR) process modeling have been published. Gujer et al. [1995] extended ASM No. 1 for carbon and nitrogen removal to include the modeling of biological phosphorus removal. The resulting ASM No. 2 included 17 processes and 17 components. Typical values of its 40 kinetic parameters were listed, although they have not been verified from experimental data. In a companion paper, procedures of wastewater and biomass characterization for use with ASM No. 2 have been presented [Henze et al., 1995]. Mino et al. [1995] modified ASM No. 2 to include the denitrification capability of phosphorus-accumulating organisms (PAO) by including two new processes: anoxic polyphosphate storage and anoxic growth of PAO. The modified model improved the simulation of phosphates in the anoxic zone of a BNR plant. ASM No. 2 was also modified to be consistent with anoxic P-uptake by including the process of denitrification by PAO using internal polyhydroxyalkanoates (PHAs) [Issacs et al., 1995a]. Based on pilot-plant phosphate and nitrate data, 46 model parameters and 19 initial concentrations were identified after about 2,000 iterations of a random search algorithm, although most parameters were insensitive to the data.

Occasionally, the model structure of ASM No. 1, 2 and so on requires very complex estimation algorithms and it is hard to identify their numerous parameters. Jeppsson and Olsson [1993] proposed a reduced order model for on-line parameter identification of WWTP. With a simplified Extended Kalman Filter, 8 basic reactions and 13 components in IAWQ ASM No. 1 were reduced to 4 reactions and 10 components. It has been verified against ASM No. 1 to investigate whether it incorporates the important dynamic phenomena in the actual time scales or not. More procedures for validation and details can be found in the literature [Jeppsson, 1996].

1-2. Secondary Settler Model

In most previous models, the clarifier has been treated as a pure concentrator, sometimes with time delay. More structured models that incorporate both the clarification and the thickening phenomena have been presented. However, the dependence of the settling parameters on the biological conditions of the sludge is not straightforward. It is usually assumed that there is no biological activity outside the bioreactor. There are, however, indications that some biodegradation takes place in the settler. A secondary settler separates the biomass from the treated wastewater and is a key mechanism in operation of biological WWTP. The model of the settler can be divided into four categories: first, the most general, multi-layer model which considers the settler as a number, n, of horizontal slices (layers) with the feed into slice m. Each slice has a bulk movement of liquid and solids either upwards (above the feed) or downwards (below the feed). Solids settle into the slice from the above and settle out of the slice to the below. Second is the settling flux model that uses settling velocity due to gravity force. However, there are some limitations in that it has a problem of determining constants in the model and it is applicable to the region of zone settling. Third, the clarification model, describes the effluent concentration by using a double-exponential form of the flux model. Fourth, the compartment model is a simpler approach that considers two well-mixed compartments, one above and one below the sludge blanket level.

Keinath et al. [1977] obtained a settling velocity model that satisfied the solid flux model and the underflow condition of that: the downward solid flux is the sum of the gravity settling flux and the solid flux due to the bulk movement of the liquid in a continuous flow settler. Vitasovic [1986] developed a more rigorous analysis of dynamics of the settler. Vitasovic's model predicts the solids concentration profile in the settler by dividing it into 10 layers of constant thickness and by performing a solid balance around each layer. However, the model is reasonable only in the hindered settling condition due to limitation of its settling velocity model. Takács et al. [1991] classified the settling characteristics into four regions and suggested a double exponential settling velocity model in order to take all kinds of sedimentation into account. Dupont and Henze [1992] developed a model for the secondary clarifier based on the general flux theory that can be used in combination with the activated sludge model to form a complete dynamic WWTP. In addition to the flux model, it includes a simple and purely empirical model for predicting the contents of particulate components in the effluent. Nowadays, a more sophisticated model has been developed. Diehl and Jeppsson [1998] proposed a new one-dimensional model based on the theory of nonlinear partial different equations and constructed an entire WWTP model combining the settler model with ASM No. 1.

**2. Data-driven Modeling**

To date, the most successful model and the industrial standard is the mechanical model (ASM No. 1, No. 2 and No. 3). However, the model structure requires a high dimension and the model possesses a large number of kinetic and stoichiometric parameters. Some substrate components and model parameters are difficult to estimate, partly due to the limitation of available measurement techniques. And some processes of ASM No. 1, 2 and 3 are theoretical in nature and rate equations are difficult. Any particular plant has its own process environmental conditions and process operations, which make it difficult to develop an accurate general model. It is not easy or desirable to spend considerable time and effort to simulate peculiarities and non-idealities of a process using ASM models. As a result, the actual application of such a complex model to process control and operational strategies is limited.

In a black box modeling strategy, the model development is mainly driven by measured data from the actual system that has to be modeled. Its main advantage is the fact that, within a reasonable amount of time, one can obtain a highly accurate mathematical model without detailed knowledge of a system. The applicability of black box modeling has greatly increased because of the availability of mathematical concepts that can approximate any continuous nonlinear function, such as artificial neural networks (ANN), fuzzy and genetic algorithms (GA).

Capodaglio et al. [1991] used neural networks to model the sludge volume index (SVI) in order to model forecast sludge bulking, and Tyagi and Du [1992] predicted the effect of heavy metals on the performance of WWTP. Su and McAvoy [1992] used a parallel training approach of recurrent neural networks to predict biological removal efficiency in the wastewater treatment process. Boger [1992] reviewed various applications of neural networks in the field of wastewater engineering and discussed both advantages and limitations of neural approach. Roche et al. [1995] developed a secondary clarifier model that predicted the return sludge concentration based on the settling hydraulic retention time (HRT) by using a shifted power model whose coefficients were correlated to the incoming suspended solid (SS) and the sludge volume index (SVI). Häck and Köhne [1996] estimated the wastewater process parameters using neural networks. A simplified hybrid neural net approach was applied to the modeling and subsequent analysis of a chemical WWTP to reduce the occurrences of overflow in the clarifier caused by filamentous bulking and thereby increase wastewater treatment capacity [Miller, 1997]. Hamoda et al. [1999] examined plant dynamics and modeling techniques with emphasis on the digital computing technology of ANN. Lee and Park [1999] used the ANN model to estimate the nutrient dynamics in a sequentially operated batch reactor. Yoo et al. [2000] predicted and classified the state of the secondary settler using Kalman filtering and neural networks. Gontarski et al. [2000] simulated and predicted an industrial WWTP using ANN. Recently, neural networks have been successfully applied to biological WWTP as well as chemical industries summarized comprehensively by Himmelblau [2000].

However, a conventional ANN model suffers from the drawback that it is synthesized on the available data, without detailed knowledge of the underlying principles. When the data are sparse and noisy, such an empirical black box model may be inadequate and inaccurate for prediction and extrapolation because it possesses no physical basis. Furthermore, the ability to learn nonparametric approximation can lead to over-fitting of the noise as well as the underlying function. Therefore, it often becomes necessary to implement some form of empirical or semiempirical modeling to develop a system representation suitable for further analyses. The potential advantages of hybrid modeling approaches relative to a fully empirical approach include a reduced demand on experimental data and more reliable extrapolation. Consequently, the alternative of using a hybrid model that integrates both a mechanical model and ANN appear promising. The serial configurations used neural networks to represent poorly defined terms in the first-principle model (ASM model). For example, material balance on the biological reactor might yield a set of ordinary differential equations including a number of poorly defined kinetic terms (reaction rates or kinetic parameters of ASM model). In a serial configuration one or more black boxes would replace these "unknown" expressions. Thus, the neural networks provide intermediate values necessary for time series prediction with the mechanical models represented schematically in Fig. 3(a). In parallel arrangements, a dynamic model of the wastewater treatment system exists, and the effort is to construct an empirical error model compensating for its fallacies or errors. For prediction of the dynamic behavior the outputs of the simple dynamic model are biased by the outputs of the error model, as in Fig. 3(b). Fig. 3 represents a hybrid model configuration incorporating prior knowledge into a data-based model with serial hybrid model and parallel hybrid model.

Cote et al. [1995] demonstrated that coupling of mechanic and ANN models resulted in improved ammonia and suspended solid prediction. Dissolved oxygen (DO) prediction was biased since erroneous measurements due to DO probe limitations were not followed closely by the ANN model. Zhao et al. [1997] suggested a hybrid model consisting of a simplified process model and a neural network (residual model) for developing a dynamic model of a sequence batch reactor system. Can et al. [1997] reviewed efficient model development strategies for bioprocesses based on neural network in macroscopic balances. They compared the serial and parallel gray box models that use available knowledge represented in the macroscopic balances and combined naturally with neural networks. Zhao et al. [1999] modeled the nutrient dynamics using simplified ASM2 and neural network in a sequence batch reactor. Anderson et al. [2000] used sequential and parallel hybrid models based on the first-principles knowledge of WWTP, which build as much prior knowledge as available and then use empirical components such as neural networks. Lee [2000] applied the gray box modeling approach to the coke wastewater treatment plant.

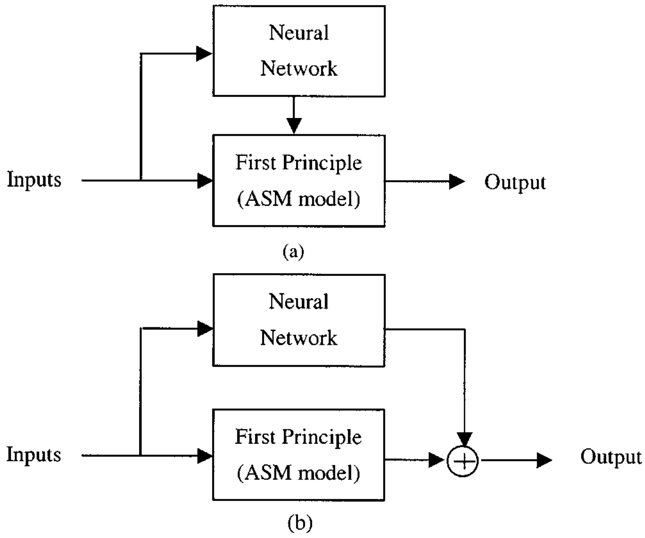


**Fig. 3. Hybrid model configuration incorporating prior knowledge into a data based model (a) serial hybrid model (b) parallel hybrid model.**

### 3. Simulation Benchmark

Many control strategies have been proposed in the literature but their evaluation and comparison, either in real-life applications or simulations, is difficult. This is partly due to the variability of the influent, the complexity of the biological and hydrodynamic phenomena, the large range of time constants (from a few minutes to several days, even weeks), and the lack of standard evaluation criteria. Different regions have different effluent requirements as well as different cost levels. To enhance the acceptance of innovative control strategies, the evaluation should be based on a rigorous methodology including a simulation model, plant layout, controllers, performance criteria and test procedures. To this end, there has been a recent effort to develop a standardized simulation protocol - '*simulation benchmark*' [COST-624, 1997]. The COST 682 Working Group No. 2 has developed a benchmark for evaluation of control strategies by simulation. The benchmark is a simulation environment defining a plant layout, a simulation model, influent loads, test procedures and evaluation criteria. For each of these items, compromises were pursued to combine plainness with realism and accepted standards.

A relatively simple layout was selected for the simulation benchmark (see Fig. 4). It combines nitrification with predenitrification,

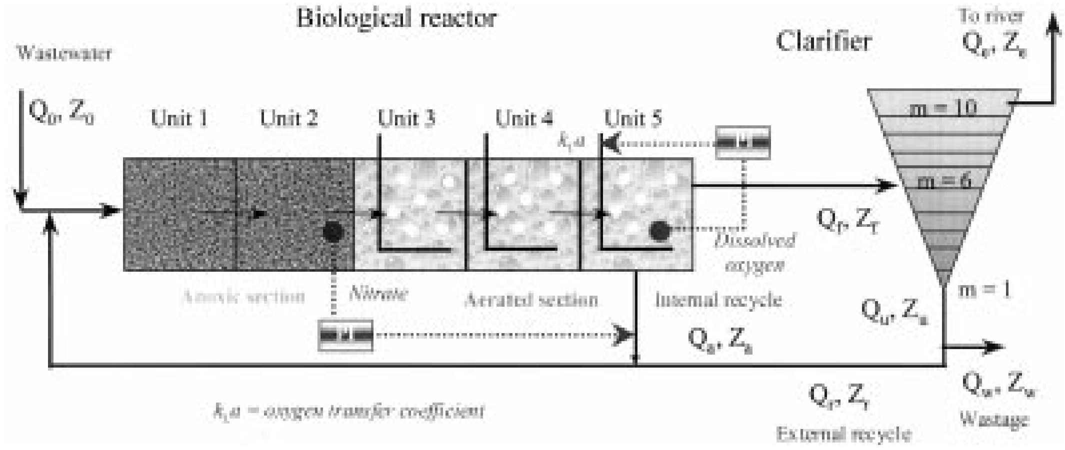


**Fig. 4. A layout of simulation benchmark.**

which is used most commonly for nitrogen removal. The plant, which was designed to treat an average flow of 20,000 $m^3 d^{-1}$, consists of a 5-compartment bioreactor and a secondary settler. To increase the acceptability of the results, two internationally accepted process models were chosen. The biological process is modeled by ASM No. 1 [Henze et al., 1987]. The behavior of the secondary settler is modeled by a double exponential settling velocity model, called *Takács' model*, with a 10-layer secondary settling tank [Takács et al., 1991]. Simulated influent data are available in three two-week files derived from real operating data. The files were generated to simulate three weather situations representing dry weather, stormy weather (dry weather+two storm events), and rainy weather (dry weather+long rain period). Each of the data contains 14 days of influent data at 15 minute sampling intervals. The full benchmark model includes approximately 150 nonlinear differential equations; the complete model can be found on a website (http://www.ensic.u-nancy.fr/COSTWWTP).

A basic control strategy is proposed to validate the user's simulation code. That is, prior to defining and testing a new control strategy users must validate their software by implementing a predefined control strategy. Once the user has validated the simulation code, any control strategy can be applied and the performance can be evaluated according to certain criteria [Alex et al., 1999; Pons et al., 1999; Copp et al., 2000; Yoo, 2000; Cho, 2001].

## CONTROL

Wastewater treatment plants are large non-linear systems subject to perturbations in flow and load, together with uncertainties concerning the composition of the incoming wastewater. Nevertheless, these plants have to be operated continuously, meeting stricter and stricter regulations. And effluent standards will become tighter than now. There are even indications in some countries that tomorrow's regulations must be met on the basis of spot checks, not monthly average. In this situation, advanced control is not the answer, but it can help.

But the behavior of biological processes occurring in a bioreactor has a complexity unparalleled in the chemical or engineering industry. Consequently, its prediction from information about the environmental conditions is extremely difficult. The number of reactions and organism species that are involved in the system may be very large. An accurate description of such complex systems can therefore result in quite involved models, which may not be useful from a control-engineering viewpoint. We can summarize some of the major problems in general: Lacking process knowledge (variations of microorganism characteristics, hydrolysis, flocculation, settling characteristics), large variations of influent load and uncertainties in the influent composition (depending on weather, industrial discharges and toxic material, etc.), multivariable with many cross-couplings, several different unit processes interconnected by various internal feedback, macroscopic modeling of microscopic reaction, highly nonlinear processes, non-stationary processes, time varying process parameters (due to the adaptive behavior of living organisms to various environmental conditions), stiff dynamics (a wide range of time constants, varying from a few minute to several days or weeks), practically non-controllable and highly variable process inputs, and lack of adequate measuring techniques. In particular, from their input/output behavior, these processes can appear to be highly stable until gross process failure occurs. On the other hand, no significant input disturbance excites any significant output response. Whereas, a very significant response can occur in the absence of any obvious motivating input disturbances. By these distinctive features, WWTP has challenged control engineers [Jeppsson, 1996; Lindberg, 1997; Islam et al., 1999].

Several advanced control strategies had been developed previously, e.g. sliding mode control [Derdiyok and Levent, 2000], but few of them are reported as appropriate. Olsson et al. [1989] listed the essential variables in the process and their measurement frequency. Important types of measurements and manipulated variables are listed in Table 1.

### 1. Dissolved Oxygen Control

Dissolved oxygen (DO) control does not require any in-depth knowledge of the microbial dynamics. Therefore, a traditional PI controller or on/off controller has been widely used [Flanagan et al., 1977] and there have been extensive experiences of DO control with feed-back controller [Briggs et al., 1967; Wells, 1979; Ko et al., 1982; Stephenson, 1985; Rundqwist, 1986; Holmberg et al., 1989; Carlsson et al., 1994; Lindberg and Carlsson, 1996a]. Despite the straightforward task of DO dynamics, several difficulties are involved. First, DO dynamics contain both nonlinear and time

**Table 1. Variables for measurement and manipulation**

| Measurement variables | Manipulated variables |
|---|---|
| Flow rates in different plant units<br>BOD, COD, TOC<br>Phosphorus fractions<br>Nitrogen in ammonia, nitrite and nitrate<br>pH<br>Suspended solids in different units<br>Alkalinity<br>Temperature<br>Dissolved oxygen in different locations<br>Air flow rates and air pressure<br>Sludge levels<br>Sludge flow rates<br>Gas flow rates and temperatures<br>Respiration rate | Air flow rate and its spatial distribution<br>Return sludge flow rate<br>Waste sludge flow rate<br>Influent flow rate<br>Additional carbon source flow rate<br>Chemical dosage pumping rate<br>Feeding points for step feed control |

varying properties naturally. From long time constants and random influent disturbances, any tuning of a conventional controller becomes tedious. Therefore, a self-tuning controller was implemented in a full scale plant to examine the potential of adaptive control in WWTP, where DO concentration is kept very close to its set-point under varying operating conditions [Diaz et al., 1995]. Olsson [1992] gave an example of cascade control concept for DO control. Lee et al. [1998a] suggested a discrete type autotuned PI controller using an auto-regressive exogenous model to describe DO dynamics and Yoo et al. [2001] applied a closed-loop autotuning algorithm for the PID controller tuning of DO control in a full-scale coke wastewater treatment plant. Recently, Gomes and Menawat [2000] developed a Model-Based Geometric Control Algorithm (MGA) for controlling DO in fermentation processes.

**2. Sludge Inventory Control**

There are basically two controlled variables for the sludge inventory in the biological WWTP: the waste activated sludge (WAS) flow rate and returned activated sludge (RAS) flow rate. WAS flow rate control controls the total sludge mass in the system and the sludge retention time (SRT) can be kept at a desired level. The traditional sludge age formula is a steady state calculation and does not take short term fluctuations into consideration. Therefore, it should be emphasized that the SRT calculation has to be based on the sludge concentration and flow rates averaged over several days.

The sludge distribution within the system is controlled by the step feed flow distribution or the RAS flow rate. The former can redistribute the sludge dynamically within the aeration basin while the latter can shuffle sludge between the settler and the aeration basin. Many contradictory control schemes are made for return sludge flow. The recycle flow rate can only redistribute sludge between the settler and the aeration basin, while the total sludge mass of the system remains the same. Two most common practical control principles are either constant RAS flow rate or influent flow ratio control. The influent flow ratio control appears to have several difficulties and is seldom used consistently. The constant RAS flow strategy is often found to be better empirically.

Cakici and Bayramoglu [1995] introduced a control method of sludge age and mixed liquor suspended solids (MLSS) concentration by adjusting the sludge recycle rate and wastage flow rate, respectively. For MLSS control, a conventional PID controller was used in RAS flow rate manipulation, and the sludge in the secondary clarifier was wasted using a microbial mass balance formula in the the sludge age. Nejjari et al. [1999] proposed a non-linear adaptive feedback-linearizing controller for a biological WWTP based on the non-linear model of the process and combined with a joint observer and estimator which plays a role of the software sensor for on-line estimation of biological states and parameter variables of interest.

**3. Respirometry-based Control**

Respirometry is the measurement and interpretation of the respiration rate of activated sludge. The respiration rate is the amount of oxygen consumed by the microorganisms measured per unit volume and unit time. It reflects two of the most important biochemical processes in WWTP, biomass growth and substrate consumption. Respirometry has been the subject of many studies and a number of measurement techniques and instruments have been developed.

Substrate utilization in an aerobic environment requires oxygen. A portion of the consumed substrate is oxidized to provide the energy required to reorganize, and the remainder of the substrate molecules is converted to new bacterial cell mass [Spanjers et al., 1996]. The rate of oxygen consumption can be measured relatively easily by measuring physical variables like DO or carbonaceous material by heterotrophic bacteria and the oxidation of ammonia nitrogen to nitrate nitrogen by autotrophic bacteria. Nitrification often accounts for approximately 40% of the total oxygen demand. The substrates have various biodegradation kinetics depending on their inherent characteristics and the responsible sludge condition, e.g., mineralization of carbonaceous compounds differs from that of nitrogenous substrates, and in the carbonaceous matters the same degradation pattern is not shown according to their molecular structures. Called the bisubstrates hypothesis, it was introduced first in the UCT (University of Cape Town) model [Dold et al., 1991]. According to the hypothesis, BOD in the influent waste stream can be regarded as two fractions: one is readily biodegradable substrate (RBS), which has a simple molecular structure and is able to pass through the cell wall immediately for microbial metabolism, and the other is slowly biodegradable substrate (SBS), which was assimilated in a form of

RBS through extracellular enzymatic reaction, called hydrolysis [Ekama and Marais, 1979].

Since the respiration rate is directly linked to the growth of bacteria and consumed substrates, it has been used to analyze microbial conditions of WWTP in a form of respirogram that is a graphical description of respiration rate as a function of time [Kappeler and Gujer, 1992; Spanjers and Keesman, 1994; Spanjers and Vanrolleghem, 1995; Dochain et al., 1998; Vanrolleghem et al., 1995, 1998].

Furthermore, the respiration rate can be decomposed into exogenous and endogenous parts, in which this comes from an adenosine tri-phosphate (ATP) oxidation in microorganisms and that from the external substrate oxidation. The change of the rate relies mainly on its exogenous part since the endogenous respiration rate sustains a constant level in a short time experiment [Kong et al., 1996]. Hence, the analysis of exogenous respiration rate has been used for the identification of the characteristics of substrates and microorganisms [Brower et al., 1998; Spanjers et al., 1999].

### 4. Advanced Nutrient Removal Control

Nitrogen and phosphorus are the principal nutrients of concern in treated wastewater discharges. Discharges containing nitrogen and phosphorus may accelerate the eutrophication of lakes and reservoirs and may stimulate the growth of algae and rooted aquatic plants in shallow streams. Significant concentrations of nitrogen in the treated effluents may also have other adverse effects including DO depletion in receiving waters, exhibiting toxicity toward aquatic life, affecting chlorine disinfection efficiency, presenting a public health hazard, and affecting the suitability of wastewater for reuse. Therefore, the control of nitrogen and phosphorus is becoming increasingly important in water quality management and in the design of WWTP [Lee et al., 1998b; Yoo, 2000; Cho, 2001].

#### 4-1. Model-based Control

The development of advanced nutrient analyzers has made it possible to introduce better control. In biological nitrogen and phosphorus removal, many factors influence the reaction rates, such as the amount of microorganisms, temperature, substrate composition and concentration. There are only a few ways to influence the nitrification/denitrification rates in practice: One is to adjust the DO set point for ammonia removal in the aeration zone; another is to control the dosage of external carbon for nitrate removal. Phosphorus can be removed by controlling the dosage of chemicals for phosphorus precipitation.

Many papers have dealt with the problem of removal of nitrogen compound. Henze [1991] discussed capabilities of biological nitrogen removal process for wastewater treatment and suggested that the most economic configuration for nitrogen removal should be the predenitrification system. Recent approaches to the problem of nitrate removal by external carbon source can be found. Lindberg and Carlsson [1996b] proposed an adaptive control strategy using auto-regressive moving average with exogenous input (ARMAX) model with recursive least square method for parameter estimation. Yuan et al. [1997] suggested various control strategies using proportional feedback controller with some assumption and modification of ASM No. 1. To design the controller and determine the optimal set point, they added the dynamics of an external carbon source to the denitrification model in ASM No. 1. Barros and Carlsson [1998] developed an iterative pole placement design method of a nitrate controller. The closed-loop model of the process could be obtained from input/output data during iterative design procedure.

#### 4-2. Multivariable Control

Above previous researches focused on single input single output (SISO) process control. Some examples of multivariable control of the wastewater treatment process can be found in Bastin and Dochain [1990], Dochain and Perrier [1993], and so on. Lindberg [1997, 1998] suggested multivariable modeling and control strategy of nutrient removal in WWTP using numerical algorithms for subspace state space system identification (N4SID) that can identify multivariable processes [Van Overschee and De Moor, 1996]. From the multi-input multi-output (MIMO) process model, Lindberg [1997] developed a linear quadratic (LQ) controller with integration of feedforward and feedback controller. Steffens and Lant [1999] evaluated several multivariable model-based control algorithms, such as linear quadratic controller (LQC), dynamic matrix controller (DMC) and nonlinear predictive controller (NPC) for controlling nitrogen removal in WWTP and compared that with a conventional PI controller of the SISO system. They concluded that model-based control algorithms could provide tight control of nitrogen compound removal and offer significant benefits in terms of deferred capital expenditure.

On the other hand, Isaacs and Henze [1995] and Isaacs et al. [1995] dealt with the problem of nutrient removal control in an alternating nitrification/denitrification process. Lukasse et al. [1998] developed an aeration strategy for optimal nitrogen removal in alternating nitrification/denitrification process. First, optimal control theory was applied to ASM No. 1, and then, from the result of the first simulation, a simple discrete model which could replace complex ASM No. 1 was created to design a receding horizon optimal controller. It revealed that it is impossible to control both ammonia and nitrate to their set points as their consumption/production is completely coupled.

## PARAMETER AND STATE ESTIMATION

As previously described, WWTP is a complex dynamic process influenced by many uncertain factors, such as loading and biomass composition. Successful process control requires good knowledge of process variables such as the most influential kinetic and stoichiometric parameters and resulting biomass composition. Model parameters and state estimation are based on available noisy process measurements. The parameters of biological models usually vary with the environmental conditions and need to be updated frequently through on-line and off-line algorithms. Tracking of parameters values is also useful for detection of toxic input and on-line sensor failures and sudden parameter changes. The need of state estimation arises in connection to state-feedback control schemes. Process variables that are not monitored due to unavailable or expensive sensors can be estimated or reconstructed numerically. Even in the case where process measurements are available, estimation algorithms are still necessary to optimally weigh the uncertainty of the process model with measurement accuracy and generate a more accurate state variable estimate [Bastin and Dochain, 1990; Kabouris, 1994].

It is well known that particular problems of model identification in WWTP involve the highly nonlinear nature of the dynamics, the small sensitivity of the state variables and the inability of measuring individual process variables reliably.

Goto and Andrew [1985] presented on-line estimation of oxygen uptake rate from DO mass balance in a complete mixed aeration basin, neglecting DO time derivative and measuring air and water flowrates and DO concentration. Howell and Sodipo [1985] estimated on-line respiration rate and aeration efficiency by a factorized Kalman filter algorithm. Olsson and Chapman [1985] used the Maximum Likelihood method to estimate the parameters of a time invariant linear stochastic difference equation describing clarification of effluent solid dynamics. In the case of time-varying parameters, they used the Extended Least Square method in modeling of the effluent solids response of a pilot scale settler. Holmberg and Olsson [1989] simultaneously estimated OUR and aeration coefficiencies using Kalman filter method. Marsili-Libelli [1990] designed and evaluated a real-time estimator both for oxygen uptake rate and for oxygen transfer rate coefficients. Ayesa et al. [1991] used an Extended Kalman filter (EKF) algorithm to simultaneously estimate the states and parameters of ASM No. 1 for nitrifying WWTP, including a selector reactor, and Larrea et al. [1992] attempted the simultaneous estimation of nine model parameters. Weijer et al. [1996] reviewed the recent literature on calibration strategies and methods for assessing parameter identifiability of ASM 1 and presented the identifiability results for full-scale plants by a combined analysis of the parameter sensitivity and the Fisher information matrix.

Recently, Kabouris and Georgakakos [1996a, b, c] reviewed the parameter and state estimation of WWTP about model development, application and on-line estimation. Tenno and Uronen [1995, 1996] introduced a stochastic model based on an ASM model and the outlet gas formation description. Suescun et al. [1998] proposed a simultaneous estimation of the volumetric mass transfer coefficient and oxygen uptake rate and validated the experimental results in a continuous pilot-scale plant. Jose et al. [1999] proposed a neural network-based inferential sensor for phenol monitoring using on-line biomass concentration by spectrophotometry, where the network was built with wavelets as a basis function and the adaptive algorithm for the weights was based on a Lyapunov stability analysis. Predicted output of the network showed a good agreement with experimental data over fairly broad ranges of inlet concentration and dilution rate step changes. Assis and Filho [2000] reviewed the soft sensor technologies for on-line bioreactor state estimation, such as adaptive observer, filtering techniques and artificial neural networks and predicted trends on on-line software based state estimation. Yoo and Lee [2001] suggested and experimented with a supervisory control based on simultaneous process identification and *in-situ* estimation of respiration rate in a full-scale wastewater treatment plant.

## EXPERT SYSTEM

An expert system provides expert solutions to problems in a specific domain, but it is limited by the information contained in its database. Hence, it is up to the knowledge engineer and the expert to work together to gather the correct information and inference rules contained in the knowledge base.

A typical expert system consists of two separate entities: a knowledge base and a control system. The knowledge base contains (1) a listing of rules that solve the problems of the given domain, (2) specific data, or the facts, conclusions, and other relevant information, and (3) a knowledge base editor that accesses the explanation subsystem and helps the programmer locate bugs in the program performance. It may also assist in adding new knowledge, maintaining correct rule syntax, and checking consistency on an updated knowledge base. The control system generally has (1) a user interface which makes access to the expert system more comfortable for humans and hides much of the system complexity, (2) an explanation subsystem that allows the program to explain its reasoning to the user, such as justifications for the systems conclusions, and why the system needs a particular piece of data, and (3) an inference engine, or the interpreter of the knowledge base. It applies the knowledge to the solution of the actual problems.

Stephan and Anthony [1991] designed an expert system for water treatment plants and applied it to a plant in New York. Watanabe et al. [1993] proposed intelligent operation support system (IOSS) for bulking prediction and control for WWTP with on-line process data and image signals on microbes; the data and signals come from a submerged high resolution microscope. In their research, the rules of the expert system were produced from historical data by using artificial neural networks. Wang [1996] used the decision-supporting system (DSS) in city water supply. DSS was designed to operate with an SCADA system connected to a telephone line. He suggested a triple hierarchy to infer the result of the system. The first hierarchy is used for data processing, the second is for data analysis, and the final is for reason driving with the library of knowledge base. Medsker [1996] presented a hybrid intelligent system with microcomputer and compared it to a neural network, expert system, fuzzy logic, genetic algorithms and case-based reasoning. He forecasted that the microcomputer-based hybrid intelligent system became more effective and economical. Baeza et al. [1999] suggested a real time expert system (RTES) for the supervision and control of WWTP for removal both organic matter and nutrient. He used PLC for process control and G2™ for RTES development. RTES was designed to actuate as the master in a supervisory setpoint control scheme and it is based on a distributed architecture. The method was implemented in WWTP for 600 days, and excellent performance was reported to manage the process in spite of strong disturbances.

## MONITORING AND DIAGNOSIS

Process monitoring of operating performance is extremely important for plant safety and quality maintenance in a process. It is largely divided into two main approaches such as model-based and data-based. The former makes mathematical models to identify the static and dynamic relationships of processes and so it is useful if a process is rather simple, but not useful if processes have severe nonlinearity, high dimensionality and complexity. On the contrary, the latter makes statistical guideline based on historical data in normal operation conditions, so it is available without process characteristics if there are enough available data.

The monitoring problem largely consists of three sequential parts: data rectification, detection, and diagnosis. Fig. 5 illustrates the monitoring scheme for the plant. Data rectification means the screening of available data to remove redundant information. Olsson and Newell [1999] defined the detection as a combination of process observations and measurements, data analysis and interpretation to de-

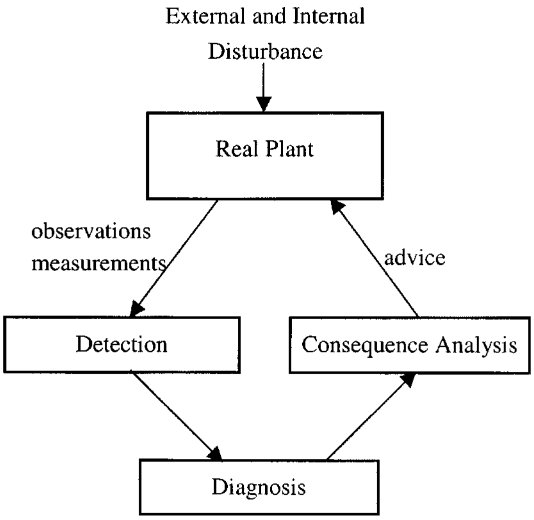


**Fig. 5. Monitoring scheme for the plant.**

tect abnormal features or effects and the isolation of faults. Diagnosis involves the analysis of effects to identify and rank likely causes. The advice involves the problem of synthesizing strategies to eliminate the causes and return the process to normal operating conditions.

Only a few researchers have been interested in process monitoring in WWTP. Monitoring in wastewater treatment has mostly focused on a few key effluent quantities upon which regulations are enforced. However, since environmental restrictions are becoming more rigid nowadays, an increased effort for higher effluent quality is required in the advanced monitoring of plant performance.

Monitoring of WWTP is very important because recovery from failures is time-consuming and expensive. That is, most of the changes in biological treatment process are very sluggish when the process is recovered back from a 'bad' state to a 'normal' state or back from a 'bad' state to a 'good' state. Therefore, early fault detection and isolation in the biological process is very important as corrective action well before a dangerous situation happens. At the same time discrimination between serious and minor abnormality is of primary concern. To accomplish these classifications, a reliable detection procedure is needed. However, few monitoring techniques are available to utilize the large on-line data sets despite the increasing popularity and decreasing price of on-line measurement systems in the field of the wastewater treatment system.

A wastewater treatment plant is a very complex system including a great deal of equipment and complex processes. The operators are under increasing regulatory pressure to reduce pollutant levels in their effluent. One response to this has been the installation of extensive on-line sampling capable of measuring flow rates, concentrations and other variables frequently. Data acquisition systems may collect a large amount of data, normally tens of process and control variables, but there are relatively few significant events. Therefore, the data from all the measurements should be mapped into a significant description of the current process. The obtained data will give much process information, if only the important and relevant information can be extracted and interpreted. Not only are there many variables to be considered, but also they are often highly cross-correlated (*i.e.*, the measured variables are not independent of one another) and auto-correlated. So, redundancy that variables carry the same information at least to some extent is observed. It is desirable to develop schemes for providing reliable on-line information on the status of the plant so that early corrective actions may be taken.

Traditionally, statistical process control (SPC) has been used to monitor a few quality-related key process signals to detect trends, outliers and other anomalies. The term "SPC" is often confused with process control. SPC, however, is more related to the process monitoring, and therefore the term "statistical process monitoring" (SPM) is often used instead of SPC. Shewhart, cumulative sum (CUSUM) and exponentially weighted moving average (EWMA) are traditional univariate SPC charts. The use of univariate control charts implicitly assumes that the variables are independent and identically distributed (iid). For this reason, these procedures are of limited use with high-dimensional multivariate data that are strongly cross-correlated and auto-correlated, dynamic, multiple time-scale, non-stationary and noisy. That is, as the number of variables and the extent of collinearity increase, the interpretation of these univariate control charts can lead to false conclusions [Rosen, 1998; Teppola, 1999].

Multivariate statistical process control (MSPC) is a possible solution to dimensionality and collinearity problems. Contrary to univariate techniques, multivariate techniques are more successful solutions to monitor the process data having severe collinearity and noise. They contain such methods as principal components analysis (PCA) or partial least squares (PLS) combined with standard sorts of control charts. These methods are the basis of the field of *chemometrics*, which has traditionally been concerned with multivariate analyses in chemistry, particularly those of spectroscopy. These have also been used widely in industrial process monitoring over the past several decades. PCA and PLS aim to represent a multivariate set of measurements with a smaller number of variables. These transformed variables are linear combinations of the original ones. These methods have been used and extended in various applications [Geladi and Kowalski, 1986; Johnson and Wichern, 1992; MacGregor et al., 1995; Wise and Gallagher, 1996; Chen and McAvoy, 1998; Liu et al., 2000].

With the use of multivariate data analytical methods, the extension from univariate to multivariate control charts is very logical. Because the multivariate scores are orthogonal mathematically and they give the optimal summary of measurements and observations, they are ideally suited for displaying in control charts [Wikström et al., 1998]. The scores are also more robust to noise than original variables since they are linearly weighted averages. This allows a more efficient pattern tracking of the process over time for detecting abnormalities and for defining the time when they occur. Multivariate control charts have been explained in detail by MacGregor and Kourti [1994].

The multivariate Shewhart charts are constructed simply by plotting the appropriate quantity vs. time. Those of scores show how the process evolves over time in the respective principal component. Meanwhile, a Shewart chart of Hotelling's $T^2$ indicates a summary of all scores. The multivariate CUSUM charts are only available for scores. In these charts cumulative sums of deviations from the target values are calculated and visualized, then all observation are used to detect a special event, rather than only the last observation. The EWMA charts are used to model process dynamics with memory and drift. They show robust and filtered values through weighting more heavily to recent than old observations. These three kinds of control charts only show if the systematic part of an observation conforms the model. However, if a new type of event occurs and gives data that are not represented in the training set, the model will not fit these new data well and hence leave much of this observation unmodelled. Therefore, we often use simultaneous scores monitoring and residual tracking (SMART) charts to identify how the model fits current data well. They represent time series patterns of model residuals.

Besides the dimensionality and collinearity problems, process data often consist of many underlying phenomena that create their own variation and scale. The measured signal can be often very messy because some phenomena mask others. So, it is hard to observe the long-term drift of signal such as seasonal fluctuation having low frequency. In most situations, the objective is to identify transient phenomena such as faults and disturbances. However, there also exist applications where the detection of long-term disturbances such as drifting and seasonal fluctuations is important. A filtering approach can give a possible solution for this problem. The original data are compressed and analyzed at different scales by using multiresolution analysis [Teppola, 1999]. The corresponding scale representation shows different phenomena occurring at different rates. Mutiresolution analysis enables one not only to show the underlying phenomena but also to filter out unwanted and disturbing phenomena. In addition, proper clustering methods help one to discriminate different scale events.

Applications of MSPC in the biological process have recently drawn great interest by a few researchers. Krofta et al. [1995] applied the analysis techniques for dissolved air flotation. Rosen [1998] adapted multivariate statistics-based methods to the wastewater treatment monitoring system using simulated and real process data. Van Dongen and Geuens [1998] illustrated that multivariate time series analysis can be a valid alternative of the dynamic modeling in WWTP. Teppola [1999] used a combined approach of multivariate techniques, fuzzy and possibilistic clustering, and multiresolution analysis for wastewater data monitoring. Tomita et al. [2000] applied multivariate analysis in the simulated WWTP and detected three groups of variables characterizing the system.

However, the multivariate statistical analysis method has fundamental weak points in the nutrient removal process. The nutrient removal process is non-stationary, which means that the process itself changes gradually over time. Wastewater treatment plants are hardly ever “normally” operated for long periods, and what “normality” means also changes because of the nonstationarity. So, conventional static PCA is not suited for non-stationary process monitoring as it assumes data are i.i.d and they are obtained from a normal operating condition for a particular process. This is a problem for developing statistical control charts as they should be developed from a set of “normal” operating data.

Issues that need to be addressed, particularly in relation to WWTP, are the selection and transformation of data, model structure and sampling intervals. First, to implement dynamic and adaptive data based models, the methods of selecting and transforming data are required [Ku et al., 1995]. Ideally, these should demand a minimum of process knowledge. Second, adaptive algorithms for MSPC show potential for non-stationary processes. While adaptive algorithms have been developed [Dayal and MacGregor, 1997; Qin, 1998; Li et al., 2000], there has been little research on the problems of application to industrial processes. Third, the choice of sampling interval strongly affects the nature of the data and hence the model. There is a very wide range of dynamics in WWTP. That is, while some measurements are taken many times per minute, some are taken only every fifteen minutes. Quality measurements may be taken once a day or even less frequently (multirate sampling). It may be possible to block variables sampled at the same frequency and develop a multi-block model. Another possibility is to use a multiscale model through the use of wavelet transforms [Bakshi, 1998]. In addition, extensions of MSPC to monitor more complex or batch processes are made with the multiblock PCA, PLS or multiway PCA, PLS, respectively [MacGregor et al., 1994; Nomikos and MacGregor, 1994]. These monitoring methods are based on the traditional statistical analytical approach using Hotelling’s $T^2$ or sum of squared prediction error (SPE or Q statistics). $T^2$ and Q statistics methods provide reliable and correct tools for detecting that multivariable process has gone out-of-control. However, these methods do not always work well in WWTP, because they cannot detect any changes in the operating condition if $T^2$ and Q are inside the confidence limits. Therefore, a new monitoring method may be required that can effectively treat the nonstationarity of the characteristics of the biological treatment process and diagnose source causes.

Meanwhile, it is an important issue to diagnose the source causes for abnormal behavior. Chemometric methods such as PCA and PLS have been utilized for merging detection with diagnosis of source causes of abnormal situations [Ku et al., 1995; Raich and Çinar, 1995; Chiang et al., 2000; Russel et al., 2000]. Ku et al. [1995] proposed a diagnostic method in which the out-of-control observation was compared to PCA models for known disturbances. Using refinements of statistical disturbances, discriminant analysis then selects the most likely causes of the current out-of-control condition. Successful diagnosis depends on the discrimination ability of these disturbance models. Raich and Çinar [1995] suggested quantitative tools that evaluated overlap and similarity between the PCA model and discriminant analysis in order to diagnose the source causes for abnormal behavior. Chiang et al. [2000] compared the fault diagnosis methods using discriminant partial least squares (DPLS), Fisher discriminant analysis (FDA) and PCA. They showed that FDA and DPLS are more proficient than PCA for diagnosing faults. Russel et al. [2000] proposed a fault detection method using canonical variate analysis and dynamic component analysis. Recently, Kano et al. [2000a, b] proposed a new statistical process-monitoring algorithm. It is based on the idea that a change of operating condition can be detected by monitoring the distribution of time-series process data because the distribution reflects the corresponding operating condition. However, they did not consider an individual contribution of each transformed constituent in the calculation of dissimilarity index through normalization. Choi et al. [2001] proposed a modified dissimilarity measure algorithm to consider the effect of individual transformed variables. This method is used for detecting the existence of disturbances as well as for isolation of kinds of disturbances through eigenvalue monitoring.

## CONCLUSION

Process system engineering techniques such as modeling, control, estimation, expert system, and monitoring and diagnosis system in the wastewater treatment plant are significantly under development and have given very real economic benefits to be gained. In this paper, we have reviewed many papers about PSE techniques in the field of wastewater treatment plants. Among them, however, only a few techniques have been reported to work successfully in real wastewater treatment plants, while manifold monitoring and control strategies have been developed and adopted to the mechanical, chemical and electronic industries. One of the inherent differences in the wastewater treatment plant and the other physiochemical industries is that the microorganisms, which played an important role in wastewater treatment process, are living creatures with various vital forces according to the surrounding conditions. Therefore, the cell viability should be regarded as an essential factor for the wastewater treatment process operation because it is strongly correlated with the process performance. One of the possible candidate to check the activity of microorganisms is the respirometer as we discussed in Respirometry-based control. In addition, the respiration rate has been used for bio-model calibration, toxicant inhibition test, substrate state observation and biokinetic analysis between biodegradable pollutants and corresponding microbes.

Another further research topic on PSE issues is the design of an integrating operation system on wastewater treatment plants. However, since PSE technologies have borne fruitful results individually, it is time to consider that a plant-wide operating system should be developed. Integration of possible PSE techniques can be expected to play a significant role in management of wastewater treatment industry through reducing operation cost and enhancing the effluent quality.

In essence, we contend that PSE techniques will be a critical technology for meeting the increasingly stringent effluent requirements in the wastewater treatment industry over the next decade.

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