Building Blocks for Wastewater Treatment Process Control: a Review

Wastewater treatment processes can be considered as the largest industry in terms of treated mass of raw materials. In the European Community, for instance, a daily wastewater volume of approx. 40.10^6 m^3 has to be processed (Lens & Verstraete, 1992). While this has only been achieved by important investments in the last few decades, studies have shown that even well attended plants are 'out of spec' (not meeting the effluent quality standards) for 8 to 9 % of operation time (Berthouex & Fan, 1986), not including short upsets lasting less than one day. The U.S. Environmental Protection Agency estimated that 1 in 3 treatment works are in non-compliance with discharge limitations (Ossenbruggen et al., 1987) and in Germany and the Netherlands clarification problems were found to occur in almost half of the evaluated treatment plants (Chambers & Tomlinson, 1982). Besides faulty design, overloading and inadequately trained operators, a lack of process control leading to excessive effluent quality variations, was reported as main cause.

A closer look at the current operation of wastewater treatment plants learns that automation, while introduced in the late sixties (Buhr et al., 1974), can still be considered minimal. Few plants are equipped with more than some elementary sensing elements and control loops, mostly concerning flow metering and control. Since the early seventies, when a major leap forward was made by the widespread introduction of dissolved oxygen control, little progress has been made.
A number of reasons for this lack of instrumentation, control and automation (ICA) have been put forth (Buhr et al., 1974; Holmberg, 1982; Beck, 1986; Olsson, 1993):

- *Understanding:* Insight in the treatment processes is still insufficient
- *Inadequate instrumentation:* Non-existing or insufficiently reliable technology
- *Plant constraints:* Inapt and insufficient possibilities to act on the processes
- *Economic motivation:* There exists a lack of fundamental knowledge concerning benefits vs. costs of automated treatment processes. In addition, wastewater treatment processes are not productive and automation can only contribute to a decrease of operating costs but does not directly lead to increased profit
- *Education/Training:* Operators are not always adequately trained to operate advanced sensor and control equipment and most environmental engineers would need more basic understanding of process dynamics and control in order to appreciate the potential of ICA
- *Communication:* The interaction between operators, designers, equipment suppliers, researchers and government regulatory agents is often unsatisfactory and leads to poorly designed plants

It is worthwhile to confront these constraints with the potential benefits of the use of dynamic models and control systems as put forth by Andrews (1974) some 20 years ago:

- *Performance:* Maintaining plant efficiency nearer to its maximum by improved operation
- *Productivity:* Increasing the amount of waste that can be treated per unit process capacity
- *Reliability:* Decreasing the frequency of gross process failures with concommitant wastewater bypassing

- *Process Stability:* While appearingly highly stable processes, occasional upsets may have important consequences that could be avoided by increased process control
- *Operating Personnel:* Run plants with less skilled personnel or decrease time devoted to plant management
- *Operational Costs:* Reducing chemical and power consumption
- *Start-up Procedures:* Fastening of the start-up of treatment plants
- *Manual with Operational Guidelines:* making up procedures/control charts for manual operation that summarize the experience from the use of dynamic models
- *Dynamic Operation:* Improving performance by taking advantage of the process dynamics
- *Variable Efficiency Operation:* Integrating the dynamics of the receiving waters within the control of the treatment plant so as to match the assimilative capacity of the receiving waters

NEW DRIVING FORCES FOR INCREASED ICA

While the list of potential benefits given above still holds, the increased public awareness as reflected in more stringent regulations, has considerably increased the requirements imposed on treatment plants compared to the time this list was compiled. Not only the organic carbon pollution of a wastewater must be eliminated, but to this has been added the removal of nutrients (nitrogen and phosphorous). With biological nutrient removal being the most economic way of treatment in most cases, rather complex process configurations have resulted. The numerous interactions that occur among the different unit processes and the fact that the biological potential is taken to its limits make that nutrient removal plants are rather vulnerable to external disturbances or erroneous manipulations. Hence, the increased complexity is another driving force for the introduction of advanced instrumentation that can provide the necessary information on the process condition. Moreover, as process complexity increases more possibilities are required to act upon the process to guarantee satisfying treatment performance. Finally, the increasing number of measured and manipulable variables gives rise to more complex control systems that take advantage of the new possibilities.

A closely related driving force for the introduction of more ICA follows from the need to upgrade existing plants for handling increased loads or extension with nutrient removal capability. The alternative upgrade path via physical size increase (additional reactor volumes) is still preferred in many cases notwithstanding the considerably higher capital investments. Clearly, with a few exceptions (e.g. Aspegren et al., 1993), there is a lack of full-scale demonstrations of the potential of advanced ICA. Hence, designers remain rather conservative, maintaining large safety margins in the plants (Olsson, 1993). At the same time, however, too little flexibility and controllability is built into these plants which will be a set-back for future upgrades.

Finally, in some countries recent evolution of the legislation concerning surface or groundwater use is such that total recycling of process water has become an issue in certain industries, e.g. textile industry. Hence, the wastewater treatment becomes part of the production process and consequently, quality control of the effluent will be very important since failure of the treatment process may lead to important production losses. The very stringent effluent standards that will be imposed by the production processes in which the water reuse is taking place, will enforce the introduction of ICA in plant operation. Note that this new development means that wastewater treatment can no longer be regarded as non-profit.

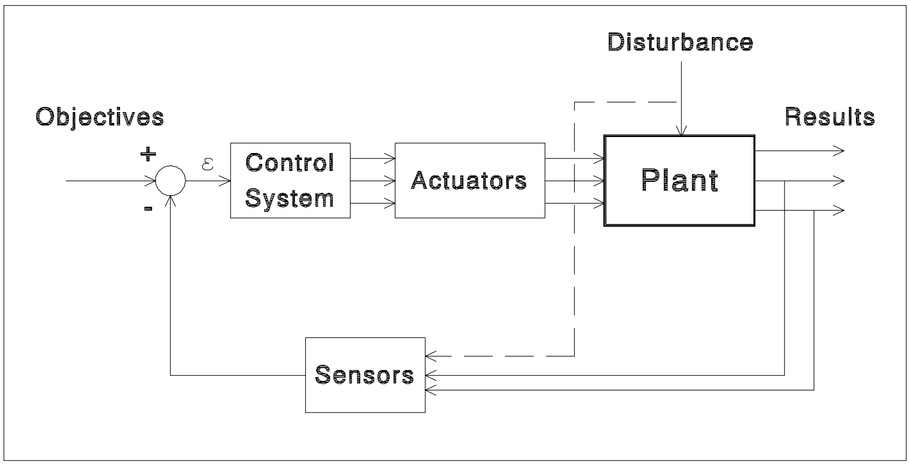

Figure 1. *Structure of the control chain of a wastewater treatment plant.*

CURRENT POTENTIAL AND PROBLEMS OF INCREASED ICA

The purpose of what follows is to give a concise overview of the insights that have been acquired during the last two decades with respect to ICA and the new possibilities for improved performance that they offer.

Control of wastewater treatment plants relies on four building blocks (Figure 1): 1) insight in the plant operation as summarized in a proper process model; 2) sensors that provide on-line data on some of the output variables of the process and disturbances acting upon it; 3) adequate control strategies which try to minimize deviations ε from the objectives and 4) actuators which implement the controller outputs on the plant.

Building Block 1: Process Models

The central building block of the control chain is the treatment process itself. Important is that one can dispose of an adequate mathematical description of process behaviour for the design of control algorithms. The different steps in model building and the current status of mathematical modelling of wastewater treatment processes is given below. First, however, the advantages of models in controller design are presented.

Use of models in control

Classical PID control systems assume that a second order process model is a sufficiently accurate description of plant behaviour. In order to tune the parameters of the controller, it is necessary to gain insights in the dynamics of the process. This information is typically obtained by experimentation on the real plant. However this may endanger process performance since important disturbances may be required to obtain the necessary data (Dunn et al., 1992). As an alternative one can use a reliable process model to simulate plant behaviour under a wide range of disturbances and concomitantly tune the controller (Vaccari et al., 1988, Heinzle et al., 1993).

More important, once process models are available the design of model-based control algorithms is possible. Since this type of controllers incorporates the process model into the control algorithm, the nonlinear nature of the bioprocesses can therefore be integrated within the control system and, as a result, improved control performance can be expected (Bastin & Dochain, 1990).

Another use for process models within the control chain stems from the lack of adequate sensor technology. As a result, a control algorithm may be deprived of such essential information as substrate concentrations or process parameters, e.g. mass transfer coefficients, growth rates. A methodology that is proposed to cope with this are the so-called "software sensors" which combine a mathematical description of the treatment plant with easily accessible measurements to estimate state variables and parameters which cannot be measured directly (Bastin & Dochain, 1990). The data produced by these software sensors are then used in the same manner as the other data to feed the control algorithm with the necessary information.

The model building exercise

The diagram of Figure 2 states the aspects and stages in model building. Three sources of information can be used to infer a model:

- *a priori knowledge:* general laws, principles and previous investigation
- e*xperimental data:* information obtained from experiments performed to study the underlying phenomena
- *goal:* information which is the result of requirements and specifications that have been set

Before a model can be applied, four steps have to be taken:

- *frame definition:* choice of the system boundaries, input and output variables, type of models considered (e.g. linear/nonlinear, input-output/state-space, ...)
- *structure characterization:* infer the level of model complexity (dimension of state vector, degrees of polynomials, ...) and determine the functional relationships between variables
- *parameter estimation:* find numerical values for the constants in the functional relationships
- *validation:* confront the resulting model performance with the purpose it was built for

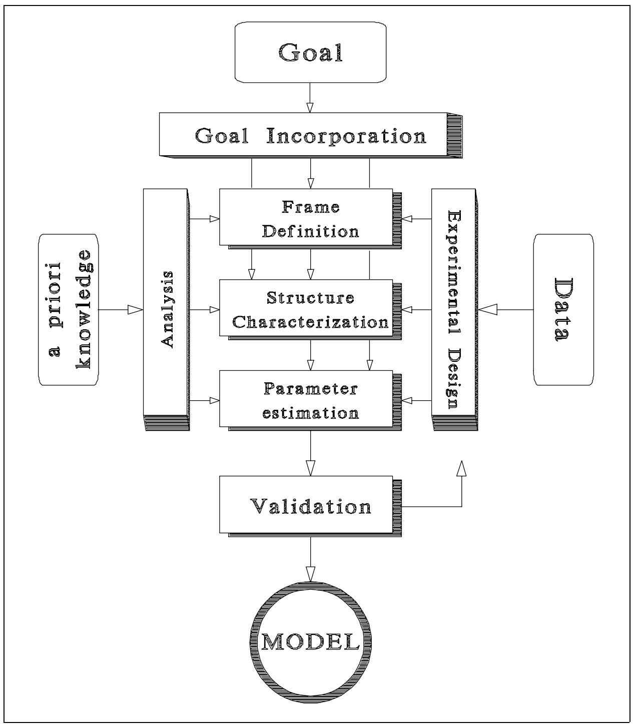

Figure 2. *Scheme of the modelling exercise (after Vansteenkiste & Spriet, 1982).*

For most physical and chemical applications, the a priori knowledge is of such high quality that the system framework and most of the model structure can be deduced from it. The modelling methodology developed for these systems is adequate to estimate the parameters and solve the minor uncertainties in the model structure by using final validation experiments and eventually iterating a small number of times through the procedure.

In contrast with this, the inherent characteristics of bioprocesses, i.e. their nonlinearity and nonstationarity, coupled with the lack of adequate measuring techniques, make that this mathematical modelling methodology cannot be applied without modification (Vansteenkiste & Spriet, 1982): more emphasis must be given to inductive reasoning to infer a larger part of the model structure from the scarce (or harder to obtain) experimental data. Consequently, structure characterization methods become a more important tool, because the chance of obtaining an invalid model is much larger and, hence, the number of modelling iterations may increase substantially.

The data scarcity also induces an important problem in the parameter estimation step. Identifiability of model parameters, i.e. the possibility to give a unique value to each parameter of a mathematical model, is a general concern in current wastewater treatment modelling efforts (Ayesa et al., 1993; Jeppsson & Olsson, 1993). This problem is however more pronounced in on-line identification because one is relying much more on real-time information to perform the parameter estimation whereas off-line model calibration can take more advantage of the off-line data.

Modelling: State of the art

In general two approaches can be discerned for the mathematical description of wastewater treatment processes (Beck, 1976):

- Black box (or input/output) models that describe the dependency of the system output y at time t_k on past and present inputs $u(t_i)$:

  $$y(t_k) = \frac{B(q)}{A(q)}\,u(t_k) \tag{1}$$

  where $A(q)$ and $B(q)$ are polynomials in the backward shift operator q, i.e.

  $$q^{-j}\Big(y(t_i)\Big) = y(t_{i-j}) \tag{2}$$

  $$A(q) = 1 + a_1\,q^{-1} + a_2\,q^{-2} + \ldots + a_n\,q^{-n} \tag{3}$$

  $$B(q) = b_0 + b_1\,q^{-1} + b_2\,q^{-2} + \ldots + b_m\,q^{-m} \tag{4}$$

  The a_i and b_i and the order of the polynomials n and m are to be determined from a set of input-output data.

  Time series models as the example given above have been developed for description of dynamic input-output relations between feeding pattern and anaerobic digester methane production rates, air flow rate and dissolved oxygen, flow rates and effluent suspended solids, carbon source dosage and denitrification rate, etc. (Beck, 1976; Berthouex et al., 1978; Novotny et al., 1992; Olsson, 1992). The essential feature of these models is that it assumes no knowledge of physical or internal relationships between the system's inputs and output other than that the inputs should produce observable responses in the output. Hence, the system is considered 'black box' and no use is made of the available a priori knowledge.

- Mechanistic models have found wider acceptance due to the possibility to incorporate the increasing a priori knowledge of the bioprocesses into these mathematical descriptions. The dynamics of the variables considered important for the adequate description of the process can be described by the following state-space model:

$$\frac{d\boldsymbol{x}}{dt} = A\,\boldsymbol{x} + B\,\boldsymbol{u} \tag{5}$$

and the output observations $\boldsymbol{y}$ are given by

$$\boldsymbol{y} = C\,\boldsymbol{x} \tag{6}$$

In this model A, B and C are matrices containing the characteristic (possibily time varying) parameters of the system, $\boldsymbol{u}$ is the vector of system inputs or forcing functions and the state vector $\boldsymbol{x}$ of the system contains such variables as the heterotrophic biomass, readily biodegradable substrate, volatile fatty acids, nitrate, etc.

The nonlinearities of the bioprocesses involved however ask for another representation than the linear one given above. A more general model for wastewater treatment processes is therefore:

$$\frac{d\boldsymbol{x}}{dt} = f\left(\boldsymbol{x}, \boldsymbol{u}, t, \theta\right) \tag{7}$$

$$\boldsymbol{y} = h\left(\boldsymbol{x}, t, \theta\right) \tag{8}$$

One can observe the nonlinear relations f and h between the state variables, inputs and outputs and the model parameters θ.

Since the early fifties when the first dynamic models were proposed (Goodman & Englande, 1974), the increasing insights have steadily been incorporated in the mathematical models of wastewater treatment processes. Lawrence and McCarty (1970) introduced the rather important nonlinear Monod relationship to describe the saturation of degradative capacity at high waste concentrations. The first structured models were presented by Andrews and coworkers (Busby & Andrews, 1975): biomass was structured in active, stored and inert compartments. The research efforts in South Africa to elucidate the effect of different wastewater fractions on treatment performance led to the structuring of substrates in the models (Dold et al., 1980). These insights and the increased interest in nutrient removal -in a first stage only nitrogen removal- eventually culminated in the IAWQ model n° 1 (Henze et al., 1987). Subsequently, important efforts have been made to model the complex mechanisms of biological phosphorous removal. While the IAWQ model n° 2 is being prepared, the model currently considered to be state-of-the-art is the nitrification-denitrification-biological enhanced phosphorous removal (NDBEPR) model of Wentzel et al. (1992). The state vector of this model contains 19 compounds and some 25 processes are included to describe the behaviour of heterotroph non-polyphosphate, autotroph and polyphosphate organisms under aerobic, anoxic and anaerobic conditions. The identification of this model is a tremendous task since no less than 19 kinetic and 24 stoichiometric parameters have to be identified to complete the model (Demuynck et al., 1993).

A remarkable parallellism in the timing of model developments can be found when reviewing the models of two other important unit processes of wastewater treatment plants, namely anaerobic digestion and final clarification.

For the sedimentation process the first models describing solid flux theory were presented in the late sixties (Dick & Young, 1972) and were based on the Kynch theory of flocculent suspensions (Kynch, 1952). The partial differential equations necessary to describe the phenomena have often been neglected in favour of empirical rules (Lech et al., 1978; Marsili-Libelli, 1989) or have been approximated by dividing the clarifier in a number of layers, typically 10, through which the suspended solids subside. Tracy and Keinath (1974) were the first to introduce this approach which has been adopted increasingly in the last few years (Laikari, 1989; Diehl et al., 1990; Ossenbruggen & McIntire, 1990; Takacs et al., 1991; Otterpohl & Freund, 1992). New developments in sedimentation modelling are mainly concerned with the numerical problems inherent to the proposed models (Diehl et al., 1990; Ossenbruggen & McIntire, 1990), the modelling of the gravity settling velocity of the suspension (Takacs et al., 1991) and the improved description of the clarification and compression processes (Takacs et al., 1991; Härtel & Pöpel, 1992; Otterpohl & Freund, 1992). While the layered models are already rather involved to treat, complexity increased even more when two-dimensional models were introduced (Krebs, 1991). Several hours of computation, even on supercomputers, are necessary to calculate concentration profiles for settlers in which not only vertical but also horizontal phenomena are described (Krebs, personal communication). Another difficulty with such 2D models is the increased need for experimental data for model calibration.

In anaerobic digestion, the structure and complexity of the models also followed developments in the level of understanding of the process at the microbiological level. For this type of wastewater treatment Andrews (1969) was again one of the pioneers in the mathematical modelling of the process. Soon the original model was extended with the interactions between volatile acids, pH, alkalinity, gas production rate and composition (Andrews, 1974). The structure of the model which defined these interactions formed the basis for many later models of the process. Structuring of anaerobic biomass in acid-forming and methanogenic bacterial groups was first introduced by Hill and Barth (1977). To accomodate the insights that the anaerobic degradation process could be described by the activity of acid-formers, acetogens, acetoclastic methanogens and hydrogen-utilizaing methanogens, Mosey (1983) formulated the four population model. Rozzi et al. (1985) combined the kinetic equations of Mosey with the mathematical description of the chemical and physical interactions of Andrews into a comprehensive model that can be regarded as the state of the art anaerobic digestion model. Costello et al. (1991) made an extension to include the reactions resulting in the possible accumulation of lactic acid in the system.

Research topics:

Current research in the area of process models is concerned with the following items (Henze et al., 1993; Olsson, 1993):

- *Incorporation of latest insights in the different processes:* important efforts are made to model 1) the phosphate removal processes as exemplified by the current preparation of the IAWQ model n° 2; 2) hydrolyisis of substrates; 3) the fate of biopolymers and 4) the sedimentation process with special emphasis on the interaction between the biological phenomena such as filament growth and the settling properties of the sludge,
- *Identifiability:* A discrepancy has grown between the amount of data needed to identify the increasingly complex models and the amount of information that can be obtained on behalf of

the process. Especially if only on-line data can be used for model identification, serious problems may occur in finding unique parameter estimates. Even combined on-line and off-line data may be insufficient for accurate modelling. Current research is therefore directed towards the development of new monitoring equipment and new off-line methodologies adapted to the information need of the new models (Vanrolleghem & Van Impe, 1992),

- *Verifiability:* The models that have been introduced recently are the result of considerable fundamental studies aimed at elucidating the mechanisms of certain microbial processes. In order to more precisely explain the detailed experimental findings, state variables and parameters have been introduced in the models which are not directly measurable, e.g. active heterotrophs (Ayesa et al., 1991, Jeppsson, 1993). Hence, since verification of a model requires that all model predictions of the states can be compared with experimental data, current models have become intrinsically unverifiable. Here too, new experimental methods are being studied to cope with this problem,
- *Model reduction for process control:* The identifiability and verifiability problems mentioned above ask for considerable efforts devoted to the development of new sensor technology and experimental methods so that the new process models can be used in adaptive model-based control systems. An alternative approach which attracts a lot of attention is directed at the reduction of the complexity of existing mechanistic models to such a level that on-line identification with existing technology is feasible, at the same time maintaining the necessary predictive capabilities of the major phenomena (Marsili-Libelli, 1989; Olsson, 1992; Jeppsson & Olsson, 1993).

Building Block 2: Monitoring Equipment

A comprehensive review of existing and new sensor technology was recently presented by Vanrolleghem and Verstraete (1993). Developments are many and increasingly sophisticated devices are proposed in an attempt to provide the necessary information on the complex processes needed to meet effluent standards. Table 1 summarizes the available sensor technology, the processes in which they can be implemented and the range of applicability, i.e. the extent to which they are considered proven technology.

Some new measuring principles have been introduced in recent years. To observe the metabolic state of the microorganisms the fluorescence of the intracellular NAD(P)H or F_{420} electron carriers is measured on-line. Practical experience with implementations of common measuring principles has allowed to improve their design and to promote the confidence in the sensors. A typical example are turbidimetric suspended solids meters that were on the market some 20 years ago (Buhr et al., 1974) but were not considered sufficiently reliable until recently.

Two significant trends in the recent developments of new on-line monitoring equipment are the application of ultrafiltration systems to bring automated wet chemistry methods to the plant on the one hand and the combination of robust, proven sensor technology with extended data interpretation on the other hand.

- *Ultrafiltration/wet chemistry:* Since the advent of reliable sample preparation units based on cross-flow UF modules in the last 5 years, a lot of efforts have been devoted to the automation of typical laboratory wet chemistry methods for on-line use. Typical applications include the analysis of the nutrients NH_4^+ , NO_3^- and PO_4^{3-}. The practical implementation of UF modules is illustrated in Figure 3.

Table 1. *On-line monitoring equipment for wastewater treatment processes (Vanrolleghem & Verstraete, 1993).*

Physical Measurements			Physico-Chemical Measurements			(Bio-)Chemical Measurements		
Variable	Applicability[1]	Process[2]	Variable	Applicability	Process	Variable	Applicability	Process
Temperature	G	∀	pH	G	∀	Respiration Rate	2,3	∀
Pressure	G	∀	Conductivity	G	∀	stBOD[4]	2,3	∀
Liquid Level	G	∀	Oxygen			Toxicity	2,3	∀
Flow Rates			- Liquid	2,3	∀	Sludge Activity	2,3	∀
- Liquid	G	∀	- Gas	2,3	∀	COD	1,2,3	O
- Gas	1,2,3	∀	Digester Gas			TOC	1,2,3	O
Suspended Solids			- CH_4	1	∀	$NH4^+$	3	∃
- 0.0 - 0.1 g/l	4	∃	- H_2S	1	∀	NO_3^-	3	∃
- 1.0 - 10.0 g/l	1,2,3	∃	- H_2	1	∀	PO_4^{3-}	3	∃
- 10.0 -100.0 g/l	4	∃	CO_2	1,2,3	∀	Bicarbonate	1,3	O
Sludge Blanket	4	∃	Fluorescence			Volatile Fatty Acids	1,3	O
Sludge Volume	4	∃	- NAD(P)H	2,3	∃			
Settling Velocity	4	O	- F_{420}	1	O			
Sludge Morphology	G	O	Redox	1,3	∀			
Heat Generation	1,2,3	O	NH_4^+ (ISE[3])	3	∃			
UV absorption	G	∃	NO_3^-					
			- ISE	3	O			
			- UV absorbance	3	∃			

[1]Applicability Range: ∀ : State of Technology; ∃ Applicable in certain cases: ;
O : Requires development work

[2]Process: Unit process in the wastewater treatment plant where the sensor can be implemented:
1: Anaerobic Digestion; 2: Activated Sludge; 3: Nutrient Removal; 4: Sedimentation; G: All

[3]ISE: Ion selective electrode

[4]stBOD: short term biochemical oxygen demand

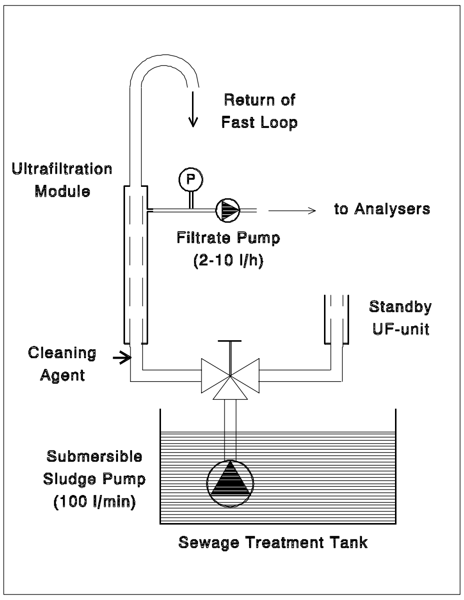

Figure 3. *Diagram of a typical ultrafiltration module with cleaning procedure and standby unit.*

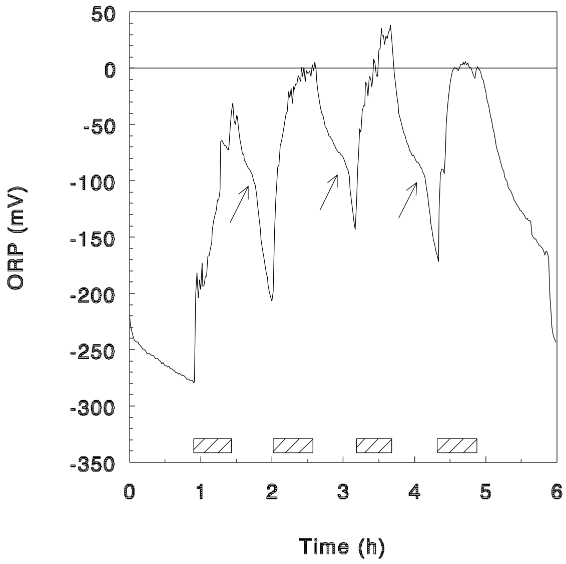

Figure 4. *Nitrate knees (indicated by the arrows) in an intermittently aerated nutrient removal plant (hatched boxes indicate aerated periods).*

- *Robust sensors/advanced interpretation:* Some sensors like dissolved oxygen, pH and redox electrodes have proven their robustness, reliability and limited demand for maintenance. Recent efforts have therefore been directed towards the extraction of as much information as possible from the primary data these sensors provide. The approach taken is to combine process knowledge with these data to produce upgraded information.

  Two simple examples of the coupling between robust sensors and process knowledge are given in Figures 4 and 5. The dynamics of the redox potential contain the necessary information to detect the disappearance of nitrate under denitrifying conditions: in Figure 4 typical "nitrate knees" can be observed during the unaerated periods reflecting the complete removal of the nitrate that was formed during the previous aerated period.
  As another example the potential of interpretation of the dissolved oxygen (DO) data is illustrated. The fast dynamics of the DO in Figure 5 are due to the type of controller used, i.e. an on/off control with dead-band. The decrease in frequency of switching the aeration on and off can be used as a measure of the oxygen demand. With the upgraded information, it is possible to detect the time when the oxygen consumption drops to the endogenous level and hence, when nitrification is completed. Alternatively, the oxygen uptake rate can readily be calculated from the DO data during the unaerated period, providing a direct measure of metabolic activity.
  The examples given illustrate the potential of this approach in providing information concerning nitrification and denitrification processes, allowing the development of more advanced control strategies (Demuynck et al., 1993).

  The combination of robust sensor and mathematical model is termed "software sensor", "observer" (if variables are calculated) or "estimator" (if model parameters are estimated) (Bastin & Dochain, 1990). The more advanced software sensors incorporate the process model as an essential element and are designed in different ways. Some currently available design methods are given below.

  Taking Eq. 5 as the process model, the basic concept of a state observer can be illustrated. On-line estimates of the states $\hat{x}$ are obtained from the following observer equation in which a

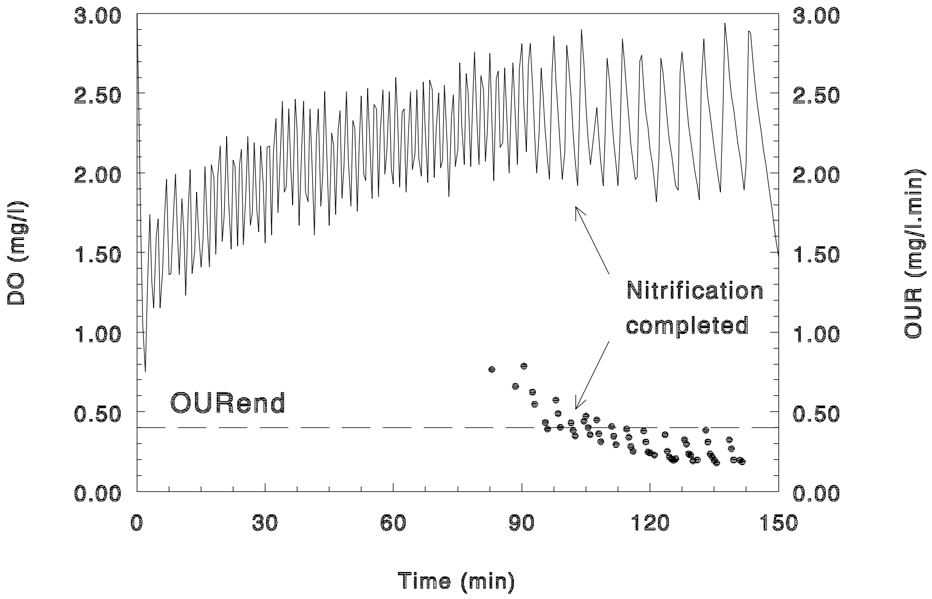

Figure 5. *Dissolved oxygen (lines) and deduced oxygen uptake rate (symbols) profiles in a sequencing batch reactor with on/off DO control with dead-band. Completion of nitrification is indicated (Demuynck et al., 1993)* .

driving term is included aimed at minimizing the "observation error" between measured values $\boldsymbol{y}$ and model predictions $\hat{\boldsymbol{y}} = C\,\hat{\boldsymbol{x}}$:

$$\frac{d\hat{\boldsymbol{x}}}{dt} = A\,\hat{\boldsymbol{x}} + B\,\boldsymbol{u} + K\,(\boldsymbol{y} - \hat{\boldsymbol{y}}) \qquad (9)$$

Estimates of the states are therefore obtained by simply integrating Eq. 9 on the supervisory computer on the basis of the experimental data. Remark that it is assumed in this example that all parameters, A, B and C and the input $\boldsymbol{u}$ are known. The design of the observer reduces to the adequate choice of the matrix K, known as the "gain matrix". The two approaches that have become standard, i.e. the Luenberger and Kalman observers, both start from the desire to minimize the observation error e. The dynamics of the observation error are readily obtained by subtracting the observer equation (9) from the process model (5):

$$\frac{de}{dt} = \frac{d\,(\boldsymbol{x} - \hat{\boldsymbol{x}})}{dt} = A\,(\boldsymbol{x} - \hat{\boldsymbol{x}}) - K\,C\,(\boldsymbol{x} - \hat{\boldsymbol{x}})$$

$$\frac{de}{dt} = \left[\,A - K\,C\,\right] e \qquad (10)$$

The aim is now reduced to the problem of designing the gain matrix in such a way that the observation error decreases in a desirable way. In the case of Luenberger observers, the eigenvalues of *[A-KC]* and, hence, the elements of K are chosen in a rather heuristic way, taking into account some constraints to guarantee stability and convergence (Bastin & Dochain, 1990). The gain matrix of Kalman observers on the other hand is the solution of a quadratic optimization problem where the mean square observation error is minimized. The solution considers knowledge of measuring errors as summarized in the covariance matrix. The expressions of the Kalman observer can be found in numerous works, e.g. Stephanopoulos and Park (1991). The multirate Kalman Filter is an interesting extension for bioprocesses since it allows to accomodate the use of a combination of sensors with multiple sampling rates (Gudi & Shah, 1993).

The design of state observers as given below holds for linear models like the one of Eq. 5. For the nonlinear models, as found for many biological systems, approximate observers have been proposed. These so-called extended Kalman (EKF) and Luenberger filters are based on linearization of the nonlinear model of Eq. 7 into the formalism of Eq. 5, for instance:

$$A(\hat{\boldsymbol{x}}) = \left[\frac{\partial f(\boldsymbol{x})}{\partial x}\right]_{\boldsymbol{x}=\hat{\boldsymbol{x}}} \qquad C(\hat{\boldsymbol{x}}) = \left[\frac{\partial h(\boldsymbol{x})}{\partial x}\right]_{\boldsymbol{x}=\hat{\boldsymbol{x}}} \tag{11}$$

The gain matrix is designed in a similar way as in the linear case (Jones et al., 1989; Bastin & Dochain, 1990; Stephanopoulos & Park, 1991).

The second type of software sensors are the parameter estimators. A number of techniques have been proposed to incorporate the process model as well.
In the "observer-based parameter estimator", the model (with the unknown parameters) is used to predict the states which are compared with the measured states. Subsequently this observation error, which is considered to reflect the mismatch between the true parameter values and the estimates, is used as the driving force in a parameter update model (Bastin & Dochain, 1990). In addition to the observer gain, the user must also supply the gain matrix of the parameter updating law.
A second approach consists of rewriting the process model in a linear form from which the parameters are readily estimated (Bastin & Dochain, 1990). This algorithm can be transformed into a standard recursive least squares algorithm for on-line use. A number of user supplied tuning parameters must be chosen, typically by trial and error. Rather important is the forgetting factor. Conceptually it determines the amount of old information retained for parameter estimation. Improper choice of this factor may lead to identifiability problems if the dynamics of the process are insufficient to provide the necessary richness of information. When the data horizon is too small it may occur that only steady-state process behaviour is observed, with the result that some parameters are unidentifiable. This may lead to considerable problems known as covariance blow up or parameter burst (Gendron et al., 1993; Yung & Man, 1993). When the forgetting factor is set to one, all collected data is retained for parameter estimation. Hence, a new observation will have a diminishing contribution on the update of the parameters. On-line variation of the forgetting factor by a recursive algorithm has been presented by Yung and Man (1993) as an elegant solution to these problems.
Extended Kalman filters have also been applied for parameter estimation. The basic idea is to consider the unknown parameter as an additional state behaving with unknown dynamics. Unless the parameter estimates are well initialized, problems of divergence and biased estimates can be expected (Bastin & Dochain, 1990).

The dual problem of estimating both unmeasurable states and parameters is a matter of intense research. Such software sensors have been termed adaptive observers because they are state observers which are adaptive by introduction of a parameter updating law. Extended Luenberger and Kalman adaptive observers have been proposed. Properties and tuning prerequisites are a combination of the characteristics of the parameter estimator and state observer algorithms.
The divergence and stability problems noticed when dealing with an EKF for parameter estimation have led to the Sequential State/Parameter Estimation (SSPE) algorithm (Stephanopoulos & Park, 1991). In SSPE the advantages of the EKF for state observation is combined with an independent parameter estimator with desirable properties. The operation of this

software sensor is as follows: first, the parameter vector is determined so as to minimize prediction errors and, subsequently, the states are estimated on the basis of the measurements and the updated model. Stephanopoulos and Park (1991) also adressed the problems of the proper choice of forgetting factors to maintain the desired convergence and tracking capabilities of the parameter update algorithm.

Research topics

Main emphasis in current research is given to the following topics (Henze et al., 1993; Olsson, 1993):

- *Development of new measuring principles*: Optic techniques to determine chemical composition of influents and effluents are a main research topic, another being the development of techniques that measure biological characteristics such as metabolic activity (respirometry) or biomass morphology (image analysis).
- *Improvement of the reliability* of sensors by incorporation of automated cleaning systems, auto-calibration and autodiagnosis,
- *Decrease of the maintenance requirements* by adapting the design to deal with the harsh conditions the sensors have to operate in,
- *Increase of the information content* of the data by combination of proven sensor technology with new process insights. It is studied how the advances in modelling methodology can be incorporated in the design of new software sensors,

Building Block 3: Actuators

A relatively limited choice of control actions exists in wastewater treatment processes. Confronting the list of manipulable variables presented 20 years ago (Buhr et al., 1974) with current practice (Table 2) shows that the possibilities have not increased although the complexity of the processes has increased significantly.

Table 2. *Variables available for manipulation of a wastewater treatment process.*

Manipulable Variable	Process	Applicability
Bypass/Overflow	1,2,3	∀
Equalization/Buffering/Calamity Basin	1,2,3	∃
Feeding Point/Step Feed	2,3	∃
Aeration Intensity	2,3	∀
External Carbon Source	3	∃
Internal Recycle Flow Rates	1,3	∀
Chemical Dosage	1,3,4	∃
Return Sludge Flow Rate	G	∀
Waste Sludge Flow Rate	G	∀
Sludge Storage	G	∃

Some advances have been made in the area of chemical additions. As an example new polyelectrolytes and filament burning agents (peroxide) have been introduced to improve settling properties (Switzenbaum et al., 1992). With respect to nutrient removal systems, chemical dosage of phosphorous precipitants and external carbon sources for increased denitrification capacity have reached widespread full-scale application (Wedi & Niedermeyer, 1992; Aspegren et al., 1993; Lötter & Pitman, 1993).

Research topics

New possibilities to act upon the wastewater treatment processes are mainly situated in the area of a more pronounced integration of all systems from the sewer to the receiving water (Henze et al., 1993; Olsson, 1993).

- *Sewer system:* While currently almost no integration of operation exists between the sewer systems and the wastewater treament plants, new possibilities are being studied, for instance in storm water flow management by manipulating pumping stations on the basis of rainfall forecasts from weather radar images (Aspegren et al., 1993). Dynamic sewer operation can be used to buffer the loading of the plant to a higher extent than achievable with installed equalization basins. Sewer operation has to consider how much load the plant can receive and bypass decisions have to be made, based on on-line calculations both in the sewer and treatment plant (Lijklema et al., 1993).
- *Sludge treatment effluents:* Recycle streams from sludge treatment may contain high nitrogen and phosphate loads. Manipulation of the recycle flows is central to overall plant management and enables the optimum use of available treatment capacity, e.g. by buffering sludge treatment effluents in highly loaded periods (Grulois et al., 1993). Another potential use of the sludge treatment facilities in control of the wastewater treatment process is the application of hydrolysed sludge as a carbon source for denitrification (Kristensen et al., 1992).

Building Block 4: Control Systems

Control strategies currently employed in wastewater treatment processes are mainly conventional controllers such as on-off and PID-type feedback control systems. While feedforward control has found some applications, other advanced control strategies, adaptive control systems in particular, have been evaluated only at pilot-scale and in a few full-scale installations for limited periods. As far as known, no regular use is made of the latter control systems in full scale treatment plants. The obstacles to be overcome by control systems are considerable, however:

- Large disturbances in influent flow, load and composition (toxicity),
- Adaptation of the sludge, making the process time varying,
- Although the available sensors and actuators are limited, multiple-input multiple-output (MIMO) systems should be considered.

The following section will revise some advances made in recent years and address some open questions.

Conventional feedback control

Although optimal control performance cannot be expected from conventional PID or on-off controllers for the timevarying, nonlinear processes considered, their widespread use in industry and the resulting familiarity with their properties and concepts for design, have made that these regulators are the most widely applied in wastewater treatment processes and this already for a long time (Andrews, 1974; Marsili-Libelli, 1989; Heinzle et al., 1993). Such controllers essentially calculate a control action on the basis of a process output which is continuously compared with a desired value or setpoint (Dunn et al. 1992). In a PID-controller the error ε between actual and desired value is used in the following way to produce the controller output:

$$u(t) = K_p \left[\varepsilon(t) + \frac{1}{\tau_i} \int_0^t \varepsilon(\sigma)\, d\sigma + \tau_d \frac{d\varepsilon(t)}{dt} \right] \quad (12)$$

The three coefficients K_p, τ_i and τ_d are weights given to the proportional, integral and derivative action respectively and must be tuned for optimum performance of the regulator. To this end either experiments on the plant must be performed or, alternatively, simulations with an accurate process model can be used (Vaccari et al., 1988; Dunn et al., 1992; Marsili-Libelli, 1992; Heinzle et al, 1993). These values depend on the process characteristics and are therefore subject to change in the nonstationary case. Moreover, since PID controllers assume a second order process model, any deviation of plant behaviour from this process model must be compensated by adaptation of the control parameters. The self-tuning PID regulators that have been developed are discussed below.

Another important remark is that while multiple inputs and outputs should be considered for the description and control of the process, the wide span of response times (time constants range from minutes to days) makes it possible to decouple many unit processes (Olsson, 1992; Lessard & Beck, 1993). Hence, separate local controllers of the conventional type can provide reasonable control performance, explaining why such SISO (single input/single output) controllers have been succesful in wastewater treatment. For instance, the fast dynamics of the dissolved oxygen concentration can be controlled independently of the control of the sludge concentration or sludge age.

Optimal control

While experimentation is required for the tuning of the abovementioned regulators, either on the plant itself or within a simulation environment, design techniques have been developed that allow to devise the optimal controller for a particular process model and performance index. Certain constraints imposed on the control action, such as a minimization of the control effort, can be accomodated during design.

In case linear (or linearized) models are considered, optimal feedback controller design has become a generally accepted technique (Marsili-Libelli, 1989). Linearization around the desired operating point was used by Fan et al. (1973) to derive an (approximative) optimal feedback control of the flow rate on the basis of effluent substrate concentration measurements. Other examples for sludge recycle and dissolved oxygen control are reported in Marsili-Libelli (1989).

For nonlinear models, only a few results of an analytical solution of the optimal control law have been published (d’Ans et al., 1971). Most results, however, have been obtained by numerical solution of the optimization problem (Sincic & Bailey, 1978; Yeung et al., 1980; Marsili-Libelli, 1982; Kabouris et al., 1992; Demuynck et al., 1993).

Problems with some of the resulting control strategies are that they are not stated as a closed-loop solution and rely on the (unrealistic) assumption of a perfect process model with fixed model structure and parameters. The results of von Jeszensky and Dunn (1976) and Yeung et al. (1980) are well-known examples of the dependency of optimal control actions on the model structure. In view of the uncertainty on the correct model and the inherent nonstationarity of the process, it is advisable to be cautious with the implementation of such control systems. However, as has been shown in Van Impe

et al. (1992) the theoretical results may indicate some process features, e.g. an optimal operating point, that could have remained unnoticed if the exercise wouldn't have been done. Results as these may lead to so-called heuristic control laws that exploit such an operating point for instance. These control laws may be less sensitive to deviations of process behaviour and may therefore give reliable control performance.
Another useful result of such optimization studies is that models can be put into jeopardy, in other words, the models are strained to their limits (Boyle & Berthouex, 1974). Model inadequacies or differences in model behaviour may stand out and, with these new insights in model behaviour, specific experiments may be designed to discriminate between the candidate models.

Advanced control

The potential of advanced control systems has been claimed for a long time, but so far only a few advanced control laws have been applied in full-scale wastewater treatment plants. Control strategies that have been studied rather well are feedforward and ratio controllers, linear and nonlinear adaptive control laws, and MIMO control systems. Recently, intensive research is going on in the field of neural net and fuzzy control. These different research themes and the potential of the resulting techniques are reviewed below.

- *Feedforward and ratio control:* One of the disadvantages of feedback control is that an error must exist before any control action is exerted. This can be a serious disadvantage for processes with a slow response to changes because considerable time may elapse before the change is detected. An extreme example is the effect of a toxic pulse where feedback action may be initiated when the plant is already down. While modifications of the traditional feedback controllers exist in which significant dead time can be compensated, their effectiveness and stability depend to a large extent on the exact knowledge of the dead time and process model (Stephanopoulos, 1984; Gendron et al., 1993).
  In feedforward control laws, on the contrary, the disturbance is measured directly and the controller tries to anticipate the effect it will have on the process output. A disadvantage of feedforward controllers, similar to the drawback of a dead time compensation solution, is the sensitivity to modelling errors. Uncertainty in the process model will therefore probably necessitate a feedback controller to adjust feedforward action (von Jeszenszky & Dunn, 1976). Ratio control is a special case of feedforward control in which a control variable is maintained proportional to a measured input value. An early example of ratio control is the strategy in which the sludge recycle flow rate is maintained proportional to the influent flow rate (Brett et al., 1973; Andrews, 1974).
- *MIMO control systems:* As mentioned above, the large differences in time constants of the different unit processes allow to decouple their control to a certain extent. Still, performance improvements can be expected by considering the MIMO nature of the process during controller design. One of the problems of designing MIMO controllers is that the number of feasible, alternative configurations of control loops can be very high (Stephanopoulos, 1984). Also, interactions between control loops may lead to instability of the controlled system (Lech et al., 1978). Minimization or complete elimination of the interaction between loops is the goal of different design techniques that have been proposed (Stephanopoulos, 1984).
- *Control of nonlinear processes:* The standard methodology to design control systems for nonlinear processes consists of linearizing the process model around a certain operating point and then

design a linear controller for this approximate model. While controller design is much facilitated in this way, actual closed loop behaviour will remain nonlinear. Hence, one can only guarantee stability in the neighbourhood of the operating point where the approximation was made. In an alternative design technique, termed linearizing control, a nonlinear controller is devised which is precisely designed so as to achieve linear closed loop behaviour for all operating points considered by the nonlinear process model (Ko et al., 1982; Bastin & Dochain, 1990).

The design procedure is as follows. Consider a nonlinear process model with one input and measurements or estimates of all states:

$$\frac{d\boldsymbol{x}}{dt} = f\left(\boldsymbol{x}, t, \theta\right) + b\,u \tag{13}$$

Suppose that the aim is to track a certain reference behaviour $\boldsymbol{x}^*(t)$, then a control law is to be devised for manipulation of u. To impose linear behaviour of the closed loop system, a stable linear reference model is imposed on the tracking error $\varepsilon = (\boldsymbol{x} - \boldsymbol{x}^*)$:

$$\frac{d\varepsilon}{dt} = -\lambda\varepsilon \tag{14}$$

Rewriting this in $\boldsymbol{x}$ gives:

$$\frac{d\boldsymbol{x}}{dt} = -\lambda(\boldsymbol{x} - \boldsymbol{x}^*) + \frac{d\boldsymbol{x}^*}{dt} \tag{15}$$

The linearizing control law is obtained by elimination of $\frac{d\boldsymbol{x}}{dt}$ between (13) and (15), yielding:

$$u = \frac{-\lambda(\boldsymbol{x} - \boldsymbol{x}^*) + \frac{d\boldsymbol{x}^*}{dt} - f(\boldsymbol{x}, t, \theta)}{b} \tag{16}$$

One should remark that the nonlinear process model f is incorporated into the control law. The extension of linearizing control towards MIMO models was presented by Dochain (1991).

- *Adaptive Control:* Since the early sixties (Elgerd, 1967) one of the most intense fields of research in control theory is the development of adaptive regulators. Adaptation of the controller may be necessary for two reasons. First, the linearized models used to design a controller depend on the operating point where linearization took place. Hence, if an operating point moves away from the design point, the controller's parameters need ajustment so as to maintain optimal performance in the new operating conditions.
  A second need for adaptation of the control law is due to the inherent nonstationarity of processes like the biotechnological systems considered in this work. Since the regulators are designed on the basis of nominal values of the process model, the need exists to adapt the controller's parameters.

Before adaptive control systems are discussed in some more detail, it is worthwhile to mention a more recent, alternative approach to deal with systems with time-varying or uncertain dynamics. In this methodology, model uncertainty is taken into account and fixed, linear time-invariant robust designs are used that are based on the minimization of the infinite-norm of a sensitivity function, hence the term H^∞ or robust control theory. A main disadvantage of these control systems is that their performance in terms of conventional performance criteria is

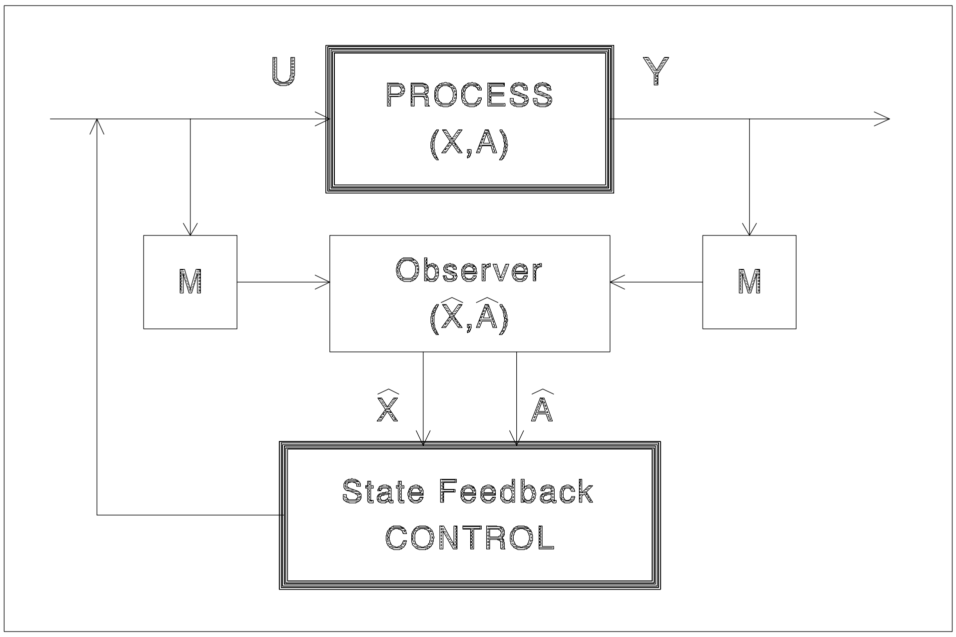

Figure 6. *Adaptive control loop with on-line state and parameter estimation (M: measuring device, X: State, A: System dynamics, U: input, Y: output).*

sacrificed to ensure robustness (Gendron et al., 1993).
Within this research field two schools of thought have grown on the way model uncertainty should be described (Goodwin et al., 1992). The hard bounding approach considers worst case behaviour, leading to overly conservative error bounds on the models and considering in fact that all values, even the worst cases, are as likely as the others. In the soft bounding school, stochastic distributions of the modelling errors are considered, leading to confidence regions of the process behaviour rather than hard bounds. Hence, in this approach an engineering tradeoff is sought between uncertainty and performance.

While in the approach mentioned above, a fixed controller is designed based on a fixed model, adaptive control systems on the other hand, will introduce a time-varying control system whose parameters are updated as process behaviour changes, for instance by a change of operating point or by the inherent time-variancy of the process characteristics. In an adaptive control loop three functions must be performed (Elgerd, 1967): 1) Identification of plant dynamics, 2) Decision on the proper control strategy and 3) Adjustment of the controller parameters.
In the case of the linearizing control mentioned above, adaptivity is simply introduced by replacing the model parameters θ in the control law (16) by their estimates obtained from an on-line parameter estimator. The resulting control scheme is schematized in Figure 6. Applications of adaptive linearizing control have been presented for anaerobic digestion and activated sludge systems (Renard et al., 1988; Dochain & Perrier, 1992).

An adaptive modification of the conventional PID controller, the self-tuning regulator (Figure 7), has found widespread application in the process industry, but, so far only some examples have been reported in wastewater treatment processes (Marsili-Libelli, 1978; Olsson et al., 1985; Marsili-Libelli, 1990). The adaptation of the PID parameters is essentially based on the on-line identification of a simple linear model that gives a local description of process dynamics. From this model, the optimal controller parameters are readily calculated using one or another control design criterion (Stephanopoulos, 1984). One should remark the three components in the

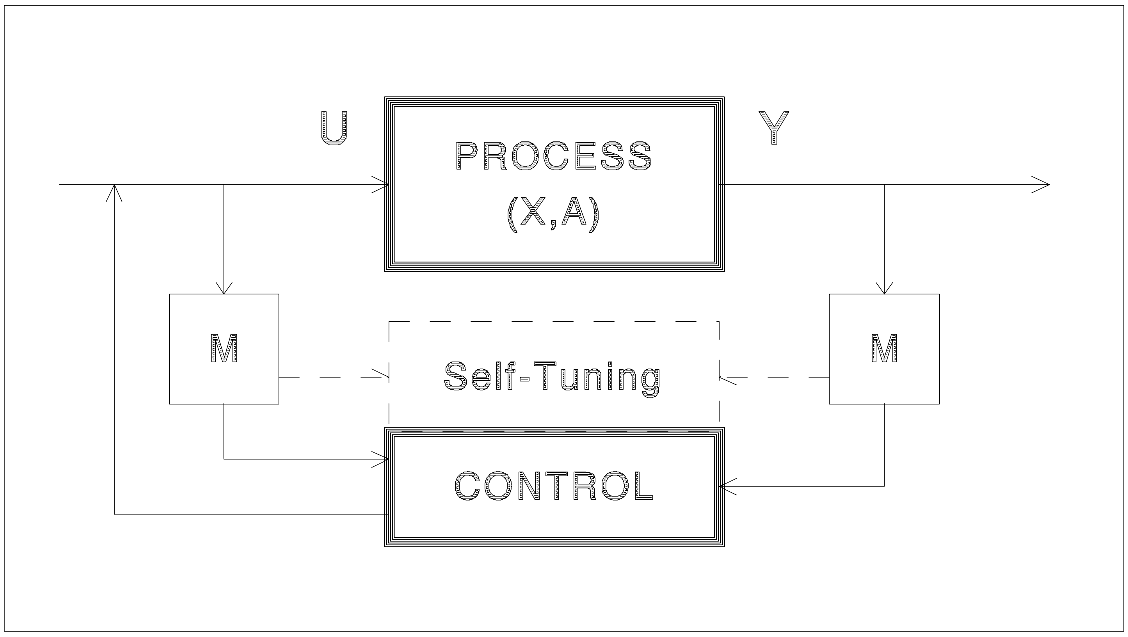

Figure 7. *Self-tuning regulator.*

adaptation procedure as mentioned above. A well studied application of self-tuning PID regulators is the control of dissolved oxygen in activated sludge plants. Such controllers have been shown to be able to deal with changes in mass transfer efficiencies and important variations in oxygen demand (Olsson et al., 1985; Marsili-Libelli, 1990).

An important problem with adaptive control systems is the necessity for on-line identification of the process model while the plant is in closed-loop operation. To illustrate the nature of this problem, the example of Figure 8 is given. Suppose one wants to control the substrate concentration in an activated sludge aeration tank. In a process model, the degradation kinetics can take different functional forms. In this example the dependence of the degradation rate on the substrate concentration is considered to be either according to the Monod or Haldane kinetic laws. However, if the plant is well controlled, it may be that measured substrate concentrations

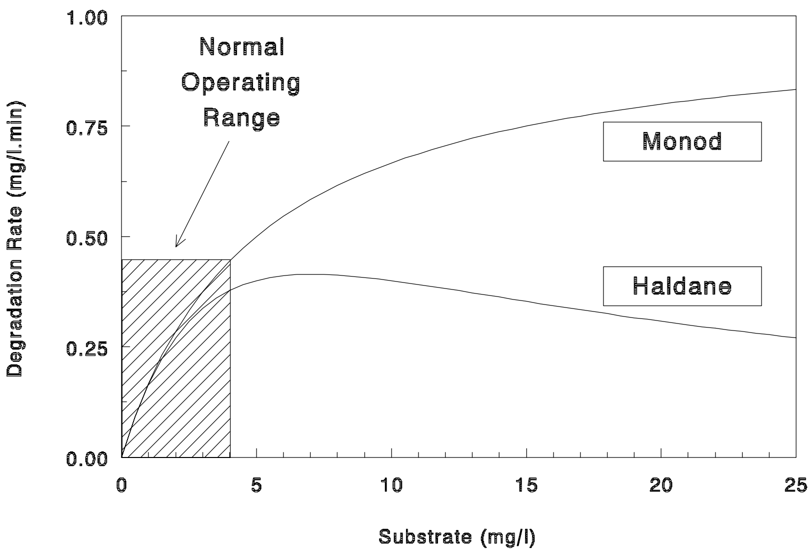

Figure 8. *Closed-loop identifiability problem when considering Haldane or Monod descriptions for substrate degradation kinetics.*

range only between 1 and 4 mg/l. With such (noisy) measurements it will hardly be possible to make a decision on the correct model. Hence, if an important disturbance affects the plant such that the substrate concentration rises above the normal concentration range, a suboptimal controller action may result because the wrong model was identified. Clearly, the substrate concentration range over which data are available should be extended to the range needed for proper identification.

This simple example illustrates that a conflict arises between control performance, which should result in very smooth operation, and need for informative data on the process for model identification, which requires sufficient variations in the measured variables. These contrasting requirements can, however, be reconciled if a probing or excitation signal is superimposed on the control action (Box & MacGregor, 1974; Aström & Hägglund, 1984; Partanen & Bitmead, 1993). Examples of this solution are found in adaptive control designs for the dissolved oxygen concentration (Holmberg, 1982; Howell & Sodipo, 1985; Holmberg et al., 1989; Marsili-Libelli, 1990; Vanrolleghem & Verstraete, 1993).

Another approach to deal with the identification problem is to include special numerical procedures, such as time-varying forgetting factors that make sure that sufficient information is retained to allow reliable estimation of model parameters (Shah & Cluett, 1991; Yung & Man, 1993).

Certain identification problems cannot be solved in this way, for instance, the estimation of dead-times in a model (Gendron et al., 1993). A novel approach consists of considering that the process model belongs to a bounded class of possible models with fixed parameters. The identification is then reduced to the choice of the correct model, or, as in the Model Weighting Adaptive Control (MWAC) approach (Gendron et al., 1993), by weighting the different models into a composite process model. Hence, the identification is simplified as only the weights need to be estimated. Weighting can be performed on the basis of the probabilities that a certain model is the true model, for instance by consideration of their respective prediction errors. The resulting identified model is then used to adjust the parameters of the adaptive controller. Gendron et al. (1993) confront this approach with the older multi-model adaptive control approach (MMAC) (Lainiotis, 1976; Athans et al., 1977). In MMAC, a number of N models, each with corresponding Kalman filters and optimal controllers are run in parallel. For each model the probability is calculated that it is a correct model. The probabilities are subsequently used to bind the control actions of the N controllers to form the control action that is applied to the process.

Neural and Fuzzy control

Application of neural networks and fuzzy logic is a recent but very intense research area. Both approaches are fit to deal with ill-defined systems, for instance, the nonlinear time-varying biotechno - logical processes considered in this work.

Neural networks are based on a black box approach, but in contrast to time series analysis, the internal structure of neural nets is adapted to nonlinear systems. An essential characteristic of the use of neural nets is the learning stage that precedes the application. During this stage, examples of desired behaviour are applied to the net and with a learning algorithm the parameters of the network are adjusted. Once trained, neural nets can be applied for different tasks, such as process control (Miller et al., 1990; Hunt et al., 1992). In a neural net for a control application, the inputs to the network consist of measurements of the process. A control action is then obtained as the network output. The neural net is previously being trained with measurement/desired output learning data. Adaptive neural nets can also be proposed, i.e. by initiating a renewed training. While neural control is being used in other applications and has been evaluated in biotechnological applications (Thibault & Van Breusegem, 1991; Chtourou et al., 1993), it has, as far as known, not been implemented in wastewater treatment plants yet. However, other applications are studied. For instance Tyagi and Du (1992) applied a neural net for operational prediction. Increasing attention is given to neural nets as pattern recognizers (Capodaglio et al., 1991). Vermeersch et al. (1992) proposed to use a neural net to differentiate among candidate bioprocess models on the basis of characteristic features contained in data records.

Fuzzy sets are a means of representing qualitative knowledge ("good", "much", "small") in mathematical terms. In view of the considerable uncertainty which surround wastewater treatment processes, it is not surprising that this methodology has also found widespread and increasing attention. These last few years an increasing number of applications have been studied and the first experimental results are presented in the literature. Fuzzy control systems have been designed for the different unit processes of wastewater treatment, e.g. controlling the influent pumping rate in a sewer system (Fukano, 1993), anaerobic digestion regulation (Boscolo et al., 1993), ammonium control in a combined nitrification/denitrification reactor (Aoi et al., 1992), the supervision of local PID controllers in an activated sludge process (Couillard & Zhu, 1992) and the recycle flow rate of a final clarifier (Marsili-Libelli, 1992).

Research topics

Current research is mainly concerned with:

- The study of the interaction between on-line model identification and adaptive control. Optimal choice of the excitation signals needed for on-line identification is one of the topics of interest. In addition, the influence of plant design on the quality of measured data is investigated. For example, treatment plants characterized by alternating operation or sequencing batch reactors have a clear edge in information quality due to their inherently dynamic operation.
- Another problem gaining a lot of attention is the improvement of the control system while the plant is in closed-loop operation. Different design methods have recently evolved in which successive iterations of closed-loop model identification and controller design are conducted. Problems currently adressed are the search for guaranteed closed loop stability during subsequent iterations, reduction of model and controller complexity, convergence rate of the design methodology and optimal experimental design procedures (Bitmead, 1993)
- New applications of fuzzy control and neural networks are proposed and validation of the theoretical results is emphasized in current studies
- From the theoretical point of view, main attention is focussed on the development of design techniques for robust control. The interaction with model identification receives fundamental study
- Hierarchical control systems have been developed in the past but are increasingly applied. Hierarchical or multi-level control consists of a set of local controllers that each act on a specific unit process, e.g. dissolved oxygen or sludge blanket control, and a supervisory control system which provides the setpoints for the local controllers in order to guarantee optimal performance of the whole plant

CONCLUSIONS

In this paper the current state of process control in wastewater treatment plants was reviewed. The four building blocks of a control loop were considered, i.e. process modelling, sensor technology, actuators and control laws.

Current research in these four areas was summarized. It was indicated that attention was mainly focussed at keeping up with the progress in understanding of the biological processes occurring in current treatment plants.

It is evident from the discussion that the nonlinear and time-varying nature of these systems strains current system theoretical insights to their limits and stimulates research in the different areas. These efforts will eventually culminate in new process models dedicated to control, highly informative measuring systems, specialized actuators and advanced control laws.

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