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MEASUREMENTS, DATA ANALYSIS AND CONTROL METHODS IN WASTEWATER TREATMENT PLANTS—STATE OF THE ART AND FUTURE TRENDS

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Abstract

This paper is a summary of a committee working for the Swedish Water and Wastewater Works Association (VAV). The purpose of the report is to present the possibilities today to measure, present and analyze data and control treatment plants. The typical audience is the operator, the process engineer, or the consulting engineer. The methods presented are all known from different disciplines, but are here presented in a form that connects the methods to wastewater treatment operation. Unlike any manual of practice the report is not a concensus report of current practice. Rather it is an attempt to show the potential of modern methods for data analysis and control. This will help the potential equipment or computer buyer to specify relevant demands for the system.

The fact that any wastewater treatment plant is highly dynamic has to be reflected both in measurements and in control. The report discusses relevant sampling times for different measurements, both from the inherent dynamics and from the variability of the disturbances. Current design practice is almost always based on steady state analysis, and disturbances are too often controlled by larger tank volumes rather than relevant control actions.

In order to obtain relevant data analysis the purpose of the measurement has to be clearly stated. Interesting and relevant measurement variables are listed. Moreover, a short survey of existing instrumentation and its status is presented. The transfer of data from the primary sensor to the computer has to be carefully designed.

Once the data is in the computer, the data structure must be specified. The different compromizes between storage capacity, data formats and other relevant information are discussed. Simple measurement handling is described before statistical analysis is discussed. Numerous examples demonstrate the results. Some methods for parameter estimation and model building from measurement data are discussed, particularly with the purpose to make the methods available for on-line use. It is shown how estimated models can be used for the operation of plants. Different control methods are discussed. The basic kind of local control to keep the plant running is first mentioned, but more emphasis is laid on plant quality control, like dissolved oxygen, return sludge and waste sludge control.

Dynamic models offer interesting possibilities for plant simulation, and simulators are being developed, that can support the operator with further predictive information. Some future possibilities of knowledge-based systems for process diagnosis are further discussed. They offer new possibilities to use natural language for systematic error analysis and diagnostic searches.

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1. Introduction

The Swedish Water and Wastewater Association (VAV) formed the TR39 working group in 1985. Its primary goal was to summarize the state of the art in practical methods for data analysis, computer technology and available software for sewage treatment plant operation. The purpose was to make this knowledge available for the typical operator, process engineer or consulting engineer at municipal treatment plants in Sweden. Since computers and on-line instrumentation are becoming increasingly common at both small and large treatment plants there is a great potential for quality improvements and cost savings. Still, there is a great gap between the state of the art in methodologies in data analysis and control and the current practice in most plants, not only in Sweden.

At an early stage of the work it became clear that a report that describes measurement analysis without mentioning the dynamic properties of the treatment system would not be valuable for the practitioner. There are several questions that have to be answered, i.e. how often to measure in order to get meaningful information or which variables are crucial to measure in order to get good operation. The demands may be quite different, depending on the purpose of the measurement. Since there is often a great confusion concerning dynamic properties the group soon decided to present some of the basic dynamic properties of treatment systems and their consequences for measurement, operation, data analysis and operator communication. The information has to be presented quite differently for the operator (often a minute-to-minute time scale), for the process engineer (minutes to months) or the regulatory agencies.

The group has completed a report in Swedish that will be presented to people involved in practical operation of treatment plants. In order to make the presentation more efficient the report will also be presented in short seminars. It differs from a typical manual of practice in an important way. The methods presented may not have been established and generally accepted, even if they have been tried out in different tests or projects. The report aims at presenting realistic methods, so that a potential customer/operator knows what to ask for. In this way we hope to have a quicker way of raising the level of competence at the plants. We also believe that by presenting modern methodology for the operator and process engineer, they can act as a pressure group for the designers and consulting engineers. At the same time it is important to emphasize that the report does not claim to be a text book. Rather it tries to show relevant areas for study.

The purpose of this paper is to maintain a discussion on the international level, since the problems are truly similar at all plants. Some highlights of the report are summarized here. The report has been presented and reviewed in a four day meeting at the Wastewater Technology Centre, Burlington, Ontario, Canada earlier this year. The paper does not claim to present new research results. Rather we try to summarize some of the methodologies that are considered useful in practice. In section 2 we review how the system dynamics influence the demands on measurement rate and accuracy. Instrumentation problems are briefly mentioned in section 3. Statistical methods are mentioned in section 4. In sections 5 and 6 some useful methods for identification and estimation are presented and their applicability in operational conditions are discussed. Control and automation methods are briefly described in section 7 and some future trends in operations are given in section 8.

2. System dynamics and measurements

A biological wastewater treatment plant is a complex dynamic system, including biological, chemical and physical phenomena. Any operator is aware of its dynamic character by observing time varying flow rates, concentrations and compositions. Those variations may be quite significant and often very sudden. The control actions have to be related to the dynamics, since the result of such an action cannot be observed momentarily. Therefore it is often not trivial to find the right cause-effect relationships. Furthermore, there are strong links between the different process units, such as the influence on sludge treatment of recycling or the settler-aerator link.

A computerized measurement system may have many objectives, such as

- detecting disturbances
- filtering noise from measurements
- presenting measurement data in different time scales
- condensing measurement data to readable information
- supervision of instrumentation
- calculation of indirect variables from primary measurements
- being the data base for automation and control

The state of the plant is described by a large number of process variables, such as concentrations, flow rates, levels, pressures, temperatures, pH etc. The operations are all the time affected by disturbances. Some of them are internally generated, such as pumps, changing recirculations or other changes in operating conditions, while others are externally generated from the influent flow. The disturbances are mostly such that the plant is never in steady state. This means that all the relevant measurements have to be made with such a sampling rate that the variations can be observed so that relevant actions can be made.

Hydraulic disturbances may be the most common ones and the most difficult to control. The influent flow rate variations are naturally dominating disturbances. However, poor pumping operation may contribute to major operational disturbances, and many plant problems, particularly clarifier operations, may be caused by inadequate pumping. Variations in concentration and composition may be both rapid (e.g. caused by pulses or recirculation of sludge) and significant in amplitude. Under dissolved oxygen control the load variation can be appreciated by the air flow variation needed to keep the DO constant. A typical case is shown in Figure 1.

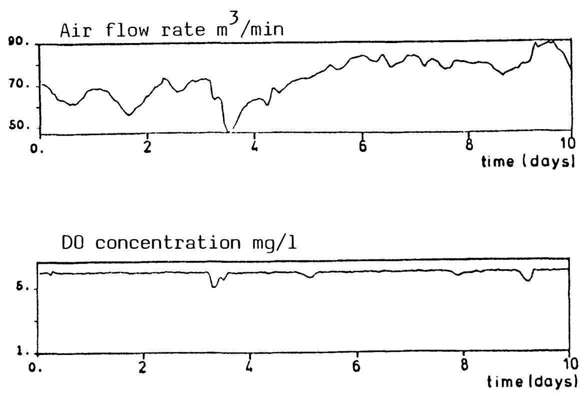

Figure 1. Illustration of air flow variations in DO control. The DO is controlled by a self-tuning regulator (Käppala sewage works, Sweden) .

Another kind of measurement variation is shown in Figure 2. The return sludge concentration is measured just under the bottom outlet of the settler. For every turn (about every 15 minutes) of the sludge scraper there is a sharp concentration peak. The true recycle concentration does not vary very quickly. However, in order to get a relevant measurement the sampling rate has to be high before the concentration values are averaged over a longer time.

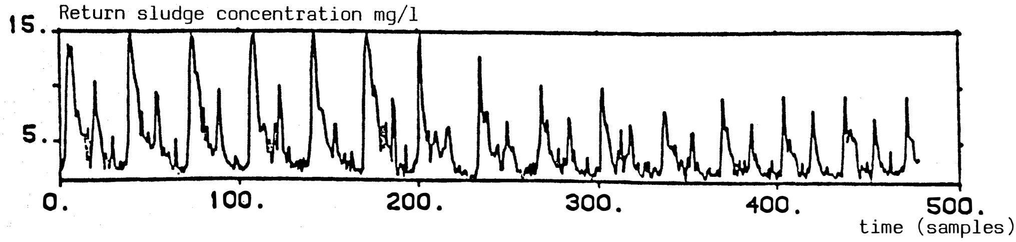

Figure 2. Recording of return sludge concentrations from a circular secondary settler unit (Pilot Plant 1) at the Wastewater Technology Centre, Burlington, Ontario.

Regulators may cause unwanted disturbances. In figure 3 a DO controller is shown. The problem is related to integrator wind-up and a limited air flow control signal. The controller can not compensate for the disturbances due to the limitation. The load increases rapidly on Friday night. The air flow is limited and the DO drops. When the load decreases the air flow rate should go down. Due to the integrator wind-up the accumulated error has grown too big and the controller overcompensates so that the DO concentration reaches a high peak. Such wind-up can be avoided completely.

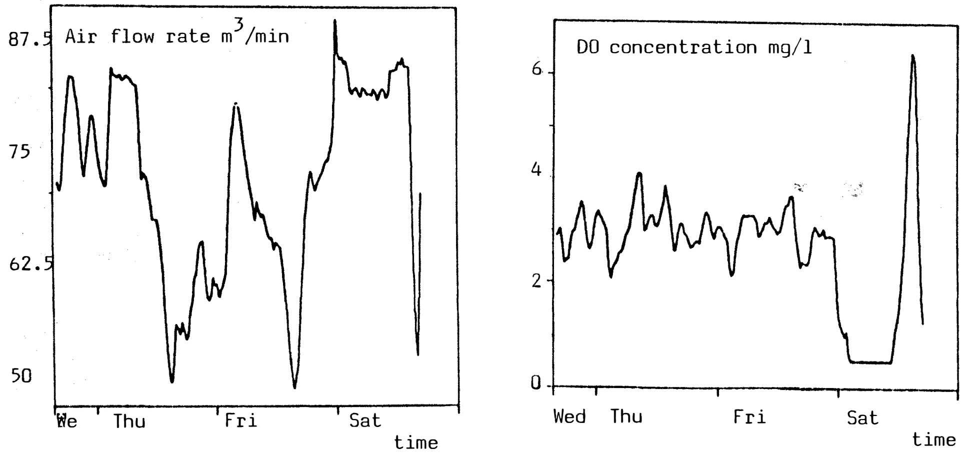

Figure 3. DO control with integrator wind-up.

The sampling time of a measurement is a crucial problem. In order to detect a short pulse disturbance the sampling rate must be sufficiently large. Since many measurements are costly there is a trade-off between the cost of measurements and the cost of not detecting the actual disturbance. In the report there is a quite comprehensive list of variables in a sewage treatment plant. For each variable the purpose of measurements have been listed (such as load detection, automatic control, regulatory agency reporting), the typical signal variation rate, and typical measurement frequency for normal data acquisition and for special purpose measurements. Such a table gives the operator a check list of interesting variables and the demand for meaningful instrumentation.

There is often a confusion of the concept sampling rate. The interesting sampling rate is the frequency between measurements stored in the computer. The reason is that it should be possible to reconstruct the true continuous measurement from the time discrete values. However, the value stored in the computer may be obtained from more frequent measurements in order to filter the noise content of the signal. It is important to know the alias problem, i.e. the problem of obtaining false information from a too low frequency sampling. The report describes how analog filtering is needed in order to filter out high frequency noise before the signal is sampled into the computer. Once the measurement value is stored some digital filtering can be executed. This is discussed further in section 3.

The inherent dynamic properties of the plant determine how quickly and significantly the system reacts to external disturbances or control actions. It is important to illustrate the wide span of dynamics of a typical treatment plant:

- a pump start will create a disturbance that propagates through the plant. The flow rate propagation may take some 20-40 minutes through a plant, which means that the clarifier effluent suspended solids concentration will be affected within this time frame. An analysis and experimental evidence are presented in Olsson et al (1985). An increasing flow rate will also give a dilution effect, which is considerably slower, and depends on the tank volume rather than the tank surface area. Thus a pump will create disturbances in different time scales;

- the transfer of gaseous to dissolved oxygen takes place within 15-30 minutes. Consequently a change in the air flow rate will not be noticed **immediately** in the DO concentration. However, the DO concentration may vary in a minute-to-minute time scale due to load disturbances. The consequence is that it is impossible to control the fast variations by air flow control. In fact, it does not pay to change the air flow signal more often than typically 10-12 minutes. For further analysis, see Olsson et al (1985b). Note, however, that measurements may be made more often;

- Zoogleal cell growth takes place in days, while nitrification and cell decay takes the order of weeks. Anaerobic treatment takes even longer time. This means that the cell population cannot be controlled in an hour-to-hour time frame. For example, the sludge age can be changed via the sludge waste flow rate. The response to such an action is slow, of the order weeks. In other words, if the sludge retention time is 5 days and should be changed to 6 days, the transient lasts for about 10-15 days before the new sludge age is obtained. In order to calculate the sludge retention time it is typically necessary to make daily averages of flow rates and concentrations;

- Seasonal variations give a temperature influence on growth, particularly for nitrification. In order to find out the relation between temperature and cell growth it is necessary to measure during several months, while the sampling rate may be typically 1-3 times a week;

To summarize, the sampling rate depends on both the speed of the signal variation and the inherent dynamic character of the plant. Figure 4 illustrates what happens if a wrong sampling interval is used: daily samples of flow rate (average values) and secondary settler effluent suspended solids (SS). The latter are grab samples. Sometimes there is a good correlation between peaks of flow rate and of SS. At other occasions the flow rate is relatively small (e.g. day 560) while the SS shows a large peak. A short but intense rain storm may be noticed clearly in the SS while the average flow rate is not significantly changed. Since the dominating time constant is shorter than an hour the sampling rate must be adjusted to this fact.

3. Instrumentation

Even if reliable sensors are not available for all interesting process variables there is a lot of possible measurements in a treatment plant. A complete inventory of available sensors, their function, availability and reliability would be most welcomed by many users. However, the work and expense to achieve this is considerable, and the results will quite soon be obsolete. In the report an attempt is made to classify different sensors with respect to their function and their reliability for on-line use. For each sensor there are demands on accuracy, reproducibility, reliability, disturbance sensitivity and possibilities to test the sensor. The three first demands are determined by both the process and the sensor quality and cost. The ultimate use of the information from the

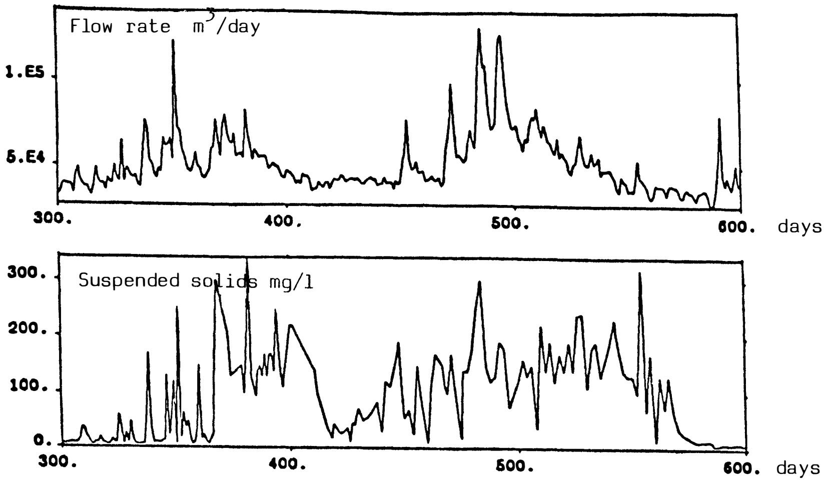

Figure 4. Daily samples of influent flow rate and secondary clarifier effluent suspended solids.

sensor has to be understood in order to weight the relative importance of the different demands. For example, a DO sensor may be accepted with a relatively poor absolute accuracy (±0.5 mg/l) but has to show a good reproduc ibility (±0.2 mg/l). On the other hand, if the DO sensor is used for checking the effluent quality there is a higher demand on the absolute accuracy.

A number of measurement principles for many plant process variables have been summarized in a table. The variables mentioned are flow rates, gas flow rates, levels, conductivity, redox, pH, temperature, dissolved oxygen, air pressure, suspended solids, dry solids, phosphorus components, nitrogen components, organic content (BOD, TOC, COD), alkalinity, toxicity, gas concentrations (methane, carbon dioxide and hydrogen sulphate), respiration rate, metal concentrations, organic acids. For each one of the parameters there is an indication if continuous or batch sensors are available, if manual analysis has to be made, available accuracy, price range and maintenance need.

In another table in the report three groups of sensor types are presented,

(1) commercially available sensors with usually satisfactory performance
(2) commercially available sensors that still have more or less problems or limitations. Generally this class of sensors are more difficult to apply, and demand better qualified personnel for their operation.
(3) sensors only available in prototypes or under development.

In group 1 we find flow rates, levels, conductivity, redox, pH, temperature, dissolved oxygen, suspended solids, dry solids and pressure. In group 2 there are sensors for phosphorus, nitrogen (ammonium nitrogen, nitrite, nitrate, total nitrogen), BOD, COD, TOC, sludge levels, alkalinity, gas concentrations, colour, toxicity and respiration rates. In group 3 we suggest sensors for iron and aluminum content, heavy metals, treatability, organic acids and settleability.

4. Statistical analysis

Before any statistical analysis is made it is important to validate the signal with respect to its limits, nonlinearities, scaling, rate of change etc. A number of such tests are listed for the potential user and is used as a checklist. Another important aspect is to clarify who is going to use the statistical analysis. Different users need the information in widely different time-scales. A process engineer may wish to smooth signals in order to study slow variations. A computer or control engineer may wish to detect changes of a signal, and consequently high-pass filtering is adequate for this purpose.

It is important to define some fundamental concepts for statistical analysis such as measurement bias, random measurement uncertainties and precision. Graphical presentation is crucial before any analysis is to be made. This is emphasized several times. By manual inspection a lot of interesting features can be detected easily, and quite sophisticated statistical methods may be needed to draw the same conclusion. One example is outliers. A trained operator may very soon detect an outlier. This is not easy to do by automatic methods. Good methods for graphical presentation are histograms and Box plots (Box-and-Whisker plots). An excellent introductory text is Gilbert (1987).

The normal and log-normal distributions are well known in environmental statistics. Of course it is interesting to test plant data with respect to their distributions. Sometimes it is possible to detect time-varying behaviour or other odd features of the data. Thus, some standard statistical package to present data graphically and make the elementary statistical tests should be available. A good survey of available packages and their usefulness has been made recently by Chapman (1988).

Digital filtering is an important tool for extracting the proper information while reducing the noise of the signal. A low-pass filter may attentuate peaks of the signal and smooth the measurement variable. A high-pass filter reduces the low frequency content of the signal and emphasizes the changes.

The simplest low pass filter may be a moving average. This can be implemented on-line. The drawback of a moving average is its insensitivity to recent measurement values, since all values are weighted with the same parameter, i.e.

$$y_{ave}(t) = [\, y(t) + y(t-1) + \ldots + y(t-k) \,] /(k+1) \tag{1}$$

The higher value of k the more damping is caused by the filter. A better filter construction is the exponential filter, defined as

$$y_{filt}(t) = \alpha\, y_{filt}(t-1) + (1-\alpha)\, y(t) \tag{2}$$

where $y(t)$ is the current measurement value and α a weighting factor between 0 and 1. For α close to 0 the filter is sensitive to the last measurement and little smoothing is obtained. For α close to 1 the current measurement has a small weight in the filter, which gives an efficient way of damping out peaks of the measurement. The drawback is that the filter is also insensitive to real changes of the signal value. Figure 5 illustrates in simulation the compromise between noise reduction and sensitivity to changes. More advanced filters can be constructed by setting two or more filters in series or by making the value of α adaptive to the error between the filtered value and the raw measurement.

5. Identification and estimation

Process identification and estimation are established fields in the research community, and quite a lot of applications have been reported in the literature. There are several useful tools for the process engineer in order to better understand specific dynamic relations in the plant, and Beck (1986) gives numerous examples.

The dynamics are typically described as an input-output model, i.e. an autoregressive, moving average model with an external input (ARMAX). Such a model can be described as

$$\begin{aligned} y(t_k) = & -a_1 y(t_{k-1}) - a_2 y(t_{k-2}) \ldots - a_n y(t_{k-n}) + \\ & b_0 u(t_k) + b_1 u(t_{k-1}) + \ldots + b_n u(t_{k-n}) + \\ & c_0 e(t_k) + c_1 e(t_{k-1}) + \ldots + c_n e(t_{k-n}) \end{aligned} \tag{3}$$

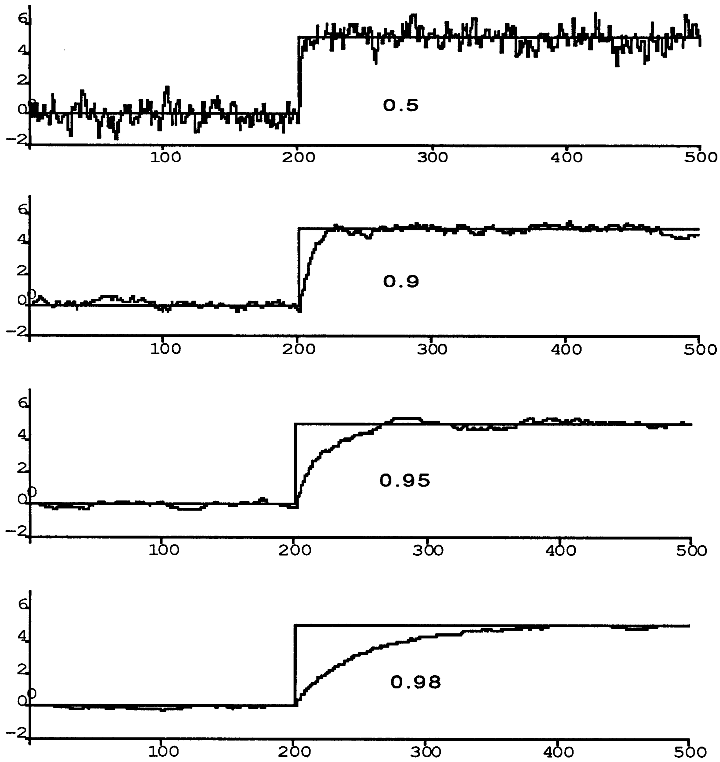

Figure 5. Illustration of a first order filtering of a simulated noisy signal. The parameter α takes the values 0.5, 0.9, 0.95, 0.98. Note that the filter follows the signal well for small values of α, while the noise level is high. The filter becomes much more insensitive, while the noise reduction is significant, as α approaches 1.

where y is the process output, u the manipulated variable and e a sequence of normally distributed stochastic variables with zero mean and unit variance. The sequence of e usually gives a realistic description of both instrumentation and process noise. The parameters a_i, b_i and c_i can be identified from observations of y and u. With the maximum likelihood method the parameters can be identified with no bias, while the parameter accuracy can be estimated. For further results, see Ljung (1987).

Experiences in identifying the dynamics of dissolved oxygen were gained in 1975 at the Käppala sewage works at Lidingö outside Stockholm, Sweden. The air flow rate to one of the aerators was manipulated off-line in order to obtain the air flow/DO concentration relationship (Olsson & Hansson 1976a, b). Some interesting conclusions were drawn. By assuming a constant oxygen uptake rate (OUR) the value of the oxygen transfer rate K_La could be calculated. The assumption of constant OUR could be tested afterwards by comparing the model with real data. This method made it possible to detect changes in K_La by on-line experiments by manually manipulating the air flow rate. Thus clogging of the diffusers or failing membranes of the DO sensors could be detected.

Since there is often prior knowledge of the dynamics available this can be taken into consideration. Often this knowledge can be combined with measurements in order to adjust specific parameters to the data. In this way more accurate models can be obtained, where the physical interpretation of the model is more obvious.

Hydraulic flow modelling was studied in Olsson,Stephenson&Chapman(1986). The purpose of the model was to describe how the flow rate propagates along the plant from the influent to the effluent part. The propagation time is not negligible and has to be modelled in order to describe how hydraulic shocks are damped before the clarifier. Thus, by modelling the hydraulics a better understanding is achieved of how to design a better pumping strategy or proper weirs in the aerator.

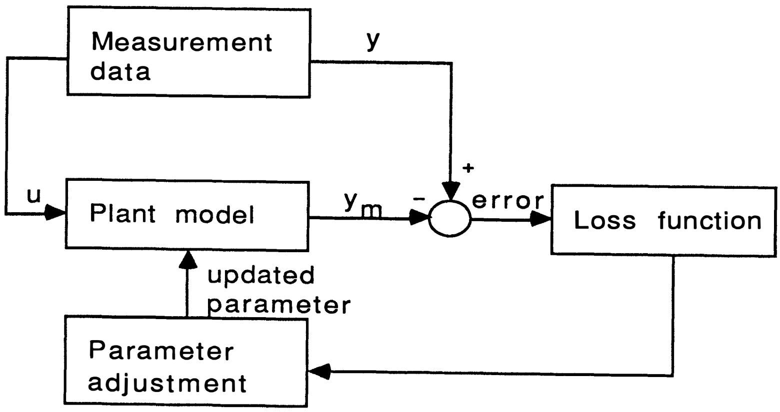

Figure 6. Illustration of the structured identification.

The modelling approach can be illustrated by figure 6. The model is assumed continuous while the data are time discrete. A transient is simulated and compared with experimental data. The parameters are then updated to adjust the model closer to the data. The simulation is repeated until satisfactory adjustment is obtained. Depending on the data quality and the accuracy of the structure of the model the identification may be more or less successful.

The clarifier dynamics were identified in Olsson-Chapman (1985) using similar techniques. In this case the relation between the influent flow rate and effluent suspended solids concentration was given, while the parameters were unknown. The structure was a second order linear system for increasing flow rates and a first order linear system (with different time constant) for decreasing flow rates.

6. On-line estimation

It is clear that more information than the primary sensor signals are required in order to get good operation. By combining a mathematical model with measurement indirect variables can be calculated. This can form the basis either for better process operation diagnosis or control based on quality related parameters. In model (3) the parameters a_i, b_i and c_i may be slowly varying with time. The parameters can in fact be tracked on-line and corrected for each new measurement obtained. This is called recursive parameter estimation and is a useful tool in wastewater treatment, since the systems are often time-varying in the parameters. Examples from respiration estimation and clarifier dynamics are given below.

In recursive parameter estimation of an input-output model a parameter vector θ is assumed to vary with time. However, the parameter variation is assumed to be considerably slower than the state variable rate of change. For model (3) θ can be defined by

$$\theta = [a_1, a_2, ..., a, b_1, ..., b_n, c_1, ... c_n]^T \quad (4)$$

The updating formula for the estimated parameter θ_m looks like

$$\theta_m(t_{k+1}) = \theta_m(t_k) + K * [y(t_k) - y_m(t_k)] \quad (5)$$

where $y(t)$ is the current measurement, $y_m(t)$ the model prediction of the measurement, and K is a gain factor. The size of K depends on the measurement as well as the model accuracies. Intuitively it is clear that poor measurement quality should be reflected in a small value of K.

For a long time it has been recognized that the oxygen uptake rate or respiration (R) is a relevant measure of organic load of the activated sludge system (Olsson & Andrews 1978). Knowledge of R along with the measurement of mixed liquor volatile suspended solids defines the value of SCOUR, the specific oxygen uptake rate. The knowledge of SCOUR is a crucial first step in sludge inventory control. With a respirometer the oxygen uptake rate can be measured directly. However, as part of a dissolved oxygen control system it can be estimated. The obvious way to estimate R on-line is by considering a DO mass balance.

If k_La is known, then the estimation of R is straightforward. In practice, however, k_La is not known and may be slowly time-varying, thus it has to be estimated together with R. The on-line estimation of R during closed loop DO control is presented at this symposium, see Holmberg et al (1988).

The dynamics of secondary clarifiers have been studied in Olsson &Chapman (1985). In the work it was attempted to obtain dynamic models with a minimum number of parameters, but still a sufficiently rich structure that would explain the physical nature of the clarifier transients. The models recognize the fact that the effluent suspended solids concentration does not momentarily change with the influent flow rate. Instead there is a dynamic relationship between the effluent suspended solids and the solids load to the clarifier, i.e. the product of mixed liquor suspended solids concentration and the flow rate. In a simplified manner the dynamics can be written as

$$c_e(t_k) = a_1 c_e(t_{k-1}) + a_2 c_e(t_{k-2}) +$$

$$+ b_1 c_x(t_{k-1})Q(t_{k-1}) + b_2 c_x(t_{k-2})Q(t_{k-2}) + v(t_k) \quad (6)$$

where

$c_e(t)$ = effluent suspended solids concentration
$c_x(t)$ = MLSS concentration
$Q(t)$ = flow rate into clarifier
$v(t)$ = stochastic disturbances

The coefficients are different for decreasing and increasing flow rates. For decreasing flow rates a first order dynamics usually will describe the behaviour. The parameters can gradually change due to two different causes. One change is a result of changing floc properties and the other is caused by instrument drift. The estimator updates the parameters θ, i.e. the a_i and b_i values, according to the recursive scheme (5) where the y represents the effluent suspended solids measurement and y_m the corresponding model prediction from (6). The a_i and b_i parameters in the clarifier model have no apparent physical interpretation. Still they can be used for monitoring purposes. If some parameter exceeds an established limit, the reason for the deviation has to be examined further, since both calibration errors and changing flow properties may cause the problem. Thus the parameters may have an empirical relation to the initial settling velocity. By observing the parameters the operator has got an early warning system for changing process behaviour.

7. Automation and control

In the operation of a plant there are several objectives that have to be met. One way to set the priorities may be (Beck 1986 ; Andrews 1974) ,

- Keep the plant running and avoid gross failures
- Minimize operating costs while satisfying permit limits
- Improve effluent quality

It is important to distinguish between local control and quality control. Any plant may contain a lot of sequencing or local feedback control in order to keep the plant running. Most of these loops are tuned based on empirical knowledge where the setpoints are not directly related to the quality of the effluent water. Among open loop sequencing there are described methods for pump sequencing, air compressor start/stop, sludge removal, waste activated sludge pumping, or bar screen cleaning. There are several examples of closed loop local control, such as different flow controls, air flow control, pressure control, dosage control or return sludge control based on flow rates or MLSS concentrations. A comprehensive overview is found in Manning et al (1980) and in Olsson (1987).

Any control that extends beyond the local control actions discussed previously has to consider quality related or model related behaviour. This means that the controller has to get information from several sensors or from estimated variables. The choice of the setpoint is often non-trivial and is closely related to the choice of operating conditions.

In order to improve operation and establish a relation between control and product quality there has to be a connection between quality measures and the control actions. The effluent water limiting concentrations are the obvious signs of the quality of the plant operation. However, there are few control systems that relate these quality numbers to controller performance criteria. Some control loops have setpoints defined that in some way are related to the quality, such as DO or sludge retention time (SRT) setpoints. However, there are other measures that are interesting to incorporate into control actions, such as respiration rate (or specific oxygen utilization rate), sludge volume index (SVI), initial settling velocity, oxidation/reduction potential (ORP), alkalinity change (in connection with nitrification), pH change etc. Here we will discuss DO control and sludge inventory control.

The control of DO as a physical variable does not require any in-depth knowledge of the microbial dynamics. There is extensive experience of DO, in most cases with traditional PI control (Flanagan 1977) . Despite the straightforward task of DO control there are several difficulties involved. The DO dynamics contain both non-linear and timevarying dynamics. Moreover, considering the long time constants and random influent disturbances any tuning of a conventional controller becomes tedious. The inherent dead-times in the system can be compensated for with digital controllers. Therefore self-tuning control was implemented in a full-scale plant, the Käppala Sewage works close to Stockholm, Sweden (Olsson, Rundqwist, Eriksson & Hall 1985 ; Rundqwist 1986) to examine the potential of adaptive control in activated sludge systems. The controller is cascaded with a pressure control system that seeks to minimize pressure demand at all times. The Käppala controller has been in use for a long time now and works satisfactorily (Rundqwist (1988). The DO concentration is kept very close to its setpoint under several operating conditions. Other experiences of self-tuning control in pilot scale have been reported by Yust et al (1987).

The self-tuning controller above does not give an explicit estimate of both k_La and the oxygen uptake rate, but calculates the controller parameters directly. From the DO control point of view the respiration can be considered a time-varying bias disturbance and can not be identified separately from k_La unless separate disturbances are made. The problem of simultaneous estimation and control has been solved by Holmberg (1986). Further experiences are reported at this symposium, see Holmberg et al (1988).

There are basicly three control variables for the sludge inventory in an activated sludge system. The waste activated sludge (WAS) flow rate controls the total sludge mass in the system. The sludge distribution within the system is controlled by the step feed flow distribution or the return activated sludge (RAS) flow rate. The former can dynamically redistribute the sludge within the aerator while the latter can shuffle sludge between the settler and the aerator. The report gives more details about possible strategies for the sludge inventory control, based on results presented in Olsson (1987).

8. Knowledge-based systems

It is clear that there is still very little, if any, coordination between the local control loops in most treatment plants. The control loops are primarily designed to respond to minor disturbances rather than major process upsets. There is still a significant lack of on-line instruments and precise quantification of the process knowledge. Therefore the man in the loop will play an important role, even if the degree of automation in the plants does increase. The time-scale also determines where computer control or guidance is successful. It is not only for the fastest control loops that the computer can assist, but also for the very slow dynamics. The plant operator or manager will have problems to observe the gradual changes that take place in the weekly and monthly timescales. Therefore it is inevitable that a knowledge-based (or expert) system would sooner or later be called for.

In some early implementations of computer systems in wastewater treatment systems the software contained some simple rules for control actions in the event of major deviations from normal operating modes. Some accumulated process knowledge was used in 1977 in two papers to design a more elaborate control system. Gillblad & Olsson (1977)defined some operational states that were associated with specific combinations of control actions. The system was implemented at a municipal treatment plant. Tong et al (1977) used fuzzy (or multiple-valued) logic to formulate linguistic rules for control actions. Already in 1974 a rule-based system for computer-assisted operation of anaerobic digesters was developed in the USA (Koch et al 1974). This was followed up in 1984 by a knowledge-based system, coded in a different way by using similar logic (Maeda 1984).

The process diagnosis part of control seems to be a crucial step. The purpose is to obtain maximum use of the combination of on-line instruments, process models, human observations and laboratory analysis. In a typical operational mode the computer may alert the operator from direct readings of sensors and from estimated parameters. In a knowledge-based diagnosis system the operator may input his own observations. The computer can help to reason and suggest further off-line and laboratory tests to trace the process fault. This kind of backward reasoning has the potential to be a good supplement for the operator. The area of applied artificial intelligence is receiving increasing attention in the field of water resources in general (Patry & Gall 1987) and wastewater engineering in particular. Research is being performed to develop failure diagnosis/prevention expert systems that can assist the operator.

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References

Andrews, J. F. (1974) Dynamic Models and Control Strategies for Wastewater Treatment Processes , Water Res., 8, 261--289.

Beck, B. (1986) Identification, Estimation and Control of Biological Waste-water Treatment Processes, IEE Proceedings, 133, 254--264.

Chapman, D (1988) Graphical methods for Presenting and Analyzing Environmental Data, Internal report, Wastewater Technology Centre, Burlington, Ontario.

Flanagan, M. J., B. D. Bracken and J. F. Roesler (1977) Automatic Dissolved Oxygen Control. Proc. Am. Soc. Civil Engrs, J. of the Environment Engineering Division, EE4, 103, 707--722.

Gilbert, R.O. (1987) Statistical Methods for Environmental Pollution Monitoring, Van Nostrand Reinhold Co, New York.

Gillblad T. and G. Olsson(1977) Computer Control of a medium-sized Activated Sludge Plant. Prog. Water Technol., 9.(5/6), 427-433.

Holmberg, U. (1986) Adaptive Dissolved Oxygen Control and On-line Estimation of Oxygen Transfer and Respiration Rates. AIChE Annual Meeting, Miami Beach.

Holmberg, U. and G. Olsson (1985) Simultaneous On-Line Estimation of Oxygen Transfer Rate and Respiration Rate. Proceedings IFAC 1st Symposium on Modelling and Control of Biotechnological Processes, Noordwijkerhout, The Netherlands, 185--189.

Holmberg, U., G. Olsson and B. Andersson (1988) Simultaneous DO Control and Respiration Estimation, Wat. Sci. Tech. 21(10/11)1185-1195.

Koch, C. M. and W. Wankoff (1974) An Experiment in Computer Assisted Control of the Anaerobic Digestion Process at Philadelphia's Northeast Pollution Control Plant. Proc. 47th Ann. Water Pollut. Control Federation Conf.

Ljung, L. (1987) System Identification: Theory for the user. Prentice-Hall.

Maeda K. (1984) A Knowledge Based System for the Wastewater Treatment Process. Preprints 9th IFAC World Congress, Budapest, Hungary, IV, 89--94.

Manning, A. W. and D. M. Dobs (1980) Design Handbook for Automation of Activated Sludge Wastewater Treatment Plants, USEPA 600/8-80-028, Municipal Environmental Research Laboratory, Cincinnati, OH 45268, USA.

Olsson, G. (1987) Automation of Wastewater Treatment Plants. Paper EWPCA symposium and IFAT exhibition, Munich, May.

Olsson, G. and O. Hansson (1976a) Modelling and Identification of an Activated Sludge Process. Proc. IFAC Symp on Identification and System Parameter Estimation, Tbilisi, USSR.

Olsson, G. and O. Hansson (1976b) Stochastic Modelling and Computer Control of a Full Scale Wastewater Treatment Plant. Proc. Symposium on Systems and Models in Air and Water Pollution. The Institute of Measurement and Control, London.

Olsson, G. and J. F. Andrews (1978) The Dissolved Oxygen Profile---a valuable Tool for the control of the Activated Sludge Process, Water Research , 12, 985--1004.

Olsson, G. and D. Chapman (1985a) Modelling the Dynamics of Clarifier Behaviour in Activated Sludge Systems. Symp. Instrumentation and Control of Water and Wastewater Treatment and Transport Systems, Advances in Water Pollution Control (R. A. R. Drake ed.), IAWPRC, Pergamon Press, 405--412.

Olsson, G., L. Rundqwist, L. Eriksson and L. Hall (1985b) Self-tuning Control of the Dissolved Oxygen Concentration in Activated Sludge Systems. Symp. Instrumentation and Control of Water and Wastewater Treatment and Transport Systems, Advances in Water Pollution Control (R. A. R. Drake ed.), IAWPRC, Pergamon Press, 473--480.

Olsson, G., J. Stephenson and D. Chapman (1986) Computer Detection of the Impact of Hydraulic Shocks on Plant Performance, WPCF, 58, 954--959.

Patry G. and B. Gall (1987) Expert System for the Identification of Wastewater Treatment Alternatives. Soc. for Computer Simulation,San Diego, California.

Rundqwist, L. (1986) Self-tuning Control of the Dissolved Oxygen Concentration in Activated Sludge Systems. Licentiat Thesis, Report TFRT-3180, Department of Automatic Control, Lund Institute of Technology, Lund, Sweden.

Tong, R. M., M. B. Beck and A. Latten (1980) Fuzzy Control of the Activated Sludge Wastewater Treatment Process, Automatica, 16, 695--701.

Yust, L. J. and J. A. Howell (1987) Application of a Self-tuning Regulator to Control Dissolved Oxygen in an Activated Sludge Plant. WPCF.