Submitted for ICA Workshop, Kyoto, Japan, October 26-27, 1989.

Estimation and control as tools for improving wastewater treatment performance

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Abstract

Several factors have contributed to increase the interest in improved operation of wastewater treatment plants. The demands for better effluent quality, more economic operation are met by significant improvements in information technology, instrumentation, control methodology and process knowledge. This has created a new platform for better plant performance, measured in effluent quality and in cost efficiency.

Two aspects - estimation and control - will be emphasized in this presentation. By using recursive estimation relevant parameters or states can be calculated, that are too expensive or impossible to measure directly. Examples will be given from the activated sludge process. By presenting these parameters to the operator there are new and better ways to interprete and identify process conditions. Moreover, by extending the on-line instruments with estimators the operator will get automatic early warning systems for process or instrumentation failures.

By using knowledge based systems the on-line estimation schemes can be added on top of the operator observations and laboratory tests. This will hopefully result in better diagnosis for complex operational conditions.

Self-tuning and other types of adaptive controllers have been used for dissolved oxygen control. Examples from these studies will show the advantage and the problems associated with more complex control.

For both estimation and advanced control tasks it is necessary to obtain relevant dynamical models. For these purposes there are other types of models necessary than for construction and simulation. A crucial problem is the verification of models from real plant experiments. This problem is valid for both controller models and for structured simulation models. Some problems on verifiability will be discussed.

Introduction

For any operator it is a wellknown fact that a wastewater treatment plant is hardly ever in steady state. Sewage works are dynamical systems, that most of the time are in different transient stages. This is a result of ever changing influent flow conditions, where both flow rates, compositions and concentrations vary. Strong couplings between different unit processes, e.g. between the settler and the aerator or between sludge supernatants and the wastewater processes, makes some kind of production planning necessary in order to obtain a successful operation (Olsson (1985)). Despite dynamical character of treatment plants most current design and operation methods are based on the assumption of steady state. Thus, wastewater treatment systems are generally regarded as intrinsically inflexible. Consequently the operation is unsatisfactory in many sewage works, as the influent flow conditions vary to a great extent, even if the average values are kept within the design limits.

Influent flow disturbances to a wastewater treatment plant may vary significantly, both in amplitude and in frequency. In a concentrated sewer network flow variations are often large, whereas they are attenuated in more widely distributed networks. Rainstorms can cause shock loads, that upset the settler and clarifier systems, and this can seriously affect the whole plant system. Some hydraulic disturbances originate within the plant as recycle, wasting or influent pumping rates change. During dry weather flow, the most significant flow variations come from the pumps lifting wastewater into the plant, which may cause both high frequency and high amplitude disturbances (Olsson et. al. (1986)).

Concentration disturbances vary in amplitude and frequency. The characterization of the disturbances is often very imprecise and measures like BOD, TOC or COD only reflect a lumped value of oxygen demand that does not necessarily inform how the system would react to the disturbances. In addition to diurnal variations in BOD, several types of additional loads may appear. The operations required to meet these disturbances have to be flexible. This demands flexible pumping and valving. Such examples are step feed control, variable speed pumps for recirculation and primary pumping and valves that allow for control actions. In several cases the situation can be significantly improved if upstream information is obtained, i.e. feedforward information. This is particularly useful in dealing with industrial effluents. Sometimes the discharge may be buffered in order to arrive at the plant during low load periods.

The need for automatic detection of large disturbances is even more significant for small and unmanned plants. These may be designed to operate satisfactorily during normal diurnal variations provided adequate flow balancing is possible. Certain discrete events, however, may upset the process and demand the attention of an operator.

Some of the control problems in sewage works resemble those in chemical process control. There are several local sequencing and feedback loops. Some of these are discussed in the paper. Recursive estimation is a powerful tool to calculate indirect parameters of the process, thus giving on-line information that may serve as an early warning system for process failures. This technique is demonstrated for the on-line calculation of respiration and for clarifier monitoring.

The use of quality parameters for the control of sewage works is not widespread. Dissolved oxygen control is getting common but many problems remain, such as the proper choice of spatial air distribution and of setpoint values. Adaptive control of the dissolved oxygen in full scale has shown some interesting features. It is possible to obtain accurate control with long sampling intervals, of the order 12-15 minutes. As part of the control the oxygen uptake rate and the oxygen mass transfer rate are estimated simultaneously, even if both the parameters are time varying. The relation between different control schemes and floc settling and clarification properties is being tested in current research projects.

Despite automation the role of the human operator is crucial and desirable. A man´s ability to look, smell, feel and hear a lot of phenomena in a biological process is superior to any sensor. With a knowledge based computer system the operator can be helped to keep track of all the information, that sometimes can be overwhelming in an alarm situation. Therefore, a combination of automation and computer assistance for the operator can be a powerful tool for a better operation.

Recursive Estimation

It is clear that more information than the primary sensor signals are required in order to get a 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.

We will discuss two types of estimation, state estimation and parameter estimation. In state estimation the process parameters are assumed to be known. Some unmeasurable state variable (such as a concentration) can be reconstructed from a dynamical model combined with measurements. For linear systems with process and instrument noise the Kalman filter is optimal under certain conditions, see e.g. Åström-Wittenmark (1984). Ordinary mass balance calculations are simple examples of estimation. By measuring flow rates and suspended solids concentrations of aerator influent and effluent streams the MLSS concentration can be predicted as well as checked against current measurements.

Several subprocesses can be modeled according to a time series model with stochastic inputs,

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

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 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 it is a useful tool in wastewater treatment, since the systems often are 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 the model above, θ can be defined by

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

The updating formula looks like

$$\hat{\theta}(t_{k+1}) = \hat{\theta}(t_k) + K \cdot \left(y(t_k) - \hat{y}(t_k)\right) \tag{2}$$

that says that the updated estimate of the parameter vector is equal to the previous value plus a correction factor. K is a gain and the bracket tells the difference between the current measurement and the model prediction of the measurement. The size of K depends on the measurement as well as the model accuracies. Intuitively it is clear, that a poor measurement quality should be reflected into a small value of K.

Oxygen Uptake Rate

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. For a complete mix reactor it is

$$\frac{dc}{dt} = \frac{Q}{V}(c_{in} - (1+r) \cdot c) + k_L a \cdot (c^s - c) - R \tag{3}$$

where

- Q = influent flow rate
- V = reactor volume
- c_{in} = influent DO concentration
- c^s = DO saturation concentration
- r = return sludge flow rate ratio, i.e. return sludge flow = $r \cdot Q$
- $k_L a$ = oxygen mass transfer rate

If $k_L a$ is known, then the estimation of R is straightforward. In practice, however, $k_L a$ is not known and may be slowly time-varying, why it has to be estimated together with R. It is often assumed that $k_L a$ is linearly related to the air flow rate in an air diffusion system,

$$k_L a = a_1 \cdot F_{air} + a_2 \tag{4}$$

where the a_i parameters have to be established independently around each operating point. They may also vary with time. Assume, that a control system keeps the DO concentration constant, $c = c_0$. Then R is directly related to the air flow rate. Consider the steady state DO mass balance,

$$0 \approx \frac{dc_0}{dt} = \frac{Q}{V}(c_{in} - (1+r)\cdot c_0) + (a_1 \cdot F_{air} + a_2)\cdot(c^s - c_0) - R \tag{5}$$

The first term of the right hand side can often be neglected in comparison with the other terms. Consequently, if F_{air} does not saturate, the respiration can be expressed in terms of the air flow rate,

$$R = b_1 \cdot F_{air} + b$$

The oxygen mass transfer rate can be estimated on-line or off-line by identification of the DO concentration dynamics. This is made possible by one simple observation and one crucial assumption. The oxygen uptake rate is independent of the DO concentration as long as the DO concentration is sufficiently large. It is crucial that R is constant during the identification experiment. Then a change of the air flow rate will create an approximate first order system response of the DO concentration. The time constant of the response is directly related to the value of k_La, i.e. for a higher value of the mass transfer rate there is a shorter response time of the DO concentration to an air flow change. When a linearized model is used, the validity of the linearization is limited if the air flow changes are large. This is the background to the identification experiments reported in Olsson-Hansson (1976a,b). In order to avoid the crucial assumption of a constant R the work has continued to estimate k_La and R simultaneously, which is further discussed below.

Still another estimator was presented in Holmberg-Olsson (1985). The purpose of the estimator was to find R directly from air flow and dissolved oxygen measurements. This is not a trivial problem, since k_La is generally not known. However, k_La and R are not simultaneously identifiable. Consider the DO mass balance above. A simultanous change in k_La and R would not change the DO concentration. Therefore the problem has been solved by some extra assumptions. Before we mentioned the assumption of constant R. Another one is of course that k_La is known. In Holmberg-Olsson (1985) it was assumed that k_La and R change in different time scales. Still another approach depends on particular excitations of the air flow rate, that will make it possible to distinguish uniquely between the parameters. However, during poor excitation (e.g. small air flow rate changes) the estimation may fail. A stochastic approach was taken in the estimation, where the parameter vector θ was considered a random variable. It has been demonstrated that this Kalman filter converges to the right parameter values. A serious drawback, however, is a slow convergence. This can be overcome by the addition of larger air flow excitations. To estimate R under closed loop needs another approach, which is discussed in the dual control section.

Clarifier Dynamics

The final settler of an activated sludge plant is crucial for the whole operation of the system. Intermittent pumping will create hydraulic waves, that propagate through the plant. Poor operation of the primary pumps often create large overshoots of suspended solids concentration in the effluent. It may take several hours before the effluent concentration will decrease to its normal value again. In the mean-time a large amount of sludge can be lost from the system (Olsson-Stephenson-Chapman (1986)).

The dynamics of secondary clarifiers has been studied in Olsson-Chapman (1985). In the work it was attempted to obtain dynamical 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 dynamical 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

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

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

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 where the y represents the effluent suspended solids measurement and predicted measurement 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.

Self tuning control

Conventional control of system parameters assume, that the plant dynamics does not change with time. In other words, a controller with constant setting is adequate. This is not generally true, and the dissolved oxygen dynamics is a typical control loop, where the tuning of the controller needs to be adjusted as soon as the loading of the plant changes. In principle, the self-tuning control system is characterized by two loops, according to figure 1.

The regulator loop acts like a conventional controller, but the regulator parameters are updated from a slower loop including parameter estimation. This kind of parameter estimation is in principle built on the same kind of model structures as the time series models. The model is updated by a recursive estimation algorithm that gives either the new regulator parameters directly or the process parameters, from which the updated regulator parameters are calculated.

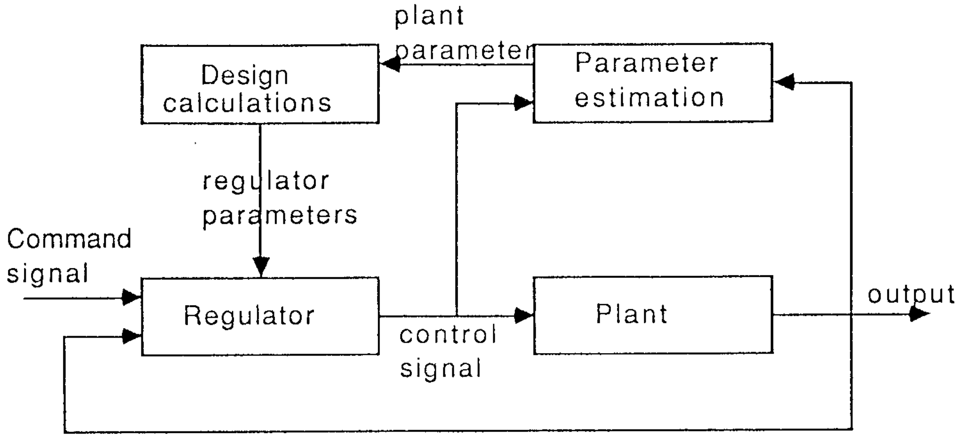

Figure 1. Block diagram of a self tuning regulator.

The self-tuning controller was first installed in one of the six aerators at the Käppala plant in 1984. This phase was reported in Olsson-Rundqwist-Eriksson-Hall (1985). During almost four years of operation the controller has behaved very well, and now all the six parallel aerators are controlled in the same way, see Rundqwist (1986). Due to the inherent non-linearities as well as changing k_La and saturation concentration the controller needs to update its parameters both in an hourly time scale and in a slower time scale. The controller operates so that the regulator parameters are updated directly. Therefore it does not give any explicit information about the plant parameters, such as k_La or the respiration rate.

Dual control

The simultaneous control of the DO and identification of the respiration is difficult due to the identifiability problem mentioned above. This has led to a special dual control method, reported by Holmberg (1986, 1987) and Holmberg-Olsson-Andersson (1988). The controller is a non-linear controller that seeks to keep the DO close to its setpoint. However, the air flow rate is excited in a special manner, so that the air flow rate has an extra disturbance in every sampling interval (15 minutes). This makes the DO to slightly oscillate around its setpoint, but also give the estimator sufficient information to identify both k_La and the OUR. The dual controller has been tested successfully in full scale at the Malmö sewage works in Sweden.

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 will 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 was used 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 about the same 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.

Model verification

The dynamics in a wastewater treatment plant cover a very wide spectrum, from minutes to months. This makes any model approach extremely complex, and there is never such a thing as *the* model. For any operator it is wellknown, that the plant responds to disturbances of widely varying nature, both in amplitude, duration and frequency. A dynamical model should reflect the plant behaviour, both its response to external disturbances and its inherent dynamical character. It is crucial to state the model purpose accurately, or otherwize the model may turn out to be of little value.

A model is in a sense a condensed version of available knowledge of the plant behaviour. Unfortunately the comprehension does not increase simply by adding new equations or coefficients to the model description. However, even an incomplete dynamical model may be useful, and may at least qualitatively verify observations of the process responses to different disturbances. Thus a dynamical model can be a valuable tool to explore the consequences of different disturbances or parameter changes. By finding out the most sensitive parts of the model better verification experiments can be designed.

A model for control purposes should not be too complex. It is crucial that it is verifiable with available on-line instrumentation. Its parameters may not have any obvious physical interpretation, but still describe a reasonable relationship between two measureable variables of the plant. We will discuss this type of models in the time series and adaptive control section. Some of the on-line models are used for control design, some other models are used for process diagnostics purposes.

The many interacting species and substrates in a treatment plant, however, suggest extremely complex models. The resolution of the trade-off between relatively simple on-line models and complex structured models seems to be the major problem in automation of biological treatment plants (Beck (1986)). Some of the complex structured models for activated sludge systems are discussed below.

In mechanistic systems it is common to assume time invariant models, i.e. any experiment can be repeated and the outcome will be the same as in earlier experiments. This is not the case in biological systems. Instead the experiments are often not reproducible. There are methods to detect this kind of process change and actually use models in a systematic way to detect variations in operating conditions. Recursive identification techniques is a useful tool in this respect.

Sometimes conventional controllers do not give sufficient control quality. Thus self-tuning and so called dual controllers have been tested for dissolved oxygen control. The purpose has been not only to get a better control performance, but also to obtain parameter information during the control. It is demonstrated how the oxygen uptake rate can be calculated on-line. Finally a model library is described, that summarizes structured models for the activated sludge process. Some aspects of the use of knowledge based systems are also described. Further references are found in Beck (1986) and Olsson (1985, 1987).

Time series analysis

There are numerous examples of the application of time series analysis in wastewater treatment modelling. Beck (1986) gives an excellent and comprehensive survey. Generally the models obtained have a relatively low order (usually less than two or three) due to the disturbances involved. Moreover the models are usually linear and time invariant. This means that the model may be valid only for the actual experimental conditions.

The dynamics is typically described as an input-output models, such as (1). 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 from the Cramér-Rao inequality. There are several other structures that can represent the input-output relation and the noise character. For other structures than (1) there are different estimation methods to find the parameters, such as the instrumental variable method. For further results, see Ljung (1987).

Experiences on identifying the dynamics of dissolved oxygen were made already 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. Models of first and second order of the structure (1) were calculated, using the Maximum Likelihoood method (Olsson-Hansson (1976a, b)). Some interesting conclusions were made. 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.

Other experiments were made to find the secondary clarifier and thickener dynamics. Time series analysis was found to be a powerful tool to detect cause-effect relationships. The parameter models need less data than conventional correlation analysis to find such relations. In Olsson-Hansson (1976b) it was found that the effluent suspended solids was more sensitive to flow rate increases than to flow rate decreases. This kind of work was extended later in Olsson-Chapman (1985).

Structured model identification

In the time series approach there is no prior knowledge of the system dynamics included in the model. With some structure added to the system it is possible to achieve better accuracy of the system and include specific non-linear structures of the dynamics. Still the structure of the model is given, and the identification is consequently a parameter estimation problem.

Hydraulic flow modelling was studied in Olsson-Stephenson (1985) and 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. A typical model assumption for each basin is the structure

$$A \cdot \frac{dh}{dt} = Q_{in}(t) - Q_{out}(t) \tag{7}$$

where

dh/dt = the rate of change of the liquid depth in the tank;
A = the tank surface area;
Q_{in} = time-varying flow entering the tank, and
Q_{out} = time-varying flow discharged from tank.

The discharge flow rate depends on the liquid height,

$$Q_{out} = N_v \alpha_v h^{\beta} \tag{8}$$

where

N = number of weirs;

α = weir coefficient, that depends on angle, width, and height;

β = exponent, that depends on weir type.

Experiments with four basins (primary settler, aerator, secondary settler and effluent tube) were modelled, and influent and effluent flow rates for the plant were recorded. Such a model was identified using a nonlinear simulation model together with measurement data, according to figure 2.

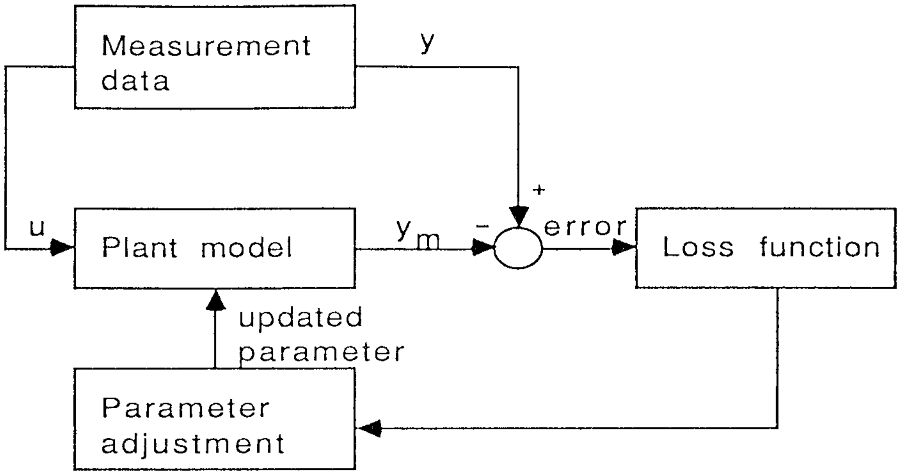

Figure 2. Illustration of the structured identification.

The model included calculated parameters according to (7) and (8). Only one unknown parameter, the return sludge flow rate, was identified in the calculations. 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 was identified in Olsson-Chapman (1985) using a 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. This approach allowed successful identifications from several experiments on the pilot plant 1 at the Wastewater Technology Centre in Burlington, Ontario.

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