Progress in sensor technology – progress in process control? Part I: Sensor property investigation and classification

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Abstract To ensure correctly operating control systems, the measurement and control equipment in WWTPs must be mutually consistent. The dynamic simulation of activated sludge systems could offer a suitable tool for designing and optimising control strategies. Ideal or simplified sensor models represent a limiting factor for comparability with field applications. More realistic sensor models are therefore required. Two groups of sensor models are proposed on the basis of field and laboratory tests: one for specific sensors and another for a classification of sensor types to be used with the COST simulation benchmark environment. This should lead to a more realistic test environment and allow control engineers to define the requirements of the measuring equipment as a function of the selected control strategy.

Keywords ASM; control of WWTPs; COST benchmark; sensor behaviour; sensor classes; sensor models

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Introduction

In recent years, the importance of on-line measurements on WWTPs has increased noticeably and more reliable sensors have become available. Their main applications are in process control and for the continuous monitoring of effluent quality (Jeppsson *et al.*, 2002). Although these two applications have completely different requirements with regard to sensor behaviour, the same instruments are often used in both cases. High accuracy is needed for monitoring quality standards, although low demands are made on the time scale, whereas control applications mainly require a high measuring frequency and a short response time. Recently developed nutrient sensors offer new perspectives for process control, but their limitations should be kept in mind. The time resolution may be essential for the control result, for example the inlet load variation must be measured quickly in feed-forward control to minimize the impact on the controlled processes. Finally, measurement noise may disturb the control behaviour.

The dynamic simulation of activated sludge systems (i.e. with the ASM family, Henze *et al.*, 2000) is a proven tool for testing and optimising control strategies. The ideal (no delay or noise) or simplified (only delay) sensor models which are commonly used represent a limiting factor as regards comparability to field applications. Two groups of sensor models will be proposed in the following treatment: the first group describes specific sensors whose main characteristics have been determined. It is envisaged that this group be applied to optimise existing control systems consisting of measurement and control equipment. The second group of sensor models is designed with respect to the COST benchmark simulation framework (Alex *et al.*, 1999; Copp, 2002). This framework was set up to test various control strategies in a standardised environment. Six classes of sensors are defined in order to specify the requirements of the control strategies on the measuring system. In a second paper (Alex *et al.*, 2003), the sensor models will be applied to simple and sophisticated aeration-control strategies in order to demonstrate the impact of sensor behaviour on the control result.

Sensor field tests

A number of ammonium analysers were tested in the laboratory as well as in field applications. The laboratory tests included measurements of calibration standards and recovery experiments on the wastewater matrix. The field tests comprised the laboratory analysis of grab samples and determination of the response time of the measuring systems. The measurement results were processed in a database which is part of a software environment dealing with a monitoring concept for on-line analysers (Thomann *et al.*, 2002). Control applications require the response time not only of the analyser but also of the entire measuring system including sample preparation where this exists. The study covered various methods for detecting the response time of the entire measuring system depending on the type of analyser (Table 1).

In general, the response (or T90) time (Figure 2 according to ISO/CD, 2000) of the sensors can be easily determined by switching between buckets containing test solutions of different concentrations. This test becomes more complicated for analysers requiring sample preparation, depending on the type of filtration unit. Analysers with a submerged filtration unit could be tested like in-line sensors subject to the required sample flow. A different method has to be used for external filtration units requiring a high sample flow rate. The inlet and return sludge flows of two lanes of a WWTP were stopped and digester supernatant was dosed into one lane in order to obtain two tanks with significantly different ammonium concentrations. The response time was determined by changing the sample supply pump from one lane to the other (Figure 1). Grab samples were taken over the test period to monitor the biodegradation.

Table 2 shows the results of the response time tests described as the T90 time (Figure 2). The buoy-type analyser could not be tested due to sensor failures. It should be borne in mind that all tested filtration units use new membrane technology, which affects the response time. Older units often have response times greater than 30 minutes. On this topic, it should also be noted that external sample preparation systems require a high pump capacity and subsequently a high pump energy. This contradicts the goal of minimising the overall energy consumption by using optimised control systems based on on-line measurements.

Sensor models

The following description of two kinds of sensor models is the result of a SIMULINK implementation and to some extent takes into account simulation performance issues which are similar for most simulation systems.

Table 1 List of analysers and filtration units investigated in the tests

No	Analyser	Filtration unit	Distance filt. – anal.	On/in-line
1	Buoy type miniaturised photometric analyser	–	0 m	In-line
2	Photometric standard analyser	Continuous submerged membrane-type probe preparation	23 m	On-line
3	Photometric standard analyser	Discontinuous submerged membrane-type probe preparation	23 m	On-line
4	Flow-through cell type analyser with ion-sensitive electrodes	–	0 m	On-line
5	Gas-sensitive standard analyser	External membrane-type probe preparation	24 m	On-line

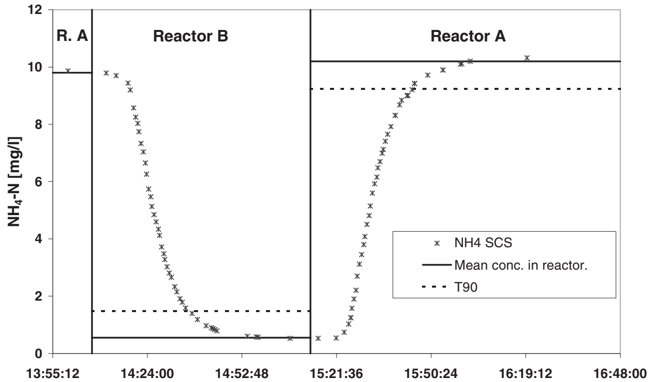

Figure 1 Response time of a standard analyser with external membrane-type probe preparation

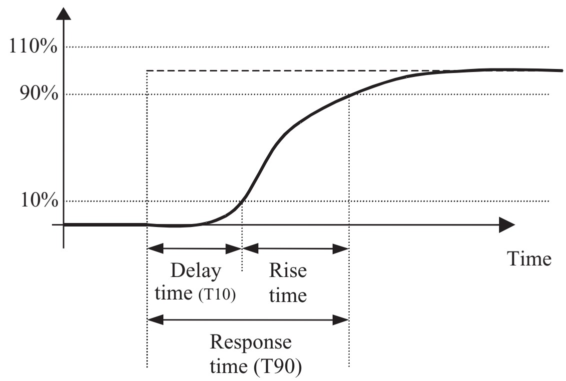

Figure 2 Definition of response time

Table 2 Response time of the determined sensors

No	Analyser	Analyser only T90 [min]	Analyser + filtration unit T90 [min]
1	Buoy-type miniaturised photometric analyser	–	9 *
2	Photometric standard analyser with filtration unit	5	15
3	Photometric standard analyser with filtration unit	6	31 **
4	Flow-through cell type analyser with ion-sensitive electrodes	–	< 5 sec.
5	Gas-sensitive standard analyser with filtration unit	3	30 ***

* Manufacturer specification, ** with discontinuous filtration, *** pump with only low flow rate (1 m^3/h)

Assumptions

First, some assumptions have to be made to ensure general applicability of the models and to keep them as simple as possible: the sensor response is linear over the entire measuring range; no systematic error is considered, since this would depend mainly on the maintenance and changing interference; and finally no attenuation is taken into account. If an attenuation is needed it can be defined within the tested controller.

Real measurement signals always include measurement noise, which can lead to unwanted control actions. A simplified noise description is included in the sensor models. The idea is not to model the noise exactly – this would make the model undesirably complex – but to take into account some of its effects. In order to obtain comparable simulation results for the COST benchmark or to have a basic definition of noise for the specific sensor model, a standard noise signal is defined in an ASCII file. If a random signal had been selected, it would have been necessary to run each simulation a large number of times in order to eliminate its influence. The noise signal has a normal distribution (standard deviation 1) and is frequency-limited. Use of a sample time of 1 minute together with linear interpolation will limit the frequency spectrum of the noise (cut-off of high frequencies – pink noise). The standard noise is then multiplied by the defined noise level (2.5% of the max. measuring range boundary for the benchmark models and user-defined for the specific sensor models). This simplification may run into problems, for instance if an autocorrelation has a significant impact on the control result. If measurements of the specific noise are available, these should be modelled instead.

Sensor model for specific sensors

This sensor model describes sensors whose response time, measurement range (with the detection limit as the lower measurement range boundary), trueness and precision is known. The trueness is implemented optionally to test the robustness of the controller against measurement failures. The precision is calculated from a standard noise defined as the standard deviation at 20 and 80% of the measuring range. Moreover, a continuous drift effect which could be an important source of unwanted control actions is modelled. An autocalibration/autocleaning system and the measuring interval are also taken into account.

In the SIMULINK implementation (Figure 3) the raw sensor signal is transformed by a linear transfer function (block "Transfer Fcn for response time") which is used to implement the step response of the sensor. The real-time behaviour of sensors is typically a combination of the delay time caused by sample transport and a dynamic part (rise/fall time) caused by a factor such as the hydraulic retention time of the analyser's measuring chamber. The draft version of a future ISO standard (ISO/CD, 2000) describing the performance of on-line sensors characterises the sensor dynamics based on a step response as presented in Figure 2. The (transport) delay time is defined as the time required to reach 10% of the final value of a step response (T10). In this context, therefore, the delay time is not exactly the same as the transport delay time or dead time defined in control engineering. The overall time required to reach (and not to leave) a band between 90–110% of the final value of the step response is introduced as a response time (here T90). For the sensor models, the desired dynamic time behaviour of the response time is modelled using a series of Laplace transfer functions. The number of first-order transfer functions in series (n) determines the ratio of delay time (T10) to response time (T90) (Figure 2):

$$G_{\mathrm{sensor}}(s) \qquad \frac{1}{(1+T\ s)^{n}}$$

G_{Sensor} = transfer function for response time
T = T90/factor = time constant to achieve defined T90 time for a given n
s = Laplace operator, n = number of transfer functions in series

Noise is considered by introducing the "standard" noise signal, which is multiplied by the measuring range (y_{max}–y_{min}). The resulting signal is multiplied by a linear function defined by the noise offset a and the slope b. This function is calculated depending on the

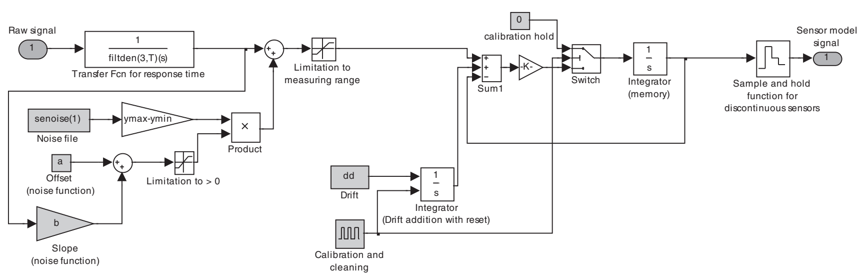

Figure 3 SIMULINK model of a specific sensor

defined noise levels at 20 and 80% (as a relative standard deviation) of the measuring range. The overall resulting noise signal is added to the output signal of the transfer function block.

A calibration and cleaning routine is modelled as a SIMULINK block containing a pulse generator (outputs 0 and 1). If the pulse falls from one to zero, the integrated drift error is reset to zero. During the calibration and cleaning routine, the last value is held using a switch block and another integrator as a memory function. A zero-order hold block is used to model the measuring interval of discontinuous sensors. This block must be deleted for continuous sensors. Figure 5 shows the original and sensor-model signals with the parameters from Figure 4.

It can be seen (Figure 5) that the noise varies depending on the actual measuring value due to the specification of the relative standard deviation at 20% (0.025) and 80% (0.2) of

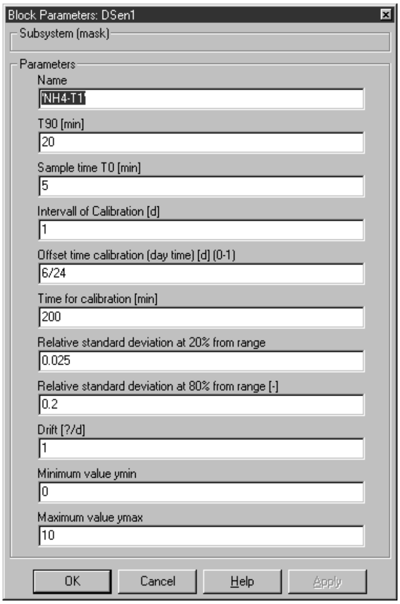

Figure 4 Parameter list of sensor model

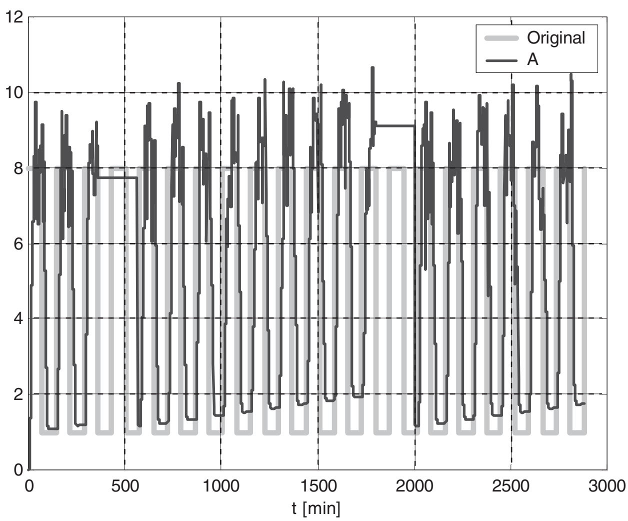

Figure 5 Raw signal (pulse generator) and output signal of the specific sensor model

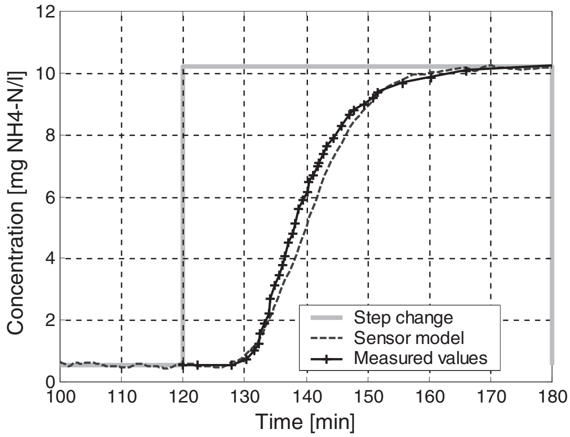

Figure 6 Measured and modelled response time of step change

the measuring range. The continuous drift, the hold time during the calibration routine and the subsequent reset are clearly visible at the lower range. At the higher measuring range, the noise covers the drift effect.

Figure 6 shows the measured response time of the fifth system (gas-sensitive standard analyser with filtration unit) to a concentration step change and the results from the sensor model using a T90 time of 30 minutes and a relative standard deviation at 20 and 80% of the measuring range of 0.5%. No drift or calibration time were taken into account.

Sensor models for the COST simulation benchmark

The aim of the classification is to describe different sensor types but also to limit the number of sensor classes in order to facilitate the comparison of the simulation results. The COST benchmark (Alex *et al.*, 1999; Copp, 2002) is concerned with testing control strategies, so only a few related criteria are used. Thus drift effects are not considered because they would be too sensor-specific. Nevertheless, this procedure could easily be implemented for test reasons. There is no point in defining a user-configurable class, as this would make it difficult to compare different benchmark studies. It is assumed that even future sensors can be classified within the proposed scheme. Should it nevertheless be impossible to choose a class, the benchmark model user would be requested to describe the specific sensor in detail. The six sensor classes are shown in Table 3 and a list of typical sensors in Table 4.

The response time includes the whole system with the filtration unit and measuring system. Class A describes – from a control point of view – almost ideal sensors: the response time of 1 minute is chosen in order to prevent insufficiently realistic control applications. Class B mainly contains classical analysers with fast filtration and short measuring

Table 3 Suggested sensor classes

Sensor classes	Response time [min]	Measuring interval [min]	Examples
Class A	1	0	Ion sensitive, optical without filtration
Class B_0	10	0	Gas sensitive + fast filtration
Class B_1	10	5	Photometric + fast filtration
Class C_0	20	0	Gas-sensitive + slow filtration
Class C_1	20	5	Photometric + slow filtration or sedimentation
Class D	30	30	Photometric or titrimetric for total components

Table 4 Typical sensor characteristics within the proposed classification scheme

Measured variable	Sensor types	Response time (min)	Measuring interval (min)
MLSS (g/l)	A	1	0
Turbidity (FNU or mg TSS/l)			
S_{NH4} (ion-sensitive)			
S_{NOx} (ion-sensitive)			
S_{NOx} (UV)			
C_{COD}, S_{COD} (UV/Vis)			
Flow rate (m^3/d)			
Water level (m)			
Temperature (°C)			
pH			
SO (mg O_2/l)			
Sludge blanket height (m)			
S_{NH4} (gas-sensitive + fast filtration)	B_0	10	0
S_{NOx} (UV + fast filtration)			
S_{NH4} (photometric + fast filtration	B_1	10	5
S_{NO3} (photometric + fast filtration)			
S_{NO2} (photometric + fast filtration)			
S_{PO4} (photometric + fast filtration)			
S_{NH4} (gas-sensitive + slow filtration)	C_0	20	0
S_{NOx} (UV + slow filtration)			
S_{NH4} (photometric + slow filtration or sedimentation)	C_1	20	5
S_{NO3} (photometric + slow filtration or sedimentation)			
S_{NO2} (photometric + slow filtration or sedimentation)			
S_{PO4} (photometric + slow filtration or sedimentation)			
C_{COD} (thermal chemical oxidation + photometric)	D	30	30
TOC (thermal oxidation + IR detector)			
C_N (thermal oxid. + IR detector or chemoluminescence detector)			
C_P (thermal chemical oxidation + photometric)			
Respirometer			
Titration biosensor (alkalinity)			

intervals. Class C describes analysers with a slow filtration or sedimentation unit. Class D includes all batch measurements including the respirometer and sensors for total components. To take into account continuously and discontinuously measuring sensors, classes B and C are subdivided into two subclasses. The measuring interval is defined as five minutes, this being a typical minimum value for photometric analysers. Longer intervals are not useful for control actions and are therefore neglected. In addition to choosing the sensor class, the user must define the measuring range for each sensor. Depending on the chosen measuring range, the standard deviation is calculated as approximately 2.5% of the maximum measuring-range boundary (see sensor model description).

The proposed sensor classes contain a set of continuous (A, B_0, C_0) and time-discrete sensor models (B_1, C_1, D). Continuous models are preferred to time-discrete ones for implementing the continuous sensors for performance reasons. The discontinuous sensors B_1 and C_1 are modelled in a similar way but include an output sample and hold function. Sensor class D is modelled only in discrete form.

Continuously measuring sensors. The following approach is suggested for classes A, B_0 and C_0. Table 5 shows the parameters for the response-time modelling (see specific sensor model) of the continuously operating sensors.

The transport delay for class A is only a small fraction of the response time typical for this sensor class. A system order of $n = 8$ is assumed for sensor classes B and C, which leads

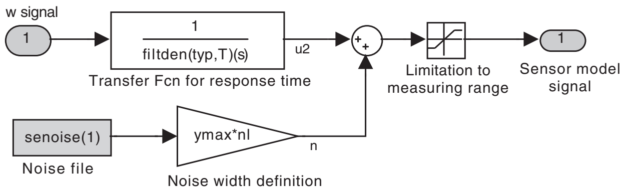

Figure 7 Simulink model of classes A, B_0, C_0

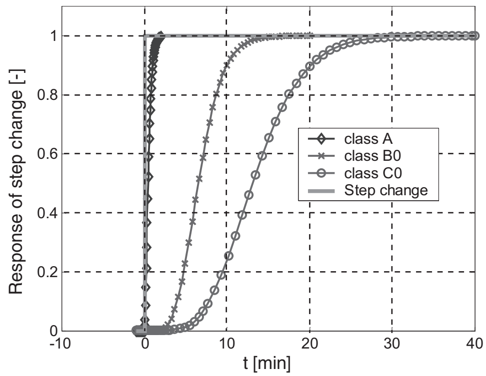

Figure 8 Step response of classes A, B_0, C_0

Table 5 Parameter for response time modelling

Sensor class	T90	*n*	T	$R = T_{10}/T_{90}$
A	1 min	2	0.257	0.133
B_0	10 min	8	0.849	0.392
C_0	20 min	8	1.699	0.392

to a delay time of approximately 40% of the response time. This is assumed to include the significant effect of the sample transport. The step responses for classes A, B_0 and C_0 are presented in Figure 8. The noise is modelled in a similar way to the specific sensor model, but only with a constant noise level *nl*. In the SIMULINK model presented in Figure 9, the noise signal is multiplied by the noise level *nl* and the maximum value of the measurement interval *ymax*. The noise is added to the delayed measurement signal and limited to the measurement interval (*ymin, ymax*). The noise level is defined as *nl* = 0.025 for all benchmark sensor classes (approximately 2.5% of the maximum boundary of the measuring range).

Discontinuously measuring sensors. Sensor classes B_1, C_1 and D are operated discontinuously using a sample time T0. An example of an implementation using a SIMULINK model is presented in Figure 9. The implementation is similar to that used in the model for

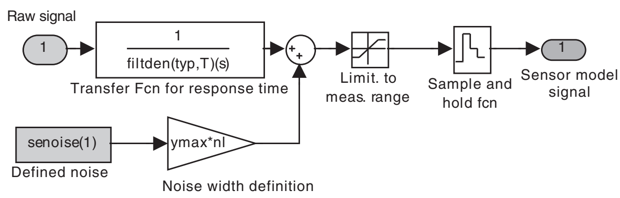

Figure 9 Simulink implementation class B_1, C_1

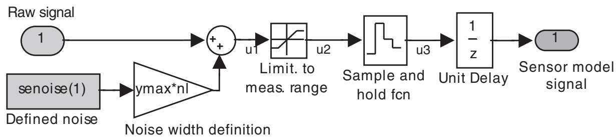

Figure 10 Simulink implementation class D

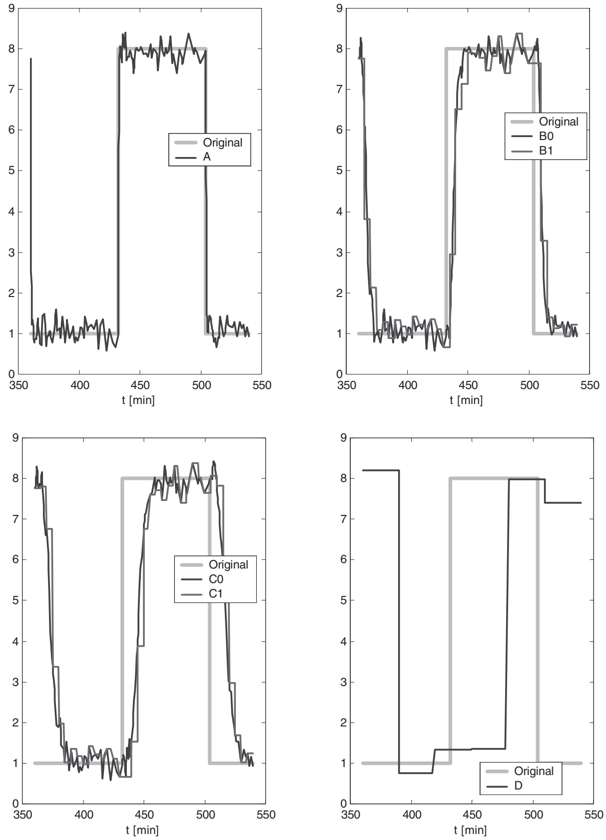

Figure 11 Pulse response of sensor classes

the continuously measuring sensors but includes an additional output sample and hold function.

Sensor class D represents batch-type reactors, for which any of the continuous delay times are negligible compared to the batch operation of the measurement. An appropriate SIMULINK implementation is demonstrated in Figure 10. This model adds noise to the original signal, limits the sum to the measuring range ($ymax - ymin$) and uses a sample and hold function followed by a unit delay ($y(k)=u3(k-1)$). Figure 11 shows examples of the output signal for all sensor classes.

Conclusions

Two groups of sensor models are proposed which allow a more realistic simulation of the control applications of activated sludge systems. The first group covers models for specific sensors. The main characteristics of existing sensors with respect to control applications are described. The aim is to choose a specific sensor or to optimise existing measurement and control systems. The control engineer can also test the robustness of the control strategy against systematic errors as well as noise effects. Under some basic assumptions such as linearity, the models include the response time, noise and drift as well as the calibration and cleaning intervals.

The second group of sensor models is designed for simulation benchmark studies. Various simulation benchmark systems such as the COST (Alex *et al.*, 1999; Copp, 2002) or IWA benchmark (Copp *et al.*, 2001) have been defined in recent years in order to compare different control strategies in a standardised environment. The widely used ideal or simplified sensor models represent a limiting factor for the comparability with field applications. A classification of sensor types and models is proposed in order to obtain more realistic and comparable results. A classification example for commonly used sensors is given. The sensor models are divided up into continuously and discontinuously operating ones, taking into account the response time, a measuring interval and a "standard" noise. The width of the noise is defined as a standard deviation of 2.5% of the maximum measuring-range boundary. This should move the benchmark environment forward towards more applicable results. Moreover, it could also be an important step for optimisation studies using dynamic simulation because it will allow control engineers to define the requirements of the measuring equipment on the basis of the selected control strategy.

An investigation of the impact of sensor behaviour on various control strategies using the defined sensor classes is presented in Alex *et al.* (2002). A next step for even more realistic simulation results would be to model the response of the activated sludge system with respect to the controllers, for example a delay due to a limitation of the start/stop frequency of a blower.

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