Application of case-based reasoning to predict sludge settling and endogenous denitrification

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Abstract For the last years, artificial intelligence (AI) approaches have become useful tools in environmental engineering. Here, one relevant application area is the optimization of waste-water treatment plants (WWTP). In this paper we present a tool for real-time control (RTC) and decision support, which has been tailored to sequencing batch reactors (SBR) plants. The tool, which is able to predict the sludge settling curves as well as the endogenous denitrification (ED) during settle and draw, is based on case-based reasoning (CBR), an AI method. The tool bases its decision on past events and situations captured in cases.

Keywords RTC, SBR, CBR, sludge settling curves, endogenous denitrification

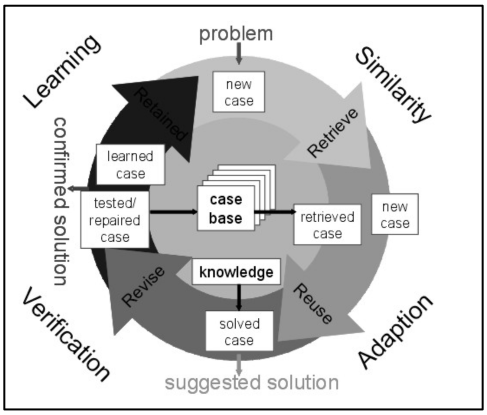
Introduction

Common control strategies for SBR plants (Figure 1, right) are still almost exclusively based on conventional controllers (e.g., two-position, PI/PID, sequential controller). So, mostly manual intervention by the plant operators is also necessary (Wilderer *et al.*, 2001). Because of the complex dynamics and structures of SBR plants these controllers are often overstretched. If SBR plants should be operated close to the capacity limit, while at the same time minimizing operating costs as well as the emissions, the consideration of the boundary conditions in the controller strategy is absolutely essential. In these cases, it is necessary to use complex controllers, which are based on model predictive control, soft sensors, multivariable or multi-objective decisions etc. At this stage, methods and technologies from AI have been discovered to play an important role. Even though sensor and control systems are improving considering costs and accuracy (Table 1), the problem of incomplete or missing data still exists because many parameters are difficult to measure or cannot be measured at all. In specific cases, the measured data might not be representative for the overall system. So, it often happens that WWTP operators must control the plants rather with their experiences from past events than with sophisticated machines. When it comes to capturing and especially drawing conclusions from experiences, AI offers with CBR (Figure 1, left) a powerful technology, which has already proved its potentials in various industrial applications (e.g., Bergmann et al., 1999). The advantages of CBR are: high transparency (very similarly to the human problem solution process), high user acceptance (the solution (process) is easy to understand), better quality of the solution (CBR can also learn from errors), lower expenditure for knowledge acquisition (it is easier to collect cases (e.g., measured process data) than to collect expert knowledge etc.), use of existing data bases (modern WWTPs are often equipped with numerous sensors etc.). Consequently, many process data are available for CBR and/or RTC. Recently, an increasing number of publications can be found that deal with CBR and WWT, e.g.: Krovvidy and Wee (1993), Sànchez-Marrè *et al.* (1996), Rodríguez-Roda *et al.* (2001) etc. Further examples can be found in Wiese *et al.* (2005a).

In this paper we present two applications of CBR for implementing intelligent control strategies for SBR plants.

Table 1 Investment costs (IC) for online sensors (prices without value added tax, prices according to information of a leading manufacturer). ([1]= Controller for up to 8 digital sensors)

No.	Measuring instruments	IC [EUR]
1	NO_3-N probe (digital)	11,400
2	Sludge level (SL) probe (digital)	3,000
3	Total suspended solids (TSS) probe (digital)	2,600
4	Sludge volume (SV) probe (digital)	5,000
5	Digital universal controller [1]	2,200



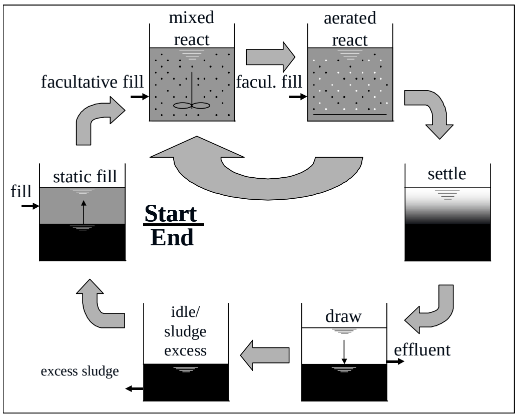


Figure 1. Left: The CBR cycle according to Aamodt and Plaza (1994). Right: the SBR cycle

Material and Methods

Input data

The input data for the CBR tools were measured on a full-scale SBR plant (WWTP Messel, 5,000 p.e., FRG). The plant is equipped with numerous online measuring devices (Figure 2). Each of the two SBRs (ca. 1,600 m^3 per reactor, height of reactor: 5.5 m) is equipped with online sensors and analyzers for NO_3-N, NH_4-N, PO_4-P, TSS, water temperature (WT), O_2, water level (WL) and sludge level (SL). Further details about WWTP Messel can be found in Wiese *et al.* (2005b). All measuring instruments are very precise (Figure 3).

Reasons for development

Even a small sludge displacement from the reactor into the plant effluent can cause an exceeding of the COD and TP effluent limits. Consequently, the duration of settle and draw is usually dimensioned for unfavourable operational conditions (e.g., high SVI). As a consequence of the static dimensioning, the duration of these both phases takes often in total 2.0 - 2.5 h. In reality, the sludge characteristics are usually much better than the design values. Consequently, in many cases a RTC for the optimisation of settle and draw as well as VER (volumetric exchange ratio = fraction of the reactor volume, which is removed during draw and replaced during fill) is economically and ecologically reasonable. Such a control strategy can be based on a SL probe and/or a TSS probe (and/or a turbidity probe).

Figure 2 1 = floating decant device with mountings for 2, 3, 4 and 5; 2 = TSS probe; 3 = NO_3-N probe; 4 = SL probe; 5 = SV probe (all devices from HACH LANGE GmbH)

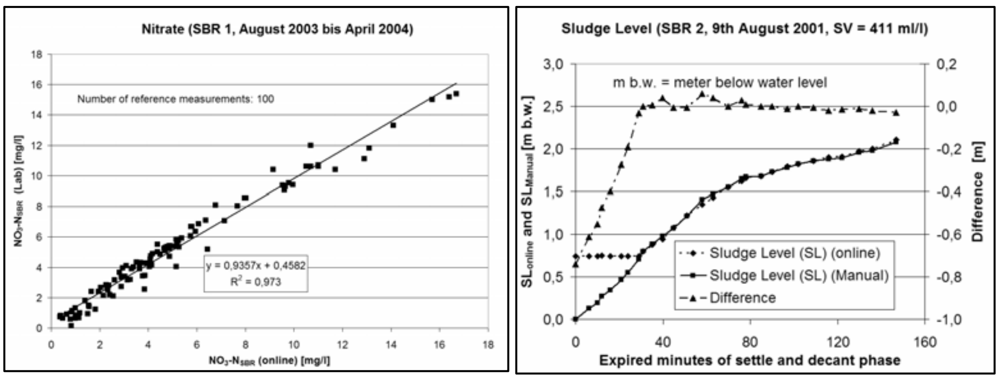
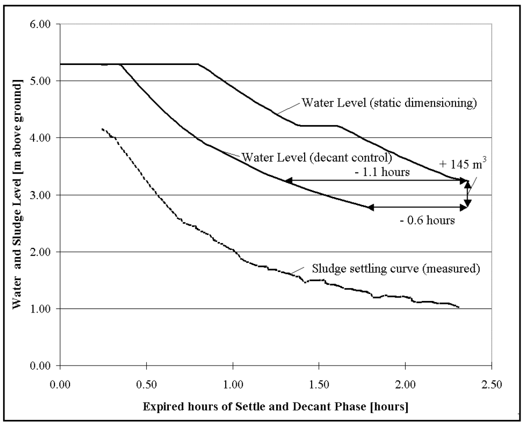


Figure 3 Reference measurements for NO_3-N (left) and SL (right) sensors.

The Example in Figure 4, left shows that it would be possible to reduce the settle and draw phase up to 1.1 h and thus to increase the hydraulic capacity (HC) up to ca. 20 %. Furthermore, it would be possible to increase the VER from 40 to 50 % (+145 m^3); this could further increase the HC. Consequently, a high optimization potential exists. In the Example shown in Figure 4, right it could be observed that the settling velocity of the sludge level mainly depends on two factors. As already published by other authors (e.g., Keudel and Dichtl, 2000), the initial settling velocity depends on the sludge volume at the beginning of the settle phase. Thus, the initial settling velocity in a full SBR is higher than in a barely filled tank, because the compression phase of the sludge starts later. Furthermore, it could be observed that the settling velocity of the sludge level depends on the last phase before the settle phase. In case of a mixed react phase (WWTP Messel: wet weather cycle), it takes at least 10 min until the sedimentation begins. In case of an aerated react phase (dry weather cycle), the turbulences at the beginning of the sedimentation phase are much smaller, thus the flocculation process is faster and the sedimentation process can start in less than 5 min. The different curves in figure 4 (right) show that the sludge settling curves (SSC) are almost identical, when the conditions (e.g., SV, type of cycle, WL) are similar. I.e., it seems to be possible to predict the SSC, when these factors can be measured.



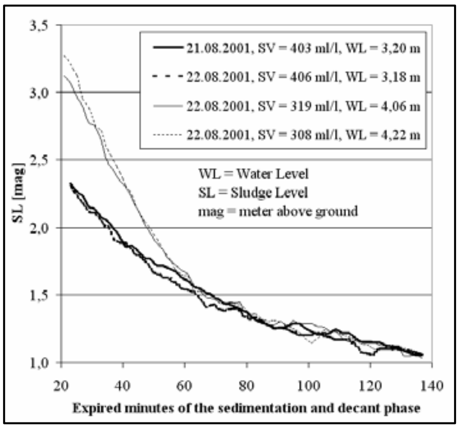


Figure 4 Left: Potential for optimization of settle and decant phase. Right: measured sludge level curves during the settle and draw phase during four following dry weather cycles

During the last years, several attempts were started to use online deterministic WWTP models for control tasks. Unfortunately, these models are very complex. E.g., the ASM 3 (IWA, 2000) model takes into consideration 12 processes, 14 model compounds and 36 kinetic and stoichiometric parameters; many of them are difficult to be determined or cannot be measured at all. Consequently, the use of deterministic online models is very expensive. Therefore, the experiment was started to predict biological processes with CBR. So, the endogenous denitrification (ED) during the settle and decant phase of a batch cycle was selected as a test example: It was found out from full-scale results of WWTP Messel that a total nitrogen reduction of approx. 20 % was achieved during settle and draw. But, the endogenous nitrate respiration is not taken into consideration within the static dimensioning process. I.e. the static and/or mixed fill and mixed react phase at the beginning of the next cycle could be reduced significantly in many cases. In some cases, it is also possible to skip over these two steps completely and thus to reduce the cycle duration by 1.0 – 1.5 h.

In principle it is possible to use a big portion of the plant-inherent optimisation potential by using conventional process-dependent controller. Nevertheless, the whole potential for optimisation can only be used, when a control strategy will be realised, which is able to act and not only to react. This particularly applies, when the SBR plant should be operated close to the theoretical capacity limit. Therefore, a controller methodology is necessary, which is able to predict as early as possible the SSC, the VER and the ED rate. Due to the enormous amount of measurement data, it would not make sense to use only one CBR model to predict the SSC as well as the ED, because the database would have to be extremely large. Furthermore, it would be more difficult to find a good match with a single domain model. So, it is promising to work with two separate domain models.

Structure of the CBR model “Sludge settling curve”

In the first step, more than 120 sludge settling curves, which have been measured under different operational conditions, were analyzed and evaluated statistically. Then, the following 4 attributes were selected for the CBR tool: cycle type, WL at the beginning of the settle phase, SV and WT (see Table 2). In order to create the initial case base, in the second step, 30 representative curves have been selected. Then, the calibration and validation process was started. The local similarity measures are mainly given by linear distance functions (Euclidean distances) between the query values and the respective case values. Only the cycle type with its two values ‘dry weather’ and ‘rain weather’ has been modeled as a simple similarity matrix. The global similarity function is a weighted sum of the local similarities. The solution part of the cases is given by the courses of the respective sludge heights, represented by sludge settling curves. The representation of these curves has been simplified approximating them by polynomials of degree six.

Table 2 Attributes for the CBR tool “Sludge settling curve” phase ([1] = once per working day)

No.	Attribute	Unit	Measuring instruments	Value range
1	Cycle type	-	-	dry weather, wet weather
2	Water level	m	water level meter	3.32 – 5.30
3	Sludge volume	ml/l	per hand [1]	241 – 446
4	Water temperature	ºC	temperature meter	8.7 – 21.4

Structure of the CBR tool “Endogenous denitrification (ED)”

The initial data base consists of 137 evaluated cycles. Thereby, the ED during settle and draw amounts between 0.1 and 5.0 kg NO_3-N per cycle (average: 2.3 kg NO_3-N). Unlike Kazmi and Furumai (2000), no significant differences between dry weather flow and combined sewage flow could be observed. 6 attributes have been chosen for the model Table 3). The number of the SBR (where the data were measured) was chosen as an attribute, because the biological activities in the different reactors can be slightly different. To describe the local similarities of the attributes, linear and polynomial similarity functions were used. The predicted ED rate is usually calculated as the mean value of 2 rates, which have been measured under the most similar operation conditions.

Table 3 Attributes for the CBR tool “Endogenous denitrification” phase (all parameters measured at the beginning of the sedimentation)

No.	Attribute	Unit	Measuring instruments	Value range
1	NO_3-N load	g	NO_3-N probe, WLM	166 – 19,285
2	NO_3-N concentration	mg/l	NO_3-N probe	0.18 – 15.37
3	Water level	m	water level meter (WLM)	3.18 – 5.28
4	Total biomass	kg	TSS probe, WLM	3,350 – 8,809
5	Water temperature	º C	Temperature meter	7.22 – 15.17
6	SBR reactor	No.	SCADA/PLC	1 or 2

Results and Discussion

Results of the CBR tool “Sludge settling curve”

The results produced by this tool are promising. Despite the fact that the database is rather small, the model is able to predict the SSC well. Thereby, the predicted SSC is a weighted function, calculated with the help of 3 measured curves, which have been measured under the most similar operation conditions. Figure 5 (left) shows an example for a good prediction. The measured and predicted curves are almost identical. Of course, not all predictions are as good as in this example. Figure 5 (right) shows an example for a worse prediction. However, even in this worse case the maximum difference is only 0.5 m. It has to be taken into consideration that the measurement inaccuracy of the SL probe can be up to 0.2 m. Furthermore, in practice such worse predictions would not cause serious problems, because with the help of a SL probe-based and/or a TSS probe-based feedback decant controller, which survey the decant phase, it is easily possible to close the decanter immediately, in case of a sludge displacement danger.

Results of the CBR tool "Endogenous denitrification"

By using this model, it is possible to predict the ED quite well: The standard deviation of the estimation is 0.6 kg NO_3-N. For comparison: The standard deviation of the estimation with the help of a multiple regression model is 0.7 kg NO_3-N. The average error of the CBR tool is 0.048 kg NO_3-N. The maximum errors are 1.6 and/or -2.7 kg NO_3-N. In 73 % of the cases the absolute error is below 0.5 kg NO_3-N; in 47 % below 0.25 kg NO_3-N.

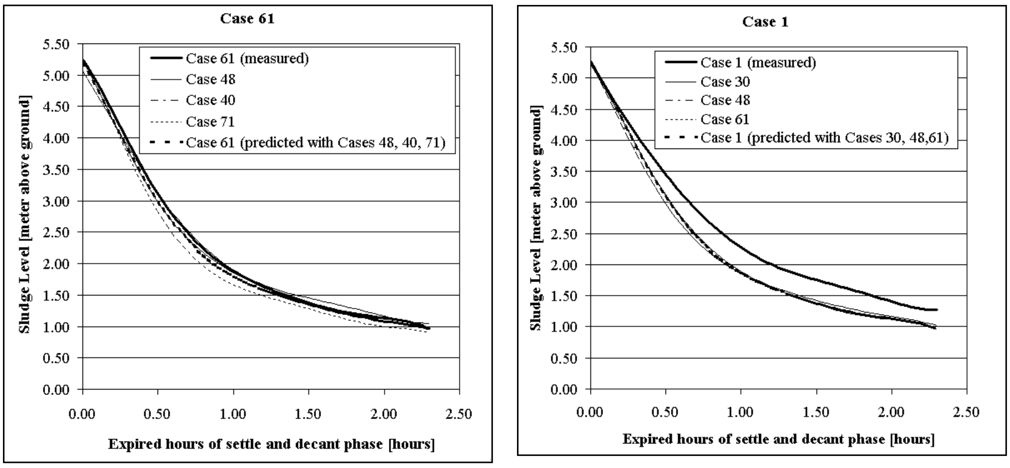


Figure 5 Left: Good prediction of the SSC. Right: Example for a worse prediction.

Outlook

Modifications, on-line implementation and further CBR models

The determination of SV in a SBR plant is very fault-prone. Hence, a SV sensor can be very useful. In combination with an online TSS sensor, it is also possible to measure the sludge volume index. Due to the high accuracy of the sensors (Table 1) (Simon *et al.*, 2005), it is also possible to include this probe in the CBR tool for the sedimentation and decant phase and thus to further improve the prediction accuracy. So far, our system only simulates the processes offline, i.e. the generated solutions are not to be returned to the CACD interface. In the next years, the CBR tools should be verified in full-scale by feeding the so generated control data into the SCADA system of WWTP Messel. As a consequence of the good results reached with the different CBR models, other components of our architecture should be developed, i.e. CBR models for nitrification, denitrification etc.

Can one reactor/plant learn from the experience of another reactor/plant?

In the CBR tool "ED" the data base consists of data, which were measured in two different reactors. This example shows that it seems to be possible – at least for specific tasks – that one reactor can learn from the experience of another reactor on the same plant. Maybe it is even possible, that one SBR plant can learn from the experience of another SBR plant. If this assumption is correct, interesting possibilities and applications would result from this: The CBR models could learn much faster and the expenditure for the model setup and model adaptation could be reduced clearly. A new SBR plant (student) would be able to learn from the positive and negative experiences of older SBR plants (teachers). Due to the fact, that more and more SCADA systems are PC- and/or Web-based systems, an “Internet Academy for SBR plants” could be established. Eventually, not every SBR plant must be equipped with a complete set of on-line equipment for development and use of CBR-based soft sensors.

Machine learning techniques

The success of any CBR application crucially depends on its capability to identify problems in the case base that are actually useful for solving the current problem. Therefore, CBR systems rely on domain specific similarity measures that are able to approximate the utility of given cases. Nowadays, these similarity measures are usually defined manually. First one has to interview domain experts in order to obtain the required knowledge. In a second step, this knowledge has to be encoded by using the complex representations provided by state-of-the-art CBR systems. However, this procedure is coupled with some drawbacks:

- It is very time consuming and hence also very cost intensive.
- Similarity measures require numerous numeric parameters (e.g., feature weights) and the determination of optimal values for such quantitative parameters is very difficult or even impossible for a domain expert.
- It is very difficult to estimate the impact of local changes in the similarity measure on the final outcome of the retrieval process.
- Often the relationships and influences of the different aspects of the problem are unknown and hence also domain experts are unable to provide the required knowledge.

In the applications described in this paper, up to now the similarity measures manually has been defined. However, in the future the employed similarity measures should be optimized, and therewith also the prediction accuracy of the systems, by applying a novel learning approach for optimizing the prediction accuracy of CBR applications in the field of WWT. Existing approaches for optimizing feature weights (see Núñez et al., 2002 or Wettschereck, 1995) are restricted to classification tasks, i.e. here the solution is simply represented by a class label. The advantage of the novel learning approach (see Stahl, 2003 for a detailed description) is that it allows flexible learning of both, feature weights and local similarity measures and that it can be applied in arbitrary application scenarios, where the solution is represented by more complex representations (e.g. sludge settling curves). The basic idea is to define a quality measure on the solution part of cases. For example, a predicted sludge settling curve can be compared with the actual measured curved by some “solution similarity measure” (Stahl and Schmitt, 2002) that can be defined easily (e.g. the integral over the two curve’s differences). This would enable us to judge the quality of the prediction accuracy and hence also the quality of the used similarity measure afterwards. This information can then be used as training data for a machine learning algorithm in order to optimize the similarity measure. For example, Stahl and Gabel (2003) have described a genetic algorithm for learning similarity measures.

Conclusions

The examples discussed in this paper show that the use of CBR for SBR plants could be very promising, especially in case of RTC and/or education. But, in order to optimize the prediction accuracy of WWT applications, it seems to be necessary to employ knowledge-intensive similarity measures that take the application and domain specific characteristics into account. The drawback of such similarity measures is the additional modelling effort and the corresponding costs. The proposed machine learning approaches allows to increase the benefit of case-based WWT applications by improving the prediction accuracy and simultaneously reducing the deployment costs. This may help to make the CBR technology more interesting for commercial applications in the WWT field.

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