Experience Management for Wastewater Treatment

Content Areas: Case-Based Reasoning (CBR), Decision Support System (DSS), Harmful Microorganisms, Real Time Control (RTC), Sequencing Batch Reactor (SBR), Wastewater Treatment Plants (WWTP)

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Abstract

Methods and technologies from Artificial Intelligence (AI) have already entered many areas other than only computer sciences. For the last few years, AI approaches have also become extremely useful tools in environmental engineering. Here, one relevant application area is the optimization of processes in wastewater treatment plants (WWTPs). Besides the examination of the technical states of the different environmental systems, their human managers' knowledge and experiences from past events gain more and more importance. In this paper, we will present two examples for approaches from Experience Management (EM), specifically based on Case-Based Reasoning (CBR) in the field of wastewater treatment (WWT): first, a DSS to Identification and Counteraction for Harmful Microorganisms in WWTPs and the second approach deals with a Predictive Controller for discontinuous Sequencing Batch Reactor (SBR) plants.

1 Introduction

During recent years, a rising complexity of the problems in the area of wastewater treatment can be observed. On the one hand, major reasons can be found in the growing requirements for purification and the interweaving to a high degree by connections and dependencies of sewer systems, WWTP, and receiving water. On the other hand, the technologies for measurements of the quality parameters as well as the process control systems have become more powerful and more inexpensive. Nevertheless, such systems are still a cost factor. Due to the fact of low public budgets, the use of latest technologies or even expensive changes in the WWTP infrastructure is often impossible.

Thus, approaches for optimisation of existing plants attract more and more the attention, which make extensive use of the plant-inherent potentials. At this stage, methods and technologies from AI have been discovered to play an important role.

Even though measuring and control technologies are improving, the problem of incomplete or missing data still exists because many parameters are difficult to be determined or cannot be determined at all. Furthermore, in specific cases, the measured data might not be representative for the overall system. Therefore, it often happens that the WWTP operator must control the plant rather with his experience from past events than with sophisticated machines. When it comes to capturing and especially drawing conclusions from experiences, AI offers with Case-Based Reasoning a powerful technology, which has already proved its potentials in different industrial applications (see, e.g., [Bergmann *et al.*, 1999]). In this paper, we will present several examples for CBR approaches in wastewater treatment.

The paper is structured as follows. In section 2, we will present a Decision Support System (DSS) based on a CBR approach to Identification and Counteraction for Harmful Microorganisms in WWTPs. Section 3 describes an architecture for a predictive WWTP controller that bases its decisions for the plant control on past events and situations captured in cases. The system has been tailored to a relatively unknown kind of WWTP, the Sequencing Batch Reactors. Furthermore, we present in Section 3 the research project "Messel", within parts of our suggested architecture have been implemented and tested in a simulated environment. In Section 4, we take a look at other CBR approaches in the field of wastewater treatment. Section 5 end with the conclusions.

2 Example 1 - DSS Harmful Microorganisms

2.1 Introduction

Growing quantities of wastewater made enlargements of treatment plants necessary. Then, trying to optimize the costs for running the plants by reducing the precipitation and minimizing the oxygen supply for the biological system in the plant sometimes leads to new problems; from the ecological and biological points of view, optimization can entail undesired side effects. Environmental conditions are created that favor filamentous organisms, which can cause foam effects or later even lead to harmful bulking sludge or scum formation [Eikelboom, 2000]. We can observe this phenomenon by a growing number of WWTPs during recent years; especially during spring and autumn time. One crucial factor amongst others is the loss of biomass needed for the biological purification in the system. The responsible harmful microorganisms affect nearly all biological processes for WWT. Additionally, the bulking sludge problem does not only influence the WWT in a negative way but also the sludge treatment. If sludge dominated by filamentous bacteria reenters the anaerobic sludge treatment foaming of the digester contents can occur. As a consequence, the digester can over boil.

The managers of WWTPs with bulking sludge problem consider this one of the most important problems to be solved. Nowadays, various approaches for counteractions exist to eliminate the problem-generating microorganisms [Eikelboom, 2000], for instance, deployment of lime, polymers or pulverized lignite, installation of selectors, increasing or decreasing of the oxygen, etc. Usually, bulking sludge problems have their individual aspects depending on the WWTP where they occur. Therefore, the next problem that is developing has to be seen in finding the right solution. This task is even harder to solve, as different harmful types of microorganisms can exist in the sludge. The same counteraction that kills one of these types of bacteria can help the growth of others.

We conclude that the only efficient way for suppressing the excessive growth of the specifically responsible microorganisms is their identification and the closely related goal-directed selection of treatment means. Our starting points are the positive and negative experiences experts made in the treatment of bulking sludge problems. Their experiences serve as successful suggestions for solutions respectively the knowledge about unsuccessful treatments (failures). So, the aim was the development of an expert system that supports the decision process for the selection of adequate counteractions. The system is fed by a query that describes parameters of the WWTP. We will have a closer look at the technology behind the scenes of our expert system and the underlying domain model in Sections 2.2 and 2.3.

2.2 The Case Representation

It is typical for CBR applications that the case representation consists of two major parts: a problem description and a solution description, as mentioned before. In the following, we give an overview of the structure of these two parts that make up the domain model for our system.

The aim of the problem description is to characterize the current situation on a WWTP when a problem caused by uncontrolled reproduction of harmful microorganisms is observed. Unfortunately, even WWTP experts are not able to determine the relevant influences exactly. Therefore, all information that may have significant impact on the microorganism problem is considered in the problem description. Basically, the information of the problem description is divided into the following four parts, represented by particular concepts in an object-oriented domain model:

WWTP data: This part contains relevant information about the respective WWTP where the problem occurred. This kind of information includes attributes that describe the structure and operating parameters of the specific plant.

Already performed counteracts: Here, all available data about already performed counteracts against the sludge problem is stored. These pieces of information are also essential because it contains important hints about the responsible microorganism species. For example, if a counteraction that works usually very well against microorganism *M* has been applied, but the bulking sludge problem is still present, this is a clear hint that microorganism *M* is not the responsible species in the current situation.

Environmental data: Due to the fact, that the occurrence of microorganism problems crucially depends on the current environmental circumstances, this information is also a core component of the problem description.

Quality information: Additionally, some attributes describing the quality of the particular case data are introduced. Because the case base contains currently observed problems as well as problems described in specific WWT literature, it is useful to assign each case a respective confidence level.

The aim of the corresponding solution description is the qualitative and quantitative identification of the species of microorganisms measured in the described bulking sludge problem. Therefore, the solution description contains one attribute for each major microorganism species relevant with respect to the sludge difficulty. The value range of these attributes is the interval of real values. These values correspond to a particular measure used when carrying out a microscopic examination of sludge probes. Here, the value 0 states that the respective microorganism is absent, while high values correspond to a high concentration. Though the described application can be characterized as a classification task, the solution description is not a simple class identifier like in common similar applications. Instead, the solution itself is again a complex object in form of a 11-dimensional vector. The consequences of this complexity will be discussed in more detail in the next section. Figures 1 and 2 partially show the used case representation and an exemplary case. The complete representation consists of 40 attributes describing the problem part and 11 attributes describing the solution part. However, many cases contain some unknown attributes, especially the cases taken from scientific literature. The corresponding uncertainty about the quality of this case data is then explicitly remarked in the already mentioned additional attributes.

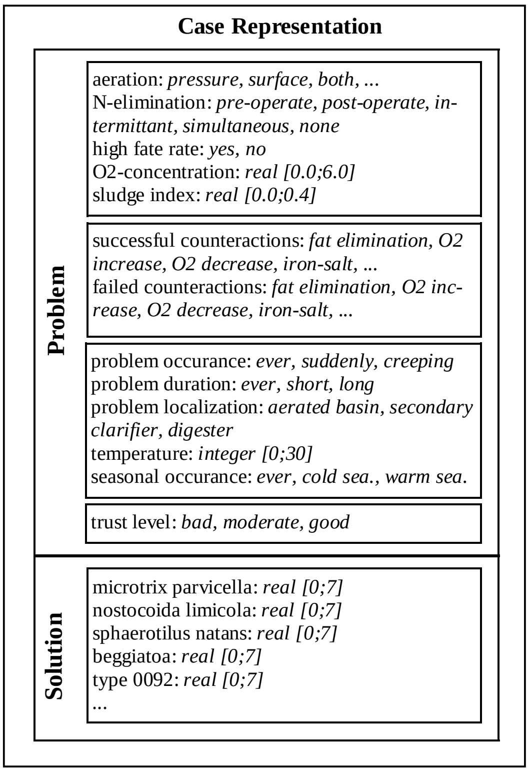

Figure 1: Parts of the case representation.

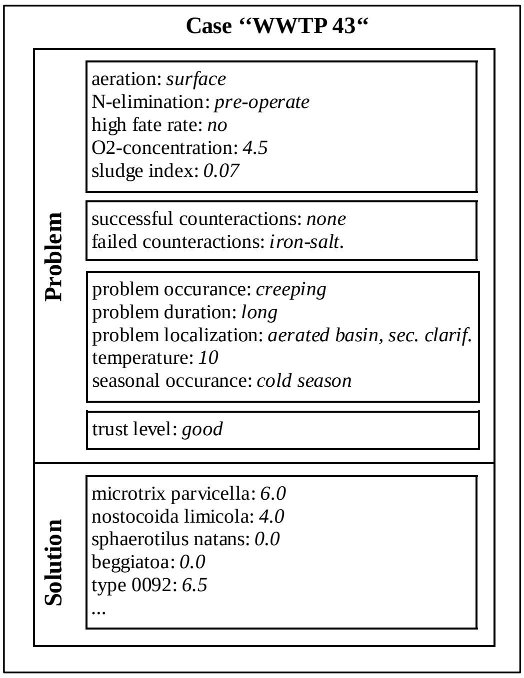

Figure 2: Parts of an example case.

2.3 Optimizing Classification Accuracy

The success of any CBR application crucially depends on the quality of the employed similarity measure used to retrieve the most *useful* cases with respect to the current problem situation. Unfortunately, due to the high complexity of our problem description, it is very hard to define an optimal similarity measure. Therefore, it is planned to apply a machine learning approach in order to optimize the similarity measure and therewith also the classification accuracy of the system. This is not an absolutely unusual procedure to improve classification systems based on CBR. A lot of approaches to learn one important part of the similarity measure, namely the feature weights, have been developed up to now [Wettschereck and Aha, 1995]. All these approaches are based on a leave-one-out test and try to find a measure that assigns a higher similarity to cases containing a “correct” classification than to cases containing an “incorrect” classification. However, this procedure is only applicable when the occurring classes are quite simple (e.g., only described by a simple class identifier represented by a string) and disjunctive. Nevertheless, as described in the precedent section our “classes” are really complex objects. Therefore, a hard distinction between “correct” and “incorrect” classes is insufficient.

To avoid this problem, we apply a novel approach that allows a more flexible validation of retrieval results. This approach is based on a new concept, that we call *solution similarity* represented by an additional similarity measure that compares solution parts of cases instead of problem parts (see Figure 3). This allows us to measure classification results as “better” or “worse” instead of only “correct/incorrect”. By using this concept, we are able to adapt one of the existing learning approaches in order to optimize the attribute weights assigned to the attributes of our problem description. We hope this allows us to define a similarity measure that sufficiently measures the *utility* of cases with respect to a current bulking sludge problem.

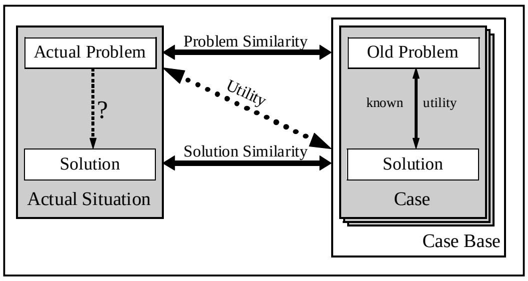

Figure 3: The concept of solution similarity.

2.4 Project Summary

The approach presented in this example is implemented in the research project ZERBERUS. In a preliminary stage of the project, the WWTP managers’ experiences had been elicited using a mail questionnaire. All relevant data was extracted from the questionnaires and transformed into cases. So, we gathered approximately 70 cases until now. Starting from this point, we divided the project into two major stages. On the first stage, we concentrated on the identification of the harmful microorganisms that caused the bulking sludge problem. A WWTP manager can specify a current problem and query the system's experiences to find out what might be the responsible bacteria. The second stage can generate an individual treatment solution for the queried problem situation. The solution will be based on the specific WWTP conditions and the retrieved solutions from the most similar experiences in the case base. The WWTP manager's feedback on the quality of the generated solution will be used to improve our system by a certain learning effect. If the generated suggestion – which counteraction to take – was successful or unsuccessful this new experience will be integrated in the case base. A few weeks ago, the implementation of the DSS was completed (see http://www.zerberus-online.de).

3 Example 2 – SBR Real Time Control

In contrast to the example from Section 2 where we showed the potentials of EM in critical situations that are already present on the WWTP, we will now focus on the prediction of the right control steps to be taken dependent on the current situation of the WWTP.

3.1 Introduction

In Germany and several other countries, urban drainage mainly consists of combined sewer systems (CSS). That means, sewage and stormwater flow are transported in one sewer. So, during rain events the amount of combined sewer flow in the sewer system is much larger than that of dry weather flow. Due to high costs and the limited flexibility of biological processes against high hydraulic and high pollution loads, the prescribed maximum influent capacity of the WWTP is much lower than that of the CSS. The fraction of combined sewage that surpasses the maximum inflow rate will either be stored in detention basins and routed to the WWTP later or directly discharged into the receiving water. The pollution load on the receiving water caused by these so-called Combined Sewer Overflow (CSO) events might be as high as that caused by the WWTP effluent at the same time; during certain rain events it can even be much higher. Until now, most sewer systems with their ancillary structures as well as WWTPs are designed and operated in a static way. One disadvantage of this method is that CSOs can occur even when there are still free storage capacities within the sewer system and/or free treatment capacities in the WWTP. Therefore, integrated Real Time Control (RTC) strategies, which are trying to reduce total emissions by operating sewer system and WWTP depending on the current capacities of both systems, are more than necessary considering environmental and economical aspects. One can find several examples for such approaches in literature (e.g., [Alex *et al.*, 1999]), but almost all refer to continuous flow plants, because this type is still mostly used in the world. But, there are several other types of WWTPs, which are far common in the world. One of these types is the SBR technology. In contrast to a continuous flow plant, in a SBR all treatment processes take place in one single reactor, step after step as illustrated in Figure 4.

The time between the beginning of the fill and the end of the treatment process is called a cycle. The SBR technology has a high process flexibility and treatment efficiency, because with the help of modern computer-aided control devices (CACD) it is easily possible to adapt the duration of a cycle, the duration of the different phases (e.g., static fill, aerated react, settle) within each cycle and the volumetric exchange ratio (the fraction of the reactor volume, which is removed during draw, and replaced during fill) to the current requirements. This especially applies when sensors are used for control purposes. For instance, it is possible to vary the duration of the settle phase depending on the sludge settling characteristics. Unfortunately, most of the SBR plants are still using fixed time control strategies; until now, measuring devices are predominately only used for monitoring.

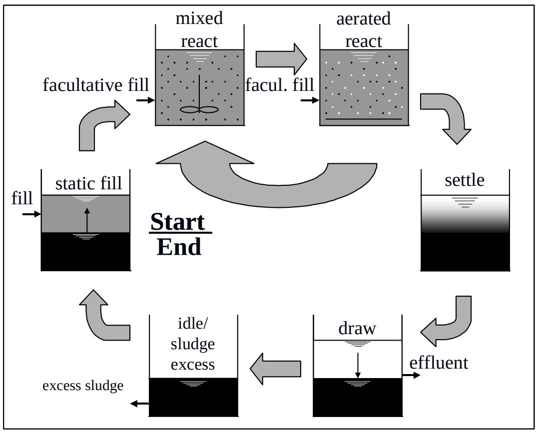

Figure 4: The concept of SBR.

But, even when there is no doubt about the high process flexibility and efficiency in general, there are still many objections to deploy this technology for plants with high hydraulic loads due to combined sewage flow. E.g., a few experts still state that SBR is not suitable to treat combined sewage as well as continuous WWTPs. This is one of the reasons why integrated RTC strategies for SBR plants with CSSs have not been developed until now. However, SBR plants, which have been designed according to the German guidelines are able to treat combined sewage very well, because the advantages of the SBR technology can also be used treating combined sewage. This especially applies because the design of a SBR plant according to the German standards caused high procedural reserves as several specific advantages of this technology could not be considered in this static dimensioning process. Due to these circumstances, it is very interesting to think about integrated RTC strategies for SBR plants with CSSs. Therefore, a research project has been initiated to realise an integrated RTC for the WWTP Messel in simulation as well as in full scale and to assess the economical and ecological benefits of such an approach [Wiese *et. al.*, 2002].

3.2 Research Project WWTP Messel

The catchment area of WWTP Messel, which is also typical for many other areas in Germany, covers 1.5 km^2, an overall impervious area of 0.6 km^2 and a population of about 3,750. Most of the inhabitants are connected to a combined sewer. Although Messel is part of the populous Rhine-Main-Area, the catchment area itself is rural. The wastewater can be characterised as domestic sewage, because there are only few commercial dischargers (500 people equivalents). There are a CSO and two storage tanks with CSOs with a total volume of 1.450 m^3 in the catchment area. The annual rainfall is about 725 mm/a.

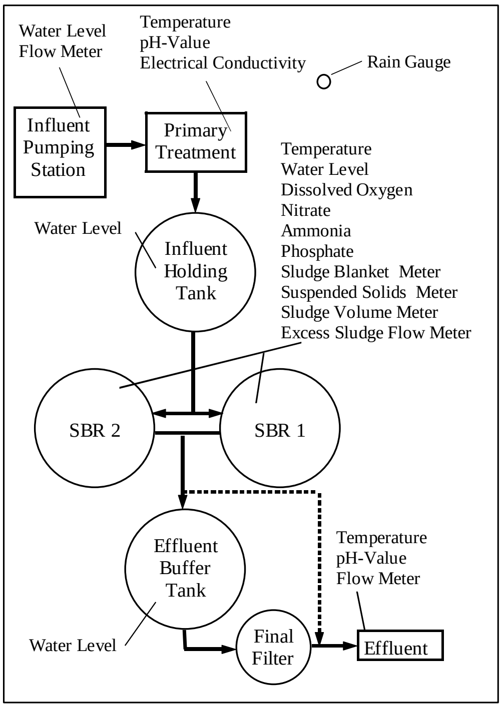

Figure 5: Scheme of WWTP Messel

The WWTP Messel schematically depicted in Figure 5, which was put into operation in 2000, is a SBR plant with a primary treatment, one influent holding tank, two SBRs, one effluent buffer tank, and a final filter. Except for the filter, this configuration is often used in Germany. The plant was designed according to the German guidelines ATV A 131 [1991] and ATV M 210 [1997] for nitrification, denitrification, biological phosphorus removal and a maximum flow rate of 230 m^3/h. The plant is equipped with a modern CACD and a lot of measurement equipment. According to the static dimensioning, the plant is operated with a cycle duration of 8 hours (h) during dry weather flow, but during combined sewage flow it is necessary to reduce the cycle duration to 6 h and thus, to increase the hydraulic capacity of the WWTP.

In the first part of the research project, very detailed models of the combined sewer system and the WWTP have been developed. These models were calibrated and validated with monitoring data. With these models, several control strategies have been developed and assessed. These strategies are based on ammonia and nitrate sensors, as well as sludge blanket and suspended solids meters. Furthermore, a rain gauge has been integrated in the control strategies. The results of the WWTP simulation show that it seems to be possible to reduce the cycle duration during combined sewage flow in full-scale in almost every case to only 4 h without exceeding the low effluent limits for BOD_5 (9 mg/l), COD (45 mg/l), and NH_4-N (3 mg/l) and thus to increase the hydraulic capacity of the plant up to 50 % by using the developed control strategies. In several cases, it should be even possible to reduce the cycle duration to less than 4 hours. That means, it would be possible to increase the maximum flow rate to the WWTP from 230 m^3/h up to more than 345 m^3/h. Furthermore, the results of the long-term pollution load simulation show that an increase of the flow rate to 345 m^3/h will lead to a reduction of the total COD emission during phases of combined sewage flow up to 30 %. So, an integrated RTC of a SBR plant seems to be very useful considering ecological aspects. But, despite these very positive results, there are still several problems:

- Due to the discontinuous principle, it is necessary in case of rainfall to switch as early as possible from the 8 hours cycle to the 3, 4, or 6 hours cycle, because the storage capacity of the influent holding tank is limited.
- The cycle duration reduction potential depends on several factors, e.g., wastewater temperature and sludge settling characteristics.
- SBRs are normally synchronised (in this case with a time delay of 3 hours), so, it can last up to 6 hours until the second SBR switch to the short cycle mode.
- Furthermore, according to the German guidelines, it is not allowed to exceed the official effluent limits.

That means, the whole potential for optimisation can only be used when a control strategy is realised, which is able to act and not only to react. Consequently, we developed a method that is serviceable for a predictive controller being able to predict as early as possible the duration of a cycle, which is necessary to achieve the treatment target. Furthermore, the controller also had to be able to predict the maximum volumetric exchange ratio.

3.3 A Case-Based Predictive Controller

From our point of view, it seemed to be promising to develop a predictive controller based on a CBR approach because of the following reasons:

- Beginning and end of the treatment process are exactly defined. With a few restrictions, this is also valid for the different treatment phases of the cycle, which helps to easily determine a case structure.
- It is important that the system works fast because the time delay between the beginning of a rainfall event and an increase of the inflow rate can be quite short.
- With cycle durations between 3 and 8 h the database will grow very fast, i.e. case acquisition is not a problem.

3.3.1 Control System Architecture

Modern SBR plants often possess much online measurement equipment. However, as a consequence of higher treatment standards, reduced prices for sensors, etc., a further increase in online monitoring, especially for quality parameters (e.g., NH_4, NO_3) can be expected. Due to this fact, it will be possible to document the curves of important processes within each cycle. Later on, it would be possible to calculate the duration of each treatment phase, which would have been sufficient to reach predefined effluent standards. The opportunities for a Case-Based predictive SBR controller resulting from these circumstances are quite interesting, especially in case of an integrated RTC strategy.

For instance, at the beginning of a rainfall event, the controller could predict the required duration and composition of the next cycle, by comparing actual process information (e.g., wastewater temperature, sludge characteristics) with historical data. In the next step, the maximum hydraulic capacity of the WWTP can be calculated. However, due to the enormous amount of measurement data, it would not make sense to use only one CBR model to predict the required cycle duration and composition, because the database would have to be extremely large. So, it is promising to work with multiple domain models.

Figure 6 shows our proposed system architecture. The specific process controlling units for the WWTP and the sewer system are connected via an interface (CACD) that mediates between our predictive control system and the controllers for the WWTP and the sewer system.

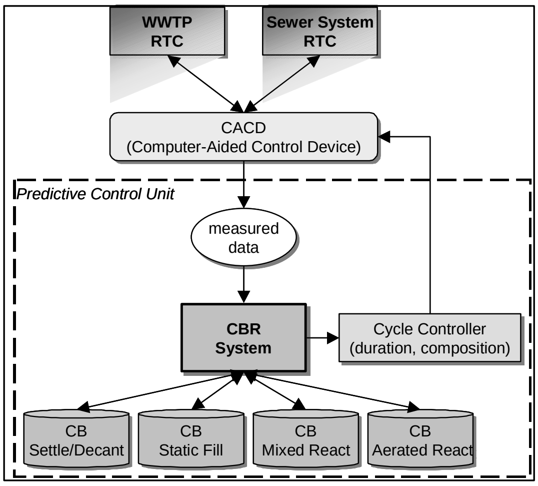

Figure 6: Principle of the predictive SBR controller.

The interface provides us with all measured data and forwards the control data resulting from the predictions depending on the current situation. Our predictive controller consists of a CBR system as the core part, which operates on multiple case bases and domain models, respectively, with respect to the WWTP subsystem to which the measured data (situation) belongs. Speaking more specifically, almost each process stage in the cycle depicted by Figure 6 is represented by its own case base. The exceptions are the "settle" and "draw" (also known as "decant") phases (see Section 3.2) that are summarised in one case base and "idle/sludge excess" phase, which we will not support with respect to time optimisation due to its very short duration.

New measured data is taken as an input to our CBR system, which generates the adequate problem descriptions for querying the different case bases. As we are dealing with an independent series of process phases in the regarded cycle, i.e. a phase can only be started after its predecessor having finished, we can optimise (predict) the processing time of each individual phase and add the predicted duration times of each single phase in order to obtain the overall cycle duration. This fact also allows us to query the single case bases simultaneously.

The cases are problem-solution pairs, where the current situation (measured data) represents the problem part and the solution is given by the respective control data for this situation. Due to the structure of the data, we are working with flat domain models.

The subsequent control data for each single phase is derived from the retrieval result of the *n* most similar cases from past situations. Adapting the solutions from the respective *n* cases generates the solution for the current situation. However, the adaptation method depends on the process phase. (An example for the "settle/decant" phase is given in Section 3.3.2.) The new solutions are forwarded to the cycle controller unit, which processes them and gives the final solution back to the CACD. Depending on the results of the different case bases, the Cycle Controller will estimate the total duration of the cycle and create the composition of the cycle. Due to the fact, that the hydraulic capacity of the WWTP depends on the duration of each cycle and the current exchange volume, the maximum flow rate to the WWTP could be calculated in the next step.

3.3.2 Example Model "Settle/Decant"

Up to now, we have only implemented one component (i.e. domain model) of the described overall architecture. So far, our system only simulates the control process offline, i.e. the generated solutions are not to be returned to the CACD interface. One of the results of project "Messel" is that there is a huge potential for optimisation of the settle and decant (draw) phase. During this phase, first the water/biomass separation takes place and then the treated wastewater will be decanted. Due to the fact that even a small sludge displacement from the reactor into the effluent of the plant can cause an exceeding of the required effluent standards, the settle and decant phase was dimensioned for unfavourable operational conditions. In order to point up the potential for optimisation, an example is depicted in Figure 7.

As a consequence of the static dimensioning, the duration of the settle and decant phase in case of WWTP Messel takes in total 140 min. In reality, however, the operational values are usually much better than the comparable design values. Therefore, sludge blanket and suspended solid meters were installed at the decant devices to investigate the potential for a reduction of the settle and draw phase. The results of this investigation are that in many cases it would be possible to reduce the settle and decant phase up to 70 min (Figure 7) and thus to increase the hydraulic capacity up to almost 20 %. Furthermore, the monitoring shows that in most of the cases it would be possible to increase the volumetric exchange ratio from appr. 40 % to appr. 50 % (+145 m^3; see Figure 7); this could further increase the hydraulic capacity. Due to the high optimisation potential of the settle and draw phase, it was decided to develop the CBR subsystem “Settle/Decant” first.

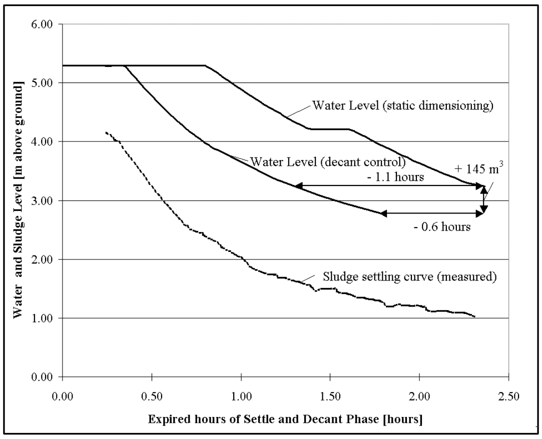

Figure 7: Potential for optimisation of settle and decant phase.

In the first step, more than 120 sludge settling curves, which have been measured under different operational conditions, were analysed and evaluated statistically. It could be observed that the settling velocity of the sludge blanket mainly depends on two factors. As already published by other authors (e.g., [Keudel and Dichtl, 2000]), the initial settling velocity mainly depends on the sludge volume at the beginning of the settle phase. For instance, the 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 depends on the last phase before the settle phase starts. For example, in case of a mixed react phase, it takes at least 10 min. until the sedimentation begins. In case of an aerated react phase, the turbulence at the beginning of the sedimentation phase is smaller, thus the flocculation process is faster and the sedimentation process can start in less than 5 min. Consequently, the cycle type, the water level in the reactor, the sludge volume, and the water temperature were chosen as attributes in the respective CBR model (see Table 1). The system has been implemented with CBR-Works® (empolis – knowledge management, Inc.)

Table 1: Attributes and their value ranges

Attribute	**Value Range**
Cycle Type	dry weather, rain weather
Max. Water Level	3.32 m – 5.30 m
Sludge Volume	241 ml/l – 446 ml/l
Water Temperature	8.7 °C – 21.4 °C

In order to create the 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 modelled 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 curves (sludge settling curves). We simplified the representation of these curves approximating them by polynomials of degree six. The idea was to be able to easily compare the coefficients a_1 to a_6 of these polynomials with each other, in order to evaluate the quality of the generated solutions.

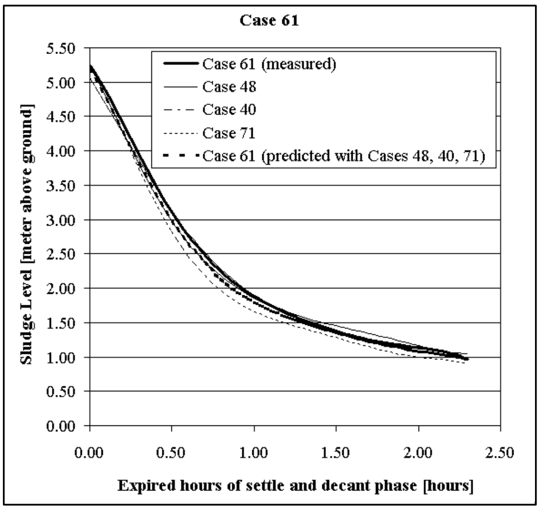

Figure 8: Good prediction of the sludge settling curve.

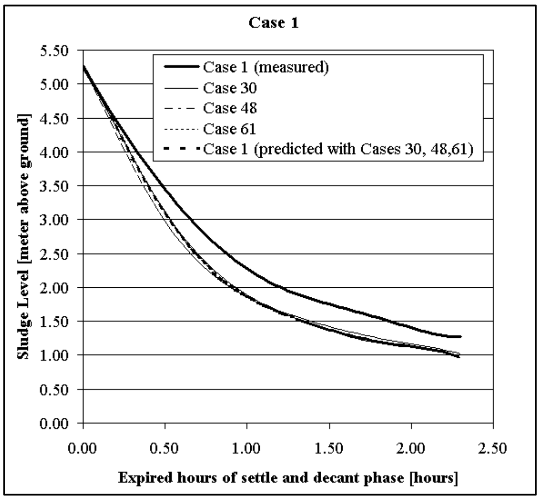

Figure 9: Example for a worse prediction.

The results produced by this subsystem are very promising. Despite the fact that the database is rather small, the model is able to predict the sludge settling curve well. Thereby, the predicted sludge settling curve is a weighted function, calculated with the help of 3 measured curves, which have been measured under the most similar operation conditions. Figure 8 shows an example for a good prediction of the sludge settling curve. The measured and the predicted curve are almost identical. Of course, not all predictions are as good as the example in Figure 8. Figure 9 shows an example for a worse prediction. However, even in this worse case the maximum difference between measured and predicted curve is only 0.5 m.

It has to be taken into consideration that the measurement inaccuracy of the sludge blanket meter can be up to 0.2 m. Furthermore, in practise such worse predictions would not cause serious problems, because with the help of a sludge blanket meter-based and/or a suspended solids meter-based feedback decant controller, which survey the decant phase, it would be easily possible to close the decanter immediately, in case of a sludge displacement danger.

3.3.4 Future Work

As a consequence of the good results reached with the CBR "Settle/Decant" model, the other components of our architecture will be developed, i.e. we will create the domain models and the respective CBR subsystems. Thereby, the monitoring established within the project "Messel" serves as a data source for the case bases. In the near future, our overall system will then be verified in full scale in a field test by feeding the so generated control data into the modern CACD of WWTP Messel.

4 Related Work

Recently, an increasing number of publications can be found that deal with WWTP control and optimisation respectively, using knowledge-based techniques, sometimes also Case-Based Reasoning:

Sànchez-Marrè [1996] presents the DAI-DEPUR system. The system is based on an integrated multi-level architecture for WWTP supervision in real-time. Like the SBR controller approach to use multiple case bases for the different control tasks, DAI-DEPUR maintains several knowledge bases that are connected for solving the global control task. In contrast to the SBR controller, DAI-DEPUR is kept more general with respect to the supported WWTPs. Furthermore, different knowledge-based approaches besides CBR are deployed. Fenner and Saward [2002] describe a methodology to produce a performance assessment model. They identify changes in the internal conditions of sewer pipes. Amongst other data, they build up a case base of performance histories. The past performances are used to predict suitable management strategies in the current situation.

5 Conclusions

Despite the fact, that CBR is a powerful technology, which has already proved its potentials in different industrial applications, CBR is not widely used in the field of wastewater treatment until now. Although approaches for optimisation of existing plants attract more and more the attention, they are still based in almost all cases on Fuzzy Logic, Neuro Fuzzy, Genetic Algorithms, and Neural Networks. Nevertheless, there are some examples that the use of CBR in the field of wastewater treatment could be very promising, especially in case of Decision Support Systems and Real Time Control. Consequently, there is a good chance, that CBR will be far more common in environmental engineering during coming years.

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