Developing a framework for continuous use of models in daily management and operation of WWTPs: a life cycle approach

Gürkan Sin, Dirk J. W. De Pauw, Stefan Weijers and Peter A. Vanrolleghem

ABSTRACT

We developed and evaluated a framework for the continuous use of dynamic models in daily management and operation of WWTPs. The overall aim is to generate knowledge and build in-house capacity for the reliable use of dynamic models in practice (within a regional water authority in The Netherlands). To this end, we have adopted a life cycle approach, where the plant model follows the different stages that make up the typical lifespan of a plant. Since this approach creates a framework in which models are continuously reused, it is more efficient in terms of resources and investment than the traditional approach where one always makes a new model for the plant whenever it is needed. The methodology was evaluated successfully at a 50,000 PE domestic EBPR plant (Haaren, The Netherlands). It is shown that the continuous use and update of models in a cyclic manner creates a learning cycle, which results in experience and knowledge generation about the plant's modelling that accumulates and translates into improvements into the modelling quality and efficiency. Moreover, a model is now always on-the-shelf for process optimization.

Key words | ASM2d, calibration, dynamic models, efficiency, life cycle, modelling, WWTP

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INTRODUCTION

During the last decade, discharge legislation has become stricter worldwide, which among others, has caused wastewater treatment to become more complex, for instance requiring carbon, nitrogen and phosphorous removal in parallel. Understanding of these processes became increasingly challenging because of the complex interactions involved. To this end, mathematical models, and more specifically, dynamic models are regarded as useful tools to gain more insight and in-depth understanding about the processes involved in wastewater treatment (Henze *et al.* 2000; Gujer 2006).

So far wastewater treatment plant modelling was primarily performed at the level of universities or consulting companies (Hulsbeek *et al.* 2002; Langergraber *et al.* 2003; Melcer *et al.* 2003; Vanrolleghem *et al.* 2003; Sin *et al.* 2005). However, some other type of companies such as water utilities, are also starting to incorporate modelling in daily management work. One of these organizations, Waterboard De Dommel (Noord-Brabant, The Netherlands), has taken such initiative: a project was set up in order to evaluate the use of modelling as a support tool for wastewater management.

In order to perform reliable modelling work in a company setting, several important requirements need to be met. Firstly, adequate expertise is required at the level of process knowledge and of modelling methodologies. Secondly, the efficiency of the classical modelling process needs to be improved. Generally speaking, there is a lack of standardization (i.e. data collection and quality check, measurement campaign set-up, model calibration, etc.) and automation (i.e. dedicated software support). Thirdly, the obtained model quality needs to be adjusted based on

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the actual goal of the modelling exercise: some decisions will need a higher quality model than others, e.g. the testing of a control strategy requires a dynamic model whereas the design of extra volume can probably do with a steady-state simulation. Our aim includes model applications that require relatively detailed and accurate models of process dynamics. Examples are assessing process performance limitations, process optimization and (model-based) process control including RTC of the wastewater chain. We present a methodology to facilitate knowledge generation, capacity building and model quality improvement for the continuous re-use of models in practice.

METHODS

Continuous model re-use methodology

The current trend of modelling in practice is oriented towards the one-time development and use of a mathematical model. After the model has been developed and used for a specific purpose it is often forgotten and not used any further. This is unfortunate since a considerable amount of time and resources are often spent on its development. Equally important is that the unique knowledge and experiences gained during the model development process often remain undocumented and is also likely to be lost. To improve on this situation, we propose a new life cycle approach to modelling in order to efficiently build, use and re-use models.

The basic idea is to have the modelling process reflect the life cycle of the actual treatment plant. A typical wastewater treatment plant goes through several phases, e.g. design, construction, start-up, operation, upgrade. Traditionally, for each of these stages, new models are developed to solve specific questions. However, it would be better to further use the model developed during the design stage, at the start-up and during the operation phase of the treatment plant. Obviously, the model will need to be adapted each time the plant moves from one phase to another. However, the required investments will be minimal as previously obtained knowledge and experience can be used. Figure 1 illustrates this procedure for a plant going from a design phase into start-up and normal operation and finally undergoing a significant upgrade. Rather than developing a new model for each of these phases, one model is continually used and adapted to the changes in the actual plant.

In using this life cycle approach, we hope to continuously and systematically gain experience and knowledge, all leading to better overall modelling quality and efficiency of the modelling process itself. Practically speaking, the life cycle modelling approach is performed using the flowchart presented in Figure 2. This figure summarises the different steps involved in a typical life cycle of a model:

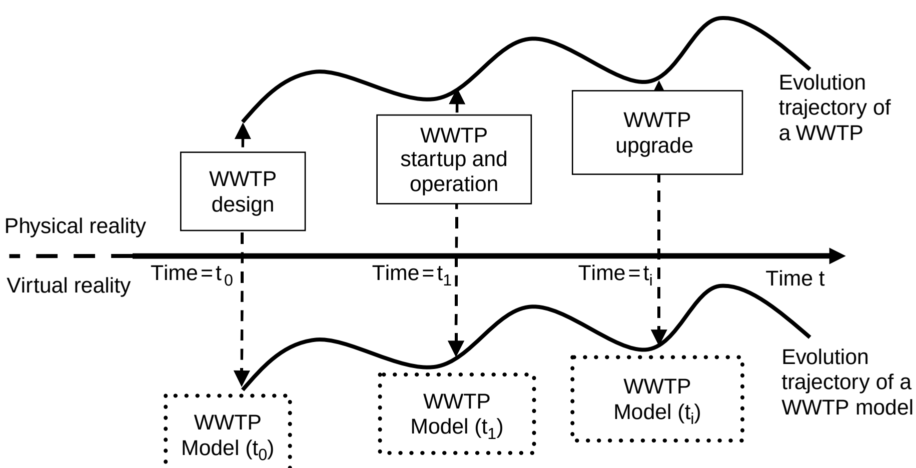

Figure 1 | Life cycle concept of modelling: life cycle of the WWTP in the physical world (top) and its life cycle in the virtual world (bottom). t stands for time and 0,1,*i* … .*N* stands for different phases in the WWTP's life-span.

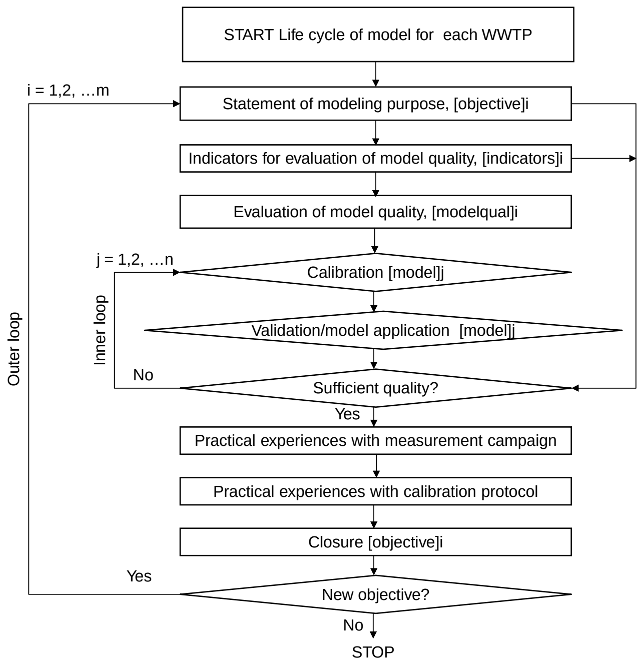

Figure 2 | Overview of different steps of the life cycle of a model. See text for explanation.

1. **Modelling purpose/aim**: initiates the process of model building for a WWTP
2. **Model building**: Selection and calibration of model to represent WWTP reality
3. **Model application/validation**: Confrontation of the model with reality
4. **Closure**: evaluation of the achievement of the modelling against the purpose.

Going through these steps, a model-based learning cycle is created, which is an accumulation of the experiences and knowledge through the whole cycle. Two iteration loops are considered: the so-called outer and inner iteration loops. In general, the outer loop iteration relates to tackling the specific purpose or objective defined for the modelling work, e.g. process optimization, upgrade, design,…

The inner loop is iterated within the outer loop in view of improving the quality of a calibrated model in view of its use at a given WWTP. This is done by first calibrating a model and then confronting the model with reality, i.e. validation. If necessary, the calibrated model can further be recalibrated and revalidated using different sets of data to increase confidence and or improve the credibility of the model. The inner loop iterations should/can be terminated following a judgement (either management decision or expert judgement) of the model quality in view of meeting the goal of the modelling study. After terminating the inner loop iterations, one will apply the model for its intended purpose. One can then document the experiences gained, particularly focusing on the data collection aspects and/or on the calibration protocol itself which is used to guide the process.

Haaren WWTP

The Haaren WWTP was used to test and evaluate the proposed modelling framework. The plant, located in Haaren, Noord-Brabant the Netherlands, is of carrousel type and serves 50,000 PE with an average dry weather flow rate approximately equal to 10,000 m^3/d. The operational SRT is around 22 days. The overall hydraulic retention time of the system is 1.8 days. The virtual lay out of the Haaren plant in the WEST® (MOSTforWATER NV, Kortrijk, Belgium) simulator is shown in Figure 3 bottom.

In the plant model, mixing and hydraulics are approximated using the tanks-in-series approach, while an ideal point settler is used for the settlers (see Figure 3 bottom). The ASM2d model presented in Henze *et al.* (2000) is used to describe the biological nitrogen and phosphorus removal processes in the plant. Three different calibrations of the Haaren model were performed, yielding so-called model 1, model 2 and model 3 respectively. An intensive measurement campaign carried in July 2000 was used to develop and calibrate model 1 (see Vanrolleghem *et al.* 2003). A measurement campaign done three years later in June 2003 was used to validate model 1, resulting in its slight re-calibration, leading to model 2 (Sin 2004). Finally, the model 3 was calibrated using long-term on-line measurements of NH_4-N and NO_3-N in the carrousels from February 15th till 11th of April 2004 and following the Monte-Carlo based calibration method (paper in preparation). The BIOMATH protocol (Vanrolleghem *et al.* 2003) was used for performing the different modelling steps, i.e. the goal definition, data collection and quality check, mathematical formulation of plant units/processes, influent characterisation.

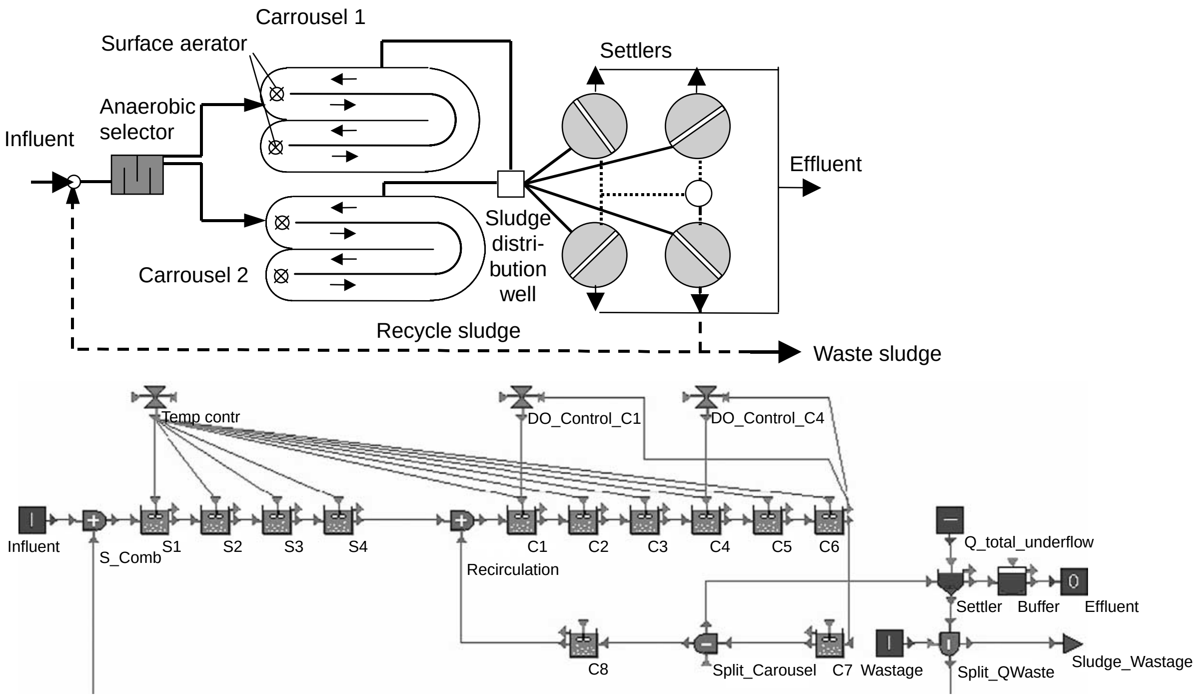

Figure 3 | The Haaren plant: Physical plant (top); virtual plant in WEST® (bottom).

RESULTS AND DISCUSSION

In this contribution, the framework is evaluated on a full-scale plant already in operation – Haaren WWTP. Note that in the mean time Waterboard De Dommel has just started the evaluation of the framework from cradle to grave for the recently built 750,000 PE Eindhoven WWTP. This work was commenced using the Waterboard's own resources and engineers, drawing on the experiences obtained from the pilot study on Haaren WWTP.

Evaluation of the proposed modelling framework at Haaren WWTP

The modelling objective (step 1, Figure 2) was set to reliably describe the nitrate and the ammonium dynamics in the carrousel and the effluent phosphate to 1) improve N removal 2) obtain insight in bio-P and 3) check the effect of installing impellers in the alternatingly aerated tanks. The model is ultimately to be used for optimisation of the aeration control strategy. Model quality and efficiency were used as indicators for the evaluation of the modelling (step 2, Figure 2). The quality refers to the ability of the model to describe the plant behaviour well and to remain valid over longer periods of time (from months to, hopefully, years). The efficiency concerns the total time it takes to obtain a calibrated model.

Inner loop iteration 1: development and validation of the Haaren model

The first dynamic model for the Haaren plant was developed (referred to as model 1 henceforth) and calibrated using the data collected in July 2000. The BIOMATH protocol (Vanrolleghem *et al.* 2003) was used. The model's fine tuning to the data largely relied on an expert-based approach. The calibration data consisted of daily effluent ortho-phosphate and effluent ammonium data and six days long of on-line nitrate data. The nitrate predictions of the model (Figure 4) were found satisfactory. The model showed that 1) N removal can be improved 2) there was significant bio-P and 3) installing impellers was beneficial.

Following the calibration, the validity of the model 1 was checked (see Figure 2). To this end, data collected three

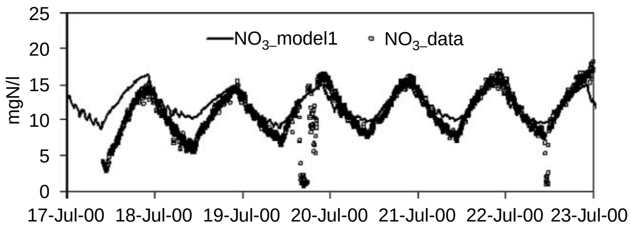

Figure 4 | Nitrate predictions by model 1 in the carrousel during the calibration (July 2000).

years after its calibration was used, as it is felt necessary to provide confidence in the long-term validity of the model. The validation data consisted of a dedicated measurement campaign and on-line ammonia and nitrate sensors. In Figure 5-left, the confrontation of model 1 with the on-line NH_4 data is shown.

While capturing the general trends in the ammonium profile, it overpredicted the ammonium peaks by up to more than 40%. The model was observed to remain largely valid for nitrate predictions, while it overestimated the phosphate release in the selector (Sin 2004). Overall this long-term model check was still felt encouraging and added confidence in the ability of dynamic models to describe the plant. It also confirmed the premise that models that are already developed for a plant can be of use for a later stage in the plant's life cycle.

Drawing on these conclusions, model 1 was used to develop optimal settings for the aeration controller. The optimisation suggested using impellers instead of surface aerators for providing mixing during anoxic phases. This was implemented in practice and the full-scale results were found to disagree with what the model had forecasted before (mainly the oxygen supply was found insufficient). Hence, another internal iteration was felt necessary for improving the model quality.

Inner loop iteration 2: re-calibration of model 1 and checking seasonal validity

In this iteration, the model 1 was recalibrated to better fit the validation data of June 2003, particularly the phosphate in the selector and the NH_4-N measurements in the carrousel. We learned this was possible by slightly changing a few parameters (Sin 2004). The recalibrated model, called model 2, matched the NH_4 data better than model 1 (Figure 5-right).

To validate this model 2, built mainly on the basis of the data collected in summer (July 2000 and June 2003), we challenged the model to describe the plant behaviour in winter, significantly different from the calibration conditions. To this end, the model 2 was confronted with the plant influent loading, temperature profile and operational data of February 2004. The validation results for on-line NO_3 and NH_4-N are shown in Figure 6.

The results show a significant deviation from the observations. The model considerably overestimated the nitrification and underestimated the denitrification capacity in the plant. One of the explanations for this model mismatch is the implementation of the controller. Previously, during anoxic phases surface aerators were operated at a low submersion depth to keep the sludge in suspension. This evidently introduced a significant amount of oxygen, hampering denitrification. From a process point of view, the inclusion of impellers may have changed the behaviour of the plant, which was obviously not captured by model 2.

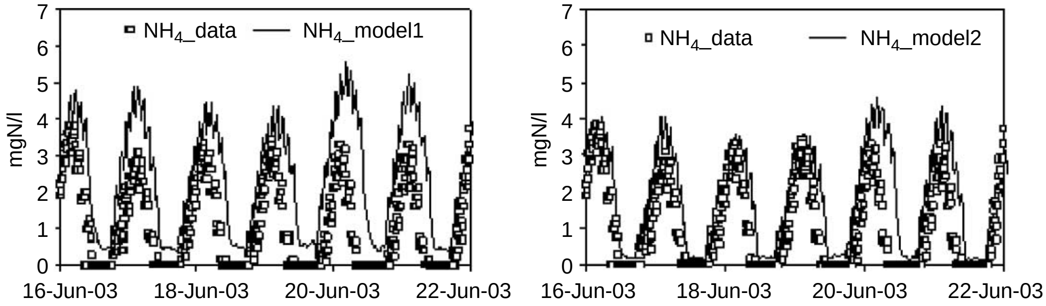

Figure 5 | Validation of model 1 three years after its calibration (left); Model 2 (recalibrated model1) (right).

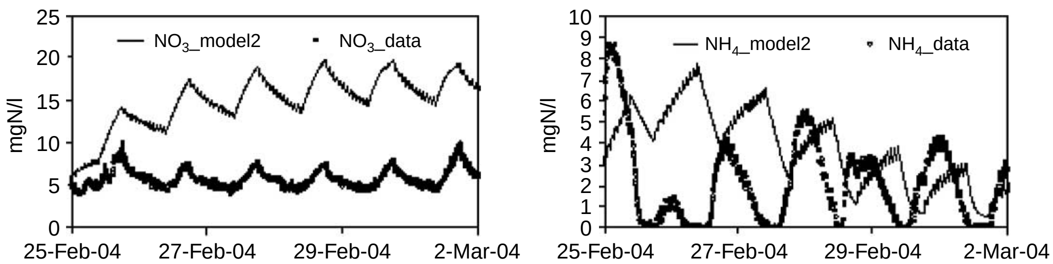

Figure 6 | Confrontation of the predictions of model 2 in winter (February 2004).

Inner loop iteration 3: moving from short-term to long-term calibration periods

To resolve the above issues, which are especially affecting the proper initialisation of the model (e.g. biomass composition), one needs to adequately consider the plant's history and one also needs to move from calibration over short periods (the predominant current practice) to longer periods. The latter will ensure that the model captures the long-term dynamic behaviour of the plant. Further, the history of the plant, long recognised by many to be important, needs to be effectively coupled to the calibration process. This shift in model calibration practice is necessary to achieve a better confidence in the model when it is to be used over the life cycle of the plant. However, such an approach results in modelling exercises with a significantly higher computational burden. These additional computational costs may hamper the manual (and expertise-driven) parameter fine-tuning as each trial will take considerable calculation time. For instance, the short-period calibration of model 1 and model 2 required approx. 10 person-days of work during which the modeller changed one parameter at a time and checked the resulting model fits to a 4–6 day long calibration data set. Each parameter trial then takes a few minutes to finish. With the new approach, the size of the calibration data set easily increases to several months and the computation time for ach parameter trial becomes prohibitively long for a manual parameter estimation. For example, it takes around half an hour on a Pentium IV PC to simulate 4 months of plant time.

To deal with this, a new partially automated parameter fine-tuning procedure was developed, which resulted in a dedicated software tool (called MOREsoft). The main idea is to use an algorithmic procedure to do the manual fine-tuning step in the model building. This new method is pragmatic and is based on a Monte-Carlo simulation approach that performs a multitude of simulations by sampling parameter values from a predefined parameter

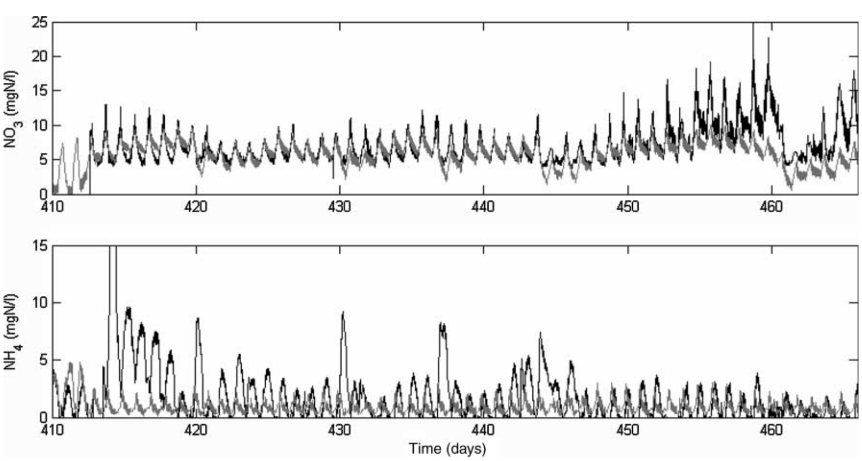

Figure 7 | Using a 3-months long data to calibrate the Haaren model 3: the resulting model fits to nitrate (top) and ammonium (bottom): data (black) and model (grey).

space and automatically evaluating the model fit. These simulations are expected to deliver at least one reasonably good model match to the measurements (paper in preparation).

The method was evaluated successfully to re-calibrate the model 2 using long-term data from February 2004 till April 2004. The resulting model is called model 3 and the model fits to the NO_3 and NH_4 data are shown in Figure 7. One observes that the long-term fits to nitrate and ammonium dynamics over a 2.5 month period were in general good. Sporadically the model deviated from reality. These deviations are believed to be caused by variations of the influent load which had to be estimated from the available weekly measurements at the plant. More detailed, on-line influent load measurements of COD (using for instance UV/VIS sensors) and ammonium will decrease the uncertainty in the input and are therefore expected to improve model quality. This is currently the focus of ongoing work. Concerning the efficiency of model building, a major part of the time was spent on preparing the input data (influent load, operational data etc). The fine-tuning of the model to the data on the other hand was done automatically by a PC (see above), taking two weeks of PC time for this particular model fitting. This considerably reduced the time of the modeller spent on this task, significantly improving the overall efficiency. Partial automation of the input data preparation will also be considered to further increase the modelling efficiency.

Perspectives and conclusions

The presented life cycle approach is expected to allow a plant model to track the history of a plant more efficiently than a set of models built using the traditional one-at-a-time approach. Indeed, the learning cycle helps (i) to systematically record experiences with modelling thereby improving the quality and efficiency, (ii) to better reuse the resources and time invested as the model will be re-used at different stages of the plant's life cycle and finally (iii) to provide a continuous check and balance on the model. In this way, one gets to better know the boundaries of validity of the model and one will therefore better use it in practice.

However, the maintenance of the WWTP models will ask for resources. Improving the modelling efficiency is thus needed to reduce these resource demands to an acceptable level and this is what is currently worked on, by providing software tools to automate certain tasks.

In conclusion, the model re-use framework leads to gradual accumulation of modelling experience and knowledge that translates into improvements of the in-house modelling methodology. The use of a model, always residing on the shelf, will increase automatically and support the continuous analysis and optimization of WWTPs during their whole life.

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