Water Science & Technology—WST | 60.8 | 2009

Wastewater treatment modelling: dealing with uncertainties

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ABSTRACT

This paper serves as a problem statement of the issues surrounding uncertainty in wastewater treatment modelling. The paper proposes a structure for identifying the sources of uncertainty introduced during each step of an engineering project concerned with model-based design or optimisation of a wastewater treatment system. It briefly references the methods currently used to evaluate prediction accuracy and uncertainty and discusses the relevance of uncertainty evaluations in model applications. The paper aims to raise awareness and initiate a comprehensive discussion among professionals on model prediction accuracy and uncertainty issues. It also aims to identify future research needs. Ultimately the goal of such a discussion would be to generate transparent and objective methods of explicitly evaluating the reliability of model results, before they are implemented in an engineering decision-making context.

Key words | mathematical modelling, prediction accuracy, uncertainty, wastewater

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doi: 10.2166/wst.2009.225

INTRODUCTION

Over the past 40 years, there has been a tremendous increase in the amount of knowledge the engineering and scientific communities have acquired in the field of wastewater treatment. This increased understanding has led us to shift our design approaches from using "rules of thumb" like F/M ratios and BOD loading rates, to more accurate methods such as minimum sludge age and detailed influent characterisation. This increased knowledge has also resulted in our ability to construct mathematical models that describe the main processes that take place in wastewater treatment. In turn, the implementation of these models to engineering projects and the drive for their validation has deepened our understanding of the same processes. By applying these new tools we have improved our designs, made our plants more efficient and been able to comply with increasingly stringent regulations.

In spite of the advances we have made to date, our approach to plant design and optimisation still implies that we work in a well defined field (Gujer 2006). For example, we select one or two 'typical' flow and load scenarios, assumed to capture the conditions a plant will experience and size the plant to meet an average effluent standard. To account for the unpredictability of the influent wastewater and the much larger variability that the plant encounters, we are forced to incorporate safety factors in our design and build redundant systems on site (US EPA 1993; WERF 2003*b*). These semi-arbitrary safety factors are lumped expressions of the individual sources of uncertainty underlying any treatment process. This lumping of uncertainty often results in overly conservative solutions. Most of the existing design guidelines do not incorporate explicit and objective methods for the evaluation of uncertainty. As a result, the risk associated with any engineering decision during a design, upgrade or optimisation project is accounted for implicitly through a combination of adhering to local or international guidelines, rules of thumb and the experience of the design engineer.

In the current regulatory environment of extremely low effluent nutrient standards (e.g. Chesapeake Bay area) and increased demands for operational efficiency, a new approach is required that provides us with an understanding of the main sources of uncertainty associated with each process (Gujer 2006). Moving away from lumped uncertainty safety factors should help us maximise existing plant capacity and avoid over-sizing new plants. A new approach should provide us with an objective way of discussing and evaluating risk and must allow the stakeholders involved in a particular project to discuss risk and who will assume it, openly.

Models can greatly assist us in the development of an objective, peer accredited methodology for evaluating process design and compliance risk. The way the models are formulated provides us with a structure which allows the identification and evaluation of the sources of uncertainty. They can thus provide the framework for the inclusion of uncertainty evaluations in plant design, upgrade and optimisation projects.

This paper summarizes the presentations and discussions held during the WWTmod2008 workshop on 'Model accuracy: dealing with uncertainties' (Belia *et al.* 2008). The workshop was organised in response to the increasing need of the engineering community to discuss uncertainty in model-based design and optimisation projects. This discussion was focused on identifying answering the question: how can we use the current modelling tools together with uncertainty analysis to develop a methodology that results in more efficient designs and explicit risk assessments?

The main objective of this paper is to serve as a problem statement of the issues surrounding uncertainty evaluations in wastewater treatment projects. The paper proposes a list of items that need to be covered in any work that aims to incorporate uncertainty evaluations into engineering projects. It also proposes an intuitive structure that allows clear identification of the sources of uncertainty introduced during a typical modelling project.

CURRENT RESEARCH

The incorporation of uncertainty evaluations in wastewater engineering is far less advanced compared to other fields. The academic and engineering communities have identified the need in our field and have tried to address it by proposing methods for the quantification of model prediction accuracy and uncertainty introduced during model development and application. Most publications to date deal with only a few of the sources of uncertainty in model-based projects such as: wastewater influent and biokinetic parameters (Bixio *et al.* 2002; Melcer *et al.* 2003; Sin *et al.* 2009); model structure (Neumann & Gujer 2008); sensor and measurement accuracy (Rieger *et al.* 2005) or prediction of future loads (Dominguez & Gujer 2006; McCormick *et al.* 2007). There are also several publications on the topic of model prediction accuracy or goodness-of-fit evaluations for model calibration (Ahnert *et al.* 2007), uncertainty propagation (Benedetti *et al.* 2006) and incorporation of uncertainty for specific design objectives (Bixio *et al.* 2002; WERF 2003*a*; Neumann 2007). What is still lacking is a broad, comprehensive discussion of the sources of uncertainty and the evaluation methods applicable to wastewater treatment projects.

The challenges highlighted in the introduction and the needs identified in the brief literature review, point to the need for the development of a comprehensive protocol that incorporates uncertainty evaluations in model-based wastewater projects. The goal of such a protocol would be to generate transparent and objective methods of evaluating the reliability of model results. The protocol must be easily applicable and be scope-specific i.e. linked to the model objective.

QUESTIONS THAT NEED TO BE ADDRESSED

A comprehensive discussion on the subject of uncertainty and prediction accuracy must address several questions, including:

1. What are the concepts and definitions that need to be discussed so that a common language is established?
2. What are the sources of uncertainty?
3. What are the available methods, quantitative or qualitative, that can be used to evaluate model prediction accuracy and uncertainty?
4. How much effort should be put into the assessment of uncertainty and model prediction accuracy? Do all model applications require the same degree of detail of uncertainty evaluations?
    - How much effort does one need to spend on data collection and reconciliation?
    - What is the appropriate level of calibration/validation for a given task? Are dynamic solutions inherently more accurate than steady state solutions?
5. What confidence levels are required for different modelling objectives? How do we quantify risk?
6. What is the added benefit of including uncertainty evaluations in modelling projects?
    - Could it provide a more objective way to determine appropriate safety factors?
    - Could it generate specific data requirements depending on project objectives?
    - Could it provide calibration guidelines for each model application?
7. How can uncertainty evaluations be incorporated into design?
8. How do stakeholders (technical and non-technical) communicate on the subject of uncertainty and risk?

It is beyond the scope of this paper to give answers to all of the questions listed above. The following sections summarize the presentations and discussions held during the WWTmod2008 workshop on 'Model accuracy: dealing with uncertainties'.

TERMINOLOGY AND DEFINITIONS

The first step in establishing an applicable methodology or protocol is to reach an understanding and agreement on terminology. That is, what do we mean when using such terms as uncertainty, accuracy, precision, confidence, error and reliability? These terms have established definitions in specific fields, e.g. in data quality management or chemical analysis. However, when we expand their definition to cover model quality, even for the most widely used terms there appears to be a lack of consensus. For the benefit of the readers, a selection of key terms and definitions has been included in this paper. The list of selected definitions has been compiled by the authors from different sources (Taylor & Kuyatt 1994; Carstensen *et al.* 1997; Dochain & Vanrolleghem 2001; ISO 15839 2003).

Trueness of measurement

The degree of closeness of the expected value of a measurement or estimate to an accepted reference value. Expected values are obtained by averaging over repeated measurements or estimates. Trueness is an expression of systematic error.

Precision of measurement

The degree of similarity or closeness between repeated measurements or estimates of the same variable, subjected to the same sources of uncertainty. Precision is an expression of random error and does not relate to the true or specified value.

Confidence interval

Instead of estimating the parameter by a single value, an interval or range likely to include the parameter is given. How likely the interval is to contain the parameter is determined by the confidence level.

Model prediction accuracy

An estimate of how close a model predicted quantity is to its measured value. The difference between model predictions and the corresponding measured values of a calibration or validation data set, during a model run.

Model calibration

The (mostly iterative) adjustment of any model parameter (physical, operational, kinetic, stoichiometric, settling,...) to improve the fit to measured data.

Model validation

The comparison of the predictions of a calibrated model to a different and independent data set not used for calibration.

Uncertainty

The degree of lack of knowledge about a system or process or degree of inability to exactly describe its existing state and/or behaviour.

Uncertainty can be further classified by its *nature* and *level* as detailed below (Walker *et al.* 2003; Refsgaard *et al.* 2007).

Nature of uncertainty

Reducible–Uncertainty that can be reduced with further research/efforts. (e.g. experimental determination of kinetic parameters).
Irreducible–Uncertainty due to the inherent variability of a system that cannot be reduced with any further research/efforts (e.g. rainfall, toxic spills).

Level of uncertainty:

Quantifiable uncertainty can be quantified and described in a statistical sense and can be attributed to uncertainties surrounding measurement and sampling errors, probabilities, etc.
Scenario uncertainty can be described with qualitative estimations of possible outcomes that may develop in the future. Realistic assumptions about relationships and/or driving forces within the model can be established. It is not possible, however, to derive the probabilities of the scenarios taking place.
Recognized ignorance is the state where fundamental uncertainty is acknowledged to exist and the scientific basis is insufficient to develop functional relationships, statistics, or scenarios.
Total ignorance is defined as the state where a deep level of uncertainty exists. It is unknown what is unknown.

Figure 1 shows a schematic representation of the levels of uncertainty ranging from full knowledge of all outcomes (determinism) to a complete lack of knowledge (indeterminacy).

SOURCES OF UNCERTAINTY

To date most researchers have classified the sources of uncertainty from the perspective of where they are located in a generic model (Walker *et al.* 2003; Refsgaard

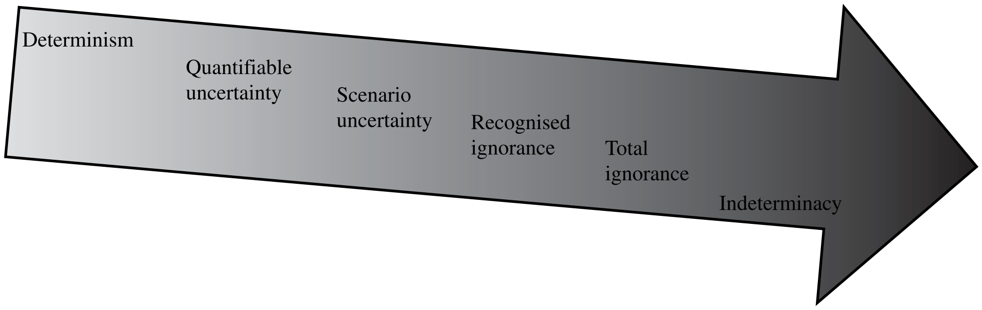

Figure 1 | Levels of uncertainty.

et al. 2004). Thus, they identify three or four main areas that introduce uncertainties to model predictions: model inputs, i.e. any type of data needed to perform a simulation (e.g. influent flow, wastewater characteristics), model structure (e.g. activated sludge model, clarifier model) and model parameters. Uncertainty in the inputs is due to random variations of the system (e.g. weather) and to errors in the measurements (e.g. imprecise sampling and measurement techniques). Uncertainty in the model is due to our incomplete understanding of the modelled processes and/or the simplified descriptions of the processes we chose to include in our models. A fourth source of uncertainty results from the implementation of the models in software packages (e.g. numerical integration, bugs, solver settings) (Yuan *et al.* 1997; Copp 2002; Reichert 2006). Table 1 shows the classification of the sources of uncertainty based on the location of uncertainty as mentioned above.

To provide a more intuitive method of identifying the sources of uncertainty, it is proposed that the focus be shifted from the *location* of uncertainty within the model to *when* this uncertainty is introduced during a typical modelling project. To aid this analysis, the typical steps of a standard modelling project can be used (Langergraber *et al.* 2004; Refsgaard *et al.* 2005; Sin *et al.* 2005; IWA GMP-TG 2008). The five steps, shown in the first row of Figure 2 are an intuitive sequence of tasks as suggested by the IWA Task Group on Good Modelling Practice - Guidelines for use of activated sludge models (IWA GMP-TG 2008).

Uncertainty can be identified and evaluated at key times during a project as suggested in the Harmoni-CA report (Refsgaard *et al.* 2004) and shown in Figure 2. Figure 2 also includes a list of items, for each project step, which need to be selected or decided upon and which identify a location of uncertainty. The figure therefore combines the traditional *location* of uncertainty within the model with a *project-step oriented* or *sequential* approach.

Table 2 includes the sources of uncertainty introduced during a typical modelling project. It provides brief explanations for each of the sources of uncertainty and classifies them according to the nature of uncertainty as reducible or irreducible. In addition, a proposed characterisation of uncertainty on the basis of its level has been included. Table 2 shows that each of the building blocks of a plant model (influent, activated sludge model, final clarifier model, etc) as implemented in a simulator introduces uncertainties that can be identified and evaluated.

QUANTITATIVE EVALUATION METHODS

As can be seen from Table 2, a significant number of the sources of uncertainty associated with a wastewater modelling project are quantifiable. Several methods exist in the literature for the evaluation of uncertainty as well as model prediction accuracy. Establishing objective methods for the quantification of the prediction accuracy of a model is very important if models are to be used as the framework around which a protocol for uncertainty evaluations is to be structured. The methods presented below are examples of the most frequently used ways of quantifying model prediction accuracy and uncertainty. The list needs to be expanded to cover both quantitative and qualitative methods that will allow the assessment of all the sources

Table 1 | Location of uncertainty

Area	Details	Examples
Inputs	Influent data	Current and future predicted flow, COD, ammonia
	Physical data	Tank volume and geometry
	Operational settings	DO set points
	Performance data	Effluent data, reactor concentrations
	Additional info	Input from connected systems e.g. sewers, catchment
	…	…
Model	Model structure	Influent model, hydraulic model, aeration system model, process models (biological, settling,…)
	Interfaces between models	Waste activated sludge pumped to an anaerobic digester; digester effluent pumped to sludge treatment
	…	…
Model parameters	Hydraulic	Number of tanks in series
	Biokinetic	Maximum growth rate
	Settling	Settling coefficients
	…	…
Software (model technical aspects)	Solver settings	
	Numerical approximations	
	Software limitations	
	Bugs	
	…	…

of uncertainty deemed important for a particular project. Systematic procedures, together with their practical application, should also be elaborated and proposed.

Evaluating model prediction accuracy

In cases where plant data are available, evaluations of predictive quality of the model start with an assessment of the model prediction error. This includes qualitative (visual, graphical) and quantitative (statistical) comparisons of model results with field observations. Most often the only form of evaluation undertaken is visual comparison of time series plots of the observations with the model predictions. The simplest quantitative analysis is the generation of a scatter plot of observations vs. model predictions or plots of the residuals (measured value minus predicted value). A more involved analysis may include the use of descriptive statistics and more advanced goodness-of-fit measures such as correlation coefficients. Examples of the statistical coefficients typically used are shown in Table 3 (Ramaswari *et al.* 2005; Ahnert *et al.* 2007 and Sin *et al.* 2008).

Typically, these coefficients will be calculated for the model predictions that are the most important indicators of plant performance for the specific modelling objective (ammonia, nitrates, phosphates, MLSS, etc.). In this way, an objective measure can be used to support subjective evaluation methods such as visual inspection of data fits. The use of statistical measures assists the comparison of the prediction accuracy obtained in different modelling projects.

Currently there does not appear to be a consensus on how to apply these statistical coefficients quantifying model prediction accuracy to wastewater models nor has there been an evaluation of their applicability at different value ranges. An evaluation of the advantages and disadvantages of each method along with suggested application guidelines is required.

Although statistical comparisons provide an objective, reproducible method for evaluating how well model predictions fit measured data, caution should be exercised when making judgements on how good a particular model is based on statistical calculations. Statistical evaluations provide very little insight into *why* model predictions

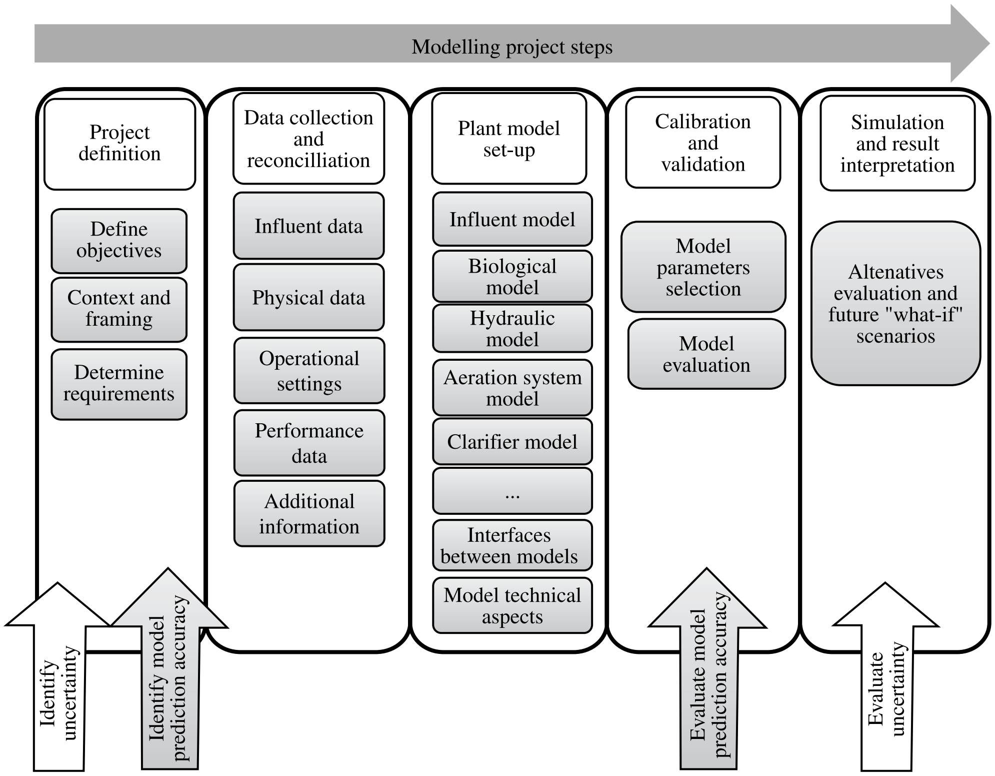

Figure 2 | Typical modelling project steps including the instances where model uncertainty and prediction accuracy should be identified and evaluated (adapted from Refsgaard et al. 2004 and IWA GMP-TG 2008).

deviate from measured data and should be combined with other assessments that are based on process expertise.

Evaluating uncertainty

As shown in Table 2, evaluating uncertainties for any mathematical model begins by specifying the scope of the model, which includes identifying the relevant sources of uncertainty. Following this, each of the uncertainties that are considered significant to the specific model application can be evaluated and where possible quantified. In the literature one finds several methods that can be used for the quantification of uncertainty, a number of which have been listed below.

1. Methods used to characterize and prioritize uncertainty:
    - data quality evaluations
    - expert elicitation
    - parameter estimation
    - sensitivity analysis
    - techniques developed for specific applications (the Numerical, Unit, Spread, Assessment and Pedigree (NUSAP) method, the uncertainty matrix)
    - …
2. Methods aiming to increase the quality of information:
    - quality assurance
    - extended peer review
    - stakeholder involvement
    - …
3. Methods used to quantify and propagate uncertainty in model calculations to evaluate uncertainty in model outcome:
    - Gaussian error propagation
    - Monte Carlo simulation
    - Inverse modelling (multiple model simulation)
    - Scenario analysis
    - …

A detailed discussion of these methods is beyond the scope of this paper. However, it is important to highlight

Table 2 | Nature and level of uncertainty introduced during each step of a typical modelling project simulating the liquid train of a wastewater treatment plant

Typical modelling project steps		Details of each step	Nature and source of uncertainty	Level of uncertainty
Project definition	Objectives	Design, operation, training	The required prediction accuracy of the model is decided at this stage of the project. This will define which of the uncertainty items listed below will be taken into account	N/A
	Context and framing	The boundaries of the system to be modelled. Biological treatment only, whole plant or sewer and river		
	Requirements	Level of model prediction accuracy, what type of data		
Data collection and reconcilliation	Influent data	Flow rate, concentrations, influent characterisation data, data from other models and other systems like sewers	Irreducible: due to the inherent variability of the real system like weather, unexpected demographic changes, unexpected factory shutdowns	Quantifiable, scenario, recognised ignorance
			Reducible: due to data collection e.g. sampling method, location, frequency, accuracy of sensors, accuracy of analytical techniques	Quantifiable
	Physical data	Process flow diagram, active (effective) tank volumes, clarifier surface areas, flow splits	Irreducible: due to the unpredictable and dynamic behaviour of structures like splitters to flow changes	Scenario
			Reducible: due to e.g. unknown true volume constructed or operational depth of structures	Quantifiable
	Operational settings	Controller set-points, valve positions, pumped flows	Irreducible: due to the unpredictability of operator decisions	Quantifiable, scenario
			Reducible: due to actions different from planned or changes not logged, e.g. a change in set-points, incorrect controller set up e.g. scales different between field and control room	Recognised ignorance, quantifiable
	Performance data	Effluent data and reactor concentrations such as MLSS (when not used as controller set-points)	Irreducible: due to the inherent variability of the real system e.g. response of microbial consortium	Quantifiable, scenario, recognised ignorance
			Reducible: due to data collection issues	Quantifiable
	Additional information	Equipment failures	Irreducible: e.g. due to unexpected equipment failures	Quantifiable, scenario, recognised ignorance

Table 2 | (*continued*)

Typical modelling project steps		Details of each step	Nature and source of uncertainty	Level of uncertainty
Plant model set-up	Influent model	Influent dynamics, characteristics, influent fractions	Reducible: due to simplifications of influent dynamics (applying a generic diurnal pattern to average vs. constructing a dynamic profile of the whole sewer system), due to simplifications of influent characteristics (fixed ratios for influent fractions)	Scenario
	Biological model	Model structure: processes (conversion, separation), calculation of composite variables, type of mathematical expression used to describe processes (Monod vs. enzymatic kinetics)	Irreducible: due to the inherent variability of the real system	Recognised ignorance
			Reducible: due to simplifications in model structure e.g. processes not included, processes included in simplified form (one step vs. two step nitrification), due to the choice of mathematical description of processes	Quantifiable
		Model parameters: fixed, a priori chosen, calibrated, time varying	Reducible: due to our lack of knowledge of the appropriate value	Quantifiable, scenario
	Hydraulic model	Model structure: transport and mixing processes, number of trains, number of tanks in series	Reducible: due to the simplification of transport and mixing processes in models, inadequate spatial resolution (CSTRs vs. CFD, selection of number of trains to model, number of tanks in series)	Quantifiable, scenario
		Model parameters: fixed, a priori chosen, calibrated, time varying		
	Aeration system model	Model structure: gas transfer processes, mechanical system details	Reducible: due to the simplification of gas transfer processes and aeration system	Quantifiable, scenario
		Model parameters: fixed, a priori chosen, calibrated, time varying		
	Clarifier model	Model structure: separation processes, calculation of composite variables and type of mathematical expression used to describe processes (1-D, 2-D, CFD analysis)	Reducible: due to simplifications in model structure e.g. processes not included, processes included in simplified form as well as due to the choice of mathematical description of processes	Quantifiable, scenario
		Model parameters: fixed, a priori chosen, calibrated, time varying	Irreducible: due to inherently varying biomass settling properties	Quantifiable, scenario
			Reducible: due to our lack of knowledge of the appropriate value	

Table 2 | (*continued*)

Typical modelling project steps		Details of each step	Nature and source of uncertainty	Level of uncertainty
	Controllers in plant operations	Control loops, sensors, actuators, time variation of set-points	Reducible: due to the oscillation of the aeration system, time delays in control loops, non-linearity of actuators	Quantifiable, scenario
	Interfaces between models	Use of one or several sets of state variables, calculation of composite variables	Reducible: due to the aggregation of state variables	Quantifiable
	Model technical aspects	Numerics: solver selections & settings, bugs	Reducible: due to numerical approximations and software bugs	Quantifiable, recognised ignorance
		Simulators: limitations of simulation platforms		
Calibration & Validation	Model parameter selection	Selection of model parameters for e.g. biological, separation models that need to be adjusted	Model prediction error calculations. Uncertainty analysis of calibration & validation parameters	N/A
	Model evaluation	Assessment of model prediction error for calibration & validation data sets through the implementation of quantification methods such as statistical coefficients		N/A
Simulation	Alternatives evaluation, future “what-if” scenarios	Generation of model desired results (probability distributions, statistics)	Post-calibration uncertainty analysis of simulations (sensitivity and Monte Carlo uncertainty analysis)	N/A

Table 3 | Statistical coefficients used to quantify model prediction accuracy

Coefficient	Definition/formula
Residuals	$r_i = C^i_{\mathrm{pr}} - C^i_{\mathrm{ob}}$
Mean of residuals (Bias)	$m = \frac{1}{n}\sum_{i=1}^{n} r_i$
Root-mean-square of residuals (RMSR)	$\sqrt{\frac{1}{n}\sum_{i=1}^{n} (r_i)^2}$
Coefficient of determination	$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(C^i_{\mathrm{ob}} - C^i_{\mathrm{pr}}\right)^2}{\sum_{i=1}^{n}\left(C^i_{\mathrm{ob}} - \mu\right)^2}$

Where: N = Number of prediction/observation pairs, C^i_{pr} = model prediction at time instant i, C^i_{ob} = observation (measurement) at time i, m = mean of residuals, μ = mean of observations.

that they are available and widely used in other fields. During the development of the proposed protocol for the inclusion of uncertainty evaluations in engineering projects, these methods need to be assessed for their applicability in the wastewater field. Further details and examples of the implementation of the methods listed above can be found in WERF (2003*a*), Refsgaard *et al.* (2005), Benedetti *et al.* (2006) and Ahnert *et al.* (2007) among others.

THE RELEVANCE OF MODEL SCOPE AND APPLICATION IN THE EVALUATION OF UNCERTAINTY

Models can be used in multiple stages of a treatment plant's life cycle: research, pre-design, detailed design, start up, process optimization, plant performance analysis, process control, plant upgrades, forecasting, education and training (students and operators) and operator decision support. These different applications require different levels of confidence in model predictions and hence different levels of effort spent on data collection, model calibration and uncertainty evaluations. For example, a preliminary design project requires results quickly and therefore steady state simulations and a series of sensitivity analyses of the parameters where the larger amount of uncertainty lies would suffice. A model used for operational decision support will require fast, robust and highly predictive results. In this case a dynamic calibration and detailed uncertainty analysis may be required.

Because the monetary cost and time input increases with increased requirements, it is important that the engineering community reaches a consensus on the level of confidence and effort required to achieve each project goal. This will be dictated by the intended model application (IWA GMP-TG 2008). One can surmise that increased effort is required with increasing complexity of the modelling objective. The development of a protocol that incorporates uncertainty evaluations will provide quantitative measures to the qualitative criteria discussed above.

CONCLUSIONS

As regulatory demands require plant owners to design and operate processes close to their limits while at the same time increasing energy efficiency and reducing greenhouse gas emissions, identifying and quantifying the uncertainties involved in a new design or plant upgrade becomes crucial. This is especially evident during final bid selection processes, when plant owners have to select a design from a list of proposals that involve different engineering approaches, different processes and costs, all meeting the same objective. One of the parameters that differentiate the bids, not explicitly stated in the proposals, is the uncertainty in each design and the risk that the engineers have assumed in each of the proposed solutions.

Historically the uncertainty involved in predicting the performance of wastewater treatment plants has been addressed through the incorporation of safety factors which are essentially lumped expressions of all the sources of uncertainty. The implementation of models provides practitioners with a structure which allows the systematic identification and quantification of the majority of the sources of uncertainty. It allows them to steer away from semi-arbitrary safety factors, which often result in overly conservative solutions. Instead, safety factors can be derived from quantifications of the uncertainty in each model. This new approach will provide stakeholders with the ability to explicitly quantify uncertainties and include risk evaluations in their decision making process. It should generate new ways of assessing process performance such as confidence intervals or probability curves which will lead to the estimation of accurate design factors.

To initiate the discussion of uncertainty evaluation in the wider engineering community, the work of academics in the field of wastewater and elsewhere needs to be combined with the needs of the engineers implementing modelling for various applications. To this end the authors of this paper are proposing a number of items that need to be discussed. These range from reaching an agreement on terminology to identifying the sources of uncertainty and the available methods for their evaluation. The authors also note the need for the development of a protocol that helps engineers to include uncertainty evaluations in model-based design and optimisation projects. Leveraging the power of models can facilitate the difficult task of evaluating risk.

OUTLOOK

This paper outlines the issues surrounding uncertainty in wastewater treatment and identifies the need for the development of a protocol that incorporates uncertainty evaluations in modelling projects. The goal of such a protocol would be to generate transparent, peer accredited methods of evaluating the reliability of model results. The same methods could be used i) for model-based plant design procedures, ii) to generate design factors and iii) define data requirements. As a first step, the following tasks need to be undertaken:

1. Establish the state of the art in the field of uncertainty evaluation for wastewater treatment projects
2. Review the current practice in respect to assessing risk in design, upgrade or optimisation projects

The work undertaken as part of the above tasks will provide the engineering community with the necessary information to be able to:

- Propose a set of terms and definitions and decide on a common terminology.
- Propose a comprehensive list of the sources of uncertainty.
- Document and evaluate the existing methods for assessing uncertainty.
- Identify gaps in current knowledge and define the developments required to provide adequate tools for practitioners to implement uncertainty evaluations in projects.
- Incorporate knowledge on uncertainty evaluation from other disciplines.

This will enable to complete follow-up tasks necessary for the development of a protocol. These may include:

1. The development of new or the modification of existing uncertainty assessment and evaluation methods.
2. The generation of transparent, peer accredited methods to replace current safety factors with new design factors, calibration requirements, data requirements, etc.
3. The development of a communication framework on uncertainty to address the "non-expert" community including regulators.

These are ambitious and demanding goals which have important implications to the current practice of wastewater treatment profession and industry. Any undertaking to achieve these goals requires a multi-disciplinary collaboration and multi-stakeholder involvement ranging from academia and consultants to regulators and professional associations.

ACKNOWLEDGEMENTS

The authors would like to acknowledge an extended group of reviewers that have contributed to the work presented in this paper, namely: Jens Alex (ifak, Germany), Eduardo Ayesa (CEIT, Spain), Joe Husband (Malcolm Pirnie, USA), Guenter Langergraber (BOKU, Austria), Paul Lessard (Université Laval, Canada), Jeff McCormick (Carollo Engineers, USA), Maureen O' Shaughnessy (ASA, USA), Mark van Loosdrecht (TU Delft, The Netherlands), Stefan Weijers (Waterschap De Dommel, The Netherlands). The authors would also like to thank all the WWTMod2008 workshop participants for their contribution.

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