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Uncertainty Evaluations in Model-Based WRRF Design for High Level Nutrient Removal

LITERATURE REVIEW AND RESEARCH NEEDS

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UNCERTAINTY EVALUATIONS IN MODEL-BASED WRRF DESIGN FOR HIGH LEVEL NUTRIENT REMOVAL

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1.0

INTRODUCTION

1.1 Uncertainty and Variability in the Design Process

Water Resource Recovery Facility (WRRF) design is most often based on static design procedures. However, inputs and outputs of WRRFs are neither stationary nor perfectly known (Belia et al., 2009). WRRF influent and operation are determined by both environmental and anthropogenic phenomena – local and global – which are both variable (changing in time) and uncertain (we cannot predict them with complete certainty) (Benedetti et al., 2013). Furthermore, forecasting of loads for design horizons of 10-30 years is based on the assumption that many of the legal, socio-economic and environmental factors will not change substantially, or are predictable, across the design horizon of a treatment plant (Dominguez, 2008).

The recent WERF study: *Nutrient Management Volume II: Removal Technology Performance & Reliability* (WERF, 2011) highlighted plant performance variability and the fact that it depends on site specific conditions: 'Local conditions impact the performance achieved on average and in terms of statistical variability. These factors include process design, climate impacts, wet weather flow influences, attributes of the service area, variation in influent flows and loadings, presence or absence of industrial contributions, whether solids processing is accomplished on the same site, sustained or interrupted supplies of chemicals, construction impacts, mechanical failures, the difficulty in operating the process, the ability to automate the controls of a process, the closeness of operation to design flows and loadings and others.' The factors mentioned above constitute sources of variability and uncertainty introduced at different stages in the lifecycle of a WRRF.

In conventional design guidelines, variability and uncertainty are handled with the use of semi-arbitrary safety factors and the evaluation of "worst case scenarios". These safety factors are lumped expressions of individual sources of uncertainty and variability. Uncertainty and variability in the influent is often evaluated with the assumption that multiple worst case conditions occur simultaneously. Uncertainty in the response of the biomass or in the reliability of a process is accounted for through the multiplication of a design parameter (e.g., sludge retention time, SRT) with a specific safety factor. For example, in the 1993 EPA Manual on Nitrogen Control, as part of a design approach for a nitrifying suspended growth system the following is mentioned: 'the anticipated variations in process conditions and the uncertainty in the kinetic coefficients warrant a safety factor of 2.0' (EPA, 1993).

This approach has several drawbacks: i) it does not make use of the knowledge that the industry has acquired over the years on plant dynamics and plant evolution, ii) it results in inflexible designs by lumping uncertainty rather than quantifying the relative importance of the individual sources of variability and uncertainty, iii) it often results in inefficient designs, assuming a combination of worst case conditions that may never happen, iv) it does not provide any information on the likelihood or frequency of any particular load reaching the plant within the selected design horizon, and v) it does not provide any information on the likelihood or frequency of non-compliance.

In the current regulatory environment of extremely low effluent nutrient standards, which require plants to operate to very low TN and TP effluent limits, a new approach is warranted which quantifies probability of non-compliance and provides new opportunities for more efficient, resilient and flexible plant designs. This approach must identify the key individual sources of uncertainty for each process, suggest methods to evaluate uncertainty and variability and provide a correct way to apply these methods. The recent work, under the WERF Nutrient Removal Program on quantifying effluent variability for low effluent nutrient concentrations, highlighted the role of variability in design and the need for quantification of the probability of non-compliance: '...A major finding of the WEF/WERF investigation was that statistical variability is a characteristic of all the exemplary plants and that this variability should be recognized in both evaluation of technologies (e.g., stratifying them in terms of their capabilities) in an engineering environment as well as determining the appropriate effluent limits in the regulatory permit setting environment......It is the obligation of the regulators, regulated community, and the design engineering profession to recognize the process variability and higher risks that are attendant with the design for very low nitrogen and phosphorus concentrations or very low maximum day ammonia concentrations' (WERF, 2011).

Dynamic, process-based water resource recovery facility models can be used as the tools to implement this approach. These models provide a structure which allows the identification of individual sources of variability and uncertainty and can complement or even replace design guidelines if they are expanded with methods to quantify uncertainty and probability of non-compliance. Such approaches are currently under development and the wider research community is using case studies and statistical techniques to quantify uncertainty in model predictions.

By extending the *one-parameter-at-a-time* scenario analysis that most engineers use to test design alternatives, with explicit uncertainty evaluations, the models can provide quantitative results on the ability of a plant to meet a given effluent permit when looking into the future. These methods are necessary if models are to be used to design for very low effluent standards to avoid the pitfalls identified in the WERF report (WERF, 2011): 'In design, highly parameterized plant process models are routinely used. When designing for effluents close to zero, these models do not accurately capture the statistical variability of nutrient removal processes. For such situations there are many unknowns that are not resolvable early in project implementation and are only partially compensated by conservatism in design. In such cases, success will only be statistically defined in the first years of plant operation'.

The industry needs a peer-reviewed method which establishes the *good modeling practice* for explicit uncertainty evaluations in model-based WRRF plant design for very low TN and TP effluent limits that can be used by practitioners. The method will leverage the power of current models and simulators and bridge the gap between the application of models for design by the engineering community and uncertainty evaluation techniques used in academia. Recent publications have shown that probabilistic design may potentially reduce key processes design variables (Bixio et al., 2002; Cox, 2004; McCormick et al., 2007). This would translate to direct savings in the order of millions to tens of millions of dollars for typical construction projects.

To address this need, in 2008, a Design and Operational Uncertainty Task Group (DOUT) initiative was established. The group is working on several coordinated projects with the ultimate goal of developing a methodology for the explicit evaluation of variability and uncertainty in model-based WRRF design.

This report presents the state of the art and research needs for the development of this methodology. It is related to the work of the IWA Task Group on Design and Operational Uncertainty (DOUT), (http://www.iwahq.org/f9/networks/task-groups/task-group-on-uncertainty.html) currently under way, which will generate a detailed summary on the state of the art of uncertainty evaluation and identify knowledge gaps.

1.2 Uncertainty, Low Nutrient Removal, and Current Regulatory Standards

The vast majority of WRRFs in North America have permit limits that require 100% compliance at the specified concentration or mass load – e.g., a maximum month permit or annual average permit need to be fulfilled every year. Having very stringent effluent limits implies that the safety that needs to be incorporated increases to guarantee no non-compliance events. As the cost for guaranteeing such safety becomes excessive, this suggests that the utility must be prepared to accept some probability of non-compliance, inherent in the system, but not explicitly stated. This aspect is widely understood, but not often directly addressed by engineers, utilities, and regulators (Bott et al., 2009; WERF, 2011).

There is a clear benefit in using probabilistic models as a process design tool by the stakeholders in this process. Such models are capable of generating predicted statistical distributions of effluent parameters and give regulators and utility managers the ability to define the level of risk they are willing to accept in terms of meeting permit. Model-based probabilistic analysis allows engineers to make the following type of statements: *Given all the information available, the model predicts with 90% confidence that the plant will be out of compliance one month in five years when treating the design load*.

1.3 The Umbrella DOUT Initiative (UDOUT)

The academic and engineering communities have been aware of the need for the incorporation of explicit uncertainty evaluations in model based design for some time as is evident from several efforts on both sides of the Atlantic. Examples include WERF Project 00CTS3, titled *Tools for Rating the Capacity of Activated Sludge Plants* (WERF, 2003) which focused on incorporating uncertainty in a nitrification plant design and the European Union Harmoni-QuA project (Refsgaard, 2002) from the field of water resources management.

Discussions on knowledge gaps and requirements for the development of a methodology for the explicit evaluation of variability and uncertainty resulted in a workshop during the 1st IWA/WEF Wastewater Treatment Modeling seminar (WWTmod2008), held in Mont-Sainte-Anne, Canada (Belia et al., 2008) which focused on providing an overview of the uncertainties introduced during WRRF modelling. As a consequence the Design and Operational Uncertainty Task Group (DOUT) (http://www.iwahq.org/f9/networks/task-groups/task-group-on-uncertainty.html) was formed. The task group has documented the *status quo* on this topic and its results are being published in a Scientific and Technical Report (STR) (Belia et al., 2013 *in preparation*).

Following the initiation of the DOUT, several coordinated projects were initiated under the Umbrella DOUT initiative (UDOUT). Each project is focusing on specific research needs ranging from reviewing current design guidelines to developing new model-based methodologies. Figure 1-1 shows an overview of the UDOUT projects under way.

The UDOUT initiative intends to bring together the collective knowledge of consulting engineers, researchers, utilities and water boards, from several countries and continents. It will incorporate specific tools, examples, and alternative design methodologies.

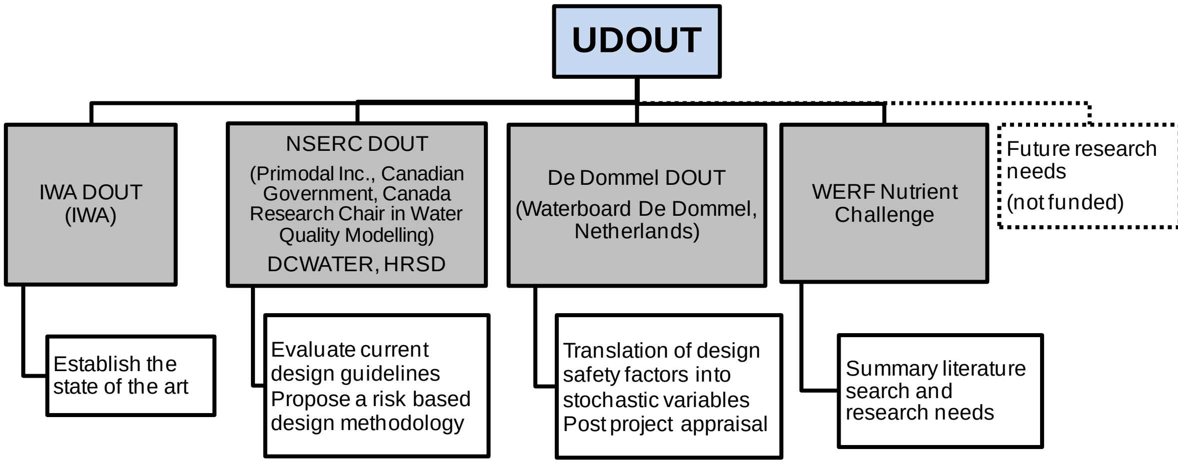

Figure 1-1. Outline of the UDOUT Projects Contributing to the Development of a Methodology for the Explicit Evaluation of Variability and Uncertainty in WRRF Design and Operations.

The goal of UDOUT is the identification, quantification, and propagation of the most relevant sources of uncertainty during the design of nutrient removal systems. The most important outcome will be improved design methods resulting in facilities that are adaptive to uncertain inputs and future technology changes. The aim is to generate robust, resilient, and flexible designs. To achieve this, uncertainty and variability must be explicitly evaluated.

1.4 Scope of the Report

This report has the following objectives:

- Discuss the need for the incorporation of explicit uncertainty evaluations and probability of non-compliance assessments in design, in response to current regulatory demands.
- Introduce to stakeholders the state-of-the-art of uncertainty analysis with a brief literature review
- Discuss the need to extend good modeling practice in the area of model reliability and explicit uncertainty evaluations.
- Present the research needs for the development of a methodology that assists engineers in the incorporation of uncertainty evaluations in model-based WRRF design.
- Highlight the opportunities that explicit uncertainty evaluation provides to trade-off cost and probability of non-compliance associated with designing high-level nutrient removal systems.

CHAPTER 2.0

UNCERTAINTY AND DESIGN: LITERATURE REVIEW

Design engineers that have to make decisions under uncertainty have traditionally relied on design guidelines. These guidelines include safety factors, which are based on the accumulated experience of the industry, and account for the uncertainty and variability inherent in the wastewater treatment process.

More recently, through the development and implementation of mathematical models, engineers and researchers have been able to use more advanced mathematical and statistical methods for the optimization of the key parameters used for design. These methods include sensitivity analysis and model based plant optimization.

Looking into the future, as the incorporation of models and statistical methods increases, probability-based designs will offer a real alterrnative to traditional approaches. In probability-based designs the quantifiable sources of uncertainty are explicitly desribed in terms of probability distribution functions and the compliance of the WRRF to the effluent standards is evaluated probabilistically.

This section covers a brief literature review of how conventional and model-based methods approach the design of WRRFs under uncertainty. More details can be found in Karmasin et al. (2013) and Sprouse et al. (2013).

2.1 Current Practice

Uncertainty and risk of non-compliance is currently handled in the wastewater treatment practice through the use of design guidelines. Historically, process design criteria have been based on regulatory requirements, industry-accepted design standards or state specific regulations (industry standards, adapted to specific state conditions with additional requirements). Some examples of these design standards include:

- Water Environment Federation Manual of Practice 8 (WEF MOP 8, 2009)
- Wastewater Treatment Disposal and Reuse, Metcalf and Eddy (Tchobanoglous et al., 2003)
- Recommended Standards for Wastewater Treatment Facilities (Ten States Standards, 2004)
- ATV Guidelines (ATV, 2000)
- EPA Nitrogen Control Manual, (EPA, 1993).
- EPA Phosphorus Removal Design Manual, (EPA, 1987)
- Biological Wastewater Treatment, (Grady et al., 2011)
- Methods for Wastewater Characterization in Activated Sludge Modeling, (Melcer et al., 2003)
- WERF/CRTC Methodologies for Evaluating Secondary Clarifier Performance, (Wahlberg, 2001)
- Virginia's Sewage Collection and Treatment Regulations (Virginia DEQ, 2008)

- Biological Nutrient Removal (BNR) Operation in Wastewater Treatment Plants, (WEF MOP 29, 2005)

Design guidelines address risk by using relatively conservative design criteria. How the criteria are to be applied is frequently open to interpretation, but engineers tend to evaluate several scenarios that include combinations of critical design parameters. This approach can result in conservative and expensive designs without necessarily providing a worthwhile benefit (Doby, 2004). Russell (2006) states that most municipal WRRFs are 30-50% overdesigned based on municipal codes and, after safety factors are used by consultants, are overdesigned by 100% or more.

2.1.1 Key Process Variables as Sources of Uncertainty

Typically design engineers will place safety in their design in a few key process variables, most of which describe the most important sources of uncertainty. They are: influent flows and mass loads, SRT, SVI, overflow rates, denitrification rates, and the design of the process air system.

2.1.1.1 Influent Flows and Mass Loads

In most projects historical information is used as the design basis for a facility. This includes plant data (e.g., influent flow), population growth projections, zoning of the service area, and capital improvement projects (e.g., infiltration and inflow improvements). In most cases, the risk and uncertainty regarding population growth projections and zoning changes is accepted by the owner.

Engineers will typically use coinciding peaking factors to account for variability in flows and wastewater strength at the treatment facility. Hydraulic peaking factors are used to verify that facilities will perform at peak flow conditions as well as to confirm loading rates on unit processes such as clarifiers and tertiary filters. Mass loading peaking factors are commonly used to design unit processes to ensure performance can be met for permit compliance. The peaking factors are generated from historical data and extrapolated to future conditions using statistical evaluation.

2.1.1.2 Effluent Criteria

Facility design is based upon meeting a numerical effluent limit or treatment performance in order to meet a permit requirement. Design engineers may employ a lower target effluent concentration in the model-based process design to account for variability and uncertainty in the design process.

2.1.1.3 Solids Retention Time

Perhaps the most common method of addressing uncertainty and variability in wastewater practice today is the use of a safety factor when determining an operating solids retention time (SRT) for a nitrifying system. With the variability and uncertainty in both bacterial growth and plant operations, safety factors are used to ensure that washout of autotrophic organisms does not occur.

For example, in the ATV-DVWK-A 131 guidelines the equation used for the calculation of the solids retention time (SRT) includes a safety factor which takes into account: a) potential variations of the maximum growth rate caused by certain substances in the wastewater, short-term variations and/or pH shifts, b) the variations of ammonium load. The guidelines suggest that the safety factor should be in the range of 1.4 to 1.8 (lower safety factors for higher population equivalents).

Similar safety factors are included in most guidelines such as Metcalf and Eddy (Tchobanoglous et al., 2003) and WRC (Ekama et al., 1984) among others.

2.1.1.4 Sludge Volume Index and Overflow Rates for Clarifier Sizing

Uncertainty relating to solids settling in secondary clarifiers typically results in the selection of a conservative design sludge volume index which is often used as a clarifier performance indicator. In order to mitigate risk and uncertainty, the secondary clarifier is evaluated using multiple state-point analyses at varying design conditions to determine the performance of the clarifier using this conservative sludge volume index. Most guidelines also include suggested surface overflow rates (e.g., ATV-DVWK-A 131E).

The WRC guidelines include an explicit safety factor that is used to multiply the estimated area of the secondary settling tank. The area of the secondary clarifier is estimated as a function of peak wet weather flow, MLSS concentration, the recycle ratio, and $SSVI_{3.5}$ using an empirical equation that has been derived based on flux settling parameters measured at 30 plants in the UK. The calculated area is multiplied by a safety factor of 1.25.

2.1.1.5 Denitrification Rates

Uncertainty relating to the denitrification rate in nitrogen removal facilities is typically handled by the appropriate sizing of the anoxic zone. For example in the ATV-DVWK-A 131E design guidelines the size of the anoxic tanks has to satisfy the recommended values for the ratio of the anoxic to total volume of the bioreactor. Ratios of less than 0.2 or greater than 0.5 are not recommended.

In the WRC guidelines the volume of the anoxic and aerated sections of the bioreactor can be calculated as a function of SRT and maximum specific growth rate of the nitrifying organisms. The recommended values for the un-aerated to the total bioreactor volume are presented graphically and they should not be larger than 60%.

Historically, the equations used for the sizing of the anoxic zones have been proven to be conservative, alleviating risk involved with meeting effluent total nitrogen concentrations. In the event that the design engineers feel that the risk has not been adequately addressed, they may choose to add tertiary treatment.

2.1.1.6 Process Air System Design

Another common location of added safety in WRRF design is the addition of safety factors in the design of the aeration system. Engineers typically select design dissolved oxygen concentrations for varying conditions (average day, maximum day, etc.) to ensure that there is adequate oxygen available for oxidation of carbonaceous and nitrogenous matter. They often assume and add safety factors to several key parameters that have large impacts on the sizing of air systems in wastewater treatment. These include the alpha value, the standard oxygen transfer efficiency (SOTE) for diffused air systems and the standard aeration efficiency (SAE) for mechanical surface aeration systems.

This may lead to an overdesigned capacity of the blowers and inefficient operation. This becomes even more important with the introduction of ammonia-based control strategies.

2.1.2 Limitations of Design Guidelines

Design guidelines typically include safety factors that are used to multiply a design quantity (e.g., SRT) or suggest conservative values for influent flow and load, kinetic coefficients or target effluent limits. These approaches have the following problems:

- Applying safety factors to the design of several unit processes could result in accounting for the same source of uncertainty more than once.
- Variables that are in reality correlated are assumed to be independent, which leads to potentially selecting combinations that are unrealistic or highly unlikely.
- Although there are some recommended ranges for design parameters and safety factors, engineers must use their subjective judgment to make the final selection.
- They assume steady state conditions and cannot predict the dynamics of the effluent.
- They do not provide methods to estimate the probability of non-compliance for a specific design.
- Guidelines are not regularly updated to reflect newer processes and more stringent effluent standards like very low effluent N and P.

2.2 Design Approaches Incorporating Uncertainty Principles – Available Methods

The introduction of more stringent effluent requirements like low nutrient effluent limits and the development of new processes have led to the increased use of mathematical models in WRRF design. During the last years, there have also been a growing number of studies that incorporate methods for the explicit evaluation of variability and uncertainty. Two areas of research and application are emerging.

One research area, driven by systems analysis methods, focuses on an appropriate characterization of biochemical and physical processes and their associated uncertainty (Vanrolleghem et al., 1995; Brun et al., 2001; Benedetti et al., 2006; Daebel et al., 2007; Flores-Alsina et al., 2008; Sin et al., 2009). The main topics in this line of research are statistical inference (the use of a sample, or subset of data to draw inferences about the population as a whole), sensitivity analysis (how the predictions of a model change with a change in the value of a model parameter), identifiability analysis (how well model parameters can be determined by the amount and quality of experimental data) and uncertainty propagation (uncertainty in model predictions resulting from uncertainty in model parameters and other inputs).

The second research area addresses uncertainty across larger time-scales: future developments of the loads (e.g., influent to WRRFs), the cycle of technological innovation, and the adaptation rate of legal requirements. Historical analysis of plant data has shown that the temporal rate of change of these three factors is often shorter than the physical lifetimes of the built structures (Dominguez and Gujer, 2006). First test cases have been performed by researchers applying foresighting techniques to assist communities in planning their infrastructure (Dominguez et al., 2009).

The following sections discuss the available methods used to characterize key sources of uncertainty used as inputs to model-based plant design and optimization. A characterization of the types of uncertainty as discussed in the literature is also included. A more detailed list of the existing studies addressing uncertainty in the field of wastewater treatment and a summary of the methods employed in the published literature can be found in Sprouse et al. (2013).

2.2.1 Classification of Variability and Uncertainty

There is an important difference between variability and uncertainty (and which quantities should be considered variable, uncertain or both) that has a significant impact on any model-based analysis of a WRRF. The following paragraphs include the definitions of the two concepts as applicable to wastewater treatment. The definitions clarify the confusion often seen in the literature that equates uncertainty with poor data (Kelly and Campbell, 2000).

Variability is the spread of "true" values of a quantity that characterizes members of a well-specified quantity. Variability arises as a result of the heterogeneity, diversity, inter-individual differences, temporal changes, etc. within the population. Variability is a property of the population, not of our state of knowledge (Kelly and Campbell, 2000).

Uncertainty is the inability to determine or predict the exact value of a quantity or behavior of a system or process both now and in the future. Uncertainty results from lack of knowledge and is *partly* reducible through the acquisition of additional knowledge e.g., more data or further understanding of a process.

Researchers have tried to classify uncertainty into categories depending on the methods and tools that can be used to quantify or characterize them (Refsgaard et al., 2007; Walker et al., 2003). One of the most popular classifications is by Walker et al. (2003) who characterize uncertainty based on its *nature, location,* and *level.*

The *nature* of uncertainty depends on whether it can be reduced with further research or measurements (e.g., experimental determination of kinetic parameters) in which case it is classified as ***reducible*** and called *epistemic uncertainty;* or whether it is due to the inherent variability of a system and cannot be reduced with any further research (e.g., rainfall, toxic spills) in which case it is classified as ***irreducible*** and called *variability-uncertainty.*

The *level* of uncertainty varies from quantifiable to total ignorance (popularly referred to as unknown unknowns). The four levels (Figure 2-1) can be defined as follows:

Quantifiable uncertainty can be quantified and described with statistical methods and can be attributed to uncertainties such as a random measurement error of a sensor.

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 exists and the scientific basis is insufficient to develop functional relationships, statistics, or scenarios.

Total ignorance is defined as the state where the actors are not aware of uncertainty. It is unknown what is unknown.

Figure 2-1 depicts these four levels of uncertainty lying between determinism and indeterminism.

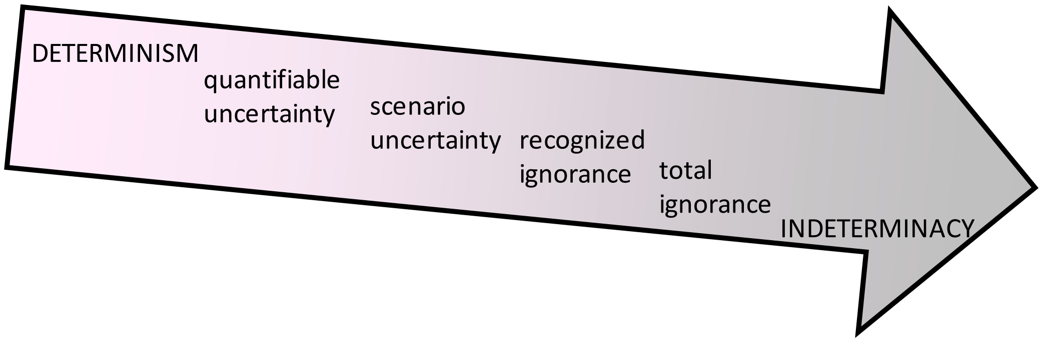

Figure 2-1. Level of Uncertainty.
Walker et al., 2003.

The *location* of uncertainty (or source) refers to the instance where uncertainty manifests itself in the modeling process. According to Walker et al. (2003), it includes: ***context uncertainty*** (i.e., uncertainty in the identification of the system boundaries), ***model uncertainty*** (i.e., both model structure uncertainty and model technical uncertainty arising from computer implementation of the model), ***input uncertainty*** (i.e., both inputs describing the reference system and external forces driving changes in the current system), ***parameter uncertainty*** (i.e., the uncertainties associated to the data and the different techniques used for model calibration), and ***model output uncertainty*** (i.e., the total uncertainty assessed by uncertainty propagation taking all model uncertainties into account).

Table 2-1 includes a list of the sources of uncertainty linked to model inputs, structure, parameter values and the numerical application of the models. The sections that follow cover the methods used to quantify key sources of uncertainty.

Table 2-1. Location of Uncertainty in WRRF Modeling.

Location	Details	Sources	Examples
Inputs	Measured data	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 parameters	Hydraulic	Number of tanks in series
		Biokinetic	Maximum growth rates
		Settling	Settling coefficients
Model structure		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
Numerics	Software (model technical aspects)	Solver settings	
		Numerical approximations	
		Software limitations	
		Bugs	
Model output	Propagation of uncertainty	Combination of above mentioned sources	

2.2.2 Uncertainty in Model Inputs

There are a number of publications in the literature that focus on quantifying the uncertainty in model inputs. Model inputs in this document include both ***measured data*** and ***model parameters***.

2.2.2.1 Methods for Assessing Uncertainty in Measured Data

Measurements contain uncertainty due to *random* errors, *systematic* errors and *gross* errors. Random errors are introduced as part of the measurement process and include sampling errors, instrument and analytical method errors. Random errors can be potentially minimized but never completely removed. Systematic errors introduce a bias due to for example offsets caused by sensor drifts. Gross errors are caused by calibration mistakes, malfunction of instruments, poor sampling or errors in data recording. Gross errors and systematic errors can be (to a large extent) detected and removed thereby reducing the uncertainty in the measured model inputs.

The uncertainty in measured data is typically assessed using statistical techniques. Examples of the implementation of such methods for the evaluation of analytical techniques include the work of Joannis et al. (2008) who found that the major sources of error were due to uncertainties in the standard solutions used for calibration and the nonlinearity of the calibration curve; and Bertrand-Krajewski et al. (2007) who compared COD measurements between standard laboratory techniques and found that sub-sampling (analyzing smaller aliquots of a larger sample) is the major source of uncertainty in the laboratory methods used for COD determination.

For on-line sensor data, Rieger et al. (2005) evaluated the uncertainty of on-line measurements at WRRFs using comparisons between independent measurements of the same sample (i.e., sensor and a reference laboratory method).

Several researchers advocate the use of multivariate statistical methods to identify outliers in water quality data because of the correlation between plant variables (Robinson et al., 2005). There are also a number of more advanced statistical methods available for detecting and removing systematic errors that range from statistical process control and fault detection methods to data reconciliation.

Data reconciliation is a common technique used to adjust process measurements so that they are consistent with known conservation laws and other process constraints. Data reconciliation can be performed using either a steady-state or dynamic analysis (Nowak et al., 1999; Barker and Dold, 1995; Meijer et al., 2002; Puig et al., 2008; Thomann, 2008). Rieger et al. (2010) have more recently published suggestions for data reconciliation that focus on planning measurement campaigns so that high quality data can be collected for the purpose of model simulation projects.

The use of formal data reconciliation in the wastewater treatment field has been limited due to a lack of data, the complexity of the solution procedure, and the lack of availability of software dedicated to data reconciliation (Rieger and Vanrolleghem, 2008; Nopens, et al., 2007).

2.2.2.2 Methods for Assessing Uncertainty in Model Parameters

Uncertainty in model parameters arises from many sources such as uncertainty in the model structure, the choice of experimental conditions used for model calibration, the uncertainty in the collected calibration data, and the method used for parameter estimation. The uncertainty in model parameters is typically assessed either through expert interviews or as part of parameter estimation methods (Bard, 1974; Bates and Watts, 1988; Cox, 2004).

Several studies have identified the fact that historical plant data are rarely suitable for estimating model parameters and for assessing their uncertainty. This is mainly due to missing data, inconsistencies in the data, limitations in the ranges of the variables due to process control, confounding effects between variables, variations in unmeasured variables as well as low identifiability (Box et al., 1978; Petersen, 2000; Vanrolleghem et al., 2003).

2.2.3 Model Structure Uncertainty

Model structure uncertainty in activated sludge models is primarily a result of the selection of the state variables and the assumptions made in the process of developing activated sludge system models.

Researchers and engineers have investigated the amount of uncertainty inherent in activated sludge models resulting from: kinetic parameters estimated at different flow schemes and residence times (Gujer, 2002); differences in results that occur between a lumped parameter (macroscopic) model structure and a microscopic model structure (Schuler, 2005 and 2006, Curlin et al., 2004) and differences in model results for different operational scenarios (Sin and Vanrolleghem, 2006). Several studies have investigated uncertainty in model structure introduced by influent fractionation (Haider et al., 2003) and by kinetic parameters (Lavallee et al., 2005). Researchers observed that kinetic parameters may depend on substrate, process configuration, and sludge age. Neumann and Gujer (2008) quantified how uncertainty estimation is affected when applying different kinetic model structures. Other studies investigating clarifier models, e.g., (Abusam and Keesman, 2002) have tested the use of the double-exponential function and concluded that the model had a structural problem related to the prediction of suspended solids in the underflow stream.

2.2.4 Methods for Assessing and Propagating Uncertainty in Model Outputs

Several researchers have published studies evaluating the sensitivity of model outputs to uncertainty in model inputs and methodologies for generating robust designs (Von Sperling, 1993; Huo, 2004). In the simplest approach to sensitivity analysis, the change in model outputs was measured by individually varying input parameters by a percentage (e.g., 10%). More recent applications of sensitivity analyses have applied regression-based methods (Benedetti et al., 2011, Sin et al., 2011).

With respect to how uncertainty affects model calibration, most publications focus on determining wastewater composition and kinetic variables based on available plant data (Koch et al., 2001; Sin et al., 2008). The available research outlines methodologies (Martin and Ayesa 2010) that can be used to determine the parameters that allow for best fit of the models along with whether the model results are statistically significant.

From the reported studies, Monte Carlo (Figure 2-2) emerges as the most commonly used method of uncertainty analysis when evaluating different WRRF plant design alternatives (Tansel, 1999; Doby et al., 2002; Huo et al., 2006; Afonso and da Conceiao Cunha, 2007; Sin et al., 2009; Benedetti et al., 2010). Monte Carlo type techniques can be used for design, sensitivity analyses, and calibration. How the Monte Carlo techniques are applied and how the results are interpreted has been approached differently with no consensus on the best approach.

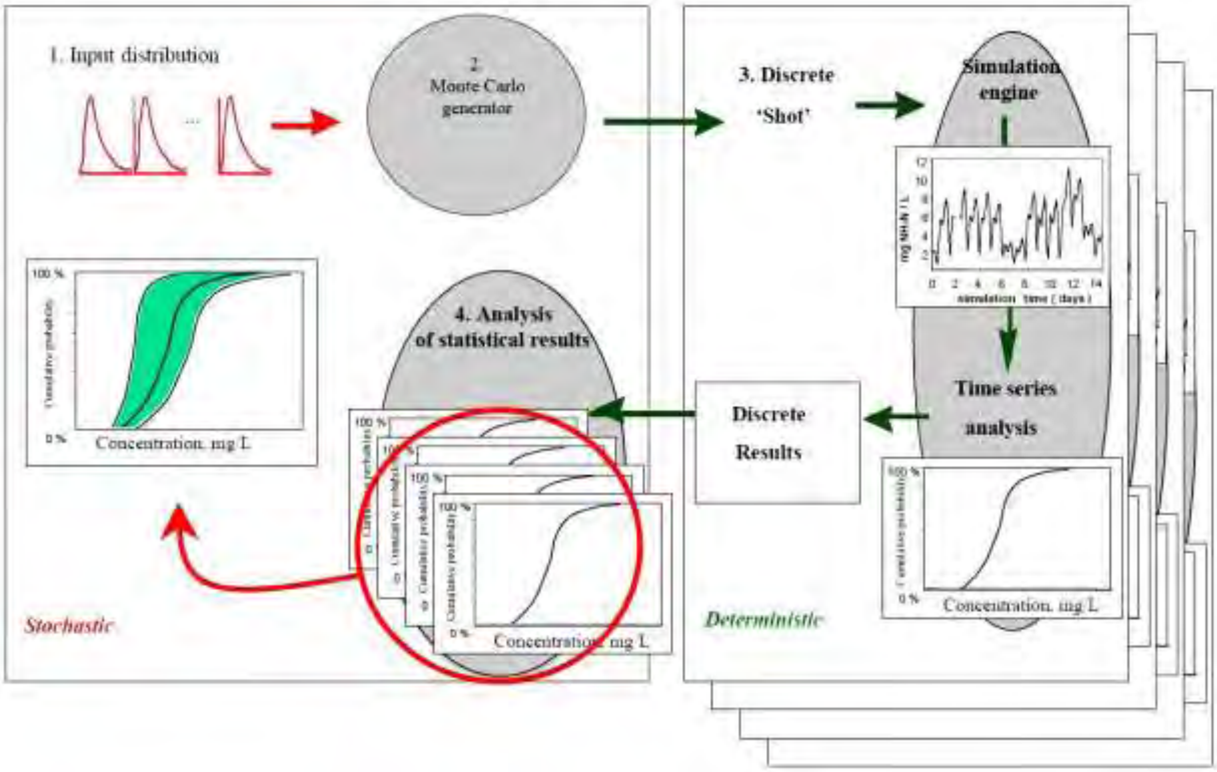

Figure 2-2. Monte Carlo Simulation Framework.
From Bixio et al., 2002.

Even though the Monte Carlo method is the most commonly used method of uncertainty analysis, it should be used with caution. Additional understanding and work are required to determine what the meaningful outputs of an uncertainty analysis are and how they can be achieved.

More research is needed to compare the different methodologies and their results to clearly understand the benefits of each. Indeed, a key element of uncertainty analysis is how the scenario for the uncertainty analysis is defined, how the objectives of the analysis are set and what the boundaries of the system under evaluation are (Sin et al., 2009).

2.2.5 Summary and Conclusions

The non-linear, stochastic and dynamic nature of wastewater treatment systems results in randomness, periodicity or chaotic behavior. It is largely recognized that wastewater treatment models have structural and input uncertainty but there are no widely accepted methods available for quantifying this uncertainty. Furthermore, there has been little investigation on how consulting engineers and utilities should deal with these uncertainties when designing, upgrading or optimizing a WRRF. More specifically, how should the wastewater industry deal with uncertainties during the planning, design and bidding stages of a wastewater treatment facility in an explicit way?

Discussions on the above topic have led the Design and Operational Uncertainty Task Group (DOUT) to suggest research into the development of a probability-based design methodology which is able to provide quantitative measures for the probability of non-compliance. The following chapter discusses the development of the methodology and the tools required for its implementation.

CHAPTER 3.0

PROBABILITY-BASED DESIGN OF WRRFS

3.1 Introduction and Methodology Overview

Incorporating evaluations of the probability of non-compliance during the design of WRRFs requires uncertainty characterization and uncertainty analysis. Figure 3-1 shows a design methodology that incorporates explicit uncertainty evaluations.

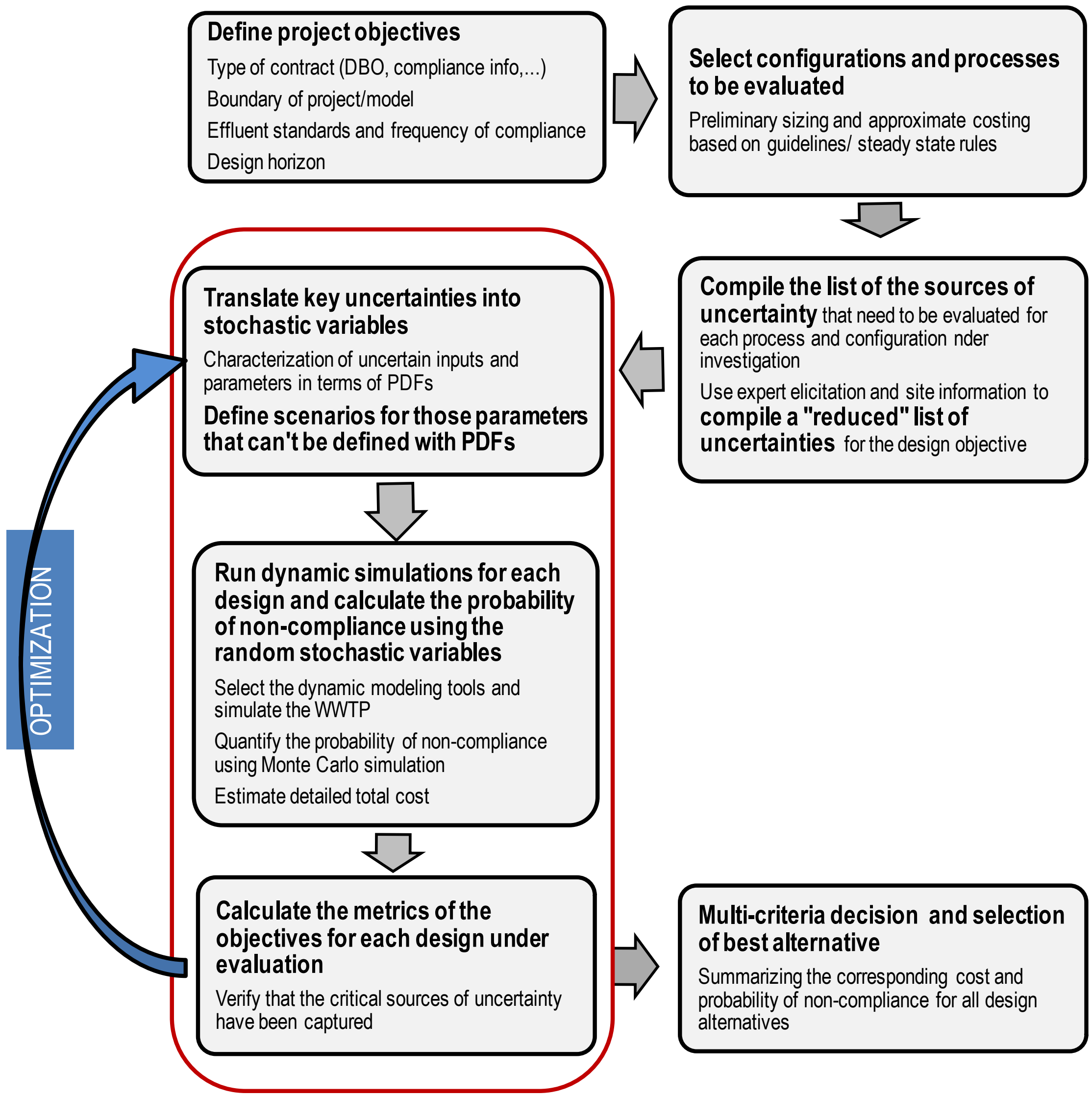

Figure 3-1. Flow Sheet of a Proposed Methodology for Probabilistic Plant Design.
Abbreviations: DBO = design build operate, PDF = probability density function.
Adapted from Talebizadeh, 2012a, NSERC-DOUT.

3.1.1 Define the Project Objectives

The type of contract, project objectives and project constraints define the boundary of the WRRF model. In conjunction with the design horizon and compliance requirements they identify the required inputs and the type of analysis required to evaluate the performance of each design alternative.

3.1.2 Select Configurations and Processes to be Evaluated

A number of alternative processes or configurations are selected and an initial estimation of the dimensions of the unit processes is made based on design guidelines or steady state models. The preliminary cost of each alternative is also calculated. The alternatives that are deemed acceptable are evaluated further.

3.1.3 Select the Most Relevant Sources of Uncertainty

A list of the most relevant sources of uncertainty is composed. Of all the potential sources of uncertainly, only the ones considered by the design engineer critical for the specific objective are evaluated.

3.1.4 The Monte Carlo Optimization Loop

The probability of non-compliance of each design is estimated by performing uncertainty analysis using Monte Carlo simulation. One of the most important factors required for the Monte Carlo simulation is the generation of random values of uncertain model inputs. To do so the most important sources of uncertainty must be characterized statistically.

3.1.4.1 Generation of Input Time Series

The variability of important external variables such as temperature which affects the kinetics of the treatment process or rainfall which affects the characteristics of flow and influent composition can be characterized (in the absence of measurements of adequate frequency and duration) by random generation of synthetic time series. The synthetic time series must observe the underlying stochastic characteristics of the different variables and their correlations.

3.1.4.2 Translation of Key Uncertainty Sources into Stochastic Variables

Uncertainty analysis using Monte Carlo simulation includes expressing uncertain variables or parameters in terms of probability data functions (PDFs). In the absence of historical data subjective judgment can be used to determine the parameters of the PDFs. When site measurements are available they should be used for the estimation of the parameters of the PDF. Any knowledge regarding the correlations among the different model parameters is also taken into account.

3.1.4.3 Dynamic Simulation of the WRRF

The responses of the model simulating the plant design under evaluation are evaluated repeatedly for each combination of external inputs time series and random realizations of uncertain parameters using a dynamic simulator.

3.1.4.4 Sensitivity Analysis

Once the parameter ranges are defined, sensitivity analysis (SA) can be used to rank the importance of various parameters in determining uncertainty for each design alternative.

3.1.4.5 Output Analysis and Compliance Calculations

For each design under evaluation, the time series of different wastewater constituents in the effluent obtained from the dynamic simulation need to be transformed corresponding to the definition of the effluent standards, e.g., by calculating averages, percentiles, exceedance frequencies, return periods, etc.

3.1.5 Selection of Best Alternative

The final decision is made based on a comparison of total cost and the probability of non-compliance for each design.

3.1.6 Tasks Under Way and Future Research Needs

The steps outlined in Figure 3-1 require several types of activities ranging from capturing existing knowledge to statistical method development. The tasks and research needs identified so far have been listed and classified in Table 3-1. Some of the tasks are being executed as part of the various UDOUT related projects (Investigating entity). Tasks not currently under way have been identified as future research (FR).

Table 3-1. Tasks Under Way and Future Research Needs.

Category	Task	Investigating Entity
Knowledge acquisition and preparatory work	Review how engineers are currently accounting for uncertainty and variability in their designs	IWA-DOUT STR
	Review current WRRF design guidelines	NSERC-DOUT
	Establish a common language for communicating on the subject of uncertainty	IWA-DOUT STR
	Propose a comprehensive list of the sources of uncertainty	IWA-DOUT STR
	Compile currently available methods for the quantification of variability and uncertainty	IWA-DOUT STR
	Critically review existing methods	NSERC-DOUT
	Identify gaps in current knowledge and define developments required to provide tools to implement uncertainty evaluations in projects	IWA-DOUT STR
	Incorporate knowledge from other fields (water resources, atmospheric science, nuclear industry, etc.) on applications of uncertainty evaluation methodologies	IWA-DOUT STR
Tasks that are an integral part of the methodology	Define desired outputs (type of deliverables and analysis)	NSERC-DOUT
	Propose methods for selecting the pertinent sources of uncertainty for each design objective	FR
	Modify or develop a new methods for risk-based design of WRRF	NSERC-DOUT
	Translate key uncertainties into stochastic variables	FR
	Generation of synthetic model input time series	NSERC-DOUT
	Statistical post processing of uncertainty propagation results	NSERC-DOUT
Tasks required for the validation of the methodology	Develop a validation process for the methodology using real plant data	FR
Tasks related to the communication of the research and the application of the methodology	Communicate the application of the method and the results	FR
	Analyze the capacity reserves in design guidelines	NSERC-DOUT

3.2 Knowledge Acquisition and Preparatory Work

A short description of the tasks has been included in the following sections.

3.2.1 Uncertainty in Current Engineering Practice

As part of IWA-DOUT, a review of the way uncertainty and risk is currently handled in the field of WRRF design has been compiled. Section 2.2 of this document includes a summary of this work (Karmasin et al., 2013).

3.2.2 Critical Review of Existing Design Guidelines

As part of the NSERC-DOUT project, a general methodology is being established that allows a comparison between three of the most used guidelines around the world: ATV, Metcalf & Eddy, and Grady.

Global Sensitivity Analysis has been used to analyse the effect of the uncertainty sources (input uncertainties) on the design output. Within NSERC-DOUT a tool to assess activated sludge process design guidelines by using Monte Carlo simulations and global sensitivity analysis has been developed (Flores-Alsina et al., 2010 and 2012). The tool is intended to help engineers during a WRRF design, by determining which of their decisions in the preliminary steps are going to have a significant influence on the result. The approach has been applied to the Metcalf and Eddy design guideline (Flores-Alsina et al., 2010), the ATV guideline (Neumann and Vanrolleghem, 2011; Talebizadeh et al., 2012b) and the Grady guideline (Aymerich-Blazquez, 2011). The approach has also been used to assess guideline-based designs with dynamic ASM models (Corominas et al., 2010).

3.2.3 Establishing a Common Language: Terms and Definitions

Establishing a common language is necessary because identical terms are used in statistics, systems theory, water resources and other fields but with different definitions. The IWA-DOUT group has compiled a list of terms commonly used in the field of uncertainty (Villez et al., 2013). The group has focused on terms relevant to wastewater and has incorporated the definitions included in existing standards such as ISO (1994, 2003) and NIST (1994). The outcome is a set of terms that cover the necessary concepts of uncertainty evaluation relevant to utilities, consultants, academia, regulators, and the public. Examples of such terms have been included below.

Confidence: The probability or degree of belief that a given outcome corresponds to its true, usually unknown, value. This applies to a given measurement and how well it reflects the true underlying variable; to a model and the degree of belief that it is representative of the true system; to a simulated result and the degree of belief that it corresponds well to the true corresponding value.

Model prediction accuracy: An estimate of how close a model predicted quantity is to the true or reference values of the described real system.

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

Reliability: Reliability is the degree to which one is certain that a given system will perform a certain task over a period of time, i.e., the degree to which one can rely on the system's performance.

3.2.4 Compilation of a Comprehensive List of the Sources of Uncertainty

As identified by Bott and Parker (2011), there are many factors that influence plant reliability and variability. In their study they compiled a list determined from the data evaluated and from plant managers' testimonies which included:

- Toxic event upsets
- Unexpected interruptions in chemical supply
- Plant upgrading projects and the impacts of construction on effluent quality
- Peak flow events
- Variations in flows and loads
- Biological treatment capacity issues during more stressed periods
- Internal sludge supernatant recycle streams containing ammonia
- Chemical feed control issues for phosphorus removal
- Fermenter control issues

All of the items listed above can be identified as sources of uncertainty and variability. Not all of the potential sources will impact every facility and similarly not all sources need to be evaluated when deciding on a plant design. However, before prioritising the relevant sources for a specific design objective, a comprehensive list of all parameters and actions affecting a treatment process needs to be compiled.

The IWA-DOUT group has compiled a comprehensive list of the potential sources of uncertainty in a typical WRRF project (Burbano et al., 2013). Examples of engineering projects can be used to illustrate where/when each source of uncertainty is introduced. The typical five-step simulation-based project execution flow sheet (Rieger et al., 2012) has been used as a basis for grouping uncertainty sources as shown in Table 3-2 (Belia et al., 2009). In addition, the critical steps in a design project have been identified (planning, conceptual design, detailed design) and linked to the main sources of uncertainty introduced during a project timeline (Weijers, 2013). In each phase of a project, design and modeling decisions are made as well as decisions on how to deal with uncertainty. These need to be made explicit and properly documented to make the decision making process of the project transparent and to follow the different model versions.

Currently Table 3-2 is being expanded to include all major aspects of a project that generate uncertainty and introduce risk. Special focus is given to those factors that contribute to uncertainty in high-level nutrient removal plants.

Table 3-2. Nature and Level of Uncertainty Introduced during Each Step of a Typical Modeling Project Simulating the Liquid Train of a Water Resource Recovery Facility.
Belia et al., 2013.

Typical Project Steps		Details of Each Step	Nature and Source 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
	Context and framing	The boundaries of the system to be modeled. Biological treatment only, whole plant or sewer and river	
	Requirements	Level of model prediction accuracy, what type of data	
Data collection and reconciliation	Influent data	Flow rate, concentrations, influent characterization 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
			Reducible: due to data collection e.g., sampling method, location, frequency, accuracy of sensors, accuracy of analytical techniques
	Physical data	Process flow diagram, active (effective) tank volumes, clarifier surface areas, flow splits	**Irreducible:** due to the unpredictable and dynamic behavior of structures like splitters to flow changes
			Reducible: due to e.g,. unknown true volume constructed or operational depth of structures
	Operational settings	Controller set-points, valve positions, pumped flows	**Irreducible**: due to the unpredictability of operator decisions
			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.
	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
			Reducible: due to data collection issues
	Additional information	Equipment failures	**Irreducible:** e.g., due to unexpected equipment failures

Table 3-2. Nature and Level of Uncertainty Introduced during Each Step of a Typical Modeling Project Simulating the Liquid Train of a Water Resource Recovery Facility, continued.
Belia et al., 2013.

Typical Project Steps		Details of Each Step	Nature and Source 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)
	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
			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
		Model parameters: fixed, a priori chosen, calibrated, time varying	**Reducible:** due to our lack of knowledge of the appropriate value
	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)
		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
		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
		Model parameters: fixed, a priori chosen, calibrated, time varying	**Irreducible:** due to inherently varying biomass settling properties **Reducible:** due to our lack of knowledge of the appropriate value
	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
	Interfaces between models	Use of one or several sets of state variables, calculation of composite variables	**Reducible:** due to the aggregation of state variables
	Model technical aspects	**Numerics**: solver, settings, bugs **Simulators**: limitations of simulation platforms	**Reducible:** due to numerical approximations and software bugs

Table 3-2. Nature and Level of Uncertainty Introduced during Each Step of a Typical Modeling Project Simulating the Liquid Train of a Water Resource Recovery Facility, continued.

Belia et al., 2013.

Typical Project Steps		Details of Each Step	Nature and Source of Uncertainty
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
	Model evaluation	Assessment of model prediction error for calibration & validation data sets through the implementation of quantification methods such as statistical coefficients	
Simulation and Results Interpretation	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)

3.2.5 Review of Available Methods

As part of the STR, IWA-DOUT has compiled a list of the existing studies which address uncertainty in the field of wastewater treatment and has summarized the methods employed in the published literature (Sprouse et al., 2013). The working group compiling the chapter on the existing literature has identified broad categories of application of uncertainty analysis methods. A brief summary has been included in Chapter 2.0 in this document.

3.2.6 Gaps in Current Knowledge and Practice Related to Uncertainty

As discussed in Chapter 2.0, there are several methods available in the literature that can be used to evaluate uncertainty and how it is propagated through wastewater treatment modeling. They include classical parameter estimation, Monte-Carlo (MC) simulations from expert-based probability density functions; the generalised likelihood uncertainty estimation (GLUE) method (Cierkens et al., 2012), etc. A need for a systematic approach on how to apply these methods is needed.

Another area where further work is required is the selection of PDFs to describe statistically a key source of uncertainty. This is necessary because the estimated uncertainty of the model outputs depends on the choice of the selected PDF (Benedetti et al. 2008; Cierkens, et al., 2012).

In addition to the examples mentioned above, further developments may be required to provide adequate/improved procedures and tools to implement uncertainty and risk evaluations in wastewater treatment projects. A critical discussion of the gaps in current methods has been compiled by the IWA DOUT group working on this topic (Shaw et al., 2013).

3.2.7 Knowledge from Other Fields

Uncertainty principles have been implemented in other disciplines over the past decades with promising results. Incorporating knowledge from other fields on the topic of uncertainty evaluation will identify whether there are more efficient ways of doing what the wastewater industry has done so far.

As part of the IWA DOUT STR methods from the fields of chemical engineering, hydrogeology (groundwater), and hydrology (surface water/watershed) were investigated (Schraa et al., 2013).

3.3 Tasks that Are an Integral Part of the Methodology

This section focuses on integral parts of the methodology.

3.3.1 Definition of Desired Outputs

The inclusion of explicit uncertainty evaluations will provide additional information to all stakeholders. For defining desired outputs the following type of questions are being pursued: 'What additional information would I want to give to my client with respect to risk/uncertainty (figures, tables, design numbers, …) and how do I expect him/her to benefit from this information?' 'How is it expected to improve the decisions?' Examples of potential outputs that will provide quantitative answers to these questions are shown in Figures 3-2 through 3-4.

Figure 3-2 shows a probabilistic design curve. The curves capture the outputs of dynamic, probabilistic models and can describe the probability of non-compliance. Similar outputs to Figure 3-2 may include probabilistic design curves, at 50, 80, 90, 95, and 99 percentiles.

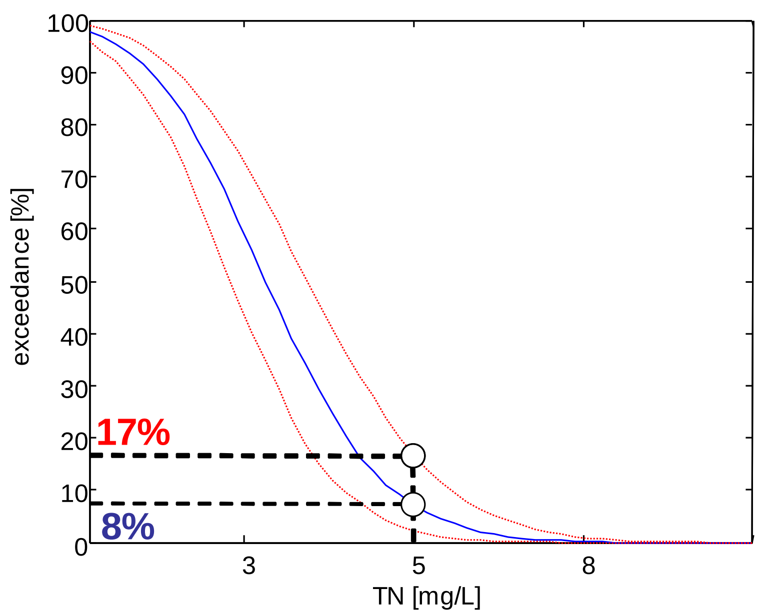

Figure 3-2. Probability of Effluent Limit Exceedance for a Specific Unit Process.
Benedetti et al., 2006.
The final effluent limit is linked to a frequency of exceedance for a deterministic model (blue line) or probability of frequency of exceedance (5 and 95 percentiles – red lines output of Monte Carlo simulations; the blue line may also indicate the median of Monte Carlo runs) for a probabilistic approach.

The curve shown in Figure 3-3 shows a link between relevant events, such as peak loads, pump failures and storm events (describing input uncertainty and variability) to effluent violations, using a steady-state model. In the graph the probability of compliance for a given effluent quality and plant description is given for any of the criteria of interest i.e., ammonia, phosphorus, TN, secondary clarifier capacity. One of the criteria will end up "driving" the selection of a design at its desired level of reliability. Figure 3-4 shows way of linking probabilistic model outputs to cost.

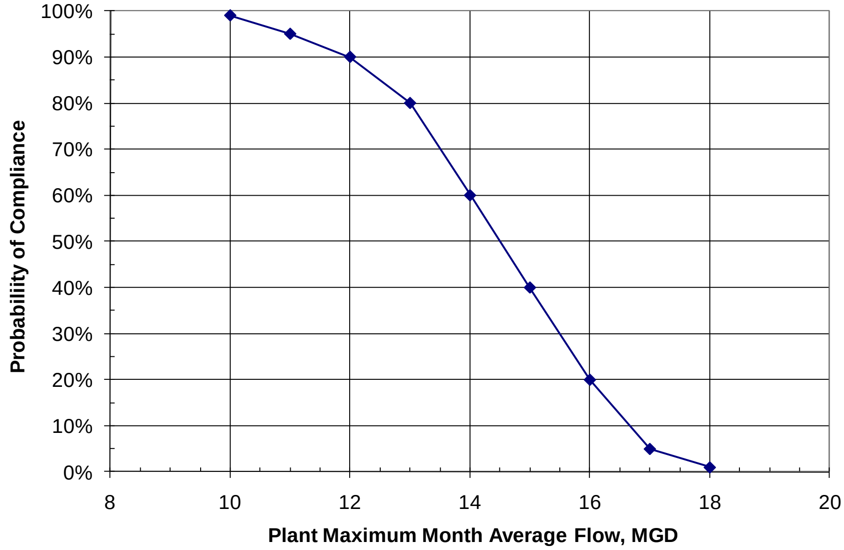

Figure 3-3. Probability of Compliance for a Given Effluent Quality and Plant Description, for Any of the Criteria of Interest i.e., Ammonia, Phosphorus, TN, Secondary Clarifier Capacity.

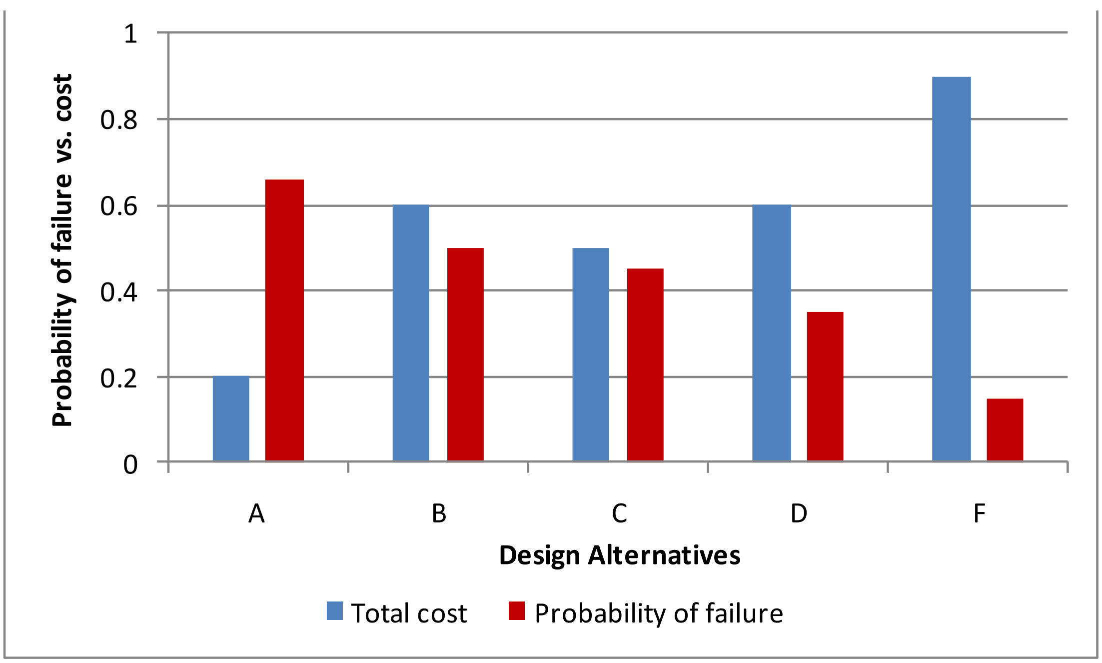

Figure 3-4. Probability of Non-Compliance and Total Cost for Several Design Alternatives.
NSERC-DOUT.

Discussions on which outputs are most relevant for each design project are under way as part of the NSERC- and De Dommel-DOUT projects. The presentation methods for probabilistic data are a key part of the effectiveness of the procedures. For example, if a graphic does not clearly show the real impacts to a non-statistics user, the meaning of the information at best will be lost, and at worst misunderstood. Therefore the graphical methods of communication are a critical part of uncertainty analysis.

3.3.2 Methods for Selecting the Most Relevant Sources of Uncertainty

This section focuses on what to consider when selecting the most relevant sources of uncertainty.

3.3.2.1 Link Model Scope and Application Area to Level of Effort Required

The users of probabilistic modeling techniques need guidance on the level of effort required to accomplish various uncertainty related modeling tasks. Since it is not feasible to generate a rigorous list that applies to every possible modeling application, a list of typical modeling applications compiled each with specific objectives and associated level of effort, is needed. Following the steps of the IWA Task Group on Good Modeling Practice (Gillot et al., 2009; Rieger et al., 2012), the selected applications for this list will be very specific and will cover the majority of projects that engineers may be called to execute especially for high-level nutrient removal plants. This list will be used to define the effort required to incorporate uncertainty analysis for the selected objectives. Based on this practitioners can:

- Decide where along the typical engineering design (or optimization) process uncertainty analysis adds most value.
- Define the required level of detail pertaining to the scope of the engineering project.

3.3.2.2 Knowledge-Based Screening Method

A crucial step of the methodology is identifying the relevant sources of uncertainty for each project objective. To compile a list of the sources of uncertainty that need to be evaluated, expert elicitation can be used. The knowledge and experience of industry experts can generate a ‘reduced’ list of the sources of uncertainty that are significant for each objective. Additional information that needs to be generated includes the range of possible values for each parameter identified as a key source of uncertainty and the preferred probability distributions for some of the selected parameters.

3.3.3 Develop New or Modify Existing Methods

This task includes the development of methods for translating key uncertainties into stochastic variables, methods relating to the optimisation of parameter estimation, optimization of control strategies, multi-criteria decision analysis etc.

New methods may need to be developed or modified to make them applicable to wastewater treatment. These methods need to be 1) scientifically sound 2) easy to use given the scarce resources of the modeler/consultant – therefore the possibility to automate the methods is a highly desired feature – and 3) understandable (therefore easy to be adopted) by the final recipient of the results, who has to decide on the acceptable level of risk of non-compliance of a design.

The NSERC-DOUT project is developing a methodology which follows the same progression of tasks as current design practices but also includes some of the sophisticated optimisation algorithms currently available in the literature used for parameter estimation, optimisation of control strategies, etc.

3.3.4 Translate Key Uncertainties Into Stochastic Variables

For each selected uncertain parameter, a PDF needs to be defined. The type of distribution and the values of the descriptors of the distribution are related to the amount of knowledge available for the parameter under investigation. If our knowledge about the uncertainty of a parameter is very limited a uniform or triangular distribution can be used.

The correlations among the different model parameters can be expressed in terms of a correlation matrix. Using this information, a joint distribution of uncertain model parameters is estimated by a parametric multivariate statistical distribution. For the Monte Carlo runs the parameters are sampled from the estimated joint distribution. By doing so the correlations among the different model parameters are taken into account.

There is no rigorous method available that can aid engineers in deciding on the appropriate distribution to be used as well as avoiding simulating unrealistic load or operational scenarios. More research is required in this area.

3.3.4.1 Scenarios

Scenario analysis can be used for those uncertainties which cannot be defined in terms of PDFs. Each scenario includes a set of plausible values for the parameters of interest. The selection, quantification and implementation of scenarios in combination with uncertainty analysis have not been fully explored.

3.3.4.2 Equipment Reliability as a Key Source of Uncertainty

Defining methods to incorporate ***equipment reliability*** in model-based design is a topic requiring further research. Equipment reliability has been repeatedly identified as an important source of uncertainty when assessing WRRF performance. The translation of key uncertainties relating to equipment failures into stochastic variables requires extensive work and an interdisciplinary approach.

3.3.5 Random Generation of Model Input Time Series

A crucial point when designing a plant with high level nutrient removal is to properly characterize the uncertainty and variability of the influent load and flow (Friedler and Butler, 1996; De Keyser et al., 2010). Within UDOUT a specified project has been conceived to study the patterns observed in the influent of a WRRF. The project is developing mathematical tools able to generate synthetic data profiles for dynamic simulation studies. The generated data reproduce the daily, weekly and yearly profiles on the basis of a limited amount of data about the catchment area such as: the inhabitant equivalents, number and type of industries, rain characteristics, etc.

Following a critical evaluation of existing influent generators, Martin and Vanrolleghem (2012) conceived a new influent generator approach. The suggested generator is a grey-box model that includes a phenomenological (mechanistic) model of the catchment area and a stochastic (data-driven statistical) model to reproduce the natural variability of the receiving load. The phenomenological component is based on the model proposed by Gernaey et al. (2010 and 2011) but it includes a much more descriptive approach for the rain generation, soil model and temperature variation, among others. The stochastic component introduces some variability to the characteristics of the influent profiles.

3.3.6 Statistical Post-Processing of Uncertainty Propagation Results

The model outputs of the uncertainty propagation for all configurations need to be converted to the design criteria or effluent criteria. For example, if the effluent criterion is a two week average, then a two week average from each MC run needs to be computed and the distribution of the two week averages can be used to compare designs. In addition, a cost function can be used to estimate the total cost of each configuration as a function of key design variables (e.g., volume of bioreactors and secondary clarifiers). The development of advanced cost functions and multivariate optimization tools that calculate the trade-off between the total cost and probability of compliance is another area requiring further research.

3.4 Validation of the Methodology with Plant Data

The validation of the methodology with data collected at existing facilities is key requirement prior to its adoption by practitioners. The WERF project evaluating the performance of plants operating at low TN and TP (WERF, 2011) has compiled data for several plants that include influent loading, process design and operating conditions, unusual events, upsets and anecdotes related to process operation, and effluent data.

Using the measured data inputs, configuration information and operational settings the proposed procedure will be applied to compute probabilistic effluent profiles. Each Monte Carlo simulation for each plant will produce a times series of concentration data which can be summarized as an empirical cumulative distribution function (ECDF). These probabilistic effluent profiles can be characterized by a 90% confidence band that is compared to the measured effluent profiles. If uncertainties have been well quantified one expects 90% of the selected plants to have effluent profiles that are within the 90% confidence band. This validation also allows discriminating between limit exceedances which are due to plant under-sizing, equipment failure or process upsets such as foaming or bulking sludge.

As shown in Figure 3-5, the 90% confidence band from the computed (e.g., 1000) ECDFs can be compared to the ECDF of the measured data (black line in Figure 3-5).

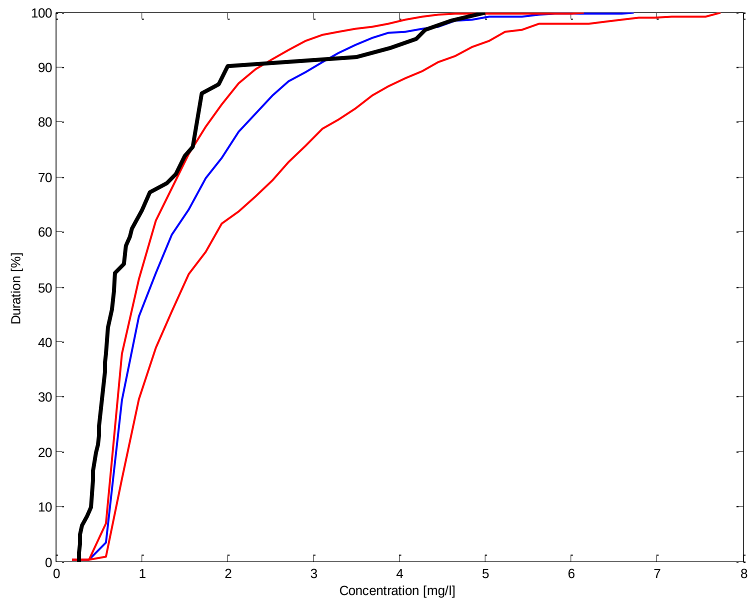

Figure 3-5. Cumulative Curves for Effluent NH_4 Concentration.
Black Line: Measured Data; Blue Line: 50th Percentile of MC Simulations; Red Lines: 5th and 95th Percentiles, Quantiles of 1000 Simulated ECDFs Obtained with the MC Simulations.
Benedetti et al., 2013.

3.5 Communication of the Methodology

Clear communication is a critical component of the new methodology. The wide–spread adoption of these approaches will require non-statistically fluent practitioners to understand the benefits of the approach in order for the techniques to be adopted. It is the plan of the UDOUT group to develop and test various approaches, some of which were described above, for clearly communicating the concepts and benefits of uncertainty analysis. The UDOUT group will be disseminating its work through WEF, WERF, and IWA communication mechanisms.

3.6 Application of the Methodology to Analyze the Capacity Reserves in Design Guidelines

One of the main benefits of linking uncertainty analysis to model-based design is the ability to quantify the reserve capacity inherent in currently practiced design guidelines (e.g., WEF-MOP8, Metcalf & Eddy, ATV-A131). The probabilistic methodology can be applied to designs generated by the guidelines for specific load scenarios and effluent guidelines. Probabilistic estimates for the effluents concentrations can be computed using the uncertainty tools and dynamic models.

Results such as the one shown in Figure 3-6 where a specific design guideline is assessed for three different effluent requirements indicate the level of safety incorporated in the design guidelines. The x-axis represents the effluent concentration requirement used to obtain the design with the guideline. A probabilistic model for the obtained design is set up and effluent concentrations are computed: The y-axis represents the predicted effluent concentrations (expected values and 90% confidence intervals). The feasibility of such an approach has been examined in a first test case comparing the Metcalf & Eddy design guidelines with a deterministic model-based design applying an ASM1 model (Corominas et al., 2010). The proposed analysis will be able to make the level of safety incorporated in design guidelines apparent.

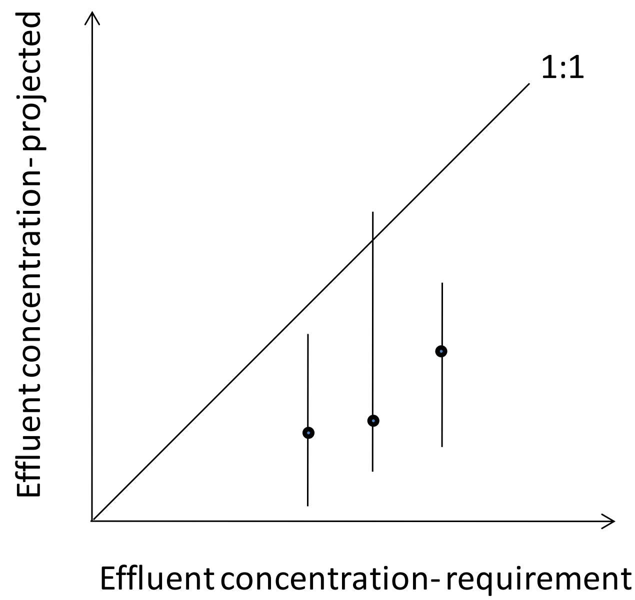

Figure 3-6. Estimation of Reserve Capacity Inherent in Design Guidelines.
Three designs are obtained from applying a design guideline to three different effluent concentration requirements. Projected effluent concentrations (bullets: expected values, line: 90% confidence intervals) are then obtained from the probabilistic model projecting plant behavior of three designs.
Vanrolleghem et al., 2010; NSERC-DOUT.

CHAPTER 4.0

SUMMARY AND CONCLUSIONS

4.1 Overview

The wastewater industry normally relies on empirical, rule-based methods for the design of water resource recovery facilities in which safety factors are applied to minimize the probability of non-compliance with effluent standards. These empirically based rules are becoming increasingly less relevant as ultra low nutrient levels are adopted. In recent years, mathematical models describing the physical, chemical and biological processes are increasingly being applied in the wastewater industry. Indeed, the increase in the complexity of process configurations and the increased nutrient removal requirements has necessitated the use of these process-based models. However, there is no consensus on how to manage the inherent uncertainties when applying these models in the context of plant design. It also remains unclear how to translate the traditional safety factor concept to model-based design procedures.

The goal of the UDOUT project is to promote the development of a methodology for model-based design of wastewater WRRFs, which is especially applicable to plants trying to achieve very high nutrient removal levels. Such a methodology should account for uncertainty in WRRF design and make designs more comparable and transparent with respect to performance and reliability. The main output of this procedure will be minimizing the over- or under-design of high nutrient removal facilities by explicitly quantifying the degree of inherent safety associated with different designs.

Recent publications have shown that probabilistic design may potentially reduce key processes design variables (Bixio et al., 2002; Cox, 2004; McCormick et al., 2007). This would translate to direct savings in the order of million to tens of millions of dollars for typical construction projects.

The resultant tools would benefit the water quality industry in the following ways:

- A utility will be able to estimate the probability of compliance associated with different designs proposed during bid selection. They will be able to select the design that corresponds to their desired level of safety and costs.
- The engineering consultant will be able to quantitatively balance an acceptable level of process risk vs. costs of a proposed design.
- A better basis for effluent guidelines may be developed and regulators may be convinced to apply probabilistic effluent limits.

In all three cases an increase in transparency can be expected as well as more efficient expenditure of public resources.

This report introduces the state-of-the-art of uncertainty analysis and highlights the opportunities that explicit uncertainty evaluation provides to high-level nutrient removal systems. This report also presents the research needs for the development of a methodology that will allow engineers to use simulators with explicit reliability calculations.

4.2 Relevance to High Level Nutrient Removal

High level nutrient removal requires the reliable achievement of very low nutrient values in effluents. These low numbers are often very close to the theoretical limits of what is possible in treatment, i.e., a 3 mg/L total nitrogen limit is very close to the refractory dissolved organic Nitrogen (rDON) in plant effluents, and thus requires very controlled operation of the facilities. Exceedances of 1 or 2 mg/L in a conventional plant can easily be recovered from in a normal averaging period, but in low nutrient removal plants, it may not be possible to recover from what is normally considered even a moderate exceedance, since there is very little room to operate below the limit. In design, these low limits require the designer to have a high level of understanding of all the factors that go into achieving this goal, so that they can produce a plant design that is reliably able to achieve these limits. Historically, this has been done through the use of conservative estimates of various parameters, sometimes resulting in an "overdesigned" facility. As an alternative to this, sometimes very expensive approach, uncertainty analysis provides the design engineer, and operator, quantitative information on where the risks are, and can be used to develop a more cost effective design to achieve the same goals as well as a better understanding of how high level nutrient removal plants need to be operated.

The current generation of wastewater models and their associated kinetics/stoichiometry are based on the historical experience of the industry and numerous past research activities. As such, most of these models are based on conventional nutrient removal goals and did not specifically examine the impacts of very low nutrient in plant effluents. In other words, there is a much higher degree of relative uncertainty in model results when these applications are examined. As such, the uncertainty principals described herein are especially applicable to situations were very low effluent nutrients are needed.

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