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Uncertainty based decisions to manage combined sewer overflow quality

By

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Abstract

Environmental regulators stipulate performance and modelling requirements for water utilities managing sewer networks to demonstrate regulatory compliance in order to limit their impact on the environment. Uncertainty in urban drainage modelling presents challenges to decision makers attempting to achieve compliance with regards to Combined Sewer Overflow (CSO) and treatment plant discharges. This study provides methodologies for making decisions to improve the environmental performance of the urban sewer systems while accounting for uncertainty in model predictions of their performance. In doing so, an objective uncertainty quantification process is first described using a case study in Belgium which enables the water utility to evaluate and report the uncertainty in their CSO spill predictions and is transparent enough to satisfy their regulator. Second, six practitioners from a water utility are interviewed to identify their preferences for uncertainty in the performance variable and the risk of non-compliance. Given identical uncertainty levels in model predictions, individuals' preferences are found to have a significant effect on the decisions taken. Subsequently, two uncertainty based decision models are presented which reflect individuals' preferences in making decisions accounting for uncertainty in model predictions. The first decision model includes the concept of Buffered Probability of Exceedance as a risk measure accounting for the magnitude of extremes along with the mean and the skewness of the performance distribution. The second decision model applies Cumulative Distribution Function (CDF) matching which minimises the difference between the CDFs of the performance variable and a target function specified by the decision maker. The decision models presented in this study enable a better-informed decision making by allowing a comprehensive understanding and representation of modelling uncertainty in evaluating decisions instead of only using exceedance probabilities or extreme values. The decision models provide a significant improvement over existing uncertainty based approaches found in literature to manage sewer overflows.

Keywords: buffered probability of exceedance, combined sewer overflows, decision making under modelling uncertainty, emission quality failures, stochastic decision modelling

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List of Abbreviations

AHP	Analytic Hierarchy Process
AMALGAM	A Multi-Algorithm Genetically Adaptive Multi-objective
ANP	Analytic Network Process
AR	Autoregressive
BASMAA	Bay Area Stormwater Agencies Association
BIC	Bayesian Information Criterion
BMP	Best Management Practices
BOD	Biological Oxygen Demand
bPOE	Buffered Probability of Exceedance
BS	British Standards
CDF	Cumulative Distribution Function
CIWEM	Chartered Institution of Water and Environmental Management
CS	Collection Systems
CSO	Combined Sewer Overflow
CW	Colebrook-White
DEFRA	Department for Environment, Food and Rural Affairs
DO	Dissolved Oxygen
DSS	Decision Support System
ELECTRE	ELimination Et Choix Traduisant la REalité
EN	European Norm (European Standards)
EP	Exceedance Probability
GAMU	Global Assessment of Modelling Uncertainties
GLUE	Generalized Likelihood Uncertainty Estimation
GSA	Global Sensitivity Analysis
IAHR	International Association on Hydraulic Engineering and Research
ICM	Integrated Catchment Modeling
ISO	International Organization for Standardization
ITN	Initial Training Network
IWA	International Water Association
LHS	Latin Hypercube Sampling
LIST	Luxembourg Institute of Science and Technology
MADM	Multiple Attribute Decision Making
MAUT	Multiple Attribute Utility Theory
MAVT	Multi- Attribute Value Theory
MCD	Minimum Covariance Determinant
MCDM	Multiple Criteria Decision Making
MCS	Monte Carlo Simulation
MODM	Multiple Objective Decision Making
MVP	Mean-Variance Portfolio theory
NSGA-II	Non-dominated Sorting Genetic Algorithm-II
OAT	One-At-a-Time
ÖWAV	Österreichische Wasser- und Abfallwirtschaftsverband
OMADM	Other Multi-Attribute Decision Making
PDF	Probability Density Function
PERT	Program Evaluation and Review Technique

POE	Probability of Exceedance
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation
QUICS	Quantifying Uncertainty in Integrated Catchment Studies
RAM	Random Access Memory
ROA	Real Options Analysis
RWB	Receiving Water Bodies
SCEM	Shuffled Complex Evolution Metropolis
SCDM	Single Criterion Decision Making
TOPSIS	Technique for Order Preference by Similarity to an Ideal Solution
UK	United Kingdom
VMM	Flanders Environment Agency (Vlaamse Milieumaatschappij)
WFD	Water Framework Directive
WSM	Weighted Sum Method
WWTP	Wastewater Treatment Plant

1. Introduction

1.1 Background and motivation

Among the various downsides of increasing urbanization is its negative impact on the water quality of natural surface water bodies such as rivers and lakes. These negative impacts include endangering and damaging the aquatic life, the water not being suitable for water treatment or bathing and the degradation of aesthetics of these natural water bodies. Often, these impacts are caused by the wastewater derived from households, commercial and industrial properties, and stormwater from the catchment surfaces carrying chemical and biological loads responsible for these aforementioned negative impacts. Sewer systems are constructed as the engineered solution to mitigate these negative impacts. There are two types of sewer systems: Combined sewer systems where the wastewater and the storm water is collected in the same pipe and conveyed to treatment; and Separate sewer systems where the wastewater and stormwater are collected in separate pipes, with only the wastewater being conveyed to treatment. Most of the older sewer systems are combined sewer systems. The wastewater is transported to the wastewater treatment plants (WWTP) for treatment and then the treated effluent is released into a natural surface water body. Wastewater treatment plants are designed to treat the wastewater to an acceptable standard depending on the receiving water body and the treated wastewater is then, released to the water body (Butler et al., 2018). In the event of high precipitation, the incoming drainage load to the WWTP might exceed the maximum limit the WWTP was designed for. In such events, the excess drainage load is discharged into the water body via a Combined Sewer Overflow (CSO) structure at the WWTP. In order to avoid sewer flooding, numerous CSO structures are located throughout any sewer network so that if the local flow capacity is being reached then excess dilute wastewater can be released to a nearby water body without treatment.

Water utility companies responsible for the management of urban drainage system are often subjected to performance assessment with regard to protecting the population from sewer flooding and protecting the receiving water bodies (RWBs) from the release of pollutants present in the wastewater (De Toffol, 2006). Environmental regulators may impose performance standards for the operation of overflow structures; one such example is the Urban Pollution Management Manual in the UK which specifies concentration-duration-frequency based criteria for ammonia concentrations and dissolved oxygen (DO) levels to control the negative ecological impacts on the RWBs caused by CSO spills (Foundation for Water Research, 2012). However, the criterion to evaluate the performance of CSOs is not uniform across different countries (De Toffol, 2006; Dirckx et al., 2011). For example, in Belgium, Denmark and Netherlands, guidelines based on annual overflow frequency are enforced while in Germany the criterion for CSO spills considers the overflow volume (Dirckx et al., 2011). Water utilities are required to comply with the performance standards applicable to their jurisdiction whatever they are, and failing to do so can result in financial penalties and reputational damage, e.g. the water utility company Thames Water in the UK was recently fined 20 million pounds for releasing untreated sewage water into the Thames river and its tributaries in contravention of its discharge consents (Carrington, 2017).

Therefore, in the context of environmental impact on the RWBs, the management of urban drainage systems involves investment and operational decisions which reduce the risk of non-compliance with the regulations. Such decision making processes aim to identify, test and implement solutions or strategies which minimize the risk of non-compliance while satisfying constraints such as available budgets, and planning constraints. However, the current status of CSO emission quality regulations in the UK and Europe suggests an absence of an explicitly defined financial penalty for breaching the regulations. As a result, for most of the cases, the calculation of risk as the probable loss associated with each decision alternative cannot be calculated in the absence of a financial penalty. Therefore, this thesis uses the probability of non-compliance with the regulatory performance standards as ‘risk’ in the absence of a consequence value the event of non-compliance.

Soncini-Sessa et al. (2003) classify the decision making for water resource systems into planning and management actions. Planning decisions involve actions which are taken once while management decisions involve sequential actions. In planning, the actions are taken without considering their effect on similar actions in future. However, management problems require the evaluation of the sequential actions and their individual impacts on the linked future actions based on current system conditions. This thesis will focus on planning type investment decisions to reduce the risk of water quality failure caused by CSO spills because often these decisions involve large capital costs.

Hydrodynamic network models are often required to assess the performance of the proposed solutions (Delelegn et al., 2011). Such models help the decision makers understand the physical behaviour of the flow and pollution over the catchment and in the sewer pipes. Based on this understanding of the flow behaviour decision makers design and implement engineering solutions to mitigate the negative impact of urban sewer systems on the water quality and avoid facing penalty by the regulators. However, it has been established that there is significant uncertainty present in the predictions of such hydrodynamic models (Thorndahl and Willems, 2008). Hence, these simulation models should also provide the level of the uncertainties accompanied with the model predictions because any unaccounted uncertainty in these model predictions may have a significant effect on the outcome of the decision making process of water utilities. In addition, investment decisions in urban drainage infrastructure are usually a long-term commitment and significant capital is involved in the construction and maintenance of such infrastructure. Hence, the efficacy of such investments should be carefully valued using the best information available on the model predictions such that they are not only complying with the regulatory standards and robust against the uncertainties in the behaviour of the physical system but also cost-effective.

1.2 Aim and objectives

Although uncertainty in the urban drainage simulations has been studied recently, there is a dearth of studies which practically quantify the uncertainty in urban drainage modelling and demonstrate how to incorporate this additional information on uncertainty to aid the decision making process. Specifically this thesis studies the influence of uncertainty in the simulation of CSO emission quantity and quality through case study catchments in different countries and applies suitable regulatory requirements. As is the case in the UK or Austria, the regulations look at the water quality of the receiving water bodies instead of the sewer overflow quality. Hence, this thesis acknowledges that the simulation of water quality in the RWBs requires consideration of the treatment processes at the WWTP, the WWTP effluent to the RWBs, and the sensitivity of the RWB itself towards the incoming pollutants. In addition, there could be a number of innovative measures to improve the CSO efficiency utilising the interconnectivity of the CSO and the WWTP (for example, Kleidorfer and Rauch (2011)). Consequently, the evaluation of such measures requires simulation of WWTP processes. It should be of note that in this thesis, the simulation case studies are communicated to demonstrate the proposed uncertainty based decision modelling approaches. The author acknowledges that the sources of uncertainties and the flow processes represented to simulate CSO emission quantity and quality in this thesis are a subset of wider uncertainties and processes e.g. simulation of mixing of pollutants in the RWBs.

This thesis aims to provide methodologies which can be used for decision making in urban drainage infrastructure investments using the sound understanding of the inherent uncertainty in hydraulic and emission quality model predictions. In order to achieve this aim, this thesis sets out following objectives:

(I) Represent the regulatory compliance requirements in the modelling and the evaluation of decision alternatives.

(II) Quantify uncertainty in the model predictions while following the regulatory modelling requirements, thereby making the uncertainty predictions acceptable to the regulator.

(III) Identify individuals' preferences for uncertainty in the performance variable and their risk behaviour in evaluating decision alternatives.

(IV) Develop decision models which represent the decision makers' preferences to select optimal decision alternatives improving the environmental performance of urban sewer systems while complying with the regulatory standards.

1.3 Contributions and thesis structure

Apart from this introductory chapter and the conclusions in Chapter 7, the thesis is organised into five chapters. These five chapters can be summarized as below.

Chapter 2 includes a literature review on two main subjects: uncertainty quantification in urban drainage modelling, and decision-making under probabilistic uncertainty. The chapter also includes a review of the decision making methodologies which have been applied in urban drainage systems to study the environmental impact of CSOs.

The contents of section 2.1 are based on

- Sriwastava, A., and Moreno, A. (2017) "Report on uncertainty frameworks and Report on application of uncertainty frameworks, potential improvements." Deliverables D.1.1 & D.4.2, Marie Curie ITN Quantifying Uncertainty in Integrated Catchment Studies (QUICS).

Chapter 3 addresses a knowledge gap on the role of model uncertainty in environmental compliance studies by describing an objective uncertainty quantification process which enables the water utilities to evaluate and report the uncertainty in their modelling predictions and is transparent enough to satisfy regulators. (Objectives I & II)

The contents of Chapter 3 are based on

- Sriwastava, A.K., Tait, S., Schellart, A., Kroll, S., Dorpe, M.V., Assel, J.V. and Shucksmith, J., 2018. Quantifying Uncertainty in Simulation of Sewer Overflow Volume. *Journal of Environmental Engineering*, 144(7). https://doi.org/10.1061/(ASCE)EE.1943-7870.0001392

Chapter 4 identifies the individuals' preferences towards the probability distribution of the performance variable through interviews with practitioners at a water utility company in Belgium. Given identical simulation results and identical risks, different decision makers might opt for different solutions regardless of the optimality of solution/s. This difference can be attributed to the decision maker's own perception of risk which was assessed through the interviews where the practitioners were asked a series of questions based on a local case study. (Objective III)

Chapter 5 proposes two stochastic optimization based decision models to express the risk-averse preferences of a decision maker and to acknowledge the uncertain modelled system performance. Both decision models are illustrated using a case study site in Luxembourg where compliance for ammonia concentration in CSO spills is tested under uncertainty associated with model inputs and model parameters. (Objective IV)

The contents of Chapters 4 and 5 are going to be submitted for journal publications.

Chapter 6 presents a detailed discussion of the issues involved with investment decisions to improve the environmental performance of the urban sewer systems and presents them in light of the findings of Chapters 3, 4 and 5.

2. Literature review

This chapter presents a literature review on the previous research dealing with the identification and quantification of uncertainty in the simulation of urban drainage processes; followed by a review of studies on decision making using the outputs from urban drainage simulation models.

2.1 Uncertainty in urban drainage simulations

Uncertainty analysis provides structured information on the limitations of simulation methodologies and tools employed to predict physical and other processes. Uncertainty analysis of hydrological and hydraulic modelling is considered an important component of good scientific practice (e.g. Pappenberger and Beven (2006)). Accounting for uncertainty may result in qualitatively and quantitatively different outcomes compared to the case which does not consider uncertainty (Morgan and Henrion, 1990).

While uncertainty in the modelling of engineering problems can have many sources, the uncertainty in modelling can be classified into two broad categories, aleatory and epistemic (Kiureghian and Ditlevsen, 2009). Aleatory uncertainty refers to the inherent randomness in any physical process and has also been termed variability, stochastic uncertainty, objective uncertainty and Type I uncertainty. Epistemic uncertainty arises from a lack of knowledge about the physical process in question. The epistemic uncertainty has also been termed as subjective uncertainty and Type II uncertainty (Sun, 2010). Kiureghian and Ditlevsen (2009) argue that the categorization of the uncertainties in any modelling study depends on the choices a modeller makes. Typically, a modeller should categorise uncertainties as aleatory uncertainties when they cannot be reduced by improved knowledge through additional data collection or better model structure or calibration improvement. In contrast to aleatory uncertainty, epistemic uncertainty is associated with the assumptions and simplifications made while formulating the mathematical equations to represent the physical processes. As a result, epistemic uncertainty can be reduced by various measures such as enhanced calibration using better or more measurements and improvement of the underlying mathematical relationships.

However, this categorization of modelling uncertainties into aleatory and epistemic can have important implications on any resulting decisions (Dubois 2010). For example, the aleatory uncertainty can be countered with decisions which are designed to cope with the impact of such uncertainties, while the decision to collect more information can be taken in order to reduce the epistemic uncertainty.

2.1.1 Sources of uncertainty in urban drainage simulation models

In urban drainage simulation models, uncertainty can have various sources. Refsgaard et al. (2007) presented a classification of the modelling uncertainty in the context of integrated water resources management. Refsgaard et al. (2007) classified the sources of uncertainty in model predictions into model input data, model parameters and model structure uncertainties, whereas Deletic et al. (2012) expressed the uncertainty in the calibration of model parameters as a separate source of modelling uncertainty. Refsgaard et al. (2007) proposed a more comprehensive framework for accounting the uncertainty in the modelling of environmental processes by including the framing of problem context, and computer implementation of the model, as additional contributors to the uncertainty in the model output. Refsgaard et al. (2007) discussed uncertainty analysis not as an additional product to be added to the finished model, but rather as a process that should be performed in parallel to the problem identification, model design, building and operation. Several approaches for accounting the uncertainty in model predictions have been presented and classified depending on their relation with the model conceptualization stage and the source and type of uncertainty. For instance, Fig. 2.1 displays an uncertainty model for a typical simulation model for an engineering system from Benke et al. (2008).

Deletic et al. (2012) presented a **G**lobal **A**ssessment of **M**odelling **U**ncertainties (GAMU) framework produced by the IWA/IAHR Joint Committee on Urban Drainage. This was an effort to provide urban drainage modellers with a unifying terminology and understanding on uncertainty analysis. Within the GAMU framework, modelling uncertainties were classified into three main sources; I) Model input uncertainties, II) Calibration uncertainties and III) Model structure uncertainties. The links between the different uncertainty sources are depicted in Fig. 2.2. The GAMU framework focuses on statistical uncertainties at the calibration and prediction phases of the model, thus diverting from the process described by Refsgaard et al. (2007).

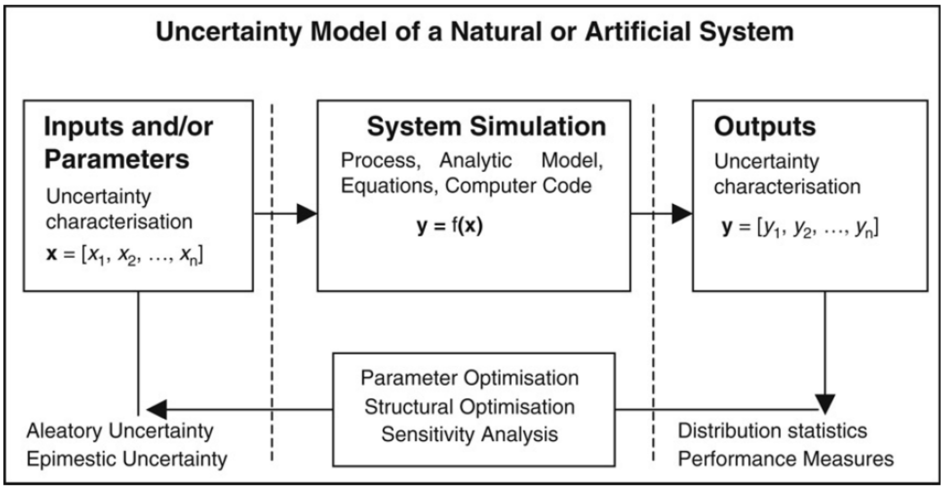

Fig. 2.1. Uncertainty in a complex system (from Benke et al., 2008).

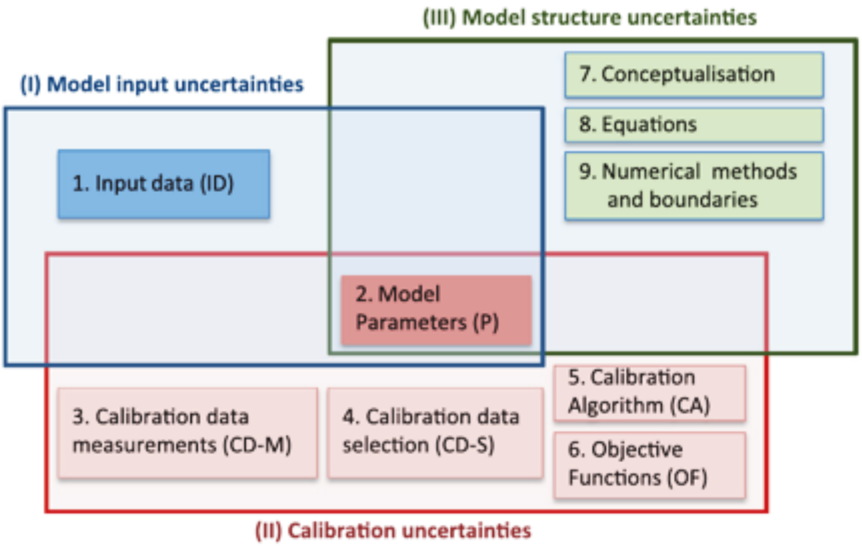

Fig. 2.2. Key sources of uncertainties in urban drainage models (from Deletic et al., 2012).

In this thesis calibration uncertainty is treated as a subset of model parameter uncertainty following the classification of uncertainty sources proposed by Refsgaard et al. (2007). The sources of uncertainty in urban drainage simulation models which are frequently encountered are described in the following sections.

2.1.1.1 Model input uncertainty

The uncertainty in model inputs and measured data arises from the inherent variation of the quantities over space, time or other factors such as, measurement errors, unrecorded growing populations, and increasing urbanisation. It can be classified under aleatory uncertainty due to the random or stochastic nature of the model inputs. A typical example of this category is rainfall data which is a major input to urban drainage simulation models whose uncertainty can have significant effects on the overall model uncertainty (Hoppe, 2008). Other inputs to urban drainage models include dry weather flow which depends on variation in contributing population numbers, human habits, and dry weather flow contributions from non-residential sources, and geometric properties of the sewer system comprising e.g. pipes, weirs, and storage tanks. Pollutant concentrations in the runoff from catchment surfaces depend on precipitation and the local catchment properties, whereas the concentrations in the dry weather flow are driven by the human habits and commercial inputs. The uncertainty in the geometric properties of the sewer network elements are primarily associated with errors in measurement and recording and communicating these measurements.

Rainfall data uncertainties are characterised by spatial and temporal variability and the error in data measurement. Freni et al. (2010) studied the impact of rainfall time resolution on urban water quality assessments and concluded that rainfall temporal resolution had a greater effect on water quality sub-models than the structure of the water quantity sub-models, due to the dependency of the wash-off sub-model on the rainfall intensity. However, when a lower temporal resolution of rainfall is applied, parameter calibration compensates this lack of information in rainfall data by adjusting the parameter values to reflect the real world behaviour. The physical significance of the parameters might have been lost as a result of this forced calibration adjustment of parameter values. The GAMU framework proposed the definition of error models for input and measured data, which should be propagated together in a total uncertainty analysis. Dotto et al. (2014) evaluated the impact of data uncertainty on urban stormwater models and found that random errors could easily be filtered by the parameterization. However, the systematic errors in the input and calibration data had a significant impact on the model sensitivity represented by parameter distributions. Biases in the measured data led to distinct parameter distributions.

2.1.1.2 Model parameter uncertainty

When a simulation model is built to represent a physical process, parameters are generally required for the definition of relationships between the physical variables. Model parameter uncertainty is the uncertainty associated with the estimation of each parameter in the model. Depending on the nature of the parameter, parameter uncertainty can be aleatory uncertainty or epistemic uncertainty. For example, the uncertainty in a parameter representing the impervious area in a catchment can be classified as epistemic because of the lack of knowledge about this parameter which can be further improved. Alternatively, a parameter representing initial soil moisture varies over time indicating an uncertainty of the aleatory nature.

Often these parameters are estimated using remote monitoring and on-site monitoring data; however, if there is no evidence or data available and the parameter value has to be determined, this may result in an unknown and possibly higher degree of uncertainty. In some cases, the desired parameter is estimated by using relationship equations from different sub-models because there is no direct measure for its estimation. The uncertainty associated with the parameter of interest consists not only of the uncertainties in the values of sub-model parameters but also of how these uncertainties propagate between sub-models. For example, roughness in sewer pipes can be estimated using the Colebrook-White equation which uses geometrical and flow characteristics in the pipe to estimate hydraulic resistance (Swaffield and Bridge, 1983). The potential uncertainty in these characteristics (flow and geometry) affects the estimated values of pipe roughness.

The steps involved in uncertainty analysis are directly linked to the estimation of the values of parameters. Standard statistical methods result in a point estimate and a measure of precision around this point estimate, for example, a 95% confidence interval. However, within a multivariate framework, an additional measure 'covariance' is also generated which reflects the relationship among parameters. Representation of the parameter uncertainty depends on the method applied. Uncertainty distribution around the 'true' parameter value (expected value) can be expressed through either Bayesian or frequentist approach. It is suggested that the assumptions to specify the probability distribution should follow standard statistical methods, for example, one may use a beta distribution for binomial data, or a gamma or lognormal for the right skewed parameter (Briggs et al., 2012).

Sometimes there is very little information available about the parameter because either there is no data or there are not many studies related to its estimation. In such cases, a conservative approach can be followed by relying upon expert opinion and the uncertainty can be explained through an appropriate range of possible estimates elicited from each expert (Garthwaite et al., 2005). However, Garthwaite et al. (2005) further add that the elicitation from experts can contain unconscious biases which can affect the elicited probabilities of the uncertain quantity. If formal elicitation is not feasible, a wide uniform distribution can be assumed to account for the uncertainty around this parameter. There has been a lack of studies where prior parameter distribution was estimated from field measurements representing the measured behaviour of a parameter. Studies such as Freni et al. (2008), Korving et al. (2002), and Vezzaro et al. (2013) proceeded with the prior assumption that the input and model parameters followed uniform or normal distributions which may not reflect reality. Apart from uniform and normal distributions, triangular distributions have also been used by assigning the minimum, the maximum, and the mode values (for example, Iooss and Lemaître (2015)). These distributions do not account for uncertainty at the extremes or beyond the specified range. In addition, continuous distributions which give a reliable estimate of uncertainty around the expected parameter value should be preferred. For instance, instead of using a triangular distribution while performing three-point estimates, it is recommended to use a PERT distribution which is a special case of a Beta distribution (Benke et al., 2008). The distribution is specified by assigning maximum, minimum values and the mode which is the most likely value. The scale parameter λ for the height of the distribution is taken as 4 by default (Vose, 2010). The PERT distribution has a distinct advantage over a triangular distribution because it can be changed from a symmetrical distribution to a skewed distribution by changing the mode. It can be used instead of a normal distribution when the parameters take values within a specified range and the extreme values are not important (Benke et al., 2008).

Following the release of the GAMU framework, Dotto et al. (2012) compared four techniques: the Generalized Likelihood Uncertainty Estimation (GLUE); the Shuffled

Complex Evolution Metropolis algorithm (SCEM-UA); AMALGAM (a multialgorithm, genetically adaptive multi-objective method); and a Bayesian approach based on Markov Chain Monte Carlo method, for parametric inference/calibration in urban drainage modelling. This work discussed the suitability of these techniques to fit parameters to observed data and to evaluate parametric correlations. Algorithms were classified according to their ability to identify parameters values, correlation, availability and the required user skills. The study Dotto et al. (2012) refers to the first step of the GAMU framework which discusses how tools for uncertainty analysis should be carefully selected in order to minimise biased outcomes.

Formal Bayesian methods are discussed in the GAMU framework as one of the main ways to infer probability density functions of parameter spaces. However, the influence of likelihood selection and posterior validation was not discussed. Schoups and Vrugt (2010) proposed a generalised likelihood function which relaxes the assumption that the residual errors are independent and follow a Gaussian distribution and thus improves the parameter and total prediction uncertainty estimates. Del Giudice et al. (2013) proposed a statistical description of bias in a likelihood function in which autocorrelation of errors are taken into account.

2.1.1.3 Model structure uncertainty

Model structure uncertainty corresponds to the inaccuracy in the simulation methodology used to represent the real behaviour of the physical process. This uncertainty can also arise from inappropriate methods to define the boundary conditions and the choice of numerical solution techniques (Deletic et al., 2009). Model structural uncertainty can be classified as epistemic uncertainty. Refsgaard et al. (2006) brought the focus of uncertainty analysis to the quantification of model structure errors. Refsgaard et al. (2006) work discusses the process to assess model structural uncertainty in cases where the data is not available. According to the GAMU framework, uncertainties due to model structure can be assessed by comparing the performance of different model conceptualisations under the same conditions (Deletic et al., 2012). For instance, a set of very similar conceptual models with same input e.g. rainfall can be compared to identify the model structure uncertainty. However, a simple conceptual model and an extended network model are not suitable for this type of comparison because of the difference in the inputs to these models.

2.1.2 Uncertainty propagation in urban drainage simulation models

Once the probability distributions of model inputs and model parameters have been defined, the objective is to compute the probability density functions of the model outputs of interest. The choice of methods to represent the uncertainty in input data and model parameters in model simulations depends on the computational requirements and complexity in implementing such methods (Dotto et al., 2012). Monte Carlo simulation is one such method which is non-intrusive, meaning it does not require modifications to the model structure. However, Monte Carlo is not easy to implement for computationally expensive models, hence this technique is usually applied to simplified models. The Monte Carlo method involves repeated simulations with samples of the selected input/model parameters drawn from the parameter space. This results in a mapping of input/model parameters to the desired model output. To cut down the required number of simulations, Latin hypercube sampling (LHS) can be used instead of random sampling because the LHS method results in a better convergence than random sampling approach for models which require long simulation time and it has the ability to generate samples representing the entire parameter space (Helton and Davis, 2003). Korving et al. (2002) propagated the uncertainty in model parameters to simulate combined sewer overflow volume using Monte Carlo simulations where the sewer system was simply represented as a reservoir connected to an external weir and a pump. Alternatively, model reduction techniques have been used for complex models, for example Schellart et al. (2010) used a response database for model reduction before applying Monte Carlo simulations for uncertainty propagation in an integrated catchment model which comprised a rainfall generator, a simplified hydrological model, a computationally expensive sewer hydrodynamic model and a simple river impact model to estimate water quality failures in a receiving watercourse over an extended time period. Model reduction is an approximation of a complex model and introduces additional uncertainty in the realisation of the physical system on top of the uncertainty in the complex model. Emulators have also been applied to quantify uncertainty in hydrodynamic simulations. An emulator is a statistical approximation of the complex simulation model (Uusitalo et al., 2015). Often, the uncertainty analysis process focuses on a dynamic model response i.e. time series of the model output. This presents an additional challenge of having a multi-variable process with heavy autocorrelation structures (time structure). Some authors have proposed strategies to deal with those cases; Carbajal et al. (2017) compared a physically based emulator (which merges a simplified physical model and error interpolation) with a fully data-driven emulator (based on Gaussian process interpolation of a decomposed time-series) for an urban drainage simulation case. Conti and O'Hagan (2010) presented three strategies to deal with the multi-output or dynamic simulators: a multivariate Gaussian process; ensemble of single-output emulators; and the use of time as an extra input. Conti and O'Hagan (2010) found the multivariate Gaussian process based emulator performing better than the other two strategies. Emulation of time-dynamic processes can also be proposed by the use of polynomial chaos expansions as in Xiu and Karniadakis (2003). This technique can also provide sensitivity analysis results, therefore, both the processes, sensitivity analysis and emulation can be done under the same model sampling scheme. However, the integration of dynamic input uncertainties in emulation based problems is still not readily solved, limiting the model to parametric uncertainty propagation.

A further approach to quantify the uncertainty of the output for complex models is to select only a small subset of dominant model inputs and parameters which can approximately explain the model output variance for uncertainty analysis or parameter estimation (Wainwright et al., 2014). Key processes to be included in the uncertainty analysis are identified by ranking all the parameters using sensitivity analyses. This reduces the computational cost by only including the most significant parameters in the uncertainty analysis. There are several methods proposed in the literature for performing sensitivity analysis which can be broadly classified as Global Sensitivity Analysis (GSA) or Local Sensitivity Analysis (Saltelli et al., 2000). Local sensitivity analysis is performed to study the effect of small input perturbations on the model output and has been performed around a point in the parameter space whereas a GSA has been performed over the whole parameter space of model inputs considered for study (Borgonovo and Plischke, 2016; Gamerith et al., 2013; Iooss and Lemaître, 2015). Global sensitivity analysis is performed using different approaches e.g. Standard regression coefficients (SRC) (Saltelli et al., 2008), Extended-FAST method (Saltelli et al., 1999), Morris Screening method (Morris, 1991), Sobol' indices (Sobol, 2001). Although Vanrolleghem et al. (2015) preferred Extended-

FAST over SRC and Morris Screening method for water quality simulation in the catchment and sewer network, they concluded that for water quantity simulations all three methods Extended-FAST, SRC, and Morris Screening produced similar results. Kroll et al. (2016) further demonstrated that Morris Screening performed on par with Extended-FAST while ranking the influence of parameters on CSO volume. It can be concluded that Morris Screening is an appropriate method for performing GSA for water quantity output because it is computationally cheap and it performs at a level with other available more computationally expensive methods.

Willems (2008) and Willems (2012) presented a methodology and application to quantify the contribution of different sources of uncertainty in urban drainage models. This method is based on a variance decomposition approach, which separates the total variance presented by the residuals in different characteristic sources; input, the parameter (expert elicited), and model structure uncertainty. Nevertheless, the variance decomposition approach described is subjected to several assumptions. First, it requires a homogeneous variance of the model-observations residuals. This is seldom found in real applications, thus Box-cox transformation was used in order to stabilise residual variance (reaching homoscedasticity). Secondly, variance decomposition relies strictly on the independence of error terms. This fact was pointed out by Freni and Mannina (2010) by comparing the relationship between the sum of partial variances and total variance. This difference indicates non-independency of the error terms. They concluded that the applicability of variance decomposition is increasingly reduced when propagating uncertainties downstream of the sub-model chain, where correlation amongst parameter uncertainties appears to be higher. The variance decomposition method provides a valuable source of knowledge by pointing out the relative importance of each contributor when the assumptions are met.

Most of the above-mentioned studies have considered the probabilistic representation of uncertainty in different model components. Fu et al. (2011) argued that the type of uncertainty in urban drainage modelling is quite broad and cannot be expressed adequately by probabilistic measures alone. They proposed a mathematical framework which facilitated the inclusion of vagueness in expert knowledge about model parameters using fuzzy sets and imprecise rainfall data using probabilities. This framework suggests the use of imprecise probabilities for input rainfall data when more than one probability distribution fits the data. Data scarcity is widely cited as one of the major problems in characterising the model parameter uncertainty. This framework includes a fuzzy set representation for such model parameter uncertainty. These two different types of uncertainty representations are combined in a joint random set using two methods, discretization and Monte Carlo method where the latter was found to be more computationally efficient.

2.1.3 Concluding remarks

Uncertainty in the simulation of water quantity or quality in urban drainage has been extensively studied. Deletic et al. (2012) serves as a framework to reach a common definition of uncertainty terminology in the urban drainage community. It correctly discusses the need for model identification, calibration and validation. However, the GAMU framework dealt only with the propagation of statistical uncertainties and recommends uncertainty analysis as a standalone and separate process than the usual modelling workflow. On the other hand, model calibration using observed data is nothing but correcting the model in order to generate predictions which are as close as possible to the measured observations. However, it does not provide any information about the accuracy of the model predictions such as by which amount the model predictions would deviate from this 'corrected' model prediction and what is the likelihood of such deviations. An uncertainty analysis acknowledges the limitation of the model predictions by providing an error band with the corresponding likelihood of model predictions. This additional information gives more confidence to the modellers on their model performance which would further facilitate a better-informed decision making process. Therefore, it is recommended that uncertainty analysis should be treated as a process which runs parallel to the model definition, building, calibration, and validation stages. For example, Deletic et al. (2012) recommended that parameter uncertainty should be quantified using observed data through Bayesian inference which provides posterior distribution for parameters by tuning the prior parameter distribution using the observed data. This process indirectly addresses the discussion on the validation of quantified uncertainty in model predictions against the observations in the real world. Even if there is limited data available about parameters, expert elicitation or literature references can be used as a prior in the Bayesian inference so that the resulting posterior distribution encompasses the expert knowledge as well as the added information from the limited available data. Therefore, instead of a traditional model calibration process giving 'corrected' parameter values, a Bayesian inference should be applied to generate a posterior probability distribution of model parameters along with the information about the correlation between the model parameters followed by uncertainty propagation of these uncertainties. This will ensure the consideration of the real world observations into the uncertainty analysis process and will also ensure that local catchment and environmental conditions are well reflected into the uncertainty predictions.

In cases where there is vagueness in the available information about the uncertainty in model components, the framework proposed by Fu et al. (2011) should be integrated into the wider uncertainty analysis framework to characterize the uncertainty in different sources using e.g. fuzzy sets, interval based probabilities or imprecise probabilities.

In terms of communicating the uncertainty to the decision makers or practitioners, the available literature does not account for regulatory restrictions on modelling procedures. The urban drainage group of the Chartered Institution of Water and Environmental Management (CIWEM) in the UK has included a new section on the 'model confidence' in their latest code of practice for the hydraulic modelling of sewer systems (Titterington et al., 2017). Although the latest CIWEM code of practice only outlines the guiding principles to assess and visualise confidence in model predictions, it is a welcome step towards promoting the culture of uncertainty analyses in practice. Many countries require the practitioners or modellers to follow a certain modelling guideline in order to predict the hydraulic or water quality performance of the sewer system (e.g. Aquafin (2017)). Therefore, uncertainty quantification or propagation methods such as surrogate models which require any change in these set modelling guidelines may not be applicable for such practitioners rendering the communicated uncertainty information invalid. Hence, there is a need for studies which provide a methodology to quantify and propagate uncertainty in urban drainage simulations satisfying the local regulatory requirements on modelling so that it can be communicated to the decision maker.

2.2 Decision making

Urban drainage models are used to support various investment and operational decisions in urban drainage systems such as (Breinholt, 2012):

- Design of new drainage systems.
- Evaluation of the performance of drainage systems against statutory environmental requirements.
- Evaluation of system upgrades, or re-design proposals against required performance standards.
- Analyse the risk of sewer flooding against required performance standards
- For real-time control of pumps, gates, orifices, weirs and waste water treatment plants.

Decision analysis techniques, in general, can be classified into three broad categories (Fig. 2.3): Single criterion decision making (SCDM), Multiple criteria decision making (MCDM) and Decision support systems (DSS) (Wang and Poh, 2014).

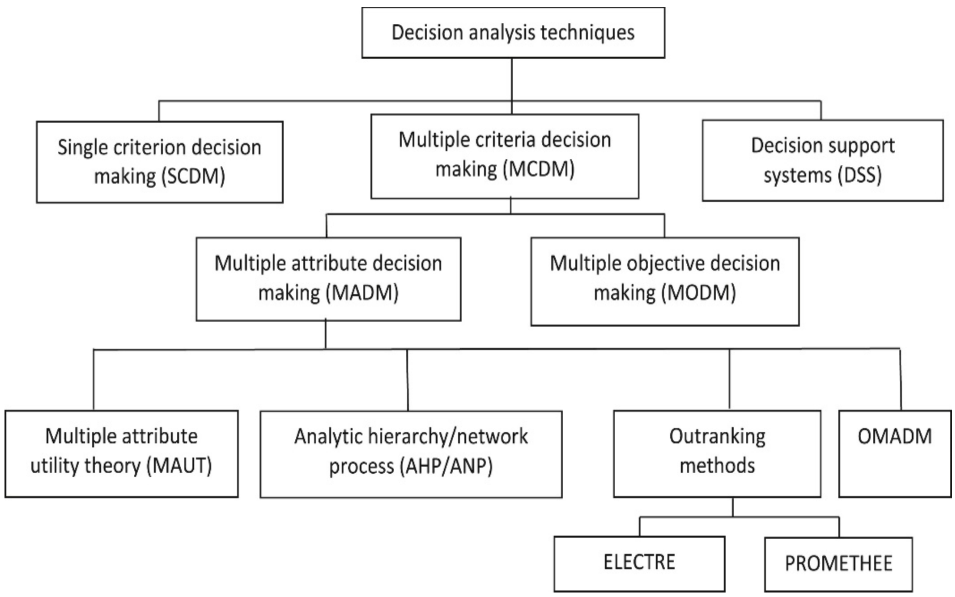

Fig. 2.3. Classification of decision analysis techniques (from Wang and Poh, 2014).

The SCDM technique applies to decision problems where the comparison of decision alternatives is made on basis of a single criterion whereas the MCDM technique is applicable to decision problems which require more than one criterion to evaluate the decision alternatives. A Decision Support System (DSS) is a software system to aid decision making which can be based on either SCDM or MCDM. Depending on the decision problem, either a Multi-attribute decision making (MADM) or a Multi-objective decision making (MODM) technique can be employed for a multi-criteria decision problem. The MODM technique represents the mathematical programming problems where the criteria are formulated mathematically as objective functions. The goal of such formulations is to search for solutions to the decision problem which minimize or maximize the multiple objectives subject to constraints. For example, Fu et al. (2008) applied a MODM formulation to select control strategies for urban wastewater systems where water quality indicators in the receiving river and cost of the control strategies were used as the objectives. The water quality indicators used in Fu et al. (2008) were dissolved oxygen (DO) level and ammonium concentration in the river and the NSGA II (Non-dominated Sorting Genetic Algorithm) developed by Deb et al. (2002) was used for multi-objective optimization. Another application of MODM techniques in urban drainage system is the study by Gillé et al. (2008), who proposed an optimization formulation for optimal real-time control of sewer network to reduce the combined sewer overflow volume.

MODM is suitable to decision problems where the number of decision alternatives is very large and/or the decision space is continuous while MADM focuses on decision problems where the set of decision alternatives has already been selected before the analysis and the decision space is discrete and finite (Triantaphyllou and Shu, 1998). MADM technique evaluates the decision alternatives using relationships such as priority, outranking and distance among different alternatives and criteria. Attributes are also termed as ‘goals or ‘decision criteria’. Examples of attributes considered in rehabilitation planning of urban sewer network are: pipe material, pipe age, economic depreciation of the pipes, hydraulic capacity etc. (Tscheikner-Gratl et al., 2017). The MADM technique is semi-quantitative in nature since it can also incorporate qualitative criteria or attributes (Ioannou et al., 2017). Table 2.1 summarises the major differences between MODM and MADM techniques.

There are many MADM techniques available in the literature and different authors have used different classifications for these techniques. For example, Wang and Poh (2014) divided MADM into four classes as Multiple Attribute Utility Theory (MAUT), Analytic hierarchy /network process (AHP/ANP), Outranking methods and Other multi-attribute decision making (OMADM) techniques. Hyde (2006) classified

MAUT and Multi-attribute Value Theory (MAVT) along with the Weighted Sum Method (WSM) and AHP into a single class of techniques which are based on value and utility theory.

Table 2.1. Comparison of MODM and MADM techniques (from Mendoza and Martins, 2006)

Criteria for comparison	**MODM**	**MADM**
Criteria defined by	Objectives	Attributes
Objectives defined	Explicitly	Implicitly
Attributes defined	Implicitly	Explicitly
Constraints defined	Explicitly	Implicitly
Alternatives defined	Implicitly	Explicitly
Number of alternatives	Infinite (large)	Finite (small)
Decision maker's control	Significant	Limited
Decision modelling paradigm	Process-oriented	Outcome-oriented
Relevant to	Design/search	Evaluation/choice

Utility or value-based techniques such as MAUT, MAVT or AHP represent the decision maker's preferences using mathematical functions. MAUT or MAVT represent the decision maker's preferences using an overall value or utility for the individual decision alternatives which is to be maximised. Consequently, MAUT and MAVT require derivation of the decision maker's utility or value functions. In MAVT, the decision maker assigns a 'value' to the decision alternatives with respect to the individual attributes and these values are combined for each decision alternative using the value function. MAVT is appropriate when there is no uncertainty in the 'values', whereas the MAUT is an extension of MAVT because it incorporates risk preferences and uncertainty (Velasquez and Hester, 2013).

The AHP represents the decision problem as a linear additive model based on a system of hierarchies by deriving relative importance of alternatives in terms of each criterion. Through a series of questions weights of criteria and scores of alternatives are determined using a pairwise comparison between criteria and alternatives respectively. ANP is a generalised form of AHP applied to networks. Dodgson et al. (2009) noted that the presentation of data in the form of pairwise comparison makes AHP a convenient and straightforward technique, however, AHP suffers from rank reversal problem. The rank reversal means that there is a possibility that adding a new alternative to the predefined set of alternatives could reverse the rankings of two alternatives which are not related to this new alternative in any way. AHP technique is easier to implement than the MAUT and MAVT because the elicitation of decision maker's preference is less complex (Ananda and Herath, 2009). Gogate et al. (2017) developed a multi-attribute decision making (MADM) framework to evaluate sustainable stormwater management alternatives based on various quantitative and qualitative criteria broadly defined as technical, economic, environmental and social. A combination of AHP with another MADM technique TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) was used to compare the alternatives. TOPSIS is goal or reference based technique which seeks to find decision alternatives closer to certain desired goals or reference levels set by the decision maker. The MADM framework proposed by Gogate et al. (2017) used the AHP technique for the elicitation of weights and quantification of qualitative criteria based on expert opinion while using the TOPSIS technique to estimate the scores.

On the other hand, the outranking techniques such as ELECTRE (ELimination Et Choix Traduisant la REalité) and PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) generate the ranking of decision alternatives based on pairwise comparison of the alternatives against each criterion using pairwise preferences for the criteria. The outranking techniques seek to eliminate the alternatives which are outranked or dominated by others. The outranking techniques assign weights to individual criteria to express decision makers' preferences for some of the criteria over others. An alternative outranks another if it performs better than the other on enough important criteria and does not perform unacceptably worse on any criterion. The outranking techniques have the notion of 'incomparability' of decision alternatives which might occur when there is not sufficient information available to characterise a relation between the alternatives. The availability of the relation 'incomparable' ensures that the decision maker does not need to assign 'indifference' or remove the comparison entirely because no relation could be assigned. The major drawback of outranking techniques is that the definitions of the thresholds to determine outranking relationships are dependent on the decision maker and are arbitrarily defined (Dodgson et al., 2009). Martin et al. (2007) applied the ELECTRE III technique which belongs to the ELECTRE family of MADM techniques to evaluate Best Management Practices (BMP) for stormwater source control using various criteria such as hydraulic efficiency, pollution retention, environmental impact, operation and maintenance, economic investment and social and sustainable urban living. ELECTRE III was selected by Martin et al. (2007) because it is based on a constructive approach which allows dialogue between the stakeholder and uses fuzzy logic to consider uncertainty in the performance values by using pseudo-criteria.

Tscheikner-Gratl et al. (2017) used the terminology multi-criteria decision making to refer to MADM techniques and compared the utility/value based techniques with the outranking techniques to integrated rehabilitation management scheme for urban water infrastructure. Tscheikner-Gratl et al. (2017) compared five MADM techniques: ELECTRE, AHP, WSM, PROMETHEE and TOPSIS using a case study. This comparative study by Tscheikner-Gratl et al. (2017) found that the definition of weights for the decision criteria and scaling of scores to value the criteria had a large effect on the outcome of the decision making process. Further, the study found that the AHP, which is a simpler technique to apply than the complex techniques such as PROMETHEE, provided similar results. For rehabilitation planning, Tscheikner-Gratl et al. (2017) suggested the use of simpler MADM techniques such AHP, WSM or TOPSIS when there is a scarcity of data and the preference information of the decision maker is difficult to be assessed; Outranking techniques proved to be more useful when the decision maker was able to define the thresholds to build preference relationships between the alternatives and criteria.

2.2.1 Risk-based Multi-criteria decision making techniques

Another type of classification of MCDM techniques is based on whether they consider risk or not. Under this classification, MAVT is classified as a riskless technique while MAUT and ELECTRE are classified as risk-based techniques (Ananda and Herath, 2009). Ioannou et al. (2017) conducted a review of risk-based methods applied in sustainable energy planning and feasibility studies to aid investment decisions and classified these techniques into quantitative techniques and semi-quantitative techniques which can also incorporate qualitative criteria required in the evaluation of decision alternatives (Fig. 2.4). Quantitative risk-based methods use the statistical definition of risk based on probability distributions whereas, semi-quantitative methods can use both statistical and non-statistical representation of risk. The Multi-criteria decision analysis in Fig. 2.4 relates to the Multi-attribute decision making (MADM) classification made by Wang and Poh (2014). Jato-Espino et al. (2014) proposed a multi-criteria model in the selection of pervious pavements to reduce the run-off from catchments by combining Monte Carlo simulations, AHP and Fuzzy Logic.

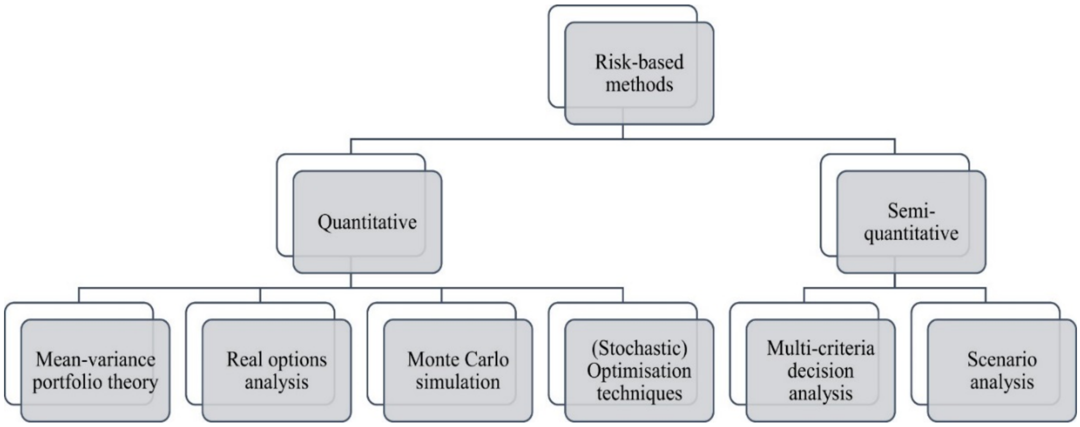

Fig. 2.4. Classification of risk-based methods applied in sustainable energy planning and feasibility studies (from Ioannou et al., 2017).

The weights of the criteria were determined based on expert opinion while the stochasticity in the values of the criteria were represented by Monte Carlo simulations. Probability density functions of an overall value index were obtained for each pervious pavement alternative, however, the model proposed by Jato-Espino et al. (2014) did not provide a methodology to compare these distributions and thus make decisions.

The Mean-variance portfolio theory (MVP) which was developed by Markowitz (1952) is one of the most popular methods for risk-based decision making in the field of finance. MVP considers the variance of the investment returns as a measure of risk in the construction of investment portfolios. MVP determines optimal portfolio by seeking to minimise the variance while maximising the expected return (mean) of investment portfolios. Real options analysis (ROA) is a technique which enables the decision maker to evaluate certain decisions which they would prefer to take at a certain time in future due to difficulty in assessing the uncertainty at the time of modelling. ROA is a capital budgeting tool which assumes there is an uncertainty in the evaluation of decision alternatives and the outcome of this uncertainty will be known over time and the decision maker can devise their strategies accordingly (Bowman and Moskowitz, 2001). ROA enables the decision maker to defer, expand, stage, contract or abandon the investment decisions once more information is available over time and the uncertainty is reduced (Ioannou et al., 2017). Radhakrishnan et al. (2014) applied real options to evaluate retrofitting decisions to prevent flooding in urban drainage systems. To determine the set of optimal solutions Radhakrishnan et al. (2014) used a single objective optimization formulation with the goal to minimize the cost of decision alternatives.

Monte Carlo Simulation (MCS) enables the decision maker to generate probabilistic scenarios when the uncertainties in the inputs of the decision models are represented as probability distributions. It involves random sampling from the input parameter distributions which enables the estimation of probability distributions of the criteria and also the sensitivity of the criteria to the changes in the model inputs. MCS can be seen as a probabilistic case of scenario analysis which generates numerous scenarios using known probability distributions rather than the most probable or extreme scenarios. An optimization process refers to the selection of a choice or decision from a range of decision alternatives by comparing the alternatives according to the objective function values subject to some constraints. In the case of MODM, the alternatives are compared using values of two or more objectives. The goal of the optimization process is to maximise or minimise such values and find ‘best’ decision alternative/s. The stochastic optimization technique enables the introduction of stochasticity in one or many input variables which are required to evaluate the objective functions or the constraints in the optimization model. In addition, stochastic optimization techniques also apply to cases where the set of decision alternatives is desired to be obtained through random search as the optimization algorithm iterates towards a solution to the decision problem (Spall, 2012). Yu et al. (2017) applied stochastic optimization for urban drainage design using conflicting objectives of investment cost and acceptable flood damage. The optimization model proposed by Yu et al. (2017) is based on a chance constrained programming model which can be written as:

$$\text{Min } f(\mathbf{x}, \boldsymbol{\xi}) \tag{2.1a}$$

Subject to:

$$g_i(\mathbf{x}) \leq 0, \qquad i = 1,2,\dots,m \tag{2.1b}$$

$$\Pr\{h_j(\mathbf{x}, \boldsymbol{\xi}) \leq 0 \,|\, \boldsymbol{\xi}\} \geq \alpha_j, \qquad j = 1,2,\dots,n \tag{2.1c}$$

Where f = objective function with decision variables $\mathbf{x}$ and stochastic variables $\boldsymbol{\xi}$; g_i are m number of deterministic constraints and h_j are n number of uncertain constraints; and α = probability of the corresponding uncertain constraint being satisfied. Yu et al. (2017) represented the uncertainty in the hydrological simulation using a probability based constraint ensuring that the total surcharge volume at all the network junctions are below an acceptable threshold.

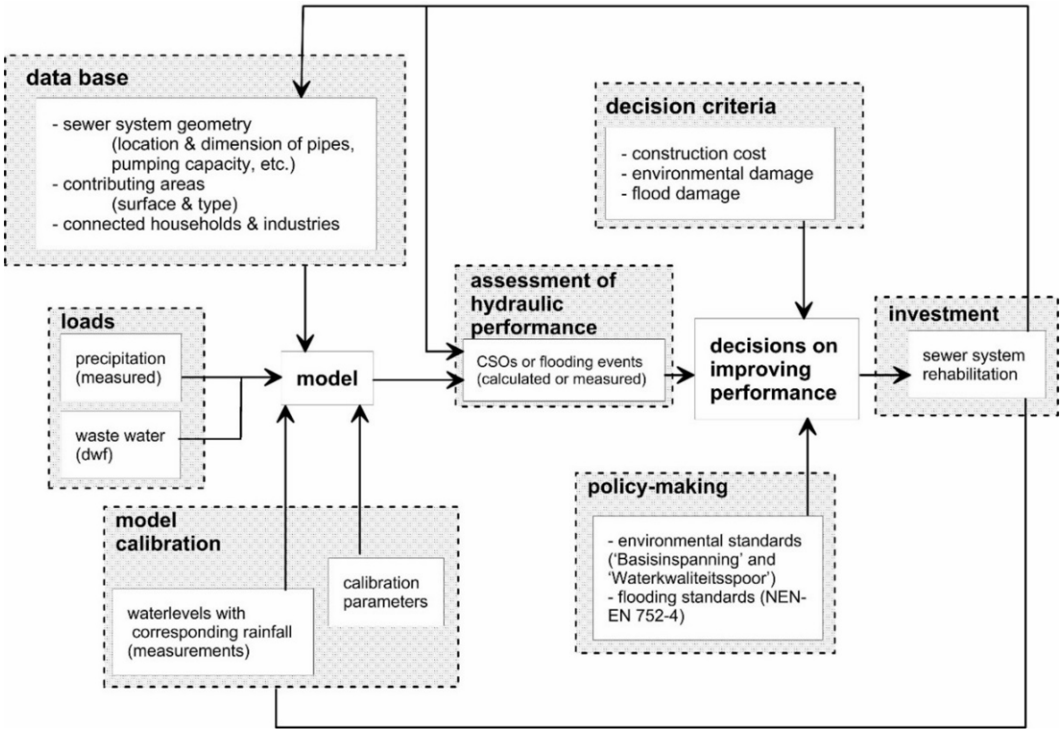

Fig. 2.5. Decision-making on sewer system management regarding hydraulic performance (reproduced from Korving, 2004).

Figure 2.5 demonstrates the decision making process to improve the performance of sewer system with regards to CSO emissions and flooding (Korving, 2004). Korving (2004) concludes that uncertainty in the various aspects of this decision making process affects the investments in the sewer system. For example, the uncertainty in the decision making components 'loads', 'model calibration', and 'data base' gets coupled together as the uncertainty in the 'model' which affects 'the assessment of hydraulic performance'. Korving and Clemens (2002) apply a Bayesian decision analysis tool to evaluate the benefits of monitoring data while taking decisions on sewer reconstruction to reduce CSO emissions. They concluded that additional information gathered from monitoring data reduced the uncertainty in model simulations further reducing the risks with investment decisions. In the wider hydrogeological applications, Freeze et al. (1990) presented a decision making framework for engineering design based on a risk-based philosophy. The decision framework (Fig. 2.6) consists of three major components: Simulation model, Engineering reliability model and the Decision model.

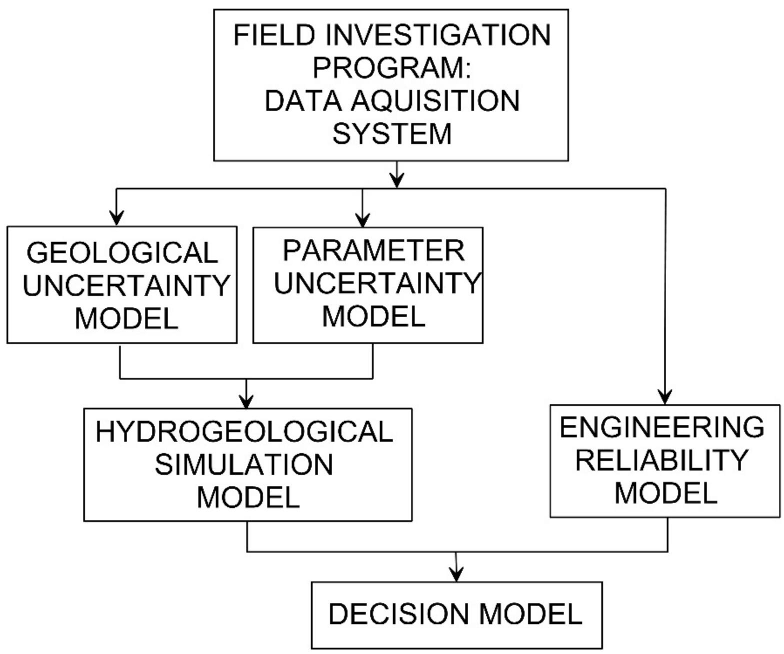

Fig. 2.6. Framework for hydrogeological decision analysis (reproduced from Freeze et al., 1990).

The simulation model estimates the hydrogeological performance of the system whereas; the reliability model assesses the performance of the engineered component of the system. The decision model compares the various decision alternatives or proposed design solutions in this case, based on a risk-cost-benefit based economic analysis. Fig. 2.7 organises the various components of the decision model for a waste management decision problem (Freeze et al.,1990).

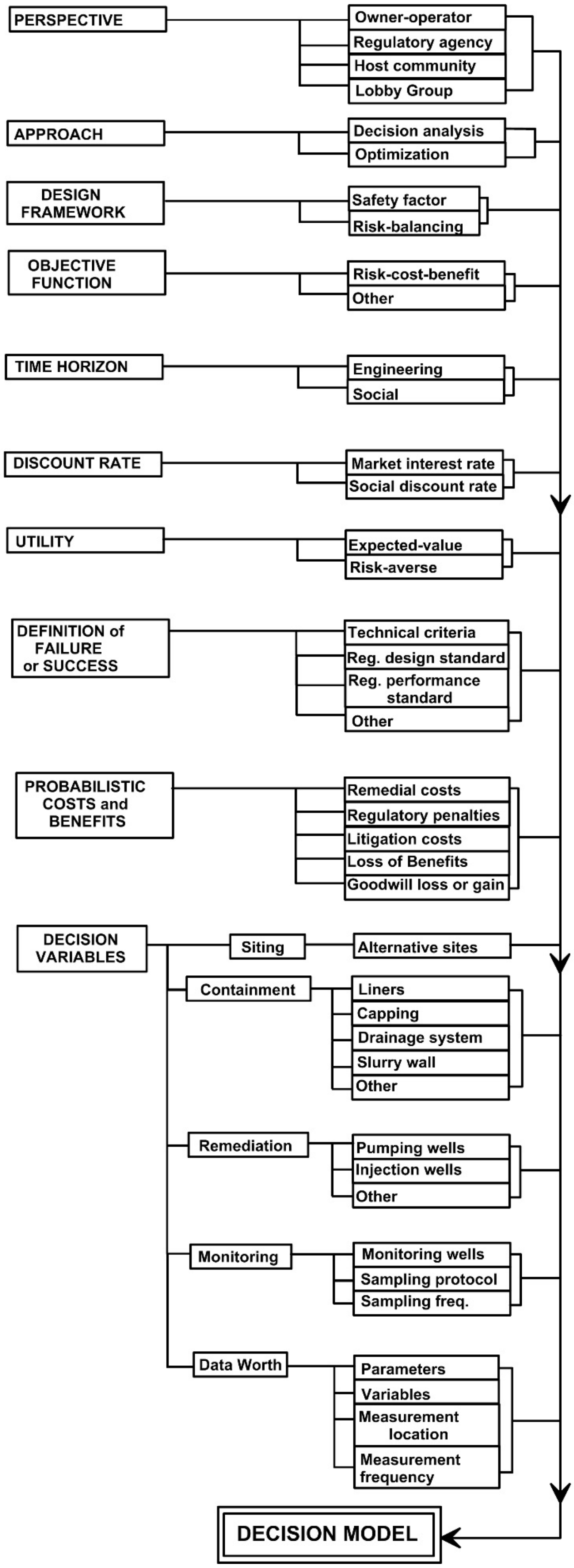

Fig. 2.7. Components of a hydrogeological decision model (reproduced from Freeze et al., 1990).

In such decision problems, the technical objective from an operator's or owner's perspective is usually to satisfy regulatory requirements whereas the economic objective becomes minimising the loss while meeting the technical objective. These objectives can be represented mathematically as an objective function which calculates the net present value of the expected benefits, costs and the risks over the engineering time horizon, discounted at the market interest rate.

As mentioned in Freeze et al. (1990), the objective function can be written as,

$$\emptyset_j = \sum_{t=0}^{T} \left(\frac{1}{(1+i)^t} [B_j(t) - C_j(t) - R_j(t)] \right) \tag{2.2}$$

where $\emptyset_j$= objective function for decision alternative j [£]; $B_j(t)$ = benefits of alternative j in year t [£]; $C_j(t)$ = costs of alternative j in year t [£]; $R_j(t)$ = risks of alternative j in year t [£]; T = time horizon [years]; and i = discount rate [decimal fraction].

The risk term $R(t)$ in Eq. (2.2) is defined as the expected costs associated with the probability of failure,

$$R(t) = P_f(t) C_f(t)\, \gamma(C_f) \tag{2.3}$$

where, $\gamma(C_f)$ = normalized utility function.

For a decision problem such as the CSO emission reduction, there might not be any direct revenue benefit which makes $B_j(t)$ = 0 in Eq. (2.2) making the decision analysis as a risk-cost minimization problem. In the field of urban drainage, Hauger et al. (2002) and Korving et al. (2009) are examples of risk-based economic optimization to make decisions. Fig. 2.8 shows the investment (cost) vs damage (risk) trade-off curves to determine the optimal storage volume by minimising total cost.

The investment cost $I(\tilde{v})$ to enlarge the storage capacity is assumed to be related to the storage volume such that (Korving et al., 2009):

$$I(\tilde{v}) = I_0(v^{\sim 0.75}) \tag{2.4}$$

The cost of environmental damage caused by CSO spills is calculated by first estimating the expected cost of a CSO spill. This expected cost is then multiplied by the annual CSO spill frequency followed by the calculation of present value for each individual year and then summing up these present values over the time horizon.

The cost of environmental damage can be written as,

$$D(\tilde{v}) = \frac{E(D(\tilde{v}, V))}{T_{CSO}} \left(\frac{\alpha}{1-\alpha}\right) \tag{2.5a}$$

$$\alpha = \frac{r}{1-r} \tag{2.5b}$$

where $E(D(\tilde{v}, V))$ is the expected cost of a CSO spill when a storage volume $\tilde{v}$ is built, and when the actual overflow volume is V, T_{CSO} is the average return period of overflow events and r is the annual market discount rate. As a result, the economic optimization becomes a problem of minimising the total cost, $I(\tilde{v}) + D(\tilde{v})$ in order to find the optimal storage volume (Korving et al., 2009). Different cost functions $D(\tilde{v}, V)$ can be used to model environmental damage from CSO overflow events. In Fig. 2.8, a Weibull-shaped cost function is used to calculate the damage.

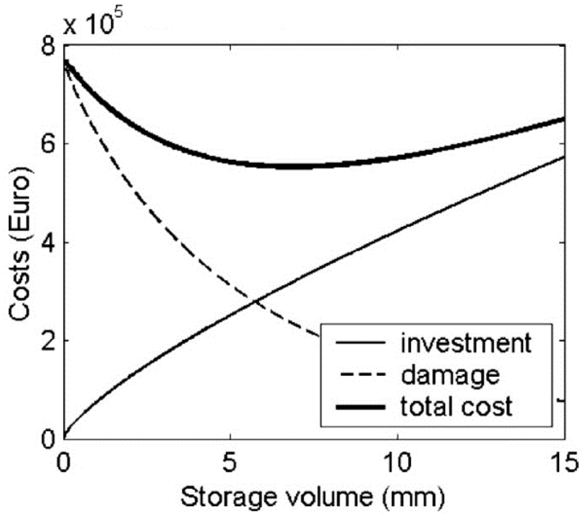

Fig. 2.8. Estimation of economically optimal storage volume (from Korving et al., 2009).

Both Hauger et al. (2002) and Korving et al. (2009) noted the difficulty in assigning a monetary value on the cost of environmental damage from CSO spills as one of the major disadvantages of this approach. Therefore, this uncertainty in the economic valuation of the losses from the CSO emission was found to have a considerable effect on the decision analysis process. Hauger et al. (2002) acknowledged another difficulty in putting monetary values to intangible benefits. Hauger et al. (2002) suggested that the workaround for the economic analysis could be the regular multi-criteria analysis where the normalization and weighting become easier but the results of the analysis become difficult to relate to. Table 2.2 lists strengths and weaknesses of the risk-based decision analysis techniques reviewed by Ioannou et al. (2017).

Table 2.2. Strengths and weaknesses of risk-based techniques (From Ioannou et al., 2017)

Techniques	Strengths	Weaknesses
Mean-variance portfolio theory (MVP)	(i) Value at Risk (VaR) and Conditional Value at Risk (CVaR) are widely recognised as alternative risk metrics allowing for assessing the maximum losses of the investment portfolio within a specified confidence level (Rockafellar and Uryasev, 1997).	(i) Focuses on monetary risk attributes (ii) Static approaches can understate, if not ignore, managerial flexibility (iii) Variance as a risk measure does not account for the asymmetry in the probability distributions
Real options analysis (ROA)	(i) Investment timing consideration (ii) It can evaluate in-depth risk factors likely to occur in the future	(i) Complicated numerical calculations (ii) Reliance on quantitative data
Stochastic optimization	(i) More suitable than deterministic optimisation approaches for a number of decision making problems in presence of uncertain inputs	(i) Lack of a standardised way to model uncertainties often leading to significant lack of precision in the results
Multi-criteria decision analysis	(i) Incorporates important non-statistical risk attributes	(i) Criteria, weights and values are difficult to accurately estimate and greatly depend on subjective judgements
Scenario analysis	(i) Provides information on the impact of potential risks which contribute most to the overall risk.	(i) Cannot account for the probability of occurrence of a scenario
Monte Carlo simulation	(i) Allows accounting for numerous varying stochastic or	(i) Requires considerable data volume (definition of

(MCS)	uncertain input parameters simultaneously (ii) Allows calculating probabilities of a parameter being below or above a certain target value or within a desired confidence interval (iii) Commercial software available to automate the tasks involved in the simulation	probability distribution functions) for random input variables or uncertain and predicted input parameters (ii) Difficult to capture extremities

2.2.2 Concluding remarks

The management of urban drainage infrastructure seeks to meet various environmental, technical, economic and social objectives. However, with respect to the compliance with environmental regulations, the environmental and economic objectives become more significant than others due to the risk of paying penalty or the reputational damage if compliance is breached. The section 2.2 reviews various decision analysis techniques which have been implemented in the literature especially in the broader field of environmental management and infrastructure management. In the context of reducing the risk of non-compliance while making infrastructure decisions under the uncertainty in the hydrodynamic simulation of urban drainage systems, only those techniques are found to be suitable for decision making which can account for this risk while integrating the uncertainty in the hydrodynamic model. Among the risk-based decision analysis techniques, the selection of a technique is dependent on the scope of the decision making problem at hand and the available information. If the number of decision alternatives is finite and pre-determined the decision problem can be modelled as a MADM problem, however, some researchers (Ioannou et al., 2017; Tscheikner-Gratl et al., 2017) have mentioned a greater deal of responsibility on the decision maker in defining the weights and score values to compare decision alternatives. While choosing an MADM technique, the decision maker should choose a method which s/he is most comfortable in using. However, in decision problems where the set of decision alternatives are not pre-determined and the decision maker desires to search for solutions in a decision space, MODM techniques should be used. Similar to MADM techniques, qualitative criteria can also be formulated as the objectives of a MODM model after quantifying to appropriate scales.

The risk of non-compliance with the environmental regulations or exceeding the threshold of a pollutant concentration in the receiving water body has only been modelled as a probability of exceedance, also termed as failure probability. However, the probability of exceeding a threshold does not provide any information about the shape of the tail of the distribution or the asymmetry of the failure probability distribution. Although in the field of finance, it has been established that the decision makers exhibit certain preferences for the asymmetry or its absence in the probability distributions and should be considered in the decision making process, such preferences have not been addressed in the field of urban drainage modelling. Also, there is a lack of studies in the modelling of the environmental impact of CSO spills where the decision maker's preference for the shape of the probability distributions of emission quality indicators is accounted while making decisions.

3. Quantifying uncertainty in the simulation of sewer overflow volume

3.1 Introduction

Chapter 2 included a review of studies which quantified uncertainty in the simulation of water quantity and quality variables in urban drainage systems. The literature review has indicated that various techniques have been applied for academic uncertainty analyses in urban drainage systems. However, to the best of the author's knowledge, modellers simulating the hydraulic performance of environmental protection schemes for water utilities do not commonly use these techniques. The applicability of the uncertainty propagation and quantification studies mentioned in Section 2.1 is very challenging for water utilities responsible for the management of urban drainage systems. Infrastructure investments for instance, for Combined Sewer Overflow (CSO) control require adherence to standard modelling procedures set by environmental regulators. In various European countries, there is a standard modelling procedure specified by the regulators to evaluate CSO performance (Dirckx et al., 2011). CSO performance evaluation by any modelling approach other than the agreed procedure will not comply with the requirements of the regulator. Hence any uncertainty quantification approach which does not conform to the standard modelling procedure in a transparent and objective way will not be acceptable to a regulator.

This chapter aims to address the practical and conceptual issues associated with the previous uncertainty quantification studies (see Section 2.1) which render them as unsuitable for environmental regulators, either because they do not use modelling tools that are specified or the proposed uncertainty assessment procedures are not transparent and objective enough to be accepted by the regulator. This chapter aims to quantify objectively the uncertainty in complex sewer network hydrodynamic models to a level that will satisfy environmental regulatory compliance.

In order to comply with the local regulations in Flanders, a complex hydrodynamic model of the sewer system has to be used with a single specified design storm. Hence, any uncertainty propagation method, which fails to use a complex hydrodynamic model, is not appropriate. Therefore, to estimate the uncertainty in the model output, a small subset of dominant input/model parameters which can explain the model output variance was selected (Wainwright et al., 2014). Dominant processes were identified by ranking the parameters using Global Sensitivity Analysis (GSA). This reduced the computational cost by including only the significant parameters in the uncertainty analysis. Monte Carlo technique was selected to propagate the uncertainty over other available techniques such as differential analysis using Taylor series approximation. The Monte Carlo technique was selected because it does not require modification in the model structure and provides a direct estimation of the probability distribution of the simulated model outputs (Helton and Davis, 2003). Since it is a sampling-based technique, using an efficient sampling method such as the Latin hypercube sampling (LHS) can ensure a full coverage of sample space. Helton and Davis (2003), and Melching and Bauwens (2001) maintained that LHS provided a faster convergence than random sampling applied to Monte Carlo simulations. Hence, LHS is applied in this study to generate samples from the parameter space.

Although the methods applied for sensitivity and uncertainty analyses are not new, their application to a modelling study satisfying environmental regulatory guidelines of an environmental regulator is. To the best of the author's knowledge, Global Sensitivity Analysis methods such as the Morris Screening method (Morris, 1991) and Monte Carlo simulations with Latin Hypercube Sampling (Helton and Davis, 2003) have not been applied to simulation results obtained from a detailed sewer hydrodynamic network model. The methodology to quantify uncertainty in the CSO spill volume laid out in this study can be implemented by water utilities for other regulatory guidelines with a different rainfall input.

3.2 Methodology

This chapter describes a modelling study conducted in three steps. First, the Morris Screening approach has been used to identify the input/model parameters, which contribute most to the uncertainty of the predicted sewer overflow volume in an urban catchment in Flanders, Belgium. Second, the uncertainty in the estimation of the shortlisted input/model parameters is quantified. For one of the input/model parameters, the process of estimating the prior parameter distribution using available field measurements is demonstrated in this chapter. In the third step, the uncertainty in the CSO spill volume is quantified by propagating the shortlisted input/model parameter uncertainty through Monte Carlo simulations on the output from a detailed hydrodynamic sewer network model. LHS is used to draw realizations of model inputs and parameters from their distributions which results in a set of CSO spill volume values. This set of model output values can be considered to be random samples of its distribution (Uusitalo et al., 2015). Although the GSA provides information about the significant parameters for a selected model output, this information is also assessed for the contribution of each of the important parameters towards the overall model output uncertainty.

3.2.1 Catchment Model

The hydrodynamic model used in this study is a subsystem of an InfoWorks CS model for the municipality of Herent in Flanders, Belgium. The sewer network serves around 2100 inhabitants with a total contributing area of about 87 hectares. The urban residential sewer system is gravity driven and has 60% of pipes with slopes ranging from 0 to 2% while a small number of pipes (around 3% of the total number of pipes) has a slope of 10% or higher. The pipes with a high slope are usually short length pipes connecting adjacent manholes. The catchment was selected because of available 5 and 10 years long flow survey datasets, which has enabled the calculation of uncertainty in the pipe hydraulic roughness. The sewer network and catchment model is a detailed model built and calibrated using the InfoWorks CS software; this software is selected as it is specified in the standard modelling procedure agreed between Aquafin (the managing water utility) and the environmental regulators in Flanders, Belgium (the Flanders Environment Agency (VMM)).

Within the InfoWorks CS model, the runoff volume after initial losses are calculated by applying a Fixed runoff coefficient and the Double Linear Reservoir (Wallingford) model (Sarginson and Nussey, 1982) is used to model runoff routing. Due to a lack of measured data required to calibrate a catchment scale runoff routing model, the Double Linear Reservoir (Wallingford) model available in InfoWorks CS is selected as per the Aquafin’s internal modelling code of practice (Aquafin, 2017). The modelling of sewer hydraulics is governed by the equations of de Saint-Venant as described by Yen (1973). InfoWorks CS uses Kindsvater and Carter equation (Kindsvater and Carter, 1959) to model flow over the weir.

3.2.2 Sensitivity Analysis

Morris Screening as a GSA method can be used to identify inputs and parameters affecting the model output variance, which if determined accurately, can greatly reduce the uncertainty in the model output. In addition, a GSA allows fixing the values of those inputs/parameters which are non-influential and do not affect the model output uncertainty if varied across their uncertainty range. The Morris Screening method uses multiple one-at-a-time (OAT) perturbations of inputs/parameters to derive sensitivity measures.

3.2.2.1 Data: Global Sensitivity Analysis

The input and model parameters selected for the GSA are initial loss value, Fixed runoff coefficient for impervious surfaces, Colebrook-White (CW) roughness in pipes, headloss coefficient in pipes, primary and secondary discharge coefficients of the weir, the weir crest level, and weir width in the CSO. After consultation with the modelling experts at Aquafin these parameters were selected because they are expected to influence the flow quantity from the catchment surfaces, in the pipes and the flow over the weir at the CSO structure thus overall affecting the estimation of CSO spill volume. The input and model parameters selected for the GSA are expected to influence the estimation of CSO spill volume for this case study catchment. However, there could be other parameters which can influence the estimation of CSO spill volume owing to specific catchment characteristics. Therefore it is suggested that the list of selected input and model parameters for the GSA should reflect the catchment characteristics and may include additional parameters if necessary.

A global sensitivity analysis using the Morris Screening method for this catchment was first outlined in Sriwastava et al. (2016). The frictional hydraulic losses in the pipes are represented by CW roughness (k_s). For GSA, the upper bound is set at 6 mm (Lind, 2015) but, the roughness values may reach higher values due to sediment deposition or isolated major pipe defects (see section 3.2.3.3. on Colebrook-White roughness calculation). During the GSA, the CW roughness values of all pipes are varied simultaneously. Since measured data on initial losses to runoff in the Herent catchment was not available, these values are obtained from studies that modelled runoff from residential urban catchments. Thorndahl et al. (2006) reported a range of 0.4 mm to 1.0 mm for initial loss values whereas Vanrolleghem et al. (2015) considered a range of 0.22 mm to 1.5 mm. The more conservative estimate of the uncertainty in initial loss values from Vanrolleghem et al. (2015) is used for the Herent catchment. The calibrated model had its Fixed runoff coefficient set at 0.8 for impervious surfaces which is found to be in accordance with the runoff coefficient values for streets and roofs (BASMAA (Bay Area Stormwater Agencies Association), 1999; McCuen, 1998). Since the Fixed runoff coefficient represents the effects of a natural random process, it is assumed to have a symmetrical variation around the value of 0.8, with a physical upper limit of 1.0 which results in having 0.6 as the lower bound. In InfoWorks CS, extra headloss due to the angle of approach of a pipe to a manhole is represented by a headloss coefficient. The default value of this multiplying factor is 1 which means no additional headloss due to the angle of approach. Headloss coefficient values could increase up to 6.6 for an angle of approach at 90 degrees to the flow direction, which is taken as its upper bound with the lower bound set at 1.0. The experimentally determined values for weir discharge coefficient from British (BS) and International (ISO) Standards (BS ISO 1438:2008) is used to define a range of 0.2 to 3 for the primary discharge coefficient of the weir at the CSO structure. InfoWorks CS uses an additional discharge coefficient termed as a secondary discharge coefficient and applies orifice/sluice gate equations when the water level reaches the roof of the CSO chamber. A symmetrical range of ± 50% (0.5 to 1.5) for the secondary discharge coefficient is considered, as it includes the discharge coefficient values given in British, European (EN) and International Standards (BS EN ISO 5167-2:2003). The weir crest level and width are varied by ±10 centimetres to account for potential measurement errors after consultation with the modelling experts at Aquafin.

For the GSA, parameter values are sampled from a uniform distribution within their respective ranges.

3.2.2.2 Morris Screening results

The results of the Morris Screening are presented in Table 3.1 in the form of Morris Screening sensitivity measures, absolute mean (μ^*) and standard deviation (σ) (Campolongo et al., 2007). Higher values of μ^* suggests a higher influence of the model parameters on the model output and higher values of σ suggests a higher degree of non-linear relationship or interactions with other parameters. The ranking of parameters was based on their respective μ^* values. The Fixed runoff coefficient is found to be the single most important parameter, it also has a high standard deviation suggesting a dependence on other parameters. The weir crest level is identified as the second most significant parameter, followed by CW roughness (which also has a relatively higher standard deviation). The model output is found to be insensitive to the remaining parameters.

Table 3.1. Morris Screening results and ranking of input/model parameters.

Parameters	Absolute mean (μ^*)	Standard deviation (σ)	Rank
Fixed runoff coefficient	0.974	0.055	1
Weir crest level	0.196	0.019	2
CW roughness	0.098	0.048	3
Headloss coefficient	0.019	0.008	4
Primary weir discharge coefficient	0.001	0.002	5
Weir width	0	0	6
Initial loss value	0	0	7
Secondary weir discharge coefficient	0	0	8

Previous studies (Vanrolleghem et al. 2015) have defined a cutoff threshold of $\mu^* = 0.1$ when selecting important parameters to be included in uncertainty analysis. Based on this guidance, the Fixed runoff coefficient, weir crest level and CW roughness are selected for inclusion in uncertainty quantification and propagation analysis.

3.2.3 Characterization of uncertainty in input/model parameters

This section describes the process of uncertainty quantification for the selected significant input/model parameters.

3.2.3.1 Fixed runoff coefficient (impervious surfaces)

The calibrated InfoWorks CS model calculates runoff from impervious surfaces using a Fixed runoff coefficient of 0.8 to represent the runoff losses. This value is in accordance with McCuen (1998) who recommended a value of 0.85 for roofs, 0.80 for brick pavements and 0.85 for asphalt and concrete pavements. McCuen (1998) suggested typical ranges of the runoff coefficient as 0.75 - 0.95 for roof surfaces and 0.70 - 0.95 for asphalt and concrete pavement. It was stated that these values were applicable for events with 5 to 10-year return periods and that higher values of runoff coefficient should be considered for less frequent, higher intensity events.

In the absence of field measurements, any continuous probability distribution type can be assumed to represent the uncertainty in the Fixed runoff coefficient. Since runoff from the catchment surfaces is a natural process and there is no available information about the mode of the distribution, a symmetrical normal distribution with the mean value of 0.8 is selected. The assumed normal distribution is truncated at the upper physical limit for the Fixed runoff coefficient i.e. 1. Since the composite design storm used in this study has a much lower return period than 5 to 10-years, values smaller than 0.70 should be taken into account for the Fixed runoff coefficient. A standard deviation of 0.1 is assumed with the mean of the normal distribution set at 0.8. The normal distribution is truncated with a lower bound 0 and upper bound 1.

3.2.3.2 Weir crest level

The absolute weir crest level is set at 35.35 m (at 1.6 m elevation with respect to the bottom of the pipe upstream to the weir) in the calibrated model based on survey data. The measurement errors in surveying the weir crest level are assumed to have a random variability. Hence a symmetrical normal distribution is used to represent the uncertainty in the measurement of weir crest level. The standard deviation of the normal distribution is selected based on a range of ±10 cm for the potential error in estimating weir crest level so that $3\sigma = 10$ cm.

3.2.3.3 Colebrook-White roughness (k_s)

The uncertainty in the CW roughness is quantified using long-term flow survey data. This dataset has been used to estimate probability distributions of the Colebrook-White hydraulic roughness parameter.

Colebrook-White Equation

The Colebrook-White equation for flow in partially filled circular pipes (Swaffield and Bridge, 1983) can be written as

$$\frac{1}{\sqrt{f}} = -2\log_{10}\left[\frac{k_s}{14.83R} + \frac{2.52}{Re\sqrt{f}}\right] \tag{3.1}$$

where f = Darcy-Weisbach resistance constant; k_s = CW roughness parameter (m); R = Hydraulic Radius (m); Re = Reynolds Number. For partially filled circular pipes, the hydraulic radius R can be calculated using the diameter of the pipe D and the measured flow depth h. If a cross section of the circular pipe was considered with θ as the angle made by the intersection of water surface and the circumference of the pipe at the centre of the circular cross section, hydraulic radius R can be expressed as:

$$R = \frac{D(\theta - \sin\theta)}{4\theta} \tag{3.2}$$

(Barr, 1986). The Darcy-Weisbach resistance constant f was calculated using the Chezy equation given in Swaffield and Bridge (1983) which argued that it can be applied for moderately smooth channels. f can be expressed as:

$$f = \frac{8gRS}{V^2} \tag{3.3}$$

where V = mean velocity of flow (m/s); S = hydraulic gradient; and g = acceleration due to gravity (m/s^2). The slope of the pipe is taken to be the hydraulic gradient as uniform flow conditions are assumed at the measurement locations during dry weather period. For wet weather conditions, the rapidly changing nature of the flow would result in non-uniform flow. This would also mean that the assumption underlying the Colebrook-White equation would be invalid. The Reynolds number was calculated as:

$$Re = \frac{4VR}{\nu} \tag{3.4}$$

where ν = kinematic viscosity of water (m^2/s). The inclusion of R in this equation makes the calculation of Re suitable for partially filled circular pipes. The year-round average temperature of wastewater in Flanders region is taken as 15°C based on in-sewer temperature observations collected in the study by Abdel-Aal et al. (2015). The value of the kinematic viscosity of water (ν = 1.139 x 10^{-6} m^2/s at 15°C) is used for the wastewater.

<u>Data</u>

Long-term measurements of flow depth (m), velocity (m/s) and derived flow rate (m^3/s) are available for 9 different locations in the catchment. A summary of the dataset is given in Table 3.2.

In order to be able to apply Eq. 3.1 and Eq. 3.3, the flow data needs to be scrutinised. Eq. 3.3 assumes that pipe slope is equal to hydraulic gradient, this means flow data can only be used if there are uniform flow conditions. Based on this criterion, data from locations M1 and M6 were found to be unsuitable because the invert levels of two connecting pipes were different. M2 and M109 were discarded due to zero or near zero pipe slope values, which means there are likely backwater effects, and M4 was discarded due to the presence of a pipe junction (making non-uniform flow likely), and M8 and M9 due to slope and pipe diameter changes close to the measurement section.

Table 3.2. Details of flow survey data

Location name	Measurement start date	Measurement end date	Pipe Shape	Pipe dimensions (mm)	Pipe material	Pipe slope (m/m)
M109	25/08/2015	24/01/2016	Circular	1000	Concrete	0.00011
M9	09/01/2009	16/09/2015	Circular	800	Concrete	0.00094
M8	09/01/2009	24/01/2016	Circular	500	Concrete	0.00135
M6	22/11/2007	09/01/2009	Circular	800	Concrete	0.00074
M5	10/08/2005	25/01/2016	Circular	600	Concrete	0.00088
M4	17/08/2005	09/01/2009	Circular	1000	Concrete	0.00250
M3	14/03/2005	08/01/2009	Circular	1400	Concrete	0.00389
M2	14/03/2005	10/08/2005	Circular	500	Concrete	0.00000
M1	14/03/2005	30/05/2005	Circular	970	Concrete	0.00133

This leaves locations M3 and M5, for which the assumption of uniform flow is strong. A data filtering procedure is followed to remove erroneous data and extract only dry weather flow measurements. Only dry weather flow measurement data is used with an assumption that flow in the pipe will be uniform during dry weather due to the slow changing nature of dry weather flow. For wet weather conditions, the rapidly changing nature of the flow would result in non-uniform flow. A regular survey of these measurement locations in the sewer network indicated little evidence of sedimentation. Hence it is anticipated that calculation of CW roughness using dry weather flow measurements will not be an overestimation in this particular case. The process for data selection is described below:

Step 1. *Ensuring Reliable flow measurements*

The data is filtered to remove water depths less than 0.02 m (the minimum submerged depth of the sensor) and negative velocity readings caused by backflow or probe malfunction.

Step 2. *Removing wet weather flow periods*

Dirckx et al. (2009) reported a threshold of 70 percentile to identify the number of rain days through a standardised cumulative curve of daily inflow. The rain days were described as the days with surface runoff contribution. Since the study by Dirckx et al. (2009) was also based in Flanders, Belgium where the catchment from the current study is located, a threshold of 70 percentile on the daily average flow depth values is assumed to remove the wet weather days. In order to apply the threshold, percentiles of the daily average flow depth values are obtained for the whole duration of flow survey.

Step 3: *Identifying sensor misreading*

Blockage of the sensor or deposition around it, can result in fluctuations in measurements and may result in artificially higher readings. These can be identified when there are substantial variations in the daily average flow trend. These variations remain stable for some time ranging from a few hours to 1-2 days. These anomalies along with the instrumentation errors have been identified using the covariance values between flow depth and velocity. These anomalies appeared as outliers when flow depth and velocity are plotted together which were identified in the next step.

Step 4: *Outlier detection*

Outliers have been identified and removed using a robust covariance method between flow velocity and flow depth values. In uniform flow conditions, water depth and flow velocity in the pipes are expected to have a positive correlation. Flow measurements displaying any discrepancy to this relation might arise from blockage or malfunctioning of the sensors.

This chapter employs the *robustcov( )* function available in Matlab R2016a. The *robustcov* function uses the Fast-MCD (Minimum Covariance Determinant) method (Rousseeuw and Driessen, 1999) to generate robust estimates of bivariate location and scatter. Nguyen and Welsch (2010) and Peña and Prieto (2001) argue that the Fast-MCD method provides a better estimate of multivariate location and scatter than other classical methods such as Maximum Likelihood Estimation based methods because such methods rely on the assumption of normality in the data and the presence of outliers induce a bias to such estimators. In order to detect outliers, the Mahalanobis distance values are calculated using the robust covariance estimates which follow chi-square distribution (Filzmoser et al., 2005). In this bivariate case, the Mahalanobis distance values has 2 degrees of freedom and the outliers are identified by setting a cut-off of 97.5% quantile of Chi-square distribution.

Distribution of calculated k_s values

The data validation resulted in approximately 55% removal of data for measurements taken at the location M3 and 41.6% removal of data at the location M5. k_s values are calculated from the filtered data at locations M3 and M5 using Eq. 3.1. Fig. 3.1a and 3.1b show the histograms of k_s values calculated at locations M3 and M5.

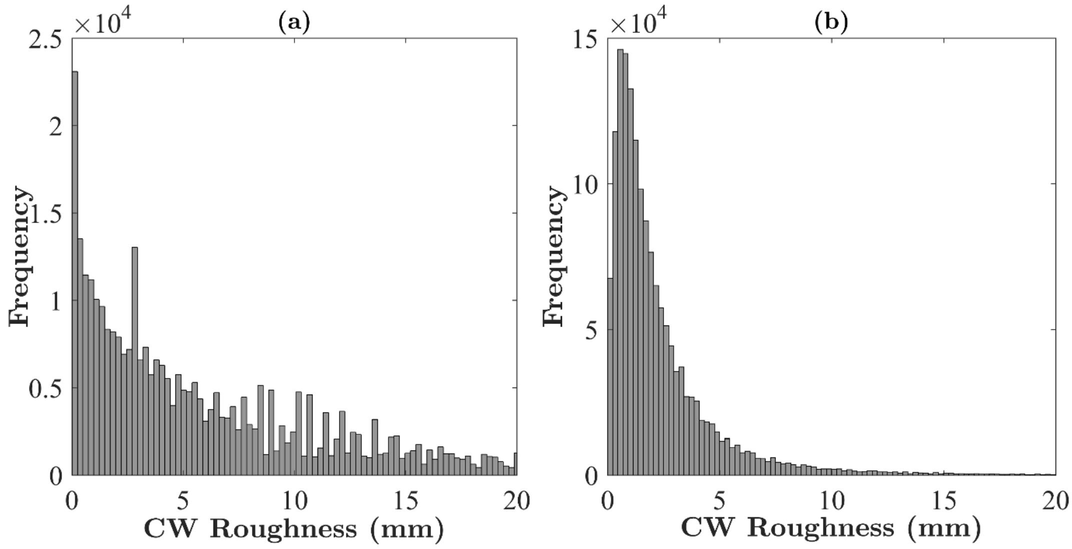

Fig. 3.1. a and b: Histograms of k_s calculated at locations M3 (left) and M5 (right) respectively.

In comparison to the distribution of k_s at M5, M3 data results in higher values of k_s (Fig. 3.1). One of the possible causes could be the significantly large dimension of the pipe at M3 compared to the pipe at M5 (1400 mm Vs 600 mm). In pipes with such large diameter, the flow depth can often be comparable to the submerged depth of the sensor and can cause data misreading by the sensor. In both these cases, it is clear that the k_s values at these locations follow a heavy-tailed probability distribution. Hence, a variety of continuous heavy-tailed distribution types such as gamma, generalized pareto, Loglogistic, Lognormal and Weibull distributions have been tested to identify the most appropriate distribution type to describe the CW roughness. Since the flow survey duration at the two locations was different, best-fitted probability distributions are obtained for each location independently. The R package *fitdistrplus* is used to fit these distributions using maximum likelihood estimation (Delignette-muller and Dutang, 2015). The Bayesian Information Criterion (BIC) is used as the goodness of fit statistic because BIC avoids overfitting by penalising distributions with greater number of parameters and also, the use of maximum likelihood as estimation method is consistent with BIC since it is based on log-likelihood (Vose, 2010). A lower BIC value is considered a better fit. The results of distribution fitting for the two locations are in Table 3.3 with the rank provided in parentheses. For both M3 and M5, the Loglogistic distribution provides the best fit with the lowest value of the goodness of fit statistic BIC (Table 3.3). This suggests consistency in the form of the uncertainty for the CW roughness parameter.

Table 3.3. Distribution fitting BIC values for k_s

Probability distribution(s)	**Bayesian Information Criterion**	
	M3	**M5**
Gamma	3239694 *(5)*	5764741 *(3)*
Generalized Pareto	3098093 *(2)*	5792316 *(5)*
Loglogistic	3097110 *(1)*	5705864 *(1)*
Lognormal	3110213 *(3)*	5745767 *(2)*
Weibull	3157747 *(4)*	5787913 *(4)*

However, in order to propagate this uncertainty in InfoWorks CS simulations, a single probability density function for k_s is needed. Between the two locations, the Loglogistic distribution parameters obtained for the location M5 are assumed to represent the uncertainty in CW roughness better due to the considerably longer flow survey (10 years) at this location.

Table 3.4. Parameters of fitted Loglogistic distribution

Location	$\boldsymbol{\alpha}$ **(mm)**	$\boldsymbol{\beta}$
M3	6.035	0.926
M5	1.490	1.749

However, in reality, CW roughness of each pipe may follow a Loglogistic distribution with different parameters similar to the M3 and M5 locations. Table 3.4 lists the parameters of Loglogistic distribution for CW roughness values calculated at M3 and M5. The probability density function of two-parameter Loglogistic distribution can be written as:

$$f(x;\alpha,\beta) = \frac{\left(\frac{\beta}{\alpha}\right)\left(\frac{x}{\alpha}\right)^{\beta-1}}{\left(1+\left(\frac{x}{\alpha}\right)^{\beta}\right)^{2}}, \qquad x > 0 \tag{3.5}$$

where $\alpha > 0$ is the scale parameter and represents the median of the distribution and $\beta > 0$ is the shape parameter. Lind (2015) reported a k_s value of 0.5 mm for a new concrete pipe and the k_s values can reach between 3 mm to 6 mm for small defects. The help manual of the InfoWorks CS software suggests a value of 1.5 mm for smooth concrete pipes and a value of 15 mm for rough concrete pipes. These suggested values do appear to agree with the distributions specified in Table 3.4.

3.2.4 Uncertainty propagation

The probability density function of the simulated CSO spill volume can be calculated via propagation of the input and model parameter distributions defined in the previous sections through Monte Carlo simulations. In Flanders, the design criteria for the CSO structure includes a threshold on the annual overflow frequency (Dirckx et al., 2011). The composite design storm *f7* is prescribed as rainfall input in order to reflect the design guidelines set by the Flanders Environment Agency (VMM) (Coördinatiecommissie Integraal Waterbeleid, 2012). The VMM regulations for CSO structures are such that the CSO should not spill for the specific design storm *f7*. The composite design storm event '*f7*' has an average frequency of occurrence of 7 times per year. The composite storm was developed by Vaes et al. (1996) using a historical rainfall series from 1967 to 1993 with a time step of 10 minutes measured at the rain gauge at Uccle in Belgium. For a frequency of 7 y^{-1}, all Intensity/Duration relationships are included in the single 'composite' *f7* design storm (Appendix A).

Monte Carlo simulations with LHS have been performed considering parameter distributions of the Fixed runoff coefficient (*rc*), weir crest level (*wc*), and CW roughness (k_s) while keeping other parameters constant as defined in the calibrated model. To draw *n* samples using the LHS method, the uncertain range of each input/model parameter is divided into *n* intervals of equal probability. This is followed by drawing a random sample from each of these n intervals. Assuming that the input and model parameters are independent to each other, the *n* samples for individual input/model parameters are combined with each other randomly to generate the sample space (Helton and Davis, 2003). For Latin hypercube sampling, the function '*randomLHS*' in the R package '*lhs*' is used to draw the samples.

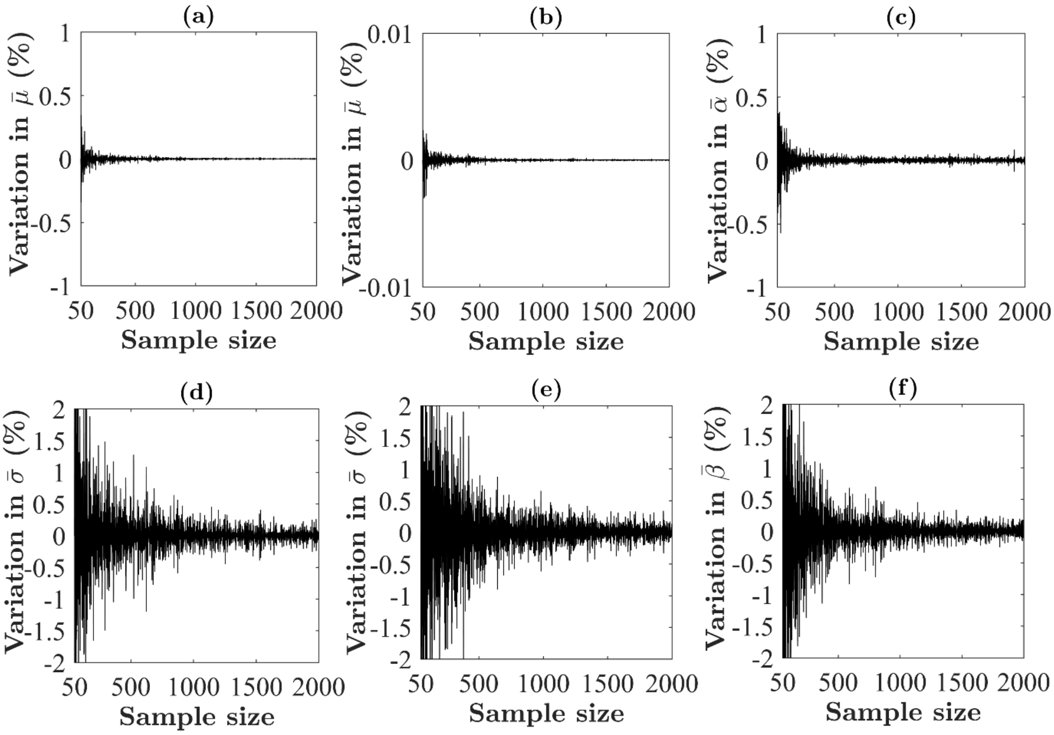

Fig. 3.2. a and b: variation (expressed in percentage) in the sample mean for Fixed runoff coefficient and weir crest level; c: sample scale parameter $\overline{\boldsymbol{\alpha}}$ (median) for CW roughness; d and e: sample standard deviation for Fixed runoff coefficient and weir crest level; f: sample shape parameter $\overline{\boldsymbol{\beta}}$ for CW roughness with increasing sample size respectively.

The sufficiency of the sample size is tested by analysing the convergence of the respective sample mean, standard deviation, scale and shape parameter estimates (Fig. 3.2). Fig. 3.2a, b, d and e show the convergence in the sample mean and the sample standard deviation for the Fixed runoff coefficient and the weir crest level, while the sample size is increased from 50 to 2000. Fig. 3.2c and f plot the variation in the sample scale and shape parameter respectively for the Loglogistic distribution fitted for CW roughness. It is evident that a stable convergence (0.5% of maximum variation) has been achieved with a sample size of 1000 for all the three parameters.

Hence, a sample size of 1000 using Latin hypercube sampling is considered sufficient.

The uncertainty propagation is performed in two steps. Firstly, uncertainty in the three selected parameters is propagated through 1000 simulations resulting in 1000 values of the model output CSO spill volume for the defined design storm. In the second step, the contribution of the individual parameters towards the 'overall uncertainty' in the CSO spill volume is assessed by propagating the uncertainty in only two parameters keeping the third parameter constant. Here, the term 'overall uncertainty' means the uncertainty in the CSO spill volume caused by the uncertainty in all three parameters.

3.3 Results and Discussion

3.3.1 Overall Uncertainty

Fig. 3.3a shows the probability density function (PDF) of the CSO spill volume obtained as a result of propagating the uncertainty in Fixed runoff coefficient, weir crest level, and CW roughness. The calculated CSO spill volume values are described by a normal distribution truncated at zero as the lower bound (Fig. 3.3a) with the mean 117.9 m^3 and standard deviation 50.8 m^3. The exceedance probability (EP) curve (Fig. 3.3b) gives information about the probability that the CSO spill volume exceeded a certain value with the *f7* design storm. The slope of the EP curve can be used to find the rate of reduction in risk from spills when additional storage capacity is planned upstream of the CSO. The benefit of adding extra storage capacity is less for the plot regions where the slope of the EP curve is high.

From Fig. 3.3b, there is a 50% probability that the CSO spill volume will exceed 116.9 m^3, however, to ensure that the system capacity is exceeded with a probability of only 10%, the total required basin storage volume is only 184.4 m^3. It is therefore thought that the practitioner is likely to reduce the probability of CSO spill from 50% to 10% by investing in additional basin storage of as little as 67.5 m^3. Therefore, incorporating uncertainty in the model based performance evaluation of the CSO, would enable the practitioners to achieve greater protection against the risk of CSO spills with better informed investment decisions. How practitioners would actually react to probabilistic model outputs and exceedance probability density curves, is another question that will be studied in chapter 4.

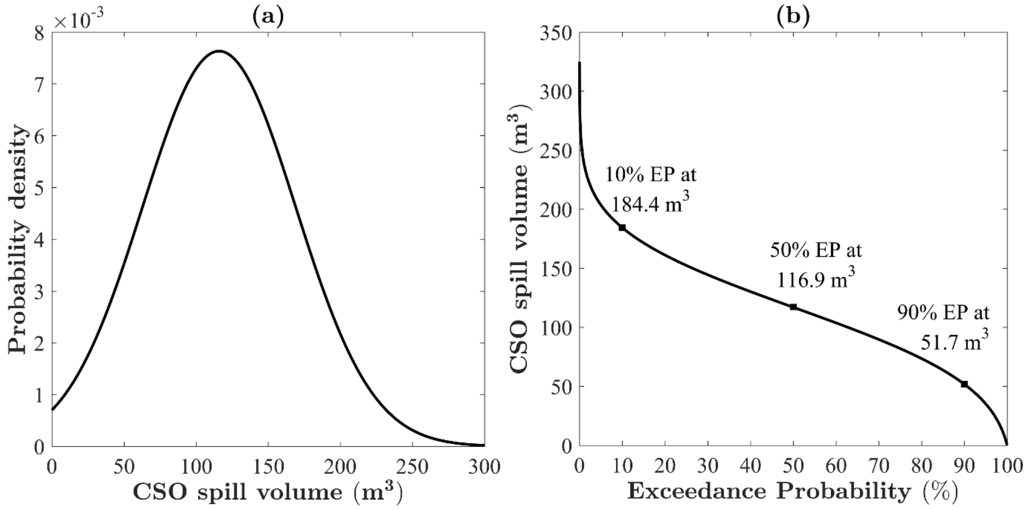

Fig. 3.3. (a) Probability density curve of CSO spill volume representing the overall uncertainty. (b) Exceedance probability curve for CSO spill volume.

3.3.2 Contribution of Individual parameters

Additional Monte Carlo simulations are performed to propagate the uncertainty in any of the two out of the three selected parameters. The value of the third parameter is kept constant at the same value as in the original calibrated model. This results into three distinct combination: Fixed runoff coefficient + CW roughness ($rc + k_s$), Fixed runoff coefficient + weir crest level ($rc + wc$), and weir crest level + CW roughness ($wc + k_s$). Fig. 3.4 displays the PDFs obtained for CSO spill volume in the three cases and the PDF representing the 'overall uncertainty' from Fig. 3.3a. Although the PDFs from Fig. 3.4 represent an underestimation of the overall true uncertainty in CSO spill volume, they provide very useful insights for decision-making. For example, comparing the PDFs from 2-parameter uncertainty propagation with the PDF from 3-parameter uncertainty propagation in Fig. 3.3a gives information on how much each parameter affects the 'overall uncertainty' in modelled CSO spill volume.

Similar to the 'overall uncertainty' in CSO spill volume (Fig. 3.3a), the uncertain pairs $rc + k_s$, and $rc + wc$ result in a normally distributed CSO spill volume with the left tail truncated at zero. However, the uncertainty in CSO spill volume caused by the pair, $wc + k_s$ is found to be best described by a Weibull distribution. The results of these three combinations and the overall uncertainty are summarised in Table 3.5 in the form of mean and standard deviation obtained for CSO spill volume. The PDF of

CSO spill volume with constant weir crest level, $rc + k_s$ is almost identical to the 'overall uncertainty' PDF which suggests that the effect of uncertainty in the estimation of weir crest level is negligible on the overall uncertainty in CSO spill volume. Similarly, when the uncertainty in CW roughness is introduced, its contribution to the uncertainty in CSO spill volume is found to be insignificant.

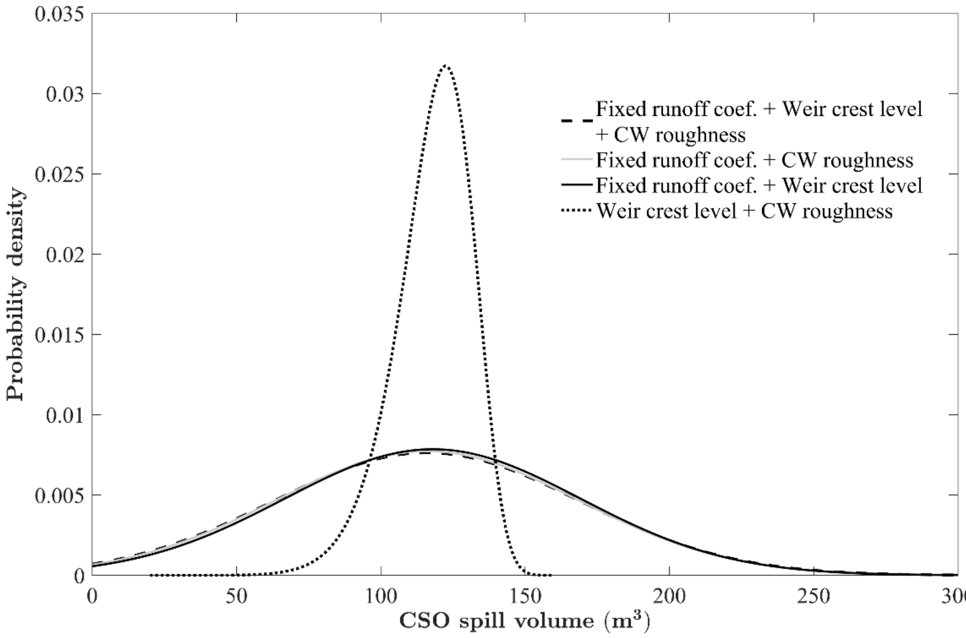

Fig. 3.4. Probability density function curves of CSO spill volume representing the uncertainty in the combinations of the Fixed runoff coefficient (*rc*), weir crest level (*wc*) and CW roughness (k_s); Fixed runoff coefficient (*rc*) and CW roughness (k_s); Fixed runoff coefficient (*rc*) and weir crest level (*wc*); and, weir crest level (*wc*) and CW roughness (k_s).

Therefore, it can be deduced that the contribution of CW roughness to the overall uncertainty is of the similar magnitude to that of weir crest level. This means that the ranking obtained as a result of Morris Screening is not clearly evident in the uncertainty quantification results for input and model parameters with low Morris sensitivity measures.

In the GSA, only the absolute mean μ^* is used to rank the parameters. The sensitivity measure, standard deviation σ of the CW roughness in the GSA analysis is higher than that of the weir crest level, which indicates roughness has a non-linear relationship with the CSO spill volume and/or, it interacts with other parameters to a higher degree than the weir crest level. Therefore, the significance of σ as an indicator of the contribution of input/model parameters to the output uncertainty needs to be investigated further, so that the relative importance of input/model parameters with low sensitivity measures such as weir crest level and CW roughness can be quantified.

Table 3.5. Summary of uncertainty analysis results

Parameters	**Probability distribution type**	**Mean (m^3)**	**Standard Deviation (m^3)**
Weir crest level + CW roughness	Weibull	117.9	13.4
Fixed Runoff Coef. + CW roughness	Truncated Normal	117.9	50.3
Fixed Runoff Coef. + Weir crest level	Truncated Normal	119.5	49.6
Fixed Runoff Coef. + Weir crest level + CW roughness	Truncated Normal	117.9	50.8

It is evident from Fig. 3.4 and Table 3.5 that the Fixed runoff coefficient is the largest contributor to the overall model uncertainty in CSO spill volume. Assuming that the true value of Fixed runoff coefficient is known, CSO spill volume follows a Weibull distribution with a considerably smaller standard deviation. In this case, there is a 50% probability that the CSO spill volume would exceed 119.4 m^3 which is close to the value of 116.9 m^3 at similar probability in the case of the overall uncertainty. However, to reduce the risk of CSO spills from 50% to 10% additional storage of at least 14.3 m^3 is required. This required additional storage is significantly smaller than the required additional storage of around 67.5 m^3 when the overall uncertainty is considered for decision-making.

With this additional available information on the individual contribution of input and model parameters, a practitioner might evaluate the trade-offs between investing resources in reducing the uncertainty in the estimation of important parameters and investing in larger basin storage to cope with the overall uncertainty. For example, the uncertainty in the estimation of runoff coefficient could be reduced by gathering more information of the runoff surfaces through a field survey campaign. The usefulness of such campaign could be assessed by comparing the cost of the survey and the potential benefit gained as a result of the smaller basin storage required.

3.4 Concluding remarks

The current chapter demonstrates a methodology to incorporate probabilistic uncertainty in a standard modelling procedure used by a water utility to conform to regulatory guidelines. Physical characteristics of different sub-processes such as rainfall-runoff, in-sewer flow, and weir flow are represented as potential sources of model uncertainty. Ranking using Morris Screening identifies the Fixed runoff coefficient, the weir crest level and Colebrook-White roughness as the three most significant parameters. The cutoff threshold on the absolute mean value μ^* to select the most significant parameters is derived from Vanrolleghem et al. (2015). However, it should be noted that determining the value of the cut-off threshold decides which parameters are going to be included in the uncertainty analysis. Hence a careful selection of the cutoff threshold is strongly advised. In this study, the absolute mean value for the Fixed runoff coefficient is significantly higher compared to the other parameters. Similarly, there is a significant relative difference in the absolute mean values for the CW roughness and the Headloss coefficient. The threshold of 0.1 suggested by Vanrolleghem et al. (2015) allows a clear selection of significant parameters in this case study but a different threshold could be more appropriate for other cases.

Following Morris Screening, the uncertainty in the three most significant parameters is propagated through Monte Carlo simulations using LHS and the uncertainty in the CSO spill volume is quantified subsequently for a single design storm specified by the local environmental regulator. Both Morris screening and LHS based Monte Carlo simulations prove to be reliable methods and easy to implement within the constraints of modelling guidelines. Since the InfoWorks CS model and the rainfall input used in this study satisfy the regulatory modelling guidelines, any random sample from the probability distribution of CSO spill volume obtained as a result of the uncertainty propagation can be used to represent performance of a compliant CSO.

For the CW roughness, this chapter demonstrates a process to quantify the parameter uncertainty using extensive flow survey data. CW roughness values are found to have a heavy-tailed distribution and a Loglogistic distribution is found to be the best fit. This study is the first where the uncertainty in CW roughness for sewer pipes has been defined based on in situ field measurements and used for uncertainty propagation. It is expected that the probability distributions obtained for CW roughness in this chapter are representative for combined sewer systems with concrete pipes in reasonable condition and limited sedimentation, and their distribution shape and spread can be used in future studies.

The resulting uncertainty in the CSO spill volume indicates that the impact of uncertainty in the Fixed runoff coefficient is much higher compared to other parameters which is in agreement with the results obtained from the global sensitivity analysis. It is imperative that the uncertainty in such dominating parameters should be carefully defined and quantified as it has been demonstrated in this study that the shape of the probability density function for Fixed runoff coefficient largely influences the shape of the uncertainty in the model output CSO spill volume.

After quantifying the uncertainty in CSO spill volume, the results can be processed to be used for decision making purposes. For example, the information available from the exceedance probability curve for the CSO spill volume can be used to develop a trade-off analysis between the provision of additional storage volume and consequent reduction in risk of predicted spill volumes, given this additional storage volume, whilst considering any budget constraints. In this study, the risk of the predicted spill volume exceeding the storage capacity could be reduced from 50% to 10% by increasing the provision of additional storage from 116.9 m^3 to 184.4 m^3.

However, it should be noted that the uncertainty in the CSO spill volume obtained through this study is still an underestimation of the overall modelling uncertainty in the CSO spill volume as only a small number of the more significant sources of uncertainty could be considered due to the regulatory guidelines. In this chapter, a single design rainfall event is used in order to follow the requirements of the local environmental regulator, however, to capture the dynamics of rainfall-runoff process, spatial and temporal variability of rainfall should also be represented in the uncertainty propagation. This would require changes in the current local regulatory framework. In addition, the runoff from permeable areas is not taken into account, it is assumed that this infiltrates into the soil, however, this may not be the case if there have been extensive antecedent wet weather conditions. Therefore, this is another source of uncertainty not taken into account in the current modelling approach, as stated the chapter aims to quantify uncertainty only in the current approach adopted by Aquafin.

Another possible future line of investigation could be the use of analytical probabilistic urban drainage models (Adams and Papa, 2000) as an alternative to the practice of computationally expensive urban drainage models. This would require a change in the way water utilities are regulated in Belgium and other European countries, where, as the far as the author is aware, the regulatory framework does not permit the use of probabilistically based modelling approaches. Therefore, it is expected that the water utilities may be able to adopt the methodology demonstrated in this chapter to account for model uncertainty whilst complying with the modelling requirements of their regulator.

4. Decision maker’s preferences for uncertainty

4.1 Introduction

A decision making process involves comparison of candidate solutions or decision alternatives against a set of performance variables such as emission quality indicators or the cost of remedial measures after a failure. In a deterministic modelling study, this process often results in a ranking of decision alternatives based on the corresponding assessment criteria, for instance the ecological performance of different schemes or the monetary cost of implementing such schemes. However, decision making under uncertainty involves ranking of decision alternatives based on the probability distribution of the assessment criteria. In such cases, the decision maker needs to identify their preferences for the shape and scale of the probability distribution of the performance variable or variables in order to rank the alternatives.

In the context of compliance with regulations on the environmental impact of CSO events, the decision maker is expected to be risk-averse i.e. making decisions which avoid or reduce the risk of non-compliance. However, decisions to improve system reliability and robustness of the system performance require investments in solutions such as data monitoring campaigns and additional infrastructure. This results in a trade-off between increased reliability and robustness against additional investment required under budgetary constraints. Therefore, it is imperative to understand a decision maker’s preference for risk under the economic constraints so that these preferences are reflected in the formulation of the decision model.

This chapter attempts to explore how a decision maker’s preferences for an uncertain performance variable can be identified. This was accomplished through the responses of water utility practitioners to a case study problem where compliance of the decision alternatives against local environmental regulations was tested. Apart from the water utility company, the environmental regulators and the local municipal authorities are also the principal stakeholders in such decision making processes. However, the scope of this thesis is limited to study the influence of urban drainage simulation uncertainty on the investment decisions which are primarily executed by the water utility companies. It can be argued that a water utility makes model-based investment decisions to ensure compliance with the environmental regulations. Hence it becomes imperative to assess the preferences of decision makers at a water utility company.

The case study site is located in the Flanders region of Belgium and is subject to the regulations set by the Flanders Environment Agency (VMM) (Coördinatiecommissie Integraal Waterbeleid, 2012). Experienced practitioners from a water utility company based in Flanders were presented with the case study problem where they were asked to evaluate and rank decision alternatives based on their costs and the uncertainty in their performance variables. In this case study the regulatory performance variable was the annual CSO spill frequency, and additional infrastructure investments were proposed as decision alternatives to limit the CSO spill frequency. The case study evaluated the effect of modelling uncertainty on the performance of proposed infrastructure solutions in reducing the annual frequency of CSO spills. A series of questions were asked to the practitioners to determine which features of the probability distribution of the system performance they found important, and what their preferences were for these features in terms of evaluating the optimum way to achieve regulatory compliance. Section 4.2 lays out a description of the case study followed by the practitioners' responses and evaluation of the decision alternatives under model uncertainty in section 4.3.

4.2 Case Study - Schilde

In order to identify the risk preferences of the practitioners, a local case study Schilde was selected. Simulation results from the case study were used to represent an indicative real-world decision problem. The local case study was selected because the practitioners were familiar with the case study catchment, and the local environmental regulations which apply to this case study catchment.

4.2.1 Description

The catchment of Schilde is situated in the north of Flanders, Belgium and to the east of Antwerp. It consists of parts of the municipalities of Schoten, Schilde, Ranst and Brecht. The treatment plant is located in the south of the catchment, in Schilde. The Schilde sewer system is a residential urban system serving 45,730 people equivalents. Like most sewer networks in Flanders, the Schilde system is mostly gravity driven with a few pumps and it consists of 3965 pipes with a total length of 342 km. The sewer system is mostly flat with 95% of the pipes having a magnitude of slope less than 0.013%. The sewer network model was built using the commercial software InfoWorks ICM as per Aquafin's internal modelling code of practice (Aquafin, 2017).

In order to improve the operation of the buffer basin at Kattenhoflaan in the area of Sint-Job in 't Goor, an infrastructure investment proposal was drawn up to improve the performance with respect to Combined Sewer Overflow (CSO) frequency. The sewer subsystem of Sint-Job in 't Goor consists of 94 km of pipes.

Proposed infrastructure

The additional infrastructure investment proposal was to disconnect the area of Sint-Job in 't Goor from the catchment of Schilde, making it a separate treatment area through the following interventions:

- Construction of a Wastewater Treatment Plant (WWTP) along the Kattenhoflaan.

- Placement of a storage basin to limit the overflow frequency.

Different sizes of the storage basin were considered as decision alternatives to limit the overflow frequency. The performance of these decision alternatives with respect to overflow frequency was evaluated using an InfoWorks ICM model. The variability in rainfall precipitation and uncertainty in the runoff coefficient were used to represent the uncertainty in the estimation of overflow frequency for these alternatives. The following sections describe the process followed to quantify the impact of modelling uncertainty on the performance of the decision alternatives.

4.2.2 Selection of decision alternatives

According to the VMM guidelines on the overflow frequency, the composite storm '*f7*' (see Section 3.2.4 & Appendix A) should be used to determine the storage volume required to limit the overflow frequency to an acceptable value. The required storage volume of the basin was modelled as the maximum overflow volume predicted for the '*f7*' storm. However, the uncertainty in the model calculations, caused by varying the run-off co-efficient results in a range of predicted storage volumes. In terms of the model outputs, any of these storage volumes satisfy the guidelines set by VMM and can be treated as a random realization of the volume required to comply with the VMM regulation of no CSO spill for the '*f7*' storm.

Hence, decision alternatives to be modelled as a storage basin were selected from the probability distribution of the compliant storage volumes. Although there could be many potential sources of uncertainty in the prediction of required storage volume, according to Chapter 3, the runoff coefficient is considered one of the major sources. Hence, as the main aim is to study the practitioners' decision making under uncertainty, and not an extensive uncertainty analysis, only runoff coefficient is used as the source of model parameter uncertainty in the prediction of required storage volume. A truncated normal distribution with mean 0.8 and standard deviation 0.1 was used to represent the uncertainty in the runoff coefficient (see Section 3.2.3.1). The probability distribution of the required storage volumes was obtained after propagating the uncertainty in the runoff coefficient, as described in a similar manner as in Chapter 3 through 1000 Monte Carlo simulations.

Table 4.1. Uncertainty in the maximum overflow volume using *f7* design storm

Mean (m^3)	**Standard Deviation (m^3)**	**10^{th} % (m^3)**	**25^{th} % (m^3)**	**50^{th} % (m^3)**	**75^{th} % (m^3)**	**90^{th} % (m^3)**	**95^{th} % (m^3)**
2929.3	620.9	2111.7	2498.3	2941.3	3375.9	3755.3	3948.1

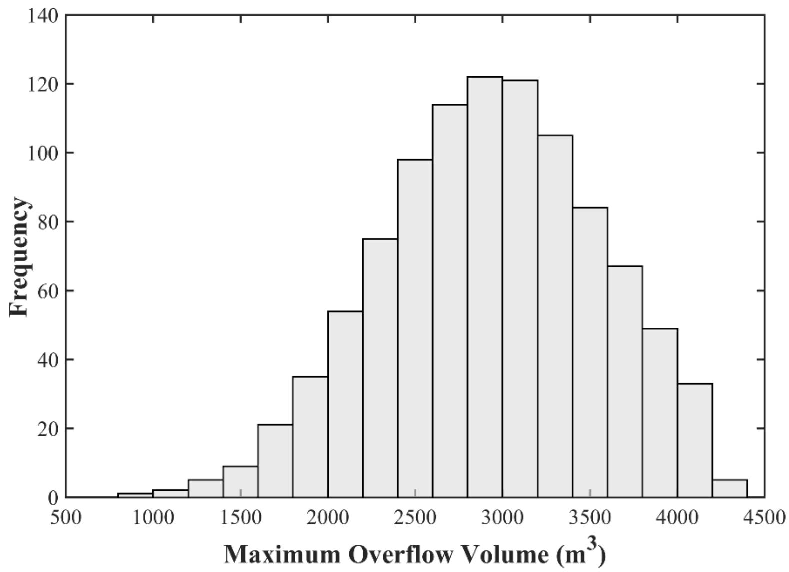

Fig. 4.1. Uncertainty in the maximum overflow volume represented as a histogram for the Schilde catchment, rainfall time series from 2004 to 2013.

Fig. 4.1 displays the result of 1000 Monte Carlo simulations randomly drawing from the truncated normal distribution that represents the uncertainty in the runoff coefficient, and then simulated in InfoWorks ICM with the '*f7*' storm event. The results are presented as a histogram of maximum overflow volume. The results are also summarised in Table 4.1.

Five values 2100 m^3, 2500 m^3, 2900 m^3, 3300 m^3 and 3900 m^3 were selected from the distribution of required storage volumes. These five storage volumes were modelled as the proposed storage basin and labelled as decision alternatives *a*, *b*, *c*, *d* and *e* respectively. These values cover the 10-95% range of the probability distribution summarized in Table 4.1. Table 4.2 lists the indicative cost estimates for the five decision alternatives which were provided by the water utility company.

Table 4.2. Indicative cost of the decision alternatives

Decision Alternatives	Storage basin capacity (m^3)	Cost (in Euros)
a	2100	2,168,021
b	2500	2,536,264
c	2900	2,905,111
d	3300	3,274,399
e	3900	3,828,935

4.2.3 Uncertainty quantification

4.2.3.1 Rainfall variability

The latest 10 years of available historical rainfall precipitation data from 2004 to 2013 with a time step of 10 minutes measured at the rain gauge at Uccle in Belgium was used as model input, in order to represent the variability in the rainfall at the catchment. The Uccle rain gauge is at a distance of approximately 55 km from the Schilde catchment. This distance between the rain gauge and the catchment introduces additional error in the rainfall input to the model. The suitability of the Uccle rain gauge data for the Schilde catchment is debatable but this was the closest rain gauge data available for the Schilde catchment. This limitation can be addressed by using spatially distributed rainfall measurements such as radar rainfall data (Thorndahl et al., 2017). Goormans and Willems (2012) compared the performance of a local area weather radar rainfall data with rain gauge measurements when used as a rainfall input to a sewer modelling case study in Belgium. The case study simulations using rain gauge measurements were found to outperform those with the local area weather radar rainfall input. In order to obtain spatially distributed rainfall measurements with high temporal and spatial resolution, radar data can be used in combination with the rain gauge measurements (Einfalt et al., 2004; Thorndahl et al., 2017).

4.2.3.2 Uncertainty in the runoff coefficient

Given the available computational resources, the simulations of the Schilde catchment model in InfoWorks ICM were found to be computationally expensive when a 10-year long rainfall timer series with a resolution of 10 minutes was used as an input. Since this chapter uses the simulation results as a representative case study for the practitioners, performing an extensive uncertainty analysis was not mandatory. Only 3 samples of the runoff coefficient were used to represent the uncertainty in the runoff coefficient. In order to represent the most populous region of the probability distribution, the 25th, 50th and 75th percentile values of the distribution were selected. This also ensured that outliers or extreme values of runoff coefficient were not included. Hence, for each of the five decision alternatives, three model simulations were performed by considering the following values of the runoff coefficient: **0.731** (25th percentile), **0.797** (50th percentile), **0.862** (75th percentile). These values of the runoff coefficient were derived from a truncated normal distribution with mean 0.8 and standard deviation 0.1.

4.2.3.3 Uncertainty in the overflow frequency

For five decision alternatives (different storage volumes), the flow at the CSO structure was calculated by modifying the runoff coefficient resulting in 5 x 3 = 15 simulations. A single simulation resulted in a 10-year long flow time series from which the overflow frequency in each of the ten years was calculated. Therefore, for each year and each decision alternative, the three values of overflow frequency obtained by changing the runoff coefficient values represented the uncertainty in the overflow frequency. These three values of overflow frequency were used to fit a 2nd order polynomial curve which would describe the relation between overflow frequency and runoff coefficient for a particular decision alternative in a given year. Random samples were drawn from the truncated normal distribution of the runoff coefficient, providing a set of overflow frequencies by reading off the fitted polynomial curve, and this was done for each of the five decision alternatives for each year. The average values of these samples of overflow frequency were calculated over the ten years to obtain the random samples of average annual overflow frequency n_{CSO} for each decision alternative. This resulted in a probability distribution of average annual overflow frequency n_{CSO} for each decision alternative.

4.2.4 Results

4.2.4.1 Uncertainty in the performance of the decision alternatives

The InfoWorks ICM model was then used to calculate overflow frequency for each decision alternative and each of the 10 years. The full set of results is provided in Appendix B, and Table 4.3 shows the annual overflow frequency averaged over 10 years for each decision alternative.

Table 4.3. Average annual overflow frequency calculated using the InfoWorks ICM model

Decision Alternatives	Runoff coefficient 0.731	Runoff coefficient 0.797	Runoff coefficient 0.862
a	11.9	14.9	18.6
b	10.5	12.7	15.7
c	9.2	11.4	13.3
d	7.9	10.3	12.2
e	6.9	8.9	11

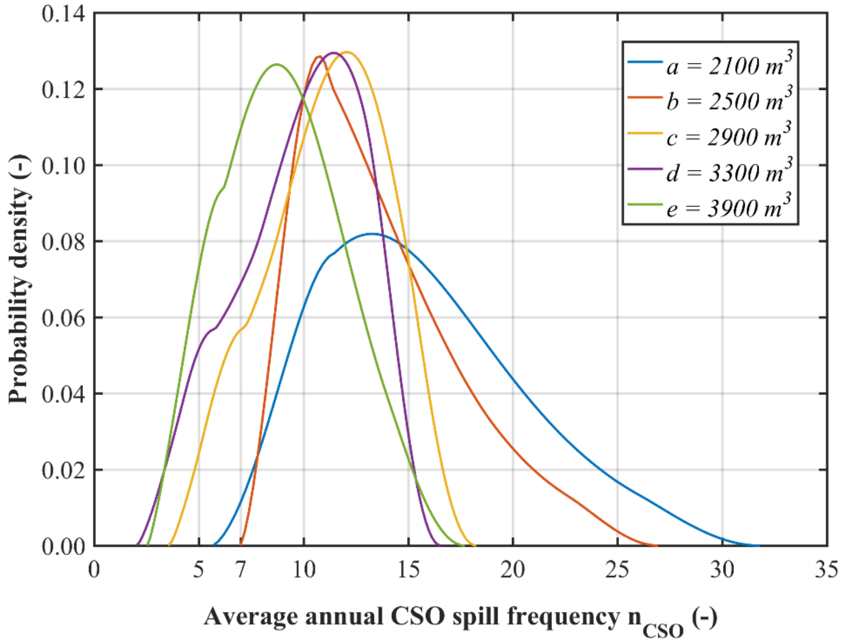

Fig. 4.2. Probability density function estimate of n_{CSO} for each decision alternative.

After fitting the overflow frequency values for each year to a 2nd order polynomial curve, random realizations of overflow frequency were obtained for each year for individual decision alternatives. Fig. 4.2 and Fig. 4.3 display the estimate of probability density function (PDF) and cumulative distribution function (CDF) of the average annual overflow frequency n_{CSO} for each decision alternative respectively.

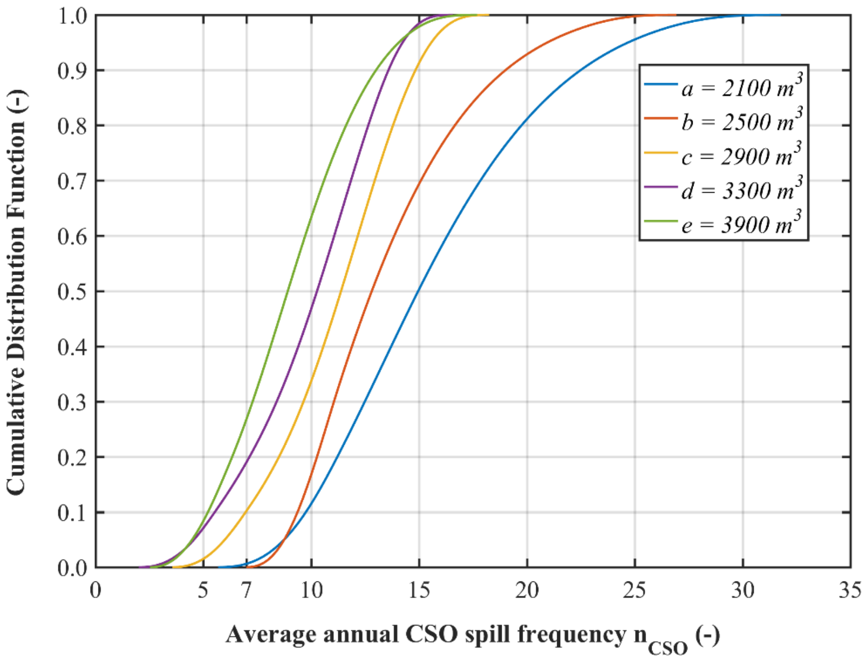

Fig. 4.3. Cumulative distribution function estimate of n_{CSO} for each decision alternative.

It is evident from both the Fig. 4.2 and 4.3 that increasing the size of the storage basin improves the performance with respect to the average annual CSO overflow frequency as the distributions shift towards the origin. Fig. 4.3 provides a clearer indication of the stochastic dominance of decision alternatives over each other. Specifically, a decision alternative x stochastically dominates another decision alternative y if

$$\forall\, n_{CSO} \in N, \qquad F_x(n_{CSO}) > F_y(n_{CSO}) \tag{4.1}$$

or alternatively

$$\forall\, h \in [0,1], \qquad F_x^{-1}(h) < F_y^{-1}(h) \tag{4.2}$$

where F and F^{-1} are the CDF and the inverse CDF of n_{CSO} respectively, and N is the set of feasible values of n_{CSO} and h is the probability value. The inverse CDF F^{-1} exists because the CDF is non-decreasing in its domain.

For a pair of decision alternatives, the alternative whose CDF curve is to the left of the other dominates (Fig. 4.3). For the alternatives *a* and *b*, alternative *b* stochastically dominates *a* for most of the uncertain range except for values in the left tail of the distributions where *a* dominates *b* (Fig. 4.3). However, the alternative *c* stochastically dominates *a* and *b* completely whereas *d* and *e* dominate *c* completely. Apart from stochastic dominance, Fig. 4.3 also provides information on the level of improvement in performance across the alternatives. However, this improvement in performance with the increase in storage capacity of the basin is not proportionate across the alternatives. For example, the level of improvement in performance appears to be quite significant between alternatives '*a* to *b*' and '*b* to *c*' compared to '*c* to *d*' and '*d* to *e*'. This can also be construed as the benefit of investment in extra storage is lower for larger storage basins.

4.3 Practitioners' response on uncertainty

The practitioners from a water utility company based in Flanders, Belgium were selected to provide insights on the evaluation of the decision alternatives from Section 4.2 when the performance variable is uncertain and represented by a probability distribution. In total 6 practitioners were approached for this exercise because of their extensive experience in modelling and designing urban drainage systems to improve the performance of Combined Sewer Overflows and the understanding of the applicable local regulatory requirements. Three of the practitioners had more than 20 years of working experience with urban drainage systems. The working experience of the other three practitioners ranged from 10 to 20 years.

4.3.1 Structure of the interviews

Each of the 6 practitioners was presented with the case study and the results from Section 4.2 and were asked a series of questions which led to the ranking of the decision alternatives based on their uncertain performance (Fig. 4.2 and 4.3) and the corresponding cost estimates (Table 4.2). An introduction on interpreting the probability distributions were provided to the practitioners before discussing the results. The practitioners were labelled as PR1, PR2, PR3, PR4, PR5 and PR6. Each interactive session with the practitioners took approximately 75 minutes.

The questions can be categorised into two broad categories: (1) Preference for a probability distribution of average annual CSO spill frequency; and (2) Trade-off between cost and performance of the decision alternatives.

Preference for the probability distributions

Given a probability distribution of the average annual CSO spill frequency, the practitioners were asked which features of the distribution they would consider important while making decisions. A probability distribution can be evaluated using its statistical moments such as the Mean (1st order moment), the Variance (2nd order moment), the Skewness (3rd order moment) or the probability of exceedance of a specified threshold (POE). While mean gives the estimate of expected value, variance provides a measure of how the data is distributed about the mean value. Skewness tells whether there is a symmetry in the distribution or not. The practitioners were asked whether they would consider the mean, variance, skewness and POE important when comparing probability distributions of a performance variable. If the answer were yes for any of these factors, they were asked their preferences for these factors and their relative importance to each other.

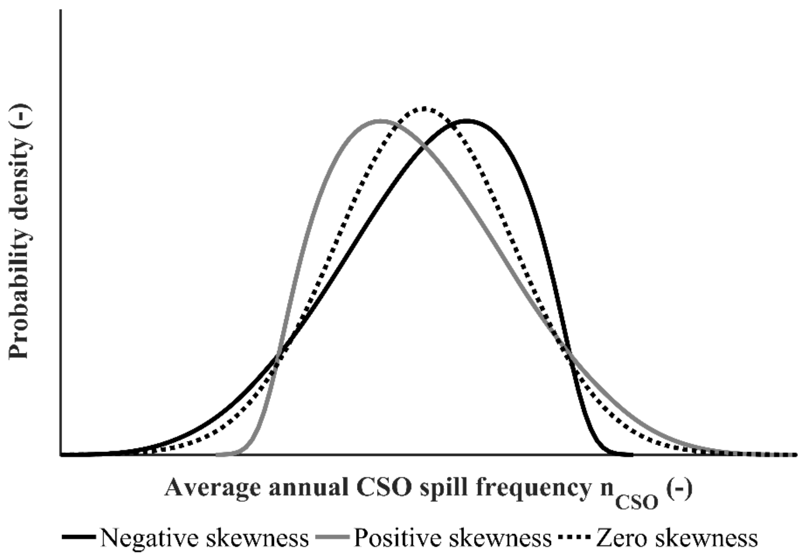

Fig. 4.4. Hypothetical probability distributions with different skewness

In order to determine their preferences for skewness, the practitioners were presented with Fig. 4.4 which displayed three hypothetical probability distributions of the emission quality indicator with equal mean and variance but different values of skewness. They were asked about whether they consider symmetry an important factor in comparing probability distributions. If the answer were yes, what would be their preference for symmetry? If a decision alternative results in a positively skewed distribution, it would have a longer right tail compared to a symmetrical distribution or a negatively skewed distribution, however, the mode of the distribution (most likely value of the average annual CSO spill frequency) would be lower. This means a positively skewed distribution will have a lower environmental impact on the receiving water bodies for most of the times while there will be a small probability that it could result in higher extreme values compared to other two distributions. Although a negatively skewed distribution does not have a longer right tail, it would result in a higher number of CSO spill events most of the times. Therefore, on a frequent basis, a negatively skewed distribution would be expected to have a worse environmental impact compared to a symmetrical and a positively skewed distribution but it also has less likelihood of very high number of CSO spill events which can be lethally degrading for the water quality. This is only valid under the assumption that when the number of CSO spill events is higher, the environmental impact on the receiving water body will become worse. However this assumption might not be true in all situations, because overflow frequency does not contain information about e.g. the pollutant concentrations in the individual spill events or, the dilution capacity of the receiving water at the time of a spill.

Trade-off between cost and performance of the decision alternatives

The cost was introduced as another performance criterion while comparing and ranking the decision alternatives because as much as the environmental performance is important, a measure of the ability of an organisation to implement solutions is also important. Fig. 4.3 shows that better performance can be achieved by investing in more expensive decision alternatives. A decision alternative can be found to provide a robust and reliable performance ensuring compliance with the regulations but if it violates the budgetary constraints of the water utility company, it will be difficult to implement and put in practice. Hence, a trade-off between cost and performance of the decision alternatives becomes very important.

The practitioners were asked to rank the decision alternatives based on the corresponding cost and performance with respect to their ability in reducing the average annual CSO spill frequency. The rationale behind this question was to find out how much importance the practitioners give to the environmental performance of a decision alternative with respect to the required investment to achieve this performance. In other words, the ranking provided by each individual indicated the risk behaviour of the individual indirectly. Although there is no financial penalty for worse environmental performance, it is assumed that there exists a non-monetary negative consequence if a decision alternative results in a high number of CSO spills. Therefore, the decision alternative *a* in Fig. 4.3 can be identified as riskier than the alternative *b* because the alternative *a* is more likely to result in high number of CSO spills compared to the alternative *b*.

4.3.2 Outcome of the interview sessions

The responses of the practitioners are summarised below according to the category of questions defined in Section 4.3.1.

Preference for the probability distributions

All the practitioners acknowledged the importance of mean and variance as representative features of a probability distribution. All of them agreed that while making decisions they would prefer a decision alternative with the lowest mean. Similarly, they would also select a decision alternative with a low variance. All the practitioners considered the probability of exceeding the threshold on n_{CSO} an important factor in comparing the alternatives. However, in the case of skewness which reflects the type of symmetry in a distribution, the practitioners had different perspectives. PR1 preferred a positively skewed distribution followed by the symmetrical distribution with the least preference given to a negatively skewed distribution. A similar preference was registered by PR6. Both the practitioners argued that CSO spills are frequent events rather than an extreme event with low probability and they considered the most likely value of the distribution more important than the right tail values. A positively skewed distribution has the lowest mode compared to the other two skewness types (Fig. 4.4), which means it will have a smaller number of CSO spills in a year for most of the time. Both PR1 and PR6 were prepared to accept the small chance in case the results predict a large number of CSO spills. PR2 and PR4 registered a similar preference for skewness as expressed by PR1 and PR6 but with certain conditions. While PR2 agreed that skewness is an important feature in comparing different distributions, it only mattered when the threshold on n_{CSO} is never exceeded or does not apply. However, if there is a chance that this threshold will be exceeded, a probability of exceedance should be treated as an important factor in the decision making process. In this case, PR2 did not consider the type of symmetry important. PR4 preferred a positively skewed distribution over symmetrical and negatively skewed distributions but only when there is less than 0.5 probability of exceeding the threshold. In this case, PR4 preferred the type of symmetry which ensured that the mode is farthest from the threshold. If a decision alternative results in a probability of exceedance greater than 0.5, PR4 would discard such decision alternative. When the threshold on n_{CSO} is never exceeded, PR4 preferred a negatively skewed distribution over the symmetrical distribution while giving the least preference to a positively skewed distribution. PR4 favoured the negatively skewed distribution because it did not have a longer right tail. PR4 argued that the simulation results can underestimate the physical behaviour of the system, therefore, even though the threshold is never exceeded as per the model predictions, in reality, it is possible that this threshold could be exceeded and this risk would be greater with a positively skewed distribution due to its longer right tail. PR4 further argued that the thresholds are defined as such to capture the environmental impact and favoured a negatively skewed distribution as long as the threshold was not breached, even though it had a higher mode compared to the other two types of symmetry. PR3 was found to be indifferent to the skewness. According to PR3, the symmetry of the distributions was not important enough to be included in the decision making process. PR5 could not express any preference for skewness.

Trade-off between cost and performance of the decision alternatives

According to the VMM guidelines, a CSO should not spill more than 7 times in a year on an average. In order to comply with this regulation, the required storage volume should be calculated by using the '*f7*' design storm with a runoff coefficient of 0.8 for impervious surfaces. Therefore, as per the design guidelines, the capacity of the storage basin should be 2958.1 m^3. A deterministic simulation based on design guidelines would indicate that decision alternative *c* should be selected. However, Fig. 4.2 and 4.3 show that all the alternatives fail the criterion of 7 average annual spills. All the practitioners attributed this to the variability in the rainfall input since the design storm '*f7*' is based on historical rainfall data from the year 1970 to 2007 whereas the case study ran simulations with historical rainfall from 2004 to 2013. Nevertheless, the decision alternatives *d* and *e* which had considerably bigger storage volume than 2958.1 m^3 were also found to be failing with more than 0.5 probability.

All the six practitioners ranked decision alternatives *a* and *b* the lowest amongst others due to longer right tail with extreme values. However, for *c*, *d* and *e* the ranking differed. Table 4.4 lists the ranking assigned by the practitioners to the decision alternatives.

Table 4.4. Ranking of the decision alternatives (lower value is better)

Decision alternatives	Practitioners					
	PR1	PR2	PR3	PR4	PR5	PR6
a	5	5	-	-	5	5
b	4	4	-	-	4	4
c	3	1	1	-	1	1
d	1	2	-	-	2	2
e	2	3	-	-	3	3

PR1 gave the decision alternative *d* the highest rank followed by *e* and *c*. PR1 argued that alternative *d* completely dominates *c* with an additional investment of 369,288 Euros whereas the difference in the performance of *d* and *e* is not significant given the substantial investment (554,536 Euros) required to upgrade from *d* to *e*. PR2 ranked the alternative *c* the highest followed by *d* and *e* as the 2^{nd} and 3^{rd} ranked alternatives respectively. PR2 remarked that on an average there is an improvement of around 1 CSO spill annually when upgrading from *c* to *d* and 1.5 CSO spills when upgrading from *d* to *e*. On the contrary, PR2 found a significant improvement in performance by upgrading from alternative *b* to *c*. PR2 further remarked that if the environmental impact of reducing 1 CSO spill annually is not known, decision alternative *c* appears to be the best candidate given the investment required in upgrading *c* to *d* or *e*. PR3 did not rank the alternatives because PR3 believed that CSO spill frequency is not a sufficient measure to capture the environmental impact of individual CSO spill events. However, given the local regulations use the CSO spill frequency as the criterion to control CSO structures, PR3 decided to choose an alternative with a small storage capacity i.e. alternative *c* with a phased investment plan which would include future interventions based on CSO monitoring. PR4 did not consider any of the alternatives suitable enough to limit the overflow frequency. PR4 decided to invest in a decision alternative with larger storage capacity than alternative *e* which would result in a probability of exceeding 7 CSO spills annually less than 0.5. Both PR5 and PR6 ranked the alternative *c* highest with *d* and *e* ranked 2^{nd} and 3^{rd} respectively. They both argued that the improvement in performance was not significant compared to the investment required if they were to choose alternative *d* or *e* instead of *c*. They provided a similar argument for ranking *d* higher than *e*.

4.4 Concluding remarks

Comparing decision alternatives on the basis of uncertain performance variable requires identification of decision maker's preferences towards the probability distribution of the performance variable. A case study site in Flanders, Belgium was used to model the impact of rainfall variability and uncertainty in runoff coefficient on the predictions of average annual CSO spill frequency. It was found that rainfall variability introduced through historical rainfall data from recent years (2004-2013) resulted in all the alternatives failing the regulatory requirement of 7 CSO spills annually on average. This could be partly due to the fact that the design guidelines use the '*f7*' design storm which is based on rainfall data from the year 1970 to 2007 while in this case study only 10 years of rainfall data from 2004 to 2013 was used. This could have resulted in a higher number of CSO spills annually even for the alternatives with substantially bigger storage capacity than the designed storage volume. For the period of 2004 to 2013, it can be concluded that the design criteria underestimated the storage volume required to comply with the regulation of maximum 7 spills in a year on average. Based on these findings, it can be argued that the use of historical rainfall data would reflect the local catchment characteristics better than the 'f7' storm. This would result in a more transparent performance assessment of proposed solutions. It is further suggested that the modelled performance should be validated against the monitored data on CSO spills to identify the error in model predictions.

Experienced practitioners working at a Belgian water utility company were asked to compare and evaluate decision alternatives based on uncertainty in their performances with respect to average annual CSO spill frequency and the corresponding investment costs. The practitioners were asked to indicate important features of a probability distribution of the performance variables and register their preferences for such features. Finally, the practitioners were asked to rank the alternatives through a trade-off between the uncertain performance variable and the cost of implementing the alternatives.

There was a consensus among the practitioners about the preference for mean and variance of the probability distribution of average annual CSO spill frequency. The practitioners preferred lower values of mean and variance in comparing distributions. All the practitioners found the probability of exceeding the threshold an important feature of the probability distribution in case the threshold were to be exceeded. While there was a general consensus on the positively skewed distribution as the preferred symmetry type over symmetrical and negatively skewed distribution, the preference for positive skewness was found to be dependent on the threshold being exceeded or satisfied. One practitioner was found to be indifferent to the type of symmetry of distributions, another preferred a negatively skewed distribution if the threshold on average annual CSO spill frequency were never to be exceeded. Overall, the majority of the practitioners treated the CSO spill events as a frequent phenomenon and considered a positively skewed distribution to have the lowest environmental impact most of the time if the overflow frequency were to be the sole criterion to assess the environmental impact.

While ranking the alternatives based on a trade-off between cost and the CDF curve of the performance variable, four out of six practitioners adopted a balanced approach between the two criteria. Their evaluation was based on whether the improvement in environmental performance was justified with additional investment or not. Even though alternatives *d* and *e* were found to be stochastically dominating to the alternative *c* with respect to CSO spill frequency, the four practitioners could not justify this improvement against the additional investment required to achieve such improvement in performance. One practitioner was found to be more risk-averse than others. Since all the proposed alternatives were found to be failing with respect to the regulatory requirement on CSO spills, this practitioner chose to select a more expensive solution than the alternative *e* which would ensure that the probability of exceeding the threshold of 7 is less than 0.5. The ranking of decision alternatives by the practitioners indicates that (i) the practitioners in general did not select the most stochastically dominant alternative for the environmental performance, (ii) the respective weights assigned to the two criteria, the environmental performance and the cost were found to be not uniform across different practitioners. Therefore, such decision problems which involve multiple criteria should be formulated as multi-objective decision models which reflect the trade-off between such criteria. Additionally, selection of the best or optimal decision alternative should only be done a posteriori unless the weights of the individual criteria can be determined and formulated in the multi-objective model accurately. From a water utility's perspective, failing to determine and/or formulate the criteria weights accurately which do not reflect the company's policy can lead to the selection of sub-optimal decision alternatives.

Overall, the practitioners were willing to accept some level of risk based on whether the additional investment on storage basin was justified and concurred that other forms of cost-effective solutions were needed to be evaluated to further reduce the risk of CSO spills exceeding 7 times in a year.

5. Stochastic decision models to manage sewer overflow quality failure

5.1 Introduction

Few studies which account for modelling uncertainty in making decisions to reduce the negative environmental impact of CSO spills have been reported. Reda and Beck (1997) modelled stormwater management strategies under uncertainty and used the extreme values i.e. maximum rates of mass flow of ammonium-N and Biological Oxygen Demand (BOD) and minimum DO concentration to rank the strategies. Portielje et al. (2000) performed a risk analysis using stochastic reliability methods and defined risk as the probability of exceeding extreme concentrations of dissolved oxygen levels in a stream. A risk-based economic optimization of in-sewer storage was implemented in Korving et al. (2009). This optimization accounted for the variability in rainfall and uncertainty in the sewer system dimensions, and uncertainty in the cost of damage from CSO spills. Impact of rainfall variability and uncertainty in the sewer system dimensions on the decision making was reflected through the probability of exceeding a threshold on CSO volume which was termed as failure probability. Recently, Meng et al. (2016) proposed a decision analysis framework to find optimal operation strategy to minimize the environmental impact of urban wastewater systems. The uncertainty in the performance of the system was evaluated by using an input data set from a different location as a worse scenario, however, the modelling uncertainty was not considered in this study. The decision framework (Meng et al., 2016) included the standard deviation of total ammonia concentration (NH_3-N) in wastewater treatment plant effluent and environmental risk based on the probability of exceeding a threshold of NH_3-N concentration in the river.

Although the aforementioned studies have incorporated uncertainty in the assessment of urban drainage processes in some form, they have not fully captured the uncertainty in the model prediction of the system performance. For example, Reda and Beck (1997) only considered extreme values and Korving et al. (2009) used the probability of exceeding a threshold. Meng et al. (2016) did consider standard deviation of total ammonia concentration in the wastewater treatment plant effluent to reflect the stability of the treatment process but only to reflect the variation in total ammonia concentration within a time series for different operational scenarios. The probability of exceeding a threshold only gives an indication of chance that this threshold will be exceeded however it does not provide any information about the magnitude of exceedance beyond the threshold. Similarly, these studies do not capture the difference in asymmetry of the probability distributions and the decision maker's preference with regard to such distributions. Therefore, this chapter aims to develop a decision model that includes all the information about uncertain system performance which is relevant to the decision maker.

Considering the previously stated limitations, this chapter presents two decision models to inform investment to manage emission quality failure accounting for modelling input and parameter uncertainty. The first decision model is a multi-objective formulation to reflect decision maker's objectives and risk-averse preferences regarding the uncertainty in the modelling of system performance and the cost of any proposed solutions. The second decision model identifies optimal solutions by comparing the CDFs of the corresponding emission quality performance variable of the decision alternatives to a target function encompassing the preferences of the decision maker. The proposed decision models are demonstrated using a case study located in Luxembourg.

5.2 Background and Methodology

5.2.1 Risk-averse decision making

The objective of a risk-averse decision making process is to find optimal solutions which reduce the predicted risk of emission quality failure caused by CSO spills while complying with the constraints imposed by the environmental regulations and minimising the costs of implementation. For example, a water utility might be required to meet a certain threshold T on the number of CSO spill events causing emission quality failures. However, uncertainty in the simulation of the frequency of such events results in an uncertainty in the predicted performance of any proposed solution to reduce this frequency.

One of the most popular approaches for risk-averse decision making has been the mean-variance approach developed by Markowitz (1952) in the field of finance. The basic assumption of this approach is that variance can be used as a measure of risk and the decision maker should search for a solution with minimum variance for a given expected return on investment. In the context of emission quality failure, the decision criterion can be translated as minimum variance for a given expected number of CSO spill events causing emission quality failures. Alternatively, a bi-objective decision problem can be formulated to search for solutions which result in minimum mean and minimum variance of the number of failure events. However, the mean-variance approach has certain limitations as it assumes that statistical distributions are Gaussian. The other limitation is that minimising variance penalizes distributions at both tails. For the number of CSO spill events that cause emission quality failures n, the decision maker would desire to limit the spread only on the right side of the probability distribution function (PDF) of failures, i.e. to limit high values of n because values of n greater than the threshold T would result in a breach of the environmental regulation.

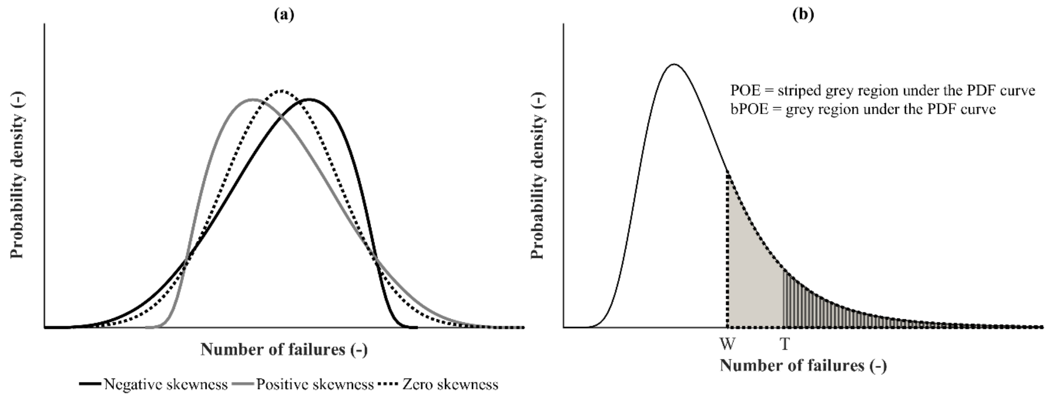

Fig. 5.1. (a) Difference in skewness for distributions with identical mean and variance. (b) Illustration of Probability of Exceedance and Buffered Probability of Exceedance for a threshold T on the number of failures.

The issue of non-normal distributions can be dealt with by considering the skewness of the distribution as one of the decision criteria such as the Mean-Variance-Skewness approach (Konno and Suzuki, 1995). Konno and Suzuki (1995) argued that the skewness of the distributions had a significant influence on the optimal selection of decision alternatives and proposed that the decision maker would prefer to maximise the skewness for the rate of return on investments. However, unlike the rate of return on financial investments, the decision maker's preference for the skewness may not clearly be defined for CSO spill events causing emission quality failure. A positive value of skewness means that the distribution of failed events will have a longer right tail compared to the left tail of the distribution. The presence of a longer right tail means a possibility of higher values of n compared to a symmetrical distribution with identical mean and variance (Fig. 5.1a). As a result, the mean of a positively skewed distribution will be higher than the mode (most likely value) of the distribution. Similarly, a negative value of skewness implies the distribution has a longer left tail compared to its right tail causing the mean to be lower than the mode of the distribution. It can be argued that both types of asymmetry have distinct advantages and disadvantages in the context of managing the possibility of emission quality failure caused by CSO spills. A positively skewed distribution will have a lower mode compared to the negatively skewed distribution which means most likely realizations of n will be less than that of the negatively skewed distribution. Therefore, a decision maker who is more concerned about the most frequent number of failure events and is prepared to absorb the small chance of a higher number of failures would prefer a positively skewed distribution. On the contrary, a decision maker who seeks to limit the possibility of high values of n would prefer a negatively skewed distribution.

Variance as a measure of risk in the Mean-Variance-Skewness approach does not address the risk of exceeding a threshold T imposed by the environmental regulations. The probability of failing this set criterion can be calculated as the Probability of Exceedance (POE). If n is a random variable representing the number of CSO spill events causing emission quality failures and T is the threshold set by the local environmental regulator for such failure events, POE for threshold T can be defined as

$$p_T(n) = P(n > T) \tag{5.1}$$

However, the POE and the threshold T do not give a clear picture of heavy-tailed distributions e.g. they do not give any information on the magnitude of the tail beyond the threshold T. Uryasev (2014) proposed a probability measure Buffered Probability of Exceedance (bPOE) to account for the tail probability and the magnitude of the tail beyond the threshold T. The Probability of Exceedance gives the likelihood that the threshold T will be exceeded, whereas the Buffered Probability of Exceedance gives the likelihood that the average of the distribution's upper tail will be equal to the threshold T (Davis and Uryasev, 2016). Consider a quantity W in the uncertain range of n such that $T = E[n|n > W]$, where $E[n|n > W]$ is the conditional expectation of the number of emission quality failure events n exceeding

W (Fig. 5.1b). From Mafusalov and Uryasev (2014) and, Davis and Uryasev (2016), the Buffered Probability of Exceedance (bPOE) for threshold T can be defined as:

$$\overline{p_T}(n) = p_W(n) = P[n > W] \qquad (5.2)$$

Since, $T \geq W$, there exists an inequality between $\overline{p_T}(n)$ and $p_T(n)$ which can be expressed as:

$$p_T(n) \leq \overline{p_T}(n) \qquad (5.3)$$

The inequality in (5.3) implies that the bPOE is a conservative estimate of the POE because it accounts for the magnitude of the tail in addition to the probability (Fig. 5.1b). Hence, it proves to be a better measure than the POE if the decision maker is risk-averse and is interested in comparing the tail performance of proposed solutions to limit the occurrence of emission quality failures.

Building on the arguments stated above, a model is proposed for risk-averse decision making to identify solutions where the decision maker is seeking to minimize the risk of non-compliance with the environmental regulations while minimizing the cost of such solutions. The decision model consists of four objectives: (i) Minimizing the expected number of emission quality failures due to CSO spills E[n]; (ii) Minimizing the bPOE for a defined threshold on the number of emission quality failures; (iii) Maximizing or Minimizing the skewness of the distribution of n; and (iv) Minimizing the cost of the proposed solution.

Since the preference for the shape of the distribution is specific to the application and the individual's risk behaviour, two versions of the multi-objective decision model are proposed to reflect the differing preferences for the skewness.

5.2.2 Formulation of the multi-objective decision model

This section presents the mathematical formulation of the proposed risk-averse decision model to manage emission quality failure under modelling uncertainty. Consider a quantity $n = f(s, u)$ which represents the response of an urban drainage system model with decision variables $s \in S$ where S is the decision space, and uncertain variables $u \in U$. Let us assume that uncertain variables u represent the uncertainty in the modelling of the urban drainage system response n defined on the uncertainty space U. For a given $s \in S$, uncertain variables u will result in random realizations of the quantity of interest n which can be represented by $n_s = f_s(\mathrm{s}, u)$.

The two risk-averse decision models D1 and D2, are posed as multi-objective problems:

$$\text{D1}:\begin{cases} \min_{s\in S} E[f_s(s,u)] \\ \min_{s\in S}\ \overline{p_T}\big(f_s(s,u)\big) \\ \max_{s\in S}\text{skewness}\big(f_s(s,u)\big) \\ \min_{s\in S}\text{cost}(s) \end{cases} \tag{5.4}$$

$$\text{D2}:\begin{cases} \min_{s\in S} E[f_s(s,u)] \\ \min_{s\in S}\ \overline{p_T}\big(f_s(s,u)\big) \\ \min_{s\in S}\text{skewness}\big(f_s(s,u)\big) \\ \min_{s\in S}\text{cost}(s) \end{cases} \tag{5.5}$$

subject to $\quad u \in U$

The optimal solutions can be found by considering either D1 or D2 as an objective function in a Multi-Objective optimization search algorithm. Due to a lack of information about the decision maker's relative preference for the individual objectives, the objectives in the decision model are treated as equally preferable to each other.

5.2.3 Pareto non-dominance

The multi-objective formulation of D1 or D2 will not necessarily lead to a single optimal solution due to the conflicting nature of the objectives, such as minimizing the cost against minimizing the bPOE or the mean of n_s. Hence, the objective is to search for non-dominated solutions in the decision space S. The dominance of one solution to the other is established by determining the Pareto optimality of the decision variables in the decision space S against the individual objectives. A Pareto optimal solution can be defined as the solution for which improvement of one objective is not possible without worsening at least one of the other objectives. According to De Weck (2004) the dominance of one solution to the other can be defined as follows:

For two solutions s^1 and $s^2 \in S$, s^1 dominates s^2 if and only if

$$\begin{gathered} s_i^1 \geq s_i^2 \ \ \forall\, i \\ \text{and } \ s_i^1 > s_i^2 \text{ for at least one objective in } i \end{gathered} \tag{5.6}$$

where i is the set of objectives.

Therefore, a solution s^* is Pareto optimal such that there exists no $s \in S$ which satisfies the following equalities (Hu et al., 2013):

$$\begin{aligned} & s_i^* \geq s_i \ \forall\, i \\ \text{and} \ \ & s_i^* > s_i \text{ for at least one objective in } i \end{aligned} \tag{5.7}$$

Solving the multi-objective decision problem D1 or D2 by searching for non-dominated solutions as per Eq. 5.6 and 5.7 will result in a set of Pareto optimal solutions s^*.

5.3 Case Study: The Haute-Sûre Catchment in Luxembourg

In this section, a case study is presented to demonstrate the risk-averse decision making approach proposed in Section 5.2 to reduce the risk of regulatory emission quality failures caused by CSO spills. The case study catchment is the Goesdorf sub-catchment which is part of the Haute-Sûre catchment in the north-west of Luxembourg. The sub-catchment has a sewer system which is combined and has a CSO structure composed of a storage tank and a weir to divert the sewage towards the receiving water body, a tributary of the Sûre river. It is known that overflow spills occur due to both intense and long storm events. The catchment of the Haute-Sûre sewer system is important from the point of view of water quality because it includes the Haute-Sûre lake, a man-made reservoir established as the main source of raw water serving 70% of the Luxembourg population (Gillé et al., 2008).

5.3.1 Compliance with the environmental regulations

This chapter studies the uncertainty in the estimation of the ammonium concentration in the combined sewer overflow and applies the risk-averse decision model to find solutions which reduce the risk of emission quality failure caused by ammonium in the sewer overflows. The concentration-duration-frequency based criterion for allowable ammonia in a receiving water body due to CSO spills specified by the Austrian water wastewater association (ÖWAV) is applied in this case study as an indicative emission quality standard (Fenz and Kroiss, 2004; ÖWAV-Regelblatt 19, 2007). This criterion for acute ammonia toxicity comprises separate thresholds for cyprinid and salmonid aquatic species in the receiving water body. The concentration of ammonia in the receiving water body due to the combined sewer overflow should not be more than 5 mg/l for one hour for cyprinid and 2.5 mg/l for salmonid species

(Fenz and Kroiss, 2004; ÖWAV-Regelblatt 19, 2007). According to the ÖWAV guidelines, the maximum allowable number of CSO spill events failing this criterion for acute ammonia toxicity is 1 per year. For the purpose of demonstrating the methodology, this case study applies the criterion for salmonid species on the ammonia concentration in the combined sewer overflow to identify overflow events considered to fail this criterion since the dilution of ammonia in the receiving water body is not simulated. The simulated concentration of ammonia in the overflow will be higher than the concentration of ammonia in the receiving water body due to dilution and this is a limitation of the current case study.

Therefore, compliance with the environmental regulation in this chapter means that a solution is required which ensures that the number of CSO spill events with ammonia concentration more than 2.5 mg/l for one hour does not exceed 1 in a year. The scope of this case study is to find optimal solutions which reduce the risk of non-compliance with the environmental regulation while minimising the cost. The performance of the proposed solutions under modelling uncertainty is evaluated using an open source CSO emission quality simulator EmiStatR developed by the Luxembourg Institute of Science and Technology (LIST).

5.3.2 The EmiStatR model

EmiStatR is the simulator used for propagating input and model parameter uncertainties in the simulation of NH_4-N concentration in the CSO spills (Torres-Matallana et al., 2016; Torres-Matallana et al., 2015). EmiStatR (Emissions and Statistics in R for Wastewater and Pollutants in Combined Sewer Systems), is a simplified urban drainage model to simulate CSO spill volume and load and concentration of ammonium (NH_4-N) in combined sewer systems. The EmiStatR simulator is divided into six main components to simulate CSO spill quantity and quality: (i) Computation of dry weather flow; (ii) Definition of water quality characteristics of the dry weather flow; (iii) Computation of rain weather flow in the sewer network with contributions from urban and rural run-off; (iv) Definition of water quality characteristics of rain weather flow from urban and rural wash-off; (v) Computation of combined sewage flow and characteristics of water quality variables in the combined sewage flow; and (vi) Computation of CSO spill volume and NH_4-N concentration.

A comprehensive description of the EmiStatR model and the Goesdorf sub-catchment can be found in Torres-Matallana et al. (2016). The model was hydraulically calibrated with measured data available for the case study catchment. For the validation data set which included measured rainfall time series from 3 June 2011 to 7 July 2011, the model displayed a good agreement (Nash–Sutcliffe Efficiency, NSE = 0.843) between the simulation results and the water quantity observations.

In the absence of water quality observations, the EmiStatR was validated using a detailed full hydrodynamic sewer network model of the catchment built using the software InfoWorks ICM 7.5. The comparison of EmiStatR and InfoWorks ICM simulations were done using 1 year-long rainfall measurements with 10-minute resolution. A good agreement (NSE = 0.904) was found between the EmiStatR and the InfoWorks ICM model for calculating the ammonium load.

5.3.2.1 Decision variables

To limit the number of CSO spill events failing the regulatory criterion defined in section 5.3.1, the storage capacity of the tank at the CSO and a reduction in the impervious area by the use of permeable paving are considered as the two potentially practical decision variables. The permeable paving is assumed to convert the impervious area into the pervious area. Consequently, the runoff calculations apply pervious runoff coefficients as model parameters for such paved area.

Combinations of different capacities of the storage tank and different values of the reduced impervious area are modelled and evaluated against the regulatory criterion and their respective costs. A range of 100 m^3 to 700 m^3 with 50 m^3 increment is considered for storage tank capacity and the impervious area is reduced from 25 ha to 20 ha with an increment of 0.5 ha. Therefore, the decision space S becomes a discrete space of 143 grid points with the decision variable s representing a grid point of the decision space S.

5.3.2.2 Cost of the decision variable *s*

Since the information about the investment cost of storage tanks and the cost of permeable paving is not available for Luxembourg, estimates from the UK are used in this study for demonstration purposes. The construction of concrete storage tanks can cost in the range of £1400 - £2000/m^3 for areas outside London whereas the implementation of permeable paving can cost approximately from £250 - £350/m^2 (Digman, 2018). These estimates can vary depending on the construction company and where the catchment is located. The average values of these ranges i.e. £1700/m^3 for the storage tank and £300/m^2 for the permeable paving, have been used in this study to calculate the cost of the decision variable s. However, it should be noted that the actual costs are expected to be different for Luxembourg from the estimates used in this chapter.

Cost of the decision variable

The cost of each decision variable $s \in S$ is calculated by adding the cost of the corresponding storage tank proposed in the solution and the cost in reducing the impervious area from 25 ha to the impervious area proposed in the solution.

5.3.2.3 Definition of uncertain variables

Table 5.1 presents the list of the uncertain variables along with the decision variables for the Goesdorf sewer system. To quantify the uncertainty in the simulation of ammonium concentration in the CSO spill, uncertainty in the rainfall precipitation, ammonium concentration in the dry weather flow, and the pervious and impervious runoff coefficients are represented. Measured data to characterise the temporal variability of the ammonium concentration in the surface runoff is not available. Hence, uncertainty in this variable cannot be accounted for. A constant value of 1 mg/l (Welker, 2007) is chosen to represent the ammonium concentration in the surface runoff. Before the uncertainty propagation is done, probability distribution functions of the selected inputs are characterised to define the input uncertainty (Heuvelink et al., 2007). For the concentration of ammonium in the dry weather flow $C_{NH4,s}$ as a variable for uncertainty propagation, it is possible to simulate $C_{NH4,s}$ by an autoregressive order one AR(1) model (Box & Jenkins, 2008):

$$y_t = \mu_1 + \varphi_1(y_{t-1} - \mu_1) + w_t, \ \ \varphi_1 \neq 0 \tag{5.8}$$

where y = Univariate variable $C_{NH4,s}$; t = Time; μ_1= Mean of the simulated variable; φ_1= Constant coefficient of autocorrelation; w_t = Gaussian white noise time series with mean zero and variance $\sigma_w{}^2$.

Since the rainfall precipitation time series is highly skewed due to many zero values, it is required to apply a different approach for characterising uncertainty in the rainfall precipitation time series.

Table 5.1. List of uncertain and decision variables

Variable	Assumed to be uncertain? (yes/no)	Definition of uncertainty
Uncertain Variables		
Wastewater		
Pollution NH_4-N, $C_{NH4,s}$ [g/(PE·d)]	yes	Autoregressive model[a] calibrated on measured data
Rainwater		
Precipitation time series, P [mm/Δt]	yes	Multivariate Autoregressive model[b] calibrated on measured data
Catchment data		
Run-off coefficient for impervious area, C_{imp} [-]	yes	$N(0.8, 0.05^2)$ truncated at 1[c]
Run-off coefficient for pervious area, C_{per} [-]	yes	$N(0.3, 0.05^2)$ truncated at 0[c]
Decision Variables		
Catchment data		
Impervious area, A_{imp} [ha]	no	-
CSO structure data		
Volume, V [m^3]	no	-

[a]Box et al. (2008), [b]Torres-Matallana, et al. (2017), [c]McCuen (1998).

A multivariate autoregressive modelling and conditional simulation of precipitation time series from Torres-Matallana et al. (2017) is used to simulate precipitation time series in the Goesdorf catchment given known precipitation time series in two nearby locations outside the catchment while accounting for the uncertainty that is introduced due to spatial variation in precipitation.

McCuen (1998) reported a range of 0.25-0.40 for the runoff coefficient of pervious surfaces and a range of 0.70-0.95 for impervious surfaces. Since the runoff process from the catchment surfaces is a natural process, a symmetrical normal distribution is assumed to represent the uncertainty in the runoff coefficients. A normal distribution with mean 0.30 and standard deviation of 0.05 is used for the runoff coefficient of pervious surfaces so that about 95% of the runoff coefficient values lie in the range 0.20-0.40. Similarly, the runoff coefficient for impervious surfaces is assumed to follow a normal distribution with mean 0.8 and standard deviation of 0.05 where about 95% of values lie in the range 0.70-0.90.

5.3.3 Solving the Risk-averse decision model

The decision models D1 or D2 presented in Section 5.2.2 can be solved using popular continuous optimization algorithms such as the non-dominated sorting genetic algorithm (NSGA-II) developed by Deb et al. (2002) which has been successfully applied to urban wastewater systems (Fu et al., 2008). However, the decision space S in this case study is discrete and finite and comprises 143 grid points making it possible to search the entire decision space. In this case, a direct grid search approach (Powell, 1998) ensures a complete coverage of the discrete decision space with a finite number of evaluation points compared to an evolutionary search algorithm such as NSGA-II. It can be argued that a decision maker who is planning to increase the size of the storage tank will be indifferent to an increment of less than 50 m^3. A minimum reduction of 0.5 ha of impervious area is selected based on the similar argument. These choices for the decision space are specific to this case study.

The decision models D1 and D2 from Eq. (5.4) and (5.5) are solved by calculating the individual objectives for each decision variable $s \in S$ through direct grid search. To calculate the objectives in Eq. (5.4) or (5.5), for each of the 143 grid points in the decision space S, $n_s = f_s$ (s, u) is calculated where n_s is the variable for number of CSO spill events with ammonium concentration more than 2.5 mg/l for one hour, s is the grid point representing decision variable and u is the uncertainty defined in section 5.3.2.3.

For each $s \in S$ the uncertainty u in the inputs and model parameters listed in Table 5.1 are propagated through 500 Monte Carlo simulation runs. The number of total simulation runs is selected based on a convergence test for ammonium load and concentration in the CSO spill. These Monte Carlo simulations result in 500 random samples of year-long time series of NH_4-N concentration in the CSO spill. The regulatory criterion of NH_4-N concentration > 2.5 mg/l for one hour is applied to calculate the number of CSO spill events for every random time series. This results in 500 random samples of the number of CSO spill events n_s for each $s \in S$.

Individual objective functions of the decision models are calculated using the random samples of n_s $\forall$ $s \in S$. The decision variables s i.e. the 143 grid points in the decision space S are compared to each other for Pareto non-dominance by using inequality Eq. (5.6). All the grid points which satisfy the inequality Eq. (5.7) are selected as Pareto optimal solutions which represent the optimal trade-off between the individual objectives set by the decision maker. The steps involved in identifying the Pareto optimal solutions for the decision models D1 and D2 are outlined in Fig. 5.2.

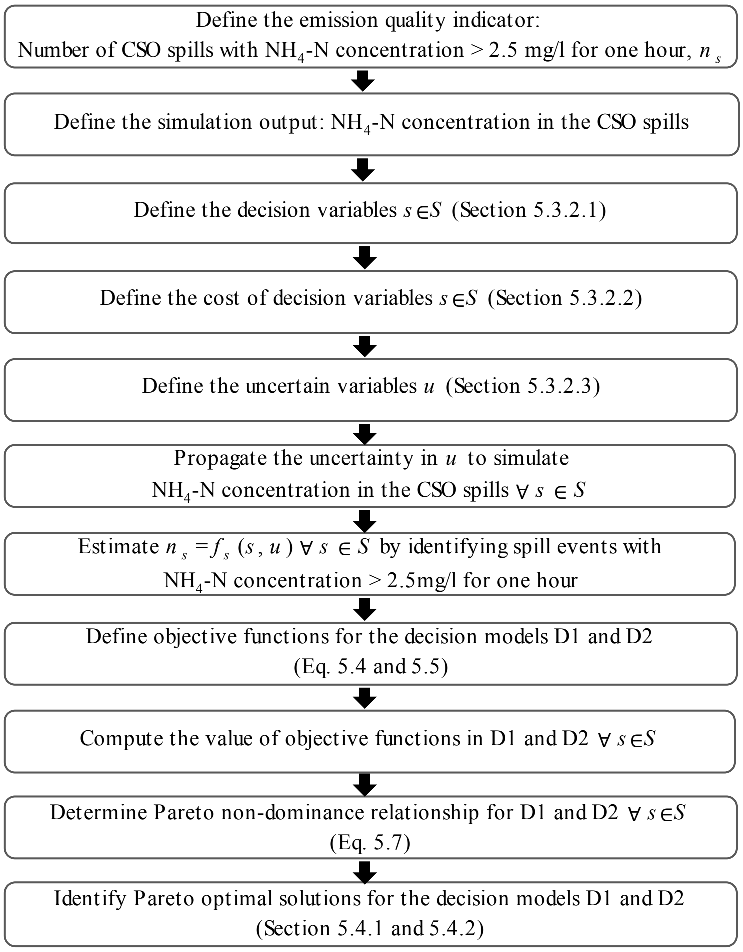

Fig. 5.2. Steps followed to identify Pareto optimal solutions for D1 and D2.

5.4 Results and Discussion

The decision models D1 and D2 are solved for the case study presented in Section 5.3 with decision variables s defined in Section 5.3.2.1 and uncertain variables u defined in Section 5.3.2.3. Computation of objectives for one grid point took approximately 150 minutes using a computer equipped with Intel Xeon 3.50 GHz processor, 32 GB of RAM and 7 cores.

Fig. 5.3 shows the difference in POE and bPOE for ∀ $s \in S$. It is evident how the magnitude of the tail values in the distribution of n_s affects the value of bPOE. For POE values greater than 0.28, the bPOE is 1 which indicates the difference in the magnitude of extreme values.

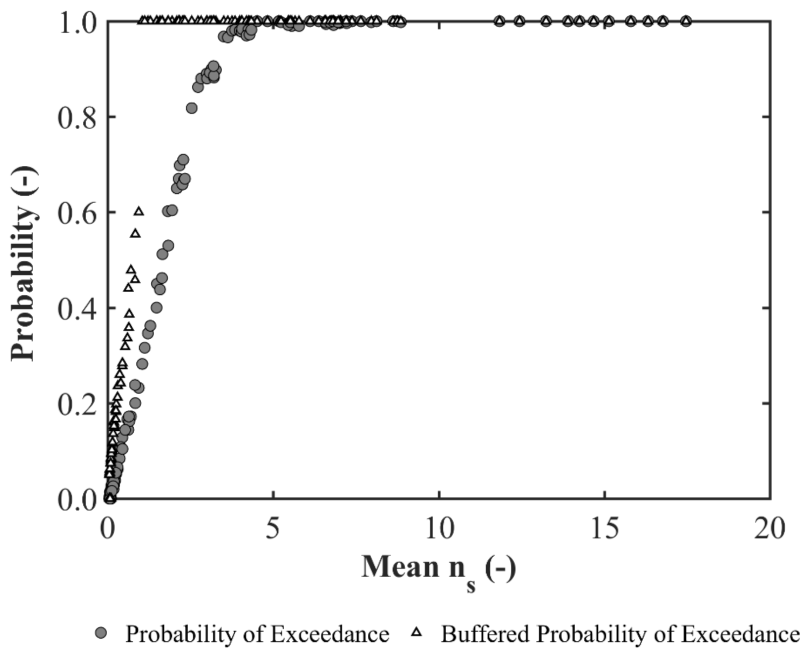

Fig. 5.3. Mean of n_s vs Probability of Exceedance (POE) and Buffered Probability of Exceedance (bPOE) for ∀ $s \in S$

The results for Pareto optimal solutions are presented separately for the decision models D1 and D2 which reflect the different preferences for skewness of the distribution of n_s.

5.4.1 Decision model D1: Preference for positively skewed distributions of n_s

For decision model D1, 18 solutions were found to be Pareto optimal out of total 143 solutions (Fig. 5.4). Fig. 5.4a and 5.4b show the variation in the calculated mean of n_s and bPOE respectively for all $s \in S$ where the decision variable s comprises combinations of storage tank volume and the impervious area.

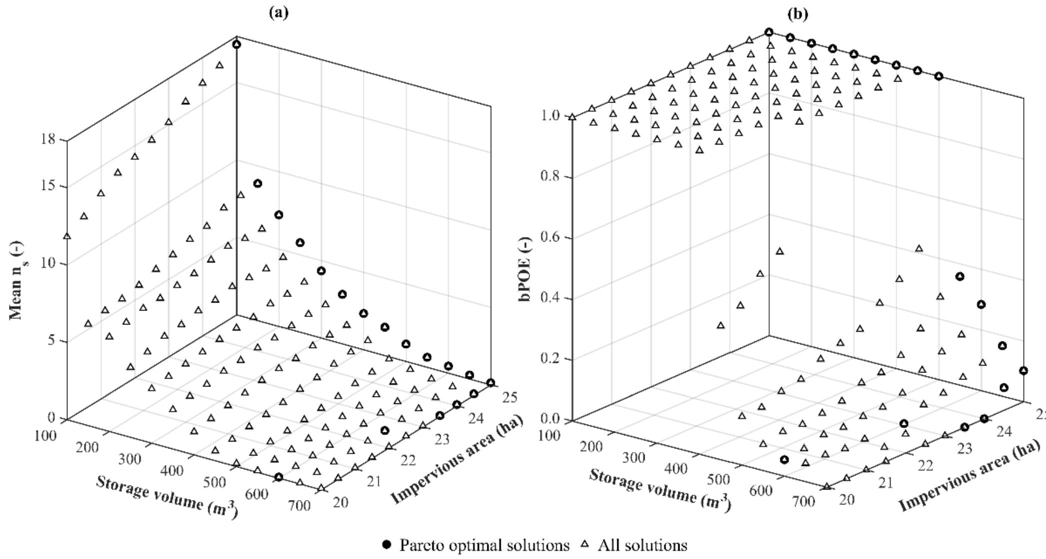

Figure 5.4. (a) D1: Mean of n_s in the discrete decision space *S*; (b) D1: bPOE in the discrete decision space *S*

As expected, the mean of n_s decreases with an increase in storage tank volume and/or a decrease in impervious area. The Pareto optimal solutions representing the optimal trade-off between the four objectives: Minimising the mean of n_s; Maximising the skewness of n_s; Minimising the bPOE and Minimising the cost of s, are displayed as data points in a solid black circle in Fig. 5.4. It can be observed that the Pareto optimal points tend to favour storage tanks with large capacity than a substantial reduction in the impervious area. This is due to the comparatively higher cost of reducing the impervious area. Also, the decrease in the mean of n_s is steeper for an increase in storage tank capacity. For example, at the storage tank capacity of 100 m^3, the mean n_s reduces from 17.5 to 11.8 when the impervious area is reduced from 25 ha to 20 ha. On the contrary, at the impervious area of 25 ha, the mean of n_s reduces from 17.5 to 0.1 when the storage tank capacity is increased from 100 m^3 to 700 m^3. Since the cost of reducing the impervious area is much higher than the cost of increasing the storage tank capacity, the improvement in environmental performance per unit value of cost is found to be higher for the storage tank. A similar trend can be observed for bPOE values (Fig. 5.4b). Fig. 5.5 shows the variation in the mean of n_s, the skewness of n_s, the bPOE and the cost for the Pareto optimal solutions. Since the decision model D1 specified a preference for minimizing the mean while maximizing the skewness, the Pareto optimal solutions tend to lie in the lower region of the plot as expected. Similarly, Pareto optimal solutions tend to lie towards low cost and low bPOE values, however, there are few Pareto solutions which have either very high cost and low bPOE or high value of bPOE and low cost. This can be attributed to an equal preference for all the objectives which means that these solutions must have performed well for other objectives compared to the non-optimal solutions with similar cost or similar bPOE e.g. the Pareto optimal solution with very high cost has a very low value of bPOE. A decision maker whose preferences are specified by the decision model D1 would select a solution from the lower region of Fig. 5.5 with a dark blue coloured marker. A parallel coordinate plot is provided in Appendix C which maps the Pareto optimal solutions to their corresponding objective function values (Fig. C.1).

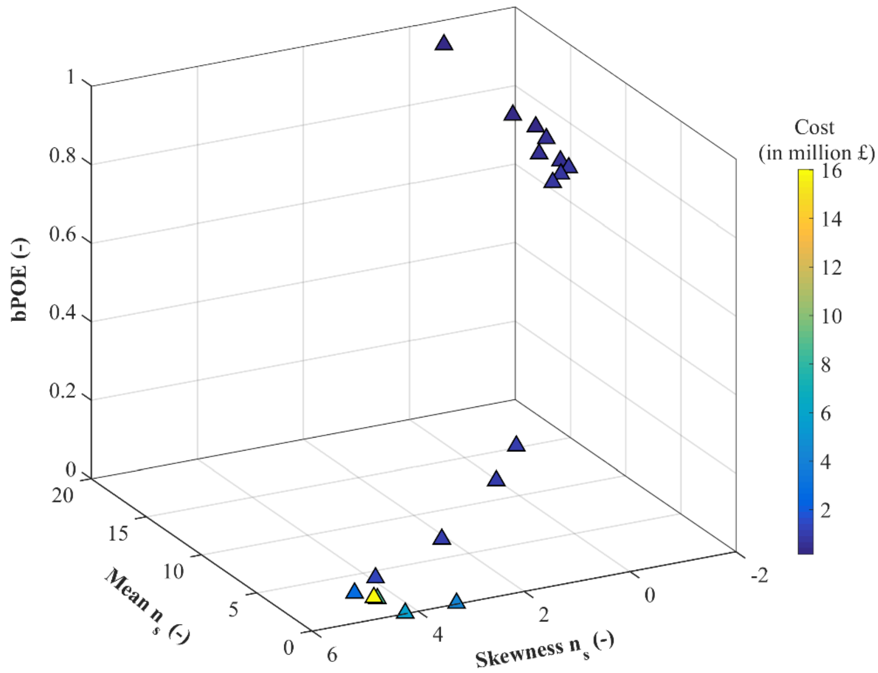

Fig. 5.5. D1: Objective function values of Pareto optimal solutions

5.4.2 Decision model D2: Preference for negatively skewed distributions of n_s

For decision model D2, 88 solutions were found to be Pareto optimal out of total 143 solutions (Fig. 5.6). This substantial increase in the number of Pareto optimal solutions compared to the decision model D1 is because solutions with higher mean have low skewness values (Fig. 5.5).

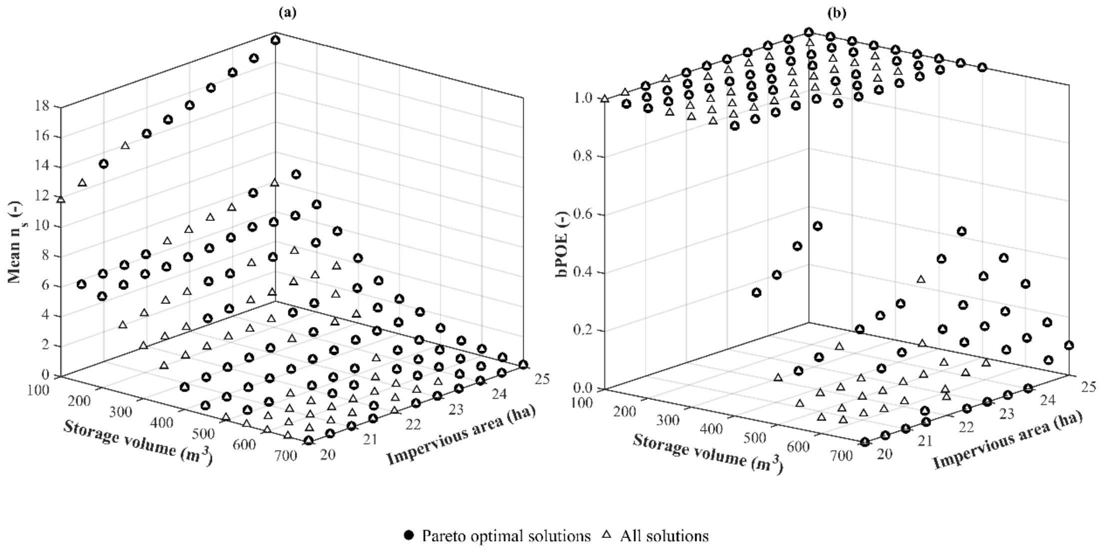

Fig. 5.6. (a) D2: Mean of n_s in the discrete decision space S; (b) D2: bPOE in the discrete decision space S

Therefore, solutions which have relatively high mean are also Pareto optimal solution because they satisfy the objective of minimizing the skewness (Fig. 5.7). Because of the decision maker's objective to minimize skewness, the Pareto non-dominance results in a diverse range of Pareto optimal solutions as far as cost and bPOE are concerned (Fig. 5.7).

Compared to Fig. 5.5, a higher number of Pareto optimal solutions have very high cost and (or) high bPOE values and this is due to the equal preference for all the four objectives. In such situations, preference for individual objectives needs to be updated in order to reflect the scope of the decision making. For example, in this case study, the primary goal of the decision maker could be compliance with the environmental regulations while minimising the cost. Therefore, the Pareto optimal solutions which lie in the lower left region of Fig. 5.7 should represent the decision maker's updated preference for the decision model D2. The preferences for individual objectives can be expressed by weight multipliers or exponents and combining all the objectives into a single objective problem.

Although this formulation enables explicit representation of decision maker's preference for individual objectives, determination of weights or exponents for the objectives becomes challenging especially when the units and scales of these objectives are different.

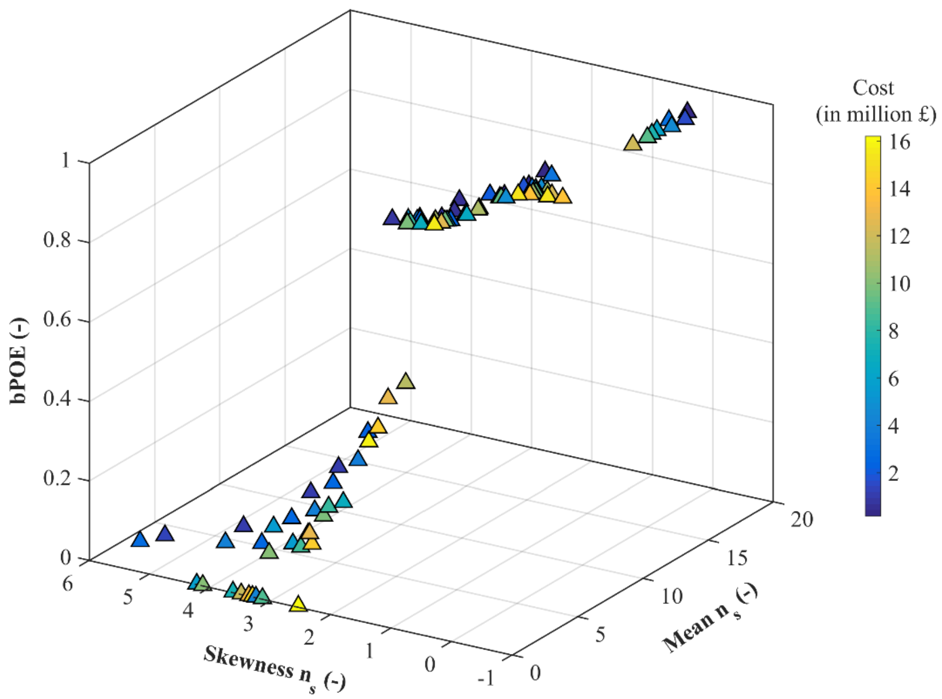

Fig. 5.7. D2: Objective function values of Pareto optimal solutions

Also, a single objective formulation would result in a single optimal solution and it can be difficult to visualize the level of improvement achieved for individual objectives when compared to sub-optimal solutions. The formulation of D1 and D2 enables decision makers to compare the Pareto optimal solutions and select one solution which satisfies their individual preferences for different objectives.

The proposed decision models D1 and D2 focus primarily on the uncertainty in modelled system performance and do not include any uncertainty in the cost estimation of solutions. However, the decision models D1 and D2 do provide the flexibility of representing the cost as a function of uncertain model inputs and model parameters. Similarly, if the decision making process requires consideration of other criteria in addition to the modelled emission quality performance and the investment cost, the decision model can be scaled up to include such criteria as objectives or constraints. The direct grid search method is employed to this case study because it enabled a complete coverage of the finite discrete space. However, when the number of decision variables is more than 2, the number of grid points increases significantly and it may not be computationally efficient to evaluate the objectives using this method. Therefore, in cases where the decision space is continuous and/or the number of decision variables is more than 2, it is recommended that efficient continuous search algorithms are employed to find Pareto optimal solutions.

Finally, integrating uncertainty propagation analysis of hydrodynamic models with optimization can be computationally expensive and for that, the readers are directed towards the use of surrogate models for hydrodynamic simulation which are faster to compute and so permit the practical use of this approach (Carbajal et al., 2017).

5.4.3 Comparison with a deterministic decision making approach

When the simulator predictions are assumed to be certain i.e. there is no uncertainty in the estimation of n_s $\forall s \in S$ and it is no longer a random variable, the decision problem becomes searching for solutions $s \in S$ which minimise n_s and the cost of s. Such a decision model can be expressed as a deterministic decision problem:

$$\mathrm{D_{det}} : \begin{cases} \min_{s \in S} n_s \\ \min_{s \in S} \mathrm{cost}(s) \end{cases} \tag{5.9}$$

Since the two objectives in the deterministic decision problem $\mathrm{D_{det}}$ are conflicting in nature, optimal solutions can be determined using Pareto non-dominance similar to the multi-objective decision problems D1 and D2. Fig. 5.8a displays the number of failures for every solution $s \in S$. Similar to the uncertain decision models, increasing the storage volume has a greater effect on lowering the number of failures than reducing the impervious area. In addition, the worst performing solution for the number of failures (Storage 100 m^3 + 25 ha of Impervious area) results in 6 failures. When the uncertainty is accounted in the model predictions, the worst expected number of failures is 17.5 which indicates a substantially large impact of uncertainty. Fig. 5.8b plots the cost of the 143 solutions against the number of failures n_s.

For decision model $\mathrm{D_{det}}$, 5 solutions were found to be Pareto optimal out of 143 solutions. The Pareto optimal solutions are marked by solid black circles and appeared to form a Pareto front in Fig. 5.8b. All the solutions to the right of the Pareto optimal solutions are sub-optimal. For a decision maker trying to achieve compliance with the regulations i.e. maximum 1 failure event, 2 Pareto optimal solutions satisfy the constraint of $n_s \leq 1$. Since the decision maker also prefers less expensive solutions, only one solution (Storage volume 250 m^3 + Impervious area 25 ha) comes across as the preferred Pareto solution which is marked by the blue circle in Fig. 5.8b.

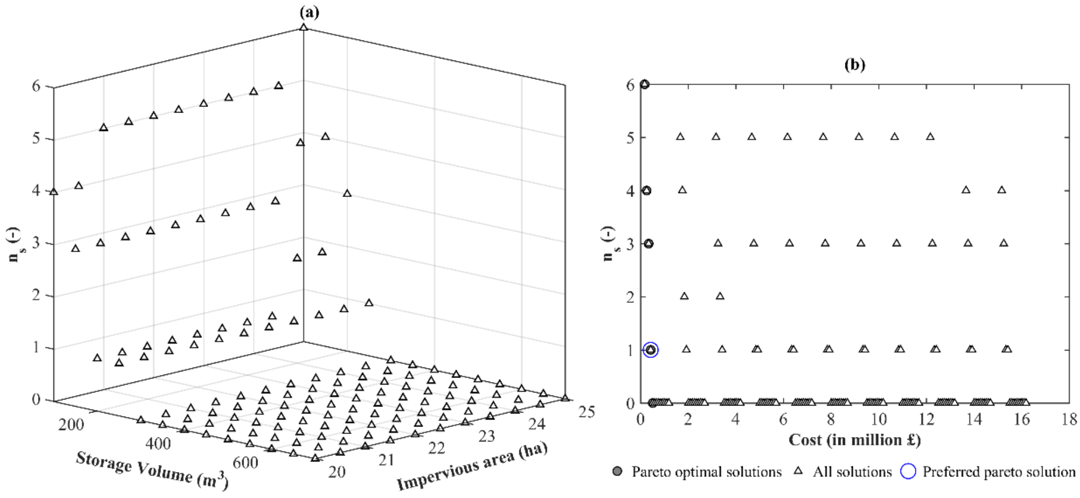

Fig. 5.8. (a) D_{det}: n_s in the discrete decision space S; (b) D: Cost of n_s vs n_s

However, when uncertainty in the model predictions is introduced, the bPOE for this solution is 1 with a POE value of 0.99. This means that if the decision maker had selected the preferred Pareto solution using a deterministic decision making approach which did not consider uncertainty in the model predictions, there would be a 99% chance that their decision would breach the compliance with the environmental regulations.

5.5 CDF matching approach for decision making under uncertainty

The decision model presented in Section 5.2 includes statistical moments and the buffered probability of exceedance as criteria to account for the shape of the probability distributions and the magnitude of the extreme values. The multi-objective formulation from Section 5.2 enables the decision maker to explicitly represent their preferences for the mean, the skewness and the bPOE; the decision maker searches for alternatives which minimise or maximise such criteria. However, an alternative and a complete representation of the decision maker's preference for the uncertainty in the emission quality performance variable would be if the decision maker specifies a target function which would encompass all the information about mean, skewness, bPOE etc. In other words, the decision maker is searching for optimal decision alternatives by optimizing the entire distribution instead of optimizing statistical moments or probability of exceedance values. Seshadri et al. (2016) developed a density matching approach where the optimal solution is obtained by minimising a distance metric calculated between the PDF of an engineering design and a target PDF specified by the designer. However, for evaluating the decision alternatives, it becomes difficult to identify which alternatives stochastically dominate other alternatives using the PDFs. For instance, by comparing the PDFs of the decision alternatives in Fig. 4.2 it becomes difficult to establish a stochastic dominance relationship among the alternatives. However, while comparing the CDFs in Fig. 4.3 gives a clear indication of stochastic dominance relationship. For example, it is clear that alternative *c* stochastically dominates alternatives *a* and *b*. Cook and Jarrett (2017) proposed the Horsetail matching for performing optimization under uncertainty. The horsetail matching approach minimises the difference between the CDFs of decision alternatives and a target function specified by the decision maker. In doing so, the horsetail matching approach avoids stochastically dominated solutions. Fig. 5.9 illustrates the horsetail matching concept where the optimization search is targeted towards minimising the difference between the CDF of a decision alternative and the target function.

This section implements the horsetail matching approach proposed by Cook and Jarrett (2017) to the risk-averse decision making to improve the environmental performance of the urban sewer systems with regards to CSO discharges. Cook and Jarrett (2017) use the term 'horsetail matching' as a generic term which is a CDF matching approach when the probabilistic representation of uncertainty is used. Hence, this thesis uses the term 'CDF matching' from here on to refer to the horsetail matching approach.

Consider the quantity of interest $n = f(s, u)$ from Section 5.2.2 where n represents the response of an urban drainage system model with decision variables $s \in S$ where S is the decision space, and uncertain variables $u \in U$. Again, for a given $s \in S$, uncertain variables u will result into random realizations of the quantity of interest n which can be represented by $n_s = f_s(s, u)$. Let $F_s(n)$ and $F_s^{-1}(h)$, be the CDF and inverse CDF of n_s respectively where $h \in [0, 1]$ represents the value of the CDF. Consider that the decision maker specifies the target function as $t(h)$.

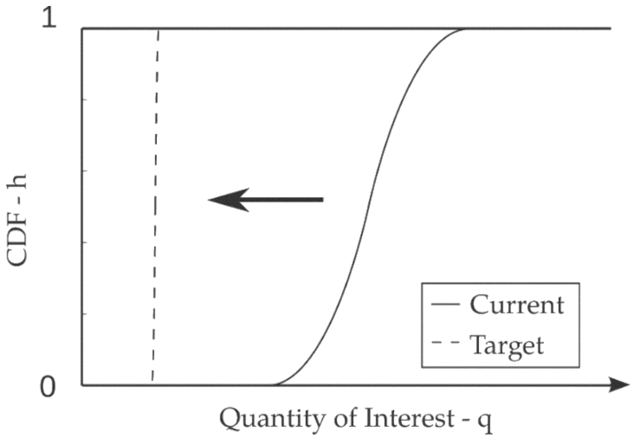

Fig. 5.9. The horsetail matching concept (CDF matching under probabilistic uncertainty) (From Cook and Jarrett, 2017).

The CDF matching proposes the L_2 norm as the measure of difference between the decision alternative's CDF and the target function which is represented as follows:

$$d_{dm}(s,t) = \left(\int_0^1 (F_s^{-1}(h) - t(h))^2\, dh\right)^{1/2} \tag{5.10}$$

Therefore, the optimization problem seeks to find the decision alternative s^* for which d_{dm} becomes minimum. However similar to the decision model presented in 5.2.2, the decision makers identify the optimal solutions through a trade-off between the environmental performance and the investment costs. Hence, the decision model based on CDF matching can be posed as:

$$D_{dm} : \begin{cases} \min_{s \in S}\ d_{dm}(s,t) \\ \min_{s \in S} \text{cost}(s) \end{cases} \tag{5.11}$$

Similar to the decision models D1, D2, and D_{det}, the two objectives in the decision model D_{dm} are conflicting in nature, hence the optimal solutions can be determined using Pareto non-dominance specified in Section 5.2.3.

5.5.1 Calculation of d_{dm}

To calculate the value of d_{dm}, it is necessary to evaluate the integral in Eq. 5.10. In the horsetail matching approach (Cook and Jarrett, 2017), numerical quadrature of the integral in Eq. 5.10 is performed using the trapezium rule to find an approximation $\hat{D}$ of the integral. Subsequently, d_{dm} can be calculated as $\hat{D}^{1/2}$. $\hat{D}$ can be expressed as:

$$\widehat{D} = \sum_{i=1}^{N} w_i \left(F^{-1}(h_i) - t(h_i)\right)^2 = \sum_{i=1}^{N} w_i \left(n_i - t(F_s(n_i))\right)^2 \qquad (5.12)$$

where N is the number of quadrature points and w_i are the corresponding weights for these quadrature points.

For each $s \in S$, N random values of n_i are obtained after propagating the uncertainty u. Empirical CDF values are estimated corresponding to the n_i to obtain h_i values as an approximation of $F_s\ (n)$. These N values of h_i are used to calculate $t_i = t(h_i) = t\ (F(n_i))$ which results in N pairs of (n_i, h_i) and (t_i, h_i) which are in turn used to calculate $d_{hm} = \widehat{D}^{\ 1/2}$ using Eq. 5.12. The weights w_i in Eq. 5.12 are calculated using following equation:

$$w_i = 0.5\ (h_{\min(i+1,N)} - h_{\max(1,i-1)}) \qquad (5.13)$$

5.5.2 Applying the decision model D_{dm} to the Haute-Sûre case study

The Haute-Sûre catchment described in Section 5.3 is used to demonstrate the decision model based on CDF matching. Random values of $n_s = f_s\ (s, u)$ calculated for the decision variables s specified in Section 5.3.2.1 by propagating the uncertainty u defined in Section 5.3.2.3 are used here as well for demonstration purposes. The quantity of interest n_s is the variable for the number of CSO spill events with ammonium concentration more than 2.5 mg/l for one hour. 500 Monte Carlo simulations performed in Section 5.3.3 resulted into 500 random values of n_i for each $s \in S$. The corresponding h_i values are obtained by estimating the empirical CDF value of each n_i using the *ecdf* function available in the *stats* package of the statistical software *R*.

5.5.2.1 Defining the target functions

Three target functions are used to demonstrate the CDF matching based decision model D_{dm}. Since the regulatory threshold on n_s is 1, one target function is defined as such to reflect the risk-averse behaviour of the decision maker. Due to its shape, the risk-averse target penalises the extreme values of n to a greater degree because of the extreme values of n for a decision alternative with high CDF values being farther from the risk-averse target. A standard target for which n = 0 is used to identify solutions which provide an environmental performance as good as possible. A specific distribution is used as the third target to demonstrate the flexibility of the CDF matching approach. The specific distribution is the CDF of Beta PERT distribution which is defined by assigning a minimum value, a mode and a maximum value with a scale parameter λ (Vose, 2010). This means that the corresponding PDF of the specific distribution is positively skewed with maximum value set at 1. Fig. 5.10 displays the shape of these target functions and the details of the three target functions are provided in Table 5.2.

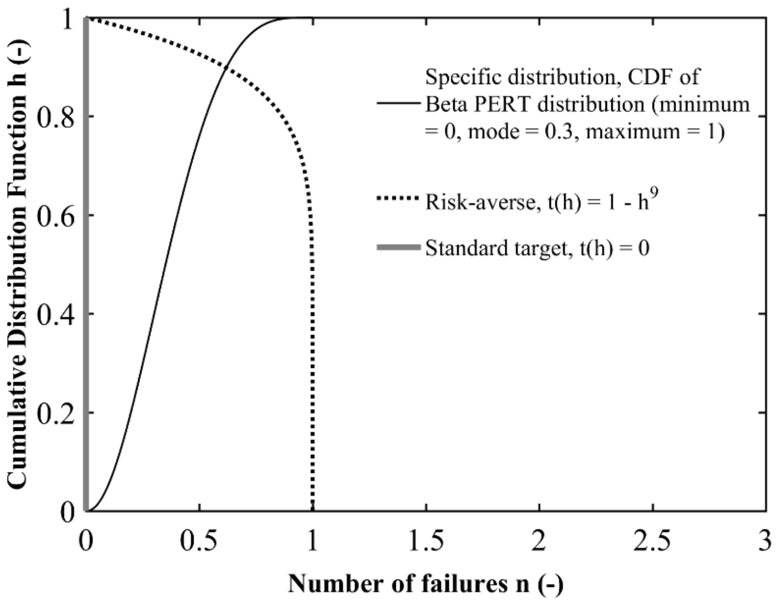

Fig. 5.10. Hypothetical target functions depicting different preferences.

Table 5.2. Target functions used in the case study

Target type	Target function
Standard	$t(h) = 0$
Risk-averse	$t(h) = 1 - h^9$
Specific distribution	CDF of Beta PERT (minimum = 0, mode = 0.3, maximum = 1)

5.5.2.2 Results and discussion

The two objectives in the CDF matching based decision model D_{dm} are evaluated for the 143 decision variables and the Pareto optimal solutions are identified by applying the Pareto non-dominance for the three target functions. Amongst the 143 decision alternatives, 16 are found to be Pareto optimal for both standard and risk-averse targets. For the specific distribution, 17 decision alternatives are found to be Pareto optimal. Fig. 5.11 plots the values of two objectives i.e. the CDF matching metric and the investment cost for the standard target.

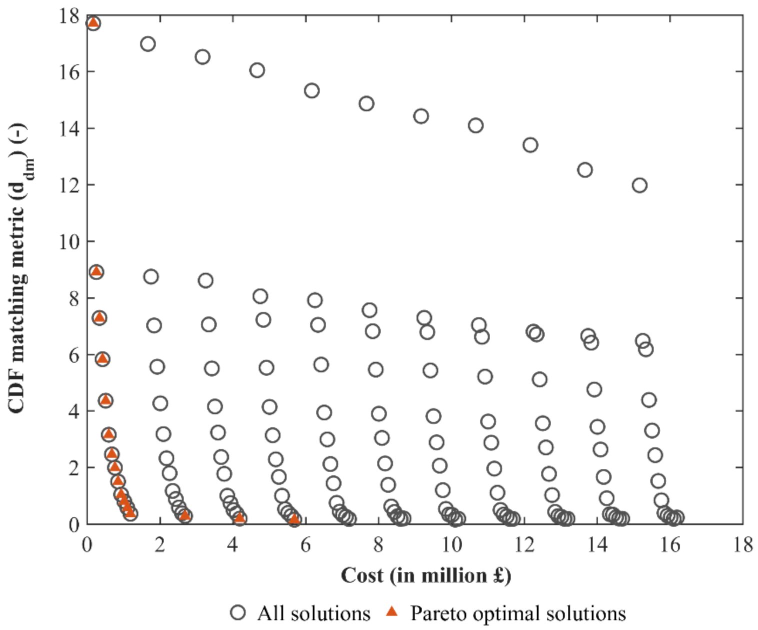

Fig. 5.11. CDF matching metric vs Cost of n_s for the standard target.

The Pareto optimal solutions are marked with solid triangles. It is clear from the Fig. 5.11 that these Pareto optimal solutions appear to form a Pareto front which envelops the sub-optimal solutions. Fig. 5.12 shows the Pareto optimal solutions obtained by solving the decision model D_{dm} for the three targets. As expected the CDF matching metric is highest for the standard target which would be farthest from the CDFs of the decision alternatives. Similarly the value of d_{dm} is lowest for the risk-averse target in comparison with the other two targets.

However, despite having different shapes, there seems to be no significant effect on the Pareto optimal solutions except the specific distribution target results in an additional alternative as the Pareto optimal solution. This is due to the fact that these targets have a small difference in terms of the range of n compared to the uncertain range of n for the decision alternatives. Both risk-averse and specific distribution target have n ranging from 0 to 1 therefore, the effect of different shapes is not very significant in the calculation of the CDF matching metric. However, these targets are defined as such to identify solutions with an environmental performance as good as possible.

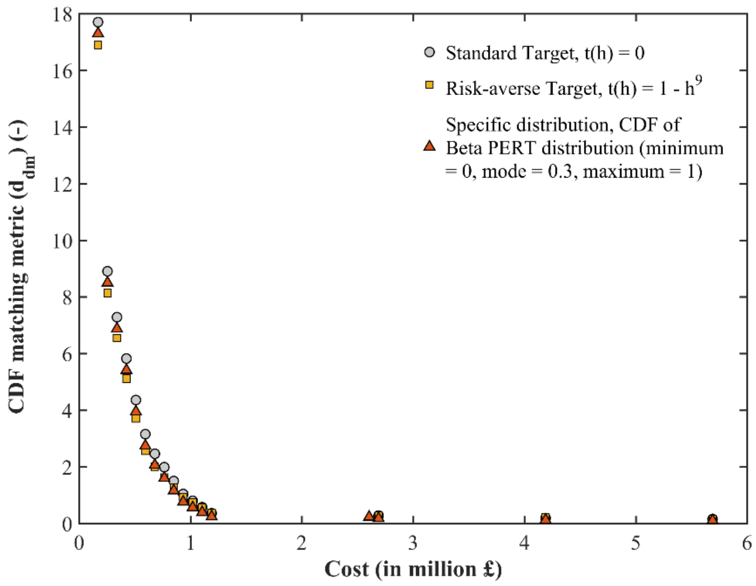

Fig. 5.12. Pareto optimal solutions for different target functions.

5.6 Concluding remarks

This chapter presents two decision making approaches which incorporate the model input and model parameter uncertainty in the hydrodynamic and emission quality simulations. Both the decision making approaches integrate hydrodynamic and emission quality simulation, uncertainty analysis and multi-objective optimization. The first decision making approach consists of a trade-off between three objectives representing uncertainty in the system performance (mean, skewness, and the bPOE) and the cost of the proposed solutions as the fourth objective. The second approach consists of a trade-off between minimising a CDF matching metric and minimising the cost of the proposed solutions. The CDF matching metric measures how close the uncertain environmental performance of the decision alternatives are to a target function specified by the decision maker.

Uncertainties in the simulation of urban wastewater system pose challenges to decision makers in managing the environmental impact on receiving water bodies. Using low-order statistical moments (mean or variance) or using the probability of exceedance as a failure probability does not provide any information about the shape of the non-normal probability distributions of the emission quality performance variable or the magnitude of the extreme values. This becomes very important if the system performance is distributed with a heavy tail. In the case of CSO spills, the environmental impact not only depends on the number of failed CSO spill events but also on the sensitivity of the receiving water body. A large number of CSO spills with ammonium concentration exceeding the threshold (values on the right tail of the distribution) can be very damaging to the ecology of a receiving water body which is very sensitive to additional pollutants but may not be as damaging for a less sensitive body such as a river with a greater capacity for assimilating pollutants than sensitive rivers or streams. The type of symmetry and the tail of the distribution provide useful information in this regard.

In the first decision making approach, in addition to the expected value of the system performance, skewness is used as one of the objectives through which the decision makers can specify their preference of symmetry in the distribution. The concept of *Buffered Probability of Exceedance* (bPOE) is used as an objective which is a conservative estimate of the traditional probability of exceedance. bPOE provides a probability measure which is not only based on the threshold but also on the magnitude of the tail of the distribution.

The second decision making approach allows the decision maker with the flexibility to include their preferences about the entire distribution of the emission quality performance variable. While defining the target function, the decision maker can include information about the statistical moments and the probability of the exceedance along with the magnitude of the extreme values. However, it should be noted that the CDF matching metric only provides information about how close the environmental performance of the decision alternatives is with respect to the specified target function. Hence, this approach requires the decision maker to be familiar with the elicitation of the target function and its implication on the outcome of the decision making process. Also, a minimum value of the CDF matching metric does not ensure compliance with the regulatory threshold if the target function is not appropriately defined. Such limitation with the compliance requirements can be addressed by including the buffered probability of exceedance as a constraint in the decision model D_{dm}.

Compared to previous studies, the proposed decision models (D1, D2 and D_{dm}) provide decision makers with the flexibility to express their preferences for the uncertainty in the system performance variables when they are expressed as probability distributions. Decision makers can find solutions satisfying their preference for the shape of the distribution and the level of risk acceptance under budget constraints.

This chapter does not take into account future changes affecting urban wastewater system such as population growth, the effect of climate change on rainfall precipitations, changes in environmental regulations. In addition, decision making processes may involve different stakeholders for whom different criteria such as adaptability and public acceptance of the proposed solutions, environmental aesthetics, land acquisition for proposed infrastructure investments, might be important.

6. Discussion

The objective of this thesis is to develop and provide methodologies for making investment decisions and so improving the environmental performance of urban sewer systems while accounting for uncertainty in model predictions. To achieve this objective, this thesis tries to address three important aspects which affect the decision making process in urban sewer systems: (i) the influence of the form of the regulations used to ensure compliance of sewer systems with environmental regulations, (ii) accounting for the impact of the uncertainty in model predictions when used to demonstrate compliance with the environmental regulations while conforming to standard modelling guidelines or codes of practice, (iii) the role of individuals' preferences in decision making when informed by predictions obtained with model uncertainty, and developing decision models representing such preferences.

6.1 Influence of regulatory compliance requirements on modelling decisions

Specifically, this thesis focuses on investment decisions which seek infrastructural improvements of urban sewer systems such that the sewer systems comply with environmental regulations on the overflow discharges to the receiving water bodies. Decision makers are required to make investment decisions which improve the sewer system's performance with respect to the overflow discharges and to take actions to reduce the risk of non-compliance with such regulations. The environmental performance of the sewer system with respect to the overflow discharges is evaluated through emission quality indicators defined by the regulatory guidelines (e.g. the concentration-duration based emission quality indicator from Austrian guidelines applied in Chapter 5). However, some regulations use overflow quantity or overflow frequency as an indirect measure of the ecological impact on the water quality in the receiving water bodies. For example, the Flanders Environment Agency (VMM) in Belgium uses the overflow frequency as an emission quality indicator to evaluate the performance of CSOs (Chapter 3). Here, the emission quality indicator is the number of CSO spills which does not constitute any information about the concentration of pollutants in the CSO spills and how they might affect the water quality status of the receiving water body. Compliance with the environmental regulations on CSO discharges often means meeting a threshold on the emission quality indicator. In Flanders, Belgium an upper threshold of 7 is defined for the number of CSO spills in a year. The Austrian guidelines define thresholds for different pollutants which are applied to the CSO spill events satisfying specific concentration-duration criteria. For instance, acute ammonia toxicity for salmonid species in the receiving water body caused by CSO spills is regulated by identifying CSO spills where the concentration of ammonia is more than 2.5 mg/L for one hour and allowing maximum one such CSO spill in a year (Chapter 5). In this case, the emission quality indicator is the number of CSO spills failing the concentration-duration criterion defined in the guidelines and a threshold of 1 is applied to the number of failures in a year.

Although the emission quality indicators applied in Chapters 3 and 5 are different, regulations in both the countries apply a threshold on the number of failures. Therefore, despite using different definitions of the emission quality indicator, the requirements for regulatory compliance have a similar form. However, the scope of simulation is expected to differ in both the cases. In the Belgian context, simulation of the urban sewer system is required in order to predict the number of CSO spills. On the other hand, the Austrian regulations require simulation of water quality of the receiving water body. This would require simulation of not only the urban sewer system but also the wastewater treatment plant processes, river flow, and the mixing of pollutants in the river in an integrated modelling approach. The Belgian context disregards the receiving water quality directly, it might be possible that the CSO structure is spilling frequently than what is allowed but the receiving water has a very low sensitivity to the incoming pollutants. In this case, even if the aquatic quality of the RWB is not negatively affected the decision maker is required to make investments. Therefore, the form of the regulatory requirements plays a significant role in determining which processes are going to be modelled and how effective they are in enforcing the decision makers to improve the quality of RWBs.

Considering model uncertainty in this context, the decision making process seeking compliance with the regulations becomes a risk-based decision making process where the risk of breaching the threshold needs to be quantified and the decision makers' risk behaviour needs to be assessed. The risk-based decision models proposed in Chapter 5 are applicable to all those regulations which use a threshold-emission quality indicator based compliance requirements.

6.2 Accounting for modelling uncertainty in demonstrating compliance

The infrastructural investment decisions are supported by evidence obtained in the predictions from urban drainage models and the emission quality indicator values are estimated subsequently. The decision maker evaluates the environmental performance of various decision alternatives on the basis of the corresponding values of emission quality indicators. As it has been observed in Chapter 3, the local environmental regulatory authorities may require the operators of urban sewer systems to use urban drainage models which are developed or calibrated following a certain code of modelling practice. In Chapter 3, the case study catchment is located in the Flanders region of Belgium where the regulatory authority is VMM. The water utility companies operating within the purview of VMM, use only those urban drainage models to evaluate the performance of sewer systems which are developed following standard modelling procedures in agreement with the regulator, such as the internal modelling procedure adopted by Aquafin (Aquafin, 2017). This means that the performance evaluation of the sewer system, with regard to the stated regulatory requirement using any other modelling procedure, is not acceptable for decision making purposes. This poses restrictions on the application of a variety of uncertainty analysis techniques proposed in recent academic studies. For instance, many academic studies on uncertainty analysis of urban drainage model predictions have used parsimonious conceptual models. Similarly, surrogate models have been reported in academic studies to facilitate uncertainty analyses for computationally extensive urban drainage models because uncertainty analyses require multiple simulation runs. However, similar to the regulator's modelling requirements in Flanders, the results of uncertainty analyses using conceptual models or surrogate models will not be applicable because these models are not developed using the standard modelling procedure accepted by the regulator. Hence, only those uncertainty analysis techniques which do not change the structure of the model developed using the standard modelling procedure can be used. Sampling-based uncertainty propagation using Monte Carlo simulations ensures that the model structure is preserved while propagating the uncertainty in various model components. However, the Monte Carlo type technique requires a large number of simulation runs which could prove to be impractical for a computationally extensive model. Chapter 3 addresses the issue of computational burden by performing a sensitivity analysis and using Latin Hypercube Sampling method to generate samples from inputs and model parameter sample space. A sensitivity analysis identifies inputs and model parameters which affect the model output in consideration and contribute to its variance. This means that the rest of the inputs and model parameters which are found to be not important for this model output can be fixed and need not be varied over their uncertain sample space. As a result, the decision maker can use their resources practically to quantify or reduce the uncertainty in a smaller number of inputs and model parameters which contribute to the uncertainty in the model output. Although the use of conceptual models or surrogate models would have reduced the computational burden to a greater extent as it has been reported in the literature (e.g. Freni et al., (2008); Schellart et al., (2010); Vezzaro et al., (2013)), the uncertainty quantification process proposed in Chapter 3 follows the standard modelling procedure used by Aquafin, making the results suitable for taking investment decisions to improve the performance of sewer system with respect to CSO discharges.

Apart from the standard modelling procedures or codes of modelling practice such as the one used by Aquafin in Flanders, Belgium, the regulators may impose some additional modelling criteria to demonstrate compliance. For instance, in Flanders, if a decision maker wants to invest in additional storage so that a particular CSO does not spill more than 7 times in a year, the required storage volume needs to be estimated using a composite design storm '*f7*'. This means that an urban drainage model which has been developed following the standard modelling procedure will be used to estimate the CSO volume using the design storm '*f7*' as the rainfall input. In this case, if the decision maker is interested in evaluating the uncertainty in the model prediction of the required CSO volume, the uncertainty in the rainfall cannot be accounted for hence underestimating the uncertainty in CSO volume. Rainfall being one of the most important inputs to the sewer system, this underestimation can have a significant effect on the investment decisions. In fact, this is reported in Chapter 4, where the required storage volume calculated using the design storm '*f7*' is found to be insufficient in limiting the number of spills below or equal to the threshold of 7 in a year when historical rainfall is used to predict the number of CSO spills. Chapter 4 suggests a larger storage volume is required to limit the number of CSO spills up to 7 times in a year than what is predicted using the '*f7*' storm. A holistic uncertainty analysis of model predictions is only feasible if the regulatory guidelines for compliance allow such approaches.

6.3 Individuals' preferences for uncertainty and risk-averse decision making

In this thesis, the infrastructure investment solutions are evaluated against two major criteria: environmental performance and the cost of investment. The scope of decision making in this thesis involves only infrastructure investment decisions which are required to be taken 'now' i.e. at time $t = 0$. Consequently, any uncertainty associated with future changes in the urban sewer systems is not considered while modelling uncertainty and decisions in this thesis. Hence, this thesis assumes that once the investment decision alternatives are defined, for instance, volume of a proposed storage tank, the corresponding investment costs can be accurately estimated by the water utility at the time of decision making.

Once the infrastructure investment solutions as decision alternatives are modelled and the corresponding uncertainty in the emission quality indicator is quantified, each decision alternative results in a probability distribution of the emission quality indicator defined by the regulator. To compare the environmental performance of decision alternatives, the decision makers are faced with the challenge of comparing the probability distributions of the emission quality indicator. Studies on risk-based decision making in urban sewer systems (e.g. Korving et al., 2009; Meng et al., 2016; Portielje et al., 2000; Reda and Beck, 1997) have either used a probability of exceeding a threshold or extreme values to represent the uncertainty in the emission quality indicator. Reda and Beck (1997) used extreme values of the emission quality indicator with the preference of minimising these extreme values. Similarly, Portielje et al. (2000) preferred solutions which minimise the probability of exceeding the defined threshold for the emission quality indicator. Korving et al. (2009) used the probability of exceedance to estimate the cost of environmental damage due to CSOs and preferred solutions which minimise the total cost which combined the damage cost and the cost of investment. However, due to the non-linear behaviour of the sewer system, the predicted probabilistic uncertainty in the emission quality indicators are often non-normal (e.g. Schellart et al., 2010)). The first two statistical moments of a probability distribution, mean and variance do not provide any information about the shape of the distribution that where the distribution is skewed or not, and if it is, then to what degree. The third statistical moment skewness of the distribution of the emission quality indicator provides information about the symmetry of the distribution. Literature from other fields of study such as Konno and Suzuki (1995) acknowledged the importance of skewness and included it as a criterion while comparing the decision alternatives. However, to the best of the author's knowledge, the preference for skewness i.e. whether the optimal decision alternatives should result in a positively skewed or a negatively skewed or a symmetrical distribution of the emission quality indicator is not recorded so far.

Six practitioners from a water utility in Flanders were interviewed to record their preferences for the uncertain emission quality indicator. All the practitioners were found to be risk-averse and they preferred lower values of the emission quality indicator which was number of CSO spills in a year (Chapter 4). All the practitioners agreed that they would prefer a decision alternative which results in a lower value of mean and variance of the emission quality indicator. They further agreed that they consider the probability of exceeding the threshold as an important criterion while evaluating decision alternatives and prefer lower values of probability of exceedance. This preference is in agreement with a risk-averse behaviour reported in earlier studies. However, when they were asked about their preference for the skewness of the distributions, the majority of these practitioners preferred a positively skewed distribution over a symmetrical or negatively skewed distribution with comparable mean and variance values. Although a positively skewed distribution tends to pose a risk of breaching the threshold, these practitioners were found to be willing to accept a small chance of breaching the threshold in favour of a larger probability of smaller values of the emission quality indicator. The practitioners argued that the CSO spills are frequent events and the values of the emission quality indicator would be lower on a frequent basis if the emission quality indicator follows a positively skewed distribution. One practitioner was indifferent to the type of symmetry of the probability distribution while another preferred a negatively skewed distribution if the threshold is never breached. Although the number of such individuals whose preferences deviated from the majority is very low i.e. 1 out 6, if such individuals were to be the only decision maker, the change in the criteria or their preferences would affect the outcome of the decision making process. Therefore it is imperative for a water utility to carefully define all the criteria to compare the alternatives and the corresponding preferences for such criteria which reflect its policy and risk preferences.

While the practitioners preferred a decision alternative which would result in the lower values of emission quality indicator, the majority of the practitioners appeared to compromise on the environmental performance in favour of cost-effective decision alternatives. This indicated a trade-off between the environmental performance and the investment cost. Only one practitioner was found to be extremely risk-averse and this practitioner assigned little importance to the cost. The other practitioners appeared to rank the decision alternatives on their cost-effectiveness in improving the sewer system's performance with respect to the emission quality indicator. These practitioners assigned the highest rank to a decision alternative despite the fact that this alternative was found to be stochastically dominated by other alternatives. This suggests that the practitioners did not favour the stochastically non-dominated alternative albeit considered both the criteria i.e. the environmental performance and the investment cost important while ranking the alternatives. Therefore, it can be concluded that merely searching for decision alternatives which display stochastic non-dominance with respect to the emission quality indicator does not represent the decision makers' preferences in this context. All the practitioners were found to rank the decision alternatives essentially through a trade-off between the environmental performance and the investment cost, however, the assigned relative weights or importance values were different among these practitioners. Even amongst a very small number of practitioners, a difference in preferences for the criteria and their relative importance was noticed due to individuals' risk behaviour. It is expected that in general, the decision makers would evaluate the decision alternatives through a trade-off between the defined criteria but the assigned weights could be varying depending on the scope of the decision making. For example, if the receiving water body is classified as highly sensitive to the incoming pollutants from the CSO spills and the regulation allows little or no CSO spill at all, the decision maker could assign very high importance to the environmental performance. In such cases, the decision maker would choose an alternative which ensures compliance even at a high investment cost. Therefore, such decision making problems need to be formulated as multi-objective problems where the individual criteria and their preferences are represented as objective functions. Also, a multi-objective formulation enables searching for optimal decision alternatives by comparing a large number of candidate solutions through optimization.

Chapter 5 presents two decision models which represent the risk-averse behaviour of the decision makers as observed through the interviews described in Chapter 4. The first decision model considers the mean, the Buffered Probability of Exceedance (which is a probability of exceedance measure), the skewness and the investment cost. In Chapter 4, all the interviewed practitioners unanimously preferred decision alternatives with lower mean, lower probability of exceedance and lower cost but had different preferences about the skewness; two decision models are proposed with reverse preferences for skewness. A probability measure Buffered Probability of Exceedance is used instead of the probability of exceedance to account for the magnitude of extreme values greater than the threshold. Two distributions may have identical probabilities of exceeding the threshold but it is possible that their extreme values may have different magnitudes. The Buffered Probability of Exceedance captures this difference which otherwise would be ignored. In the second decision model D_{dm}, the decision maker can specify their preferences for the uncertain emission quality indicator by defining a target function and identify decision alternatives which are predicted to perform as well as the specified target function. The decision model D_{dm} is based on a CDF matching approach which minimises the difference between the CDFs of the emission quality indicator for the decision alternatives and the specified target function. Using the CDF matching metric d_{dm} as the sole objective would result in the decision alternatives whose CDF is closest to the target function. Three different types of target functions are used to demonstrate the CDF matching approach to find cost-effective investment decisions improving the environmental performance of the sewer system. While the CDF matching metric offers more flexibility by considering the entire distribution of the emission quality indicator, the decision models D1 and D2 provides transparent information about the risk of non-compliance associated with the Pareto optimal solutions. However, if required the bPOE can be included as another objective in the CDF matching based decision model to explicitly evaluate the risk of non-compliance with the regulatory requirements.

Since the relative importance of the criteria to the decision makers is not quantified, the multi-objective formulations assign equal weights or importance to the individual criteria or objectives and seek to search for Pareto optimal solutions by testing the

Pareto non-dominance of the decision alternatives for the specified objectives. It is expected that the decision makers would select an optimal decision alternative from the set of Pareto optimal solutions by assigning the relative importance or weights to the individual criteria *a posteriori*.

The decision models presented in Chapter 5 are scalable which means that any additional criteria can be included as objectives and these additional criteria can be represented as certain or uncertain. For instance, additional target functions can be defined for criteria other than the environmental performance e.g. the uncertain flood levels and a corresponding CDF matching metric can be included in the decision model D_{dm}.

Also, it is recommended that multi-criteria decision problems such as the one posed in Chapter 5, should be formulated as multi-objective functions instead of converting the decision problem into a single objective decision model through linear scalarization of individual objectives. This is due to the fact that linear scalarization requires identification of weights of the criteria *a priori* and it can be difficult to analyse the trade-off between individual objectives post optimization.

In Chapter 5, a comparison between the uncertainty based decision making process and the deterministic process revealed that if a decision were to be made without considering the modelling uncertainty, the selected decision would have a 99% chance of breaching the threshold set by the regulations on the emission quality indicator. This outcome establishes the importance of incorporating uncertainty in model predictions while making investment decisions. However, the impact of modelling uncertainty on the outcome of the decision making cannot be generalised and is expected to depend on the decision problem at hand.

7. Conclusions and Outlook

7.1 Conclusions

This PhD thesis reports on studies into the use of uncertainty based methodologies to aid decisions on improving the performance of urban sewer systems so as to comply with environmental regulatory performance standards. While doing so this thesis sets out to achieve the following objectives:

(I) Investigate the influence of different regulatory compliance requirements in the modelling and the evaluation of decision alternatives.

Chapter 3 and 5 analyse the influence of regulatory compliance requirements on the modelling process of decision alternatives. Regulatory performance standards on CSO discharges in two European countries, Belgium and Austria are studied. While the Belgian regulatory standards use CSO spill frequency as a emission quality indicator, the Austrian standards use concentration-duration-frequency type emission quality indicators. The catchment in Chapter 3 is based in Belgium; hence only uncertainty in the water quantity simulation of CSO spills is studied because the regulatory performance standard does not require emission quality assessment. On the other hand, Chapter 5 uses the Austrian regulations to assess water quality failure, which does require simulation of water quality parameters in the sewer overflow. Therefore, the type of emission quality indicator specified in the regulatory compliance requirements defines which physical processes of the urban sewer system needs to be modelled. Also, both the regulations specify a threshold on the emission quality indicator to demonstrate compliance, thereby making the risk of breaching the threshold as the primary criterion in the evaluation of decision alternatives.

However, it should be noted that both these local regulations are intended to ensure the requirement of the attainment of at least a *good ecological status* of surface water bodies defined in the European Water Framework Directive (WFD). Since the WFD uses only a normative definition of *good ecological status*, member European Union countries use their own individual regulations to achieve this target. The WFD focuses on a combined approach requiring performance standards on emission limits and environmental quality. The performance standard in Flanders, Belgium only includes a limit on emission, it does not give any indication of the impact on environmental quality. Hence, any investment decision evaluated on the basis of this emission limit only – based standard may not achieve the target of the good ecological status of the surface water bodies because the decision alternatives are not modelled and evaluated against their environmental quality performance. While the Austrian standard does account for emissions and environmental quality and sets different thresholds for different aquatic species, it does not differentiate overflow events which results into very high concentrations of pollutants from those events with concentrations moderately exceeding the thresholds. Therefore, the WFD should entail a quantitative definition of the *good ecological status* which is not only based on concentration duration frequency but also on the sensitivity of the receiving water body so that there is no discrepancy in the implementation of WFD across member countries. Following a letter from Richard Benyon MP, the Minister for Natural Environment and Fisheries in the UK, there has been a drive to improve the CSO monitoring. The letter was addressed to the Chief Executives of the water and sewerage companies in the UK asking to put CSO monitoring for the vast majority of their CSOs by the year 2020 (DEFRA, 2013). As a result, the CIWEM published a guide for Event Duration Monitoring at the CSOs (CIWEM, 2016). Although this CSO monitoring only considers the CSO spill frequency but not the flow or the quality, monitoring of the vast majority of CSOs is a significant step forward in understanding how the CSOs are performing.

(II) Quantify uncertainty in the model predictions while following the regulatory modelling requirements, thereby making the uncertainty predictions acceptable to the regulator.

Chapter 3 presents a practical, transparent and objective uncertainty quantification process which conforms to the modelling requirements specified by the regulator, VMM. In Flanders, Belgium, the regulator requires the water utilities evaluate the performance of CSO structures following specific modelling guidelines. These guidelines include the use of a specific design storm to estimate the storage volume required to limit the frequency of CSO spill events below the specified threshold. The sewer network is modelled in InfoWorks CS, and the model is calibrated and validated according to a defined procedure to test the spill frequency performance of CSOs. Uncertainty in the model and input parameters is propagated using Monte Carlo simulations with Latin hypercube sampling. However, it should be noted that these modelling requirements in Flanders are not defined to accommodate the uncertainty in model predictions and hence, limiting a full-scale uncertainty analysis. For instance, due to the requirement of using the specific design storm, uncertainty in the rainfall measurements and its spatial and temporal variability could not be accounted for. This means that the uncertainty levels predicted in Chapter 3 are expected to be an underestimation of overall uncertainty in the prediction of CSO spill volume. Since the predicted uncertainty levels conform to the current regulatory modelling requirements, they can be used by the water utility to support investment decisions in improving sewer system's performance. Chapter 3 reported significant levels of uncertainty in the model predictions despite the uncertainty levels being an underestimation. Since the investment decisions are made based on such model predictions, not accounting for modelling uncertainty these can lead to investments which may not able to limit the CSO spill frequency below the threshold.

The uncertainty quantification methodology demonstrated in Chapter 3 focuses on current regulatory modelling requirements for a better-informed decision making. However, the regulatory requirements themselves should provide the practitioners with the flexibility to consider all the important sources of uncertainty in the model predictions so that the practitioners have more confidence in the model predictions. This would result in a better assessment of the decision alternatives and help the practitioners in making investment decisions which are reliable against the regulatory performance standards.

(III) Identify individuals' preferences for uncertainty in the performance variable and their risk behaviour in evaluating decision alternatives.

In Chapter 4, six experienced practitioners from a water utility in Belgium were interviewed in order to assess the influence of individuals' preferences on the outcome of the decision making process given identical model predictions. Uncertainty in the performance of the decision alternatives was modelled for a local case study catchment. The practitioners are asked a series of questions so as to identify their preferences for uncertainty in the emission quality indicator and their risk behaviour. While it is found that all the practitioners displayed a risk-averse behaviour, the majority of these practitioners evaluate the decision alternatives based on their cost-effectiveness hence consider the investment cost also important. All these practitioners compare the decision alternatives through a trade-off between the performance and the investment cost. However, they appear to assign different weights or importance to these two criteria which indirectly indicated different levels of risk-averseness among the practitioners. Even for a sample as small as 6 individuals, the level of risk averseness varies resulting in different rankings of the decision alternatives. This means that given the identical model predictions, these individuals make decisions with varying investment costs and predicted environmental performance. For instance, one practitioner prefers to invest in a much larger storage volume than those of the selected decision alternatives while another practitioner prefers a phased investment plan. These two choices result in two different investment strategies and the environmental performance assessment for the water utility. Therefore it is advised that a water utility should derive and define a standard risk-behaviour which reflects its policy towards achieving the regulatory compliance subject to its own budget constraints. This would ensure that given identical model predictions, the practitioners make decisions which reflect the company's risk behaviour, not the individuals'.

(IV) Develop decision models which represent the decision makers' preferences to select optimal decision alternatives improving the environmental performance of urban sewer systems while complying with the regulatory standards.

Section 5.2 presents a stochastic optimization based decision model which provides the decision makers with the flexibility of representing their individual preferences for the criteria they find important. To evaluate the risk of non-compliance, the concept of Buffered Probability of Exceedance (bPOE) is introduced which accounts for the magnitude of extremes in the distribution of predicted system performance. This risk measure is a better indicator than the probability of exceedance to evaluate the decision alternatives, because the probability of exceedance does not provide any information about the magnitude of extreme values which could have a significant negative impact on the ambient water quality. Hence, the reliability of model-based decisions against the regulatory threshold should be tested against their Buffered Probability of Exceedance values. The bPOE is a conservative probability measure of exceeding the specified threshold. Its value depends on the magnitude of the extreme values and their corresponding probabilities. Therefore, it is possible that two decision alternatives result in identical probabilities of exceedance but different values of bPOE owing to the different shapes of the distribution tails. Besides the risk measure and the expected value (mean) of the distribution, the third statistical moment skewness is also used to account for asymmetry of these distributions. The optimal solutions are identified by comparing the decision alternatives using Pareto non-dominance criteria.

Section 5.5 presents a decision model which uses a CDF matching metric to evaluate how close the CDFs of the decision alternatives are from a target function specified by the decision maker. This CDF matching metric calculates the distance between the CDFs of the emission quality indicator of the decision alternatives and the target function. The decision model seeks to find optimal decisions through a trade-off between minimising the distance metric and minimising the investment cost. The target function provides the decision maker with a great amount of flexibility where they can include all their preferences for the statistical moments and the Buffered Probability of Exceedance. Using only the

CDF matching metric ensures that the decision alternative with the minimum value of the metric stochastically dominates all the other alternatives. Since it is observed in Chapter 4 that the practitioners do consider investment cost an important criterion along with the environmental performance, the decision model includes the investment cost as well. The possible downside of this approach is that it puts a great amount of responsibility on the decision maker in defining the target function. The optimal solutions are identified based on their closeness to the target function hence the definition of this target function can control which solutions are going to be determined optimal. Again, different individuals might define different target functions owing to the difference in their risk preferences. Also, the target function might depend on the sensitivity of the receiving water body. For instance, a very strict target function might be required for a highly sensitive river which would be equivalent to the worst-case optimization seeking to identify a decision alternative with 100% predicted reliability against the threshold. Therefore the water utilities should have a standard procedure to define such target functions. Target functions can also be defined for uncertain criteria other than the emission quality indicator such as flood levels, uncertain investment costs. If the decision maker is unable to define a target function the multi-objective decision model from section 5.2 should be applied in such cases because the outcome of the decision making process is highly dependent on the choice of the target function.

A deterministic decision making process for a case study in Luxembourg reveals that the deterministic solution would have breached the regulatory performance standard with a probability of 0.99. This means that the uncertainty levels in the model predictions are so significant that the decision alternative which is found optimal using the deterministic approach proves not reliable under the modelling uncertainty. This again demonstrates that accounting for modelling uncertainty provides the decision maker with a method to justify the confidence in their decisions. However, it should be noted that the reported performance of the deterministic solution is valid for the specific case study only. For this case study, post the uncertainty quantification the decision maker is better-informed about their selected decision and its modelled performance.

7.2 Outlook

The literature review in Chapter 2 reports that uncertainty based decision making in urban sewer systems has been limited to the use of probability of exceedance values. These literature sources do not consider other important information contained in the probability distributions such as the shape of the distribution characterised by its statistical moments and the magnitude of extreme values which can significantly influence the performance of the decision alternatives. While the focus of this thesis has been incorporating uncertainty in the model predictions to the decision making process influenced by regulatory compliance requirements, the methodologies proposed in the thesis use only a probabilistic representation of uncertainty in the model predictions. However, uncertainty in the model components might be described qualitatively or using an interval rather than a probability distribution due to a lack of data or information needed to characterise the probability distribution. In this regard, future research can be built upon this thesis so as to accommodate a variety of uncertainty representations. Again, such representations need to be approved by the regulators in order to use the resulting model predictions for making investment decisions.

As reported in Chapter 3, the uncertainty quantification process itself can be computationally expensive for complex hydrodynamic network models. The proposed decision model in Chapter 5 is demonstrated using a simple conceptual water quality simulator. However, searching for solutions using optimization algorithms coupled with uncertainty propagation can be computationally demanding. This thesis does not address such practical limitations but in the literature, there is evidence of using surrogate models which enable a large number of optimization searches. Currently, the use of such models is dependent on their qualification to the regulatory modelling requirements hence the regulatory requirements should provide practitioners with the flexibility to use surrogate models to support optimization under uncertainty. Since surrogate models are an approximation of the complex simulation models, there exists a compromise between the computational ease and the accuracy of model predictions. Analyses using surrogate models pose a risk of misleading outcomes and therefore, a benchmark modelling procedure should be defined to assess the performance of surrogate models (Razavi et al., 2012). However, statistical emulators which are a statistical approximation of the simulation models also provide a probability distribution of model outcomes which represents the uncertainty associated with the emulation process (Uusitalo et al., 2015).

The interviews in Chapter 4 identify that the practitioners assign different weights to the environmental performance and the investment costs, however, these weights are not quantified. Also, the decision model proposed in Chapter 5 does not allow assignment of weights or importance to the individual criteria. The decision model proposed in this thesis allows a decision maker to select the best solution from a set of Pareto optimal solutions *a posteriori*. Future research should focus on developing methodologies which identify and represent the importance of individual criteria relative to each other mathematically and incorporate this representation into a multi-objective decision model *a priori*. In this regard, a possible line of investigation could be an integration of MADM techniques to the decision models presented in Chapter 5. MADM techniques such as AHP, PROMETHEE and ELECTRE build upon identifying decision makers' preferences to compare different alternatives. The mechanism of identifying and representing the decision makers' preferences from these techniques can be investigated so as to test their suitability to the multi-objective decision model formulations presented in this thesis.

With respect to the type of decisions modelled in this thesis, another line of investigation can be to devise uncertainty based decision making methodologies which aid sequential decision making process incorporating management type decisions where a sequence of decisions is required to be modelled over a time horizon. The management type decisions often involve a series of actions to be taken over a time horizon where the action taken at $t = 0$ affects the future actions and so on. Such a decision is observed in the interview response of one practitioner in Chapter 4 where the practitioner prefers a phased investment plan starting with a small storage basin and increase the basin storage volume in future depending on the measured performance of the current investment. A decision time horizon may also affect the uncertainty quantification process. For instance, climate change might affect the meteorological conditions in future affecting the estimation of uncertainty in rainfall measurements. Also, description of uncertainty in the model inputs and parameters may change with time. For example, the probability distribution of pipe roughness can also change as the sewer pipes age over time. Therefore, an appropriate uncertainty quantification process and the modelling of such decisions need to be investigated.

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Appendix A

The Composite Design Storm '*f7*'

Fig. A.1 displays the rainfall profile of the composite storm '*f7*' which was developed by Vaes et al. (1996). The '*f7*' includes all the Intensity/Duration relationships for the annual rainfall frequency of 7 at Uccle, Belgium. These relationships are based on rainfall measurements taken at Uccle with 10-minute resolution. The main meteorological station of Belgium is situated in Uccle.

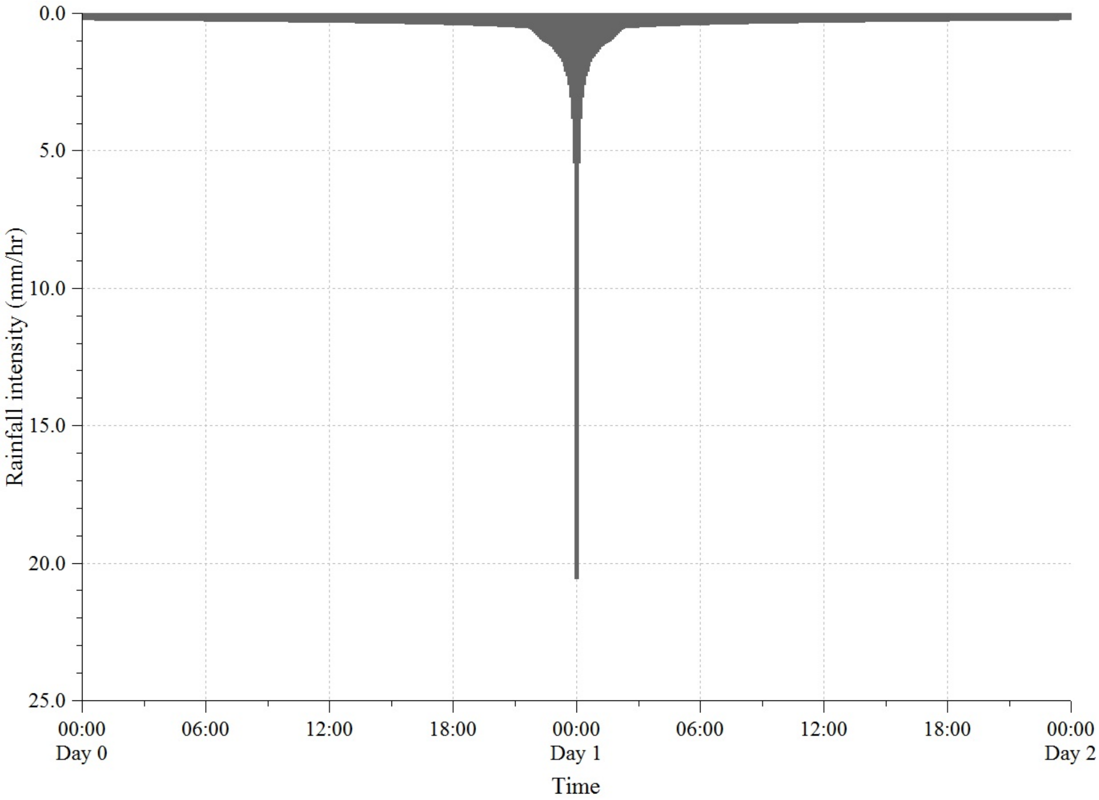

Fig.A.1. Composite design storm '*f7*' with an annual frequency of 7.

Appendix B

Overflow frequency for decision alternatives

Decision alternative *a*: Storage basin volume 2100 m^3

	Runoff coefficient		
Year	**0.731**	**0.797**	**0.862**
2004	17	19	20
2005	10	13	17
2006	14	17	21
2007	8	12	22
2008	13	16	18
2009	10	12	14
2010	11	13	21
2011	10	13	15
2012	15	20	22
2013	11	14	16

Decision alternative *b*: Storage basin volume 2500 m^3

	Runoff coefficient		
Year	**0.731**	**0.797**	**0.862**
2004	15	19	19
2005	10	11	14
2006	11	15	19
2007	8	8	15
2008	13	14	16
2009	6	10	12
2010	10	12	14
2011	9	11	14
2012	14	16	20
2013	9	11	14

Decision alternative *c*: Storage basin volume 2900 m^3

Year	Runoff coefficient 0.731	0.797	0.862
2004	14	16	19
2005	7	10	12
2006	9	13	16
2007	7	8	9
2008	13	13	14
2009	6	8	10
2010	9	11	13
2011	8	10	11
2012	13	15	18
2013	6	10	11

Decision alternative *d*: Storage basin volume 3300 m^3

Year	Runoff coefficient 0.731	0.797	0.862
2004	13	15	19
2005	7	9	10
2006	5	11	14
2007	5	7	8
2008	11	13	13
2009	5	6	9
2010	9	10	12
2011	7	9	11
2012	12	15	15
2013	5	8	11

Decision alternative *e*: Storage basin volume 3900 m^3

	Runoff coefficient		
Year	**0.731**	**0.797**	**0.862**
2004	12	14	17
2005	6	7	10
2006	4	7	12
2007	4	6	7
2008	10	13	13
2009	4	6	7
2010	8	9	10
2011	6	8	10
2012	11	13	15
2013	4	6	9

Appendix C

Parallel Coordinate plot to visualise solutions to a multi-objective decision model

Fig. C.1 displays the Pareto optimal solutions obtained in Section 5.4.1 for the decision model D1. The parallel coordinate plot maps the 4 objectives in D1 (mean, skewness, bPOE and cost) to the 2 decision variables (storage volume and impervious area). The mapping is displayed using straight lines connecting the decision variables to the corresponding values of the objective functions.

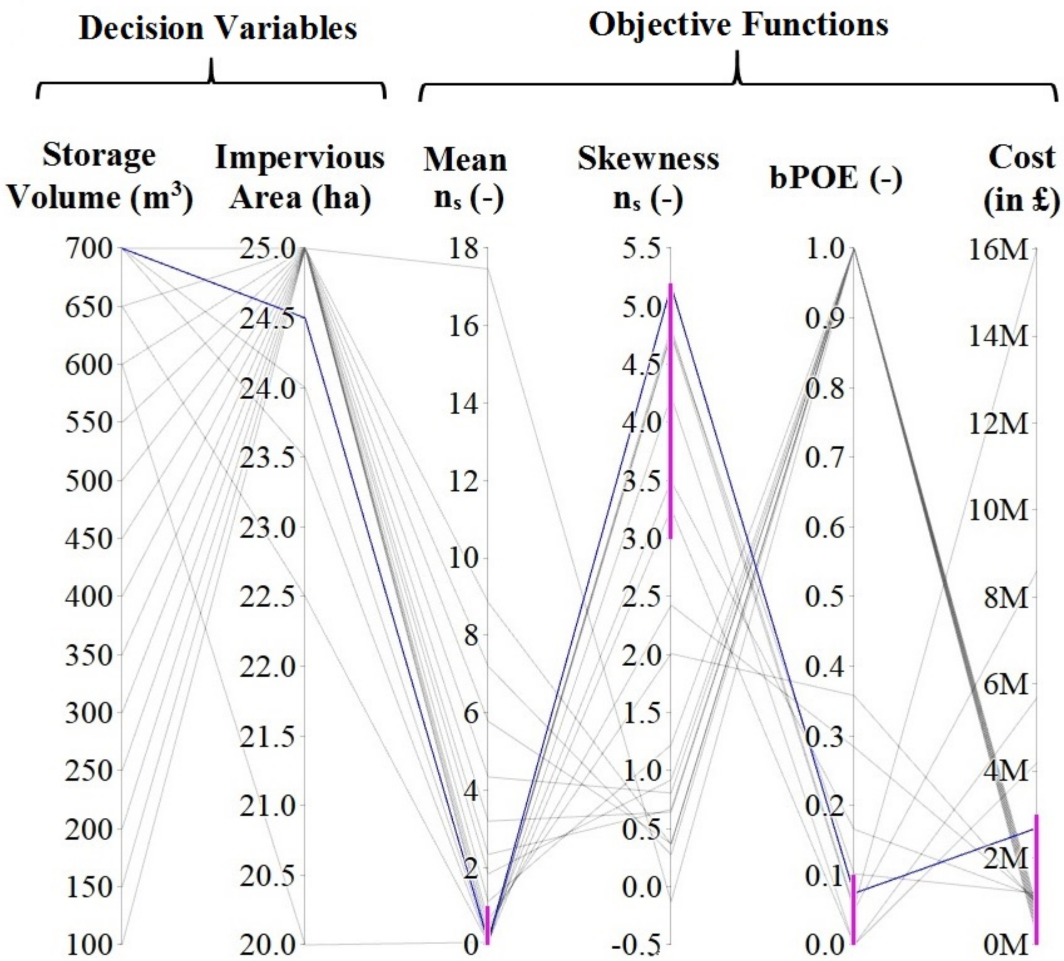

Fig.C.1. Parallel coordinates mapping the Pareto optimal solutions for D1 to the objective functions.

The mapping of Pareto optimal solutions to the corresponding objective function values is displayed as grey coloured lines. The blue coloured line displays an example of the preferred Pareto optimal solution for specific constraints on the values of the objective functions. In this case, the decision maker specifies a mean value ≤ 1, a skewness value ≥ 3, a value of bPOE ≤ 0.1 and a total cost of $\leq$ £3 million. The constraints are displayed as pink coloured range specified on the coordinates of the 4 objectives. The only Pareto optimal solution which satisfies the specified constraints is a combination of Storage tank with a volume of 700 m^3 and an Impervious area of 24.5 ha.