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Implications of model uncertainty for investment decisions to manage intermittent sewer overflows

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Abstract

Uncertainty in urban drainage modelling studies presents challenges to decision makers with limited investment resources attempting to achieve regulatory compliance for intermittent discharges from Combined Sewer Overflows. This paper presents the development of a new decision-making approach to address two key challenges encountered when attempting to manage sewer overflows, these are (i) the implications of different risk preferences of individuals for investment decisions; and (ii) how to utilize information on uncertainties in system performance predictions due to input or parameter uncertainty while comparing decision alternatives. The developed decision-making approach uses a multi-objective decision formulation to analyse the trade-off between investment and predicted system performance under uncertainty while accounting for risk preferences of the individual decision maker. The proposed uncertainty based decision-making approach is able to incorporate any threshold-based regulatory criteria for intermittent sewer overflows and is illustrated using a case study catchment in Luxembourg. The results from this case study highlight the significant impact of individuals' risk preferences on the level of investment recommended to comply with threshold-based regulatory criteria. It was demonstrated that differing levels of risk-averseness can result in a substantial increase in investment cost for solutions that are regulatory compliant. This paper demonstrates the need for water companies to rigorously define a corporate risk preference strategy to ensure consistent investment decisions across their operations; otherwise, individual preferences may cause significant over-investment to meet the same regulatory goals.

Keywords

Buffered probability of exceedance; Decision making under modelling uncertainty; Intermittent sewer overflows; Investment cost; Risk preference.

1. Introduction

Environmental regulators may impose performance standards for the operation of overflow structures in combined sewer systems, which release excess wastewater to receiving water bodies when the flow capacity of the urban drainage system is exceeded. For example, the Urban Pollution Management Manual in the United Kingdom specifies concentration-duration-frequency based criteria for ammonia concentrations and dissolved oxygen (DO) levels to mitigate ecological impacts caused by combined sewer overflow (CSO) spills (Foundation for Water Research, 2012). However, the criterion to evaluate the performance of CSOs is not uniform across EU countries (De Toffol, 2006; Dirckx et al., 2011; Milieu, 2016). For example, in Belgium, Denmark and Netherlands, regulations 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 regulations applicable to their country, and failing to do so can result in financial penalties and reputational damage, e.g. the UK water utility Thames Water was recently fined 20 million pounds for releasing untreated sewage via overflows in contravention of its discharge consents (Environment Agency, 2017).

Therefore, the successful management of sewer systems involves investment and operational decisions which are often risk-averse in character because they aim to "eliminate" the risk of non-compliance. More specifically, such decision-making aims to identify, test and implement solutions or strategies which minimize the risk of non-compliance, while satisfying constraints such as available budgets, land use and other planning or technical system constraints. Hydrodynamic network models are often used to assess the performance of the proposed solutions and strategies (Delelegn et al., 2011). However, it has been established that there is significant predictive uncertainty when using such hydrodynamic models (e.g. Deletic et al., 2012; Schellart et al., 2010; Thorndahl and Willems, 2008). Yu et al. (2017) mentioned that in addition to the system performance modelling uncertainty, uncertainty in cost estimation also poses challenges in finding optimal solutions that satisfy the objectives and constraints set by the decision maker. Several studies which explicitly account for modelling uncertainty when making decisions to mitigate the negative impact of CSO spills have been reported (e.g. Reda and Beck (1997), Portielje et al. (2000), Korving et al. (2009), Meng et al. (2016)). Lin et al. (2020), Mohammadiun et al. (2018), Yu et al. (2017), and Zhang et al. (2019) are recent studies which applied uncertainty based evaluation of decision alternatives for the mitigation of flood risk from urban sewer systems.

Although the aforementioned studies have incorporated uncertainty in the prediction of urban drainage processes in some form, they have not fully captured the uncertainty in 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 the 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. Mohammadiun et al. (2018) implemented a stochastic formulation for the design of urban drainage systems using blockage probability and probability of the failure, as the measure of resilience under stochastic conditions. However their approach only uses probability estimates and does not capture detailed information on uncertainty. Similarly, Yu et al. (2017) applied a stochastic optimization model for urban drainage design by applying chance constrained programming. The uncertainty arising from the simulation models is handled by limiting the total surcharge volume to an acceptable value by specifying a risk level as probability value. Zhang et al. (2019) applied a surrogate model based optimization to aid design for urban flood mitigation. They accounted for uncertainty arising from surrogate models and compared the surrogate model based optimization results to results from a 2D dynamic flood model using different rainfall scenarios. Lin et al. (2020) implemented a multi-objective optimization based design of urban drainage systems for protection against flooding. In order to make the design resilient against future uncertainties, they minimized the standard deviation of the maximum water depths in pipes. Similar to the studies mentioned before the representation of uncertainty by the use of standard deviation does not account for any asymmetry or the extremes of the distribution of predicted performance.

The probability of exceeding a threshold only indicates the chance that this threshold will be exceeded, however, it does not provide any information about the magnitude of the exceedance beyond the threshold. Studies such as Moreno-Rodenas et al. (2019) and Rico-Ramirez et al. (2015) have shown that the uncertainty in sewer system simulation outputs were generally found to have asymmetrical distributions. In the case of CSO spills, the environmental impact not only depends on the number of CSO spill events but also on the size and duration of each failure and the pollutant concentration and loads released. The authors argue that in this field a decision maker is likely to prefer asymmetry in a system’s performance. The preference for asymmetry relates to the sensitivity of the receiving water body. A receiving water body highly sensitive to incoming pollutant loads may drive the decision maker to prefer a negatively skewed distribution which does not have a long tail of rare but impactful events. A less risk-averse individual, however, may accept a small chance of a high negative impact in order to reduce the overall risk of failure.

Unlike existing studies, this paper fully utilizes the information provided by the uncertainty quantification process by including information on skewness and the magnitude of the tail of a probability distribution of a system performance measure. In doing so, this paper aims to develop a new decision-making approach, which accounts for decision makers' risk preferences using information on uncertainty in the sewer system's predicted performance.

In this new approach, the decision model uses a multi-objective formulation to reflect both the decision maker's objectives as well as his/her risk-averseness. As far as the authors are aware, the inclusion of risk preferences when accounting for uncertainty in making decisions for the management of intermittent CSO spills has not been reported before, and can have considerable implications for investment costs. Key contributions of this paper are: (i) identifying the characteristics of probability distributions to represent the risk preference of the decision maker, and (ii) analysing the implications of the risk preference of the decision maker on the investment decisions in the presence of conflicting objectives using uncertain system performance predictions.

The proposed decision-making approach is demonstrated using data from a case study catchment located in the North-West of Luxembourg.

2. Background and Methodology

2.1. Background

One of the most popular approaches for risk-averse decision-making has been the mean-variance approach developed by Markowitz (1952) for investment portfolio selection in the field of finance. This approach assumes that variance of the rate of return can be used as a measure of risk and that the decision maker should search for a selection with minimum variance for an expected rate of return on investment. In the context of this study, the desired decision criterion can be translated to a minimum variance for a given expected number of CSO spill events above a regulatory threshold. A bi-objective decision problem can be formulated to search for solutions which result in minimum mean and minimum variance of the number of predicted spill events. However, the mean-variance approach has certain limitations. It assumes that statistical distributions are Gaussian and that minimising variance penalizes distributions equally at both tails. For CSO spill events, the number of failures is usually defined as a threshold to the number of events (n) exceeding an allowed number of CSO spills in a defined time period, or a threshold exceeding an allowed number of events which are causing one or more water quality indicators to exceed a regulatory limit (for example, duration high ammonia concentration levels in the receiving water). As the method works for any threshold, a threshold is defined simply as 'T'. Hence, the decision maker would desire to limit the spread only on the right side of the probability distribution of n, i.e. to limit high values of n because only values of n greater than the threshold T would result in a breach of the regulatory requirements.

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 adopted in the Mean-Variance-Skewness approach proposed by Konno and Suzuki (1995) for investment portfolio selection. Konno and Suzuki (1995) argued that skewness of the distributions had a significant influence on the optimal selection of decision alternatives and proposed that the decision maker should prefer to maximise the skewness to optimise the rate of return on investment. However, unlike the rate of return on financial investments, the reasoning for the decision maker's preference to maximise skewness may not be so apparent for CSO spill events that cause regulatory failure. It can be argued that both types of asymmetry have distinct strengths and weaknesses in the context of managing water quality failure caused by intermittent CSO spills. For example, a small probability of a large number of spills may not be very significant when regulations only focus on a number of spills, and/or because these spills may be small in size. However, if the regulations are related to receiving water quality parameters and/or volume of spills, a small chance of a single huge event that destroys particular species of aquatic life in the receiving water could be a significant concern.

A positively skewed distribution (Fig 1a) will have a lower mode compared to a negatively skewed distribution, which means the most likely realizations of spill events n will be less than that of a negatively skewed distribution. Therefore, a decision maker who is more concerned about the most likely value of the number of CSO spill events and is prepared to absorb the small chance of high values of n (i.e. a long tail of the distribution of n), would prefer a positively skewed distribution. On the contrary, a decision maker who seeks to limit the possibility of very high values of n would prefer a negatively skewed distribution. Such a decision maker can be considered more risk-averse because their goal is to seek protection against the occurrence of very high number of CSO spills (i.e. avoiding long right tail) rather than limiting the most likely number of spill events.

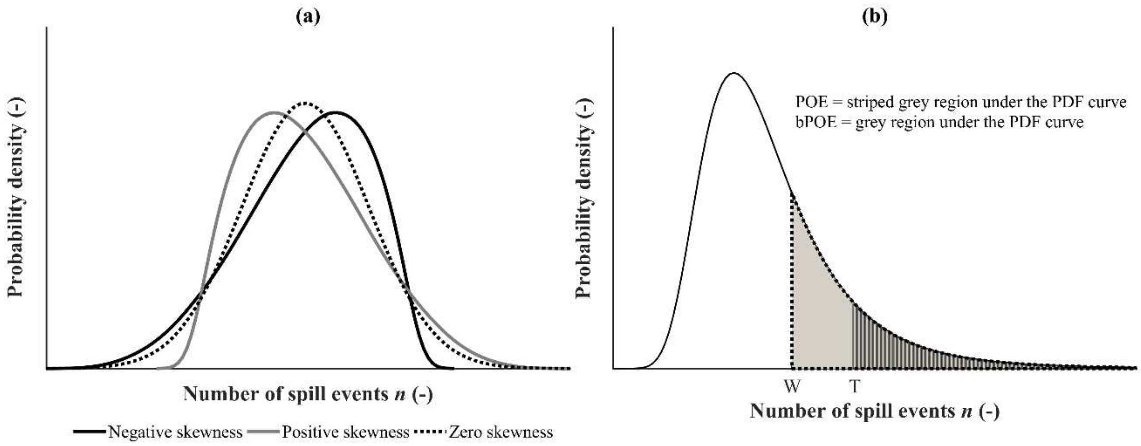

Fig. 1. (a) Difference in skewness for distributions with identical mean and variance. (b) Illustration of Probability of Exceedance and Buffered Probability of Exceedance for a threshold T on the number of spill events n.

Considering variance as a measure of risk in the Mean-Variance-Skewness approach does not address the risk of exceeding a threshold T imposed by 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 and T is the threshold set to determine CSO emission failure, POE for threshold T can be defined as

$$\mathrm{POE}(n) = \mathrm{P}(n > T) \tag{1}$$

However, the POE and the threshold T do not fully describe the shape of heavy-tailed distributions, they do not provide any information on the magnitude of n in the tail beyond threshold T. Uryasev (2014) proposed a measure called the Buffered Probability of Exceedance (bPOE) to reflect the magnitude of the probability in the tail beyond the threshold T. The POE gives the likelihood that the threshold T will be exceeded whereas, the bPOE 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 $T = \mathrm{E}[n|n > W]$, where $\mathrm{E}[n|n > W]$ is the conditional expectation of the number of spill events n exceeding

W (Fig. 1b). From Mafusalov and Uryasev (2014) and, Davis and Uryasev (2016), the bPOE for threshold T can be defined as:

$$\mathrm{bPOE}(n) = \mathrm{P}[n > W] \tag{2}$$

Since, $T \geq W$, there exists an inequality between bPOE and POE which can be expressed as,

$$\mathrm{POE}(n) \leq \mathrm{bPOE}(n) \tag{3}$$

The inequality in (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. 1b). Hence, it will be a better measure than the POE if the decision maker is risk-averse and is interested in comparing the tail performance of the distribution of the number of CSO spills for modelled engineering interventions to limit the occurrence of CSO emission failure.

2.2. Methodology

Building on the previous arguments, a decision model is proposed where the decision maker is seeking to minimize the risk of non-compliance with environmental regulations while minimizing the intervention cost. The proposed decision model has four objectives: (i) Minimizing the expected value of the number of CSO spill events E[n]; (ii) Minimizing the bPOE for a defined threshold on the number of CSO spill events; (iii) Maximizing or Minimizing the skewness of the distribution of n; and (iv) Minimizing the cost of any proposed engineering intervention.

Since the preference for the shape of the distribution (objective iii) is specific to this application and an individual's risk behaviour, two versions of the decision model (D1 and D2) are proposed to reflect the differing preferences for the skewness in the context of managing the impact of CSO emission failures. Since the decision models D1 and D2 seek solutions which minimise the bPOE value which is an indicator of risk, both D1 and D2 can be considered as risk-averse decision models.

2.2.1. Formulation of the multi-objective decision model

This section presents the mathematical formulation of the proposed risk-averse decision model. Consider a quantity n = f(s, u) which represents the performance of a combined sewer system model with decision variables $s \in S$ where S is the decision space, and uncertain inputs and parameters $u \in U$. Let us assume that uncertain inputs and parameters u represent the uncertainty in the modelling of the sewer system performance n defined on the uncertainty space U. For a given $s \in S$, uncertain inputs and parameters u will result into random realizations of the quantity of interest n which can be represented by $n_s = \mathrm{f}_s$ (s, u).

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

$$\mathrm{D1}: \begin{cases} \min_{s\in S} \mathrm{E}[\mathrm{f}_s(s,u)] \\ \min_{s\in S} \mathrm{bPOE}(\mathrm{f}_s(s,u)) \\ \max_{s\in S} \mathrm{skewness}(\mathrm{f}_s(s,u)) \\ \min_{s\in S} \mathrm{cost}(s) \end{cases} \tag{4}$$

$$\mathrm{D2}: \begin{cases} \min_{s\in S} \mathrm{E}[\mathrm{f}_s(s,u)] \\ \min_{s\in S} \mathrm{bPOE}(\mathrm{f}_s(s,u)) \\ \min_{s\in S} \mathrm{skewness}(\mathrm{f}_s(s,u)) \\ \min_{s\in S} \mathrm{cost}(s) \end{cases} \tag{5}$$

$$\text{subject to} \qquad u \in U$$

A decision maker may have biased i.e. have unequal preferences for the individual objectives; however, the objectives in D1 and D2 are treated as equally preferable to each other. Consequently, the decision maker may apply their preferences for the objectives *a posteriori*.

2.2.2. 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. Hence, the decision model searches 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. 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

$$\begin{gathered} s_i^1 \geq s_i^2 \quad \forall i \\ \text{and } \; s_i^1 > s_i^2 \text{ for at least one objective in } i \end{gathered} \tag{6}$$

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 inequalities:

$$\begin{gathered} s_i^* \geq s_i \quad \forall\, i \\ \text{and } \; s_i^* > s_i \text{ for at least one objective in } i \end{gathered} \tag{7}$$

Solving the multi-objective decision problem D1 or D2 by searching for non-dominated solutions as per Eq. 6 and 7 will result in a set of Pareto optimal solutions s^*. The approach is illustrated using a case study.

3. Case Study: The Haute-Sûre Catchment in Luxembourg

The case study catchment is part of the Haute-Sûre catchment located in the North-West of Luxembourg. The case study catchment has a combined sewer system, serving the urban area of Goesdrof with a single CSO structure composed of a storage tank and a weir to divert excess flows during intense rainfall events towards a tributary of the Sûre river. The CSO structure currently has a storage volume of 190 m^3 and the case study catchment size is 36 ha with an impervious area of 25 ha. This catchment is selected because the receiving water body is considered sensitive to the high ammonium and ammonia concentrations and thus exhibits aspects common in many situations in which investment may be required to better manage intermittent discharges in line with regulatory requirements. Further details of the case study catchment are given in Torres-Matallana et al., (2018)

3.1. Compliance with the environmental regulations

The uncertainty of the predicted ammonium concentration in the CSO emission is estimated and applied in the risk-averse decision model to find solutions which reduce the risk of regulatory failure caused by ammonium in the sewer overflows and also attempt to minimise cost. The concentration-duration-frequency based criterion used as a compliance tests was originally specified by the Austrian water wastewater association (ÖWAV) for receiving surface waters and is applied in this case study as an indicative emission quality standard (ÖWAV-Regelblatt 19, 2007), This standard is more restrictive than standards defined in several other European countries. The criterion for acute ammonia toxicity comprises separate thresholds for cyprinid and salmonid aquatic species. According to the ÖWAV guidelines, the maximum allowable number of CSO spill events failing this criterion for acute ammonia toxicity is 1 per year. This case study applies a dilution ratio to the predicted CSO spill ammonium concentration in order to account for the reasonably expected dilution of the CSO spill with the receiving water body. Morgan et al. (2017) list a range of dilution ratios which indicate the significance of stormwater overflows (SWO) to different types of receiving water bodies. They report a dilution ratio < 2:1 for SWOs with high significance, between 2:1 and 8:1 for medium significance while dilution ratio would be in the upwards of 8:1 for SWOs with low significance. For the purpose of demonstrating the decision methodology, this paper uses a value of 4 as a reasonable indicative dilution ratio for representing the dilution of CSO spills by flows in receiving waters.

3.2. The EmiStatR model

The performance of proposed solutions is evaluated using an open-source CSO water quality simulator EmiStatR, This scalable and highly computationally efficient simulator had been specifically developed to obtain water quantity and quality predictions with a similar level of accuracy compared to the results from complex mechanistic hydrodynamic models, such as InfoWorks. Its computationally efficiency made it ideal for studies in which computationally intense Monte Carlo based approaches were used to quantify the impact of uncertainty.. EmiStatR has therefore been used in earlier studies that investigated the propagation of input and model parameter uncertainties in the simulation of NH_4-N concentration in CSO spills (Torres-Matallana et al., 2018). The EmiStatR simulator uses 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 wet weather flow in the sewer network with contributions from urban and rural runoff; (iv) Definition of water quality characteristics of 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 and load.

A comprehensive description of the EmiStatR model can be found in Torres-Matallana et al. (2018) including the model calibration and validation approaches. The hydraulic calibration data set, contained three rainfall/spill events and consisted of detailed precipitation and CSO water level observations from 15 May 2011 to 3 June 2011 with the temporal resolution aggregated to 10 min to ensure identical temporal resolution in simulated and observed data. The DiffeRential Evolution Adaptive Metropolis (DREAM) algorithm (Vrugt et al., 2009) was used for calibration. The calibrated model displayed good agreement with the CSO water level observations in the calibration data set with a Nash-Sutcliffe Efficiency, NSE of 0.95.

The hydraulically calibrated EmiStatR model was validated using observations of precipitation and water level at the CSO storage chamber, at aggregated 10 minute intervals containing nine rainfall/spill events collected from 3 June 2011 to 7 July 2011. The EmiStatR model displayed a reasonable agreement (NSE = 0.78) with the observations in the validation data set. Additional validation of the hydraulic performance of the calibrated EmiStatR model included a comparison against a detailed hydrodynamic sewer network model of the catchment built and calibrated using InfoWorks ICM 7.5 covering an entire year (2010) at 10 minutes resolution, including 16 CSO spill events. For this validation period, the EmiStatR simulations of CSO volume displayed good agreement (NSE = 0.79) with the InfoWorks ICM model. This suggests that the EmiStatR can be used as a suitable rapid hydrodynamic simulation tool to demonstrate the proposed decision-making approach, with the advantage that EmiStatR is deployed as a scalable parallel simulator that allows multi-core simulation with a lower computational demand when it is compared to a detailed hydrodynamic sewer network model.

In the absence of water quality observations in CSO spills, the EmiStatR was further validated against water quality predictions using the calibrated InfoWorks ICM model for this catchment. The comparison of EmiStatR and InfoWorks ICM hydraulic and water quality simulations were done using a 1 year-long rainfall timeseries with 10-minute resolution. A good agreement was found between the EmiStatR and the InfoWorks ICM model for simulating CSO spill volume (NSE = 0.78) and ammonium load (NSE = 0.82).

3.2.1. Decision variables

To limit the number of CSO spill events failing the criterion defined in section 3.1, two types of solutions are considered: changing the storage capacity of the tank at the CSO and a reduction in impervious area through the provision of permeable paving to replace impermeable surfaces (Table 1). Combinations of solutions are then modelled and evaluated against emission failure criterion and cost. For storage tank capacity, 4 values: 100 m^3, 500 m^3, 900 m^3 and 1700 m^3 have been selected. These values have been selected as such to enable the evaluation of the performance of storage volume over a range that is expected to show a wide range of failures relative to regulatory requirements. This case study evaluates the decision model at impervious area values 20 ha, 23 ha and 25 ha. Similar to the selected range for storage tank capacity, a limited, but reasonable range of impervious area reduction from 25 ha to 20 ha was used. These choices for the decision space are specific to this case study.

3.2.2. Cost of the decision variable *s*

Detailed information about the capital cost of storage tanks and permeable paving is not available for Luxembourg, estimates from the UK are therefore used in this study. The construction of storage tanks can cost in the range of £1,400 - £2,000/m^3 for areas outside London whereas the implementation of permeable paving can cost approximately from £250 - £350/m^2 (Digman, 2018). Costs can vary depending on the construction company and catchment characteristics, such as location, property values and urban density. Fixed average values of solution costs i.e. £1,700/m^3 for the storage tank and £300/m^2 for the permeable paving have been used in this study to estimate the cost of the decision variable *s*, as the quality of the cost data provided did not allow a robust estimate of cost uncertainty to be made. No uncertainty is considered for the cost estimate for any solution, this was deemed reasonable given the quality of the cost data and that the main aim of the study was to examine the influence of predictive model uncertainty on risk perception.

3.2.3. Definition of uncertain inputs and parameters

Table 1 presents the list of inputs and parameters that could be considered uncertain for the Goesdorf sewer system. The list contains all the input parameters for which data was available to characterise uncertainty in their estimates. Measured data to characterise any temporal variability of the ammonium concentration in the surface runoff for this catchment is not available. Hence, uncertainty in this variable for this catchment could not be quantified and accounted for. Welker (2007) reported the ammonium concentration in surface runoff to be at 1mg/l as a representative value for a catchment in Germany following an extensive literature survey of pollutant concentrations in surface runoff. In the absence of more information on ammonium concentration in surface runoff for a catchment in Luxembourg, this paper uses the value of 1mg/l which could be considered suitable for a European catchment subject to similar farming regulations and practices.

Before the uncertainty propagation, 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 wastewater 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):

$$y_t = \mu_1 + \varphi_1(y_{t-1} - \mu_1) + w_t, \quad \varphi_1 \neq 0 \tag{8}$$

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 σ_w^2.

Table 1. List of uncertain and decision variables.

Variable	Assumed to be uncertain? (yes/no)	Definition of uncertainty
Uncertain Inputs and Parameters		
Wastewater – Dry Weather		
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		
Runoff coefficient for impervious area, C_{imp} [-]	yes	N(0.8, 0.05) truncated at 0 and 1[c]
Runoff coefficient for pervious area, C_{per} [-]	yes	N(0.3, 0.05) truncated at 0 and 1[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).

This paper uses the available rainfall precipitation measurements from the Esch-sur-Sûre rain gauge which is located around 3.5 km away from the Goesdorf CSO structure. The rainfall time series has a resolution of 10 minutes and contains 10 year-long precipitation measurements from January 2010 until December 2019. Since the rainfall precipitation time series contains many zero values, a different approach for characterising uncertainty in the rainfall time series has to be applied. 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 a measured precipitation time series in a nearby location outside the catchment while accounting for the uncertainty that is introduced due to spatial and temporal variation in precipitation. The inherent uncertainty in the measured rainfall is considered as a function of two neighbouring stations to assess the uncertainty i.e. Dahl and Esch-sur-Sure rainfall stations are used to define the rainfall time series at Goesdorf catchment while accounting for uncertainty. Torres-Matallana et al. (2017) note that their method does not capture the distribution tails well and in a small number of cases, results in an overestimation of the simulated precipitation.

McCuen (1998) reported an indicative 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. Table 1 indicates the normal distributions selected, such that about 95% of the runoff coefficient values lie in these ranges.

3.3. Solving the decision model

The decision space S in the current case study is discrete and finite, and comprises 12 grid points (s) for each decision model. In this case, the objective functions are evaluated at each grid point covering the decision space.

Fig. 2 outlines the steps involved in identifying the Pareto optimal solutions for the decision models D1 and D2. To evaluate the objectives in Eq. (4) or (5), for each of the 12 grid points in the decision space S, $n_s = f_s(s, u)$ is calculated where n_s is the emission quality indicator, s is the grid point representing decision variable and u is the uncertainty defined in section 3.2.3. For each $s \in S$ the uncertainty u in the inputs and model parameters listed in Table 1 are propagated through 500 Monte Carlo simulation runs for a 10 year period. The number of runs was selected after a convergence test that demonstrates this number as suitable to perform Monte Carlo simulations. For the simulation outputs CSO volume and ammonium concentration, standard deviation of the output variables at each time step from two different Monte Carlo simulations with different seed for the pseudo-number generator algorithm was compared. Convergence tests indicated 500 Monte Carlo simulations are sufficient to obtain consistent results (NSE ≈ 0.999 for CSO volume and NSE ≈ 0.998 for NH_4-N concentration).

These Monte Carlo simulations result in 500 random samples of 10 year-long time series of NH_4-N concentration in the CSO spill. According to ÖWAV guidelines, during 1 year the concentration of ammonia in the receiving water body due to a combined sewer overflow should not be more than 5 mg/l for one hour for cyprinid species (ÖWAV-Regelblatt 19, 2007). As per the criterion whenever the concentration of ammonia exceeds the threshold for an hour or more, it is counted as one failing CSO spill event. Two consecutive events are separated whenever, the concentration of ammonia drops below the threshold concentration. After multiplying with a dilution ratio of 4:1, this emission failure criterion is applied to the simulated NH_4-N concentration time series to calculate the number of non-compliant CSO spill events for every random time series. This results in 500 random samples of the emission quality indicator 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 are compared to each other for Pareto non-dominance by using inequality Eq. (6). All the grid points which satisfy the inequality Eq. (7) are selected as Pareto optimal solutions which represent the optimal trade-off between the individual objectives (Minimising mean of n_s; Maximising or Minimising skewness of n_s; Minimising bPOE, and; Minimising cost of s) set by the decision maker in D1 and D2.

Step 1: Define

- Emission quality indicator n_s: Number of CSO spills with NH_4-N concentration > (5 × dilution ratio) mg/l for one hour
- Simulation output: NH4-N concentration in the CSO spills
- Decision variables $s \in S$ (Section 3.2.1)
- Cost of decision variables $s \in S$ (Section 3.2.2)
- Uncertain variables u (Section 3.2.3)
- Objective functions for the decision models D1 and D2 (Eq. 4 and 5)

Step 2: Propagate the uncertainty in u to simulate NH_4-N concentration in the CSO spills $\forall s \in S$

Step 3: Estimate $n_s = f_s(s, u) \ \forall s \in S$ by identifying spill events with NH_4-N concentration > (5 × dilution ratio) mg/l for one hour, during 1 year on average

Step 4: Compute the value of objective functions in D1 and D2 $\forall s \in S$

Step 5: Determine Pareto non-dominance relationship for D1 and D2 $\forall s \in S$ (Eq.7)

Step 6: Identify Pareto optimal solutions for the decision models D1 and D2

Fig. 2. Steps followed to identify Pareto optimal solutions for D1 and D2.

It can be argued that it would be computationally more efficient to deterministically optimize the system for cost and number of critical spills without considering model predictive uncertainties then carry out MC simulations only for the non-dominated solutions and calculate bPOE and skewness only for these solutions. However, the Pareto optimality or non-dominance of solutions will change when model predictive uncertainty is considered, therefore, any solution deemed non-dominated or Pareto optimal based on a deterministic performance indicator is unlikely to be non-dominated if model predictive uncertainty is considered and this difference justifies the use of the more computationally expensive approach.

4. Results and Discussion

The decision models D1 and D2 are evaluated for the case study presented in Section 3 with decision variables s defined in Section 3.2.1 and, uncertain inputs and parameters u defined in Section 3.2.3. Fig. 3 shows an example of the distribution of n_s in the form of a histogram for the solution (900 m^3; 23 ha). Fig. 3a and 3b demonstrate the skewness present in the distribution of n_s.

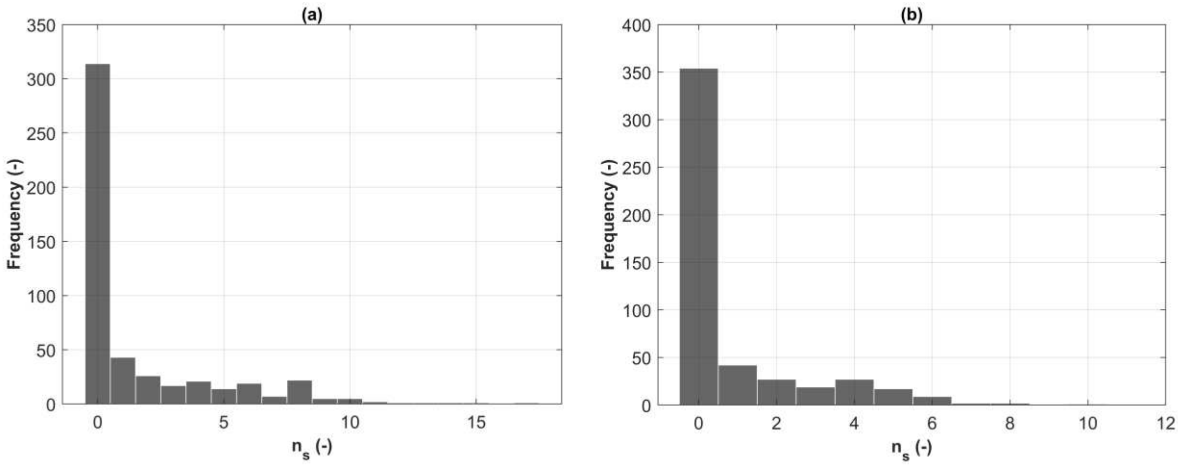

Fig. 3. Histogram of n_s for the solutions: (a) (100 m^3; 25 ha); (b) (900 m^3; 23 ha)

Fig. 4 shows the difference in POE and bPOE for $\forall\ s \in S$. It is evident how the magnitude of the tail values in the distribution of n_s affects the value of bPOE. The results for Pareto optimal solutions are presented separately for the decision models D1 and D2 which reflect the different preferences for the skewness of the distribution of n_s.

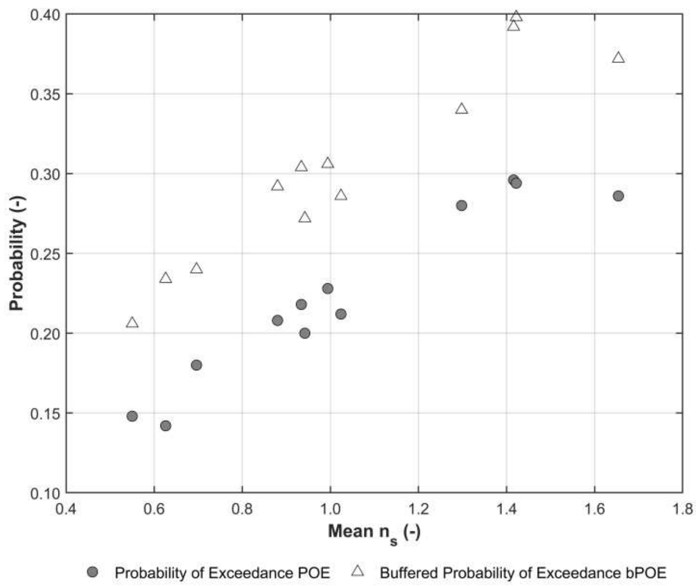

Fig. 4. Mean of n_s vs Probability of Exceedance (POE) and Buffered Probability of Exceedance (bPOE) for ∀ s ∈ S

4.1. Decision model D1: Preference for positively skewed distributions of n_s

For decision model D1, 10 solutions were found to be Pareto optimal or non-dominated out of the 12 solutions (Fig. 5). Fig. 5a and 5b 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 impervious area. 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 mean of n_s; Maximising skewness of n_s; Minimising bPOE and Minimising cost of s) are displayed as data points in a solid black circle in Fig. 5.

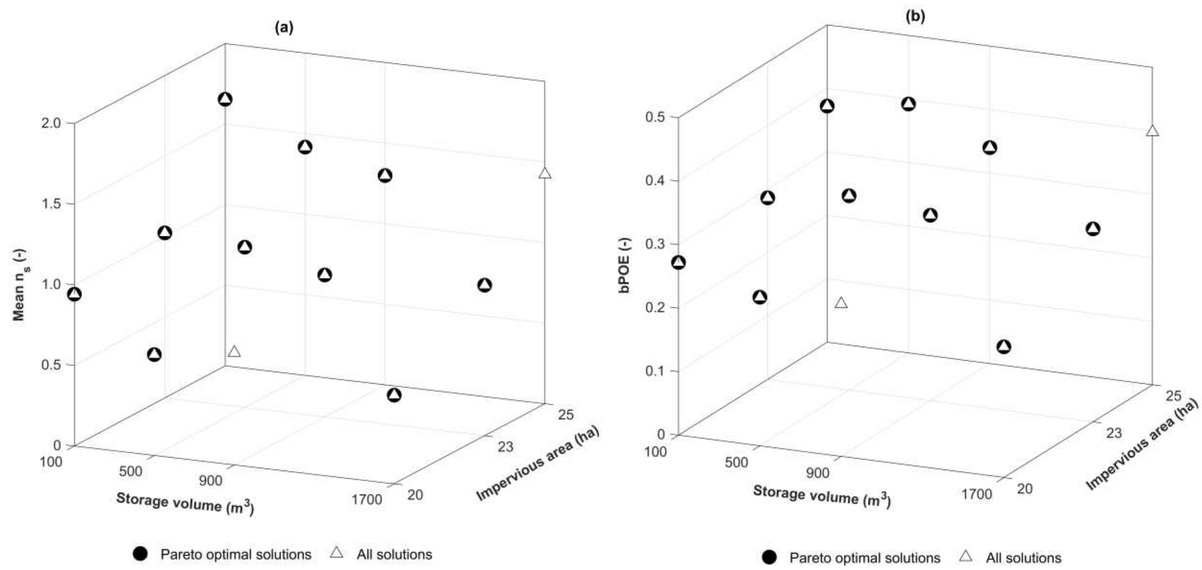

Fig. 5. (a) D1: Mean of n_s in the discrete decision space S; (b) D1: bPOE in the discrete decision space S

It can be observed that the decrease in the mean of n_s is steeper for a reduction in impervious area. For example, at the storage tank capacity of 900 m^3, the mean n_s reduces from 1.3 to 0.7 when the impervious area is reduced from 25 ha to 20 ha. On the contrary, at the impervious area of 20 ha, the mean reduces from 0.9 to 0.5 when the storage tank capacity is increased from 100 m^3 to 1700 m^3. A similar trend can be observed for bPOE values (Fig. 5b). Despite the considerably higher cost associated with impervious area reduction when compared to increasing the storage tank capacity, they are non-dominated solutions due to their better performance for the uncertainty related objectives.

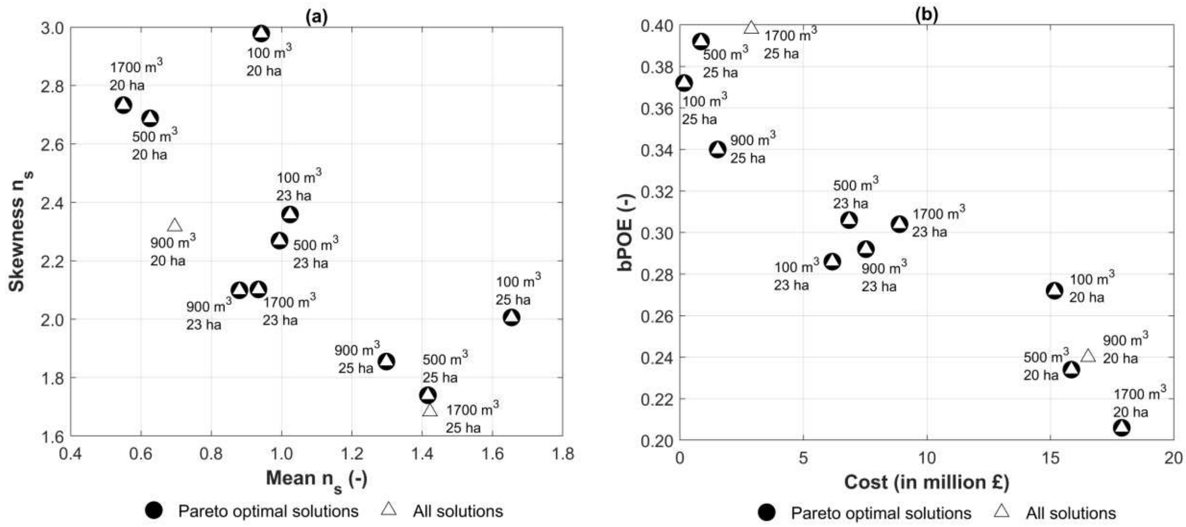

Fig. 6. (a) D1: Mean of n_s vs Skewness of n_s; (b) D1: Cost of n_s vs Buffered Probability of Exceedance (bPOE)

Fig. 6a shows the variation in the mean of n_s vs the skewness of n_s. Fig. 6b shows the cost of the decision variables vs their respective bPOE values. Pareto optimal solutions would be expected to lie towards low cost and low bPOE values however there are a 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 the other objectives compared to the non-optimal solutions with similar cost or similar bPOE.

4.2. Decision model D2: Preference for negatively skewed distributions of n_s

For decision model D2, 11 solutions were found to be Pareto optimal out of 12 solutions (Fig. 7). The only dominated or sub-optimal solution for D2 is (1700 m^3; 23 ha) since D2 seeks to minimise the skewness value. The rest of the 11 solutions remain Pareto optimal due to their better performance in one or more objectives. The solution (1700 m^3; 25 ha) performs worse for the mean, bPOE and the cost objective however it has the lowest skewness value which makes it non-dominated when one of the objectives is to minimise skewness.

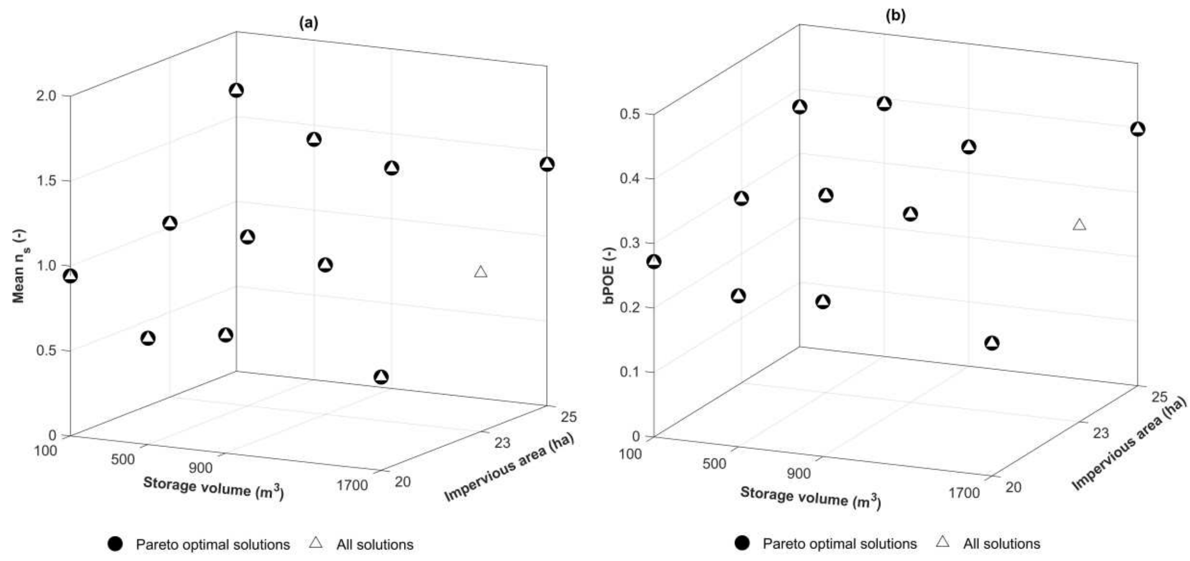

Fig. 7. (a) D2: Mean of n_s in the discrete decision space S; (b) D2: bPOE in the discrete decision space S

This clearly demonstrates that how a poorer performing solution can become non-dominated with differing preferences of decision makers. Therefore, solutions which have a relatively high mean, are also Pareto optimal solutions because they satisfy the objective of minimizing the skewness to address desired risk preferences (Fig. 8a). However, this is more evident in Fig. 8b where the Pareto optimal solutions for decision model D2 are displayed on the cost vs bPOE plot. 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 only cost and bPOE are concerned. In such situations, preference for individual objectives needs to be updated 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 are closer to the lower-left region of Fig. 8b should represent the decision maker's updated preference for the decision model D2.

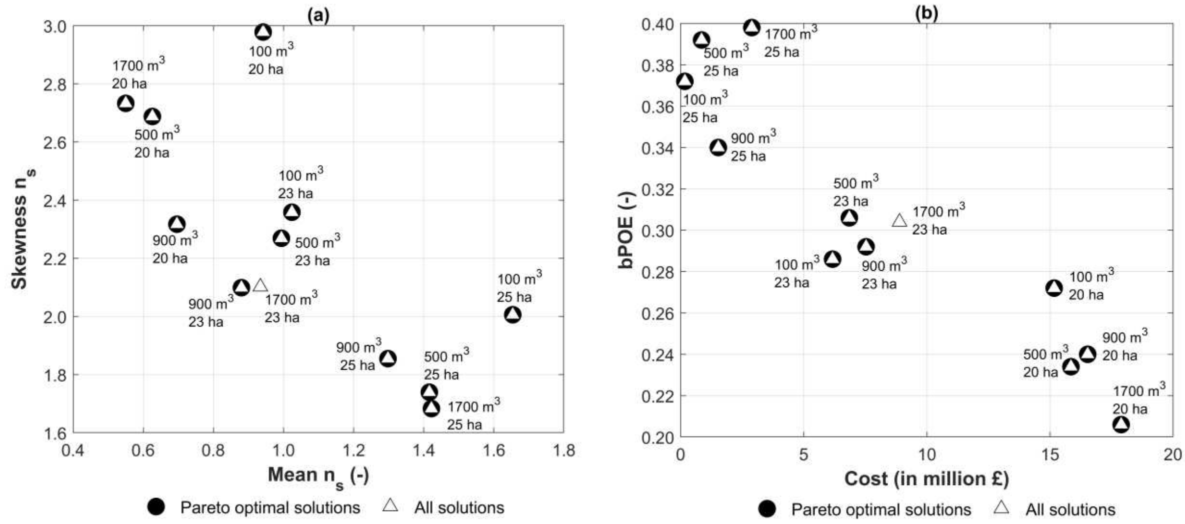

Fig. 8. (a) D2: Mean of n_s vs Skewness of n_s; (b) D2: Cost of n_s vs Buffered Probability of Exceedance bPOE

The decision models D1 and D2 provide the flexibility of representing other criteria in addition to the modelled system performance and cost; the decision model can be scaled up to include such criteria as objectives or constraints.

4.3. Implications of risk preferences on investment decisions

The proposed decision-making approach incorporates the uncertainty information in the predicted CSO's performance variable n_s through three objective parameters: mean n_s, bPOE and skewness of the distribution of n_s, with the cost added as a fourth objective parameter. The goal of the decision-making process is to minimise the mean and bPOE values. Different decision makers may exhibit varying degrees of risk aversion to regulatory failure and this can be accounted for in the value of the skewness of the n_s distribution and the bPOE among the four objectives in selecting their preferred solution. As a result, the selected investment at the end of the decision-making process can be greatly influenced by the individual risk aversion level of the decision maker, as illustrated by an example based on the case study outputs, as shown in Table 2. Consider an example, in which a certain value of the mean of the CSO's performance variable n_s are desired, and in each case, the financial impact of the risk aversion level of the decision maker as represented by the skewness is shown.

Table 2. Illustrative investment decisions for different asymmetry preference.

	Investment solution	**Mean n_s**	**Cost**
Example			
Minimising skewness	1700 m^3 ; 23 ha	0.93	£ 8,890,000
Maximising skewness	100 m^3 ; 20 ha	0.94	£ 15,170,000

Table 2 lists an illustrative example of comparing solutions with different preferences for skewness. In this example, the average protection, i.e. mean of n_s is kept at a very similar level. If the decision-maker prefers maximising the skewness, to achieve the same protection level as someone who prefers minimising skewness, the amount of investment required would be approximately two times higher. It should be noted here that maximising skewness may not always result in more expensive solutions when trying to achieve similar protection levels. These observations are specific to this case study example only. The example illustrates the potential for significant financial impact on a water utility, which is looking to meet the regulatory requirements but does not have a consistent risk acceptance or preference policy within its organisation to moderate the risk preferences of individual decision makers.

Similarly, two solutions can have identical values of POE but different values of bPOE indicating different tail magnitudes. Table 3 lists an example for illustrating the impact of tail magnitudes on an investment solution's performance. It is evident that the solution (900 m^3; 25 ha) is better than the solution (100 m^3; 25 ha) based on bPOE value meaning the tail of (100 m^3; 25 ha) has higher magnitude.

Table 3. Impact of the magnitude of tails in the distribution.

Investment solution	POE	bPOE
Example		
100 m^3 ; 25 ha	0.28	0.37
900 m^3 ; 25 ha	0.28	0.34

However, if the decision maker were to compare both the solutions only based on their POE value, they would assess them as equivalent in performance.

5. Conclusion

Uncertainties in the simulation of the performance of urban sewer systems pose challenges to decision makers in managing the environmental impact of intermittent sewer overflows. This paper presents a rigorous risk-averse decision-making approach, which incorporates detailed information on the shape of the probability distribution in the simulation of the performance of solutions. The decision model consists of a trade-off between three objectives representing uncertainty in the system performance, with the cost of the proposed solutions as the fourth objective.

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 distribution or the magnitude of the tails of the distributions that describe the system performance in relation to regulatory thresholds. In this paper, the inclusion of skewness and bPOE as objectives enables the decision maker to compare solutions against the symmetry and tail characteristics of their uncertain performance explicitly.

Compared to the existing literature on managing sewer overflow impact, the proposed decision-making approach provides decision makers with the flexibility to express their preferences for risk averseness. Decision makers can find solutions satisfying their preference by analysing the shape of the regulatory failure distribution and the level of risk acceptance under known budget constraints. The case study illustrated that utilising a rigorous decision-making approach would probably lead to considerably different investment solutions compared to approaches that do not account for the level of risk-averseness of decision makers. This shows the importance of taking into account uncertainty as well as the shape of the probability distribution of the regulatory performance indicator. The case study clearly illustrated that the level of risk averseness of an individual or a team in an organisation would have a considerable impact on any investment decision, and that this impact is of a same order of magnitude as the impact due to uncertainty in the predictive model parameters. Differing risk preferences could result in a selection of investment solutions which cost substantially more or less for comparable values of mean or POE failure performance.

This means that within the organisation of a water utility, a considerable difference in the cost of approved regulatory compliant engineering solutions can be obtained owing to risk preference of individuals or small teams within an organisation. These differences in individuals' risk preferences have an impact of the same order of magnitude as the impact of uncertainty in the predictive model parameters. To reduce the impact of different risk preferences on individual investment decisions it is recommended to define a consistent corporate risk preference policy within a water utility. Internationally there are a number of regulatory frameworks (e.g. Water Framework Directive, NPDES CSO Control Policy, (USEPA, 1994)) that require water utilities to reduce the impact of intermittent discharges on surface waters. Integrated models are often used to demonstrate compliance with regulatory requirements. This work indicates that understanding predictive uncertainty and the role of the risk preferences of individual decision makers could have a significant impact on the cost of such regulatory driven environmental protection programs. It is appreciated there are many more sources of uncertainty in integrated water quality models, such as uncertainty in cost, however not all sources of uncertainty were included as the main aim of the study was to examine the impact of predictive model uncertainty on the risk preferences of individuals involved in the investment decision making process. However, the proposed methodology is flexible and can be adapted to incorporate the impact of other sources of uncertainty on investment decisions to manage systems to ensure regulatory compliance that is determined using performance thresholds.

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