Coping with uncertainty in sewer system rehabilitation

H. Korving
HKV Consultants, Lelystad, the Netherlands & Department of Civil Engineering, Delft University of Technology, Delft, the Netherlands

J.M. van Noortwijk
HKV Consultants, Lelystad, the Netherlands & Department of Applied Mathematics, Delft University of Technology, Delft, the Netherlands

P.H.A.J.M. van Gelder
Department of Civil Engineering, Delft University of Technology, Delft, the Netherlands

R.S. Parkhi
Management Science Department, University of Strathclyde, Glasgow, United Kingdom

ABSTRACT: In decision-making on sewer rehabilitation risk and uncertainty are not taken into account. However, the assessments on which the decisions are based are considerably affected by uncertainties on external inputs, system behaviour and effects. In this paper, a risk-based approach is presented considering uncertainty in sewer system dimensions, natural variability in rainfall and uncertainty in the cost function describing environmental damage. The use of risk based optimisation is illustrated with an example.

1 INTRODUCTION

Decisions on sewer rehabilitation have large, long-lasting consequences and the decisions have to be made under uncertainty. Annually, approximately 1 billion Euro is invested in sewer rehabilitation in the Netherlands. Uncertain information about the structural condition and the hydraulic performance of the sewer system serves as the basis for decision-making. Therefore, the investments involve considerable risks, i.e. sewer rehabilitation that appeared to be dimensioned too large, or too small, or to be even unnecessary later on.

In the past, however, uncertainty analysis with regard to sewer system rehabilitation achieved very limited attention. Only recently, uncertainties influencing decisions on sewer rehabilitation are increasingly examined. For example, when it comes to impacts on receiving waters, such as CSOs (combined sewer overflows) and wwtp (wastewater treatment plant) emissions (Reda & Beck 1997 and Willems 2000), water quality criteria such as dissolved oxygen depletion (Beck 1996 and Hauger et al. 2002) or the assessment of eco-toxicological risks (Novotny & Witte 1997), risk based approaches are used to some extent.

Decision-making on sewer system rehabilitation requires the use of models to predict compliance of the system with performance criteria, i.e. CSO volumes and flooding. The decisions are usually based on a single computation of CSO volumes using a time series of rainfall as system loads. Consequently, uncertainties in knowledge of sewer system dimensions and natural variability in rainfall are ignored. Besides, statistical uncertainties are not taken into account. Uncertainties in sewer system assessment, however, are not restricted to calculated CSO volumes. The effects of CSOs on natural watercourses are just as much uncertain. Quantification of these effects is problematic because the determinative processes are complex and the knowledge on them is very limited (Harremoës & Madsen 1999). Moreover, measurement data on pollution loads from sewers are lacking and existing sewer models are unable to predict the loads (Ashley et al. 1998).

This paper discusses the sensitivity of optimal storage capacity of a sewer system to uncertainties in model input, i.e. model parameters and rainfall input, using probabilistic cost-benefit analysis. Monte Carlo analysis is applied to systematically study uncertainty propagation in a sewer model. For this purpose, model parameters and rainfall input are varied in each run of the Monte Carlo simulation in order to compute CSO volumes. Statistical uncertainty is treated by means of Bayesian estimation. Environmental damage is translated into a cost function. Based on estimated return periods of CSO volumes the sensitivity of decisions to the input uncertainties is evaluated for a discrete and a continuous damage cost function. The optimal storage capacity is determined by optimally balancing the cost of investment and the damage due to CSOs.

2 SEWER SYSTEM ASSESSMENT FOR REHABILITATION PURPOSES

Sewer systems have been designed to protect society from two important hazards: flooding of urban areas during storms and the endangering of public health due to exposure to faecal contamination. Besides, the environmental effects of CSOs should not exceed the carrying capacity of receiving natural watercourses. Overflow structures serve as emergency outlets to natural watercourses when rainfall volumes exceed the system capacity.

In the Netherlands, the approach to deal with the environmental impacts of sewer systems aims at reducing pollution loads by 50% compared to the 1985 situation. This approach has been translated into practical guidelines for calculations (see e.g. Van Mameren & Clemens 1997). The required pollutant reduction is expressed in terms of maximum allowable CSO discharges from a sewer system of 50 kg COD (chemical oxygen demand) discharged to the receiving waters per ha contributing area and per year (CIW 2001).

Assessing sewer overflows requires the use of a continuous rainfall series of a certain length, taking into account the interdependency of storm events and dry periods, thus enabling the calculation of return periods of the effects of medium and heavy storms. The Dutch guidelines prescribe a rainfall series with an interval of 15 minutes as observed during the years 1955-1979 in De Bilt (the Netherlands). Adding pollutant concentrations to calculated CSO volumes would enable the assessment of environmental impacts. However, these calculated pollutant loads are rather uncertain, since the prevailing pollutant concentrations in overflow volumes are unknown and the knowledge of determinative processes is limited.

In case a sewer system does not comply with the discharge limits several interventions can be planned, such as building additional in-sewer storage, enlarging pumping capacity, cleaning of sewers or improving pumping station performance.

3 UNCERTAINTIES IN SEWER SYSTEM ASSESSMENT

We can conclude from the previous that each assessment contains a certain measure of uncertainty because it is based on calculated CSO volumes and their pollutant loads. Therefore, the question, which arises, is which elements in the assessment of sewer systems should be acknowledged as uncertain and to what extent are decisions sensitive to such uncertainties.

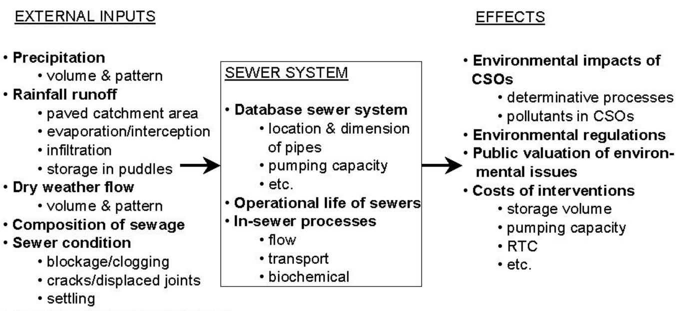

Figure 1. Uncertainties influencing sewer system assessment: external inputs/driving forces, the system itself or effects of the functioning of the system.

Uncertainties can be part of the external inputs, the system itself or the effects of the functioning of the system (see Figure 1). Input comprises a wide range of relevant driving forces, whereas output reflects the interests of parties that depend on the performance of the sewer system. Uncertainties may cause wrong decisions.

3.1 *Input uncertainties*

Uncertainties in external inputs may result from rainfall measurement errors (Rauch et al. 1998), spatial and temporal variability in rainfall (Schilling & Fuchs 1986, and Lei & Schilling 1996 and Willems 1999), variation in dry weather flow (dwf) due to varying inputs from households (Butler 1991 and Butler *et al.* 1995) and leaking groundwater (Clemens 2001).

Besides, uncertainty is introduced because the rainfall runoff process is described in a strongly simplified way in the model. Variability of runoff in time and local differences in runoff parameters (initial losses, infiltration, etc) is not taken into account and knowledge of processes is insufficient (Van de Ven 1989 and Clemens 2001).

Finally, hydraulic performance is assessed assuming perfect technical functioning of all objects in a sewer system leading to uncertainty in model assumptions. For example, risk of technical failure of pumping stations, settling of sewer pipes and clogging of culverts are not taken into consideration.

3.2 *System uncertainties*

The data set applied in a sewer model is never entirely perfect. Data errors (geometric structure of the sewer system, catchment area, runoff parameters, etc.) considerably influence calculation results (Price & Osborne 1986 and Clemens 2001).

Sewer models are imperfect because the physical phenomena are not exactly known and some variables of lesser importance are omitted for efficiency reasons. This results in model uncertainty with respect to hydraulics (Beck 1996 and Lei & Schilling 1996) and in-sewer processes determining sewage composition (Ashley et al. 1998). Besides, model uncertainties may stem from estimation (or calibration) of model parameters (Price & Catterson 1997 and Clemens 2001) and numerical calculation errors (Clemens 2001).

In addition, the influence of time dependent sewer deterioration is not accounted for in hydraulic sewer assessments. Except for biogenic sulphuric acid corrosion of sewer pipes there are no reliable models describing sewer deterioration because knowledge of deterioration processes (e.g. clogging, root intrusion, fouling, ingress of soil and longitudinal or radial pipe displacement) is limited. Therefore, assessment of sewer deterioration is performed by means of visual inspection and coding of observations. However, the assumed relationship between observations and actual structural deficiencies is debatable. As a result, prediction of the remaining operational life of sewers highly depends on the limitations of the assessment method.

3.3 *Impact uncertainties*

It is generally accepted that the quality of natural watercourses deteriorates due to CSOs (see e.g. House et al. 1993). Deterioration comprises water quality changes (dissolved oxygen, polluted sediments, etc.), human health risks and aesthetic contamination (floating waste, algal growth, etc.).

However, the severity is uncertain because CSOs are intermittent loads and their composition strongly varies (Beck 1996). Measurement data of pollution loads from sewers are unavailable and current sewer models are unable to predict them (Ashley et al. 1998). Moreover, translation of uncertain pollutant loads to effects on natural watercourses and their ecology is problematic because the knowledge of water quality processes is rather limited and the resilience of receiving water bodies is uncertain (Shanahan et al. 1998 and Harremoës & Madsen 1999). Therefore, environmental regulations based on available knowledge also incorporate uncertainties.

In addition, the valuation of environmental effects may also give rise to uncertainties in sewer assessments. Some authors claim that environmental effects can be quantitatively expressed in terms of money (see e.g. Crabtree et al. 1999 and Novotny et al. 2001). Others, on the other hand, oppose to this approach and value the effects in a more qualitative way (see e.g. Nijkamp & Van den Berg 1997 and Gilbert & Janssen 1998). An example of the former is the 'Contingent Valuation Method' as applied to urban water management by Novotny et al. (2001) which explores the public 'willingness to pay' for environmental restoration projects. Authors supporting the more qualitative approach, however, stress that quantitative valuation is unable to take into account uncertain and imprecise information that plays an important role in environmental impact modelling.

3.4 *Uncertain future developments*

Because of the long operational life of sewers (30-60 years) future developments significantly influence the system performance, not only developments in system input but also in public perception and policy-making. There are a number of examples of infrastructure designs that failed to meet a change in the demand for the goods or services it supplied (Hall 1980). Future developments with respect to sewer assessment include deterioration of sewers, change of regulations, climatic change, change of public perception of the environment and development of receiving water quality.

4 RISK BASED OPTIMISATION OF IN-SEWER STORAGE

As stated before, CSOs may cause serious deterioration of receiving water quality. Therefore, their influence should be reduced. One obvious intervention to reduce effects is to enlarge the in-sewer storage in such a way that CSO emissions diminish.

Currently, however, uncertainty and risk are not taken into account in decision-making on interventions such as enlarging the storage (see e.g. NEN-EN 752-4). As a result wrong decisions are possible because the effectiveness of a proposed intervention (e.g. construction of additional in-sewer storage) depends on the quality of the information supporting the decision-making.

Economic optimisation, as applied for dike design by Van Dantzig (1956), would enable decision-making on additional storage considering uncertainties in sewer system dimensions and natural variability in rainfall. It determines the optimal storage volume by a minimisation of total cost comprising initial investment for construction and cost of environmental damage due to overflows. Expected total costs are discounted over an unbounded horizon assuming that the value of money decreases with time.

According to Van Dantzig (1956), the decision problem can be formulated as follows (see Figure 2): 'Determine the optimal storage volume of the sewer system taking into account the cost of building in-sewer storage, the environmental damage in case of an overflow and the frequency distribution of CSO volumes.'

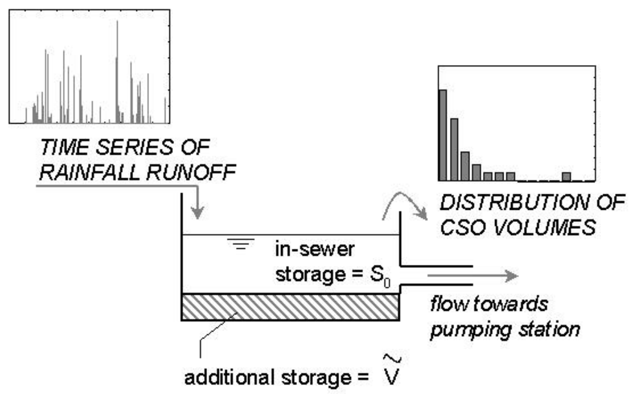

Figure 2. Schematic representation of the decision problem: enlarging in-sewer storage capacity in order to prevent CSOs (optimal storage volume = in-sewer storage (S_0) + additional storage ($\tilde{v}$)).

The cost of enlarging the storage capacity is proportional to the volume, i.e. the cost of building an additional m^3 diminish with increasing volumes. It can be described as,

$$I = I_0 v^{0.75} \tag{1}$$

where I_0 is investment per m^3 storage volume (Euro) and v is storage volume to be built.

The expected cost of damage due to overflows is discounted over an unbounded time horizon,

$$D = D_0 \frac{P_f(v)}{T_{CSO}} \left(\frac{\alpha}{1-\alpha} \right) \tag{2}$$

$$\alpha = 1/(1 + r/100) \tag{3}$$

where D_0 is the cost resulting from an overflow event (Euro), $P_f(v)$ is the probability of failure of sewer system given an overflow event occurs, T_{CSO} is the average return period of overflow events (y), α is the discount factor (-) and r is the discount rate (%). Eq. (2) follows from the expected number of overflows exceeding a volume v per year given as,

$$\sum_{k=0}^{\infty} k \cdot \Pr\{\text{number of overflows in period } (0,t] = k\}$$
$$= \sum_{k=0}^{\infty} k \frac{(\lambda \cdot p \cdot t)}{k!} \exp\{-\lambda \cdot p \cdot t\} \tag{4}$$
$$= \lambda \cdot p \cdot t = \lambda \cdot p \;\text{, for } t = 1$$

with λ=1/(T_{CSO}) being the frequency of overflows, p=$P_f(v)$ being the probability of failure of the sewer system and a Poisson process describing overflow events, the expected costs of failure per year can be discounted over an unbounded time horizon as follows,

$$\frac{P_f(v)}{T_{CSO}} \times \left[\alpha + \alpha^2 + \alpha^3 + \ldots \right] = \frac{P_f(v)}{T_{CSO}} \times \frac{\alpha}{1-\alpha} \tag{5}$$

The expected total cost equals,

$$E(TC) = I + D = I_0 v^{0.75} + \frac{D_0 P_f(v)}{T_{CSO}} \left(\frac{\alpha}{1-\alpha} \right). \tag{6}$$

Subsequently, the economic optimum of the storage volume is found by minimising total cost.

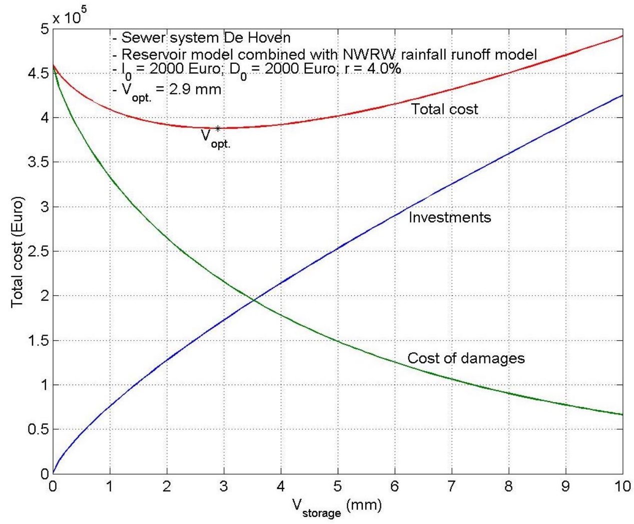

Figure 3. Economic optimisation of storage volume. (I_0=2000 Euro, D_0=2000 Euro (constant cost function), r=4.0 %).

Assuming D_0 is constant (see Figure 6), i.e. each overflow event has an immediate effect which is independent of its volume, and CSO volumes are Weibull distributed (Korving 2002), the optimal storage volume can be calculated given the variables I_0, D_0 and r. For example, for the sewer system of 'De Hoven', the Netherlands, (see Section 5) with I_0 = 2000 Euro, D_0 = 2000 Euro and r = 4.0% the optimum storage volume becomes 2.9 mm this equals 370 m^3 (Figure 3). The cost function appears to be relatively flat around the optimal volume indicating some robustness of the decision to be taken.

5 SENSITIVITY ANALYSIS OPTIMAL STORAGE SEWER SYSTEM 'DE HOVEN'

Risk based optimisation is applied to the sewer system of 'De Hoven'. Storage capacity is optimised taking into account (1) uncertainties in knowledge of sewer system dimensions, (2) natural variability in rainfall and (3) uncertainties in the cost function describing damage due to CSOs. Uncertainties in both system dimensions and rainfall input are separately modelled by means of Monte Carlo simulation. Subsequently, the expected value of the optimal storage is determined. Finally, the sensitivity of optimal volume to uncertainty in parameters of the cost function describing environmental damage is studied.

The influence of variations in system dimensions (storage capacity, pumping capacity and contributing areas) and natural variability in rainfall on the optimal storage volume of a sewer system is studied by modelling the sewer system of 'De Hoven'. The catchment 'De Hoven' (2200 inhabitants) is situated in the Netherlands on the banks of the river IJssel in the city of Deventer and comprises 12.69 ha paved catchment area. The sewer system (storage 865m^3 = 6.82mm) is of the combined type and comprises one pumping station (119m^3/h = 0.94mm/h) transporting the sewage to a treatment plant and three CSO structures (external weirs).

5.1 *Sewer model*

The sewer system is modelled as a reservoir with an external weir and a pump (Figure 4). The rainfall runoff is modelled with the so-called NWRW 4.3 model (Figure 4), the standard rainfall runoff model in the Netherlands. In this model evaporation, infiltration, storage on street surfaces and overland flow are modelled as described in Van Mameren & Clemens (1997). The model input is a 10-year rainfall series (1955-1964) of KNMI (De Bilt, the Netherlands). Dwf is assumed constant (26.4 m^3/h).

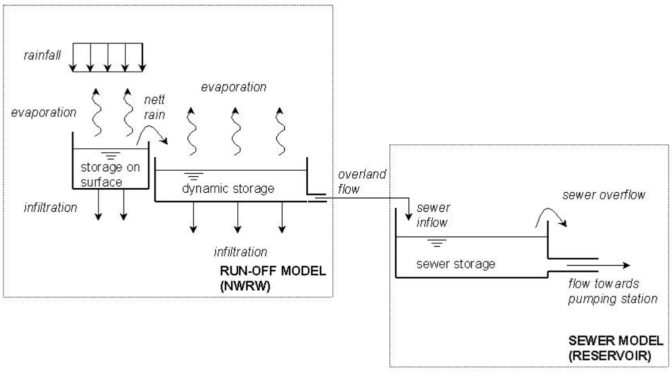

Figure 4. Sewer model comprising a rainfall runoff model (NWRW 4.3) and a reservoir model with external weir and pump.

5.2 *Modelling uncertainties in system dimensions*

The influence of variability in four sewer system dimensions is studied: storage volume (S), pumping capacity (pc), contributing area (A) and overflow coefficient (CC). These dimensions are assumed to be normally distributed and independent. Averages and standard deviations are based on expert judgement (Clemens 2001).

A Monte Carlo simulation of 500 runs is performed. In each run a random value of the model parameters (S, pc, A, CC) is drawn from the probability distribution functions. The parameter values are drawn independently, since their covariances are equal to 0 in the reservoir model. The samples are substituted in the reservoir model.

Table 1. Variations in system parameters (Clemens 2001).

System parameter	μ	σ	CV (%)
S (m^3)	865.00	43.25	5.0
pc (m^3/h)	119.00	5.95	5.0
A (ha)	12.69	0.64	5.0
CC ($m^{0.5}$/s)	1.40	0.35	25.0

5.3 *Modelling natural variability in rainfall*

Natural variability in rainfall is described with a spatial rainfall generator (Willems 2001). The generator has been especially developed for the small spatial scale of urban catchments. Therefore, a detailed description of individual rain cells is required. Spatial distribution of rainfall intensity in an individual rain cell is assumed Gaussian shaped. The generator is based on a model that distinguishes rainfall entities at different macroscopic scales, i.e. rain cells, cell clusters, and small and large meso scale areas (rainstorms) (see Figure 5). The model structure is twofold: a physically based part describing individual rain cells and cell clusters and a stochastic part describing the randomness in the sequence of the different rain cells and storms.

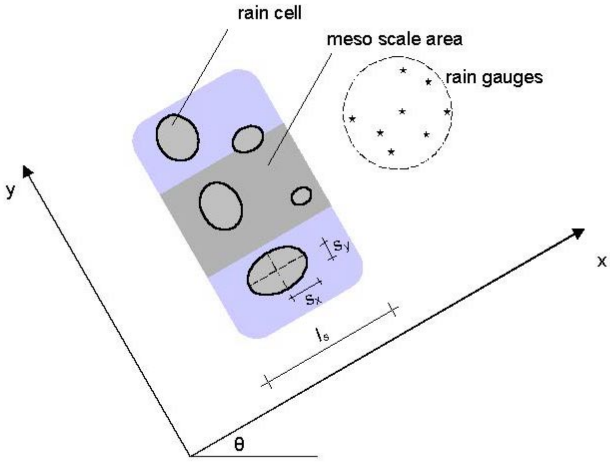

Figure 5. Schematic representation of spatial structure of rainfall including rain cells and meso scale areas or rainstorms (adapted from Willems 2001), where s_x is spatial extent of rain cell in moving direction, s_y is spatial extent of rain cell perpendicular to moving direction, θ is average moving direction of rain cells, l_s is spatial extent of rainstorm (meso scale area) and i is number of rain gauges.

Data from a dense network of rain gauges in Antwerp (Belgium) have been used for generator calibration. The calibrated rain properties comprise moving velocity, moving direction, spatial extent and intensity of rain cells, and inter-arrival times of rain cells and rainstorms.

Based on the above-mentioned properties of the rainfall the spatial rainfall generator has been constructed (see Willems 2001). Subsequently, using a random generator a large number of rain cells can be simulated taking into account their interdependencies. The generated time series of spatial rainfall has the same statistical properties as the data observed with the rain gauge network.

A Monte Carlo simulation of 500 runs is performed. In each run a random time series of rainfall volumes is generated. Although a spatial rainfall field is generated, only the volumes generated at a central location in Antwerp are used as system loads for the sewer model.

The rainfall generator calibrated for Antwerp can be used in 'De Hoven' because the generated rainfall series show considerable agreement with rainfall measurements in Ukkel (Belgium) in terms of IDF (Intensity-Duration-Frequency) relationships (Willems 2001). The Ukkel measurements, for their part, are similar to rainfall data observed in De Bilt (the Netherlands) with respect to IDF relations (Vaes et al. 2002).

5.4 *Estimation of distribution type and statistical parameters*

The calculated CSO volumes from the Monte Carlo simulations, as described in 5.2 and 5.3, are summed over the individual storm events and analysed statistically. Using Bayes weights the distribution function with the best fit to the CSO data is chosen (see e.g. in Van Noortwijk et al. 2001). . Exponential, Rayleigh, normal, lognormal, gamma, Weibull and Gumbel distributions are considered. The Bayesian approach quantifies both inherent and statistical uncertainty

The Weibull distribution type appears to fit best with the CSO data, has the largest Bayes weight (Korving et al. 2002). Therefore, it is chosen to describe the CSO volumes per storm event statistically. Given the CSO data $\mathbf{v} = (v_1,\ldots,v_n)$ the shape parameter a and the scale parameter b of the Weibull distribution,

$$f(v) = \frac{a}{b}\left(\frac{v}{b}\right)^{a-1} \exp\left\{-\left(\frac{v}{b}\right)^{a}\right\} \tag{7}$$

are estimated using the Maximum Likelihood method. The corresponding survival function of the Weibull distribution is defined as,

$$\overline{F}(v) = \exp\left\{-\left(\frac{v}{b}\right)^{a}\right\} \tag{8}$$

5.5 *Cost functions describing environmental damage*

Two types of cost functions are considered to model environmental damage due to overflows: a discrete and a continuous cost function (Figure 6). The discrete case is described in Section 4.

The continuous cost function is a more realistic description of the environmental effects of overflows. If damage is assumed to be a function of the actual overflow volume, the cost function can be described as,

$$D(v) = \begin{cases} D_0\left[1-\exp\left\{-\left(\dfrac{v-\widetilde{v}}{b_1}\right)^{a_1}\right\}\right] & \text{for } v \geq \widetilde{v} \\ 0 & \text{for } v < \widetilde{v} \end{cases} \tag{9}$$

where v is an actual overflow volume, which is a random quantity, $\widetilde{v}$ is the storage volume to be built, a_1 and b_1 are parameters on which the shifted Weibull-shaped cost function is dependent. They differ from the parameters a and b of the Weibull distribution describing the inherent uncertainty of overflow volumes.

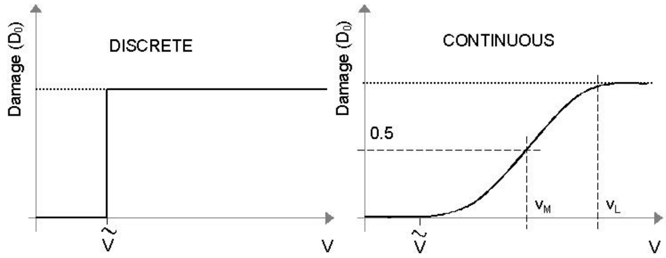

Figure 6. Cost functions describing environmental damage due to CSOs, v is an actual overflow volume, which is a random quantity, and $\widetilde{v}$ is the storage volume to be built.

Since the overflow volume v is a random quantity, in the actual calculation the expectation of Eq. (9) is required,

$$\begin{aligned} E[D(V)] &= \int_{v=\widetilde{v}}^{\infty} D_0\left[1-\exp\left\{-\left(\frac{v-\widetilde{v}}{b_1}\right)^{a_1}\right\}\right] f(v)dv \\ &= \int_{v=\widetilde{v}}^{\infty} D_0\left[1-\exp\left\{-\left(\frac{v-\widetilde{v}}{b_1}\right)^{a_1}\right\}\right] \\ &\quad * \frac{a}{b}\left(\frac{v}{b}\right)^{a-1} \exp\left\{-\left(\frac{v}{b}\right)^{a}\right\}dv \end{aligned} \tag{10}$$

In Eq. (10) the Weibull distribution describing actual CSO volumes has been introduced. Since $v \geq \widetilde{v}$ for all $\widetilde{v}$, the left-truncated Weibull distribution is considered. This distribution can be obtained from the Weibull by conditioning on values larger than $\widetilde{v}$,

$$\begin{aligned} \Pr\{V > v | V > \widetilde{v}\} &= \frac{\Pr\{V > v \cap V > \widetilde{v}\}}{\Pr\{V > \widetilde{v}\}} = \frac{\Pr\{V > v\}}{\Pr\{V > \widetilde{v}\}} \\ &= \exp\left\{-\left(\frac{v}{b}\right)^{a} + \left(\frac{\widetilde{v}}{b}\right)^{a}\right\} \end{aligned} \tag{11}$$

Using the left-truncated Weibull distribution, the expected damage (Eq. (10)) can be reformulated as,

$$\begin{aligned} E[D(V)] &= \int_{v=\widetilde{v}}^{\infty} D_0\left[1-\exp\left\{-\left(\frac{v-\widetilde{v}}{b_1}\right)^{a_1}\right\}\right] \frac{a}{b}\left(\frac{v}{b}\right)^{a-1} \\ &\quad * \exp\left\{-\left(\frac{v}{b}\right)^{a} + \left(\frac{\widetilde{v}}{b}\right)^{a}\right\} \exp\left\{-\left(\frac{\widetilde{v}}{b}\right)^{a}\right\}dv \\ &= D_0 P_f(\widetilde{v}) \int_{v=\widetilde{v}}^{\infty} \left[1-\exp\left\{-\left(\frac{v-\widetilde{v}}{b_1}\right)^{a_1}\right\}\right] \\ &\quad * \frac{a}{b}\left(\frac{v}{b}\right)^{a-1} \exp\left\{-\left(\frac{v}{b}\right)^{a} + \left(\frac{\widetilde{v}}{b}\right)^{a}\right\}dv \end{aligned} \tag{12}$$

The integral is numerically solved using Monte Carlo simulation. In each Monte Carlo run a value is sampled from the left-truncated Weibull distribution.

Subsequently, the expectation of the damage cost can be given by,

$$E[D(V)] \approx D_o P_f(\tilde{v}) \frac{\sum_{i=1}^{n}\left[1-\exp\left\{-\left(\frac{v_i-\tilde{v}}{b_1}\right)^{a_1}\right\}\right]}{n} \quad (13)$$

where n is the number of runs in the Monte Carlo simulation and v_i is a sample from left-truncated Weibull distribution.

The parameters a_1 and b_1 in the Weibull-shaped cost function describing environmental damages are estimated as follows. Let v_L be the CSO volume at which the damage cost becomes almost constant, i.e. the damage cost is almost D_0, say, $0.99*D_0$ (see Figure 6). Let v_M be half of this volume, i.e. v_M=$v_L/2$ (see Figure 6). The cost at v_M is equal to $0.5*D_0$. The value of v_M determines the steepness of the cost function (Eq. (9)). Choosing v_M completes the description of the Weibull-shaped cost function because it is uniquely described with two percentiles (v_M and $p(v_M)$, v_L and $p(v_L)$). According to Eq. (9) $p(v)$ is defined as,

$$p(v) = 1-\exp\left\{-\left(\frac{v-\tilde{v}}{b_1}\right)^{a_1}\right\} = \frac{D(v)}{D_0}\ , \text{ for } v \geq \tilde{v} \quad (14)$$

Finally, the expected costs of damage are substituted in the total cost function similar to Eq. (4) and Eq. (5).

5.6 *Sensitivity analysis of optimal storage volume*

Using both types of cost functions the storage volume is optimised. For each Monte Carlo simulation (n=500) this results in a set of 500 optimal volumes. The set represents the uncertainty in storage volume to be built resulting from either system dimension uncertainty or natural variability in rainfall.

The uncertainty in storage due to input uncertainties can be expressed in the expected value of the optimal volume, which is given by,

$$E(V_{opt}) \approx \frac{1}{n}\sum_{i=1}^{n} V_{opt}(i) \quad (15)$$

where $V_{opt}(i)$ is the optimal storage volume resulting from the i^{th} run and n is the total number of runs in the Monte Carlo simulation (n=500). Besides, the 95% uncertainty interval of optimal volumes (i.e. 95% of calculated values of V_{opt} is within the given boundaries) is calculated to reflect the distribution.

The results based on the discrete damage function are shown in Table 2 (first row), whereas Table 3 (first row) presents the results with respect to the continuous case.

Table 2. Expected value of optimal volume (in mm) using discrete damage function (r=4.0% and I_0=2000€). System dimension uncertainty and natural variability in rainfall are separately considered.

	Dimension uncertainty		Variability rainfall	
	E(V_{opt}) (mm)	95% interval (mm)	E(V_{opt}) (mm)	95% interval (mm)
D_0=2500€	4.09	2.25 - 5.84	1.17	0 - 2.68
D_0=2250€	3.50	1.73 - 5.23	0.71	0 - 2.00
D_0=2750€	4.63	2.77 - 6.40	1.67	0 - 3.32

Subsequently, the sensitivity of calculated optimal storage to uncertainty in the assumed cost functions has been tested. For this purpose, the value of D_0 in Eq. (2) is both increased and decreased with 10%. In the continuous damage function the values of D_0 and v_M are changed with 500 € and 2mm respectively. This implies varying parameters a_1 and b_1 in Eq. (9). The results are presented in the remainder of Table 2 and Table 3.

Table 3. Expected value of optimal volume (in mm) using continuous damage function (r=4.0%and I_0=2000€). System dimension uncertainty and natural variability in rainfall are separately considered.

	Dimension uncertainty		Variability rainfall	
	E(V_{opt}) (mm)	95% interval (mm)	E(V_{opt}) (mm)	95% interval (mm)
D_0=7500€ v_M=5mm	5.23	3.15 – 7.01	1.15	0 - 5.79
D_0=7000€ v_M=5mm	4.56	0 – 6.54	0.67	0 – 4.81
D_0=8000€ v_M=5mm	5.78	3.77 – 7.46	1.71	0 – 6.15
D_0=7500€ v_M=3mm	7.59	5.86 – 9.21	4.40	0 – 8.11
D_0=7500€ v_M=7mm	1.76	0 – 4.80	0.07	0 - 3.76

The results show considerable variation in calculated CSO volumes resulting from uncertainty of sewer dimensions and variability in rainfall. Besides, variation increases with increasing return period. Subsequently, variability in CSO volumes is transferred to uncertainty in optimal storage volumes (see 95% uncertainty interval in Table 2 and Table 3).

The cost of damages due to CSOs, however, is difficult to estimate in absence of sufficient data. Therefore, estimation of optimal storage volumes by minimising expected total cost is uncertain. Sensitivity analysis shows that the optimal volume is rather sensitive to changes in the damage cost (D_0) for both cost functions and the steepness of the cost function (v_M) for the continuous case only.

Uncertainty in sewer dimensions results in larger expected optimal volumes but mostly smaller variability within these volumes than rainfall variability. Compared to current practice (CIW 2001) the additional storage should be at least 2.18mm (given a pumping capacity of 0.7mm/h plus dwf the storage volume should exceed 7+2mm). With respect to dimension uncertainty the calculated values are slightly larger.

Uncertainty analysis of the cost function is needed to quantify the relative influence of all significant uncertainties in the calculation of the optimal storage volume.

6 CONCLUSIONS

Combining probabilistic optimisation techniques and currently available deterministic sewer models enables assessment of uncertainty in sewer rehabilitation on the basis of calculated CSO volumes.

The paper presents a risk based approach to optimise the required storage volume of a sewer system in order to comply with performance criteria. Sensitivity of optimal storage to uncertainty in model parameters, natural variability in rainfall and uncertainty in type and parameters of the cost function describing environmental damage is taken into account.

The results show that there is considerable variation in optimal storage volume due to the uncertainties in calculated CSO volumes. Besides, uncertainty of sewer dimensions predominantly causes uncertainty. Therefore, investing in more accurate knowledge of the dimensions is worth while. In conclusion, uncertainty analysis of the cost functions is needed in order to allow for the lack of knowledge of environmental damages due to CSOs.

7 ACKNOWLEDGEMENTS

This paper describes the results of a research, which is financially supported by and carried out in close co-operation with HKV Consultants (Lelystad, the Netherlands) and the RIONED Foundation (Ede, the Netherlands). The authors would like to thank HKV and RIONED for their support. They are also grateful to Patrick Willems (KU Leuven, Belgium) for providing the spatial rainfall generator.

REFERENCES

Ashley, R.M., Hvitved-Jacobsen, T. & Bertrand-Krajewski J.-L. (1998). Quo Vadis Sewer Process Modelling? *Water Science and Technology*, 39(9): 9-22.

Beck, M.B. (1996). Transient polluton events: acute risks to the aquatic environment. *Water Science and Technology*, 33(2): 1-15.

Butler, D., Friedler, E. & Gatt, K. (1995). Characterising the quantity and quality of domestic wastewater inflows. *Water Science and Technology*, 31(7): 13-24.

CIW (2001). *Riooloverstorten Deel 2. Eenduidige basisinspanning. Nadere uitwerking van de definitie van de basisinspanning.* (In Dutch). June 2002. Den Haag: CIW.

Clemens, F.H.L.R. (2001). *Hydrodynamic Models in Urban Drainage: Application and calibration.* PhD thesis. Delft: Technische Universiteit Delft.

Crabtree, B., Hickman, M. & Martin, D. (1999). Integrated water quality and environmental cost-benefit modelling for the management of the River Tame. *Water Science and Technology*, 39(4): 213-220.

Gilbert, A.J. & Janssen, R. (1998). Use of environmental functions to communicate the values of a mangrove ecosystem under different management regimes. *Ecological Economics*, 25: 323-346.

Hall, P. (1980). *Great Planning Disasters.* Weidenfeld & Nicolson: London.

Harremoës, P. & Madsen, H. (1999). Fiction and reality in the modelling world - Balance between simplicity and complexity, calibration and identifiability, verification and falsification. *Water Science and Technology*, 39(9): 47-54.

House, M.A., Ellis, J.B., Herricks, E.E., Hvitved-Jacobsen, T., Seager, J., Lijklema, L., Aalderink, H. & Clifford, I.T. (1993). Urban drainage – Impacts on receiving water quality. *Water Science and Technology*, 27(12): 117-158.

Korving, H., Clemens, F., Van Noortwijk, J. & Van Gelder, P. (2002). Bayesian estimation of return periods of CSO volumes for decision-making in sewer system management. In: *Proc. of 9th Int. Conf. on Urban Drainage. Sept. 2002, Portland, Oregon, USA*.

Lei, J.H. and Schilling, W. (1996). Preliminary uncertainty analysis - A prerequisite for assessing the predictive uncertainty of hydrological models. *Water Science and Technology*, 33, 2: 79-90.

Nijkamp, P. & Van den Bergh, J.C.J.M. (1997). New advances in economic modelling and evaluation of environmental issues. *European Journal of Operational Research*, 99: 180-196.

NEN-EN 752-4. *Drain and Sewer Systems Outside Building. Part 4: Hydraulic design and environmental considerations.* March 1998.

Novotny, V., Clark, D., Griffin, R.J. & Booth, D. (2001). Risk based urban watershed management under conflicting objectives. *Water Science and Technology*, 43, 5: 69-78

Novotny, V. & Witte, J.W. (1997). Ascertaining aquatic ecological risks of urban stormwater discharges. *Water Research*, 31, 10: 2573-2585.

Parkhi, R. (2002). *Influence of Natural Variability in Rainfall on Decision-Making for Sewer System Management.* MSc thesis. Lelystad: HKV Consultants.

Price, R.K. & Catterson, G.J. (1997). Monitoring and modelling in urban drainage. *Water Science and Technology*. 36 (8-9): 283-287.

Price, R.K. & Osborne, M.P. (1986). Verification of sewer simulation models. In: *Proc. of Int. Symp. on Comparison of Urban Drainage Models with Real Catchment Data. UDM'86. Dubrovnik, Yugoslavia*: 99-106.

Rauch, W., Thurner, N. and Harremoës, P. (1998). Required accuracy of rainfall data for integrated urban drainage modeling. *Water Science and Technology*, 37 (11): 81-89.

Reda, A.L.L. & Beck, M.B. (1997). Ranking strategies for stormwater management under uncertainty: sensitivity analysis. *Water Science and Technology*, 36 (5): 357-371.

Schilling, W. & Fuchs, L. (1986). Errors in stormwater modelling - A quantitative assessment. *Journal of Hydraulic Engineering*, 112 (2): 111-123.

Shanahan, P., Henze, M., Koncsos, L., Rauch, W., Reichert, P. Somlyódy, L. & Vanrolleghem, P. (1998) River water quality modelling: II. Problems of the art. *Water Science and Technology*, 38 (11): 245-252.

Vaes, G., Clemens, F., Willems, P. & Berlamont, J. (2002). Design rainfall for combined sewer system calculations. Comparison between Fanders and the Netherlands. In: *Proc. of 9th Int. Conf. on Urban Drainage. Sept. 2002, Portland, Oregon, USA.*

Van Dantzig, D. (1956). Economic decision problems for flood prevention. *Econometrica*, 24: 276-287.

Van de Ven, F.H.M. (1989). *Van neerslag tot rioolinloop in vlak gebied.* (In Dutch). Lelystad: Rijkswaterstaat,

Van Mameren, H. & Clemens, F. (1997). Guidelines for hydrodynamic calculations on urban drainage in the Netherlands: overview and principles. *Water Science and Technology*, 36 (8-9): 247-252.

Van Noortwijk, J.M., Kalk, H.J., Duits, M.T. & Chbab, E.H. (2001). The use of Bayes factors for model selection in structural reliability. In: *Proc. of 8th Int. Conf. on Structural Safety and Reliability (ICOSSAR). June 2001, Newport Beach, California, USA.*

Willems, P. & Berlamont, J. (1999). Probabilistic modelling of sewer system overflow emissions. *Water Science and Technology*, 39 (9): 47-54.

Willems, P. (2001). A spatial rainfall generator for small spatial scales. *Journal of Hydrology*, 252: 126-144.