Simulation of sewer overflow volume in Flanders using a global sensitivity analysis

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Abstract
To quantify uncertainty in urban drainage models, it is important to prioritise the model input parameters based on their contribution towards the variation in the model outputs. Global sensitivity analysis proves to be a stepping stone for uncertainty analyses by serving this purpose. This paper uses Morris screening method to identify important input parameters influencing combined sewer overflow (CSO) volume in an urban catchment in the Flanders region of Belgium. The sewer system is modelled in InfoWorks CS and a composite design storm is used in order to reflect the local modelling practice. Despite a low precision threshold applied on variability, stable convergence was achieved with Morris screening with as few as 900 model simulations. Runoff coefficient, weir crest, and Colebrook-White roughness came across as the most influential input parameters. Except the runoff coefficient and roughness, all the other input parameters displayed a linear relationship with the CSO volume.

Keywords
Combined sewer overflow uncertainty; Global Sensitivity Analysis; InfoWorks CS; Morris screening

INTRODUCTION

Efficient decision making in the management of sewer network infrastructure is strongly influenced by compliance with regulatory/policy guidelines while satisfying budget constraints. Regulatory authorities set certain environmental permits and combined sewer overflows (CSO) spills managed by the utility companies need to comply with these regulations. In many countries utility companies face the risk of paying penalties or reputational damage if they fail to comply. This risk of penalty can be managed by taking appropriate decisions on investing in additional infrastructure to reduce the risk of CSO spills. Decisions on such investments are mainly based on performance criteria which are defined to compare suitable decision alternatives. These performance criteria can be estimated using hydrodynamic urban drainage network models; hence any uncertainty in these urban drainage models can have a significant effect on the outcome of the decision making process.

In recent years many studies have been done to focus on the sources of uncertainty in these models and their implications on the determination of system failure required in any design process. For example, Deletic et al. (2012) laid out a general framework for assessing the uncertainty in urban drainage models. Butts et al. (2004) classified the uncertainty in modelling into model input data, parameters, calibration data and model structure uncertainties whereas, Refsgaard et al. (2007) combined the input and calibration data together making the classification into three categories: data, parameter and model structure uncertainty.

Sensitivity analyses give us insights on model behaviour, its structure and its response to the variations in the model input (Borgonovo & Plischke, 2016). They can also be used to identify

which model inputs and parameters influence the model output the most (Iooss & Lemaître, 2014). There are several methods proposed in the literature for performing sensitivity analysis. These analyses can be classified as Global Sensitivity Analysis (GSA) and Local Sensitivity Analysis (Saltelli et al., 2000). A local sensitivity analysis is used to study the effect of small input perturbations on the model output and it is performed around a point in the parameter space whereas a GSA is performed over the whole parameter space of input and model parameters considered for the study (Gamerith et al., 2013; Iooss & Lemaître, 2014; Borgonovo & Plischke, 2016). For complex models having a large number of model parameters, a small subset of model inputs and parameters can be selected by ranking all the parameters based on GSA. This can reduce the computational cost by only keeping the important parameters which explain the model output variance for uncertainty analysis or parameter estimation (Wainwright et al., 2014). Global sensitivity analysis can be performed using different approaches such as Standard regression coefficients (SRC) (Saltelli et al., 2008), Extended-FAST method (Saltelli et al., 1999), Morris screening method (Morris, 1991), Sobol' indices (Sobol, 2001) etc. Although Vanrolleghem et al. (2015) prefer Extended-FAST over SRC and Morris screening method for water quality simulation using a conceptual model, they further conclude that for water quantity all the three methods Extended-FAST, SRC and Morris screening produce similar results. Gamerith et al. (2013) applied SRC and Morris screening method on a conceptual sewer rainfall-runoff model and concluded that both methods result in similar ranking of parameters for water quantity.
In this study, we identify the model input parameters which could potentially contribute most to the uncertainty of the modelled values of sewer overflow volume in an urban catchment in Flanders region of Belgium. In this study wherever mentioned, the terms 'model input parameters' or 'input parameters' refer to the model inputs selected for the GSA whose values remain fixed during a single model simulation. Morris screening is applied on the simulation results of the sewer system modelled in InfoWorks CS. The Global Sensitivity Analysis is performed using selected model input parameters and the sensitivities of these input parameters are evaluated using a single model output. As far as authors are aware the Global Sensitivity Analysis methods such as Morris screening method have not been applied on simulation results obtained from a detailed sewer network modelled in InfoWorks CS.

METHODS

Model and Data

The catchment model used in this study is a subsystem of a model for Herent which itself is a subsystem of a larger model for the city Leuven in Belgium which was developed by the water company Aquafin. The general characteristics of the Herent catchment are described in the study by Fischer et al. (2009). The subsystem catchment model used in this study is not identical to the one used by Fischer et al. (2009) and it consists of 179 nodes and 175 pipes with the total sewer length measuring at 12.5 km. This sewer subsystem serves around 2100 inhabitants with a total contributing area of about 87 hectares. The catchment model along with the location of the CSO structure is shown in Figure 1. The CSO volume is selected as the model output variable. Table 1 displays the model input parameters selected for this study and their ranges.
The Colebrook-White roughness values for concrete pipes have been taken from (Lind, 2015) which says the Colebrook-White roughness value for new concrete pipes could be 0.5 mm and could reach up to 3-6 mm for small defects. In this study we have used a maximum value of 6 mm but in reality the roughness values can reach even higher values due to sediment deposition in the pipes or major pipe defects. References for initial loss values for an urban catchment can be found in Thorndahl et al. (2006) and Vanrolleghem et al. (2015). We have found the range from

Vanrolleghem et al. (2015) reasonable and suitable for an urban catchment such as the one used in this study.

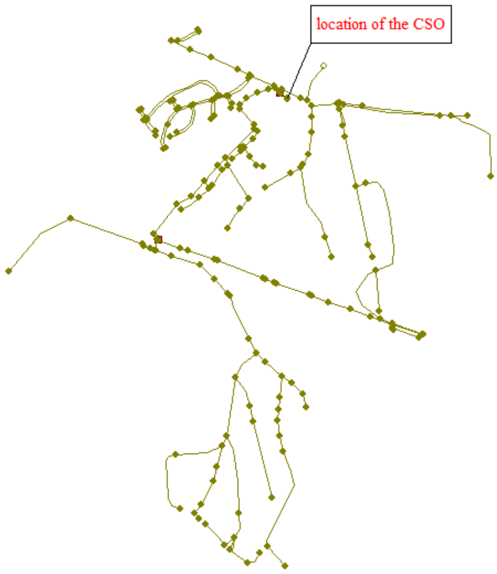

Figure 1. The sewer subsystem network within Herent, Belgium modelled in InfoWorks CS.

Table 1. Model parameters and ranges used in the Global Sensitivtiy Analysis.

No.	Parameters	Description	Unit	Minimum	Maximum
1	conduit_bottom_roughness_CW	Colebrook-White roughness	mm	0.5	6.0
2	initial_loss_value	Initial loss value	mm	0.22	1.5
3	runoff_coeff	Fixed runoff coefficient - Impervious	-	0.6	1.0
4	headloss_coeff	Headloss coefficient	-	1	6.6
5	weir_discharge_coefficient	Primary Discharge Coefficient - Weir	-	0.2	3.0
6	weir_secondary_discharge_coefficient	Secondary Discharge Coefficient - Weir	-	0.5	1.5
7	weir_crest	Weir crest level	m	35.25	35.45
8	weir_width	Weir width	m	9.9	10.1

The reference model has runoff coefficient set at 0.8 for impervious surfaces so we have considered a symmetrical range ± 25% of this value considering the upper physical limit being 1. The range for headloss coefficient has been taken from suggested values in InfoWorks help manual. The value of headloss coefficient from the reference model is 1 and its value can increase up to 6.6 for an angle of approach at 90 degrees as per the InfoWorks CS help manual. The primary discharge coefficient of the weir at the CSO structure is varied based on the range suggested in the help manual of InfoWorks CS modelling package. For secondary discharge coefficient of the weir, InfoWorks CS applies orifice equations. The secondary discharge coefficient of the weir is varied by ± 50% of its value from the reference model. We have considered this symmetrical range which includes the discharge coefficient values given in the British Standard (BS EN ISO 5167-2, 2003). The ranges for weir crest level and width are obtained by varying their values in the reference model by ±10 centimetres in order to reflect the potential measurement error in the manual methods used in estimating their values. For an even and uniform representation of the parameter space, parameter values are sampled from a uniform distribution within their respective ranges. The simulations have been performed using a composite design storm event 'f7'which has an average frequency of occurring 7 times in one year. The composite storm was developed by Vaes et al. (1996) at the Hydraulics Laboratory, University of Leuven in Belgium. A historical rainfall series from 1967 to 1993 with a time step of 10 minutes measured at the rain gauge at Uccle in Belgium was used to develop the composite storms for Flanders. For a frequency of 7, all Intensity/Duration relationships are included in the single f7 design storm which is why it is called composite storm. This particular design storm is selected following the design guidelines of Flanders Environment Agency (VMM) which is the regulatory authority in the Flanders region of Belgium (Coördinatiecommissie Integraal Waterbeleid, 2012). The VMM regulations for CSO structures are such that the CSO should not spill for the specific design storm f7.

Morris screening method

The Morris screening method (Morris, 1991) is used in this study for global sensitivity analysis which uses multiple one-at-a-time (OAT) perturbations of model input parameters selected for the study. Morris sampling design is employed in this study in which the parameter space is partitioned into p discrete levels and a random sampling is performed to generate r Elementary Effects (EE). The total number of required model simulations is $r*(n+1)$ where n is the number of parameters considered in the study. Modifications to the sensitivity measures given by Morris (1991) is proposed by Campolongo et al. (2007) which is used in this study. To determine the sensitivity of a parameter, sensitivity measure absolute mean (μ^*) is also generated along with the Morris sensitivity measures mean (μ) and standard deviation (σ) of the EEs. A high value of μ^* for a particular parameter suggests that a change in this parameter has high effect on the model output whereas a high value of σ indicates non linearity and/or interactions with other parameters which affects the variability of model output. For this study, the model input parameters reported in Table 1 are used. The parameter space is discretized into p=20 levels with number of repetitions, r=100. This results into the required model simulations of 100*(8+1)=900.

Convergence Analysis. To analyse the cost of computation and its efficiency in determining stable sensitivity measures, a convergence analysis is performed by varying the number of repetitions r up to 100. A percentage change in the variability of sensitivity index value is used to analyse convergence. The method for convergence analysis and definition of variability is taken from Vanrolleghem et al. (2015).

Cutoff Threshold. Ranking of input parameters is done based on their respective absolute mean (μ^*) values. However in order to select important model input parameters, a cutoff threshold on μ^* needs be defined. We have taken the cutoff threshold CT=0.1 as used by Vanrolleghem et al. (2015).

RESULTS AND DISCUSSION

Convergence analysis

Figure 2 and 3 display the results from convergence analysis for the model output variable CSO volume. The change in variability (expressed in percentage) is plotted in Figure 2 as the number of simulations increase. Vanrolleghem et al. (2015) apply a precision threshold of 0.5% to 3.5% to determine the number of simulations required for different output variables. By analysing Figure 2, it can be deduced that a precision threhold of 0.1 % is achieved after 400 or more number of simulations. Therefore, by considering 100 repetitions for 8 model input parameters, we achieve a stable convergence within a precision threshold of 0.1%. Figure 3 displays the convergence of the sensitivity measure μ^* for each model input parameter.

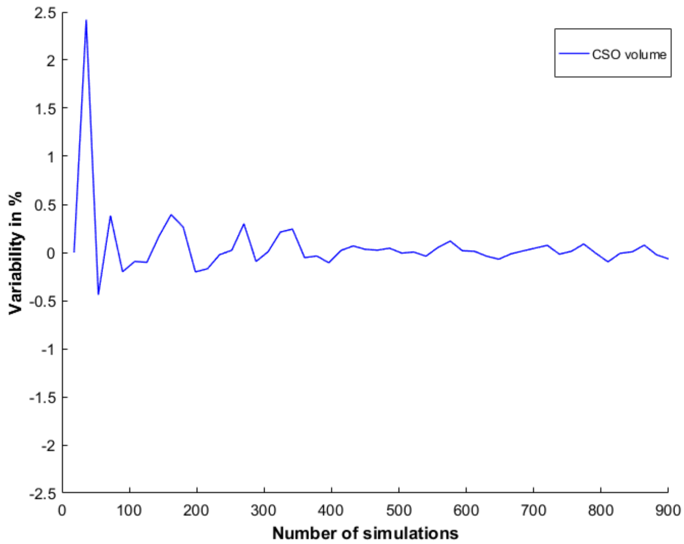

Figure 2. Convergence analysis using change in variability with increasing number of simulations.

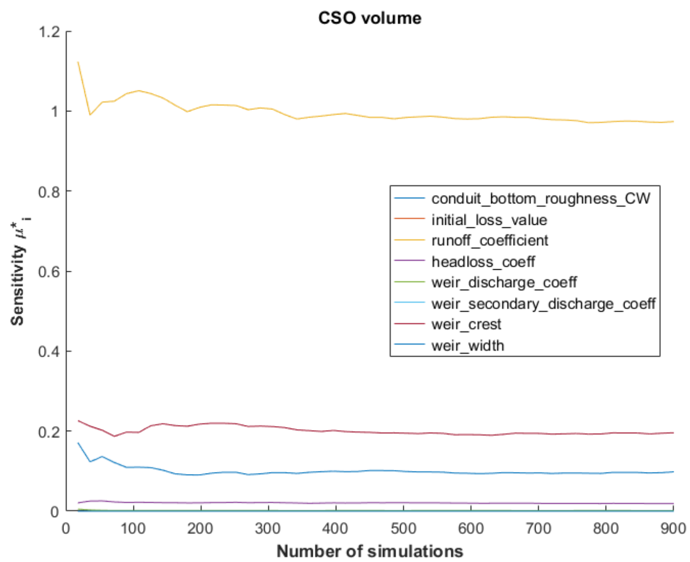

Figure 3. Convergence analysis for model input parameters with increasing number of simulations.

Morris screening results

Morris screening results with 100 repetitions (900 model simulations) are listed in Table 2. For the model output CSO volume, only three parameters are found to be important. These are runoff coefficient, conduit bottom roughness and weir crest The ranking of parameters has been done based on their respective μ^*. Runoff coefficient is coming out as the single most important parameter because of its high value of μ^* compared to the rest of the parameters. It does also have a very high standard deviation compared to others which suggests dependence on other parameters and/or non linearity. Same can be said about Colebrook-White roughness which has high standard deviation measure where as the sensitivity measure μ^* is not comparatively high (nearly equal to the cutoff threshold of 0.1). Also, the difference in μ^* values of conduit_bottom_roughness_CW (rank 3) and headloss_coeff (rank 4) is substantial so it is safe to conclude that Colebrook-White roughness can be considered as one of the most important input parameters along with runoff coefficient and weir crest for model output CSO volume.

Table 2. Morris screening results and ranking of parameters.

No.	Parameters	Mean (μ)	Absolute mean (μ^*)	Standard deviation (σ)	Ranking
1	conduit_bottom_roughness_CW	-0.096	0.098	0.048	3
2	initial_loss_value	0	0	0	7
3	runoff_coeff	0.974	0.974	0.055	1
4	headloss_coeff	-0.019	0.019	0.008	4
5	weir_discharge_coefficient	0.001	0.001	0.002	5
6	weir_secondary_discharge_coefficient	0	0	0	8
7	weir_crest	-0.196	0.196	0.019	2
8	weir_width	0	0	0	6

Figure 4 displays the histogram of CSO volume obtained from 900 model simulations done for the global sensitivity analysis. The histogram shows the range of the model output variable CSO volume when it is subjected to varied input parameters.

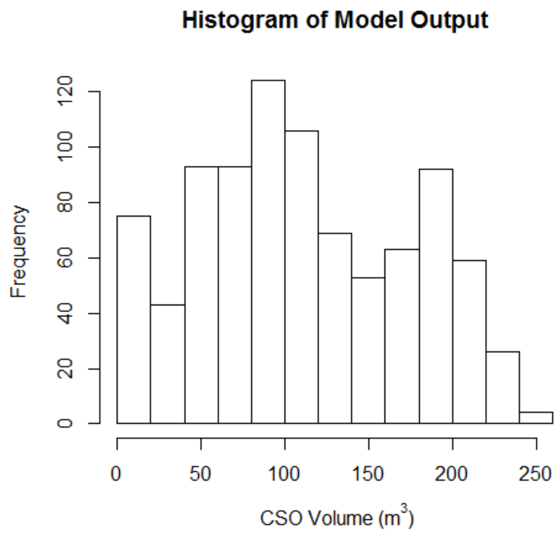

Figure 4. Histogram of CSO volume.

CONCLUSION

Even with as few as 900 model simulations, with Morris screening a stable convergence (Figure 2) is achieved which reflects its low computational cost design and its usefulness in performing sensitivity analysis of complex models. Apart from runoff coefficient and Colebrook-White roughness, all the other input parameters considered in this study can be said to have linear relationship with CSO volume owing to small values of σ. Also using the modifications suggested by Campolongo et al. (2007) in the form of absolute mean μ^* did not result in a significant difference in the selection of important parameters.

The global senstivity analysis performed in this study helps in identifying important model input parameters affecting the uncertainty of the CSO volume calculations using InfoWorks CS modelling package. We were able to quantify the resulting variation in modelled CSO volume however in order to better understand the uncertainty in CSO volume, an uncertainty analysis should be performed using these shortlisted input parameters. It is expected that using more realistic probability distributions for input parameters, instead of uniform distributions, could result in a different shape of the CSO volume histogram. Defining such probability distributions and carrying out an uncertainty analysis will form part of the ongoing further work on this case study.

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