Multi-Objective Optimization of Cost-Benefit of Urban Flood Management using a 1D2D Coupled Model

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Abstract

This paper presents a multi-objective optimization (MOO) tool for urban drainage management that is based on a 1D2D coupled model of SWMM5 (1D sub-surface flow model) and BreZo (2D surface flow model). This coupled model is linked with NSGA-II, which is an Evolutionary Algorithm-based optimizer. Previously the combination of a surface/sub-surface flow model and evolutionary optimization has been considered to be infeasible due to the computational demands. The 1D2D coupled model used here shows a computational efficiency that is acceptable for optimisation. This technological advance is the result of the application of a triangular irregular discretisation process and an explicit finite volume solver in the 2D surface flow model. Besides that, OpenMP based parallelization was employed at optimizer level to further improve the computational speed of the MOO tool. The MOO tool has been applied to an existing sewer network in West Garforth, UK. This application demonstrates the advantages of using multi-objective optimization by providing an easy-to-comprehend Pareto-optimal front (relating investment cost to expected flood damage) that could be used for decision making processes, without repeatedly going through the modelling-optimization stage.

1. Introduction

Urban drainage infrastructure planning or modification is associated with large investments and, particularly in a restrictive financial atmosphere, optimal use of funds can not be overemphasized. In this regard, two conflicting objectives need to be considered, namely, the investment cost in infrastructure and the performance (hydraulic, environmental etc.). However, infrastructure performance measures can often be expressed in terms of monetary units as well (e.g. flood damage cost) and, in this way, the planning problem can be expressed as one of minimizing total cost (Abebe and Solomatine, 1998). Even so, in practice, these two cost types are very different, in terms of timing, frequency, uncertainty, etc. This paper, therefore, argues that it is beneficial to treat these costs as separate objectives. In optimization problems that involve two objectives, there exist a number of optimal solutions arising from trade-offs between the conflicting objectives, which is known as the Pareto-optimal front. In making decisions for urban drainage infrastructure provision or renewal, Pareto-optimal solutions between investment cost and expected flood damages can serve as the basis for stakeholder dialog.

There are numerous different investment options available with different cost structures; increasing the pipe capacity, storage reservoirs, numerous source-control measures like disconnection, infiltration, to name a few. Often for an existing system, the increasing of pipe capacity is a major investment and is not financially viable at small increments (e.g. increasing capacity by 10-15%). All source-control options and storage reservoirs often yield well to incremental improvements. In this study we considered only one type of intervention, namely, providing storage reservoirs. Implications of the limitation are further discussed later in this paper.

The use and utility of multi-objective optimisation for urban drainage management has been studied before (Barreto, et al., 2006, Rauch and Harremoes, 1999). Previously, the application of a combination of surface/sub-surface flow models for optimization was prohibitively expensive in terms of computing time, which prevented the scholars from using this tool. Instead, a measure of the excess flow out of the underground system was used as a proxy for the expected flood damages. Yet, at present, the use of 1D2D coupled models for urban drainage management has become a viable option due to the increasing availability of powerful computing facilities, the development of more efficient 2D surface flow models and the possibility of parallelizing models.

In this paper, a multi-objective optimization (MOO) tool for urban drainage infrastructure renewal is presented. The objective functions involved are investment cost and expected flood damages. This paper briefly describes how the optimization model has been developed by using the Genetic Algorithm (GA) based optimizer, NSGA II, and a 1D2D coupled model of the Storm Water Management Model (SWMM5) (1D subsurface flow model) in conjunction with BreZo (2D surface flow model). The performance of the developed MOO tool is tested and demonstrated for the case study area of West Garforth, UK.

2. Optimization Problem

Two objectives are involved in planning or modification of urban drainage systems, namely, the investment cost and the performance.

Investment cost
The investment cost (C) for building detention ponds is computed as follows:

$$C = \sum_{i=1}^{i=n} A_i * D_{\max} * C_d \qquad \mathbf{1}$$

Where, Cd is unit cost of detention, n is the number of detentions in the network having an area Ai and a maximum depth $D_{max.}$

Expected annual damage
A key performance measure for urban drainage management is the reduction of flood risk. As a measure of flood risk, the Expected Annual Damage (EAD) is used in this paper. EAD can be calculated as the integral of damage probability function:

$$EAD = \int_{f=0}^{\infty} D(z_f)df \qquad \mathbf{2}$$

Where f is frequency of occurrence (inverse of return period) and D is the flood damage due to the flood level corresponding to the event with frequency f.

The following approximation was used to compute EAD (D) under the assumption that it is a continuous function of frequency (i.e. storm return period) (*Equation 3*).

$$EAD = \sum_{i=1}^{n} \left(\frac{D_{i+1} + D_i}{2} \times \left(\frac{1}{R_i} - \frac{1}{R_{i+1}} \right) \right) \qquad \mathbf{3}$$

Where, EAD is expected annual damage, D_i is the flood damage due to i^{th} storm return period event, and n is the number of storm return periods considered in the approximation. Note that Equation 3 hypothesizes that the flooding return period is equal to the storm return period. This is done for the purpose of computational efficiency, although it is known to be erroneous.

In practice, the set of return periods considered should range from a very frequent event that does not cause significant flooding to a very rare (extreme) event that has a negligibly low probability, and n should be large enough to have a good (logarithmic) spread of events, as D is a highly non-linear function of f. At the same time n should not be too large in order to reduce the computational expense (Messner, et al., 2007).

Flood damage is influenced by different factors like depth, duration and velocity, but the depth of flooding is generally used as the most influential parameter for small-scale urban. The common method for assessment of flood damages based on flood depth is using a flood damage curve (Dutta, et al., 2006, Freni, et al., 2010, Jonkman, et al., 2008).

Rationale for Using Multi Objective Optimisation

The investment cost, C (equation 1), occurs at the start of the construction project and is expressed in monetary units in the terms of the inception time. The *EAD* is by definition the probabilistic expected flood damage cost per year for all kinds of events and is expressed in monetary units as well. If the planning horizon of the storage facility is m years, the EAD can be translated into a cost at the time of construction, $EAD_{tot,0}$, as:

$$EAD_{tot,0} = \frac{(1+r)^{-m} - 1}{r(1+r)^m} * EAD \qquad 4$$

Where r is rate of return. With a typical planning horizon for urban drainage infrastructure of several decades or more and a typical rate of return of three to six percent this rapidly approaches to $1/r$, a value independent of the planning horizon. At this stage it is possible to add $EAD_{tot,0}$ to C, making it a single optimization problem, whose goal is to minimize overall cost (hereafter UO).

There are several reasons however for considering these two cost types as separate objectives, leading to a multi-objective optimization problem with a Pareto-optimal relationship between $EAD_{tot,0}$ and C (hereafter PO). Particularly in an uncertain context or restrictive financial atmosphere, it may sometimes be impossible to secure the capital funds needed for the optimal investment according to the UO. It is then advantageous to be able to answer the question: what is the most optimal way to invest X amount of funds? Furthermore, PO can readily provide information on the payback period of any given level of investment. For example a municipality may have long-term plan of completely overhauling the urban drainage network in 20 years time and needs to take certain interim measures to contain the flood damage within that period. The PO approach can then aid deciding making on the optimal amount of investment in this scenario. PO thus provides the opportunity for decision makers to have an interactive dialog on different alternative investment levels and the associated cost-benefit ratio, without the engineers having to 'return to the drawing boards' to evaluate each investment level.

While the computational effort involved in producing a PO is often higher than finding the UO, our experience in this study shows that it is definitely within reach of typical modern computing facilities.

NSGA II for Optimization

Among the different types of optimization approaches, genetic algorithms (Mitchell, 1997) have become quite popular largely due to their ability to optimize without knowledge of any governing rules of the problem. While indeed most of the urban hydrological/hydraulic problems, including urban drainage models, clearly have a set of physical governing equations, the emergent behavior of these models is too complicated to define a workable set of rules for the formulation of an optimization problem. GAs excel in handling such complex problems. There are many efficient implementations of GAs for both single and multi objective optimization.

For the MOO model presented in this paper, the genetic algorithm optimizer Non-dominated Sorting Genetic Algorithm (NSGAII) (Deb, et al., 2000) is used. NSGAII has been widely applied and is reported to perform efficiently in solving complex optimization problems (Deb, 2002). The offspring population Q_t is first created by using the parent population P_t, based on mating and mutation processes (quite similar to normal GA). Then, these two populations are combined forming a new population R_t of size 2N. At this stage, non-dominated sorting—a technique of selection that ensures a good distribution of solutions across the Pareto-front, in addition to the fitness of the solutions—is used to select N solutions from the new population.

The Hydraulic Models Used

The assessment of flood damages caused by surcharged sewers in urban drainage systems necessitates the combination of surface and sub-surface flow modelling (Hsu, et al., 2000, Leandro, et al., 2009, Maksimovic, et al., 2009, Pathirana, et al., 2008, Schmitt, et al., 2005). In this paper a 1D2D coupled model of SWMM5 (1D sub-surface flow model) (Rossman, 2004) and BreZo (2D surface flow model) (Begnudelli and Sanders, 2006) has been implemented for the purpose of flood damage assessment.

SWMM5 is a physically based discrete-time simulation model which is developed under the support of United States Environmental Protection Agency. It is a dynamic rainfall-runoff simulation model used for single event or long-term (continuous) simulation of runoff quantity and quality from primarily urban areas. BreZo is a hydrodynamic model developed for unsteady, two dimensional, shallow water flows over an arbitrary topography with wetting and drying. In BreZo, the shallow water equations are solved using a Godunov-type finite volume algorithm—explicitly ensuring the mass balance. The model runs on an unstructured triangular grid, making it possible to efficiently represent urban flow paths. Both SWMM and BreZo employ explicit solving techniques, which require that CFL condition is satisfied for stability.

1D2D coupled model

The interaction of the 1D and 2D models was implemented as mass exchange at point sources. When the sewer system overflows, the flood water is introduced in the inundation model as excess flow out of manholes. The coupling was implemented only in the direction of flow from 1D model to the 2D model. The only conservation quantity considered in the coupling is mass, as the momentum transfer can usually be neglected in this type of interaction.

Often the solution time step dictated by CFL condition in BreZo is much smaller than that of SWMM. Therefore an internal time-splitting algorithm is used to run multiple steps of BreZo for one step of SWMM as required. The maximum inundation depth at each triangular grid is used to compute the flood damage using a stage-damage curve.

Details on the development of the coupled model and its basic application are described elsewhere (Adeogun, et al., 2010).

Computational Challenge

In order to obtain a usable Pareto front in MOO, a reasonably large population (practically around 50) should be used and the generation process should be iterated until a stable Pareto front is obtained (indicating optima). For example if a population of 40 is used for 40 generations, and if four return periods are used to calculate EAD, the 1D2D model has to run 6400 times. For a typical case (e.g. the case study shown below), less than 1 percent of the total time is spent on the NSGA-II operations, while approximately 99 percent is spent on the 1D2D model computation. The location of the computational bottleneck at the evaluation stage (hydraulic models) provides an excellent opportunity of parallel computation. Using a computer with 8 shared-memory processing cores and simple OpenMP directives (Chapman, et al., 2007), we have achieved almost eight times speed up as compared to using a single processor only.

Application and Results

The MOO model was applied to a case study in West Garforth (West Yorkshire, UK). The area has been affected by several flood events since the 1980's (DEFRA (Department for Environment). For the purpose of planning, the area is divided into two parts known as Central Catchment and the Southeast Catchment (Figure 1). Each part has its own urban drainage system or scheme that is largely independent of the other, making it possible to analyse them separately. A sub-surface flow model was produced for both of the drainage systems as part of the IUD pilot project (LCC, 2008). This study also proposed a wide range of possible measures that could be implemented in West Garforth. This range was then reduced by eliminating the less feasible, more costly measures. Based on the results of this process, the current paper has identified 4 locations for potential detention ponds. The objective of the MOO application is to find the set of optimal sizes for these detention ponds. It should be noted that only the context of the drainage system for the Central Catchment (
Figure 2) is taken for the implementation of the MOO tool.

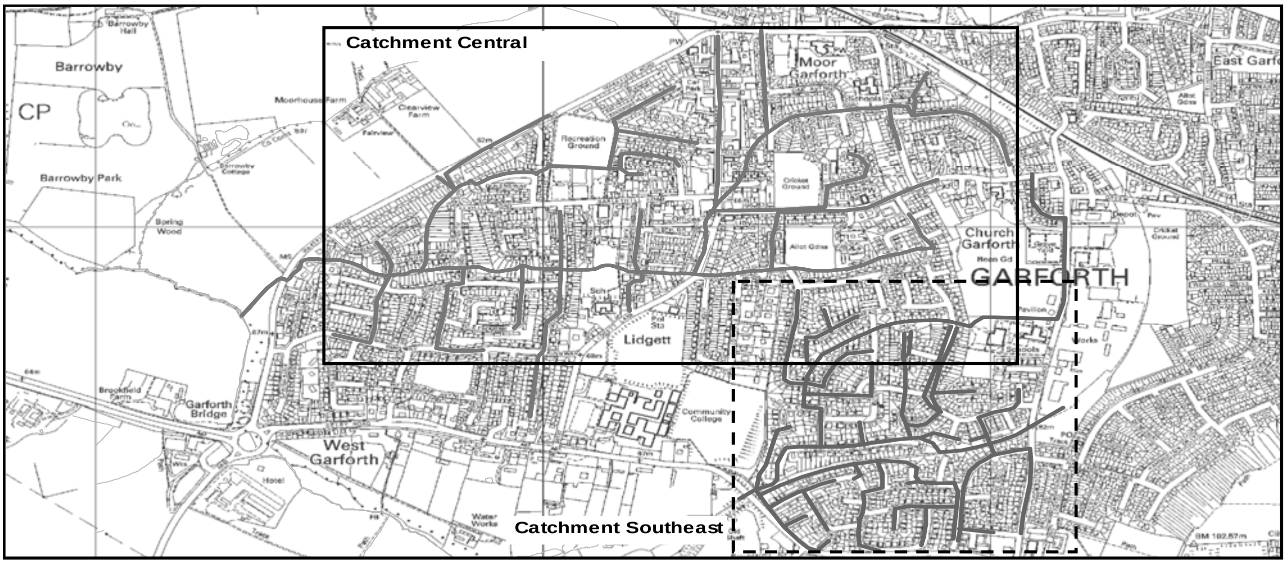

Figure 1: *Catchment division of West Garforth Drainage area*

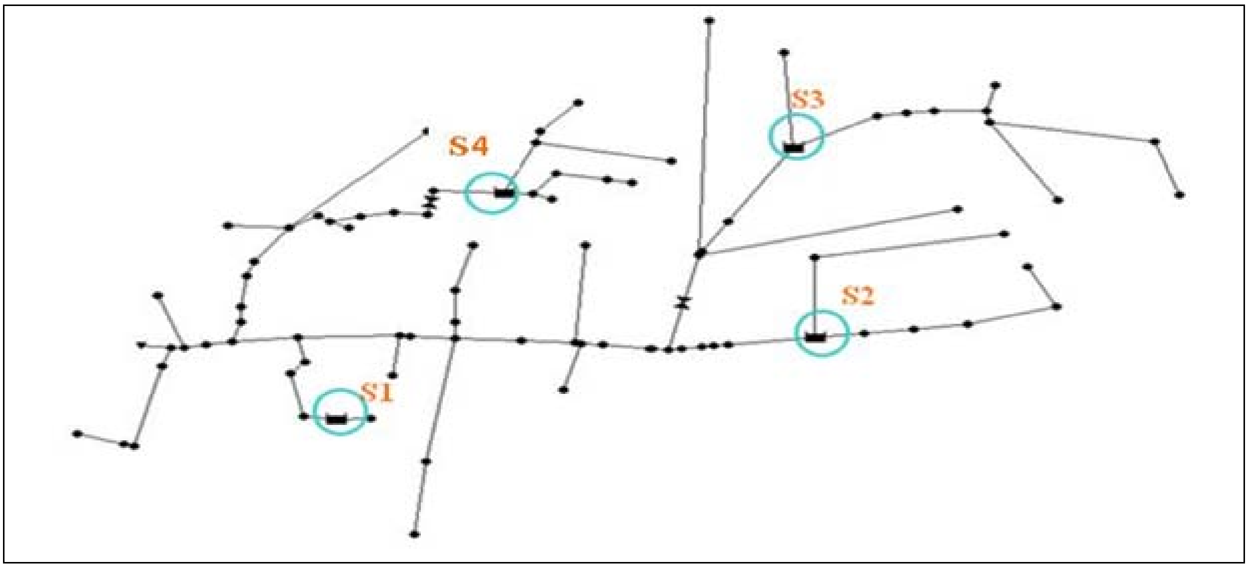

Figure 2: ***Drainage Network for the Central Catchment.***

Model Inputs

The investment cost calculation was carried out according to equation 1, with a C_d of £70. The flood damage curve shown in Figure 3 was used to calculate EAD, employing storm return periods of 1, 10, 50 and 100 years (for critical storm events). This curve is taken from Penning-Rowsell (Penning-Rowsell, et al., 2003) and is based upon the damage cost to an average type house of average age and with occupants of an average social class, and for a flood of average duration.

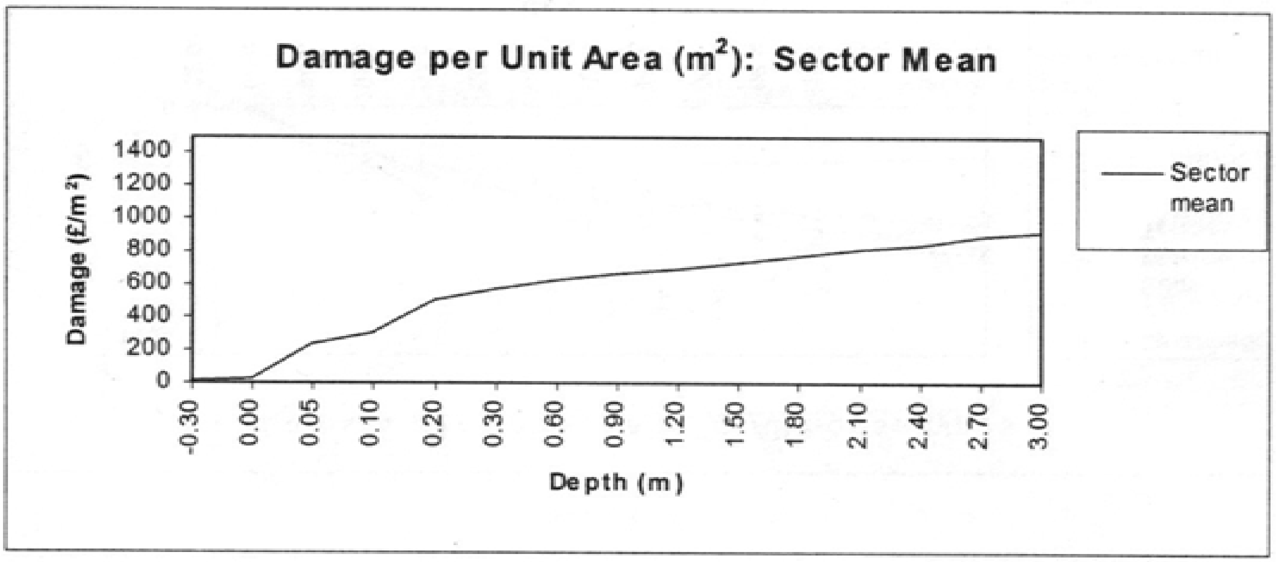

Figure 3*: Depth-Damage relationship used for West Garforth*

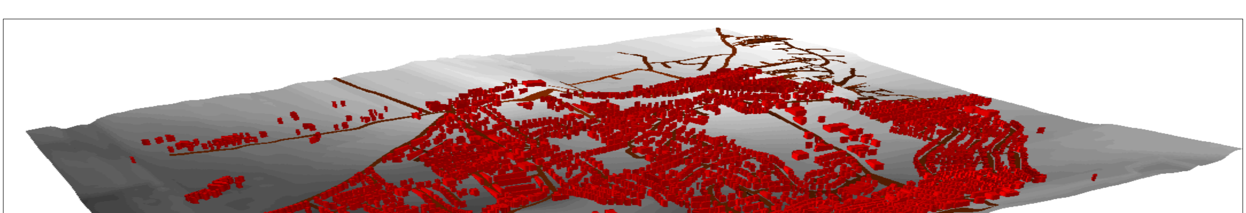

Figure 4*: 3D view of DEM of West Garforth (attributed with roads and buildings*)

The Digital Elevation Model (DEM) of the area was prepared by digitizing a contour map and superimposing road and building features (

Figure 4). Gaja3D (Rath, 2007)—a meshing library for unstructured finite element mesh generation for hydrodynamic simulations—was used together with Triangle (Shewchuk, 1996)—a two-dimensional mesh generator and delaunay triangulator—for generating the irregular mesh from the DEM. Based on a sensitivity analysis of flood inundation characteristics and mesh size, the maximum triangle area was constrained at $20m^2$.

NSGA II was set-up using population size of 48. Probability of crossover and mutation were chosen to be 0.6 and 0.1 respectively.

Output Pareto Front

Simulations were undertaken in parallel computing system using a computer with 8 cores (each running at 2GHz with 8 GB of physical memory). The model performance averaged at 1h per generation. Thirty generations were deemed adequate for convergence based on the incremental improvement of the results from generation to generation. The 1D2D model completed 5760 simulations in the course of optimization.

Figure 5 shows the final Pareto front. For the first £60.000 investment there is a dramatic reduction in EAD—97% of flood damage can be prevented by this investment. However, after that the improvement becomes significantly smaller: in order to reduce the flood damage by a further 3%, an additional £80.000 is needed.

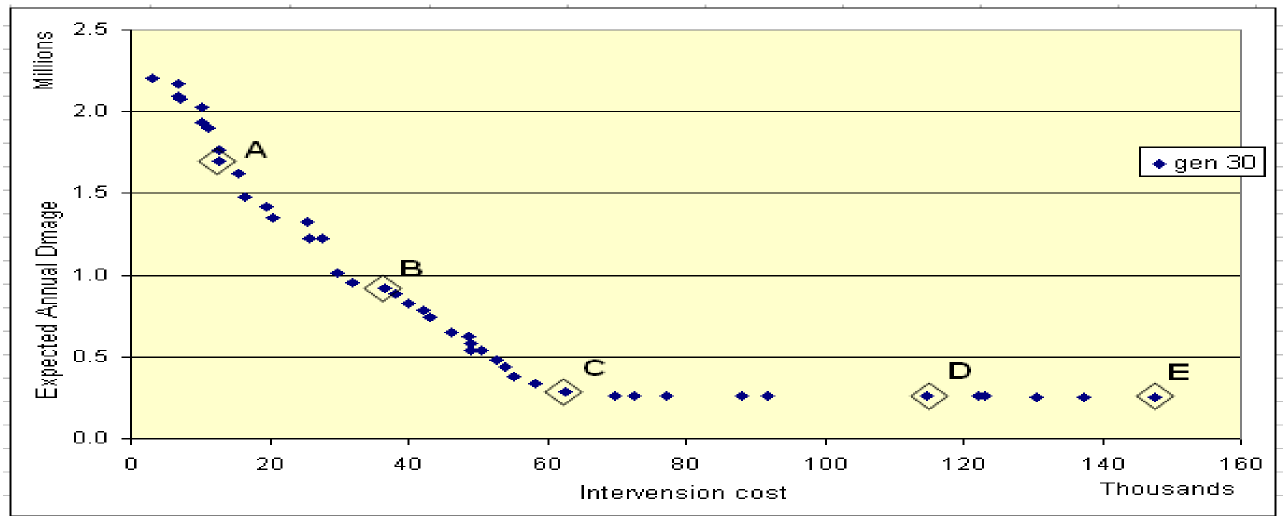

Figure 5*: Output Pareto front. (gen 30 = the 30th generation)*

n.b. Vertical axis is in EAD units. The detail results for point A-E are given in Table 1.

Table 1: *Decision points from Figure 5*

Solution	**S1**	**S2**	**S3**	**S4**	**Investment**	**Flood risk**	**Total cost**
	[m3]	[m3]	[m3]	[m3]	[k£]	[k£]	[k£]
A	60	0	50	0	13	27200	27213
B	0	10	260	0	37	14720	14757
C	190	15	310	0	63	4800	4863
D	395	15	540	0	115	4144	4259
E	215	85	690	20	150	4112	4262

Table 1 summarizes the optimization results, and also shows the storage volumes for each of the four detention basins associated with the Pareto-optimal solutions. The total (net) present value of flood risk was computed for a 6% discount rate and 50 years of planning horizon. The results show that it is beneficial to invest in additional storage capacity up to point D. After that the total cost does not decrease anymore.

Conclusions

A multi-objective optimization tool has been developed to assist decision making in urban flood management. Two objective functions were considered that account for investment cost in urban drainage infrastructure and hydraulic performance (in terms of EAD). In the MOO tool, a 1D2D coupled model was used for hydraulic evaluation and flood damage estimation, while NSGA II was used for the optimization process. The MOO tool has been applied to the optimization of 4 detention ponds for the case study of West Garforth (UK). As part of the optimisation process, it was achieved to run 30 generations, having 48 populations, in 30 hours using parallel computing. These results demonstrate that multi-objective optimization (MOO), which involves a 1D2D coupled model for hydraulic evaluation, can be applied to urban drainage planning and rehabilitation using typically available computer hardware.

We have also emphasised the advantages of the MOO approach over single objective optimization: the resulting Pareto-front facilitates stakeholder dialog and enables decision making without 'revisiting the drawing-boards'. In the context of the present day's need for multi-stakeholder participation in and the multi-disciplinary nature of finding solutions for urban drainage problems, this is an advantage that can justify the increased (but affordable) computational cost.

As mentioned earlier, one of the significant limitations of the study is to do with its exclusive consideration of storage reservoirs as the intervention -- a measure needed to control the number of variables in the optimization problem. In reality it is possible that other interventions like source-control could be more effective in cost-benefit terms.

The major significance of this study lies in the combination of a surface/sub-surface water model and optimization procedure. Previously this has been considered to be infeasible due to the computational demands.

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