Simulation-Based Optimisation of Sustainable Urban Drainage Systems

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Contents

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Abstract

Sustainable urban drainage systems (SuDS) are multi-functional nature-based solutions to stormwater management problems. During the past years, there has been a growing interest in the application of multi-objective optimisation methods to facilitate design of SuDS. This has allowed decision-makers to select efficient system designs that best trade-off their design objectives. However, the literature also reports on the computational burden of optimisation methods when applied to large-scale drainage systems, which hinders their application in the industry. Moreover, design of SuDS has been limited to a narrow set of cost-effectiveness objectives overlooking socio-economic implications of the design decisions. Besides, multi-objective optimisation models generally result in multi-dimensional Pareto-fronts, which embody a large number of solutions making it difficult to survey trade-offs between the objectives. This thesis brings together different data science approaches to expedite, simplify, and improve design of SuDS. A multi-criteria design approach is proposed, which combines traditional design objectives, such as lowering investment costs and reaching target service levels, with social goals like reducing inequality in the spatial distribution of services, such as flood damages and green infrastructure co-benefits. It helps planners to make trade-offs between spatial equity and cost-effectiveness when selecting future interventions in SuDS. A novel emulation-optimisation approach is also proposed that allows optimising a portion of a drainage network while the remaining part is represented by a surrogate model that maps changes in the region of interest to hydraulic head time-series at synthetic nodes shared with the remaining part of the network. The proposed approach is demonstrated with an application to many-objective optimisation of SuDS in two urban areas indicating its high efficiency in reducing computational time of the optimisations compared to models that simulate the whole network dynamics. Finally, a decision-making strategy is proposed for design of SuDS, which exploits a soft clustering technique to reduce Pareto-fronts with thousands of solutions into a handful of representative solutions in order to simplify the process of surveying trade-offs between the objective functions.

Declaration

No portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

Copyright Statement

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1 Chapter one: Introduction

1.1 Background

The impact of urbanisation on pluvial flood risk has long been a key factor in deliberations around urban drainage infrastructure design. According to the common perception, cities are recognised for better transportation facilities, business opportunities, and lifestyle when compared to rural areas. However, this brings its own complications and vulnerabilities. During the past few decades, migrations from villages to cities have led to an expanding urbanisation process as far as most people in the world are currently living in cities and if this trend continues the number of buildings in urban areas will be doubled by 2060 (Dean et al., 2016; United Nations, 2014). Urbanisation involves converting undeveloped areas into impervious surfaces, including roads, parking lots, and rooftops, which can intensify pluvial flooding on one hand and deprive groundwater recharge, on the other hand (Ali et al., 2012). The reason lies in the way the received precipitation is converted into surface runoff infiltration, evaporation, and transpiration. For example, in temperate climates, rainfall on natural surfaces can lead to 40 per cent evapotranspiration, 25 per cent shallow infiltration, 25 per cent deep infiltration, and 10 per cent runoff while these percentages turn to around 30, 10, 5, and 55 per cent in high-density urban areas (Figure 1-1) (Szöllösi-Nagy & Zevenbergen, 2018).

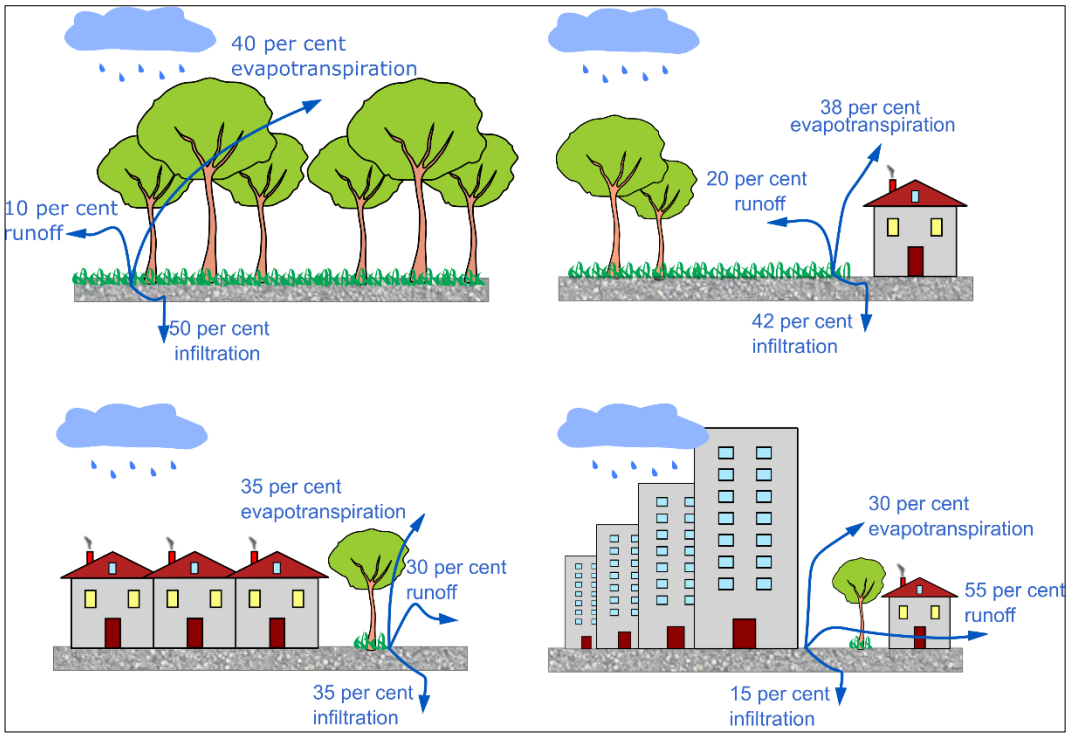

Figure 1-1. Urbanisation effect on the water cycle in undeveloped and urbanised areas.

Global climate change and the ageing process of conventional drainage systems are other important factors that have increased the number and intensity of urban floods causing significant damages to properties, loss of lives, and pollution of receiving waters (Yazdi, 2018). In the United Kingdom, for instance, floods are recognised as the most frequently occurring natural hazards with a financial loss of around £1 billion annually, such as the reported flooding incidents during 2015-2016 that resulted in £1.6 billion in economic losses (Environment Agency, 2018; Tomlinson et al., 2018).

Urban drainage infrastructure can pollute its neighbouring natural environment depending on its network type and applied drainage practices. There are mainly two types of sewer systems: separate sewer systems, in which the dry and wet weather flows are transferred separately by two different networks, and combined sewer systems that are designed to convey wet and dry weather flows together (Szöllösi-Nagy & Zevenbergen, 2018). The origin of stormwater pollution is also two-fold: firstly, the wash-off of accumulated pollutants, including nutrients, phosphorus, heavy metals, lubricants, and soil particles, on impervious surfaces like roads and parking

lots; and secondly, the pollutants leaching into rivers and surface water bodies due to combined sewer overflows (CSOs) (Even et al., 2004). The latter normally occurs during rainfall events when the amount of stormwater exceeds capacity of a combined sewer system. In this situation, the drainage system may leach high concentrations of contaminants into recipient rivers, putting human health and the environment at risk (Hung & Hobbs, 2019; Weyrauch et al., 2010). These issues must be addressed by a holistic drainage system design approach that not only improves the drainage process in urban areas but also decreases stormwater pollution. Auxiliary urban drainage practices, including nature-based drainage systems, may be considered for this purpose.

1.1.1 Urban drainage systems

Urban drainage infrastructure design is a complicated and time-consuming task, which entails cooperation between practitioners with different areas of expertise. Urban drainage generally comprises hydrologic and hydraulic processes within a network of interlinked elements, such as subcatchments, manholes, conduits, pumps, reservoirs, weirs, valves, and gates. Generally, normal rainfall events are considered as design scenarios for drainage systems, however, the evaluation of the overall performance of an urban drainage infrastructure must also consider less frequent intense flood events (Szöllösi-Nagy & Zevenbergen, 2018). Besides, trade-offs between capital costs and potential flood damages must be taken into account in conjunction with other decision-making criteria, such as stormwater pollution as well as stakeholder satisfaction in the provision of drainage services. However, due to the nonlinear nature of trade-offs between system design goals and the fact that rehabilitation and/or system capacity expansion plans may target several goals simultaneously, the use of classical trial-and-error analysis and/or design may not be convenient.

Generally, urban drainage infrastructure improvement plans fall into three main categories: first, improving performance of the existing drainage systems; second, applying real-time control (RTC) by means of appropriate flow control assets in the

drainage system; and third, using sustainable urban drainage systems (SuDS) to reduce the amount of surface runoff close to its source.

1.1.2 Sustainable urban drainage systems

As shown in Figure 1-1, in non-urban watersheds no more than 10 per cent of the received precipitation turns into surface runoff and the rest is generally contained in natural detention basins or goes back to the atmosphere through evaporation and transpiration by vegetations and trees. However, in urbanised regions around 55 per cent of the precipitation turns into surface runoff increasing probability of pluvial flooding in urban areas. Traditionally, stormwater flood management strategies were focused on refurbishment and/or expansion of existing conventional drainage networks by increasing the cross-sectional area of drainage conduits for fast conveyance of stormwater or using detention tanks to accommodate large surface runoff volumes. However, this can jeopardise water quality in urban streams and downstream surface waters as floods mobilise large amounts of pollutants, e.g. oil, lubricants, heavy metals, and toxic substances (Vojinovic, 2015).

The literature highlights the effectiveness of SuDS for flood management and stormwater pollution control due to their capabilities to facilitate evapotranspiration, storage, and in situ detention and infiltration of surface runoff (Ahiablame et al., 2012). SuDS, also referred to as low impact developments (LIDs), water sensitive urban design (WSUD), and best management practices (BMPs), are nature-based solutions to urban flood management that can help to maintain hydrologic function of urban areas closer to their undeveloped situations (Fletcher et al., 2015). Using sustainable drainage assets for flood mitigation was first conceptualised in the 1990s by the Environmental Resources department of Prince George's County, USA (Wu et al., 2019). Currently, the concept of nature-based drainage systems is being advocated throughout the world. For example, new regulations for urban stormwater management are defined in the Sewerage Sector Guidance, in England, which enable water and wastewater utility companies to implement sustainable drainage facilities (*Sector Guidance in relation to the adoption of sewerage assets by sewerage*

companies in England, 2019). Moreover, the National Planning Policy Framework in the UK states "Major developments should incorporate sustainable drainage systems unless there is clear evidence that this would be inappropriate" (*National Planning Policy Framework*, 2019).

In contrast to conventional urban drainage infrastructure, SuDS have a number of co-benefits, in terms of ecosystem protection, in addition to their flood mitigation capability that makes them desirable for flood management. They can reduce pollution discharge into downstream water bodies and improve aquifer recharge in urban areas by increasing the hydraulic residence time as well as infiltration rate of surface runoff, leading to removal of total suspended solids (TSS). Additionally, the phytoremediation capability of specific vegetation types used in green urban drainage assets helps to remove other stormwater contaminants, including heavy metals.

Other characteristics of SuDS include, but are not limited to:

- improving biodiversity and amenity in urban areas (Wright, 2011);
- improving mental and physical health of the residents (Mell, 2010);
- improving landscape of urban neighbourhoods and delivering recreational opportunities in urban areas (Q. Zhou, 2014);
- reducing energy costs of pumping stations (Thurston et al., 2003);
- reducing the heat island effect and regulating the temperature in urban areas (He et al., 2019; Ketabchy et al., 2019; D. Zhou et al., 2015);
- alleviation of water scarcity by naturally enhancing stormwater retention and infiltration in urban areas (He et al., 2019).

Generally, sustainable urban drainage infrastructure includes permeable pavements, infiltration trenches, bio-retention cells, rain gardens, rain barrels, green roofs, rooftop disconnections, and vegetative swales, out of which the first six drainage facilities were considered for SuDS optimisation in this thesis (Lewis A. Rossman & Huber, 2016; Woods Ballard et al., 2015).

1.1.2.1 Permeable pavements

Permeable pavements (Figure 1-2) are stormwater management facilities generally comprised of pervious layers laid on a stone reservoir (Lewis A. Rossman & Huber, 2016). Adsorption, filtration, and sedimentation are the treatment processes that can take place within these SuDS components. Accordingly, conventional asphalt/concrete roads, pavements, or parking lots can be replaced by permeable paving materials, e.g. bricks or permeable asphalt/concrete, for infiltration and retention of stormwater runoff near to its source (Hu et al., 2018; Woods Ballard et al., 2015).

Figure 1-2. A typical continuous permeable pavement system, adopted from Rossman L. A. (2015).

1.1.2.2 Infiltration trenches

Infiltration trenches (Figure 1-3) are excavations refilled with void-forming substances, such as crushed stone, which are mainly used as storage pits to reduce runoff volume and peak flow by increasing infiltration rate (Mays, 2001; Lewis A. Rossman & Huber, 2016; Woods Ballard et al., 2015). Rocks are used to stabilise trench walls, however, plastic boxes with high porosity are also used as alternatives (Błażejewski et al., 2018).

Figure 1-3. A typical infiltration trench, adopted from Rossman L. A. (2015).

The runoff reduction efficiency of infiltration trenches depends on the permeability of their surrounding soil and their depth to groundwater level ratio. Accordingly, they are suitable for regions where the groundwater table is adequately below the bottom of the drainage facility (Locatelli et al., 2015).

1.1.2.3 Bioretention cells

Bioretention cells have been found promising in reducing stormwater pollution and improving hydrologic quality in developed urban areas (Olszewski & Davis, 2013). Bioretention cells (Figure 1-4) are landscaped depressions with porous layers, which are mainly used due to their stormwater retention, treatment, evapotranspiration, groundwater recharge properties, and inherent amenity value (James et al., 2010; Woods Ballard et al., 2015). They are generally constructed using nature-based materials in a way to mimic wetlands. Bio-retention cells operate by retaining surface runoff on their surface layers allowing its gradual infiltration, evaporation, and/or transpiration from the soil and vegetation surfaces.

Figure 1-4. A typical bio-retention cell, adopted from Rossman L. A. (2015).

1.1.2.4 Rain gardens

Rain gardens (Figure 1-5) are less engineered bio-retention cell variants generally without a porous layer. They can reduce the surface runoff volume and associated peak flow rate by capturing the runoff from rooftops and impervious surfaces allowing it to creep down into the ground. Just like bio-retention cells they use various flood control processes, including runoff retention, infiltration, and evapotranspiration. Rain gardens are recommended for their capabilities in efficient reduction of runoff volume and removal of non-point source pollutions (Morsy et al., 2016; Lewis A. Rossman & Huber, 2016).

Figure 1-5. A typical rain garden in an urban area, adopted from Hoban A. (2019).

1.1.2.5 Rain barrels

Rain barrels and cisterns are micro-scale stormwater storage facilities that are typically connected to rooftops to capture and store rainwater. In intensive rainfalls, they can temporarily detain runoff and limit the flow into the gutters to reduce the

pressure imposed on conventional drainage systems. The stored non-potable water can be used for watering garden plants or released into the drainage in dry weather periods. Figure 1-6 shows a cistern in an urban area (Lewis A. Rossman, 2014).

Figure 1-6. A typical cistern installed in an urban area, adopted from Myers B. R. and Pezzaniti D. (2019).

1.1.2.6 Green roofs

Using green roofs, impermeable rooftops can be converted to green communal terraces. Green roofs can absorb and retain stormwater runoff, reduce energy costs of buildings, increase life of the roofing systems, and decrease the heat island effect in urban areas (Takebayashi & Moriyama, 2007). There are mainly two types of green roofs, including extensive and intensive roof systems with shallow (0.0254 m to 0.1270 m) or deep (>0.1524 m) soil layers, respectively (Lewis A. Rossman & Huber, 2016). Due to its wide application, the extensive type is considered in this research. Figure 1-7 shows a typical green roof (Lewis A. Rossman, 2014).

Figure 1-7. A typical green roof system, adopted from Graham A. (2016).

1.2 Research questions

This section presents the research questions addressed in this thesis. One of the major challenges that engineers encounter is to apply optimisation methods to large drainage systems. The question in this regard is how to efficiently apply an optimisation method for design of UDS while the focus is on a region of interest in a large drainage system. Optimisation methods normally involve iterative numerical simulations to calculate design objectives. In this light, each function evaluation must be completed in an acceptable amount of time. This is the case for large drainage systems that has hindered the application of optimisation methods in the industry as in some cases an optimisation run can take months or years to complete. In response, there has been a rise in research focus during the past years towards the application of surrogate models for fast prediction of objective functions in optimisations (Latifi et al., 2019; W. Zhang et al., 2019). However, in this situation, as the optimisation algorithm evolves, prediction errors accumulate making optimisation solutions unreliable. Besides, the complexity of surrogate model construction may increase significantly with the number of input variables and design objectives. Accordingly, another question to be answered in this regard is how to efficiently apply many-objective optimisation methods to design of large urban drainage systems (UDS).

Stormwater management in urban areas is generally viewed as building structural flood mitigation measures and sizing drainage conduits while other sustainability aspects, such as socio-economic factors, are overlooked (Behzadian & Kapelan, 2015; Huang et al., 2013). An urban drainage rehabilitation plan with these shortages will probably fail as unintended negative societal consequences, such as discrimination due to unfair distribution of resources and/or services, may be incurred (Szöllösi-Nagy & Zevenbergen, 2018). Accordingly, another question to be answered by drainage engineers is: how to integrate equality factors with cost-effectiveness objectives in urban drainage infrastructure design? This should address spatial equity in the distribution of investment and infrastructure services among urban communities. This issue becomes more important when green drainage practices are to be used in the

drainage infrastructure design. During the past years, optimisation of traditional and sustainable urban drainage infrastructure stood in focus for minimisation of flood risk and other cost-effectiveness factors in design of UDS. However, there is a lack of insight about how to include equity/equality factors in the optimisation of UDS and SuDS.

Visualisation analytics can be used by decision-makers to survey trade-offs between objective functions and come up with a final decision. However, the number of optimisation solutions increases with the accuracy of a search algorithm and also the number of objective functions (Hadka & Reed, 2013). This can result in situations where decision-makers must deal with hundreds or thousands of optimisation solutions making it impossible to single out their final decisions as they can only process a limited amount of information at a time. The question to be answered in this regard is: how to efficiently reduce the number of obtained optimisation solutions for simplified decision-making? How to assist decision-makers and stakeholders without the required urban hydrology background to obtain a realistic appreciation of the obtained optimisation solutions and survey trade-offs between the design objectives. In this dissertation, the main goal is to find answers to these questions.

1.3 Aims and objectives

The questions outlined in the previous section raise opportunities for research in improving current achievements in traditional/sustainable urban drainage infrastructure design approaches. This can be done by developing optimisation models, which can be efficiently applied to large UDS while addressing socio-economic and environmental aspects of urban drainage infrastructure.

Accordingly, the main objective of this thesis is threefold: first, to develop a system disaggregation and optimisation approach, which should allow to focus on a portion of a large sustainable urban drainage infrastructure and run optimisation only in that region while system integrity is preserved. This system disaggregation-optimisation

strategy would be especially useful when the drainage facilities are planned to be installed on a portion of a drainage system while it is intended to overlook the rest of the network in order to speed up the required iterative numerical simulations. Second, to develop a multi-criteria design approach aiming at quantifying spatial metrics of equity, which can be used in optimisation models with the provision of preventing unintended discrimination in accessing co-benefits of SuDS among different regions of a city. Third, to reduce the number of solutions, obtained from multi/many-objective optimisation of urban drainage infrastructure for simplified decision-making. In this way, decision-makers should be able to focus on a handful of multi-dimensionally efficient ('Pareto-optimal') solutions.

1.4 Literature review

1.4.1 Multi-objective evaluation of urban drainage infrastructure

Urban drainage system design involves deciding on a set of parameters that characterise the functionality of a drainage infrastructure. In case of conventional urban drainage infrastructure, these parameters generally include cross-sectional area, burial depth, and slope of conduits to determine transferring capacity of drainage systems (Duan et al., 2016; Fecarotta & Cimorelli, 2021; Ho et al., 2021). There can be also a set of design restrictions to be met, including ranges of pipe diameters that can be found in the market and the minimum and maximum allowed depths of excavation (Haghighi & Bakhshipour, 2012). Furthermore, there can be several stakeholders with different professional backgrounds, interests, and objectives involved in the decision-making process towards a final urban drainage infrastructure design.

Generally, design of UDS is carried out using computer modelling assets. The Storm Water Management Model (SWMM) developed by the United States Environmental Protection Agency (USEPA) (Gironás et al., 2010), is an urban drainage modelling software commonly used for this reason (Jang et al., 2007; Rabori & Ghazavi, 2019).

Designers generally tend to approach design of UDS in a trial-and-error fashion guided by engineering insight (J. Zhang et al., 2018). However, due to the inherent complexity of sewer system modelling, this can be a time-consuming and energy-draining task. A comprehensive design framework is required for UDS to find efficient drainage portfolios that are commensurate with decision-makers' design objectives, constraints, and preferences.

The advent of optimisation methods in urban water management has enabled researchers and engineers to approach an optimal, or a set of Pareto-optimal, urban water infrastructure design/s in an efficient way (Heydari Mofrad & Yazdi, 2021; Leng et al., 2021; Q. J. Wang, 1991; H. Xu et al., 2020; Yazdi et al., 2017). Optimisation algorithms can be used to approach efficient drainage system designs that are in accordance with the physical and budgetary constraints of a project. Wang (1991) was among the first who suggested the application of evolutionary algorithms (EAs), which are based on natural evolution and survival of the fittest, in rainfall-runoff models. Haghighi and Bakhshipour (2012) employed an adaptive EA to optimise pipeline settings in a sewer system. They considered pump station operation and pipeline diameters as decision variables to be translated into the binary format and used in an optimisation model. Moussavi et al. (2017) extended their work by also taking into account conduit slopes for a case study located in Ahvaz, Iran. Wang et al. (2018) compared the application of the non-dominated sorting genetic algorithm II (NSGA-II), MATLAB's global optimisation toolbox (MLOT), and a hybrid optimiser namely the genetically adaptive leaping algorithm for approximation and diversity (GALAXY) for designing conventional UDS. The models were linked to SWMM aiming at minimised total flood volume and capital cost in a region of interest in Hohhot City, China.

Stormwater management in urban areas with existing drainage systems can also be improved by real-time (on-line) and/or static (off-line) control strategies (García et al., 2015) though the latter may not be preferable for large drainage systems with complex system dynamics. This approach involves training and tuning the so-called real-time control (RTC) facilities aiming at capacity expansion of UDS by improved

detention, storage, and stormwater deposition when appropriate. Several studies have been reported the application of RTC facilities in flood management demonstrating their reliability and cost-effectiveness (Beeneken et al., 2013; Capodaglio, 1994; Jamieson et al., 2007), which have been further improved when tuned by optimisation algorithms (Abou Rjeily et al., 2018; Pleau et al., 2005). Pleau et al. (2005) applied an optimisation method to the RTC of a drainage system to reduce the polluted stormwater entering a downstream river located in Quebec, Canada. Abou Rjeily et al. (2018) developed an RTC optimisation strategy for flood management in an urban area located in Lille, France. The model was set to automatically change opening ratios of the dynamic valves in the drainage system based on a set of rules found to be efficient by an optimisation model.

When applied to design of UDS, an EA explores a range of design portfolios trying to find one, or a set of, efficient drainage infrastructure design/s. The solution exploration process generally entails tens of thousands of numerical simulations wherein large drainage systems can become a computationally intensive process. The literature has addressed this problem by using simplified model alternatives and surrogate models. However, finding a balance between accuracy and efficiency has long been a challenge in this sense. According to the research conducted by Karamouz and Nazif (2013) the kinematic wave routing method, available in SWMM, can reduce the computational time of an optimisation model by allowing faster numerical simulations of the drainage process. However, the kinematic wave routing method lacks accuracy when dealing with pressurised flows and situations in which stormwater ponds atop a manhole as is the case in floods. In surrogate modelling techniques, on the other hand, black boxes are trained and used to suppress unnecessary details in order to speed up iterative function evaluations in an optimisation run. To this end, computationally intensive numerical simulations are replaced with fast surrogate models, such as the Gaussian process emulator (Mahmoodian, Torres-Matallana, et al., 2018; Owen & Liuzzo, 2019), artificial neural networks (ANNs) (Kim et al., 2019; Latifi et al., 2019; Sayers et al., 2019; She & You, 2019), or alternative numerical models with simplified structures that can mimic

specific outputs of the real system (Mahmoodian, Carbajal, et al., 2018; Mahmoodian, Torres-Matallana, et al., 2018). For example, Zhang et al. (2019) applied a neural network-based emulation model to predict two objective functions for optimisation of urban drainage infrastructure. Latifi et al. (2019) and Raei et al. (2019) also used a similar approach to emulate numerical results of a stormwater model for an urban drainage network in Tehran, Iran.

Although these models tend to be computationally efficient, there are concerns about their accuracy and applicability. Since objective functions are explicitly predicted in this methodology, even slight errors in the predications (function evaluations based on emulation models) can accumulate throughout the search process and bias the search algorithm leading to degraded optimisation results. Moreover, the larger the number of training inputs/outputs the more computationally intensive the training/tuning process of the emulation model.

1.4.2 Multi-objective evaluation of sustainable urban drainage systems

Fast conveyance of stormwater through pipe systems to downstream watercourses is generally considered as the main objective of conventional drainage systems. However, this process can alter the water cycle in urban areas in many ways. Reducing groundwater recharge is an example, which can lead to water scarcity in arid areas or regions where the water supply is dependent on groundwater abstraction (Ali et al., 2012). Picking up pollutants on its way, untreated stormwater pollutes surface waters having the most impact on smaller streams and their aquatic ecosystems (Hatt et al., 2004; Paul & Meyer, 2008). Nevertheless, nature-based drainage solutions with less environmental impact that mainly operate based on onsite infiltration, storage, and evapotranspiration can help to achieve sustainable flood management. Considering the co-benefits associated with SuDS, and especially with their green facilities, such system designs require reasonable investment plans to find a balance between their technical, economic, and environmental aspects in a way to improve the life quality of the city dwellers. The same difficulties, and more, are to be expected in designing an optimal sustainable urban drainage infrastructure as an ensemble of new interlinked

design aspects, such as local standards and land availability, are to be satisfied while approaching stakeholder satisfaction (Water Research Centre, 2006). These factors have stimulated and maintained the application of EAs to attain efficient design of SuDS (Baek et al., 2015; Eckart et al., 2018; Ghodsi et al., 2016; Giacomoni & Joseph, 2017; Hooshyaripor & Yazdi, 2017; Y. Liu et al., 2016; Nasrin et al., 2017; Niazi et al., 2017; T. Xu et al., 2017, 2018).

Generally, reported research mirrors design of SuDS in terms of finding optimal (single-objective optimisation) or Pareto-optimal (multi-objective optimisation) schemes for spatial distribution and/or decisions about surface areas of sustainable drainage facilities in urban areas. For example, Baek et al. (2015) proposed an optimisation model to reduce mass first flush as an indicator of first flush effect in drainage systems by searching for optimal types of sustainable urban drainage assets and their sizes in a commercial urban area located in South Korea. The model was developed based on a single-objective optimisation algorithm. However, SuDS can bring about several co-benefits, such as recreational opportunities, for their end-users that entail addressing a set of design objectives rather than just trying to minimise capital costs or flood volume. To address this requirement, Liu et al. (2016) applied a multi-objective optimisation model addressing cost-effectiveness of a sustainable urban drainage infrastructure located in the Crooked Creek watershed in Indiana, USA. Applying multi-objective optimisation methods to SuDS design can be ideal to help engineers approach a set of Pareto-optimal portfolio designs. However, its subsequent decision-making stage can be a challenging task as it generally necessitates involvement of multiple decision-makers, potentially with conflicting design objectives and/or constraints. Ghodsi et al. (2016) addressed this issue by formulating an optimisation approach, which involved a bargaining strategy for selecting design portfolios. To this end, sizes of four sustainable drainage assets, including permeable pavements, infiltration trenches, bio-retention cells, and vegetative swales, were optimised for 10, out of 24, sub-catchments in an urban catchment located in Tehran, Iran. They adopted the NSGA-II optimisation algorithm and targeted capital costs, stormwater pollution, and surface runoff volume as design

objectives. Giacomoni and Joseph (2017) optimised spatial distribution of green roofs and permeable pavements in an illustrative case study, available in the SWMM software package (Gironás et al., 2010), applying the NSGA-II. Cano et al. (2017) used the multi-objective, socio-economic, boundary-emanating, nearest distance (MOSEBEND) optimisation method for design of sustainable drainage infrastructure in an urban catchment located in Lámud, Peru. Eckart et al. (2018) used the Borg multi-objective evolutionary algorithm (MOEA) (Hadka & Reed, 2013), to find efficient designs of SuDS with sustainable facilities, including rain barrels, rain gardens, permeable pavements, and infiltration trenches, in an urban area located in Windsor, Canada. These studies have mainly focused on the cost-effectiveness of SuDS while overlooking their co-benefits to be improved as design objectives. To address this issue, Alves et al. (2019) showed that when applying green and grey drainage infrastructure in a flood management optimisation model, search algorithms may overlook sustainability of the drainage system by suggesting grey drainage assets as they tend to be more efficient in reducing flood volume. They proposed a monetisation technique, which involves appraisal of costs and benefits of a design portfolio for a case study located in Sint Maarten Island, in the Caribbean Sea.

Multi-objective optimisation models deal with two or three optimisation objectives to be simultaneously minimised or maximised resulting in a set of Pareto-optimal solutions ('Pareto-front'), which best trade-off between the objectives. Many-objective optimisation models, instead, involve more than three objective functions (Fleming et al., 2005). Although this is often the case in stormwater infrastructure design only a few studies have addressed the application of many-objective optimisation methods for design of SuDS (F. Li et al., 2019; Michael Di Matteo et al., 2019). Li et al. (2019) applied the NSGA-II optimisation method to find Pareto-optimal designs of SuDS with reduced flood risk and improved stormwater quality. Di Matteo et al. (2019) used a four-objective optimisation method for design of SuDS minimising total nitrogen output of the drainage system and its capital cost while maximising stormwater reuse and the co-benefits associated with green drainage facilities.

The literature so far has focused on optimisation frameworks for design of SuDS that mainly deal with the cost-effectiveness of design portfolios in terms of improving drainage capacity in areas with the highest degrees of impact. However, the socio-environmental aspects of sustainable urban drainage infrastructure have been overlooked apart from a few studies that have considered them in system design approaches without optimisation methods (Heckert & Rosan, 2016; La Rosa & Pappalardo, 2020). This is important because green drainage assets have restorative effects on the mental and physical health of its end-users and also can improve urban landscapes (Fábos, 2004; Hordyk et al., 2015). SuDS optimisation models without proper equity/equality factors can result in unfair system designs where drainage facilities with socio-environmental co-benefits are unevenly distributed between different neighbourhoods of the same city. La Rosa and Pappalardo (2020) has addressed the issue by developing a design framework in which drainage engineers can manually decide on the location of green roofs based on heterogeneity of their spatial distribution in an urban area. There is currently a paucity of insight on how to apply spatial equity factors in design of SuDS when using optimisation methods.

These shortcomings in the literature on efficient, simplified, and/or fair multi-objective design of sustainable urban drainage infrastructure can raise opportunities for research in this area.

1.5 Summary of methods

During the past years, several models, including the SWMM, HydroCAD, and Rainwater+, have been proposed for numerical simulation of UDS. These models generally consist of two sub-models responsible to carry out hydrologic and hydraulic simulations each of which comprises several modules. The hydraulic modules normally involve numerical models to simulate stormwater flow in open and closed conduits, manholes, storage units, pumps, and flow dividers while sub-catchments, rainfall data, and sustainable drainage assets are related to hydrological modules.

1.5.1 Numerical modelling

In this study, the SWMM (Gironás et al., 2010), was implemented to simulate rainfall-runoff and drainage processes when required. SWMM can simulate rainfall, runoff, evaporation, infiltration, pollution transport, and water flow in closed- and open-channels (Elliott & Trowsdale, 2007; Lewis A. Rossman & Huber, 2016). In its hydraulic simulation engine, SWMM includes three flow routing models, including steady flow, kinematic wave, and dynamic wave schemes (James et al., 2010). Due to its vast modelling capabilities and open-access nature, SWMM has drawn the attention of urban drainage engineers and researchers for analysis of drainage systems and flood management purposes (Alamdari, 2018; Awol et al., 2018; Banik et al., 2017; Jamali et al., 2018; M. Di Matteo et al., 2019). The model has been used in various urban drainage system studies for analysis and design of drainage system expansion or rehabilitation in urban areas (F. Li et al., 2015; J. Li et al., 2017; McGarity, 2012). It has also been used for estimating infiltration and exfiltration (McCutcheon et al., 2010) and pollution transfer (Tsihrintzis & Hamid, 1997) in UDS. SWMM has been also adopted by vendors and extended to commercial variants, such as PCSWMM, MIKE SWMM, InfoSWMM, and XPSWM.

In order to simulate flow routing in UDS, SWMM solves the one-dimensional Saint-Venant equation (SVE) system, which expresses the principles of conservation of mass and momentum as follows:

$$\frac{\partial A}{\partial t} + \frac{\partial Q}{\partial x} = 0 \tag{1-1}$$

$$\frac{\partial Q}{\partial t} + \frac{\partial (Q^2/A)}{\partial x} + gA\frac{\partial h}{\partial x} + gAS_f + gAh_L = 0 \tag{1-2}$$

where t is time, x is distance, A is the flow cross-sectional area, Q is flow discharge, g is gravitational acceleration, h is the hydraulic head, S_f is the friction slope, and h_L is the local energy loss per unit length of the conduit.

Three flow routing methods are available in SWMM that are defined based on three levels of simplification of the mass and momentum conservation equations. The steady flow routing model links each pair of upstream and downstream system junctions with steady hydrographs making it the fastest routing model available in SWMM. This model is suitable for preliminary analysis of drainage systems, yet, inapplicable in situations that encounter pressurised flows, entrance or exit hydraulic losses, and backflow effects (James et al., 2010). The kinematic wave routing model, instead, uses the 1D continuity equation and a shortened form of the momentum equation that makes the hydraulic grade line slope, between each pair of system junctions, equal to slope of the corresponding conduits. This implies that the kinematic wave routing method would not be able to simulate pressurised flows. Moreover, using the kinematic wave routing method, the excess flows exiting a manhole will be lost from the system. Accordingly, the kinematic wave is not efficient for simulating drainage systems in which network loops, pressurised pipes, surcharging, and backflow effects are significant (James et al., 2010). In this light, when using this method, effects of downstream structures will not impact upstream flow conditions. When using the dynamic wave flow routing model, instead, the full SVEs is solved without further approximations (James et al., 2010). Consequently, the dynamic wave model can be used in situations where the previous two flow routing models are not applicable.

Besides simulating stormwater transfer, a reliable urban flood management model must be able to numerically simulate stormwater pollutant transfer in drainage systems. Using a set of empirical methods SWMM is capable of simulating pollution build-up, wash-off, and transport in drainage systems (Gironás et al., 2010). Moreover, in its latest versions, SWMM allows simulation of source control practices, including bio-retention cells, rain gardens, green roofs, infiltration trenches, permeable pavements, rain barrels, rooftop disconnections, and vegetative swales (James et al., 2010; Lee et al., 2010; Meza & Oliva, 2003; Lewis A. Rossman & Huber, 2016).

1.5.2 Surrogate modelling

When using optimisation models, one or several search algorithms may be used to explore a solution space for optimisation solutions by performing iterative mathematical calculations or numerical simulations. This methodology can only be used in cases where the simulations are performed in a reasonable amount of time. For example, it will take more than 33 hours to complete an optimisation run that involves 30,000 function evaluations, each of which is completed in 4 seconds. However, an optimisation run can take months to complete when each function evaluation is to be completed in a few minutes, which is the case for large UDS. This hampers the application of optimisation methods in the industry.

To solve this problem, researchers have proposed different surrogate modelling techniques for fast prediction of drainage system behaviour (Latifi et al., 2019; Maier et al., 2010; Raei et al., 2019; W. Zhang et al., 2019). ANNs have been frequently used as surrogate models, for this purpose, due to their high integration capability and convenience of use. They are input-output mathematical models developed based on the operation of biological nervous systems comprising interconnected neurons (Du & Swamy, 2006; Tadeusiewicz, 1995). ANNs have two main advantages that make them suitable to be used as surrogate models in order to speed up optimisation runs. First, they can learn non-linear relations between different compartments of a system; and second, they are developed based on an inherently distributed nature that allows better implementation across distributed systems.

Artificial nerve cells (neurons) are the basic processing elements of ANNs, which are connected to each other via a set of artificial neuronal junctions (synapses) that are multiplied by weight factors (Du & Swamy, 2006). Generally, a set of training inputs is encoded in the first layer and passed through a set of hidden layers via the weighted links. In each neuron, the weighted data are summed up together with the scalar parameter b known as “bias” to be used by a predefined transfer function. The information obtained from the transfer function is the input data to be passed to a subsequent layer.

Depending on their performances, different transfer functions may be used in ANNs, including the sigmoid and linear transfer functions.

The outputs of the first neuron would be as follows:

$$O = f\left(\sum_{i=1}^{n_e}\left(U_i w_{1,i}\right) + b\right) \tag{1-3}$$

where U is the input vector, n_e denotes the number of elements in the input vector, $w_{1,i}$ is the ith weight of the neuron, b is the bias, and f stands for the transfer function.

In this thesis, the generalised regression neural network (GRNN) and multilayer perceptron (MLP) algorithms were applied as surrogate models to predict flow behaviours in UDS. The MLP network is a feedforward ANN architecture (Hornik et al., 1989), which is by far the most popular ANN used in a wide range of water engineering prediction/emulation applications (Broad et al., 2005; Maier et al., 2010; Seyedashraf, Rezaei, et al., 2018). In feedforward ANNs, each node of a layer receives information from nodes of a preceding layer and feeds neurons of a subsequent layer by the processed data. Generally, there is a minimum of three layers in MLP networks, including an input layer, at least one hidden layer, and an output layer where each node of a layer connects to every node of a subsequent layer with certain weighting factors (Figure 1-8).

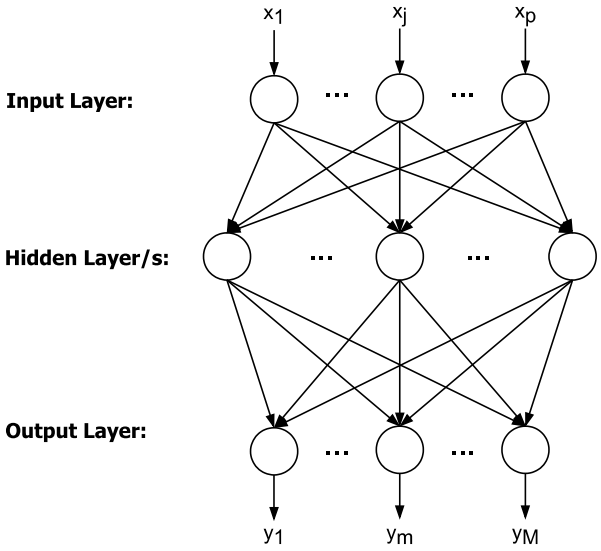

Figure 1-8. Typical architecture of the multilayer perceptron (MLP).

According to the network architecture, the input-output relationships of the nodes is identical to Equation (1-3) whereas the transfer function is generally selected of a sigmoid form defined as follows:

$$f(z) = \frac{1}{1 + \exp(z)} \tag{1-4}$$

Design complexity and accuracy of an MLP model depends both on the number of layers and number of neurons in each layer. An efficient combination of the number of layers and neurons can be found by a trial-and-error procedure. However, it must be noted that a lower number is always preferable as complexity of training process increases with the number of layers, which may lead to overfitting (Seyedashraf, Mehrabi, et al., 2018).

The GRNN is a one-pass learning algorithm with a feed-forward architecture that is especially suitable for multi-dimensional problems with sparse data (Specht, 1991). Generally, there are four layers in the GRNN: first, an input layer that comprises the input data and feeds them to the next layer; second, a pattern layer that calculates the activation function and the Euclidean distance between the training sample and their corresponding input data; third, a summation layer that contains two types of

neurons, including numerator and denominator, which calculate the summation of the pattern layer with and without weights, respectively; and fourth, an output layer that contains one neuron and calculates network outputs according to the information received from the summation layer.

Figure 1-9 shows the architecture of a GRNN model with *p* inputs.

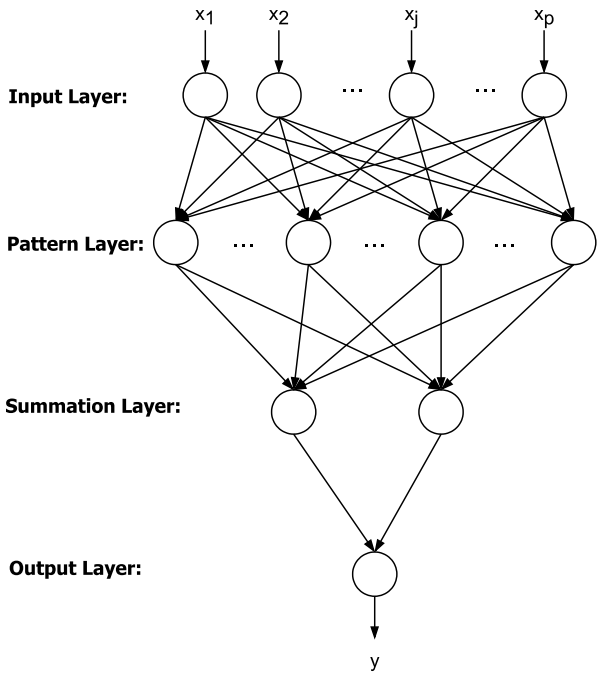

Figure 1-9. Typical architecture of the generalised regression neural network (GRNN).

The GRNN maps the input space to the output space as follows (Specht, 1991; X. Zhang et al., 2019):

$$y(x) = \frac{\sum_{i=1}^{n_{sa}} y_i \exp\left(\frac{-D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^{n_{sa}} \exp\left(\frac{-D_i^2}{2\sigma^2}\right)} \tag{1-5}$$

$$D_i = \sqrt{(x - x_i)^T (x - x_i)} \tag{1-6}$$

where y_i is the ith output corresponding to input x_i, n_{sa} is the number of samples in the input vector, and σ is the smoothing factor, which is used to adjust neurons' sensitivity to changes in the input vector.

When using the GRNN, it must be noted that large smoothing factors result in smooth function approximations and improves the generalisation of the predictions while reducing prediction accuracy. Accordingly, a trial-and-error procedure may be used to calibrate the smoothing factor according to the desired prediction accuracy.

1.5.3 Optimisation methods

During the past two decades, a variety of optimisation methods have been developed with different features and levels of sophistication to meet the increasing demand for efficiency in engineering design problems. Generally, optimisation methods fall into two classes, including deterministic and meta-heuristic methods. Deterministic optimisation methods, such as the gradient descent algorithm, generally operate based on calculating derivatives of objective functions. Several disadvantages are associated with this class of optimisation methods in engineering problems as they can only be applied to simple problems with continuous search spaces (Al-Azza et al., 2016). This issue becomes more significant when dealing with multi-objective optimisation problems, which necessitate integration of the objective functions using weights. Meta-heuristic optimisation methods, instead, mainly rely on population-based search algorithms that operate by iterative mathematical calculations aimed at finding an optimal solution or set of Pareto-optimal solutions (Gomes de Alvarenga et al., 2000). The search algorithm conducts an intelligent search in the solution space for improvements in model performance using a series of analytical calculations or numerical simulations. Meta-heuristic optimisation methods can offer effective criteria and features to escape local optima and find efficient solutions. They are not problem-specific and can be generalised to different tasks without major changes in their algorithms. EAs are population-based meta-heuristic methods, which can solve optimisation problems by mimicking the biological mechanisms of evolution (Galletly, 1998). Numerous EAs have been proposed and applied to different engineering

problems out of which the genetic algorithm (GA) has emerged as the most commonly used operator. First proposed by Holland (1992), the GA operates by randomly producing a set of initial populations (chromosomes) and evolves them towards better generations by evaluation and selection strategies aiming at minimised, or maximised, optimisation objectives. A chromosome consists of a series of genes each of which represents a decision-value and definition of a solution to the optimisation problem. New populations are created from parent solutions with superior fitness values using crossover, mutation, and selection techniques and the iterative search procedure runs until a termination criterion is met.

GA can be used to solve single- and multi-objective optimisation problems. In single-objective optimisation, the aim is to find an optimal solution in terms of the minimum (or maximum) reached values of an objective in the respective decision space. The latter case, instead, deals with more than one optimisation objective. In this situation, improving one objective can have an opposite impact on other objectives making it unfeasible to find the minimum (or maximum) values for all objectives simultaneously. Accordingly, unlike single-objective optimisation problems, there is no single solution to a multi-objective optimisation problem, yet the final solution must be selected between a set of solutions approximating a Pareto-front. Single-objective optimisation methods can also be applied to multi-objective problems by integrating the objective functions. However, this entails defining weighting factors, which requires knowledge about the relative importance of each objective and trade-offs between them prior to the optimisation run. For example, in the case of applying a single-objective optimisation method to design of SuDS, prior knowledge about trade-offs between flood duration and amount of TSS may be required, which is generally not feasible.

Several multi-objective optimisation methods have been developed and reported in the literature among which MOEAs have received substantial attention during the past two decades. In this thesis, two multi-objective optimisation methods, including the Borg MOEA and controlled NSGA-II (CNSGA-II) were implemented to demonstrate

the proposed optimisation methodologies and concepts for sustainable urban drainage infrastructure design (Deb & Goel, 2001; Hadka & Reed, 2013).

Proposed by Deb et al. (2002), NSGA-II is a popular MOEA that has been proved to be efficient in many engineering design problems, including design of stormwater management facilities (Ghodsi et al., 2016; Hooshyaripor & Yazdi, 2017; G. Liu et al., 2019; Manocha & Babovic, 2018; Ngamalieu-Nengoue et al., 2019; Penn et al., 2013; T. Xu et al., 2017). Here, the solution space is explored using an elitist genetic algorithm, in which solutions with better ranks are preferred in each generation until a set of non-dominated solutions is found. The NSGA-II has been recommended in terms of accuracy and efficiency for design of UDS (Giacomoni & Joseph, 2017; Q. Wang et al., 2015). There are other variants of the NSGA-II such as CNSGA-II, which is designed based on the same optimisation logic with few modifications that allow the search algorithm to favour non-elitist individuals that can widen distribution of the resulting Pareto-front (Deb & Goel, 2001). Accordingly, the CNSGA-II has improved functionality in maintaining diversity of Pareto-fronts with a better convergence behaviour (Deb & Goel, 2001).

One of the difficulties associated with implementing multi-objective optimisation methods is that the user must decide on values of the recombination operators, which can impact efficiency of the optimisation, *a priori* to the optimisation run. The Borg MOEA (Hadka & Reed, 2013) and a multi-algorithm, genetically adaptive multi-objective (AMALGAM) (Vrugt et al., 2009) have addressed this issue by adaptively selecting recombination operators. Accordingly, owing to its adaptive multi-operator behaviour, the user does not need to deal with algorithm parameterisations before the optimisation process (Hadka & Reed, 2013). This feature helps to identify search stagnations, escape from local optimisation traps, and find correct search paths by restarting the search process (Hadka & Reed, 2013). Borg is specially designed to handle complex many-objective optimisation problems. It has been tested against state-of-the-art multi-objective optimisation methods, which was found to have superiority over them. Moreover, its robustness is affirmed in applications related to

water resources management and urban water infrastructure design problems (Eckart et al., 2018; Gupta et al., 2020; Khadem et al., 2020; Zatarain Salazar et al., 2016). In Chapters 4 and 5 of this dissertation, Borg is used to demonstrate the proposed optimisation methodologies for SuDS design.

1.6 Outline of the thesis

The remainder of this thesis is structured as follows: Chapter 2 represents the first published paper entitled "Many-Objective Optimization of Sustainable Drainage Systems in Urban Areas with Different Surface Slopes," in which a many-objective optimisation model is proposed along with a multi-criteria decision-making framework for design of sustainable urban drainage infrastructure. The model is applied to a synthetic case study with different average surface slope configurations to demonstrate how urban catchment slope can change optimisation model results, when it is run with the same initial populations, in finding cost-effective drainage system designs. Chapter 3 embodies the paper entitled "A Design Framework for Considering Spatial Equity in Urban Water Infrastructure," which proposes a new optimisation methodology for design of urban water infrastructure, especially SuDS, based on equity factors to ensure justice in spatial distribution of flood risk and drainage services, especially the co-benefits associated with green drainage facilities, between different neighbourhoods of a city. Another published paper entitled "A Disaggregation-Emulation Approach for Optimization of Large Urban Drainage Systems" forms the fourth chapter, in which a new surrogate-based optimisation approach is presented for disaggregation and optimisation of a portion of a large drainage network. Chapter 5 presents the last paper entitled "A Clustering Assisted Approach for Many-Objective Design of Sustainable Urban Drainage Systems," in which a simplified multi-criteria decision-making framework is proposed for design of SuDS. The framework can be used to reduce a Pareto-front, obtained from a multi/many-objective optimisation model, with thousands of solutions to a handful of solutions as representatives of the Pareto-front. Finally, Chapter 6 summarises the

findings of this study, draws the research conclusions, and suggests future research directions in the field.

1.7 List of publications

So far, the findings of this PhD study are presented, published, or under review in the following conferences and journals.

1.7.1 Journal pubications

- Seyedashraf, O., Bottacin-Busolin, A., Harou, J.J., "A Disaggregation-Emulation Approach for Optimization of Large Urban Drainage Systems", Water Resources Research, 57, e2020WR029098, 2021.
- Seyedashraf, O., Bottacin-Busolin, A., Harou, J.J., "Many-objective optimization of sustainable drainage systems in urban areas with different surface slopes", Water Resources Management, 2021.

1.7.2 Conference proceedings

- Seyedashraf, O., Bottacin-busolin, A., Harou, J.J., "A Surrogate-Based Optimization Approach for Sustainable Drainage Design in Large Urban Areas", EGU General Assembly 2021.
- Seyedashraf, O., Bottacin-busolin, A., Harou, J.J., "A Partitioning Approach to Support the Design of Urban Drainage Infrastructure", Proceedings of the 2021 MACE PGR conference, The University of Manchester, Manchester, UK, 25-27 May 2021.
- Seyedashraf, O., Bottacin-busolin, A., Harou, J.J., "A Many-Objective Trade-off Analysis of Sustainable Urban Drainage Systems", Proceedings of the 2020 MACE PGR conference, The University of Manchester, Manchester, UK, 12-15 May 2020.

1.7.3 Submitted journal articles

- Seyedashraf, O., Bottacin-Busolin, A., Harou, J.J., “A Design Framework for Urban Water Infrastructure”, submitted to Sustainable Cities and Society.

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2 Chapter two: Many-objective optimisation of sustainable drainage systems in urban areas with different surface slopes

Many-objective optimisation of sustainable drainage systems in urban areas with different surface slopes

Abstract

Sustainable urban drainage systems (SuDS) are multi-functional nature-based solutions that can facilitate flood management in urban catchments while improving stormwater runoff quality. Traditionally, the evaluation of the performance of sustainable drainage infrastructure has been limited to a narrow set of design objectives to simplify their implementation and decision-making process. In this chapter, the spatial design of SuDS is optimised considering five objective functions, including minimisation of flood volume, flood duration, average peak runoff, total suspended solids, and capital cost. This allows selecting an ensemble of admissible portfolios that best trade-off capital costs and the other important urban drainage services. The impact of the average surface slope of the urban catchment on the optimal design solutions is also discussed in this chapter and in terms of spatial distribution of sustainable drainage types. Results show that different subcatchment slopes, in this study, result in non-uniform distributional designs of SuDS, with higher capital costs and larger surface areas of green assets associated with steeper slopes. This has two implications. First, urban areas with different surface slopes should not have a one-size-fits-all design policy. Second, spatial equality must be taken into account when applying optimisation models to urban subcatchments with different surface slopes to avoid unequal distribution of environmental and human health co-benefits associated with green drainage infrastructure.

2.1 Introduction

Global climate change, rapid expansion of cities, and the ageing of existing urban drainage infrastructure raise new challenges for urban flood management (Arfa et al., 2021; Raei et al., 2019). The accelerated conversion of undeveloped areas into residential and commercial areas has altered the natural water cycle, resulting in extreme flood events, groundwater shortages, and pollution of receiving water bodies as stormwater runoff picks up pollutants from urban surfaces (Abou Rjeily et al., 2017, 2018; Luodan et al., 2019; Zhang et al., 2020). Conventional UDS (UDS) are designed for rapid drainage of stormwater runoff. However, SuDS are designed to facilitate the detention, infiltration, and evapotranspiration process of stormwater runoff while removing its pollutants (Geberemariam, 2021; Tang et al., 2021).

The design of SuDS is a daunting task due to their inherent hydrological and hydraulic complexity together with the conflicting stakeholder interests that often characterise urban planning (Horgan & Dimitrijević, 2019). Traditionally, drainage systems have been designed using trial-and-error approaches resulting in poor project outcomes that often fail to achieve an appropriate balance of community's interests. To overcome this problem, researchers have linked rainfall-runoff simulation models with multi-objective optimisation methods for multi-dimensionally efficient Pareto-optimal urban drainage system designs. By exploring discrete and continuous systems while satisfying problem constraints, multi-objective evolutionary algorithms have proven effective in facilitating urban drainage system design (Banihabib et al., 2019; Li et al., 2015, 2019; Martínez et al., 2018; Riaño-Briceño et al., 2016; T. Xu et al., 2018). Several studies have applied evolutionary algorithms to optimisation of sustainable drainage system design taking into account up to three objectives, including minimisation of capital cost, flood volume, and total suspended solids as proxies for flood damage and stormwater pollution, respectively (Eckart et al., 2018; Ghodsi et al., 2016; Latifi et al., 2019; H. Xu et al., 2020). For example, Ghodsi et al. (2016) linked the NSGA-II with the SWMM to optimise the design of SuDS. The combination was used along with a bargaining approach to handle several stakeholders' deliberations

in the decision-making process. Duan et al. (2016) linked the same hydrodynamic simulation model with the particle swarm optimisation algorithm and applied the framework to find a set of Pareto-optimal locations of detention tanks and sustainable infrastructure facilities for a real case study located in China. Giacomoni and Joseph (2017) applied the NSGA-II optimisation model to find an efficient spatial distribution of green roofs and permeable pavements in an idealised case study. Later, Eckart et al. (2018) implemented the Borg MOEA (Hadka & Reed, 2013), to optimise surface areas of different sustainable drainage facilities in an urban catchment in Windsor, Canada. Alves et al. (2019) investigated benefits of synergetic use of green, blue, and grey drainage infrastructure facilities for flood management designs. They showed that flood mitigation objectives and environmental co-benefits of sustainable drainage infrastructure must be jointly taken into account in optimisation models to maximise efficiency of the drainage systems. This needs to consider the relative efficiency of grey and green drainage infrastructure in reducing flood damage and stormwater pollution (Yang & Zhang, 2021), in line with the findings by Leng et al. (Leng et al., 2021) which demonstrate the benefits of synergistic implementation of grey and green infrastructure as well as the superiority of the latter in providing environmental benefits. Lu and Qin (2019) proposed a combination of the genetic algorithm and fuzzy simulation while considering uncertainties in reducing total flood volume in urban catchments. Taking into account the impacts of climate change on rainfall intensities, Ghodsi et al. (2020) considered the average peak runoff as an optimisation objective to find efficient designs of sustainable drainage infrastructure. More recently, Taghizadeh et al. (2021) linked the SWMM with a multi-objective particle swarm optimisation model to find efficient spatial distributions of permeable pavement, infiltration trenches, and bio-retention cells to reduce pollutant concentrations in an urban catchment located in the north-west of Tehran, Iran.

Despite the extensive literature on the subject, most of the simulation-optimisation studies address one to three design goals, which are insufficient to comprehensively assess the co-benefits associated with sustainable urban drainage infrastructure. Moreover, there is still a paucity of insight into the effect of the average surface slope

on the spatial distribution of sustainable drainage system components when this is determined using optimisation models. The importance of this lies in the fact that subcatchment slopes can affect the pattern of stormwater detention and infiltration resulting in a biased distribution of floods in cities with various topographic features. Accordingly, when using an optimisation model on this subject, the search algorithm may find a sustainable drainage system cost-effective where specific drainage facilities are allocated to particular subregions. Although the optimisation solution may become efficient in terms of flood management, it can raise concerns about spatial equality, as one of the pillars of the sustainable development goals, in urban drainage system design (Taguchi et al., 2020; Zheng et al., 2020).

This chapter shows how the average surface slope of urban catchments can impact equality in the spatial distribution of sustainable drainage components in urban areas in case of using an optimisation model to support design decisions. To this end, a many-objective optimisation approach is applied to a synthetic case study under different slope scenarios. Application of parallel axis plots laid alongside system design maps is also introduced as a summary graphical representation of optimisation results for stakeholder deliberations. Results show that urban areas with varying slopes within the same catchment should not have a one-size-fits-all sustainable drainage design. At the same time, care should be taken in ensuring that differences in average surface slope do not result in an unequal distribution of co-benefits associated with green drainage infrastructure.

2.2 Methods

2.2.1 Hydraulic simulation model

The simulation of an urban drainage system requires a rainfall-runoff and hydraulic routing model. The SWMM (Rossman, 2017), was used to simulate rainfall, runoff, infiltration, pollution transport, and drainage process in the region of interest. This numerical model can perform flow routing simulations using the steady flow,

kinematic wave, or dynamic wave method (Rossman, 2017). In this chapter, the dynamic wave routing method was used, which allows simulation of open-channel flows with backwater effects as well as pressurised flow in drainage pipes by solving the full one-dimensional Saint-Venant equations (Rossman, 2017).

2.2.2 Sustainable drainage assets

The sustainable drainage assets considered in this chapter include permeable pavements, infiltration trenches, bio-retention cells, rain gardens, rain barrels, and green roofs. Since each of these assets has different performance characteristics, their efficient combination can help achieve an effective design for a specific urban drainage system (Leng et al., 2021; Yang & Zhang, 2021). For instance, conventional asphalt and concrete pavements may be replaced by permeable paving materials to enhance infiltration. This can reduce stormwater runoff by enhancing infiltration and disposing of the excess runoff (Hu et al., 2018). Moreover, infiltration trenches may be employed as storage pits to reduce the runoff by improving water retention and infiltration. Bio-retention cells and rain gardens may also be used to facilitate the infiltration rate and boost groundwater recharge while enhancing stormwater quality (Rossman, 2017). Rain barrels and cisterns are useful to temporarily detain runoff and limit its flow into gutters to reduce pressure imposed on the drainage system. Furthermore, green roofs can slow down, absorb, retain runoff, reduce the energy use of buildings, increase the life of roofing systems, and regulate building temperature (Bolliger & Silbernagel, 2020). Given their different properties and performance in terms of decreasing flood volume and stormwater pollution, cost-effective combination and spatial distribution of these assets are desirable.

2.3 Model application

2.3.1 Case study

A 29-hectare synthetic urban drainage system case study with 8 subcatchments, 13 junctions, and 13 conduits, was selected to demonstrate the design formulation described above and investigate the relationship between average surface slope and drainage element performance (Figure 2-3). Three average surface slopes, i.e. 0.01%, 3%, and 6%, are considered.

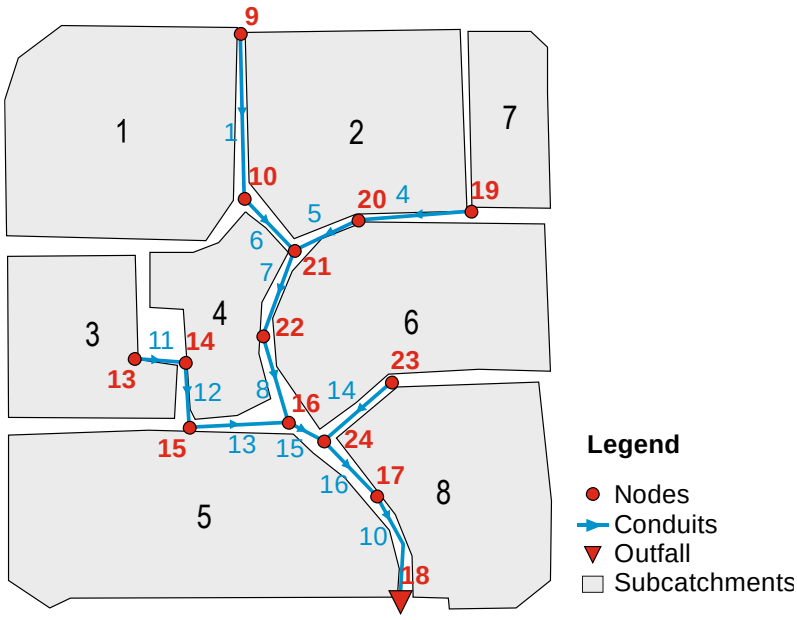

Figure 2-1. Schematic map of the synthetic case study.

A synthetic 100-year, 2-hour hyetograph with 5-minute increments was defined using the Alternating Block Method as an extreme rainfall event. The impervious surfaces were assumed to be composed of rooftops and driveways with equal ratios of surface areas. Two land-use classifications were defined, including residential and undeveloped areas, and the Event Mean Concentration method was applied to estimate wash-off load of TSS. To maximise efficiency of the sustainable drainage system, the decision variables consider combinations of two sustainable drainage types and their surface areas, represented by four integer values in each subcatchment. The surface area of the sustainable drainage components was

parameterised as a percentage of the impervious surfaces in each subcatchment. The maximum allowable surface area was set to 15% of the impermeable area of each subcatchment. The area of the subcatchments, land coverage and slope scenarios are summarised in Table 2-1.

Table 2-1. Subcatchment settings for the case study.

Subcatchment	Surface area (ac)	Coverage		Average surface slope (%)		
		Residential	Undeveloped	Scenario 1	Scenario 2	Scenario 3
S1	10	100%	-	0.01	3	6
S2	10	100%	-	0.01	3	6
S3	5	100%	-	0.01	3	6
S4	5	100%	-	0.01	3	6
S5	15	75%	25%	0.01	3	6
S6	12	100%	-	0.01	3	6
S7	4	100%	-	0.01	3	6
S8	10	50%	50%	0.01	3	6

The CNSGA-II (Deb and Goel 2001; Deb et al. 2002) optimisation algorithm was linked to the SWMM. NSGA-II is a fast, elitist multi-objective genetic algorithm, which is commonly used in different water engineering and urban infrastructure problems (Alamdari & Sample, 2019; Khorshidi et al., 2018; Manocha & Babovic, 2018). The CNSGA-II was used, however, as it can additionally control the extent of elitism while favouring individual vectors that can increase diversity of the population in the optimisation process (Deb & Goel, 2001).

2.3.2 Many-objective optimisation model formulation

As mentioned, several simultaneous benefits may be sought in sustainable urban drainage infrastructure design related to efficiency of a drainage system in reducing flood damages and improving its environmental performance (CRC for Water Sensitive Cities, 2016; Horton et al., 2016; Macro et al., 2019). For example, urbanisation increases the impermeable surface area of catchments and therefore increases the potential flood volume, flood duration, and peak runoff rate, which requires a drainage system with a large capacity and therefore higher capital cost. A higher average peak runoff rate can increase surface erosion and stormwater pollution by

washing sediments and pollutants off the catchment surface. To handle these design objectives, a many-objective optimisation model can be used to reach a set of efficient solutions while satisfying various design objectives and constraints.

In this paper, the following five objective functions are considered:

Minimise: $$\boldsymbol{F(x)} = (F_{Cost}, F_{FloodV}, F_{FloodD}, F_{PeakR}, F_{TSS}) \quad (2\text{-}1)$$

The objective function terms, including capital costs, F_{Cost}, flood volume, F_{FloodV}, flood duration, F_{FloodD}, peak runoff, F_{PeakR}, and total suspended solids, F_{TSS}, are defined next.

The capital cost was calculated for the urban catchment as follows:

$$F_{Cost} = \sum_{i=1}^{n_s} \sum_{j=1}^{n_t} \left(c_{ij} \times a_{ij}\right) \quad (2\text{-}2)$$

where n_s is the number of subcatchments, n_{t} is the number of sustainable drainage system types in each subcatchment, and a_{ij} and c_{ij} are the surface area and capital cost of each drainage component, respectively.

The capital costs for the drainage assets were extracted from databases published by Herrera Environmental Consultants (2012) and online vendors.

The total flood volume is defined as:

$$F_{FloodV} = \sum_{i=1}^{n_m} FV_i \quad (2\text{-}3)$$

where n_m is the number of manholes and FV_i is flood volume at the ith manhole.

The average manhole flood duration in the urban catchment is defined as:

$$F_{FloodD} = \frac{\sum_{i=1}^{n_f} FD_i}{n_f} \tag{2-4}$$

in which FD_i is flood duration at the ith manhole and n_f represents the number of flooded nodes.

Peak runoff is defined as:

$$F_{PeakR} = \frac{\sum_{i=1}^{n_s} P_i}{s} \tag{2-5}$$

where P_i is the peak runoff in each subcatchment.

Finally, the overall TSS load was extracted from the numerical results.

To represent locations of sustainable drainage components, the crossover, mutation, and reproduction operators in the genetic algorithm were adapted to produce integer-valued individuals. Moreover, as an optimisation constraint, solutions with two identical sustainable drainage types in each subcatchment were flagged as infeasible solutions. This, however, does not prevent the model from finding solutions with just one type of sustainable drainage system or even a no-intervention option in a subcatchment, as these can be obtained by selecting the no-intervention option or zero surface area for sustainable drainage assets. A function tolerance of 10^{-3} for 100 consecutive iterations was used as the stopping criterion, which resulted in around 22,000 function evaluations before the optimisation run stopped.

2.4 Results and Discussion

Many-objective optimisation allows analysts and their stakeholder clients to identify Pareto-optimal engineered water system designs and their performance trade-offs considering multiple metrics of performance. The term “many-objective” (Fleming et al., 2005), refers to an optimisation model with four or more objectives. This high dimensionality means effective multi-criteria visualisation techniques must be used to

help identify designs that best satisfy stakeholder design goals. The multi-objective optimisation approach used here focuses on the *a posteriori* optimisation (Zatarain Salazar et al., 2017), i.e. weights do not have to be assigned to objectives *a priori* (i.e., before seeing results), of SuDS. This means stakeholders can develop their own views about the relative importance of design criteria by assessing the impact of favouring one performance metric over another and seeing the impact these varying priorities have on drainage design. This deliberative design process could be enhanced by using interactive versions of the plots below.

To illustrate here how a range of high-value designs can be extracted from the Pareto-optimal solution set provided by the many-objective optimisation, three example design solutions that correspond to alternative sets of stakeholder priorities are considered. The first set of priorities selects the least-cost drainage system design that fits within a prescribed range of acceptable flood volume and flood duration. Such a design might be sought if priority is given to reducing flood damages and securing normal transportation traffic near flooded manholes. The second design selects the least-cost option amongst designs that fit within a prescribed range of flood volume and average peak runoff. Finally, a third design option is chosen which corresponds to the least-cost option that meets a given constraint on the TSS.

Figure 2-2 presents a five-dimensional plot of the Pareto front for 0.01%, 3%, and 6% average surface slopes. Flood volume, TSS, and flood duration are shown on the x, y, z-axes, and capital cost and average peak runoff are represented by the colour and the marker size, respectively. The green-to-blue colour scale represents low-to-high capital costs and larger markers represent larger average peak runoff values. The five-dimensional plot in Figure 2-2 provides an overview of the system performance with respect to the various performance metrics. The figure shows that the variation in flood volume and flood duration for the 0.01% slope is smaller than that of 3% and 6% slopes. The graphs also show that higher flood volumes are not necessarily associated with higher flood durations.

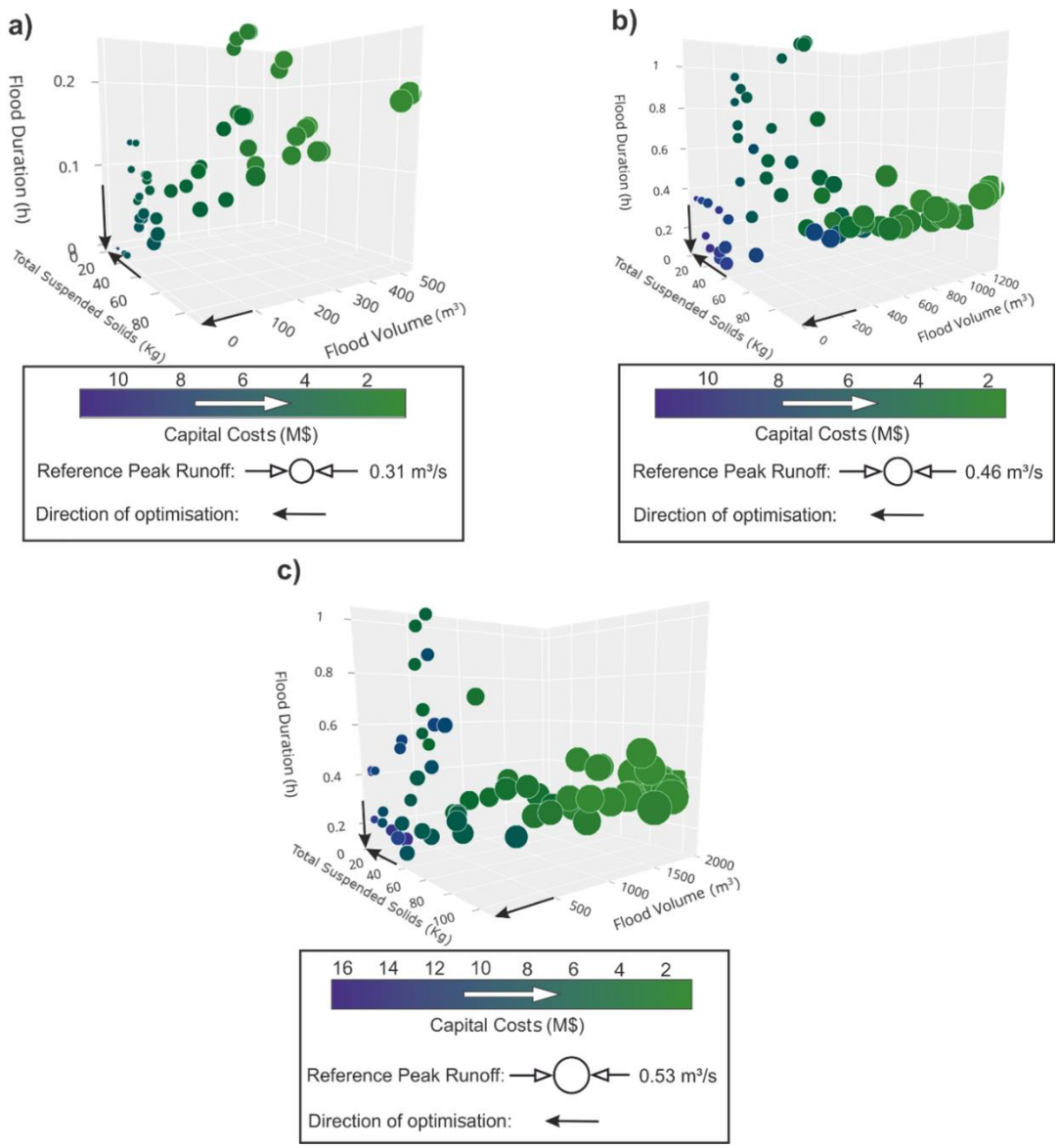

Figure 2-2. Five-dimensional representation of the Pareto-front for the selected case study considering three surface slopes scenarios including a) 0.01% slope, b) 3% slope, and c) 6% slope (Table 2-1). The green-to-blue colour scale represents low-to-high capital costs and marker sizes are proportional to the average peak runoff values in each scenario. The graphs show that higher flood volumes are not necessarily associated with higher flood durations.

Although these plots are accurate and complete, they do not lend themselves easily to urban stakeholder learning and design deliberation. To enable this, the parallel axis plots (Inselberg, 2009) of the Pareto-fronts are presented beside system design schematics. This allows exploring trade-offs between the optimisation objectives and their implications on spatial design as illustrated in Figures 2-3, 2-4, and 2-5 for the three surface slope scenarios. In these plots, each axis represents a different objective

function, and each line connecting the axes represents the performance of a particular non-dominated portfolio of interventions. This visualisation technique allows the user to interactively select the set of solutions that satisfy given post-optimisation constraints for each objective in the plot. Figures 2-3, 2-4, and 2-5 show the performance of the non-dominated optimal solutions for the case of 0.01%, 3%, and 6% average surface slopes, respectively. Here, preferred solutions lie at the bottom of the graph. The solutions with the lowest capital cost among those in the prescribed ranges of flood volume and duration were marked in red and singled out as final sustainable drainage system designs. This corresponds to the first design preference described above. In this chapter, the permissible range of flood duration and volume was selected to be one-third of the range in the solution space.

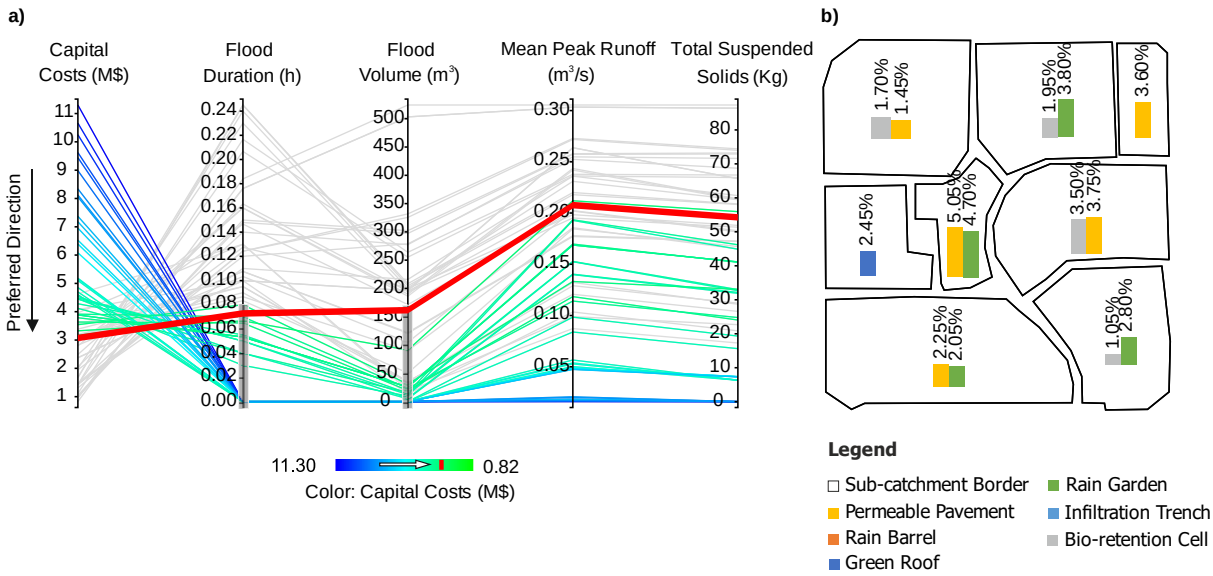

Figure 2-3. Many-objective optimisation of sustainable drainage infrastructure in a flat urban catchment prioritising flood attenuation; a) objective trade-offs and selected solution (marked in red), b) types, combinations, spatial distribution, and surface areas of the selected portfolio (red line in panel (a)) described as a percentage of the respective subcatchment surface area. The grey boxes on the axes of the panel (a) are interactive filter bars, which allow urban designers to isolate a subset of efficient designs that meet their preferences.

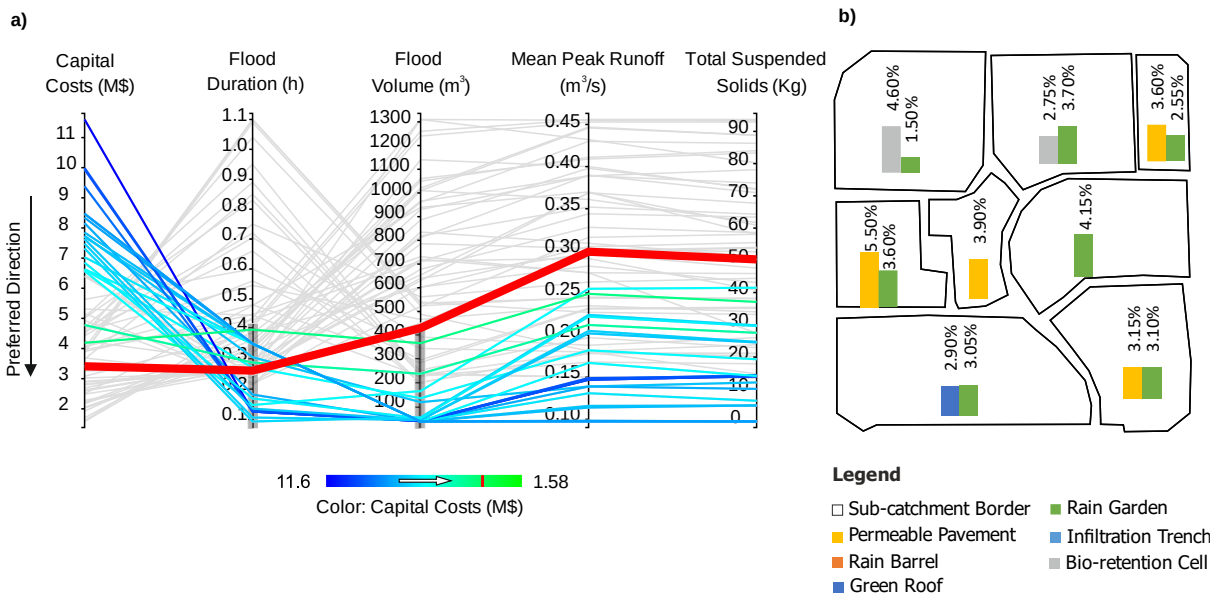

Figure 2-4. Many-objective optimisation of sustainable drainage infrastructure in an urban catchment with an average surface slope of 3% prioritising flood attenuation; a) objective trade-offs and selected solution (marked in red), b) types, combinations, spatial distribution, and surface areas of the selected portfolio (red line in panel (a)) described as a percentage of the respective subcatchment surface area. The grey boxes on the axes of the panel (a) are interactive filter bars, which allow urban designers to isolate a subset of efficient designs that meet their preferences.

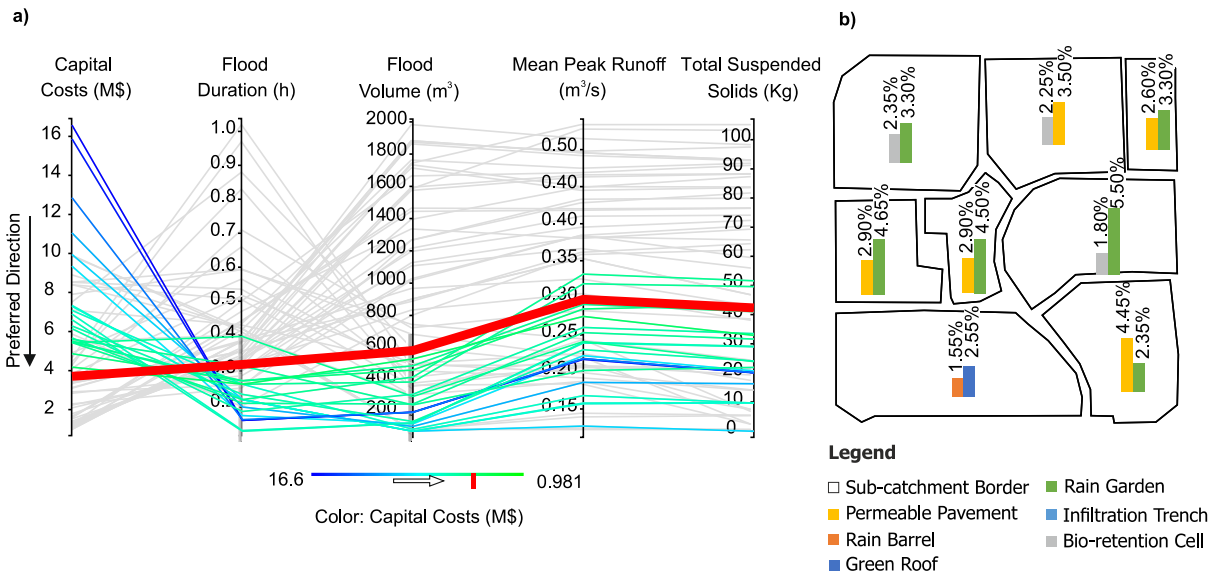

Figure 2-5. Many-objective optimisation of sustainable drainage infrastructure in an urban catchment with an average surface slope of 6% prioritising flood attenuation; a) objective trade-offs and selected solution (marked in red), b) types, combinations, spatial distribution, and surface areas of the selected portfolio (red line in panel (a)) described as a percentage of the respective subcatchment surface area. The grey boxes on the axes of the panel (a) are interactive filter bars, which allow urban designers to isolate a subset of efficient designs that meet their preferences.

The results show the value of applying a many-objective optimisation approach when there are multiple design goals that facilitate the necessary functionality of SuDS. For example, in Figure 2-5 it is shown that, with a $3.78 million investment in sustainable urban drainage interventions, the total flood volume is decreased from 2,555,000 m^3 to 582,000 m^3 in regions with steeper surface slopes while the mean peak runoff and total suspended solids are reduced by 57% and 70%, respectively. The results also imply that the average surface slope can bias the search algorithm in favour of specific types of sustainable urban drainage components. For instance, larger surface areas of rain gardens are found to be preferable in steeper slope scenarios compared to small slopes. However, no significant change was observed in surface areas of green roofs in response to changes in the surface slope, whereas the optimisation suggests the use of rain barrels only for steeper surface slopes. Here, the number of barrels can be obtained based on the surface area values of interventions allocated to each subcatchment. For example, in Figure 2-5, 7,647 rain barrels with the capacity of 100 litres and L32×W36×H95 cm dimensions may be installed on subcatchment S5 covering a surface area of 1.55% of the subcatchment. Alternatively, underground cisterns may be used, provided that the required overall storage capacity is preserved.

Using the same procedure described above, six portfolios were extracted from the set of Pareto-optimal solutions according to the second and third set of preferences. Figure 6 depicts bar chart plots of surface areas of sustainable drainage facilities against the spatial distribution, types, and combinations of these assets in each subcatchment.

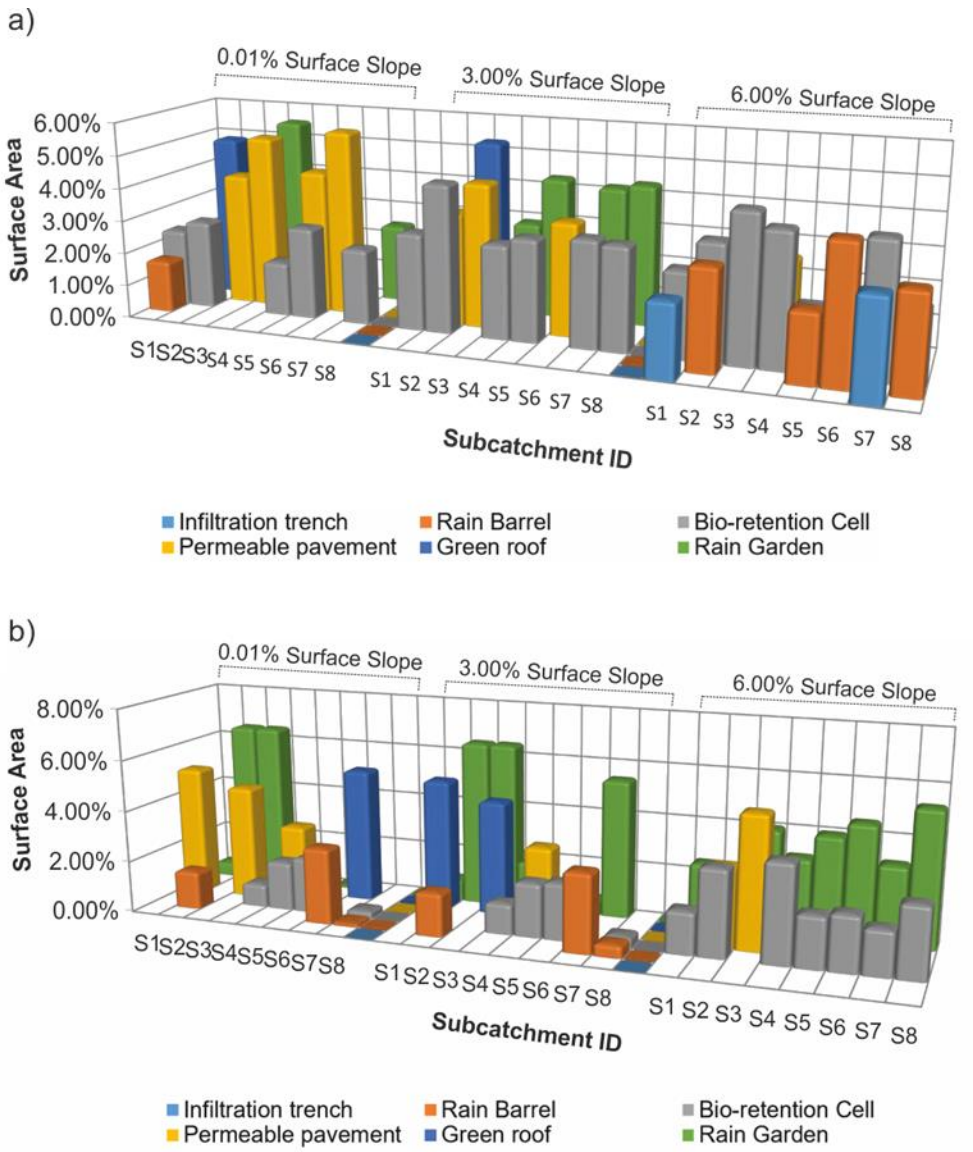

Figure 2-6. Bar chart representation of the Pareto-optimal sustainable urban drainage infrastructure for each catchment surface slope scenario according to; a) the second and b) the third set of preferences.

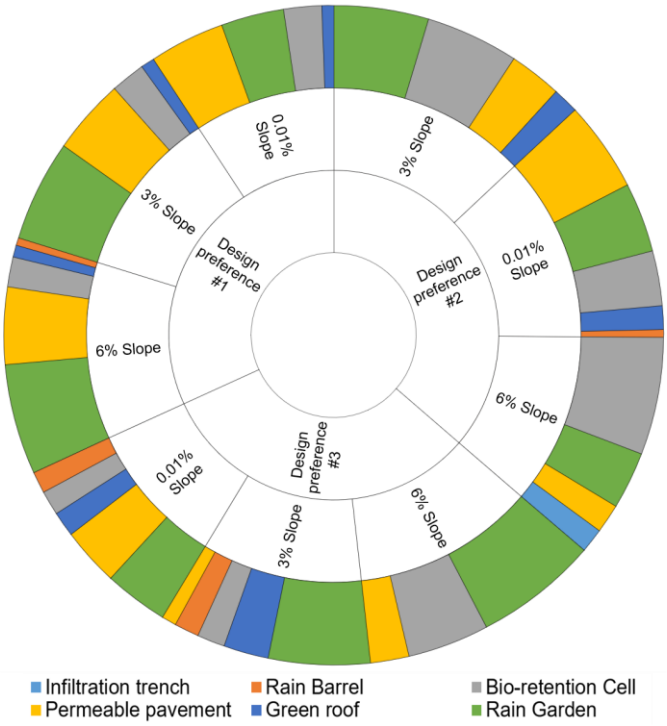

Figure 2-7. Sunburst diagram summarising surface areas of the selected sustainable urban drainage system designs for each surface slope scenario and design preference. The figure shows the impact of average surface slope on sustainable urban drainage design obtainable from an optimisation model.

Figure 2-7 presents a summary sunburst diagram of the selected portfolios for different average surface slopes and design preferences. The results show that the diversity of drainage asset types is reduced as the average surface slope increases for the sets of design preferences. For example, the optimisation mainly suggests rain gardens on steeper slope catchments for all preference sets. For the second preference set, Figure 2-6a and Figure 2-7 show that bio-retention cells are more suited for reducing the average peak runoff in the urban catchment as well as flood volume for all three slopes. Conversely, permeable pavements and rain gardens are mainly associated with catchments with lower or average slopes. For the third preference set, where the stormwater quality is prioritised, the results are biased towards green drainage facilities for all surface slope scenarios. For this set of priorities, the optimisation mainly suggests bio-retention cells and rain gardens on steeper slope catchments. The bias towards particular types of sustainable drainage components induced by the surface slope can potentially raise concerns regarding

fairness in the spatial distribution of green drainage co-benefits. These could be mitigated by considering proper metrics of spatial equity in the optimisation problem.

2.5 Conclusions

Urban drainage system design is a complex problem, which necessitates several performance criteria to facilitate sustainability and resilience of cities against floods. Large cities are usually characterised by spatial variations of surface slopes, affecting infiltration and detention patterns of stormwater runoff. Surface slope is an important topographic factor that can influence the efficiency of sustainable urban drainage components. This chapter has demonstrated the use of a many-objective optimisation approach for selecting portfolios of drainage infrastructure within an urban catchment with three average surface slope scenarios. The SWMM was linked to an evolutionary optimisation algorithm (CNSGA-II) to search for Pareto-optimal configurations of sustainable drainage assets in several urban subcatchments interconnected by a conventional drainage network. For each subcatchment, the algorithm selects a combination of two types of drainage assets from amongst seven different options and determines the efficient surface areas of each component type by five design objectives, i.e., minimising capital cost, flood volume, flood duration, average peak runoff, and total suspended solids. To demonstrate the selection of particular drainage designs corresponding to different trade-offs between the design objectives, the solution space was narrowed down by filtering specific optimisation objectives according to stakeholder preferences and/or environmental constraints. Different visualisation techniques were employed to analyse the results, including a novel plot where a system design schematic is placed alongside a parallel axis trade-off plot. This optimisation approach was applied to urban catchments with three different slope scenarios to investigate how surface slope impacts the design of SuDS.

In this chapter, it was found that variations of surface slopes in an urban area play an important role in controlling efficient distribution of sustainable drainage components, suggesting higher investment in specific drainage facilities, in this case

study green facilities, in subcatchments with steeper surface slopes. However, since sustainable drainage assets provide a set of co-benefits for both the environment and human health, an unbalanced distribution of sustainable drainage assets in large urban areas may raise equity concerns. In this sense, in Chapter 3 a new strategy is proposed for application of optimisation approaches in sustainable urban drainage infrastructure design that allows engineers to consider equality or equity metrics to ensure fairness in the spatial distribution of green infrastructure benefits.

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3 Chapter three: A design framework for considering spatial equity in urban water infrastructure

A design framework for considering spatial equity in urban water infrastructure

Abstract

The design of urban water infrastructure systems has traditionally aimed for cost and service objectives without considering broader socio-economic implications of design decisions. This can result in designs with unequal distributions of infrastructure services among urban communities. In this chapter, a design approach is proposed for urban water infrastructure systems which combines traditional design objectives, such as reliability and cost-effectiveness, with social goals like reducing inequality in the spatial distribution of infrastructure benefits. A multi-dimensional search algorithm is linked to an urban rainfall-runoff simulation model to identify portfolios of Pareto-optimal and spatially equitable drainage infrastructure developments. A measure of the difference in flood damage between different subregions is considered as a decision-making aide along with other criteria. An illustrative case study shows how the design framework can help planners make trade-offs, for example between spatial equity and cost-effectiveness, when selecting future interventions in urban water systems.

3.1 Introduction

In the past decades, population growth and migration to cities have increased urbanisation and changed the ways different socio-cultural groups are distributed within urban areas (Zwiers et al., 2018). It has been empirically observed in some cities that disadvantaged groups in low-income neighbourhoods benefitted less from infrastructure investments (Taguchi et al., 2020; X. Wang & Pan, 2016) and for

example experienced more frequent flooding events (Collins et al., 2019). The concept of environmental justice was first introduced during a social movement in the 1980s in the United States (L. Liu et al., 2014). Since then, the discussion of justice and equitable spatial distribution of resources, services, and environmental hazards has become a topic of interest for infrastructure designers, urban planners, and stakeholders (Fielding & Burningham, 2005; O'Hare & White, 2018; Reckien et al., 2017; Thaler & Hartmann, 2016). Urban infrastructure design techniques and decision-making methods used by practitioners can affect design decisions made by planners and therefore the lives of city dwellers. Although engineered urban infrastructure design is well developed, the topic of spatial equity in infrastructure services is relatively new (Taleai et al., 2014; D. Wang et al., 2021; Xing et al., 2020). To assist urban planners and water infrastructure designers, a multi-criteria design approach can help urban water infrastructure planning avoid relying on single criteria analysis (e.g. cost) and consider spatial and distributional aspects of environmental infrastructure system services. This includes addressing several often conflicting urban infrastructure service objectives, which include, but are not limited to, spatial equity of service provision, equitable access to recreation opportunities, and equitable distribution of failure risk (Keeler et al., 2019).

In the case of UDS, the increasing frequency of extreme rainfall events due to climate change in conjunction with rapid urbanisation has led to increased risk of flooding in urban areas (Kalantari & Sörensen, 2019; Kourtis & Tsihrintzis, 2021; Li et al., 2021; Pour et al., 2020). There are three common approaches to urban flood management: first, refurbishment of conventional UDS which mainly relies on the use of structural measures to improve conveyance of stormwater (Abawallo et al., 2013; Barreto et al., 2010; Vojinovic et al., 2014); second, application of real-time control and operational management of drainage infrastructure (García et al., 2015; Ocampo-Martinez et al., 2013; Riaño-Briceño et al., 2016); and third, using SuDS (Alves et al., 2020; Eckart et al., 2017; Hu et al., 2016). SuDS are nature-based solutions for stormwater management that allow restoring natural hydrologic processes by onsite detention, infiltration, and evapotranspiration of stormwater runoff (Nesshöver et al., 2017;

S.Ferreira et al., 2020). Beyond their intended role as flood mitigation facilities, SuDS have several direct and indirect co-benefits. Examples include improved water and air quality, increased groundwater recharge, enhanced landscapes, biodiversity, and amenity. All these together can improve the physical and mental well-being of city dwellers (Baik et al., 2012; Blicharska et al., 2019; Jensen et al., 2010; Kaplan, 1995; Keeler et al., 2019; Londoño Cadavid & Ando, 2013; Ward Thompson et al., 2012; Woods Ballard et al., 2015).

SuDS have often been designed using standardised design templates which limits their potential benefits due to differences in hydrologic and hydraulic characteristics of different urban areas (Taguchi et al., 2020). Optimisation models can be used to find efficient customised SuDS designs while targeting a variety of design objectives and constraints (Duan et al., 2016; Ghodsi et al., 2016; Vojinovic et al., 2014; Yazdi et al., 2018). To explore potential SuDS designs and identify ones in line with the preferences and needs of decision-makers, an optimisation algorithm can be linked with a rainfall-runoff model, such as MIKE FLOOD (W. Zhang et al., 2019) or the SWMM (Gironás et al., 2010; Macro et al., 2019; Seyedashraf et al., 2021a; Vojinovic et al., 2014; T. Xu et al., 2017). Infrastructure decisions for hazard alleviation are commonly made based on aggregate hazard mitigation objectives (Penning-Rowsell & Pardoe, 2012) such as minimised flood volume (Giacomoni & Joseph, 2017; Tavakol-Davani et al., 2019; Torres et al., 2020), flood duration (Tavakol-Davani et al., 2019), and/or stormwater pollution (M. Wang et al., 2017).

Optimised design approaches focused on cost-effectiveness lack awareness of other benefits and may overlook equity in the spatial distribution of interventions and design benefits (Carden & Winter, 2014; Chui et al., 2016; Giacomoni & Joseph, 2017; Torres et al., 2020). In this light, SuDS optimisation results may inadvertently contribute to biased allocation of resources. For example, since the spatial distribution of flood risk and damage in urban catchments depends on topographical features of the area, an optimisation approach may find it cost-efficient to sacrifice one or a few regions of an urban area by making them prone to flooding while decreasing flood risk

in other regions, or at least will leave the cost and spatial distribution of services trade-off unexplored. Equally, in an optimised design a search algorithm may find it cost-efficient to allocate more green infrastructure assets to certain regions, perhaps because more land is available for conversion, at the expense of overlooking other regions. As a result, a limited number of neighbourhoods might disproportionately benefit from green infrastructure/amenities while other urban areas, potentially with lower-income residents, may experience recursive or severe flooding events (Collins et al., 2019). Optimised urban infrastructure design could inadvertently contribute to social inequality in cities if the spatial distribution of benefits is not adequately considered.

Spatial equality metrics have been taken into account in assessments of water resources management design (Hu et al., 2016), urban water distribution systems (Dai et al., 2018; J. Xu et al., 2019), and floodplain restoration of agricultural regions (Gourevitch et al., 2020). For instance, Hu et al. (Hu et al., 2016) proposed a multi-objective optimisation approach to address inequality in water resources management using a conceptualised water distribution framework. La Rosa and Pappalardo (2020) used Shannon entropy as a measure of the heterogeneity of system design benefits to manually allocate green roofs in urban catchments. Gourevitch et al. (2020) linked HEC-RAS (Brunner, 1995) with an optimisation algorithm to maximise equity-weighted utility of reduced flood damages while minimising restoration costs in agricultural lands in a river basin. In their study, the flood damage restoration costs were weighted according to the wealth of individuals in a way that low-income regions were weighted more heavily in comparison with high-income regions. Intergenerational equality in urban infrastructure planning has been also addressed in energy and water distribution system design (Gonzalez et al., 2020; J. Xu et al., 2019; J. Zhang et al., 2020). Xu et al. (2019) applied the *Gini* coefficient to establish an intergenerational equity framework for sustainable water allocation in the Minjiang River Basin, Sichuan, China.

To the knowledge of the author, no study has yet considered spatial equity in the multi-criteria design of urban drainage infrastructure. In this chapter, an urban water infrastructure design framework is proposed which embeds the 'three E's' of sustainability, i.e. environmental, economic, and equity factors (Goodland, 1995). The framework uses a multi-criteria design approach to optimise various engineering performance objectives while maximising two metrics of spatial equity that account for fairness in the distribution of potential flood damage and green infrastructure co-benefits. The approach is applied to a case study to synergistically identify the selection, extent, and spatial distribution of portfolios of sustainable drainage assets. A post-optimisation metric that looks at the disparity of flood damage in the study area is also introduced and visualised in parallel with the other optimisation objectives. Results highlight trade-offs between cost-effectiveness and spatial equity in infrastructure investment decisions.

3.2 Methodology

3.2.1 An integrated approach to urban water infrastructure design

Urban infrastructure design can be framed as a multi-stakeholder process that benefits from participative design approaches aiming to reduce conflicts between various interest groups and constituencies (Smets et al., 2020). When applied to urban water infrastructure with several co-benefits, such approaches can help identify relevant trade-offs, for example between cost-effectiveness and spatial equity.

The system design framework proposed here seeks to find a group of efficient designs which are cost-effective, equitable, and environmentally friendly and whose relative merits can be deliberated by stakeholders. This is achieved using a multi-criteria portfolio selection method that considers equality in the spatial distribution of co-benefits and deficiencies. The framework can be used to seek balance in certain aggregate benefits, e.g. reduced capital cost and environmental pollution, and spatial benefits, e.g. flood protection in the case of urban drainage system design or equal

distribution of water pressure in water distribution networks. In the proposed framework the *Gini* coefficient was applied to quantify spatial equity in the distribution of benefits. The *Gini* coefficient, or *Gini* index, is a statistical measure of dispersion, which relies on cumulative percentages of distributional variables in a system. It has been commonly used for the evaluation of resource allocation and analysis of income and wealth inequalities between different communities (Dai et al., 2018; Milanovic, 1997; Münnich Vass et al., 2013). The *Gini* coefficient ranges from 0, representing a perfectly even distribution of system assets, to 1, which denotes a fully concentrated distribution. Consequently, in the spatial distribution of system benefits, the closer this measure is to 0, the fairer the system design.

The proposed urban water infrastructure design approach incorporating spatial equity is summarised in Figure 3-1.

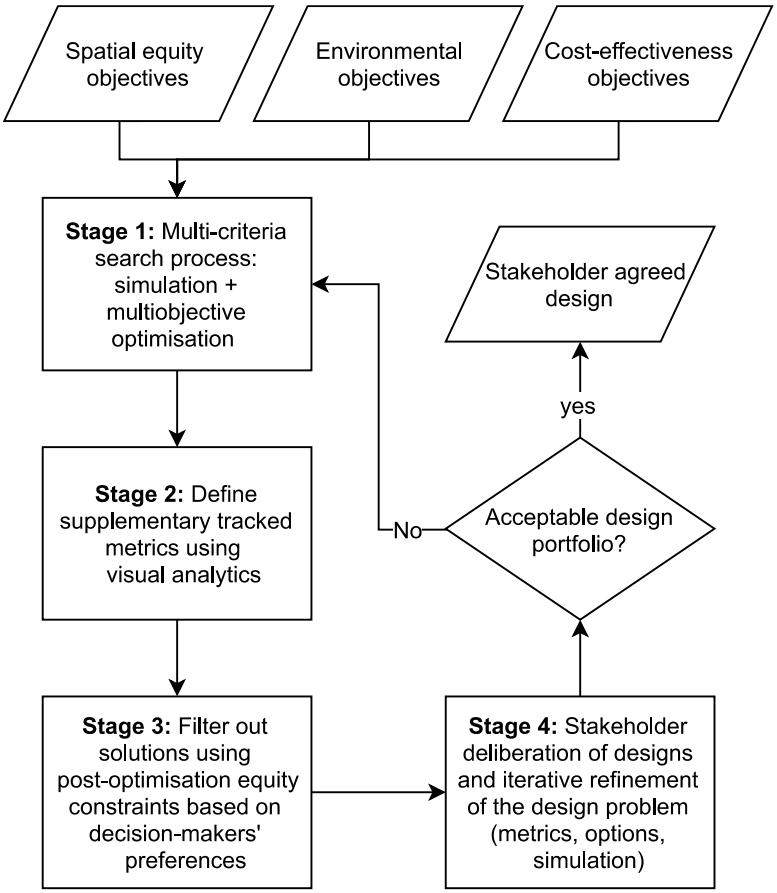

Figure 3-1. Flowchart of the proposed approach for multi-criteria urban water infrastructure design considering spatial equity of service provision. Parallelograms indicate inputs and outputs.

The decision variables and design objectives in urban water infrastructure can be mathematically formulated as a set of goals to be minimised or maximised as a function of the decision variables. Here, optimality is defined as a trade-off between multiple conflicting objectives, where no performance metric can be improved without making another performance metric worse off. To solve such problems, modern multi-objective optimisation can be used (Deb, 2008; Hadka & Reed, 2013; Kollat & Reed, 2006).

To this end, an ensemble of SuDS designs was randomly generated, using random initial seeds, and passed to the optimisation method which is used to secure diversity in the final solutions (Hadka & Reed, 2012). The proposed many-objective optimisation approach is summarised in the flow chart in Figure 3-2.

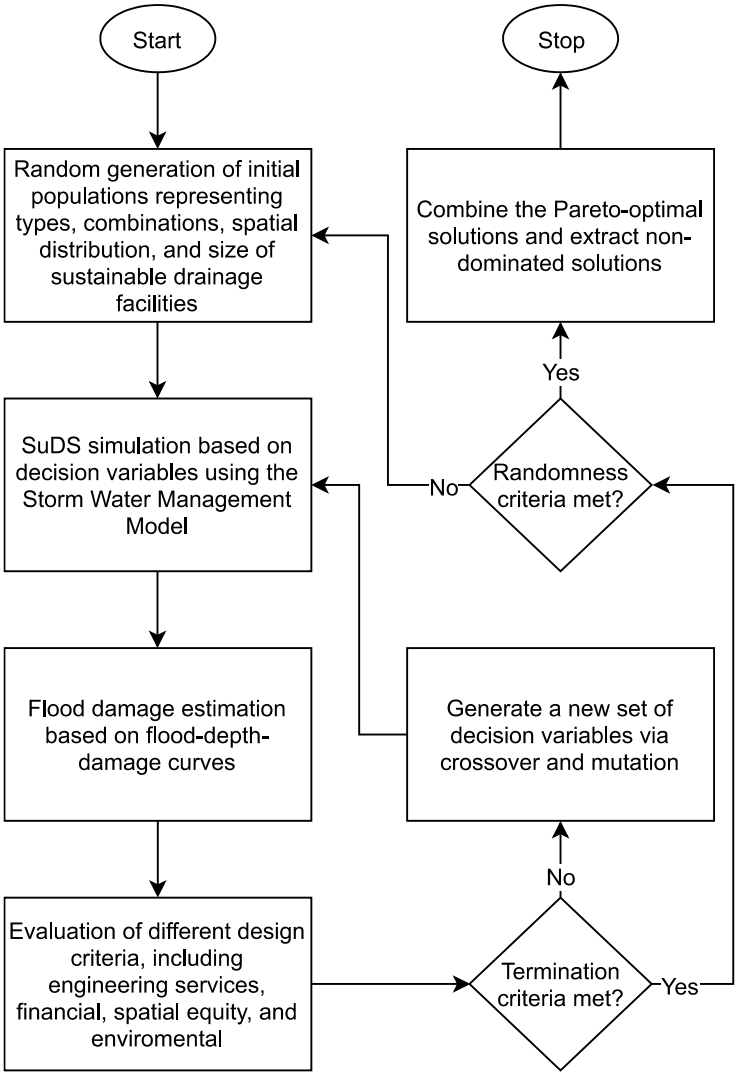

Figure 3-2. Flowchart of the proposed many-objective optimisation model based on spatial equity factors for design of sustainable urban drainage infrastructure.

3.2.2 Design objectives

The proposed framework is implemented using a selection of optimisation objectives. In the case of urban drainage system design, the following are considered: minimisation of capital cost, stormwater pollution, average flood damage, and maximisation of equality in the allocation of green infrastructure and spatial distribution of flood damage in the urban area.

The multi-criteria design problem can be stated as follows:

Minimise: $$\boldsymbol{F}(\boldsymbol{x}) = \left(F_{Cost}(\boldsymbol{x}), F_{TSS}(\boldsymbol{x}), F_{AD}(\boldsymbol{x}), F_{ED}(\boldsymbol{x}), F_{EG}(\boldsymbol{x})\right) \quad (3\text{-}1)$$

where $\boldsymbol{x}$ is the decision variable vector (a list of variables that describe the design decisions), $\boldsymbol{F}(\boldsymbol{x})$ is the vector of objective functions, including capital cost, F_{Cost} , TSS load at the system outfall, F_{TSS}, average flooding damage, F_{AD}, equity in the spatial distribution of flood damage, F_{ED}, and spatial equity in the allocation of green drainage practices, F_{EG}, which are defined below.

To represent the relationship between flood depths and flood damages, a polynomial function can be fitted to the depth-damage curves. As an example, function was developed to fit data from North America presented by Huizinga et al. (2017). The resulting polynomial is given by:

$$F_D(d_i) = 0.0055 \times d_i^3 - 0.0765 \times d_i^2 + 0.425 \times d_i + 0.0256 \quad (3\text{-}2)$$

where n_j is the number of junctions and d_i is the flood depth near the ith system junction. This relationship was applied to convert the maximum flood depth at each system junction into a percentage of the value of the assets located in the ponded area of the junction.

3.2.2.1 Maximisation of spatial equity in flood damage distribution

To quantify the level of equality in the spatial distribution of benefits, each SuDS design was compared with a perfect spatial equity scenario where system resources and design deficiencies are distributed equally between subcatchments. The *Gini* coefficient was used to quantify the spatial equity in the system, where a smaller *Gini* coefficient represents higher equality in system design. Accordingly, the spatial equity in flood damage distribution was formulated as follows:

$$F_{ED} = \frac{1}{2{n_j}^2 \times F_{AD}} \sum_{i=1}^{n_j} \sum_{j=1}^{n_j} \left|F_D(d_i) - F_D(d_j)\right| \quad (3\text{-}3)$$

where the average flood damage under each SuDS design was calculated as $F_{AD} = (1/n_j) \times \sum_{i=1}^{n_j} F_D(d_i)$. Here, the *Gini* coefficient is defined as the mean difference between the calculated values of flood damage near each pair of manholes divided by twice the average flood damage.

3.2.2.2 Maximisation of spatial equity in green infrastructure allocation

The Gini coefficient was also used to quantify spatial equity in the allocation of green drainage components. Here, minimising the Gini coefficient maximises spatial equity in the allocation of green spaces, and therefore of SuDS co-benefits, in the region of interest.

$$F_{EG} = \frac{1}{2{n_s}^2 \times \bar{s}} \sum_{i=1}^{n_s} \sum_{j=1}^{n_s} |s_i - s_j| \tag{3-4}$$

where n_s is the number of subcatchments, s_i is the ratio of surface area of green drainage components to the area of the subcatchment, and s_{avg} is the average value of s_i.

3.2.2.3 Other objectives

The average flood damage formulated in section 3.2.2.1 was also considered as an objective in this study. The capital cost of the drainage system was calculated as $F_C = \sum_{i=1}^{n_s} \sum_{j=1}^{2} (c_{ij} \times a_{ij})$, where a_{ij} and c_{ij} are the surface area and capital cost of each sustainable drainage asset. Moreover, the overall TSS load of the urban watershed, at the outfall node, was obtained from the numerical simulation outputs and considered as the fifth design objective.

3.2.3 Visualisation and selection of designs

The proposed design framework uses visualisation to simplify the decision-making process. In many-objective optimisation, the number of solutions increases with the number of objective functions and also accuracy of the search algorithm (Hadka &

Reed, 2013; Matrosov et al., 2015; Woodruff et al., 2013). Moreover, in *a posteriori* analysis of optimisation results, decision-makers should analyse trade-offs between the design objectives and use decision criteria that reflect their requirements (Coello et al., 2007; Hadka & Reed, 2013). In this sense, it is significant not to only visualise a resultant Pareto-front but also to allow users to survey trade-offs between the objectives and single out desirable design portfolios that are in line with their preferences. This process becomes even more significant when decision-makers have conflicting interests, such as the TSS reduction task and capital cost control. Visualisation techniques can be helpful to simplify this process by providing a clear representation of trade-offs between design goals implied by the identified efficient (optimised) designs.

In this study, three visualisation techniques, including the two-dimensional, many-dimensional, and parallel coordinates system were used to visualise the obtained Pareto-front (the performance levels of the set of efficient designs). Parallel axis plots are a useful visualisation tool for decision-making (Inselberg, 2009), in which each axis represents a design objective and each line connecting the vertical axes stands for a particular portfolio. An interactive version of a parallel coordinate plot allows decision-makers to interactively put post-optimisation constraints on the front and isolate a set of promising urban water infrastructure design portfolios for further consideration (Zatarain Salazar et al., 2017). As part of a deliberative urban water infrastructure design, the stakeholders and/or regulators can refer to the Pareto-optimal set and negotiate their design preferences, goals, and constraints. The interactive visualisation techniques used here allow them to check the optimisation results and single out their preferred design portfolios or iteratively reformulate the optimisation model and repeat the process to find alternative, potentially better, design portfolios. The employed parallel coordinate plots also include a post-optimisation criterion, as a supplementary tracked metric of performance. This metric helps ensure the disparity in potential flood damage in the region of interest does not exceed a threshold selected by designers.

3.3 Application

3.3.1 Case study

The proposed design framework was applied to the design of sustainable drainage infrastructure in an 11.7-hectare illustrative urban catchment with 7 urban subcatchments (drainage areas), 11 nodes, and 11 conduits (Figure 3-3). In this case study, spatial equity is considered with respect to flood protection and access to local green amenities for communities residing in different subcatchments.

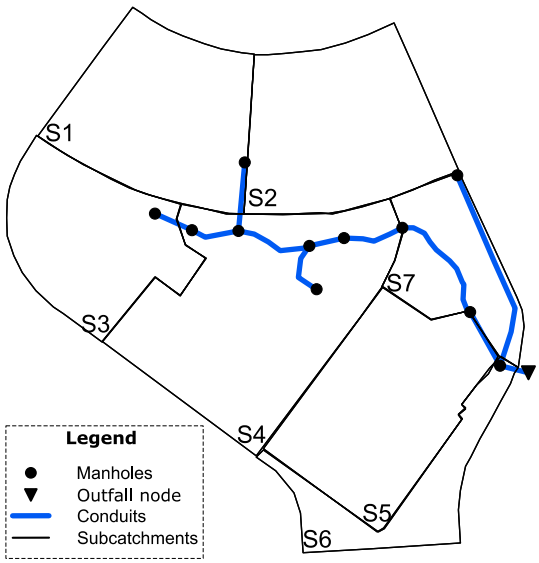

Figure 3-3. Schematic map of the illustrative case study. Here, an urban catchment is discretised into 7 subcatchments named S1, S2, … S7, manholes (black circles) collect runoff and route it into the conduits network to be discharged into receiving water at the outfall.

This case study is a modified version of an example urban drainage system available in the SWMM software package (Gironás et al., 2010), and has been used as a standard benchmark in a number of previous works (Giacomoni & Joseph, 2017; Nehrke & Roesner, 2002, 2004; Sambito et al., 2020). The catchment incorporates different land uses, i.e. commercial, residential, and undeveloped areas. Across the catchment, there are 6 subcatchments with impervious surfaces (S1 to S6 in Figure 3-3) suitable for SuDS allocation (Table 3-1).

Table 3-1. Subcatchment properties in the case-study area.

Subcatchment	Surface area (ha)	Imperviousness (%)	Surface slope (%)
S1	1.84	56.8	2
S2	1.92	63	2
S3	1.51	39.5	3.1
S4	2.75	49.9	3.1
S5	1.94	87.7	2
S6	0.80	95	2
S7	0.94	0	3.1

A 2-hour design storm with a return period of 100 years and 5 minutes increments was used (L A Rossman, 2015). For this case study, capital cost of each sustainable drainage asset was extracted from cost databases published by the Washington State Department of Ecology & Herrera Environmental Consultants (Washington State Department of Ecology & Herrera Environmental Consultants, 2012) and online vendors. Two main assumptions were made to simplify the numerical modelling of the drainage system. First, due to unavailability of ground-level data, the average surface area occupied by ponded stormwater near each manhole was assumed to be 325 m^2. Second, the same flood damage functions of residential buildings were used for both residential and commercial land uses. Accordingly, land use types were only taken into account for stormwater calculation purposes.

The developed optimisation model allows allocation of up to two different types of sustainable drainage assets in each subcatchment. An ensemble of 35 initial SuDS designs was generated using random seeds and used as initial populations to increase diversity in the optimisation solutions. The corresponding decision variables were used to evaluate flood damage for each subcatchment using SWMM as well as a tracked metric defined as the difference between the maximum and minimum values of flood damage in different neighbourhoods. Optimisation objectives and tracked metrics are visualised using parallel axes plots which allow designers to view all relevant metrics at once, including their trade-offs and synergies (Geressu et al., 2020; Kasprzyk et al., 2013; Matrosov et al., 2015).

3.3.2 Numerical simulation model

In this chapter, the SWMM was used to simulate rainfall-runoff and flow routing process in the drainage system. SWMM is an open-source drainage simulation model, which has been extensively used to simulate quantity and quality of stormwater in urban areas (Gironás et al., 2010). SWMM includes various recognised empirical correlations to account for pollution build-up, wash-off, and also transport, and different types of sustainable drainage systems, comprising permeable pavements, bio-retention cells, green roofs, rain barrels, vegetative swales, rooftop disconnections, and infiltration trenches (Gironás et al., 2010; James et al., 2010; Meza & Oliva, 2003; Lewis A. Rossman & Huber, 2016). SWMM includes three flow routing models, i.e. steady flow, kinematic wave, and dynamic wave. Here, the latter model was used due to its capability to represent the backwater effect and pressurised flow by solving the full Saint-Venant equations (Meza & Oliva, 2003; Seyedashraf et al., 2021b; Triki, 2017).

3.3.3 Multi-objective global search algorithm

The CNSGA-II was used with 35 random seed optimisations resulting in an ensemble of 35 Pareto-fronts of SuDS designs (Deb & Goel, 2001). The CNSGA-II is an improved variation of the NSGA-II, which is a commonly used population-based multi-objective optimisation method. In addition to the advantages of the NSGA-II, this evolutionary search algorithm benefits from superior convergence properties and improved diversity in the resulting Pareto-fronts (Deb & Goel, 2001).

In this case study, the variables vector consists of integer numbers representing SuDS types, combinations, surface areas, and spatial distribution of the drainage assets subjected to allocating up to two dissimilar types of sustainable drainage components in each subcatchment. The model was set to run with a function tolerance of 10^{-3} for 100 consecutive function evaluations as the stopping criterion, which resulted in around 11,000 successful function evaluations in each experiment. To further verify the convergence of the optimisation process, the hypervolume

indicators of each set of Pareto-fronts were calculated and compared with each other. Figure 3-4 illustrates the evolution of the hypervolume in each experiment versus the number of function evaluations, each represented by a different colour. The hypervolume indicator was first introduced by Zitzler et al. (2003) and represents the size of a multi-dimensional space that is enveloped by a Pareto-front. Therefore, the hypervolume indicator can be used to measure performance of optimisation methods in multi-objective problems.

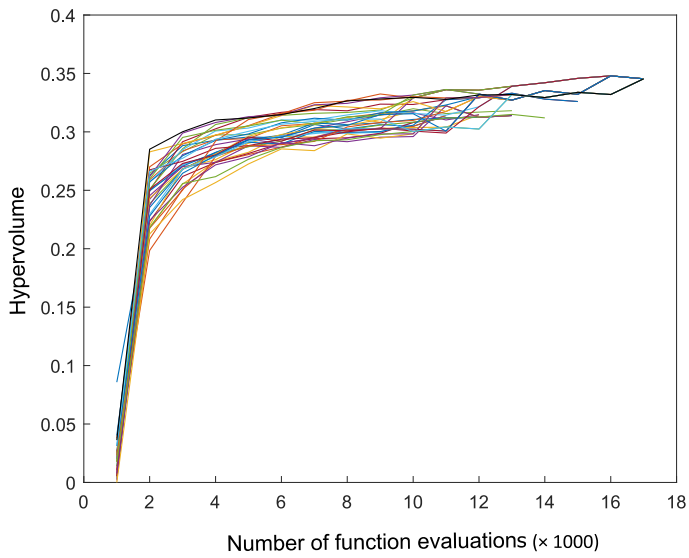

Figure 3-4. Hypervolume over the number of function evaluations. The model was set to run with an objective function tolerance of 10^{-3} for 100 consecutive calculations as a stopping criterion. Here each colour represents a particular random seed used to initialise the optimisation process.

3.4 Results and Discussion

Figure 3-5a shows a five-dimensional scatter plot of the obtained Pareto-optimal solution set, where the average flood damage is shown on the x-axis and the spatial distribution of flood damage and green SuDS are shown on the y and z axes, respectively. The TSS metric is symbolised by marker size, where larger circles represent larger amounts of TSS. A colour map is also used to show capital cost; blueish colours represent cost-effective system designs. Figure 3-5b also shows pairwise trade-offs between capital cost and other optimisation objectives.

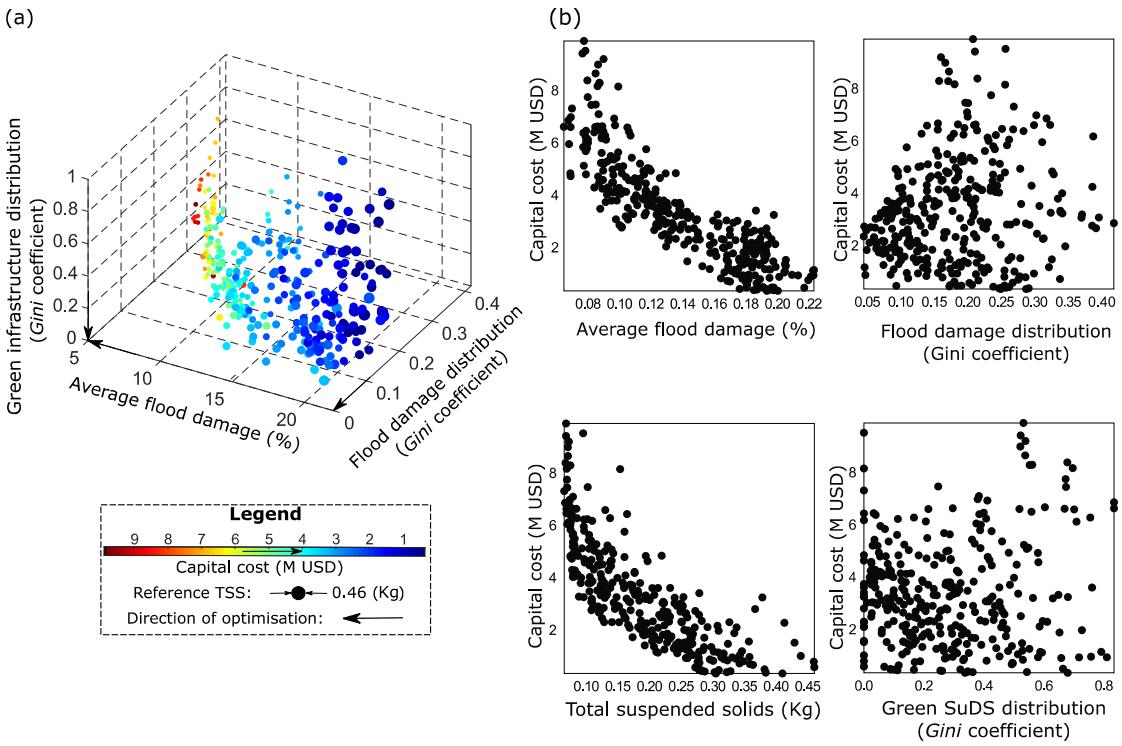

Figure 3-5. Most efficient balances of planner goals in sustainable urban drainage infrastructure design considering spatial equity in flood damage and green drainage infrastructure distribution; (a) five-dimensional representation of Pareto-optimal design portfolios; (b) two-dimensional scatter plots of pairwise trade-offs between capital cost and non-monetary objectives. The five-dimensional plot provides an overview of system performance and design metrics, where marker size and colour represent the overall TSS load and capital cost in each solution set, respectively

Multi-dimensional scatter plots show the trade-offs between the design objectives. However, they are not particularly helpful to deliberatively choose a design. It is especially difficult to follow trade-offs between design objectives when there are more than three decision criteria. Conflicting interests can make it more complicated to reach an agreement on a design. To solve this issue many-dimensional plots may be supplemented with parallel coordinate plots in Figure 3-6 to showcase a complete survey of the trade-offs between the optimised design objectives. Here, each line contains information about spatial allocation, types, combinations, and surface areas of sustainable drainage practices, where diagonal lines reflect the conflicts between design objectives. The preferred optimisation direction is downwards so that an ideal solution candidate would be a horizontal line located at the bottom of the figure. The specified colour range represents equity in spatial distribution of flood damage.

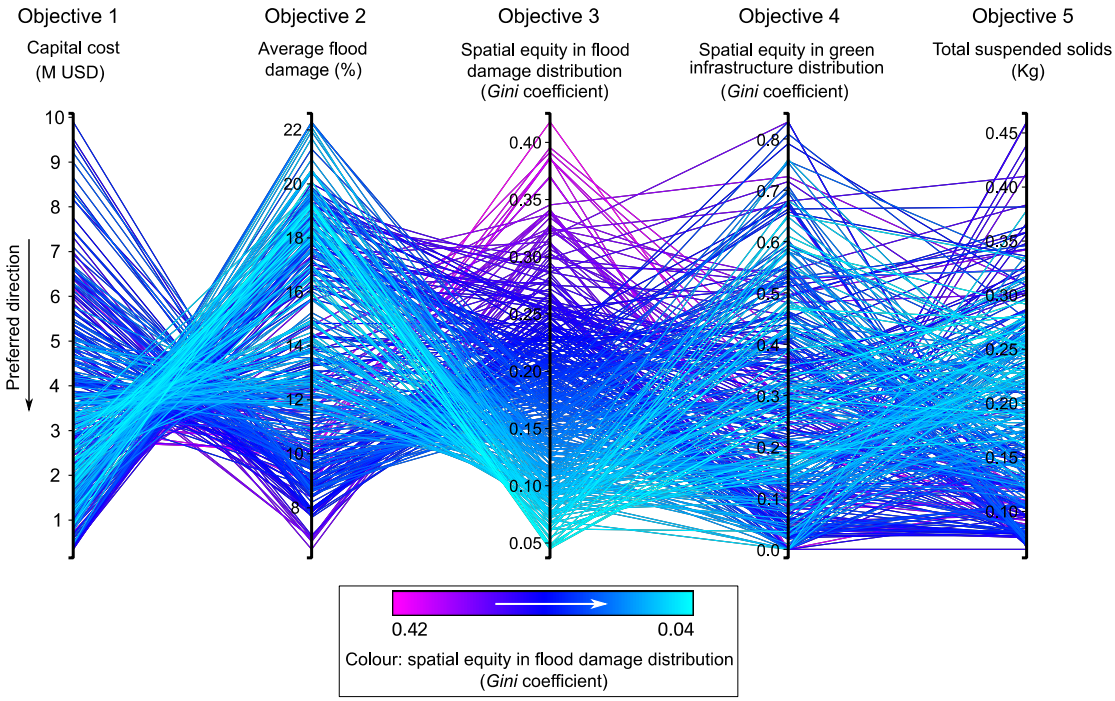

Figure 3-6. Trade-offs between objectives for the case study drainage system. Here, each axis represents an objective and each line connecting the axes denotes performance of one of the highest achieving designs (the 'efficient' or 'Pareto-optimal' set). The y-axis arrow shows the direction of preference. In this figure, a flat line along the bottom would represent an unattainably perfect design and the crossing lines indicate trade-offs.

A classification for the level of inequality in the distribution of benefits can be given based on the range of the *Gini* coefficient. Typically, $Gini \leq 0.2$ implies a high level of equality, $0.2 < Gini \leq 0.3$ denotes a relatively average level of equality, $0.3 < Gini \leq 0.4$ denotes a relatively reasonable level of equality, $0.4 < Gini \leq 0.5$ represents a relatively large non-uniformity, and $Gini > 0.5$ stands for an unfairly large disparity in the system (Gini, 1921; Z. Liu et al., 2020; Y. Wang et al., 2020).

Results highlight trade-offs between equity in spatial distribution of flood damage and average flood damage. In fact, in most portfolios the lower the average flood damage the worse the spatial equity in the distribution of flooding, which shows the importance of considering spatial equity factors in SuDS optimisation.

Although the *Gini* coefficient provides a statistical estimate of the level of inequality in a system, decision-makers may also find it useful to look at the difference between the maximum and minimum values of the objective functions in the study area. To this

end, a new metric was introduced in the parallel axis plot, allowing decision-makers to limit the maximum differences in flood damages between the areas associated with each manhole. This metric was used to further narrow down the Pareto-front based on decision-makers' preferences without increasing the computational cost of the optimisation process. In this sense, the metric was not considered in the optimisation process but was evaluated afterwards by running a SWMM simulation for each of the Pareto-optimal solutions. Several tracked metrics can be introduced in the same way without increasing the complexity of the optimisation. The new axis is shown in green colour in Figure 3-7.

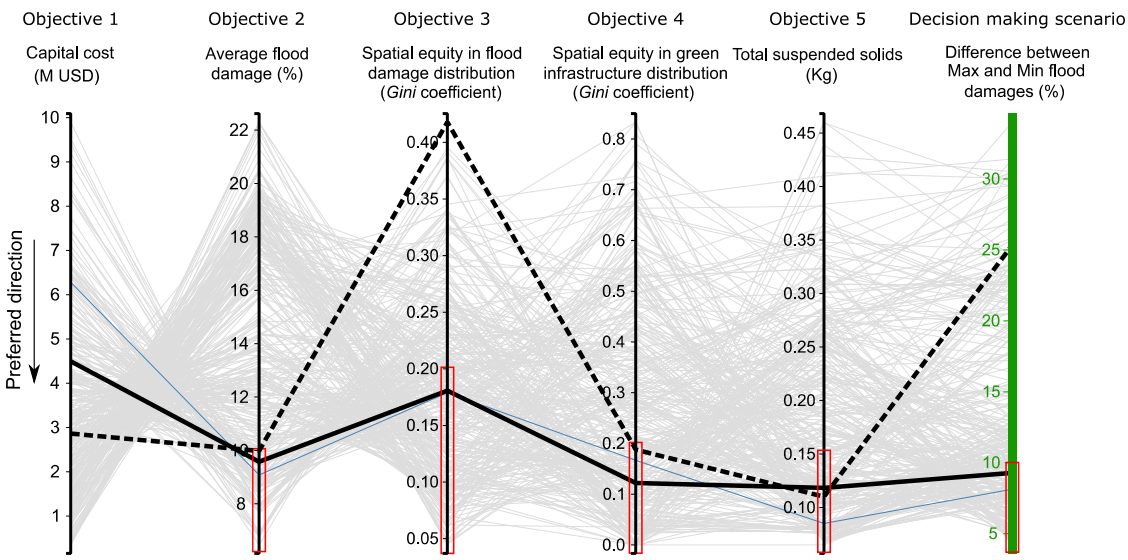

Figure 3-7. Parallel axis plot of Pareto-front in many-objective optimisation of SuDS considering spatial equity in flood damage and allocation of green drainage infrastructure. In this figure, the black vertical axes represent optimisation objectives while the green vertical axis is a post-optimisation metric. Moreover, red boxes on the parallel axes are interactive confining bars that allow decision-makers to single out solutions that meet their interests and filter out those that do not. The solid black line represents an example of selected sustainable infrastructure design. The dashed line is an example of a design that may have been selected in a design process that overlooks spatial equity in flood damage distribution while taking into account equity in spatial distribution of green drainage infrastructure.

The portfolio with the lowest capital cost was selected within a constrained set of non-dominated solutions (Figure 3-7). This portfolio is represented by the solid black line in the figure. A second portfolio (dashed line) with lower capital cost was also considered that takes into account equality in spatial distribution of green drainage facilities while overlooking it in spatial distribution of flood damage. The second SuDS

design portfolio might be preferred by decision-makers who may want to reduce capital costs while ensuring some degree of equality only in the distribution of green SuDS components.

Figure 3-8 depicts the SuDS designs selected in Figure 3-7 as maps. Here, different types of sustainable drainage assets are represented by different colours while their surface areas are presented as percentages of their allocated subcatchments. With a *Gini* coefficient of 0.12 for the spatial equity in allocation of green drainage facilities in the first portfolio, it can be seen that at least one of the two green assets, including bio-retention cells and rain gardens, is assigned to each subcatchment with relatively similar surface areas. For the first portfolio (Figure 3-8a), the *Gini* coefficients of flood damage distribution and green drainage infrastructure allocation in the region of interest are 0.18 and 0.12, respectively. Moreover, the *Gini* coefficients for flood damage distribution and spatial allocation of green drainage infrastructure in the second portfolio (Figure 3-8b) are 0.42 and 0.19, respectively. This denotes a relatively large gap in the spatial distribution of flood damage and high equality in its green drainage infrastructure allocation.

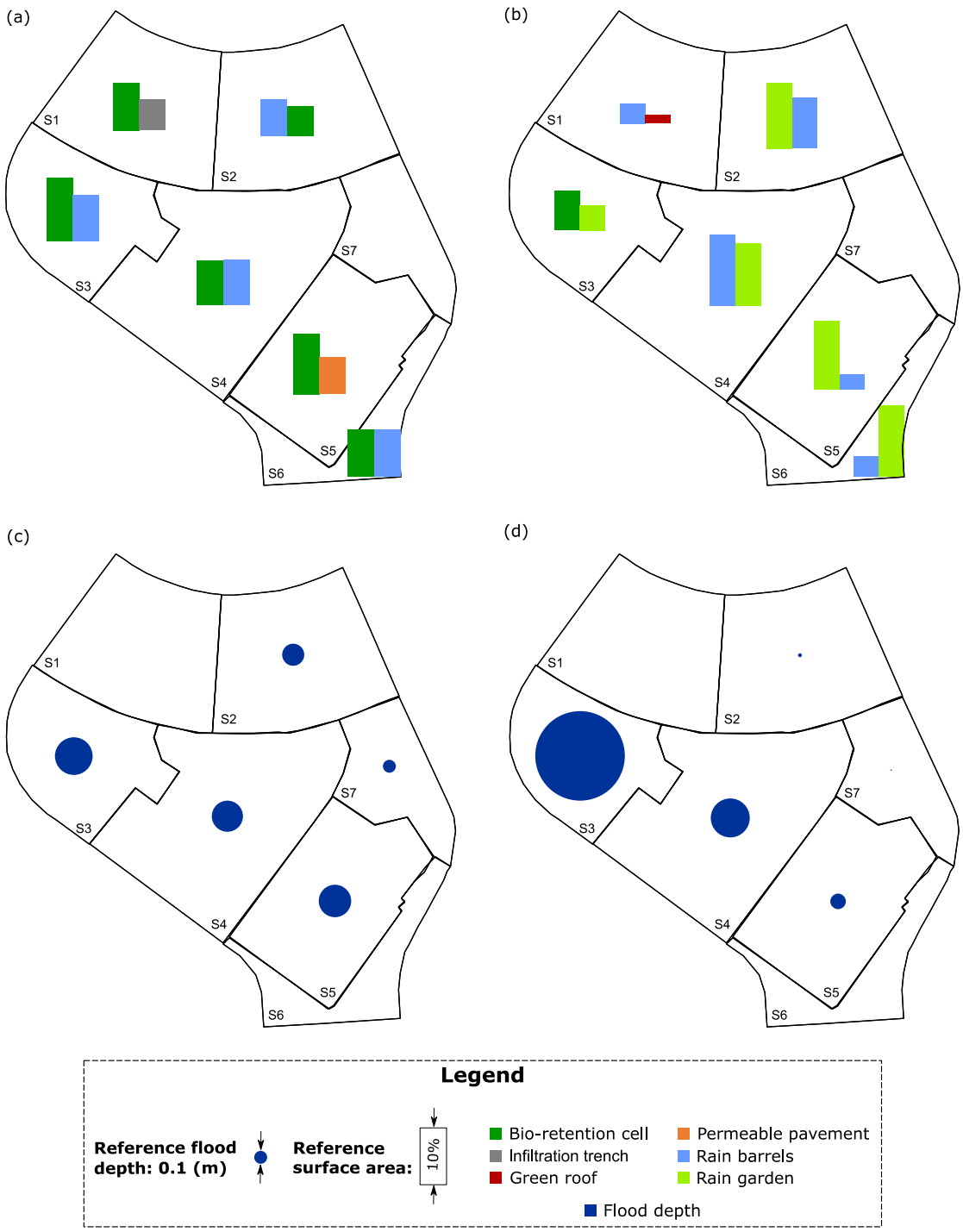

Figure 3-8. Pareto-optimal design of SuDS and spatial distribution of flood depths in the first, the solid black line in Figure 3-7, and second, the dashed line in Figure 3-7, portfolios: (a) design of the first portfolio that considers post-optimisation equity constraints in the spatial distribution of flood damages and green drainage facilities; (b) design of the second portfolio that does not consider post-optimisation equity constraints in the spatial distribution of flood damages; (c) spatial distribution of flood depths in the first portfolio; and (d) spatial distribution of flood depths in the second portfolio.

According to the results obtained, although both portfolios have resulted in similar average flood damages, there is a 58% discrepancy in the spatial distribution of flood damages and a 36% discrepancy in the maximum and minimum values of flood damage, which makes the second portfolio (Figure 3-8b) an unfair SuDS scheme in terms of spatial distribution of flood damages between neighbourhoods of the same city.

Figure 3-9 visualises the *Gini* coefficient for the selected portfolios using the Lorenz curve against the cumulative number of manholes in the urban drainage system. The Lorenz curve is a graphical tool commonly used to represent distribution of income and/or wealth in communities (Lorenz, 1905). In this study, the Lorenz curve represents the cumulative share of flood damage and/or green SuDS as a function of the cumulative share of manholes or subcatchments, respectively. Here, the smaller the deviation from the 1:1 line (absolute equality) the fairer the corresponding SuDS design. In Figure 3-9, the *Gini* coefficient can be formulated as the ratio of the area lying between the observed Lorenz curve and the 1:1 line to the area beneath it.

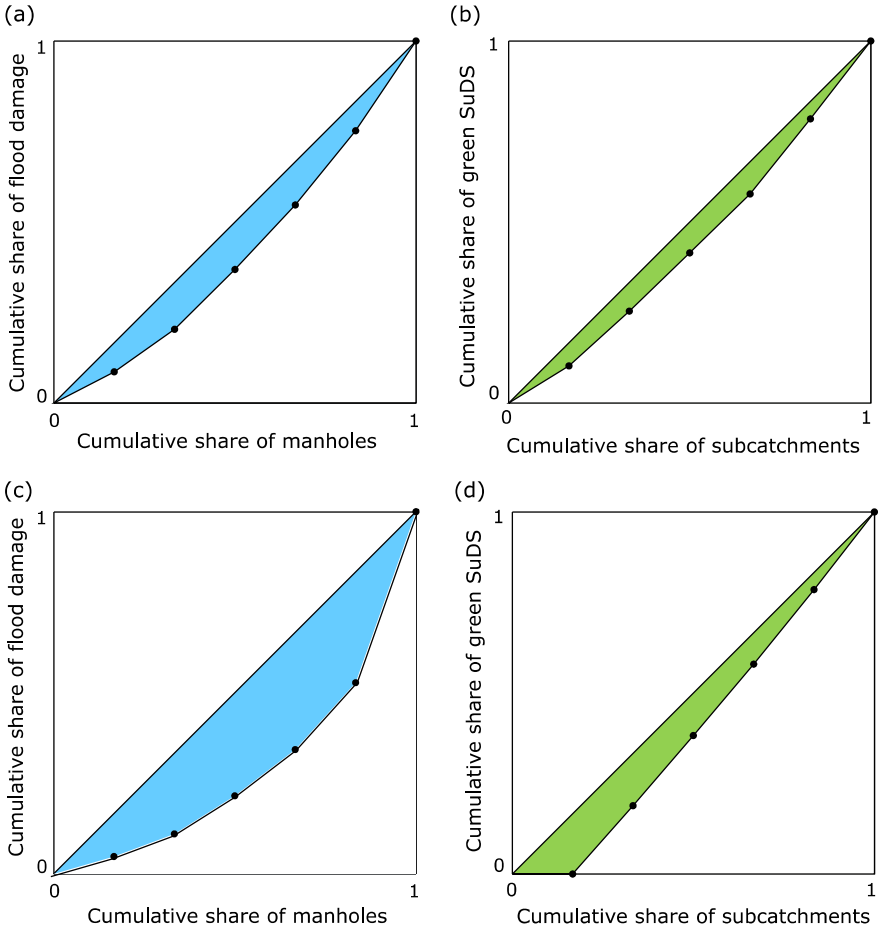

Figure 3-9. Visualisation of spatial equity using Lorenz curve for; (a) flood damage distribution in the first portfolio with a *Gini* coefficient of 0.18 (Figure 3-8a); (b) spatial allocation of green drainage infrastructure in the first portfolio with a *Gini* coefficient of 0.12 (Figure 3-8a); (c) flood damage distribution in the second portfolio with a *Gini* coefficient of 0.42 (Figure 3-8b), and (d) spatial allocation of green drainage infrastructure in the second portfolio with a *Gini* coefficient of 0.19 (Figure 3-8b). Here, the ratio of the highlighted area to the area under the absolute equality line (diagonal line) represents the *Gini* coefficient of the respective SuDS.

The results above show that average flood damage and equity in its spatial distribution are not necessarily correlated, as in most portfolios the lower the average flood damage the worse the *Gini* coefficient. A similar trade-off can also be seen between the *Gini* coefficients of flood damage distribution and green drainage infrastructure. This indicates that the overall reduction of flood damage in an urban area can be achieved at the expense of a non-uniform distribution of both positive and negative impacts, which may result in a lack of spatial fairness. The proposed multi-criteria design framework and the decision-support tools presented in this work can help decision-makers identify cost-effective drainage designs while ensuring some

level of equity in the spatial distribution of flood damage and green infrastructure benefits.

3.5 Conclusions

Urban water infrastructure has traditionally been designed considering a limited set of performance objectives which can lead to design decisions for which infrastructure benefits are not fairly distributed across a city. Given that urban areas may include areas or communities where urban water services are more difficult to provide, automated design methods that use single or limited number of criteria could inadvertently generate system designs with lower services to certain geographic areas thereby creating under-served communities. To support equitable urban development, a multi-criteria design framework was proposed that considers equity in the spatial distribution of system benefits. The framework was applied to sustainable urban drainage infrastructure design using a many-objective optimisation formulation where spatial equity factors are quantified in terms of area extension of green drainage infrastructure and flood damage within different subregions of an urban area. *Gini* coefficients were defined as inequality indicators in the optimisation model, and Lorenz curves helped visualise the degree of inequity in system design. Additionally, the minimisation of capital cost, average flood damage, and stormwater pollution were considered as optimisation objectives. The application to a case study showed the existence of a trade-off between spatial equity and cost-effectiveness, highlighting the importance of considering spatial equity in urban water infrastructure investment decisions. The difference between the maximum and minimum flood damage in the region of interest was also considered as an additional post-optimisation criterion that allows filtering out Pareto-optimal solutions with a prescribed maximum difference in flood damage. The proposed approach was demonstrated with an application to the design of SuDS but could be applied to the spatial planning and management of urban infrastructure more generally.

In this chapter, a relatively small illustrative case study was considered to demonstrate the proposed SuDS design framework. However, the application of the proposed framework to large drainage systems can be hampered by their extensive computational requirements as the optimisation time increases with the number of decision variables and required time for each function evaluation. To address this issue, Chapter 4 develops a new strategy for application of similar optimisation approaches to large drainage systems.

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4 Chapter four: A disaggregation-emulation approach for optimisation of large urban drainage systems

A disaggregation-emulation approach for optimisation of large urban drainage systems

Abstract

Multi-objective optimisation can help identify efficient and appealing designs of urban drainage systems. However, their application to large-scale problems is hindered by the computational cost of urban drainage simulation. In this chapter a novel disaggregation approach is proposed that allows simulating a portion of a drainage network while the remaining part is represented by a surrogate model that maps changes in the region of interest to hydraulic head time-series at synthetic nodes shared with the remaining part of the network. The proposed approach is demonstrated with an application to the many-objective optimisation of sustainable urban drainage systems (SuDS) in two urban areas. The design problem's decision variables include the types of sustainable drainage systems, their combination within a subcatchment, their surface areas and spatial distribution, whereas the objectives include the minimisation of capital cost, flood volume, flood duration, and total suspended solids or average peak runoff. The results show that the proposed disaggregation-emulation approach can provide an accurate representation of the system dynamics while significantly reducing the computational time compared to a model that simulates the whole network dynamics. Two alternative surrogate models are considered based on the MLP and GRNN. MLP is found to be more accurate compared to GRNN at the cost of a larger computational time for the training process.

4.1 Introduction

Rapid expansion of cities has increased the severity of flooding events by converting large pervious areas into impervious roads, rooftops and parking lots, which inhibit the natural storage and infiltration of runoff water. SuDS can help reduce the risk of flooding, while providing a number of additional co-benefits, such as improved water quality, aesthetics, and recreational value. Flood mitigation plans require consideration of several, often conflicting objectives, which complicates the design process. Several previous studies have tackled this multi-criteria design problem using meta-heuristic optimisation algorithms (Duan et al., 2016; Vojinovic et al., 2014; Yazdi et al., 2018) coupled with simulation tools such as the SWMM (Duan et al., 2016; K. Eckart et al., 2018; Gironás et al., 2010; Lin et al., 2020; Macro et al., 2019; Vojinovic et al., 2014; Xu et al., 2017; Yazdi et al., 2018), the Soil and Water Assessment Tool (SWAT) (Geng et al., 2019; Maringanti et al., 2009), or MIKE FLOOD (W. Zhang et al., 2019). However, optimisation methods usually entail tens (or hundreds) of thousands of numerical simulations, which are computationally demanding when applied to large drainage networks. This is the main reason why optimised design is not commonly used in the industry. A possible solution to this problem is to replace the simulation of the system dynamics with computationally cheaper surrogate models. These include the Gaussian process emulator (Mahmoodian, Torres-Matallana, et al., 2018; Owen & Liuzzo, 2019), ANNs (Kim et al., 2019; Latifi et al., 2019; Sayers et al., 2014, 2019; Seyedashraf, Mehrabi, et al., 2018; Yazdi & Salehi Neyshabouri, 2014), or conceptual models with simplified structures that mimic specific outputs of the real system (Mahmoodian, Carbajal, et al., 2018; Mahmoodian, Torres-Matallana, et al., 2018).

ANNs have been widely used to describe the relationship between rainfall and flooding (Abou Rjeily et al., 2017, 2018; Chang et al., 2014; Chiang et al., 2010; Kim et al., 2019; She & You, 2019). Chiang et al. (2010) used the recurrent neural networks to track water level patterns in a sewerage system using the historical rainfall records in an urban catchment. Later, Abou Rjeily et al. (2017) used a nonlinear autoregressive model with exogenous inputs (NARX) to establish similar relationships between

rainfall events and flood volume patterns in a drainage system in Lille, France. She and You (2019) coupled NARX with the radial basis function (RBF) network to predict outflow rates of a drainage system using an identical approach. In these studies, the emulation models were used to predict water depth changes based on different hyetographs but did not consider the possibility of changes to the network properties, making them inapplicable to design optimisation problems. In this regard, surrogate models were used to predict system design objectives, e.g. flood volume (W. Zhang et al., 2019) and TSS (Latifi et al., 2019; Raei et al., 2019), for specific network designs. For example, Zhang et al. (2019) used ANNs to emulate the outputs of MIKE FLOOD in a two-objective urban drainage infrastructure design problem. ANN was used to predict the overall flood volume in the urban catchment. Later, Raei et al. (Raei et al., 2019) and Latifi et al. (2019) used MLP neural networks as objective functions in a multi-objective optimisation problem. They used multi-objective evolutionary optimisation to minimise biochemical oxygen demand and TSS in an urban catchment in Tehran, Iran.

The main motivations of existing surrogate-based optimisation approaches are (1) delivering quick predictions with lower computational burden, (2) ability to deal with complex nonlinear problems, and (3) accommodating several input variables and outputs in a single model run (Seyedashraf, Rezaei, et al., 2018). However, there are also inherent limitations associated with these approaches. For instance, using emulation models to evaluate objective functions in optimisation approaches can bias the search process and lead to suboptimal decisions. As model errors accumulate over subsequent iterations, the optimisation becomes increasingly unreliable. This is further exacerbated in multi-objective optimisation problems where several objectives need to be evaluated, and where several different scenarios may need to be considered to evaluate system performance. Furthermore, the complexity of the emulation model can increase dramatically with the number of input variables in large drainage networks. There is also need for methods that allow the application of optimisation algorithms to sub-regions of a larger urban area without having to solve the network dynamics for the whole system. This is often the case because constraints

in capital and human resources require infrastructure investment decisions to be taken sequentially for different subcatchments within an urban area.

To overcome these limitations this chapter proposed a novel method for large-scale urban drainage infrastructure optimisation which involves disaggregation and optimisation of only one part of the system. Surrogate modelling is used to emulate the hydraulic head at synthetic nodes at the cut-points between the region of interest and the remaining part of the system, and thereby provide interface boundary conditions for the hydraulic head and the inflow in response to changes in drainage assets within the region of interest. This approach is demonstrated with an application to many-objective optimisation of sustainable drainage infrastructure in two relatively large urban areas. Performance of the MLP network and GRNN, as two alternative surrogate models, was evaluated. The results show that MLP provides best performance in terms of computational time and accuracy. The proposed approach significantly decreases the computational cost of large-scale optimisation problems when the design area of interest is a subregion of a larger area.

4.2 Methodology

The proposed disaggregation methodology allows a region of interest within a larger urban catchment to be simulated without having to simulate the dynamics of the full drainage network. Firstly, new synthetic computational nodes are generated along the conduits at the cut-points between the region of interest and the remaining part of the network. These nodes are represented as junctions with a sufficiently high maximum surcharge depth to allow water to pond atop the ground surface in case of pressurised flow in the conduits, and to flow back into the drainage system as the pressure decreases. At each synthetic node, a surrogate model is used to represent the boundary conditions for the region of interest. When applied to the optimisation of drainage infrastructure within the region of interest, the surrogate model must be able to predict changes in the boundary conditions in response to changes to the infrastructure in the same region. To this end, the surrogate model is trained to

represent the time-series of hydraulic head and inflow rates at the cut-points for several alternative infrastructure designs. Training datasets can be constructed by randomly generating several instances of the decision variables and evaluating the system dynamics using an urban drainage model representing the whole network. In this work, drainage simulations are conducted using SWMM, and an MLP neural network and a GRNN are evaluated as two alternative surrogate models for the boundary condition at the synthetic junctions. Accordingly, the surrogate model provides flow and/or hydraulic head at the synthetic junctions for each drainage infrastructure design evaluated by the optimisation algorithm. Drainage is then simulated for the region of interest only, with the emulated boundary conditions representing the interactions between the region of interest and the remaining part of the drainage network. A flow chart of the proposed emulation-based optimisation approach is presented in Figure 4-1. The proposed methodology is applied to two optimisation problems where sustainable drainage systems are used to expand the capacity of two urban drainage networks in different subregions.

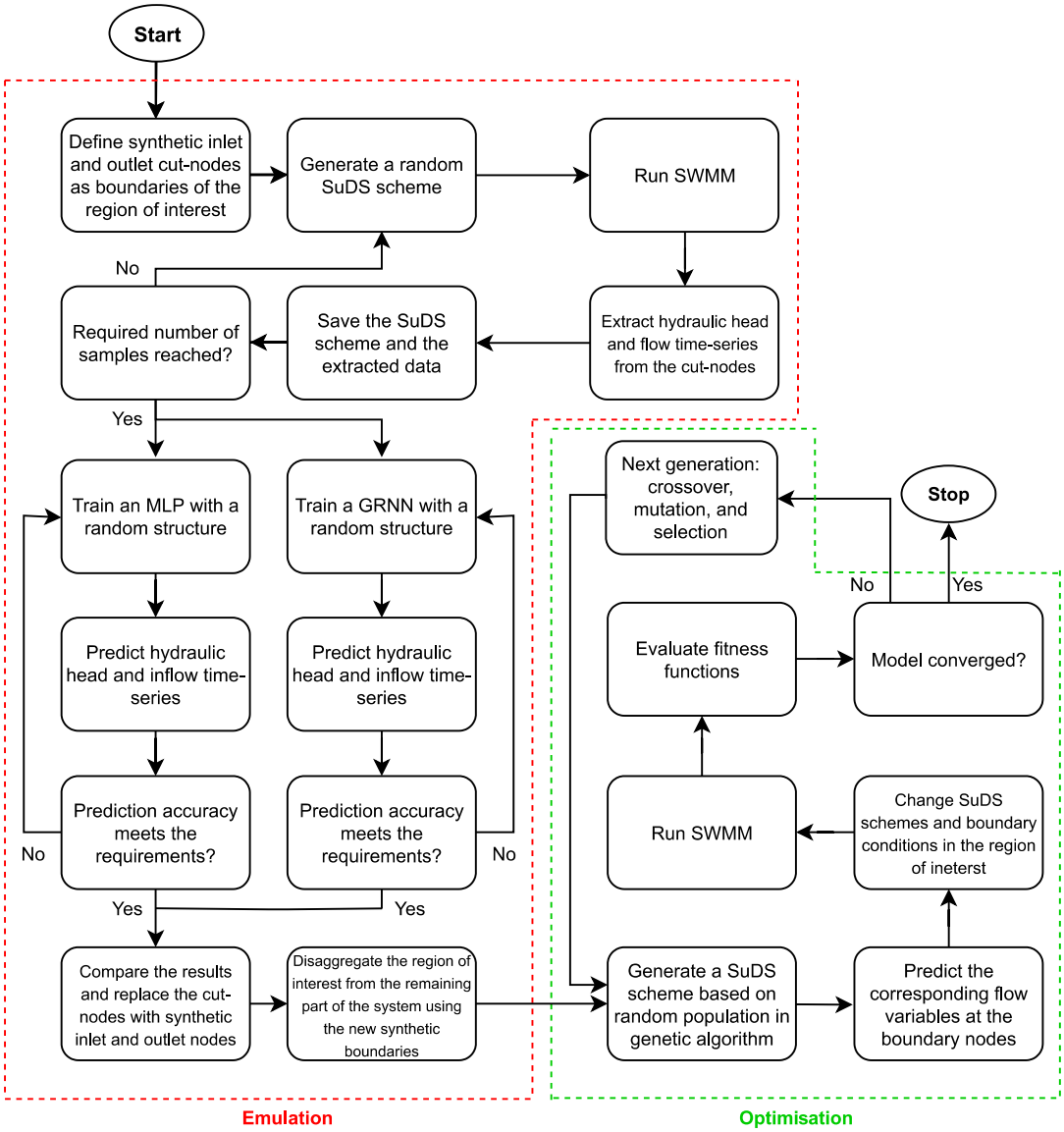

Figure 4-1. Flowchart of the proposed surrogate-based optimisation approach applied to the design of sustainable drainage systems (SuDS).

4.2.1 Numerical drainage model

The SWMM model was used to simulate the dynamics of the drainage system. As explained in Chapter 1 of this dissertation, the SWMM is a dynamic rainfall-runoff, flow routing, and water quality modelling software, which has been widely used for urban drainage analysis and design (Gironás et al., 2010). Three flow routing models can be used in SWMM, including steady flow, kinematic wave, and dynamic wave. In this chapter, the latter model was used, as it can replicate pressurised and backwater flow effects. SWMM is capable of simulating stormwater pollution build-up, wash-off,

and transport (Gironás et al., 2010) using different empirical relationships. In its latest versions, SWMM allows modelling of different types of SuDS (James et al., 2010; Meza & Oliva, 2003; Rossman & Huber, 2016), including bio-retention cells, rain gardens, green roofs, infiltration trenches, permeable pavements, rain barrels, rooftop disconnections, and vegetative swales (Rossman & Huber, 2016).

4.2.2 Surrogate model for interface boundary conditions

Two ANN-based machine-learning methods are used as surrogate models to represent the hydraulic head and total inflow at the synthetic junctions at the interface between the region of interest and remaining part of the system. ANNs are input-output mathematical models based on the operation of biological nervous systems that consist of interconnected neurons (Du & Swamy, 2006; Tadeusiewicz, 1995). ANNs have three main advantages: (1) they can learn non-linear relationships between system components, (2) they have inherently distributed nature that allows better implementation across distributed systems, and (3) they use specific internal optimisation methods to find efficient architecture components. Neurons are the basic processing elements of ANNs with synapses considered as weights. Training inputs are encoded in the first layer and passed through the hidden layers via weighted links while the data redistribute through the neurons. In each neuron, the weighted data are summed up, together with a scalar parameter b known as “bias” to be used by a predefined transfer function. The information obtained from the transfer function is the input data to the nodes in the subsequent layers. The outputs of the first neuron would be as follows:

$$O = f\left(\sum_{i=1}^{n_e}(u_i w_i) + b\right) \tag{4-1}$$

where u_i is the input vector, n_e denotes the number of elements in the input vector, w_i is the ith weight of the neuron, b is the bias, and f is the transfer function.

Various transfer functions may be used, including sigmoid transfer function and a linear transfer function, which are commonly used in hidden and output layers, respectively (Seyedashraf, Rezaei, et al., 2018). In this chapter, two ANN models, namely MLP and GRNN, were evaluated in terms of accuracy and efficiency.

4.2.2.1 Multilayer Perceptron (MLP) network

MLP is a feedforward ANN architecture (Hornik et al., 1989), which is by far the most popular ANN used in a variety of water engineering applications (Broad et al., 2005; Maier et al., 2010; Seyedashraf, Rezaei, et al., 2018). In feedforward ANN, each node of a layer receives information from nodes of a preceding layer and processes it before feeding it to the neurons of a subsequent layer. There is a minimum of three layers in MLP networks, including an input layer, at least one hidden layer, and an output layer. Each node of a layer connects to every node of a subsequent layer with certain weighting factors.

The input-output relationship is the same for all the nodes of the network and is expressed by equation (4-1), where the transfer function f is most commonly a sigmoid function in the form:

$$f(z) = \frac{1}{1 + \exp(z)} \tag{4-2}$$

The complexity and accuracy of an MLP network changes with the number of hidden layers. A lower number is preferable, as the complexity of the training process increases with the number of hidden layers.

4.2.2.2 Generalised Regression Neural Network (GRNN)

GRNN (Specht, 1991) is a one-pass learning algorithm with a feed-forward architecture. This network is especially suitable for prediction purposes in multidimensional problems with sparse data (Specht, 1991). There are four layers in this network: (1) an input layer that includes the input vectors and feeds encoded input information to the next layer; (2) a pattern layer that calculates the Euclidean

distance and activation function; (3) a summation layer that contains two types of neurons, including numerator and denominator, which calculate the arithmetical sum of the pattern layer with and without weights, respectively; and (4) an output layer, which contains one neuron and calculates model outputs according to the information received from the summation layer.

GRNN maps the input space to the output space as follows (Specht, 1991; X. Zhang et al., 2019):

$$y(x) = \frac{\sum_{i=1}^{n_{sa}} y_i \exp\left(\frac{-D_i^2}{2{\sigma_s}^2}\right)}{\sum_{i=1}^{n_{sa}} \exp\left(\frac{-D_i^2}{2{\sigma_s}^2}\right)} \tag{4-3}$$

$$D_i = \sqrt{(x - x_i)^T (x - x_i)} \tag{4-4}$$

where y_i is the ith output corresponding to input x_i, n_{sa} is the number of samples in the input vector, and σ_s is the smoothing factor, which is used to adjust neurons' sensitivity to changes in the input vector.

A larger smoothing factor results in smooth function approximations and improves the generalisation of the predictions while reducing the accuracy of the predictions.

4.2.3 Optimisation

A multi-objective optimisation problem consists of a set of objective functions to be minimised (or maximised):

$$\underset{\boldsymbol{l} \in \phi}{\text{Minimise:}} \qquad \boldsymbol{F}(\boldsymbol{x}) = \left(F_1, F_2, \dots, F_{n_o}\right) \tag{4-5}$$

where $\boldsymbol{F}$ is a vector of objective functions representing the performance of the system, $\boldsymbol{x}$ is a vector of decision variables, n_o is the number of objectives, and ϕ is the decision space. Typically, the solutions to Equation (4-5) must satisfy a set of constraints, which can generally be written in the form:

$$C_{eq,j}(\boldsymbol{x}) = 0 \qquad j = 1, \dots, n_q \tag{4-6}$$

$$C_{in,k}(\boldsymbol{x}) \leq 0 \qquad k = 1, \dots, n_r \tag{4-7}$$

where $C_{\mathrm{eq},j}(\boldsymbol{x})$ and $C_{\mathrm{in},k}(\boldsymbol{x})$ are functions of the decision variables, and n_q and n_r are the number of equality and inequality constraints, respectively.

Multi-objective optimisation models can be used to find non-dominated multi-dimensionally efficient solutions. In a multi-objective optimisation problem, the decision space is mapped into the objective space, and extreme points are located using a search algorithm. Initially proposed by Deb et al. (Deb et al., 2002), NSGA-II is a popular and efficient multi-objective optimisation algorithm widely used in stormwater management problems (Hooshyaripor & Yazdi, 2017; Liu et al., 2019; Manocha & Babovic, 2018; Ngamalieu-Nengoue et al., 2019; Penn et al., 2013; Xu et al., 2017). In NSGA-II, optimisation objectives are explored based on an elitist genetic algorithm, in which individuals with better ranks are selected in each generation until non-dominated solutions are found. In this chapter, the CNSGA-II (Deb & Goel, 2001) is used, which also favours non-elitist individuals that can widen the distribution of the population space. Comparing to the original NSGA-II, CNSGA-II has superior convergence properties and can find solutions with improved distributions by maintaining diversity in Pareto-fronts (Deb & Goel, 2001).

In case study 2, the Borg MOEA was used. Borg is an advanced optimisation algorithm based on genetic principles that relies on various search algorithms to provide improved reliability (Hadka & Reed, 2013). The Borg MOEA has been shown to perform well in multi- and many-objective optimisation problems of urban drainage and sewer system design (K. Eckart et al., 2018; Q. Zhang et al., 2021).

4.3 Application of the proposed approach

Two case studies were considered to demonstrate the applicability of the proposed framework. In the first case study, the region of interest is located in the middle of an

urban catchment and has several cut-nodes connecting the region of interest to the rest of the network. In the second case study, instead, the region of interest is located in the upstream part of an urban drainage system. This case study highlights the impact of alterative SuDS schemes on the hydraulic head time-series at the cut-nodes.

4.3.1 Case studies

Case study 1 is an 8.0×10^5 m^2 urban catchment, comprising 64 subcatchments, 566 manholes, and 511 conduits. This case study is taken from the work of Riaño-Briceño et al. (2016), which presents an open-source toolbox for real-time control in drainage systems. The case study is a modified version of a real urban drainage system in Bogotá, Colombia. As explained before, the urban drainage system was artificially disaggregated into a region of interest and the remaining part of the system. In this case, there are three conduits linking the two sub-systems, therefore three synthetic manholes are created at the cut-points between the two. The region of interest includes 5 subcatchments, 29 junctions, and 23 conduits. Figure 4-2 shows a planview of the drainage system with indication of the conduits, manholes and subcatchments, and with the region of interest highlighted in yellow colour.

Figure 4-2. Case study 1 with the region of interest highlighted in yellow. The urban drainage system is artificially divided into two sub-systems, with synthetic manholes representing the cut-nodes between them. The schematic shows the position of the two synthetic inflow nodes (green and blue markers) and the synthetic outfall (red marker) for the region of interest. This case study was taken from the work of Riaño-Briceño et al. (2016).

Case study 2 is a 6.3 $\times 10^5$ m^2 urban catchment area located in Windsor, Canada (K. Eckart et al., 2018; K. B. C. Eckart, 2015), comprising 227 subcatchments, 117 junction nodes, and 122 conduit links. Only one conduit links the region of interest to the remaining part of the network (Figure 4-3). The boundary of the region of interest encloses all the nodes that receive an inflow from such region. The synthetic outfalls are located at the cut-points where the boundary of the region of interest intersects the drainage pipes.

Figure 4-3. Case study 2 and region of interest highlighted in yellow. The urban drainage system is artificially divided into two sub-systems, with a synthetic outfall (red marker) between them. In this case, the region of interest is located in the upstream part of the catchment and has no inflows from upstream. This case study was taken from the work of Eckart (2018, 2015).

To capture the extent of the potential variation of the hydraulic head in the training of the emulation model, surface areas of the SuDS components from 4 intervals of the impervious surface area were sampled in each subcatchment, namely 0-7.5%, 7.5-15%, 15-20%, as well as the overall interval 0–20%. The optimisation model searches for Pareto-optimal types, combinations, spatial distributions, and surface areas of SuDS in the region of interest based on four design objectives in each case study, including minimisation of capital cost, flood volume, flood duration in both case studies, and TSS and average peak runoff rate in case study 1 and 2, respectively. Six different types of sustainable drainage assets are considered. These include bio-retention cells, rain gardens, green roofs, infiltration trenches, permeable pavements, and rain barrels. The exponential function and event mean concentration methods were used for estimating TSS build-up and wash-off load (Rossman & Huber, 2016).

4.3.2 Optimisation of SuDS design

The proposed disaggregation approach was demonstrated with an application to many-objective SuDS optimisation problems, where the term "many-objective" denotes a problem with four or more objectives (Fleming et al., 2005). Four design parameters, including type of drainage assets and combination within a subcatchment, spatial distribution, and surface area, were considered for each subcatchment, along with four design objectives in each case study, including minimisation of capital cost, flood volume, average flood duration (in both case studies), and TSS (case study 1) or average peak runoff (case study 2). Accordingly, the following four objective functions were considered:

Minimise:

$$\boldsymbol{F} = (F_{Cost},\ F_{FloodV}, F_{FloodD}, F_{TSS}\ or\ F_{PeakR}) \tag{4-8}$$

in which F_{Cost} is overall SuDS capital cost, F_{FloodV} represents system flood volume, F_{FloodD} is average flood duration in the catchment, F_{TSS} denotes the TSS discharge at the outfall (case study 1), and F_{PeakR} is the mean peak runoff (case study 2).

The capital cost was calculated for the SuDS as follows:

$$F_{Cost} = \sum_{i=1}^{n_s} \sum_{j=1}^{n_t} (c_{ij} \times a_{ij}) \tag{4-9}$$

where n_s is the number of subcatchments, n_t is number of types of SuDS in each subcatchment, a_{ij} is the surface area of each drainage asset, and c_{ij} denotes its capital cost per unit area, which was extracted from online databases (Washington State Department of Ecology & Herrera Environmental Consultants, 2012) and vendors' catalogues.

The flood volume objective function was defined as:

$$F_{FloodV} = \sum_{i=1}^{n_m} FV \tag{4-10}$$

where n_m is the number of manholes and FV is the overall flood volume at each manhole.

The average flood duration in the drainage system was calculated as:

$$F_{FloodD} = \frac{\sum_{i=1}^{n_f} FD_i}{n_f} \tag{4-11}$$

where FD is flood duration at each manhole and n_f denotes the number of flooded manholes. The overall TSS load at the outfall (case study 1) and average peak runoff were (case study 2) obtained from SWMM simulation results.

Two different optimisation models were applied in this chapter. In case study 1, the optimisation model uses CNSGA-II for multi-objective optimisation, and SWMM to represent the system dynamics in the region of interest, with the boundary condition at the outfall provided by the applied MLP neural network. Each optimisation individual contains 20 integer values, corresponding to two different types of SuDS and their surface area in each of the 5 subcatchments in the case study area. The integer values defining the SuDS types and their surface areas can vary within the intervals [0 7] and [0 20], respectively.

An infinite number of generations were allowed to be explored by CNSGA-II, and the search process was set to stop when the average relative change in the spread of Pareto solutions was less than the function tolerance of 10^{-4} over 50 consecutive iterations. With these settings, the optimisation model converged in 1.6 hours after 18,000 function evaluations, as opposed to 34.8 hours required if the entire system had been considered in the numerical simulations.

In case study 2, the Borg MOEA was applied to the disaggregated region and the search process was set to stop after 30,000 function evaluations. The hypervolume indicator was used to check the convergence of the optimisation process. The hypervolume of a Pareto-front represents the volume of the multi-dimensional space enveloped by the front (Zitzler et al., 2003). The hypervolume indicator was used as

the main convergence criterion for the Borg MOEA in case study 2 and as a further check for convergence of CNSGA-II in case study 1. The evolution of the hypervolume during the optimisation process is presented in Figure 4-4a for case study 1 and Figure 4-4b for case study 2.

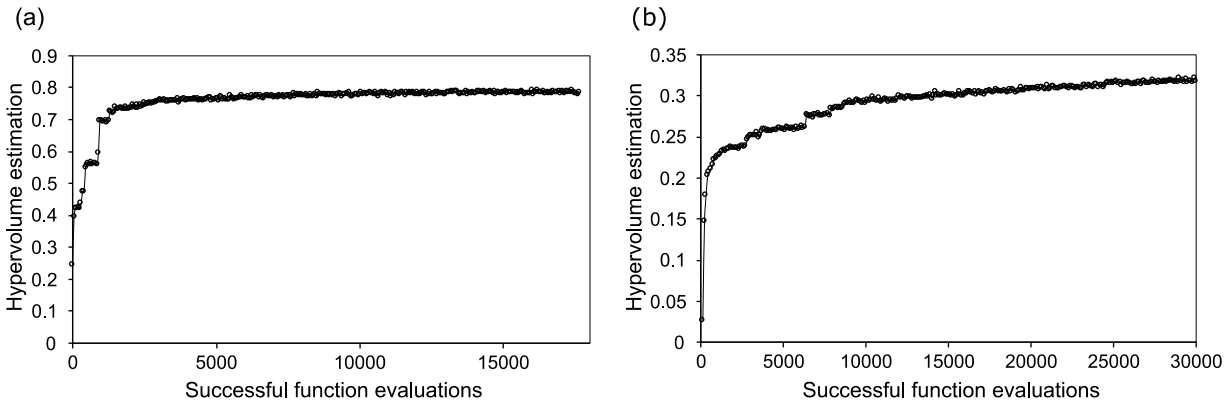

Figure 4-4. Hypervolume evolution throughout the optimisation processes for; (a) case study 1, and (b) case study 2.

4.4 Results and Discussion

The surrogate model used to represent the hydraulic head at the cut-node must be able to map the decision variables involved in SuDS design to the resulting hydraulic head time-series at the cut-node, which makes the problem highly non-linear. In this chapter, 2000 random SuDS configurations were simulated in SWMM to obtain 2000 sets of hydraulic head time-series, each of them consisting of 20 time steps. The time-series dataset was randomly divided into training, validation, and testing sets comprising 70%, 15%, and 15% of the available data, respectively. To compare the efficiency of the ANN used for emulation, the same input-output data were considered in the training process. To find the best MLP architecture, trial-and-error analyses were conducted, where the number of layers and the number of neurons for each layer were changed, and the resulting error in the hydraulic head was evaluated compared with that predicted by simulating the whole system. In case study 1, out of about 130 different MLP architectures for the outfall emulation model with up to two hidden layers, and up to 20 neurons for each layer, the best performing network has

7 neurons in its first layer, and 15 neurons in its second hidden layer. The same number of MLP architectures was tested for the inflow emulation model, and the best-performing architecture was found to have 7 neurons in its first layer and 12 neurons in its second hidden layer. Moreover, the best performing MLP network in case study 2 was obtained with 14 and 15 neurons in its first and second layers, respectively, with a similar trial and error procedure.

In GRNN training, the smoothing factor σ was found to be 0.35 and 0.25 for the emulation models of the outfall and inflow nodes in case study 1, and 0.67 for the emulation model of the outfall node in case study 2 based on a trial-and-error analysis where 40 different GRNN architectures were tested in each case. The resulting ANN predictions were compared with the numerical outputs in terms of mean square error (MSE), root mean square error (RMSE), mean error (μ), standard deviation of errors (σ), and correlation coefficient (R). These error metrics are defined as follows:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(h_i - \hat{h}_i\right)^2 \tag{4-12}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(h_i - \hat{h}_i\right)^2} \tag{4-13}$$

$$\mu = \frac{1}{n}\sum_{i=1}^{n}\left(h - \hat{h}_i\right) \tag{4-14}$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(h_i - \mu)^2} \tag{4-15}$$

$$R = \frac{cov(h, \hat{h})}{\sqrt{var(h)}.\sqrt{var(\hat{h})}} \tag{4-16}$$

where n is the number of data, h and $\hat{h}$ stand for numerical and predicted hydraulic head, respectively, and cov(·) and var(·) denote covariance and variance. Similar error metrics were used for the inflow rates.

The results of the application of MLP and GRNN to the prediction of the hydraulic head and inflows at the synthetic outfall and inflow nodes in the case study area are

presented in Table 4-1. Figure 4-5 compares the emulated hydraulic heads at the outfall cut-nodes with that predicted by SWMM considering the whole drainage system for both case studies. Here, the red markers represent model results, whereas the continuous lines represent identity ($h = \hat{h}$). The figure shows good agreement between the predictions of the surrogate model and the full drainage model for the outfall cut-node, and that MLP has better predictive performance (R = 0.998 for case study 1, R = 0.999 for case study 2) than GRNN (R = 0.996 for case study 1, R = 0.976 for case study 2).

Table 4-1. Comparison of calculated RMSE, MSE, R, σ, and μ of MLP and GRNN predictions for the synthetic outfall and inflow nodes.

			RMSE	MSE	R	μ	σ
Case study 1	MLP	Outfall	0.024274	0.000589	0.998321	0.000291	0.024274
		Upper inflow node	0.488066	0.238209	0.999998	-0.01455	0.487890
		Lower inflow node	0.160321	0.025703	0.999998	-0.00365	0.160293
	GRNN	Outfall	0.038364	0.001472	0.995886	-0.00041	0.038364
		Upper inflow node	0.767876	0.589634	0.999996	-0.01542	0.767798
		Lower inflow node	0.215930	0.046626	0.999996	-0.00804	0.215802
Case study 2	MLP	Outfall	0.028521	0.000813	0.998867	-0.00013	0.028524
	GRNN	Outfall	0.131974	0.017417	0.976418	0.00110	0.131985

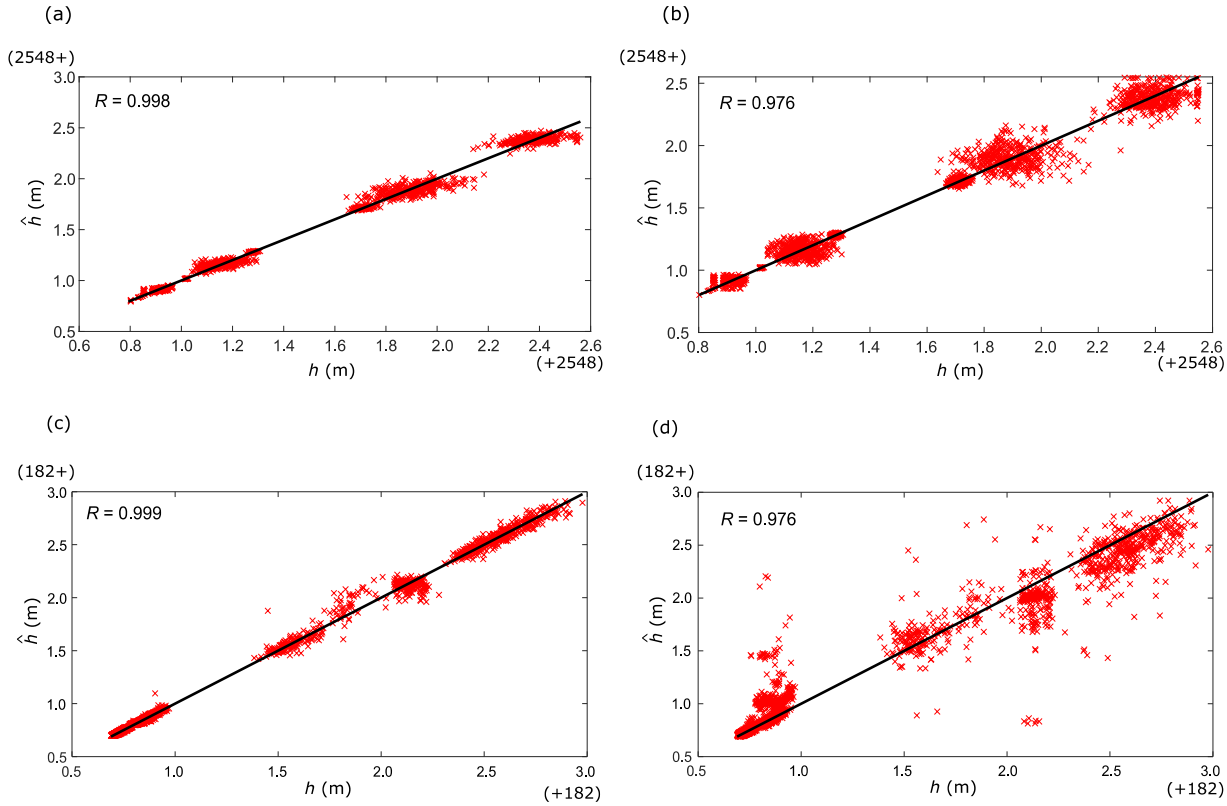

Figure 4-5. Scatter plots of the numerical results and (a) MLP predictions for case study 1, (b) GRNN predictions for case study 1, (c) MLP predictions for case study 2, and (d) GRNN predictions for case study 2. The plots show that, in both case studies, the MLP network outperforms GRNN in estimating the hydraulic head at the synthetic outfall node of the disaggregated drainage system. Here, h and $\hat{h}$ stand for numerical and predicted hydraulic heads, respectively. Hydraulic head values are reported in meters above the reference elevation, 2548 m and 182 m for the first and second case studies, respectively.

Error distributions of MLP and GRNN predictions at the synthetic outfall node are illustrated in Figure 4-6, in which the height of each bar indicates the number of predictions with similar errors. In both cases, the mean of the distribution is close to zero with slightly smaller values for MLP, which implies better performance on average.

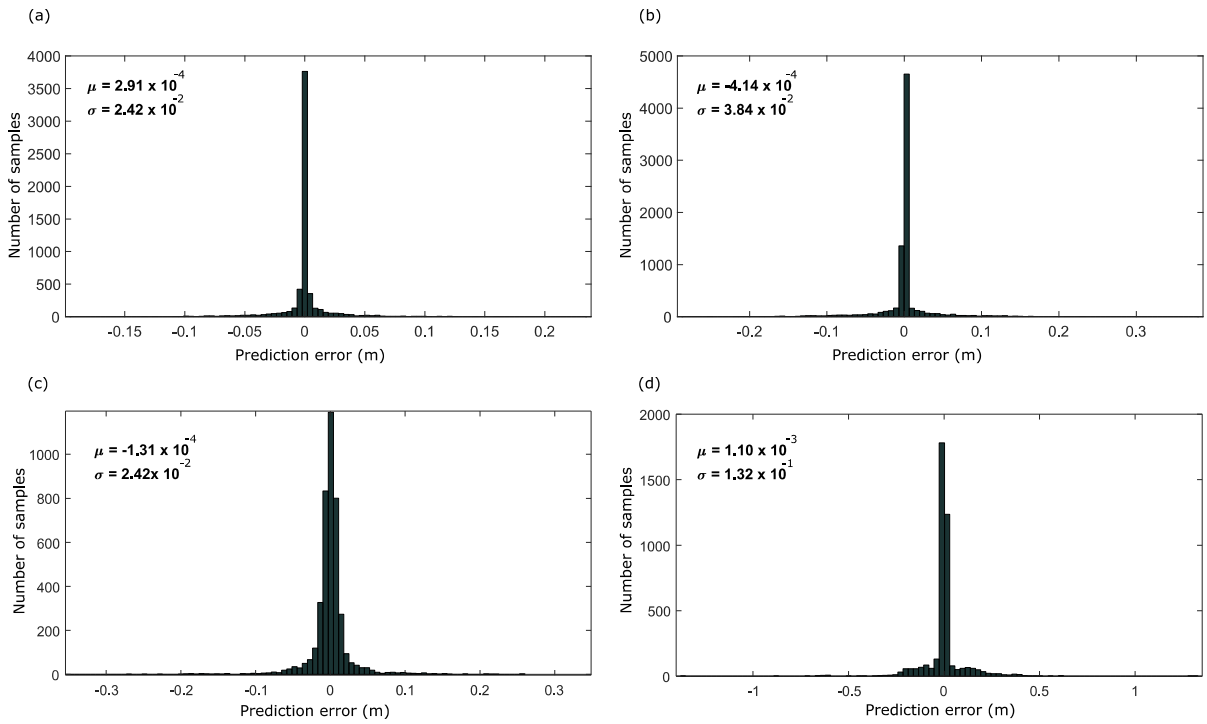

Figure 4-6. Error distributions of (a) MLP predictions for case study 1, and (b) GRNN predictions for case study 1, (c) MLP predictions for case study 2, and (b) GRNN predictions for case study 2 at the synthetic outfall node. The height of each bar indicates the number of predictions. A smaller standard deviation means better performance on average.

Figure 4-7 compares the time-series of hydraulic head at the synthetic outfall predicted by MLP and GRNN with those calculated by the full drainage model for five random SuDS configurations in each case study. Both surrogate models provided a reasonably good estimate of the time-series of hydraulic head, but the MLP model outperformed GRNN by providing more accurate predictions.

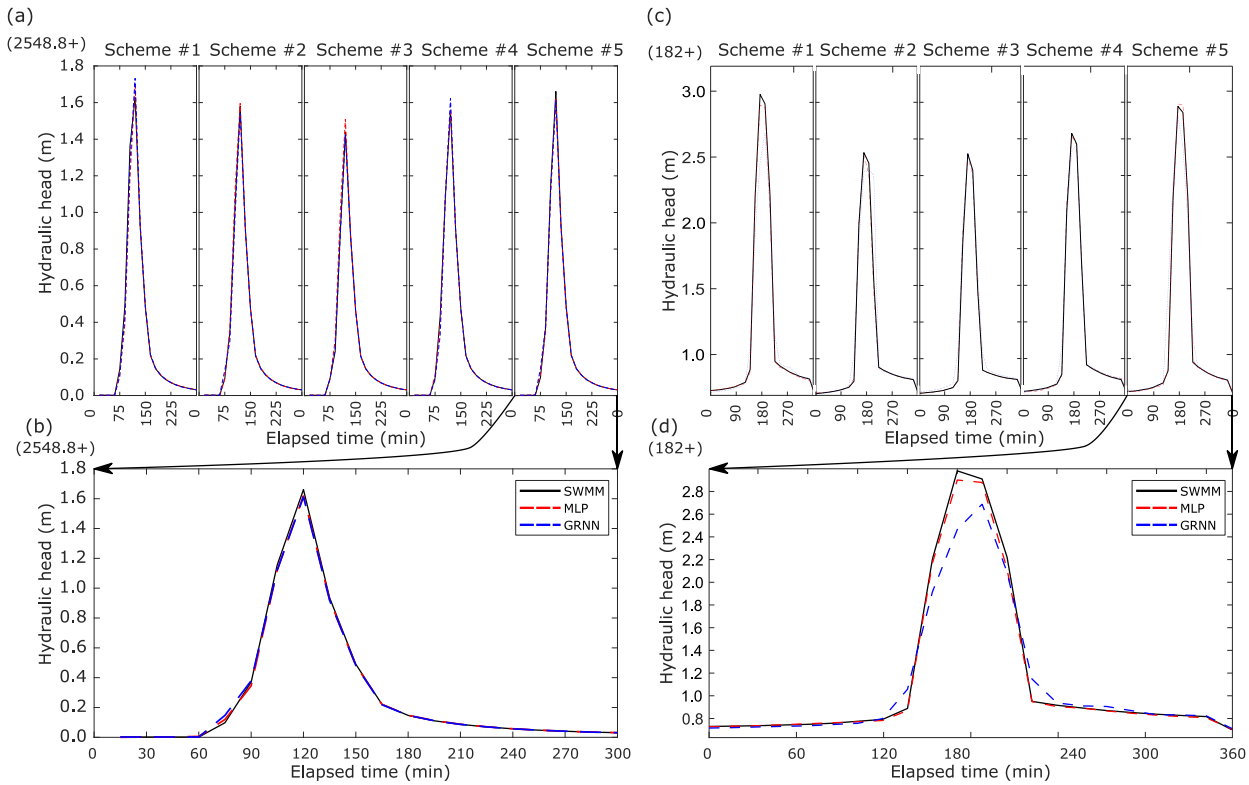

Figure 4-7. Comparison between hydraulic head time-series at the synthetic manholes obtained using SWMM, MLP, and GRNN. The time-series are shown for five random SuDS schemes in (a) case study 1, with (b) results in particular for the fifth scheme in case study 1; and five random SuDS schemes in (c) case study 2, with (d) results, in particular, the fifth scheme in case study 2. The plots indicate that the MLP network outperforms GRNN by returning predictions closer to SWMM simulations. It can be seen that changing SuDS design in the region of interest impacts the hydraulic head at the synthetic nodes.

In Figure 4-7, it is evident that changing SuDS design in the region of interest impacts hydraulic head time-series at the synthetic nodes. A 30% change in the peak hydraulic head values as the surface area of SuDS is changed from 0% to 20% of the subcatchment is especially evident in case study 2. To exemplify the performance of the selected MLP architecture the flood volume, flood duration, and TSS loads were evaluated comparing the disaggregated model with the full model of the entire drainage network for a randomly selected SuDS design in case study 1. The prediction error was found to be about 3.6% for flood volume values with accurate predictions of flood durations. The results obtained for flood duration and flood volume at each manhole in the region of interest are summarised in Table 4-2.

Table 4-2. Comparison of flood volume and flood duration results of SWMM simulations in flooded manholes of a random SuDS scheme in case study 1.

Manhole	Flood duration (hrs)		Flood volume (m^3)	
	Reduced map	Global model	Reduced map	Global model
PMI92736	0.25	0.25	43	48
PMI92751	0.37	0.37	340	344
PMI92782	0.34	0.34	179	178

Table 4-3 compares the computational times for training and executing the MLP network and GRNN with those of the SWMM simulations for the whole urban catchment in both case studies. The computations were performed on a single processor of an Intel Core i7-8565U CPU clocked at 4.60 GHz with 8 GB of DDR4 RAM.

Table 4-3. Surrogate model training and execution time comparison with numerical results in case study 1.

	Operation	**Execution time (ms)**
Case study 1	Numerical simulation of global catchment	8,199
	Numerical simulation of the reduced model	163
	Optimisation function evaluation for global catchment	8,585
	Optimisation function evaluation for the reduced model	394
	MLP training	35,635
	GRNN training	292
	MLP prediction	9
	GRNN prediction	64
Case study 2	Numerical simulation of global catchment	3,498
	Numerical simulation of the reduced model	153
	Optimisation function evaluation for global catchment	2,982
	Optimisation function evaluation for the reduced model	251
	MLP training	29,899
	GRNN training	286
	MLP prediction	10
	GRNN prediction	82

Table 4-3 indicates that GRNN benefits from a significantly faster training process, but the time required for training by both MLP and GRNN is smaller compared to the time required to generate the training datasets. GRNN has a larger execution time compared to MLP, and therefore MLP is preferable for optimisation problems that require a large number of objective function evaluations. While the computational

time required to train the surrogate models was relatively small in the case studies presented in this chapter, the training process can become more computationally expensive if the optimisation problem involves a larger number of decision variables, or if multiple rainfall events are considered. Yet, if the decision variables are confined to a region of interest, the overall computational cost required for optimisation would be significantly higher if the whole drainage network had to be simulated.

Figure 4-8 illustrates a four-dimensional plot of the Pareto-optimal solutions obtained in both case studies. Capital cost, flood volume, and flood duration are shown on the x, y, z-axes, respectively. TSS and average peak runoff rate values are represented by marker sizes in Figure 4-8a and 4-8b, respectively, where larger markers represent larger TSS loads and/or peak runoff rates. The four-dimensional plots provide an overview of the system performance and design metrics for the solution space.

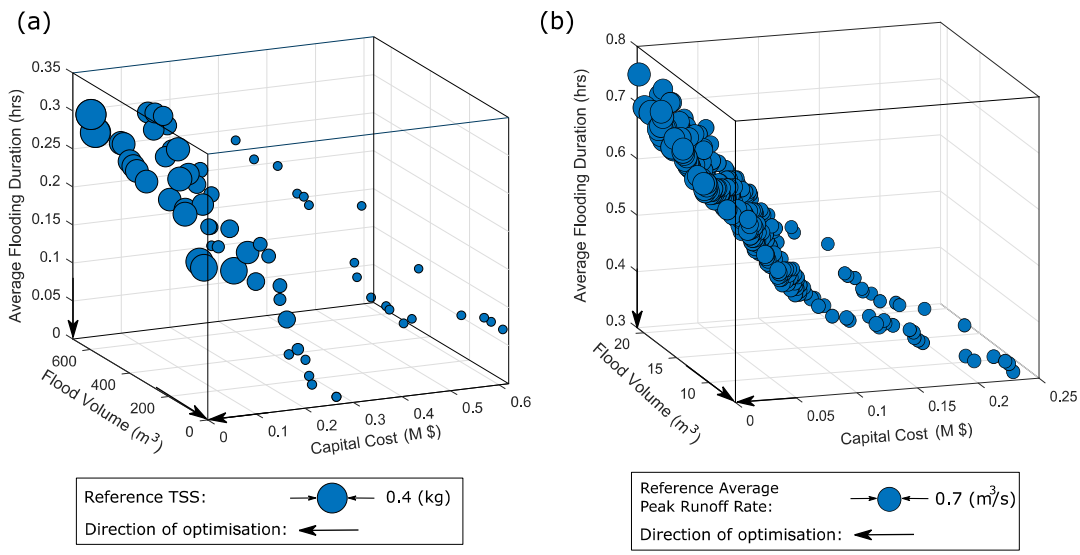

Figure 4-8. Four-dimensional representation of trade-offs between design objectives in (a) case study 1 and (b) case study 2, where marker size represents overall TSS load and average peak runoff rate in the first and second case studies, respectively. The CNSGA-II and Borg MOEA optimisation algorithms were applied to the first and second case studies, respectively.

Figure 4-9 depicts a parallel axis plot (Inselberg, 2009) of the objective functions together with the final SuDS schematic, as an example, for case study 1. The parallel

axes represent optimisation objectives, in which the preferred direction is downwards, and the lines connecting the axes represent Pareto-optimal designs. The ideal solution candidate is a horizontal line at the bottom of the axes. This visualisation technique allows practitioners to interactively set final design constraints on the problem objectives. Here, the lower third of each non-monetary objective was selected as an acceptable range of solutions to narrow down the solution space. A candidate solution with lowest capital cost among those within the specified ranges was then singled out as the final SuDS design for the region of interest. This is illustrated in Figure 4-9b, where the bar colour represents the type of asset, and the bar height represents the surface area expressed as a percentage of the total surface area of the subcatchment. An identical approach can be applied to single out a final SuDS design portfolio for case study 2.

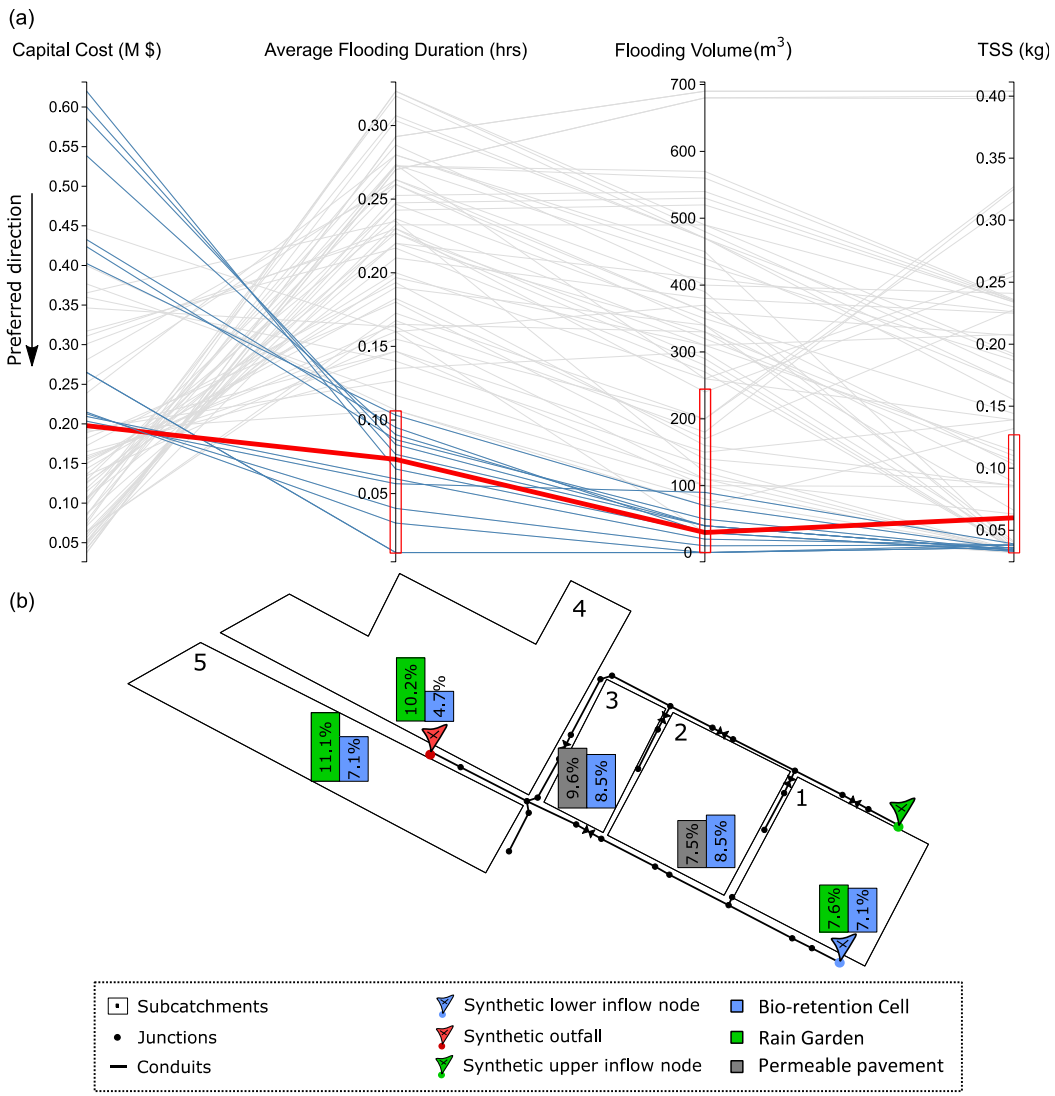

Figure 4-9. Many-objective optimisation of SuDS in case study 1; (a) parallel axis plot of the non-dominated solutions; (b) Pareto-optimal SuDS types, combination, spatial distribution, and surface areas of the selected portfolio (red line in panel a) described as a percentage of the respective subcatchment area. Each axis represents an objective and each line connecting the axes denotes performance of a candidate solution. The red boxes on the axes of panel a) are interactive filter bars that allow drainage designers to isolate a subset of Pareto-optimal designs that meet their preferences. The arrow shows the direction of preference.

Figure 4-9 shows how the proposed disaggregation-emulation approach can help practitioners efficiently use an optimisation model for SuDS design in an area of interest without considering the remaining part of drainage system. The spatial distribution on SuDS components in Figure 4-9b pertains to the portfolio highlighted with a bold red line in Figure 4-9a. Here, the optimisation model explores potential combinations of green, blue, and grey urban drainage infrastructure for each subcatchment to maximise efficiency of the SuDS design in reducing stormwater

runoff and pollution according to geographical and hydrological characteristics of each subcatchment (Alves et al., 2019; K. Eckart et al., 2018). Accordingly, SuDS components appear as pairs of sustainable drainage assets in each subcatchment. Here the colour of each bar stands for a particular SuDS type, whereas the bar height is proportional to the SuDS surface area.

4.5 Conclusions

In this chapter, a new surrogate-based optimisation approach was presented for disaggregation and optimisation of large-scale sustainable urban drainage networks. The approach is applicable to problems where part of a network needs to be optimised and allows the computational cost of simulating the system dynamics for the whole system to be significantly reduced by disaggregating the region of interest and representing the remaining part of the system using an interface boundary condition. The latter is determined from a surrogate model that maps changes in the optimisation variables to hydraulic head and total inflow time-series at synthetic outfalls and inflow nodes, respectively, at the cut-points between the region of interest and the remaining part of the drainage network. ANNs are used as surrogate models for both the inflow and outflow boundary conditions. The proposed approach was demonstrated with an application to a many-objective optimisation problem involving the design of sustainable urban drainage infrastructure for capacity expansion in two urban catchments. The decision variables include the types of sustainable drainage assets, their combinations and surface area in five different subcatchments. Four objective functions are considered in each case study, i.e. the minimisation of capital cost, flood volume, flood duration, and total suspended solids in case study 1, or average peak runoff rate in case study 2. For the ANN representing the interface boundary conditions at the cut-points, two alternative approaches were evaluated: an MLP network and a GRNN. Results show that both emulation models can provide acceptable approximations of the hydraulic head and total inflow at the synthetic outfall and inflow nodes, respectively, but MLP provided more accurate and

efficient predictions, making it suitable for use in real-world design problems. GRNN benefits from a faster training process, which makes it efficient for problems with large calibration datasets. Using the proposed disaggregation-emulation approach, the computational time required for a single drainage simulation in the region of interest was about 50 times smaller than that required for simulation of the whole drainage network, allowing to speed-up the optimisation process by factors of 22 and 12 in the first and the second case study, respectively.

In this chapter, the proposed approach was used to expand the capacity of an existing drainage network within a region of interest using sustainable drainage assets. However, the approach can be used more generally for optimisation, calibration or trial-and-error analysis of urban drainage, water distribution, and a broader variety of water resources networks. In a similar way to the application presented in this work, a surrogate model may be used in design and control problems concerning water distribution networks to represent changes in flows and hydraulic heads at the boundary of a region of interest.

Two Pareto-front visualisation techniques were used in this chapter to survey trade-offs between the considered design objectives. However, when the number of Pareto-optimal solutions increases decision-making normally end up in situations, in which decision-makers must deal with hundreds, or thousands, of design portfolios. Although a crowded Pareto-front can better showcase a real solutions space in multi-objective optimisation problems it may not assist decision-makers to analyse the existing solutions as they can only process a limited amount of information at a time. Chapter 5 addresses this issue by proposing a decision-making strategy that reduces Pareto-fronts while preserving their structures. A set of post-optimisation Pareto-front analysis techniques are also applied that can help decision-makers to keep an eye on future performances of their selected design portfolios in case of having model input deviations from that of envisaged situations.

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5 Chapter five: A clustering assisted approach for many-objective design of sustainable urban drainage systems

A clustering assisted approach for many-objective design of sustainable urban drainage systems

Abstract

During the past years, there has been an increasing interest in the application of multi-criteria decision-making approaches to sustainable urban drainage systems (SuDS). Generally, these approaches result in multi-dimensional Pareto-fronts which embody a large number of non-dominated solutions. However, since decision-makers can only process a limited amount of information at a time, the results obtained from multi- and many-objective optimisation models can be difficult to analyse. This study marks the first attempt to simplify decision making in many-objective optimisation problems in the context of drainage systems by efficiently reducing Pareto-fronts. A soft clustering algorithm is applied, which identifies similarities between the solutions, partitions the front accordingly, and selects a set of representative solutions while preserving the multi-dimensional structure of the front. The performance of the representative solutions can be further characterised by looking at the range of variation of the objective functions in response to different rainfall events. Moreover, three new post-optimisation metrics are introduced that can be used to quantify the overall performance with respect to several design objectives, which can be used for ranking solutions that satisfy a given set of constraints. Results show that the proposed clustering algorithm is able to reduce Pareto-fronts with thousands of solutions to a handful of representative Pareto-optimal solutions and can therefore help decision-makers easily understand complex trade-offs between the objectives.

5.1 Introduction

Urban drainage networks have been commonly designed to protect cities from standard design rainfall events (Butler & Davies, 1999). However, climate change and rapid urban expansion have made existing drainage infrastructure insufficient to protect cities from intense rainfall events. Potential solutions include refurbishment of traditional grey drainage infrastructure (Barreto Cordero, 2012), real-time flow control (Abou Rjeily et al., 2018), and SuDS (Seyedashraf et al., 2021b). Among these, SuDS have received extensive attention due to their multi-functional properties, such as improvement of water quality in receiving water bodies by promoting sediment settling, filtering and biological breakdown of pollutants (BMT WBM, 2009; Woods Ballard et al., 2015), improving biodiversity (Wright, 2011), delivering recreational opportunities, and improving the mental and physical health of the residents (Mell, 2010).

Several studies have demonstrated the application of multi-objective optimisation models as effective tools for SuDS design (Baek et al., 2015; Eckart et al., 2017, 2018; Giacomoni & Joseph, 2017; Macro et al., 2019; Mani et al., 2019). For example, Giacomoni and Joseph (2017) used the NSGA-II for SuDS design to find Pareto-optimal spatial distribution of permeable pavements and green roofs. Eckart et al. (2018) applied the Borg MOEA (Hadka & Reed, 2013) to design of SuDS problem in Windsor, Canada. The model was used to find efficient surface areas of four types of sustainable urban drainage facilities, including infiltration trenches, rain gardens, permeable pavements, and rain barrels.

In *a posteriori* optimisation problems, decision-makers evaluate trade-offs between optimisation objectives and single out a final solution based on their engineering insight, understanding of costs and benefits, and their past experiences. In this sense, identifying best trade-offs between several design objectives is a complex task (Blasco et al., 2008), especially when mutual agreement must be achieved between several decision-makers. The decision-making process can be further complicated if decision-makers lack relevant expertise or operate under strict time constraints. Moreover, the

psychology literature indicates that human decision-makers have difficulties in processing large data sets and using them to take measured decisions (Duro et al., 2014; Kaplan, 1995). Additionally, sole reliance on decision-makers' explicit preferences, while neglecting overall performance of alternative portfolios, may result in decisions that lack objectivity, repeatability, and coherence (Duro et al., 2014).

In multi/many-objective optimisation problems there is generally an infinite number of solutions in the Pareto-front, making it unrealistic to accurately visualise them. Besides, the higher the accuracy of a search algorithm, the larger the number of solutions in the resultant Pareto-approximate set (Hadka & Reed, 2013). This chapter marks the first attempt to simplify the decision-making process in many-objective optimisation of sustainable urban drainage infrastructure by simplifying Pareto-fronts. To this end, the use of a soft clustering algorithm is proposed, which partitions the Pareto-front into a desired number of clusters. A representative solution is then assigned to each cluster. Accordingly, a Pareto-front with thousands of solutions can be reduced to a handful of design portfolios. Three postoptimisation metrics are also introduced to quantify overall performance which can be used to rank the solutions that satisfy a given set of constraints. This allows decision-makers to select portfolios when there is no preference for any of the design of objectives as long as some essential requirements are met. Finally, this chapter demonstrates how a postoptimisation uncertainty analysis can be carried out for the representative Pareto-optimal solutions to characterise variation in performance under different rainfall scenarios. Results show that the proposed framework can effectively simplify the decision-making process in many-objective optimisation problems of sustainable urban drainage system design.

5.2 Methodology

A simulation-optimisation framework was developed along with a set of decision-making tools to evaluate the resultant Pareto-front. Here, *a posteriori* optimisation is considered, in which prior preferences on design objectives are not defined and

decisions are made based on results of a multi-objective optimisation model (Coello et al., 2007). The optimisation model used in this work considers minimisation of average flood duration, total flood volume, TSS, and capital cost of SuDS components as design objectives. The Borg MOEA (Hadka & Reed, 2013) was coupled with the SWMM (L A Rossman, 2015) for optimisation run and the fuzzy c-means clustering algorithm (Bezdek, 1973) was used to explore data structure in the Pareto-front and classify SuDS design portfolios in a trial-and-error fashion. Figure 5-1 shows the flowchart of the implemented many-objective SuDS optimisation framework which involves using SWMM for evaluating system performance, coupled with the Borg MOEA to obtain a set of Pareto-optimal design portfolios. Subsequently, the fuzzy c-means clustering algorithm was used to determine a smaller set of representative solutions for which the performance is further evaluated considering uncertainties in the input variables. In the final postoptimisation analysis, additional metrics can be used to quantify the overall performance of the representative solutions.

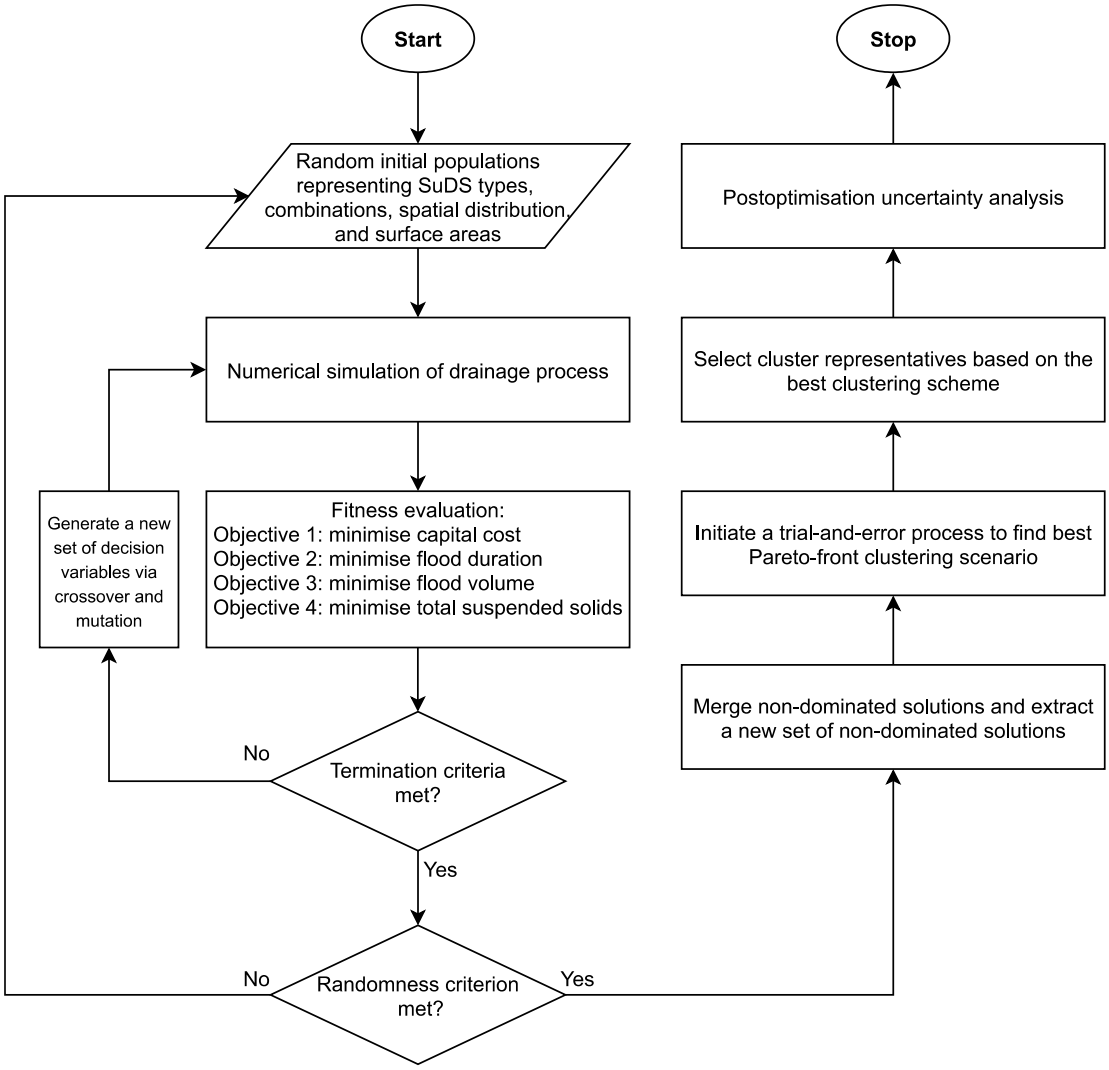

Figure 5-1. Flowchart of the proposed many-objective optimisation approach for design of sustainable urban drainage infrastructure.

5.2.1 Urban drainage system simulation

In this chapter, SWMM (Gironás et al., 2010) was used to simulate drainage processes in the study area. SWMM incorporates three flow routing models, including steady flow, kinematic wave, and dynamic wave models, to simulate the flow of runoff through the drainage network (Lewis A Rossman, 2017). The dynamic wave flow routing model was used in this study due to its ability to reproduce pressurised and backwater flow conditions by solving the full Saint-Venant equations (Meza & Oliva, 2003). SWMM can simulate pollution build-up and transport, and in its latest versions, it allows simulation of sustainable urban drainage facilities such as rain gardens, bio-

retention cells, green roofs, permeable pavements, infiltration trenches, rain barrels, rooftop disconnections and vegetative swales (Gironás et al., 2010; James et al., 2010; Meza & Oliva, 2003; Lewis A. Rossman & Huber, 2016).

5.2.2 Many-objective optimisation

In multi-objective optimisation problems, one or several search algorithm/s may be implemented to reduce the decision space to a set of solutions that maximise and/or minimise multiple design objectives subject to a given set of design constraints. This process can be mathematically formulated as follows:

$$\underset{\boldsymbol{l} \in \phi}{\text{Minimise:}} \quad \boldsymbol{F}(\boldsymbol{x}) = \left(F_1(\boldsymbol{x}), F_2(\boldsymbol{x}), \dots, F_{n_o}(\boldsymbol{x})\right) \tag{5-1}$$

$$\text{Subject to:} \quad \begin{cases} C_{eq,j}(\boldsymbol{l}) = 0 & j = 1, \dots, n_q \\ C_{in,k}(\boldsymbol{l}) \leq 0 & k = 1, \dots, n_r \end{cases} \tag{5-2}$$

where $\boldsymbol{F}(\boldsymbol{x})$ is a vector of objective functions, $F_i(\boldsymbol{x})$, which characterise performance of the vector of decision variables, $\boldsymbol{x}$, with n_o number of objectives in the decision space, $\boldsymbol{\phi}$. Moreover, $C_{\mathrm{eq},j}(.)$ and $C_{\mathrm{in},k}(.)$ are equality and inequality functions with n_q and n_r constraints, respectively.

5.2.3 Data clustering

Clustering algorithms are generally used to discover groupings of data points in large datasets based on measures of similarity between data points. They have helped data scientists to organise, compress, and categorise large amounts of data for diverse applications, including image segmentation, text mining, speech recognition, and health monitoring (Bezdek et al., 1984; Mitra et al., 2004; Ng et al., 2006; Satour et al., 2020). In the past years, such algorithms have also been applied in the context of urban water infrastructure design in order to investigate spatial characteristics of system components (Huang et al., 2015; Liu et al., 2016; Muhammed et al., 2017). Various clustering algorithms have been introduced based on the three data partitioning approaches, including: (1) hierarchical, such as clustering using

representatives (CURE) (Guha et al., 1998); (2) exclusive, like k-means clustering algorithm (MacQueen, 1967); and (3) overlapping clustering approaches, such as the fuzzy c-means clustering algorithm (Bezdek, 1981). Hierarchical clustering algorithms operate by successive clustering of initially partitioned data points via a dendrogram in which the root of all subsets corresponds to the main data set. Exclusive clustering algorithms partition datasets into a number of groups with crisp boundaries where each data point belongs to only one cluster (MacQueen, 1967). Overlapping clustering algorithms allocate membership grades to each data point allowing them to fit in multiple groups (Bezdek, 1981; Bezdek et al., 1984; Zadeh, 1965), for which the membership values can range between 0 and 1 and sum up to 1 for all clusters. The closer the membership values to 0 the better the clustering process. In this category, the fuzzy c-means clustering algorithm is the most widely used clustering method, which operates by selecting and iteratively updating hypothetical cluster centres, C_k.

$$C_k = \frac{\sum_{i=1}^{n_c} (dm_{ik})^w \times Dl_i}{\sum_{i=1}^{n_c} (dm_{ik})^w} \tag{5-3}$$

so as to minimise a loss function, L,

$$L = \sum_{i=1}^{n_c} \sum_{k=1}^{n_p} (dm_{ik})^w \times R_{ik} \tag{5-4}$$

subjected to the following constraint (Bezdek, 1981):

$$\sum_{k=1}^{n_s} dm_{ik} = 1 \tag{5-5}$$

where dm_{ik} is the membership degree of the ith data point to the kth cluster, n_p is the number of data points, n_c is the number of clusters, w is a weighting factor, Dl_i is the ith data point, and R_{ik} is the distance between the ith data point and k^{th} cluster centre, which must be minimised by an integrated optimisation model.

5.3 Application of the proposed approach

5.3.1 Case study

An illustrative urban drainage system comprising 7 subcatchments, 11 junctions, and 11 conduits (Figure 5-2), was considered to demonstrate the application of the proposed optimisation and decision-making framework.

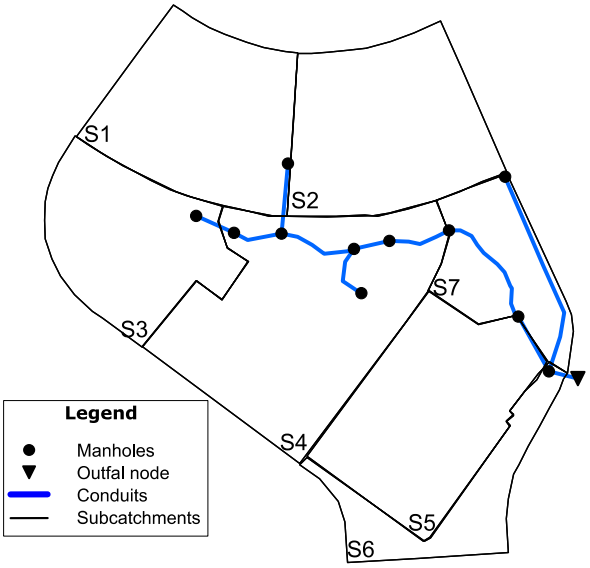

Figure 5-2. Schematic map of the synthetic case study.

This case study is a modified version of the case study presented by Lewis A Rossman (2017) and has been used as a standard benchmark in different drainage design studies (Giacomoni & Joseph, 2017; Nehrke & Roesner, 2002, 2004; Sambito et al., 2020). To reduce model complexity, it was assumed that there are no restrictions on placing different types of SuDS in the subcatchments. Moreover, the pipe diameters were halved, compared to the original case study presented by (Lewis A Rossman, 2017), in order to generate a scenario where additional drainage infrastructure would be needed to avoid flooding in the area.

5.3.2 Optimisation model

A many-objective optimisation and decision-making approach is developed to find an efficient drainage system design where the decision variables include types, combinations, surface areas, and spatial distribution of SuDS components in the catchment. To this end, four optimisation objectives were considered as follows:

Minimise: $$\boldsymbol{F}(\boldsymbol{x}) = \left(F_C(\boldsymbol{x}), F_{FD}(\boldsymbol{x}), F_{FV}(\boldsymbol{x}), F_{TSS}(\boldsymbol{x})\right) \quad (5\text{-}6)$$

where F_C is capital cost, F_{FD} is average flood duration, F_{FV} is overall flood volume, and F_{TSS} is TSS load at system outfall. The capital cost function is defined as:

$$F_C = \sum_{i=1}^{n_s} \sum_{j=1}^{2} (c_{ij} \times a_{ij}) \quad (5\text{-}7)$$

where n_s is the number of subcatchments, a_{ij} and c_{ij} are respectively the surface area and capital cost of each SuDS component extracted from cost-databases published by the Washington State Department of Ecology & Herrera Environmental Consultants (Washington State Department of Ecology & Herrera Environmental Consultants, 2012) and online vendors.

The overall TSS at the system outfall was extracted from numerical simulations whereas the average flood duration, F_{FD}, and overall flood volume, F_{FV}, for each SuDS design were calculated as follows:

$$F_{FD} = \frac{\sum_{i=1}^{n_j} fd_i}{n_j} \quad (5\text{-}8)$$

$$F_{FV} = \sum_{i=1}^{n_j} fv_i \quad (5\text{-}9)$$

where n_j is the number of system junctions, and fd_i and fv_i are flood duration and flood volume for each system junction, respectively.

In this study, the Borg MOEA was used (Hadka & Reed, 2013) for optimisation due to its widely proven performance in dealing with complex problems of water system design, planning, and management (Geressu et al., 2020; Zatarain Salazar et al., 2017; Zhang et al., 2021). Borg benefits from a combination of various search algorithms, which operate by evolving an initial population of solutions towards solutions with higher fitness values.

5.4 Results and discussion

5.4.1 Pareto-optimal solutions

To ensure a sufficient level of diversity in the final set of Pareto-optimal solutions, a total of 30 optimisation runs were conducted with random initial populations. Figure 5-3 shows 15,000 non-dominated solutions in a parallel coordinate plot where vertical axes represent design objectives. Here, each line connecting the axes represents a sustainable urban drainage infrastructure design corresponding to different trade-offs between the design objectives.

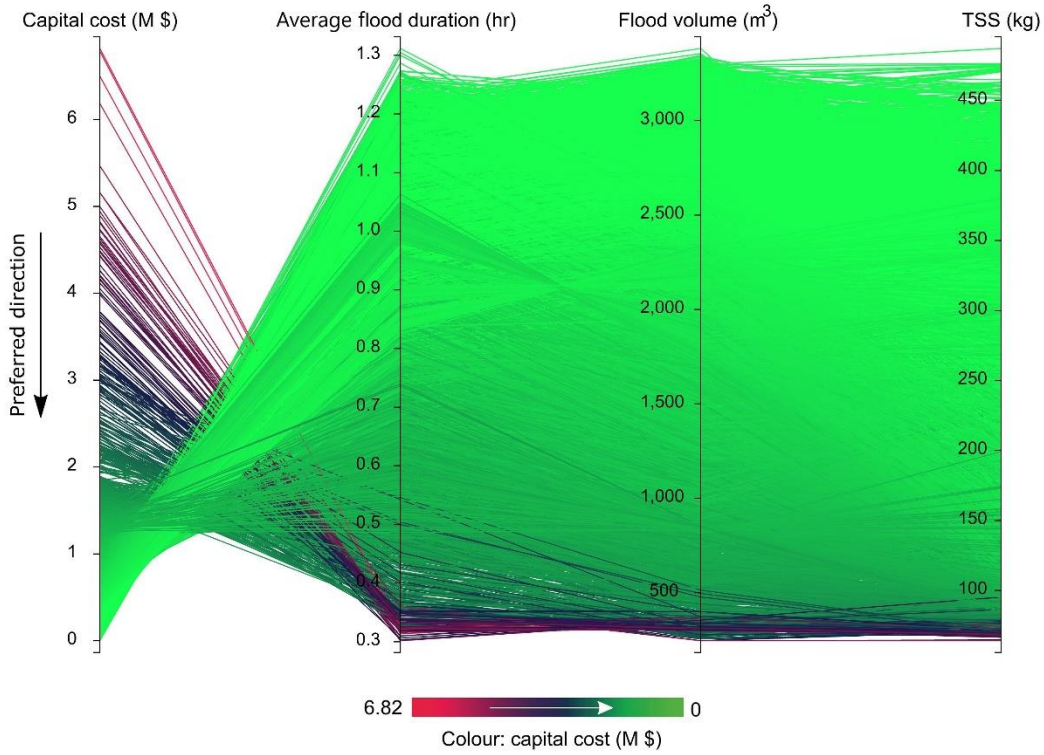

Figure 5-3. Parallel axes plot of around 15,000 non-dominated sustainable urban drainage infrastructure designs showing trade-offs between optimisation objectives, including capital cost, flood volume, average flood duration, and TSS. The arrows show direction of preference.

To verify convergence of the optimisation process, the evolution of the hypervolume indicator was evaluated for each optimisation run against the number of objective function evaluations across the initial populations. Figure 5-4 depicts the hypervolume evolution across initial populations over the number of objective function evaluations. The shaded area bounds the hypervolume indicators of Pareto-fronts and the solid line represents the mean hypervolume of the different runs. According to the hypervolume evolution, the Pareto front stabilises after completing around 20,000 objective function evaluations.

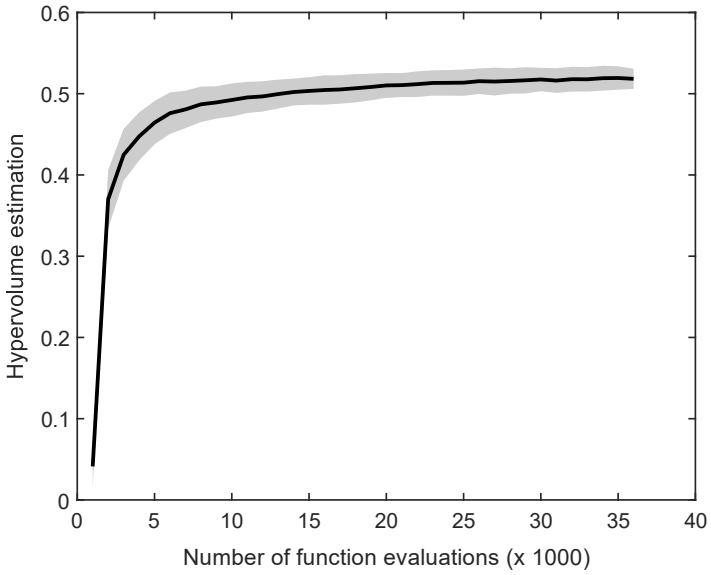

Figure 5-4. Hypervolume evolution across 30 random initial populations over the number of objective function evaluations. The shaded area bounds the hypervolume of Pareto-optimal sustainable urban drainage infrastructure designs and the solid line represents mean hypervolume indicator reached through the experiments.

5.4.2 Simplifying the decision-making process

5.4.2.1 Clustering the Pareto-front

Parallel axes plot visualisation techniques (Inselberg, 2009) have been widely used in multi-objective optimisation problems relating to water management and water infrastructure design to support decision-making and exploration of relationships between design goals (Geressu et al., 2020; Hurford et al., 2020; Seyedashraf et al., 2021b). However, Pareto-fronts lose clarity when they represent a dense set of optimisation solutions, making it difficult for decision-makers to analyse optimisation results based on their preferences. Besides, accurate visualisation of Pareto-fronts in optimisation problems involving multiple objectives is impossible. In this study, a decision-making framework for multi/many-objective SuDS optimisation is proposed that can be used to narrow down Pareto-fronts to a handful of design portfolios while preserving their distributional structure. To this end, design portfolios with similar trade-offs between optimisation objectives were grouped together using a data clustering technique to obtain a set of representative solutions. The clustering

algorithm determines partitions with homogeneous optimisation solutions while heterogeneity of their representative solutions is maximised. Most commonly used clustering algorithms are based on calculating distances between data points and cluster centres, including the k-mean (MacQueen, 1967) and fuzzy c-means (Bezdek, 1973). In this study, the fuzzy c-means clustering algorithm was used with its weighting factor and number of clusters to be determined based on a trial-and-error method that calculates the global silhouette index for each clustering scheme as a measure to evaluate quality of the generated clusters (X. Sun et al., 2015). The silhouette index, s, ranges between -1 and $+1$, where $s = +1$ implies that a solution is distant from other portfolios in the nearest partition, $s = -1$ indicates that the solution is assigned to a wrong partition, and $s = 0$ means that the solution is not distinctly assigned to a particular partition.

The global silhouette index, GS, is calculated as follows:

$$GS = \frac{1}{n_c}\sum_{j=1}^{n_c}\left(\frac{1}{n_{sd}}\sum_{i=1}^{n_{sd}} s(i)\right) \tag{5-10}$$

where n_{sd} is the number of SuDS designs in each cluster, and $s(i)$ is the silhouette index of the ith design solution defined as follows:

$$s(i) = \frac{D_b(i) - D_a(i)}{max\{D_a(i), D_b(i)\}} \tag{5-11}$$

where $D_a(i)$ and $D_b(i)$ are average distances of the ith SuDS design from other portfolios in the same and nearest clusters, respectively.

Here, it is assumed that the design portfolios are acceptable if the capital cost is lower or equal to $1.5\ \mathrm{M\$}$. Accordingly, any arrangement of weighting factors and numbers of clusters covering this range may be considered suitable to narrow down the Pareto-front. Figure 5-5 illustrates the trial-and-error process carried out to select

a fuzzy c-means clustering scheme that results in a maximum global silhouette index of around 0.68 with five clusters and a weighting factor of 2.

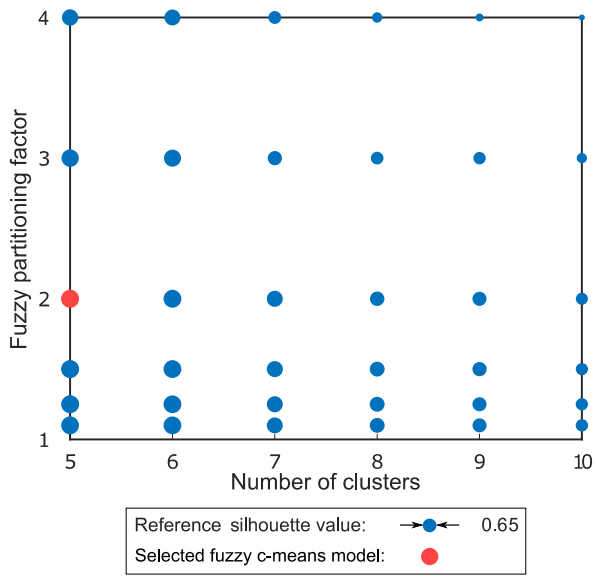

Figure 5-5. The trial-and-error process used to find an efficient clustering scheme to compress and categorise Pareto-optimal designs of sustainable urban drainage infrastructure. In this figure, marker sizes represent their global silhouette values where the larger a marker the more successful the clustering scheme.

Figure 5-6 depicts the 2D scatter plot of the primary Pareto-front (Figure 5-3) along with their synthetic cluster centres and cluster representatives (design portfolios nearest to the synthetic cluster centres). In this figure, the colour range indicates the extent to which portfolio designs belong to each cluster.

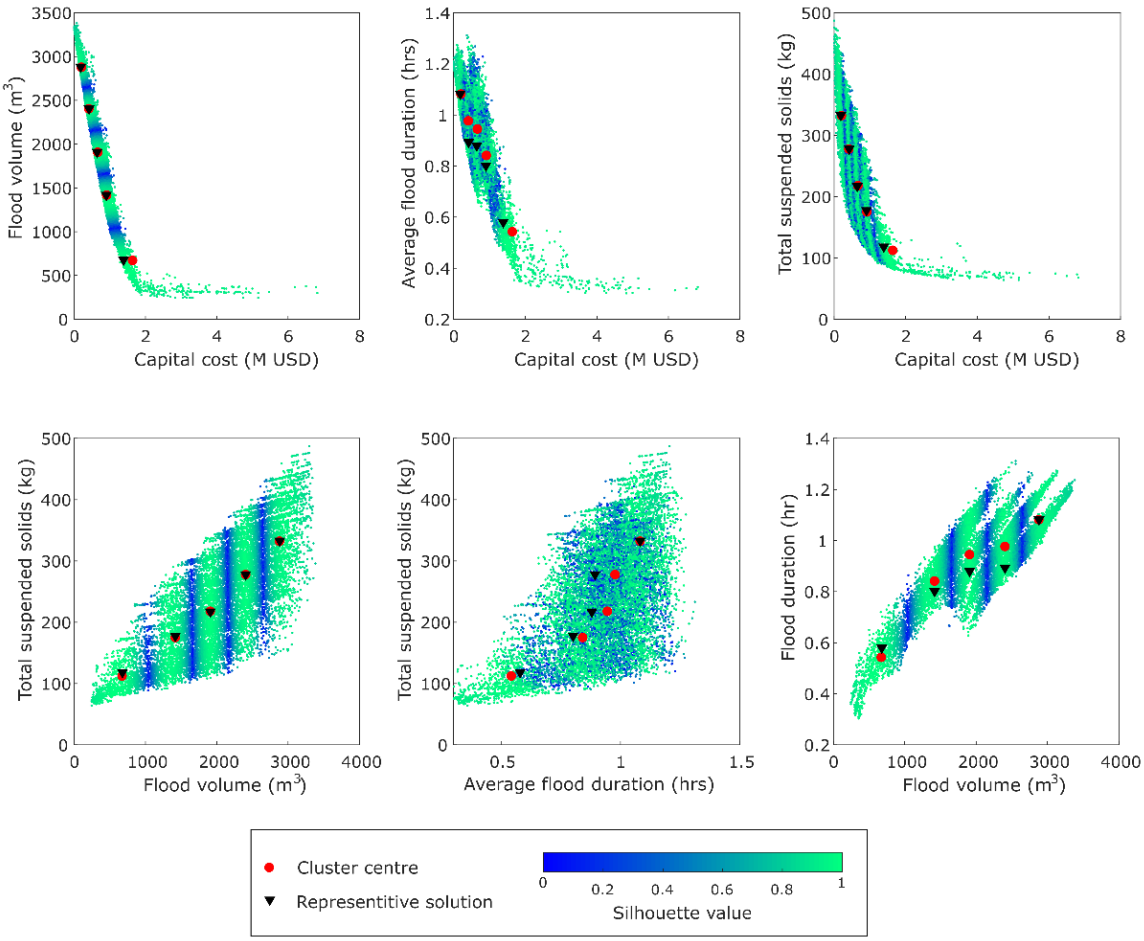

Figure 5-6. 2D scatter plot of Pareto-optimal designs of sustainable urban drainage infrastructure along with their cluster centres (red circle marks) and cluster representatives (black triangle marks). The colour range represents silhouette indices of the portfolios according to the clusters they belong to.

Figure 5-7 shows the overall trade-offs between optimisation objectives of the cluster representatives. In this figure, grey boxes are filters acting as postoptimisation constraints to reflect decision-makers' explicit preferences/requirements by removing undesired solutions from further evaluations. Here, each coloured line represents a particular cluster representative solution, dashed lines are SuDS designs that do not fit in the post-optimisation constraints, while the solid line is the final solution.

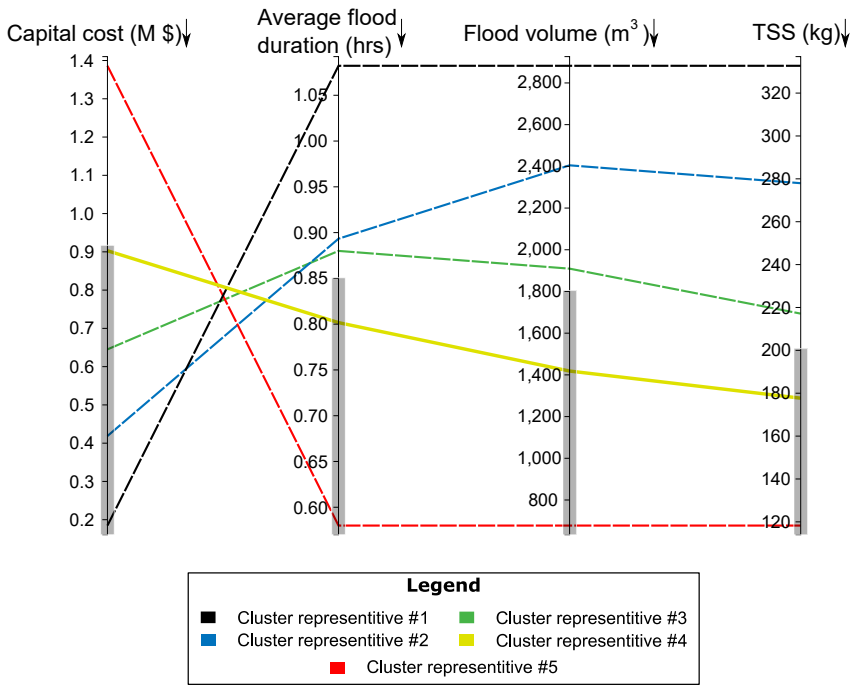

Figure 5-7. Parallel axes plot representation of the reduced Pareto-front where each coloured line represents a particular cluster representative, dashed lines are sustainable urban drainage system infrastructure designs that do not fit in the postoptimisation constraints while the solid line is the final solution. The arrows show direction of preference and grey boxes represent filters to eliminate undesirable solutions from further analysis.

This decision-making process is intrinsically based on subjectivity and dependant on decision-makers' previous experiences, which may potentially result in inconsistent decisions that lack repeatability and coherence (Duro et al., 2014). The assessment of the performance of the optimised portfolios can be aided by the decision support tools described in the following sections.

5.4.2.2 Overall performance metrics

To provide a measure of the overall performance of the Pareto-optimal solutions, three decision support metrics are introduced. These are defined based on normalised distances of objective function values from the minimum values obtained. The kth normalised objective in the ith solution, $\bar{F}_k(i)$, is defined as:

$$\bar{F}_k(i) = \frac{F_k(i) - F_{k,min}}{F_{k,max} - F_{k,min}}, \qquad k = 1, 2, \dots, 4 \;\; and \;\; i = 1, 2, \dots, 5 \qquad (5\text{-}12)$$

where $F_k(i)$ is the kth objective of the ith SuDS solution and $F_{k,\min}$ and $F_{k,\max}$ are the maximum and minimum values of the kth objective in the Pareto-front.

The overall performance of each design portfolio was quantified using the 1-norm ($\|N\|_1$), 2-norm ($\|N\|_2$), and the infinity norm ($\|N\|_\infty$) of the vectors of normalised objectives (Reynoso-Meza et al., 2013; Sánchez-Orgaz et al., 2015). In this chapter, the 1-norm $\|N\|_1$ corresponds to the summation of the normalised objectives for a particular design solution, and is calculated as follows:

$$\|N\|_1 = \sum_{k=1}^{n_{pt}} |\bar{F}_k| \tag{5-13}$$

where $\mathrm{n_{pt}}$ is the number of portfolios in the reduced front.

Alternatively, the 2-norm can be used to find the normalised Euclidian distance between a point in the objective function space and the point corresponding to the best objective function values obtained. The 2-norm is calculated as follows:

$$\|N\|_2 = \sqrt{\sum_{i=k}^{m} |\bar{F}_k|^2} \tag{5-14}$$

An alternative performance metric can be defined using the infinite norm, which gives the maximum value of the normalised objective functions in the available portfolios. This metric is helpful to find a solution with least-worst objective function values, i.e.:

$$\|N\|_\infty = max(|\bar{F}_1|, |\bar{F}_2|, |\bar{F}_3|, |\bar{F}_4|) \tag{5-15}$$

When put side by side in a parallel axes plot, these metrics can help decision-makers understand the overall performance of each portfolio and identify best solutions within their design preferences (Figure 5-8).

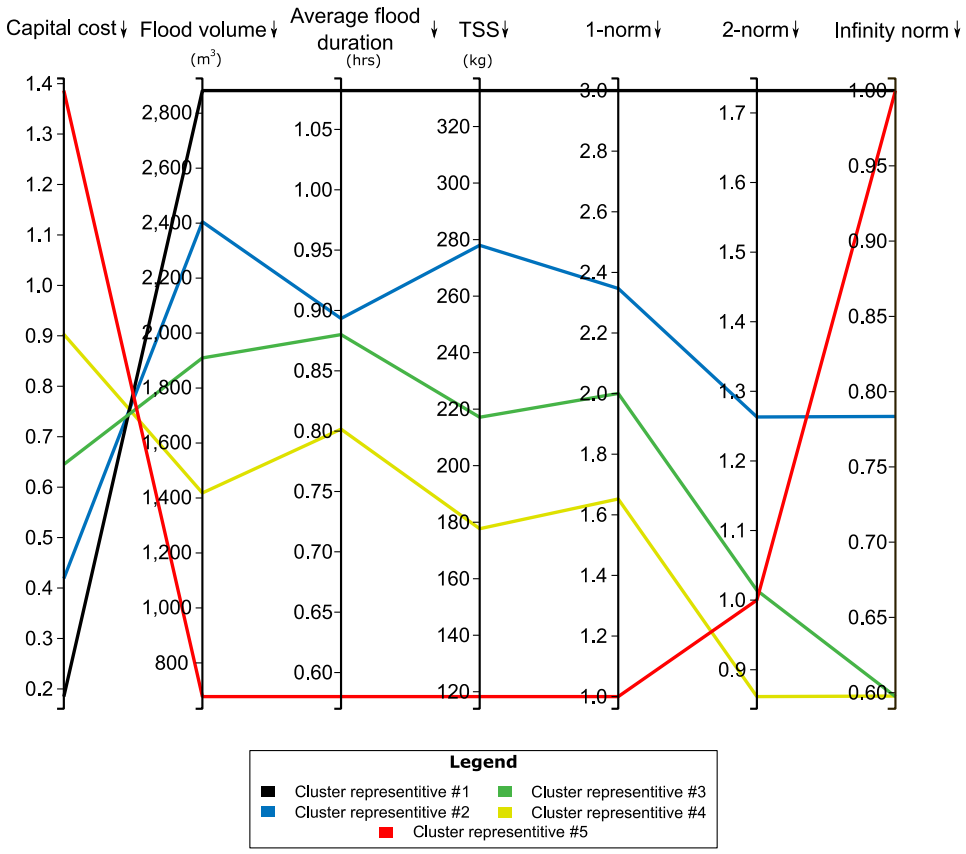

Figure 5-8. Parallel axes visualisation of Pareto-optimal sustainable urban drainage infrastructure designs. This figure illustrates trade-offs between the design objectives and ranks each portfolio in terms of its 1-norm, 2-norm, and infinity norm values. The arrows show direction of preference and each coloured line represents a particular cluster representative.

According to the results, the third cluster representative is a relatively economical design and its non-monetary objectives roughly fall in the middle of the vertical axes, which is consistent with its 1-norm value. Although the third and the fifth cluster representatives almost share identical 2-norm values there is a noticeable difference between their infinity norm values. The first and fifth portfolios include at least one worst-case objective value, and the second solution comprises objective values close to the worst-case values, as indicated by the infinity norm. Moreover, it can be seen that the fourth solution is 40% more costly compared to the third solution and performs best with respect to non-monetary objectives while sharing an identical infinity norm of 0.60.

5.4.2.3 Post-optimisation uncertainty analysis of design portfolios

Typically, decision-makers may be interested in knowing how their selected portfolio designs may perform under various scenarios, such as rainfall events with different intensities or durations. Besides, UDS may exhibit high degrees of performance uncertainty due to uncertainties in model parameters (N. Sun et al., 2014; Xu et al., 2020). Although model uncertainty can be considered in the optimisation process, it can dramatically increase the computational cost. Generally, there are two possible approaches to this issue: first, to use emulation models that mimic specific outputs of a drainage system with faster, although less accurate predictions (Mahmoodian et al., 2018; Owen & Liuzzo, 2019; Seyedashraf et al., 2021a); second, to perform a post-optimisation uncertainty analysis in order to quantify how robust the Pareto-optimal solutions are and how much the system performance can vary in response to variations in the model parameters (Paton et al., 2013, 2014; Singh & Minsker, 2008). In this chapter, the latter case is considered to gain insight into how Pareto-optimal sustainable urban drainage infrastructure designs operate under different rainfall events. Accordingly, system performance for the cluster representatives was evaluated for multiple 2-hour rainfall events corresponding to return periods of 2, 10, 100, and 200 years. A graphical representation of the system performance under the different scenarios is given in Figure 5-9.

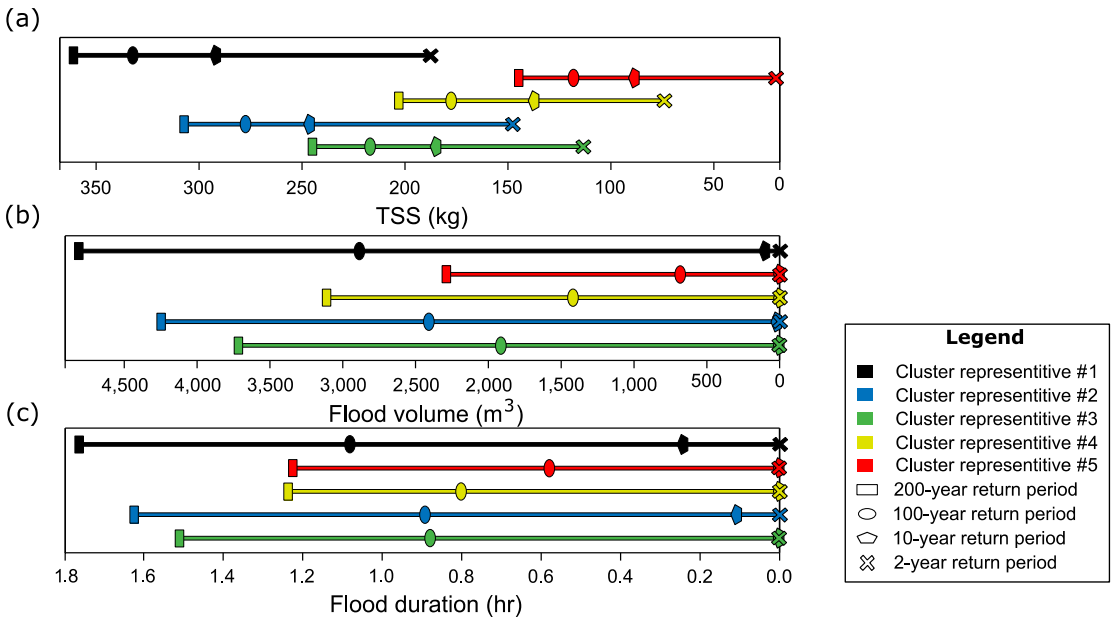

Figure 5-9. Post-optimisation uncertainty analysis of Pareto-front representatives under multiple rainfall scenarios, including 2-, 10-, 100-, and 200-years 2-hour rainfall events, to assess performance of the Pareto-optimal designs; to decrease the (a) TSS, (b) flood volume, and (c) flood duration, under different rainfall intensities.

The results of the post-optimisation uncertainty analysis imply that the first portfolio, followed by the second and third portfolios, have the largest variation in performance with respect to flood duration, flood volume, and TSS values, whereas the fourth and fifth portfolios are more robust and therefore likely to be preferable regardless of other decision parameters.

5.5 Conclusions

Multi/many-objective optimisation models have been increasingly used in sustainable urban drainage system design problems, which, typically result in large numbers of non-dominated solutions. However, decision-makers can only appraise performance of a few design portfolios, whereas the application of many-objective optimisation models generally results in a large number of candidate solutions. To address this issue, this chapter proposes a new decision-making framework for optimisation of sustainable drainage infrastructure design which systematically narrows down the number of solutions in a Pareto-front while preserving its multi-

dimensional structure. To this end, a soft clustering algorithm was applied that can group Pareto-optimal solutions based on their performance similarities. For each cluster, the non-dominated solution closest to the cluster centre is selected as the cluster representative. Moreover, a decision-making strategy was proposed to analyse and interpret the overall performance of the reduced Pareto-front in conjunction with a postoptimisation uncertainty analysis procedure to provide an indication of its future pathways in terms of rainfall uncertainties. The proposed methodology shows evidence that multi/many-objective optimisation models can be applied to sustainable urban drainage infrastructure design with a simplified yet consistent and repeatable decision-making approach.

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6 Chapter six: Summary, conclusions, and future work

6.1 Summary and conclusions

The purpose of this dissertation was to answer three major questions: 1) how to efficiently apply MOEAs to multi-criteria design of large SuDS where project investments are to be made on a portion of the drainage system only? 2) how to include spatial equity factors for design of sustainable urban drainage infrastructure using MOEAs? 3) how to simplify decision-making in many-objective optimisation of SuDS?

Several surrogate-based optimisation models have been proposed in the literature to speed up optimisation run for large UDS. These models generally operate by employing surrogate models to directly predict optimisation objectives in each function evaluation. However, in this way, prediction errors may accumulate over iterative calculations making optimisation solutions increasingly unreliable. This thesis, instead, proposes a novel optimisation approach based on surrogate modelling to disaggregate a large drainage system into two parts and optimise a portion of the system while the objective functions are still extracted from the corresponding numerical simulations. As an answer to the first question, the proposed framework allows users to numerically simulate stormwater drainage in the region of interest without solving network dynamics for the whole system. Using the proposed framework, surrogate modelling is only used to disaggregate the region of interest from the remaining part of the system while mapping changes in this part of the network to hydraulic head and inflow variations at the synthetic nodes shared with the remaining part of the network. The proposed framework significantly reduces computational cost of optimisation and also allows the user to extract extra information about the drainage process from the numerical simulations during and after the optimisation run.

In Chapter 2 of this thesis, it was shown that variations of surface slopes in urban areas can result in unbalanced spatial distribution of system services when using optimisation methods for SuDS design. To the best of the author's knowledge, no study has yet considered spatial equity in multi-objective optimisation of urban

drainage infrastructure. Chapter 3 of this thesis attempts to fill this research gap by answering the second question and by proposing a new optimisation framework that takes into account equity measures for design of SuDS. The framework combines traditional urban drainage system design goals, such as reducing capital costs and flood volume, with social goals, like lowering inequality in spatial distribution of flood risk and green infrastructure co-benefits. In this sense, new inequality factors are defined as objective functions to be minimised during an optimisation run aimed at reaching spatial equity in design of SuDS. It also proposes a post-optimisation criterion, which guarantees that differences in spatial distribution of flood damages between different neighbourhoods of the same city will not exceed the threshold defined by decision-makers.

Finally, Chapter 5 of this thesis answers the third question by exploiting clustering techniques to simplify and promote decision-making in multi-criteria design of SuDS. The framework makes it easier for decision-makers to analyse trade-offs between objective functions by reducing Pareto-fronts obtained from multi-objective optimisation of SuDS. To this end, a soft-clustering algorithm was applied to efficiently reduce Pareto-fronts with thousands of solutions to a handful of representative solutions. In this way, decision-makers can focus on a limited number of Pareto-optimal solutions that showcase the overall structure of a Pareto-front rather than dealing with thousands of design portfolios to single out a design portfolio.

6.2 Future work

The developed emulation-optimisation approach can be used more generally for optimisation, calibration, and/or trial-and-error analysis of traditional drainage systems, water distribution systems, and water resources networks. For example, future work could use the proposed approach for optimising design of water distribution networks by mapping changes in pipe diameters, as decision variables, to water flow conditions in synthetic cut-nodes defined as boundaries of a region of interest in the network. Future work could also apply the proposed framework to

optimise the design of large SuDS by partitioning them into a set of subregions and optimising them sequentially. Taking into account uncertainty in the proposed emulation-optimisation approach is another way to take forward the application of the presented study in this dissertation. For example, reformulating the developed system disaggregation approach based on different climate change scenarios requires further studies.

The proposed optimisation model, which takes into account equity factors for design of SuDS, can also be more generally applied to design of water distribution networks, and water resources management problems. For instance, the framework can be used in a similar way to improve spatial equity for controlling water quality and water pressure in water distribution systems to meet stakeholders' equity objectives. Besides spatial equity metrics, temporal equity measures can also be envisaged in multi-criteria design and refurbishment of UDS. This can be done by defining new objective functions that represent fair designs of UDS/SuDS both for current and future generations.

The Pareto-front clustering technique and post-optimisation track metrics introduced in Chapter 5 can be applied to a wider set of multi-objective optimisation applications in urban water infrastructure design and water resources management problems to simplify the decision-making process. Finally, future work could target adaptive optimisation of sustainable urban drainage infrastructure taking into account uncertainty of decision variables and model parameters.