Multiobjective Planning and Design of Distributed Stormwater Harvesting and Treatment Systems through Optimization and Visual Analytics

by

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Thesis submitted to The University of Adelaide,
Faculty of Engineering, Computer and Mathematical Sciences,
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in fulfilment of the requirements
for the degree of Doctor of Philosophy

Contents

Abstract

Stormwater harvesting (SWH) is an important water sensitive urban design (WSUD) approach that provides an alternate water source and/or improves runoff quality through stormwater best management practice technologies (BMPs).

Through integrated SWH system design at the development scale practitioners must account for trade-offs between cost, harvested volume, and water quality improvement performance which are usually dependent on design decisions for the type, size, and spatial distribution of BMPs. In catchment management planning, additional objectives such as catchment vegetation improvement and public recreation benefit need to be maximized for a catchment region within a limited budget. As such, planning and design of SWH systems with distributed BMPs is a complex problem that requires optimal allocation of limited resources to maximize multiple benefits.

In this thesis, two innovative formal optimization approaches are presented for formulating and identifying optimal solutions to problems requiring distributed BMPs.

Firstly, a multiobjective optimization framework is presented and applied to a case study for the conceptual design of integrated systems of BMPs for stormwater harvesting. The aim of this work is to develop a conceptual design modelling framework that handles the optimal placement of stormwater harvesting (SWH) infrastructure within an urban development. The framework produces preliminary SWH system designs representing optimal trade-offs between cost, water harvesting, and water quality improvement measures.

Secondly, a many (>3) -objective optimization framework is presented and applied to a case study for catchment planning requiring the selection of a portfolio of distributed BMP projects. The framework produces portfolios that are optimal with respect to four objectives, and enables exploration of the many-objective trade-off surface using interactive visual analytics. In addition, a multi-stakeholder method is presented, which enables catchment managers and local government authorities to identify solutions that represent a compromise between 16 objectives and eight optimization problem representations using interactive visual analytics to encourage a negotiated solution.

This thesis contains one paper accepted in the Journal of Water Resources Planning and Management (Paper 1), and one paper submitted (Paper 2), and one paper to be submitted (Paper 3) to peer-reviewed journals in the field of water resources management.

Statement of Originality

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

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Di Matteo, M., Dandy, G.C. & Maier, H.R., 2017. *Multiobjective optimization of distributed stormwater harvesting systems*. Journal of Water Resources Planning and Management, 10.1061/(ASCE)WR.1943-5452.0000756.

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Acknowledgements

Firstly, I would like to thank my supervisors, Em. Prof. Graeme Dandy and Prof. Holger Maier, for their supervision, support, and dedication during my PhD research. I thank Em. Prof. Graeme Dandy for his guidance, encouragement during periods of adversity, and insightful ideas throughout my candidature. I equally thank Prof. Holger Maier for his dedication to the quality of the research, determination and enthusiasm in helping me to complete this thesis.

I would like to thank Dr. Robin Allison (Senior Environmental Engineer, DesignFlow, Adelaide, Australia), Dr. Joshua Cantone (Product Manager, Optimatics, Chicago, USA), and Dr. Dale Browne (Senior Environmental Engineer, e2DesignLab, Melbourne, Australia) for their support involving the provision of data and technical assistance enabling innovative contributions to Water Sensitive Urban Design practice through this PhD research.

I am grateful to the Faculty of Engineering, Computer & Mathematical Sciences and Goyder Institute for Water Research for sponsoring my scholarship, opportunities to share my work with practitioners, and professional development.

I acknowledge my colleagues, Dr. Joanna Szemis and Mr. Jeffrey Newman, for their support in developing the initial optimization algorithms. I also acknowledge all staff and other postgraduate students in the School of Civil, Environmental and Mining Engineering for an especially memorable time during my candidature.

I am grateful to my friends for their encouragement, and I now look forward to seeing you much more often. And, to my mentors Danger and Tina I owe a great deal for providing feedback and supporting me during my candidature.

I would like to thank my parents (John and Dora Di Matteo), my brother (Andre Di Matteo), and my family for their unwavering encouragement, love and support. I am truly grateful to be a part of you, and will continue to make you proud. Finally, I would like to dedicate my work to my fiancé, Dr Kiana Kashefi, and thank her for her love and trust. She has brought a great joy to the final year of my candidature, and with her, God willing, I will continue to create and grow.

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List of Abbreviations

BATNA	Best Alternative To Negotiated Agreement
BMP	Best Management Practice
CAPEX	Capital Expenditure
CMA	Catchment Management Authority
LGA	Local Government Authority
NSGA II	Non-dominated Sorting Genetic Algorithm II
OPEX	Operational Expenditure
PACOA	Pareto Ant Colony Optimization Algorithm
PWF	Present Worth Factor
SWH	Stormwater Harvesting
TN	Total Nitrogen
TP	Total Phosphorous
TSS	Total Suspended Solids
WSUD	Water Sensitive Urban Design
WQ	Water Quality

Glossary

Best Management Practices (BMPs), or stormwater best management practices, are structural or non-structural technologies used to detain, harvest, infiltrate, evaporate, and transport urban stormwater runoff, and remove pollutants. BMPs in stormwater harvesting systems typically include wetlands, biofiltration devices, storage ponds, tanks, and basins located near runoff sources or near an integrated catchment outlet

Biofiltration systems (biofilters) are stormwater treatment devices that typically consist of a vegetated basin overlaying a geomembrane-lined or free-draining filter medium with a drainage pipe at the bottom. Water biofiltration is the process of improving water (stormwater and wastewater) quality by filtering water through biologically influenced media (Payne, Hatt et al., 2015).

Constraints can be either hard or soft. Hard constraints set firm limits on the values of the decision variables that are required to be satisfied or limit the possible solutions to the problem. Soft constraints have some decision variable values that are penalized in the **objective function** if certain conditions on the variables are not satisfied. The amount of the penalty can be fixed or can depend on the extent to which the condition is violated.

Decision variable is a quantity that the decision-maker controls.

Formal optimization refers to finding the best solution from all feasible solutions of a problem where the decision variables, objectives and constraints are mathematically formulated.

Many-objective optimization is an **optimization** problem with four or more objectives (Purshouse and Fleming 2007).

Multi-objective optimization (also multiobjective optimization) refers to an optimization problem with two or more objectives. Typically, the **Pareto front** consists of more than one solution, and as such trade-offs between objective function values often exist for **Pareto optimal solutions**.

Non-dominated solution is a member of a set of solutions where none of the objective functions can be improved in value without degrading one or more of the other objective values (Purshouse, Deb et al. 2014).

Objective function (formal objective) is a function of the decision variables that is to be maximised or minimised. It is usually expressed in mathematical terms.

Pareto optimal solution is a member of the **Pareto front**.

Pareto front (sometimes called **non-dominated solution** set, or **Pareto optimal solution** set), is the set of **non-dominated solutions** to a **multi-objective optimization** problem. A solution is sometimes called non-dominated, Pareto optimal, Pareto efficient or noninferior if it is a member of the Pareto front.

Sediment basins are deep open-water ponds designed to facilitate settlement of suspended particles from stormwater runoff.

Swales are linear, depressed channels that collect and transfer stormwater. They can be lined with grass or more densely vegetated and landscaped. Swales can provide physical screening of sedimentation (coarse and fine) and/or infiltrate stormwater into soils.

Visual Analytics is "an iterative process that involves information gathering, data preprocessing, knowledge representation, interaction and decision making. The ultimate goal is to gain insight in the problem at hand which is described by vast amounts of data from heterogeneous sources (Keim, Andrienko et al. 2008)."

Water Sensitive Urban Design (WSUD), in Australia, is "commonly used to reflect the paradigm in the planning and design of urban environments that is 'sensitive' to the issues of water sustainability and environmental protection." In particular, it pertains to the "interactions between the urban built form (including urban landscapes) and the urban water cycle (as defined by the conventional urban water streams of potable water, wastewater, and stormwater) (Wong 2006)." Similar concepts include Sustainable Drainage Systems (SuDS), used in the United Kingdom, and Low Impact Development (LID), used in the United States.

Wetlands (constructed wetlands) are shallow, extensively vegetated basins that use enhanced sedimentation, fine filtration and pollutant uptake processes to remove runoff pollutants.

CHAPTER 1

Introduction

The future economic, environmental and social prosperity of urban environments hinges upon effective management of urban water sources (Walsh, Fletcher et al. 2005). Demand for clean water supply in urban areas increases with urban population growth, resulting in water shortages and other supply security risks (Cook and Bakker 2012). In addition, urban stream health is degraded by untreated stormwater runoff from developed areas. This is due to increased generation of pollutants through urban land use and pollutant mobilisation and transport of runoff volumes along impervious drainage channels (Wong 2006). Urban stream health is further impacted by increases in the volume of runoff and alteration to the pre-development flow regime that comes with the introduction of paved surfaces. The impact of urban development is influential at multiple spatial scales. These may range from degraded stream health within developments, to the introduction of nutrients into marine bodies receiving flows from a large regional catchment, and local to city-wide water supply security. Consequently, urban water management strategies need to mitigate multiple economic, environmental and social impacts targeted at multiple spatial scales where possible.

1.1 Background on Water Sensitive Urban Design (WSUD) systems

Modern urban stormwater management approaches, such as Water Sensitive Urban Design (WSUD), including similar concepts such as Sustainable Drainage Systems (SuDS) and Low Impact Development (LID), aim to mitigate impacts of development on urban water sources (Askarizadeh, Rippy et al. 2015). To achieve this, WSUD uses integrated systems of structural and non-structural stormwater best management practice technologies (BMPs) for detention, harvesting, infiltration, evaporation, and transport of urban runoff (Lerer, Arnbjerg-Nielsen et al. 2015). An increasingly popular WSUD technique is urban stormwater harvesting (SWH), which is used to capture, store, treat and distribute surface stormwater runoff for later reuse (Mitchell, Deletic et al. 2007). SWH can provide a cost-effective and reliable alternative water supply source for irrigation that reduces stormwater runoff volumes and complements existing (often stressed) water supplies (Clark, Gonzalez et al. 2015, Marchi, Dandy et al. 2016). SWH systems comprise BMPs that detain, harvest, infiltrate, evaporate, and transport urban runoff, and remove pollutants. BMPs in SWH systems typically include wetlands, biofiltration devices, storage ponds, tanks, and basins located near runoff sources or near an integrated catchment outlet (Askarizadeh, Rippy et al. 2015).

BMPs integrated into the urban environment though WSUD approaches can provide multiple human and ecosystem co-benefits (Mitchell, Deletic et al. 2007). Given the possibility to maximize multiple benefits, objectives for WSUD planning and design approaches include i) minimizing economic costs (Taylor and Wong 2002); ii) maximizing the volume of harvested water, which can improve urban water supply (Clark et al. 2015); iii) maximizing improvements in urban flow regimes by restoring stormwater a) runoff quality and b) the streamflow regime (base flow, peak flow, annual runoff volume, and flow variability) to be closer to pre-development conditions, thereby promoting urban stream health (Askarizadeh, Rippy et al. 2015); and iv) maximizing social benefits (Mitchell, Deletic et al. 2007), such as public amenity, community acceptance, recreation, and reduced construction risks (Inamdar 2014, Sharma, Pezzaniti et al. 2016). Which of the above objectives should be considered is case study specific and generally determined through stakeholder consultation (for example, between regulators, land developers, designers and the local community). In many instances, the above objectives are in conflict with one another, necessitating decision-makers to consider trade-offs between objectives when assessing the performance of WSUD systems.

1.2 Multiobjective optimization for planning and design of WSUD systems

Despite the potential to achieve multiple benefits using WSUD approaches, there are always limited resources to achieve them. Compounding this difficulty are the multiple possible spatial scales at which BMPs can be distributed throughout a catchment, the large number of different types of system components and interaction between components, and the large number of decision options (e.g. size, type and location of BMPs) and therefore large number of possible solutions. Therefore, many WSUD planning and design tasks can be formulated as multiobjective optimization problems (Purshouse and

Fleming 2007, Purshouse, Deb et al. 2014), where a set of decisions needs to be selected to achieve multiple objectives (including minimizing cost) that meet a set of practical constraints. There are a multitude of problems, at varying spatial scales, that need to be considered in the planning and design of WSUD systems, and it is difficult to select an optimal management solution that maximizes benefits. The particular problems addressed in this thesis, and their features, are as follows:

1. Optimizing stormwater harvesting systems design. Designing systems of BMPs for stormwater management, including harvesting, is complex because practitioners need to consider:
    a. multiple, often competing, objectives
    b. different types of system components
    c. the spatial distribution of components
    d. a large number of design options.
2. Integrated catchment plan optimization. The issues with complex BMP systems are compounded where multiple BMP systems distributed over a large region need to be selected for a management strategy, for example in an integrated catchment management plan to achieve multiple regional catchment objectives. Decision support approaches for catchment management should be able to:
    a. handle several objectives
    b. consider the full trade-off space of possible solutions
    c. develop "trusted" solutions based on current modelling practice.
3. Optimization involving multiple stakeholders. Where multiple stakeholder groups are responsible for the funding and operation of BMP systems over a large region, it is difficult to identify catchment plans that compromise the costs and benefits between all parties equitably, which encourages 'buy-in' into the adopted solution. Adapting decision-making approaches, in particular optimization approaches, to account for different stakeholder groups is difficult because:
    a. stakeholders have different value sets and interests, making it difficult to arrive at a consensus on one mathematical formulation that all stakeholders will accept, which may affect how likely it is that

stakeholders will trust the optimization process and buy-into suggested solutions

b. exploration and analysis of optimization solutions should enable stakeholder engagement and expert input

c. the non-intuitive nature of multi-dimensional value analysis and unanticipated and emergent trends can further prevent decision-makers from understanding and trusting optimization results

d. the optimization framework used should facilitate a final negotiated outcome and/or exploration of resource management alternatives to be considered further.

The challenges identified in the previous optimization and decision support literature addressing these three problems, and opportunities for solving them in new ways, are discussed in more detail below.

1.2.1 Optimizing stormwater harvesting systems design

Considering the design of stormwater harvesting systems, given the large number of types of system components, the many different ways in which they can be distributed spatially and the large number of available design choices, it is difficult to identify distributed BMP planning and design outcomes that are optimal with respect to the desired competing objectives. Consequently, there is a need for an integrated framework that considers all of the above factors in a holistic fashion. Given the potentially large number of options, incorporation of a formal optimization approach (for example, using an optimization algorithm) in such a framework is also likely to be of significant value. However, previous studies in this field are limited, have not presented an integrated approach, and have only considered a subset of the above factors. For example, Sample and Heaney (2006) considered the impact on net present value of the size and spatial distribution of integrated infiltration basins and irrigation systems, but did not consider multiple objectives, nor a formal optimization approach. While Browne, Breen et al. (2012) and Inamdar (2014) considered multiple objectives in conjunction with a range of BMP alternatives for various SWH projects within a region, they also did not utilize formal optimization approaches, making it unlikely that the solutions that provide the best trade-offs among objectives were identified. In contrast, Marchi, Dandy et al. (2016) used a formal multiobjective optimization technique to design surface runoff SWH system components (the dimensions of a wetland, detention basins, and aquifer storage transfer infrastructure). However, they did not consider how trade-offs were influenced by a mix of different BMP alternatives for the capture, treatment, and storage of surface runoff, optimal locations for BMPs within a catchment, or water quality improvement as a formal objective. Formal optimization methods have also been used to identify the optimal mix, size, and location of distributed BMPs (Perez-Pedini, Limbrunner et al. 2005, Maringanti, Chaubey et al. 2009, Lee, Selvakumar et al. 2012), but these studies have not considered SWH.

1.2.2 Integrated catchment plan optimization

For integrated catchment management planning, decision support approaches need to handle several objectives, consider the full trade-off space, and develop trusted solutions based on current modelling practice. However, current approaches have failed to meet all of these needs. While existing multi-criteria decision analysis (MCDA) (Goicoechea, Hansen et al. 1982, Hyde and Maier 2006) methods allow many performance criteria to be considered when selecting a portfolio of BMPs (Ellis, Deutsch et al. 2006, Moglia, Kinsman et al. 2012, Jia, Yao et al. 2013, Aceves and Fuamba 2016a, Aceves and Fuamba 2016b), and have been accepted in practice (Moglia, Kinsman et al. 2012), they require decision-makers to define their preferences without knowledge of the full-trade-off patterns between portfolios. Many-objective optimization approaches (Purshouse and Fleming 2007) overcome this limitation since they produce an approximation of the Pareto front (i.e. solutions to the problem where none of the objective functions can be improved in value without degrading one or more of the other objective values (Purshouse, Deb et al. 2014)), which allows an exploration and analysis of a large number of portfolios to identify solutions that represent a desirable compromise between performance criteria. However, many-objective optimization approaches can be computationally expensive and produce a large number of solutions to select from (Purshouse and Fleming 2007, Purshouse, Deb et al. 2014), which is why existing catchment management simulation-optimization approaches have considered only a limited number of objectives including cost and water quality improvement (Lee, Selvakumar et al. 2012, Chichakly, Bowden et al. 2013, Chen, Qiu et al. 2015, Zou, Riverson et al. 2015). In addition, simulation-optimization based approaches may not be feasible within a catchment management authority's planning capacities (Moglia, Kinsman et al. 2012), complementary to existing practices, nor desirable if decision-makers do not trust the solutions developed by the optimization algorithm.

Furthermore, while it is important to consider many objectives, as well as trade-offs between them (rather than having pre-defined weights, as in MCDA), this makes the analysis of many-objective optimization results difficult. This is because: (1) visualizing the trade-offs between objectives in more than three dimensions can be cumbersome, (2) many-objective Pareto fronts can have large numbers of non-dominated (i.e. none of the objective functions can be improved in value without degrading one or more of the other objective values) solutions, as the number of Pareto optimal solutions grows exponentially with the number of formal objectives (Hughes 2005, Keim, Andrienko et al. 2008), (3) human decision makers have a limited cognitive load and can select between only a small number of solutions at a time (Miller 1956); this requires techniques to reduce the Pareto frontier to a sub-set of diverse and promising solutions to present to decision-makers, and (4) visualizing solution performance separately from decision options may cause decision maker biases (Kasprzyk, Reed et al. 2012, Giuliani, Herman et al. 2014, Matrosov, Huskova et al. 2015). Recently, advanced interactive visual analytics (Keim, Andrienko et al. 2008) approaches have been applied to help humans make sense of large and complex data sets such as those generated by many-objective optimization (Kasprzyk, Reed et al. 2009). However, these approaches have not been applied in the catchment management optimization literature.

1.2.3 Optimization involving multiple stakeholders

In previous research, there has been little focus on adapting optimization frameworks to make them useful for stakeholder groups in real-life problem solving (Maier, Kapelan et al. 2014). However, there has been some progress in relation to this in recent years, including:

- The use of iterative approaches, which has allowed for multiple formulations of the decision variables, objectives and constraints to be developed to progressively better define optimization problems and provide an opportunity for stakeholders to learn about the problem (Kollat and Reed 2007, Woodruff, Reed et al. 2013, Piscopo, Kasprzyk et al. 2015, Wu, Maier et al. 2016).

- The development of an optimization framework that provides opportunities for stakeholders to provide input into the various stages of optimization studies, including problem definition, the optimization process, and final decision-making (Wu, Maier et al. 2016).
- The development of many-objective optimization approaches, as a result of advances in optimization algorithm performance, which identify solutions to complex problems that represent the optimal trade-off between numerous (>3) objectives to better capture stakeholder values (Kollat, Reed et al. 2011, Kasprzyk, Reed et al. 2012, Woodruff, Reed et al. 2013, Cruz, Fernandez et al. 2014, Chand and Wagner 2015, Hadka, Herman et al. 2015, Matrosov, Huskova et al. 2015, Borgomeo, Mortazavi-Naeini et al. 2016, Woodruff 2016).
- The use of visual analytics approaches to better communicate the outputs of optimization studies to stakeholders to help with exploration and analysis of the trade-offs between objectives, to identify the impact of decisions on performance, and ultimately select trusted solutions for further consideration (Kollat and Reed 2007, Kollat, Reed et al. 2011, Woodruff, Reed et al. 2013, Hadka, Herman et al. 2015, Matrosov, Huskova et al. 2015, Borgomeo, Mortazavi-Naeini et al. 2016, Woodruff 2016). Visual analytics approaches can include the use of interactive software package that allows multiple visualisations of the same data set in high-dimensional plots. This enables the data set to be explored and analysed rapidly. Techniques to explore and analyse data include dynamic filtering to eliminate undesirable solutions, interactive brushing, and multiple linked plots,

These advances have made optimization approaches more applicable to complex, real-world problems with multiple stakeholders and many objectives. However, in previous studies, the optimization problem to be solved has generally been represented by a single formulation, including all decision variable options, objectives and constraints deemed to be important. This can result in the inclusion of a large number of objectives and decision variable options, making it difficult to identify solutions that represent the best trade-offs between objectives (i.e. the solutions on the Pareto front), as mentioned in the previous section. This is because the number of solutions required to characterise the Pareto front increases exponentially as the number of objectives increases, thus making this process very computationally expensive and beyond the capability of current optimization algorithms (Cruz, Fernandez et al. 2014, Purshouse, Deb et al. 2014). In addition, despite the recent advances in visual analytics approaches mentioned above, the inclusion of a large (e.g. >10) number of objectives makes the identification of solutions that provide acceptable trade-offs for different stakeholders extremely difficult, as this can be cognitively challenging for decision-makers faced with large solution sets (Purshouse and Fleming 2007).

In order to address the above difficulties, an innovative approach for identifying stakeholder-driven, optimal compromise solutions is proposed for problems with distinct stakeholder groups with potentially competing sets of objectives. An example of this would be the integrated management of a river system and its catchment, where the objectives of stakeholders managing separate sub-areas of the catchment would most likely be different from each other, and different from those of stakeholders concerned with managing the catchment as a whole. For example, stakeholders may weigh the importance of water quality, runoff volume and volume harvested differently. As part of the proposed approach, the overall optimization problem is represented as a series of smaller, interconnected optimization problems, reflecting individual stakeholder sets and interests. The Pareto optimal solutions resulting from this analysis provide the input into a collaborative, multi-stakeholder negotiation process, as part of which visual analytics are used to identify trusted and accepted compromise solutions. A key feature of the proposed approach is the use of 'best alternative to negotiated agreement (BATNA)' solutions as a benchmark during the collaborative negotiation process. These are the solutions that individual stakeholder groups would implement if they were to act in isolation. This has been shown to increase the efficiency with which negotiated compromise solutions can be achieved (Fitzgerald and Ross 2013, Fitzgerald and Ross 2015, Fitzgerald and Ross 2016).

1.3 Research objectives

In order to address the problems outlined above, this thesis develops general optimization frameworks for the selection of stormwater best management practices (BMPs), firstly for the optimal preliminary design of stormwater harvesting systems and secondly for selecting a portfolio of BMPs for an integrated catchment management plan.

As part of the frameworks, mathematical optimization formulations are presented and are solved using multiobjective metaheuristic algorithms. Visual analytics approaches are used to identify trade-offs in objective and decision spaces. Furthermore, a multi-stakeholder optimization framework is presented, which uses visual analytics to assist with determining a negotiated solution to a complex integrated catchment management problem. Overall, this study has the following three main objectives:

Objective 1: To develop a generic multiobjective optimization framework for conceptual design of stormwater harvesting systems with components distributed throughout a development-scale catchment (Paper 1).

Objective 2: To develop a generic optimization framework for selecting a portfolio of stormwater best management practices (BMPs) to assist in regional integrated catchment management decision-making (Papers 2 and 3).

Objective 2.1: To present a formal optimization approach that identifies the best combinations of BMPs for many (> 3) objective integrated catchment planning (Paper 2).

Objective 2.2: To implement the optimization framework in Objective 2.1 in a multi-stakeholder optimization-visualisation framework that is geared towards the identification of negotiated compromise solutions for problems with multiple stakeholders with distinct sets of objectives (Paper 3).

Objective 3: To evaluate the utility of the frameworks in Objectives 1 and 2 by applying them to relevant case studies (Papers 1, 2 and 3).

Objective 3.1: To apply the framework in Objective 1 to a case study for stormwater harvesting system design for a new housing development in Northern Adelaide, South Australia (Paper 1).

Objective 3.2: To apply the framework in Objective 2.1 to a real-world case study based on a single-stakeholder integrated catchment management plan for a major city in Australia (Paper 2).

Objective 3.3: To apply the framework in Objective 2.2 to a real-world case study based on a multi-stakeholder integrated catchment management plan for a major city in Australia (Paper 3).

1.4 Thesis overview

This thesis is organized into five chapters, with the main contributions being presented in Chapters 2 to 4. Each of these chapters is presented in the form of a technical paper. The first of these (**Chapter 2**) has been published in Journal of Water Resources Planning and Management.

Chapter 2 introduces a generic framework for the conceptual design of SWH systems that considers multiple objectives, a range of BMP types and their design options, the spatial distribution of BMPs, and a formal optimization approach for identifying designs that represent near-globally optimal trade-offs among competing objectives in an integrated fashion (Objective 1). The utility of the framework is then illustrated (Objective 3) by applying it to a case study SWH system for a residential development in Adelaide, South Australia (Objective 3.1).

Chapter 3 introduces an optimization framework for many-objective (i.e. >3 objective) integrated catchment management (Objective 2) for a single catchment management authority. This features the use of an interactive visual analytics approach to identify promising solutions. The utility of the approach is demonstrated on a case study for an integrated catchment management plan for a region of a major Australian city (Objective 3.1 and 3.2). The case study is used to demonstrate the benefits of the approach by investigating the possible many-objective trade-offs between lifecycle cost, water quality improvement, stormwater harvesting capacity and urban vegetation and amenity improvement, and the importance of a many-objective approach compared to a bi-objective water quality-cost optimization, as has been undertaken in previous studies (Objective 3.2).

Chapter 4 introduces an optimization-visual analytics framework for complex environmental management problems (Objective 2) involving multiple stakeholders (Objective 2.2), incorporating the optimization approach developed in **Chapter 3**. In the approach, the problem is represented as a series of smaller, interconnected optimization problems, reflecting individual stakeholder sets and interests. The approach features interactive visual analytics used to explore and analyse optimization results, and an approach to reframe visualizations to encourage stakeholder negotiation. To demonstrate the utility of the framework, it is applied to a realistic case study which involves multiple stakeholder groups funding different parts of BMP projects for an integrated catchment plan for a region of a large city in Australia (Objective 3.3).

The linking of each of the papers to the objectives is shown in Table 1-1. The scale of WSUD implementation, optimization problem addressed, method for visualization of optimization results used, case studies considered, algorithms used, simulation models used, and case study formal optimization objectives considered, and number of objectives considered in each of the papers are summarised in Table 1-2. Although the manuscripts have been reformatted in accordance with University guidelines, and sections renumbered for inclusion within this thesis, the material within these papers is otherwise presented herein as published (or submitted for publication). A copy of the first paper "as published" is provided in Appendix A.

Conclusions of the research within this thesis are provided in **Chapter 5**, which summarises: 1) the research contributions, 2) limitations and 3) future directions for further research.

Table 1-1 Linking of each of the papers to the objectives

	Objectives	Paper 1	Paper 2	Paper 3
1	To develop a generic multiobjective optimization framework for conceptual design of stormwater harvesting systems with components distributed throughout a development-scale catchment.	X		
2	To develop a generic optimization framework for selecting a portfolio of stormwater best management practices (BMPs) to assist regional integrated catchment management decision-making.		X	X
2.1	To present a formal optimization approach that identifies the best combinations of BMPs for many (> 3) objective catchment planning.		X	
2.2	To implement the optimization framework in Objective 2.1 in a multi-stakeholder optimization-visualisation framework that is geared towards the identification of negotiated compromise solutions for problems with multiple stakeholders with distinct sets of objectives.			X
3	To evaluate the utility of the frameworks in Objectives 1 and 2.	X	X	X
3.1	To apply the framework in Objective 1 to a case study for stormwater harvesting system design for a new housing development in Northern Adelaide, South Australia	X		
3.2	To apply the framework in Objective 2.1 to a real-world case study based on a single-stakeholder integrated catchment management plan for a major city in Australia.		X	
3.3	To apply the framework in Objective 2.2 to a real-world case study based on a multi-stakeholder integrated catchment management plan for a major city in Australia.			X

Table 1-2 Classification of the papers by the different topics addressed

Category	**Sub-category**	**Paper 1**	**Paper 2**	**Paper 3**
Spatial Scale	Development	X		
	Regional		X	X
Optimization Problem	Stormwater harvesting systems design	X		
	Integrated catchment management (single stakeholder)		X	
	Integrated catchment management (multiple stakeholders)			X
Visualisation of Results	Multi-dimensional plots	X	X	X
	Interactive visual analytics		X	X
Case Study	Northern Adelaide, South Australia	X		
	Major Australian city (undisclosed)		X	X
Multiobjective Optimization Algorithm	Non-dominated Sorting Genetic Algorithm II (NSGA-II)	X		
	Pareto Ant Colony Optimization Algorithm (P-ACO)		X	X
Simulation Model	eWater *MUSIC* (integrated stormwater model)	X	X	X
	WSUD LifeCycle Cost Model	X	X	X
Case Study Optimization Objectives	Cost	X	X	X
	Stormwater harvesting capacity	X	X	X
	Water quality improvement	X	X	X
	Urban vegetation and amenity improvement		X	X
Number of Formal Optimization Objectives	Three objectives	X		
	Four objectives		X	
	Sixteen objectives			X

CHAPTER 2

Paper 1 - Multiobjective Optimization of Distributed Stormwater Harvesting Systems (Accepted paper)

Statement of Authorship

Statement of Authorship

Title of Paper	Multiobjective Optimization of Distributed Stormwater Harvesting Systems
Publication Status	☑ Published ☐ Accepted for Publication ☐ Submitted for Publication ☐ Unpublished and Unsubmitted work written in manuscript style
Publication Details	Di Matteo, M., Dandy, G.C. & Maier, H.R., 2016. *Multi-objective optimization of distributed stormwater harvesting systems*. Journal of Water Resources Planning and Management, in press.

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Overall percentage (%)	85		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
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By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Abstract

Stormwater harvesting (SWH) is an important water sensitive urban design (WSUD) approach that provides an alternate water supply source and improves runoff quality through integrated systems of stormwater best management practice (BMP) technologies. In SWH system design, practitioners must account for trade-offs between cost, supply volume, and water quality improvement performance, which are dependent on design decisions for the type, size, and spatial distribution of BMPs. As such, design of SWH systems with distributed BMPs is a complex, multiobjective optimization problem with a large decision space. This paper presents a multiobjective optimization framework to assess trade-offs in spatially distributed SWH system designs. The framework was applied to a case study for a housing development in Adelaide, South Australia. Results illustrated the potential benefits of distributing BMPs in an integrated SWH system where space at the catchment outlet is limited. Trade-offs between volumetric reliability and total suspended solids (TSS) reduction indicate large gains in TSS reduction can be achieved with limited reduction in volumetric reliability. Concept designs in low-cost/moderately reliable and low-cost/high TSS reduction trade-off regions contained biofilters in locations receiving large inflows.

Author Keywords: stormwater harvesting, optimization, BMP, biofilter, wetland, water-sensitive urban design (WSUD), sustainable drainage systems (SuDs), low impact development (LID), green infrastructure, genetic algorithm, *MUSIC*

2.1 Introduction

Recently, the application of Water Sensitive Urban Design (WSUD) has demonstrated an ability to mitigate the impacts of development on urban water supply security and natural ecosystem health (Askarizadeh, Rippy et al. 2015). An increasingly popular WSUD technique is urban stormwater harvesting (SWH), which is used to capture, treat, store and distribute surface stormwater runoff for later reuse (Mitchell, Deletic et al. 2007). SWH can provide a cost-effective and reliable alternative water supply source for irrigation that reduces stormwater runoff volumes and complements existing (often stressed) water supplies (Clark, Gonzalez et al. 2015, Marchi, Dandy et al. 2016). SWH systems are comprised of best management practice (BMP) technologies that detain, harvest, infiltrate, evaporate, and transport urban runoff, and remove pollutants. BMPs in SWH systems typically include gutters, pipes, drainage channels, wetlands, biofiltration devices, storage ponds, tanks, and basins located near runoff sources or near an integrated catchment outlet (Askarizadeh, Rippy et al. 2015). Although SWH systems can incorporate flood control measures (Mitchell, Deletic et al. 2007), peak flood flows typically bypass SWH system components that are designed separately for water quality control. Planning and designing urban SWH systems is complex because practitioners need to consider: i) multiple, often competing, objectives; ii) different types of system components; iii) the spatial distribution of these components; and iv) a large number of design options, as detailed below.

Potential SWH system design objectives include: i) minimizing costs (Taylor and Wong 2002); ii) maximizing the volume of harvested water, which can improve urban water supply (Clark, Gonzalez et al. 2015); iii) maximizing the amount of pollutant removed, which is achieved by treating stormwater prior to harvesting, and by removing pollutants in the harvested water supply; iv) maximizing improvements in urban hydrology by restoring stormwater runoff quality and the streamflow regime (e.g., base flow, peak flow, annual runoff volume, and flow variability) closer to pre-development conditions, thereby promoting urban stream health (Askarizadeh, Rippy et al. 2015); and v) maximizing social benefits (Mitchell, Deletic et al. 2007), such as public amenities, community acceptance, recreation, and reducing construction risks (Inamdar 2014). Which of the above objectives are considered and which are prioritized is site specific and generally determined through stakeholder consultation (for example, between regulators, land developers, designers and the local community). In many instances, the above objectives are in conflict with one another, necessitating decision-makers to consider trade-offs between objectives when assessing the performance of SWH systems.

As far as the design components of SWH systems are concerned, these include: BMPs to capture, treat, and store raw harvested runoff; and infrastructure to further treat and distribute harvested stormwater to end users. The BMP type and size can influence: the volume of runoff captured for harvesting; evapotranspiration and infiltration losses, which affect supply capacity; and pollutant control performance and harvested water quality, which depends on BMPs operating within a preferable hydraulic loading range per unit area that varies for different pollutants. The infrastructure required to transport treated runoff will depend largely on site constraints and locations for balancing storage, advanced treatment and distribution. The end use of harvested water, and its associated risks (e.g. health, environmental), often drive decisions on the final harvested water quality and thus the level of treatment required.

In relation to the spatial distribution of components, the optimal placement of distributed BMPs is complex (Perez-Pedini, Limbrunner et al. 2005). BMP performance is a function of catchment connectivity, land use type, catchment size, distance to channels, connected impervious area, and level of pre-treatment in contributing catchments (Perez-Pedini, Limbrunner et al. 2005, Sample and Liu 2014). BMPs at locations closer to catchment outlets must be able to treat larger volumes of runoff efficiently (Lee, Selvakumar et al. 2012). However, the treatment effectiveness of BMPs can decrease with increasing inflow rates and pollutant concentrations. In addition, at sites where limited area is available to capture, treat and store harvested water, supply capacity can be limited (Marchi, Dandy et al. 2016). Consequently, distributing BMPs throughout a catchment can increase treatment and storage capacity of SWH systems.

With respect to design options, for the various types of treatment BMPs, surface area is typically the most important design parameter influencing cost and performance. The selection of optimal BMP basin side slope, depth, and transfer infrastructure design parameters can also be important (Marchi, Dandy et al. 2016), however, ranges for these parameters are typically constrained based on best practice guidelines.

Given the large number of types of system components, the many different ways in which they can be distributed spatially and the large number of available design choices, it is difficult to identify distributed SWH designs that are optimal with respect to the desired competing objectives. Consequently, there is a need for an integrated framework for the conceptual design of SWH systems that considers all of the above factors in a holistic fashion. Given the potentially large number of options, incorporation of a formal optimization approach in such a framework is also likely to be of significant value. However, existing studies in this field have not presented such an approach and have only considered a subset of the above factors. For example, Sample and Heaney (2006) considered the impact on net present value of the size and spatial distribution of integrated infiltration basins and irrigation systems, but did not consider multiple objectives, nor a formal optimization approach. While Browne, Breen et al. (2012) and Inamdar (2014) considered multiple objectives in conjunction with a range of BMP alternatives for various SWH projects within a region, they also did not utilize formal optimization approaches, making it unlikely that the solutions that provide the best trade-offs among objectives were identified. In contrast, Marchi, Dandy et al. (2016) did use a formal multiobjective optimization method to design surface runoff SWH system components (the dimensions of a wetland, detention basins, and aquifer storage transfer infrastructure). However, they did not consider how trade-offs were influenced by a mix of different BMP alternatives for the capture, treatment, and storage of surface runoff, optimal locations for BMPs within a catchment, nor water quality improvement as a formal objective. Formal optimization methods have also been used to identify the optimal mix, size, and location of distributed BMPs (Perez-Pedini, Limbrunner et al. 2005, Maringanti, Chaubey et al. 2009, Lee, Selvakumar et al. 2012), but these studies have not considered SWH.

To address the shortcomings in existing literature outlined above, the objectives of this paper are:

1. to introduce a generic framework for the conceptual design of SWH systems that considers multiple objectives, a range of BMP types and their design options, the spatial distribution of BMPs, and a formal optimization approach for identifying designs that represent near-globally optimal trade-offs among competing objectives in an integrated fashion;
2. to demonstrate the application of the generic framework to a case study SWH system for a residential development in Adelaide, South Australia; and
3. to use the case study to investigate
    a. potential benefits achievable by distributing SWH components throughout the catchment compared to systems with components only at the catchment outlet
    b. trade-offs between lifecycle cost, supply volume, and water quality improvement, which is achieved by linking an integrated stormwater model with a multiobjective evolutionary optimization approach, and
    c. impacts of design decisions including the type, size and location of BMPs on SWH performance.

2.2 Proposed distributed stormwater harvesting system design optimization framework

This section contains a description of distributed SWH systems, a mathematical formulation of the multiobjective optimization design problem (decision variables, objective functions and constraints) and the proposed formal optimization framework for solving it.

2.2.1 Description of SWH systems

A spatially distributed SWH system for an urban catchment, detailed for one of multiple sub-catchments, is illustrated in Figure 2-1. In the figure, BMPs are shown by closed green (shaded) boxes, runoff sinks (or demands) by parallelograms, drainage paths by solid arrows, pipe flow for treated runoff by purple (large dash) arrows, and SWH system losses by black (small dash) arrows. After rainfall on an urban catchment, some allotment (land parcel) roof runoff is diverted to rainwater tanks to supply water for toilet flushing and household irrigation. Some impervious (roads, car parks) and pervious (grassed areas, open space) surface runoff, and roof runoff overflowing or bypassing the tank, is captured and treated in BMPs located along streetscapes or in open (green) spaces. BMPs can include, for example, smaller biofiltration systems servicing a cluster of allotments integrated into the streetscape or urban open space, or larger sedimentation basins, biofiltration systems, or constructed wetlands servicing a catchment comprised of multiple clusters. Biofiltration systems (biofilters) for SWH typically consist of a basin overlaying a geotextile-lined filter medium with a drainage pipe at the bottom. Sedimentation basins consist of a pond to promote settling of sediments through the reduction of flow velocities and temporary detention. Constructed wetlands are shallow, extensively vegetated basins that use enhanced sedimentation, fine filtration and pollutant uptake processes to remove runoff pollutants.

After passing through a BMP, treated stormwater is typically stored at the multiple-cluster or catchment scale in open water ponds, storage tanks, or an aquifer. Harvested water is often transferred from sub-catchments to a central balancing tank for advanced treatment and distribution to an irrigation network. Surface runoff that overflows or bypasses BMPs, or is not harvested, is lost through evapotranspiration, infiltration to deep groundwater storages (possibly after exfiltrating from BMPs), or reaches urban streams via shallow ground water flow, overland flow, or impervious drainage channels. Intercepting and harvesting runoff in upstream sub-catchments affects runoff into BMPs in lower sub-catchments. Downstream impacts should be considered with the aid of an integrated stormwater model (Bach, Rauch et al. 2014).

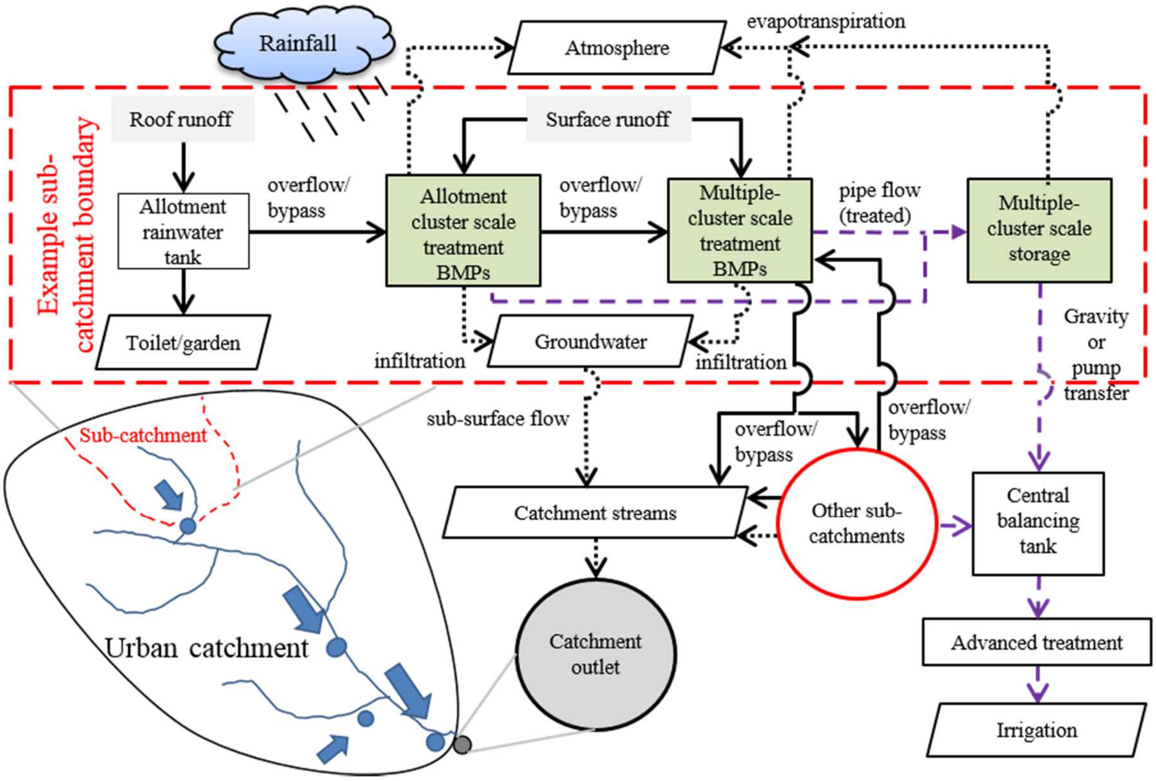

Figure 2-1 Schematic diagram of generic distributed stormwater harvesting system with central balancing tank

2.2.2 Problem formulation

2.2.2.1 Decision Variables

In the conceptual design of distributed SWH systems, decision-makers consider the type, location, and design parameters of BMPs and transfer infrastructure. Appropriate types and locations of BMPs largely depend on site characteristics, including soil type, topography, infiltration rate, contributing connected impervious area, and sufficient space for maintenance and transfer infrastructure. Site characteristics are typically assessed through site and geospatial studies (Inamdar 2014). After site assessment, a short-list of appropriate options is agreed upon amongst stakeholders, taking into account the desired SWH objectives and other socio-political preferences (Chichakly, Bowden et al. 2013).

After short-listing, often multiple BMP types and size options are available at each location. These decision variables are denoted *BMP* [integer], each with associated surface area options, denoted as *SA* [fraction]. *SA* is formulated as a fraction of the maximum available area for a BMP at a location, denoted SA_{max} [area]. Where one BMP type is available at a location, *BMP* is a fixed parameter, and *SA* is a decision variable. Where multiple BMP types are available at a location, both *BMP* and *SA* are decision variables. In the latter case, the surface area options depend on the type of BMP selected, since SA_{max}, based on guidelines and site constraints, varies among BMP types. BMP design parameters, such as the dimensions of basins, can be included as decision variables. Other parameters required to model BMPs are either fixed *a priori* based on design guidelines or site constraints, or dependent on the BMP surface area and calculated once this is known. Pipes and pump configuration and parameters are selected to transfer treated water from storage sites to central balancing storage.

2.2.2.2 Objectives

Although objectives depend on stakeholder interests, three formal objectives are typically considered and therefore included in the proposed framework: cost, supply volume, and water quality improvement. Cost is a key concern for decision-makers responsible for maximising the return on investment, including capital and ongoing costs. Maximising supply volume is a primary motivation for implementing SWH systems in order to reliably meet irrigation demand (and contribute to runoff volume reduction). Water quality improvement is a key environmental objective considered by regulatory bodies (Chichakly, Bowden et al. 2013, Yang and Best 2015). As explained by Chichakly, Bowden et al. (2013), due to their qualitative and political nature, social considerations are taken into account through stakeholder consultation utilized when selecting available BMP types, sizes and locations, and determining constraints, as well as when assessing alternative candidate conceptual designs.

2.2.2.2.1 Cost

In the proposed framework, the cost of SWH concept designs is represented as a life cycle cost LCC [$] (Equation (2-1)), which is a discounted sum of expected future costs for stormwater management assets, including BMPs and transfer infrastructure (Taylor and Wong 2002). The life cycle cost objective function for each candidate SWH system is given by:

$$MINIMIZE\ \mathrm{LCC} = LCC_{harvest} + LCC_{transfer}$$

Equation (2-1)

where

$$LCC_{harvest} = \sum_{i=1}^{N} \{ (TAC_{BMP_i}) + PWF_{estab,BMP_i} (SA_{BMP_i} \times SA_{max,BMP_i} \times ECF_{BMP_i} \times M_{BMP_i}) + PWF_{maint,BMP_i} (SA_{BMP_i} \times SA_{max,BMP_i} \times M_{BMP_i} + TAC_{BMP_i} \times Ren_{BMP_i} + TAC_{BMP_i} \times Decomm_{BMP_i}) \}$$

Equation (2-2)

$$LCC_{transfer} = C_{CapPump} + C_{CapTransPipe} + PWF_{maint} (C_{mPump} + C_{mPipe})$$

Equation (2-3)

where a sum of the cost of BMPs to harvest stormwater runoff, $LCC_{harvest}$ [$] (Equation (2-2)), and to transfer harvested water to balancing storage for further treatment and distribution, $LCC_{transfer}$ [$] (Equation (2-3)) is applied with BMP_i representing the BMP type in the i^{th} location in the candidate SWH system, N [integer] is the number of BMPs, and TAC [$] is the total acquisition cost as a function of SA.

The times during and immediately after BMP construction are critical to promote plant growth and prevent erosion. Consequently, intensive maintenance is required in an initial establishment period to ensure BMPs can meet functional performance criteria. After this period, less intensive, lower cost, annual maintenance is required to maintain functional performance. Consequently, PWF_{estab} [fraction], for the establishment period, and PWF_{maint} [fraction], for the remaining design life of system components, are the present worth factor for a series of annual costs computed using a discount rate. ECF [fraction] is the establishment cost factor (i.e., multiplier) for the annual maintenance cost M [$] during the establishment period for each BMP. *Ren* is the annualised renewal cost and *Decomm* the decommissioning cost [represented as fractions of TAC]. $C_{CapPump}$ [$] and $C_{CapTransPipe}$ [$] are the capital costs for required pump stations and pipes, and C_{mPump} [$] and C_{mPipe} [$] are the annual pumping and maintenance costs. Balancing storage, UV disinfection, and distribution costs apply to solutions equally, and are thus excluded.

2.2.2.2.2 Supply volume

In the proposed framework, volumetric reliability (Equation (2-4)) is adopted as an indicator of urban supply volume performance. This is a measure of the average annual proportion of demand volume supplied by a SWH system over a simulation period (Mitchell, McCarthy et al. 2008). This metric was selected because it facilitates comparison of the ability of SWH concept designs to supply potential customers under several demand scenarios as required in the framework, can easily be converted to a total volume to estimate annual runoff reduction and imported supply substitution due to harvesting, and is used in practice (Browne, Breen et al. 2012). Typically, a volumetric reliability of 75% to 80% is acceptable for SWH systems, since imported supply is usually available to 'top-up' the balancing tank to meet demand when SWH is unable to. The supply volume objective function is:

$$MAXIMISE\ R_V = 1 - \frac{\sum_{k=1}^{P}\{\sum_{t\in f_n}(D_{t,k} - D'_{t,k})\}}{\sum_{k=1}^{P}\{\sum_{t\in N} D_{t,k}\}}$$

Equation (2-4)

where R_V [fraction] is the system volumetric reliability, k [integer] is the storage BMP number, P [integer] is the number of distributed storages in the SWH system, f_n [integer] is the number of failure intervals (i.e., where demand fails to be met), D'_t [volume] is the actual supply during the t^{th} [integer] failure interval, D_t [volume] is the target demand during the t^{th} interval, and N [integer] is the number of intervals in the simulation period.

2.2.2.2.3 Water quality improvement

The water quality improvement indicator adopted in the proposed framework is the total average annual pollutant load reduction of one target pollutant (Equation (2-5)). This indicator is widely adopted to assess the performance of WSUD approaches, including SWH systems (Browne, Breen et al. 2012). The target pollutant will depend on stakeholder interests. The objective function is:

$$MAXIMIZE\ LoadRedn = 1 - \frac{Resid}{Source}$$

Equation (2-5)

where, *LoadRedn* [fraction] is the mean annual pollutant load reduction proportion of each candidate SWH system, *Resid* [mass year^{-1}] is the mean annual mass of pollutant leaving the development area, and *Source* [mass year^{-1}] is the mean annual mass of pollutant that reaches the catchment outlet in a post-development catchment baseline scenario without WSUD. *Resid* and *Source* should be determined using an integrated stormwater model (Bach, Rauch et al. 2014).

2.2.2.3 Constraints

In the proposed optimization framework, constraints apply to conditions on types of BMPs combined in solutions; and pollutant load reduction performance for a range of pollutants. Each solution is assessed against conditions on the presence and size of BMPs to avoid candidate SWH system solutions that would not be adopted in practice. Impractical solutions can arise due to randomness in the selection of decision variables in the optimization process (see Section 2.2.3). For example, a candidate solution might consist of a storage device without a BMP providing inflows or a BMP may treat runoff but not have adjacent storage where needed. Particular practical constraints need to be agreed upon by practitioners on a case-by-case basis. In addition, many regulatory bodies require a proportion of pollutant load generated by the development to be retained by the SWH system to promote the health of environments receiving runoff. The proportion of load reduction retained by the candidate SWH system is given as:

$$LoadRedn_c \geq LoadRednTarget_c, \forall\, c = 1, \dots, CN$$

Equation (2-6)

where, *LoadRedn* [fraction] is determined using Equation (2-5), *LoadRednTarget* [fraction] is the mean annual proportion of pollutant load reduction target set by regulators, *c* [integer] represents a target pollutant, and *CN* [integer] is the number of target pollutants. As discussed by Marchi, Dandy et al. (2016), additional SWH constraints may arise due to decision variable value ranges, land available for BMPs, physical processes (e.g. water and energy balance), and local regulations.

2.2.3 Optimization framework

In the proposed framework, a multiobjective optimization evolutionary algorithm (MOEA; Figure 2-2) is suggested to solve the SHW system optimization problem. MOEAs have several advantages over traditional optimization approaches (e.g., linear programming). They can deal with multiple objectives simultaneously (Maier, Kapelan et al. 2014) and have been used successfully in recent planning and design optimization studies considering SWH (Beh, Dandy et al. 2014, Paton, Dandy et al. 2014a, Marchi, Dandy et al. 2016) and distributed BMP systems (Chichakly, Bowden et al. 2013). Furthermore, they can be linked with multiple simulation models required to calculate multiple objective functions and check constraints of candidate solutions (Maier, Kapelan et al. 2014), can provide confidence in the results of the optimization process, as simulation models that are already used in local SWH decision-making can be used (Maier, Kapelan et al. 2014), and can enable problems with complex mathematical properties to be considered without simplifying the optimization problem, which is not the case when more traditional optimization approaches are used.

As part of the optimization process (Figure 2-2), a number (population) of solutions is generated with the aid of an MOEA. Each solution represents decisions, on the type, size and location of BMPs in a particular SWH concept design, formulated as a vector of decision variable options. Then, solutions are 'pre-emptively' checked against conditions on the configuration of BMPs. If a solution violates these conditions (i.e., is impractical), it is not evaluated with the aid of the simulation model(s), which saves computational time (Asadzadeh, Razavi et al. 2014). Next, the performance of practical solutions is evaluated by calculating objective functions and checking constraints. This evaluation requires two simulation models, including a life cycle cost model, and an integrated stormwater model. The cost model can be a lookup table of costs associated with SWH system components. The integrated stormwater model is needed to evaluate the volumetric reliability and water quality improvement achieved with the distributed SWH conceptual designs under consideration. The integrated model should be able to model: hydrologic behaviour; pollutant generation; hydraulic and treatment behaviour of BMPs; downstream impacts of BMPs; and water recycling through SWH. According to Bach, Rauch et al. (2014), eWater *MUSIC* (eWater 2009) is the only readily available model that includes all of these.

After evaluation, penalties are applied to objective function values of solutions that fail to meet pollutant reduction targets. The MOEA uses objective function values to assess the fitness of solutions and iteratively modify the population using evolutionary processes, such as reproduction, mutation, crossover and selection. Over generations, the population of solutions converges towards the set of Pareto optimal SWH concept designs, which are the non-dominated designs (i.e. none of the objective functions can be improved in value without degrading one or more of the other objective values) in the set of all possible designs. The MOEA evolves the population until specific termination criteria are met. The algorithm is run from a new initial population for a number of demand scenarios in order to estimate the potential supply volume from the catchment, which is not typically known *a priori*. The non-dominated solutions identified by the MOEA are Pareto optimal or near Pareto optimal SWH concept designs for each scenario.

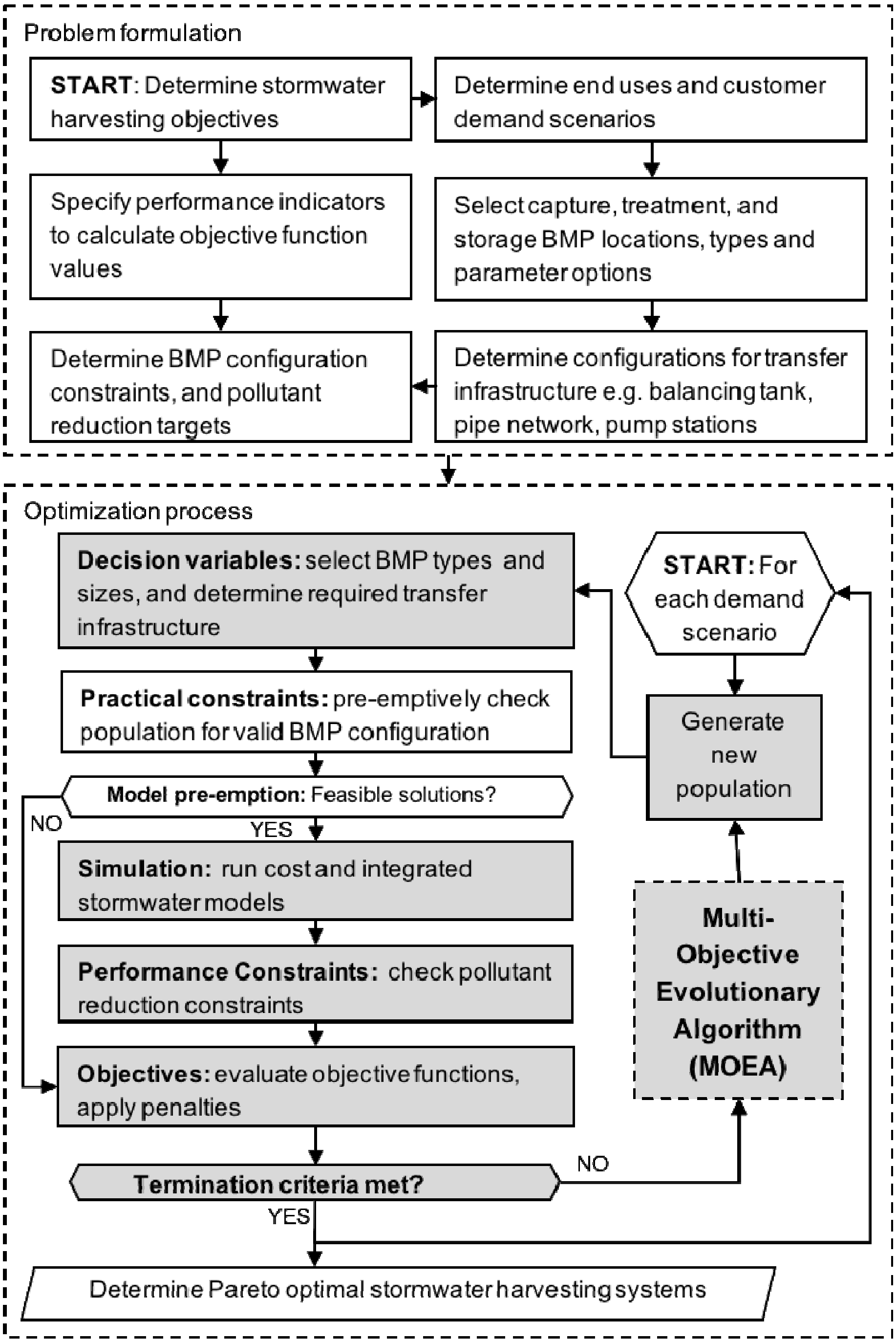

Figure 2-2 Optimization framework for distributed stormwater harvesting system design. Typical steps in an optimization process are shaded

2.3 Case study

The proposed optimization framework was applied to a SWH system design case study for a proposed housing development consisting of 3342 allotments on 245 ha of underutilized farmland north of Adelaide, South Australia. Figure 2-3 shows the proposed catchment layout, including four sub-catchments. Catchment characteristics are listed in Table 2-1. A natural creek flows to the catchment outlet at the southwest of sub-catchment 4. The footprint of flood retarding basins (proposed for the future development) were available for multiple-cluster-scale wetlands and biofilters. South Australian regulations require a minimum 1 kL rainwater tank per allotment.

In this study, there was no opportunity to consult stakeholders directly. Rather, consultants who developed a SWH system for the case study site, provided planning and design data but were not available to comment on results. Decision variable values corresponding to BMP types and surface areas were generated using a MOEA, which were combined with fixed and decision variable dependent parameters to form a candidate SWH system. The objective function values were evaluated with a lookup-table cost model and an integrated stormwater simulation model developed using the eWater *MUSIC* version 6.1 software (eWater 2009). Details of the case study decision variables, parameters, objectives, constraints, MOEA and simulation model are presented below.

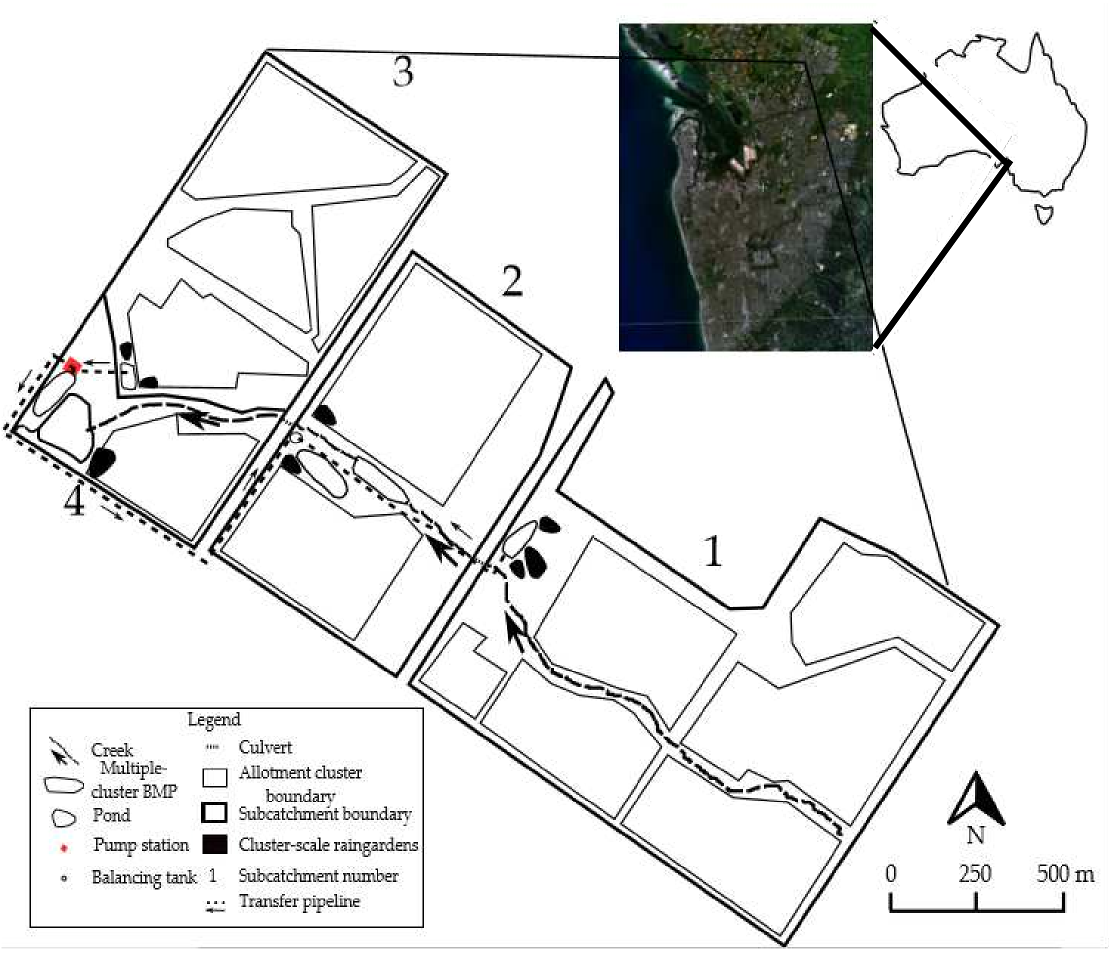

Figure 2-3 Location of potential BMPs for proposed housing development in Adelaide, South Australia. An irrigation balancing tank is located in sub-catchment 2

Table 2-1 Case study catchment characteristics

Sub-catchment	Area (ha)	Fraction Impervious (%)
1	120.2	50
2	70.4	50
3	54.7	60
4	30.2	55
Roof to RWT	33.4	100

Note: For all sub-catchments field capacity = 30 mm; impervious area rainfall threshold = 30 mm/day; pervious area soil storage capacity = 40 mm; groundwater daily recharge rate = 25%; groundwater daily base flow rate = 5%. RWT = rainwater tank.

2.3.1 Decision variables and model inputs

The decision variables corresponding to each location were the surface area and, if multiple BMPs were available at a location, the type of BMP. The decision variable options corresponding to locations within sub-catchments are summarised in Table 2-2. BMP type (*BMP* [integer]) options in sub-catchments 2 and 4, where more than one BMP type was available, included wetlands, geotextile-lined biofilters, and sediment basins suitable for SWH in South Australia. Two locations for wetlands were available, both at the base of retarding basins in the creek. These locations had adequate space for a wetland inlet pond and a macrophyte zone and received sufficient inflows from multiple-clusters. Biofilters were also available at the retarding basin footprints (as an alternative to wetlands), and distributed at the cluster-scale. Cluster biofilters were suitable for locations where space was limited near residential open spaces in catchments 1, 2, 3 and 4.

Table 2-2 Case study decision variables

Decision variable #	Sub-catchment #	BMP Type	DV Type	Max. available area (ha)
1	1	CB	area	0.92
2	1	P	area	0.50
3	2	CB	area	0.55
4	2	SB,W, or MCB	type	NA
5	2	SB,W, or MCB	area	[a]
6	2	P	area	1.00
7	3	CB	area	0.50
8	3	P	area	0.35
9	4	SB,W, or MCB	type	NA
10	4	SB,W, or MCB	area	[b]
11	4	P	area	1.00

Note: CB = cluster-scale biofilter, P = pond; SB = sediment basin; W = wetland; and MCB = multiple-cluster scale biofilter. NA = not applicable.
[a] SB = 0.869 ha; W = 1.00 ha; MCB = 0.730 ha.
[b] SB = 0.836 ha; W = 2.20 ha; MCB = 0.730 ha.

Open-water ponds were available to store treated stormwater at four locations within the development site (one in each sub-catchment). The surface area (*SA* [fraction]) options for BMPs were 0% (no BMP), 33.3%, 66.6%, or 100% of the available area for a location. If a BMP size of 0% was selected by the MOEA, a sediment basin was set at multiple-cluster-scale locations (even if a wetland or biofiltration basin was selected as the BMP type) and a junction was set at cluster scale locations. The wetland macrophyte zone area was limited by the space available in the retarding basin footprints. The maximum total sizes of biofilters were limited to 1.5% of contributing impervious catchment area or limited by site constraints, as per the relevant design guidelines (Payne, Hatt et al. 2015).

The sediment basin at each location had fixed sizes designed to accommodate peak 1 in 1-year annual recurrence interval inflows from upstream sub-catchments. Discretization of the decision variables was selected to limit search space size due to the long run times (approx. 12.5 seconds) required to evaluate each candidate solution with the stormwater model.

Stormwater model inputs included fixed- and decision variable dependent- design parameters, as follows. Wetlands had an inlet pond with surface area fixed at 15% of the macrophyte zone area and 2 m depth. Inflows higher than those with peak 1 in 1-year annual recurrence interval peak flows were diverted to an overflow bypass. A 48-hour nominal detention time (residence time) was used. This is typical for SWH wetlands in South Australia, which is a function of the wetland volume and is achieved by calculating the corresponding nominal outlet orifice size. A 300 mm extended detention depth limited the duration and frequency of inundation of wetland flora, but also the available detention capacity. A 300 mm average permanent pool depth was adopted for the macrophyte zone and was assumed to be initially full. Biofilters included biofiltration cells with a maximum area of 800 m^2 (Water by Design Australia 2015) and were modelled as a lumped single cell for each catchment. Multiple-cluster-scale devices received inflows, diverted from the natural creek channel, that were lower than the 1 in 1-year annual recurrence interval peak flow rate for upstream catchments to prevent scour of the filter media. Multiple-cluster-scale biofilters had less restrictive site constraints than cluster-scale biofilters. This is reflected in their fixed dimensions. These are: (1) at the multiple cluster scale, 400 mm for biofilter detention depth, 800 mm for filter depth and 400 mm for the submerged zone; and (2) at the cluster-scale, 200 mm for biofilter detention depth, 500 mm for filter depth, and 200 mm for the submerged zone. Both devices had 200 mm/hr hydraulic conductivity, an underdrain with geotextile liner to maximize harvesting potential by preventing exfiltration, and a submerged zone to promote plant health in extended dry periods and to maximize volume retention. The interested reader is referred to Payne, Hatt et al. (2015) and Water by Design Australia (2015) for comprehensive diagrams illustrating these dimensions for lined biofilters. Storage ponds had 2 m total depth and 0.1 mm/hr exfiltration rate. Extended detention depth was set to 100 mm (minimum allowable in *MUSIC*) to minimize treatment modelled in the storage pond. All RWT parameters were fixed for a 1 kL tank size. RWTs in a sub-catchment were modelled as a lumped tank node. RWTs were connected to 100 m^2 of roof area (40% of total roof area) per allotment and supplied 50 L/day for toilet flushing. Gross pollutant traps were not modelled, as per relevant modelling guidelines (Water By Design Australia 2010).

Cost model inputs included lifecycle cost parameters associated with BMPs in a solution and with pipe and pump infrastructure selected to transfer water from storage ponds to an underground balancing storage in sub-catchment 2. All transfer pipes were assumed to be 150 mm PVC to minimise pipe velocities and head losses for the highest demand scenario. Where a BMP was selected in sub-catchment 3 or 4, an 8 kW submersible pump supplied 9 L/s at 60 m head to the balancing storage, as per the detailed design adopted for the real-life SWH system (J. Cantone, personal communication, 2014).

2.3.2 Objectives

The objective function for lifecycle cost, *LCC* [\$], was calculated using Equation (2-1) to (2-3). The parameters for $LCC_{harvest}$ [\$] (Equation (2-2) were estimated from cost schedules developed by Melbourne Water Australia (2013) and the eWater *MUSIC* (eWater 2009) lifecycle costing tool (Table 2-3). A typical lifecycle period of 50 years was adopted. A discount rate of 5.5% per year was used to calculate the present worth factors. Although RWTs were a major cost of the SWH system (\$10.7 M), this cost was incurred in all solutions and, therefore, omitted from the life cycle cost objective function. The parameters for $LCC_{transfer}$ [\$] (Equation (2-3)) were estimated as follows. Capital costs for pipe and pump infrastructure, $C_{CapTransPipe}$ [\$] and $C_{CapPump}$ [\$], were derived from costing data for the SWH system developed for the site (J. Cantone, personal communication, 2014; Table 2-4). The capital cost of a transfer component was included if at least one pond requiring the component was selected by the MOEA. The net present value (NPV) of operating costs of pipe maintenance and pumping, C_{mPipe} [\$] and C_{mPump} [\$], were assumed to be negligible compared to the BMP establishment and maintenance costs, based on analysis of detailed costings for several SWH conceptual designs in Inamdar (2014). The costs of gross pollutant traps were not included in the objective function value since the costs applied to all solutions. Volumetric reliability (R_V [fraction]) was calculated (Equation (2-4)) using SWH model results. R_V was the total demand supplied divided by total demand requested for the *N* ponds in each SWH concept design. Total Suspended Solids (TSS) reduction was the specific pollutant constituent adopted for the water quality objective. Maximising TSS load reduction was particularly important since TSS limit the ability of a water body to support diversity of aquatic life, introduce contaminants, such as heavy metals and nutrients, limit navigability and fish passage due to sedimentation, and have undesirable aesthetic affects (Bilotta and Brazier 2008). Load reduction ($LoadRedn_{TSS}$ [fraction]; Equation (2-5)) was calculated based on catchment outlet total TSS load divided by a baseline scenario TSS load without SWH or RWTs, determined using the stormwater model.

Table 2-3 Breakdown of life cycle costs

Lifecycle cost components	Wetland	Sediment Basin	Pond	Cluster biofilter	Multiple-cluster biofilter
Total Acquisition Cost (TAC)($/m^2) [a]	100	150	150	500	250
Annual Maintenance Cost ($/m^2) [a]	2	5	5	10	5
Establishment Cost Factor [a]	2	2	2	2	2
Establishment Period (years) [a]	2	2	2	2	2
Annualized Renewal cost ($/m^2) [b]	0.00641 × TAC	0.0172 × TAC	0.0172 × TAC	0.0243 × TAC	0.0243 × TAC
Renewal Period (years) [b]	25	15	25	20	25
Decommissioning cost ($/m^2) [b]	0.52 × TAC	0.47 × TAC	0.47 × TAC	0.49 × TAC	0.49 × TAC

Note: Annual establishment period maintenance cost = Annual maintenance cost × establishment cost factor. Costs are in Australian Dollars (2015$).
[a] Based on Melbourne Water Australia (2013).
[b] Based on eWater (2009).

Table 2-4 Breakdown of transfer component costs

Transfer component	Transfer component required?				$C_{CapTransPipe} + C_{CapPump}$ ($ M)
	Pond 1	Pond 2	Pond 3	Pond 4	
Pipe 1	Yes	No	No	No	0.168
Pipe 2	Yes	Yes	No	No	0.044
Pipe 3	No	No	Yes	Yes	0.205
Pipe 4	No	No	Yes	Yes	0.205
Pipe 5	No	No	Yes	Yes	0.184
Pump station	Yes	Yes	Yes	Yes	0.692

2.3.3 Constraints

Solutions generated by the MOEA that violated practical constraints were allocated extreme objective function values ($1.0 × 10^9 life cycle cost and 0.0% reliability), and were not simulated. The practical constraints on BMP configuration specific to the case study were: in sub-catchments 1 and 3, if a BMP was selected, an adjacent pond had to be selected, and conversely, if no BMP was selected, no adjacent pond could be selected; and in sub-catchments 2 and 4, ponds could not be selected unless adjacent to at least one BMP. Three pollutants and load reduction targets ($LoadRednTarget_i$ [fraction]; Equation (2-6)) were recommended for Adelaide (Myers, Cook et al. 2011): TSS; 80%; total nitrogen (TN, 45%); and total phosphorous (TP; 45%).

2.3.4 Multiobjective optimization algorithm

The non-dominated sorting genetic algorithm (NSGA-II; Deb, Pratap et al. (2002)) was used as the multiobjective optimization engine, as its variants have been successfully applied to optimization of BMP systems (Marchi, Dandy et al. 2016) and it has been found to perform well when compared with more recent algorithms applied to a number of water distribution system optimization problems (Wang, Guidolin et al. 2015, Bi, Dandy et al. 2016, Zheng, Zecchin et al. 2016). In this study, an NSGA-II variant, the Water System Multiobjective Genetic Algorithm, developed by Wu, Simpson et al. (2010), was used. The algorithm has been applied to a range of water resources studies (Paton, Maier et al. 2014b, Beh, Maier et al. 2015); see https://github.com/jeffrey-newman/WSMGA-with-Wrapper-and-Analytics). The left-hand side of Figure 2-4 shows the major steps in the NSGA-II for one scenario. The algorithm randomly selects decision variable values for an initial population of candidate solutions. Each solution is evaluated to determine its objective function values, which influence optimization operators (selection, crossover, and mutation) to generate new populations until convergence criteria are met.

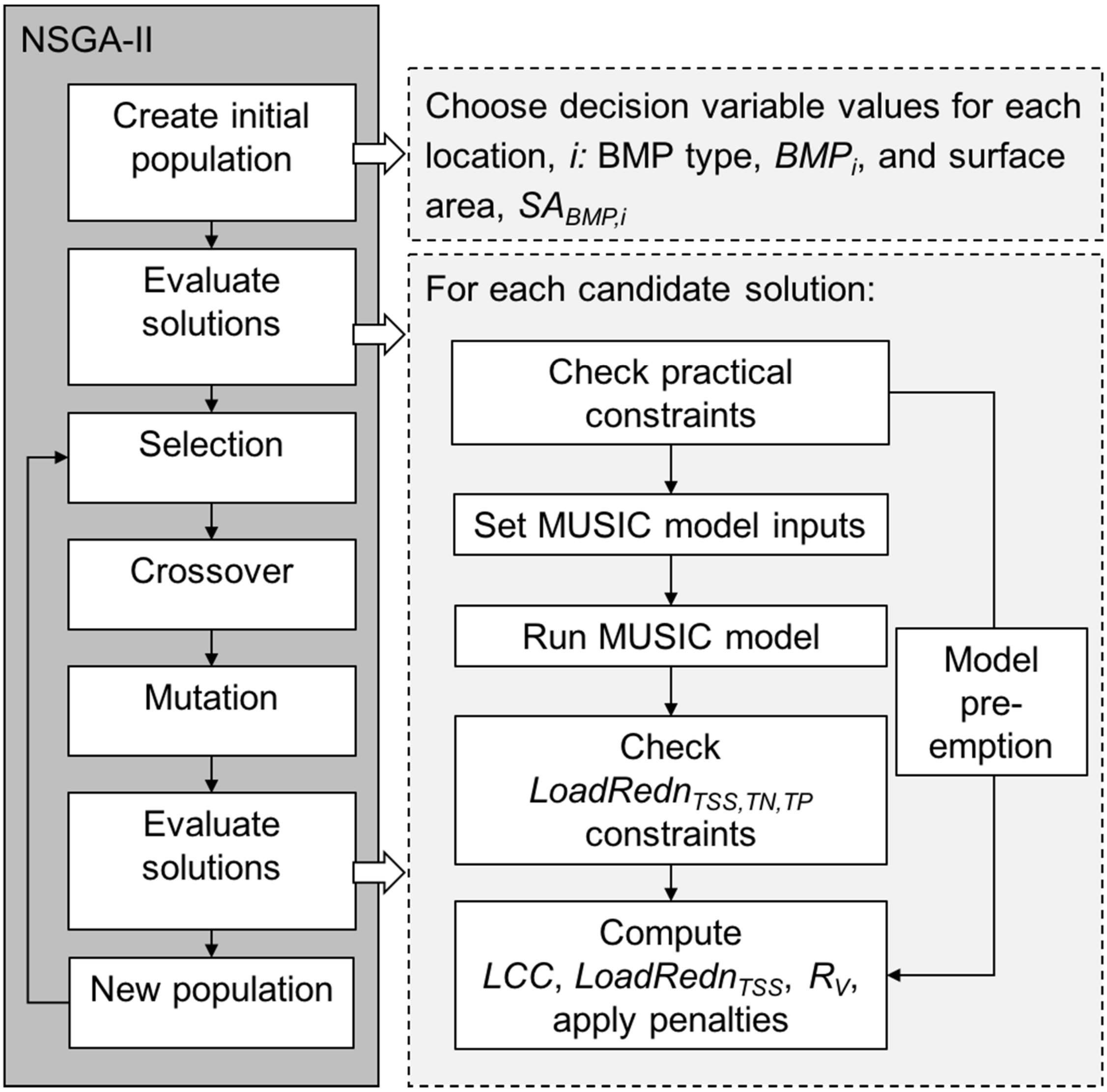

Figure 2-4 Details of case study optimization process (adapted from (Marchi, Dandy et al. 2016))

2.3.5 Integrated stormwater simulation model

The Model for Urban Stormwater Improvement Conceptualizion (*MUSIC* version 6.1; eWater (2009)) was used to evaluate harvested water supply and water quality improvement objectives, and pollutant reduction performance. *MUSIC* is an integrated stormwater model that evaluates rainfall/runoff and pollutant generation and transport, hydraulic and pollutant removal performance of BMPs, and SWH water balance (Bach, Rauch et al. 2014). *MUSIC* is used as a SWH design tool in Australia and the UK and has been used in watershed-scale SWH system reliability analysis (Browne, Breen et al. 2012) and WSUD optimization (Montaseri, Hesami Afshar et al. 2015). *MUSIC* algorithms simulate runoff based on models developed by Chiew and McMahon (1999) and urban pollutant load relationships based on analysis by Duncan (1999). The model SWH drainage networks consisted of nodes representing: BMPs (and junctions at locations where no BMP was selected by the MOEA); catchment runoff sources including roof, ground impervious and pervious fractions of each sub-catchment; and a catchment outlet. Nodes were connected via drainage links. The right-hand side of Figure 2-4 shows how *MUSIC* models were linked with NSGA-II. Input parameters for *MUSIC* included: BMP type and surface areas generated by the MOEA; catchment model parameters determined *a priori*; and fixed design parameters determined *a priori* or calculated after the surface areas were known. *MUSIC* modelled the spatial distribution of BMPs through routing flow and pollutant transport between nodes at each time step.

2.3.6 Analyses conducted

The optimization framework was run for three demand scenarios. These were Scenario 1) low irrigation demand (61.0 ML/year), Scenario 2) high irrigation demand (for high amenity open space; 122.0 ML/year), and Scenario 3) high demand plus 40.0 ML/year export to a neighbouring school for non-potable use (162.0 ML/year). Annual demand was disaggregated in proportion to potential evapotranspiration minus rainfall in each hour for each year, using the 'PET-rainfall' demand function in *MUSIC*, as suggested in the *MUSIC* guidelines. After a solution was selected by the MOEA, each storage pond demand was allocated as follows: firstly, ponds were allocated their local sub-catchment irrigation demand; then demand for sub-catchments without ponds was allocated to the closest downstream pond, or the closest upstream storage pond if no downstream ponds existed. At each time-step, demand was extracted until a water depth of 500 mm was reached. Regional pervious surface storage parameters in the *MUSIC* manual (eWater 2009) calibrated for Adelaide were adopted, which is considered an appropriate approach for *MUSIC* (Inamdar 2014), especially since the proposed development had a high impervious fraction dominating runoff volumes (Dotto, Deletic et al. 2011). A one-hour time step was adopted, since larger steps can result in harvested volume underestimation (Coombes and Barry 2007). As recommended by Mitchell, McCarthy et al. (2008) for SWH simulation, a series of mostly complete rainfall data over a 10-year period that include representative long-term rainfall characteristics was selected for simulation purposes. Consequently, data from 1990-1999 were used, as they have a mean annual rainfall of 409 mm/year, which is close to the long-term annual average (430 mm/year).

It should be noted that this is not the case for more recent data, as South Australia experienced a severe drought between 2001-2010. As the selected data were stationary (unlike the more recent data), they are also suitable for perturbation for use in climate impact studies, if desired (see Paton, Maier et al. (2013)). Flood retention, peak flow attenuation performance, and routing were not included as these analyses are typically carried out separately to water quality and water balance assessment using separate simulation packages with a smaller time step, and do not form part of SWH objectives (Water By Design Australia 2010). Flows exceeding the 1 in 1-year design volume were diverted away from BMPs in the *MUSIC* model. A baseline scenario for a catchment without SWH or rainwater tanks (i.e. only catchment runoff source nodes connected to a catchment outlet node) was simulated in *MUSIC*, in order to obtain the *Source* (Equation (2-5)) pollutant load values. The baseline catchment generated an annual average runoff of 479 ML with 57,900 kg TSS, 139 kg TP, and 871 kg TN.

The NSGA-II runs had a population size of 200 with crossover and mutation parameters of 0.9 and 0.1, respectively, and were each terminated after 100 generations. These parameters were selected after trial-and-error runs with various parameter combinations. NSGA-II was run eight times using different random starting seeds in decision variable space in order to minimize the influence of the stochastic generation of the initial population and the probabilistic effects of some of the parameters controlling the search. Each run took approximately 45 hours on a 3.10GHz computer with 8 GB of RAM. For each demand scenario, non-dominated solutions from the eight seed runs were merged and the non-dominated solutions identified.

The optimization results were compared with a catchment-outlet SWH approach to provide a benchmark comparison. The catchment-outlet approach describes a design approach where treatment and storage BMPs are located in areas of the catchment that receive large inflows, near the catchment outlet, which is a typical approach for designing SWH systems in practice (Browne et al. 2012; Inamdar 2014). The catchment-outlet conceptual designs were feasible (not necessarily optimal) solutions of the SWH problem formulation in this paper. The catchment-outlet designs considered had a pond and wetland or biofilter located near the catchment-outlet (sub-catchment 4), and a sedimentation basin (sub-catchment 2). A design for each combination of BMP size options was manually evaluated for each demand scenario using the cost model and *MUSIC*. The results were sorted to identify the non-dominated catchment-outlet solutions, which were compared with Pareto optimal solutions identified in the NSGA-II optimization runs. All model source code, input data, and results are available (Michael, Dandy et al. 2016a).

2.4 Results and discussion

2.4.1 Distributed versus catchment-outlet approaches

The results indicate that there is significant benefit in using the optimization framework, since the distributed SWH system optimization results dominate the catchment-outlet designs, except for two low-cost catchment outlet approaches that lie on the Pareto front under scenario 3 (Figure 2-5). Distributed approaches were able to supply more of the demand requested than the largest capacity catchment-outlet design, which indicated space at the catchment outlet limited the harvest capacity of catchment outlet approaches (Figure 2-5). Additionally, the catchment outlet approaches had limited capacity to reduce TSS loads. Therefore, distributed systems achieved higher supply and TSS reduction levels by utilizing several locations for SWH components. Optimization results comparing distributed and catchment-outlet system performance could be used in negotiation with stakeholders to support a distributed approach, especially where catchment outlet space is limited.

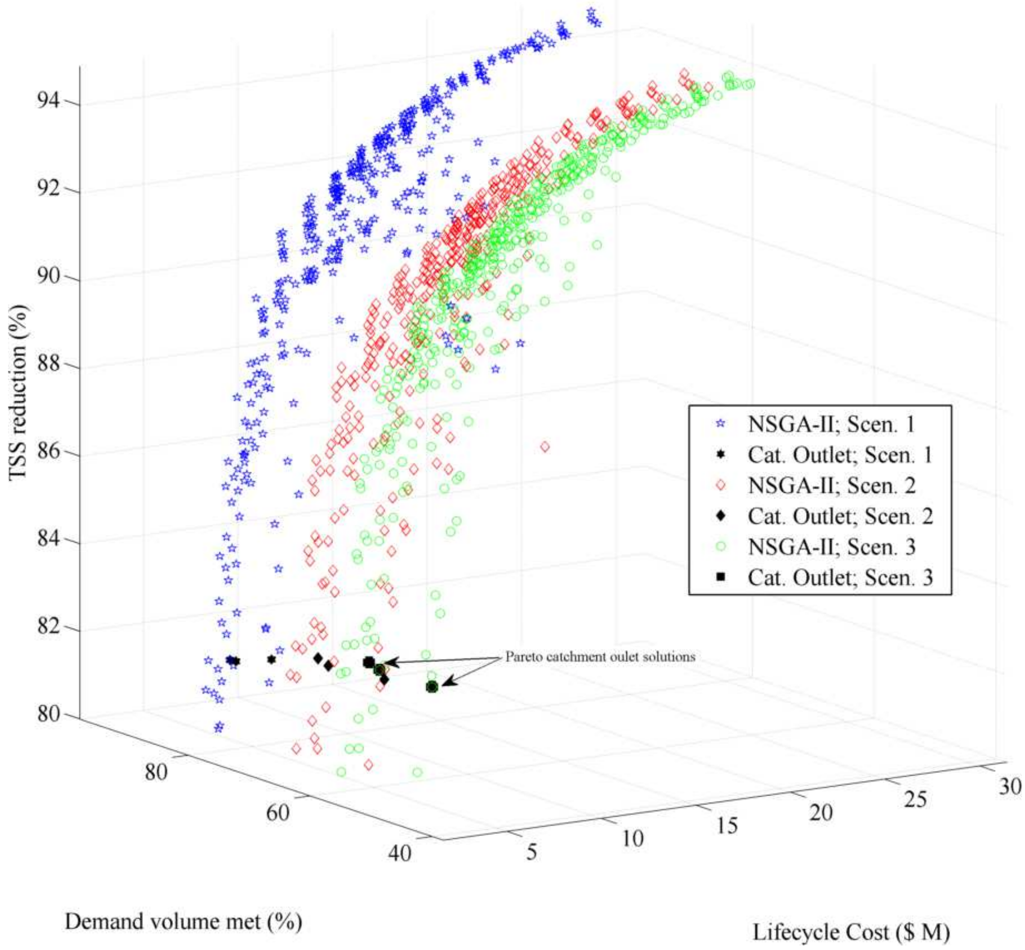

Figure 2-5 Pareto optimal and catchment outlet solutions

2.4.2 Trade-offs in cost and volumetric reliability objectives

The cost and volumetric reliability trade-off projections in Figure 2-6. show that there is a 'knee' region for each demand scenario. Moving along each front in a direction away from the knee region, there is a diminishing return in cost or reliability, suggesting that solutions in this region may represent a desirable trade-off between reliability and cost. Noticeably, the knee regions occur at different levels of reliability in each demand scenario. For example, to achieve an acceptable volumetric reliability of 80%, an investment of $4.19 M is required for demand scenario 1 and a $9.42 M investment is required for scenario 2; no scenario 3 solution was able to achieve a volumetric reliability of 80% (the maximum value achieved was 76.1% at $20.6 M). For demand scenario 1, limited returns in volumetric reliability were available away from the knee region in the direction of increasing costs. For example, a supply reliability of 93.2% was available for $7.52 M, whereas the maximum system reliability of 93.8% required an additional 38.7%

investment (i.e. $10.43 M). Compared to scenarios 2 and 3, the demand scenario 1 front had noticeable discontinuities and the knee region had a smaller cost range. These were a result of the limited number of BMPs utilized in scenario 1's non-dominated cost-reliability solutions, as discussed below.

2.4.3 Trends in design decisions in cost-volumetric reliability Pareto optimal solutions

Performance and design decision values of selected solutions are given in Table 2-5 and Table 2-6. The solutions represent an extreme objective function value (solutions 1, 16, 17, 42, 43, and 77) or occur at a trade-off 'break point' in the objective space or design decision space. The solutions were identified by visual inspection of the Pareto optimal solution objective and design decision spaces. These solutions utilized multiple-cluster-scale BMPs, as shown in the sub-catchment 2 and 4 BMP size columns in Table 2-6. Furthermore, multiple-cluster-scale biofilters and ponds at a central location (sub-catchment 2) and near the catchment-outlet (sub-catchment 4) were the *only* BMPs in all demand scenario 1 solutions, and in low cost scenario 2 and 3 solutions, for example solutions 17, 19, and 43. For demand scenario 1, BMPs at these locations captured sufficient inflows and had sufficient pollutant load reduction performance to meet water quality targets, without having to rely on cluster-scale BMPs. For demand scenarios 2 and 3, moving from low to high cost solutions, the maximum available area for BMPs at multiple-cluster locations was utilized before additional cluster-scale BMPs. Distributed cluster biofilters and ponds were selected more frequently in solutions with higher levels of reliability and to meet higher demand supply volumes. These results are consistent with sensitivity analysis of distributed BMP systems (Lee, Selvakumar et al. 2012) designed for flow reduction and water quality improvement, which demonstrated BMPs at locations receiving large inflows consistently appeared in Pareto optimal solutions. Biofilters provided best return on investment for supply volume and TSS reduction, since all Pareto optimal solutions had a biofilter in at least one location (Table 2-6). Only two, high cost, Pareto optimal solutions had wetlands and none had a sedimentation basin.

Table 2-5 Objective function and performance indicator values of selected solutions

Demand Scenario	Solution #	*LCC* ($ M)	R_V (%)	TSS reduction (%)	$LCC_{harvest}$ ($ M)	$LCC_{transfer}$ ($ M)	Avg. Supply (ML/yr)	TN reduction (%)	TP reduction (%)
1	1	3.462	72.31	81.9	2.726	0.736	44.10	53.8	59.3
	3	4.186	82.68	80.4	3.451	0.736	50.43	51.9	58.6
	4	4.762	84.68	80.2	3.637	1.125	51.65	53.0	62.7
	7	5.672	89.57	80.8	4.547	1.125	54.63	54.3	63.9
	8	6.455	89.71	83.8	5.330	1.125	54.72	57.5	65.5
	16	10.427	93.84	87.2	9.302	1.125	57.23	63.9	72.5
2	17	4.374	58.84	80.6	3.293	1.081	71.77	52.6	62.1
	19	5.284	70.08	80.4	4.204	1.081	85.49	53.7	64.5
	20	5.672	75.70	81.8	4.547	1.125	92.34	58.3	66.9
	27	9.428	80.88	86.0	8.303	1.125	98.66	64.8	73.5
	28	10.761	81.01	85.8	9.636	1.125	98.82	63.8	73.1
	29	12.152	81.12	80.9	10.860	1.293	98.95	57.5	68.9
	40	17.592	83.59	89.4	16.299	1.293	101.97	69.9	77.7
	41	18.241	83.66	88.1	16.948	1.293	102.05	67.6	76.6
	42	19.760	83.67	88.8	18.467	1.293	102.06	68.8	77.5
3	43	4.374	50.88	80.8	3.293	1.081	82.42	53.5	62.9
	44	4.762	61.75	81.5	3.637	1.125	100.02	58.0	66.5
	45	5.486	66.82	80.0	4.361	1.125	108.24	56.5	66.0
	47	6.424	68.37	80.4	5.299	1.125	110.75	57.7	67.0
	58	10.682	72.86	85.8	9.352	1.330	118.02	64.9	74.3
	63	12.978	73.56	89.6	11.648	1.330	119.15	71.4	78.4
	64	13.136	73.68	85.7	11.843	1.293	119.35	65.8	74.3
	77	20.555	76.13	90.2	19.057	1.498	123.32	72.1	79.9

Note: TSS = total suspended solids, TN = total nitrogen, TP = total phosphorous.

2.4.4 Trade-offs between cost, reliability, and water quality objectives

Figure 2-6 shows all Pareto optimal solutions identified by NSGA-II projected in 2-D objective space. For all demand scenarios, solutions providing the best trade-off between volumetric reliability and cost did not provide high TSS reduction, indicating a trade-off exists between TSS reduction and volumetric reliability. Lower-cost solutions tended to have lower TSS reduction, whereas high reliability was achievable at relatively low-cost. For a given cost, higher TSS reduction was achievable for a compromise in reliability. A similar maximum TSS reduction (of approximately 95%) was achieved in all scenarios coinciding with the maximum cost solutions. This is contrasted with volumetric reliability, which diminished with increasing demand volumes as systems reached supply capacity more frequently. From Table 2-6, in lower-cost and lower-reliability solutions, higher TSS load reduction was achieved by investing in larger biofilters and smaller ponds. For example, the highest reliability solution in demand scenario 1 (solution 16) had a TSS reduction performance of 87.2%; however, solutions with a slightly lower reliability and similar cost (with smaller pond sizes shown in Table 2-6) provided far higher TSS reduction. When assessing solutions that are non-dominated in cost-reliability space, stakeholders should consider slightly inferior solutions with respect to these objectives that provide considerably higher TSS reduction. In order to explain conflicting trade-offs in the SWH system objectives, design decisions are discussed further below.

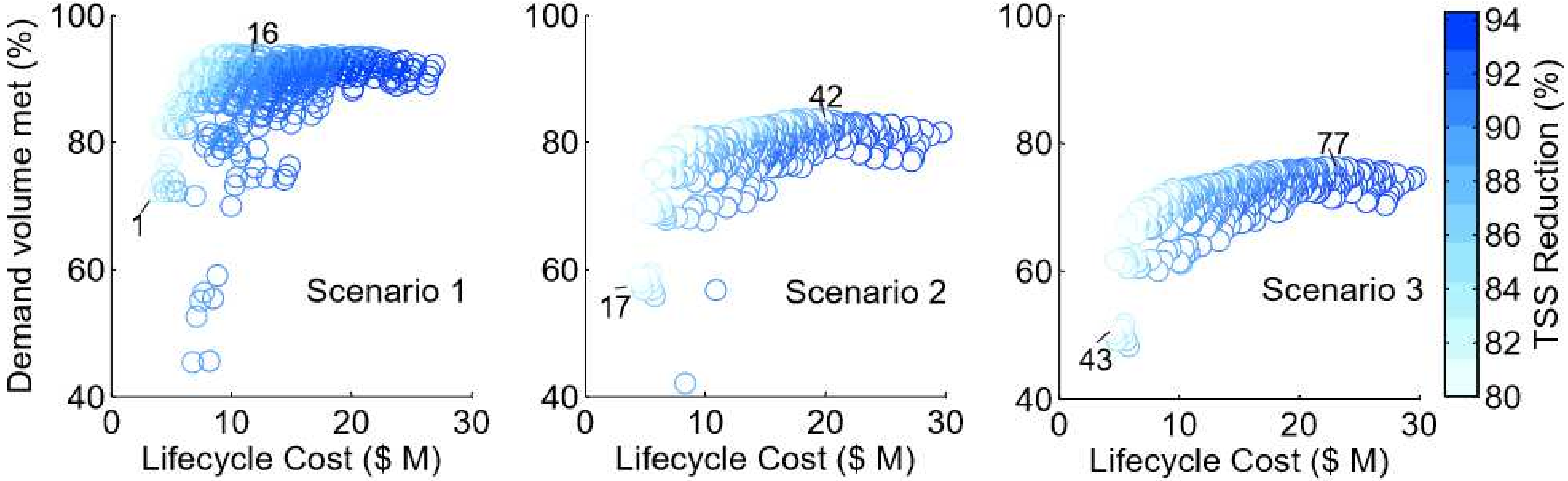

Figure 2-6 Pareto optimal solutions for three demand scenarios

Table 2-6 Decision variable values of selected solutions

Demand scenario	Solution #	Biofilter Cluster 1	Pond Cluster 1	Biofilter Cluster 2	*BMP* 2 (central)	*SA* 2 (central)	Pond 2 (central)	Biofilter Cluster 3	Pond Cluster 3	*BMP* 4 (outlet)	*SA* 4 (outlet)	Pond 4 (outlet)
1	1	1	-	-	-	B	100	33.3	-	-	B	33.3
	3	3	-	-	-	B	66.6	66.6	-	-	B	33.3
	4	4	-	-	-	B	100	33.3	-	-	B	33.3
	7	7	-	-	-	B	100	66.6	-	-	B	33.3
	8	8	-	-	-	B	66.6	66.6	-	-	B	66.6
	16	16	-	-	-	B	100	100	-	-	B	100
2	17	17	-	-	-	B	33.3	-	-	-	B	66.6
	19	19	-	-	-	B	33.3	-	-	-	B	66.6
	20	20	-	-	-	B	100	66.6	-	-	B	33.3
	27	27	-	-	-	B	100	100	-	-	B	66.6
	28	28	-	-	33.3	B	66.6	100	-	-	B	66.6
	29	29	33.3	100	-	B	33.3	100	-	-	B	33.3
	40	40	66.6	100	33.3	B	100	100	-	-	B	66.6
	41	41	66.6	100	33.3	W	100	100	-	-	B	66.6
	42	42	66.6	100	66.6	W	100	100	-	-	B	66.6
3	43	43	-	-	-	B	33.3	-	-	-	B	66.6
	44	44	-	-	-	B	100	33.3	-	-	B	33.3
	45	45	-	-	-	B	66.6	66.6	-	-	B	33.3
	47	47	-	-	-	B	66.6	100	-	-	B	33.3
	58	58	-	-	-	B	100	100	33.3	66.6	B	33.3
	63	63	-	-	-	B	100	100	33.3	100	B	100
	64	64	33.3	100	33.3	B	100	100	-	-	B	33.3
	77	77	66.6	100	33.3	B	100	100	66.6	100	B	33.3

Note: BMP type (*BMP*): B = biofilter; W = wetland. Surface area (*SA);* percentage of maximum available): ▪ = 0.0% (junction).

2.4.5 *Impact of design decisions on cost, reliability, and water quality*

Figure 2-7 shows that biofilters at the central (sub-catchment 2) and outlet (sub-catchment 4) locations (labelled as ‘BMP 2’ and ‘BMP 4’ in Table 2-6) were preferred in most Pareto optimal solutions for scenario 1. This indicates, in addition to volumetric reliability benefits as discussed previously, multiple-cluster-scale biofilters provided cost-effective TSS reduction. In addition, in solutions with high TSS reduction, the central sub-catchment 2 storage pond, and not the outlet sub-catchment 4 pond, was preferred. The sub-catchment 2 pond contributed to the supply volume objective only and was mandatory where the sub-catchment 2 multiple-cluster-scale biofilter was selected, whereas pond 4 was not mandatory. Cluster-scale biofilters were selected more frequently than other cluster BMPs in solutions with TSS reduction levels above 90%. In particular, cluster biofilter 3 was selected frequently and provided desirable cost-TSS reduction performance. This may be because cluster biofilter 3 treated runoff from the sub-catchment with the highest impervious fraction (60%), which had inflows with higher pollutant concentration and volumes than other cluster biofilters, resulting in higher treatment efficiency, and intercepted runoff which otherwise reached the catchment-outlet BMPs, which overflowed quickly due to the large contributing catchment and limited capacity at the outlet.

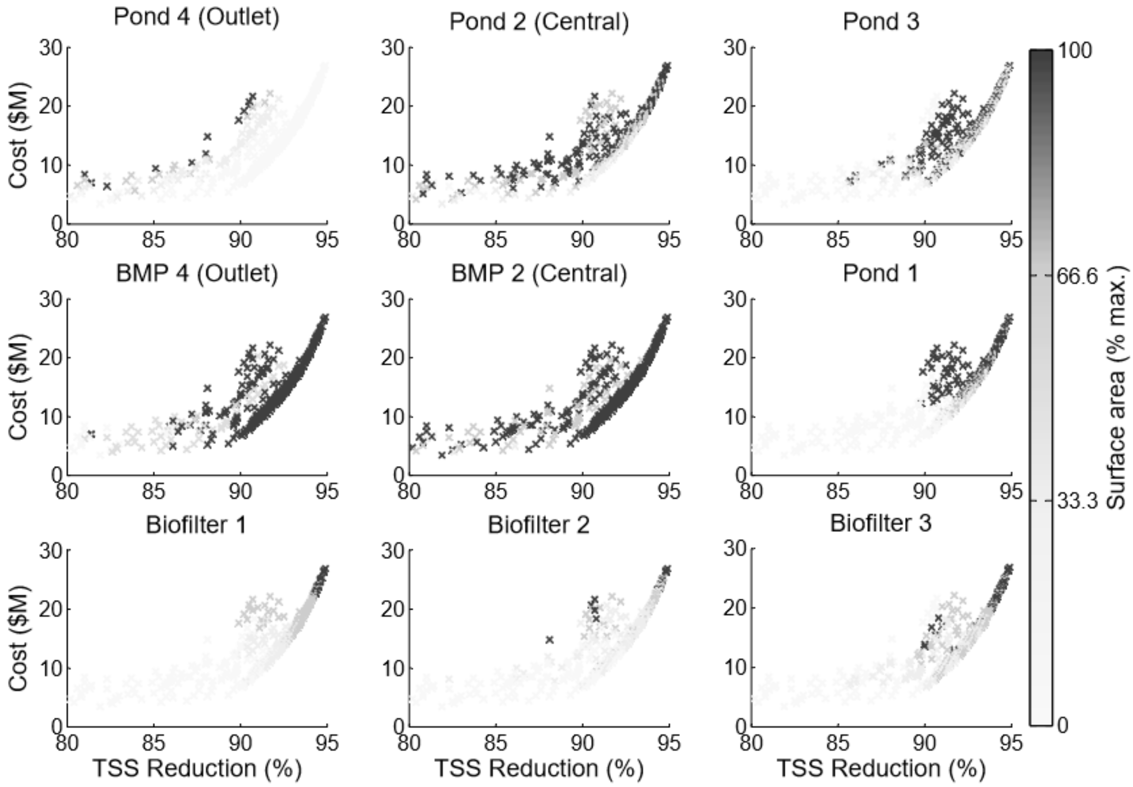

Figure 2-7 Heat maps of Pareto optimal solution decision variable values for scenario 1

2.5 Summary and conclusions

A general multiobjective optimization framework was developed for the conceptual design of spatially distributed stormwater harvesting (SWH) systems to address knowledge gaps in the SWH optimization literature. The approach was applied to a case study SWH system for a housing development north of Adelaide, South Australia. The results demonstrate the benefits of adopting Pareto optimal spatially distributed SWH systems identified using the framework, compared with traditional catchment-outlet approaches. Results indicate that where storage space is limited at the catchment outlet, in addition to better water quality improvement, better harvested stormwater supply reliability can be achieved by distributing capture, treatment, and storage BMPs in an integrated SWH system. In the case study, biofilters in locations with high runoff inflows were preferred in solutions that were non-dominated with respect to all three objectives: lifecycle cost, volumetric reliability and TSS reduction. Maximum TSS reduction was limited primarily by available treatment BMP sizes. In addition, solutions with the highest reliability did not coincide with those with the highest TSS reduction. This is because although pollutant load reduction through abstraction of harvested water contributed to improved runoff quality, major drivers for TSS reduction performance were the size and location of BMPs. Of the cluster-scale biofilters, those strategically placed in a sub-catchment with the highest impervious fraction that otherwise directly contributed to the catchment outlet BMP provided the best return on investment for improvement in reliability and TSS reduction. If decision-makers with a particular budget accepted a slightly lower harvested water supply reliability, solutions with significantly higher TSS reduction were available as an alternative to solutions non-dominated in cost-reliability space.

There were several limitations to the work carried out in this study and further research opportunities were identified. Firstly, future studies could include operating rules as decision variables to optimize transfer and release between storage ponds, to maximize supply volume and optimize detention storage size. Secondly, in the case study application, *MUSIC* simulations were a major contributor to computer run-times. Consequently, decision variable options were limited in order to limit the search space and hence the number of model evaluations. This allowed convergence towards Pareto optimal solutions in a practical time frame. Parallelization of model simulations, surrogate modelling techniques, or additional optimization operators to prevent simulation of inferior solutions could reduce run-time further, as discussed in Maier, Kapelan et al. (2014). This would permit additional decision options, scenarios including the impact of climate change on optimal BMP placement, as well as consideration of solution robustness and uncertainty analyses.

Despite these limitations, the results presented in this study clearly show the potential benefits provided by optimization of distributed SWH systems. As recommended by Askarizadeh, Rippy et al. (2015), optimization frameworks, such as the one proposed in this study, will be important decision support tools for the selection and siting of BMPs for urban SWH into the future.

2.6 Acknowledgements

Research funding was provided by the Australian Postgraduate Award, the University of Adelaide, and the Goyder Institute for Water Research. The authors thank Dr. Joshua Cantone and Dr. Robin Allison for assistance with the case study data, Mr. Jeffry Newman for assistance with software development, and Associate Professor David Rosenberg and the anonymous reviewers for their comments, which helped improve the quality of the paper.

CHAPTER 3

Paper 2 - A Many-Objective Optimization and Visual Analytics Approach to Project Selection for Integrated Catchment Management (Submitted paper)

Statement of Authorship

Statement of Authorship

Title of Paper	A Many-Objective Optimization and Visual Analytics Approach to Project Selection for Integrated Catchment Management
Publication Status	☐ Published ☐ Accepted for Publication ☑ Submitted for Publication ☐ Unpublished and Unsubmitted work written in manuscript style
Publication Details	Submitted to Water Resources Research

Principal Author

Name of Principal Author (Candidate)	Michael Di Matteo		
Contribution to the Paper	Developed software and methodology, performed computational analysis, interpreted data, wrote manuscript and acted as corresponding author.		
Overall percentage (%)	85		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature	Michael Di Matteo	Date	20 Dec 2016

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Holger R. Maier		
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Contribution to the Paper	Helped in data interpretation and to evaluate and edit the manuscript.		
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Abstract

Catchment management often involves the selection of a portfolio of stormwater best management practices (BMPs) to achieve desired social, environmental and economic benefits. However, selection of BMPs requires the optimum use of limited resources to obtain the maximum possible benefit. In previous studies, BMP selection has either been formulated as a multi-criteria decision analysis problem without optimization, or a formal optimization problem with water quality and cost as objectives. However, modern BMP technologies are designed to provide multiple catchment benefits, and decision-makers are required to select from large numbers of combinations of BMPs whilst considering many objectives. This study presents a formal many-objective optimization approach to identify and select from efficient portfolios of BMPs. The optimization approach was applied to a 4-objective case study to identify portfolios of biofilters, wetlands and swales for a regional-scale urban catchment in a major Australian city. Visual analytics was used to identify the trade-offs and impacts of decision options on Pareto optimal portfolio performance. Case study results show that significant trade-offs exist between total nitrogen reduction and cost, and between stormwater harvesting capacity and cost. This indicates that large increases in these benefits are possible for small increments in cost by adopting selected combinations of BMPs. Low-cost portfolios required a small number of cost-effective ‘flagship’ projects, but had low urban greening and amenity benefits. Portfolios that provide a desirable compromise between the four objectives were identified by considering information from the problem objective and decision spaces.

3.1 Introduction

Sustainable integrated catchment management often involves the selection of a portfolio of stormwater best management practices (BMPs) with precinct-sized contributing catchments (i.e. < 1 km^2) to achieve desired social, environmental and economic benefits within a larger catchment or region (Marlow, Moglia et al. 2013). BMPs may include structural and non-structural measures for detention, harvesting, infiltration, evaporation, and transport of non-point urban stormwater runoff (Lerer, Arnbjerg-Nielsen et al. 2015). Catchment managers must consider a range of performance criteria due to several socio-political drivers including: water supply security, public health protection, social amenity, urban flow regime improvement, environmental protection and flood mitigation (Marlow, Moglia et al. 2013, Askarizadeh, Rippy et al. 2015). In response to these drivers, BMPs have been developed to provide multiple functions in addition to water quality improvement, for example stormwater harvesting (Mitchell, Deletic et al. 2007, Clark, Gonzalez et al. 2015, Di Matteo, Dandy et al. 2017) and urban vegetation and amenity improvement (Sharma, Pezzaniti et al. 2016).

To maximize total catchment benefits for a given budget, decision-makers must select a combination, or portfolio, of BMPs that provides the best trade-off between many objectives. This is difficult for the following reasons (Moglia, Kinsman et al. 2012): (a) many planning objectives need to be considered (Mitchell, Deletic et al. 2007); (b) there are often many viable BMPs and therefore a large number of combinations of BMPs to choose from (Maringanti, Chaubey et al. 2009); (c) identifying and representing the trade-offs between many (more than 3) objectives can be computationally expensive and cognitively challenging for decision-makers (Purshouse and Fleming 2007); (d) the non-intuitive nature of multi-dimensional value analysis and unanticipated and emergent trends can prevent decision-makers from understanding and trusting portfolio analysis results (Fitzgerald and Ross 2015); and (e) the ability to identify the best portfolio of BMPs is made even more difficult in practice, as often limited resources are available for performing this task (Moglia, Kinsman et al. 2012). Therefore, to assist with selection of suitable portfolios of BMPs to implement in a catchment management strategy, catchment managers would benefit from a decision support approach that 1) considers numerous, possibly conflicting, performance criteria; 2) handles a large number of decision options and potential strategies; 3) facilitates the identification and representation of trade-offs between performance criteria; 4) develops trusted strategies; and 5) operates within the limits of existing planning capacities.

To enable consideration of many performance criteria, a number of multi-criteria decision analysis (MCDA) techniques (Goicoechea, Hansen et al. 1982) have been developed for ranking and selecting individual BMPs (Ellis, Deutsch et al. 2006, Moglia, Kinsman et al. 2012, Jia, Yao et al. 2013), and portfolios of BMPs (Aceves and Fuamba 2016a, Aceves and Fuamba 2016b), and have been adopted in practice (Moglia, Kinsman et al. 2012). The multi-criteria decision analysis (MCDA) approaches consider many (>3) performance criteria but require an *a priori* definition of stakeholder weightings for each criterion, or exploration within a limited region of interest, to determine 'the most preferred' portfolio of BMPs or a small set of preferred portfolios for further consideration. However, in practice decision makers often "…don't know what they want until they know what they can get…" (Loucks 2012, Maier, Kapelan et al. 2014). This means a change in preferences and a better understanding of the problem may occur once a full representation of the trade-offs between the various performance criteria is visualized and explored (Woodruff, Reed et al. 2013, Matrosov, Huskova et al. 2015). Therefore, although MCDA approaches allow for many performance criteria to be considered when selecting BMPs, they do not allow decision makers to understand the full range of trade-offs for the given problem before determining their preferences, which limits the ability to identify a suitable compromise solution. In addition, a limited number of alternative portfolios are generated in MCDA, which limits exploration and analysis of the influence of BMPs on the performance of portfolios that provide the best trade-offs.

Formal multiobjective optimization approaches have been developed for catchment management problems to assist in identifying the set of BMPs that represent the best possible trade-offs among the competing performance criteria from among the large number of combinations possible. Recent approaches have typically included an integrated stormwater simulation model (Bach, Rauch et al. 2014) linked with an evolutionary algorithm for the optimal sizing and placement of BMPs (Di Matteo, Dandy et al. 2017) within a watershed to achieve environmental benefits from treating stormwater runoff. However, formal objectives have been limited to ecosystem health benefits and cost for regional-scale catchment management problems (Lee, Selvakumar et al. 2012, Chichakly, Bowden et al. 2013, Chen, Qiu et al. 2015, Zou, Riverson et al. 2015). A potential reason for this is that the number of solutions required to characterise the Pareto front increases exponentially as objectives are added, making this process exceptionally computationally expensive for more than two or three objectives for many complex water resources problems (Purshouse, Deb et al. 2014). As discussed in recent optimization studies (Kasprzyk, Reed et al. 2012, Kasprzyk, Reed et al. 2015, Matrosov, Huskova et al. 2015, Woodruff 2016) optimizing management solutions for a sub-problem of a many-objective problem can lead to 'cognitive myopia', which is a negative decision-making bias that arises due to drawing incorrect inferences and conclusions from limited problem information. In this light, the limited number of formal objectives in existing studies may have encouraged solutions with sub-optimal performance with respect to criteria that are not included as formal objectives in the optimization problem but that are important to contemporary catchment managers (Woodruff, Reed et al. 2013).

It is therefore preferable to optimize with respect to many (relevant) formal objectives where possible.

While it is important to consider many objectives, as well as trade-offs between them (rather than having pre-defined weightings, as in MCDA), this makes the analysis of many-objective optimization results difficult. This is because: (1) visualizing the trade-offs between objectives in more than two or three dimensions can be cumbersome, (2) many-objective Pareto fronts can have large numbers of non-dominated solutions, as the number of Pareto optimal solutions grows exponentially with the number of formal objectives (Hughes 2005, Chand and Wagner 2015), (3) human decision makers have a limited cognitive load and can select between only a small number of solutions at a time (Miller 1956), which requires techniques to reduce the Pareto frontier to a sub-set of diverse and promising solutions to present to decision-makers (Purshouse, Deb et al. 2014), and (4) visualizing solution performance separately from decision options may cause decision maker biases (Kasprzyk, Reed et al. 2012, Giuliani, Herman et al. 2014, Matrosov, Huskova et al. 2015). Recently, advanced interactive visual analytics (Keim, Andrienko et al. 2008) approaches have been applied to help humans make sense of large and complex data sets such as many-objective optimization results (Kasprzyk, Reed et al. 2009). However, these approaches have not been applied in the catchment management optimization literature.

In order to enable trusted catchment management strategies that are likely to be adopted in practice to be developed within existing planning capacities, stakeholder engagement should be encouraged in all aspects of optimization studies applied to water resources problems (Voinov and Bousquet 2010, Maier, Kapelan et al. 2014). The problem formulation and system models should incorporate existing practitioner modelling practice. In addition, practitioners should aim to use optimization as a complementary tool to existing approaches where possible. In the existing BMP optimization literature, there is a lack of end-user input or use of problem domain knowledge that influences optimization algorithm behaviour (Bi, Dandy et al. 2016). Consequently, catchment management strategies developed by algorithms may not be trusted and adopted by decision-makers who are unfamiliar with the optimization process and who may perceive the process of selecting the Pareto set of BMP portfolios to be a 'black box' (Maier, Kapelan et al. 2014). In addition, integrated catchment simulation-optimization approaches (Srivastava, Hamlett et al. 2002, Maringanti, Chaubey et al.

2009) may not complement current practice for management of large regional urban catchments, which typically involves ad hoc selection and implementation of BMPs as funding becomes available. In addition, since existing data are often insufficient to develop useful integrated catchment models at the regional scale (Bach, Rauch et al. 2014), model development may not be feasible within a limited planning time-frame and resources. Therefore, a formal decision approach that involves stakeholders in the selection, evaluation and analysis of portfolios of individual BMPs, but without requiring a catchment simulation model, might encourage uptake of formal decision support approaches by decision-makers, which would improve upon current practices.

As identified in the above discussion, catchment management decision support approaches need to handle several objectives, consider the full trade-off space, and develop trusted solutions based on current modelling practice. However, current approaches have failed to meet all of these needs. While MCDA methods allow many performance criteria to be considered when selecting a portfolio of BMPs, they require decision-makers to define their preferences without knowledge of the full-trade-off patterns between portfolios. Many-objective optimization approaches overcome this limitation since they produce an approximation of the Pareto front, which allows an exploration and analysis of a large number of portfolios to identify solutions that represent a desirable compromise between performance criteria. However, many-objective optimization approaches can be computationally expensive and produce a large number of solutions to select from. In addition, simulation-optimization based approaches may not be feasible within a catchment management authority's planning capacities, complementary to existing practices, nor desirable if decision-makers do not trust the solutions developed by the optimization algorithm.

In order to address the shortcomings of existing approaches discussed above, the objectives of this paper are: (i) to present a formal optimization approach that identifies the best combinations of BMPs for many (> 3) objective catchment planning; (ii) to demonstrate the utility of the approach by applying it to a case study based on an integrated catchment management plan for a major city in Australia; and iii) to use the case study to a) investigate the possible many-objective trade-offs between lifecycle cost, water quality improvement, stormwater harvesting capacity and urban vegetation and amenity improvement, b) investigate the importance of a many-objective approach compared to a bi-objective water quality-cost optimization, as has been done in most previous studies, c) demonstrate trends in the impact of particular BMP projects on Pareto optimal portfolio performance, and how this may influence decision-making, and d) identifying opportunities in the application of the framework for improving stakeholder buy-in to optimization results.

3.2 Proposed Many-Objective Optimization Approach

This section contains a description and mathematical formulation of the multiobjective BMP portfolio optimization problem (decision variables, objective functions and constraints) and the proposed formal optimization framework for solving it.

3.2.1 Conceptual Outline of the Proposed BMP Selection Approach

A conceptual outline of the proposed approach to address limitations in existing approaches to many-objective best management practice (BMP) selection for integrated catchment management is shown in Figure 3-1. To ensure only viable and trusted BMPs are considered, initially, a list of potential catchment management BMPs, *p*, is determined by stakeholders. These BMPs are then evaluated individually by stakeholders and the interdependencies between them determined. All possible combinations of these individual projects make up the full portfolio solution space, which is expected to be too large to adequately evaluate by trial-and-error or enumeration. Therefore, in order to allow consideration of many performance criteria, **F**, and a wide exploration of the potential portfolios, **P**, a formal optimization approach is adopted. The best combinations of BMPs are represented as Pareto optimal solutions, **P***, to a many-objective portfolio optimization problem formulation (Cruz, Fernandez et al. 2014). In order to analyse the large number of Pareto optimal solutions produced by the optimization process, interactive visual analytics are used to explore trade-offs and impacts of BMPs on portfolio performance. To ensure results are trusted and determined within limited planning capacity, the domain knowledge of practitioners is required to evaluate the performance of individual projects. This is also useful to identify interdependencies between projects and to ensure appropriate constraints and interactions are incorporated into the evaluation of portfolio objective functions. This is a pragmatic and parsimonious alternative approach to integrated urban water simulation models that model interactions in urban drainage, water supply and broader integrated urban water systems (Bach, Rauch et al. 2014), but may be costly to develop for catchment management planners. The approach is appropriate where a large number of potential BMPs are worthy of consideration within a large catchment area, especially where integrated models may not be available or necessary. The approach can be used in a preliminary planning-phase to screen and select BMPs for further consideration. To further ensure decision-makers trust the optimization results, the visual analytics enable end-users to help make the selection of a final portfolio by illustrating the complicated logic and benefits of performance criteria trade-offs and impact of individual BMPs on total portfolio performance.

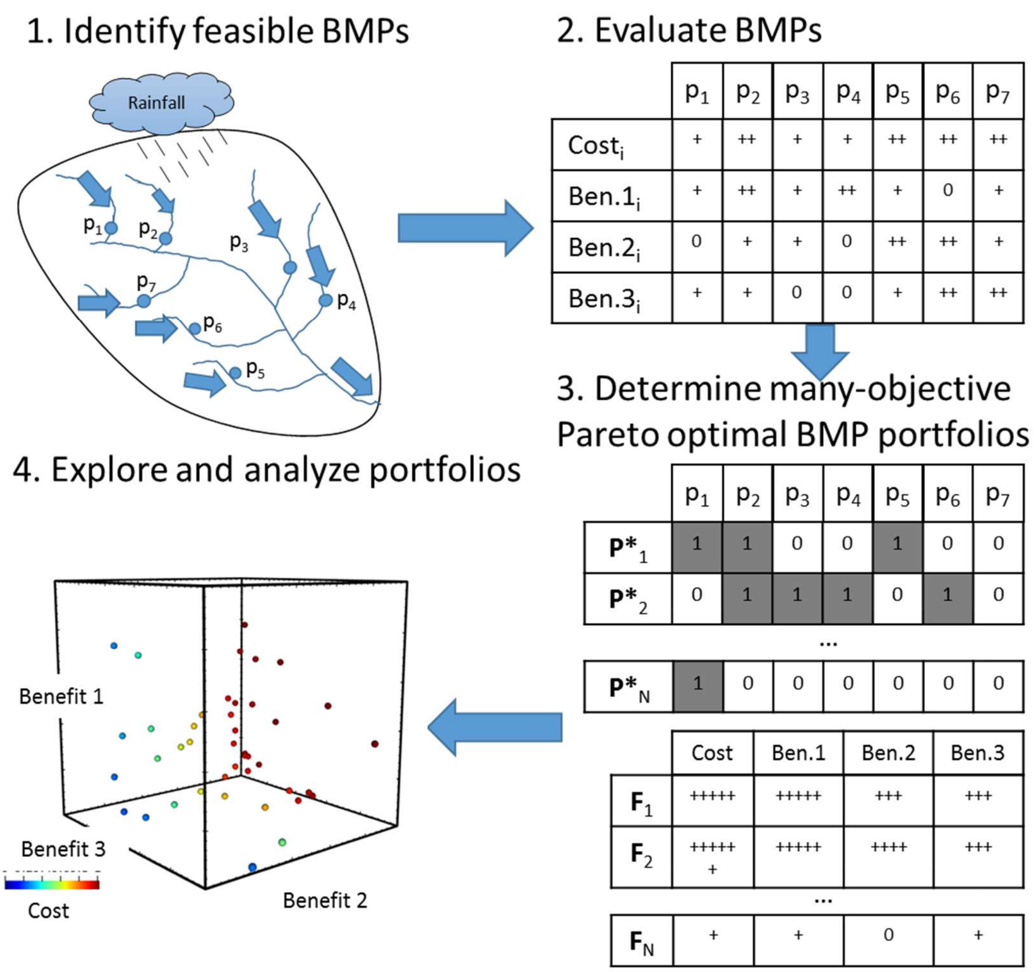

Figure 3-1 Conceptual outline of the proposed many-objective optimization approach for catchment management best management practice (BMP) selection.

3.2.2 Proposed Formal Optimization Framework

The proposed formal optimization framework for selection of BMPs for a catchment management strategy is shown in Figure 3-2, and explained in the following sections.

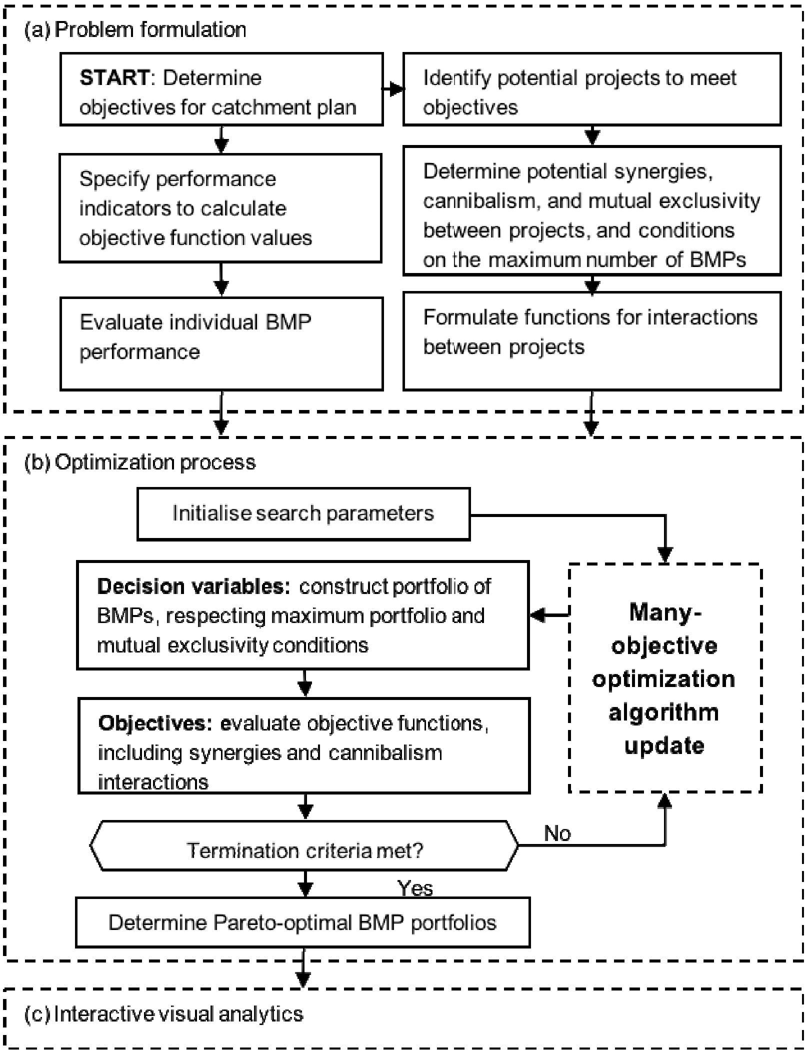

Figure 3-2 Formal optimization framework for selecting portfolios of BMPs.

3.2.2.1 Problem Formulation

The first part of the optimization framework consists of steps required to formulate a portfolio optimization problem that represents the catchment management problem. To achieve multiple catchment benefits, numerous stormwater best management practices (BMPs) are typically considered to intercept and deal with runoff, at locations distributed throughout a catchment. Examples of BMPs may include: biofiltration systems (biofilters), which typically consist of a basin overlaying a filter medium; constructed wetlands, which are shallow, extensively vegetated basins that use enhanced sedimentation, fine filtration and pollutant uptake processes to remove runoff pollutants; and swales, which are vegetated channels. Appropriate types and locations of BMPs largely depend on site characteristics including soil type, topography, infiltration rate, contributing connected impervious area, and sufficient space to access for maintenance.

Site characteristics are typically assessed through on-site and geospatial studies (Inamdar 2014). After site assessment, a short-list of feasible BMPs is agreed upon amongst stakeholders taking into account the potential to achieve desired performance criteria and other socio-political factors (Chichakly, Bowden et al. 2013, Sharma, Pezzaniti et al. 2016).

The performance of each BMP is then evaluated independently against multiple criteria, using accepted models based on the contributing sub-watershed for each BMP, and in consultation with experienced local experts (Inamdar 2014). In the absence of an adequate regional-scale integrated model to evaluate the downstream impact of BMPs, interactions (for examples of formulating interactions in portfolio optimization see (Cruz, Fernandez et al. 2014)) between BMPs that influence individual BMP performance are evaluated based on expert judgment and modelling of BMPs and multiple contributing sub-watersheds, to determine decision-making rules or performance models for interdependent projects. The individual projects, their performance, interdependencies and practical limitations on portfolio size are then formulated as the decision variables, objectives and constraints of a mathematical optimization problem (see Section 3.2.3).

3.2.2.2 Optimization Process

The second part of the optimization framework describes the algorithmic processes used to solve the optimization problem. Only portfolios that are non-dominated (i.e. none of the objective functions can be improved in value without degrading one or more of the other objective function values) can be considered as portfolios that represent the best trade-off between objectives. To identify the non-dominated, or 'Pareto optimal' solutions to the mathematical optimization formulation a many-objective metaheuristic algorithm is suggested as part of the optimization framework. Metaheuristic algorithms have several advantages over traditional optimization approaches (such as linear programming). They can deal with multiple objectives simultaneously (Maier, Kapelan et al. 2014) and have been successful in recent planning and design optimization studies considering urban water planning (Szemis, Maier et al. 2012, Beh, Dandy et al. 2014, Paton, Dandy et al. 2014a, Marchi, Dandy et al. 2016) and distributed BMP systems (Chichakly, Bowden et al. 2013, Di Matteo, Dandy et al. 2017). Furthermore, they can be linked with the evaluation models required to calculate multiple objective functions and check constraints of candidate solutions (Maier, Kapelan et al. 2014), and can provide confidence in the results of the optimization process, as simulation models that are already used in local catchment planning decision-making can be used (Maier, Kapelan et al. 2014).

As part of the optimization process, a number of solutions are generated with the aid of a many-objective metaheuristic algorithm. Each solution represents a set of binary decisions on whether or not to adopt each available project in a portfolio. In the construction of a solution, projects are added to a portfolio until a maximum number of projects is reached, or all projects have been considered i.e. a portfolio can consist of fewer than the maximum number of projects. Then, portfolios are evaluated against logical and strategic conditions. If a portfolio violates these conditions, the objective function values are set to a penalty value. Next, the performance of valid portfolios is evaluated by calculating objective functions, including interactions. This evaluation requires a model of the objective values of individual projects, and a model for each interaction, to determine the total portfolio objective function values. After evaluation, final penalties are applied to objective function values of solutions that fail to meet defined constraints. The metaheuristic algorithm uses objective function values to assess the fitness of solutions and to iteratively modify solutions. Over a number of iterations, solutions converge towards the set of Pareto optimal portfolios, which are non-dominated in the set of all feasible portfolios. The metaheuristic iterative approach continues until specific termination criteria are met (for example, a maximum number of iterations). The non-dominated solutions identified by the optimization process are Pareto optimal or near Pareto optimal catchment management portfolios.

3.2.2.3 Visual Analysis of Pareto optimal Portfolios

An interactive visual analytics package (Kollat and Reed 2007, Hadka, Herman et al. 2015) is suggested to assist decision makers to explore, analyse and ultimately select appropriate portfolios that represent a desired compromise between performance criteria and practical catchment management strategies (Maier, Kapelan et al. 2014). Firstly, the Pareto optimal portfolio performance and decision data, as well as alternative data that may be useful for decision-making (e.g. average contributing catchment size, BMP type, number of projects) are uploaded into the visual analytics package. Then, high-dimensional coordinate plots or parallel coordinate plots (Inselberg 2009) are used to visualize the performance of the large number of Pareto optimal portfolios in many-objective space. Then, in order to reduce the number of portfolios considered for further analysis, dynamic filtering to eliminate undesirable solutions can be carried out by analysts based on the decision-maker's budget constraints and minimum preferences for each benefit, and eliminate apparently undesirable combinations of BMPs not anticipated *a priori* (Piscopo, Kasprzyk et al. 2015). Within the reduced set, decision-makers and analysts can use brushing to highlight sub-sets of interesting solutions. Multiple linked plots of the same data set can assist with identifying and rationalizing trade-offs, such as conflicts and areas of diminishing returns between objectives and emergent behaviour caused by the inclusion of particular BMPs within portfolios. Interactive visualization of optimization objective and decision spaces simultaneously enables stakeholders, with the assistance of analysts, to rapidly identify subsets of portfolios that contain preferred projects and compare their performance to other portfolios. In this way, browsing through solutions to investigate and learn about the impact of individual project preferences on total catchment benefits can allow decision-makers to overcome institutional decision-making biases (Kollat and Reed 2007, Matrosov, Huskova et al. 2015). Ultimately, several desirable portfolios are selected for further consideration.

3.2.3 Optimization Problem Formulation

To identify portfolios that represent the best trade-off between many objectives, the project portfolio selection problem is defined as the optimization of vector **F**(**P**), composed of *n* objective functions:

$$\mathbf{F}(\mathbf{P}) = [f_1, f_2, \ldots, f_n]$$

Equation (3-1)

where **P** is a portfolio of projects, and **F** is a vector of the associated costs and benefits of a portfolio. The decision variables, objectives, and constraints particular to the catchment management portfolio selection problem are as follows.

3.2.3.1 Decision Variables

In the framework, it is assumed that each BMP project has a pre-determined size, type and location. As such, each decision variable is a binary variable, d_i, that represents the decision whether or not to adopt project, p_i. There are N_p possible projects, and thus N_p

decision variables, given by: $\mathbf{d} = d_1, d_2, \ldots, d_N$, where $d_i \in 0,1$, for all $i \in$ (positive integers). A portfolio, $\mathbf{P}$, is defined as the set of projects $\mathbf{p}_i$ for all i where $d_i = 1$.

3.2.3.2 Objectives

Although objectives depend on stakeholder interests, four formal objectives addressing one or more economic, social, or environmental catchment management goals are included in the proposed framework: economic cost, water quality improvement, stormwater harvesting capacity, and combined urban vegetation and amenity improvement. Economic cost is a primary concern for decision-makers responsible for maximizing return on investment, including capital maintenance and operating costs. Water quality improvement is a key environmental objective considered by catchment management authorities (Chichakly, Bowden et al. 2013, Yang and Best 2015). Maximizing stormwater harvesting volume is a primary motivation for implementing projects with SWH capacity in order to reliably meet irrigation demand, which can contribute to runoff volume reduction and groundwater recharge known to produce ecosystem health benefits (Askarizadeh, Rippy et al. 2015). An amenity improvement score was selected as the social criterion, as BMPs are typically located in public open spaces and are maintained using public resources and urban vegetation and amenity improvement are often important criteria for evaluating BMPs.

3.2.3.2.1 Cost

In the proposed framework, the economic cost of a portfolio of projects is represented as a life cycle cost LCC [$] (Equation (3-2)) (Di Matteo, Dandy et al. 2017), which is a discounted sum of expected future costs for stormwater management assets, including BMPs and transfer infrastructure required to harvest stormwater (Taylor and Wong 2002). The life cycle cost objective function for each candidate portfolio of BMPs is given by:

$$\text{MINIMIZE: } f_{cost} = LCC_{BMP} + LCC_{SWH}$$

Equation (3-2)

where

$$LCC_{BMP} = \sum_{i=1}^{N} \{ (TAC_{BMP_i}) + PWF_{estab,BMP_i}(SA_{BMP_i} \times ECF_{BMP_i} \times M_{BMP_i}) + PWF_{maint,BMP_i}(SA_{BMP_i} \times M_{BMP_i})\}$$

Equation (3-3)

$$LCC_{SWH} = C_{CapTank} + C_{CapPipe} + C_{CapControl} + C_{CapPump} + PWF_{maint}\left(C_{mTank} + C_{mPipe} + C_{mControl} + C_{mPump}\right)$$

Equation (3-4)

where a sum of the cost of BMPs to capture and treat stormwater runoff, LCC_{BMP} [$] (Equation (3-3)), and to transfer harvested water to a balancing storage for further treatment and distribution, LCC_{SWH} [$] (Equation (3-4)) is applied with BMP_i representing the i^{th} BMP in the candidate portfolio, N [integer] is the number of projects in the portfolio, and TAC [$] is the total acquisition cost as a function of SA, the surface area of BMP_i.

PWF_{estab} [fraction], for the establishment period, and PWF_{maint} [fraction], for the remaining design life of system components, are the present worth factor for a series of annual costs computed using a discount rate. ECF [fraction] is the establishment cost factor (i.e., multiplier) for the annual maintenance cost M [$] during the establishment period (typically 1-2 years) for each BMP. For BMPs with a stormwater harvesting function, $C_{CapTank}$ [$], $C_{CapPipe}$ [$],$C_{CapControl}$ [$], and $C_{CapPump}$ [$] are the capital costs for required storage tanks, control systems, pipes, and pump stations, and C_{mTank} [$], C_{mPipe} [$], $C_{mControl}$ [$], and C_{mPump} [$] are the annual maintenance costs for the tank, pipes, control systems, and pumps, and operating costs, respectively.

3.2.3.2.2 Water Quality Improvement

The water quality improvement indicator adopted in the proposed framework is the total average annual pollutant load reduction of one target pollutant (Equation (3-5)). Only one target pollutant is adopted to limit the number of objectives and therefore limiting the difficulty in identifying optimal solutions, however if the trade-offs between multiple water quality constituents needs to be known then these can be added as objectives. This indicator is widely adopted to assess performance of WSUD approaches, including SWH systems (Browne, Breen et al. 2012). The target pollutant(s) will depend on stakeholder interests. The water quality improvement objective function is:

$$\text{MAXIMIZE: } f_{quality} = \sum_{i=1}^{N} Source_i - Resid_i$$

Equation (3-5)

where, $f_{quality}$ [mass year^{-1}] is the mean annual pollutant mass retained by BMPs in each candidate portfolio, N is the number of BMPs in a portfolio, $Resid_i$ [mass year^{-1}] is the mean annual mass of pollutant leaving the i^{th} BMP's contributing catchment area, and *Source* [mass year^{-1}] is the mean annual mass of pollutant that reaches the i^{th} BMP's catchment outlet in a post-development catchment baseline scenario without intervention. *Resid* and *Source* should be determined using a stormwater quality assessment model accepted by the catchment management authority (Coombes, Kuczera et al. 2002, Bach, Rauch et al. 2014).

3.2.3.2.3 Stormwater Harvesting

Average annual supply capacity (Equation (3-6)) is adopted as an indicator of stormwater harvesting performance (Mitchell, McCarthy et al. 2008). This metric was selected because it can be determined from generic storage-yield-reliability curves for a catchment at the project screening phase of catchment management planning (Browne, Breen et al. 2012, Hanson and Vogel 2014), or other techniques (Inamdar 2014). In addition, the average annual capacity approximates the runoff volume reduction due to harvesting, which has ecosystem health benefits (Askarizadeh, Rippy et al. 2015). The supply stormwater harvesting objective function is:

$$\text{MAXIMIZE: } f_{supply} = \sum_{i=1}^{n} Supply_i$$

Equation (3-6)

where $Supply_i$ [volume] is the average annual stormwater harvesting supply capacity for the i^{th} BMP in a portfolio, and N [integer] is the number of projects in a portfolio.

3.2.3.2.4 Urban Vegetation and Amenity Improvement

The urban vegetation and amenity improvement indicator depends on stakeholder interests, which may include maximizing vegetation and tree coverage and quality of recreation spaces. Each project should be appraised and evaluated (scored) by vegetation experts. The cumulative urban vegetation improvement objective function is:

$$\text{MAXIMIZE: } f_{green} = \sum_{i=1}^{n} Green_i$$

Equation (3-7)

where *Green*$_i$ [integer] is a score, determined by expert assessment, attributed to the i^{th} project in a portfolio.

3.2.4 Constraints

Strategic and logical constraints on the selection of projects and performance of portfolios could be considered, and are case specific (Cruz, Fernandez et al. 2014). For example, where multiple sub-region catchment institutions fund an integrated catchment strategy, constraints on the selection of projects could (1) ensure equitable distribution of projects amongst constituent catchment management sub-regions, (2) limit the maximum number of projects in a portfolio, N_{max}, and projects within each sub-region, (3) prevent the presence of mutually-exclusive projects, as some BMPs may be redundant in the same portfolio, and (4) limit budget allocated to projects within each sub-region. Additional considerations for portfolio-based constraints are discussed in Cruz, Fernandez et al. (2014).

3.3 Case Study

In this study, we demonstrate the many-objective BMP selection approach on a regional catchment management strategy for a major coastal city in Australia. A catchment management authority (CMA) commissioned engineering consultants to identify sites for stormwater BMPs within an integrated catchment with an outlet flowing into a prominent marine body. The integrated catchment covers an area of approximately 700 km^2, with average annual rainfall of 400-700mm, and comprised of highly urbanized and peri-urban regions managed by three local government authorities (LGA). A primary objective for the CMA was to reduce the nutrient load from urban stormwater runoff flowing into the marine body. In addition, since the potential sites for BMPs were within public open spaces managed by LGAs, stormwater harvesting for irrigation of open spaces, increasing vegetation and public amenity value were considered important additional benefits. The consultants identified 70 (N_p=70) potential biofiltration, wetlands and swale projects at locations distributed in open spaces throughout the three LGA regions. Thirteen of these have a capacity for stormwater harvesting. In addition, the consultants agreed that a portfolio of 20 projects or fewer (N_{max}=20) was practical. The BMPs were considered mutually independent, as the contributing catchment areas to each

BMP did not coincide i.e. downstream impact of BMPs would not affect the performance of other BMPs within the large regional catchment.

The application of the proposed optimization approach was part of a real-world study involving a multi-criteria analysis conducted to identify a portfolio of BMP projects for a regional catchment. This allowed the authors to demonstrate how the proposed approach can consider existing BMP selection practices, which is a study objective. As the case study application was only intended to demonstrate the optimization approach, the results of the study were reviewed by consultants but were not used to inform decision-making. The names of stakeholders and catchment regions involved are not disclosed in this study for reasons of confidentiality.

Engagement between stakeholders, engineering consultants, and the optimization analysts (who are the authors of this study), was carried out as follows. Firstly, engineering consultants ran one workshop where the broad catchment management objectives were established, which was attended by a stakeholder working group, from LGAs and the CMA, of approximately 16 people. Consultants then identified sites, assessed them for quantitative metrics (e.g. required size of BMPs to meet water quality constraints, cost, and stormwater harvesting capacity) and made a preliminary effort to score each of the qualitative metrics (e.g. vegetation improvement and amenity value) using objective thresholds. Consultants then sent these preliminary scores to LGAs and asked to provide a response. These were generally reviewed by landscape, bushland, horticultural and parks and open space staff. The staff involved and level of response varied between the LGAs. Consultants then had a workshop with each of the individual LGAs to review the sites, establish a common understanding of the whole catchment management opportunity and confirm the proposed individual project scoring. Then, important objectives were refined into formal optimization objectives by the consultants and optimization analysts. The analysts used the multi-criteria evaluation data to inform the optimization problem formulation including decision variables (projects), developing objective functions and project objective function values, and constraints. The data used for this study are listed in the references, tables, supplements and repository at Di Matteo, Maier et al. (2016b).

3.3.1 Problem Formulation

3.3.1.1 Decision Variables

The 70 potential BMPs (Table 3-1) were formulated as 70 decision points with two corresponding decision options; to adopt or not adopt a BMP in a portfolio. Following a preliminary desktop analysis, BMPs were determined by stakeholders to have contributing catchments ranging in size from 3 ha to 421.2 ha, with an assumed 50% pervious and 50% impervious area. The functional areas of BMPs were pre-determined by consultants and sized to meet functional requirements for total nitrogen, total phosphorous and total suspended solids runoff pollutant reduction targets (Dale Browne, personal communication, 2016).

Table 3-1 Details of available catchment management projects

Local government area (LGA)	Project ID	BMP Type	Contributing catchment area (ha)	Lifecycle cost ($NPV)	TN Reduction (kg/yr)	Total Supply (ML/yr)	Green score
1	3	Biofilter	22.5	305,157	72.75	0	4
	4	Biofilter	11.6	271,251	37.4	0	4
	5	Biofilter	7.7	175,626	24.86	0	5
	6	Biofilter	9.3	131,719	30.16	0	5
	7	Biofilter	8.2	43,906	26.63	0	5
	8	Biofilter	9.4	87,813	30.25	0	5
	12	Biofilter	50.3	1,220,630	162.82	0	5
	13	Wetland	4.8	169,532	15.49	0	5
	23	Wetland	3.0	98,438	9.58	0	5
	24	Wetland	13.5	459,379	43.63	0	5
	25	Wetland	13.2	459,379	42.79	0	5
	35	Wetland	21.5	918,757	69.5	0	5
	36	Biofilter	45.2	949,379	146.3	0	5
	45	Biofilter	24.8	271,251	80.17	0	7
	46	Swale	64.5	123,814	208.58	0	7
	50	Biofilter	9.6	187,282	31.08	11.95	6
	55	Biofilter	8.7	305,157	28.27	0	8
	56	Biofilter	84.9	237,345	274.58	0	5
	57	Wetland	29.4	1,206,996	95.12	12.83	5
2	1	Biofilter	20.4	508,596	55.79	0	4

	2	Biofilter	25.4	542,502	69.5	0	4
	9	Wetland	91.9	1,220,630	251.32	0	4
	16	Biofilter	28.5	474,689	78.09	0	6
	19	Wetland	22.5	787,506	61.66	0	4
	20	Wetland	14.8	525,004	40.55	0	4
	21	Wetland	59.0	718,815	161.29	0	4
	22	Wetland	21.3	406,877	58.23	0	4
	27	Biofilter	15.3	305,157	41.89	0	6
	29	Wetland	6.2	196,877	16.89	0	6
	37	Wetland	13.6	590,630	37.31	0	5
	42	Wetland	37.5	951,570	102.47	0	6
	47	Biofilter	57.9	712,034	158.47	0	7
	49	Biofilter	36.0	610,315	98.48	0	7
	51	Wetland	17.4	590,630	47.56	0	6
	52	Wetland	21.3	721,881	58.23	0	6
	58	Biofilter	25.5	592,986	69.9	3	6
	59	Biofilter	7.8	224,031	21.21	10	6
	60	Biofilter	50.4	189,135	137.78	2.42	6
	61	Biofilter	57.7	381,297	157.92	40	6
	63	Biofilter	10.4	178,041	28.59	1.5	6
	66	Biofilter	88.6	2,027,127	242.49	5	6
	68	Wetland	98.4	976,171	269.13	2	7
	70	Wetland	22.0	768,630	60.29	2.5	7
3	10	Biofilter	53.1	1,017,191	145.28	0	5
	11	Biofilter	32.8	305,157	89.68	0	5
	14	Wetland	11.5	295,315	31.52	0	6
	15	Biofilter	16.0	203,438	43.78	0	6
	17	Biofilter	43.7	474,689	119.47	0	7
	18	Biofilter	417.2	474,689	1141.49	0	7
	26	Wetland	4.5	164,064	12.44	0	6
	28	Biofilter	10.6	87,813	29.13	0	6
	30	Biofilter	40.8	542,502	111.75	0	6
	31	Biofilter	7.2	131,719	19.65	0	6
	32	Swale	10.1	114,970	27.73	0	7
	33	Swale	13.5	88,438	37.02	0	7
	34	Wetland	51.4	732,378	140.6	0	5

38	Biofilter	97.7	213,213	267.23	1.73	6
39	Biofilter	15.9	175,626	43.59	0	6
40	Biofilter	27.2	610,315	74.48	0	6
41	Biofilter	97.7	97,587	267.23	1.73	6
43	Biofilter	18.7	440,783	51.25	0	7
44	Biofilter	43.7	576,409	119.47	0	7
48	Biofilter	421.2	915,472	1152.38	0	7
53	Wetland	15.1	525,004	41.28	0	6
54	Wetland	63.1	962,941	172.58	0	7
62	Wetland	14.0	576,409	38.19	0	7
64	Wetland	18.8	656,255	51.43	0	7
65	Biofilter	47.4	847,660	129.69	0	7
67	Biofilter	8.4	95,157	23.11	1.29	6
69	Biofilter	47.4	169,532	129.69	0	7

3.3.1.2 Objectives

3.3.1.2.1 Cost

The objective function for lifecycle cost of each portfolio, *LCC* [$], was calculated using Equation (3-2) to (3-4). The parameters for LCC_{BMP} [$] (Equation (3-3)) were estimated from cost schedules developed by Melbourne Water Australia (2013) (Table 3-2). A typical lifecycle period of 25 years, a discount rate of 6.5% per year, an establishment cost factor of 3, and an establishment period of 2 years, were adopted. The parameters for LCC_{SWH} [$] (Equation (3-4)) were estimated as follows. A linear cost model for the total net present value (NPV) of stormwater harvesting components was determined using regression (r^2 = 0.814) between levelized lifecycle cost [$/ML] and estimated annual volume supplied [ML/yr], using detailed costing data for six stormwater harvesting projects derived by Inamdar (2014) (Appendix B, Table B-1). Thus, the lifecycle cost of stormwater harvesting components from Equation (3-4) was calculated using the following equation:

$$LCC_{SWH} = \begin{cases} \sum_{i=1}^{N}(-104.49 \cdot Supply_{\mathrm{i}} + 6622.6)[\frac{\$}{ML}] \cdot \mathrm{Supply}_i[ML] & \text{, if } Supply_{\mathrm{i}} > 0 \\ 0 \quad otherwise \end{cases}$$

Equation (3-8)

where $Supply_i$ is the average annual supply capacity of the i^{th} BMP in a candidate portfolio of N BMPs.

Table 3-2 Cost variables for BMPs.

BMP Surface Area (SA) (m2)	Construction Cost ($\$/m^2$; year 0)	Establishment Cost ($\$/m^2/yr$; year 1-2)	Maintenance Cost ($\$/m^2/yr$; year 3-25)
Wetland			
$0 < SA \leq 500$	150	30	10
$500 < SA \leq 10{,}000$	100	6	2
$SA > 10{,}000$	75	1.5	0.5
Biofiltration basin			
$0 < SA \leq 100$	1,000	15	5
$100 < SA \leq 500$	350	15	5
$SA > 500$	250	15	5
Swale			
All sizes	35	9	3

Note: Establishment cost = Annual maintenance cost × establishment cost factor. Costs are in Australian Dollars (2013$). Values were scaled using an inflation adjustment factor of 1.03053 from 2013$ to 2016$.

3.3.1.2.2 Water Quality Improvement

Total Nitrogen (TN) was the specific pollutant constituent adopted for the water quality objective. TN load reduction was particularly important since in the urban catchment it was found by consultants that maximizing TN reduction through treatment of stormwater also tended to reduce phosphorous, total suspended solids and other pollutants to within target levels (Dale Browne, personal communication, 2016). The introduction of excess anthropogenically-generated nutrients into coastal systems can cause eutrophication, which has negative impacts. These impacts often include excessive, and sometimes toxic, production of algal biomass, loss of important nearshore habitat, changes in marine biodiversity and species distribution, increased sedimentation of organic particles, and depletion of dissolved oxygen. The mean annual pollutant mass of TN retained by each candidate portfolio ($f_{quality}$ [fraction]; Equation (3-5)) was calculated based on the sum of average annual TN mass retained by individual BMPs in a portfolio. The water quality improvement of individual BMPs (i.e. not an integrated system of a portfolio of BMPs) (*Source*$_{i,}$ - *Resid*$_i$; Equation (3-5) was assessed using the integrated catchment model, *MUSIC* version 6.1 (Model for Urban Stormwater Improvement Conceptualizion, eWater (2009)), as suggested by the CMA regulations. *MUSIC* is an integrated stormwater model that evaluates rainfall/runoff and pollutant generation and transport, hydraulic and pollutant removal performance of BMPs (Bach, Rauch et al. 2014). *MUSIC* algorithms simulate runoff based on models developed by Chiew and McMahon (1999) and urban pollutant load relationships based on analysis by Duncan (1999). An assessment of interactions between BMPs was not deemed necessary because the contributing catchments of individual BMPs were spatially mutually exclusive.

3.3.1.2.3 Stormwater Harvesting

To determine stormwater harvesting capacity of projects, experts on stormwater harvesting from each LGA were asked to evaluate the stormwater harvesting potential of BMPs within their jurisdiction. They estimated the expected irrigation demand required by open spaces near each BMP, and the average annual potential capacity to supply the demand. The estimates were based on procedures specific to each LGA, and reflect the stormwater harvesting objective performance values accepted by decision-makers.

3.3.1.2.4 Urban Vegetation and Amenity Improvement

The 'green' score' of individual projects (which is a weighted score of several indicators, and was developed by the authors and agreed to be used as an optimization objective by consultants), use scores assigned by experts (see section 3.3) from each LGA interviewed in a workshop session by consultants. The experts were asked to answer the following questions about the BMP projects within their jurisdiction: Answer 'Yes' 'No' or 'Maybe' to the following questions: 1) "will native vegetation increase at the site?", 2) "will tree cover increase at the site?", and, 3) "will the quality of recreation spaces in the area increase?". The total catchment 'green' score objective function was:

$$Green_i = \sum_{j=1}^{3} Score_j$$

Equation (3-9)

$$Score_j = \begin{cases} 3 & if\ answer\ is\ 'Yes' \\ 2 & if\ answer\ is\ 'Maybe' \\ 1 & if\ answer\ is\ 'No' \end{cases}$$

Equation (3-10)

where $Green_i$ is the sum of scores for each project, and $Score_j$ is the number of points assigned to the answer to the j^{th} question. Since there were three questions, each project could achieve a maximum of 9 green points, and each portfolio a theoretical maximum of (20 × 9 =) 180 total green points.

3.3.1.2.5 Evaluation of Individual BMPs

Before the optimization process was run, the costs and performance values of each BMP were determined (Table 3-1). Firstly, the stormwater harvesting capacity of individual projects was determined from LGA expert interviews. Secondly, the individual project lifecycle costs were determined using cost parameters from Equation (3-2) to (3-4) and (3-8) for each project. Thirdly, the water quality performance of each BMP was determined with the aid of *MUSIC*. To do this, a catchment model for a 1 ha catchment area for each LGA was developed. The model consisted of a 0.5 ha pervious catchment node, a 0.5 ha impervious catchment node, and an outlet node to estimate the average annual TN load per unit area of catchment with an average 50% impervious surface area (Browne, Breen et al. 2012). One year of continuous climate data and pervious surface parameters provided by the CMA were adopted for the catchment nodes. To estimate *Source* [kg] for each BMP, the TN load from a 1 ha unit catchment area for the respective LGA was multiplied by the contributing catchment area to each BMP in hectares. Each BMP size was selected to remove 45% of the TN load from its contributing catchment (i.e. $Resid_i$ = (1 - 0.45) × $Source_i$), which was suggested as an acceptable performance based on advice from the consultants (D. Browne, personal communication, 2016). Finally, Equation (3-7), (3-9) and (3-10) were applied to determine the individual project green scores.

3.3.1.3 Constraints

A single constraint was applied to limit portfolios to 20 or fewer projects, since more than 20 projects was determined to be impractical to design and construct by the CMA, as mentioned previously. The projects were assumed be independent in that the inclusion of one project did not influence the expected benefit, cost, or feasibility of another. This assumption was considered acceptable since the catchments contributing to each BMP were mutually exclusive, and customers for stormwater harvesting projects could receive supply from only one project.

3.3.2 Pareto-Ant Colony Optimization (P-ACO) Algorithm

To solve the optimization problem, a variant of the Pareto-Ant Colony Optimization algorithm (P-ACO; (Doerner, Gutjahr et al. 2004)) metaheuristic search algorithm was used. P-ACO was selected because it was originally developed to solve portfolio optimization problems (Doerner, Gutjahr et al. 2004, Doerner, Gutjahr et al. 2006), has been used successfully and adopted as a benchmark algorithm in recent three-objective portfolio optimization applications (Cruz, Fernandez et al. 2014), and has been applied to complex multiobjective water resources problems (Szemis, Dandy et al. 2013, Szemis, Maier et al. 2014, Nguyen, Dandy et al. 2016). The variant adopted here, PACOA, was demonstrated to outperform other multiobjective ant colony optimization algorithms in a recent water resources allocation study (Szemis, Dandy et al. 2013). The algorithm mimics the cooperative foraging behaviour of an ant species that leaves a chemical pheromone on a ground surface. In real-life, since ants traverse short paths to food more frequently, more pheromone is laid on short (efficient) paths. Thus, paths with higher pheromone levels are more likely to be selected by an ant. In the algorithm, artificial ants select between paths, which represent decisions whether or not to adopt a BMP in a portfolio in this instance. An input template and executable for the algorithm are available as Data Set 3 in the Supporting Information.

A summary of the steps in the PACO algorithm is shown in Figure 3-3. In the initialization phase, the PACO search control parameters are set. The iterative process commences where *b* ants are generated, each ant starting with an empty portfolio x = (0), and the objective weights (i.e., the ant's individual preferences) are determined randomly for each ant. In the construction phase of the algorithm, first the order of BMPs is randomly shuffled, to ensure BMPs are provided an equal chance of being considered first by each ant. Then, the ant decides whether to add each BMP to a portfolio, x, by applying a pseudo-random-proportional rule using pheromone information τ_i. The pheromone information is stored in one 2xN matrix for each j^{th} objective, representing the binary options for the N possible BMPs. If the ant adds the maximum number of BMPs, N_{max}, before all BMPs have been considered, then none of the remaining BMPs are selected. After a portfolio has been constructed, its performance is evaluated using the objective functions (Equation (3-2) and (3-5) to (3-7)). In this case, as individual projects were determined to be independent, the portfolio objective functions were a summation of the constituent individual project objective function values in Table 3-1.

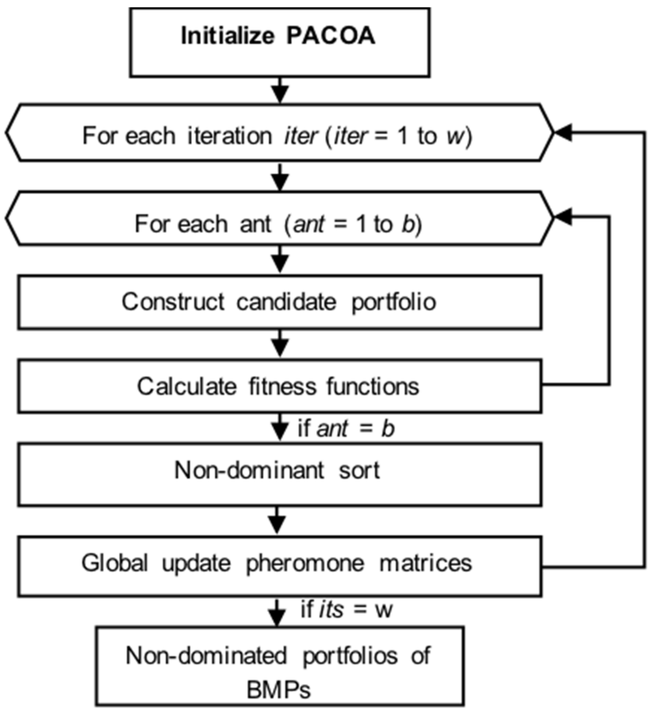

Figure 3-3 Portfolio optimization process for Pareto Ant Colony Optimization Algorithm (PACOA)

After each iteration, of the b portfolios generated by the b ants, the non-dominated portfolios are stored offline in an array. Then, as part of a global update of every element of the j pheromone matrices, the first and second best performing solutions ranked for each j^{th} objective are used to apply the following equation.

$$\tau_t^j = (1-\rho) \cdot \tau_t^j + \rho \cdot \Delta\tau_t^j$$

$$\Delta\tau_t^j = \begin{cases} 15, & t \text{ in both best and 2nd best portfolio} \\ 10, & t \text{ in best portfolio} \\ 5, & t \text{ in second best portfolio} \\ 0, & \text{otherwise} \end{cases}$$

Equation (3-11)

where, for each BMP, the current pheromone value for each t^{th} binary option and j^{th} objective is reduced by pheromone evaporation, ρ, and increased by a pheromone value ($\Delta\tau_t^j$). Pheromone is evaporated from decisions that are not in the best solutions for each objective, which makes it less likely these decisions will be selected again in future iterations. In this way, the ant's decision-making landscape is modified to guide ants into regions of the search space that contain non-dominated portfolios. Since the single constraint was handled in the construction phase, no penalty function is required for this case study as all constructed portfolios are feasible. The interested reader is referred to Szemis, Maier et al. (2014) for examples of objective penalty functions. The process of developing, assessing and updating the pheromone trails to guide the PACOA to near-optimal trade-offs continues until a specified maximum number of iterations, *w*, is reached.

Before the PACOA was applied, a sensitivity analysis was conducted to identify suitable values of parameters that control the searching behaviour of the algorithm to maximize the likelihood the best possible approximation of the Pareto front was generated. The ranges of parameter values tested and the final parameters selected are given in Table 3-3.

Table 3-3 PACOA parameters tested and adopted in sensitivity analysis

PACOA Parameter	Range of Values Tested	Adopted Value
Number of ants ($\boldsymbol{b}$)	20, 200, 300,500	500
Initial pheromone ($\boldsymbol{\tau o}$)	0.5, 1.0, 10.0	0.5
Evaporation rate ($\boldsymbol{\rho}$)	0.1, 0.15, 0.2, 0.4, 0.5	0.4
Evaluations ($\boldsymbol{b} \times \boldsymbol{w}$)	Up to 2,000,000	600,000

In this study, the PACO was run for 1200 iterations of 500 ants, which equates to 600,000 objective function evaluations. This number of evaluations was selected because the progress of the Pareto front ceased to have meaningful progress (assessed by visually inspecting the Pareto optimal solution set at 5,000 evaluation intervals) after this number of evaluations in a trial run of 2,000,000 evaluations. The optimization results were replicated 50 times using different random starting seeds for the pseudo-random number generator used in the algorithm to minimize the influence of probabilistic effects of some of the operators that influence the search. Each run took approximately 26 minutes on a 3.10GHz computer with 8 GB of RAM, although multiple instances were run on one machine simultaneously. The Pareto optimal solutions shown in this paper are the result of a non-dominated sort of the solutions from the 50 replicate runs.

3.3.3 Interactive Visual Analytics to Explore Pareto Optimal Solutions

To visualize and analyse the objective and decision space trade-offs of the Pareto optimal set of portfolios, an interactive visual analytics package was selected. The combined objective space and decision space visualizations were carried out using the approach of Kollat and Reed (2007) using the DiscoveryDV software package (DiscoveryDV Version 0.72; available at https://www.decisionvis.com/discoverydv/). The package features an interactive data plot that allows brushing, linked views of solutions, marking and tracing of solutions of interest, as well as rapid browsing through solution objective, decision and non-objective performance data. The package has been used successfully in several recent many-objective optimization studies (Woodruff, Reed et al. 2013, Piscopo, Kasprzyk et al. 2015). The Pareto optimal solution objective and decision data were uploaded into the interactive visual analytics package. This allowed the analyst to 1) visualize and analyse trade-offs between the four objectives, 2) isolate portfolios from several regions of the trade-off front using interactive brushing and visualization in multiple linked plots, and 3) visualize the decision and objective space to analyse the impact and prevalence of particular projects on the performance of Pareto optimal solutions. The Pareto optimal solution data file uploaded into the package is available as Data Set 3, and a .ddv file for the DiscoveryDv program containing the visualizations is included as Data Set S4 in the Supporting Information (Di Matteo, Maier et al. 2016b).

3.4 Results and Discussion

This section presents the results of the many-objective optimization process for the catchment management portfolio selection case study outlined in Section 3.3. The results of the PACOA runs, from 50 random starting positions, show the algorithm identified 3654 Pareto optimal (or near-Pareto optimal) portfolios as solutions to the optimization problem.

3.4.1 Identifying Many-Objective Trade-Offs Between Pareto Optimal Catchment Management Portfolios

Figure 3-4 shows the trade-offs between four objectives of the Pareto optimal portfolios in a 4-dimensional coordinate plot. A sharp trade-off exists between TN reduction and cost, and between reuse capacity and cost, indicating small increments in cost can return large increases in both of these objectives. In contrast, green score tends to increase with cost, which is expected as higher cost portfolios have more BMPs distributed in the catchment to enable larger total catchment urban greening and amenity improvement.

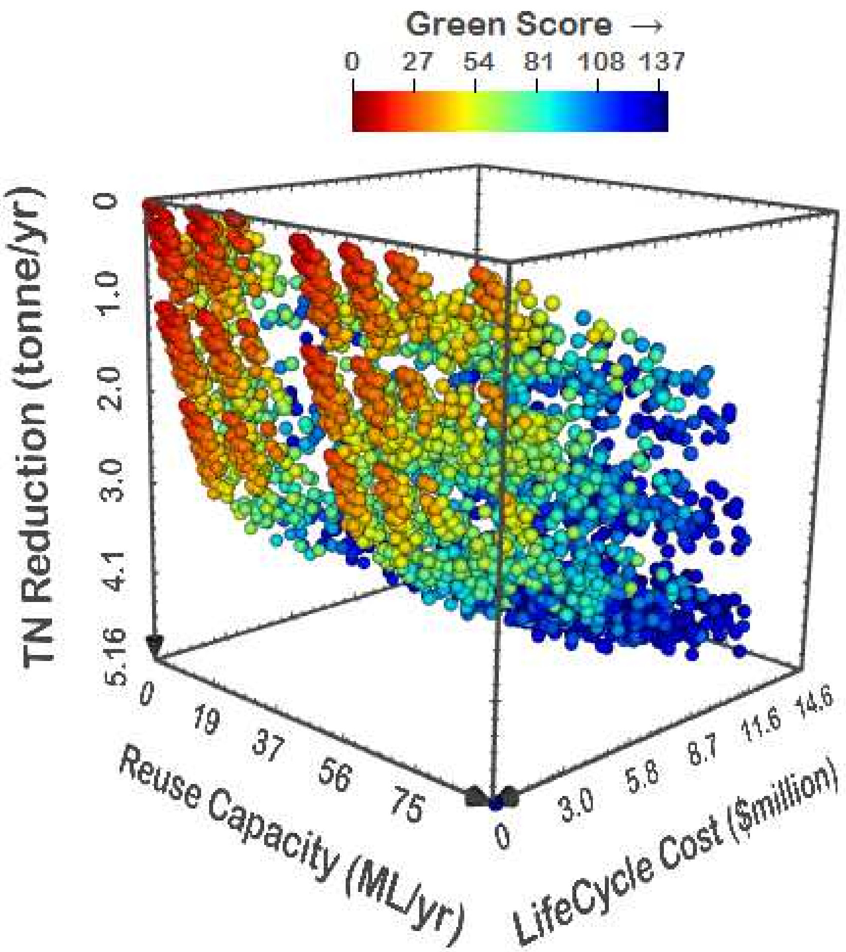

Figure 3-4 A many-dimensional interactive coordinate plot showing the objectives performance of Pareto optimal solutions. Each sphere represents a portfolio of catchment management BMPs. The lifecycle cost, average annual total nitrogen (TN) reduction, and average annual stormwater reuse capacity performance are represented on the cardinal axes. The green score performance is represented in colour.

The above inferences are supported and supplemented by the alternate representation of the trade-off surface in parallel coordinates (Inselberg 1997). In Figure 3-5, small slopes on some line segments between the adjacent axes of lifecycle cost and stormwater reuse indicate high reuse portfolios exist for low costs. However, these low cost-high reuse capacity solutions appear to have lower TN reduction and green score compared to other solutions. As mentioned above, green score appears to be correlated with lifecycle cost, however, some solutions exist that have a high green score and relatively low cost.

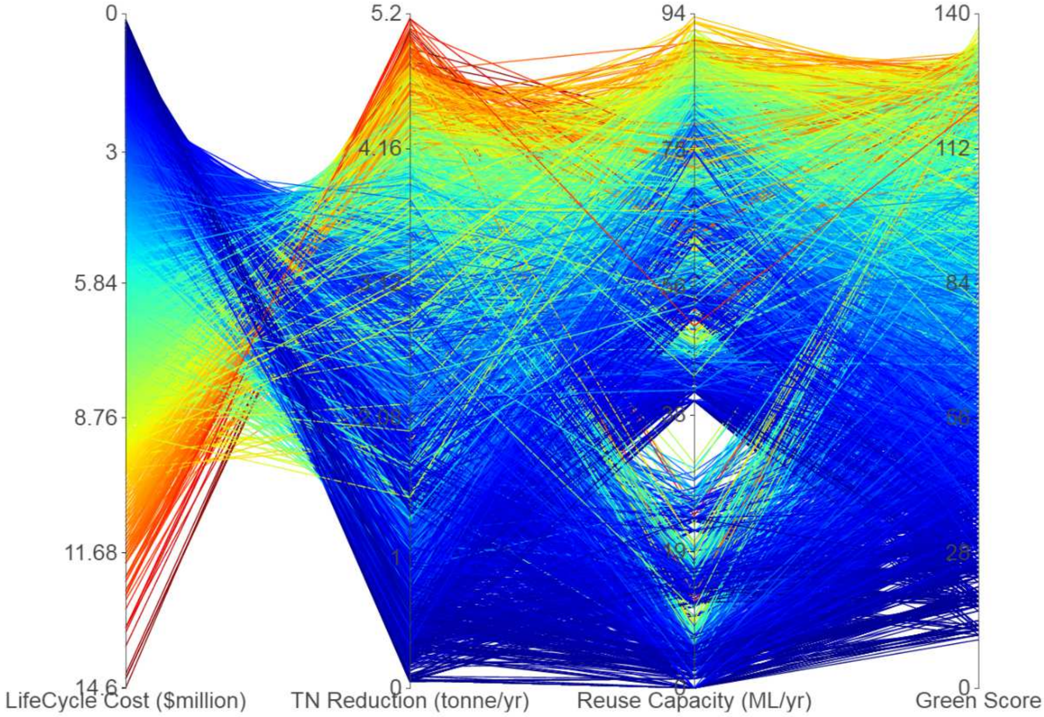

Figure 3-5 Parallel coordinate plot, where each portfolio is represented as a line interval over four vertical axes indicating objective performance values. Lifecycle cost is also represented by color to identify the cost trade-offs against each objective.

In the low-cost region, from Figure 3-4, clusters of solutions form in TN reduction-reuse capacity space. This indicates that individual projects dominate the contribution to total portfolio reuse capacity or total nitrogen reduction in this region. Analysis of the BMPs comprising solutions in these clusters shows that these portfolios contain a small number of 'flagship' projects with exceptionally large reuse capacity (e.g. project 61, 40 ML/year; project 67, 12.8 ML/year; project 18, 12.0 ML/year) or TN reduction (e.g. project 48, 1152 kg/year; project 18, 1141 kg/year) appear. Portfolios containing only a few of these flagship projects can achieve relatively high total reuse capacity or TN capacity at relatively low cost, but also a low green score. This causes the noticeable discontinuity in the objective space in the low-cost region, characterized by clusters of solutions emanating from a small number of portfolios in the low-cost region in Figure 3-4 and overlapping dark blue (low-cost) line segments joining parallel axes in Figure 3-5. Moving in the preferred objective direction, adding a flagship project to create a new portfolio on the front can cause a large increase in TN reduction or reuse capacity. Therefore, decision-makers desiring low-cost trade-off solutions could consider portfolios of a small number of 'flagship' projects, but this would considerably compromise the urban greening and amenity performance of the catchment management strategy.

3.4.2 Importance of a Many-Objective Problem Formulation for Catchment Planning

The cost and total nitrogen reduction trade-off projections in Figure 3-6 show trade-offs between water quality and cost objectives, which have been a typical formulation in catchment management optimization studies to date. On the front, a slight 'knee' region appears such that when moving along the front away from the knee region, there is a diminishing return in these objectives. This suggests that solutions in this region may represent a desirable trade-off between total nitrogen and cost. The trade-off pattern is consistent with those in other catchment planning studies (Maringanti, Chaubey et al. 2009, Lee, Selvakumar et al. 2012, Chichakly, Bowden et al. 2013). However, only considering trade-offs between water quality and cost objectives neglects the influence of other objectives that may be important to catchment management decision makers (Moglia, Kinsman et al. 2012). This could bias decision makers towards selection of solutions that would lie at extremities in objective space should other formal objectives be considered (Kollat, Reed et al. 2011).

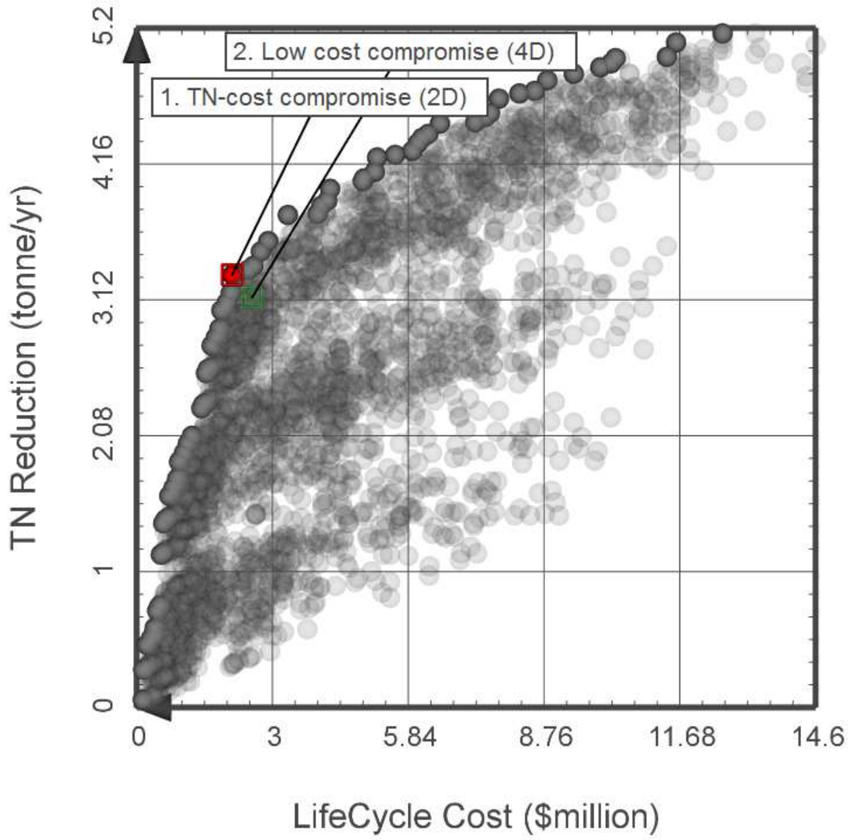

Figure 3-6 Pareto optimal solutions identified by the optimization process projected in water quality-cost objective space, which have been typical objectives in previous stormwater management optimization studies. Non-dominated solutions with respect to the two objectives are shown as solid, and approximate the best trade-off between total nitrogen (TN) reduction and cost. Other Pareto optimal solutions in 4-objective space, but dominated in water quality-cost space, appear transparent.

The importance of the many-objective representation of the catchment planning problem adopted in this study is demonstrated by tracing a solution from the two-objective knee region in Figure 3-6 through higher dimensional objective space represented in Figure 3-7. For this purpose, Portfolio 1 (Table 3-4) is selected and marked for further analysis because it lies at an inflection point (observed by visual inspection) in the knee region of the two-objective trade-off front (Figure 3-7). Using the visual analytics package, an additional harvesting capacity axis and a green score color axis are added to create a 4-dimensional plot of the objective space (Figure 3-7). To compare Portfolio 1 with other solutions similar in cost, the analytics package's data brushing tool is used to highlight solutions with lifecycle costs in the range [$1.90 M, $2.70 M]. In Figure 3-7, these solutions of interest appear opaque, and the remaining solutions that have been ‘brushed out’ appear transparent. Portfolio 2 (Table 3-4) is selected for comparison because although it has a 22% greater lifecycle cost and similar TN reduction compared to Portfolio 1, it has a vastly higher reuse capacity and green score. Therefore, although Portfolio 1 appeared in the region of best trade-off (knee region) in the lower-dimensional TN reduction-cost representation of the objective space (Figure 3-6), it performed poorly in reuse capacity and green score objectives. Portfolio 2 lies *near* but not *on* the non-dominated water quality-cost front in Figure 3-7. Thus, it would not have been available to decision makers in a bi-objective Pareto optimization approach, which has been typical in catchment planning optimization studies to date.

When considering the project options selected in the two portfolios (Table 3-4), it is apparent Portfolio 2 is almost identical to Portfolio 1 except for one small project (Project 38 instead of Project 33) and, importantly, two additional projects located in municipality 1 (Projects 60 and 61). Consequently, decision-makers may consider that Portfolio 2 provides a better compromise between objectives compared with Portfolio 1, due to the reuse capacity and green score benefit the two additional projects provide.

The above results are consistent with findings in several other studies including (1) a finding by Kollat, Reed et al. (2011) and Woodruff, Reed et al. (2013) that, generally in optimization studies, lower dimensional problem formulations may bias selection of solutions that would otherwise exist at low-performing extremes if additional performance criteria were considered as formal optimization objectives, (2) a finding by Chichakly, Bowden et al. (2013) that, for catchment planning optimization, desirable solutions lie near but away from the two-objective non-dominated Pareto front for water quality improvement and cost objectives, and (3) trade-offs for a stormwater harvesting system design determined by Di Matteo, Dandy et al. (2017), which showed slight increases in system costs could provide large increases in both water quality improvement and harvesting capacity.

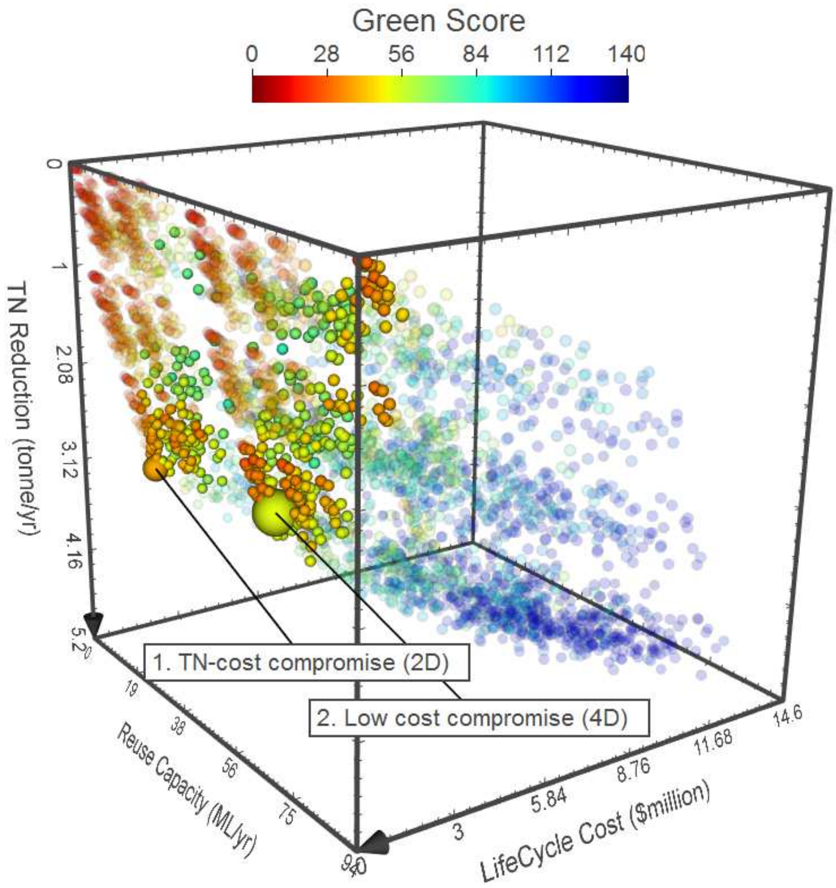

Figure 3-7 4-dimesional coordinate plot showing the trade-off space with solutions in a defined low-cost range as solid, with all other solutions brushed out and appearing transparent. Portfolio 2 may provide a more desirable alternative to Portfolio 1 in 4-objective space.

Table 3-4 Objective values and decision options of selected solutions

Solution	**TN- cost compromise (2D)** Portfolio 1	**Low cost compromise (4D)** Portfolio 2
Objectives		
Lifecycle Cost ($M)	2.06	2.51
Total Nitrogen Reduction (kg/yr.)	3312	3377
Stormwater reuse capacity (ML/yr.)	3.46	44.15
Green Score (no units)	38	51
Portfolio project decisions		

Projects in Municipality 1	-	60, 61
Projects in Municipality 2	46, 56	46, 56
Projects in Municipality 3	18, 38, 41, 48	18, 33, 41, 48
Total No. projects	6	8

3.4.3 Identifying Impacts of Project Options on Pareto Optimal Portfolio Performance

Figure 3-8 shows combined objective performance and decision characteristics of the Pareto optimal portfolios, which helps the analyst to overcome biases arising from artificial distinctions between objective performance and other characteristics of the problem (Matrosov, Huskova et al. 2015). For example, the visual interactive plot allows the analyst to inspect which area of the trade-off front each project features in Pareto approximate portfolios. In this way, an analyst can infer the impact of particular projects on portfolio performance.

In Figure 3-8 (a) the opaque spheres represent portfolios containing Project 61 (lifecycle cost $381,297; TN reduction 157.92 kg/year; reuse capacity 40 ML/year; green score 6), which was the project with the highest reuse capacity. Importantly, all portfolios with 40 ML/year or greater reuse capacity include Project 61, and these portfolios occur in nearly the full range of cost, TN reduction and green score of Pareto solutions. Therefore, this indicates decision makers should probably consider Project 61 in their final portfolio. In Figure 3-8 (b), the opaque spheres represent portfolios containing Project 48 (lifecycle cost $915,472; TN reduction 1152 kg/year; reuse capacity 0 ML/year; green score 7), which was the project with the highest TN reduction. Importantly, in the lower cost region, Pareto optimal portfolios with a number of smaller solutions dominated inferior portfolios containing Project 48. This was because although the green score of Project 48 was high (7 out of 9), the cumulative green score and/or reuse capacity of low-cost portfolios with more projects dominated portfolios containing a small number of projects including Project 48. This indicates multiple additional benefits can be achieved for a similar cost by using a portfolio of projects rather than one 'flagship' project. In addition, decision-makers can view and assess additional (non-objective) characteristics that may influence decision-making, for example the percentage of the catchment treated, spatial distribution of projects throughout the catchment, or socio-political preferences for particular projects.

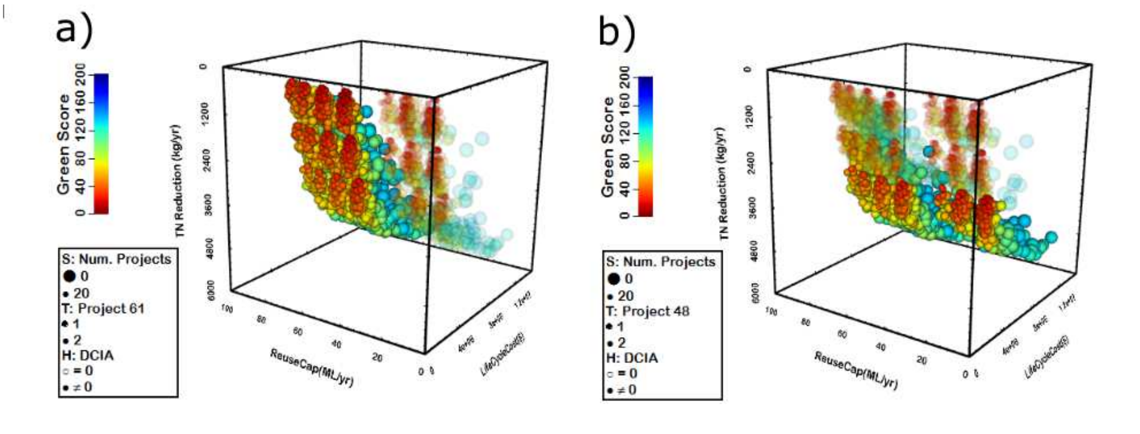

Figure 3-8 Coordinate plot showing the combined Pareto optimal objectives, decisions, and alternate data spaces. Portfolios that include, in part a) Project 61, and in part b) Project 48, are shown as opaque spheres, other portfolios are brushed out and appear transparent. The size of spheres is proportional to the number of projects in a portfolio.

3.4.4 Improving Stakeholder Buy-In to Optimization Results

Adopting the portfolio optimization approach and involving stakeholders in the formulation, exploration and analysis makes the decision support framework open to stakeholder influence and complementary to existing decision analysis practices, which can improve trust in the optimization results and increase the likelihood they will influence final decision-making. For example, the portfolio optimization approach allows individual BMPs to be provided by practitioners familiar with which BMPs are likely to be technically feasible and socio-politically acceptable, which is not ensured in simulation-optimization based BMP placement approaches (Chichakly, Bowden et al. 2013). In addition, the portfolio approach complements existing practices where MCDA approaches are used to handle many-objective preferences to rank BMPs based on individual or portfolio performance (Moglia, Kinsman et al. 2012), but has the advantage that it allows trade-offs and a large number of Pareto optimal portfolios to be explored and analysed. When formulating objective functions, stakeholders are encouraged to consider the interdependencies between BMPs, which may result in the discovery and deeper understanding of aspects of the problem that had not been considered previously (Wu, Maier et al. 2016). Interactively exploring the full Pareto optimal data set enables analysts to discover the full trade-offs between objectives, which can help decision-makers to rationalize preferences for different benefits and may change during the exploration process. In addition, stakeholders with a preference for particular BMPs can explore the impact of removing portfolios containing the BMP from the Pareto set to rapidly analyse the importance of the BMP and possible alternatives, which may help overcome institutional biases favouring particular BMP types. In this way, exploration may help to rationalize the benefits of a distributed stormwater harvesting and treatment approach with a large number of BMPs over a centralized approach with high capacity BMPs, or a mix of both (Di Matteo, Dandy et al. 2017).

3.5 Summary and Conclusion

A general multiobjective optimization framework was developed for the selection of a portfolio of BMPs for catchment management. The framework addresses the need for a decision support approach for the selection of BMPs that 1) considers numerous, possibly conflicting, performance criteria, 2) handles a large number of decision options and potential strategies, 3) facilitates the identification and representation of trade-offs between performance criteria, which 4) develops trusted strategies, 5) within the limits of existing planning capacities. The approach was applied to a case study catchment plan for a catchment authority in a major coastal city in Australia. The results demonstrate the benefits of exploring full portfolio solution trade-offs in a many-dimensional Pareto optimal front. A comparison between the trade-off spaces of the lower dimensional water quality-cost problem formulation, and the many-objective formulation, demonstrated that low-objective formulations can result in Pareto optimal portfolios with low performance in non-objective performance criteria. In this study, when stormwater harvesting and vegetation and amenity improvement scores were included as objective functions, solutions that were in a region of best trade-off in water quality-cost space performed poorly in these additional objectives. The many-objective optimization results show that sharp trade-offs exist between TN reduction and cost, and between reuse capacity and cost, indicating small increments in cost can return large increases in both objectives. Portfolios in the low-cost regions typically featured a small number of projects including cost-efficient ‘flagship’ projects that provide high TN reduction or reuse capacity. However, in order to maximize the vegetation improvement and amenity benefits, portfolios with a larger number of lower cost BMPs distributed throughout the catchment were preferred. Notably, the optimization formulation in the case study does not consider interaction between having a higher harvest capacity might allow for more irrigation of green spaces. Using the visual analytics approach to explore combined optimization and decision spaces, the impact of individual projects that may be preferred by decision-makers was rapidly visualized. This approach could assist in overcoming institutionally influenced biases to include particular projects or BMP technologies to demonstrate alternative similar cost options to decision-makers.

Future studies applying the framework could account for differences in preferences between multiple stakeholders that may be responsible for funding over different periods of the project lifecycle. For example, in some funding schemes, CMAs fund the capital expenses, whereas LGAs fund the maintenance and ongoing expenses. The many-objective problem formulation could be adapted to include specific objectives important to LGAs, which might include individual LGA expected operating expenses, in addition to total catchment benefits. In addition, the Pareto optimal solutions could be explored taking into account individual objective and non-objective preferences of multiple stakeholders. In this way, decision-makers can visualize their preferences on a trade-off curve and compare and, through an iterative approach, visualize and negotiate acceptable outcomes and solutions. This may be preferable to other approaches where weightings are set *a priori*, which do not account for decision maker preferences in the decision space, nor allow a visual comparison of the regions of interest preferred by several decision-makers. Finally, the constraint for number of projects could consider the difficulty of constructing individual BMP types (e.g., 20 swales might be easier to construct than 20 wetlands).

3.6 Acknowledgements

Research funding was provided by the Australian Postgraduate Award, the University of Adelaide, and the Goyder Institute for Water Research. The authors thank Dr. Dale Browne and e2DesignLab, Australia for assistance with the case study data. The data used are listed in the references, tables, supplements and repository at Di Matteo, Maier et al. (2016b).

CHAPTER 4

Paper 3 - A Multi-Stakeholder Optimization-Visual Analytics Framework Applied to Integrated Catchment Management Project Selection (Submitted paper)

Statement of Authorship

Statement of Authorship

Title of Paper	A Multi-Stakeholder Optimization-Visual Analytics Framework Applied to Integrated Catchment Management Project Selection
Publication Status	☐ Published ☐ Accepted for Publication ☑ Submitted for Publication ☐ Unpublished and Unsubmitted work written in manuscript style
Publication Details	Submitted to Environmental Modelling & Software.

Principal Author

Name of Principal Author (Candidate)	Michael Di Matteo		
Contribution to the Paper	Developed software and methodology, performed computational analysis, interpreted data, wrote manuscript and acted as corresponding author.		
Overall percentage (%)	85		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature	Michael Di Matteo	Date	20 Dec 2016

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Graeme C. Dandy		
Contribution to the Paper	Supervised development of work, helped in data interpretation and manuscript evaluation.		
Signature		Date	21/12/16

Name of Co-Author	Holger R. Maier		
Contribution to the Paper	Helped in data interpretation and to evaluate and edit the manuscript.		
Signature		Date	23/12/16

Please cut and paste additional co-author panels here as required.

Abstract

In this paper, an optimization-visual analytics framework for complex environmental management problems involving multiple stakeholders is developed and illustrated. In the framework, problems are represented as a series of smaller, interconnected optimization problems, reflecting individual stakeholders' interests. The framework uses interactive visual analytics to explore and analyze optimization results, and Best Alternatives to a Negotiated Alternative (BATNAs) and an approach to reframe visualizations to encourage stakeholder negotiation. To demonstrate the utility of the framework, it is applied to a realistic case study involving multiple stakeholder groups funding different aspects of an integrated catchment management plan for a region of a large city in Australia. The problem features sixteen objectives from four stakeholders. The results indicate that the proposed framework enables the identification of solutions that provide the best trade-offs between many objectives and provides an effective and efficient means of assisting stakeholders with identifying acceptable compromise solutions. (147 words)

4.1 Introduction

Evolutionary algorithms (EAs) have been used successfully and extensively for solving water resources optimization problems in a number of areas, such as engineering design, the development of management strategies, and model calibration (Nicklow, Reed et al. 2010, Zecchin, Simpson et al. 2012). Ultimately, EAs are intended to be used to support decision-making through application to complex real-world problems. However, for real-world problems, the identification of a good decision may be difficult, highly subjective, and dependent on stakeholder values and perceptions (Maier, Kapelan et al. 2014). These issues are compounded in problems that involve multiple stakeholders, each with their own understanding of the problem stemming from their values and priorities placed on outcomes, costs to be borne, and responsibilities once solutions are implemented. Therefore, in order to improve the uptake of EAs for use as decision support tools for complex problems, there is a need to develop optimization approaches that can handle multiple stakeholder groups, with multiple objectives for each.

As pointed out by Maier, Kapelan et al. (2014), adapting optimization approaches to account for different stakeholder groups is difficult because: i) stakeholders have different value sets and interests, making it difficult to arrive at a consensus on one mathematical formulation that all stakeholders will accept, which may affect the likelihood that stakeholders will trust the optimization process and buy-into suggested solutions, ii) the exploration and analysis of optimization solutions requires stakeholder engagement and expert input, iii) the non-intuitive nature of multi-dimensional value analysis and unanticipated and emergent trends can further prevent decision-makers from understanding and trusting optimization results, and iv) the optimization framework is required to facilitate the identification of a final negotiated outcome and/or exploration of resource management alternatives to be considered further.

In the past, there has been little focus on these aspects of optimization (Maier, Kapelan et al. 2014), which largely featured studies on algorithm development, rather than optimization approaches for decision-making support in practice. However, there has been some progress in relation to this in recent years, including:

- The use of iterative approaches, which has allowed for multiple formulations of the decision variables, objectives and constraints to be developed to progressively better define optimization problems and provide an opportunity for stakeholders to learn about the problem (Kollat and Reed 2007, Woodruff, Reed et al. 2013, Piscopo, Kasprzyk et al. 2015, Wu, Maier et al. 2016).
- The development of an optimization framework that provides opportunities for stakeholders to provide input into the various stages of optimization studies, including problem definition, the optimization process, and final decision-making (Wu, Maier et al. 2016).
- The development of many-objective optimization approaches that identify solutions to complex problems that represent the optimal trade-off between numerous (>3) objectives to better capture stakeholder values (Kollat, Reed et al. 2011, Kasprzyk, Reed et al. 2012, Woodruff, Reed et al. 2013, Cruz, Fernandez et al. 2014, Chand and Wagner 2015, Hadka, Herman et al. 2015, Matrosov, Huskova et al. 2015, Borgomeo, Mortazavi-Naeini et al. 2016, Woodruff 2016).
- The use of visual analytics approaches to better communicate the outputs of optimization studies to stakeholders to help with exploration and analysis of the trade-offs between objectives, to identify the impact of decisions on

performance, and ultimately select trusted solutions for further consideration (Kollat and Reed 2007, Kollat, Reed et al. 2011, Woodruff, Reed et al. 2013, Hadka, Herman et al. 2015, Matrosov, Huskova et al. 2015, Borgomeo, Mortazavi-Naeini et al. 2016, Woodruff 2016).

These advances have made EAs more applicable to complex, real-world problems with multiple stakeholders and many objectives. However, in previous studies, the optimization problem to be solved has generally been represented by a single formulation, including all decision variable options, objectives and constraints that were considered to be relevant. This can result in the inclusion of a large number of objectives and decision variable options, making it difficult to identify solutions that represent the best trade-offs between objectives (i.e. the non-dominated solutions on the Pareto front, where none of the objective functions can be improved in value without degrading one or more of the other objective values). This is because the number of solutions required to characterise the Pareto front increases exponentially as the number of objectives increases, thus making this process exceptionally computationally expensive and beyond the capability of the majority of current EAs (Cruz, Fernandez et al. 2014, Purshouse, Deb et al. 2014). In addition, despite the recent advances in visual analytics approaches mentioned above, the inclusion of a large (e.g. >10) number of objectives makes the identification of solutions that provide acceptable trade-offs for different stakeholders extremely difficult, as this can be cognitively challenging for decision-makers, particularly when dealing with large solution sets (Purshouse and Fleming 2007).

In order to address the above difficulties, an innovative framework to identifying stakeholder-driven, optimal compromise solutions is proposed in this paper for problems with distinct stakeholder groups with potentially competing sets of objectives. An example of this is the integrated management of a river system and its catchment, where the objectives of stakeholders managing separate sub-areas of the catchment are most likely different from each other, and different from those of stakeholders concerned with managing the catchment as a whole. As part of the proposed framework, the overall optimization problem is represented as a series of smaller, interconnected optimization problems, reflecting individual stakeholders and their interests. The Pareto optimal solutions resulting from this analysis provide the input into a collaborative, multi-stakeholder negotiation process, as part of which visual analytics are used to identify trusted and accepted compromise solutions. A key feature of the proposed framework is the use of 'best alternatives to negotiated alternative' (BATNAs)' as a reference point during the collaborative negotiation process, which correspond to the solutions individual stakeholders would implement if they were to act in isolation. This has been shown to increase the efficiency with which negotiated compromise solutions can be achieved (Fitzgerald and Ross 2013, Fitzgerald and Ross 2015, Fitzgerald and Ross 2016).

The objectives of this paper are: (i) to present an optimization-visualisation framework that is geared towards the identification of negotiated compromise solutions for problems with multiple stakeholders with distinct sets of objectives; (ii) to demonstrate the utility of the framework by applying it to a case study based on the integrated management of a catchment in a major city in Australia; and iii) to use the case study to a) illustrate how the use of BATNAs can encourage the efficient identification of compromise solutions, and b) investigate how to identify solutions that distribute benefits and costs equitably across stakeholders.

The remainder of this paper is organized as follows. In the next section, the proposed framework is presented. This is followed by a description of the catchment management case study, analyses, discussion of results, and conclusions, including limitations and future research.

4.2 Proposed multi-stakeholder optimization-visual analytics framework

A conceptual outline of the proposed framework to addressing the limitations of existing optimization approaches outlined in the Introduction is shown in Figure 4-1. As can be seen, the first step involves the solution of independent, multiobjective optimization problems for each stakeholder group in order to identify 'best alternatives to negotiated alternative' (BATNAs)' for each of these groups, which represent the solutions each stakeholder would implement if they were to act in isolation. Knowledge of these solutions provides a reference point for each stakeholder group during the collaborative negotiation stage (steps 3 and 4), which is likely to increase final solution quality and the speed with which acceptable compromise solutions between stakeholders are identified. Identification of the solutions that are considered during the collaborative negotiation stage occurs in steps 2 and 3. In step 2, a number of interconnected optimization problems, one for each stakeholder, are formulated and solved, leading to the identification of joint Pareto optimal solutions. These, and the BATNAs, are then analysed in step 3 with the aid of visual analytics in order to identify solutions that represent suitable compromise trade-offs between the objectives of different stakeholder groups, which are then considered in the collaborative negotiation process (step 4) in order to arrive at an optimal compromise solution that is acceptable to all stakeholders. Details of each of these steps are given in the subsequent sections.

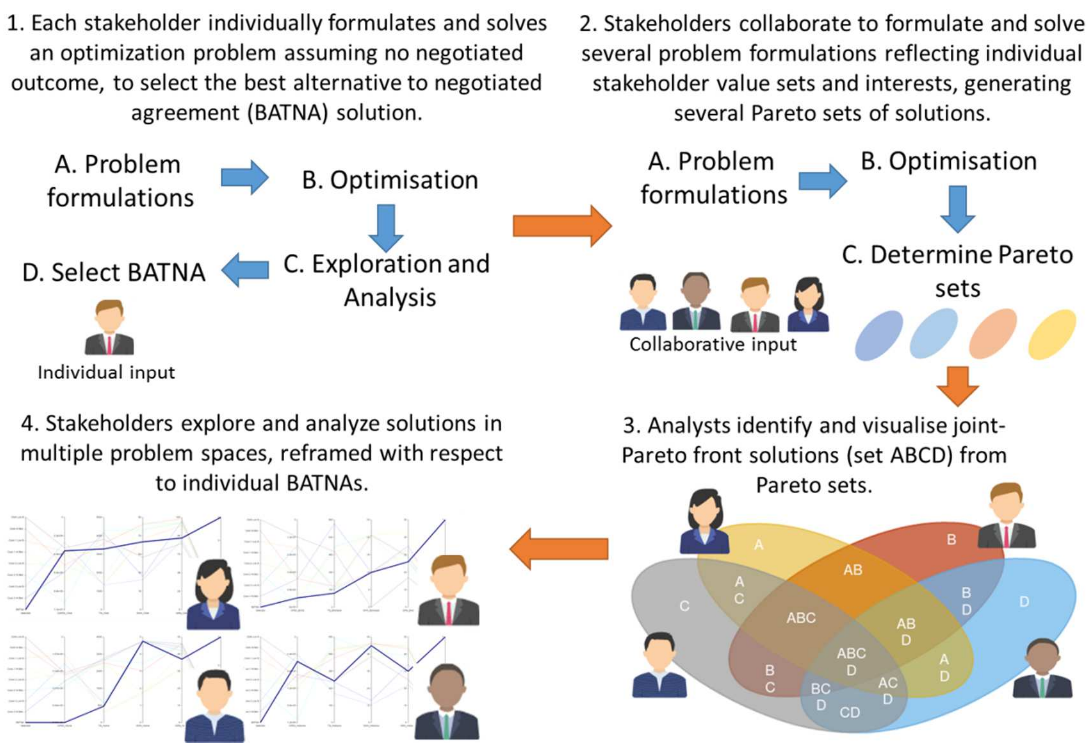

Figure 4-1 Conceptual outline of the proposed multi-stakeholder optimization-visual analytics framework incorporating multiple problem formulations to encourage a negotiated outcome. Steps are adapted from recommendations by Fitzgerald and Ross (2016).

4.2.1 Selection of best alternative to negotiated agreement (BATNA)

The concept of using a BATNA for multi-stakeholder negotiation applied to engineering systems design was developed and tested by Fitzgerald and Ross (2015) based on principles from negotiation theory (Keeney and Raiffa 1993, Fisher, Ury et al. 2011). Fitzgerald and Ross (2015) 're-framed' the visualisation of the performance of engineering systems options about an origin defined by the performance of the BATNAs of individual stakeholders, which improved the quality of solutions selected by collaborating stakeholder groups, as well as the speed this was done. When used as a reference point for alternative solutions to the problem, BATNAs defines what the theoretical benefits and losses to stakeholders are of arriving at a compromise solution. This improves decision-making, since humans have been shown to be more strongly averse to decisions that result in outcomes below a reference value (losses) than they are positive about results above the reference value (gains) (Fitzgerald and Ross 2014). There is often some synergistic benefit to collaboration, for example through cost efficiencies and access to more funding or a wider range of possible options and outcomes. Therefore, setting theoretical ‘go it alone’ BATNAs as reference points highlights what is ‘lost’ by not reaching a negotiated outcome, encouraging stakeholders to avoid the costs of not collaborating during the exploration and analysis of alternative solutions.

As part of the proposed approach, it is suggested to identify the BATNA for each stakeholder group with the aid of multiobjective optimization, as shown in Figure 4-1. In this case, the formulation of the optimization problem represents a theoretical scenario where each stakeholder develops solutions in isolation, instead of developing joint solutions with other stakeholders in a collaborative manner. These multiobjective optimization problems are solved using a suitable algorithm and the resulting Pareto optimal solutions are explored and analysed using visual analytics by individual stakeholders, with each selecting their ‘best alternative to a negotiated agreement’ (BATNA). Details of each of these steps are given in the following sub-sections.

4.2.1.1 BATNA optimization problem formulations

To identify solutions that represent the best trade-off between many objectives for each individual stakeholder’s ‘go it alone’ solution, a separate optimization problem is formulated for each stakeholder as follows:

$$Minimize\ F_{BATNA,s}(P_s) = F_{BATNA,s} = [f_{\mathrm{BATNA1}}, f_{\mathrm{BATNA2}}, \dots, f_{\mathrm{BATNA}n}]$$

$subject\ to$

$$g_i(P) \leq 0, \qquad \mathrm{i} = 1, \dots, \mathrm{m}$$

$$h_i(P) = 0, \qquad i = 1, \ldots, p$$

Equation (4-1)

where P_s is a set of decisions taken in isolation i.e. without collaboration by an individual stakeholder, s, F_{BATNA} is a set of the associated costs and benefits of the decisions, $f_{\mathrm{BATNA}i}$ is an objective function used to measure a cost or benefit of P under the BATNA scenario, n is the number of objective functions representing the stakeholder's values, g is a set of inequality constraints, and h a set of equality constraints bounding the feasible solution space. It should be noted, that each objective function used in the BATNA problem formulation should be comparable with one of the objective functions used in the collaborative scenario outlined in Section 4.2.2. Although the indicators of performance of objectives might be different, the type of objectives should be consistent for each stakeholder to allow for comparison of the optimization results between the two scenarios.

4.2.1.2 Solving the BATNA optimization problems

Only solutions to Equation (4-1) that are Pareto optimal for an individual stakeholder can be considered as solutions that represent the best trade-off between objectives within each stakeholder's problem space. It is suggested to use many-objective metaheuristic optimization algorithms to identify these Pareto optimal points, as these algorithms have several advantages over more traditional optimization approaches (such as linear programming), including their ability to deal with multiple objectives simultaneously (Maier, Kapelan et al. 2014), their successful application in recent planning and design optimization studies (Szemis, Maier et al. 2012, Beh, Dandy et al. 2014, Paton, Dandy et al. 2014a, Marchi, Dandy et al. 2016) and their successful linkage with many-objective visual analytics packages (Matrosov, Huskova et al. 2015). Furthermore, they can be linked with the models required to calculate multiple objective functions and check constraints of candidate solutions (Maier, Kapelan et al. 2014), and can provide confidence in the results of the optimization process, as simulation models that are already used in stakeholder decision-making can be used (Maier, Kapelan et al. 2014).

4.2.1.3 Selecting a BATNA solution

In order to enable each stakeholder to select a BATNA solution from their Pareto optimal solutions, use of the approach introduced by Di Matteo, Dandy et al. (2017) is suggested. The approach uses a metaheuristic to generate optimization results, and visual analytics to assist decision makers to explore and analyse their Pareto optimal solutions, enabling solutions that represent an acceptable compromise to be identified. Further details of the approach are given in Section 3.3.

4.2.2 Formulation and optimization of multiple stakeholder problem spaces

While the solutions obtained in this step still correspond to optimal alternatives from the perspective of individual stakeholders, as was the case for the BATNAs, these solutions are to problems that are formulated collaboratively between different stakeholder groups, taking into account interactions and dependencies between the problems faced by these groups, as well as any efficiencies gained. Consequently, this step also provides an opportunity for relationship-building for stakeholders and to record informal attributes of the problem that may assist in exploring and analysing solutions. It is possible after collaboration commences that stakeholders find that their values align to a degree that they form a 'coalition' and negotiate as one stakeholder group from a shared position. Consequently, there may be fewer stakeholder groups undertaking the negotiation than there were individual stakeholders assessing their BATNA.

This step consists of a number of sub-steps, including the formulation of individual optimization problems for each stakeholder, the solution of this problem with an appropriate multiobjective optimization algorithm and determination of the joint Pareto front. Details of each of these steps are given in the following sub-sections.

4.2.2.1 Collaborative optimization problem formulations

To identify solutions that represent the best trade-off between many objectives for each stakeholder group, s´, a separate optimization problem is formulated for each stakeholder group as follows:

$$Minimize\ F_{s'}(P_{s'}) = F_{s'} = [f_{\mathrm{COLLAB},1}, f_{\mathrm{COLLAB},2}, \dots, f_{\mathrm{COLLAB},n}]$$

$subject\ to$

$$g_{s',i}(P) \leq 0, \quad \mathrm{i} = 1, \dots, \mathrm{m}$$

$$h_{s',i}(P) = 0, \quad i = 1, \ldots, p$$

Equation (4-2)

where P is a set of decisions taken by a stakeholder group, $F_{s'}$ is a set of the associated costs and benefits of the decisions, $f_{i,s'}$ is an objective function used to measure a cost or benefit of P under the collaborative scenario (which should be comparable to one objective function in the BATNA problem formulation of each individual stakeholder in the group, see Section 4.2.2.1), n is the number of objective functions, g is a set of inequality constraints, and h a set of equality constraints bounding the feasible solution space.

During the formulation of each of the s' optimization problems, stakeholders should collaborate to ensure interdependencies between the benefits and costs of decisions, available decision options and constraints are reflected in the mathematical formulations. For each formulation, performance indicators corresponding to different objective functions can represent the individual values of a stakeholder. However, the selected cost indicators should enable a comparison between formulations in order to make it possible to analyse how equitably a solution distributes costs and benefits amongst stakeholders. For example, while the cost performance indicator could be represented as a lifecycle cost or as separate objectives for capital and operating expenses, the corresponding indicator should allow for consistent comparison amongst the optimization problems for the different stakeholders. In addition, if an option selected by one stakeholder affects another stakeholder's available decision options or objective function value(s), then this should be included in the decision variables of affected stakeholders.

As part of the above process, apart from the formal problem aspects, analysts should also record the key elements of the problem structure that may be useful during later negotiations (Fitzgerald and Ross 2016). These may include interests of stakeholders that are divisible (for example, the possibility of sharing capital expenditure for certain projects), or relationships between stakeholders, which can be important in informing how the exploration and analysis should be conducted. For example, if there are known pre-existing negative relationships between stakeholders, directly comparing desired alternatives may limit the effectiveness of exploration and should be avoided.

4.2.2.2 Solving the collaborative optimization problems

As discussed in Section 4.2.1, it is proposed to use metaheuristic optimization algorithms for the identification of the solutions that represent the best trade-offs within each stakeholder's problem space. In the context of solving the collaborative optimization problem, the fact that these algorithms can be linked with existing simulation models has the additional advantage that selection of an appropriate system model can assist with relationship-building and increase the likelihood of a negotiated outcome. This is because models can potentially be developed amongst stakeholders through a 'joint fact finding' exercise to establish credible and objective data to support models; this being one of the foundations of principled negotiation (Fitzgerald and Ross 2015). Alternatively, where models cannot be determined through joint fact finding, stakeholders may offer existing system models in order to promote a '*Full, Open, and Truthful Exchange*', which is important in successfully achieving negotiated outcomes (Fitzgerald and Ross 2015).

4.2.2.3 Determining the joint-Pareto front

Solutions that lie in all Pareto sets for the solutions to the *s'* individual stakeholder problems, that is the joint-Pareto solutions, are an obvious choice for potential compromise solutions. This is because these solutions do not require stakeholders to consider solutions that are not optimal for their particular problem, although changes in their relative preferences for different objectives might be required in order to identify a solution that satisfies all stakeholders. To determine the joint-Pareto front, firstly the Pareto optimal solution data sets from the *s'* optimization problems are aggregated. Next, the joint Pareto front solutions, that is, solutions that lie on the Pareto front for every stakeholder, are identified and selected. As suggested by Fitzgerald and Ross (2013), if no joint solutions can be identified, then the Fuzzy Pareto Number (FPN) of solutions close in objective space to the Pareto fronts for each stakeholder can be considered (Smaling 2005, Fitzgerald and Ross 2012).

4.2.3 Visualization of the multi-stakeholder trade-off space

In the third step of the proposed framework, an analyst generates a visualisation of the solution set on the joint-Pareto front for interactive exploration and analysis by stakeholders so that they can ultimately select solutions that represent a desirable compromise between performance criteria amongst the multiple representations of the problem space (Maier, Kapelan et al. 2014). This may occur in a workshop setting or virtually in real-time and can be done with the aid of an interactive visual analytics package (Kollat and Reed 2007, Hadka, Herman et al. 2015), as part of which high-dimensional coordinate plots or parallel coordinate plots (Inselberg 2009) can be used to visualize the performance of the large number of Pareto optimal solutions in many-objective space.

As part of the proposed framework, a separate plot is generated for each stakeholder. These plots should be linked such that isolating or marking a solution in one plot updates automatically on other plots. In this way, the performance of a solution can be compared simultaneously in each stakeholder's problem space. The individual BATNA solution of each stakeholder should be plotted using a distinctive style (e.g. bold or coloured line) to act as a reference point. Axes representing objective values should be oriented such that positive outcomes point in the same direction. It should be noted that in parallel coordinate plots, if the positive direction is at the top of the axis, the solutions with all objective values above (or equal to) the BATNA represent an improvement on the reference point.

In visualisation of trade-offs between many-objectives using multiple axes, it is possible that solutions improve upon the BATNA in one benefit but not others. For solutions with these characteristics, whether the BATNA is superior depends on stakeholder preferences. Therefore, an indicator of the performance of solutions relative to the BATNA should also be visualised within each stakeholder's problem space. This allows stakeholders to rapidly detect how a solution performs relative to their own BATNA and the BATNAs of other stakeholders by inspecting the multiple problem space visualisations. An example of possible categories for a problem formulation with four objectives – one cost, three benefits – is shown in Table 4-1. In the example, Category 1 solutions are obviously superior to those in Category 8. However, when choosing amongst Category 2-7 solutions, stakeholder input is necessary, as improvements or losses in one benefit might be valued more highly than those in others. In addition to visualising the category of solutions, automated preference selection techniques might further assist with selecting between solutions and reducing the size of a large solution set (Fitzgerald and Ross 2016).

Table 4-1 Categories of solutions indicating performance relative to BATNA

Category	Lower cost than BATNA?	Number of benefits exceeding BATNA
1	Yes	3
2	Yes	2
3	Yes	1
4	No	3
5	Yes	0
6	No	2
7	No	1
8	No	0

4.2.4 Exploration of the multi-stakeholder trade-off spaces

In the fourth step of the proposed framework, an analyst guides stakeholders through an exploration and analysis of the solution set. A method to do this is adapted from steps for a multi-stakeholder trade-off space analysis suggested by Ross, McManus et al. (2010), as outlined below.

4.2.4.1 Each stakeholder selects several 'good' solutions

Firstly, several good solutions are selected by individual stakeholders, only considering the performance of joint-Pareto solutions in their own problem space (i.e. the problem spaces of other stakeholders are hidden). To do this, the stakeholder can use a visual analytics method to isolate promising solutions. For example, in order to reduce the number of solutions considered for further analysis, dynamic filtering to eliminate undesirable solutions can be carried out by an analysts based on the decision-maker's budget constraints and minimum preferences for each benefit. This process will eliminate apparently undesirable combinations of decision options not anticipated when formulating the problem (Piscopo, Kasprzyk et al. 2015). Within the reduced set, decision-makers and analysts can use brushing to highlight sub-sets of interesting solutions. Multiple linked plots of the same data set can assist with identifying and rationalizing trade-offs, such as conflicts and areas of diminishing returns between objectives and emergent behaviour influenced by the selection of various decision options. Interactive visualization of optimization objective and decision spaces simultaneously enables stakeholders, with the assistance of analysts, to rapidly identify subsets of solutions that contain preferred decisions and compare their performance to that of other solutions. In this way, browsing through solutions to investigate and learn about the impact of individual decision preferences can allow decision-makers to overcome institutional decision-making biases (Kollat and Reed 2007, Matrosov, Huskova et al. 2015). Ultimately, several desirable solutions are selected for further consideration.

4.2.4.2 Stakeholders share their preferred solutions

Stakeholders then share their selected solutions and visualise the selected solutions of others in their problem space. Stakeholders can record which solutions they will consider further. Negotiations and compromises in preferences commence. As an indicator of solution performance that can be compared among stakeholders, the solution category relative to the BATNA can drive negotiation for compromise in preferences of stakeholders whose solutions are more favourable. Stakeholders may express which objectives they are willing to compromise in, and can set minimum limits on particular benefits using brushing tools, that hide solutions that do not meet their minimum performance criteria on other stakeholders' problem spaces. The many-objective plots show explicit trade-offs in each objective, and stakeholders can make judgements on the benefits lost or gained when opting for one solution over another. Compromises can be expressed through negotiation, which makes explicit what is being compromised and traded.

4.2.4.3 Negotiate and identify compromise solutions

Advanced techniques for eliminating solutions through relaxation of value constraints and cost bargaining can be undertaken to isolate one or two solutions for further analysis (Fitzgerald and Ross 2013). If stakeholders determined they are indifferent to the values a particular objective takes, they may remove that objective from the visualisation of the problem space. Omitting one objective may reduce the number of solutions in the joint-Pareto set. If the visualisation dataset is linked to the full set of optimization results, a new Pareto sort on the remaining objectives will eliminate solutions dominated in the lower-objective space. As a compromise for removing an objective, stakeholders might increase their minimum acceptable benefit on other objectives. For minimum performance constraints on objectives that eliminate a large number of solutions, a stakeholder might consider accepting a lower benefit in exchange for lowering the maximum cost to contribute to a solution. In addition, cost bargaining might be undertaken amongst stakeholders, especially where slight increases in cost for one stakeholder make available solutions that create much higher benefits for others. Ultimately, one or two acceptable compromise solutions should be determined for further consideration.

4.2.4.4 Explore better compromise solutions

Once acceptable compromise solutions have been identified, stakeholders search the full set of joint-Pareto solutions for comparable solutions that are ‘fairer’. These are identified by negotiation. The compromise solutions are plotted with an identifying marker. To compare the solution set to the compromise solutions, an additional indicator that measures the distance in objective space from the solution for each stakeholder problem can be determined. An additional plot with axes of equity indicators and/or a breakdown of the distribution of costs can be used to identify solutions that improve on the compromise.

4.2.4.5 Further consider selected solutions

Finally, solution(s) that are acceptable to all stakeholders may be explored and tested in more depth e.g. for robustness or other metrics (Herman, Reed et al. 2015, Giuliani and Castelletti 2016, Maier, Guillaume et al. 2016), and a final solution selected.

4.3 Case study

The proposed framework was demonstrated on a case study for an urban catchment management problem in Australia, which expands upon the case study originally formulated in Section 3.3. The problem involved four stakeholders. A catchment management authority (CMA) was responsible for funding the capital expenses of stormwater control systems distributed throughout a catchment. Three local government authorities (LGAs) managed regions within the catchment and were responsible for maintenance to ensure systems remain functional over their design life. It should be noted that there was no stakeholder involvement in the application of the proposed framework to the case study, which was undertaken solely by the analyst for the sake of illustrating the approach. However, although stakeholders were not involved directly in this exercise, the generic preferences and motivations of stakeholders were discussed between the analyst and engineering consultants who had interviewed stakeholder groups in workshops related to the problem under consideration.

The application of the proposed optimization approach was part of a real-world study involving a multi-criteria analysis conducted to identify a portfolio of BMP projects for a regional catchment. This allowed the authors to demonstrate how the proposed approach can consider existing BMP selection practices, which is a study objective. As the case study application was only intended to demonstrate the optimization approach, the results of the study were reviewed by consultants but were not used to inform decision-making. The names of stakeholders and catchment regions involved are not disclosed in this study

Engagement between stakeholders, engineering consultants, and the optimization analysts (who are the authors of this study), was carried out as follows. Firstly, engineering consultants ran one workshop where the broad catchment management objectives were established, which was attended by a stakeholder working group, from LGAs and the CMA, of approximately 16 people. Consultants then identified sites, assessed them for quantitative metrics (e.g. required size of BMPs to meet water quality constraints, cost, and stormwater harvesting capacity) and made a preliminary effort to score each of the qualitative metrics (e.g. vegetation improvement and amenity value) using objective thresholds. Consultants then sent these preliminary scores to LGAs and asked to provide a response. These were generally reviewed by landscape, bushland, horticultural and parks and open space staff. The staff involved and level of response varied between the LGAs. Consultants then had a workshop with each of the individual LGAs to review the sites, establish a common understanding of the whole catchment management opportunity and confirm the proposed individual project scoring. Then, important objectives were refined into formal optimization objectives by the consultants and optimization analysts. The analysts used the multi-criteria evaluation data to inform the optimization problem formulation including decision variables (projects), developing objective functions and project objective function values, and constraints.. The data used for this study are listed in the references, tables, supplements and repository at Di Matteo, Maier et al. (2016b).

4.3.1 Background

4.3.1.1 Catchment management problem considered

Sustainable integrated catchment management often involves the selection of a portfolio of stormwater best management practices (BMPs) with precinct-sized contributing catchments (i.e. < 1 km^2) to achieve desired social, environmental and economic benefits within a larger catchment or region (Marlow, Moglia et al. 2013). BMPs may include structural and non-structural measures for treatment, detention, harvesting, infiltration, evaporation, and transport of non-point urban stormwater runoff (Lerer, Arnbjerg-Nielsen et al. 2015). Catchment managers must consider a range of performance criteria due to several socio-political drivers, including: water supply security, public health protection, social amenity, urban flow regime improvement, environmental protection and flood mitigation (Marlow, Moglia et al. 2013, Askarizadeh, Rippy et al. 2015). In response to these drivers, BMPs have been developed to provide multiple functions in addition to water quality improvement, such as stormwater harvesting (Mitchell, Deletic et al. 2007, Clark, Gonzalez et al. 2015, Di Matteo, Dandy et al. 2017) and urban vegetation and amenity improvement (Sharma, Pezzaniti et al. 2016). To maximize total catchment benefits for a given budget, decision-makers must select a combination, or portfolio, of BMPs that provides the best trade-off between many objectives. Selection of a portfolio of BMPs is made more difficult in practice, as often limited resources are available for performing this task (Moglia, Kinsman et al. 2012).

4.3.1.2 Multi-stakeholder aspects of the problem

In recent years, millions of dollars have been invested into stormwater treatment best management practices (BMPs) in Australia to improve urban ecosystem health. The investment strategy may involve an integrated catchment approach, where a catchment authority subsidises construction and establishment of distributed BMPs to be operated and maintained by LGAs (Eadie 2013). Without incentives, maintenance of BMPs – which is essential for functional performance of BMPs and therefore catchment ecosystem benefits – may cease to be a priority for LGAs over the lifetime of BMP assets. Fortunately, LGAs may be willing to bear maintenance costs if BMPs produce local benefits, in addition to benefits to the total catchment. For example, BMPs functioning as part of a stormwater harvesting system for open space irrigation, or providing high urban amenity and recreation benefits, are more likely to be maintained. The ongoing maintenance promotes optimal runoff quality improvement, thereby improving urban ecosystem health. The benefits of BMPs are valued differently by LGAs depending on their local area planning strategies. Therefore, to maximize return on investment, integrated catchment planners need to target funding to a portfolio of BMP projects that provides multiple ongoing benefits to individual LGAs and catchment management stakeholders, in addition to overall catchment benefits.

4.3.1.3 Potential solutions

In the case study considered, the CMA commissioned engineering consultants to identify sites for potential stormwater best management practices (BMPs) within a regional catchment with an outlet flowing into a prominent marine body. The catchment covers an area comprised of highly urbanized and peri-urban regions managed by three local government authorities (LGA). A primary objective for the CMA was to reduce the nutrient load from urban stormwater runoff flowing into the marine body. In addition, since the potential sites for BMPs were within public open spaces managed by LGAs, stormwater harvesting for irrigation of open spaces, increasing vegetation and public amenity value were considered to be important additional benefits. The consultants identified 70 (N_p=70) potential biofiltration, wetlands and swale projects at locations distributed in open spaces throughout the three LGA areas (see Table C-1 in Appendix C). Thirteen of these projects have a capacity for stormwater harvesting. In addition, the consultants agreed that a portfolio of 20 projects or fewer (N_{max}=20) was desirable from a practical perspective. The BMPs were considered mutually independent, as the contributing catchment areas to each BMP did not coincide i.e. downstream impact of BMPs would not affect the performance of other BMPs within the large regional catchment.

4.3.2 Selection of best alternative to negotiated agreement (BATNA)

For the sake of demonstrating the proposed approach, BATNAs were selected by analysts based on a 'build alone' scenario, where each stakeholder is responsible for the capital and operating costs (total lifecycle costs) of the projects they select. The optimal solutions were identified with the aid of the general multiobjective optimization framework introduced in Section 3.2, as this was developed for the selection of a portfolio of BMPs for catchment management, as is the case here. The formulation of the optimization problem is detailed in Section 4.3.2.1, details of the objective functions and how they were evaluated are given in Section 4.3.2.2 and the specifics of the optimization engine used are provided in Section 4.3.2.3.

4.3.2.1 BATNA optimization problem formulations

Details of the optimization problem formulations for obtaining the BATNAs for each of the four stakeholders are given in Table 4-2. As can be seen, LGA stakeholder portfolios consisted of up to 7 projects located within their jurisdictions. The catchment management authority was assumed to have permission to build and operate up to a total of 20 projects should no agreement to share capital and operating costs be negotiated.

Table 4-2 Optimization problem formulations for stakeholder best alternative to negotiated agreement (BATNA)

Formulation	Stakeholder problem space	Decision variables	Objectives (F_{BATNA})	Constraints
1	Catchment management authority (CMA)[1]	All projects	$LCC_{,\mathrm{CMA}}$ $f_{\mathrm{quality,CMA}}$ $f_{\mathrm{SWH,\ CMA}}$ $f_{\mathrm{Green,\ CMA}}$	≤ 20 projects
2	LGA 1	LGA 1 projects	$LCC_{,1}$ $f_{\mathrm{quality},1}$ $f_{\mathrm{SWH},1}$ $f_{\mathrm{Green},1}$	≤ 7 projects
3	LGA 2	LGA 2 projects	$LCC_{,2}$ $f_{\mathrm{quality},2}$ $f_{\mathrm{SWH},2}$ $f_{\mathrm{Green},2}$	≤ 7 projects

4	LGA 3	LGA 3 projects	$LCC_{,3}$ $f_{\text{quality},3}$ $f_{\text{SWH},3}$ $f_{\text{Green},3}$	≤ 7 projects

1. Optimization of problem formulation 1 (only) was undertaken in Section 3.3, and the results from that study are used here.

4.3.2.2 Objective function formulation and evaluation

The objectives considered for each of the four stakeholders include cost minimisation, total nitrogen reduction, maximisation of stormwater harvesting, and urban vegetation and amenity improvement. The mathematical formulations of these objectives were adapted from those in Di Matteo, Dandy et al. (2017), and are detailed in Appendix D. Based on these mathematical formulations, values for all four objectives were obtained for each of the BMPs, shown in Table C-1 in Appendix C as detailed below.

Firstly, the stormwater harvesting capacity of individual projects was determined from LGA expert interviews. Secondly, the individual project lifecycle costs, *LCC*, were determined using cost parameters from Equations (D-1) to (D-4) for each project. Thirdly, the water quality performance of each BMP was determined with the aid of the integrated catchment simulation model eWater *MUSIC* version 6.1 (Model for Urban Stormwater Improvement Conceptualization, eWater (2009)), which is further explained in Appendix E. To do this, a catchment model for a 1 ha catchment area for each LGA was developed. The model consisted of a 0.5 ha pervious catchment node, a 0.5 ha impervious catchment node, and an outlet node to estimate the average annual total nitrogen load per unit area of the catchment with an average 50% impervious surface area (Browne, Breen et al. 2012). One year of continuous climate data and pervious surface parameters provided by the CMA were adopted for the catchment nodes. To estimate the catchment TN load in Equation (D-5), *Source* [kg], for each BMP, the TN load from a 1 ha unit catchment area for the respective LGA was multiplied by the contributing catchment area to each BMP in hectares. Each BMP was assumed to remove 45% of the TN load from its contributing catchment. To calculate the pollutant removal performance of BMPs, the residual TN load at the catchment outlet $Resid_i$ was calculated as a proportion of $Source_i$ (i.e. in Equation (D-5), $Resid_i = (1 - 0.45) \times Source_i$), which was suggested as an acceptable performance based on advice from the consultants. Finally, Equations (D-7) to (D-9) were applied to determine the individual project green scores.

4.3.2.3 *Optimization algorithm and analyses*

As mentioned previously, the above multiobjective optimization problem formulations for each of the four stakeholders were solved using the many-objective portfolio optimization approach in Section 3.2. The approach uses a metaheuristic algorithm, the Pareto Ant Colony Optimization Algorithm (PACO), which was previously demonstrated successfully for the single stakeholder case study version of the catchment management problem, also in Section 3.3. The algorithm mimics the cooperative foraging behaviour of an ant species that leaves a chemical pheromone on a ground surface. In real life, since ants traverse short paths to food more frequently, more pheromone is laid on short (efficient) paths. Thus, paths with higher pheromone levels are more likely to be selected by an ant. In the algorithm, artificial ants select between paths, which represent decisions whether or not to adopt a BMP in a portfolio in this instance, with paths that result in better objective function values receiving more pheromone.

The steps in the PACO algorithm are shown in Figure 4-2. In the initialization phase, the PACO search control parameters are set. The iterative process commences where b ants are generated, each ant starting with an empty portfolio x = (0), and the objective weights (i.e., the ant's individual preferences) are determined randomly for each ant. In the construction phase of the algorithm, first the order of BMPs is randomly shuffled, to ensure that all BMPs are provided an equal chance of being considered early on by each ant. Then, the ant decides whether to add each BMP to a portfolio, x, by applying a pseudo-random-proportional rule using pheromone information, τ_i. The pheromone information is stored in one 2xN matrix for each j^{th} objective, representing the binary options for the N possible BMPs. If the ant adds the maximum number of BMPs, N_{max}, before all BMPs have been considered, then none of the remaining BMPs are selected. After a portfolio has been constructed, its performance is evaluated using the objective functions (Equation (D-2) and (D-5) to (D-7)). In this case, as individual projects were determined to be independent, the portfolio objective functions were a summation of the constituent individual project objective function values in Table D-1.

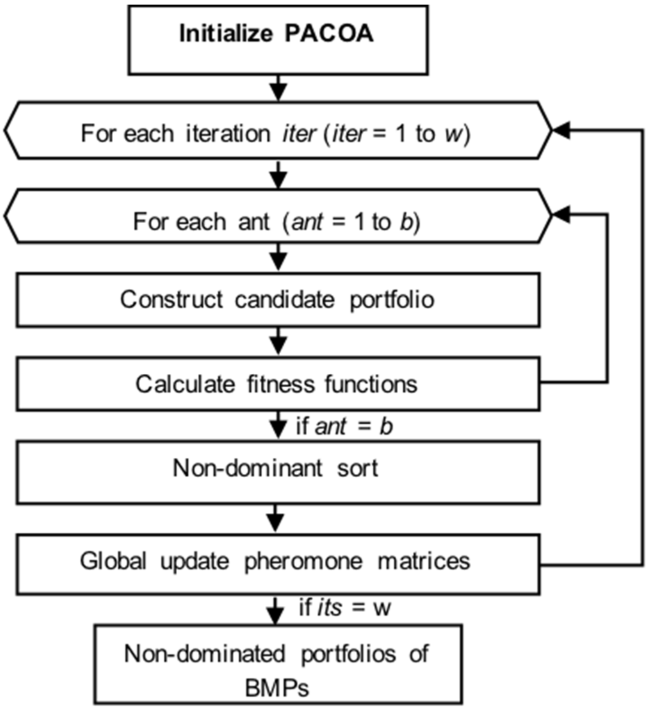

Figure 4-2 Portfolio optimization process for Pareto Ant Colony Optimization Algorithm (PACOA)

After each iteration, of the *b* portfolios generated by the *b* ants, the non-dominated portfolios are stored offline in an array. Then, as part of a global update of every element of the *j* pheromone matrices, the first and second best performing solutions ranked for each j^{th} objective are used to apply the following equation.

$$\tau_t^j = (1-\rho)\cdot\ \tau_t^j + \rho\cdot\varDelta\tau_t^j$$

$$\varDelta\tau_t^j = \begin{cases} 15, & t\ in\ both\ best\ and\ 2nd\ best\ portfolio \\ 10, & t\ in\ best\ portfolio \\ 5, & t\ in\ second\ best\ portfolio \\ 0, & otherwise \end{cases}$$

Equation (4-3)

where, for each BMP, the current pheromone value for each t^{th} binary option and j^{th} objective is reduced by pheromone evaporation, ρ, and increased by a pheromone value, $\varDelta\tau_t^j$. Pheromone is evaporated from decisions that are not in the best solutions for each objective, which makes it less likely these decisions will be selected again in future iterations. In this way, the ant's decision-making landscape is modified to guide ants into regions of the search space that contain non-dominated portfolios. Since the single constraint was handled in the construction phase, no penalty function is required for this case study as all constructed portfolios are feasible. The process of developing, assessing and updating the pheromone trails to guide the PACOA to near-optimal trade-offs continues until a specified maximum number of iterations, w, is reached.

Before the PACOA was applied, a sensitivity analysis was conducted to identify suitable values of parameters that control the searching behaviour of the algorithm to maximize the likelihood the best possible approximation of the Pareto front was generated. The sensitivity analysis was applied to one stakeholder problem formulation, formulation 1, which is the CMA's BATNA scenario formulation. The results of formulation 1 were explored in depth in Section 3.3. The ranges of parameter values tested and the final parameters selected for all formulations (i.e. formulations 1-8 in this study) are given in Table 4-3.

Table 4-3 PACOA parameters tested and adopted in sensitivity analysis

PACOA Parameter	Range of Values Tested	Adopted Value
Number of ants (b)	20, 200, 300,500	500
Initial pheromone (τ_o)	0.5, 1.0, 10.0	0.5
Evaporation rate (ρ)	0.1, 0.15, 0.2, 0.4, 0.5	0.4
Evaluations ($b \times w$)	Up to 2,000,000	600,000

In this study, as in Section 3.3.2, the PACO was run for 1200 iterations of 500 ants, which equates to 600,000 objective function evaluations. This number of evaluations was selected because there were no further meaningful changes in the Pareto front (assessed by visually inspecting the Pareto optimal solution set at 5,000 evaluation intervals) after this number of evaluations in a trial run of 2,000,000 evaluations. The optimization results were re-run 50 times using different random starting seeds for the pseudo-random number generator used in the algorithm to minimize the impact of probabilistic effects of some of the operators that influence the search. Each run took approximately 26 minutes on a 3.10GHz computer with 8 GB of RAM, although multiple instances were run on one machine simultaneously. The Pareto optimal solutions for each stakeholder shown in this paper are the result of a non-dominated sort of the solutions from the 50 replicate runs. Once the Pareto set of portfolios was determined, a suitable BATNA portfolio was selected for each stakeholder, as detailed in Section 4.4.1.

4.3.3 Formulation and optimization of multiple stakeholder problem spaces

The overall process used to identify the solutions that provide the input into the collaborative, multi-stakeholder negotiation process is identical to that used to identify the BATNAs in that individual optimization problem formulations are developed for each of the four stakeholders, which are solved using the many-objective portfolio optimization approach in Section 3.2. However, the formulations of the optimization problems were altered to reflect the proposed shared funding scheme in the collaborative scenario, as shown in Table 4-4. These formulations reflect the proposed strategy where the CMA funds capital costs and the LGAs fund ongoing costs of projects.

Table 4-4 Optimization problem formulations for stakeholder negotiations

Formulation	Stakeholder problem space	Decision variables	Objectives (f_{COLLAB}')	Constraints
5	Catchment management authority (CMA)	All projects	$CAPEX_{CMA}$, $f_{quality,CMA}$, $f_{SWH,CMA}$, $f_{Green,CMA}$	$\leq$ 20 projects
6	LGA 1	LGA 1 projects	$OPEX_1$, $f_{quality,1}$, $f_{SWH,1}$, $f_{Green,1}$	$\leq$ 7 projects
7	LGA 2	LGA 2 projects	$OPEX_2$ $f_{quality,2}$, $f_{SWH,2}$, $f_{Green,2}$	$\leq$ 7 projects
8	LGA 3	LGA 3 projects	$OPEX_3$, $f_{quality,3}$, $f_{SWH,3}$, $f_{Green,3}$	$\leq$ 7 projects

The objective functions for total nitrogen reduction, stormwater harvesting, and urban vegetation and amenity improvement used were identical to those used for the BATNA formulations (see. Equation (D-4) to (D-8)). This means that the values of $f_{quality}$, f_{SWH}, f_{Green} are simply the sum of the values for the LGAs. However, the cost objective functions were revised for the stakeholder collaboration problem as the CMA funded capital costs

(CAPEX) and LGAs funded operating costs (OPEX). The OPEX cost objective function used for formulations 5-7, representing the maintenance of BMPs, was:

$$\text{MINIMIZE: } OPEX_{LGA} = LCC_{BMP,OPEX} + LCC_{SWH,OPEX}$$

Equation (4-4)

where

$$LCC_{BMP,OPEX} = \sum_{i=1}^{N} \left\{ PWF_{maint,BMP_i}\left(SA_{BMP_i} \times M_{BMP_i}\right)\right\}$$

$$LCC_{SWH,OPEX} = PWF_{maint}\left(C_{mTank} + C_{mPipe} + C_{mControl} + C_{mPump}\right)$$

Equation (4-5)

The CAPEX cost objective function used for formulation 8, representing the construction and establishment cost of BMPs, was:

$$\text{MINIMIZE: } CAPEX_{CMA} = LCC_{BMP,CAPEX} + LCC_{SWH,CAPEX}$$

Equation (4-6)

where

$$LCC_{BMP,CAPEX} = \sum_{i=1}^{N}\left\{ \left(TAC_{BMP_i}\right) + PWF_{estab,BMP_i}\left(SA_{BMP_i} \times ECF_{BMP_i} \times M_{BMP_i}\right)\right\}$$

$$LCC_{SWH,CAPEX} = C_{CapTank} + C_{CapPipe} + C_{CapControl} + C_{CapPump}$$

Equation (4-7)

Where $OPEX_{LGA}$ are the ongoing maintenance costs of BMPs and of SWH infrastructure situated within an LGA's jurisdiction, and $CAPEX_{CMA}$ is a sum of the construction and establishment costs of BMPs to capture and treat stormwater runoff, $LCC_{BMP,CAPEX}$ [$] (Equation 4-7), and to transfer harvested water to a balancing storage for further treatment and distribution, $LCC_{SWH,CAPEX}$ [$] (Equation (4-6)). The terms in Equations (4-4) and (4-5) are identical to those in the lifecycle cost equation used for the BATNA formulations, i.e. Equation (D-2) and (D-3), which are detailed in Appendix D.

Similarly to the BATNA formulation, LGA stakeholder portfolios consisted of up to 7 projects located within their jurisdictions and the catchment management authority was assumed to have permission to build and operate up to a total of 20 projects within each LGA, should no agreement to share capital and operating costs be negotiated.

The optimization results from formulations 5-8 were aggregated into one data set. The joint-Pareto front was determined as the subset of full CMA portfolios that were exclusively combinations of Pareto optimal portfolios from each LGA. It should be noted that by definition, every portfolio on the joint-Pareto front consists of a Pareto optimal portfolio from each stakeholder.

4.3.4 Visualization of the multi-stakeholder trade-off space

To visualize and analyse the objective and decision space trade-offs of the Pareto optimal set of portfolios, an interactive visual analytics package was used. The combined objective space and decision space visualizations for four plots representing stakeholder problem spaces were carried out using the approach of Kollat and Reed (2007) and the approach in Section 3.2 using the DiscoveryDV software package (DiscoveryDV Version 0.80; available at https://www.decisionvis.com/discoverydv/). The package features an interactive data plot that allows brushing, linked views of solutions, marking and tracing of solutions of interest, as well as rapid browsing through solution objective, decision and non-objective performance data. The package has been used successfully in several recent many-objective optimization studies (Woodruff, Reed et al. 2013, Piscopo, Kasprzyk et al. 2015), as well as in the single stakeholder version of this catchment management case study in Section 3.3.

The joint-Pareto optimal solution objective and decision data were uploaded into the interactive visual analytics package. Then, a parallel coordinate plot was generated for each stakeholder, with the objectives of each stakeholder oriented such that positive values were at the top of the axes. The BATNA solution for each stakeholder was visualised using a thick bolded line on each stakeholder's plot. The plots were visualised simultaneously on a large screen, and the analyst performed the role of exploring and analysing solutions.

In each of the plots, the relative objective function values were shown in the first four vertical axes, with the last two axes showing the solution category relative to BATNA and solution type (on the BATNA axis: BATNA = 1, Pareto optimal = 2). The colour of the line segment indicated whether the solution has lower or higher cost and benefits compared with the BATNA. A blue line segment indicated the most desirable (Category 1) solutions, which has all three benefits higher, and a lower cost than the BATNA of the stakeholder. A red line segment indicated the least desirable (Category 8) solutions, which have all three benefits lower, and a higher cost than the BATNA. Other colours represent categories that have a combination of benefits improved and not improved, and higher or lower costs, compared to the BATNA, as described in Table 4-1. It should be noted that the category indicator should not be used as an absolute indicator of preference, as it does not take into account which of the benefits is compromised. It may be desirable to compromise on some objectives and not others, which is dependent on stakeholder preferences.

Visualising the solution categories with colour for all stakeholders simultaneously allows analysts and stakeholders to inspect the performance of negotiated solutions compared to what they would otherwise achieve (i.e. relative to the BATNA). As the benefits/consequences of a negotiated outcome for all stakeholders are visualised, framing the solution space in this way can encourage stakeholders to continue to engage in negotiations until a compromise is found and to 'buy into' the negotiated outcome.

4.3.5 Exploration of the multi-stakeholder trade-off spaces

To demonstrate the proposed framework, an analyst performed the task of stakeholders selecting solutions from the collaborative problem formulation optimization results and analysing them with respect to the individual stakeholder spaces. Stakeholders were not available, and also a workshop setting with multiple participants was outside the scope of this study. Instead, this study aimed to include tested technologies (i.e. interactive visual analytics, and approaches in multi-stakeholder tradespace analysis) into a novel framework to solve many-objective optimization problems. First, 'good' solutions were selected for each stakeholder from the joint Pareto set. Using interactive visualisation, a small number of solutions preferred by each stakeholder was selected individually, and shown in the trade-off space of other stakeholders to visualise their performance. To do this, using the visual analytics package, the analyst identified one or two solutions that each stakeholder would be comfortable with as the negotiated outcome. The process for selecting these solutions was like the selection of the BATNA, except the trade-off space consists of the joint-Pareto front solutions. The solutions were then visualised in the multi-stakeholder trade-off space to determine how solutions selected for individual stakeholders perform for all other stakeholders. Finally, for each stakeholder, each solution was analysed against the performance of the preferred solution and BATNA of that stakeholder, and suggested reasoning for whether the stakeholder would accept, maybe accept or not accept the solution were recorded in a table.

4.4 Results and discussion

4.4.1 Identifying Best Alternatives to Negotiated Agreement (BATNAs)

The outcome of the multiobjective optimization process of the 'stand-alone' formulations developed for each of the four stakeholders (Section 4.3.2) is a parallel coordinate plot for each stakeholder, where each line corresponds to a Pareto optimal solution, as illustrated in Figure 4-3 for one of the LGAs. The plots are linked via a data set, in that manipulations (e.g. brushing out solutions) in one plot are updated immediately on all others. In order to determine the BATNA from these solutions, the following process was used.

For each LGA, firstly the lifecycle cost budget was limited by constraining the assumed capital expenditure (CAPEX) available for portfolios using a brushing tool on the interactive plot in order to reduce the number of solutions from which to select the BATNA. Although not a formal objective, CAPEX was selected as a limiting constraint, as it was assumed LGAs had limited funds available to spend on projects in the short-term. Next, solutions that provided a desirable trade-off between stormwater harvesting and green score (with TN reduction as a less influential objective for LGAs) were selected. This was done by gradually increasing the minimum allowable green score or SWH until two solutions with equal performance in these objectives remained. The solution with the highest TN reduction was then selected as the BATNA, as shown by the dark blue solution in Figure 4-3. For the catchment management authority (CMA), the portfolio that maximized TN reduction after the solution space was constrained to a lifecycle cost budget of $5 million was assumed. The BATNAs for each stakeholder resulting from the above process are shown in Table 4-5.

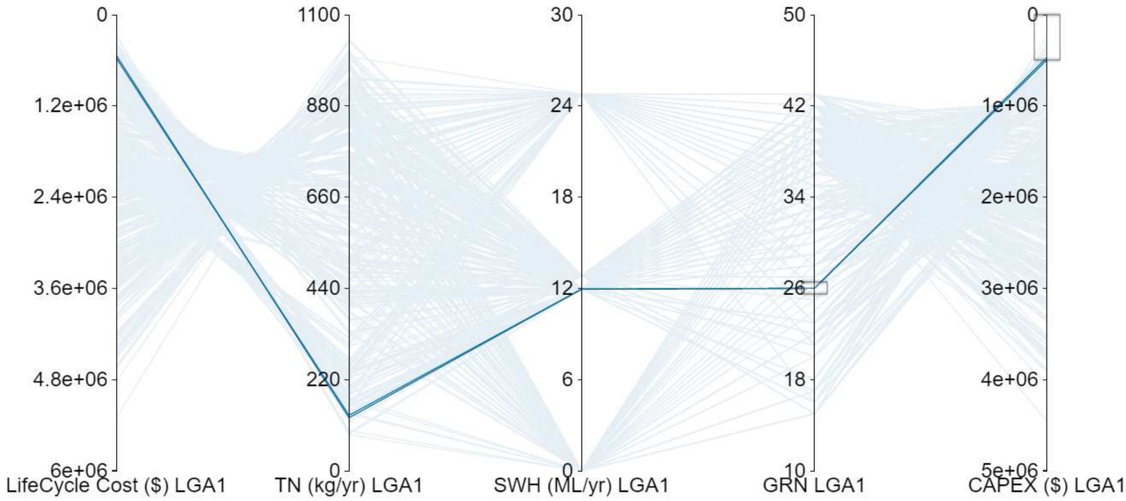

Figure 4-3 Interactive parallel coordinate plot of Pareto optimal catchment management portfolios for one stakeholder. Axes include four objectives (Lifecycle cost, total nitrogen reduction, stormwater harvesting capacity, and green score) and an additional axis (capital expenditure) to assit with isolating a best alternative to negotiated agreement (BATNA).

Table 4-5 Objective values for Best Alternative to Negotiated Agreement (BATNA) for stakeholders

Stakeholder	Lifecycle Cost ($NPV)	TN Reduction (kg/yr)	SWH (ML/yr)	Green score
CMA	4,900,000	3282.9	66.1	93
LGA 1	467,000	127.71	11.95	26
LGA 2	968,000	387.39	53.92	30
LGA 3	703,000	759.96	4.75	37

4.4.2 Visualizing the multi-stakeholder trade-off space

Figure 4-4 shows the linked parallel-coordinate plots, described in Section 4.3.4, of the Pareto optimal solutions for the collaborative optimization problem formulations, presented in Section 4.3.3, for each of the four stakeholders. The BATNAs, identified in Section 4.4.1, are shown as bolded lines as a reference point for assessing the performance of solutions. As can be seen, the LGA stakeholders have a large number of solutions in Category 1 (blue), which indicates negotiated solutions will provide them additional benefit for all objectives at lower cost compared with the BATNA. This is because the BATNA requires individual LGAs to fund both OPEX and CAPEX of their projects, whereas the CMA funds CAPEX in a negotiated solution. Therefore, disregarding external factors impacting decision-making, all LGAs have an incentive to arrive at a negotiated solution. Although individual solutions may lie in Category 1 for some, but not other, LGAs, visualising the trade-off space in his way can remind stakeholders that improvements on the BATNA are possible, which may facilitate negotiation.

The CMA, however, does not have any solutions in Category 1, which means it must compromise on at least one benefit achieved by the BATNA and/or opt for a higher cost solution. Although Category 1 solutions were featured in the CMA's full trade-off space of 2535 solutions, the joint-Pareto front solutions were not among these. Since the CMA must compromise in at least one benefit to improve on its BATNA for an equal or lower cost, it could suggest ways to arrive at a compromise with other stakeholders. For example, the CMA could indicate to stakeholders it will only accept a solution that provides much higher benefit in one of its primary objectives (e.g. reducing TN load to the bay). Alternatively, it may request additional contributions from the LGAs towards the CAPEX.

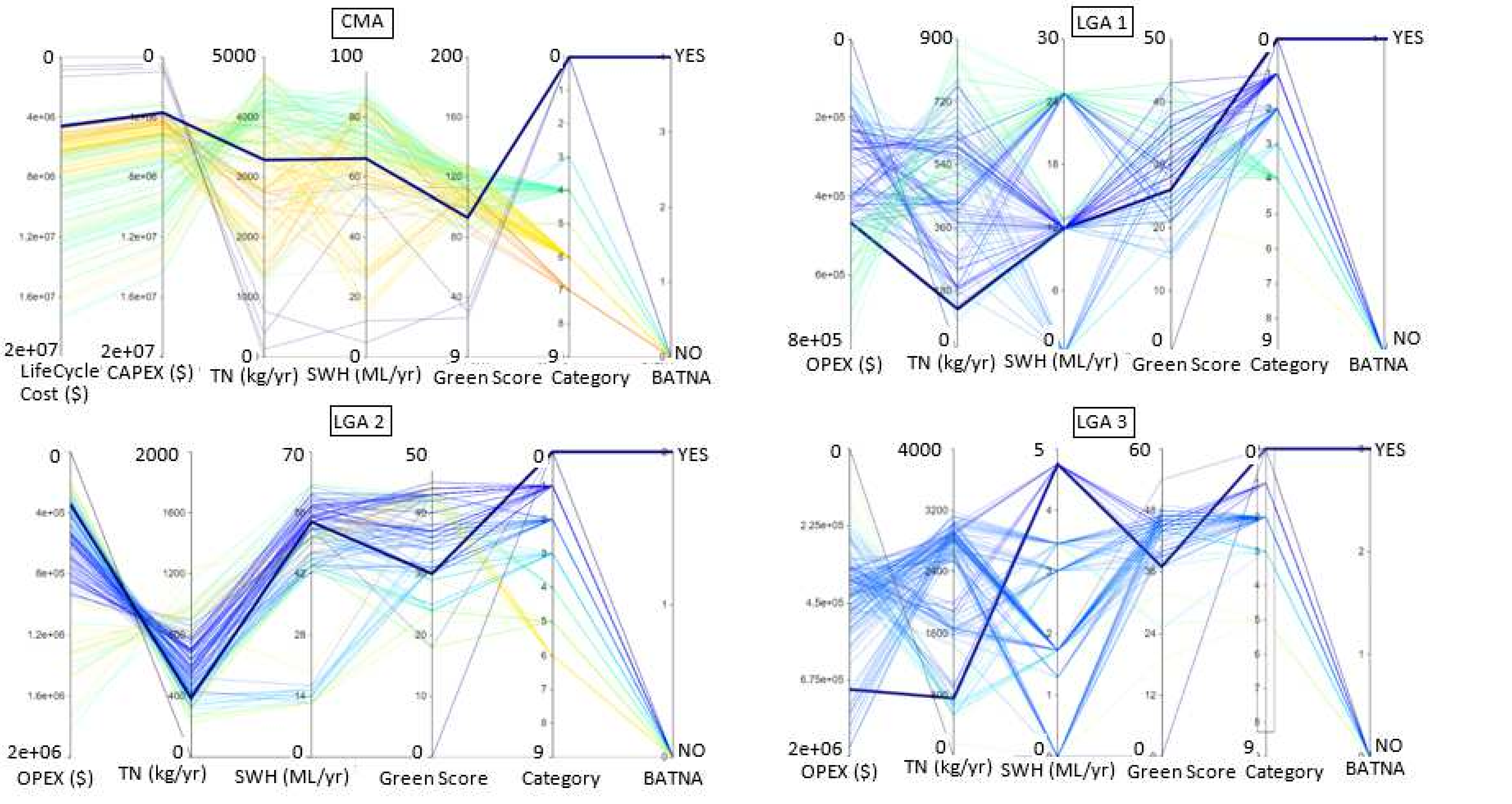

Figure 4-4 Interactive many-objective, multi-stakeholder trade-off space plot. Parallel coordinate plots showing joint Pareto front of full portfolios and individual stakeholder BATNAs visualised with respect to each stakeholder's objectives. The colour axis represents the 8 solution categories grouped by performance relative to the BATNA. A category (1) dark blue solution costs less and outperforms the BATNA in all benefits, whereas a category (8) red line solution costs more and underperforms the BATNA in all benefits. Categories 2-7 have a combination of higher or lower cost and improvement in various numbers of benefits, therefore stakeholder input is required to determine which of these categories are preferred

4.4.3 Exploring the multi-stakeholder trade-off spaces

The results of an analyst exploring the individual stakeholder problem spaces to select 'good' individual options, presenting those options in a visualization intended to illustrate their distribution of costs and benefits amongst stakeholders, and analysis of the solutions in the individual trade-off space of stakeholders, as described in Section 4.3.5, are presented in this section.

4.4.3.1 Selecting 'good' solutions

For the case study considered, individual LGA and CMA solutions were selected by an analyst using parallel coordinate plots of stakeholder objectives, as stakeholders were not available, as mentioned previously. To select LGA solutions, only Category 1 solutions were considered. Two solutions were selected for each LGA, one from high-cost and one from low-cost Category 1 solutions. Stormwater harvesting capacity and green score were prioritised over total nitrogen removal for solutions proximate in the cost regions. To select CMA solutions, Category 2, 3 and solutions that exceeded the BATNA's TN removal with cost less than $6M, were considered. Two CMA solutions were selected, one high cost and one low cost. The selected solutions are shown in Table 4-6.

Table 4-6 Individual stakeholder selected solutions

Solution characteristic	CMA Low Costs	CMA High Benefits	LGA 1 Low Costs	LGA 1 High Benefits	LGA 2 Low Costs	LGA 3 High Benefits	LGA 3 Low Costs	LGA 2 High Benefits
	Selected Solution							
CMA data								
$CAPEX_{CMA}$	3,650,000	5,710,000	4,130,000	7,450,000	5,880,000	6,510,000	2,970,000	10,200,000
TN_{CMA}	3,802	3,581	1,357	3,967	1,753	4,150	1,345	4,295
SWH_{CMA}	51.17	83.22	69.1	76.93	84.45	32.12	29.12	78.16
GRN_{CMA}	86	118	109	114	111	115	90	113
BATNA Category	3	4	6	4	6	6	5	4
LGA 1 data								
$OPEX_1$	118,000	405,000	193,000	517,000	357,000	406,000	177,000	565,000
TN_1	509.79	190.68	187.81	500.1	162.41	765.57	166.15	550.44
SWH_1	-	24.78	11.95	24.78	24.78	11.95	11.95	24.78
GRN_1	17	29	33	43	21	35	26	28
$CAPEX_1$	639,000	1,530,000	799,000	2,120,000	1,270,000	1,900,000	641,000	2,350,000
BATNA Category	3	1	1	1	2	1	1	4
LGA 2 data								
$OPEX_2$	358,000	589,000	626,000	735,000	703,000	529,000	248,000	1,160,000
TN_2	384.58	605.27	685.65	706.57	681.71	376.57	270.37	793.51

SWH_2	46.42	55.42	55.42	50.42	54.92	15.42	12.42	49.92
GRN_2	25	43	44	31	45	34	22	39
$CAPEX_2$	1,210,000	2,230,000	2,430,000	3,100,000	2,850,000	2,430,000	1,030,000	5,360,000
BATNA Category	5	1	1	2	1	3	5	2
LGA 3 data								
$OPEX_3$	351,000	372,000	166,000	428,000	351,000	432,000	261,000	482,000
TN_3	2,907.40	2,784.80	483.88	2,760.50	908.93	3,007.90	908.33	2,951.10
SWH_3	4.75	3.02	1.73	1.73	4.75	4.75	4.75	3.46
GRN_3	44	46	32	40	45	46	42	46
$CAPEX_3$	1,800,000	1,960,000	901,000	2,230,000	1,760,000	2,180,000	1,300,000	2,520,000
BATNA Category	1	2	5	2	1	1	1	2
Miscellaneous								
Directly Connected Impervious Area (ha)	680	649	243	711	316	737	241	769
No. Projects	14	19	18	18	18	19	15	18
LifeCycle Cost ($NPV)	4,480,000	7,080,000	5,120,000	9,130,000	7,290,000	7,880,000	3,660,000	12,400,000

4.4.3.2 Sharing preferred solutions

Figure 4-5 shows the parallel coordinate plot used to identify solutions that are a compromise between stakeholder preferences. Axes show the CMA capital expenditure breakdown by LGA, and solution equity indicators relevant to the problem. In this case, solutions that are likely to be preferred by stakeholders should distribute CAPEX funding amongst stakeholders fairly whilst ensuring return on investment through total catchment benefits are achieved. Visualising how a solution distributes costs and benefits amongst stakeholders can assist in the negotiation process. This can be done by visualising objective performance (CAPEX), non-objective data (CAPEX of LGAs), as well as equity indicators (maximum BATNA category) in parallel coordinate plots. The interactive plots allow analysts to rapidly brush out unfavourable solutions. This reduces the number of solutions to consider and thus the cognitive load on stakeholders.

In addition, Figure 4-5 shows how CAPEX from the CMA is distributed amongst LGAs for the selected solutions. Although the CAPEX here is more than the CMA's BATNA cost, the CMA may investigate higher cost solutions, as it had no Category 1 solutions in the joint Pareto front. This could result in the avoidance of solutions that have extremely low or high individual LGA CAPEX expenditures. Since the CMA is compromising its preferences by increasing its CAPEX over its BATNA cost, it would most likely want to maximize its primary objective, which is to reduce total nitrogen reduction to the bay. The 'maximum category' axis is an equity indicator that assumes that a smaller number of categories is preferable. However, which of the benefits are compromised is important to decision makers. For example, the CMA may be willing to accept a higher category solution (e.g. higher cost and compromise in one or more benefits) that has a much higher total catchment TN reduction than other solutions. An additional axis isolates solutions that appear in Category 1 for all LGAs, as there were numerous Category 1 solutions available in the LGA trade-off spaces. The indicator shows none of the selected solutions lie in Category 1 for all LGAs. Determination of how each solution performs with respect to all stakeholder objectives would be required in order to better understand the compromises and return on investment for the CMA.

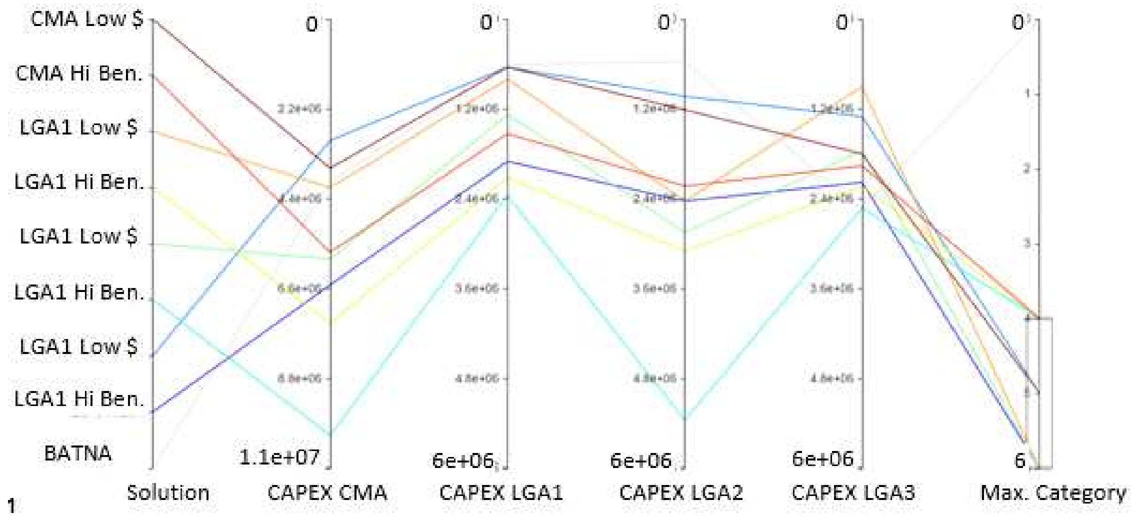

Figure 4-5 Breakdown by recipient LGA of the catchment management authority capital expenditure for joint Pareto solutions. Colour axis shows the selected solutions. A lower maximum category number indicates a solution that is likely to be preferable or equitable to all stakeholders (in this case, since all LGA solutions were Category 1, maximum category reflects the CMA category). BATNAs are not shown.

4.4.3.3 Identifying compromise solutions

Figure 4-6 shows the selected solutions, visualised on a screenshot of interactive many-objective, multi-stakeholder trade-off space plots (BATNAs are not shown). The analyst evaluated the performance of the selected solutions with respect to each stakeholder's values, by visualizing the solutions' performance in each stakeholder objective space and comparing each solution to the stakeholder's preferred options. The stakeholder evaluated the relative performance of other stakeholder solutions with their own BATNA and own selected solutions. An analyst recorded the likelihood that each stakeholder will accept each solution, and the rationale for the evaluation, shown in Table 4-7. A "yes" was recorded where there was a large increase in benefits at similar cost or lower costs with similar benefit, compared to solutions suggested by the stakeholder; a "maybe" was recorded if there was an increase in some benefits and not others at additional cost; a "no" was recorded where costs were higher with small or no increases in benefits. Recording the rationale may be useful for further bargaining.

In the "CMA low $" solution, all stakeholders are likely to be satisfied with the solution except LGA 2, who is concerned about a lower benefit in both stormwater harvesting capacity and green score compared to their BATNA. To assist with identifying a compromise solution that agrees with LGA2's values, stakeholders can consider the projects making up the portfolio using the visual analytics package, as was done in Section 3.3. Looking at the projects making up the portfolio, the LGA2 projects include Project 60 and 61, two small biofilters, and Project, 70 a large wetland. This provides information for bargaining, e.g. to identify the impact of replacing or adding projects to the portfolio with those that LGA2 would like to implement and that other stakeholders might be willing to fund. Alternatively, returning to a visualisation of the full trade-off space, isolating selected solutions and using the brushing tool, would enable the selection of solutions proximate to the "CMA low $" solution in each stakeholder's objective space, which represents a good compromise solution.

The results here show one iteration of the negotiation process. If none of the selected solutions can be agreed upon, stakeholders should be allowed to revise their BATNA or selected solutions as new information about the problem arises (Fitzgerald and Ross 2016).

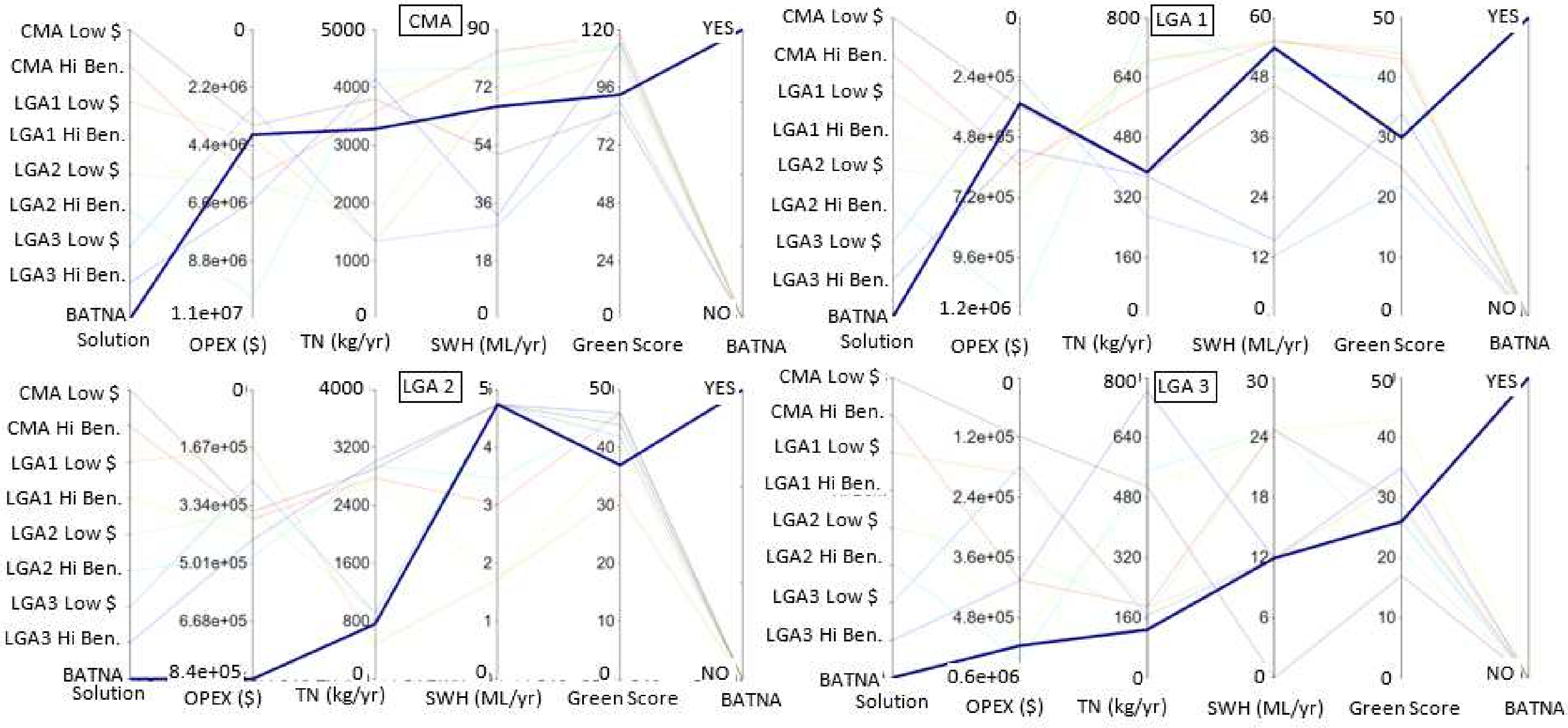

Figure 4-6 Interactive multi-stakeholder trade-off space showing selected solutions.

Table 4-7 Indicative stakeholder preferences for selected solutions

Stakeholder	CMA Low $	CMA High Ben.	LGA 1 Low $	LGA 1 High Ben.	LGA 2 Low $	LGA 2 High Ben.	LGA 3 Low $	LGA 3 High Ben.
CMA Reason	Yes	Yes	Yes	No low TN	Maybe	No low TN	Yes	Yes
LGA 1 Reason	Yes Category 1	Yes Category 1	Yes	Yes	Maybe high cost	Maybe low Green	Yes Category 1	No low SWH
LGA 2 Reason	Maybe low benefit	Maybe low benefit	Yes	Yes	Yes	Yes	No low SWH	No low SWH
LGA 3 Reason	Yes	Maybe low SWH	No low benefit	No low SWH	Yes	Maybe low SWH	Yes	Yes
Viable?	Maybe	Maybe	No	No	Maybe	No	No	No

4.5 Summary and conclusions

In this study, a general optimization-visualisation framework that deals with multiple stakeholders with multiple objectives, and encourages a negotiated outcome for a portfolio optimization problem, was presented. The framework addresses the need for a decision support approach for identifying solutions to complex environmental problems that i) handles multiple stakeholder formulations of the problem reflecting their interests and values, ii) enables interactive exploration and analysis of possible solutions by stakeholders, iii) encourages stakeholder trust in the final selected solution, and iv) facilitates a final negotiated outcome. Improvements on existing multi-stakeholder exploration approaches were developed. These include visualisation of the full trade-offs between extremely large numbers of objectives using multiple linked parallel coordinate plots in a visual analytics package. Solutions were framed within the plots to compare proposed solutions to a best alternative across multiple objectives. This was done to facilitate negotiation by emphasising the benefits gained and losses prevented through accepting a negotiated outcome. This also highlights inequities between stakeholders and facilitates bargaining where equitable outcomes are available

An innovative indicator for determining the relative improvement upon a Best Alternative to a Negotiated Alternative (BATNA) solution allows stakeholders to rapidly assess how well a solution performs across multiple objectives and multiple objective spaces. In addition, as the joint-Pareto solutions are Pareto optimal with respect to each stakeholder's individual problem formulation, this assists with arriving at a consensus on a final compromise solution. This is because stakeholders do not have to compromise by accepting a solution that is dominated in the objective space of their preferred formulation, nor do they have to explore and analyse results of a single problem formulation with aggregated or agreed upon objectives that do not necessarily reflect their values.

The approach was demonstrated on a multi-stakeholder catchment management problem, requiring 16 different objectives from stakeholders to assess solutions. Eight optimization formulations were solved to generate solutions to a best alternative scenario and a collaborative scenario. From a set of solutions that were joint-Pareto optimal within the collaborative scenario, a set of selected solutions were identified for further consideration by stakeholders.

4.6 Acknowledgements

Research funding was provided by the University of Adelaide, and the Goyder Institute for Water Research. The authors thank Dr. Dale Browne and e2DesignLab, Australia for assistance with the case study data.

CHAPTER 5

Conclusion

Recently, the application of Water Sensitive Urban Design (WSUD) has demonstrated an ability to mitigate the impacts of development on urban water supply security and natural ecosystem health (Askarizadeh, Rippy et al. 2015). An increasingly popular WSUD technique is urban stormwater harvesting (SWH), which incorporates stormwater best management practices (BMPs) in systems used to intercept and capture, treat, store and distribute surface stormwater runoff for later reuse. WSUD approaches, especially SWH, can provide multiple benefits such as a reliable water supply for irrigation, improvement in urban vegetation and amenity, and restoration of urban runoff quality and quantity closer to pre-development levels (Fletcher, Mitchell et al. 2007). However, optimizing WSUD systems to achieve these multiple objectives, which are often conflicting, can make planning and design tasks more complex than traditional stormwater management systems. Compounding this difficulty are the multiple possible spatial scales at which BMPs can be distributed throughout a catchment, the large number of different types of system components and interaction between components, and the large number of decision options (e.g. size, type and location of BMPs) and therefore large number of possible solutions. Consequently, many WSUD system planning and design problems are suited to be formulated mathematically as multiobjective optimization problems with large and complex solution spaces; which consist of a set of planning or design decisions that need to be selected to maximize a set of objectives given practical constraints.

While formal multiobjective optimization approaches, including the use of metaheuristics linked with models to evaluate the objective function performance, may be well suited to solving WSUD planning and design problems, their application also presents a number of challenges. An optimization framework that considers all aspects of the SWH system preliminary design problem is necessary to take into account multiple objectives, different system components, the distribution of components throughout a catchment and a formal optimization approach. In addition, to ensure the results of the application of optimization approaches are trusted and used in practice, it is necessary to adapt approaches to incorporate stakeholder input and facilitate negotiation between multiple stakeholder groups with different preferences to encourage the adoption of a final WSUD solution. In order to address these issues, three optimization frameworks using multiobjective metaheuristic algorithms were introduced in this thesis, which are able to: 1) handle SWH systems preliminary design incorporating multiple objectives, different types of system components, distribution of BMPs, and a large number of decision options in a holistic fashion, 2) encourage the adoption of the results of optimization by incorporating input from stakeholders in the problem formulation and evaluation using portfolio optimization approach, and exploration of analysis of optimization results using visual analytics, and 3) facilitate negotiation between a number of stakeholder groups, each with different value sets and interests, through a innovative multi-stakeholder visual analytics approach to identify, explore, analyse and select from jointly optimal solutions.

5.1 Research Contribution

The overall contribution of this research is the development of three optimization frameworks for optimal WSUD systems planning and design using multiobjective optimization algorithms. In the first framework, optimal SWH systems with components distributed at the development scale are identified to maximize water quality improvement and SWH capacity, at minimal cost, subject to practical limits on the combination of BMPs within systems and pollution reduction requirements set by regulators. The benefits of this framework are demonstrated using a real-world case study based on a new housing development located north of Adelaide, South Australia. The second framework produces optimal integrated catchment management plans consisting of BMP projects for maximizing water quality improvement, SWH capacity, and urban vegetation and amenity improvement at the regional scale and is applied to a real case study for a major Australian city. The third framework incorporates the optimization approach in the second framework into a multi-stakeholder optimization-visual analytics framework to facilitate the selection of a solution to complex environmental planning problems through negotiation between parties. This uses visual analytics considering extremely large numbers (>10) of objectives and is applied to a sixteen objective multi-stakeholder catchment management plan problem for a real case study for a major Australian city.

The specific research contributions to address the objectives stated in the Introduction are as follows:

1. A generic multiobjective optimization framework to assess trade-offs in spatially distributed SWH system designs, featuring the Non-Dominated Sorting Genetic Algorithm (NSGA-II) linked with an integrated stormwater model (eWater *MUSIC*) and a lifecycle cost model, was developed in Paper 1. This framework is able to identify SWH system designs that maximize trade-offs between water quality, stormwater harvesting capacity and minimize lifecycle cost of BMPs and water transfer infrastructure. A SWH systems design problem for a real case study for a new housing development north of Adelaide, South Australia was used to demonstrate the utility of the framework. The results demonstrate the benefits of adopting Pareto optimal spatially distributed SWH systems identified using the framework, compared with traditional designs with BMPs located at the catchment-outlet. Results indicate that, where storage space is limited at the catchment outlet, better harvested stormwater supply reliability as well as better water quality improvement can be achieved by distributing capture, treatment, and storage BMPs in an integrated SWH system.
2. A general multiobjective optimization framework for the selection of a portfolio of BMPs for catchment management was developed in Paper 2. The framework addresses the need for a decision support approach for the selection of BMPs that considers numerous, possibly conflicting, performance criteria, handles a large number of decision options and potential strategies, facilitates the identification and representation of trade-offs between performance criteria, which develops trusted strategies, within the limits of existing planning capacities. The approach was applied to a case study catchment plan for a catchment authority in a major coastal city in Australia. The results demonstrate the benefits of exploring full portfolio solution trade-offs in a many-dimensional Pareto optimal front. A comparison between the trade-off spaces of a lower dimensional water quality-cost problem formulation (typical in previous catchment management plan optimization studies) and the many-objective formulation, demonstrated that low-objective formulations can result in Pareto optimal portfolios with low performance in non-objective performance criteria. The study demonstrated that the use of the visual analytics approach to explore combined optimization and

decision spaces could assist in overcoming institutionally influenced biases to include particular projects or BMP technologies to demonstrate alternative similar cost options to decision-makers.

3. A general optimization-visualisation framework that deals with multiple stakeholders with multiple objectives, and encourages a negotiated outcome for a portfolio optimization problem, was presented in Paper 3. The framework addresses the need for a decision support approach for identifying solutions to complex environmental problems that i) handles multiple stakeholder formulations of the problem reflecting their interests and values, ii) enables interactive exploration and analysis of possible solutions by stakeholders, iii) encourages stakeholder trust in the final selected solution, and iv) facilitates a final negotiated outcome. Improvements on existing multi-stakeholder exploration approaches were developed. These include visualization of the full trade-offs between extremely large numbers of objectives using multiple linked parallel coordinate plots in a visual analytics package. Solutions were framed within the plots to compare proposed solutions to a best alternative across multiple objectives. This was done to facilitate negotiation by emphasising the benefits gained and losses prevented through accepting a negotiated outcome. This also highlights inequities between stakeholders and facilitates bargaining when equitable outcomes are available. An innovative indicator for determining the relative improvement upon a Best Alternative to a Negotiated Alternative (BATNA) solution allows stakeholders to rapidly assess how well a solution performs across multiple objectives and multiple objective spaces. In addition, as the joint-Pareto solutions are Pareto optimal with respect to each stakeholder's individual problem formulation, this assists with arriving at a consensus on a final compromise solution. The approach was demonstrated on a multi-stakeholder catchment management problem, requiring sixteen different objectives from four stakeholders to assess solutions. Eight optimization formulations were solved to generate solutions to a best alternative scenario and a collaborative scenario.

5.2 Limitations

The limitations of this research are discussed below.

1. The framework for a SWH preliminary design in Paper 1 considers harvesting and water quality control functions, but not flood control functions as is the case in many WSUD systems. The case study was selected to allow the water quality control volumes in BMPs to be sized separately from any flood control infrastructure dealing with greater than 1 in 1 year flood events.

2. The objective functions selected in Papers 1, 2, and 3 reflect commonly used WSUD indicators of performance but additional objectives may also be important. Where additional objectives are added to optimization problem formulations in application of the framework this may require the use of multiobjective metaheuristic algorithms that have been demonstrated to work on problems with more than four objectives.

3. The utility of the proposed framework in Paper 1 has been demonstrated via the development-scale case study, as its application enabled optimal solutions to be identified within a given computational budget. However, application of the framework will not necessarily support real-world decision making, particularly in places where a large number of nodes in a system are possible, requiring orders of magnitude more simulations and much longer model run-times.

4. Although economic factors (e.g., capital and maintenance costs of WSUD components) have been included in the proposed frameworks, there is no consideration of the sensitivity of the optimal WSUD systems obtained to different cost assumptions. In particular, the long-term cost of maintenance to maintain functional performance of WSUD assets, as well as uncertainty about these costs, is a subject of ongoing research. For example, the cost model assumes a proportional relationship between the size of BMPs and cost, however does not take into account the amount of sediment captured in BMPs, which means smaller BMPs may have underestimated costs compared with those estimated by a model including associated costs to remove sediment to maintain functional performance.

5. The water quality, stormwater harvesting and urban vegetation and amenity values were not subjected to a sensitivity analysis to model inputs, therefore optimization results should be tested further. In particular, to determine the

pollutant load reduction of a WSUD system in *MUSIC* it is typical practice to simulate the system several times with a stochastic function for the pollutant wash-off model in *MUSIC* switched on, and to then to calculate an average performance value. This was not possible in the framework in Paper 1 due to limitations on run-time. The stormwater harvesting performance of optimization solution should be further tested using several climate scenarios as suggested in (Marchi, Dandy et al. 2016).

6. The visualization method presented in Paper 3 has not yet been demonstrated in a stakeholder workshop setting, and impacts of the real-world application are yet to be tested and understood.

   In the proposed frameworks, the WSUD systems are developed using one rainfall pattern, whereas the harvesting performance is may be impacted by future climate changes (although, Clark et al. 2015 have found climate change is not likely to be critical to urban runoff when compared to increasingly dense urban development, in South Australia). Demand for alternate water supplies (i.e. non-potable quality) is also a critical variable that should be considered.

7. Notably, the optimization formulations in the case studies in Paper 2 and 3 do not consider interaction between having a higher harvest capacity, which might allow for more irrigation of green spaces.

5.3 Future Work

From the above limitations, some future studies are recommended below.

1. Future application of the framework in Paper 1, might consider an additional flood control objective and linking a flooding model to the framework. This would be possible through the use of metaheuristic algorithms that allow for multiple linked models to evaluate multiple objectives.

2. As long model run-time and computational budget limited the size of case study available to apply the framework in Paper 1, in addition to the model pre-emption method employed, future studies could consider parallelization of model simulations, surrogate modelling techniques, or additional optimization operators

to prevent simulation of inferior solutions that could reduce run-time further, as discussed in Maier, Kapelan et al. (2014). This would permit larger WSUD systems, additional decision options, scenarios including the impact of climate change on optimal BMP placement, as well as consideration of solution robustness and uncertainty analyses.

3. Future studies on the impact of climate changes on distributed systems of BMPs used for stormwater harvesting should be investigated, as has been done for BMP systems not including harvesting (Chichakly, Bowden et al. 2013).

4. As economic sensitivities, as well as other model parameter and objective function sensitivities are important for real-world WSUD systems planning and design, there is a need to take into account this factor in further studies. Furthermore, risk management should be also addressed to evaluate the impact of maintenance cost sensitives.

5. Adding more objectives to the optimization formulations could provide decision-makers with even more insight into the performance trade-offs of optimal WSUD systems. However, the number of solutions that represent Pareto front increases exponentially with the number of objectives, making solutions representing optimal trade-offs more difficult to identify, explore and analyse. Therefore, metaheuristics that have been demonstrated to work on problems with high numbers of objectives should be used to identify optimal solutions (e.g. BORG; Hadka and Reed (2012)). Nonetheless, visual analytics approaches are particularly useful for exploring and analysing optimization results of problems with large number of objectives as demonstrated in Paper 3, in particular.

6. The optimization-visual analytics presented in Paper 3 should be tested in an experimental workshop setting, to demonstrate its ability to facilitate the rapid selection of compromise solutions.

7. The problem formulation in Paper 2 and 3 should consider synergistic (or cannibalistic) interaction between objectives such as projects with higher harvesting capacity, which may increase the irrigation capacity, thus increasing green score of projects nearby.

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APPENDIX A

Paper 1 Published Version

Published version of Paper 1 from Chapter 2:

Di Matteo, M., Dandy, G.C. & Maier, H.R., 2017. *Multiobjective optimization of distributed stormwater harvesting systems*. Journal of Water Resources Planning and Management, 10.1061/(ASCE)WR.1943-5452.0000756.

APPENDIX B

Paper 2 Supplemental Data

This appendix contains a table of cost data used to determine the model for stormwater harvesting lifecycle cost for the case study in Paper 2 (Equation (3-8)).

Table B- 1 Detailed costings of stormwater harvesting components used to develop the model for LCCSWH [$] (Eqn. 8) in the case study application of the optimization framework. Based on values in Inamdar (2014). SWH component cost values were adjusted from 2012$ to 2016$, at 1% p.a (D. Browne, personal communication, 2016)

		Underground Conc. Storage		Stormwater pipes		Control System		Pump system		Electricity				
	Volume Supplied ML/yr	Capital Cost ($)	Annual Cost ($/year)	Capital Cost ($)	Annual Cost ($/year)	Capital Cost (2016$)	Annual Cost ($/year)	Capital Cost (2016$)	Annual Cost ($/year)	Annual Cost ($/year)	NPV Capital Cost (2016$)	NPV Annual Cost (2016$)	Total NPV (2016$)	**Levelized cost (2016$/ML)**
Pleasance Garden	**5.6**	191750	3020	49500	650	30000	1400	19180	5000	156	302221	128544	430765	**6306**
Ievers Reserve	**5.6**	153400	3020	65250	650	30000	1400	19428	5000	173	278962	128757	407719	**5969**
Batman Park	**5.7**	191750	3020	20925	650	30000	1400	19428	5000	173	272744	128757	401502	**5775**
Birrarung Marr Park	**15.1**	536900	3020	82620	650	30000	1400	39300	5000	864	716786	137443	854230	**4638**
Holland Park	**18.5**	920400	3020	47790	650	30000	1400	48190	5000	605	1088863	134188	1223051	**5420**
Clayton Reserve	**26**	767000	3020	151200	650	30000	1400	29102	5000	735	1016980	135822	1152802	**3635**

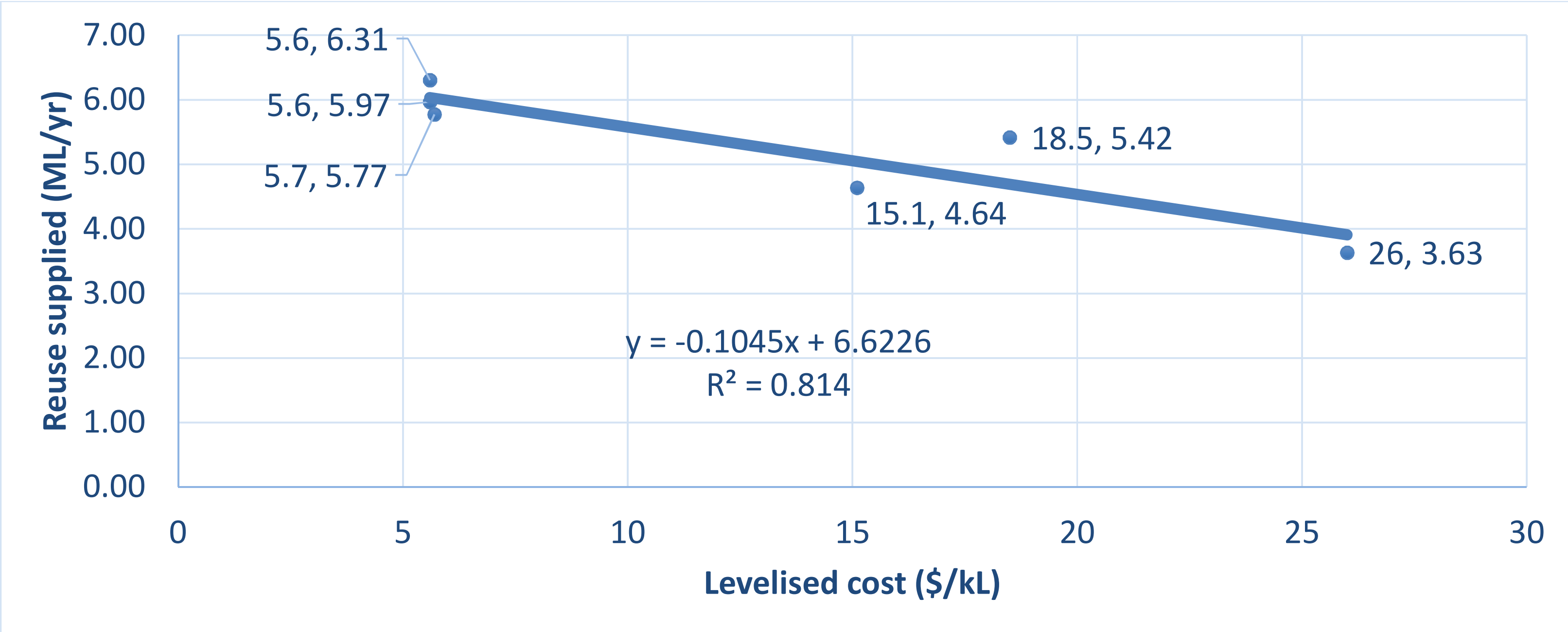

Figure B-1 Capacity vs cost per volume supplied for Melbourne stormwater harvesting projects. Based on values in Inamdar (2014). SWH component cost values were adjusted from 2012$ to 2016$, at 1% p.a (D. Browne, personal communication, 2016).

APPENDIX C

Paper 3 BMP project data

The data associated with the 70 stormwater best management practice (BMP) projects evaluated in the case study application of the proposed optimization approach are presented in Table C.1 below.

Table C-1 Details of available catchment management projects

Local government authority (LGA)	Project ID	BMP Type	Contributing catchment area (ha)	Lifecycle cost ($NPV)	CAPEX ($NPV)	OPEX ($NPV)	TN Reduction (kg/yr)	Total Supply (ML/yr)	Green score
	3	Biofilter	22.5	305,157	257,198	48,123	72.75	0	4
	4	Biofilter	11.6	271,251	228,621	42,776	37.4	0	4
	5	Biofilter	7.7	175,626	155,531	21,388	24.86	0	5
	6	Biofilter	9.3	131,719	116,649	16,041	30.16	0	5
	7	Biofilter	8.2	43,906	38,883	5,347	26.63	0	5
	8	Biofilter	9.4	87,813	77,766	10,694	30.25	0	5
1	12	Biofilter	50.3	1,220,630	1,028,792	192,493	162.82	0	5
	13	Wetland	4.8	169,532	142,888	26,735	15.49	0	5
	23	Wetland	3	98,438	116,649	16,041	9.58	0	5
	24	Wetland	13.5	459,379	400,086	74,858	43.63	0	5
	25	Wetland	13.2	459,379	400,086	74,858	42.79	0	5
	35	Wetland	21.5	918,757	800,172	149,717	69.5	0	5
	36	Biofilter	45.2	949,379	800,172	149,717	146.3	0	5

	45	Biofilter	24.8	271,251	228,621	42,776	80.17	0	7
	46	Swale	64.5	123,814	400,086	74,858	208.58	0	7
	50	Biofilter	9.6	187,282	116,649	21,415	31.08	11.95	6
	55	Biofilter	8.7	305,157	257,198	48,123	28.27	0	8
	56	Biofilter	84.9	237,345	200,043	37,429	274.58	0	5
	57	Wetland	29.4	1,206,996	1,000,215	192,428	95.12	12.83	5
2	1	Biofilter	20.4	508,596	428,663	80,206	55.79	0	4
	2	Biofilter	25.4	542,502	457,241	85,553	69.5	0	4
	9	Wetland	91.9	1,220,630	2,571,981	481,233	251.32	0	4
	16	Biofilter	28.5	474,689	400,086	74,858	78.09	0	6
	19	Wetland	22.5	787,506	685,862	128,329	61.66	0	4
	20	Wetland	14.8	525,004	457,241	85,553	40.55	0	4
	21	Wetland	59	718,815	1,514,611	283,393	161.29	0	4
	22	Wetland	21.3	406,877	857,327	160,411	58.23	0	4
	27	Biofilter	15.3	305,157	257,198	48,123	41.89	0	6
	29	Wetland	6.2	196,877	171,465	32,082	16.89	0	6
	37	Wetland	13.6	590,630	514,396	96,247	37.31	0	5

	42	Wetland	37.5	951,570	828,749	155,064	102.47	0	6
	47	Biofilter	57.9	712,034	600,129	112,288	158.47	0	7
	49	Biofilter	36	610,315	514,396	96,247	98.48	0	7
	51	Wetland	17.4	590,630	514,396	96,247	47.56	0	6
	52	Wetland	21.3	721,881	628,706	117,635	58.23	0	6
	58	Biofilter	25.5	592,986	485,819	97,209	69.9	3	6
	59	Biofilter	7.8	224,031	155,531	26,966	21.21	10	6
	60	Biofilter	50.4	189,135	155,531	27,758	137.78	2.42	6
	61	Biofilter	57.7	381,297	257,198	50,566	157.92	40	6
	63	Biofilter	10.4	178,041	142,888	33,201	28.59	1.5	6
	66	Biofilter	88.6	2,027,127	1,686,076	321,575	242.49	5	6
	68	Wetland	98.4	976,171	3,286,420	621,322	269.13	2	7
	70	Wetland	22	768,630	657,284	129,343	60.29	2.5	7
3	10	Biofilter	53.1	1,017,191	857,327	160,411	145.28	0	5
	11	Biofilter	32.8	305,157	257,198	48,123	89.68	0	5
	14	Wetland	11.5	295,315	257,198	48,123	31.52	0	6
	15	Biofilter	16	203,438	171,465	32,082	43.78	0	6

17	Biofilter	43.7	474,689	400,086	74,858	119.47	0	7
18	Biofilter	417.2	474,689	400,086	74,858	1141.49	0	7
26	Wetland	4.5	164,064	142,888	26,735	12.44	0	6
28	Biofilter	10.6	87,813	77,766	10,694	29.13	0	6
30	Biofilter	40.8	542,502	457,241	85,553	111.75	0	6
31	Biofilter	7.2	131,719	116,649	16,041	19.65	0	6
32	Swale	10.1	114,970	371,508	69,511	27.73	0	7
33	Swale	13.5	88,438	285,776	53,470	37.02	0	7
34	Wetland	51.4	732,378	1,543,189	288,740	140.6	0	5
38	Biofilter	97.7	213,213	171,465	38,524	267.23	1.73	6
39	Biofilter	15.9	175,626	155,531	21,388	43.59	0	6
40	Biofilter	27.2	610,315	514,396	96,247	74.48	0	6
41	Biofilter	97.7	97,587	77,766	17,136	267.23	1.73	6
43	Biofilter	18.7	440,783	371,508	69,511	51.25	0	7
44	Biofilter	43.7	576,409	485,819	90,900	119.47	0	7
48	Biofilter	421.2	915,472	771,594	144,370	1152.38	0	7
53	Wetland	15.1	525,004	457,241	85,553	41.28	0	6

54	Wetland	63.1	962,941	2,029,007	379,639	172.58	0	7
62	Wetland	14	576,409	485,819	90,900	38.19	0	7
64	Wetland	18.8	656,255	571,551	106,941	51.43	0	7
65	Biofilter	47.4	847,660	714,439	133,676	129.69	0	7
67	Biofilter	8.4	95,157	77,766	17,182	23.11	1.29	6
69	Biofilter	47.4	169,532	142,888	26,735	129.69	0	7

APPENDIX D

Paper 3 Objective function formulations

The objective function formulations for the case study application of the proposed approach are presented below. The objective functions are adapted from a single stakeholder catchment management optimization problem presented in Chapter 3. The objective functions include a mathematical formulation of cost, a water quality improvement indication (total nitrogen (TN) reduction), a stormwater harvesting indicator, and an urban vegetation and amenity indicator, as outlined below.

Cost

The economic cost of a portfolio of projects is represented as a life cycle cost $LCC_{,S}$ [$] (Equation (D-1)), which is a discounted sum of expected future costs for stormwater management assets, including BMPs and transfer infrastructure required to harvest stormwater (Taylor and Wong 2002). The life cycle cost objective function for each candidate portfolio of BMPs is given by:

$$\text{MINIMIZE: } \mathrm{LCC} = \mathrm{LCC_{BMP}} + \mathrm{LCC_{SWH}}$$

Equation (D-1)

where

$$\mathrm{LCC_{BMP}} = \sum_{i=1}^{N}\left\{ (\mathrm{TAC_{BMP_i}}) + \mathrm{PWF_{estab,BMP_i}}\left(\mathrm{SA_{BMP_i}} \times \mathrm{ECF_{BMP_i}} \times \mathrm{M_{BMP_i}}\right) + \mathrm{PWF_{maint,BMP_i}}\left(\mathrm{SA_{BMP_i}} \times \mathrm{M_{BMP_i}}\right)\right\}$$

Equation (D-2)

$$\mathrm{LCC_{SWH}} = \mathrm{C_{CapTank}} + \mathrm{C_{CapPipe}} + \mathrm{C_{CapControl}} + \mathrm{C_{CapPump}} + \mathrm{PWF_{maint}}\left(\mathrm{C_{mTank}} + \mathrm{C_{mPipe}} + \mathrm{C_{mControl}} + \mathrm{C_{mPump}}\right)$$

Equation (D-3)

where a sum of the cost of BMPs to capture and treat stormwater runoff, LCC_{BMP} [$] (Equation (D-2)), and to transfer harvested water to a balancing storage for further treatment and distribution, LCC_{SWH} [$] (Equation (D-3)) is applied with BMP_i representing the i^{th} BMP in the candidate portfolio, N [integer] is the number of projects in the portfolio, and TAC [$] is the total acquisition cost as a function of SA, the surface area of BMP_i. *M [$) i*s this the annual maintenance cost per unit surface area

PWF_{estab} [fraction], for the establishment period, and PWF_{maint} [fraction], for the remaining design life of system components, are the present worth factor for a series of annual costs computed using an appropriate discount rate. *ECF* [fraction] is the establishment cost factor (i.e., multiplier) for the annual maintenance cost M [$] during the establishment period (typically 1-2 years) for each BMP. For BMPs with a stormwater harvesting function, $C_{CapTank}$ [$], $C_{CapPipe}$ [$], $C_{CapControl}$ [$], and $C_{CapPump}$ [$] are the capital costs for required underground storage tank, control systems, pipes, and pump stations, and C_{mTank} [$], C_{mPipe} [$], $C_{mControl}$ [$], and C_{mPump} [$] are the annual maintenance costs for the tank, pipes, control systems, and pumps, and operating costs, respectively.

For the case study, the objective function for lifecycle cost of each portfolio, $LCC_{,S}$ [$], was calculated using (Equation (D-1) to (D-3)). The parameters for LCC_{BMP} [$] (Equation (D-2) were estimated from cost schedules developed by Melbourne Water Australia (2013) (Table D-1). A typical lifecycle period of 25 years, a discount rate of 6.5% per year, an establishment cost factor of 3, and an establishment period of 2 years, were adopted. The parameters for LCC_{SWH} [$] (Equation (D-3)) were estimated as follows. A cost model for the total net present value (NPV) of stormwater harvesting components was determined using regression ($r^2 = 0.814$) between levelized lifecycle cost [$/ML] and estimated annual volume supplied [ML/yr], using detailed costing data for six stormwater harvesting projects derived by Inamdar (2014) (see Section 3.2.3.1). Thus, the lifecycle cost of stormwater harvesting components from Equation (D-4) was calculated using the following equation:

$$LCC_{SWH} = \begin{cases} \sum_{i=1}^{N} (-104.49 \cdot Supply_i + 6622.6)[\frac{\$}{ML}] \cdot Supply_i[ML] & \text{, if } Supply_i > 0 \\ 0 \quad \text{otherwise} \end{cases}$$

Equation (D-4)

where *Supply* $Supply_i$ is the average annual supply capacity of the i^{th} BMP in a candidate portfolio of N BMPs.

Table D-1 Cost variables for BMPs

BMP Surface Area(SA) (m^2)	Construction Cost ($\$/m^2$; year 0)	Establishment Cost ($\$/m^2/yr$; year 1-2)	Maintenance Cost ($\$/m^2/yr$; year 3-25)
Wetland			
0 < SA <499.99	150	30	10
500 < SA ≤ 9,999	100	6	2
SA > 10,000	75	1.5	0.5
Biofiltration basin			
0 < SA ≤ 99.99	1,000	15	5
100 < SA ≤ 499.99	350	15	5
SA > 500	250	15	5
Swale			
All sizes	35	9	3

Note: Establishment cost = Annual maintenance cost × establishment cost factor. Costs are in Australian Dollars (2013$). Values were scaled using an inflation adjustment factor of 1.03053 from 2013$ to 2016$.

Water Quality Improvement

The water quality improvement indicator, $f_{quality,S}$, is the total average annual pollutant load reduction of one target pollutant (Equation (D-5)). The water quality improvement objective function is:

$$\text{MAXIMIZE: } f_{quality} = \sum_{i=1}^{N} (Source_i - Resid_i)$$

Equation (D-5)

where, $f_{quality}$ [mass year^{-1}] is the mean annual pollutant mass retained by BMPs in each candidate portfolio, *N* is the number of BMPs in a portfolio, $Resid_i$ [mass year^{-1}] is the mean annual mass of pollutant leaving the i^{th} BMP's contributing catchment area, and $Source_i$ [mass year^{-1}] is the mean annual mass of pollutant that reaches the i^{th} BMP's catchment outlet in a post-development catchment baseline scenario without intervention. *Resid* and *Source* should be determined using a stormwater quality assessment model accepted by the catchment management authority (Coombes, Kuczera et al. 2002, Bach, Rauch et al. 2014).

Total Nitrogen (TN) was the specific pollutant constituent adopted for the water quality objective. The mean annual pollutant mass of TN retained by each candidate portfolio was calculated based on the sum of average annual TN mass retained by individual BMPs in a portfolio. The water quality improvement of each BMP ($Source_i$, - $Resid_i$; Equation (D-5)) was assessed using the integrated catchment model, *MUSIC* version 6.1 (Model for Urban Stormwater Improvement Conceptualization, (eWater 2009)), as suggested by the CMA regulations. *MUSIC* is an integrated stormwater model that evaluates rainfall/runoff and pollutant generation and transport, hydraulic and pollutant removal performance of BMPs (Bach, Rauch et al. 2014). *MUSIC* algorithms simulate runoff based on models developed by Chiew and McMahon (1999) and urban pollutant load relationships based on analysis by Duncan (1999). An assessment of interactions between BMPs was not deemed necessary because the contributing catchments of individual BMPs were spatially mutually exclusive.

A.3 Stormwater Harvesting

Average annual supply capacity (Equation (D-6)) is adopted as an indicator of stormwater harvesting performance. The supply stormwater harvesting objective function is:

$$\text{MAXIMIZE: } f_{supply} = \sum_{i=1}^{n} Supply_i$$

Equation (D-6)

where $Supply_i$ [volume] is the average annual stormwater harvested volume for the i^{th} BMP in a portfolio, and N [integer] is the number of projects in a portfolio.

Experts on stormwater harvesting from each LGA were asked to evaluate the stormwater harvesting potential of BMPs within their jurisdiction. They estimated the expected irrigation demand required by open spaces near each BMP, and the average annual potential capacity to supply the demand. The estimates were based on procedures specific to each LGA, and reflect the stormwater harvesting objective performance values accepted by decision-makers.

Urban Vegetation and Amenity Improvement

The urban vegetation and amenity improvement indicator depends on stakeholder interests, which may include maximizing vegetation and tree coverage and quality of recreation spaces. Each project should be appraised and evaluated (scored) by vegetation experts. The cumulative urban vegetation improvement objective function is:

$$\text{MAXIMIZE: } f_{green} = \sum_{i=1}^{n} \text{Green}_i$$

Equation (D-7)

where $Green_i$ [integer] is a score, determined by expert assessment, attributed to the i^{th} project in a portfolio.

The 'green' score' of individual projects (which is a weighted score of several indicators, and was developed by the authors and agreed to be used as an optimisation objective by consultants), use scores assigned by experts (see section 3.3) from each LGA interviewed in a workshop session by consultants. The experts were asked to answer the following questions about the BMP projects within their jurisdiction: Answer 'Yes' 'No' or 'Maybe' to the following questions: 1) "will native vegetation increase at the site?", 2) "will tree cover increase at the site?", and, 3) "will the quality of recreation spaces in the area increase?". The total catchment 'green' score objective function was:$\text{Green}_i = \sum_{j=1}^{3} \text{Score}_j$

$$\text{Score}_j = \begin{cases} 3 & \text{if answer is 'Yes'} \\ 2 & \text{if answer is 'Maybe'} \\ 1 & \text{if answer is 'No'} \end{cases}$$

Equation (D-8)

where $Green_i$ is the sum of scores for each project, and $Score_j$ is the number of points assigned to the answer to the j^{th} question. Since there were three questions, each project could achieve a maximum of 9 green points, and each portfolio a theoretical maximum of 180 (20 × 9) total green points.

APPENDIX E

Paper 3 *MUSIC* model background

The Model for Urban Stormwater Improvement Conceptualizion (*MUSIC* version 6.1; eWater (2009)) was used to evaluate pollutant reduction performance. *MUSIC* is an integrated stormwater model that evaluates rainfall/runoff and pollutant generation and transport, hydraulic and pollutant removal performance of BMPs, and water balance (Bach, Rauch et al. 2014). *MUSIC* is used as a stormwater management design tool in Australia and the UK and has been used in watershed-scale stormwater management system reliability analysis (Browne, Breen et al. 2012) and WSUD optimization (Montaseri, Hesami Afshar et al. 2015). *MUSIC* algorithms simulate runoff based on models developed by Chiew and McMahon (1999) and urban pollutant load relationships based on analysis by Duncan (1999).