# Short-term operational planning of water grids

**by**

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Doctor of Philosophy

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# Abstract

Water grids are a diverse and interconnected water supply systems that are emerging in response to the pressures of climate variability, climate change, and population growth. Water grid operation is guided by operating rules, which aim to manage supply and demand to meet multiple management criteria such as maximising water security, minimising operational cost, and minimising energy use. However, the diversity and interconnectedness of these water grids increases the number of possible configurations of the operating rules, and combined with uncertainty in forecast conditions, makes find optimal operating rules more challenging. Further, trade-offs between the criteria mean that multiple sets of operating rules can be considered optimal. Thus, this thesis proposes and demonstrates a framework of methods to meet these challenges and identify a set of optimal operating rules to support short-term – 1 to 5 year – operational planning of water grids.

This framework centres around multi-objective simulation-optimisation of the water grid to find a set of operating options that are Pareto-optimal for multiple management objectives and for forecast conditions over the short-term planning period. Each of these operating options comprises a set of operating rules for major grid infrastructure. However, this Pareto-optimal set is large and complex, and characterised by trade-offs between objectives; it is difficult to select a single option for implementation without applying preferences on the objectives or assessing performance of options against additional criteria. To this end, a combination of cluster, visual, and post-optimisation analysis is used firstly to shortlist a set of operating options from the Pareto-optimal set. Then, multi-criteria analysis is used to assess and rank the performance of the shortlisted operating options against the full set of management criteria and to choose an operating option to form the basis of an operational plan.

The operating rules resulting from multi-objective optimisation will be optimal for the inflows that are input to the simulation-optimisation model. Optimising to forecast streamflow conditions allows the operating rules to be tailored to expected inflows for the planning period. Incorporating the uncertainty in these forecasts also allows operating rules to be robust to a range of possible inflows.

This study also demonstrates how forecast streamflow information, with uncertainty, can be used within the framework to improve objective performance of the operating rules.

This framework is demonstrated for a case study based on the South East Queensland Water Grid. This case study identifies a set of operating rules that is both optimal for the management objectives and performs well across multiple management criteria and inflow scenarios for the planning period.

# Student declaration

“I, Stephanie Camille Ashbolt, declare that the PhD thesis by Publication entitled 'Short-term operational planning of water grids' is no more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work”.

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# Details of included papers

| Chapter number | Paper title | Publication Status | Year | Vol. | Issue | Pages | Publication Title | Impact Factor | ERA Rank (2010) | Scimago Rank/ H Index |
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| 1 | Towards a framework for optimal operation of water grids | Published | 2011 | N/A | N/A | 1961-1968 | 34th IAHR World Congress (10th Hydraulics Conference, 33rd Hydrology & Water Resources Symposium) | N/A | B | N/A |
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| 4 | Using multiobjective optimization to find optimal operating rules for short-term planning of water grids | Published | 2016 | 142 | 10 | 0401 6033 | Journal of Water Resources Planning and Management | 2.676 | A* | Q1/75 |

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# Chapter 1: Introduction

## 1.1 The challenges of water grid management

The water grid is a highly complex and interconnected water supply system that is emerging as a response to the increasing pressures of drought, climate variability, climate change, and population growth. These water grids comprise a diversity of water sources that are connected to demands across catchments via multiple supply paths. Typically, water grid operation is guided by operating rules, which need to satisfy multiple objectives or criteria such as maximising water security, minimising operational cost, minimising energy use, and minimising flood risk; whilst taking into account forecast inflows and demands over the next 1-5 years. The many supply-demand possibilities, combined with the trade-offs between multiple objectives and uncertainty in forecast inflows and demands, makes determining optimal operating rules difficult. Therefore decision support tools are needed to assist the decision-maker in identifying optimal operating rules.

This section contains the following conference paper describing the water grid and its benefits, and surveys two examples of water grids in Australia – the South East Queensland and Victorian Water Grids – to identify the key challenges for water grid management. It concludes by suggesting a decision support framework to meet these key challenges. It also outlines several research questions for this decision support framework, which are used to establish the research aim and research questions in Section 1.2.

> Ashbolt, S. C., Maheepala, S., and Perera, B.J.C., 2011, 'Towards a framework for optimal operation of water grids', *34th IAHR World Congress – Balance and Uncertainty, 10th Hydraulics Conference, 33rd Hydrology & Water Resources Symposium,* Engineers Australia, Brisbane, Australia.

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# Towards a framework for optimal operation of water grids

S. C. Ashbolt, S. Maheepala and B.J. C. Perera

**Abstract:** The concept of a water grid is emerging in the Australian water industry as a potential solution to address water scarcity in urban areas. A water grid comprises a network of pipelines that interconnect bulk water sources across supply systems to allow water from areas of surplus to be moved to areas that face a shortfall, managing risk at a regional level beyond the catchment. The operation of water grids raises new challenges, such as:

- optimising movement of water across a complex network to meet multiple objectives such as resource and energy efficiency, operational cost and environmental flows;
- incorporating multiple sources of uncertainty; and
- implementing water trading and markets.

This paper reviews such challenges of water grid management and outlines a framework to further investigate some of the research questions.

**Keywords:** water grid, urban water management, operational planning, systems modelling

## 1. Introduction

Water grids are becoming a critical component of strategies to meet present and future water needs of urban areas. A water grid consists of a network or ‘grid’ of pipes and open channels that connects water sources to water demands in a region, and may comprise traditional sources such as surface and groundwater storages, as well as alternative sources such as desalination, stormwater and recycled water. Examples of water grids in Australia include those in southeast Queensland and Victoria.

Water grids may arise due to a need to increase water supply in over-allocated catchments by extending supplies beyond the catchment boundaries. This consolidates resource and risk management at a regional level and facilitates water markets and trading. Whilst water security might be the initial objective of implementing a grid, management may involve additional objectives such as minimising cost and energy usage, managing water quality, and optimising environmental flows. The implementation of a grid introduces challenges for water resource managers in operating a network with the increased diversity of sources and pathways for supply. Existing water resources studies have not addressed these challenges in terms of water grid operations.

This paper outlines part of an ongoing research project on management and operation of water grids. This paper describes details and outcomes of this project thus far, including what constitutes a water grid; the operation of such grids; the key challenges faced in operation of these grids; and a preliminary framework to investigate some of the research questions these challenges raise.

## 2. What is a Water Grid?

A water grid is a network of one-way and reversible pipelines that connect water sources to customers throughout a region, not limiting supply to within a river basin. Water grids operate at the bulk water supply level and are here defined as involving multiple supply paths of a given source to its connected demands. They differ from a more linear branched network, which typically conforms to river basin boundaries. Whilst no standard definition exists in the literature, some examples of what the authors consider as grids are shown in Figure 1.

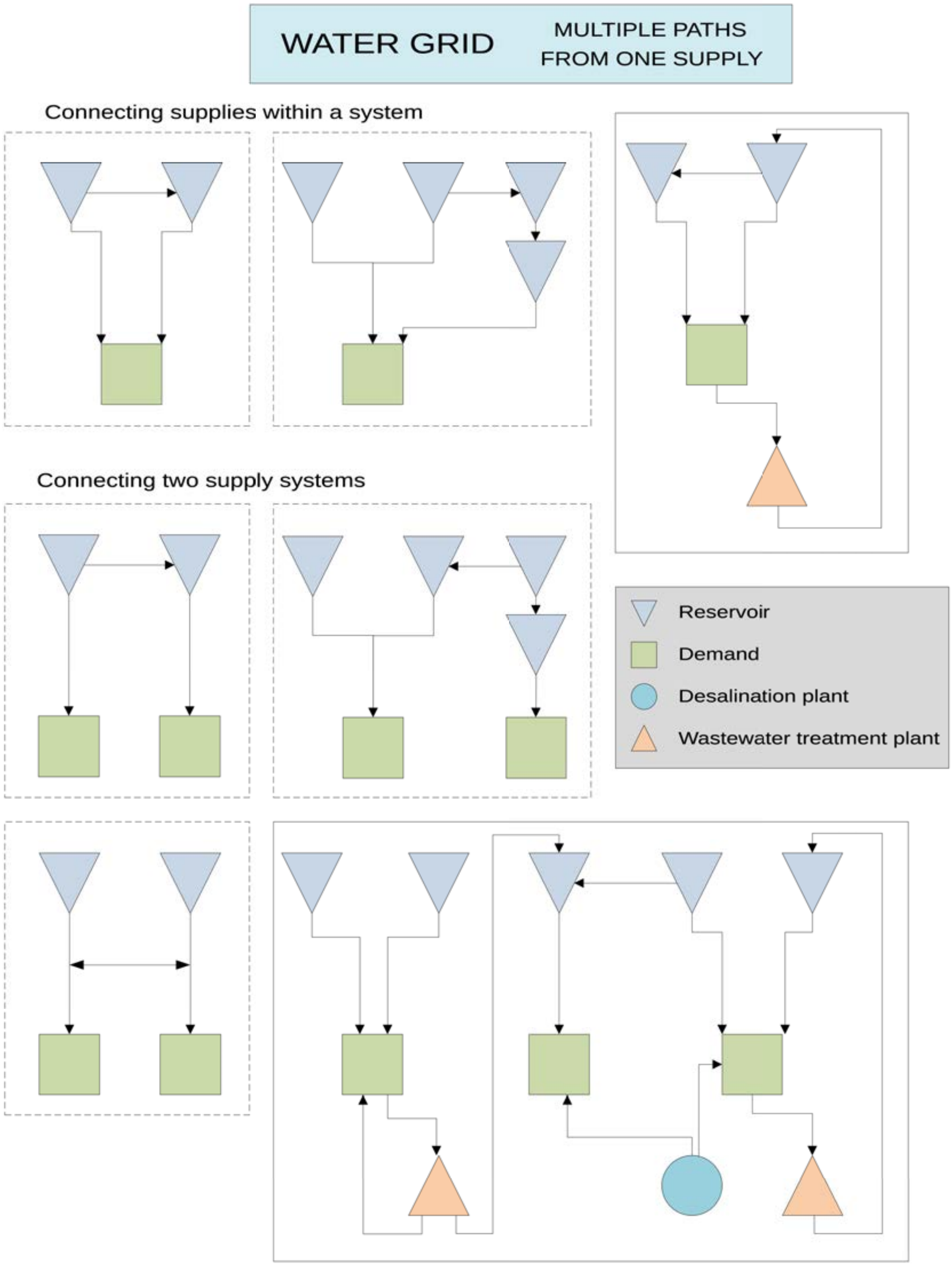


**Figure 1: Examples of water grids**

It should be noted that the term ‘grid’ in regard to water supply is a relatively new concept and is not prevalent in the literature beyond Australia and is more commonly used to refer to electricity grids. Nevertheless many supply systems currently in operation could be considered grids. Moreover, whilst this research focuses on outcomes relevant to water grids, the outcome may be relevant to other supply systems not considered as grids.

Benefits of moving to a water grid may include:

- Increased supply system yield through access to greater storage capacity and demand
- Increased water availability without the construction of new sources or storages
- Ability to manage supply risks at a regional scale, rather than source-by-source
- Increased capacity to address local management issues
- Reduced reliance on local climatic conditions, by reducing the impact of spatial variability in surface water flows
- Risk-spreading, or the ability to transfer problems in one area to a benefit for other areas, e.g. minimising spills from a storage in a flood-prone area through transfers to drought-affected storages
- Increased flexibility in options to meet water quality and quantity requirements for each demand and environmental need in a ‘fit-for-purpose’ manner
- Ability to mix supply sources to improve water quality
- Increased cost efficiency or access to low-cost sources
- Increased capacity for water markets and trade

## 2.1. Examples of water grids

The following sections briefly outline two examples of water grids in Australia in terms of the drivers for developing a water grid; key features of these grids; governance arrangements; operations; and key challenges faced.

### *2.1.1. South East Queensland Water Grid*

The South East Queensland Water Grid is designed to provide water security to the south east region of the state of Queensland, in the face of drought, future climate changes, and population growth. The grid network includes the interconnection of surface water storages, groundwater sources, a wastewater recycling scheme, and desalination plants which by implementation in 2008 resulted in a 14% increase in the system yield (Queensland Water Commission, 2009). Construction of the grid involved restructuring institutions and statutes to better manage the grid, which also includes an emerging water market.

When first conceived, the main objective of the SEQ Queensland Water Grid was to provide water supply security beyond the individual surface water storage schemes: during the ‘Millennium’ drought (starting around year 2000), the three major supply reservoirs declined from 60% of combined capacity in April 2004 to 17% in August 2007 (Queensland Water Commission, 2009). Since then, significant rainfall events increased the volume held in the surface water storages such that they reached 100% capacity in October 2010 (Seqwater, 2010). Thus, new objectives for grid management have arisen.

Key challenges now centre around how to optimise the operation of the grid, given multiple objectives and constraints, and include (Dennien et al., 2009); (Dennien, 2010):

- Optimising operations for multiple objectives such as energy consumption, operational cost and minimising reservoir spills
- Identifying, preferencing and quantifying objectives for grid management and operations
- Incorporating climate uncertainty/variability and change
- Satisfying contractual obligations that may conflict with other objectives: minimum levels of desalinated or recycled water must be maintained even if resource, energy and cost outcomes are reduced by doing so
- Utilising off-peak operations to minimise energy consumption
- Emergency management of the complex network for events such as flooding, equipment breakdown

- Managing differing water quality due to blending of a number of sources
- Maintaining level of service and compliance with market rules
- Availability and validation of data on the water grid network
- Involving all service providers and stakeholders: prior to grid implementation, a government restructuring act reformed the water supply industry, leading to establishment of new statutory authorities, roles and responsibilities
- Adapting the decision support framework to meet these challenges

Decision making in water grid operations is influenced by operating rules and objectives in the System Operation Plan (Queensland Water Commission, 2010) under the market rules (Queensland Government, 2008). Decisions are supported by simulation of water supply and demand using Wathnet (Kuczera, 1997); demand forecasting using the End Use Model (Water Services Association of Australia, 2006); and a spreadsheet based model for economic analysis. The models use 5 year supply and demand forecasts; data are updated monthly. Monthly instructions are issued.

### *2.1.2. Victorian Water Grid*

The Victorian Water Grid involves the construction of pipelines that connect regional water supply systems across the state of Victoria. The augmentation of water supply systems in Victoria has been driven by recent low level rainfall and record low inflows, which dropped to 28% of long-term average inflows in 2006 (Department of Sustainability and Environment, 2008), as well as in response to predicted climate change. These rainfall patterns are evidently a significant departure from those for which the original supply system was designed. An expanded water grid allows water to be more readily traded between regions in Victoria to increase security of supply by reducing the impact of localised droughts and maximising available storage.

The Victorian Government plans large-scale infrastructure development and controls use of water in the grid. The management and operation of regional catchments, water supply, and distribution systems is the responsibility of the regional and metropolitan water authorities (Department of Sustainability and Environment, 2010). The Victorian grid is currently not operated as a grid by a single entity.

Water resources are currently managed for supply security. However management objectives may change in the future depending on the climatic conditions, i.e. they may switch from simply providing a level of service for customers, to minimising financial cost or energy usage. Decision making for the Melbourne region is supported by the REALM water supply monthly model (Perera et al., 2005) for assessing options in planning and forecasting supply and demand. The REALM model uses rules-based linear programming to determine water allocations on each timestep, and works alongside an optimisation tool OPTIMISR (Kularathna, 2009) currently under development to meet optimisation needs for the entire forecast period.

Key challenges for Victorian grid management include (Preston et al., 2010); (White, 2010):

- Optimisation over various spatial scales
- Including multiple objectives (e.g. cost) in decisionmaking that may change dependent on climatic conditions
- Integrating decision support models into water supply models
- Adapting existing models and knowledge to address the new challenges
- Applying the regulatory framework and objectives in changing conditions
- Optimising institutional arrangements
- Integrating and managing additional water sources and customers into the grid
- Linking operational and investment planning
- Overcoming political and institutional barriers to water trading
- Reflecting the true value of water in allocation and pricing of supply

# 3. Key Challenges in Water Grid Management

Management of water grids entails the short-term planning and operation of water sources and allocation of water to meet demands, whilst meeting other rules or objectives as determined by policy or legislation. Grid management is generally concerned with operation of a system once in place, rather than longer term planning for system design and augmentation. Grid management generally involves monthly decisions for operation of bulk pipelines, sources and storages, planning ahead for periods of 1 to 5 years.

Objectives for water grid management may be guided by levels-of-service promised to customers and organisational and governmental policy and regulations. Objectives may include:

- Optimising water use efficiency, including frequency, duration, and severity of restrictions
- Minimising energy use and greenhouse gas emissions
- Providing suitable water quality for each demand or matching source quality to end use
- Minimising cost of supply
- Meeting environmental water quantity and quality needs in water ways and receiving waters

Many of the issues in water grids arise from the challenge of integrating an increasingly complex and heterogeneous new network, with multiple flow paths and directions. Newly linked subsystems may have differing management rules and objectives, established separately without optimisation over the entire network. Within this network, multiple sources of uncertainty also need to be considered, including climatic variability and change and infrastructure reliability. It also requires mixing of multiple sources, including the water quality implications.

The following sections briefly outline the key challenges and associated issues identified in water grid operations. These are organised around the key themes emerging from the examples of water grids investigated in Section 2.1.

## 3.1. Optimal Operation

Optimal operation involves maximising the efficiency of water resource use in terms of the desired or required management objectives and targets. The complexity of this task is affected by the nature of the system and the number of objectives to be considered. Management questions include:

- How do we optimise operations for multiple objectives, such as maintaining environmental flows, and minimising cost and energy use? This involves:
  - Managing conflicting demands
  - Addressing conflicts between the multiple management goals or objectives of a complex network
  - Incorporating or modifying existing operating rules, constraints and service delivery requirements
  - Accounting for changes in source priorities and rules under different climatic conditions
- How do we move from a primarily rules-based to an optimised network?
- How do we link between outcomes of different decision timescales in systems modelling and management (e.g. operations and planning)?
- How do we manage or address shortcomings in the heterogeneity and complexity of information to be collected, maintained and assessed?
- How do we determine objectives and their relative importance?
- How do we arrive at a suitable value for water?

Optimal operation requires a system modelling or decision support tool capable of optimising the grid network to multiple objectives, whilst incorporating condition-based operating rules and constraints. Outputs should be able to link smoothly to other system models, or the tool should be able to incorporate different timescales or decision/management outcomes. Flexibility in input data and modelling of system features would be desirable in order to address the heterogeneity and complexity of the system. If multiple supply systems or institutions have been recently been merged, decision-making practices may vary system-by-system and original models may need to be replicated based on data availability or for calibration purposes.

The experience in water resource optimisation has primarily focused on optimising supply to meet required demands or to maximise economic objectives, and for long-term planning or network design. Optimisation for an operational timeframe, and incorporating level of service and energy efficiency goals would be a novel element in a multi-objective optimisation framework. The applicability of current methodology used for water planning timescales and for energy grid operations should be investigated within the water grid operations framework.

The choice of objectives is also an important aspect in the optimisation of the systems. Methods must consider the complexity in selection of objectives, their quantification and relative importance (weighting).

Techniques that may contribute to the required solutions include multi-objective optimisation techniques, such as:

- Weighted summation techniques that aggregrate multiple objectives to a single objective
- Multi-objective methods such as evolutionary or genetic algorithms that produce two or three dimensional Pareto fronts showing trade-offs between objectives
- Simulated annealing
- Linear programming
- Goal programming
- Hybrid methods such as a combination simulated annealing and genetic algorithms

Multi-criteria analysis is another technique which has been widely used in water resources to compare options in terms of their performance against multiple management objectives.

The most common software tools for urban water allocation in Australia are REALM (Perera et al., 2005) and Wathnet (Kuczera, 1995). Source Rivers (eWater CRC, 2010) is also an emerging tool that serves a similar purpose. Broadly, these are simulation models that use linear programming techniques that operate on each timestep to optimise one objective, but also incorporate constraints such as environmental flows. Extension of these would be needed to improve multi-objective optimisation capabilities.

## 3.2. Incorporating uncertainty

Given the increased complexity and diversity in the components that comprise a water grid and their interactions, there is likelihood of increase in the sources of uncertainty. This uncertainty is a key component of acknowledging risk in decisionmaking and may significantly affect the outcome. The combination of multiple sources of uncertainty may be greater than individual sources alone. Therefore a key question is how, within a water grid management decisionmaking process, do we incorporate or acknowledge uncertainty in demand; climate and streamflow, infrastructure reliability, and management objectives?

We need the capability to incorporate sources of uncertainty into decisionmaking tools. This should be well integrated either within or in addition to multi-objective optimisation as it will likely have a significant impact on initial conditions and behaviour of a system. Understanding of the degree of uncertainty involved in a system will inform confidence in the modelling outcomes. Uncertainty will pertain not only to system components, but also the model algorithms themselves.

Whilst incorporation of uncertainty in infrastructure and objectives would be a new area, climate uncertainty has been addressed in water allocation planning models using various methodologies, such as: stochastic timeseries of variables of distribution of parameters, stochastic fuzzy programming, interval programming, placing bounds of certainty on solutions, and Monte-Carlo simulation. A significant consideration for these methods is the associated intensity in use of computer resources or run time.

## 3.3. Market operation and the institutional space

A water grid may involve water trading, where participants are given licences and entitlements to transfer and pricing is set centrally or a water market, where pricing of water is set by participants in the system. A system may also be in transition between these states, where flexible markets and price structures are yet to be determined, and trading is still controlled by a central body. Each of these operation modes will involve unique methodology and challenges for water allocation. Within or between these operational states, questions faced for water grid managers include:

- How do we incorporate market operations into water system modelling?
- What is the appropriate pricing to reflect water value or source cost?
- How do we remove institutional or political barriers to optimised operations or water trading?

In addition, the institutional arrangements need to allow for efficient operation of water grids and their markets. This raises further questions such as:

- How do we coordinate or consolidate management of newly linked supply systems and their respective management authorities?
- How do we reconcile multiple management rules and objectives?
- How do we incorporate ‘inherent knowledge’ in systems and modelling?

To date, decisions on the value of water and market structure have been heavily influenced by local policy and infrastructure. Guidance may be needed on an approach to institutional restructuring and valuing of water which will best enable efficient operation of water grids. In this area, there may be something to learn from electricity grid markets, which have some aspects in common with water grid structures and have been in operation in Australia for some time. Direction on these issues could also be assisted through improved integration in system simulation and optimisation.

# 4. Conclusions and further research

A review of the challenges faced in water grid management has led to the identification of a number of research priorities. These include optimal operation, accounting for uncertainty, market operation and institutional arrangements. In light of these challenges, the ongoing research will focus around a proposed modelling and decision framework to support water grid operations, shown in Figure 2.

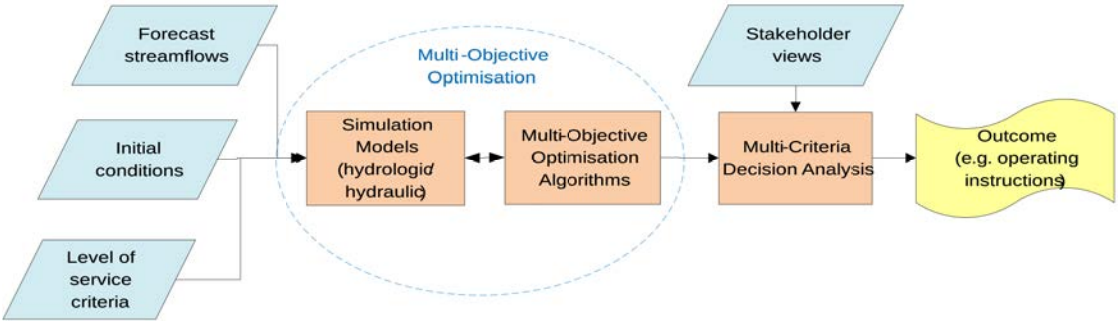


**Figure 2: A water grid management decision framework**

It is proposed that this framework will aid in the identification and linking of tools and processes that may address the needs of water grid managers. In particular the research will look to answer the following questions:

- Is this a suitable framework? How does it fit with the current frameworks used by grid managers?
- What is the required outcome of the framework?
- What is the timeframe (frequency and period) of this process?
- What is/are the most suitable method/s for each component of the framework to achieve this outcome? How well do current models perform in this space?
- How do we ensure compatibility between components or models?

- What are the sources of uncertainty and risk and how can they be addressed?
- Can we use this framework to reflect the true value of water respective to stakeholders in decision making? How does the relationship between cost and value of water affect the determination of operating rules and objectives?
- What are the optimisation objectives, and how are they decided upon? What are their performance measures? How is uncertainty in the target value of objectives handled?
- How do we enable simulation models to produce outcomes required to quantify performance of the objectives?
- How do we reconcile multiple or conflicting rules and objectives?
- How do we incorporate inherent knowledge and complexity in data, systems and modelling?
- How do we allow for changes of policy based on initial conditions such as climate?
- How are stakeholders involved? What form of input is required, where, and how frequently? How are outputs of the process presented to stakeholders?
- Will there be feedback between the outcomes of different components of the framework? How and when should this occur?
- How do we consider water markets and water trading in decisionmaking?

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## 1.2 Research aim and research questions

This research addresses two of the key challenges of water grid management identified in the paper in Section 1.1, namely:

- Identifying operating rules that are optimal for multiple objectives
- Incorporating uncertainty in streamflow into operational planning

To address these challenges, the paper in Section 1.1 proposed the development of a framework of modelling methods to assist optimal operation of water grids. Thus the research aim is to develop and demonstrate a modelling framework to identify optimal operating rules for water grids, which incorporates uncertainty in streamflow inputs.

The paper in Section 1.1 also posed a number of research questions, relating to the research aim of developing and demonstrating a framework for water grid management. These can be summarised as:

1. What is the desired outcome of this framework?
2. What methods and tools can be used together to achieve the desired outcome of the framework?
3. Does this framework incorporate some of the key requirements identified in Section 1.1, such as:
    - uncertainty in input data such as streamflow;
    - multiple and conflicting management objectives and criteria, performance measures, and preferences on these objectives and criteria;
    - changes in these objectives and criteria;
    - changes in initial conditions and input data;
    - stakeholder values;
    - feedback between framework components and planning

timeframes; and

- existing data and models?

4. Does this framework actually provide the required outcome when implemented for a case study?

This study aims to answer these research questions by: identifying the required outcome of a modelling framework for short-term planning; proposing a framework of methods and tools, based on literature review, that can meet the required outcome and the key requirements listed in Research Question 3; and demonstrating the application of this modelling framework to a case study. For brevity, the modelling framework is hereafter referred to as the 'framework'.

Section 1.1 identified additional research questions regarding how water markets, water trading and the value of water can be considered in short-term operational planning and the modelling framework. These research questions are not explicitly addressed in this study but are recommended for future investigation.

## 1.3 Short-term operational planning

The paper in Section 1.1 identified that key challenges for water grid management lie in developing short-term operational plans or operating rules. Short-term planning differs from long-term planning in aim and scope, required outcome and modelling and data needs. Therefore this study focuses on short-term planning.

Long-term planning typically considers operating rules and supply measures to ensure a balance between supply and demand, over a long forecast horizon of around 50 years. It includes the development of urban water or regional water strategies and may involve an assessment of system yield. System yield describes the maximum average demand the system can supply, subject to long-term climate variability or climate change, without breaching level of service criteria. The long-term planning process identifies required supply augmentations – e.g. new reservoirs or alternative water sources such as recycled water, and desalination – to increase system yield to match long-term demand forecasts with an acceptable reliability of supply.

Short-term planning involves identifying operating rules to ensure security of supply over a shorter period of 6 months to 5 years, usually without augmentations. The aim is to pro-actively manage variability in supply over the short-term, based on forward outlooks of streamflow and demand. Efficient short-term plans may enable delays to augmentation proposed in longer-term planning. Short-term planning includes development of annual operating plans, drought response plans, permanent/temporary water saving plans, and water conservation plans. Operating rules for short-term planning are generally consistent with the long term operating rules, but can deviate from them with the intention of addressing short-term issues with security of supply. This deviations could happen because current conditions and forward outlooks are not representative of the long-term average conditions used in the long-term planning studies.

## 1.4 Research significance

The significance of each component of this research is outlined in each paper included in this thesis. Overall, there exists limited literature and demonstrated practice of using the decision support tools proposed for the framework in the short-term operational planning space, in a combined manner, and beyond one- or two-reservoir systems. The key novel aspects of this study are:

- Understanding and addressing the challenges of water grid management
- Using multi-objective optimisation for operational planning of complex multi-reservoir systems
- Providing a framework for incorporating multi-objective optimisation into the planning process, and demonstrating each step from problem definition to a final set of operating rules
- Demonstrating the use of streamflow forecasts in multi-objective optimisation of short-term operating rules for water grids
- Providing a use-case for streamflow forecasts provided by the Bureau of

Meteorology in Australia

- Providing a use-case of the emerging Source software tool, particularly for multi-objective optimisation

## 1.5 Outline of the thesis

This thesis contains eight chapters, outlined in Figure 1.1. The second chapter reviews the literature to establish a framework of methods that can meet the needs of operational planning of water grids. This addresses the first three research questions outlined in Section 1.2, by identifying the required outcomes of the framework, the methods and tools that can be used to achieve these outcomes, and whether the framework incorporates the key requirements identified in Section 1.1. The third chapter introduces a case study of short-term operational planning for a water grid based on the South East Queensland Water Grid in Australia. Chapters four to seven examine the fourth research question of whether or not each of the framework components and methods can provide the required outcomes, by demonstrating their application to the case study. The fourth chapter demonstrates the application of the first part of the framework, multi-objective simulation-optimisation, to the case study. This results in a large Pareto set of operating options, each of which represents a set of operating rules that are optimal for three management objectives. The fifth chapter demonstrates the application of the second part of the framework to interpret the case-study Pareto set, by examining the trade-offs between objectives and selecting a shortlist of operating options. The sixth chapter demonstrates the third and final part of the framework, multi-criteria analysis, by assessing the performance of the case-study shortlist of operating options against the full set of management criteria and a range of inflow conditions. The seventh chapter investigates how streamflow forecast scenarios can be used in multi-objective optimisation to improve objective performance and robustness of the operating rules. The final chapter provides a summary and conclusions of this work, assessing the overall ability of the framework to answer the research questions, and providing recommendations for further research.

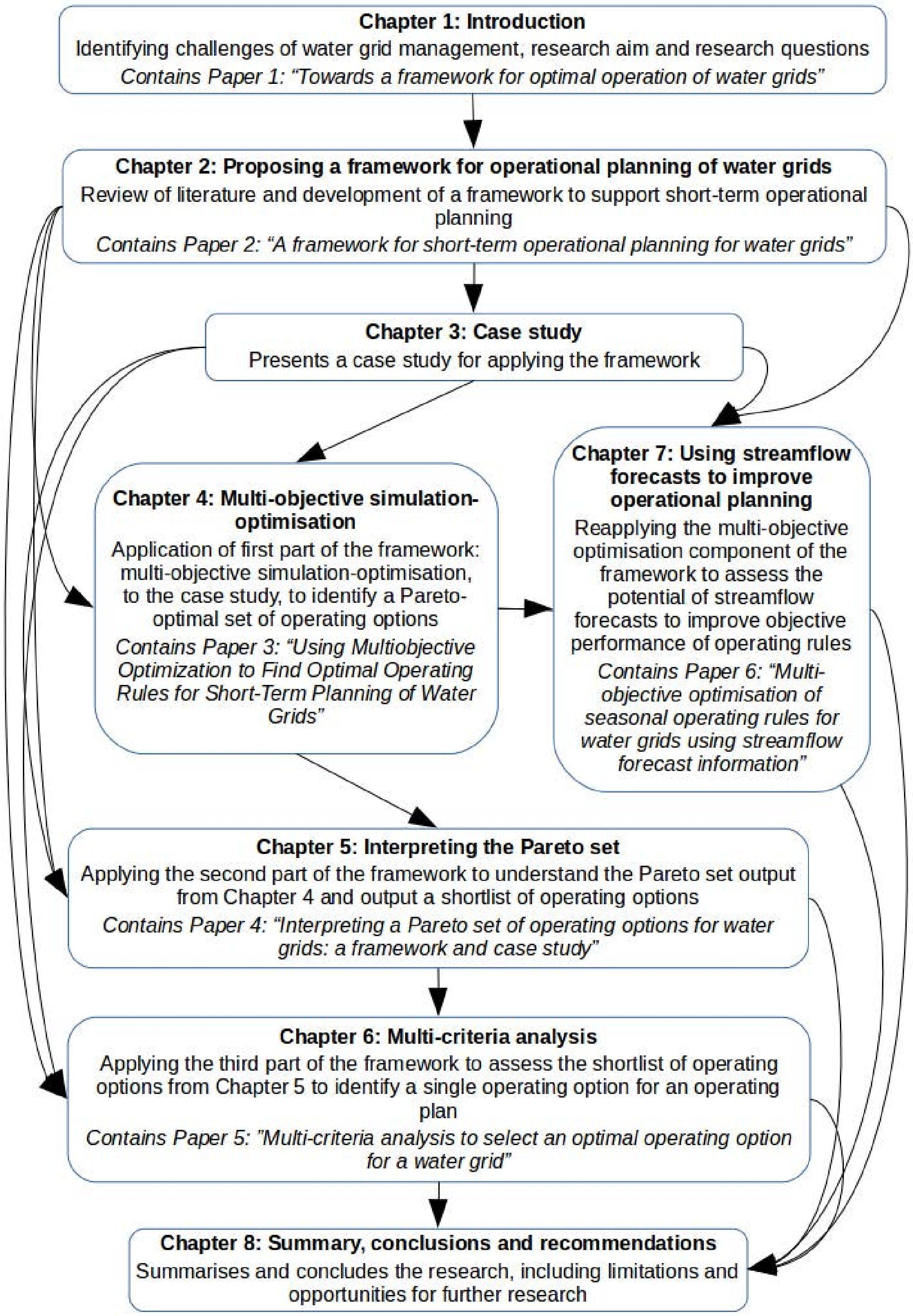


**Figure 1.1: Outline of thesis**

# Chapter 2: Proposing a framework for short-term operational planning of water grids

This chapter reviews the literature and water grid practice, to meet the research aim, outlined in Section 1.2, of developing a framework for short-term operational planning for water grids. It also considers the first three research questions outlined in Section 1.2.

Multi-objective optimisation forms the core of this framework and study. Multi-objective optimisation allows for a large number of optimal operating possibilities to be identified from a complex web of possible operating rule configurations, with a range in objective performance and trade-offs. This differs from scenario or 'what-if' analysis, which considers a more limited set of operating rule possibilities of interest to the decision-maker or stakeholder, that may or may not be optimal in terms of their objectives. However, if desired, a decision-maker may add 'what-if' scenarios of particular interest to be considered in the multi-criteria analysis step of the framework.

Although the focus of this framework and study is on meeting the challenges of short-term operational planning (1-5 years), many of the tools and methods identified for the framework are also used in longer-term planning. Thus the framework could be potentially be applied to longer-term planning. However, the problem definition and input data as discussed in this chapter and demonstrated in later chapters are specific to the short-term operational planning space and therefore provide unique challenges.

This chapter contains the following journal paper, which addresses the above three research questions:

> Ashbolt, S. C., Maheepala, S., and Perera, B.J.C., 2014, 'A framework for short-term operational planning for water grids', *Water Resources Management,* 28(8), pp. 2367-2380, Springer Netherlands.

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## DECLARATION OF CO-AUTHORSHIP AND CO-CONTRIBUTION: PAPERS INCORPORATED IN THESIS BY PUBLICATION

*This declaration is to be completed for each conjointly authored publication and placed at the beginning of the thesis chapter in which the publication appears.*

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### 2. CANDIDATE DECLARATION

I declare that the publication above meets the requirements to be included in the thesis as outlined in the HDR Policy and related Procedures – policy.vu.edu.au.

| [redacted] | 04/07/2016 |
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| **Signature** | **Date** |

### 3. CO-AUTHOR(S) DECLARATION

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| Name(s) of Co-Author(s) | Contribution (%) | Nature of Contribution | Signature | Date |
|---|---|---|---|---|
| Stephanie Ashbolt | 85 | Research, analysis, writing | [redacted] | 4/7/16 |
| Shiroma Maheepala | 7.5 | Feedback and discussion on the research and writing | | 4/7/16 |
| Chris Perera | 7.5 | Feedback and discussion on the research and writing | | 6/7/16 |
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# A Framework for Short-term Operational Planning for Water Grids

S. Ashbolt & S. Maheepala & B. J. C. Perera

**Abstract:** Water grids are emerging as a response to water scarcity in many urban areas. These grids comprise not only traditional surface and groundwater supplies, but also alternative, climate-independent water sources such as desalination and wastewater recycling, as well as one and two-way pipelines connecting surface-water supplies in different regions. The complexity and heterogeneity of these water supply networks brings new challenges to water management. Water managers need to determine strategies to operate the system in terms of multiple objectives, subject to uncertainty and boundary conditions relating to climate, demand and infrastructure. This paper outlines a framework of methodologies for developing optimal operating plans for short-term planning for water grids, in terms of the objectives of interest.

**Keywords:** Multi-objective optimisation; Operational planning; Optimisation; Short-term planning; Urban water management; Water supply

## 1. Introduction

Water supplies in many urban areas have come under strain due to the twin pressures of population growth and climate variability. Furthermore, projections indicate a decrease in water availability in many regions due to climate change (Bates et al. 2008). The resulting water scarcity brings both water supply insecurity and negative impacts on freshwater ecosystems (Martin-Carrasco et al. 2013; Rijsberman 2006).

The standard, or ‘first wave’ approach to address water scarcity is to augment supply through construction of a new dam or groundwater wells. Where these supplies have been exhausted or are no longer acceptable in environmental or social terms (Turton and Meissner 2002), a ‘second wave’ approach uses demand management measures such as water efficient devices, volumetric water tariffs, education, and water restrictions. Whilst these measures are important, they have a limit based on basic human needs, at which point they are no longer sufficient to address water scarcity. Behavioural changes may also weaken over the long-term (Fielding et al. 2013). Hence a ‘third wave’ approach involves increasing the efficiency of use of existing water sources through diversification and interconnection of supply to establish ‘water grids’.

The water grid concept was first proposed by Reynolds (1978), as a system with similarities to the large-scale electricity networks, such as diversity of supply and inter- regional transfers. Thus the water grid increases water supply yield, security and resilience on two fronts: firstly by connecting existing water supplies and demands into a network or ‘grid’; and secondly by constructing alternative climate-independent water sources, such as desalination and wastewater recycling. Two-way pipelines allow water storage to be balanced across catchments, and demands to be supplied via multiple paths and sources. These connections also insulate against consequences of failure of individual infrastructure. The diversity of options to meet each demand allows for the consideration of a number of factors beyond water security, such as cost, energy use, and water quality. The water grid concept and application has seen recent growth in response to the aforementioned population and climate change pressures. Examples include those in Australia in Victoria and South East Queensland (Department of Sustainability and Environment 2010; Queensland Water Commission 2010) California (California Department of Water Resources 2010) and under proposal in India (International Water Management Institute 2010).

As these heterogeneous water grids are more complex and diverse than a traditional catchment-based system, they bring new challenges to water supply management. Operating rules developed over time for traditional systems, may not perform as well for new water grids. The larger number of possible supply–demand and supply path configurations multiply to give an even larger set of possible decisions, from which a decision set that provides an optimal outcome for the entire grid may be difficult to identify. Selection of an optimal outcome is driven by the management objectives, but the heterogeneity of the grid means that each infrastructure option will perform differently in terms of these objectives. Furthermore, when multiple objectives exist, there is likely no single optimal outcome and trade-offs must occur between them. For example, desalinated water may have significantly higher cost than freshwater supply, but higher reliability. A decision-maker (manager of the water grid) must 'trade-off' the higher cost of reliable desalinated water against using cheaper surface water in dams that is needed for water security into the future. The impacts of decisions on objective performance will also vary over time, depending on expected surface water inflow and storage levels, as well as operational constraints or requirements such as minimum flows, contracts for manufactured water, and costs associated with turning infrastructure on and off. Furthermore, the objectives themselves may change, for example as reservoirs refill and there is risk of flooding, minimising spills from reservoirs may become an additional objective.

In summary, the trade-offs in objectives add another layer of complexity to water grid planning. Given the diversity of supplies and demands in a water grid, their interdependencies, as well as changing physical and policy conditions, finding decisions that provide the best outcomes for the grid as a whole may be very difficult. Thus, water grid managers require decision support tools to explore operating options, strategies or rules for managing supply systems to meet forecast demands under expected inflow and infrastructure conditions. These tools will need to help identify and assess potential management decisions in terms of multiple objectives, to support development of an operating plan.

## 2. Short-term operational planning for water grids

Short-term operational planning is defined here as short to medium term (1–5 year) planning of operation for existing infrastructure, updated on a regular basis (6–12 months), which meets criteria and rules set out in policy and longer-term planning. Examples of such operating plans can be seen for South East

Queensland Water Grid (seqwater 2013) and the Colorado River Basin (U.S. Department of the Interior Bureau of Reclamation 2012). Short-term planning allows balancing of small capacity storages, but decisions made on these shorter timescales can also affect long-term planning by impacting water levels in multi-year capacity storages and reaching triggers for augmentation. It is the authors' view that operational planning of water grids is of similar importance to long-term planning of water grids because lack of clear and optimal strategies to operate water grids can result in inefficient usage of already built infrastructure and water resources. Efficient operation of the grid can also prove a complementary strategy to demand management and augmentation in addressing the pressures of water scarcity.

Efficient operation can be aided by optimisation, a technique that has been widely applied to water resources management (Nicklow et al. 2010; Rani and Moreira 2010; Singh 2012). There are several examples reported in the literature concerned with finding multi-objective optimal solutions for water supply networks. They include applications in long-term or strategic planning (Chang and Chang 2009; Hakimi-Asiabar et al. 2010; Mortazavi et al. 2012), system design (Babayan et al. 2005; Kapelan et al. 2005; di Pierro et al. 2009), and real- time operation of water supply (Ahmadi et al. 2014; Broad et al. 2010; Fallah-Mehdipour et al. 2012). On an operational planning timescale, single objective optimisation has been conducted for multiple reservoirs (Kularathna et al. 2011a), and multi-objective optimisation for a single reservoir (Kim 2008), irrigation network (Fernández García et al. 2013) and four-reservoir system (Kumphon 2013). As far as the authors are aware, there have been no published literature on the application of multi-objective optimisation for development of short-term operational plans for complex networks such as water grids, and that outline the additional steps required to implement and interpret optimisation tools in this context. Thus the objective of this paper is to identify tools and methods that can be used by the water grid manager to apply and support multi-objective optimisation. This forms a proposed framework for decision support in short-term operational planning of water grids.

# 3. A framework for short-term operational planning of water grids

The aim of the framework proposed here is to identify an operating plan for water grid infrastructure that is optimal in terms of multiple objectives. These objectives might relate to infrastructure operational cost, water security, environmental flows, energy use, greenhouse gas emissions, or water quality. Operational planning decisions are traditionally determined by rules for operating the system, for example reservoir levels that trigger use of alternative sources or operation of interbasin transfers. Thus the focus of the framework may be to determine an optimal set of rules. These operating rules will apply to the entire planning period (i.e. they should not change on each timestep) and will inform the operating plan.

The proposed framework is shown in Fig. 1, and discussed in detail in following sections. It centres around multi-objective optimisation, but a number of additional elements support the optimisation process. The implementation of the framework processes [1–7] occurs broadly in sequence of the numbers in the diagram, however many of these processes are iterative or interdependent. *Stakeholder engagement* [1] helps to identify *objectives and assessment criteria* of importance to operational planning, their priorities or importance (*criteria weights*), and the *performance measures* against which these are assessed. The *multi-objective optimisation* [2] algorithm is used to trial possible management decisions (*decision variables*), to find those that have the best outcomes in terms of the objectives, quantified as *objective functions* using information from the simulation model. There may be *bounds on decision variables* or *constraints* on objective functions that reduce the feasible decision space, e.g. budgetary constraints.

The *system simulation* [3] model determines the supply–demand behaviour or the system response to the decision variables and forecast conditions. The model will simulate at a minimum, water quantity, but may also include water quality, cost, and energy use, depending on the capability of the model and the objectives to be quantified. *Forecast inflows* [c], *demands* [b], and *infrastructure* *conditions* [a] and *additional operational data* [d] for the planning period are input to the simulation model to provide a basis for decision-making. The multi-objective optimisation process (simulation and optimisation) results in a number of sets of potential management decisions (decision variables) which are optimal in terms of all objectives. These can be plotted as a *Pareto front of decision sets*. If the Pareto front has a very large number of solutions, *clustering of results* [4] with similar characteristics may reduce the number of possible decision sets for further comparison.

Finally, in order to select a single decision set, *multi-criteria analysis* [5] is used to assess decision sets against a number of criteria, including those identified in the stakeholder engagement process as well as in *long-term planning* [e]. The simulation model and additional data may be used again at this point to calculate performance of each decision set against the criteria. The effect of uncertainty in streamflow or demand on criteria performance of potential decision sets can be assessed using *uncertainty analysis* [6] or by evaluating for multiple scenarios of demands/inflows. The outcome of multi-criteria analysis is an *optimal decision set* consisting of operating rules or decisions that form the basis of the *operational plan* [7]. The methods and requirements for each of the components are discussed in the following sections.

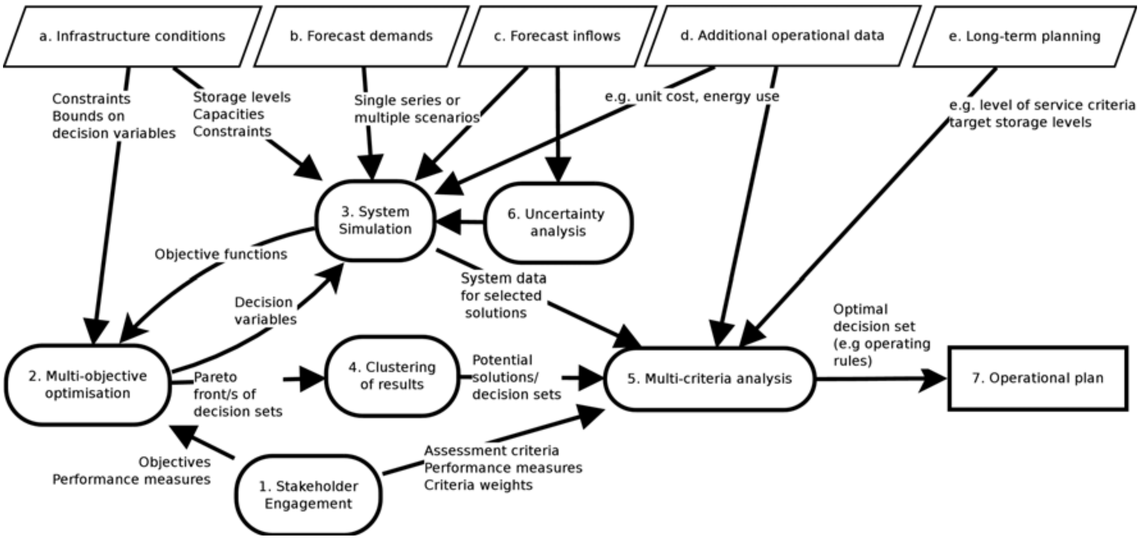


**Figure 1:** A framework for optimal short-term operational planning for water grids. Rounded rectangular boxes (numbered) indicate framework processes or elements, rhomboids (lettered) show the inputs, and inputs/outputs between processes are indicated on the arrows.

## 4. Inputs

The required inputs for the framework will depend on the objectives, criteria and the simulation model. This includes both the data type (e.g. streamflow), and the format (e.g. single or multiple/stochastic timeseries). For the simulation model, a minimum of forecast streamflow, forecast demand, and forecast/initial infrastructure conditions will be needed [Fig. 1c, b, a]. Additional data for calculating objective and criteria performance may include fixed and unit cost and energy use for each infrastructure element [Fig. 1d]. Long-term planning criteria and targets may also be considered for multi-criteria analysis [Fig. 1e].

Since operational planning considers the management of existing infrastructure, for a given set of objectives the initial and forecast conditions are the key variables altering the decision outcome. Operating decisions are optimal for the short-term *and* these conditions. This is in contrast to long-term or strategic planning where historical, scenario-based or stochastic data may be used to assess robustness of decisions against possible future conditions. Thus forecasts of streamflow and demand are integral to sound decision-making.

Although forecasts are subject to uncertainty, they provide a better picture of future conditions than relying on historical averages, and moreover, the predictive uncertainty can be quantified (Krzysztofowicz 2001). For example, Sankarasubramanian et al. (2009) demonstrated that reservoir inflow forecasts achieved better results for seasonal and intra-seasonal water allocation in minimising reservoir spills and meeting end-of-season target storage. Wang and Liu (2013) used operational inflow forecasts to simulate reservoir operation and one- month-ahead hedging rules over a 10 year period, showing that they resulted in less breaches of targets for end-of-month storage, water supply and environmental demands than using historical average inflow and were mostly comparable to simulations based on actual observed data.

A variety of methods exist to forecast seasonal or longer-term streamflow, which fall generally into two categories: 1) statistical methods which derive relationships between climatic indicators and streamflow, and 2) dynamical methods which run hydrological models with forecast or historically sampled climate variables (Wang et al. 2009). Dynamical methods can be further classified as deterministic or probabilistic forecasts. Deterministic forecasts use a single scenario of rainfall or climate to provide a single timeseries of forecast streamflow, whereas probabilistic forecasts (ensemble streamflow prediction) use multiple climate inputs (ensemble members) to produce multiple or probabilistic flows (Wang et al. 2011). Multi-model ensemble streamflow predictions provide further attention to model and parameter error uncertainty by combining probabilistic forecasts from multiple climate and hydrologic models (Block et al. 2009). Probabilistic forecasts better capture the potential range of flows, based on uncertainty in climate projections and/or hydrological models, allowing for more transparent and risk-based decision-making (Krzysztofowicz 2001). Any of these forecasts may be ‘correct’; information is only given about the expected probability of each flow estimate. Forecast skill depends highly on initial catchment conditions, model, model user, location, and time of year (van Dijk et al. 2013; Wang et al. 2011).

In order to use probabilistic streamflow forecasts, water managers must determine how to integrate them into decision-making. Ideally all ensemble members would be simulated for optimisation, especially where probabilistic objectives are desired, however this would result in an infeasible number of simulation runs and Pareto fronts. Therefore is most practical to use a single value or timeseries of the most probable flow, and to assess the impact of uncertainty in flow, using simulation only, when evaluating options at the multi-criteria analysis stage. At this point, uncertainty analysis of solution performance using the probabilistic forecasts can provide some insight into the effect of input conditions on the optimal decisions. This could involve either directly sampling the probability distribution to obtain low, medium or high flow scenarios, or where the criteria are probabilistic in nature, random sampling using Monte Carlo simulation methods (Mannina and Viviani 2009; Vrugt et al. 2003; Yang et al. 2005). An alternative or additional approach would involve using a few streamflow possibilities, e.g. low, medium and high flows selected from the probabilistic forecast or historic distribution, to generate multiple Pareto fronts. These would then form multiple sets of options which would in turn need to be assessed for performance under all the same flow scenario/s. This approach would however multiply the simulation-optimisation computer run-time.

A number of methods have been used to forecast short-term demands, many similar to those used for streamflow forecasting. Linear regression analysis is a relatively straightforward technique that develops statistical relationships between demand and a number of predicted variables. However this method struggles with non-linear relationships and noisy data (Adamowski and Karapataki 2010). Similarly, time series models relate forecasts to past values in the timeseries. They do not consider climate data during the modelling process, but are useful where such data is not available (Adamowski and Karapataki 2010). Artificial neural networks (ANNs) are a learning algorithm used to develop more complex non-linear relationships in a demand model, and have been found to outperform regression and time series models in case study comparisons (Adamowski et al. 2012; Bougadis et al. 2005). Donkor et al. (2012) suggest that the forecast horizon and timestep are the key drivers to selecting a demand forecast method and model; also of consideration is the data available to represent the many variables that influence demand. They consider that ANNs are the most commonly used for operational planning, and that probabilistic forecasting methods will help to improve decision outcomes. Similar to streamflow, uncertainty in demand forecasts can be considered by assessing multiple Pareto fronts or calculating performance against criteria using uncertainty analysis.

Depending on the model input data, forecast streamflow and demand values may not be on the time-step of the simulation model: a disaggregation method may be required, e.g. from seasonal forecasts to a daily timeseries. This could be achieved by selecting periods of the historical record that match the total forecast value, or by developing statistical relationships between historic flow on different timescales. For example, Abrishamchi et al. (2006) used a ratio of long-term average monthly to seasonal streamflow to disaggregate their seasonal streamflow forecasts to a monthly timestep for reservoir operation modelling. Additionally, the forecast horizon may be shorter than the timeframe of the planning period; in this case historical data will be required to extend the time series.

The proposed framework emphasises streamflow and demand forecasts as inputs to the simulation model, as they provide the best picture of possible conditions to which decisions are to be applied. Rather than suggest here a particular method, coordination with local hydrologists, climate scientists and retail water authorities is encouraged to utilise existing forecasts or tools for the case study regions. Preferably, these forecasts will include probabilistic elements, so that uncertainty can be assessed. This is of particular importance to streamflow. Where streamflow forecasts are not available, information about expected climate outlooks may be used to select appropriate segments from the historical record; or low, medium and high historical flow scenarios can be tested. The impact of uncertainty in demand or streamflow can be considered by using a limited number of flow scenarios as inputs to the simulation-optimisation process to produce a number of Pareto fronts, and/or assessing performance of criteria under select scenarios; this choice will depend on the chosen criteria and the computer and time resources available.

## 5. Multi-objective optimisation

Optimisation is the process of finding the option or options out of a range of alternatives that performs “best” in terms of the *objectives* of interest to the decision maker. The objective performance is assessed by the optimiser using *objective functions*, which one may seek to minimise or maximise. Objectives for water grid operational planning may include: minimising operating cost, maximising security of supply or meeting environmental flows. The corresponding objective functions may be, respectively, the sum of fixed and variable infrastructure operating costs; total or average system storage for the planning period; and the deviation of environmental flows from target values. The objective functions may be subject to soft or hard constraints that are represented in the simulation model or the optimiser, such as infrastructure capacities, budget constraints, and minimum and maximum flow requirements. The optimisation process involves changing multiple *decision variables*, which represent choices or elements of the system, to produce the different alternatives which are assessed by the objective functions. Decision variables for the water grid may be the operating rules or releases or transfers from water sources, for example the trigger storage volume in the reservoirs below which to increase production of alternative sources, or the threshold difference between regional storage levels at which to switch pipe direction. These decision variables may be subject to constraints which limit the possible values of each of the variables.

For multi-objective optimisation, improvements in the value of one objective function, without degrading performance of the other functions will result in a better solution. Such an improvement is called a Pareto improvement, and a solution that is not dominated by any other solution is called a Pareto optimal solution. Thus the aim of a multi-objective optimisation is to find a set of Pareto optimal solutions, that approximate a *Pareto front*, a set of solutions that are optimal in terms of all objectives. Where trade-offs exist between multiple objectives, there will be no single optimal solution. These trade-offs can be explored, and selection of a single option will depend on the value that one places on each objective. In the water grid, a key trade-off might be that between water security and cost, driven by the higher cost of manufactured or alternative water sources.

A number of algorithms for multi-objective optimisation exist, which differ in their approach to searching the feasible decision variable space. These algorithms may be available as computer source code or in toolboxes such as Matlab (Mathworks 2011) and must be dynamically linked with the system simulation model, or integrated into the system simulation software such as is the case for Source IMS (Blackmore et al. 2009) and AquatorGA (Vamvakeridou-Lyroudia et al. 2010). In water resources management, multi-objective optimisation has been explored widely in long-term planning, system design, operations, and parameter determination using genetic algorithms (Hınçal et al. 2011; Nicklow et al. 2010; Tolson et al. 2004), fuzzy methods (Yang and Yang 2010; Zarghami 2010), ant colony optimisation (Kumar and Reddy 2006; Maier et al. 2001; Mortazavi N et al. 2009) and particle swarm techniques (Gaur et al. 2011; Kumar and Reddy 2007; Reddy and Kumar 2009).

Evolutionary algorithms, of which genetic algorithms are a subset and most common technique, have recently been applied to a variety of water resource applications (Nicklow et al. 2010). These are based on simulating competitive evolution with random mutation to explore the decision space. For each iteration, the most successful ‘offspring’ (population) are chosen as the basis for further mutation. This continues for a set number of iterations (generations) until probable convergence is reached. The advantages of genetic or evolutionary algorithms for optimisation (as compared to ‘classical’ techniques) lie in their ability to find global optima in complex non-linear decision spaces by using random search; many other techniques using point-by-point deterministic searches will find only the local optima (Deb 2004; Rani et al. 2013). Genetic algorithms can also handle discrete as well as continuous decision variables, e.g. set operating possibilities. Thus, genetic algorithms have the flexibility to be applied to a wide variety of decision variables and decision spaces. They also allow utilisation of parallel computing resources, with parallel evaluation of individuals in the population, as opposed to single solution search techniques (Deb 2004; Sharif and Wardlaw 2000). Overall, genetic algorithms have shown greater performance and speed than other techniques in determining optimal solutions for case studies of planning for complex water resource systems (Jothiprakash et al. 2011; Mortazavi N et al. 2009).

With reference to the previously described nature of the water grid, there is a high likelihood of a complex decision space and discrete decision variables. Therefore a genetic algorithm is suggested for this framework, with preference to those available in existing software tools. The non-dominated sorted genetic algorithm (NSGA II) (Deb et al. 2002) is one of the most popular genetic algorithms (Reed et al. 2013) and has already been applied and favourably compared in many applications in water resource planning (Chang and Chang 2009; Fernández García et al. 2013; Shokri et al. 2013; Tabari and Soltani 2013). This popularity is reflected in its availability in the Source IMS water supply planning tool (Welsh et al. 2013) which also has functionality for simulation modelling. Thus the NSGA- II application in Source is a suitable candidate for application in this framework.

## 6. Simulation modelling

As discussed, multi-objective optimisation requires evaluating the value of the objective function. For water resources management, most of this information is typically obtained using a simulation model, which models the system response to input conditions and forms the core of decision support. The simulation model determines the effect of different decision variable values on the variables used to calculate the objective functions. This combined interactive simulation-optimisation is becoming a common approach to water resources management (Rani and Moreira 2010).

The simulation models themselves may differ in the way they determine water allocation and releases from reservoirs. Water allocation may be rules-based, or they may have limited optimisation capabilities to efficiently allocate water on each time-step by using techniques such as network linear programming. Simulation models with such capabilities include REALM (Perera et al. 2005), WATHNET (Kuczera 1997), Source IMS (Welsh et al. 2013), Riverware (Center for Advanced Decision Support for Water and Environmental Systems 2011) and WEAP (Stockholm Environment Institute 2011). Many simulation models have been linked to a multi- objective optimisation algorithm for water resources planning. For example, Vamvakeridou- Lyroudia et al. (2010) integrated a module of a multi-objective algorithm with the Aquator simulation software to optimise a reservoir control curve; Kularathna et al. (2011a) have linked a single objective optimisation algorithm tool OPTIMISR to the REALM software for operational planning; Kularathna et al. (2011b) have linked a multi-objective optimisation algorithm to REALM for long-term planning; WATHNET has been linked to a number of algorithms for long-term planning (Mortazavi et al. 2012; Mortazavi N et al. 2009); and a module for multi- objective optimisation has been developed for Source IMS (Blackmore et al. 2009).

To support the needs of the proposed framework, a simulation model will ideally have the ability to:

- link and inter-operate with a multi-objective optimisation algorithm
- run in an automated fashion for optimisation
- explicitly model the decision variables of interest
- generate data needed for calculating objective functions and criteria performance measures
- handle multiple supply paths using optimisation or rules-based methods
- represent grid features such as wastewater recycling, desalination, and two-way pipelines

Desirable features include:

- capacity for uncertainty/stochastic analysis
- an existing application to the case study with a calibrated and validated model

If a currently implemented simulation model has most of these features then it is the sensible choice. Otherwise, the Source IMS software tool is suggested as a suitable and simple simulation candidate because it can meet the capabilities outlined above, including fully integrated optimisation capabilities using NSGA

II, as well as limited Monte Carlo analysis functionality for uncertainty analysis (Blackmore et al. 2009).

## 7. Multi-criteria analysis

The multi-objective optimisation process produces a Pareto front of optimal solutions in terms of all objectives. These must be examined further to select a final decision set which informs the operating plan. The aim is to select a decision set that reconciles trade-offs in a way that represents the values of stakeholders, balancing outcomes for different purposes (e.g. human and environmental demands) and objectives, as well as meeting policy-based targets.

Multi-criteria analysis (MCA) is a tool or framework that assists decision-makers in identifying trade-off solutions, allowing for subjectivity and compromises in the decision process. It involves ranking or scoring the performance of decision options against multiple criteria. These criteria may be quantitative, semi-quantitative or qualitative, and consider a range of factors outside the scope of systems modelling. The MCA process facilitates communication of decision options and their implications, allowing for more transparency and wider participation in decision-making. MCA typically involves identifying:

- a set of decision options
- a set of criteria against which to assess these options
- performance measures to assess options against the criteria
- weights to represent the importance of each criteria

The decision options will be obtained from the multi-objective optimisation outcome, ie. decision sets on the Pareto front. For each point on the Pareto front, the optimisation algorithm provides information about the objective performance and the decision variables that were used. Determination of the criteria, performance measures and weights is aided by the involvement of stakeholders in the decision process. These criteria can be changed over time, to reflect changes in policy and values. Criteria are the targets or objectives for short-term planning, examples of which include drinking water quality targets; minimum environmental flows; operating cost; and level of service and risk criteria as set out in long-term planning. The simulation model and the multi-objective optimisation outcomes can provide data to help calculate the performance measures. Criteria weights then allow performance measures to be combined to a single score or ranking for each decision option.

MCA has been widely used as a decision support model in water resource management. Commonly used methods include: multi-criteria value functions (e.g. weighted summation), outranking (e.g. PROMETHEE, ELECTRE), distance to ideal point methods (e.g. compromise programming, TOPSIS), pairwise comparison (e.g. AHP), and fuzzy set analysis. For water resources management, fuzzy set analysis (El-Baroudy and Simonovic 2004), compromise programming (Geng and Wardlaw 2013), AHP (Chung et al. 2011), ELECTRE (Bolouri- Yazdeli et al. 2014), and PROMETHEE (Mutikanga et al. 2011) have been the most popular (Hajkowicz and Collins 2007). These methods have been used both standalone and in combination with multi-objective optimisation models, and have been widely applied in policy evaluation, strategic or long-term planning, and infrastructure selection (Hajkowicz and Collins 2007). Hajkowicz and Higgins (2008) compared the performance of a range of methods for six water management decision problems and found strong agreement between methods on the outcome of the decision process. They suggested that thoughtful structuring of the decision problem and understanding of the method used was most important to success.

For this framework, a simple to use MCA methodology is desirable, allowing for frequent updates in criteria and preferences as they change with each operational planning cycle. Hajkowicz and Higgins (2008) found that weighted summation was in agreement with other methods but is relatively easy to understand and use, able to be modelled with a simple spreadsheet. Hence, unless a technique is already well known or used by the water grid manager, weighted summation is suggested as the method for MCA in this framework.

Dependent on the population size of the genetic algorithm, the Pareto front may contain too many solutions to feasibly evaluate in multi-criteria analysis, so a representative subset may be chosen. This can be done by clustering solutions in terms of their performance against the objectives, either by visual means or using a cluster analysis algorithm (Zio and Bazzo 2011). K-means clustering is a simple and widely used clustering method which assigns data points to non-overlapping clusters, represented by their centroid or mean (Wu 2012). The user specifies the number of clusters, k, to be located by the clustering algorithm, and the centroids are optimised based on the least squared distance of the clustered data points. In this application, a variation, k- medoid clustering, would be used to restrict cluster centroids to a member of the dataset so that a feasible decision variable set is selected. Thus this framework may incorporate k-medoid clustering into the methodology, when needed to easily reduce the number of decision options for assessment.

## 8. Implementation of the framework

This framework will be demonstrated for a case study based on features of the South East Queensland Water Grid in Australia. This grid includes major reservoirs, a desalination plant, potable recycled water treatment plants, two-way pipelines connecting these supply sources and the major demand centres, as well as various local surface and groundwater supply schemes. The case study will use the Source software tool (Welsh et al. 2013), which is capable of integrated simulation and multi-objective optimisation using genetic algorithm NSGA-II (Blackmore et al. 2009). The Source software tool also has basic functionality for Monte Carlo analysis, which can be used for analysis of uncertainty surrounding potential operating plans due to the forecast inputs. Inputs will include locally available streamflow forecasts, demand forecasts, and initial and forecast infrastructure conditions. Management objectives include minimising cost and maximising water security, and decision variables include storage volume trigger values in operating rules for manufactured water production and pipeline direction. Multiple streamflow scenarios will be used to assess the impact of uncertainty on decision set performance. Multi- criteria analysis using weighted summation, as well as stakeholder engagement, will aid in identifying objectives, criteria, weights and performance measures to derive an optimal set of operating rules which can form the basis of an operating plan.

## 9. Conclusions

This paper identified challenges and suggested a gap in decision support for water grid management. This triggered the development of a framework of methods to better support short-term operational planning of water grids. The framework is tailored for the needs of water grids and operational planning by explicitly considering multiple objectives, complex and heterogeneous water supply systems, and forecast conditions. The framework has the flexibility to consider a range of decision variables and objectives, and for these to change between planning cycles. The framework can be applied to any case study, with the methods or tools adapted to suit.

Specific methods have been suggested for each of the framework elements. Previous applications of these methods indicate they have the capabilities to meet the desired outcomes of each stage of the framework. Multi-objective optimisation, coupled with a simulation model, allows for the exploration of many possible operating rules or decisions and quantification of the outcomes in terms of the objectives of interest. The use of forecast inflows and demands allows decisions to adapt and be tailored to the expected conditions. Uncertainty analysis or multiple scenarios of flow and demand using probabilistic forecasts provides information on the possible range of performance against management criteria. Multi-criteria analysis and stakeholder engagement provide flexibility and transparency in decision-making by exploring and reconciling trade-offs inherent in the decision possibilities.

Thus this paper has provided proof of concept of a framework to be applied to short-term planning for water grids. It is recommended that application of this framework and its methods can improve decision-making in water grid management. However, this framework is not intended as a ‘black-box’: whilst specific methods and tools have been suggested, thought needs to be given in their implementation and interpretation, as well as to what is appropriate for the case study. The complexity in models and data need only be at a level suitable to give an adequate understanding of the supply system. This is especially true for forecast streamflows and demands, as these need to be used with an understanding of their assumptions and capabilities. Thus, familiarity with both the system and the tools used are required. Ultimately, the framework is a decision support tool, allowing numerous options to be identified and quantified, and the trade-offs and contingencies inherent in the choices to be considered when making a final decision.

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# Chapter 3: Case study

The previous chapter identified a framework of methods and tools to assist operational planning of water grids that satisfied the first three research questions in Section 1.2. The literature review in Chapter 2 provided a proof-of-concept that the proposed framework and methods can meet the challenges and needs of water grid management. However, a case study is required to help demonstrate the fourth research question, namely:

5. Does this framework actually provide the required outcome when implemented for a case study?

This research question can be answered by applying the methods and tools recommended for each of the framework components in Chapter 2, to a case study. This case study is based on the SEQ Water Grid, with some details and processes simplified for the purposes of this research. Information about the SEQ Water Grid is used to develop a case study to demonstrate the methods and tools of the framework in Chapters 4-7. This chapter provides a brief overview of the South East Queensland Water Grid, its system characteristics and current short-term operational planning process. It is this short-term operational planning process that is the focus of this research. Further details of the case study – e.g. the simulation-optimisation model, operating rules, objectives, criteria, decision variables, and input data – are provided in Chapters 4-7.

## 3.1 System Characteristics

The South East Queensland (SEQ) Water Grid serves 3.1 million people in the south east region of the state of Queensland, Australia. It is designed to provide water security in the face of drought, future climate changes, and population growth. The water grid consists of 26 dams, both on- and off-stream; 2 borefields; 51 weirs; 3 advanced water treatment plants that provide purified recycled water to drinking quality standards; 37 water treatment plants; 18 service reservoirs; a desalination plant; 22 pump stations; and 600km of bulk water supply pipelines. One- and two-way pipelines link water supply systems extending from Sunshine Coast in the north, to Gold Coast to the south, and Stradbroke Island to the east. With the implementation of this infrastructure in 2008, the water grid resulted in a 14% increase in the system yield compared to the previously disconnected water supply systems (Queensland Water Commission 2009). The connection of supply systems also necessitated restructure of management institutions, with 17 separate management entities being replaced by a single bulk water authority (Seqwater) and five water retailers. The SEQ Water Grid is illustrated in Figure 3.1.

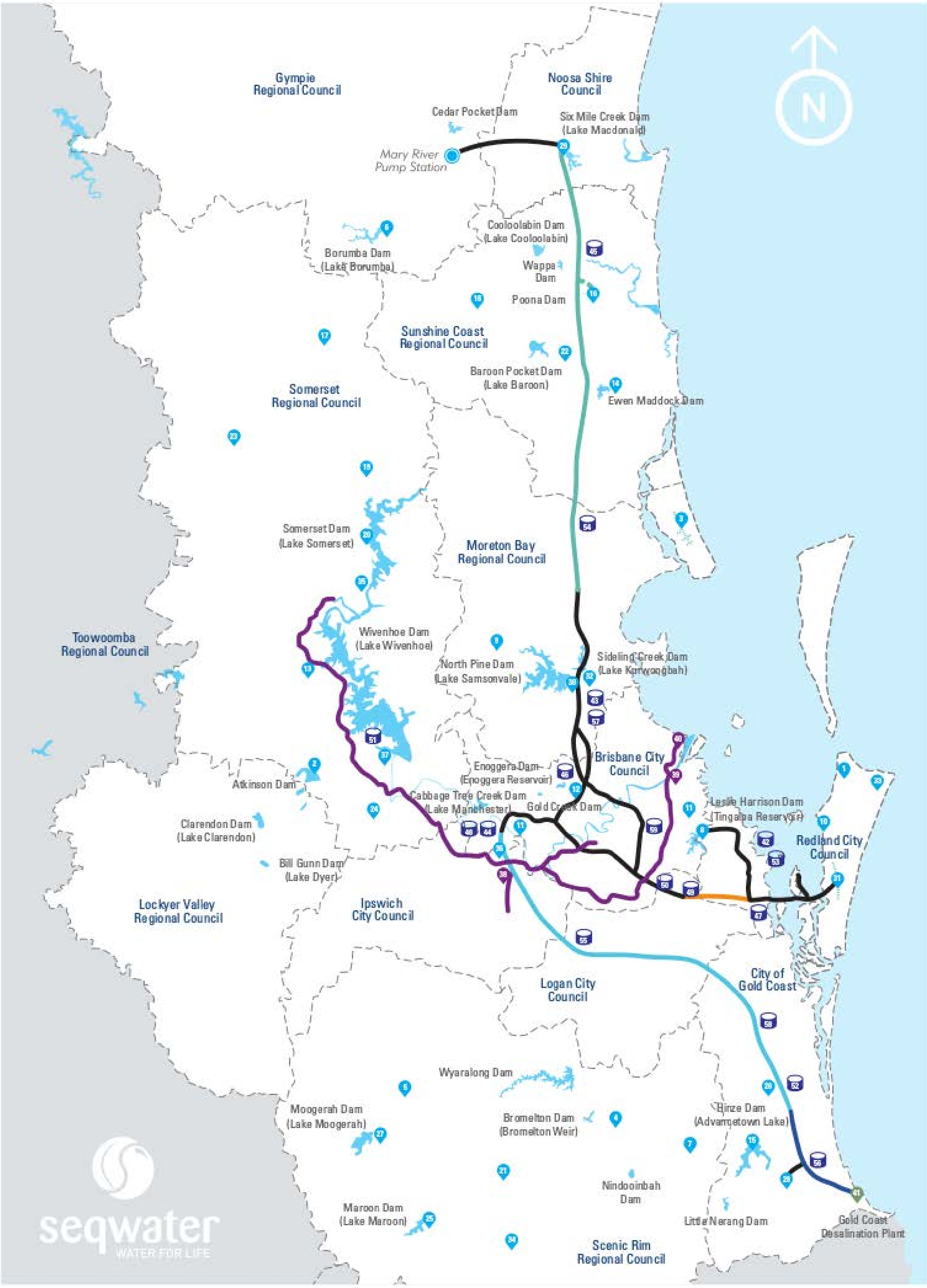


**Figure 3.1:** South East Queensland Water Grid regional extent and key infrastructure. The legend is provided on the following page. © Seqwater

# Legend

- Northern Pipeline Interconnector
- Western Corridor Recycled Water Scheme
- Southern Regional Water Pipeline
- Eastern Pipeline Interconnector
- Network Integration Pipeline
- Other bulk water pipelines connecting the SEQ water grid
- Local government boundary
- Reservoirs
- Water treatment plants
- Western Corridor Recycled Water Scheme
- Desalination plant

### Water Treatment Plants (WTP)

1 Amity Point WTP[2]
2 Atkinson Dam WTP[1]
3 Banksia Beach WTP
4 Beaudesert WTP[2]
5 Boonah Kalbar WTP[2]
6 Borumba Dam WTP[1]
7 Canungra WTP[2]
8 Capalaba WTP
9 Dayboro WTP[2]
10 Dunwich WTP[2]
11 East Bank (Mount Crosby) WTP
12 Enoggera WTP
13 Esk WTP[2]
14 Ewen Maddock WTP
15 Hinze Dam WTP[1]
16 Image Flat WTP
17 Jimna WTP[2]
18 Kenilworth WTP[2]
19 Kilcoy WTP[2]
20 Kirkleagh WTP[1]
21 Kooralbyn WTP[2]
22 Landers Shute WTP
23 Linville WTP[2]
24 Lowood WTP[2]
25 Maroon Dam WTP[1]
26 Molendinar WTP
27 Moogerah Dam WTP[1]
28 Mudgeeraba WTP
29 Noosa WTP
30 North Pine WTP
31 North Stradbroke Island WTP
32 Petrie WTP
33 Point Lookout WTP[2]
34 Rathdowney WTP[2]
35 Somerset Dam (Township) WTP[2]
36 West Bank (Mount Crosby) WTP
37 Wivenhoe Dam WTP[1]

### Western Corridor Recycled Water Scheme

38 Bundamba Advanced Water Treatment Plant (AWTP)
39 Gibson Island AWTP
40 Luggage Point AWTP

### Desalination Plant

41 Gold Coast Desalination Plant

### Reservoirs

42 Alexandra Hills Reservoirs
43 Aspley Reservoir
44 Camerons Hill Reservoir
45 Ferntree Reservoir
46 Green Hill Reservoirs
47 Heinemann Road Reservoirs
48 Holts Hill Reservoir
49 Kimberley Park Reservoirs
50 Kuraby Reservoir
51 Lumley Hill Reservoir
52 Molendinar Reservoir
53 Mt Cotton Reservoir
54 Narangba Reservoirs
55 North Beaudesert Reservoirs
56 Robina Reservoir
57 Sparkes Hill Reservoirs
58 Stapylton Reservoir
59 Wellers Hill Reservoirs

[1] *Recreation water treatment plant*
[2] *Standalone community water treatment plant*

## 3.2 Short-term operational planning

Current at May 2014, short-term operational planning of the SEQ Water Grid is governed by the System Operating Plan (SOP) (Queensland Water Commission 2012). The SOP provides hydrological guidance to the Queensland Bulk Water Supply Authority, Seqwater, for optimum use of storages and manufactured water within the grid, including key infrastructure operating rules and water security criteria. It also sets out the need for an Annual Operations Plan (AOP). The AOP is developed by Seqwater every 6 months and demonstrates how it intends to meet forecast water demands for the next 12 months (Seqwater 2014). The plan involves assessing the current status of the grid, and developing and comparing a number of alternative operating options that consider:

- expected hydrological conditions based on the climate outlook
- forecast demand scenarios
- compliance with water security criteria and operating rules outlined in the SOP
- current infrastructure capabilities and constraints, including maintenance, recommissioning or decommissioning
- water quality issues or constraints
- reliability of system infrastructure and vulnerability to failure
- operational cost

Assessment of operating options is undertaken using the South East Queensland Regional Water Balance Model (SEQRWBM). The SEQRWBM consists of a WATHNET (Kuczera 1997) model with Excel interface, and is used to simulate the behaviour of the water grid over the next 5-10 years, on a monthly timestep, using single or multiple stochastic scenarios of inflow. An operating option is chosen for implementation from amongst the alternatives, based on its ability to provide an appropriate balance between water security and cost criteria for expected inflow and demand conditions, whilst meeting system constraints. This operating option guides operations over the next 12 months, and outlines operating modes or operating rules for key infrastructure such as the direction and flowrate in two-way pipelines, production of desalinated and potable recycled wastewater, and target storage levels.

# Chapter 4: Multi-objective simulation-optimisation

Chapter 2 presented a framework for short-term operational planning of water grids, and Chapter 3 introduced a case study which will be used to test that this framework provides the desired framework outcome. This chapter examines the multi-objective simulation-optimisation components of the framework in more detail, as highlighted in Figure 4.1, and demonstrates their application to short-term planning for the case study. This is expected to result in a Pareto-optimal set of operating options, which forms the input to the next part of the framework.

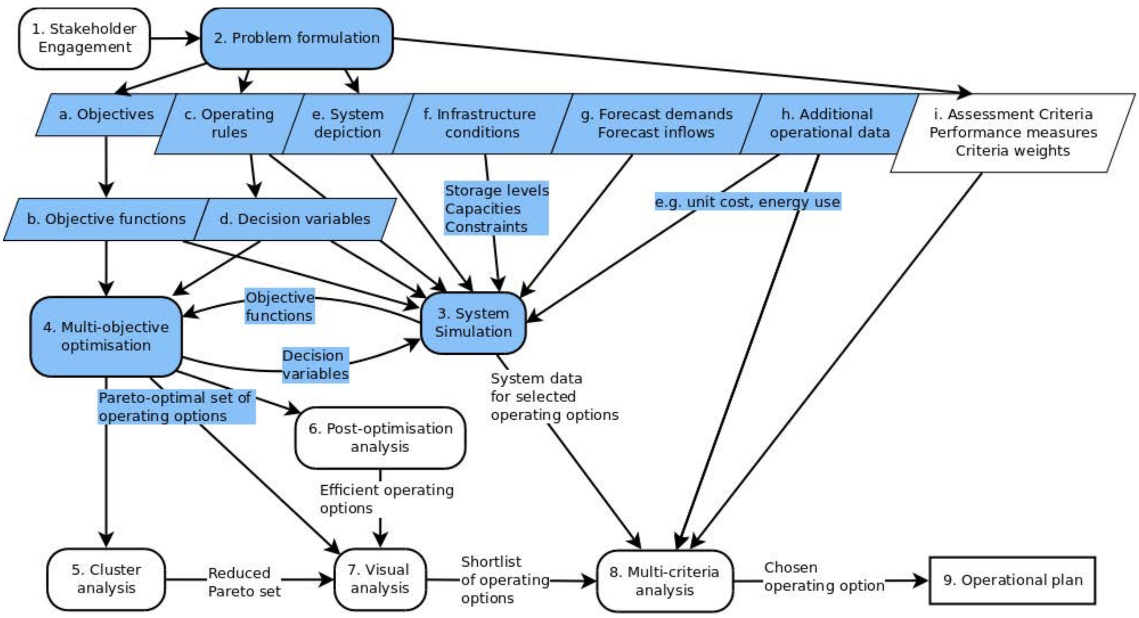


**Figure 4.1:** The framework for short-term operational planning of water grids, highlighting the components relating to multi-objective optimisation, covered in this chapter.

As the South East Queensland Regional Water Balance Model is not available for reuse, its input data and network schematic, as well as publicly available data such as storage characteristics and the Annual Operating Plan, are used to build a new simulation-optimisation model tailored to demonstrating the framework.

This chapter contains the following journal paper, which demonstrates the components of the framework highlighted in Figure 4.1:

> Ashbolt, S. C., Maheepala, S., and Perera, B.J.C., 2016, 'Using Multiobjective Optimization to Find Optimal Operating Rules for Short-Term Planning of Water Grids', *Journal of Water Resources Planning and Management,* 04016033, ASCE.

VICTORIA UNIVERSITY
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| Chris Perera | 10 | Feedback and discussion on the research and writing | | 6/7/16 |
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# Using Multiobjective Optimization to Find Optimal Operating Rules for Short-Term Planning of Water Grids

Stephanie C. Ashbolt; Shiroma Maheepala; and B. J. C. Perera

**Abstract:** Water grids are emerging as a means to address water scarcity in urban areas. These water grids are more complex than traditional supply systems, bringing new challenges to water-grid management. This paper seeks to address these challenges by demonstrating the capability of multiobjective optimization to aid in short-term operational planning for water grids. A framework for applying multiobjective optimization to short-term operational planning is demonstrated for a case study based on the South East Queensland Water Grid in Australia. The aim of the case study application is to find short-term (1 year) operating rules that maximize water security, minimize operational cost, and minimize spills from reservoirs. The results of the optimization process are a number of operating options, comprising sets of operating rules that perform optimally in terms of the objectives. The range of operating rules and objective performance found in the optimization process allows the decision-maker to explore the trade-offs in decision-making and to choose a set of operating rules based on their preferences on the management objectives.

**Author keywords:** Multiobjective optimization; Operational planning; Short-term planning; Simulation; Urban water management; Water grid; Water supply planning.

# 1. Introduction

Water grids are interconnected regional-scale water supply systems that aim to increase water supply yield, security, and resilience. They build on traditional catchment-based surface and groundwater supply systems by establishing alternative water sources such as desalination and wastewater recycling, and by connecting these sources across catchments with one-way or two-way pipelines. This creates a diversity of water supply options, each of which will perform differently in terms of management objectives such as maximizing water security and minimizing cost. The objective performance of the supply options will also vary depending on system conditions such as inflows, storage levels, and infrastructure constraints. To guide the operation of the water grid, water grid managers need to develop short-term operating plans every 3–12 months that identify operating rules for key infrastructure over the next 1 to 5 years. These operating rules will in turn inform the operating decisions made on a monthly or submonthly basis. The operating rules should perform optimally in terms of multiple management objectives and for the expected system conditions, without compromising longer-term performance. Thus decision-makers require decision support systems that can negotiate this complex decision and objective space to identify optimal operating rules for short-term planning for water grids.

Previous studies have indicated the potential of multiobjective optimization to optimize operating rules for water supply networks. On the short-term planning timescale, multiobjective optimization has been applied to optimize operation of single reservoir (Giuliani et al. 2014) and multireservoir systems (Kumphon 2013; Schardong and Simonovic 2015; Smith et al. 2015). However, in multireservoir system applications, single-objective optimization is more commonly employed (Hınçal et al. 2011; Li et al. 2014; Vieira et al. 2011). For the water grid, some current operational plans use single-objective optimization or scenario modeling to identify operating rules (Kularathna et al. 2011; Seqwater 2014), but multiobjective optimization has been applied only on the long-term planning timescale (Cui et al. 2013; Paton et al. 2014). There has been no reported application of multiobjective optimization to short-term operational planning for water grids and limited demonstration of how to integrate multiobjective optimization into real-world decision-making (Maier et al. 2014).

Thus the current paper seeks to demonstrate the application of multiobjective optimization to short-term operational planning for water grids. It is proposed that multiobjective optimization can assist decision-makers in navigating the complex decision space to find operating rules that are optimal in terms of the management objectives. These optimized operating rules are expected to improve objective performance compared to the use of longer-term operating rules, since the operating rules are updated and optimized to the expected conditions. Multiobjective optimization also allows the decision-maker to explore a variety of possibilities in terms of the decision and objective space and consider the trade-offs in decisions, reducing policy myopia (Giuliani et al. 2014; Wu et al. 2010). However, multiobjective optimization can present challenges in its application. To this end, a framework for short-term optimal operational planning for water grids was proposed in Ashbolt et al. (2014). This paper demonstrates the core multiobjective optimization components of this framework, for a case study based on the South East Queensland Water Grid in Australia. The objective performance of the resulting sets of optimal operating rules are evaluated and compared to rules-based operation based on long-term operating rules.

## 2. Framework

A framework for short-term operational planning for water grids is shown in Figure 1. This framework is updated from the framework described in Ashbolt et al. (2014). This paper tests the multiobjective optimization components of the framework, shaded in Figure 1. The aim of these components is to optimize the operating rules for the short-term planning timeframe. The multiobjective optimization process involves (numbers and letters indicate elements in Figure 1):

- Problem formulation (2): identifying the (a) objectives of relevance to the decision-maker and other stakeholders and (b) objective functions that quantitatively describe objective performance; the (c) operating rules that are to be optimized; (d) decision variables that comprise the operating rules; and (e) a system depiction that identifies and describes the infrastructure to be included in the analysis. Stakeholder engagement (1) can be used to aid the problem formulation, but is not covered in this paper.

- Simulation (3): developing a system simulation (3) model representing the water supply system according to the system depiction, and including the operating rules, decision variables, any constraints, and (depending on the particular simulation model) the objective functions. Inputs to the simulation model include (e) infrastructure conditions, (f) forecast demands and inflows, and (g) any additional operational data required to compute the objective functions.
- Optimization (4): configuring a multiobjective optimization (4) algorithm that dynamically links with the simulation model to optimize system operating rules with respect to the objective functions by trialing alternative decision variable values within a user-defined range. The objective functions may be calculated by the optimization algorithm if they are not determined by the simulation model.

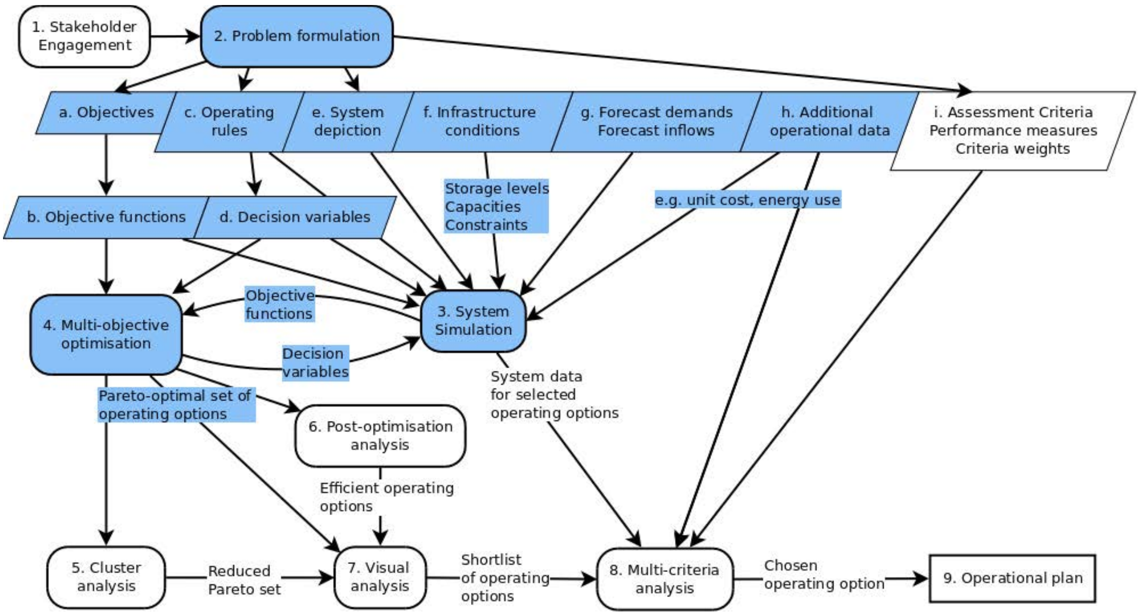


**Figure 1:** Framework for optimal operational planning for water grids; components covered in this paper are shaded; rounded rectangles (numbered) indicate decision processes; parallelograms (lettered) indicate decision inputs; arrows indicate interactions between components (adapted from Ashbolt et al. 2014).

The output of the multiobjective optimization process is a Pareto-optimal set of operating options (Pareto set). Each operating option comprises a set or vector of decision variables with associated objective function performance for the planning time period. These decision variables comprise the operating rules. Whilst not covered in this paper, the framework recommends that the decision-maker then use a combination of cluster (5), postoptimization (6), and visual analysis (7) to identify a shortlist of operating options. These can be assessed against additional management criteria in multicriteria analysis (8) and preference weights on these criteria are used to choose an operating option that will form the basis of the operational plan (9).

Ashbolt et al. (2014) suggest suitable tools and processes to implement the components of the framework, based on ease-of-use and flexibility. The suggested tools are used in the case study presented here, described in the following sections. However, existing tools can be used where possible, assisting the transfer of knowledge and providing consistency across planning timeframes and processes. A key example of this is the use of existing simulation models, which assists in gaining trust in the simulation-optimization process (Basdekas 2014). Since short-term operational plans must be updated on a regular basis, the decision- maker has the opportunity to regularly refine and update the process, learning more about the problem formulation and the tools over time.

The following section describes the case study. Subsequent sections describe the framework components and their application to the case study. This is followed by presentation and discussion of the Pareto set resulting from the multiobjective optimization process, including a comparison to the performance, for the planning period, of base-case operation using existing longer-term operating rules.

## 3. Case Study

The case study is based on the water grid in Southeast Queensland, Australia. This water grid supplies 3.6 million people and aims to provide water security and climate resilience in the face of drought, future climate changes, and population growth. These aims are achieved through the use of diverse water sources including surface and groundwater supplies, a wastewater recycling scheme, a desalination plant; and the use of two-way pipelines to link catchments and water sources to demands across the region. This creates a diverse and highly interconnected system. A simplified version of this system used as this case study, based on information obtained from publicly available documents and directly from the water supply managers. While every effort has been made to represent the key elements of the real-life water grid, simplifications have been required in the problem formulation and simulation model. Due to these simplifications, the results of this case study should not be compared directly to operation of the actual system.

Current operational plans in South East Queensland have a 1-year horizon, with impacts of operating decisions on the objectives assessed over a longer period of 5 years (Seqwater 2014). These plans are updated every 6 months.

Therefore a 5-year planning period is used to apply the framework to this case study. In other words, the operating rules are optimised for 5 years; the chosen operating rules can then be implemented for the 1 year planning period. It would be expected that the framework would then be reapplied every 6 months.

# 4 Problem Formulation

The problem formulation forms the basis of the system representation in the simulation model and determines the objective functions and decision variables to be used by the optimization algorithm. The problem formulation includes developing a system depiction of the case-study system to be optimized, and identifying the operating rules, decision variables, and objectives and objective functions that govern its operation. This process may be repeated iteratively as the decision-maker gains new insights from the multi- objective optimization process (Kasprzyk et al. 2012). The problem formulation is also informed by the planning timeframe that is used.

## 4.1. System Depiction

Figure 2 provides an illustration of the case study supply–demand network. This network corresponds to the infrastructure considered in current Southeast Queensland operational planning, but with aggregation of some pipelines and demands. Supply sources include 28 dams and weirs, 3 borefields, a wastewater recycling scheme, and a desalination plant. The wastewater recycling scheme involves treatment of wastewater to potable quality. This water is supplied to the major reservoir, Wivenhoe Dam, when the dam levels are low. At other times, it is supplied to industrial demands. These sources are connected to demands across the region by a network of seven two-way pipeline interconnectors, one-way pipelines, and streams.

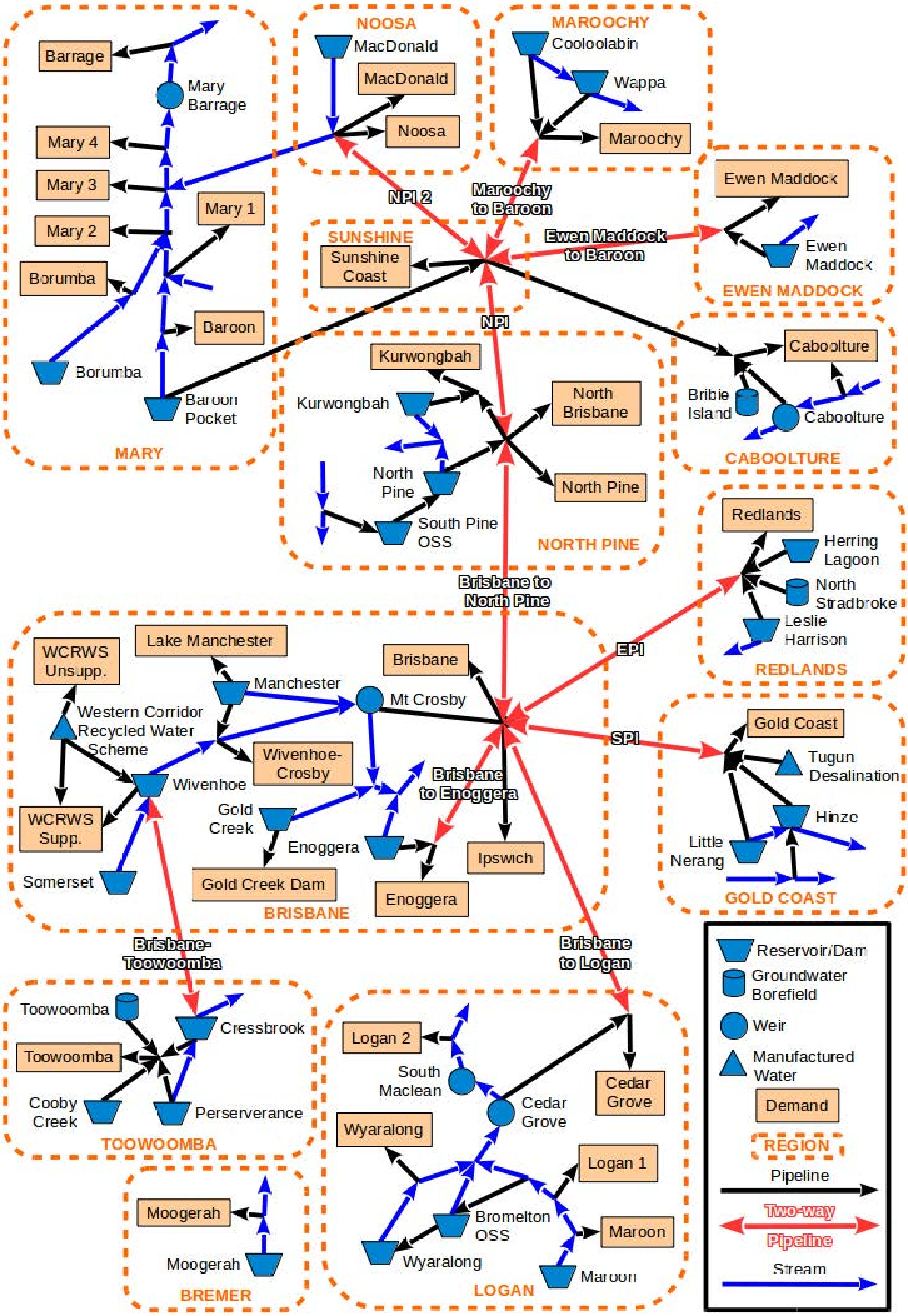


**Figure 2:** South East Queensland Water Grid network as simplified and represented in the system simulation model

## 4.2. Operating Rules

Operating rules govern system behavior and state the actions to be taken as a function of variables such as hydrological conditions and storage volume (Lund and Guzman 1999; Oliveira and Loucks 1997). For traditional catchment-based surface water supply systems, the aim of these rules is usually to maximize available stored water and minimize chance of spills or flooding from the system, while meeting policy and regulatory constraints. Such rules may include:

- Storage targets: volumes to be maintained/reached in reservoirs;
- System-wide release rules: volumes to be released from reservoirs;
- Allocation rules: dividing releases between multiple demands;
- Hedging rules: allowing deficits now to minimize deficits later;
- Space rules: equalizing volume in multiple reservoirs with respect to anticipated refill;
- Flood control rules: balancing flood storage volumes;
- Demand-dependent storage rules: maintaining volume relative to demands; and
- Hydropower production or energy storage rules: minimizing loss of potential energy.

For the water grid, reservoir operation would still be managed using storage rules similar to those listed in the preceding paragraph. Firstly, however, bulk-level water supply rules are needed to govern supply, transfer, and allocation across the water-grid region, and the production of alternative water sources such as desalination. These bulk-level operating rules then influence the operation of reservoirs within the catchment. It is these bulk-level rules that are the focus of the case study presented here, and releases from reservoirs are guided by the bulk-level rules. Where there is a choice between reservoirs and this choice is not specified by the bulk-level rules, water will be drawn evenly from these reservoirs to maintain an equal ratio of volume to capacity.

Thus the aim of the case study is to optimize bulk-level operating rules for the key grid infrastructure, namely the two-way pipeline interconnectors, wastewater recycling scheme, and desalination plant. Operation of this infrastructure is determined by the capacity of the surface water storages and will determine the volume to be drawn from the storages. The format of these operating rules are based (where available) on operating rules and policies used in current South East Queensland Water Grid short-term operational planning (Seqwater 2014). These operating rules are shown in Figure 3, in the callout boxes attached to the infrastructure they govern. This figure is drawn from the same network shown in Figure 2, but shows only the infrastructure relevant to the operating rules, and only the operating rules that are to be optimized. The operating rules are storage-dependent rules that specify the percentage of surface water storage fullness (ratio of current available volume to capacity), or the difference between storage fullnesses in reservoirs that trigger a change in the operating mode, production volume, or flow rate of the infrastructure. Different configurations of these operating rules will form the different operating options that result from optimization. Figure 3 also shows the decision variables that constitute these operating rules, discussed in the next subsection.

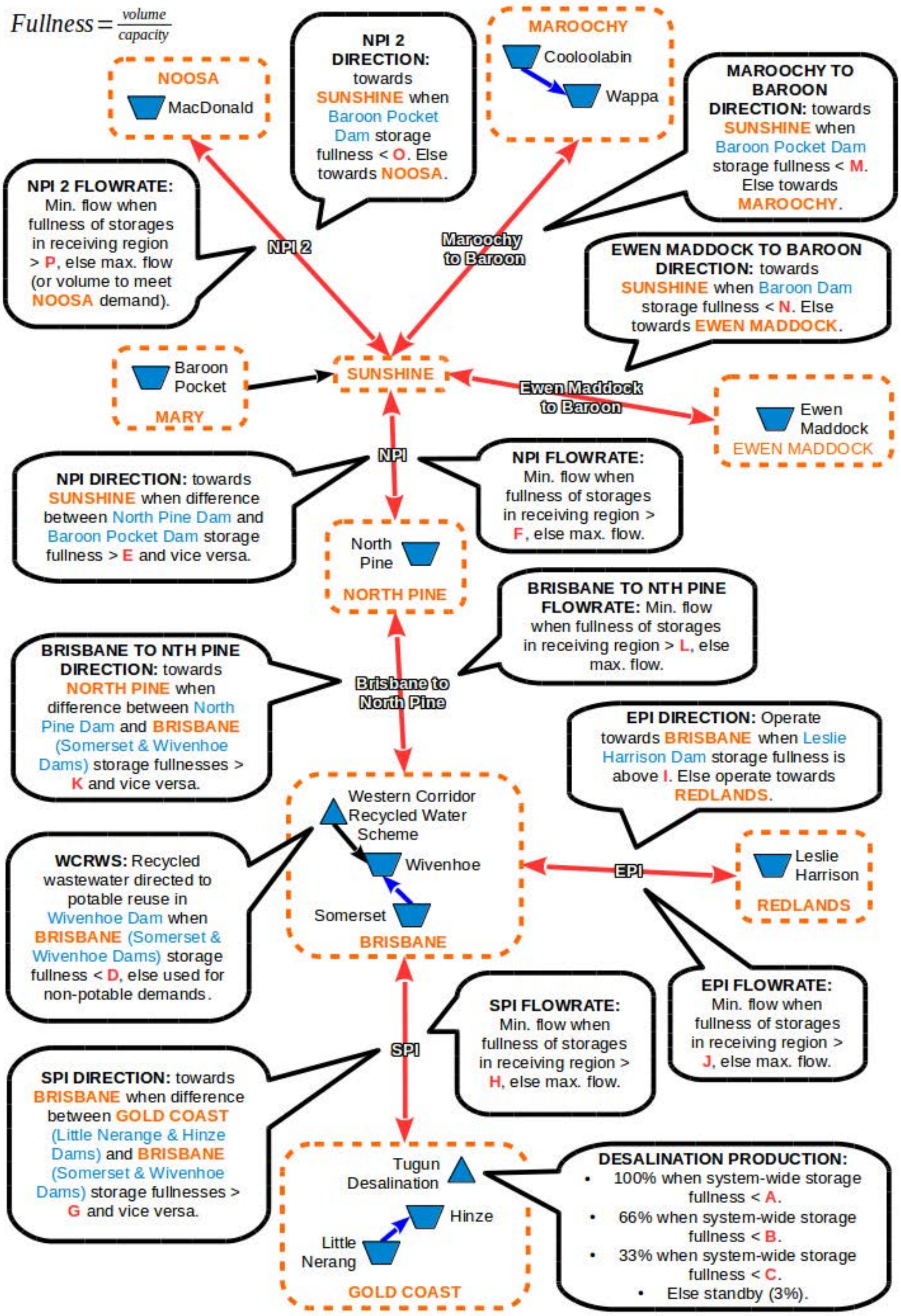


**Figure 3:** Infrastructure operating rules and decision variables for the case study; operating rules are shown in the callout boxes, with the decision variables indicated by bold capital letters; decision variable names are listed in Table 1; infrastructure is the same as Fig. 2, but only those relevant to the operating rules are shown in this diagram.

A base-case operating option is also identified for the case study so that the objective performance of operating options found in the optimization process can be compared to rules-based operation using existing operating rules. These operating rules are represented by inserting fixed values in place of the decision variables in the operating rules shown in Figure 3. These fixed values are drawn where possible from operating rules or policy in the current South East Queensland operating plan (Seqwater 2014). These base-case operating rules have generally been formulated to perform well over the longer-term and for a range of possible conditions. Thus it would be expected that optimizing these rules for the current or expected conditions would improve performance. Table 1 shows the values used to replace the decision variables to represent the base-case operating rules.

**Table 1:** Values Used to Replace the Decision Variables in the Operating Rules to Create Fixed Operating Rules to Represent the Base Case of Rules-Based Operation

| **Decision variable** | **Decision variable name** | **Base case (rules-based operation) (%)** |
|---|---|---|
| A | Desalination Full Threshold | 40 |
| B | Desalination 2/3 Threshold | 50 |
| C | Desalination 1/3 Threshold | 60 |
| D | Potable Recycled Water (PRW) Threshold | 40 |
| E | Northern Pipeline Interconnector (NPI) Threshold | 50 |
| F | NPI Flowrate Threshold | 60 |
| G | Southern Pipeline Interconnector (SPI) Threshold | 50 |
| H | SPI Flowrate Threshold | 60 |
| I | Eastern Pipeline Interconnector (EPI) Threshold | 60 |
| J | EPI Flowrate Threshold | 60 |
| K | Brisbane to Nth Pine Threshold | 50 |
| L | Brisbane to Nth Pine Flowrate Threshold | 60 |
| M | Maroochy to Baroon Threshold | 50 |
| N | Ewen Maddock to Baroon Threshold | 50 |
| O | NPI 2 Threshold | 50 |
| P | NPI 2 Flowrate Threshold | 60 |

## 4.3. Decision Variables

The decision variables are variables that can be altered by the optimization algorithm to alter the operating rules, e.g., the trigger points that change the operation of infrastructure. These should be numerical, but can be either discrete (a set of values) or continuous (a range of values). For this case study, the decision variables are the thresholds of storage fullness in the operating rules that trigger the changes in operating mode, production volume, or flow rate. There are 16 decision variables in total, forming a decision variable set or vector of [A, B, C, ... P]. The decision variables are identified alongside the operating rules they comprise in Figure 3, with one decision variable for each operating rule. For the purposes of optimization, these decision variables are unconstrained, with feasible continuous values ranging from 0 to 1 (representing 0 to 100%).

## 4.4. Objectives and Objective Functions

The aim of the multiobjective optimization process is to find operating rules that perform optimally in terms of the management objectives. Objective performance is represented by objective functions, which in turn depend on information reported by the simulation model. Management criteria for short-term operational planning in South East Queensland currently include water security and operational cost. Proposed operating rules are also assessed for their potential to minimize flood risk or spills from storages, meet environmental flow and water quality targets, and minimize energy use (Seqwater 2014). Three of these concerns are included as objectives in this case study: maximizing water security, minimizing operational cost (including energy cost), and minimizing spills from reservoirs. Environmental flows are also included as minimum flow requirements or constraints within the model. It is anticipated that environmental flow, water quality, and energy-use criteria will be considered as part of multicriteria analysis after optimization. Objective functions have been identified for the three objectives as follows.

The first objective is to maximize water security. Operational plans for the South East Queensland water grid do not include an explicit water security objective, but water security concerns are expressed through level of service criteria and risk criteria (Queensland Water Commission 2012). The key aim of these criteria is to avoid low levels of system storage. Thus, this case study includes an objective of maximizing the minimum surface water-storage volume experienced over the planning period. This objective is represented by maximizing an objective function determining the minimum storage volume as shown in Equation 1:

$$MinimumSystemStorage = min\left(SystemStorage for t = 1, \ldots, T\right) \qquad \textbf{Eq. 1}$$

where $t$ is a time-step of the planning period of length $T$; and *System Storage* is the sum of storage volumes in the surface water storages (megalitres) for the time-step $t$.

The second objective of minimizing operational cost can be represented by an objective function summing the total cost of infrastructure operation on each time-step. Costs for this case study come from the same source used in South East Queensland (SEQ) operational planning, the Final report SEQ grid service charges (Queensland Competition Authority 2012). This report includes flow-based costs of major infrastructure elements such as pumping stations, treatment plants, and manufactured water sources. Since these costs include the cost of energy use, minimizing cost could also reduce energy consumption. Cost data are not available for switching direction in the pipeline, which will incur labor and other costs and thus in reality would affect the operational cost. Therefore a nominal value of AUS $40,000 per switch in pipeline direction is included in the objective function to avoid frequent switches. Checks confirmed that this nominal cost was sufficient to avoid frequent switching of pipeline direction in the planning period. The total cost objective function adds the costs for each time-step to reach a total cost for the time period as shown in Equation 2:

$$TotalCost = \sum_{t=1}^{T} \left[ \sum_{f \in F} Unit\,Cost * FlowRate + \sum_{p \in P} \$\,40{,}000 * Switch \right] \qquad \textbf{Eq. 2}$$

where $t$ is a time-step of the planning period of length $T$; $f$ is a node or link in the network (e.g., treatment plant, pumping station, or desalination plant) of the entire set $F$ with a unit cost ($/ML) and flow rate (ML/day); and $p$ is a two-way pipeline in the entire set $P$ with a cost ($) assigned to each *Switch* in direction.

The third objective is to minimize spills from the reservoirs in order to reduce the risk of flooding as well as place a value on surface water that might otherwise be spilled due to the effect of the minimum storage objective. This objective is expressed as the objective function in Equation 3, which adds the spills for each time-step to determine a total spill volume for the time period :

$$TotalSpillVolume = \sum_{t=1}^{T} \left[ \sum_{r \in R} SpillVolume \right] \quad \textbf{Eq. 3}$$

where t = time-step of the planning period of length T; r = reservoir of the entire set R; and Spill volume is given in ML.

No bounds (constraints) are put on the values of the objective functions to be considered by the optimization model. Additionally, due to the simplified nature of the case-study system, the values of the resulting objective functions should not be considered as representative of the real system, but used for comparative purposes only.

# 5. Methods and Techniques

## 5.1. System Simulation

System simulation software is needed to model the behavior of the water grid network under a set of operating rules. In the background framework paper (Ashbolt et al. 2014), Source (Dutta et al. 2013) was suggested as a suitable system simulation (and optimization) software tool for the purposes of the operational planning framework. Source is capable of modeling a variety of urban water supply system features in a node-link format, and also includes modules for integrated multiobjective optimization, catchment rainfall-runoff modeling, and river management. A function editor can be used to create functions to determine or represent the operating rules, decision variables, and objective functions. These functions can call upon system variables or other functions to determine their value and can be applied to the relevant nodes or links in the network. The optimization module interrogates the functions that represent decision variables and objective functions to perform the optimization. Given the capabilities of Source, this software tool was chosen to simulate (and optimize) the water grid for this case study.

A simulation model was constructed, using Source, to represent the case study as per the node-link network in Figure 2. Given the relatively short assessment period of 5 years, a daily time-step was chosen for simulation. This also allows the behavior of smaller storages such as weirs to be represented. Monthly inflow time-series and average monthly demand, sourced from current SEQ models, were disaggregated to a daily time-step with equal weighting. A 5-year period of the available modeled data, namely January 1, 2001, through December 31, 2005, was chosen as the inflow scenario, with initial conditions based on a long-term simulation ending at January 1, 2001. This time period is of lower flow conditions than average, with a mean flow of 9,961 ML/month compared to 37,958 ML/month for the whole period of available inflow data from July 1890 to June 2007. This would be expected to place the system under stress. Ideally, operating rules would be optimized across multiple inflow and/or demand scenarios; however, this significantly increases the model run time. For this paper, a single-scenario optimization is deemed sufficient for the framework proof-of-concept. Simulation can be used to assess performance of the operating rules against multiple inflow scenarios.

The simulation model also includes minimum environmental flow demands, storage losses, in-stream losses, storage-based restrictions on medium-priority demands, and diversions to off- stream storages. Functions were created to represent or calculate the decision variables, objective functions, and operating rules. Network Linear Programming using the RELAX IV algorithm (Bertsekas and Tseng 1994) is used to manage orders along multiple supply paths and implements the reservoir operating rules of equal draw-down of storages.

In order to compare the objective performance of optimized operating rules to the performance of rules-based operation using longer-term rules, the simulation model was used to determine objective performance of the base-case operating option using the existing operating rules outlined in Table 1.

## 5.2. Multiobjective Optimization

The multiobjective optimization process is an attempt to find operating options that are optimal in terms of the objective functions, by trialing different values of the decision variables that comprise the operating rules. The result of this process is a Pareto set of non- dominated operating options where no one option is better than any of the others in terms of performance against all objectives. In other words, for any given option, no other option will give an improvement in any of the objectives without sacrificing performance in another objective. This a posteriori approach allows for full consideration of the trade-offs in objective performance before articulating preferences on the objectives (Blasco et al. 2008; Zio and Bazzo 2011). This is particularly useful as it can be difficult to articulate preferences when the range of feasible objective performance is not known.

A genetic algorithm is used for optimization of the case study, as suggested in the background framework paper (Ashbolt et al. 2014). Genetic algorithms perform well when solving complex, nonlinear, and discontinuous problems since they have the ability to perform both exploration (global search) and exploitation (local search) of the search space and can exploit parallel computing to reduce run time (Nanda and Panda 2014; Reed et al. 2013). Genetic algorithms also do not require simplification of the optimization problem, so they can be linked directly to a simulation model. For this reason, they have been used widely in conjunction with simulation models in water-resource planning (Nicklow et al. 2010; Peralta et al. 2014). The ability to use existing and trusted simulation models can provide greater confidence in the results as well as a link to other planning processes through a common representation of system behavior (Labadie 2004).

The particular genetic algorithm used for this case study is NSGA-II (Deb et al. 2002), which has been used previously to optimize water supply operating rules for multiple objectives (Giuliani et al. 2014; Peralta et al. 2014), and performs well across a range of optimization problems (Wang et al. 2014). The NSGA-II algorithm is available in the Source software tool also used for simulation of this case study. The algorithm is linked directly to the simulation module. The default settings for the NSGA-II Source implementation were used. The default settings are a crossover probability of 0.9, mutation probability of 0.5, crossover distribution index of 5, mutation distribution index of 10, and a random seed for the first generation. Due to the random seed used, five optimization runs were undertaken, with five random seeds. The nondominated solutions from these five Pareto sets are then combined. A population of 200 and 150 generations were used for each seed, as inspection of the hypervolume (Zitzler and Thiele

1998) indicated this to be more than sufficient to converge on a well-distributed Pareto set. Ideally, the parameters of the NSGA- II algorithm would be calibrated to this problem, but the emphasis here is on proof-of-concept and user-friendly tools that can be implemented without expert knowledge. The population size is considered the key parameter to influence the reliability and efficiency of genetic algorithms, with the influence of algorithm parameters being most evident when the computational budget is limited (Deb 2001; Gibbs et al. 2015).

# 6. Results and Discussion

The result of a multiobjective optimization process is a Pareto set of non-dominated operating options. Applying the case study problem formulation and method described in the previous sections, a Pareto set of 677 non-dominated operating options was obtained from a total set of 1,000 options found from the five optimization runs. This Pareto set of operating options is optimal in terms of the three objectives of maximizing minimum surface water storage, minimizing operational cost, and minimizing spill from reservoirs, for the 5-year planning period (2001–2005). This Pareto dataset and source code for the following figures are available at https://github.com/StephanieCA/OptimisationWaterGrid.

Each of the operating options of the Pareto represents a set of 16 decision variable values comprising the operating rules. The objective performance and trade-offs of the Pareto set are shown in two-dimensional plots for pairs of objectives in Figure 4. The performance of the base-case operating option (rules-based operation), determined by simulation of fixed operating rules, is also shown in these figures as a large circle.

Figure 4(a) shows that there is a fairly linear trade-off between increasing minimum system storage and increasing total cost. However, this increase occurs in roughly three bands of minimum storage for cost. The grayscale shading indicates that total spill increases with minimum storage across these bands. While there is some increase in spill with minimum storage and cost, these bands indicate that a number of operating options have similar cost but different minimum storage and total spill. This suggests that different proportions of the high-cost water sources are being used for similar cost, with each source having different or conflicting impacts on the storage and spill.

Figure 4(b) shows that a clearer relationship exists between minimum system storage and total spill. For operating options with lower volumes of minimum storage, there is only a slight increase in spill with minimum storage. However, there is an inflection point beyond which there is a strong trade-off of increasing minimum storage for increasing total spill volume. This implies that for the operating options below this inflection point, a significant portion (in volumetric terms) of the surface water storages remain below capacity. For operating options beyond the inflection point, the increase in minimum storage places storages closer to capacity, resulting in higher quantity of spill. As for Figure 4(a), the grayscale indicates that cost varies significantly with spill and minimum storage, but that higher cost (lighter gray/white) is associated with higher spill and minimum storage.

Figure 4(c) shows a more-complex relationship between total cost and total spill. In the preferred region of lowest spill and lowest cost, the operating options create a small curve, where a decrease in spill trades-off for an increase in cost. However, for most of the operating options with medium to high spill volume, increasing cost is correlated with increasing spill. This may be due to a greater use of desalinated or potable recycled water, leaving surface water storage closer to capacity and increasing the probability of spills in response to high flow events. The grayscale indicates that these operating options also have fairly high minimum storage (darker gray). Finally, there are a range of operating options from medium to high cost with similar low levels of spill, and mostly low minimum storage (lighter gray). As per Figure 4(b), this may be partly due to most storages remaining below capacity despite an increase in minimum storage (which comes at a cost).

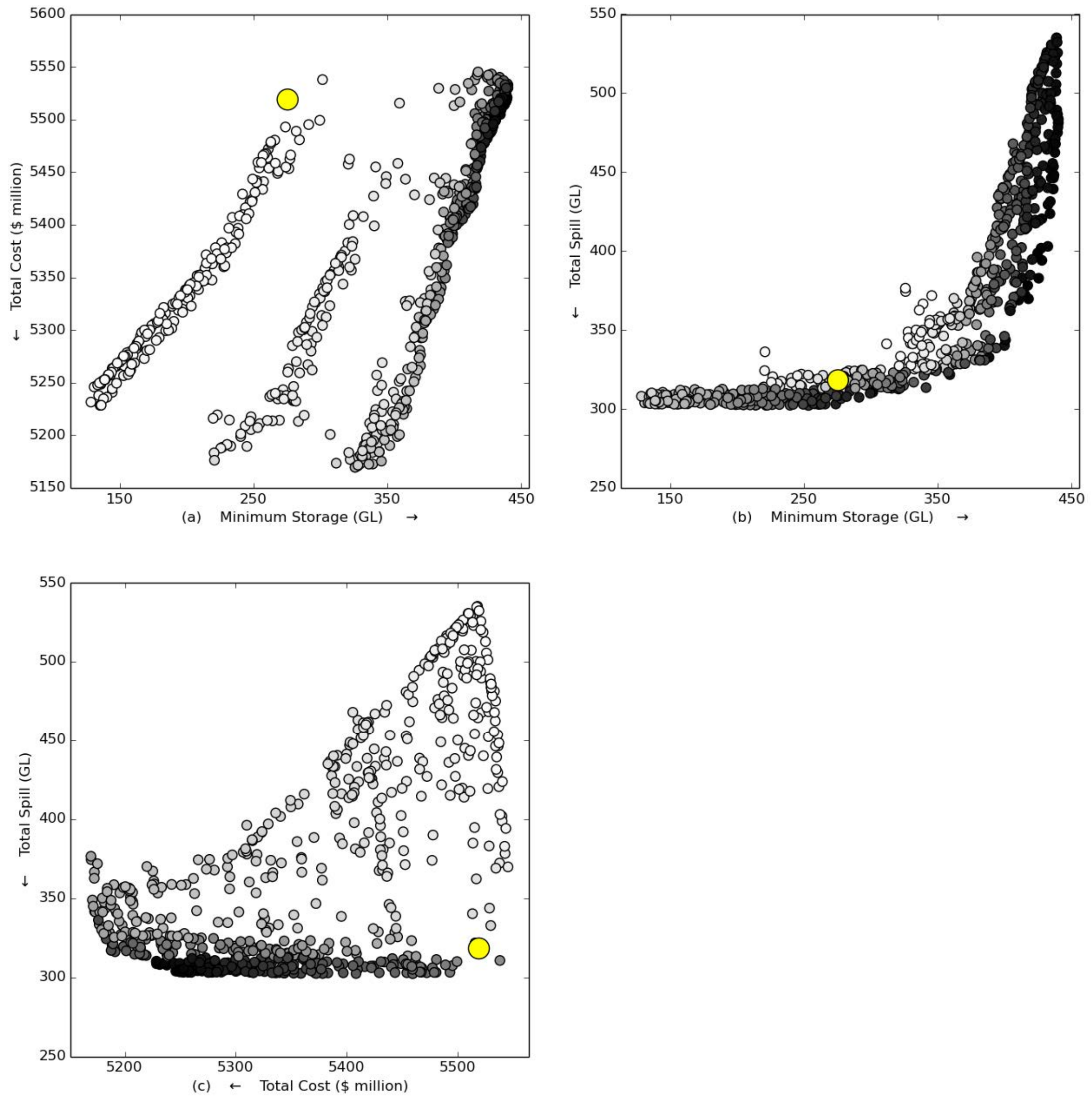


**Figure 4:** Pairwise decision maps of the Pareto set, showing values of the three objective functions of minimum system storage, total cost, and total spill volume; arrows on the axes indicate the direction of preference of each objective function: (a and b) towards bottom right corner; (c) towards left corner; grayscale is used to indicate the relative value of the third objective missing from each plot, with darker grays indicating better values (higher minimum storage, lower total cost and spill) and lighter grays indicating worse values (lower minimum storage, higher total cost and spill); the objective performance of the base-case operating option is shown by the larger circles.

The complex relationships between the three objectives, shown in Figure 4, suggest that different combinations of infrastructure usage can result in similar cost, but with different results for minimum storage and spill. This is likely due to the different characteristics of the higher-cost infrastructure. Greater production of desalination would be expected to increase the operational cost (compared to the use of surface water) and leave more water in reservoirs, increasing the minimum surface water storage and spill volume. Greater use of the two-way pipeline interconnectors, however, would be expected to also increase cost but potentially reduce spills without changing the minimum storage by drawing water from reservoirs that have higher storage fullness. Different proportions of use of these infrastructures would create the complexity seen in the trade-off curves.

Figure 4 also shows the objective performance of the base-case operating option using longer-term rules. While the base-case appears to outperform a few operating options in terms of the two-objective trade-offs in Figures 4(b and c), in terms of all three objectives, it is dominated by all the optimized operating options in terms of the three objectives. For example, one operating option has a higher minimum storage of 324 GL (compared to 275 GL), lower spill of 314 GL (compared to 318 GL), and a lower cost of $5,409 million (compared to $5,519 million).

Table 2 provides more details of selected operating options from the Pareto set: the operating options with lowest and highest total cost, lowest total spill, and highest minimum storage, as well as a moderate operating option with relative average performance on each of the three objectives and the base-case of rules-based operation. This table shows the objective performance, costs and production volumes of each of these operating options. The switching of pipeline direction appears to have little effect on the total cost, but is highest for the lowest spill option. Pumping cost is mostly associated with the flowrate in the two-way pipelines. Again, higher flowrate in the pipeline avoids spill but also increases cost. Treatment cost is associated with use of surface water and is the majority of the total cost. Higher desalinated water production is associated with higher cost, spill, and minimum storage.

**Table 2.** Details of objective performance, costs, and production volumes for selected operating options. Shading indicates the highest value for each column.

| Operating Option | Total Spill Volume (GL) | Minimum System Storage (GL) | Total Cost ($ million) | Switching Cost ($ million) | Pumping Cost ($ million) | Desalination Cost ($ million) | Treatment Cost ($ million) | Recycled water Cost ($ million) | Two Way Pipeline Flow (GL) | Desalination Total Production Volume (GL) | Potable Recycled Water Inflow (GL) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Lowest Total Cost | 332 | 328 | 5,180 | 0.28 | 23 | 1.2 | 4503 | 652 | 0.14 | 15 | 0 |
| Highest Total Cost | 378 | 417 | 5,542 | 0.2 | 43 | 338 | 4509 | 652 | 0.35 | 486 | 0.23 |
| Lowest Total Spill | 303 | 239 | 5,412 | 1 | 52 | 192 | 4515 | 652 | 0.35 | 272 | 0.23 |
| Highest Total Spill | 534 | 439 | 5,520 | 0.28 | 27 | 338 | 4502 | 652 | 0.21 | 486 | 0.23 |
| Lowest Min. System Storage | 308 | 128 | 5,232 | 0.28 | 51 | 1.2 | 4527 | 652 | 0.35 | 15 | 0.23 |
| Highest Min. System Storage | 484 | 440 | 5,530 | 0.12 | 33 | 338 | 4507 | 652 | 0.19 | 486 | 0.23 |
| Moderate/Balanced Option | 328 | 332 | 5,186 | 0.28 | 23 | 7.6 | 4504 | 652 | 0.14 | 22 | 0 |
| Base Case | 318 | 275 | 5,519 | 0.12 | 51 | 313 | 4503 | 652 | 0.35 | 448 | 0 |

Figure 5 shows the objective performance of the operating options given in Table 2, and how the performance of these operating options varies with different scenarios of inflow. The objective performance of the optimized operating options is shown as a bar plot. The inflow for optimization is around the second percentile of 5-year total flow. The lines indicate how the objective performance varies from the 10th to the 90th percentile flows, shown by two crosses connected by bars. These lines indicate that cost varies relatively little with inflow, but that minimum storage and total spill increase in flow. The spill is most significant, likely due to large flood events. This highlights the importance of including inflow sensitivity in multicriteria analysis, as this may change the operating option that is selected. However, while the performance varies with inflow scenario, this plot does not indicate whether this changes the optimality of the operating rules. Indeed, Figure 5 shows that operating options with higher minimum storage in the optimized inflow scenario also have higher minimum storage across inflow scenarios.

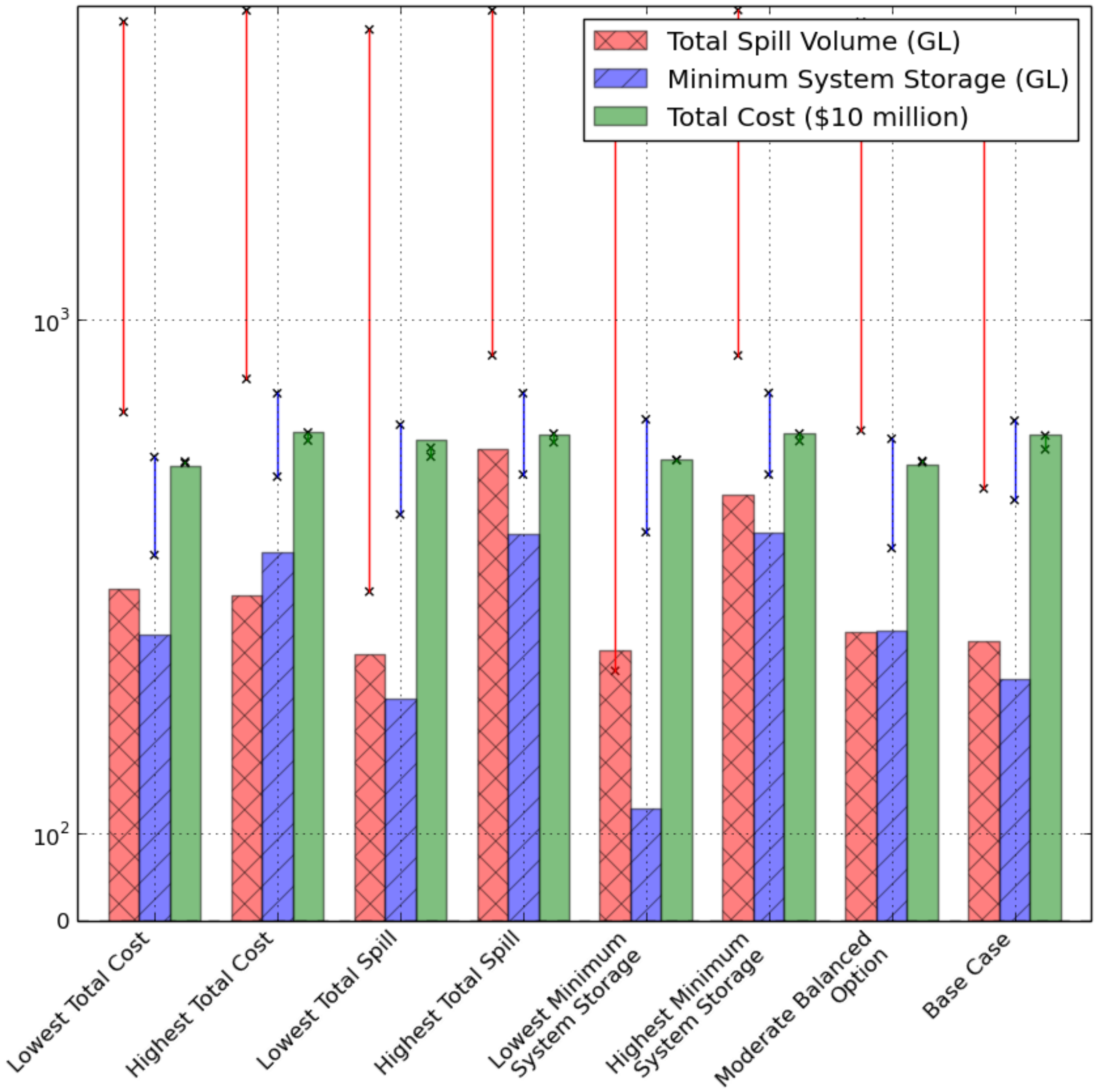


**Figure 5:** Objective performance of selected operating options; bars show the performance with the inflow scenario used in optimization; crosses indicate the performance with the 10th percentile 5-year low flow (lower cross), and the 90th percentile 5-year high flow (higher cross), connected by lines; a part log axis is used for clearer presentation.

Figure 6 shows histograms indicating the frequency and range of decision variables in the Pareto set. This plot shows that most of the optimized decision variable values vary across the possible range of 0 to 1 (representing 0 to 100%), but the values are often concentrated over a small range. This suggests that these decision variables may have a realm of optimality. Conversely, other decision variable values are distributed throughout the feasible range. The objective performance may be more sensitive to these decision variables.

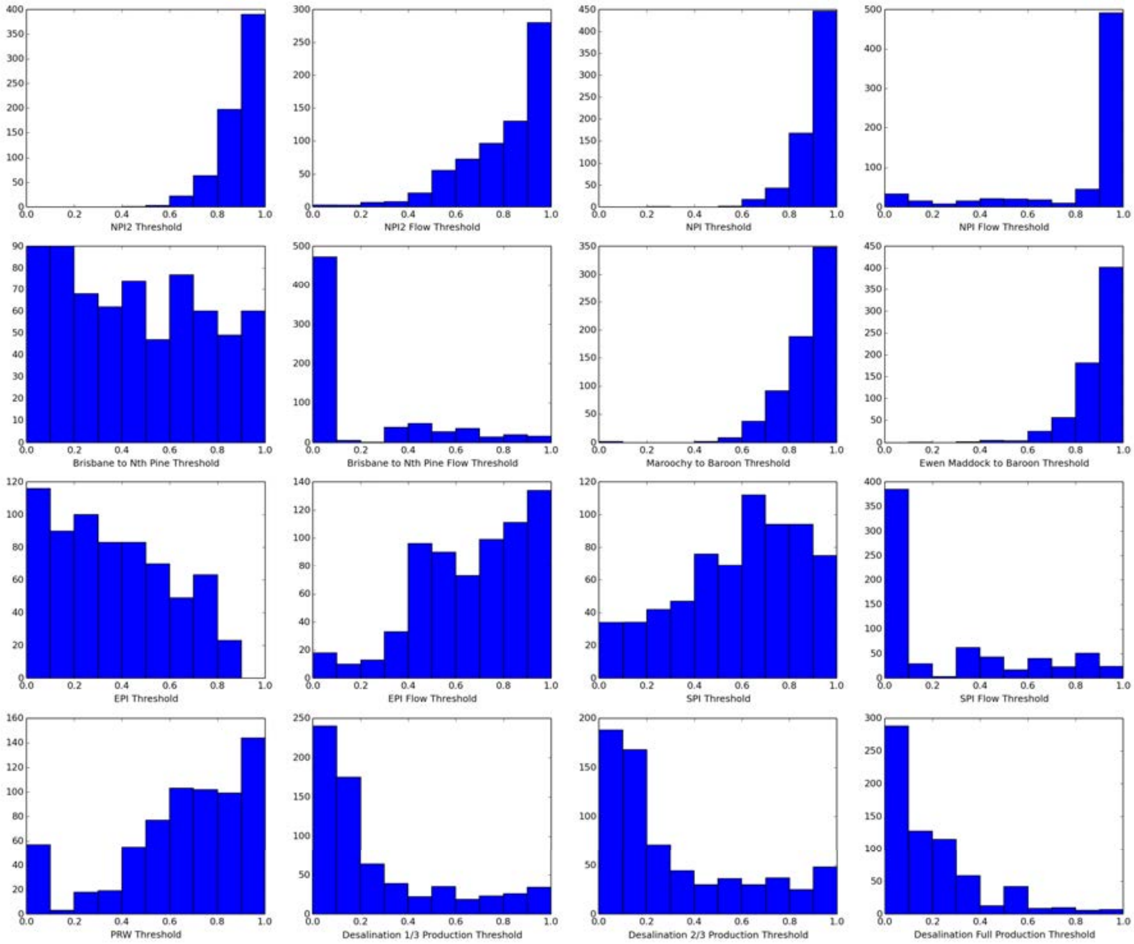


**Figure 6:** Histograms showing distributions of values of each decision variable across the Pareto set on separate plots; x-axis values range from 0 to 1, representing the decision variables values of 0 to 100%.

## 7. Conclusions

This paper demonstrates how multiobjective optimization can be used to find optimal operating rules for short-term planning for a complex water supply network such as a water grid and provide an improvement in objective performance over rules-based operation. The application of this method to a case study based on the South East Queensland water grid, using eWater Source software, shows that multiobjective optimization can be applied to a real-life water grid using publicly available tools and without requiring computer programming or complex mathematical knowledge. This successful implementation of the multiobjective optimization components of the framework also indicates the potential of the framework to support operational planning for water grids.

The operating options resulting from the multiobjective optimization process allow the trade-offs between multiple operating possibilities to be examined before placing preferences on the objectives. This transparency is the key to the a posteriori method of multiobjective optimization, and it allows the decision-maker to comprehend the decision and objective space before choosing a final operating option. For the case study, increasing the minimum system storage over the planning period generally comes at a trade-off of higher operational cost and higher volume of spills from reservoirs. These operating options represent a wide range of operating rules, represented by the decision variables.

The complexities in the trade-offs between operating options and distributions of the decision variables for the case study made it difficult to draw specific conclusions about the trade-offs between objectives and their relationship to the decision variables. Visual analysis tools are useful in understanding the objective and decision spaces. Such an understanding will provide the foundation for selecting promising operating options for further analysis, and for identifying sensitive or insensitive decision variables. For these reasons, further visual analysis is recommended as part of the framework, and a suite of visual analysis tools for analyzing the Pareto set will be demonstrated in a future paper.

Similarly, the large and complex Pareto set of the case study highlights the difficulty in identifying a single operating option to form the basis of the operating plan. For this reason, cluster, visual, and postoptimization analysis tools were recommended in the framework, for selecting a shortlist of promising operating options from the Pareto set. Multicriteria analysis can then be used to assess the operating options against additional management criteria. These criteria may include long-term planning criteria and objectives to ensure that short-term optimal operating rules do not compromise long-term performance. The remaining components of the operational planning framework for water grids will be demonstrated in future papers.

Finally, this paper assumes perfect knowledge of streamflow by optimizing operating rules to a historical planning period using modeled flow. This shows the potential benefits of optimization, but is evidently not the case in reality. Ideally, multiple possible scenarios of flow encompassing the range of historical or forecast conditions may be used for optimization, or optimized operating rules will be assessed against these multiple scenarios postoptimization. The sensitivity of operating rules to the inflow scenarios may be included as a criterion in multicriteria analysis, which is not part of the framework covered in this paper. Both the use of streamflow forecast scenarios and multicriteria analysis are part of the framework to be included in future papers.

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# Chapter 5: Interpreting the Pareto set

Chapter 4 identified a Pareto set of 677 operating options for the case study. Each operating option comprises 16 operating rules that provide optimal outcomes for the 1 year planning period and 5 year assessment period in terms of the three management objectives of maximising minimum system storage, minimising operational cost, and minimising spills from reservoirs. As concluded in the previous chapter, the size and complexity of the Pareto set makes it difficult to understand the trade-offs and select a single operating option. Thus this chapter proposes a combination of cluster, visual and post-optimisation analysis methods to interpret the Pareto set, to understand the relationships between objectives and identify a shortlist of operating options for further analysis. These components create an expanded version of the framework presented in Chapter 2, as shown in Figure 5.1.

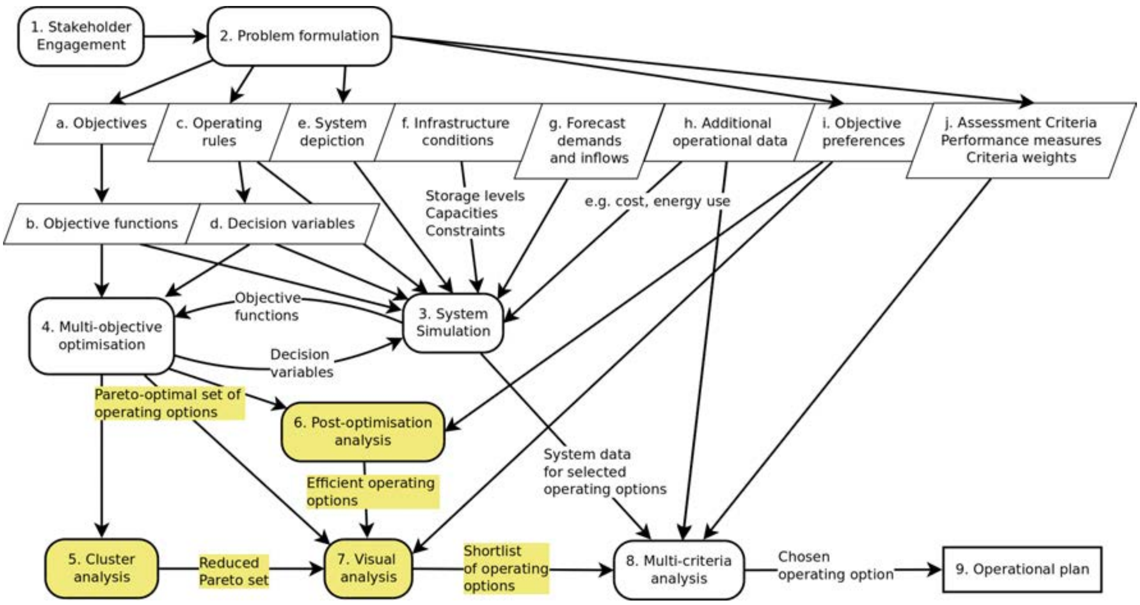


**Figure 5.1:** The framework for short-term operational planning of water grids, highlighting the components used for interpreting the Pareto set, covered in this chapter.

This chapter contains the following journal paper, which demonstrates the application of the framework components highlighted in Figure 5.1:

Ashbolt, S. C., Maheepala, S., and Perera, B.J.C., 2016, 'Interpreting a

Pareto set of operating options for water grids: a framework and case study', *Hydrological Sciences Journal,* Submitted.

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| Chris Perera | 10 | Feedback and discussion on the research and writing | | 6/7/16 |
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# Interpreting a Pareto set of operating options for water grids: a framework and case study

**Stephanie C. Ashbolt, Shiroma Maheepala, B. J. C. Perera**

## Abstract

Multi-objective optimisation is being increasingly applied in water supply management to identify optimal operating options. However, a key challenge in the implementation of multi-objective optimisation is interpreting the large and multi-dimensional Pareto-optimal set. This paper shows how cluster, visual and post-optimisation analysis can aid the decision-maker in addressing this challenge. This is demonstrated for a case study based on South East Queensland Water Grid, Australia, as part of a broader operational planning framework. Firstly, cluster analysis identifies a smaller set of representative options to aid in visual analysis. Secondly, visual analysis techniques are used to identify the trade-offs between objectives, the relationships between decision variables and objective performance, and to shortlist promising operating options. Finally, post-optimisation analysis techniques identify efficient operating options from the Pareto set, based on decision-maker preferences. Together these techniques can be used to identify a shortlist of operating options, for further consideration using multi-criteria analysis.

**Keywords:** visual analysis, post-optimisation analysis, cluster analysis, Pareto-optimal set, multi-objective optimisation, water supply planning

## Software/data availability

The case study dataset, diagrams, and results, as well as the source code (Jupyter notebooks and R project file) used to generate them are available to view at https://github.com/StephanieCA/visualisation-pareto-set.git. To run the Jupyter notebooks requires Jupyter Notebook with the interactive Python (IPython) kernel, and the Python programming language. For this study, version 4.1.0 of Jupyter, IPython 4.1.1 and Python 2.7.6 were used. These are free and open source. Installation instructions for Jupyter Notebook, including IPython and Python, are available at https://jupyter.readthedocs.org/en/latest/install.html. R (Project for Statistical Computing) is required to run the R project file. R version 3.1.1 was used, with R Studio version 0.99.879. R is available free at https://www.r-project.org/. R Studio provides a graphical user interface for R and is free and open source, available at https://www.rstudio.com/products/rstudio/download/.

# 1 Introduction

Urban water supply networks are growing in complexity as they are expanded, interconnected and diversified to meet the challenges of climate variability, climate change and population growth. Water supply managers need to identify operating rules for these systems that satisfy multiple objectives such as maximising water security, reliability, and environmental flows; and minimising operational cost, flood risk and energy use. Multi-objective simulation-optimisation is a useful decision support tool to navigate this complexity. It can help the water manager to find operating rules amongst a vast number of possibilities, that are optimal in terms of the management objectives. *A posteriori* multi-objective optimisation of these operating rules results in a Pareto set of operating options, each of which is optimal (non-dominated) in terms of all objectives due to the trade-offs between them. Examining the Pareto set *a posteriori* allows the decision-maker to consider the performance possibilities and trade-offs before supplying preferences on the objectives and selecting a single operating option (Coello Coello et al., 2007). However, the Pareto set usually contains a large number of operating options in a complex multi-dimensional objective and decision space, which can be overwhelming to interpret (Lotov and Miettinen, 2008). Further, the decision-maker needs to reduce this Pareto set to a shortlist or smaller set of alternatives that is easier to comprehend, compare and assess against additional management criteria (Brill et al., 1990). Multi-criteria analysis can then be used apply preferences select a single operating option for implementation (e.g. Kasprzyk et al., 2013; Malekmohammadi et al., 2011; Matrosov et al., 2015). The preferences of decision-makers may evolve during consideration of the Pareto set, as the relationships between objectives become understood (Brown et al., 2015). Thus tools and guidance are required for interpreting and comprehending the Pareto set, to understand the relationships between objectives and decision variables, to refine preferences on objectives, and to identify efficient options from the Pareto set as a shortlist for multi-criteria analysis. Indeed, the ability to visualise trade-offs and select efficient operating options has been identified as one of the research challenges and barriers to the implementation of multi-objective optimisation algorithms (Branke et al., 2008; Maier et al., 2014).

Guidelines on the application of optimisation algorithms recommend a range of techniques for interpreting or managing the Pareto set (Branke et al., 2008; Deb, 2001). These techniques fall into three broad categories: cluster, visual, and post-optimisation analysis. Cluster analysis can help reduce the number of operating options by grouping those with similar objective and/or decision variable performance (Zio and Bazzo, 2011). This reduced set of operating options allows for easier application of visual analysis techniques, or can be used to identify a shortlist of operating options that encompass the full range of objective performance. Visual analysis is useful for exploring the multidimensional Pareto set, identifying innovative operating options, and understanding relationships between the decision variables and the objectives (Fleming et al., 2005; Giuliani et al., 2014b; Kollat and Reed, 2007). Finally post-optimisation analysis techniques are a group of analysis tools that are implemented after optimisation to identify efficient and/or preferred operating options on a numerical basis (Deb, 2001). Combinations of several visual, post-optimisation, and cluster analysis techniques have been shown to help in the understanding the trade-offs of the multi-objective Pareto set (Kasprzyk et al., 2013; Kollat and Reed, 2007; Matrosov et al., 2015; Zio and Bazzo, 2011). Additionally, many of these techniques have been discussed in depth in the optimisation literature (e.g. Blasco et al. 2008; Lotov and Miettinen 2008). Miettinen (2014) also provides a review of different visual analysis techniques and how they can be used to compare a shortlist of alternatives obtained from multi-objective optimisation or multi-criteria analysis. However, a gap exists in demonstrating how cluster, visual, and post-optimisation analysis techniques can be applied in combination, to a real-world large Pareto set, to understand the decision and objective space, and from this understanding to identify a shortlist *a posteriori*. Thus in this paper, the authors demonstrate how cluster, visual, and post-optimisation analysis techniques can be used in water supply operational planning to better understand the Pareto set and to generate a shortlist of operating options for multi-criteria analysis. Application of these techniques is expected to result in a shortlist of operating options that represent the breadth of the Pareto-optimal set, efficiency of trade-offs in objectives, and the preferences of decision-makers. This is demonstrated for a case study of short-term operational planning for a complex water supply network based on the water grid in South East Queensland, Australia.

## 2 Case study

This paper examines a case study considering the multi-objective optimisation of operating rules for short-term operational water supply planning. The case study is based on the water grid in South East Queensland, Australia. This water grid consists of 28 surface water storages, 3 groundwater borefields, a wastewater recycling scheme for potable reuse, a desalination plant, and 48 urban and irrigation demands. Seven two-way pipeline interconnectors also connect these water sources and demands across catchment boundaries. The case study has three management objectives for 5 year short-term planning: minimising total operational cost, minimising total spill volume from storages, and maximising the minimum system storage volume. These are the objectives against which operating rules were optimised, measured by three objective functions which are aggregated over the five-year planning period. There are 16 operating rules identified for optimisation. These govern the operating mode and flow rate of the 7 two-way pipeline interconnectors, wastewater recycling scheme and desalination plant. These operating rules include 16 decision variables (A, B, …, P), which represent the thresholds of storage levels which trigger a change in the operating mode or flow rate, and thus alter the operating rules. These decision variables can range in value from 0 to 1, and refer to the ratio of 'fullness' (volume/capacity) of local, regional, or system-wide surface water storage. The key features of the case study system, as well as the operating rules and decision variables are shown in Figure 1. In Ashbolt et al. (2016) multi-objective simulation-optimisation was applied to the case study using the Source simulation-optimisation software (Dutta et al., 2013) to identify operating rules that are optimal in terms of the three management objectives. Source uses the NSGA-II genetic algorithm (Deb et al., 2002). Further details of the multi-objective simulation-optimisation process is provided in Ashbolt et al. (2016).

The result of multi-objective optimisation of the case study problem was a Pareto set of 677 operating options that are optimal in terms of the three objectives of minimising total operational cost, minimising total spill, and maximising minimum storage (Ashbolt et al., 2016). These 677 options were the non-dominated options obtained from combining five Pareto sets of 200 individuals optimised using different random seeds. The objective performance of the Pareto set of operating options is shown in the scatter plot in Figure 2. The cluster, visual, and post-optimisation analysis techniques discussed in Section 3 will be used to better understand this Pareto set and to shortlist promising operating options for further multi-criteria decision analysis.

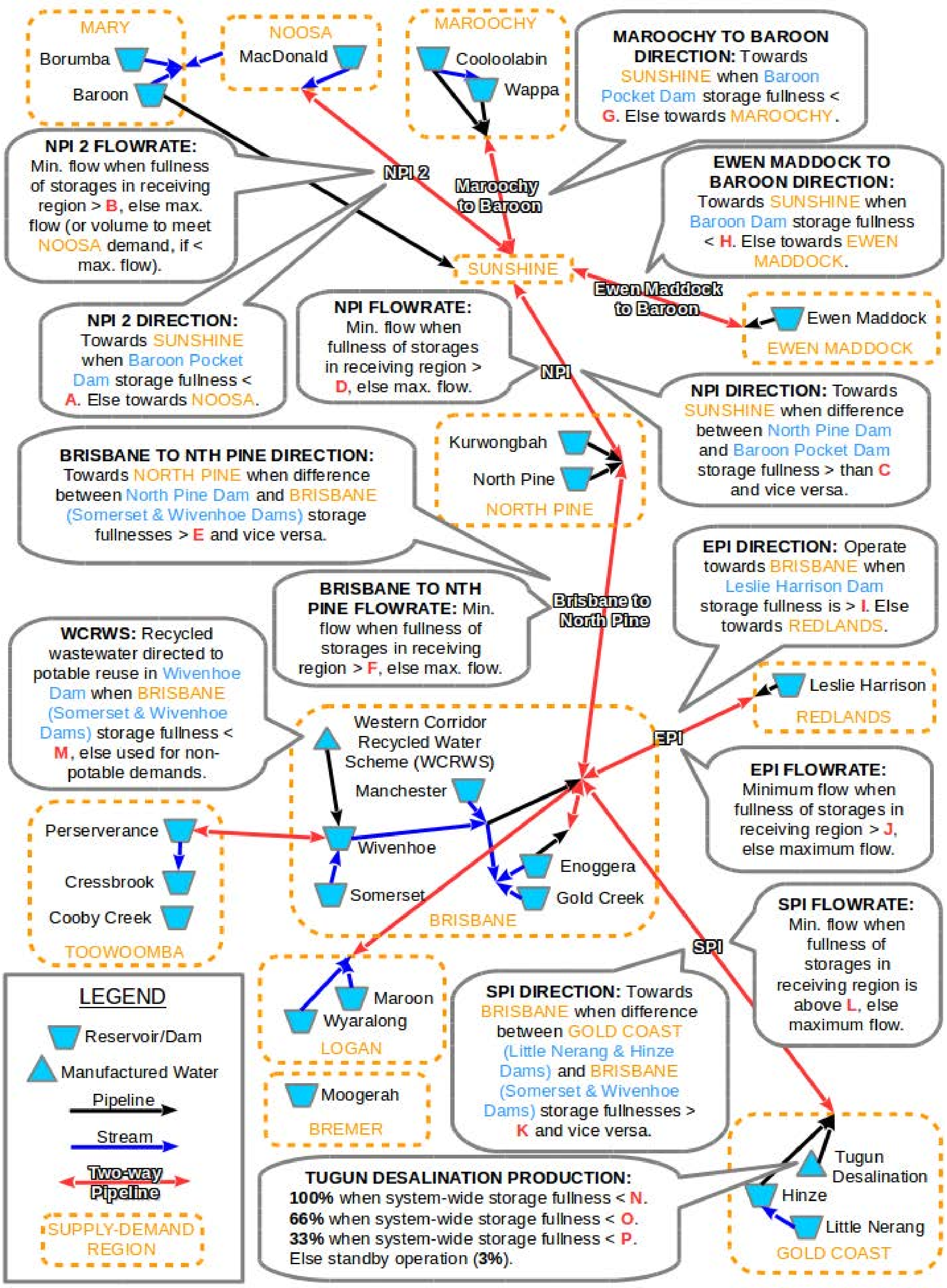


*Figure 1: Schematic of the case study network, showing major infrastructure and supply-demand regions. The operating rules which govern this infrastructure are outlined in the call-out boxes. The decision variables pertaining to these operating rules are highlighted in bold (A, B, …, P). The supply-demand regions also include a number of demands as well as pipelines, streams, weirs and groundwater supplies, not shown on this figure but included in the simulation model.*

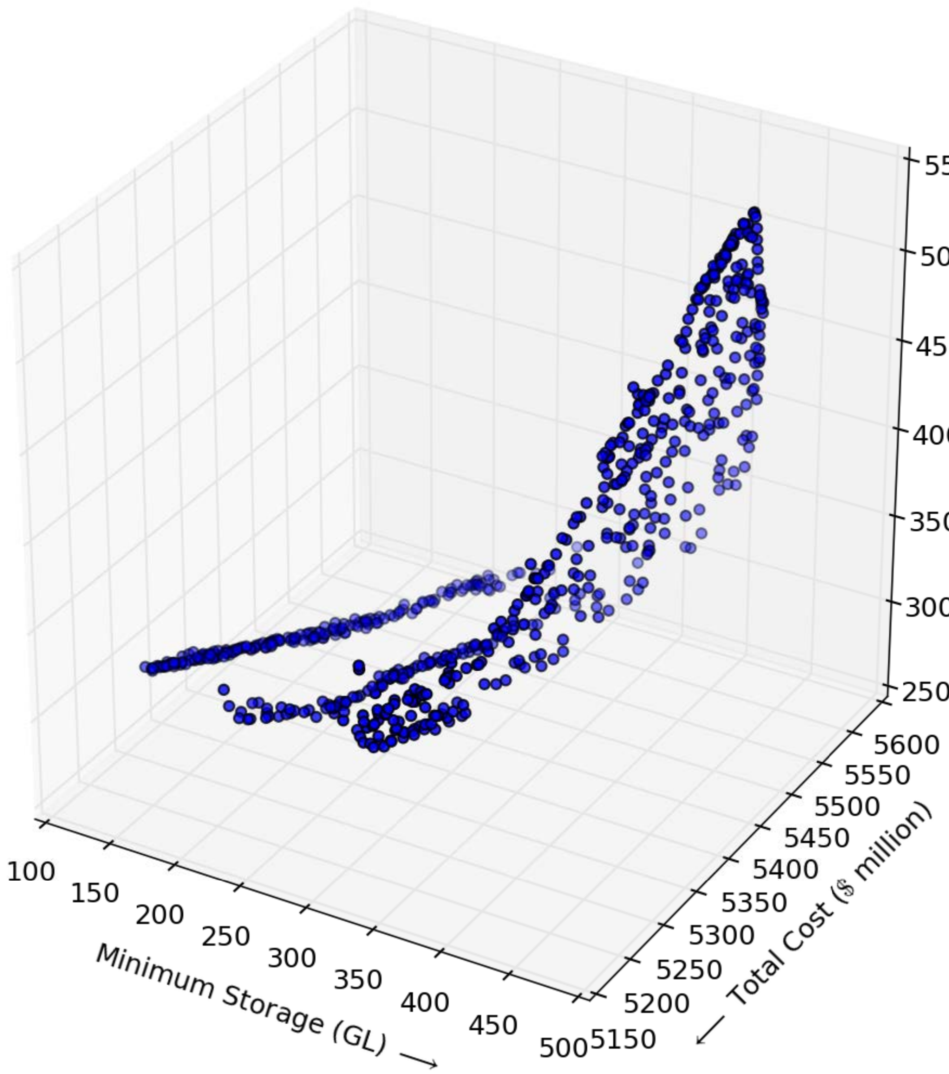


*Figure 2: Objective performance of the case study Pareto set of operating options. Points with lighter shades indicate greater distance or depth from the viewer. The preferred direction of objective performance is indicated by arrows on each axis label and lies towards the bottom front of the figure.*

# 3 Methods, Techniques and Application

## 3.1 Framework

The method forms part of a framework for operational planning for water grids, first presented in Ashbolt et al. (2014) and shown in Figure 3. Steps 1 to 4 of the framework concern problem formulation and multi-objective simulation-optimisation of operating rules. Steps 2-4 were demonstrated in Ashbolt et al.,

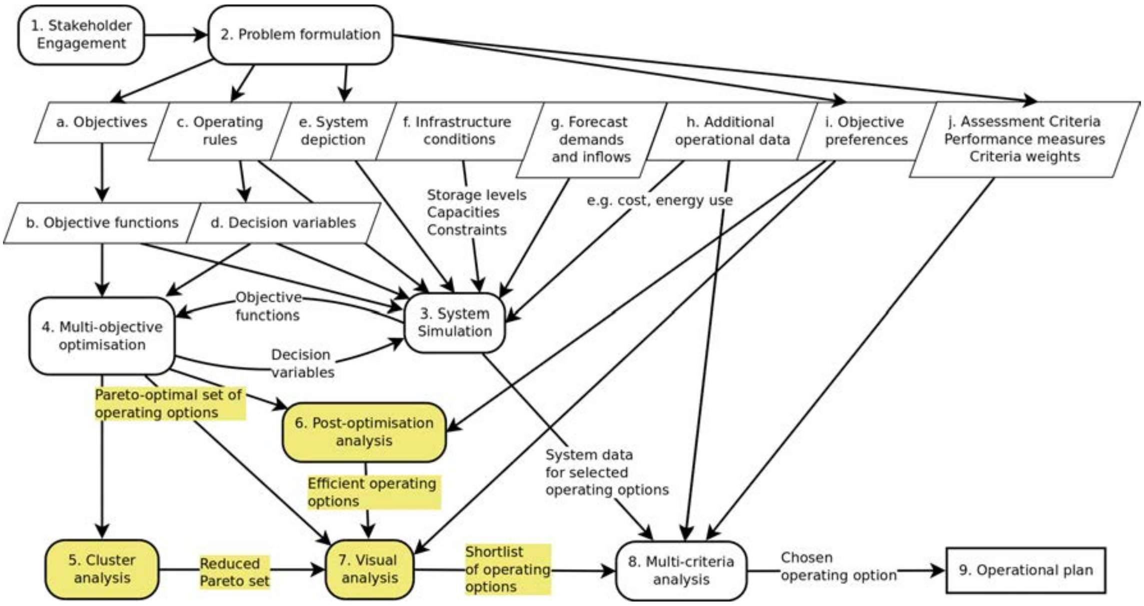


*Figure 3: Framework for operational planning for water grids, adapted from (Ashbolt et al., 2014). Processes are represented as rounded rectangles 1-9, and inputs as parallelograms a - j. Methods for interpreting the Pareto set, including cluster, visual and post-optimisation analysis are highlighted in the figure and form the methodology for this study.*

(2016), and the outcome is a Pareto set of operating options such as that presented in Figure 2. Steps 5 to 7 involve methods for interpreting and understanding the Pareto set and reducing it to a shortlist of efficient operating options and/or those that reflect decision-maker preferences. Step 8 involves multi-criteria analysis to assess the shortlist against additional management criteria, and rank options by incorporating preferences on this criteria. The highest ranked option can be used to inform an operational plan in Step 9. Steps 5 to 7, highlighted in Figure 3, are demonstrated in this paper.

Steps 5 to 7 work as follows. The multi-objective optimisation process results in a large *Pareto set of operating options.* Each *operating option* consists of a set of decision variables that is optimal in terms of objective performance. These decision variables represent the operating rules. *Cluster analysis* is used to divide the operating options of the Pareto set into a small number of groups with similar objective performance. The *cluster representatives* at the centre of each of these clusters form a reduced set of options that cover the full range of objective performance and make visual analysis easier. Cluster representatives can also be added directly to the shortlist, if the decision-maker wishes to create a shortlist encompassing the full range of objective performance. *Visual analysis* helps to explore the trade-offs between objectives and the relationships between decision variables and objective functions. During visual analysis, the decision-maker may also identify promising operating options to add to the shortlist, based on their preferences. Their preferences may also evolve during this process. Multiple visual analysis techniques are presented as part of this step, since each of these techniques differ in their abilities to illustrate the decision variable and objective function space, and thus the insights they provide. Finally, *post-optimisation analysis* techniques is used to identify *efficient operating options* from the entire Pareto set to add to the shortlist. Several post-optimisation analysis techniques are available, each of which differs in how it measures efficiency and how or whether it incorporates preference weights on the objectives. The decision-maker could select a final option using a single post-optimisation analysis technique and a single set of preferences. However, this reduces the advantages of *a posteriori* analysis, where the full Pareto set of possibilities is examined. Further, each technique and preference scenario will likely identify a different operating option as most efficient, creating some uncertainty in this selection process. Therefore it is recommended that the decision-maker implement multiple post-optimisation analysis methods and preference scenarios, and add multiple operating options to the shortlist for further consideration. The shortlist identified from both visual and post-optimisation analysis can then be further examined and assessed using multi-criteria analysis to select a final operating option.

During the visual and post-optimisation analysis, preferences on the objectives are used to guide the selection of efficient or promising operating options for the shortlist. These preferences may be those of the decision-maker and/or stakeholders, and may range from a single explicit (numerical) set of preference weights to a more general preference for objective performance. For the case study, an example of an explicit set of preferences would be a 70% weighting on cost, and 15% weighting each on minimum storage and spill, and an example of a general preference may be for selecting low-cost operating options. These preferences may arise or be refined during visual or post-optimisation analysis. Multiple preference scenarios may also be considered, to create a shortlist that encompasses a range of objective performance. For the case study, current operational planning does not include explicit preferences on the objectives. Therefore the authors create three hypothetical preference scenarios to be considered whilst shortlisting operating options: for balanced operating options, i.e. those that perform relatively equally in terms of the three objectives; for low cost operating options; and for at least one high minimum storage option. These preference scenarios are used to guide the identification of promising operating options from the visual analysis and post-optimisation analysis examples. Due to the reproducible or repeated nature of the analysis, these preferences could be updated as further information is gathered, or as they change over planning cycles.

The cluster, visual, and post-optimisation analysis components (Steps 5-7) of the operational framework are described and demonstrated in Sections 3.2, 3.3, and 3.4, through application to the case study Pareto set. As discussed in Ashbolt et al., 2014, a single suite of simple and readily available tools are recommended and demonstrated as suitable for implementing each component of the framework. For implementation to other systems, alternative tools may be added or substituted according to the preferences or needs of the decision-maker. The output of these analyses is a shortlist of operating options for the case study, described in Section 4. The shortlist can be used in multi-criteria analysis for selection of a final option, however this step will be covered in a future paper. The visual analysis techniques implemented in Section 3.3 also result in various insights into the Pareto set, including the relationships between objectives and between decision variables and objective functions. Both R (R Core Team, 2015) and IPython (Pérez and Granger, 2007) have been used to implement the cluster, visual and post-optimisation analysis, and the scripts used for this analysis are made available for the reader at https://github.com/StephanieCA/visualisation-pareto-set.

### 3.2 Cluster analysis

Cluster analysis is a method used in data mining to group data-points with similar characteristics, and can be achieved using one of a variety of algorithms (Nanda and Panda 2014; Wu 2012). It can be applied to the Pareto set to divide it into a number of groups (clusters) with similar objective performance (Obayashi and Sasaki, 2003; Pryke et al., 2007; Zio and Bazzo, 2010) or decision variable values (Cela and Bollaín, 2012). A representative operating option from each cluster can then be used to form a reduced set of operating options that can be used to simplify visual representation of the Pareto set. Even when the entire Pareto set is represented in visual analysis, cluster membership can also be used to highlight or group operating options based on similarity in objective performance or decision variable values. The reduced set of cluster representatives could also be added directly to the shortlist to provide a set of options that encompass the full range of objective performance (Zio and Bazzo, 2011), if there are no preferences on the objectives or decision variables.

Epsilon-dominance sorting is one technique for reducing the size of the Pareto set during the optimisation process, by adapting the population size between generations to achieve a user-specified resolution in objective performance (Laumanns et al., 2002; Salazar et al., 2016). However, the resolution is likely to remain too large for some of the visual analysis techniques, or for direct addition to the shortlist. Nevertheless, optimisation algorithms that incorporate epsilon dominance could be used to improve the diversity, convergence and reduce the resolution of the Pareto set. This reduced resolution may also make visualisation easier. However, such an algorithm is currently not available in the Source software used for this case study so is not implemented here.

For application of the framework in Figure 3, a cluster analysis algorithm is required that can divide the Pareto set *a posteriori* into a given number of roughly even-sized non-overlapping clusters around a representative operating option (cluster representative). This cluster representative must be a member of the Pareto set, rather than interpolated from cluster members. Only one cluster analysis algorithm is desired, to produce a single reduced set for visual analysis. However, different clustering algorithms will likely identify different cluster groupings and representatives (Cela and Bollaín, 2012; Nanda and

Panda, 2014), and so the decision-maker should consider adjacent operating options if selecting cluster representatives for the shortlist.

K-medoids is a simple partitioning prototype-based algorithm that divides a dataset into non-overlapping clusters around representative medoids (Kaufman and Rousseeuw, 1990; Wu, 2012). It involves optimisation to group a dataset of vectors into a specified number of clusters, such that the distance from each medoid (central datapoint in the cluster) is minimised. The medoid becomes the cluster representative, and is a member of the Pareto set. K-medoids is available in R (R Core Team, 2015) as the function *pam* in the *cluster* package using the partitioning around medoids (PAM) algorithm (Maechler, 2013). The user specifies the number of clusters, *k,* and the algorithm randomly selects *k* of the data points as medoids, allocating the remaining data points to the nearest cluster medoid. The process is then repeated by swapping in alternate medoids to find the configuration that has the lowest distance of cluster members to medoid. Where the user does not wish to specify a particular number of clusters, the function *pamk* in the fpc R package (Hennig, 2013) can be used to implement the *pam* algorithm and determine the optimal number of clusters (*k*) using the silhouette method (Rousseeuw, 1987), within a range specified by the user.

The *pamk* function is applied to the case study Pareto set of 677 operating options, to identify clusters and cluster representatives (medoids) based on the values of the three objective functions, and with an upper limit of 20 clusters. As a result, 10 clusters are identified. The clusters and their medoids are highlighted on the Pareto set scatterplot in Figure 4, with points coloured according to cluster membership, and cluster medoids indicated as larger points. The cluster medoids provide a reduced Pareto set of 10 operating options, encompassing the range of objective performance. This reduced set can be used for the visual analysis techniques. For this case study, the medoids are not added directly to the shortlist, but instead considered for the shortlist when they are presented during visual analysis.

For the case study, the Pareto set is clustered according to objective function

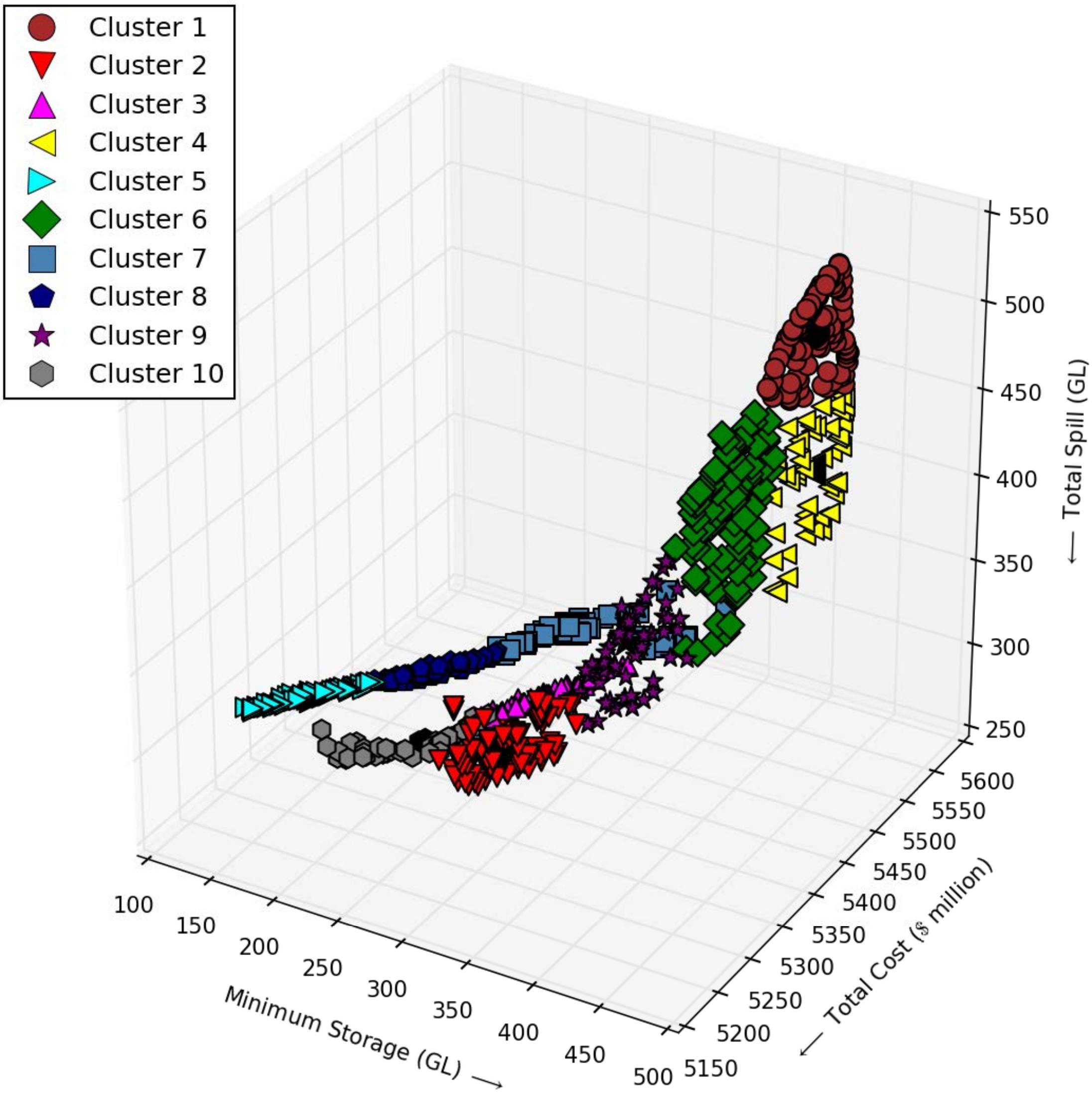


*Figure 4: Scatterplot of the Pareto set clustered using k-medoid algorithm, with 10 clusters identified as different colours and markers. Medoids of clusters are indicated by black markers.*

values, since the aim is to aid in visualisation of objective performance, rather than directly produce a reduced set for shortlist. Further, the case study has no preferences on decision variables that may lead to consideration of clusters based on these values. However, alternative approaches could be to cluster based on decision variable values, or both decision variable and objective function values. For the latter case, the objective function values can be normalised to place them on the same scale as the decision variables (i.e. 0 to 1). Cluster analysis results from these alternative approaches are shown in the datafiles at https://github.com/StephanieCA/visualisation-pareto-set.git, and in the supplementary figures. All three clustering approaches result in different clusters for the case study, indicating that decision variables do not always correlate closely with objective performance. Thus the decision-maker should be mindful of these limitations when identifying or choosing clusters, and choose the cluster scenario/s that best reflect their needs or interests.

In summary, cluster analysis can be used to group operating options with similar objective performance and/or decision variable values, to assist in visual analysis. Clustering can also be used to identify operating options for the shortlist, however the decision-maker should be mindful that clusters based on objective functions may differ significantly in their decision variables. Thus it is recommended that clustering based on objective performance not be used to directly reduce the Pareto set for shortlist if there are preferences on the decision variables. Instead, clustering is best used to aid in visualisation. When shortlisting, the decision variables of adjacent cluster members with similar objective performance should be considered. For the case study, 10 clusters and cluster representatives are identified based on objective function values, resulting in a set of options which encompass the full range of objective performance of the case study Pareto set. These are used to aid the visual analysis techniques.

### 3.3 Visual analysis

The following subsections describe a number of visual analysis techniques and demonstrate their application to the case study multi-objective Pareto set. These techniques are summarised in Table 1. Numerous techniques have been included as they each elucidate different aspects of the decision variable and objective function space, or present the Pareto set in a different format. Additionally, the techniques are suited either to demonstrating the full Pareto set or a reduced set of cluster representatives (cluster medoids). Cluster membership can also be colour-coded in visual analysis, to enable operating options with similar objective performance to be traced between plots.

*Table 1: Summary of visual analysis techniques presented as part of the framework for interpreting the Pareto set.*

| | Technique | Input | Best illustrates |
|---|---|---|---|
| 1 | Scatterplot, 3D Scatterplot | Entire Pareto set | Objective function performance of 2 or 3 objectives |
| 2 | Scatterplot matrix | Entire Pareto set | Objective function performance of > 3 objectives; relationships between objective functions and/or decision variables |
| 3 | Histogram | Entire Pareto set | Distribution of objective functions or decision variables |
| 4 | Density plot | Clusters | Distribution of objective functions or decision variables |
| 5 | Line diagram | Cluster representatives | Objective function performance of > 2 objectives |
| 6 | Bar chart | Cluster representatives | Objective function performance of > 2 objectives |
| 7 | Radar chart | Cluster representatives | Objective function performance of > 2 objectives |
| 8 | Parallel coordinates | Entire Pareto set | Objective function performance of > 2 objectives or decision variable values |
| 9 | Level diagram | Entire Pareto set | Relationships between decision variables and objective function performance |
| 10 | Decision maps | Entire Pareto set | Objective function performance of 3 objectives |
| 11 | Glyph plot | Entire Pareto set | Objective function performance of > 3 objectives; relationship between decision variables and objective function performance |
| 12 | Heatmap | Cluster representatives | Objective function performance of > 2 objectives and decision variable values |

Sequential or parallel examination of the figures resulting from visual analysis can provide insight into different aspects of the objective function and decision variable spaces. Whilst there is some cross-over in the information presented by the visual analysis techniques in Table 1 – e.g. line diagram, bar chart, and radar chart – they present this information in different formats which may lead to different insights. However, a decision-maker may wish to choose a subset of these techniques depending on the number of objectives, what the decision-maker wishes to illustrate, and preferences of a decision-maker for a particular format (e.g. line diagram vs radar chart). In this paper, we present all these techniques and discuss their insights for the case study, thus providing some information on the key advantages of each technique. The visual analysis techniques in the following subsections are presented in a sequential manner, with each technique demonstrated by providing progressive insight into different aspects of the case study. However, it is recommended that the decision-maker consider these figures in parallel.

Whilst the primary purpose of visualisation is to understand the characteristics of the Pareto set, promising operating options may be selected for the shortlist if they reflect decision-maker preferences. During the application of the visual analysis techniques to the case study, a number of operating options are identified for the shortlist, which are presented in Section 4.

### 3.3.1 Scatterplot and scatterplot matrix

The results of optimisation are most commonly visualised as a scatterplot of the objective function performance of the Pareto set, as was shown in Figure 2. This type of graph is straightforward to interpret when there are only two objectives. However, the plot becomes more difficult to interpret for three objectives, and cannot show more than three objectives. For example, in Figure 2 it is somewhat difficult to discern the nature of the trade-offs. Instead, a scatterplot matrix can be used to represent three or more objective functions as a series of 2-dimensional plots (Cleveland, 1985). This involves plotting scatterplots of all possible combinations of variables as pairwise comparisons. Such a plot allows the relationships between variable pairs to be more clearly seen. The diagonal of the scatterplot matrix is also frequently plotted as a histogram or kernel density plot, which illustrates the distribution of values of each variable. A scatterplot matrix of the objective function performance of the case study Pareto set is shown in Figure 5, including histograms indicating the distributions of the values of the three objective functions. The plot points are coloured and marked according to cluster membership, with the same scheme as used in Figure 4 and subsequent plots. This enables clusters, i.e. operating options with similarity in overall objective performance, to be traced across the subplots and plots.

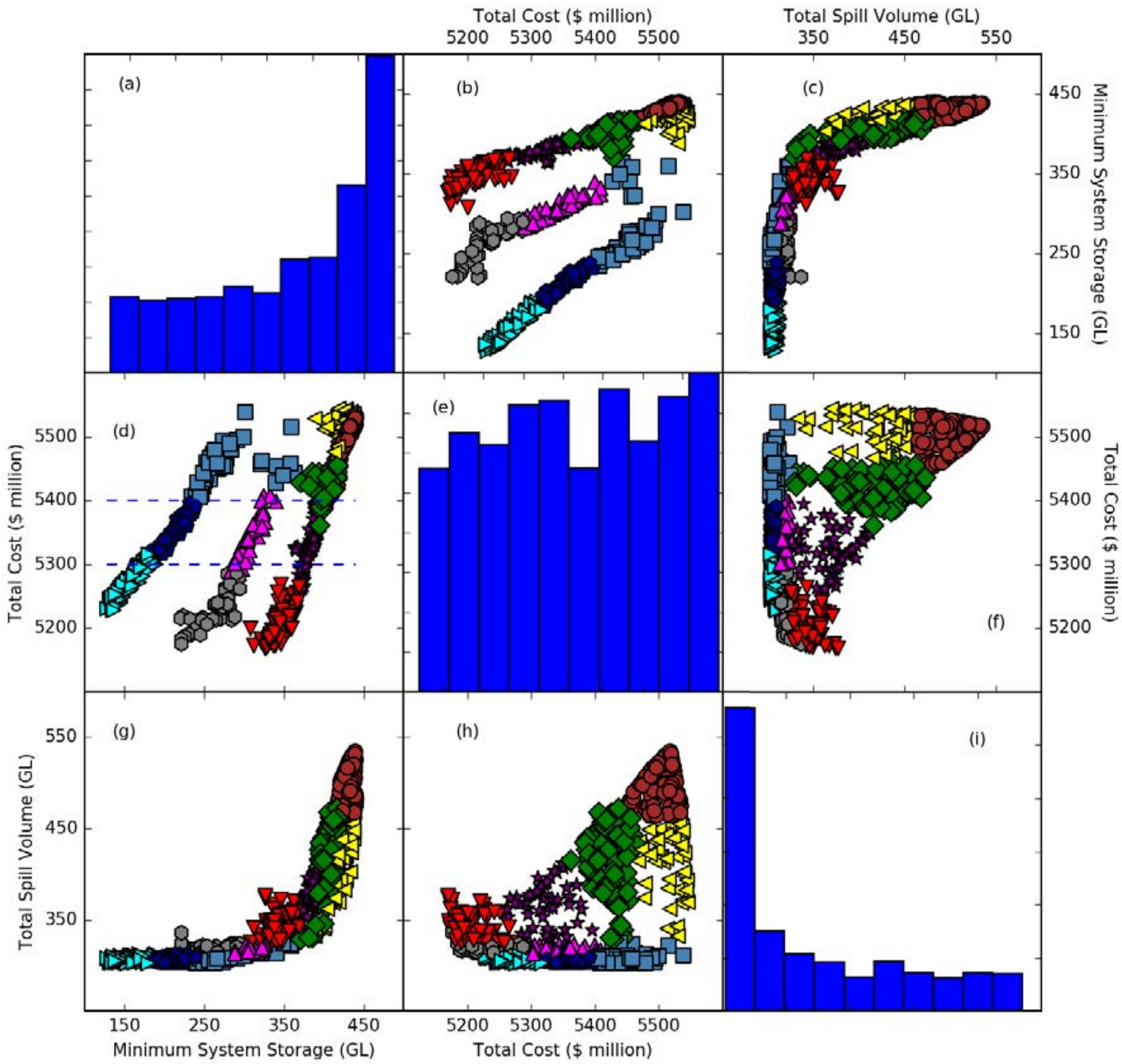


*Figure 5: Scatterplot matrix showing pairwise comparisons of the objective function performance of the case study Pareto set of operating options. Points are coloured according to cluster membership. This colouring is consistent between subplots and the other figures shown in visual analysis. Histograms showing the distribution of each objective function are plotted on the diagonal.*

The scatterplot matrix in Figure 5 illustrates the trade-offs between objectives for the case study more clearly than the three dimensional scatterplot in Figure 2. The plots of minimum system storage against total cost (Figures 5 b and d) indicate that cost increases fairly linearly with minimum storage across the operating options. This is as expected, since the use of higher cost sources such as desalination to meet demand is likely to leave more surface water in the storages. However, these plots also indicate that there is a range in value of minimum storage for a given cost, indicated by the dashed lines marked on Figure 5 d, which cross roughly three bands in the 2-dimensional slice of the Pareto surface. This suggests that the remaining objective function, total spill from reservoirs, has a strong influence on the optimality of the operating options. Indeed, Figures 5 c and g clearly show that spill increases with minimum storage. Figures 5 c and g also show that spill remains at a relatively constant low volume across low to medium minimum storage operating options, but there is an inflection point beyond which an increase in minimum storage is associated with a significant increase in spill. This is an expected consequence of higher storage volumes placing reservoirs closer to capacity and therefore increasing the risk of spill. However, Figures 5 f and h show a more mixed relationship between total spill and cost. Approximately half of the operating options have similar low spill volumes, but range widely in cost. The remaining operating options with higher spill volumes tend to see an increase in cost with spill. This suggests that some high cost infrastructure increases spill, whilst others have little effect on spill. Finally, the histogram in Figure 5 e indicates that operating options are fairly evenly distributed across the range of possible total cost, but Figures 5 a and i indicate that operating options are skewed towards high minimum storage and low spill volume.

Scatterplots or a scatterplot matrix can also be used to examine the relationship between decision variables and the objective functions. Figure 6 shows scatterplots of the values of the case study Desalination Full Production Threshold decision variable against the three objective functions. This decision variable represents the threshold of system storage fullness (ratio of volume to capacity) below which desalinated water is produced at full capacity. These figures indicate that overall, an increase in the Desalination Full Production Threshold correlates with an increase in minimum system storage, cost and spill. This relationship is strongest for cost and spill, and at higher decision variable values. This means that initiating full production of desalinated water at higher storage volumes is associated with higher minimum storage, cost and spill over the planning period. This is as expected, since greater use of desalinated water to meet demand should leave more surface water in the reservoirs, increasing minimum storage and likelihood of spill. This desalinated water comes at a higher cost than the surface water sources.

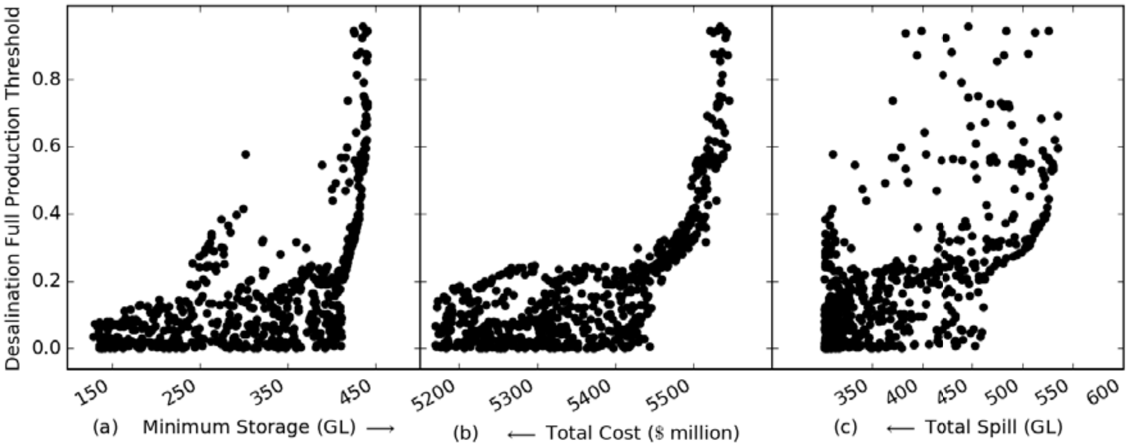


*Figure 6: Scatterplots of desalination full production threshold (decision variable) plotted against the three objective functions: (a) Minimum storage, (b) Total Cost and (c) Total Spill. Arrows on the x axes indicate preferred direction of objective function.*

In summary, the scatterplot is a straightforward method to illustrate the objective performance and trade-offs of the Pareto set. However the scatterplot is limited to three dimensions, and the three-dimensional format can be difficult to read. The scatterplot matrix makes the Pareto set trade-offs easier to discern by plotting all possible combinations of variables in two-dimensions. The key drawback of the scatterplot matrix is that only partial trade-offs are shown on each plot, and what might appear to be a promising operating option on the two-objective plane may not be when the other objectives are considered. Thus promising operating options may not be selected for the shortlist from the scatterplot. Instead the three-dimensional scatterplot is best used to provide a simple overview of objective performance, and the scatterplot matrix to understand objective trade-offs in more detail and to investigate relationships between the objective functions and the decision variables. Indeed a scatterplot matrix of all decision variables and objective functions can be used to identify interesting relationships between objective and decision variable pairs.

### 3.3.2 Histogram and density plot

A histogram provides an illustration of the distribution of a dataset, by dividing the dataset into a number of bins over set intervals across the range of the dataset and counting how many points of the dataset fall into each bin. It can be used to examine the distribution and density of the objective functions or decision variables of the Pareto set. The scatterplot matrix of the case study Pareto set in Figure 5 included histograms indicating the distribution of the objective functions throughout the entire Pareto set. Figures 5 a, e, and i showed that whilst the operating options are fairly evenly distributed in cost, there are a higher concentration of high minimum storage and low spill options.

The density plot is closely related to the histogram. It estimates the likely density or distribution of a variable, assuming that the data given are a sample of a larger set. In this application, the key advantage of the density plot over the histogram is that it provides similar information but with a smoothed line rather than bars. This allows distributions of multiple datasets or subsets to be plotted legibly on the one figure. The density plot is particularly useful for illustrating the distribution of objective functions or decision variable values for each cluster, to assess their similarity or differences. Figure 7 uses kernel density estimation, applied in Python's pandas data library, to compare the distribution of values of the case study Desalination Full Production Threshold decision variable for each cluster. This plot shows that many of the clusters have similar and overlapping values of this decision variable. The main exceptions are Cluster 5 with particularly low values and Clusters 1 and 4 with a wide range in values, across much of the feasible range (0 to 1). Although the clusters were determined by objective function value, and have similar performance (as shown in Figure 4), Figure 7 indicates that this does not mean they have similarity in the decision variable values. The conclusion is that the decision variables of an operating option at one point in the three-dimensional objective function space of the case study are not necessarily similar to those of operating options at adjacent points.

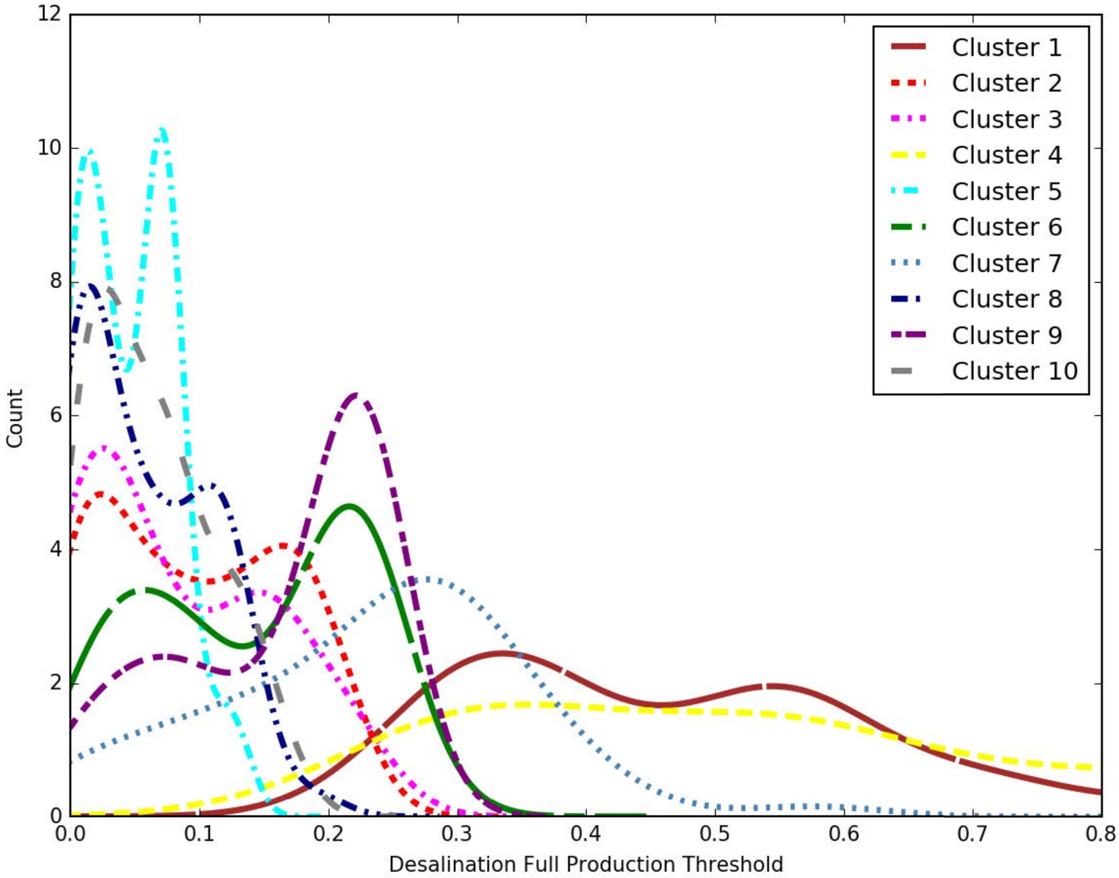


*Figure 7: Density plot of Desalination Full Production Threshold decision variable for each cluster*

In summary, both the histogram and the density plot can be used to understand the distribution of operating options within the objective and decision spaces. The histogram is best suited to illustrating the distribution of individual objective functions or decision variables. The density plot can be used to overlay and compare distributions of variables between clusters. This indicates whether or not operating options that are adjacent in the objective space are also adjacent in the decision space. This similarity or dissimilarity of decision variables should be considered when selecting an operating option from the cluster representatives. It must be noted that since the density plot provides a smoothed estimated distribution rather than actual values of the Pareto set, it is not as accurate as the histogram and should be used only for comparative purposes.

### 3.3.3 Line diagram and bar chart

The line diagram and bar chart are both straightforward visual analysis methods that can be used to illustrate objective performance of multiple operating options on a single two-dimensional plot. They require the use of the reduced set of cluster representatives, in order to have a legible number of lines or bars. Both the line diagram and bar chart provide the same information, but with a different format for plotting the values. A line diagram of the objective performance of the 10 case study cluster representatives (medoids) is shown in Figure 8 and a bar chart of the same set is shown in the supplementary files. For both plots, the x-axis indicates each cluster medoid, and the y-axis shows the objective function values. Each objective function value is normalised relative to the minimum and maximum values of the entire Pareto set, with 0 representing the best value (minimum cost and spill, maximum minimum storage), and 1 the least-preferred or worst value (maximum cost and spill, minimum minimum storage). This normalisation allows the objective function values to be plotted on the same axis, and indicates the relative performance of each operating option within the entire Pareto set. Lines or bars that are further apart indicate a stronger trade-off between objectives.

Figure 8 clearly shows that there is considerable variation in objective performance between operating options. It also shows that many operating options have strong trade-offs between objectives, indicated by larger distance between lines. For Medoids 1, 4, and 6, higher cost and total spill trade-off for higher minimum storage, to varying degrees. Medoids 3, 5, 7 and 8 provide lower spill, with a trade-off of lower minimum storage and higher cost. Medoids 2 and 9 appear to be the most balanced operating options, with more similar relative objective performance. Medoid 2 is a low cost operating option that provides lower spill and lower cost than Medoid 9, for a relatively small trade-off in minimum storage. This option might be shortlisted if water security is not an immediate concern; otherwise Medoid 9 provides a similarly balanced option with higher minimum storage, for a modest trade-off in cost and spill. In this case, both are added to the shortlist.

In summary, the line diagram and bar chart can be used to compare a reduced set of operating options, such as cluster representatives. They are simple techniques that allow the decision-maker to compare relative objective performance and trade-offs of selected operating options. These plots provide similar information: the bar chart makes the values of the objective functions easier to discern, but the line diagram would be more suited to a larger number of objectives. From these plots, promising operating options can be identified for the shortlist, based on decision-maker preferences. The key disadvantage of these figures is that they are limited in the number of objectives and operating options they can clearly present.

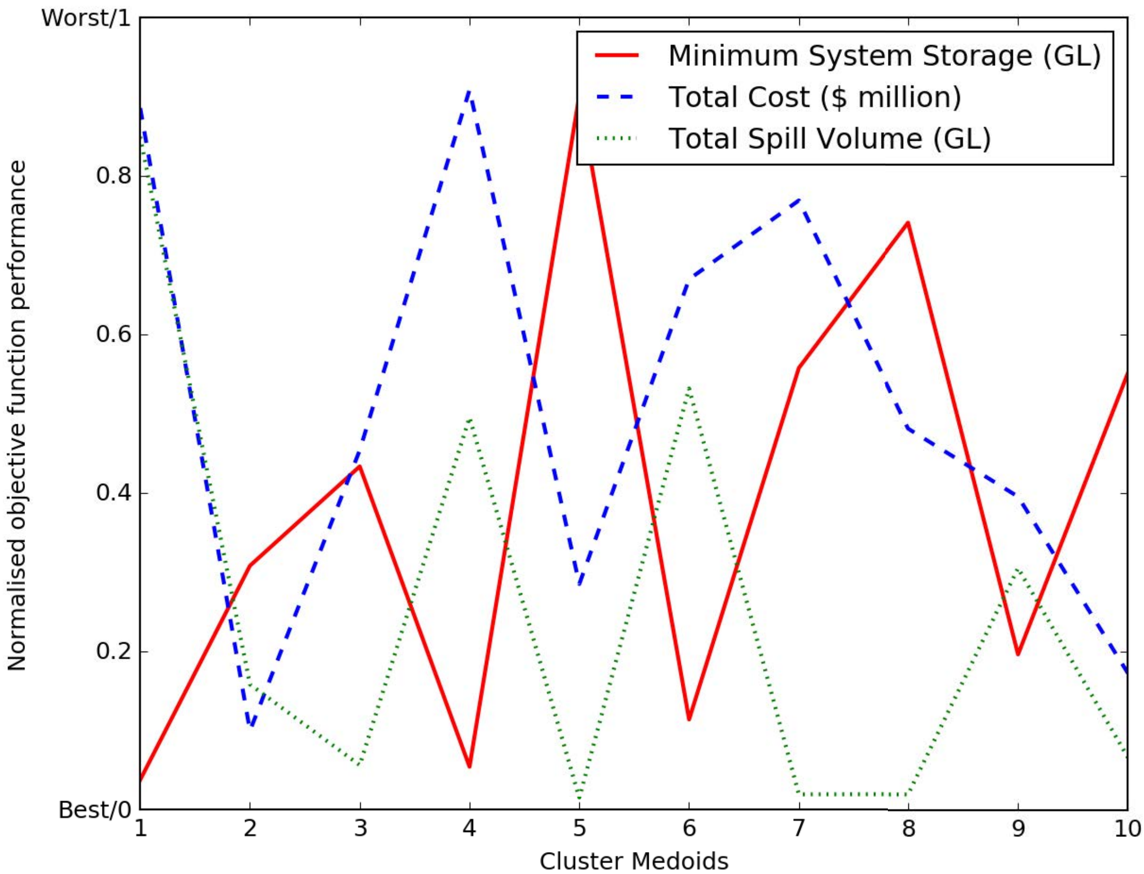


*Figure 8: Line diagram of normalised objective performance (y-axis) for each cluster medoid (x-axis) of the case study. A value closer to 0 is closer to the ideal point (minimised for cost and spill, maximised for storage) and 1 is farthest from the ideal point.*

### 3.3.4 Radar chart

The radar chart and the closely related spider-web diagram or star coordinate plot can be used to represent the multi-objective performance of operating options on a two-dimensional plot (Deb, 2001; Miettinen, 1998). Capability to plot radar charts is available in most spreadsheet or statistical software. Multiple operating options are either presented as separate lines on the one plot or on separate plots. Figure 9 shows a set of radar charts, one for each of the 10 cluster medoids of the case study Pareto set. Each objective function has a separate radial axis, and lines plot the objective function values. These values are normalised, as for the line diagram, from 0 to 1 relative to the rest of the Pareto set. A value of 0 represents the 'best' value (minimum cost and spill, maximum minimum storage), and 1 the 'worst' value (maximum cost and spill, minimum minimum storage) in the entire Pareto set. The best value is oriented at the centre of the radar chart and the worst at the outer circle. The space enclosed by the lines is filled to provide an idea of the 'shape' of each operating option. This shape provides a simple visual clue to the objective performance of each operating option. A larger size indicates a poorer objective performance, such as the high cost and spill of Medoid 1. The shape also provides an indication of the balance or trade-off between objectives. Medoids 2 and 9, which were shortlisted from the line diagram and bar chart as relatively balanced operating options, have smaller triangles with sides of similar length. The radar charts suggest Medoid 10 as promising, with low spill and cost, for a moderate trade-off in minimum storage. Thus this operating option is added to the shortlist.

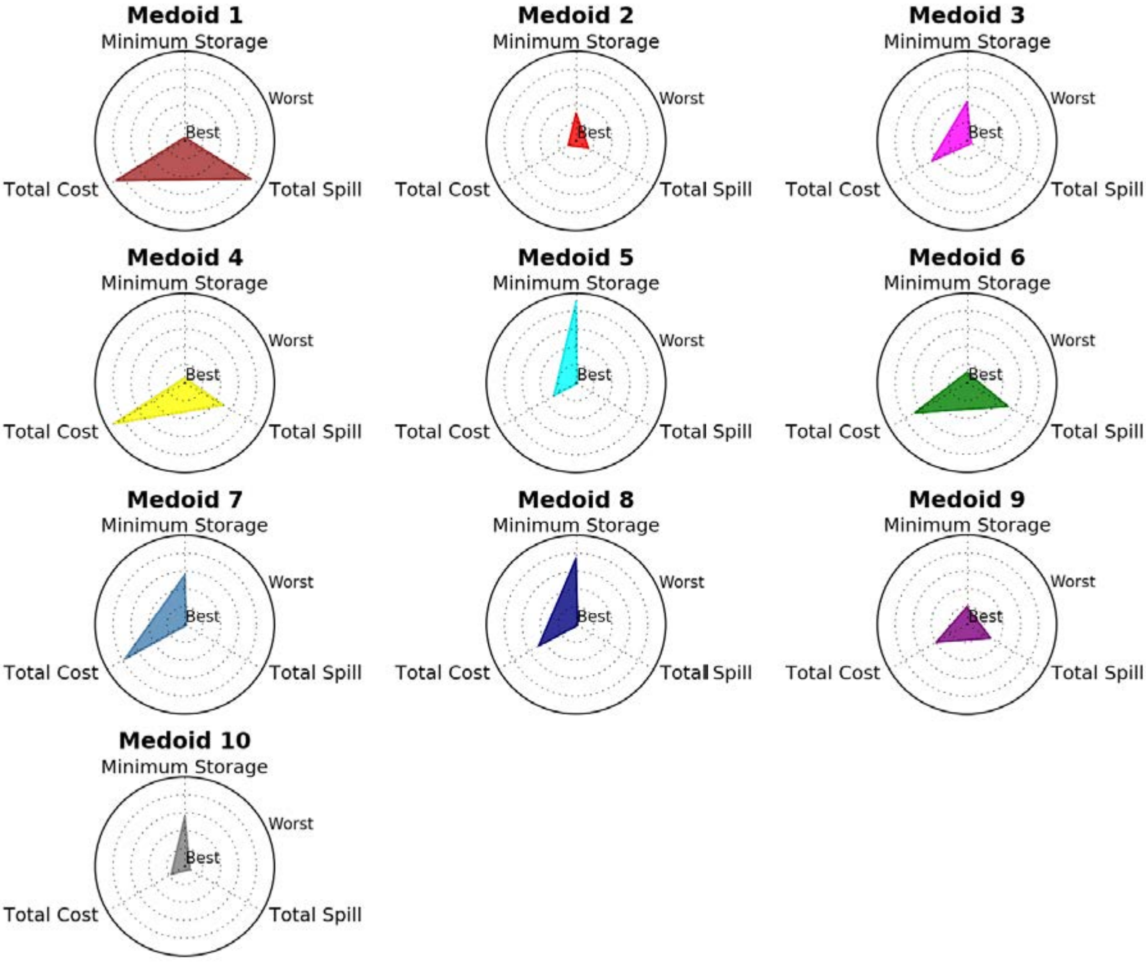


*Figure 9: Radar chart showing normalised objective performance of cluster medoids, with best performance at the centre of the circles and worst performance at the outer circle. Colours of each medoid are the same as those used to identify their clusters in other figures.*

In summary, the radar chart provides an overview of a small set of operating options, where the size and shape of the polygon creates a picture of the relative objective performance and balance between objectives. Although operating options can be drawn on the one plot as for the line diagram and bar chart, separate plots can represent more objectives and/or operating options in a legible manner. Overall it is a helpful tool in providing a snapshot of selected options and for selecting promising operating options for the shortlist.

### 3.3.5 Parallel coordinates

Parallel coordinates (also called parallel axis or value path) is a popular method for representing many dimensions on a two-dimensional plot (Inselberg, 2009).

This method can be used to compare relationships between objectives and/or decision variables, and is often used in optimisation studies to examine the Pareto set (e.g. Giuliani et al. 2014a; Kasprzyk et al. 2013; Kasprzyk et al. 2012). It can be considered is an enhancement of the line diagram, with the x-axis plotting a series of parallel y-axes, one for each variable. Each of these parallel y-axes indicate the values of a variable, bounded by the variable's maximum and minimum values. Each member of a dataset is plotted as a value on each of the parallel y-axes, connected by lines between adjacent axes. This plot gives a qualitative assessment of the spread of the variables, and of the trade-offs between adjacent variables (Deb, 2001). If the axes are oriented such that the preferred direction is the same, parallel lines between adjacent axes indicate a positive relationship between the two variables. Crossing lines, on the other hand, indicate a trade-off between variables, with a steeper slope indicating a stronger trade-off. The relationships are most clearly shown between adjacent axes: reordering of axes is required to highlight relationships between certain variable pairs. Unlike the line diagram, the entire Pareto set can be represented on the parallel coordinate plot. However, the plot can still be difficult to read with a large number of axes or lines. Colouring schemes can help to track lines across the parallel axes, by 'brushing' options according to cluster membership or the values of one or more objectives. This 'brushing' technique can be used to identify potential options of interest, such as those that perform in the best 5-10% for each objective (Inselberg, 2009).

Figure 10 shows a parallel coordinates plot of the objective function performance of the case study Pareto set. Due to the large number of decision variables of the case study, decision variables are not included on this plot. However, an example is included in the supplementary files. This plot was constructed using the *pandas* library in Python programming language. Again, as for previous figures, the objective function values are normalised respective to the minimum and maximum values, with 0 representing the best value (minimum cost and spill, maximum minimum storage), and 1 the least-preferred or worst value (maximum cost and spill, minimum minimum storage). The operating options are 'brushed' (coloured) to highlight the options that perform

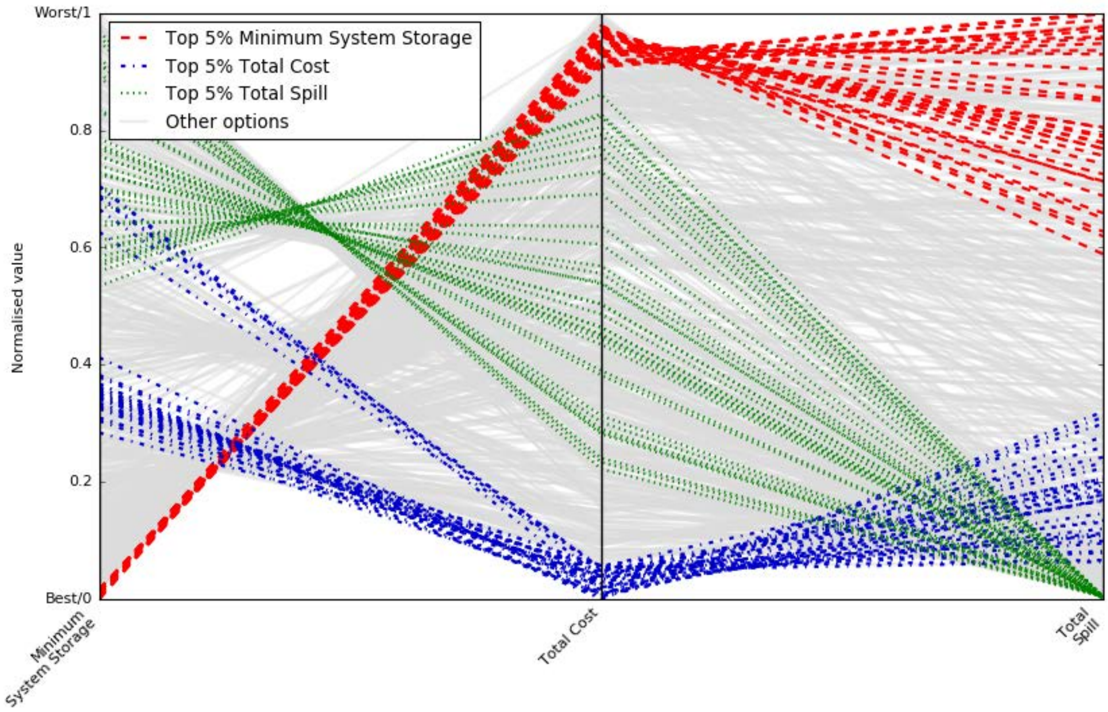


*Figure 10: Parallel coordinates plot showing objective performance of the Pareto set, brushed for the top 5% of each objective. Objective function values are normalised from 0 to 1, with 0 indicating the value closest to the ideal (preferred) point of highest minimum storage and lowest total cost and total spill.*

in the top 5% for each objective (highest minimum storage, lowest cost and spill), with the remainder of the Pareto set shown in grey. It is clear from this plot that there are strong trade-offs between objectives, indicated by the steep and crossing lines. These trade-offs are strongest between minimum storage and total cost. However, for some operating options there is correlation (parallel lines) between cost and spill. The plot also indicates that operating options that perform best in terms of total cost (blue lines) perform fairly well in terms of minimum storage and total spill, with a relatively small trade-off in these two objectives required to obtain the lowest cost. The top 5% options for minimum storage, however, are amongst the highest cost and highest spill options: it is clear that achieving the best performance in terms of minimum storage comes with a strong trade-off in terms of cost and spill. The top 5% performing options of total spill have a wide range of cost and minimum storage, although generally achieving the lowest spill requires a trade-off for low minimum storage and moderate cost. Considering these brushed options, the lowest cost option is added to the shortlist, since the low cost options have low spill and perform fairly well in terms of minimum storage.

In summary, the parallel coordinates plot is capable of illustrating the entire Pareto set and multiple objectives or decision variables on the one two-dimensional plot. The 'brushing' technique can be used to track certain options across the plot and is particularly useful for examining the objective performance or decision variables of a subset of operating options of interest, and how they compare to the rest of the Pareto set. This plot is also useful for illustrating the strength of the trade-offs between objective functions, indicated by the steepness of the slope between adjacent axes.

### 3.3.6 Level diagram

The level diagram was proposed for Pareto sets with more than 2 dimensions by Blasco et al. (2008), and further demonstrated by Zio and Bazzo (2011). The level diagram plots the relationships between the objectives and decision variables, and the overall objective performance. It consists of a set of two-dimensional scatterplots of the entire Pareto set, one for each objective function and/or decision variable. Each x-axis represents the value of the objective or decision variable, and each y-axis the distance from the ideal point on the multi-objective plane. The distance from the ideal point is represented by the 1-norm, which is the sum of the normalised objective function values. The objective functions are normalised relative to their respective minimum and maximum values of the Pareto set, with 0 being closest to, and 1 farthest from, the preferred value. The 1-norm provides a measure of overall, equally weighted, objective performance. Since the y-axes are synchronised between plots, points can also be directly compared across the y-axes. By analysing the level diagrams, the decision-maker can understand the relationships between decision variables and objective performance, and identify points closest to the ideal 0 value of the 1-norm.

Figure 11 shows the level diagram for the case study objective functions and decision variables of the entire Pareto set, with points coloured according to cluster, to aid comparison between plots. The lowest 1-norm values (best overall objective performance) correspond to Cluster 2 (red points), which has lowest cost (Figure 11 s), low spill (Figure 11 q), and above average minimum storage (Figure 11 r). The low values of 1-norm suggests overall efficiency in trade-offs. Thus the option with the lowest 1-norm value, which lies within Cluster 2, is added to the shortlist.

Figure 11 can also provide some insights into the relationship between the decision variables and objective performance. As suggested by the scatterplots in Figure 6, there is a correlation between the desalination full production threshold decision variable and objective performance (Figure 11 p). This relationship also exists to a lesser extent for the other two desalination thresholds (Figures 11 n and o). This suggests that when desalination production is initiated at higher storage fullnesses (closer to 1, indicating 100%), it reduces overall objective performance (raises 1-norm). For most of the remaining decision variables, there appears to be no clear relationship between the decision variable values and objective performance, represented by the 1-norm. This could be due several factors: the objective functions are not highly sensitive to the decision variables; the decision variable thresholds are not reached during the planning period; or that similar objective performance can result from different combinations of operating modes. Despite this, for some decision variables, values are concentrated in a particular region (e.g. the NPI and NPI 2 Thresholds in Figures 11 a-d), suggesting there may be an optimal region for these decision variables.

The level diagram also suggests potential reasons for the bands in the relationship between the minimum storage and cost objective functions that were seen in Figure 5 d, since these bands are also present in the level diagram for minimum storage (Figure 11 r). The operating options in the leftmost band belong to Clusters 5, 7 and 8, and have low minimum storage, lowest spill and higher values of Brisbane to Nth Pine Flow Threshold and SPI Flow Threshold (Figures 11 f and l). Higher values of these thresholds, representing the level below which maximum flow is initiated in these two-way pipelines, likely results in an increase in the flow-rate in these two-way pipelines. This increase in flowrate is associated with lower minimum system storage and spill. Similarly, operating options in the middle band of low to moderate minimum storage in Figure 11 r, corresponding to Clusters 3, 10, and some of Cluster 7, have low spill and higher values of SPI Flow Threshold (Figure 11 l), representing higher flowrate in the SPI two-way pipelines. On the other hand, clusters on the highest band of minimum storage, corresponding to Clusters 1, 2, 4, 6, and 9 in Figure 11 r, have mostly higher spill and minimum storage than the other clusters, but overlap in cost (Figure 11 s). The key differences for this band is the generally higher use of desalination indicated by high desalination thresholds in Figure 11 n and o, but lower flow in two-way pipelines indicated by low Brisbane to Nth Pine and SPI Flow Thresholds (Figures 11 f and l). Overall, this suggests that operating options with higher volumetric use of two-way pipelines result in lower minimum storage and spill but similar cost to operating options with higher volumetric use of desalination.

In summary, level diagrams are particularly useful for identifying the relationships between decision variables and overall objective performance, represented by the 1-norm. By colouring these plots according to cluster membership, we can identify some reasons for the differences in objective performance. The 1-norm also helps to identify a high-performing operating option, assuming an equal weighting of objectives, which can be added to the shortlist. The 1-norm could also be used to identify the best performing operating options for each cluster, assuming equal preference on the objectives (Zio and Bazzo, 2011, 2010).

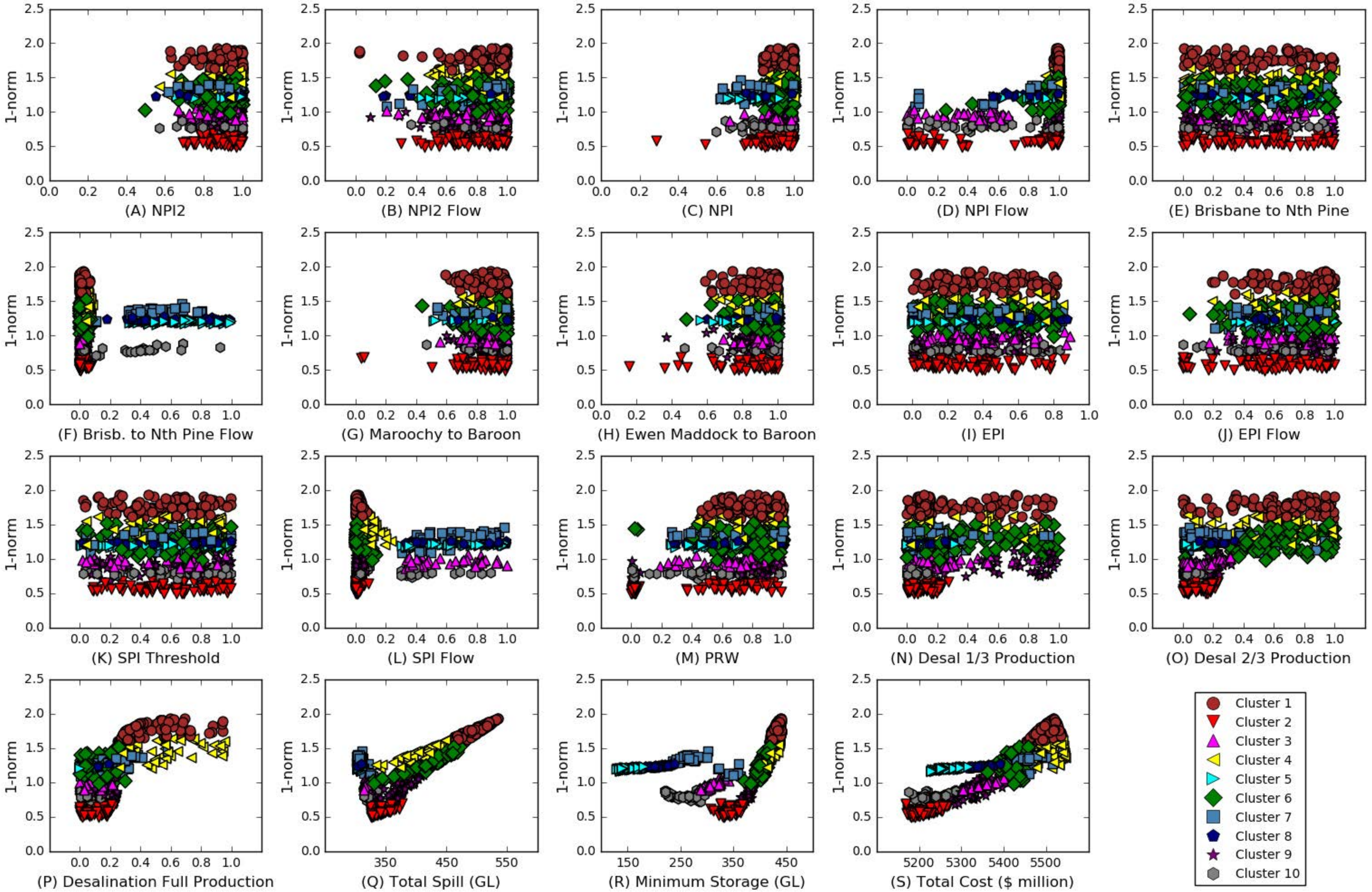


*Figure 11: Level diagram of decision variables (Thresholds, A-P) and objective functions (Q-S) plotted against 1-norm.*

### 3.3.7 Decision maps

Decision maps are a method for projecting vectors of more than two dimensions on to a two dimensional plot, and have been used to represent multi-objective Pareto sets (e.g. Lotov and Miettinen 2008; Mortazavi et al. 2012; Paton et al. 2014). The decision map enables the decision-maker to examine the Pareto set in two dimensions, whilst at the same time having information about the entire set of objective function values. In the case of three objective functions, the decision map can be plotted with the first two objective functions as a series of two-dimensional curves or slices of the three-dimensional surface, with the value of a third objective noted on each curve in a similar manner to contour lines of a topographic map. Alternatively, the first two objectives can be plotted as a scatterplot, with colour-coding to represent the relative value of the third objective. In this format it is an extension of the 2-dimensional scatterplots as seen in the scatterplot matrix (Figure 5). In the case of four objectives, the fourth objective can be set as a constraint (fixed value) to produce a three-objective slice of the four dimensional plane. For cases of four or more objectives, decision maps are best viewed in interactive software: scroll bars on the x and y axes can be used to change the three-dimensional slices by changing the values of the fourth and fifth objectives. This technique is called interactive decision maps (IDM) (Castelletti et al., 2010; Kollat and Reed, 2007; Lotov et al., 2004). Alternatively, matrices can be used to display multiple three-objective decision map slices.

Figure 12 shows a decision map of the entire case study Pareto set, with minimum storage and cost plotted on the x and y axes respectively. Values of total spill are represented using shading: white shading indicates the best performing values (lowest spill), and black the worst performing values (highest spill), with shades ranging through the spectrum of grays in between. This plot provides further information as to the reason for the three bands or fronts seen in the trade-off curve between minimum storage and cost, also seen in the scatterplot (Figure 5) and level diagram (Figure 11 r). The decision map shows that each band, from left to right (lower to higher minimum storage) is

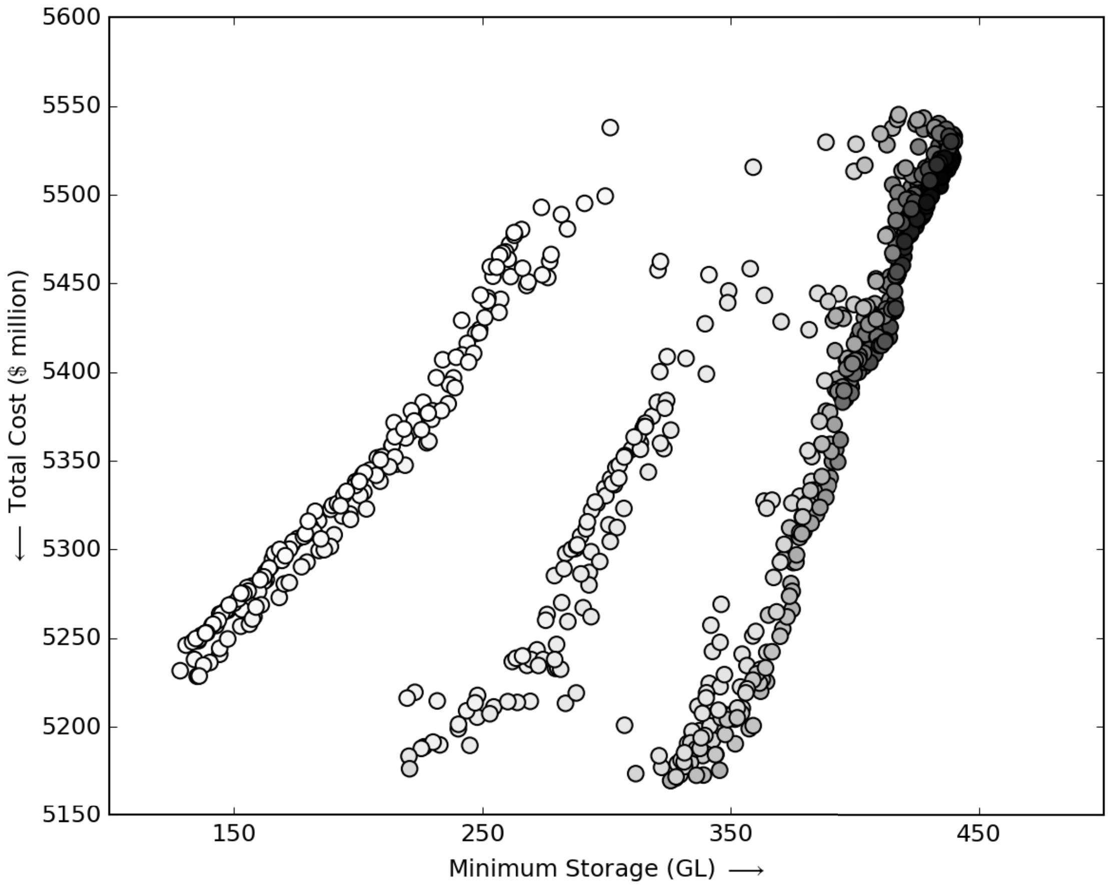


*Figure 12: Decision map showing case study objective function values of minimum storage (GL) (x-axis), total cost ($ million) (y-axis) and total spill (normalised, shading) for the entire Pareto set. Arrows show the direction of preference of the x and y axes. White points indicate those with lowest (best) values of spill, and black indicates highest (worst) values of spill. Values in between are indicated by the spectrum of grays between white and black.*

associated with progressively higher values of spill. The two left-most bands were found in analysis of the level diagrams (Figure 11) to have greater flowrate in two-way pipelines, and the right-most band was associated with higher volumetric use of desalination. The results from the decision map and the level diagram thus suggest that there are two operating paradigms that can result in similar cost but with different effects on the other two objectives. The first is one that favours greater use of two-way pipelines, avoiding spill but not adding significantly to the overall minimum storage. The second is one that favours the use of desalination, increasing minimum storage but also increasing spill. The second band may represent some overlap in these two paradigms.

In summary, the decision map improves on the scatterplot matrix of objective functions (Figure 5), by providing information about the value of additional objectives or criteria, within a two-dimensional plot. These plots are useful for exploring the trade-offs between objectives and identifying promising regions in the objective space, and can provide a large amount of information on a single plot. However, it can be difficult to identify individual points on the plot, unless an interactive plot is used. For this reason, operating options are not identified from the decision map for the case study shortlist.

### 3.3.8 Glyph plots

Glyph plots can be considered an extension of the decision map (Section 3.3.7). They are a form of scatterplot that uses size, colour, orientation and transparency of the glyphs (points) on a two or three-dimensional graph to represent up to 7 dimensions or objectives. They are often used for multi-objective optimisation applications of four or more objectives (Kasprzyk et al., 2013; Matrosov et al., 2015; Reed and Kollat, 2013). With many objectives, glyph plots can become difficult to read, but they do allow the relative values of particular points to be identified or interrogated if an interactive software tool is used. Although a decision map is sufficient for a three objective problem such as the case study, glyphs can also be used to represent the value of other management criteria or decision variables of interest.

Figure 13 shows an example of a glyph plot for the case study's three objective functions and the Brisbane to North Pine Flow Threshold decision variable. This shows the relationship between the three objectives and this decision variable. The three objective functions are shown using the x-axis, y-axis and shading, same as for the decision map in Figure 12. However, the relative size of each point is also varied to indicate the values of the Brisbane to North Pine Flow Threshold decision variable for each operating option, with the larger points having a value closer to 1 and smaller points a value closer to 0. This threshold indicates the fullness (between 0 to 1) of the receiving regional storages below which the Brisbane to North Pine two-way pipeline will operate at maximum flow. The glyph plot suggests that there is a wide range in values of the Brisbane to North Pine Flow Threshold, but that higher thresholds (closer to 1),

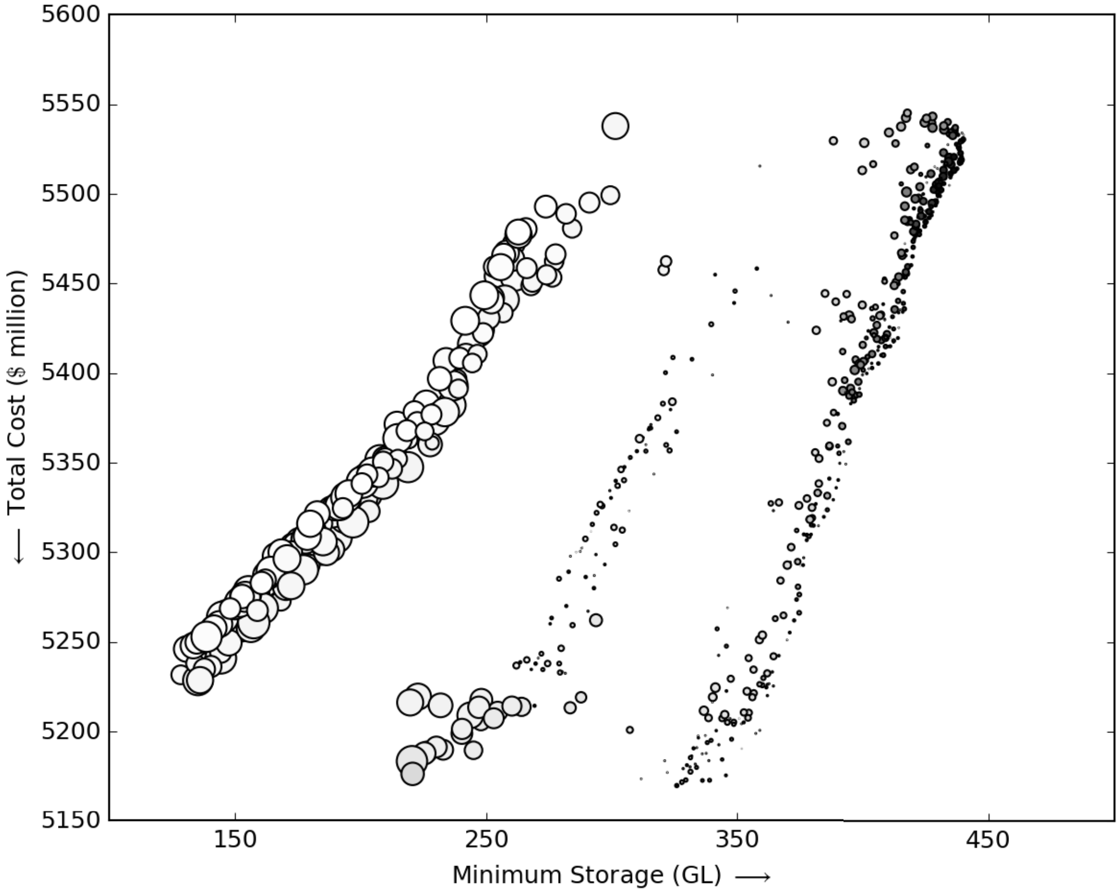


*Figure 13: Glyph plot showing case study objective functions of minimum storage (GL) (x-axis), total cost ($ million) (y-axis), total spill (normalised, glyph shading), and Brisbane to North Pine Flow Threshold (glyph size) for the entire Pareto set. White glyphs indicate those with lowest (best) values of spill, and black glyphs indicates highest (worst) values of spill, with colours ranging through the colour spectrum in between. Larger circles indicate values of Brisbane to Nth Pine Threshold closer to 1, and smaller circles indicate values closer to 0.*

are associated with lower minimum storage and lower spill. This confirms the findings of the level diagram.

In summary, the glyph plot is a convenient method for showing the relationships between three or more objective functions on the same two-dimensional plot, for the entire Pareto set. It is similar to the decision map, but is capable of showing a greater number of dimensions on a single plot. Therefore it is most useful for presentation in print. However, for online presentation, the interactive decision map may be preferred. The glyph plot may also be used to indicate the values of certain decision variables or criteria, and how they relate to objective performance. In this way it is a useful tool to query the relationships between decision variable and objective spaces. However, it can be more difficult to isolate or compare particular operating options using the glyph plot, compared to the line diagram or parallel coordinates plot. Therefore, for the case study, the glyph plot is not used to identify options for the case study shortlist.

### 3.3.9 Heatmaps

Heatmaps can be used to represent a large number of variables on the one plot, by plotting a matrix of colour shaded boxes which are used to indicate relative values of variables. In this way, the values of the objective functions and decision variables for each operating option can be presented and compared side by side (Kasprzyk et al., 2012; Pryke et al., 2007). Whilst it is possible to show the entire Pareto set, a heatmap is much easier to read when the reduced set of cluster representatives are used.

Figure 14 shows a heatmap of the decision variables and objective function values of the cluster medoids of the case study Pareto set. The values of the objective functions and decision variables have been normalised from 0 to 1, respective to their minimum and maximum values amongst the cluster medoids, to allow their relative values to be mapped as a spectrum of blue shades. The lightest blues indicate a value of a decision variable closest to 0, and an objective function closest to the preferred value. The darkest blues indicate a value of decision variable closest to 1 and an objective function farthest from the preferred value. From this plot it can be seen that there is significant variation in the values of the decision variables and objective functions between cluster representatives.  However, some decision variables, e.g. NPI and NPI 2 Thresholds, show a tendency to higher decision variable values, indicated by darker shades. The lighter shades highlight the best-performing medoids in terms of each objective. Medoid 2 performs best in terms of cost, Medoid 1 and 4 best in terms of minimum storage, and Medoids 5, 7, and 8 all perform well in terms of spill. Despite similarity in spill, the decision variables of the three low spill medoids (5, 7, and 8) vary significantly. From this figure, Medoid 2 is added to the shortlist, since it is a operating option that performs well in terms of cost, and fairly well in terms of the other two objectives. The heatmap indicates that this option favours less use of desalination (triggered at lower thresholds of system storage volumes) and lower flowrate in the Brisbane to Nth Pine and SPI pipelines (with maximum flowrate triggered at lower thresholds of receiving storage fullness).

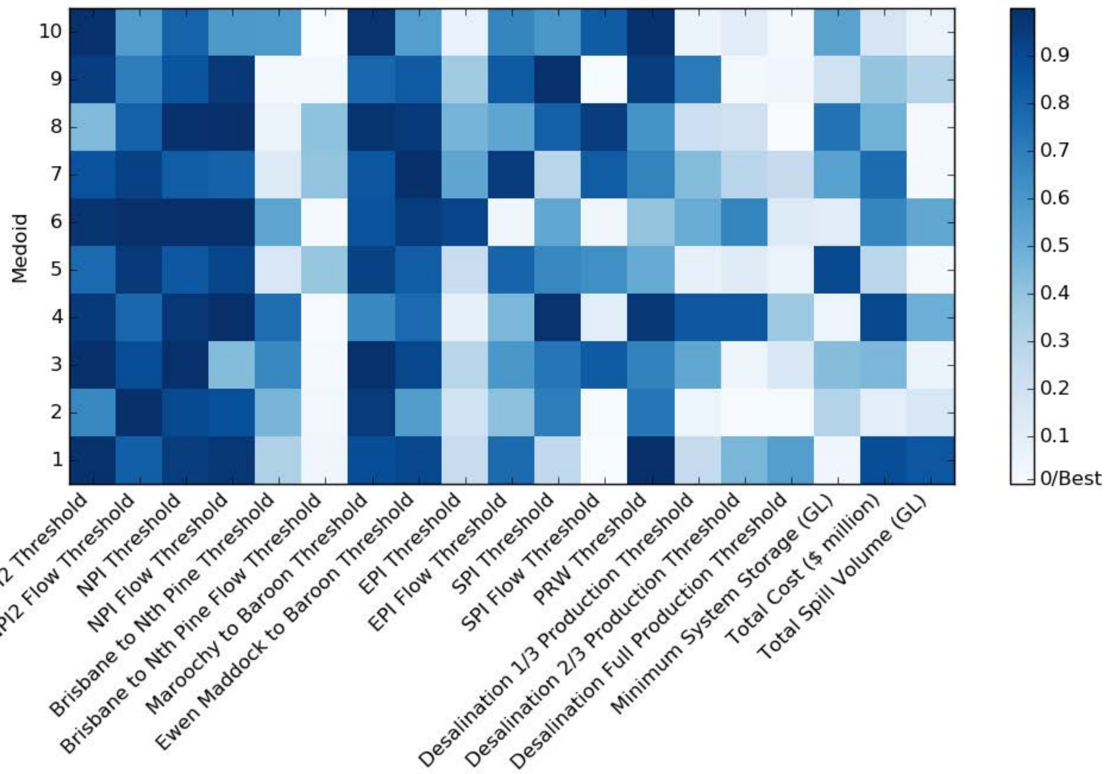


*Figure 14: Heatmap of decision variable and normalised objective function values. The lighter the blue, the closer the value of decision variable to 0 and closer the objective function to the preferred value (maximum for minimum storage, minimum for cost and spill).*

In summary, heatmaps, unlike the other visual analysis techniques, allow all decision variables and objectives of a reduced set of operating options to be represented easily on the one plot, since colour shading is used to simplify representation. Although the colour shading makes it is difficult to gauge exact values, this plot is fairly easy to interpret and operating options can summarised and compared side by side.

### 3.3.10 Interactive plotting

Interactive plots allow the user to view a plot from different angles and to identify the objective function values of the operating options using the mouse. When these interactive plots are created using an online service, plots can also be shared easily with collaborators or stakeholders. A number of tools for interactive plotting exist. Plotly (https://plot.ly) is a free tool which allows the user to create and format interactive plots online through a graphical user interface, and does not require programming knowledge. It can be used to create a number of plot types including the scatterplot, line diagram, and heatmap. Plotly may also be accessed using the user's preferred programming language such as Matlab, R, or Python. Alternatively, Glue (http://www.glueviz.org) is a Python-language tool for creating linked scatter plots, histograms and images. This tool can be used to brush or link plots, focusing on a region of the Pareto set that is of interest to the decision-maker. The resulting plots can also be output to Plotly. Interactive plotting is particularly useful for parallel coordinates plots, as brushing and reordering of parallel axes can be applied dynamically. Rosenberg (2015) provides an example of this in Matlab code, at https://github.com/dzeke/Blended-Near-Optimal-Tools.

Figure 15 shows a screenshot of an interactive 3D scatterplot of the case study Pareto set, constructed using Plotly. This plot can be explored online at https://plot.ly/13/~StephanieAshbolt/. Using an interactive plot such as this allows the shape of the Pareto set to be more easily seen than the static 3D plot (Figure 2) or scatterplot matrix (Figure 5), by rotating the angle of view. Additionally, the values of points on the plot may be queried by hovering the cursor.

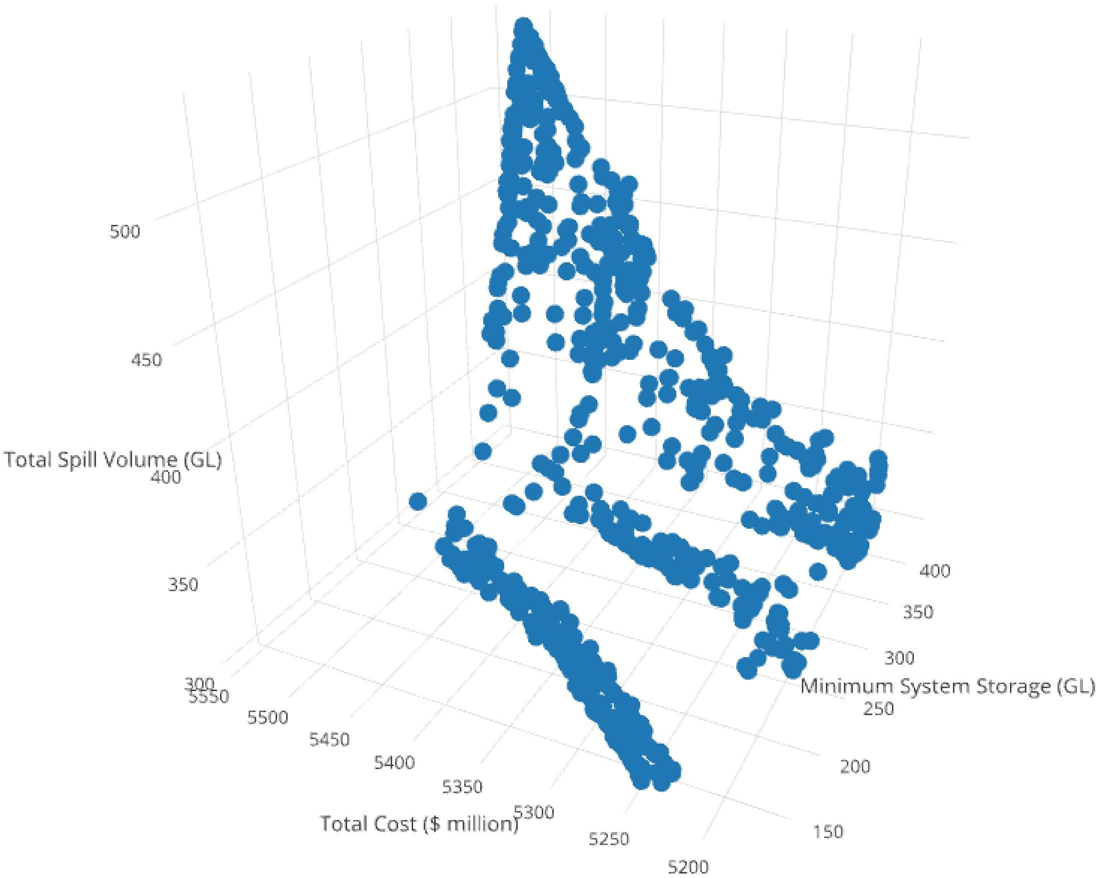


*Figure 15: Screenshot of interactive 3D scatterplot of the Pareto set using Plotly (https://plot.ly/13/~StephanieAshbolt/)*

## 3.4 Post-optimisation analysis

Post-optimisation analysis techniques are methods of determining the most efficient or optimal point in the Pareto set, in terms of the distance from the ideal point, preferences on the objectives, and/or the degree of improvement over other operating options. The ideal point typically describes a hypothetical operating option comprising the best values of each objective function obtained from the Pareto set. In most multi-objective problems, this ideal point is infeasible due to the trade-offs between objectives.

Some post-optimisation analysis techniques such as compromise programming can be applied to the Pareto set to combine objective functions in a manner similar to *a priori* optimisation, and identify a single operating option. However, the advantage of applying them *a posteriori* is that it allows exploration of the full objective space, with the application of visual analysis and other post-optimisation techniques. These alternative techniques can be used to understand the objective and decision spaces, shortlist alternative options, and assist in developing preferences. The use of multiple post-optimisation techniques is recommended, since each technique may identify a different operating options due to the different approaches to defining efficiency and applying preferences. Additionally, the use of multiple preference scenarios allows the decision-maker to identify efficient operating options based on the preferences of different stakeholders; to consider a wider range of operating option types; or to explore the sensitivity of the selection of efficient operating options to the supplied preferences.  Since it may be difficult to declare a single technique or preference scenario as intrinsically 'better' than the other, this uncertainty should be incorporated in a shortlist for further analysis. Thus the approach recommended here is to identify a number of options for the shortlist by applying multiple post-optimisation analysis techniques and objective preference scenarios.

### 3.4.1 Compromise programming

Compromise programming is an optimisation technique that has been widely used in multi-criteria analysis (Zeleny, 1973). It involves finding a decision option that has minimum distance from the ideal point. In this context, the ideal point is a hypothetical objective function vector consisting of the most preferred (minimum or maximum) value of each objective function that exists amongst the Pareto set. The minimum distance from the ideal point can be determined using a variety of possible distance metric methods, and preference weights on the objectives are used to combine the distances for each objective function into a single value. Ballestero (2007) presented a novel distance metric for compromise programming for multiple criteria which combines both linear and quadratic distance metrics. A linear metric favours higher achieving options (in terms of any one objective) and a quadratic metric favours more balanced options (across all objectives). The combined metric allows a compromise between emphasis on balanced and higher achieving options. The function to find the distance from the ideal point as per Ballestero (2007) is shown in

Equation 1, and explained further in that paper.

$$\Delta=\sum_{j=1}^{n}[\frac{n}{200}Y_j(1-y_j)]+0.5\sum_{j=1}^{n}[\frac{n}{200}Y_j(1-\frac{n}{200}Y_j)(1-y_j)^2] \qquad \textbf{Equation 1}$$

Where Δ is the distance (to be minimised), *j* is an objective function, *n* is the number of objective functions, *y* is the 1-normalised objective function value (ideal value *y* = 1, non-ideal *y* = 0, drawn from feasible values), and *Y* is the objective preference weight in %. Weights for each objective function ($Y_j$) act as coefficients that influence both the preference of objective functions and the proportion of the distance metrics (degree of balance vs achievement) in the operating option. Finding the member of the Pareto set with minimum distance will identify the most efficient option, for the chosen preference weights on the objective functions. Several scenarios of preference weights can also be trialled, to address different decision-maker or stakeholder views or to provide a sensitivity analysis of the effect of the preference weights on the chosen option.

Figure 16 shows two efficient operating options for the case study Pareto set, identified using compromise programming according to Equation 1, and using two scenarios of preference weights from the case study (Section 2). The first option, highlighted in red, results from a fairly balanced weighting scenario with slight emphasis on cost: a weight of 30% on minimum storage and total spill, and 40% on cost. Such a preference scenario might be used when there are no major water security and flooding concerns for the planning period. This point is close to the lowest cost, and has low spill and moderate performance in terms of minimum storage. The second operating option, highlighted in blue, considers a preference scenario of higher emphasis on minimum storage (60%), with some emphasis on cost (30%) and less on total spill (10%). This preference scenario is used to identify a more water-secure operating option for consideration in the shortlist. This option has similar low spill to the first option, but improves over the first option in terms of minimum storage, for a small trade-off in cost. These two operating options are added to the shortlist. Despite having significantly different preference weights on the objectives, the two operating options are relatively close together in the objective space, suggesting that this region may be optimal for relatively wide range of preferences. Indeed, trialling a preference scenario of 20% on minimum storage, 50% on total cost and 30% on spill identified the same efficient operating option as the 40% total cost scenario above.

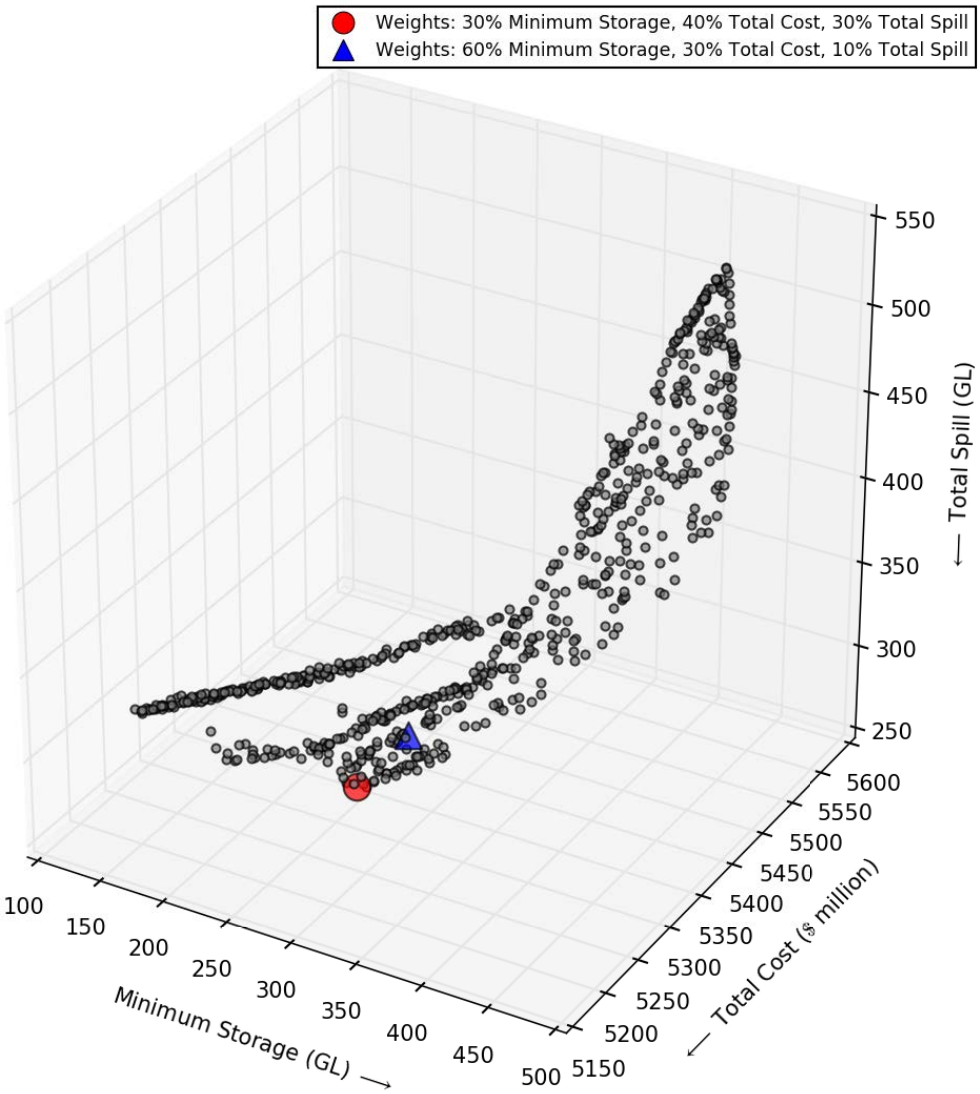


*Figure 16: Scatterplot of objective function performance of the case study Pareto set, highlighting (in red and blue) the operating options identified by compromise programming as the most efficient, for two scenarios of preference weights. Arrows on axes indicate direction of preference of objectives.*

In summary, compromise programming can be used to identify one or more operating options that are efficient in terms of both distance from the ideal point, and decision-maker preferences. Preference scenarios can be used to shortlist a number of options, or to assess the sensitivity of options to decisionmaker preferences.

### 3.4.2 Trade-off quantity and marginal rate of substitution

The trade-off quantity is used to describe a two-dimensional objective space and is the ratio of improvement in value of one objective function $f_i$, that is achieved to the detriment in value of another objective function $f_j$. The option with the greatest trade-off quantity is the most efficient operating option in terms of the objective $f_i$. In essence, it describes the greatest slope between two adjacent operating options in a two-objective space, identifying the option that lies closer to the preferred region than its neighbours. For a multi-objective problem with 3 or more objectives, this trade-off quantity is a partial trade-off as it describes only two-objectives at a time. The trade-off quantity is calculated as per Equation 2, for combinations of two-objectives (partial trade-offs) of a multi-objective space (Miettinen, 1998):

$$\Lambda_{i,j}(x^1,x^2)=\frac{f_i(x^1)-f_i(x^2)}{f_j(x^1)-f_j(x^2)} \qquad \textbf{Equation 2}$$

where $\Lambda_{i,j}$ is the partial trade-off of the objective function $f_i$ for objective function $f_j$, for the operating options $x^1$ and $x^2$. The operating options should be ordered such that $f_i(x^2)$ is an improvement over $f_i(x^1)$. The maximum value of $\Lambda_{i,j}$ can be considered the most efficient operating option in terms of objective $i$; i.e. the largest trade-off for unit of $j$, or the greatest slope in the trade-off curve of two objective functions. These partial trade-offs can be determined for all objective pairs. Since the trade-off quantity is directional along the partial trade-off curve, two maximum values $\Lambda_{i,j}$ and $\Lambda_{j,i}$ and their corresponding operating options will be identified for a given pair of objectives, as one travels along the curve in both directions.

For the case study Pareto set of three objectives, six sets of partial trade-off quantities can be determined. The points of maximum trade-off ($\Lambda$) for the six combinations of objective functions of the case study Pareto set are shown in Figure 17. From this plot, two options are selected for the shortlist: the operating options with maximum trade-offs of minimum storage for cost and cost for minimum storage, shown as the red and blue dots respectively in Figure 17. These are chosen as greater preference is placed on these two objectives for the case study.

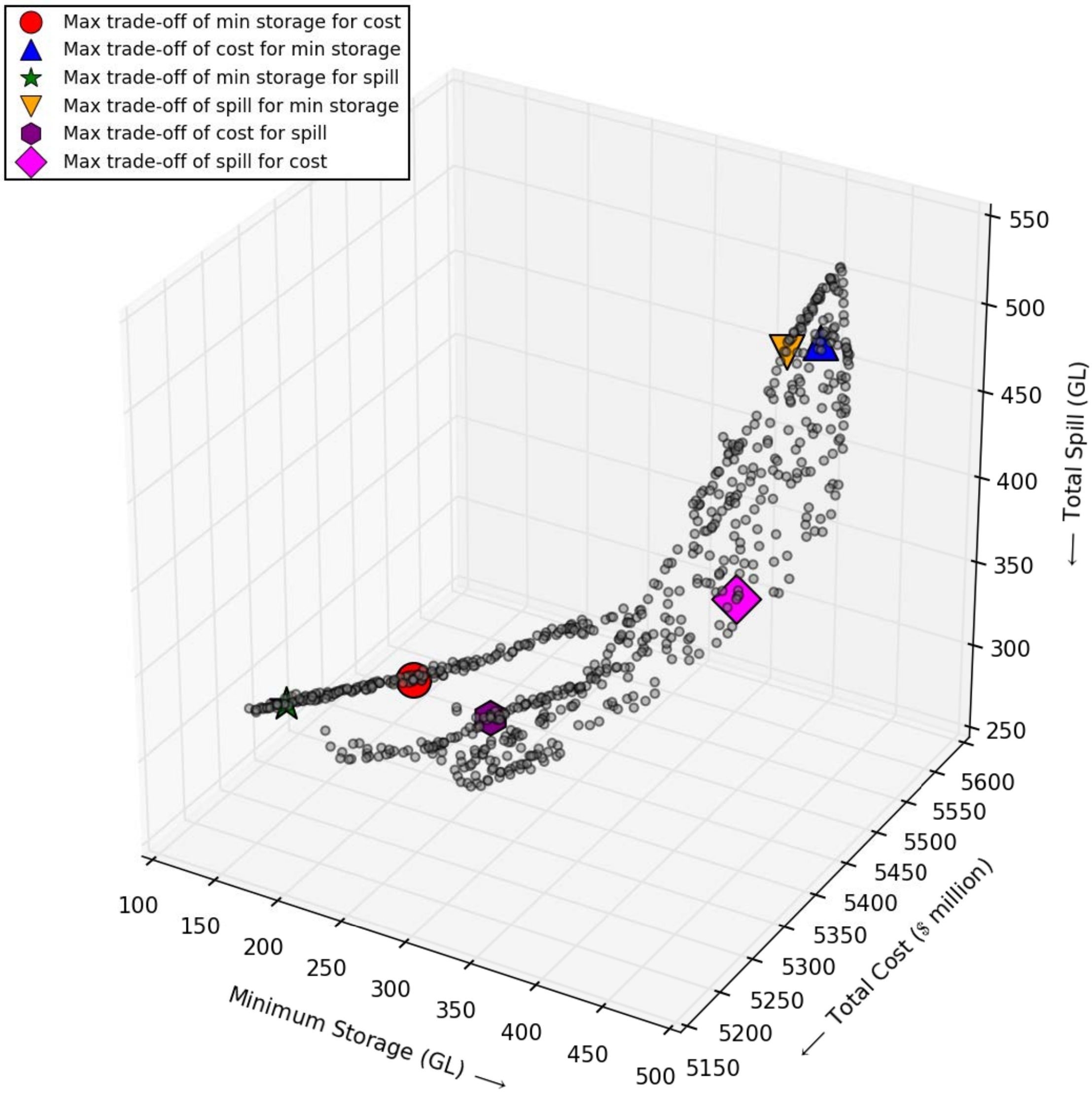


*Figure 17: Scatterplot of objective function performance of the case study Pareto set, highlighting points of maximum trade-off. Arrows on axes indicate direction of preference of objectives.*

The trade-off quantity can also be used in combination with the Marginal Rate of Substitution (MRS) method to determine the operating option with the most efficient trade-off, based on the values of the decision-maker (Deb, 2001; Miettinen, 1998). This requires an indifference curve describing acceptable trade-offs, established from stakeholder or decision-maker consultation. The point at which this indifference curve intersects the trade-off curve of the Pareto set is defined as the most efficient option. Since such consultation was beyond the scope of this case study, the indifference curve is not demonstrated here.

In summary, the trade-off quantity identifies efficient options in terms of the maximum gain in one objective for unit loss of another. This identifies operating options in the Pareto surface which lie closer to the optimal region than their neighbours due to unevenness in the curve of the Pareto set. Unlike compromise programming, it does not consider preferences on the objectives and thus efficient options may be located across the full objective range. A key limitation of this method for a problem with more than two objectives, is that it looks at partial trade-offs only, and the number of possible combinations of partial trade-offs may identify a large number of efficient options. Thus this technique is most useful for cases with two objectives.

### 3.4.3 Pseudo-weight vector approach

The pseudo-weight vector approach is a method which describes the relative performance or 'pseudo-weight' of each objective function, for each operating option in the Pareto set. The pseudo-weight vector, for minimised objectives, is a vector of relative distances of a operating option from the worst (maximum) values of the objective functions, calculated as per Equation 3 (Deb, 2001):

$$w_i = \frac{(f_i^{max} - f_i(x))/(f_i^{max} - f_i^{min})}{\sum_{m=1}^{M} (f_m^{max} - f_m(x))/(f_m^{max} - f_m^{min})} \qquad \textbf{Equation 3}$$

where $w_i$ is the weight of objective function $f_i$ (representing the $i$-th objective) for operating option $x$, $f_i^{max}$ and $f_i^{min}$ are the maximum and minimum values respectively of the objective function $f_i$, and $m$ is an objective of the set of $M$ objectives. The higher the value of $w_i$, the better the operating option in terms of that objective, since it reflects a greater distance from the worst value. The pseudo-weights of each objective function for each operating option are calculated as a ratio of relative distance from the worst value for that objective function (the numerator in Equation 3), to the sum of all objective function distances from worst values for that operating option (the denominator in

Equation 3). For each operating option, a vector of pseudo-weights (one for each objective) is determined, which will sum to 1. Equation 3 applies to objective functions that are minimised: in order to incorporate those that are maximised, the objective function values can simply be negated. For visualisation purposes, the pseudo-weight vector approach is best applied to the cluster representatives to reduce the number of options for comparison. The decision-maker can then choose the option that has 'pseudo-weights' closest to weights that reflect their objective preferences. However, if a specific preference weight is given by the decision-maker, this can easily be compared to a table of pseudo-weight vectors for all operating options. Such a table is provided in the supplementary files.

Figure 18 indicates the pseudo-weights of each of the cluster medoids of the case-study Pareto set, calculated according to Equation 3. These pseudo-weights are shown with the scatterplot so that the operating options and their pseudo-weights can be considered in the context of the objective space. The pseudo-weights vary significantly across operating options. Medoids 2 and 9, which were identified in the line diagram (Figure 8) as relatively balanced options, are confirmed as such here, with weights for each of the three objectives close to 0.33. Since these operating options are already included in the shortlist, an option is also sought the shortlist that is reasonably balanced but places greater weight on minimum storage (~50%). Medoid 6 has a pseudo-weight vector of 0.53 for minimum storage, 0.20 for total cost, and 0.28 for total spill. Therefore this operating option is added to the shortlist.

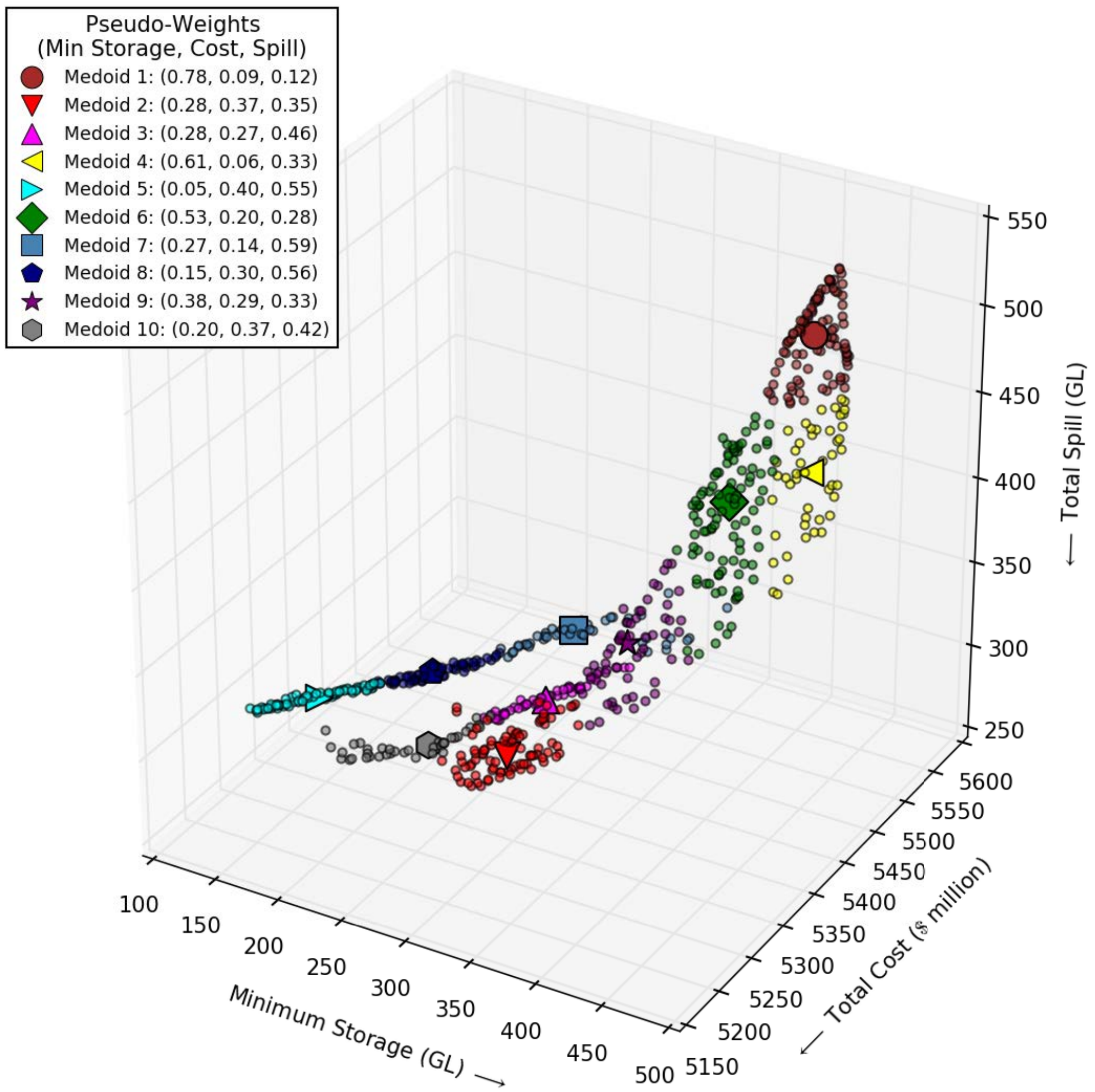


*Figure 18: Scatter plot of objective function performance of the case study Pareto set, indicating cluster medoids as larger circles and their pseudo-weight vectors in the legend. Arrows on axes indicate direction of preference of objectives.*

In summary, the pseudo-weight vector approach is similar to compromise programming in that it allows the decision-maker to identify an operating option that reflects their preferences on the objectives. However, the key difference is in how the preferences are incorporated. The compromise programming approach takes preference weights as an input to identify a single operating option. The pseudo-weight vector approach, on the other hand, allows the decision-maker to examine the preference weights of the entire Pareto set and to select an operating option based on their preferences, in the context of the other options. Compromise programming and the pseudo-weight vector also have different approaches to incorporating weights and determining distance from the ideal/non-ideal point, which can result in an operating option having different weights and pseudo-weights. For example, for the case study Pareto set, operating option 472 is identified in compromise programming as the most efficient option for a weight of 30% on minimum storage, 40% on total cost and 30% on total spill. However, this operating option has a pseudo-weight vector of 26%, 39% and 36% respectively.

# 4 A shortlist of promising operating options

Application of the visual and post-optimisation analysis techniques in the previous sections showed how these techniques can be used to identify a number of candidate operating options for a shortlist. This shortlist provides a reduced set of operating options of a manageable size for further decision analysis, and reflects the interests or preferences of the decisionomaker. The shortlist can be used as input to multi-criteria analysis, where the options may be assessed against additional criteria. Alternatively, the shortlist may be presented as-is for discussion and selection by decision-makers and stakeholders.

A total of nine operating options were identified for shortlist in the visual and post-optimisation analysis of the case study Pareto set. These options are summarised in Table 2, alongside their source (visual or post-optimisation analysis technique) and key characteristics for which they were chosen. These options were chosen based on either providing a balance or relatively similar performance between objectives (Options 139, 219, and 510), higher performance for cost (Options 296, 406, and 472), or higher performance for minimum storage (Options 349, 671, and 673), reflecting the three preference scenarios on objectives stated for the case study in Section 2. Whilst some of these options were selected for higher performance on minimum storage or cost, most of the visual or post-optimisation analysis techniques were able to show that the trade-off in-terms of the other objectives remained reasonable, i.e. better performance in one objective was not at the expense of a particularly large trade-off in the other two objectives. This can be seen through the objective performance of the shortlist as shown as a series radar charts in Figure 19. Radar charts were chosen since they are a useful tool for summarising the objective performance or shape of a small set of operating options (Section 3.3.4). The radar charts show that most of the shortlisted operating options perform well for minimum storage, and fairly well for the other two objectives. The key exceptions are Options 671 and 296, which were identified as providing efficient trade-offs compared to neighbouring operating options, but did not guarantee overall high performance in cost and minimum storage. Option 349 also placed a higher priority on minimum storage which came with a larger trade-off in terms of cost and spill.

*Table 2: Shortlist of operating options, the source of their selection (in visual and/or post-optimisation analysis), and key characteristics*

| **Operating Option** | **Source** | **Characteristic** |
|---|---|---|
| Medoid 2 (Option 219) | Line diagram/bar chart; heatmap | Balanced option with lower cost. |
| Medoid 9 (Option 510) | Line diagram/bar chart | Balanced option with higher minimum storage. |
| Medoid 10 (Option 139) | Radar chart | Well-performing/balanced option with low spill and cost. |
| Option 406 | Parallel coordinates | Lowest cost option. |
| Option 472 | Level diagram; compromise programming | Lowest 1-norm; efficient option for weight of 30% on minimum storage, 40% on total cost, and 30% on total spill. |
| Option 673 | Compromise programming | Efficient option for weight of 60% on minimum storage, 30% on total cost and 10% on total spill. |
| Option 671 | Trade-off quantity | Maximum trade-off of minimum storage for cost. |
| Option 296 | Trade-off quantity | Maximum trade-off of cost for minimum storage. |
| Medoid 6 (Option 349) | Pseudo-weight vector | Emphasis on higher minimum storage with pseudo-weight of 53% on minimum storage, 20% on total cost and 28% on total spill. |

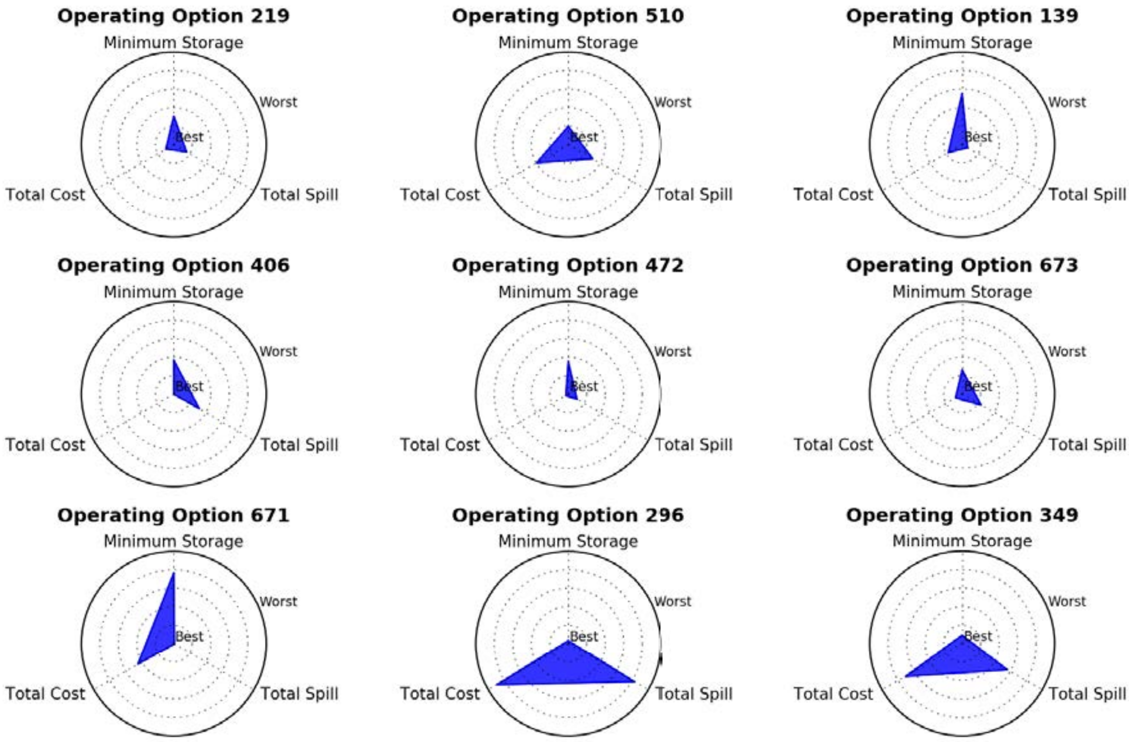


*Figure 19: Radar charts of the objective performance of the shortlist of operating options for the case study Pareto set.*

Each of the visual or post-optimisation analysis techniques examined either the entire Pareto set or the cluster representatives (medoids) from a different perspective or using different metrics. Despite these differences, Table 2 indicates that many of the shortlisted operating options were identified by more than one technique. This provides some confidence in the efficiency of these options, but also reflects the overlaps in the information provided by the visual analysis techniques in this space. For example, the line diagram and heatmap were used to identify Medoid 2 (Option 219) for the shortlist. However, the heatmap provides additional information on the decision variables, and the line diagram (or bar chart) provide a clearer picture of objective performance. Thus using both visual analysis techniques remains useful for understanding the Pareto set. The post-optimisation analysis techniques had no overlap in the identification of efficient options, even for the same weights on the objectives, demonstrating the utility of applying different post-optimisation analysis techniques for creating a robust or diverse shortlist.

The selection of cluster medoids for the shortlist may raise some concerns regarding how well they represent they are of the decision variables within their cluster, since clustering for the case study was performed based on objective functions only. As was found in Sections 3.2 and 3.3.2, and shown as an example for Medoid 2 in the supplementary files, there is signficant within-cluster variation in decision variable values. By examining adjacent cluster members, a decisionmaker could adjust their choice of operating option to one with similar objective performance but more preferred decision variable values. For example, a cluster member with decision variables closer to those of the previous planning period might be chosen. This may be a more palatable option, since it would require a less radical change in the operating rules between planning periods. However, since decision variable preferences or historic values are not available for the case study, the ccluster medoids will remain on the case study shortlist.

The shortlist provides a smaller reduced set of options that are easier to analyse or compare. The visual analysis techniques presented in this study that used cluster representatives as their input can be reapplied to the shortlist to provide more insight into the characteristics of this reduced set, including their decision variables. However, without a clear set of preferences on objectives from the decisionmaker, or without agreement between post-optimisation analysis techniques, it is difficult to select a single operating option from the shortlist. Multi-criteria analysis can be used to explicitly incorporate preferences on the objectives to rank operating options, and to consider their performance against other criteria not included in optimisation. The performance against additional criteria may also help to differentiate operating options. For example, two operating options in the case study may have similar objective performance, but may perform significantly differently when assessed against different inflow scenarios, or for their ability to meet or exceed environmental flow requirements. This additional information may make the selection process easier.

## 5 Summary and Conclusions

This paper has demonstrated how cluster, visual, and post-optimisation analysis techniques can be used to assist a decision-maker in comprehending a Pareto set and reducing it to a manageable set for further assessment against management criteria. These techniques form part of a framework for operational planning for water grids, and were demonstrated for a Pareto set of 677 operating options for a case study based on the South East Queensland Water Grid.

A shortlist of nine promising operating options were identified from the Pareto set of 677 options, using insights from visual and post-optimisation analysis. Cluster analysis aided the visual analysis by producing a reduced set that reflected the range of objective performance in the Pareto set. The visual and post-optimisation analysis techniques allowed the selection of operating options for the shortlist using both explicit articulation of preferences (compromise programming), and implicit articulation of preferences within the context of the entire Pareto set (pseudo-weight vector, visual analysis). The use of both different preferences on objectives and different visual and post-optimisation analysis techniques resulted in the shortlist of a number of operating options with a range of objective performance. This shortlist is of a manageable size for comparing operating options in more detail, however the selection of a single option remains difficult. It is recommended that multi-criteria analysis be used to assess and compare operating options against additional criteria and explicitly incorporate preferences on these criteria to select a final operating option.

A range of visual analysis techniques have been presented for the framework, which help to understand the trade-offs between objectives and the relationships between the decision variables and objectives. Each of the visual analysis techniques differs in how they illustrate the objective function and decision variable space. They may plot the entire Pareto set, or a reduced set of cluster representatives. They may show the objective function performance and/or decision variable values; the relationships between objective functions and decision variables; or the distribution of decision variables or objective functions. Finally they may have different approaches to showing the multiple dimensions of the decision space, e.g. the multiple plots of the scatterplot matrix or the single glyph plot. Applications of each of the techniques allowed different insights into the characteristics of the decision and objective space of the case study. Therefore it is recommended that a decision-maker, at least initially, trials multiple visual analysis techniques to capture the range of information they can provide. Use of scripts for visual analysis, such as those provided for the case study, can assist this process. Through implementing these techniques, the decision-maker can identify those that provide the insights required for their case study or those that suit their preferences. It is also recommended that cluster analysis is used to reduce the Pareto set to a manageable size to support implementation of many of the visual analysis techniques. The use of reusable code such as that provided alongside this case study, will help to make the cluster and visual analysis process faster and repeatable.

Three post-optimisation analysis techniques were included in the framework, to help identify efficient operating options. Each of these techniques differ in their approach to measuring efficiency. As a result, even for the same scenario of preference weights, different options may be identified using different techniques. The compromise programming and pseudo-weight vector approaches also differ in their method of incorporating preferences. Combining these two approaches could take advantage of these differences. Firstly, application of the pseudo-weight vector approach could help to identify or reinforce decision-maker preference weights. Then these weights could be used in compromise programming to identify the most efficient operating option in the Pareto set. It is possible that this may provide a similar outcome to single-objective optimisation using a weighted objective function combining multiple objectives. However, the advantage of the multi-objective optimisation process is that it allows the decision-maker to see the operating option that reflects their objective preferences in the context of other feasible operating options, and to consider a range of options for further analysis. This may result in a different option being considered, or at the very least provides an understanding of the advantages or disadvantages of the chosen option over the other feasible options.

Whilst this case study has shown some cross-over between shortlisted options identified from the visual and post-optimisation techniques, in general the different techniques and preference scenarios identified different options for shortlist. Therefore, the implementation of multiple post-optimisation analysis techniques and preference scenarios, alongside visual analysis techniques, is recommended to capture a diverse and robust shortlist for further analysis.

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# Chapter 6: Multi-criteria analysis

In Chapter 5, the case study Pareto set of 677 operating options was reduced to a shortlist of nine operating options using cluster, visual and post-optimisation analysis. These operating options are optimal for the three management objectives and reflect different scenarios of decision-maker preferences and measures of efficiency in objective trade-offs. The optimisation process considered only three of a wider set of management criteria as objectives, and a single inflow scenario; the shortlist is of a manageable size for assessment against the full set of management criteria as well as additional inflow scenarios. As recommended in the framework, multi-criteria analysis can be used to assess performance of operating options against multiple management criteria, and to select a single operating option using preferences on the criteria. Thus this chapter applies multi-criteria analysis to the shortlist of nine operating options from Chapter 5, using the framework components highlighted in Figure 6.1.

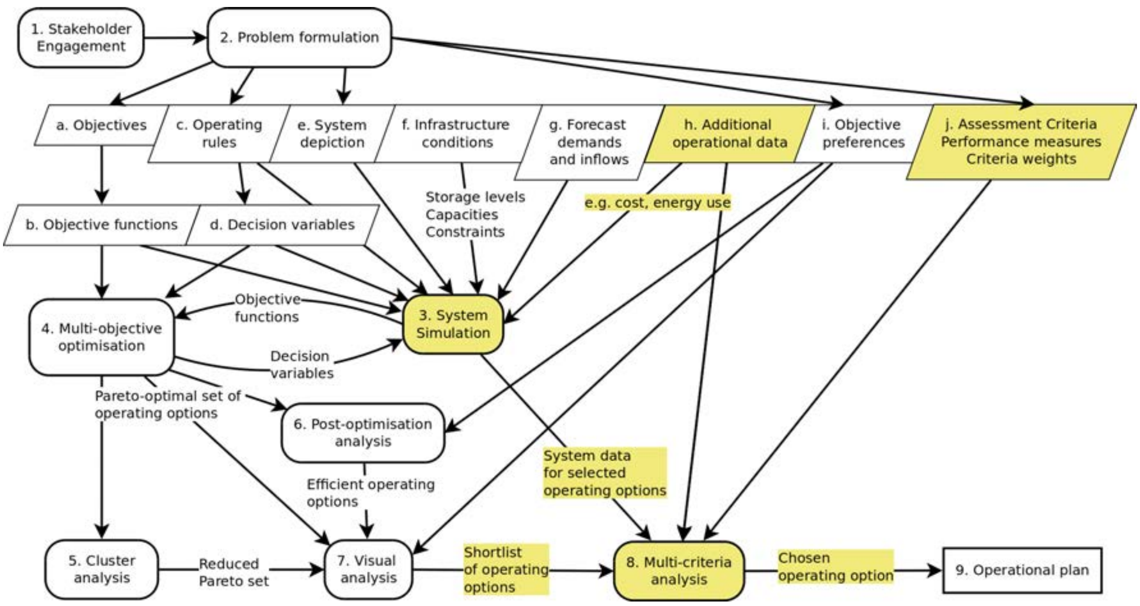


**Figure 6.1:** The framework for short-term operational planning of water grids, highlighting the components used in multi-criteria analysis applied in this chapter.

This chapter contains the following journal paper, which demonstrates the application of the multi-criteria analysis framework components, highlighted in Figure 6.1:

> Ashbolt, S. C. and Perera, B.J.C., 2016, 'Multi-criteria analysis to select an optimal operating option for a water grid', *Submitted to Water Resources Planning and Management*.

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|---|---|---|---|---|
| Stephanie Ashbolt | 85 | Research, analysis, writing | [redacted] | 4/7/16 |
| Chris Perera | 10 | Feedback and discussion on the research and writing | | 6/7/16 |
| | | | | |
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# Multi-criteria analysis to select an optimal operating option for a water grid

**Stephanie C. Ashbolt, B. J. C. Perera**

## Abstract

Water supply systems are diversifying and expanding in response to climate pressures and population growth. However, these water grids present challenges for the water supply manager in identifying optimal operating options for the short-term. This study demonstrates the final step in a framework to address these challenges, multi-criteria analysis, using a case study based on the South East Queensland water grid. A shortlist of nine water grid operating options have been identified, which are optimal in terms of minimizing total operational cost, maximizing water security, and minimizing spills from reservoirs, over a five-year period. This study assesses the performance of each of these nine operating options against a wider set of eighteen criteria reflecting cost, supply reliability, environmental flow, water quality, reservoir spill, and water security concerns. The weighted summation multi-criteria analysis technique is used to combine and rank performance of the nine operating options against the eighteen criteria. An operating option is selected that performs best on average across the eighteen criteria and four scenarios of preference weights. This operating option comprises a set of operating rules that can form the basis of a short-term optimal annual operating plan.

**Keywords:** decision support; framework; multi-criteria analysis; operating rules; multi-objective optimization; short-term planning; water grid; weighted summation.

## 1 Introduction

Water grids are diverse and interconnected water supply systems that are emerging as a response to the challenges of drought, climate variability, climate change, and population growth in urban areas. These water grids include interbasin transfers, alternative supply sources, and centralized management. They connect traditionally separate catchments or sources to increase supply availability in a manner similar to national electricity grids (Desai et al. 2005; Reynolds 1978; Spiller 2008). Operation of water grids is typically guided by operating rules that aim to meet multiple and competing criteria or objectives, such as minimizing operational cost, energy use, and flood risk; and maximizing water security and environmental flows. Determining optimal operating rules for these water grids is challenging due to trade-offs between objectives or criteria, differing decision-maker or stakeholder values on objectives or criteria, uncertainty in forecast streamflow and demand, and the heterogeneity and complexity of the supply-demand network. These factors make predicting outcomes of operating decisions more difficult. Thus decision support and analysis tools are required that are capable of meeting these challenges. To address these challenges, Ashbolt et al. (2014) proposed a framework for short-term planning for water grids, shown in Figure 1. This framework aims to support the decision-maker to identify an optimal set of operating rules, or operating option, for a water grid. It is this operating option that will provide the basis for a short-term (1-5 year) operational plan. Further details on the rationale and methodology of this framework are provided in Ashbolt et al. (2014).

In Ashbolt et al. (2016a) the authors demonstrated how the core component of this framework, multi-objective simulation-optimization (Figure 1, Steps 3 & 4), can be used in water grid management to identify a set of operating options that are optimal both for selected management objectives or criteria and for expected conditions over the planning period (Figure 1, a-g). This Pareto-optimal set of operating options is generally large and complex, due to the trade-offs between multiple objectives. Ashbolt et al. (2016b) demonstrated the use of cluster, visual and post-optimization analysis techniques to better understand the trade-offs and characteristics of the Pareto-optimal operating options and to identify a shortlist of operating options (Figure 1, Steps 5 to 7). However, additional preference information and assessment against a broader set of management criteria are required to select a single option from the shortlist. This broader set of criteria includes those excluded from optimization to limit the computational and conceptual complexity or due to their qualitative nature. Thus, the next step in the framework is the application of multi-criteria analysis to a shortlist of operating options to select a single operating option (Figure 1, Step 8). This can be achieved by assessing performance against a number of management criteria beyond those used in optimization, such as meeting environmental flows, supply reliability, storage targets and cost. Preferences or weights on these criteria are then used to combine performance into a single score to rank solutions. The highest ranked operating option could then be used to form an operational plan (Figure 1, Step 9).

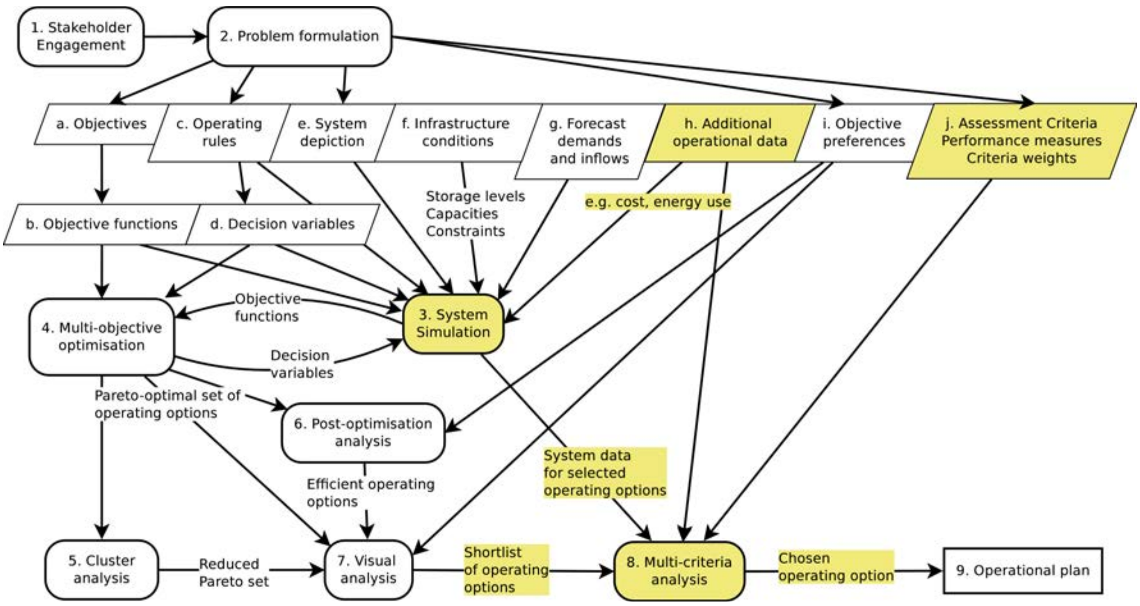


**Figure 1:** A framework for short-term operational planning for water grids, adapted from Ashbolt et al. (2014). Highlighted elements are those demonstrated in this paper. Inputs are shown in parallelograms *a* to *j*; processes/steps as boxes 1 to 9.

Multi-criteria analysis is a method that assists decision-makers to a select a trade-off solution from a set of alternatives by assessing performance against a range of criteria, whilst allowing for subjectivity and compromise. It has been widely applied in water resources planning and management (Hajkowicz and Collins 2007), including in combination with multi-objective optimization (Ko et al. 1994; Kularathna et al. 2011; Malekmohammadi et al. 2011; Weng et al. 2010). It is a useful tool for: assessing performance of options against quantitative and/or qualitative criteria beyond those included in the multi-objective optimization model; incorporating decision-maker and stakeholder values and preferences; and selecting one option from amongst a number of theoretically equally optimal options that result from multi-objective optimization.

A number of methods are available for applying multi-criteria analysis. Commonly applied methods in the water resources management domain include: value functions such as weighted summation and weighted multiplication; outranking approaches such as ELECTRE [ELimination Et Choix Traduisant la REalité] (Figueira et al. 2010) and PROMETHEE [Preference Ranking Organization METHod for Enrichment of Evaluations] (Brans and Mareschal 2005); distance to ideal point methods such as compromise programming (Ballestero 2007; Zeleny 1973); pairwise comparisons such as Analytic Hierarchy Process (AHP) (Saaty 1987); and fuzzy set analysis (Buckley 1984; Leberling 1981). Multi-criteria analysis techniques differ in their approach and complexity in ranking and combining criteria performance, and whether they assess quantitative (cardinal) data, qualitative (ordinal) data, or both. As discussed by (Hajkowicz and Higgins 2008), whilst it is important to select an appropriate method to suit the case study problem, these methods can provide similar rankings if the decision problem (criteria, decision options, weights and performance measures) is well structured and considers the limitations of the technique. Therefore any of these methods could feasibly be applied by the water resources manager as part of the framework in Figure 1. Selection would be based on the specifics of their case study decision problem, and preferences for or familiarity with the techniques. However, in the absence of such preferences or familiarity, the background paper to this framework (Ashbolt et al. 2014) recommends weighted summation, since it is a simple and transparent quantitative (cardinal) technique (Hajkowicz and Higgins 2008), which can be easily understood and demonstrated for the case study presented in this paper. This technique is discussed further in Section 3.4.

This paper demonstrates the application of the multi-criteria analysis component of the framework presented in Figure 1, to a shortlist of operating options for the case study described in Section 2. The application of multi-criteria analysis in this study involves four components of the framework, as highlighted in Figure 1: identification of assessment criteria, performance measures, and criteria weights (input *j*); collation of additional operational data required to calculate the criteria performance measures (input *h*); measurement of the performance of shortlisted operating options using the system simulation model (Step 3); and multi-criteria analysis to combine performance and criteria preference weights (Step 8). Stakeholder engagement (Step 1) is recommended as a valuable tool to involve stakeholders in decision-making and to help identify criteria, performance measures and weights for input *j.* However, explicit stakeholder engagement to identify criteria, performance measures and weights has been beyond the scope of the case study. Instead, this is achieved implicitly by drawing from current operational plans for the system upon which the case study is based.

Implementation of multi-criteria analysis to a shortlist of operating options is expected to identify a set of operating rules for short-term planning that are both optimal in terms of the management objectives and satisfy the management criteria according to decision-maker preferences. This set of short-term optimal operating rules, or operating option, can form the basis of an operational plan. This forms Step 8 of the framework illustrated in Figure 1, and combined with the previous studies (Ashbolt et al. 2016a; Ashbolt et al. 2016b), is expected to demonstrate the ability of the framework as a whole to support short-term operational planning for water grids.

## 2 Case study and a shortlist of operating options

The case study is based on the key features of the South East Queensland water grid located in the state of Queensland, Australia. A schematic of the case study water grid and its operating rules are illustrated in Figure 2. The water grid comprises 28 surface water storages, three groundwater borefields, a wastewater recycling scheme for potable or non-potable reuse, a desalination plant, and 48 urban and irrigation demands. These supplies and demands are connected by a network of one- and two-way pipelines and streams, with many demands connected to multiple sources via multiple paths.

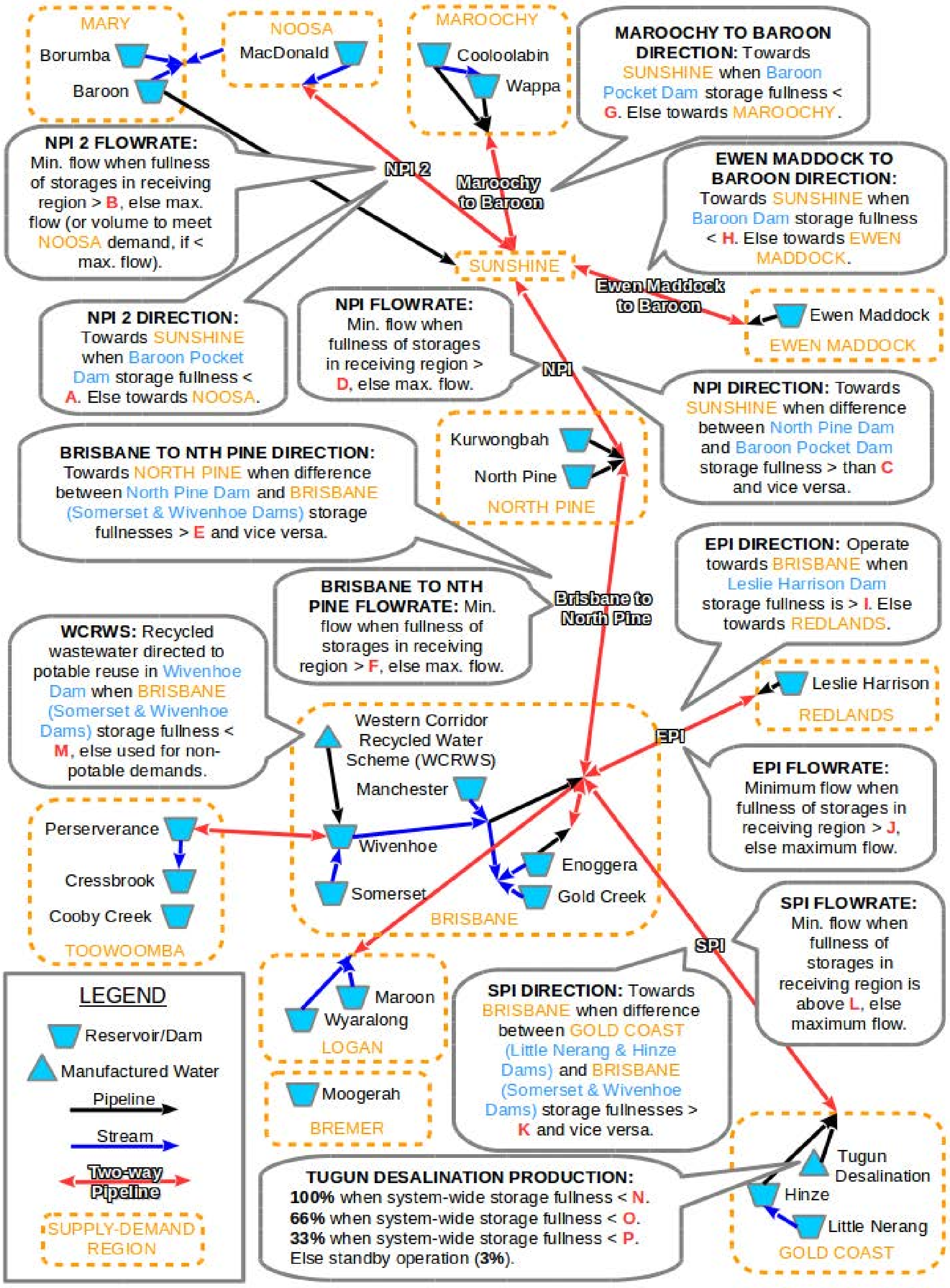


**Figure 2:** Schematic of the case study water grid, showing major infrastructure and supply-demand regions. The major infrastructure operating rules are outlined in the call-out boxes. The decision variables pertaining to these operating rules are highlighted in bold **(A, B, … P)**. The supply-demand regions include a number of demands as well as pipelines, streams, weirs and groundwater supplies not shown on this figure but included in the simulation model.

Short-term operational planning for this case study involves determining operating rules for the major infrastructure for the next 12 months. This planning process is repeated every 6 months, and looks at the impacts of potential operating rules over a longer five-year assessment period (Seqwater 2014). Therefore, although the operational plan is intended to apply for a one-year outlook (planning period), assessment of options occurs using a five-year outlook period (assessment period). There are 16 operating rules, shown in Figure 2 (callout boxes). The operating rules contain thresholds based on surface water storage volume, highlighted as A to P in Figure 2, that when reached, trigger changes in operation of the desalination plant, wastewater recycling scheme, and two-way pipelines. It is these thresholds that can be altered as decision variables to determine optimal operating rules for the planning period.

In Ashbolt et al. (2016a), a daily simulation-optimization model was developed using eWater Source (Dutta et al. 2013) to model the supply-demand behavior of the water grid and to optimize the operating rules for a five-year assessment period of 2001-2005. The operating rules were optimized by changing the decision variables (A-P in Figure 2) that comprise the rules. Multi-objective simulation-optimization was used to determine the optimal decision variables for maximizing water security (minimum system storage), minimizing operational cost, and minimizing spills from reservoirs, and for 2001-05 observed inflow. This multi-objective simulation-optimization process, using the NSGA-II genetic algorithm (Deb et al. 2002), resulted in a set of 1000 operating options, 677 of which were Pareto-optimal (non-dominated) in terms of the three management objectives and for the inflow and demand conditions experienced over the five-year assessment period. This Pareto-optimal set (Pareto set) outperformed operation according to a base case of fixed rules configured to perform well over longer-term conditions.

The objective performance of the Pareto set and the base case is shown in Figure 3; more detail of the case study and simulation-optimization process is provided in Ashbolt et al. (2016a). Figure 3 shows that in general, for this planning period, operating options that provide increased minimum system storage trade this increased performance for increases in total cost and total spill. Because of the size and trade-offs of the Pareto set, it is difficult to select a single operating option from this set without further understanding the reasons for the trade-offs or implementing preferences on the objectives.

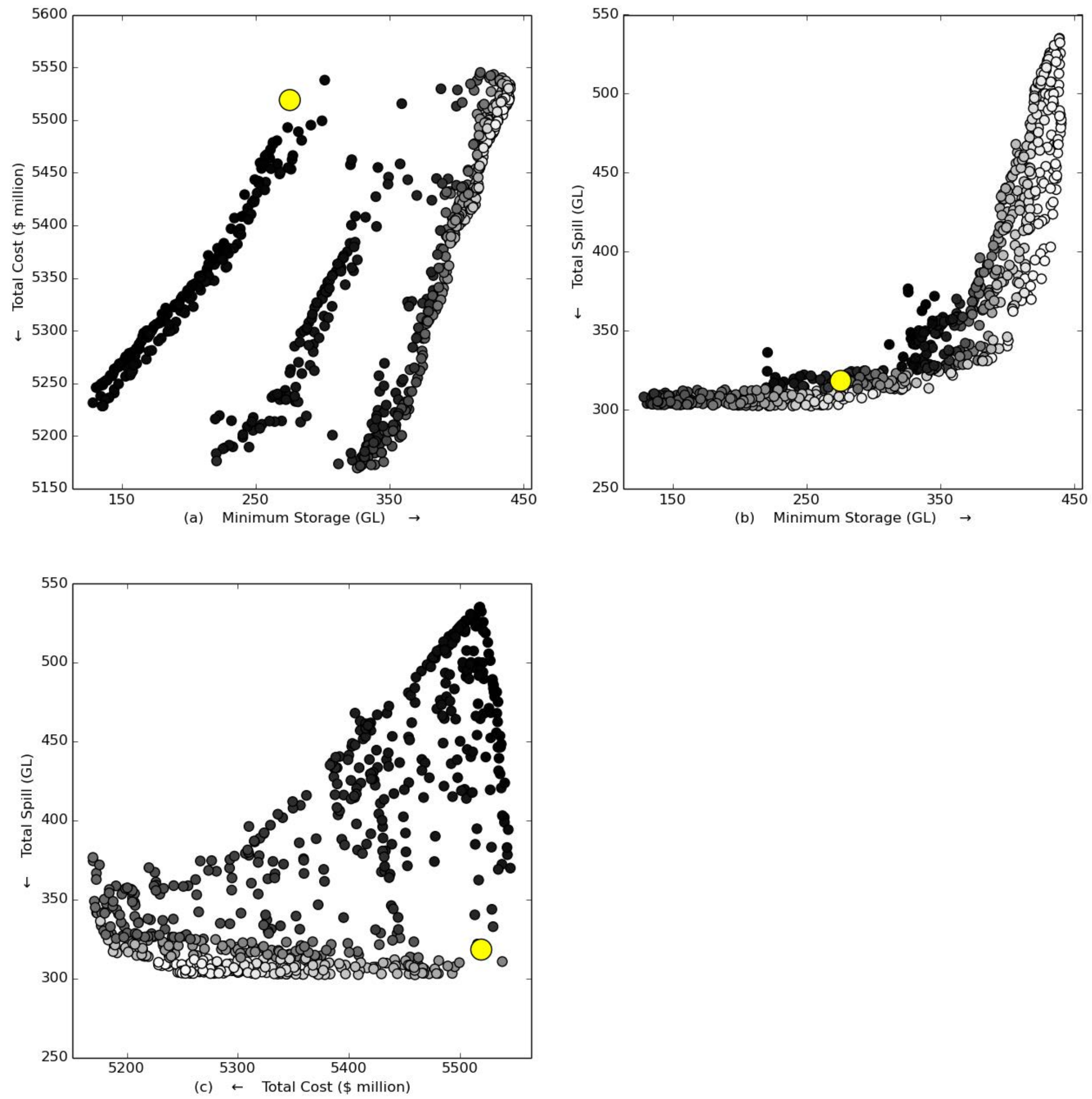


**Figure 3:** Objective performance of the Pareto set of operating options for the case study from Ashbolt et al. (2016a). Each plot shows two of the three objectives on the x and y axes, with arrows indicating direction of preference. Greyscale indicates the relative value of the third objective, with darker greys indicating better performance, and whites indicating poorer performance. The large circles indicate the performance of a base case scenario of fixed/historical operating rules.

In Ashbolt et al. (2016b), a combination of cluster, visual, and post-optimization analysis techniques were applied to the Pareto set of 677 options of Ashbolt et al. (2016a). These techniques were used to understand the relationships between the operating rules and objective performance, and to identify a shortlist of operating options for further analysis. The shortlisting process identified nine promising operating options, based on efficiency in objective trade-offs and three scenarios of decision-maker preferences on the objectives: for balanced performance (relatively equal performance across the three objectives), for low cost, and for high minimum storage. Further details of the process are provided in Ashbolt et al. (2016b). Figure 4 shows the objective performance of these nine operating options, relative to the best and worst performance in the Pareto set. These radar charts indicate that many of the options have close to highest (best) minimum storage, or lowest (worst) cost, or spill, but not all three. Others offer relatively equal performance (balance) across the three objectives. Each of these options are named according to their number in the Pareto set as presented in Ashbolt et al. (2016b), and represent a different set of 16 operating rules governing desalination production, potable reuse of recycled water and direction and flow-rate of two-way pipelines.

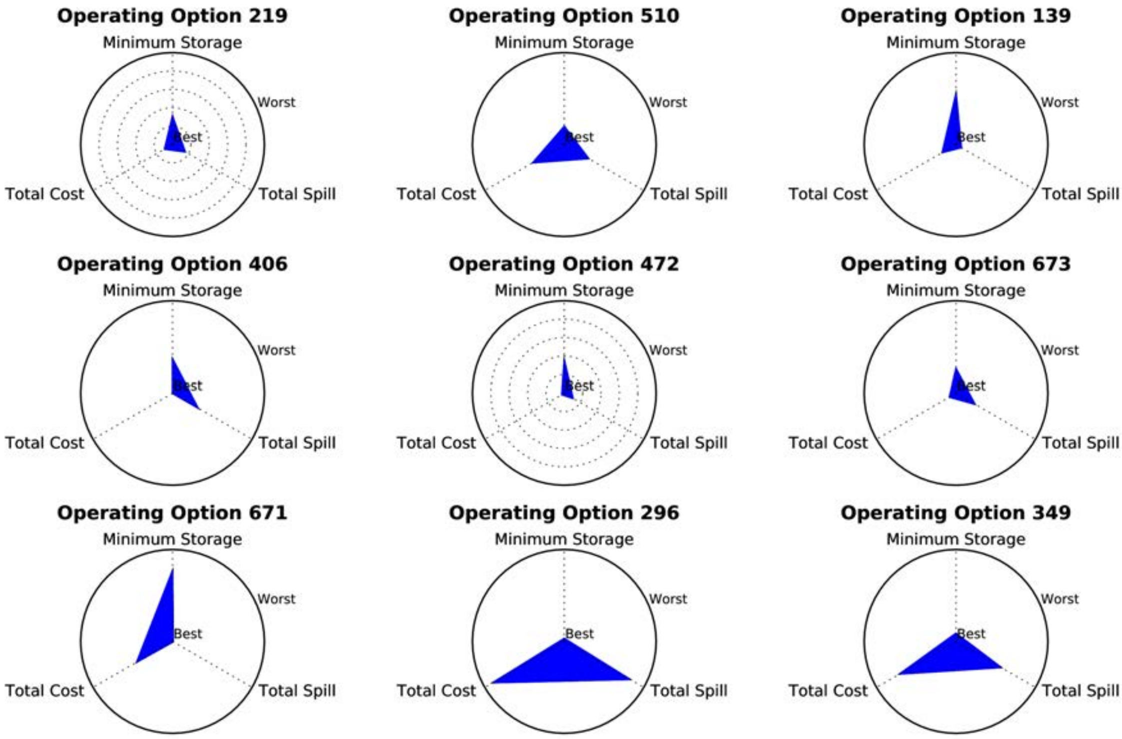


**Figure 4:** Shortlist of operating options selected from the Pareto set of 677 operating options, numbered as presented in Ashbolt et al. (2016b).

Table 1 outlines the decision variables A-P that differentiate the nine shortlisted operating options, and are used to comprise the operating rules in Figure 2. For example, Option 139 directs recycled water for potable reuse via the Western Corridor Recycled Water System when system storage fullness is below 99% of capacity. Options 406, 472, and 673, on the other hand are unlikely to use recycled water for potable reuse as it is only triggered when system storage is below 2% of capacity. Table 1 also indicates that Options 296 and 349 trigger full desalination production at the highest levels of system storage, 55% and 22% respectively. These options have the highest cost according to Figure 4, showing how desalinated water use is a considerable component of cost. Further details on the relationships between the decision variables and objective performance are provided in Ashbolt et al. (2016b).

**Table 1:** Decision variables A-P for the nine optimal operating options shortlisted from Ashbolt et al., (2016b) corresponding to the variables in the operating rules shown in Figure 2. NA (not applicable) indicates that a particular desalination threshold is not used, since it is superseded by one of the other thresholds. Items in bold indicate highest values amongst options, bold italic indicates lowest values.

| **Decision variable** | | **Option** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | **139** | **219** | **296** | **349** | **406** | **472** | **510** | **671** | **673** |
| **A** | NPI2 Direction | **100%** | ***83%*** | 95% | 89% | 85% | 97% | 97% | 93% | 96% |
| **B** | NPI2 Flowrate | 59% | **100%** | 66% | 62% | 70% | ***46%*** | 71% | 98% | 97% |
| **C** | NPI Direction | 86% | 93% | 92% | 89% | 90% | ***85%*** | 90% | ***85%*** | **94%** |
| **D** | NPI Flowrate | 59% | 88% | 99% | **100%** | ***0%*** | 37% | 96% | **100%** | 98% |
| **E** | Brisbane to Nth Pine Direction | 59% | 47% | 66% | **91%** | 48% | 14% | ***2%*** | 48% | 28% |
| **F** | Brisbane to Nth Pine Flowrate | ***0%*** | 3% | 5% | 5% | ***0%*** | ***0%*** | 3% | **43%** | ***0%*** |
| **G** | Maroochy to Baroon Direction | 99% | 96% | 97% | **100%** | ***6%*** | 99% | 80% | **100%** | 97% |
| **H** | Ewen Maddock to Baroon Direction | 64% | 64% | 78% | 99% | ***45%*** | 82% | 86% | **100%** | 96% |
| **I** | EPI Direction | ***6%*** | 17% | 34% | 19% | 7% | 36% | 33% | 67% | 14% |
| **J** | EPI Flowrate | 67% | 42% | 82% | 74% | ***0%*** | 54% | **84%** | 54% | 65% |
| **K** | SPI Direction | 61% | 71% | 66% | ***6%*** | 82% | 64% | **99%** | 76% | 81% |
| **L** | SPI Flowrate | **83%** | 1% | ***0%*** | ***0%*** | ***0%*** | ***0%*** | 1% | 71% | ***0%*** |
| **M** | WCRWS | **99%** | 73% | 82% | 86% | ***2%*** | ***2%*** | 95% | 54% | ***2%*** |
| **N** | Desalination Full Production | 2% | ***1%*** | **55%** | 22% | ***1%*** | 2% | 4% | 12% | 18% |
| **O** | Desalination 2/3 Production | 11% | NA | NA | **93%** | 10% | 3% | NA | 18% | NA |
| **P** | Desalination 1/3 Production | NA | 5% | NA | NA | NA | ***4%*** | **71%** | NA | NA |

Despite the reduced number of options shown in Figure 4, it remains difficult to select a single operating option without explicit preferences on the objectives or information about performance against additional management criteria. Thus multi-criteria analysis is used in this paper to select one of these nine shortlisted operating options for implementation by assessing and ranking performance based on a full set of case study management criteria and preferences on these criteria, over a wider range potential inflows than that used in optimization.

# 3 Method

The method implements multi-criteria analysis of the nine shortlisted operating options. It has four parts: identifying management criteria and performance measures; developing one or more sets of preference weights for each of the criteria; assessing the performance of the shortlisted operating options against these criteria, using the simulation model; and applying multi-criteria analysis using weighted summation to score and rank the operating options. These are discussed in the following sub-sections.

## 3.1 Management criteria and performance measures

The first step in multi-criteria analysis involves identifying the management criteria and how performance of operating options should be measured for each criterion. For the case study, the criteria and performance measures are mostly identified from those considered both explicitly and implicitly in current South East Queensland (SEQ) operational planning, represented by the Annual Operations Plan (AOP) (Seqwater 2014). These criteria and their performance measures are described in the following sections, and summarized in Table 2 and in Section 3.1.7.

### *3.1.1 Total operational cost*

Total operational cost is a key criterion in the AOP, and was also an objective in the optimization of the case study operating rules as described in Section 2. Operational cost is measured in two components, summed over the five-year assessment period. The first component is the total operational cost due to pumping, treatment, and production of water at different points in the network. These costs are sourced from the Queensland Competition Authority (2012). The second component is a nominal cost per switch in pipeline direction. Whilst cost data is not available for switching pipeline direction, discussion with grid managers revealed that frequent switches are avoided as they are expected to incur labor and other operational costs, as well as potential water quality issues due to change in flow direction. Therefore a nominal cost of $40,000 (AUD) was added to total operational cost, identified through sensitivity testing as sufficient to reduce frequency of switching but still low enough to allow switching to occur. In future, this nominal cost should be updated. Total operational cost is measured according to Equation 1:

$$\text{TotalCost} = \sum_{t=1}^{T}\left[\sum_{f\in F}\text{UnitCost} * \text{FlowRate} + \sum_{p\in P}\$40{,}000 * \text{Switch}\right] \qquad \textbf{Equation 1}$$

where *Total Cost* is the total operational cost, which is the sum of: the *Unit Cost* multiplied by the *Flow Rate* at a node or link in the network, *f,* of the set *F*; and the nominal cost of $40,000 per *Switch* in pipeline direction for each two-way pipeline *p*, in the set *P.* These costs are summed across each timestep *t* of the entire planning period *T*. The total operational cost should be minimized where possible.

### 3.1.2 Total spill volume

A total spill volume criterion is not explicitly included in the AOP. However, it was one of the objectives in the optimization of the operating rules described in Section 2, with the aim to minimize spills (uncontrolled releases) from reservoirs to reflect the value of surface water and potentially reduce the risk of flooding. For the same reasons, it is included in this case study. Performance for this criterion is measured using Equation 2:

$$\text{TotalSpill Volume} = \sum_{t=1}^{T}\left[\sum_{r\in R}\text{SpillVolume}\right] \qquad \textbf{Equation 2}$$

Where *Total Spill Volume* is determined as the sum of the *Spill Volumes* for each reservoir *r* in the set *R*, for each timestep *t* over the entire planning period *T*. The aim of operation is to minimize the value of this performance measure.

### 3.1.3 Environmental flows

Environmental flows are also not explicitly addressed in the AOP. However, minimum passing flows are required at certain points in the river network, and are included as minimum flow requirements in the simulation-optimization model. Therefore the ability to meet these flow requirements is included as a criterion in this case study. The ability of an operating option to meet environmental flow requirements can be measured by the quantity of the environmental flow deficit, measured as the deviation below the minimum flow. This is calculated as per Equation 3:

$$D_E = \sum_{e \in E} \left[ \sum_{t}^{T} \left( EF_R - EF \right) \right] \qquad \textbf{Equation 3}$$

where $D_E$ is the deficit in minimum environmental flows, calculated as the difference between the minimum environmental flow required, $EF_R$, summed over all timesteps *t* in the planning period of length T, and for all environmental flow requirement points *e* in the set *E*. When the flow volume is greater than the minimum flow, a deficit of zero is recorded. The aim of operation is to minimize the value of this performance measure.

### 3.1.4 Demand

The ability to meet demand is a key consideration in the AOP. This is considered by assessing current status of supply assets and comparing their volumetric capacity to demand. Since this capacity assessment requires information on asset status, which is unavailable for the case study assessment period, it is not included in this study. However, an alternative criterion, with similar aim, is the volumetric reliability of supply. This criterion can be measured in the simulation model, and is included in this study. Performance of this criterion is measured as the ratio of volume supplied to demands to the volume ordered by demands, as per Equation 4:

$$R_S = \frac{\sum_{t=1}^{T} \left[ \sum_{d \in D} V_S \right]}{\sum_{t=1}^{T} \left[ \sum_{d \in D} V_O \right]} \qquad \textbf{Equation 4}$$

where $R_S$ is volumetric reliability of supply, $V_S$ is the volume of water supplied, and $V_O$ is the volume of water ordered by a demand *d* of the set of demands *D* on timestep *t*, summed over each timestep for the planning period of length *T*. The aim is to maximize values of this performance measure.

### 3.1.5 Water quality

Water quality concerns in the AOP center around compliance with contractual requirements, the Australian Drinking Water Guidelines (National Health and Medical Research Council 2016), and community aesthetic expectations.

Health-related water quality issues are considered as a hard constraint that must be met, and are largely addressed by not using water sources with current quality concerns, and maintaining minimum flows in the major pipelines. Whilst information on water quality output of assets for the assessment period is not available for the case study, a criterion for maintaining minimum pipeline flows can be included. The key minimum flow requirements are in the SPI, NPI, NPI2, and EPI two-way pipelines (Figure 2). Performance against this minimum pipeline flow criterion can be measured by the deficit or deviation from the minimum flow, when flow is less than the minimum flow. This is calculated according to Equation 5:

$$D_P = \sum_{p \in P} \left[ \sum_{t}^{T} \left( MF_R - MF \right) \right] \qquad \textbf{Equation 5}$$

where $D_p$ is the deficit in minimum flow in the pipelines, calculated as the difference between the minimum flow required, $MF_R$, and the minimum flow in the pipeline $MF$, summed over all timesteps $t$ in the planning period of length $T$, and for all pipelines $p$ in the set $P$. When the flow volume is greater than the minimum flow the deficit is recorded as zero. The aim is to minimize the value of this performance measure.

### *3.1.6 Water security*

Water security for South East Queensland is measured by the water security criteria, consisting of risk criteria and level-of-service (LOS) objectives. These are set out in the System Operating Plan (Queensland Water Commission 2012) and Annual Operations Plan (AOP) (Seqwater 2014). They are represented as storage targets, listed in Table 2, however performance can be improved beyond these targets. Most of the criteria are measured relative to the combined volume of the Grid 12 storages, which comprise approximately 90% of total grid storage capacity: Wivenhoe, Somerset, North Pine, Hinze, Baroon Pocket, Leslie Harrison, Ewen Maddock, Cooloolabin, Lake Kurwongbah, Lake MacDonald, Little Nerang and Wappa Dams. The water security criteria are included in this case study.

There are four risk criteria, R1 to R4 (see Table 2). These set out the acceptable probability of the combined Grid 12 storage volumes falling below 40% of combined capacity in the next 1 and 5 years, and below 30% in the next 3 and 5 years respectively. This probability can be determined by simulating the behavior of operating options over 1,000 replicates of 1, 3 or 5-year stochastic inflow, and counting the fraction of replicates where the combined 12 key storage volumes fall below 30% or 40% of capacity. The performance of each risk criterion is measured as per Equation 6:

$$R = \frac{N_r \, \text{where} F_{Grid12} < F}{N_r}$$ **Equation 6**

where $R$ is the risk criterion, $F_{Grid12}$ represents the percentage Grid 12 storage fullness, $F$ the percentage storage fullness threshold relevant to the criterion (e.g. 40%), and $N_r$ is the number of replicates, of length relevant to the criterion (1, 3 or 5 years). These performance measures are to be minimized, and should be below the target values in Table 2.

The level of service criteria, L1 to L7, set out the acceptable average recurrence of the combined Grid 12 storage volume dropping below 40%, 30%, 10%, and 5% of combined capacity; and the Wivenhoe, Baroon Pocket, and Hinze Dams dropping below the dead storage volume (see Table 2). Their performance is measured as the Average Recurrence Interval (ARI), which is the average number of years between spell events; a spell is a period of time when a storage or storages fall below the relevant percentage storage fullness threshold. The ARI can be calculated as the inverse of the average Annual Spell Probability (ASP) across 1,000 replicates of 10-year stochastic inflow. The ASP describes the probability that any one year will contain a spell event. The ASP for a single replicate is calculated as per Equation 7:

$$ASP_{S,F} = \frac{Y_{S,F}}{Y}$$ **Equation 7**

where $ASP_{S,F}$ is the annual spell probability for falling below $F$ percentage storage fullness, calculated by dividing the number of years, $Y_{S,F}$, where storage/s, $S$, fall below $F$, by the number of years in the replicate, $Y$. For this case study, $Y$ is equal to 10 years. For example, criterion L1 calculates $ASP_{40}$

as the number of years where the Grid 12 volume falls below 40% of capacity ($Y_{S,\,40}$), divided by the 10 year replicate length ($Y$).

The $ARI_{S,F}$, the average recurrence interval of the storage or storages $S$ falling below $F$ percentage fullness, is then calculated as per Equation 8:

$$\mathrm{ARI}_{S,F} = \frac{1}{\mathrm{Average}\left(\mathrm{ASP}_{S,F}\right) \mathrm{for}\, r \in \mathrm{R}} \qquad \textbf{Equation 8}$$

which is the inverse of the *Average* of the $ASP_{S,F}$ values across all replicates $r$ in the set R. These performance measures are to be maximized, and should be above the target values in Table 2.

Additional water security criteria considered in the AOP include the probability of the Grid 12 volume reaching 40% and 60% of capacity in 10 years. These are not part of the risk criteria but are two of the four criteria explicitly used to compare possible operating plans in the Annual Operations Plan May 2014 (Seqwater 2014) (alongside total cost C1 and the risk criterion R2). These additional criteria are also included in this case study and their target values are listed in Table 2. They can be calculated in the same manner as the risk criteria, but using longer stochastic inflow replicates of 10 years.

### *3.1.7 Criteria summary*

The previous sections identified eighteen criteria, in six categories, for the case study multi-criteria analysis. These criteria are listed in Table 2. This table also includes required thresholds that must be met for the water security criteria.

Criteria performance is measured over multiple scenarios of inflow to capture probability and uncertainty in the performance measures. For the water security criteria, the probabilities and average recurrence intervals are measured using 1,000 stochastic inflow replicates and evaluated over 1, 3, 5, or 10 year outlooks as stated for each criterion. For the remaining criteria, performance is averaged across five inflow scenarios from across the five-year historic probability distribution, described in Section 3.3. This inflow assessment across multiple scenarios provides an indication of robustness or sensitivity of criteria performance to different inflow conditions that might be experienced over the

**Table 2:** Criteria and required values

| **Category** | **Criterion** | **Description** | **Required thresholds** |
|---|---|---|---|
| Total Cost | C1 | Total operational cost ($ million AUD) | N/A |
| Spills/Flooding | S1 | Total spill volume (GL) | N/A |
| Environmental Flows | E1 | Environmental flow deficit (GL) | N/A |
| Demand | D1 | Volumetric reliability of supply | N/A |
| Water Quality | Q1 | Pipeline minimum flow deficit (GL) | N/A |
| Water Security | R1 | Probability of Grid 12 storages falling below 40% in 1 year | < 0.2% |
| | R2 | Probability of Grid 12 storages falling below 40% in 5 years | < 5% |
| | R3 | Probability of Grid 12 storages falling below 30% in 3 years | < 0.5% |
| | R4 | Probability of Grid 12 storages falling below 30% in 5 years | < 1% |
| | A1 | Probability of Grid 12 storages falling below 40% in 10 years | N/A |
| | A2 | Probability of Grid 12 storages falling below 60% in 10 years | N/A |
| | L1 | Average Recurrence Interval of Grid 12 falling below 40% | > 25 years |
| | L2 | Average Recurrence Interval of Grid 12 falling below 30% | > 100 years |
| | L3 | Average Recurrence Interval of Grid 12 falling below 10% | > 1,000 years |
| | L4 | Average Recurrence Interval of Grid 12 falling below 5% | > 10,000 years |
| | L5 | Average Recurrence Interval of Wivenhoe Dam reaching dead storage | > 10,000 years |
| | L6 | Average Recurrence Interval of Baroon Pocket Dam reaching dead storage | > 10,000 years |
| | L7 | Average Recurrence Interval of Hinze Dam reaching dead storage | > 10,000 years |

five-year assessment period, and incorporates some of the risk in solution performance due to inflow uncertainty (Higgins et al. 2008). Averaging is a relatively risk-tolerant approach, with equal weighting on over- and under-performance (Mortazavi-Naeini et al. 2015). However, various measures of robustness exist, each of which will affect the performance of a given option based on its acceptance of risk (Giuliani and Castelletti 2016). Therefore this robustness measure may be changed in the future to reflect changes in decision-maker preferences. In the meantime, the minimum and maximum values are also reported to help identify options that may significantly under- or over-perform for selected inflow scenarios.

## 3.2 Preference weights

Section 3.1 identified eighteen criteria, in six categories: cost, spills/flooding, environmental flows, demand reliability, water quality, and water security; the next step is to identify one or more scenarios of preference weights for each of these criteria. These preference weights can be used in multi-criteria analysis to combine criteria performance to a single score for each option. In practice, internal and/or external stakeholder engagement is generally used to help identify preference weights on the criteria. Stakeholder interaction may result in a single consensus or compromise set of preference weights, or multiple sets of weights that reflect contrasting opinions. However, stakeholder engagement is outside the scope of this case study. Instead, four sets of preference weights are formulated based on four preference scenarios: two hypothetical, and two based on the preferences implied in the Annual Operations Plan (AOP) (Seqwater 2014). Implementing these preference scenarios will provide a degree of sensitivity analysis in how changes in criteria preferences affect performance of solutions and the selection of the highest-ranked option.

The four scenarios of criteria preference weights are shown in Table 3. Preference Scenario 1 has equal weighting on all eighteen criteria, which assumes essentially no preferences for one criteria over another. This scenario means that each criterion performance measure will be summed equally, but will also provide a higher effective weight on the water security criteria as they number thirteen of the eighteen criteria. Preference Scenario 2 has an emphasis on cost and water security criteria, with a total of 40% weighting on each category, reflecting these concerns as key objectives and requirements in the AOP and prioritizing options that perform well on these measures. Preference Scenario 3 adjusts Scenario 1 to have equal weighting across the six categories of criteria, compensating for the higher number of water security criteria in the total. Preference Scenario 4 puts higher weighting of 20% each on the four key criteria explicitly considered in the AOP: total cost (C1), probability of key storages falling below 40% in 5 years (R2), probability of key storages falling below 40% in 10 years (A1) and the probability of key storages falling below 60% in 10 years (A2). This scenario would be expected to best represent current operational planning. These four preference scenarios are used in the multi-criteria analysis described in Section 3.4.

**Table 3:** Four preference weight scenarios for the case study, showing percentage weights for each of the eighteen criteria, totaling to 100%. ARI refers to the Average Recurrence Interval; Grid 12 refers to the 12 largest storages, comprising 90% of the total.

<table>
<tr><th colspan="2" rowspan="2">Category</th><th rowspan="2">Criterion</th><th rowspan="2">Description</th><th colspan="4">Preference Weights (%)</th></tr>
<tr><th>Scenario 1 (Equal weighting)</th><th>Scenario 2 (Cost and security emphasis)</th><th>Scenario 3 (Equal weighting of categories)</th><th>Scenario 4 (Emphasis on 4 key criteria)</th></tr>
<tr><td colspan="2">Total Cost</td><td>C1</td><td>Average Total Operational Cost ($ AUD)</td><td>5.6</td><td>40</td><td>16.7</td><td>20</td></tr>
<tr><td colspan="2">Spills/Flooding</td><td>S1</td><td>Average Total Spill (ML)</td><td>5.6</td><td>5</td><td>16.7</td><td>1.4</td></tr>
<tr><td colspan="2">Environmental Flows</td><td>E1</td><td>Average Environmental Flow Deficit (ML)</td><td>5.6</td><td>5</td><td>16.7</td><td>1.4</td></tr>
<tr><td colspan="2">Demand</td><td>D1</td><td>Average Volumetric Reliability of Supply</td><td>5.6</td><td>5</td><td>16.7</td><td>1.4</td></tr>
<tr><td colspan="2">Water Quality</td><td>Q1</td><td>Average Two-Way Pipeline Minimum Flow Deficit (ML)</td><td>5.6</td><td>5</td><td>16.7</td><td>1.4</td></tr>
<tr><td rowspan="13">Water Security</td><td rowspan="4">Risk Criteria</td><td>R1</td><td>Probability of Grid 12 falling below 40% in 1 year</td><td>5.6</td><td>3.1</td><td>1.3</td><td>1.4</td></tr>
<tr><td>R2</td><td>Probability of Grid 12 falling below 40% in 5 years</td><td>5.6</td><td>3.1</td><td>1.3</td><td>20</td></tr>
<tr><td>R3</td><td>Probability of Grid 12 falling below 30% in 3 years</td><td>5.6</td><td>3.1</td><td>1.3</td><td>1.4</td></tr>
<tr><td>R4</td><td>Probability of Grid 12 falling below 30% in 5 years</td><td>5.6</td><td>3.1</td><td>1.3</td><td>1.4</td></tr>
<tr><td rowspan="2">Additional Risk Criteria</td><td>A1</td><td>Probability of Grid 12 falling below 40% in 10 years</td><td>5.6</td><td>3.1</td><td>1.3</td><td>20</td></tr>
<tr><td>A2</td><td>Probability of Grid 12 falling below 60% in 10 years</td><td>5.6</td><td>3.1</td><td>1.3</td><td>20</td></tr>
<tr><td rowspan="7">Level of Service Criteria</td><td>L1</td><td>ARI of Grid 12 falling below 40%</td><td>5.6</td><td>3.1</td><td>1.3</td><td>1.4</td></tr>
<tr><td>L2</td><td>ARI of Grid 12 falling below 30%</td><td>5.6</td><td>3.1</td><td>1.3</td><td>1.4</td></tr>
<tr><td>L3</td><td>ARI of Grid 12 falling below 10%</td><td>5.6</td><td>3.1</td><td>1.3</td><td>1.4</td></tr>
<tr><td>L4</td><td>ARI of Grid 12 falling below 5%</td><td>5.6</td><td>3.1</td><td>1.3</td><td>1.4</td></tr>
<tr><td>L5</td><td>ARI of Wivenhoe Dam reaching dead storage</td><td>5.6</td><td>3.1</td><td>1.3</td><td>1.4</td></tr>
<tr><td>L6</td><td>ARI of Baroon Pocket Dam reaching dead storage</td><td>5.6</td><td>3.1</td><td>1.3</td><td>1.4</td></tr>
<tr><td>L7</td><td>ARI of Hinze Dam reaching dead storage</td><td>5.6</td><td>3.1</td><td>1.3</td><td>1.4</td></tr>
</table>

## 3.3 Assessment of criteria performance

The simulation model described in Section 2 is used to assess the criteria performance of the nine operating options according to the performance measures described in Section 3.1. As described in Section 3.1, the water security criteria are simulated using 1,000 stochastic replicates of 1-10 year inflow, to determine probabilistic and average recurrence performance measures. The remaining criteria are simulated to determine their average performance across five scenarios of inflow, spanning the historical flow duration curve of five-year inflows: the $10^{th}$, $25^{th}$, $50^{th}$, $75^{th}$, and $90^{th}$ percentiles. These inflow scenarios are generated by sampling periods of the historical inflow timeseries that match the $10^{th}$, $25^{th}$, $50^{th}$, $75^{th}$, and $90^{th}$ percentile total inflow volumes, as per the method described in (Ashbolt and Perera 2016). These inflow volumes are different to the single period of inflow for 2001-2005 used in optimization, which corresponded to observed inflow over the assessment period. The result of this performance assessment will be a decision matrix which shows the criteria performance for each operating option.

## 3.4 Weighted summation

Weighted summation is used to combine the criteria performance measure for each option using the preference weights. It is a simple and commonly used method for multi-criteria analysis that can be implemented in spreadsheet or other software. In short, it involves normalizing performance on a common scale, with larger values indicating better performance, multiplying that performance by weights, and summing these weighted measures into an overall utility function. Although it is a simple technique, it can provide similar results to other techniques, providing that careful attention is made to simplifications or assumptions in transforming and aggregating criteria (Hajkowicz and Higgins 2008). Key assumptions of the weighted summation technique include: that good performance on one criteria can offset poor performance in another; that linear normalization of criteria performance is appropriate; and that qualitative performance measures may be treated as quantitative when combining criteria performance. These assumptions are considered appropriate for this case study application, which deals only with quantitative criteria which can be traded-off against one another in a linear fashion.

The weighted sum of each alternative option can be determined by Equation 9:

$$A_i = \sum_{j=1}^{n} w_j norm(a_{ij}) for\ i = 1, 2, 3, \ldots, m$$

**Equation 9**

where $A_i$ is the weighted sum of an alternative option, *I*; *j* is a criterion of a set of *n* criteria; $w_j$ is the preference weight for criterion *j*; and norm($a_{ij}$) is the unity-normalized performance of alternative *i* for criterion *j*, on a scale from 0 to 1, where 0 indicates worst performance and 1 indicates best performance, calculated as per Equation 10:

$$norm(a_{ij}) = \frac{a_{ij} - min(a_{mj})}{max(a_{mj}) - min(a_{mj})}$$

**Equation 10**

where $a_{ij}$ is the performance of alternative *i* for criterion *j*, and $a_{mj}$ is the performance of all alternatives *m* for the criterion *j*. The weights $w_j \ldots w_n$ across all *n* criteria for an option should sum to 1. This weighted summation is repeated for all alternatives *i* of the set *m*.

# 4 Results and discussion

The nine shortlisted operating options shown in Figure 4 were assessed against the eighteen criteria, using the performance measures described in Section 3.3. These performance measures are shown in the decision matrix in Table 4. This matrix indicates that there is significant variation in performance between options, as well as trade-offs between criteria. For example, Option 296 has the best performance for all but two of the water security criteria (highlighted in bold), with many of the level of service criteria thresholds not reached (DNO). However, perhaps as a result of these higher storage volumes, this same option has the highest average spill volume of 2,971 GL over the 5-year planning period. Option 406 has a different set of trade-offs with the poorest performance for the risk criteria, volumetric reliability of supply (96.7%), and water quality

**Table 4:** Decision matrix of criteria and performance measures for the nine operating options. The best performance across options for each criterion is highlighted in bold; worst performance in bold italic. For the water security criteria, the performance measure is a probability across 1,000 stochastic replicates of 1-10 year inflow. For the remaining criteria, performance shown is the average across 10$^{th}$, 25$^{th}$, 50$^{th}$, 75$^{th}$, and 90$^{th}$ scenarios of 5-year inflow, with the range in performance (minimum to maximum) indicated in parentheses. DNO (Did Not Occur) for the water security criteria indicates that the storage threshold was not reached throughout all replicates.

| | | | Option | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Category** | **Criterion** | **Description** | *139* | *219* | *296* | *349* | *406* | *472* | *510* | *671* | *673* |
| *Total Cost* | *C1* | *Total Cost ($ million AUD)* | 2,717 (2,715 - 2,719) | 2,705 (2,703 - 2,707) | 2,798 (2,763 - 2,842) | ***2,802*** (2,797 - 2,805) | **2,700** (2,695 - 2,704) | 2,704 (2,700 - 2,709) | 2,750 (2,745 - 2,756) | 2,714 (2,710 - 2,716) | 2,704 (2,699 - 2,709) |
| *Spills/ Flooding* | *S1* | *Spill Volume (GL)* | 2,702 (626 - 5,058) | 2,828 (700 - 5,190) | ***2,971*** (924 - 5,305) | 2,968 (854 - 5,329) | 2,801 (742 - 5,078) | 2,774 (693 - 5,066) | 2,890 (772 - 5,257) | **2,549** (449 - 4,898) | 2,786 (698 - 5,069) |
| *Environmental Flows* | *E1* | *Environmental Flow Deficit (GL)* | 29.9 (20.9 - 38.6) | 29.1 (19.8 - 37.2) | 28.1 (19.6 - 35.5) | 28.3 (20.9 - 35.7) | **27.4** (19.8 - 35.2) | ***30.0*** (20.9 - 38.4) | 28.5 (19.6 - 36.1) | 28.4 (21.0 - 36.0) | 28.8 (19.6 - 36.3) |
| *Demand* | *D1* | *Volumetric Reliability (%)* | **98.0** (97.8 - 98.4) | 97.7 (97.2 - 98.1) | 97.7 (97.4 - 98.1) | 97.7 (97.5 - 98.2) | ***96.7*** (94.7 - 97.9) | 97.1 (95.7 - 98.1) | 97.8 (97.6 - 98.2) | 97.8 (97.1 - 98.4) | 96.9 (94.9 - 98.1) |
| *Water Quality* | *Q1* | *Pipeline Minimum Flow Deficit (GL)* | 0.917 (0.338 - 2.77) | 1.43 (0.368 - 5.27) | 0.970 (0.292 - 3.48) | 0.883 (0.259 - 3.19) | ***1.81*** (0.664 - 4.33) | 0.846 (0.278 - 2.66) | **0.534** (0.278 - 1.33) | 1.29 (0.259 - 5.35) | 1.36 (0.203 – 5.63) |
| *Risk Criteria* | *R1* | *Probability of Grid 12 < 40% in 1 year* | ***100%*** | 60.2% | **45.1%** | 46.6% | ***100%*** | ***100%*** | 48.1% | ***100%*** | 56.4% |
| | *R2* | *Probability of Grid 12 < 40% in 5 years* | ***100%*** | 92.0% | **84.5%** | 85.0% | ***100%*** | ***100%*** | 86.1% | ***100%*** | 92.2% |

| Category | | Criterion | Description | Option | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | *139* | *219* | *296* | *349* | *406* | *472* | *510* | *671* | *673* |
| *Water Security* | | *R3* | *Probability of Grid 12 < 30% in 3 years* | ***100%*** | 98.1% | **95.6%** | 96.1% | ***100%*** | ***100%*** | 96.4% | ***100%*** | 98.0% |
| | | *R4* | *Probability of Grid 12 < 30% in 5 years* | 49.9% | 51.7% | **28.6%** | 31.4% | ***75.0%*** | ***75.0%*** | 35.3% | 49.9% | 48.3% |
| | *Additional Risk Criteria* | *A1* | *Probability of Grid 12 < 40% in 10 years* | 49.9% | 60.8% | **42.3%** | 45.2% | ***75.0%*** | ***75.0%*** | 50.1% | 49.9% | 64.6% |
| | | *A2* | *Probability of Grid 12 < 60% in 10 years* | ***100%*** | ***100%*** | ***100%*** | ***100%*** | ***100%*** | ***100%*** | ***100%*** | ***100%*** | ***100%*** |
| | *Level of Service Criteria* | *L1* | *ARI of Grid 12 < 40%* | 1.60 | 1.56 | **1.81** | 1.79 | ***1.48*** | 1.54 | 1.75 | 1.67 | 1.53 |
| | | *L2* | *ARI of Grid 12 < 30%* | 4.00 | ***2.75*** | **5.23** | 4.80 | 2.86 | 3.08 | 4.38 | 4.00 | 2.97 |
| | | *L3* | *ARI of Grid 12 < 10%* | **DNO** | ***34.6*** | **DNO** | **DNO** | **DNO** | **DNO** | 1249 | **DNO** | **DNO** |
| | | *L4* | *ARI of Grid 12 < 5%* | **DNO** | ***9990*** | **DNO** | **DNO** | **DNO** | **DNO** | ***9990*** | **DNO** | **DNO** |
| | | *L5* | *ARI of Wivenhoe Dam reaching dead storage* | **DNO** | **DNO** | **DNO** | **DNO** | **DNO** | **DNO** | **DNO** | **DNO** | ***833*** |
| | | *L6* | *ARI of Baroon Pocket Dam reaching dead storage* | **DNO** | ***37.1*** | 45.6 | 57.5 | **DNO** | **DNO** | 56.8 | **DNO** | 49.0 |
| | | *L7* | *ARI of Hinze Dam reaching dead storage* | **DNO** | **DNO** | **DNO** | **DNO** | **DNO** | **DNO** | **DNO** | **DNO** | **DNO** |

(1.81 GL deficit); but lowest average cost ($2,802 million) and environmental flow deficit (27.4 GL). Overall, none of the options perform best across all criteria, and at this point it is difficult to identify the best performing option from the matrix. This selection is further complicated by the multiple preference scenarios and uneven preferences on the criteria. This highlights the need for multi-criteria analysis techniques such as weighted summation to score and rank alternatives using the preference information.

Table 4 also shows the range in performance measures across the five-year percentile inflow scenarios for the cost, spill, environmental flow, demand, and water quality criteria. For the water quality criterion, the range in performance, e.g. 0.20 – 5.63 GL for Option 673, is generally greater than the differences between the worst and best average measures across the operating options (0.53 – 1.81 GL). This suggests that the deficit in pipeline minimum flows is more dependent on reservoir inflow than the operating rules. Total operational cost, on the other hand, has a similar range within operating options, e.g. $2,763 – 2,842 million for Option 296, as between the worst and best performing options ($2,700 – 2,802 million). Thus, for some criteria, it is important for the decision-maker to appreciate the potential variation in performance measures due to inflow, particularly where this range might violate target values. Viewing such information may also cause the decision-maker to revise performance measures for selected criteria.

Comparing the required threshold values for the water security criteria in Table 2 to the performance measures in Table 4 indicates whether the required thresholds for the risk and level-of-service criteria are met for the nine operating options. Due to the water scarce initial conditions at the start of this planning period, with storages at 45% of capacity, the water security criteria show a high to 100% probability of storages falling below 40% or 30% in the next 1-5 years for all operating options. None of the nine options meet the risk criteria threshold requirements shown in Table 2 of less than 0-1% (depending on criterion). Likewise, none of the options meet the Level of Service criteria L1 and L2 of > 25 and > 100 years respectively. However, all but option 219 meet the L3 criterion required value of ARI > 1,000 years and many of the options meet the required value of ARI >10,000 years for L5-L7. The failure to meet many of the water security criteria may trigger the decision-maker to revise the optimization problem formulation (objectives, decision variables, or constraints), or to consider additional measures to improve water security, such as enacting demand restrictions.

Weighted summation was applied to the decision matrix of performance measures of the nine operating options in Table 4, using the four preference scenarios in Table 3. Table 5 shows an example of the weighted summation process for Preference Scenario 1, which places equal weighting on the criteria. This table shows the normalized weighted performance of each option against each criterion and the overall weighted sum of each option. The maximum possible score of 100 indicates best performance. For this preference scenario, Option 296 performs best, with an overall weighted sum of 73.7/100. This high performance is due to the combination of high performance and high weighting on the water security criteria. Option 406 performs worst for this preference scenario, with a weighted sum of 41.4/100. This is due to it having the lowest performance and thus a weighted sum of 0 for the risk criteria, water quality, and volumetric reliability of demand. Based on this preference scenario alone, Option 296 would likely be chosen for implementation. However, such a decision does not take into account the other preference scenarios. For example, Preference Scenario 2 has a higher weight on cost, for which Option 296 performs poorly due to the trade-off between cost and water security; therefore Option 296 would be expected to perform poorly for that preference scenario. Indeed, Table 6 indicates that this is the case.

Table 6 shows the overall weighted sum (across the eighteen criteria) for all four preference scenarios and nine operating options. None of the options performs best across all preference scenarios, highlighted in bold. Therefore it is not straightforward to select the best performing option. However, the average and range of the weighted sum for each option across the preference scenarios can be used to combine or summaries performance. Averaging the four weighted sums for each option combines performance into a single score, with an assumption of equal weighting on each preference scenarios. By this measure,

**Table 5:** Weighted summation for Preference Scenario 1 (equal weighting on criteria). The best performance across options for each criterion are highlighted in bold; worst performing in bold italic.

| Category | | Criterion | Description | Option | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | *139* | *219* | *296* | *349* | *406* | *472* | *510* | *671* | *673* |
| *Total Cost* | | *C1* | *Average Total Operational Cost ($ AUD)* | 4.6 | 5.3 | 0.2 | ***0*** | **5.6** | 5.3 | 2.8 | 4.8 | 5.3 |
| *Spills/ Flooding* | | *S1* | *Average Total Spill (ML)* | 3.5 | 1.9 | ***0*** | ***0*** | 2.2 | 2.6 | 1.1 | **5.6** | 2.4 |
| *Environmental Flows* | | *E1* | *Average Environmental Flow Deficit (ML)* | 0.1 | 2.0 | 4.2 | 3.7 | **5.6** | ***0*** | 3.2 | 3.5 | 2.6 |
| *Demand* | | *D1* | *Average Volumetric Reliability of Supply* | 5.6 | 4.5 | 4.6 | 4.6 | ***0*** | 1.7 | 4.8 | 5.0 | 1.0 |
| *Water Quality* | | *Q1* | *Average Two-Way Pipeline Minimum Flow Deficit (ML)* | 3.9 | 1.7 | 3.6 | 4.0 | ***0*** | 4.2 | **5.6** | 2.2 | 2.0 |
| *Water Security* | *Risk Criteria* | *R1* | *Probability of Grid 12 storages falling below 40% in 1 year* | ***0*** | 4.0 | **5.6** | 5.4 | ***0*** | ***0*** | 5.3 | ***0*** | 4.4 |
| | | *R2* | *Probability of Grid 12 storages falling below 40% in 5 years* | ***0*** | 2.9 | **5.6** | 5.4 | ***0*** | ***0*** | 5.0 | ***0*** | 2.8 |
| | | *R3* | *Probability of Grid 12 storages falling below 30% in 3 years* | 3.0 | 2.8 | **5.6** | 5.2 | ***0*** | ***0*** | 4.8 | 3.0 | 3.2 |
| | | *R4* | *Probability of Grid 12 storages falling below 30% in 5 years* | 4.3 | 2.4 | **5.6** | 5.1 | ***0*** | ***0*** | 4.2 | 4.3 | 1.8 |
| | *Additional Risk Criteria* | *A1* | *Probability of Grid 12 storages falling below 40% in 10 years* | ***0*** | 2.4 | **5.6** | 4.9 | ***0*** | ***0*** | 4.5 | ***0*** | 2.5 |
| | | *A2* | *Probability of Grid 12 storages falling below 60% in 10 years* | ***0*** | ***0*** | ***0*** | ***0*** | ***0*** | ***0*** | ***0*** | ***0*** | ***0*** |
| | *Level of Service Criteria* | *L1* | *ARI of Grid 12 storages falling below 40%* | 2.0 | 1.4 | **5.6** | 5.2 | ***0*** | 1.0 | 4.6 | 3.1 | 0.8 |
| | | *L2* | *ARI of Grid 12 storages falling below 30%* | 2.8 | ***0*** | **5.6** | 4.6 | 0.2 | 0.7 | 3.6 | 2.8 | 0.5 |
| | | *L3* | *ARI of Grid 12 storages falling below 10%* | **5.6** | ***0*** | **5.6** | **5.6** | **5.6** | **5.6** | 0.7 | **5.6** | **5.6** |
| | | *L4* | *ARI of Grid 12 falling below 5%* | **5.6** | ***0*** | **5.6** | **5.6** | **5.6** | **5.6** | ***0*** | **5.6** | **5.6** |
| | | *L5* | *ARI of Wivenhoe Dam reaching dead storage* | **5.6** | **5.6** | **5.6** | **5.6** | **5.6** | **5.6** | **5.6** | **5.6** | ***0*** |
| | | *L6* | *ARI of Baroon Pocket Dam reaching dead storage* | **5.6** | ***0*** | ***0*** | ***0*** | **5.6** | **5.6** | ***0*** | **5.6** | ***0*** |
| | | *L7* | *ARI of Hinze Dam reaching dead storage* | **5.6** | **5.6** | **5.6** | **5.6** | **5.6** | **5.6** | **5.6** | **5.6** | **5.6** |
| **Weighted Sum** | | | | **57.6** | **42.3** | **73.7** | **70.4** | ***41.4*** | **43.3** | **61.3** | **62.1** | **46.0** |

Option 671 performs best with an average weighted sum of 59.7. The range in the weighted sums provides a picture of the sensitivity of performance to preference scenarios. This measure indicates that Option 671 also has the largest range of 40.9 between the lowest and highest scores across the preference scenarios. This makes this option less attractive if there is uncertainty in preference scenarios. Option 510, on the other hand, has an average score of 59.6 close to that of Option 671, with a significantly reduced range of 5.9 across preference scenarios. This option would be a better candidate if relative insensitivity to preference scenarios is desired. This option also performs best for Preference Scenario 4, which is based on the Annual Operations Plan. Based on these measures, Option 510 is recommended for this case study for implementation for an operating plan.

**Table 6:** Weighted sums for each of the operating options and preference scenarios. Best performing options for each preference scenario, as well as the highest average weighted sum, and lowest range, are highlighted in bold The worst performing options for each preference scenario, lowest average weighted sum and largest range are highlighted in bold italic.

| Option | Preference Scenario 1 (Equal weighting) | Preference Scenario 2 (Cost and security emphasis) | Preference Scenario 3 (Equal weighting of categories) | Preference Scenario 4 (Emphasis on 4 key criteria) | Average | Range |
|---|---|---|---|---|---|---|
| *139* | 57.6 | 67.0 | 62.4 | 30.2 | 54.3 | 36.8 |
| *219* | 42.3 | 61.9 | 52.0 | 46.1 | 50.6 | 19.7 |
| *296* | **73.7** | 46.5 | 51.8 | 56.8 | 57.2 | 27.2 |
| *349* | 70.4 | ***43.2*** | 50.4 | 52.5 | 54.1 | 27.1 |
| *406* | ***41.4*** | 62.5 | ***46.5*** | 29.2 | ***44.9*** | 33.3 |
| *472* | 43.3 | 62.2 | 48.2 | ***28.9*** | 45.6 | 33.3 |
| *510* | 61.3 | 57.7 | 62.6 | **57.0** | 59.6 | **5.6** |
| *671* | 62.1 | **72.0** | **72.9** | 32.0 | **59.7** | ***40.9*** |
| *673* | 46.0 | 63.5 | 47.4 | 47.4 | 51.1 | 17.6 |

# 5 Summary and conclusions

This study examined the performance of nine operating options for a case study water grid, identified from the previous studies (Ashbolt et al. 2016a; Ashbolt et al. 2016b). Each of these operating options were Pareto-optimal for three management objectives: maximizing minimum storage, minimizing operational cost, and minimizing reservoir spills. However it was difficult to select a single option due to the trade-offs between objectives. Therefore this study involved assessing these options against the full set of eighteen management criteria, including volumetric reliability of supply, water quality, cost, environmental flow and water security criteria. Clear differences were seen in the decision matrix of criteria performance of operating options, with trade-offs between criteria. Due to these trade-offs it remained difficult to select a single preferred operating option from the decision matrix. Multi-criteria analysis using weighted summation offered a simple and transparent method to combine criteria performance to a single score for each option, applying preference weights on the criteria and averaging the weighted sum across four preference scenarios. Ranking options by the weighted sum allowed for the selection of a single candidate operating option, Option 510, which can form the basis of an operating plan.

In conclusion, this study has shown how multi-criteria analysis can be used to select a single option from a set of short-term multi-objective optimal operating options for a water grid. This option can be used to form an annual operating plan. Along with the previous studies (Ashbolt et al. 2016a; Ashbolt et al. 2016b), this study provides proof-of-concept of the framework proposed in Ashbolt et al. (2014) to support short-term operational planning for water grids.

This study has also highlighted the advantages of the framework for short-term operational planning of water grids in using both multi-objective optimization and multi-criteria analysis together to identify suitable operating options for water supply management. Multi-objective simulation-optimization allows the decision-maker to efficiently explore the possibilities in terms of a limited number of priority management criteria or objectives. Representation of a greater number of criteria in the optimization process may be infeasible due to the increasing complexity of the objective space, or the need for multiple stochastic inflow scenarios for assessing probabilistic criteria. Multi-criteria analysis is useful in assessing performance against the remaining management criteria not considered in optimization. Applying multi-criteria analysis to Pareto-optimal solutions also allows objective performance to be combined in a single score in a transparent and flexible manner, placing the chosen solution in context with the alternative possibilities. It also allows the decision-maker to distinguish solutions that might otherwise seem similar in the Pareto set. For example, in terms of the three management objectives considered in the case study Pareto set, Options 472 and 673 have the same low operational cost. However, Option 472 performs worst amongst the options in terms of environmental flow deficit and risk criteria, for a slight reduction in spill in comparison to Option 673. An alternative approach of using single objective optimization does not consider the trade-offs between the key criteria and narrows the search space, reducing the range of operating possibilities that are considered. Alternatively, using multi-criteria analysis without optimization may make it difficult to explore the full range of feasible operating rules or to identify options that are optimal in terms of the priority management criteria.

This case study has considered eighteen criteria, in six categories. The preference weight scenarios were established based on the six categories, limiting their complexity. For the water security criteria, where there are multiple criteria within the one category, equal weighting was assumed for all criteria within the category. This was considered suitable for this study, since the water security criteria and performance measures describe similar objectives. However, a large number of criteria multiplies the uncertainty in developing preference scenarios due to their subjectivity. Careful consideration of the trade-off between this uncertainty and the number of criteria and preference weights is recommended for future studies. Stakeholder input is a key component of multi-objective optimization and multi-criteria analysis (Brown et al. 2015; Kodikara et al. 2010; Maier et al. 2014; Wu et al. 2016) and is recommended for future applications of the multi-criteria analysis component of the framework, both to refine criteria and performance measures and to combine the preference weights into a single preference scenario.

For the case study the multi-criteria analysis process was complicated by the use of multiple scenarios of preference weights on the criteria. This provided some sensitivity analysis of the weighted sums to the preference weights; each preference scenario changed the weighted sum and ranking of operating options. The average and range in performance was used to assess performance across scenarios; Option 510 was recommended as a candidate for the case study operating plan as it had the second highest average performance, but the lowest range in performance across the four preference scenarios. Averaging the performance across preference scenarios assumed equal weighting on each scenario; unequal weighting could be used to represent weights on the preference scenarios. Alternatively, a single preference scenario could be developed that represents this compromise. Regardless of approach, since preference weights are subjective, it is recommended that a decision-maker test a wider range of preference scenarios to understand their sensitivity to ranking of options. This could help in understanding which criteria or preference weights most affect performance and ranking of options, and require more attention in their selection. In some cases, different preference scenarios may identify the same option as having best performance, bringing confidence to the results. For example, in this case study, whilst the preference scenarios changed the overall ranking of options, both Preference Scenario 2 and 3 identified the same option (671) as the best performer. Where it is difficult to articulate preferences, a similar approach could be used by the decision-maker to identify an option that is robust to a range of criteria preference weights.

Depending on the availability of data and the preferences of decision-makers, the multi-criteria analysis presented in this study could be improved by assessing performance under forecast inflows. In Ashbolt and Perera (2016), the authors demonstrate the use of streamflow forecasts for this case study to improve objective performance in optimization of operating rules. However the forecast horizon is limited to three months, which reduces their utility for the five to ten year criteria assessment periods. Nevertheless, the three-month forecast inflow scenarios developed in that study could be used to formulate additional criteria or performance measures, or be used directly if 1 year forecasts are developed in the future. Additionally, performance under a range of forecast demands could be assessed; combining demand scenarios with scenarios of forecast streamflow could be used to develop scenarios to assess robustness of options (Beh et al. 2015; Maier et al. 2016). Similarly, multiple multi-criteria analysis techniques could be implemented to assess the sensitivity or robustness of the result to the method that is used (Hajkowicz and Collins 2007).

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# Chapter 7: Using streamflow forecasts to improve short-term operating rules

Chapter 4 demonstrated the multi-objective simulation-optimisation components of the framework and identified a set of operating rules for the case study water grid that were Pareto-optimal in terms of the three management objectives of maximising water security (minimum storage), minimising operational cost, and minimising spills from reservoirs. This showed the potential of multi-objective optimisation to optimise operating rules to improve objective performance over using fixed rules that are tailored to perform well over the long-term. However, a key limitation was that only a single scenario of inflow timeseries from the record was used; this does not reflect the reality of uncertainty in predicted inflow.

As per the recommendations in Chapter 2, it is preferable to use streamflow forecasts when applying the operational planning framework. Additionally, one of the key challenges for water grid management outlined in Section 1.2 is incorporating streamflow uncertainty into operational planning. Thus this chapter assesses the potential of publicly available streamflow forecast information, such as that provided by the Bureau of Meteorology in Australia, to improve objective performance of operating rules. However, the forecast streamflow forecast information currently available for the case study extends only to a three-month horizon, rather than the 1 year planning or 5 year assessment periods. Therefore this chapter instead applies the multi-objective optimisation component of the framework only, to find operating rules for the case study using forecast streamflow and a revised three-month planning period. If forecasts with a 1-year horizon become available in the future, a 1-year forecast-optimised Pareto set could be input to the other framework components for the case study covered in Chapters 5 and 6.

This chapter contains the following journal paper, which demonstrates the use of streamflow forecasts to improve operating rule performance, using the framework components highlighted in Figure 7.1:

Ashbolt, S. C. and Perera, B.J.C., 2016, 'Multi-objective optimisation of short-term operating rules for water grids using streamflow forecasts', *Submitted to Water Resources Planning and Management.*

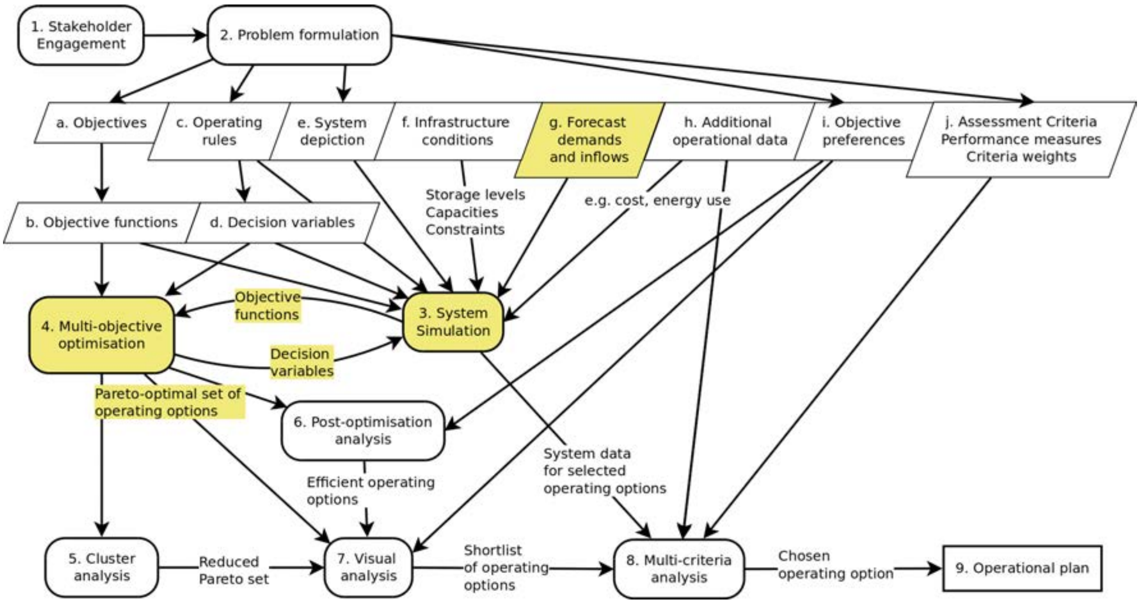


**Figure 7.1:** Framework for operational planning of water grids, highlighting components demonstrated in this chapter.

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|---|---|---|---|---|
| Stephanie Ashbolt | 85 | Research, analysis, writing | [redacted] | 4/7/16 |
| Chris Perera | 10 | Feedback and discussion on the research and writing | | 6/7/16. |
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# Multi-objective optimisation of seasonal operating rules for water grids using streamflow forecast information

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## Abstract

Multi-objective simulation-optimisation is a useful tool for determining operating rules for water supply that are optimal for multiple management objectives and for expected conditions over the planning period. Previous studies have shown the benefits of streamflow forecasts in improving optimised objective performance of reservoir operating rules. This study demonstrates a simple method to update historic inflow scenarios for a case study water grid, using publicly-available streamflow forecast information. Multi-objective optimisation is used to find operating rules that are optimal for three management objectives – maximising minimum system storage, minimising operational cost, and minimising spills from reservoirs – and for the forecast inflow scenarios. These forecast-optimised rules are compared to those optimised using inflow scenarios from the historical distribution, representing operation in the absence of forecast information. The results across three seasonal (3 month) planning periods indicate that, on average, operating rules optimised using forecast streamflow information perform slightly better in terms of the management objectives than those optimised using historical inflow information. Using multiple scenarios of inflow that span the forecast distribution increases the robustness of operating rules and reduces the risk of under-performance due to forecast inaccuracy. The results suggest that even a relatively simple method for incorporating streamflow forecast information into multi-objective simulation-optimisation has the potential to provide improvements in short-term operating rules for a water grid.

## Keywords

Multi-objective optimisation; operating rules; simulation; streamflow forecasts; short-term operational planning; water grid

## 1. Introduction

Water supply managers typically need to develop seasonal (3-month), annual (1 year) or short-term (up to 5 year) operating plans, to identify operating rules that can achieve their desired outcomes. These desired outcomes are typically expressed in terms of multiple management objectives or criteria which aim to maximise water security, minimise energy use, minimise operational cost, or meet environmental flows. Multi-objective simulation-optimisation is a useful tool to determine operating rules that are optimal for multiple management objectives (Ashbolt et al. 2016a; Ashbolt et al. 2014; Kim 2008; Kumphon 2013). The operating rules found using multi-objective simulation-optimisation will be optimal not only for the management objectives, but also for the inflow timeseries that are input to the simulation-optimisation model. Therefore, operating rules may only remain optimal during the planning period if the inflow assumptions in the simulation-optimisation process hold true in reality (Beh et al. 2015; Walker et al. 2013). For this reason, uncertainty in expected inflow should be incorporated into simulation-optimisation to identify options that perform optimally over – are robust to – a range of expected inflow probabilities (Maier et al. 2014).

Multiple inflow scenarios, sampled from the historic inflow record, can be used in simulation-optimisation of the water supply system to identify operating rules that are robust to various inflow possibilities. However, using such historical inflow scenarios assumes no knowledge of the probability of these scenarios in the near future; many may be extremely unlikely based on current catchment conditions (Faber and Stedinger 2001). Streamflow forecasts that reflect both current catchment conditions and the climate outlook over the planning period may suggest different probabilities of inflow. The historic-sampling approach could be updated by selecting inflow scenarios that reflect the forecast probability distribution for the planning period. Used with optimisation, this forecast-based sampling approach should allow operating rules to be tailored for expected conditions over coming months. Although streamflow forecasts are uncertain, they can provide a more honest and risk-aware indicator of future conditions than relying on historical averages (Krzysztofowicz 2001; Piechota et al. 2001); optimising operating rules to multiple scenarios from across the forecast inflow distribution should improve the robustness of operating rules and system performance if observed inflow volumes deviate from the forecast median (Georgakakos and Graham 2008).

Seasonal to annual streamflow forecasts are becoming more widely and publicly available for catchments in Australia (e.g. Bureau of Meteorology 2015) and the United States (e.g. Harrison and Bales 2016; National Oceanic and Atmospheric Administration 2016). Whilst the skill of these forecasts varies across catchments and seasons, the use of streamflow forecasts in operational planning of single and multiple reservoir systems has been shown to improve objective performance. Alemu (2011) found that incorporating streamflow forecasts in multi-objective optimisation improved system performance of 12-month operating rules for a two-reservoir hydroelectric project. Gelati et al. (2013) optimised dual-reservoir releases using a multi-stage single-objective optimisation process to minimise hydropower deficit and meet target storage levels, using a set of 100 stochastic 9 month forecast inflows based on synthetic ENSO data. They found that forecast-optimised operation provided improvements over historical-optimised operation and over rule-curve based operation. Sankarasubramanian et al. (2009a) demonstrated that simulation of water allocation using streamflow forecasts, downscaled from monthly precipitation forecasts, helped to reduce reservoir spill, increase hydropower generation and meet end-of-season target storage when compared to the use of historical values. Gong et al. (2010) demonstrated a simple method to update reservoir rule curves for three reservoirs using simulations based on streamflow forecast probabilities, resulting in a reduction in drought emergency days. Finally, Li et al. (2014) found that using ensemble streamflow forecasts in a stochastic linear programming model helped to reduce deviations from end-of-season target storage for a multi-reservoir system with inter-basin transfers.

These studies have all shown the potential of streamflow forecasts to improve seasonal to annual operating rules for systems of one to three reservoirs. A gap exists in demonstrating the use of forecast information to improve short-term operating rules for larger, more complex, water supply systems. These studies also used forecast inflows developed specifically for the case study. An additional opportunity arises to discover whether existing publicly available forecasts, such as those provided by the Bureau of Meteorology in Australia (Bureau of Meteorology 2015), can be used in a forecast-based sampling approach to update historically-sampled reservoir inflow data for simulation and optimisation of operating rules.

In Ashbolt et al. (2016a), the authors of this study showed how multi-objective simulation-optimisation can be used to identify short-term optimal operating rules for a case study based on the water grid in South East Queensland, Australia. The study showed that multi-objective simulation-optimisation can improve objective performance for the short-term compared to a base-case of operation using fixed longer-term rules. This formed proof-of-concept of the core part of a framework for short-term operational planning for water grids, shown in Figure 1 (3-4). However, the operating rules in that study were optimised for a single scenario of historical observed flow, assuming perfect knowledge of inflow volume which cannot be achieved in practice. In Ashbolt et al. (2014), the authors recommend that multiple inflow scenarios based on forecast information be used as part of this framework to improve consideration of uncertainty and estimates of future conditions, particularly in context of publicly-available data such as that provided by the Bureau of Meteorology in Australia. Thus an opportunity exists to demonstrate how this streamflow forecast information can be used to improve multi-objective performance of short-term operating rules for this case study.

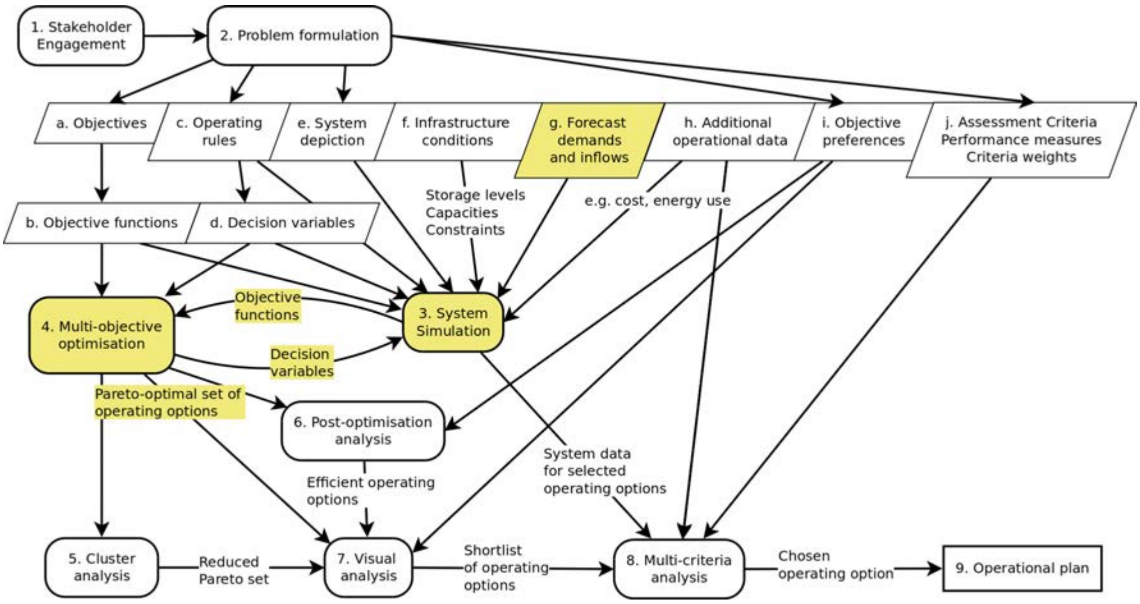


**Figure 1:** A framework for short-term operational planning for water grids, adapted from Ashbolt et al. (2014). Elements covered in this paper are highlighted in yellow.

Incorporating probabilistic streamflow forecast information into practice remains a key challenge for water supply management (Brown et al. 2015; Pagano et al. 2002; Sankarasubramanian et al. 2009b). However, developing a method of translating such forecasts to existing simulation-optimisation models and data can increase the likelihood of adoption of forecasts by industry (Gong et al. 2010). Therefore this study aims to demonstrate a simple method for leveraging publicly-available, probabilistic streamflow forecast information to generate a limited number of inflow scenarios for an existing multi-objective simulation-optimisation model. The number of scenarios is limited to reduce the computational burden and thus run-time. This simple method involves sampling the historical inflow data currently available for the simulation-optimisation model, based on a distribution of forecast inflow volumes such as those provided by the Bureau of Meteorology (2015). This method follows two of the three uncertainty modelling paradigms outlined by Maier et al. (2016): use of best available knowledge (publicly available streamflow forecasts); and quantification of uncertainty (probability distribution of forecasts). It also aligns with the future research directions discussed by (Maier et al. 2014), by providing an example of how optimisation with uncertainty could be used in real decision-making, within a reasonable timeframe. The method is applied to the multi-objective simulation-optimisation model and water grid case study developed in Ashbolt et al. (2016a) to optimise operating rules for a seasonal planning timeframe corresponding to the forecast data availability. These operating rules are expected to improve objective performance for the planning period, compared to operating rules optimised to historical inflow. This improvement is expected since operating rules are optimised for forecast inflow volumes that should average closer to the observed flow than the average or median historic inflow volume. The use of multiple scenarios from the forecast distribution is expected to improve robustness of operating rules if observed inflow deviates significantly from the forecast median, compared to the alternative of a single historic or forecast inflow scenario.

## 2. Case study

The case study was previously defined in Ashbolt et al. (2016a), and involves identifying short-term optimal operating rules for a complex water supply system based on the water grid in South East Queensland, Australia. This water grid serves 3.6 million people and includes: 28 dams and weirs in 11 catchments, 3 groundwater borefields, a desalination plant, and a wastewater recycling scheme. The supply sources are connected to 48 demands via multiple supply paths along a network of streams and one- and two-way pipelines that cross catchment boundaries (inter-basin transfers). Operating rules need to be determined for this water grid to guide operation of key supply and transfer systems. These operating rules aim to meet three management objectives: maximising water security, minimising total operational cost, and minimising total spills from reservoirs. The operational planning period used in Ashbolt et al. (2016a) and in recent operational plans for South East Queensland (Seqwater 2014) is one year, with operating rules assessed for objective performance over a longer five-year horizon.

Currently, streamflow forecasts are available for catchments located within the case study area, published online on a monthly basis by the Bureau of Meteorology (2015). However, these streamflow forecasts have a seasonal three-month horizon, shorter than the one-year planning or five-year assessment period normally required for the case study. For the purposes of the current study, a revised three-month seasonal operational planning period is examined to enable direct use of the streamflow forecast information. In the future, the Bureau of Meteorology plans to extend the seasonal forecasts to a 1 year horizon (Wang et al. 2014); these updated forecasts can then be used in the case study simulation-optimisation model. Regardless of the length of the planning period used, the method presented in this study can be repeated every month to reflect updated forecast inflow information.

Four retrospective (past) seasonal planning periods are examined for the case study: July-September 1989, 1991, 1997, and 2000. These four seasonal planning periods are chosen to assess the potential improvement in operating rule performance due to incorporation of streamflow forecast information compared to using historical inflow information, as well as to assess how the accuracy in the forecast affects this improvement. Here, forecast accuracy is measured as the difference between observed flow and the forecast median, as a single-year variant of the forecast skill score used by the Bureau of Meteorology, described in Section 2.2. Two of the planning periods are selected based on their higher forecast accuracy, with the forecast median relatively close to observed inflow. The other two planning periods are selected based on their lower forecast accuracy, with the forecast median significantly different to observed inflow. All four planning periods cover the same July-September season, to avoid any variability in results due to differing historic forecast skill or inter-seasonal variability. The four planning periods are examined from the perspective of a historical decision-maker at July 1989, 1991, 1997, and 2000 respectively. The inflow scenarios developed for these planning periods can be used to identify short-term operational planning rules using the multi-objective simulation-optimisation model and streamflow forecast information described in the following sub-sections.

## 2.1. Problem formulation and simulation-optimisation model

In Ashbolt et al. (2016a), a multi-objective optimisation problem was formulated for the case study. Apart from the difference in retrospective planning periods and inflow scenarios (described in more detail in Section 3), the problem formulation and simulation-optimisation model for this study are unchanged from that described in Ashbolt et al. (2016a). A brief overview is provided here; the reader is referred to that paper for further detail.

The aim of the case study is to determine operating rules that are optimal in terms of the three management objectives of maximising water security, minimising total operational cost, and minimising total spills from reservoirs. Objective performance is calculated using the three objective functions shown in Equations 1-3. Where multiple inflow scenarios are used, the aim of optimisation is minimise or maximise the sum of the objective functions across simulations using the different inflow scenarios. Since there are trade-offs between these objectives, e.g. an increase in water security might be obtained at the expense of an increase in operational cost and spill volume, the results of multi-objective optimisation will be multiple possible operating options that represent trade-offs between the three objectives.

The water security objective is measured by an objective function determining the minimum system storage over the planning period. *Minimum System Storage* is calculated as:

$$Minimum\,System\,Storage = min\left(System\,Storage\,for\,t = 1, \ldots, T\right) \qquad \textbf{Equation 1}$$

where $t$ is a time-step of the planning period of length $T$; and *System Storage* is the sum of storage volumes in the surface water storages (in megalitres) for the time-step $t$. This objective function is to be maximised.

The total operational cost objective concerns costs occurring due to treatment, pumping, production of manufactured water, and switching direction of the two-way pipelines. It is measured by the objective function, *Total Cost*, calculated as:

$$Total\,Cost = \sum_{t=1}^{T} \left[ \sum_{f \in F} Unit\,Cost * Flow\,Rate + \sum_{p \in P} \$40{,}000 * Switch \right] \qquad \textbf{Equation 2}$$

where *t* is a time-step of the planning period of length *T*; *f* is a node or link in the network (e.g., treatment plant, pumping station, or desalination plant) of the entire set *F* with an associated flow-dependent treatment, pumping or production *Unit Cost* ($AUD/ML) and *Flow Rate* (megalitres/day) on timestep *t*; and *p* is a two-way pipeline in the entire set *P* with a nominal cost of $40,000 AUD used to penalise a *Switch* in direction on timestep *t*. The total cost is the sum of operational costs over all timesteps of the planning period. This objective function is to be minimised.

The total spill volume objective is measured by an objective function, calculated as:

$$Total\,Spill\,Volume = \sum_{t=1}^{T} \left[ \sum_{r \in R} Spill\,Volume \right] \qquad \textbf{Equation 3}$$

where *t* is the time-step of the planning period of length *T*; *r* is the reservoir of the entire set *R*; and *Spill Volume* is the spill volume from the reservoir in ML. The total spill is the sum of spill volumes over all timesteps of the planning period. This objective function is to be minimised.

A daily timestep simulation-optimisation model of the case study was constructed using eWater Source (Dutta et al. 2013). This model was chosen based on its ability to simulate and multi-objective optimise operating rules for a complex water grid (Ashbolt et al. 2014). The key features of the supply system represented in the model are illustrated in Figure 2. This figure shows a schematic representation of the major water sources, demand regions, and pipelines; the operating rules to be optimised; and the decision variables which constitute the operating rules. Not shown in this figure, but included in the model are 39 inflows and 48 demand nodes, groundwater supplies, weirs, smaller pipelines and streams, and a number of environmental flow requirements. Daily inflow timeseries are available for 39 inflow sites in the model, disaggregated from monthly calibrated timeseries covering 117 years from 1890-2007. There are sixteen operating rules, outlined in the callout boxes

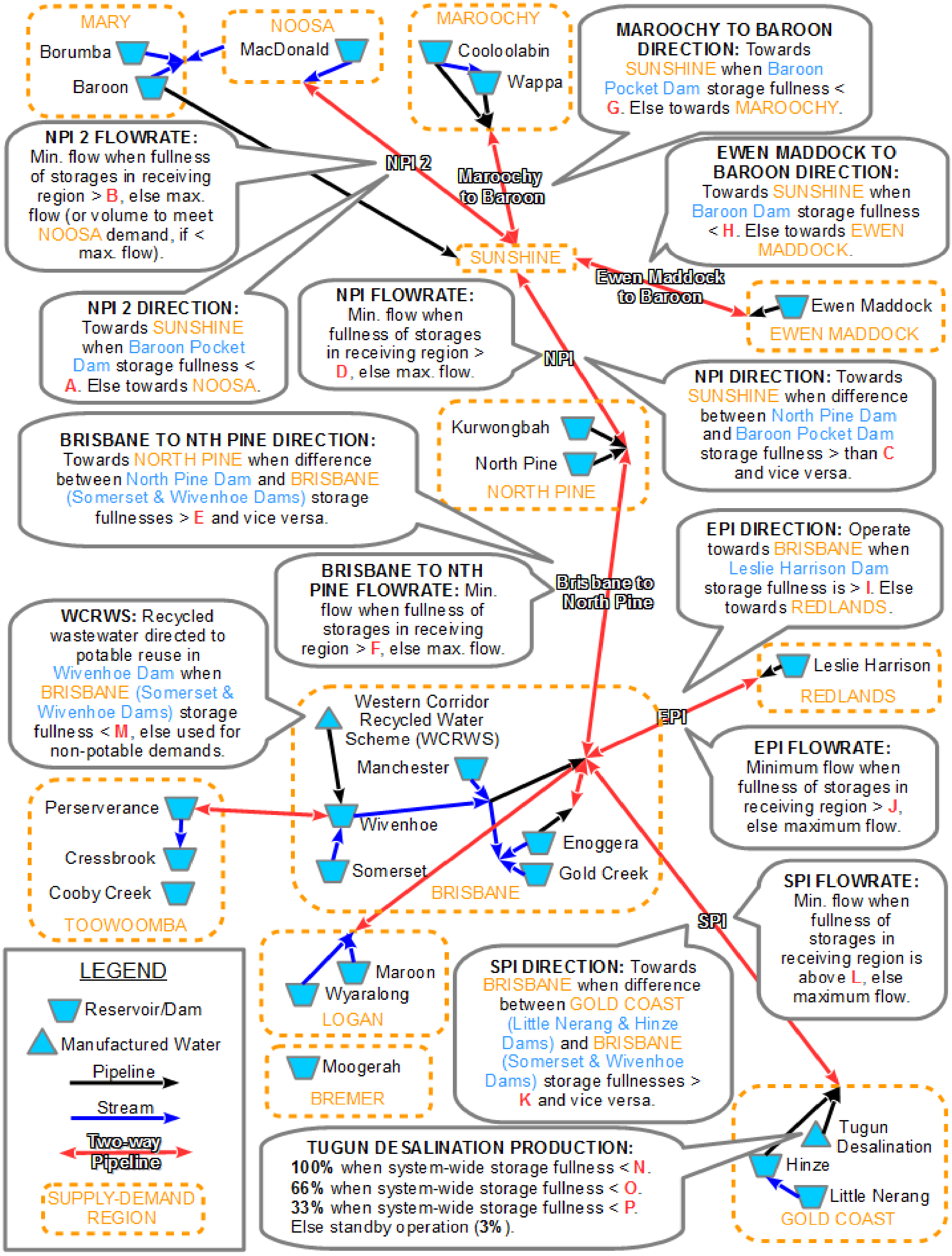


**Figure 2:** Schematic of the case study network, showing major infrastructure and supply-demand regions. The operating rules which govern this infrastructure are outlined in the call-out boxes. The decision variables pertaining to these operating rules are highlighted in bold [**A, B, …, P**]. The supply-demand regions also include a number of inflows and demands as well as pipelines, streams, weirs and groundwater supplies, not shown on this figure but included in the simulation-optimisation model.

in Figure 2, which govern the direction and flowrate of the seven two-way pipelines, production volume of the desalination plant, and whether or not the potable recycled water is directed for reuse in the reservoir or to non-potable demands. These operating rules contain sixteen decision variables, which form a set [**A, B, C, … P**] also shown in Figure 2. These decision variables represent thresholds of storage fullness in the operating rules that trigger changes in operating mode, production volume, or flow rate, and are to be determined by the optimisation algorithm. The optimisation component of the model is configured to minimise or maximise the three objective functions in Equations 1-3 by altering the 16 decision variables, using the NSGA-II genetic algorithm (Deb et al. 2002).

### 2.2. Available streamflow forecasts

The Bureau of Meteorology (BoM) is the Australian national weather, climate and water agency. Each month, it provides three-month-ahead seasonal streamflow forecasts for a number of catchments across the country, including within the case study area (Bureau of Meteorology 2015). These forecasts provide a probability distribution of three-month seasonal total predicted inflow volumes, and use a Box-Cox transformed multivariate normal distribution to model intersite correlations (Wang et al. 2009). The probabilistic forecasts are composed of an ensemble of 5000 equally probable forecast volumes, produced from simulations using a Bayesian Joint Probability (BJP) model (Wang et al. 2009). The BJP model is a probabilistic statistical forecast method that predicts streamflows at multiple sites based on multiple and uncertain predictors such as climate outlook and initial catchment conditions (Robertson and Wang 2009). In addition to the probabilistic forecast distribution, an indication is given of the skill score, i.e. the historical accuracy of the model for that season. The Root mean Square Error in Probability (RMSEP) indicates the level of skill for each of the forecast sites and catchments, as the square root of the average difference between the historical probabilities of the observed value and forecast median (Wang and Robertson 2011). A RMSEP of <10 is deemed very low skill, 10-20 low skill, 20-40 moderate skill, and >40 high skill. Forecast skill depends on the initial catchment conditions, and the time of year (Wang et al. 2011); where the skill score is very low, the historical probability distribution is used for the forecast.

An example of a forecast for one of the sites in the case study area is shown in Figure 3, for the July-September 2015 season at the confluence of Brisbane River and Gregors Creek, upstream from Wivenhoe Dam. This season and site has a high skill, with a RMSEP of 44. Figure 3 shows the probability of exceedance of a given three-month flow (flow duration curve), based on both the forecast and historical July-September reference (1970-2015) streamflow distributions. This shows that for July-September 2015, the forecast distribution indicated lower than usual streamflow volumes, indicated as a shift in the flow duration curve compared to the historic flow duration curve. It also shows that, for this particular year, the forecast was relatively accurate, i.e. that the observed streamflow was closer in volume to the forecast median (50% exceedance probability) than the historical median. It is this type of flow duration curve information that is used in developing forecast inflow scenarios for this study.

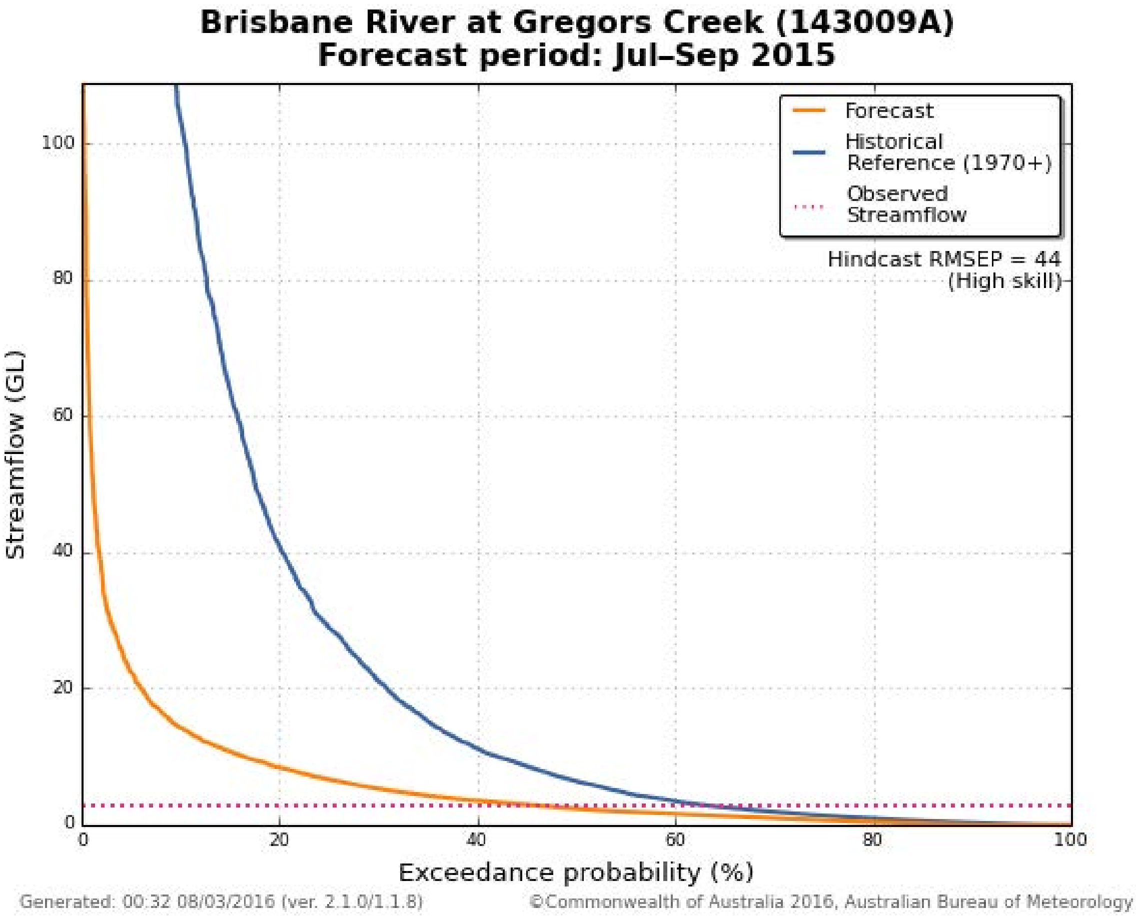


**Figure 3:** Example forecast and historic flow duration curves for Brisbane River at Gregors Creek, a forecast site within the case study area. Source: Bureau of Meteorology, http://www.bom.gov.au/water/ssf/forecasts.shtml

### 2.3. Forecast sites and spatial grouping of inflows

Seasonal three-month streamflow forecasts are available from the Bureau of Meteorology (BoM) within four of the eleven case study catchments. These BoM forecast sites can be used to provide information about the forecast inflow distribution, to sample historical inflow at nearby inflow sites represented in the simulation-optimisation model. Four forecast sites are listed in Table 1, Column 2. To identify which forecasts should be linked to which model inflow sites, the 39 model inflow sites are grouped to the four forecast sites, on a per-catchment basis. The first step in this spatial grouping is to pair the four forecast sites with four *model catchment group representatives* (Table 1, Column 3), which are the most highly correlated inflow sites in the simulation-optimisation model.

Correlation for these sites is measured based on the available flow-duration curve, as it will be used to translate streamflow forecast information in Section 3.2.1. The eleven model catchments are then clustered in four *model catchment groups,* based on the correlation of July-September inflow with the four model catchment group representatives, as shown in Table 1, Column 4. Correlation was used rather than physical distance as it is a more reliable measure of similarity in streamflow (Archfield and Vogel 2010). Kendall's tau-b rank correlation coefficient was used to measure this correlation; this measure is non-parametric and can be used for time-series with zero-flow values (Wang and Robertson 2011). The four catchment groups in Table 1 are used to connect forecast and historic inflow distributions to model inflow scenarios as described in Section 3.2.

**Table 1:** List of model **c**atchment groups for the case study, including four Bureau of Meterology (BoM) forecast sites, model catchment group representatives, and model catchments within the catchment group.

| **Group** | **BoM forecast site** | **Model catchment group representative** | **Model catchments within group** |
|---|---|---|---|
| 1 | Back Creek at Beachmont | Little Nerang Dam Inflow | Gold Coast, Redlands |
| 2 | Burnett Creek upstream of Maroon Dam | Maroon Dam Inflow | Bremer, Logan |
| 3 | Tinana Creek at Tagigan Road | Lake MacDonald Downstream Inflow | Caboolture, Mary, Maroochy, Mooloolah |
| 4 | Brisbane River at Gregors Creek | Wivenhoe Dam Inflow | Brisbane, Pine, Toowoomba |

For the July-September forecast season of the four case study retrospective seasonal planning periods, the historical forecast skill score of the four BoM forecast sites is moderate to high (Table 2, Column 2). Three of the four forecast sites have Root Mean Square Error in Probability (RMSEP) indicating high skill (>40), with the Tinana Creek forecast site having moderate skill (20-40). Due to these relatively high skill scores, the forecasts for these sites would typically be expected to be fairly reliable. The forecast volumes and observed flows for the two retrospective planning periods at the BoM forecast sites are shown in Table 2. Each of the planning seasons and sites has different forecast inflow and accuracy relative to the historic median. Both the July-September 1989 and 2000 planning periods have average forecast median flows significantly above the average historic median ($85^{th}$ and $69^{th}$ percentile). However the July-September 1989 had higher accuracy, with an average difference of 14% between the observed inflow and forecast median for the four case study forecast sites. On the other hand, the July-September 2000 observed flow had lower accuracy, with the observed inflow 67% lower on average than the forecast median, closer to or below the historic median. Both the July-September 1991 and 1997 periods had forecast median flows below the historic medians. However, the 1997 planning period had higher accuracy in the forecast, with an average difference of -4%. The observed flows for July-September 1991 were even lower than the forecast medians, with an average difference of -81%. In summary, a decision-maker planning for the July-September season would expect reasonably high skill in the forecast on average. However, the forecasts for the case study planning periods had varying levels of accuracy, with both under- and over-prediction of inflows and observed flows both lower and higher than the historic median.

**Table 2:** Forecast median, observed (obs.) flow, and percentage difference in volume (% diff.) for the July-September season for the four Bureau of Meteorology forecast sites and four retrospective planning periods. The percentiles of the forecast and observed flows within the historical distribution for each site are shown in square brackets [%ile].

| **BoM forecast site** | **RMSEP skill score (Jul-Sep)** | **Historical Jul-Sep median (GL)** | **1989** | | | **1991** | | | **1997** | | | **2000** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | **Forecast median (GL) [%ile]** | **Obs. Flow (GL) [%ile]** | **% diff.** | **Forecast median (GL) [%ile]** | **Obs. flow (GL) [%ile]** | **% diff.** | **Forecast median (GL) [%ile]** | **Obs. flow (GL) [%ile]** | **% diff.** | **Forecast median (GL) [%ile]** | **Obs. flow (GL) [%ile]** | **% diff.** |
| Back Creek at Beachmont | 53 | 0.34 | 1.1 [90] | 0.8 [83] | -27 | 0.2 [39] | 0.1 [9] | -50 | 0.3 [46] | 0.3 [46] | 0 | 0.4 [58] | 0.2 [39] | -50 |
| Burnett Creek upstream of Maroon Dam | 53 | 0.48 | 2.2 [85] | 1.5 [79] | -32 | 0.1 [17] | 0 [3] | -100 | 0.1 [17] | 0.2 [29] | 100 | 1.4 [77] | 0.4 [46] | -71 |
| Tinana Creek at Tagigan Road | 31 | 1.0 | 4.2 [79] | 8.7 [90] | 107 | 0.4 [31] | 0 [0] | -100 | 0.4 [31] | 0.3 [25] | -25 | 2.9 [72] | 1.2 [54] | -59 |
| Brisbane River at Gregors Creek | 44 | 6.4 | 59.4 [84] | 62.6 [85] | 5 | 3.2 [39] | 0.8 [18] | -75 | 1 [21] | 0.1 [6] | -90 | 17 [67] | 1.9 [30] | -89 |
| **Average** | **45** | **2.1** | **16.7 [85]** | **18.4 [85]** | **14** | **0.98 [32]** | **0.23 [8]** | **-81** | **0.45 [29]** | **0.225 [27]** | **-4** | **5.4 [69]** | **0.93 [42]** | **-67** |

# 3. Method

## 3.1. Aim and overview

The aim of the method is to compare the objective performance of operating rules optimised using inflows based on the forecast inflow probability distribution, to the objective performance of operating rules optimised using inflows based on the historical probability distribution. Since any of the inflows from the forecast or historic probability distributions may be 'correct', objective performance is optimised over multiple inflow scenarios to explicitly address this uncertainty (Krzysztofowicz 2001). Comparing forecast- and historic-optimised operating rules should show whether or not integrating streamflow forecast information into simulation-optimisation can improve objective performance. These forecast- and historical-optimised operating rules are also compared to operating rules optimised using a single scenario of observed inflow over the planning period. This allows the improvement of forecast-optimised operating rules over historic-optimised to be assessed relative to theoretical maximum performance that could be obtained using a perfect forecast of observed flow. These comparisons are done separately for the four retrospective planning periods described in Section 2. Comparing the relative improvement obtained from forecasts for the four planning periods should show the impact of forecast accuracy on objective performance, and the ability of optimisation using probabilistic inflow scenarios to ameliorate this impact by improving the robustness of operating rules.

Figure 4 outlines the method used in this study. This method contains four steps:

1. Developing forecast, historical and observed inflow timeseries scenarios for input to the simulation-optimisation model, by sampling from historical inflow data.

2. Developing forecast, historical and observed optimisation problem formulations using the respective inflow scenarios from Step 1 and the problem formulation and simulation-optimisation model described in

Section 2.1.

3. Multi-objective optimisation to obtain forecast-, historical- and observed-optimised Pareto sets of operating rules, one set for each of the optimisation formulations from Step 2.

4. Using compromise programming, a multi-criteria analysis technique (Zeleny 1973), to select and compare one operating option each from the three Pareto sets from Step 3, using preferences on the objectives.

More detail on each of the steps are provided in the following subsections.

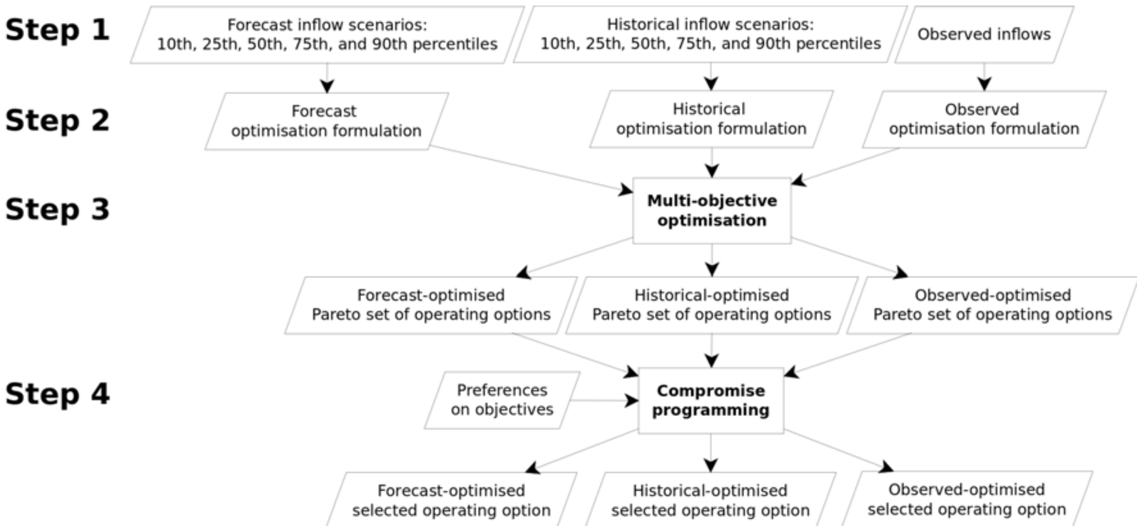


**Figure 4:** Flow diagram of the four-step method used in this study.

## 3.2. Developing inflow scenarios (Step 1)

Step 1 of the method involves developing inflow scenarios for three optimisation formulations: forecast, historical and observed. Each of these problem formulations requires daily inflow timeseries at each of the 39 inflow nodes in the simulation-optimisation model. The forecast and historical optimisation formulations require multiple scenarios of inflow timeseries, generated from the forecast and historical distributions for the relevant planning periods, to capture the uncertainty in expected inflows. Optimising to these inflow scenarios should increase the robustness of operating rules to a range of inflow possibilities and incorporate some of the risk in solution performance due to inflow uncertainty

(Higgins et al. 2008). The 10th, 25th, 50th, 75th, and 90th percentile flows are selected based on the forecast and historical distribution of inflows. These are the inflows that have 90%, 75%, 50%, 25% and 10% probability of exceedance respectively. Whilst a greater number of inflow scenarios is desirable, this limited number of scenarios restricts the run-time of the multi-objective optimisation model to a manageable timeframe. Unlike the forecast and historical optimisation formulations, the observed optimisation formulation requires just a single timeseries of observed data for the four planning periods. The following sections describe the method for developing forecast, historic and observed inflow scenarios. This method is repeated for each of the planning periods.

### *3.2.1 Forecast inflow scenarios*

A simple method is used here to develop inflow scenarios for the forecast optimisation formulation, based on the available data. This available data includes: forecast and historic flow duration curves of three-month total inflows at the four BoM forecast sites described in Sections 2.2 and 2.3; and daily 117-year (1890-2007) modelled historical inflow timeseries at the 39 simulation-optimisation model inflow sites described in Section 2.1. The 39 model inflow sites do not correspond directly to the forecast sites, both in their location and timestep. Therefore, the 10th, 25th, 50th, 75th, and 90th percentile forecast streamflow volumes cannot be used directly as model inputs. Instead, the forecast flow volumes at the forecast sites are spatially mapped to daily forecast timeseries for each of the model inflow nodes using the flow duration curves at the forecast and model catchment group representative sites listed in Table 1.

The first stage of developing the forecast inflow scenarios involves identifying the 10th, 25th, 50th, 75th, and 90th percentile forecast inflow volumes from the forecast distributions at each of the four forecast sites in Table 1. Figure 5 (a) and Table 3 (Column 2) show an example of the forecast inflow scenario volumes for the Brisbane River at Gregors Creek forecast site (Catchment Group 4 in  Table 1) for the July-September 1989 retrospective planning period.

**Figure 5:**

**(a)** Forecast three-month total inflow volumes for July-September 1989 planning period for the Brisbane River at Gregors Creek BoM forecast site for Model Catchment Group 4 (Table 1).

**(b)** Flow duration curve representing the historic distribution of total July-September inflow at Brisbane River at Gregors Creek. The dots indicate the 10th, 25th, 50th, 75th, and 90th percentile forecast inflow volumes from (a) (y-axis), and their corresponding percentiles within the historic July-September distribution (x-axis).

**(c)** Historic flow duration curve representing the historical distribution of total July-September inflows for Wivenhoe Dam, model catchment group representative for Model Catchment Group 4. The dots indicate the 5 forecast percentile inflow scenarios from (b) (x-axis), and their corresponding inflow volumes from the historic distribution for July-September (y-axis).

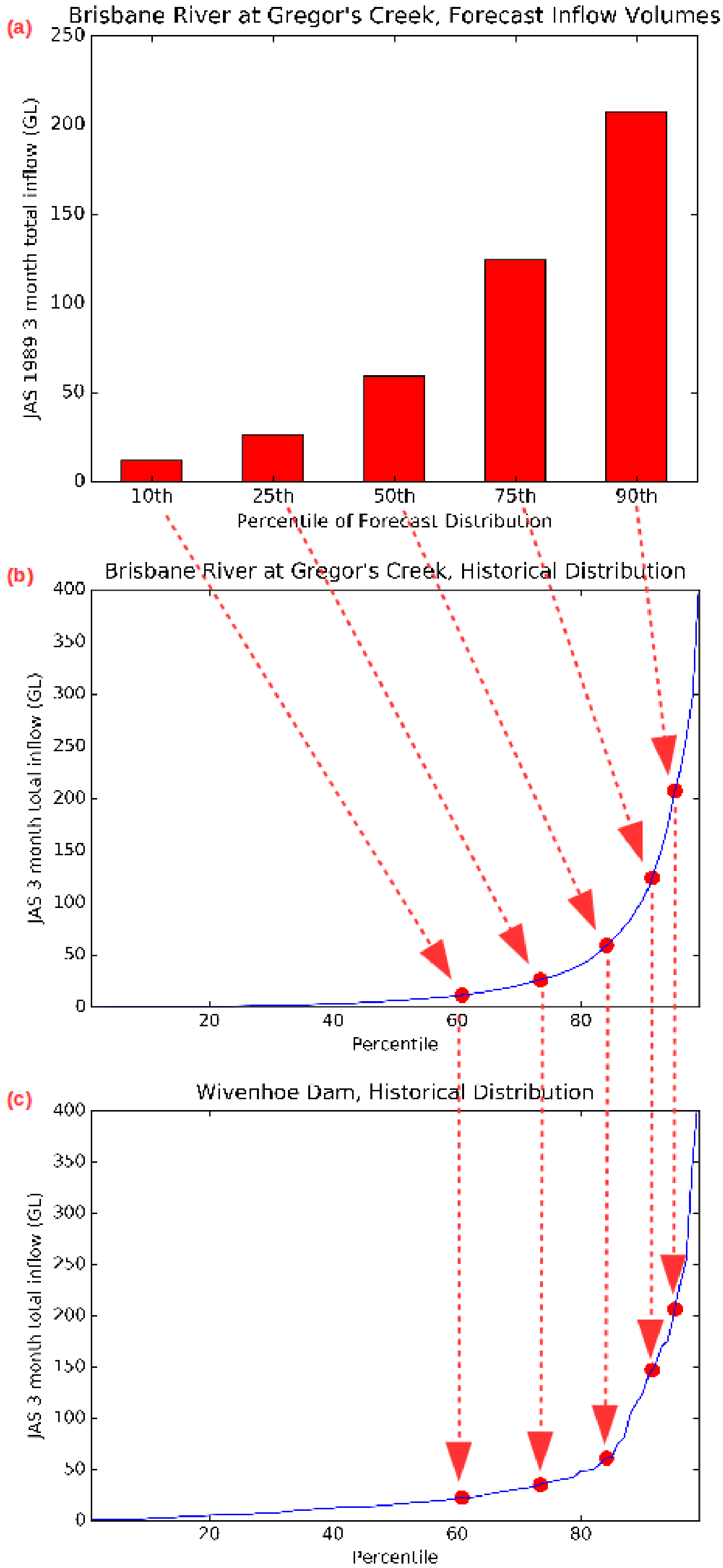

**Table 3:** Example of forecast optimisation formulation for Model Catchment Group 4 (Brisbane, Pine and Toowoomba Catchments), for the July-September 1989 planning period.

| Forecast scenario (percentile) | Forecast inflow volume at forecast site (GL) | Forecast percentile relative to historic distribution at forecast site | Forecast volume for catchment group representative (GL) | Time period corresponding to forecast volume for catchment group representative |
|---|---|---|---|---|
| 10th | 11.8 | 61st | 22.5 | Dec-Feb 1992-93 |
| 25th | 26.6 | 73rd | 41.4 | Nov-Jan 1896-97 |
| 50th | 59.4 | 84th | 68.6 | Jun-Aug 1892 |
| 75th | 124.2 | 91st | 150.2 | Nov-Jan 1955-56 |
| 90th | 207.6 | 95th | 194.3 | Jul-Sep 1956 |

The second stage of developing the forecast inflow scenarios involves determining where the forecast inflow scenario volumes for the forecast sites fit within their historic distribution for that season. An example of the July-September flow duration curve (historic distribution) for the Brisbane River at Gregors Creek forecast site is shown in Figure 5 (b). The dots in Figure 5 (b) and the values in Table 3 (Column 3) identify where the inflow volumes of Figure 5 (a) lie within the historic distribution. This indicates that for this planning period and catchment group, the forecast predicts a high probability of above-median inflows, with the 10th-90th percentiles of the forecast distribution corresponding to the 61st-95th percentiles of the historic distribution for the forecast site. This stage creates a set of historic-adjusted forecast percentiles that can be used to translate streamflow forecasts at the BoM forecast sites to the simulation-optimisation model sites.

Stage three of developing forecast inflow scenarios involves translating the forecasts for each of the BoM forecast sites Figure 5 (a) to inflow volumes for each of the model catchment group representatives Figure 5 (c), as per the catchment group pairings in Table 1. This translation is achieved by determining the inflow volumes from the historic distribution of the model catchment group representatives that correspond to the historic-adjusted forecast percentiles from the second stage. Essentially, for a given forecast inflow scenario, the same (historic-adjusted) percentile flow at the forecast site is used as for the model catchment group representative site. This means that although the magnitude of inflows at the model sites may be different to those at the forecast sites, the percentile or quantile of that flow is the same. This approach is used because the two sites are spatially close and highly correlated, and thus would be expected to have similar relative flow. Thus a 10th percentile forecast volume of 11.8 GL for Brisbane River at Gregors Creek forecast site (Table 3 Columns 1 & 2) is translated to a Wivenhoe Dam Inflow 10th percentile forecast volume of 22.5 GL (Table 3 Column 4): both volumes sit at the same relative point in the historic distribution, ie. the 61st percentile.

Finally, stage four of the method involves translating the three-month forecast scenario volumes for the four model catchment group representatives to daily inflow timeseries at each of the 39 model inflow nodes. This is achieved by determining the periods of the historic 117 year daily inflow timeseries for the four model catchment group representatives that most closely match each of the forecast inflow volumes, on a monthly timescale. These time periods are then used to sample the modelled historic inflow timeseries for all sites within the catchment group. For example, the three-month time period within the historic daily inflow timeseries for Wivenhoe Dam with total volume most closely matching the 10th percentile forecast inflow of 22.5 GL is December 1992 – February 1993, as shown in Table 3, Column 5. This time period is then used to sample timeseries for all model inflow sites in Model Catchment Group 4, i.e. within the Brisbane, Pine and Toowoomba catchments Table 1. The sampled inflow timeseries for all of the catchment groups can then be input to the simulation-optimisation model as the 10th, 25th, 50th, 75th, 90th percentile forecast inflow scenarios.

Since the forecast volumes at the four BoM forecast sites are spatially correlated, total seasonal inflow volume is correlated across all catchment group representatives. However, in developing the forecast inflow scenarios from historic model flows, different time periods are sampled for each of the four catchment groups. This means that whilst sub-seasonal spatial correlation is preserved within catchments and catchment groups, it is not preserved between catchment groups. For this case study, it was considered more important to achieve higher accuracy and coherence in total inflow volume (seasonal correlation) than flow pattern (sub-seasonal correlation), since operating rules are used to drive transfers across basin boundaries based on total storage volume. Sub-seasonal correlation was considered less critical between catchment groups, since inflows are less correlated between catchment groups (e.g. Table 2) and because catchment groups are connected only via two-way pipelines which convey controlled releases from multi-year storages. Seasonal serial correlation between timesteps is preserved for all sites, since a continuous time period is sampled. In future, a more sophisticated method for disaggregating seasonal flow volumes to daily timesteps that preserves spatial and temporal correlation in flow patterns across basin groups should be implemented using disaggregation techniques such as k-nearest neighbours (e.g. Kumar et al. 2000; Lee et al. 2010) or the Schaake Shuffle (Clark et al. 2004).

#### *3.2.2 Historical inflow scenarios*

The historical inflow scenarios are determined in a similar manner to the forecast inflow scenarios. The key difference is that forecast sites and historic-adjusted forecast percentiles (e.g. Table 3 Columns 2 and 3) are not used to determine inflow volumes for the four catchment group representatives. Instead, the 10th, 25th, 50th, 75th, and 90th percentile volumes from the historic distribution for each of the model catchment group representatives in Table 1 are determined. Next, the periods of the historic 117 year daily inflow timeseries for the four model catchment group representatives that most closely match each percentile historic inflow volume are identified. These time periods are then used to sample all inflow timeseries within the catchment group. An example of historic inflow scenarios for Model Catchment Group 4 for the July-September 1989 planning period is shown in Table 4. The 10th, 25th, 50th, 75th, and 90th percentile inflow timeseries scenarios for all of the catchment groups provide the historical inflow scenarios for the historical optimisation formulation.

**Table 4:** Example of historical optimisation formulation for Model Catchment Group 4 (Brisbane, Pine and Toowoomba Catchments), for the July-September 1989 planning period.

| Historical scenario (percentile) | Historical volume for catchment group representative (GL) | Time period corresponding to historical volume for catchment group representative |
|---|---|---|
| $10^{th}$ | 5.3 | Jun-Aug 1953 |
| $25^{th}$ | 12.4 | Jun-Aug 1899 |
| $50^{th}$ | 17.8 | Dec-Feb 1964-65 |
| $75^{th}$ | 44.8 | Jun-Aug 1966 |
| $90^{th}$ | 126.7 | Aug-Oct 1973 |

### *3.2.3 Observed inflow scenario*

The observed inflow scenario involves sampling the historic 117 year daily inflow recorded for each of the model inflow nodes for the four retrospective planning periods.

### *3.2.4 Comparison of inflow scenarios*

Table 5 shows shows how the total forecast and historic inflow volumes, averaged across the five scenarios, compare to the observed inflow for each planning period. The historic volumes are different for each year, as the planning year is omitted when calculating the historic distribution. This table shows that, following translation to model inflows, the prior description of the relative accuracy of forecasts for the four planning periods for the forecast sites (Table 2), holds true. Both July-September 1989 and 2000 planning periods have forecasts higher than average flows. July-September 1989, however, has forecast average closer to the observed total inflow, whereas July-September 2000 has observed inflow significantly lower than both the forecast and historic average. Both July-September 1991 and 1997 have forecast average volumes significantly lower than historic averages. For both periods, the observed inflow is lower than average, however the July-September 1997 forecast volume is closer to the observed volume than for July-September 1991. However, it should be noted that even when the forecast is relatively close to observed volumes, the volumetric difference is still significant. This highlights the role of the multiple percentile inflow scenarios in mitigating the impact of forecast inaccuracy.

**Table 5:** Total inflow volumes for case study simulation-optimisation model, for the four planning periods. The forecast and historic inflow volumes are averaged across the five percentile scenarios.

| | **July-September 1989** | **July-September 1991** | **July-September 1997** | **July-September 2000** |
|---|---|---|---|---|
| **Forecast Average Total Inflow (GL)** | 474.7 | 143.0 | 155.0 | 385.8 |
| **Historic Average Total Inflow (GL)** | 222.7 | 307.5 | 321.8 | 315.0 |
| **Observed Total Inflow (GL)** | 654.7 | 53.2 | 89.4 | 85.2 |

### 3.3. Optimisation formulations (Step 2)

The inflow scenarios described in the previous section, together with the problem formulation described in Section 2.1, are used to develop forecast, historical and observed optimisation formulations for the four retrospective planning periods. These optimisation formulations are used to configure the multi-objective simulation-optimisation model. For the forecast and historical optimisation formulations, operating rules are to be optimised to be robust over the five inflow scenarios (10th, 25th, 50th, 75th, and 90th percentiles) representing uncertainty in the forecast and historical distributions. Robustness can be measured in a number of ways; the choice of measure depends on the decision-maker's preferences or biases and will effect the performance of a given option (Giuliani and Castelletti 2016). For this case study, robustness is measured by maximising minimum system storage, minimising total operational cost, and minimising total spill volumes from reservoirs, averaged across the five scenarios of inflow.  This is a relatively risk-tolerant approach (Mortazavi-Naeini et al. 2015; Ray et al. 2014), which assumes equal probability of each inflow scenario occurring and equal weight on under- or over-performance due to higher or lower inflows.

### 3.4. Multi-objective optimisation (Step 3)

The multi-objective simulation-optimisation model described in Section 2.1 is used to optimise the 16 operating rules according to the optimisation formulations described in Section 3.3. For the forecast and historical optimisation formulations, the model is configured to optimise the operating rule decision variables to maximise or minimise objective performance over five simulation scenarios that simulate the five percentile inflow scenarios. For the observed optimisation formulation, a single simulation scenario is used.

A population of 200 and 150 generations are used for optimisation, as well as the default settings for the NSGA-II implementation in Source. These default settings are a crossover probability of 0.9, mutation probability of 0.5, crossover distribution index of 5, mutation distribution index of 10, and a random seed for the first generation. This configuration appears to be sufficient to converge to a diverse Pareto set before 150 generations, indicated by a plateau in the hypervolumes of each run (Zitzler and Thiele 1998). Two Pareto sets, based on two random seeds, are generated for each optimisation formulation; these provide 400 operating options. When combining the two seeds, some of the options will be dominated by others, i.e. they are outperformed by another option in terms of all three objectives. These dominated options can be discarded, resulting in a combined Pareto set of less than 400 operating options. The simulation-optimisation process is run for each of the three optimisation formulations, and for each planning period, resulting in three Pareto-optimal sets of operating options for each planning period. The simulation model is also used to determine the performance of the Pareto-optimal operating options when implemented under observed conditions for the relevant planning period, as represented by the observed inflow scenarios.

### 3.5. Compromise programming (Step 4)

In evaluating the impact of inflow scenarios on the objective performance, it is useful to assess how a single operating option, selected by a decision-maker for implementation, might change based on each of the optimisation formulations. Selecting and comparing a single option from each of the forecast-, historical-and observed-optimised Pareto sets will allow a more concrete comparison of the quantitative difference in performance between operating options due to the differences between inflow scenarios.

Compromise programming (Zeleny 1973) is an optimisation technique, widely used in multi-criteria analysis, that can be used to select an efficient option from a Pareto set by placing weights on objectives or criteria. It involves finding the option of minimum distance to an ideal point represented by a hypothetical objective function vector comprising the best performance of each objective in the entire Pareto set. For this case study, the ideal point would be a vector of the maximum minimum system storage, minimum total cost, and minimum total spill, found within the Pareto set. The distance of each option to the ideal point can be measured by one of a number of distance metrics; here, the distance metric presented by Ballestero (2007) is used. The distance is a combination of individual objective distances combined using the preference weights. The function to find the distance from the ideal point as per Ballestero (2007) is shown in Equation 4, and explained further in that paper.

$$\Delta=\sum_{j=1}^{n}[\frac{n}{200}Y_j(1-y_j)]+0.5\sum_{j=1}^{n}[\frac{n}{200}Y_j(1-\frac{n}{200}Y_j)(1-y_j)^2] \qquad \textbf{Equation 4}$$

Where Δ is the distance (to be minimised), j is an objective function, n is the number of objective functions, y is the 1-normalised objective function value (ideal value y = 1, non-ideal y = 0, drawn from feasible values), and Y is the objective preference weight in %. Finding the member of the Pareto set with minimum distance from Equation 4 will identify the most efficient operating option, for the chosen preference weights on the objective functions.

Equation 4 will be applied to identify a single operating option for each of the forecast-, historical- and observed optimised Pareto sets, for both planning periods, using a preference weights of 30% on minimum system storage, 40% on total cost, and 30% on total spill. This preference scenario reflects a desire for balanced performance across all three objectives, with a slight emphasis on minimising cost (Ashbolt et al. 2016b).

# 4. Results and discussion

For each of the four retrospective planning periods, three optimisation formulations – forecast, historical and observed – were developed. These three optimisation formulation were used to obtain three corresponding Pareto sets of non-dominated operating options. These Pareto sets are referred to as the forecast-, historical-, and observed-optimised Pareto sets. Each Pareto set contains multiple options, none of which can be said to outperform another (are non-dominated) due to the trade-offs between the three objectives. The forecast- and historical-optimised Pareto sets indicate operating options that optimise objective trade-offs across the five percentile forecast and historical inflow scenarios, whilst the observed-optimised set optimises objective trade-offs for a single scenario of observed inflow. Each of the operating options comprises 16 decision variables, which can be used to formulate the operating rules in Figure 2.

## 4.1. Objective performance and trade-offs

Figure 6 shows an example of the objective performance of forecast-, historical-, and observed-optimised Pareto sets for the July-September 1989 planning period. This figure shows the trade-offs between the three objectives, and the difference in predicted objective performance under each optimisation formulation (forecast, historical and observed). Each sub-plot shows two of the objectives on the x- and y-axes, with arrows on the axes indicating the direction of preferred performance. The relative value of the third objective is indicated by shading of the points, with darker shading indicating better performance (higher minimum storage, lower cost and spill).

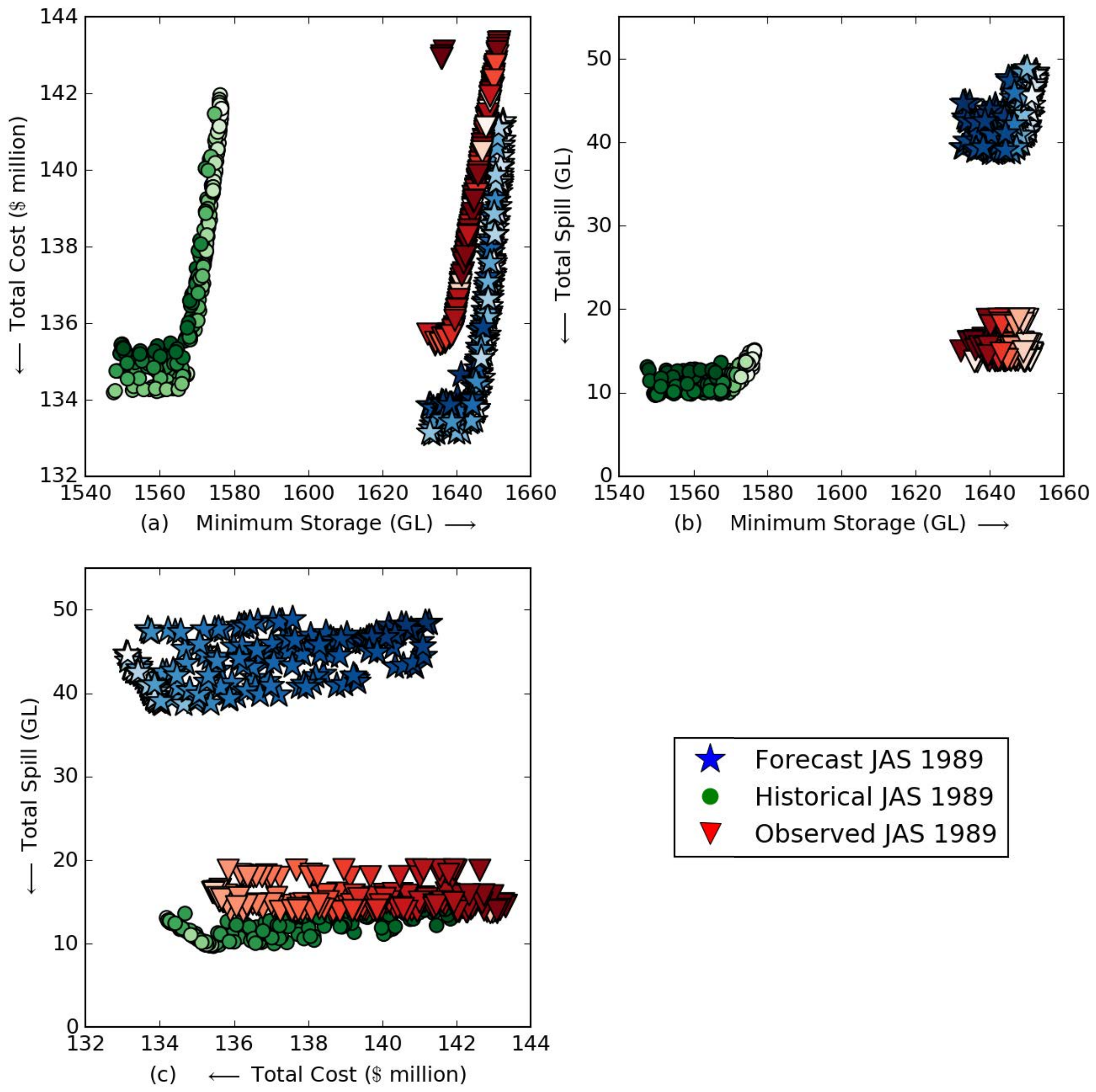


**Figure 6:** Average objective performance of Pareto sets from the forecast (stars), historical (circles), and observed (triangles) optimisation formulations for the July-September (JAS) 1989 historical planning period. The performance shown is that for that averaged over the forecast, historical, and observed inflow scenarios respectively.

Figure 6 illustrates that for the July-September 1989 period, all three Pareto sets show a trade-off between an increase in minimum storage for an increase in cost (Figure 6a), and a moderate increase in spill (Figure 6b). There is an increase in total spill with cost (Figure 6c) for the forecast- and historical-optimised Pareto sets, but there is some scatter in this relationship. There appears to be relatively little or no increase in spill with cost for the observed-optimised Pareto set. An increase in cost is likely associated with increased use of desalination in particular, leaving more water in the storages (increasing minimum storage). Whilst it is difficult to determine the exact cause from this plot, the inflection point in the relationship between cost and minimum storage likely indicates options that result in the trigger of desalinated water production. The relationships between the three objectives for the case study and the decision variables have been elaborated further (for a 5-year assessment period) in Ashbolt et al. (2016b).

Figure 6 also illustrates the difference in objective performance when operating rules are optimised according to the three different optimisation formulations, for the July-September 1989 planning period. The range in cost of the three Pareto sets are fairly similar, with slightly higher cost for the observed optimisation formulation. The historical optimisation formulation has lowest minimum system storage and spill (Figure 6 b). This is expected as it has the lowest total inflow (Table 5). Performance of the forecast-optimised Pareto set is most similar to the observed-optimised set for the objective trade-off curve of minimum storage and total cost (Figure 6 a). This is to be expected, as the average inflow of the forecast optimisation formulation is closest to the observed inflow (Table 5). However, the historical-optimised set is closer to the observed-optimised set in terms of spill (Figure 6 c). The reason for relatively low spill in the observed optimisation formulation, despite having higher total inflow volume (Table 5) than the forecast-optimised Pareto set, is less clear. A possible reason is a greater use of two-way pipelines, which can keep minimum storage higher but reduce spill by balancing water storages Ashbolt et al. (2016b). Another key difference between the observed optimisation formulation and the other two formulation is that operating rules are optimised to maximise performance for a single inflow condition, rather than average performance across five inflow scenarios. This may allow the operating rules to be 'more optimal' for the narrower range of inflow conditions. Similar behaviour was seen for the three other planning periods, with differences in relative performance due to the differences in forecast, historic, and observed inflows.

## 4.2. Operating rules

Comparing the decision variables of the forecast-, historical- and observed-optimised Pareto sets can show how the operating rules vary between the optimisation formulations and provides possible reasons for the differences in objective performance seen in Figure 6. Figure 7 illustrates the distributions of the 16 decision variables for the forecast-, historical- and observed-optimised Pareto sets for July-September 1989, as kernel-density estimation (KDE) plots. These decision variables A to P pertain to the operating rules and infrastructure as shown in Figure 2. KDE plots are a variation on the histogram, where lines show a smoothed distribution of a variable, allowing for the distributions of multiple datasets to be overlaid on the one plot (Ashbolt et al. 2016b). The KDE plots in Figure 7 show that for many of the decision variables, the distributions of the three Pareto sets are fairly similar: for example, decision variable I and J, which governs the operation of the EPI two-way pipeline, and decision variables N-P, which govern the production volume from the desalination plant. However, the historical-optimised Pareto set shows significant difference to the other two sets in the distribution of decision variables C, D, and L which govern the direction and flowrate in the NPI and flowrate in the SPI two-way pipelines. These figures suggest, for example, that the direction of the NPI two-way pipelines is switched more frequently (at lower thresholds) for the historic optimisation formulation than for the forecast and observed optimisation formulations, to avoid spills from storages or direct water to relatively water-scarce catchments. In general, the distributions of the forecast-optimised set track observed set, excepting decision variable B, D and L, which govern flowrate in the NPI2, NPI and SPI two-way pipelines.

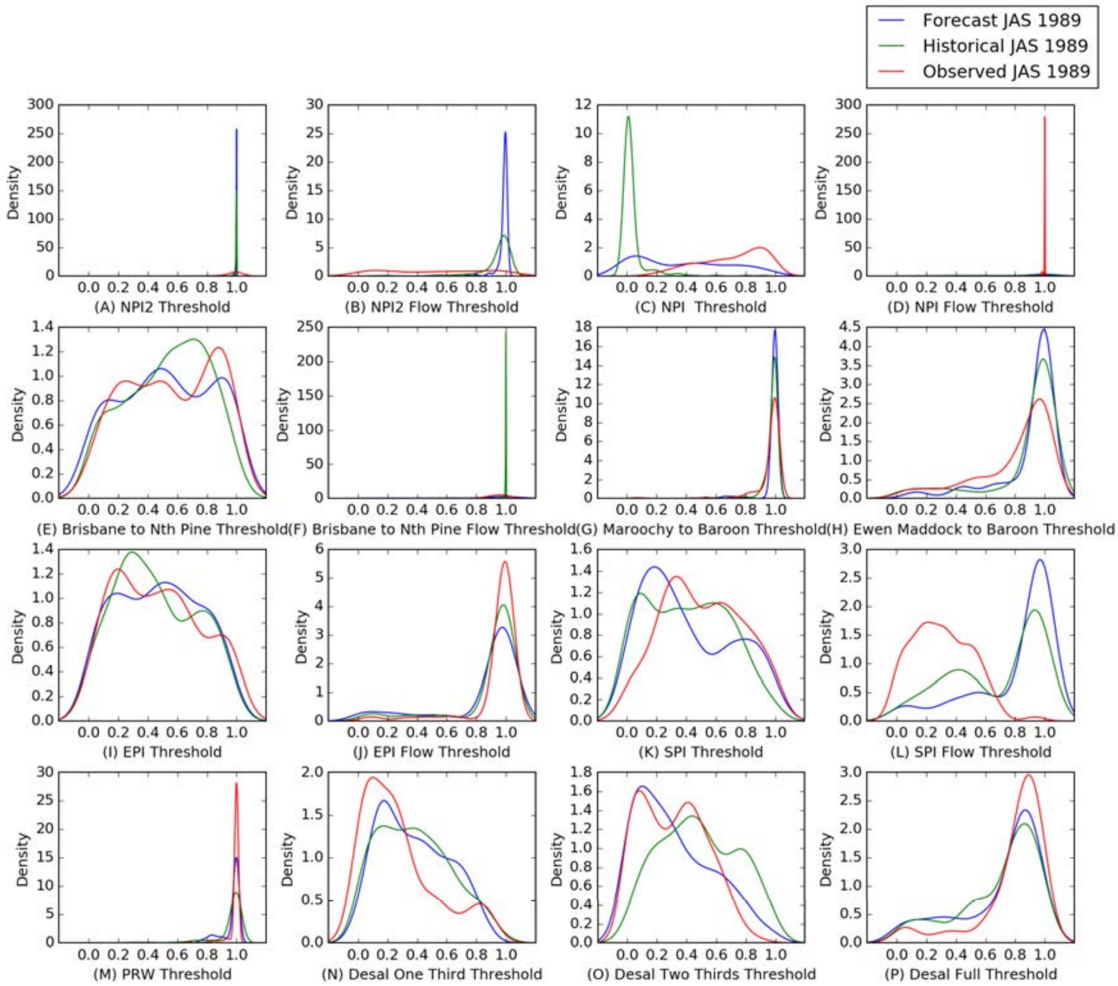


**Figure 7:** Distributions of the decision variables for July-September 1989 forecast, historical, and observed optimised scenarios, as kernel density estimation plots.

### 4.3. Objective performance under observed conditions

Figure 6 showed the objective performance of three Pareto sets for July-September 1989, each of which were optimised and assessed to different average inflow conditions as outlined in Table 5. Based on such a figure, one Pareto set cannot be said to outperform another, since performance is dependent on different inflow volumes. Instead, simulating the performance of the forecast- and historical-optimised Pareto sets using the observed inflow for each planning period will allow a direct comparison of the Pareto sets and an idea of their performance as implemented over the planning period.

Figure 8 shows boxplots of the distribution of performance for each objective when simulated using observed flow, for each of the four retrospective planning periods. This figure indicates the differences in distribution of objective performance between the three Pareto sets, indicated by the median (bar), box (25th – 75th percentile) and whiskers (minimum to maximum). Whilst there is significant overlap in the objective performance range, the differences between distributions of the optimisation formulations vary between planning periods. For the July-September 1989 planning period (1st column), the median and range of performance of all three objectives is most similar between the forecast- and observed-optimised Pareto sets. This is expected, since median forecast inflow was closer to observed flow than the historic median. For the July-September 2000 planning period (2nd column), the correlation between objective performance is mixed, with the historical-optimised Pareto set having more similar minimum system storage to observed, but the forecast-optimised set having more similar cost. However, the variation between Pareto sets is less than for July-September 1989. This period had lower accuracy in the forecast, with observed inflow lower than but closest to the historic median. For the July-September 1997 planning period (3rd column), which had higher accuracy in the forecast, but below-median observed inflow, the distribution of total cost and spill is most similar between the forecast- and observed-optimised Pareto sets. However, the minimum storage of the historical-optimised Pareto set is most similar to the observed-optimised set. For the July-September 1991 planning period (4th column), there is most similarity between the distributions of the forecast- and historical-optimised Pareto sets. This may be expected, since observed flow was significantly lower than both the forecast and historical median. This period has the lowest observed inflow, and the greatest variation in objective performance between the three optimisation formulations.

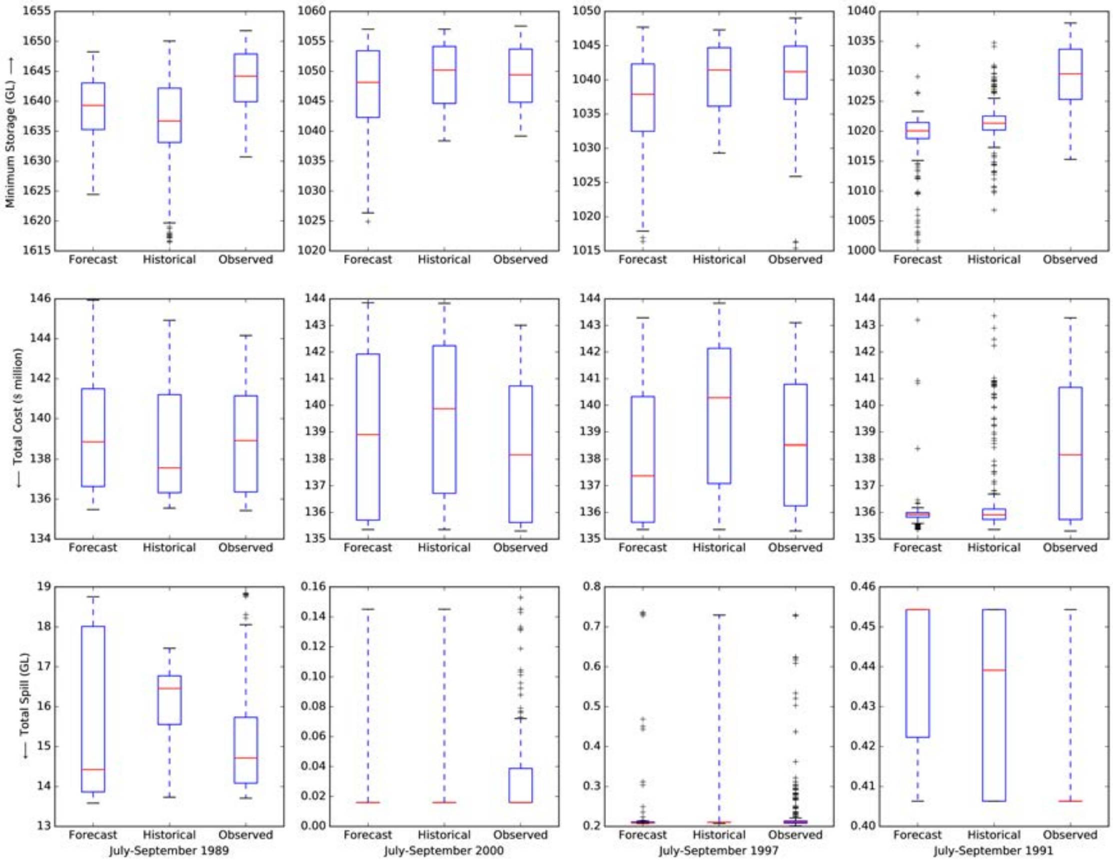


**Figure 8:** Boxplots of objective performance of the forecast-, historical- and observed-optimised Pareto sets for the four retrospective planning periods – July-September 1989, 2000, 1997, and 1991 – simulated using the observed inflow data for each period. Each box and whisker plot indicates the distribution and range of the 200+ operating options within each Pareto set, with the boxes indicating 25th-75th percentiles, bars indicating 50th percentiles, and whiskers indicating minimum and maximum values.

## 4.4. Optimality under observed conditions

The boxplots in Figure 8 indicate the relative similarity of the forecast-, historical- and observed-optimised Pareto sets based on performance of individual objectives. However, they do not compare performance of operating options across all three objectives simultaneously. This comparison is important, as multi-objective optimisation is characterised by trade-offs between objectives and aims to find operating options that outperform others on all three objectives, i.e. are non-dominated. Whilst the three Pareto sets were non-dominated in terms of all three objectives for the optimised inflow, the objective performance of the forecast- and historical-optimised Pareto sets changed when simulated for observed inflow conditions. This means that the operating options as shown in Figure 8 may no longer be non-dominated under observed inflow conditions. The observed-optimised set, on the other hand, will remain non-dominated as it was optimised to observed inflow.

The proportion of non-dominated operating options within the forecast- and historical-optimised Pareto sets were reassessed using the observed inflow. This can be used as a measure of the relative optimality of the operating options resulting from the two optimisation formulations for the four different planning periods. The percentage of non-dominated operating options in each optimisation is shown in Table 6.

**Table 6: Percentage of operating options in the forecast- and historical-optimised Pareto sets for each of the four retrospective planning periods.**

| Retrospective planning period | Optimisation formulation | Percentage of operating options that are non-dominated for observed inflow |
|---|---|---|
| July-September 1989 | Forecast | 14 |
| | Historical | 7 |
| July-September 1991 | Forecast | 8 |
| | Historical | 9 |
| July-September 1997 | Forecast | 23 |
| | Historical | 19 |
| July-September 2000 | Forecast | 19 |
| | Historical | 16 |

This table indicates that for three of the four planning periods, there are a greater percentage of non-dominated operating options in the forecast-optimised Pareto sets. The difference is greatest for the July-September 1989 planning period, which had relatively high accuracy and was the only planning period with observed flow higher than forecast inflow. The July-September 2000 planning period had a higher number of non-dominated forecast-optimised operating options, despite the historical median being closer to the observed flow. The July-September 1991 planning period, which had lowest accuracy in the forecast, had a slightly higher percentage of non-dominated operating options for the historical-optimised Pareto set. These results indicate that the forecast optimisation formulation provided benefits over the use of the historical optimisation formulation for most of the planning periods. Despite this, the differences between the historical optimisation formulation were relatively small for 3 of the 4 planning periods. This suggests that the benefits of using multiple inflow scenarios have mitigated some of the risk in observed inflow deviating from both the forecast- or historical-median.

### 4.5. Comparison of options selected using compromise programming

Compromise programming was used to identify the most efficient operating option from each of the Pareto sets, measured as the closest to the theoretical ideal option of maximum minimum storage, minimum total cost and minimum total spill. Comparing the most efficient options from the forecast-, historical- and observed-optimised Pareto sets gives an idea of how, for a given set of decision-maker preferences, the performance might vary based on the different inflow assumptions used in the optimisation formulations. Table 7 shows the objective performance of the most efficient operating options from each of the three Pareto sets for each of the four planning periods, simulated for observed inflow conditions and using a preference of 30% weighting on minimum system storage, 40% on total cost, and 30% on total spill. This table shows that whilst some options have equal performance, none of the operating options outperforms all the others. Generally, the observed optimisation formulation has the best performance, which is equalled by the forecast-optimised option for the July-September 2000 period. The forecast-optimised option outperforms the historical-optimised option for the July-September 1997 and 2000 planning periods. However, the historical-optimised option equals or improves on the forecast-optimised option for the July-September 1991 period. There is most similarity in cost between the options, perhaps due to the higher weighting on this objective. Overall, the forecast-optimised options perform better than the historical-optimised options, and similarly to the observed-optimised options. However the historical-optimised options also perform reasonably well, and there is often a relatively small difference between options.

**Table 7:** Objective performance of the most efficient operating options selected from the forecast-, historical- and observed-optimised sets for each of the four planning periods, for a preference weighting of 30% on minimum system storage, 40% on total cost, and 30% on total spill volume, simulated using observed inflow. Bold type indicates the best-performing option for each objective, for each planning period.

| Planning period | Optimisation formulation | Minimum System Storage (GL) | Total Cost ($ million) | Total Spill Volume (GL) |
|---|---|---|---|---|
| July-September 1989 | Forecast | 1,636 | 138 | 13.8 |
| | Historical | 1,636 | 137 | **13.7** |
| | Observed | **1,640** | **136** | 13.9 |
| July-September 1991 | Forecast | 1,019 | **136** | 0.454 |
| | Historical | 1,022 | **136** | **0.406** |
| | Observed | **1,025** | **136** | **0.406** |
| July-September 1997 | Forecast | 1,035 | **136** | 0.209 |
| | Historical | 1,034 | 137 | 0.213 |
| | Observed | **1,037** | **136** | **0.210** |
| July-September 2000 | Forecast | **1,045** | **136** | **0.016** |
| | Historical | 1,042 | 137 | **0.016** |
| | Observed | **1,045** | **136** | **0.016** |

### 4.6. Sensitivity analysis

Comparing the objective performance of operating options using the optimised inflow and observed inflow (e.g. Figures 6 and 8) suggested that the objective performance is significantly influenced by the total inflow volume. To understand how changes in the inflow volume affect the objective performance, the forecast-optimised Pareto set for July-September 1989 was also simulated using the 10$^{th}$, 25$^{th}$, 50$^{th}$, 75$^{th}$, and 90$^{th}$ percentile historical inflow scenarios. Figure 9 shows boxplots of the sensitivity of objective performance of the forecast-optimised Pareto set for July-September 1989 to different inflow possibilities, including the observed inflow. These figures indicate that the both the minimum storage and total spill increase significantly with total inflow volume, to a degree much larger than the differences between optimisation formulations seen in Figure 8. The total cost on the other hand, is fairly similar across the different percentile flow scenarios, with lower cost incurred for 50th and 75th percentile flows. Overall, the minimum storage and spill objectives are highly sensitive to the inflow volume, but total cost is relatively insensitive to inflow volume. This type of sensitivity analysis may be particularly useful for the decision-maker to consider if there are constraints on the values of the objectives.

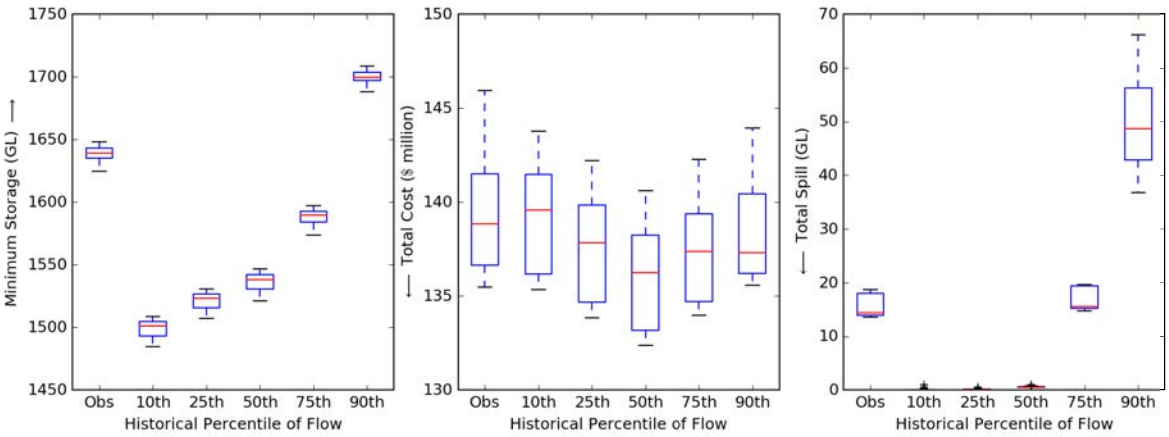


**Figure 9:** Performance of forecast-optimised Pareto set for July-September 1989, simulated using observed (obs) flow, and different percentile scenarios of inflow from the historical distribution of the July-September season.

The results also indicate that objective performance under observed inflow is sensitive to the inflow volume used in optimisation. Figure 10 compares the performance of the observed (obs.) and forecast-optimised (multi-forecast) Pareto sets shown previously in Figure 8, to Pareto sets optimised using single forecast 10th, 50th and 90th percentile inflow scenarios for July-September 1989. The performance shown is that under observed inflow conditions, which for this planning period, was between the 50th and 75th percentile forecast inflows. These plots indicate that the observed and multi-scenario forecast-optimised Pareto sets provide better results in terms of minimum storage and spill. Whilst the forecast 10th and 90th percentile optimised Pareto sets have lower median cost, this comes at a trade-off for lower minimum storage or higher spill. The 10th percentile scenario experiences significantly higher spill as it was optimised to a much lower inflow volume than observed. The 90th percentile scenario experiences significantly lower spill as it was optimised for higher flow conditions than observed, but the minimum storage is significantly lower. These plots indicate the importance of considering multiple inflow scenarios in optimisation, particularly for the minimum system storage objective.

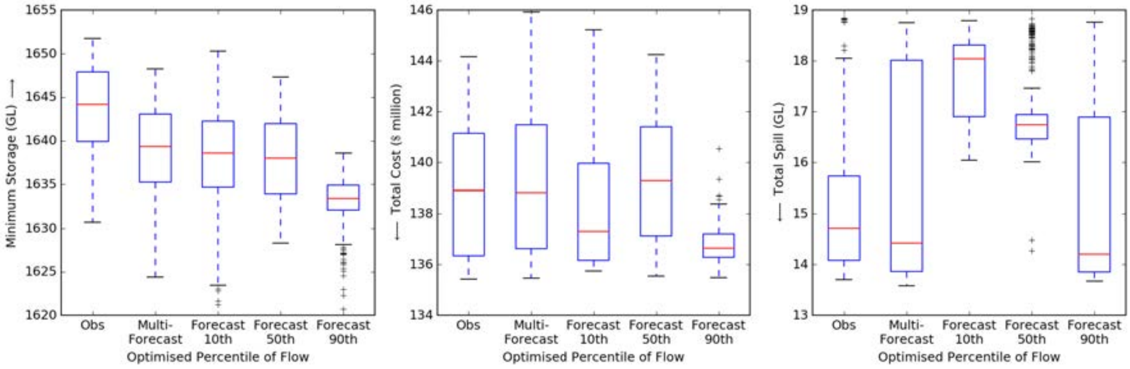


**Figure 10:** Performance of Pareto sets for July-September 1989, optimised to different scenarios of inflow: observed, averaged across multiple inflows (10, 25th, 50th, 75th and 90th), 10th percentile forecast inflow, 50th percentile forecast inflow, and 90th percentile forecast inflow. For this time period, total observed inflow was between the volumes of the 50th and 75th inflow scenarios.

## 5. Summary and conclusions

In summary, this study has shown how including streamflow forecast information in short-term operational planning for water grids has the potential to improve multi-objective performance of operating rules. This improvement was measured as a positive change in objective performance compared to operating rules optimised to inflows from the historical distribution. This was demonstrated for a case study water grid, for four retrospective (past) three-month planning periods, by optimising operating rules to meet multiple management objectives – maximising water security, minimising operational cost, and minimising spill volumes averaged across multiple scenarios of historically-sampled inflow. Forecast-optimised Pareto sets of operating options were identified by optimising operating rules for inflow scenarios sampled from historical inflow based on publicly-available forecast probabilities. Similarly, historic-optimised Pareto sets of operating options were identified by optimising operating rules for inflow scenarios sampled from the historic probability distribution.

On average, forecast-optimised operating options improved objective performance compared to historic-optimised options and approached close to the performance of options optimised using a scenario of observed inflow for the planning period. The results also indicate that even for a planning period when the median of the forecast distribution is significantly different to the observed median, operating rules optimised using streamflow forecast information can still improve over historical-optimised options. This suggests that impacts on objective performance due to inaccuracy in the forecast may be ameliorated by optimising options to be robust across multiple scenarios from the forecast probability distribution. However, in some cases, the historical-optimised Pareto set performed similarly or outperformed the forecast-optimised Pareto set, particularly when the forecast was less accurate. Therefore, the analysis of more planning periods is required before making a definitive conclusion. Further analysis of the relationships between objective performance and optimised or observed inflow might provide some insights into the conditions under which forecast inflow scenarios may provide the greatest benefit or risk.

Nevertheless, the relatively good performance of the forecast-optimised set across all planning periods suggests that using forecast information, with multiple scenarios of inflow, may provide an acceptable trade-off between the benefits and risks of forecast accuracy. The method shown in this study simply updates the distribution of sampled inflow based on current and expected conditions. This provides a small additional operational benefit with minimal additional effort or change to existing decision processes. Further study would be required by the decision-maker for their case study and planning season, to verify these benefits and the acceptable risk vs reward ratio. Whilst comparing selected efficient options optimised to historical and forecast inflow revealed only minor potential improvements, a greater advantage found for using forecast inflows was in increasing the number of options that were optimal (non-dominated) for observed inflow. The use of multiple inflow scenarios in particular, appears to provide benefits in managing inflow risk compared to a single scenario of inflow, even when the forecast is relatively accurate.

This paper has used a relatively simple method to translate publicly-available streamflow forecast information to inflow timeseries at 39 inflow nodes in the case study simulation-optimisation model, using currently available data. This method was required since forecast inflow timeseries were unavailable at locations corresponding to the model inflow nodes. Instead, the flow duration curves, representing the inflow distributions, were used to translate available streamflow forecast volumes at forecast sites to inflow volumes at nearby (highly correlated) case study model inflow sites. Whilst sub-seasonal cross-correlation was preserved within basin groups, only seasonal volumes were correlated between basin groups. Despite the simplicity of this method for translating streamflow forecast information, the results indicated potential improvements in objective performance. This suggests that available forecast information such as that provided by the Bureau of Meteorology in Australia can be used to improve existing model inputs with relatively little investment.

Developing and validating a more sophisticated statistical relationship between streamflow forecasts and the model inflow timeseries would then be expected to further increase the objective performance of the forecast-optimised operating rules, by reducing the model uncertainty and improving sub-seasonal spatial cross-correlation between basin groups. In this study, a single timeseries from the historic record was used for each of the five forecast inflow scenarios; stochastic catchment models with spatially and temporally correlated flows could be used to incorporate variability in the daily patterns of flow and to generate inflow patterns more consistent with initial catchment condition and season. Combined with a greater number of inflow scenarios from the probability distribution this could increase robustness to both different inflow volumes and different sequencing of the total inflow volume over the time period. This is important, since the pattern of flow may effect the operating rules and objective performance (Faber and Stedinger 2001). Ideally, this would be aided by stronger connection and cross-validation between the catchment models used for the operational planning model and those used to provide the forecasts.

This study has also shown the potential utility of the forecasts provided by the Bureau of Meteorology to short-term operational planning in Australia. The latest forecasts by the Bureau of Meterology provide seasonal volumes with a monthly timestep; improving the method presented here to incorporate this monthly pattern may reduce the uncertainty in the timing of intra-seasonal flow. Current plans to extend the 3 month forecasts to 1 year (Wang et al. 2014) should allow the operating rules to be optimised for expected inflows over the entire annual operational planning period for the case study. An alternative is to develop a method for extending the 3-month streamflow sequences, preferably one that preserves serial correlation (Watkins et al. 2000). The simulation-optimisation process may still be repeated on a monthly or seasonal basis, since the forecasts are more accurate for the first 3 months (Simonovic and Burn 1989; Wang et al. 2014).

Finally, a sensitivity assessment of objective performance to total inflow indicated that for the case study objectives of minimum system storage and total spill, performance is more sensitive to the inflows experienced during the planning period than the operating rules themselves. Conversely, the total operational cost objective is less sensitive to streamflow. Thus it is important for the decision-maker to simulate the performance of the Pareto set or chosen operating options under a range of inflow conditions to understand the sensitivity of objectives to observed or optimised inflow.

In conclusion, the previous study (Ashbolt et al. 2016a) showed how multi-objective optimisation of annual operating rules using historical inflow can provide improvements to objective performance compared to rules-based operation using longer-term operating rules. This study builds on that study by showing how incorporating seasonal streamflow forecast information in optimisation can further improve objective performance, by accounting for expected climate and current catchment conditions and incorporating uncertainty. Together these studies provide proof-of-concept of key components of the framework for short-term operational planning of water grids proposed in Ashbolt et al. (2014), by optimising operating rules for expected inflow conditions. Further research might connect these two studies by extending seasonal forecast inflows to cover the annual operational planning horizon and testing the method for additional planning periods. Recommended improvements to the method include the use of forecast-driven stochastic inflow sequences that account for spatial and temporal correlation and variability.

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# Chapter 8: Summary, conclusions and recommendations

## 8.1 Summary

This thesis has proposed and demonstrated a framework for short-term operational planning of water grids. Chapter 1 defined the water grid as a network or 'grid' of pipes and open channels that connects water sources to water demands across catchments, which may comprise traditional sources such as surface and groundwater storages, as well as alternative sources such as desalination, stormwater and recycled water. This interconnectedness, as well as the presence of climate-independent water sources such as desalination and recycled water, are key strategies to increase supply system yield to meet the pressures of population growth, climate variability, and climate change. These water grids are typically managed to meet multiple objectives such as maximising water security and environmental flows, minimising operational cost and energy use, and minimising flood risk. However the complexity of the water grid, compounded by trade-offs between these objectives, brings challenges to water grid management in navigating the decision and objective spaces. This research aimed to develop and demonstrate a framework for operational planning of water grids that addresses two key challenges, namely: identifying operating rules for the water grid that are optimal for multiple management objectives, and incorporating streamflow uncertainty into operational planning. Chapter 1 also identified four research questions relating to the research aim:

1. What is the desired outcome of this framework?
2. What methods and tools can be used together to achieve the desired outcome of the framework?
3. Does this framework incorporate some of the key requirements identified in Section 1.1, such as:
    - uncertainty in input data such as streamflow;

- multiple and conflicting management objectives and criteria, performance measures, and preferences on these objectives and criteria;
- changes in these objectives and criteria;
- changes in initial conditions and input data;
- stakeholder values;
- feedback between framework components and planning timeframes; and
- existing data and models?

4. Does this framework actually provide the required outcome when implemented for a case study?

Chapter 2 addressed the first three research questions by reviewing the literature and current practice to identify the needs of short-term operational planning for water grids, and to propose a novel framework of methods and recommended tools to meet these needs. The outcome of the proposed framework is a set of optimal operating rules or operating option that can form the basis of an operational plan. The framework centres around multi-objective simulation-optimisation of operating rules, to identify a Pareto set of operating options that are optimal for a subset of the management criteria, represented as multiple objectives, and for expected conditions over the planning period. Cluster, visual, and post-optimisation analysis methods can be used to better understand the characteristics of the large Pareto set and reduce it to a shortlist of ~10 operating options for more detailed analysis. Finally, multi-criteria analysis can be used to assess these operating options against the full set of management criteria, and to rank or score their performance by using preference weights on the criteria that reflect decisionmaker and stakeholder values. This ranking can be used to identify a single operating option for implementation over the planning period. Uncertainty in streamflow and demand can be incorporated as multiple input scenarios to the optimisation model, or in multi-criteria analysis to assess the potential variation in criteria performance.

Chapter 3 introduced a case study based on the South East Queensland Water Grid. This case study aims to identify a set of operating rules for the two-way pipelines, desalination production and wastewater recycling and 1 year planning period. These operating rules should be optimal for multiple management objectives and meet multiple management criteria over a 5 year assessment period. This case study was used to answer the fourth research question, by demonstrating the application of the framework in Chapters 4 to 7.

Chapter 4 formulated the short-term operational planning problem for the case study, and demonstrated how multi-objective simulation-optimisation can be used to find short-term optimal operating rules. Simulation-optimisation was undertaken using the publicly available Source software tool, which contains a node-link network simulation module, as well as a fully integrated optimisation module using the genetic algorithm NSGA-II. This provided a use-case of this new emerging software tool, which has not been demonstrated widely in the literature. The problem formulation of the case study identified 16 operating rules to be optimised to meet three of the management criteria, represented as objectives in the optimisation model: maximising minimum system storage, minimising operational cost, and minimising spills from reservoirs, over the 5 year assessment period. Multi-objective simulation-optimisation of the case study problem formulation resulted in a Pareto set of 677 operating options, each of which contains a set of operating rules that are optimal in terms of the three management objectives and for expected inflows and demands over the assessment period. This Pareto set outperformed a base-case of operation using fixed longer-term rules, by updating variables in these rules to tailor operations to predicted system conditions over the short-term. However this Pareto set remained large and complex, making it difficult to understand the trade-offs and to select a single operating option.

Chapter 5 used a combination of cluster, visual and post-optimisation analysis techniques to better understand the Pareto set and to reduce it to a shortlist of more manageable size for further analysis. Visual analysis, aided by cluster analysis, was used to understand the trade-offs between objectives and the relationships between decision variables and objectives, as well as to identify promising operating options for the shortlist. A variety of visual analysis techniques were presented, each of which provided different insights into the objectives and/or decision variables. Post-optimisation analysis techniques, such as compromise programming and the pseudo-weight vector, were also used to identify efficient options using multiple scenarios of preference weights on the objectives. This resulted in a shortlist of nine operating options with a range in objective performance, but which were efficient in terms of trade-offs between the objectives.

Chapter 6 assessed the performance of the nine shortlisted operating options against the full set of 18 management criteria and a range of inflow scenarios extending up to a 10 year horizon. This extended the assessment of options beyond the three management criteria and single inflow scenario used in multi-objective simulation-optimisation. As with the Pareto set, trade-offs were seen between criteria performance for each operating option, making selection of a single operating option difficult. Therefore, multi-criteria analysis, using weighted summation, was applied to the shortlist to combine performance of each of the options against the each of the 18 criteria using four scenarios of preference weights. A single operating option was identified that performed best on average across the four preference scenarios. This operating option can be used as the basis of an operational plan.

Finally, Chapter 7 investigated the potential of streamflow forecasts to improve objective performance of short-term operating rules. A simple method was used to translate the publicly available seasonal streamflow forecasts provided by the Bureau of Meteorology in Australia, to input timeseries for the case study simulation-optimisation model. As these streamflow forecasts have a three-month outlook, operating rules for the case study were determined using a revised three-month planning period. Apart from the revised planning period and streamflow inputs, the simulation-optimisation model and problem formulation was the same as used in Chapter 4. The operating rules were optimised to maximise or minimise the average objective performance across five three-month inflow scenarios from the forecast distribution, to tailor the operating rules to predicted inflows whilst increasing their robustness to uncertainty in the predictions. Despite the use of a relatively simple method for translating the streamflow forecast information to simulation-optimisation model inputs, the results of multi-objective optimisation indicated that using forecast inflows improved objective performance over using historical inflow scenarios.

## 8.2 Conclusions

In conclusion, this thesis has developed and demonstrated a framework for short-term operational planning of water grids, as per the research aim stated in Section 1.2. This framework considered two key challenges of water grid management: identifying operating rules that are optimal for multiple objectives, and incorporating uncertainty in streamflow into operational planning. This framework addressed the research gaps outlined in Section 1.4, including: meeting the challenges of water grid management; applying multi-objective optimisation to short-term planning of complex multi-reservoir systems; and demonstrating how multi-objective optimisation can be integrated into the short-term planning process, including each step from the problem definition to a final set of operating rules. Application of the framework to the case study demonstrated its ability to address these research gaps. This framework incorporates multiple management objectives and criteria, stakeholder and decisionmaker preferences, uncertainty in input data, existing data and models, and allows for changes in these over time. Thus this thesis was able also to satisfy the four research questions outlined in Section 1.2.

The Pareto-optimal set of operating options obtained in Chapter 4 outperformed the base-case option of using fixed longer-term operating rules, by updating the decision variables in the operating rules to improve objective performance over the short-term planning period. However, the performance of the fixed rules was within the range of the Pareto set in terms of individual objectives. This suggests that the use of fixed rules that are optimal for system conditions over the longer-term may not provide significant detriment to operation. However, the effect of even small improvements in objective performance may compound over time. Furthermore, the key advantages of multi-objective optimisation, and the framework more generally, are in allowing the decision-maker to appreciate the trade-offs between objectives or criteria and the relationships between operating rules and objective performance. Both multi-objective optimisation and multi-criteria analysis help to avoid 'policy myopia' – focussing on a single region of the objective or decision space – by considering the entire objective and criteria possibilities before finalising preferences on the criteria.

A set of easy-to-use and publicly-available tools have been recommended and demonstrated for implementation of each of the framework components. This research also demonstrated the use of publicly available streamflow forecast information, provided by the Bureau of Meteorology, for multi-objective optimisation of operating rules. However, the flexible nature of the framework allows for preferred or currently used tools, techniques, criteria, objectives and input data to be used for alternative case studies, as discussed in Chapter 2. Using such preferred or currently used methods and information can assist in problem formulation, which is a key component in the success of multi-objective optimisation and multi-criteria analysis. This approach can also provide more confidence in the framework outcome, and enable consistency with other decision processes such as long-term planning.

Finally, as demonstrated in Chapter 4, the framework can provide linkages between short- and long-term planning by readjusting longer-term operating rules for expected conditions over the short-term planning period. This linkage could be strengthened by applying the framework to the long-term planning space, by updating the problem definition and input data. Finally, the implementation of this framework will be an iterative process, as it is reapplied for each new short-term planning period. This iterative nature of the short-term planning process allows the decision-maker to update the problem formulation (e.g. objectives, decision variables, and criteria) as they gain more understanding of the impacts of these parameters on the outcome, and as system conditions or preferences change over time.

## 8.3 Recommendations

This research aimed to address the key challenges of water grid management, by demonstrating the use of a framework for short-term operational planning.

For the purposes of this thesis, there were limits in the scope of addressing the water grid management challenges discussed in Section 1.1, and in demonstrating the application of framework components to the case study. Further, some additional research opportunities were identified in the process of demonstrating the framework components. These remaining research areas are recommended for further research in the application of this framework for short-term operational planning. They include:

- How to involve stakeholders and reflect their values in the framework, including in the objectives, criteria, decision variables, criteria weights, and performance measures.
- How to consider water markets and water trading in the framework
- How to select objectives, criteria and performance measures for the framework.
- How to incorporate uncertainty in the problem formulation, i.e. the objectives, criteria, decision variables, performance measures and preference weights.
- Demonstrating the use of forecast demands and demand uncertainty as inputs to the framework.
- Incorporating stochastic streamflow and demand information as inputs to multi-objective optimisation.
- Demonstrating re-optimisation or re-simulation to refine or reassess operating rules during the planning period, e.g. on a monthly basis.
- Demonstrating the application of the framework over multiple planning periods/cycles, e.g. on a six-monthly basis.
- Demonstrating the application of the framework to long-term planning for the same case study, with different problem definition and input data suitable for strategic planning.
- Extending streamflow forecasts for the case study to cover the entire

planning period.

- Demonstrating the use of forecast-optimised operating rules for use throughout the framework.
- Improving the method for translating of Bureau of Meteorology streamflow forecast information to model inputs.

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