DEPARTMENT OF CIVIL, ENVIRONMENTAL AND GEOMATIC ENGINEERING

UNIVERSITY COLLEGE LONDON

MANY-OBJECTIVE DESIGN OF RESERVOIR SYSTEMS - APPLICATIONS TO THE BLUE NILE

A thesis submitted to the University College London for the degree of Doctor of Philosophy

Robel Tilaye Geressu

20 Feb 2019

Academic Supervisors: Prof Julien Harou (Mechanical Aeronautics Civil Engineering, University of Manchester; Civil Environmental and Geomatic Engineering, University College London)

Dr Andy Chow (Civil Environmental and Geomatic Engineering, University College London)

Declaration

I, Robel Tilaye Geressu, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Robel Tilaye Geressu

Abstract

This work proposes a multi-criteria optimization-based approach for supporting the negotiated design of multi-reservoir systems. The research addresses the multi-reservoir system design problem (selecting among alternative options, reservoir sizing), the capacity expansion problem (timing the activation of new assets and the filling of new large reservoirs) and management of multi-reservoir systems at various expansion stages. The aim is to balance multiple long and short-term performance objectives of relevance to stakeholders with differing interests. The work also investigates how problem re-formulations can be used to improve computational efficiency at the design and assessment stage and proposes a framework for post-processing of many objective optimization results to facilitate negotiation among multiple stakeholders. The proposed methods are demonstrated using the Blue Nile in a suite of proof-of-concept studies. Results take the form of Pareto-optimal trade-offs where each point on the curve or surface represents the design of water resource systems (i.e., asset choice, size, implementation dates of reservoirs, and operating policy) and coordination strategies (e.g., cost sharing and power trade) where further benefits in one measure necessarily come at the expense of another. Technical chapters aim to offer practical Nile management and/or investment recommendations deriving from the analysis which could be refined in future more detailed studies.

Impact statement

The Nile basin is characterised by poverty, conflict, unemployment and in recent years is one of the largest sources of north-bound migration. Growing populations and their associated increased demand for food, energy, and water supply requires a reliable supply of water beyond what the current infrastructure and institutional arrangement on the Nile can deliver. An agreement between the Nile riparian countries could allow joint development of the Blue Nile reservoirs to expand agricultural water supply and energy availability. However, the Eastern Nile countries have differing views on what equitable or fair water use could be and agreeing on future development of water resources has been limited because of this. These challenges are compounded by imperfect knowledge of system function, insufficient dialogue and lack of sufficient joint working between the riparian countries.

This thesis identifies gaps in the water resources planning and management literature on the topic of large reservoir system design and development. The research proposes design, management, and assessment approaches, and a negotiation framework to extend current approaches described in the literature and their application to the Nile planning problem. The approaches are applied to quantify the sectoral and country benefit trade-offs associated with water infrastructure development on the Blue Nile; assess which infrastructure designs (i.e., combinations, sizes, etc.) and management (operating rules) and the multi-country shared uses of new Blue Nile reservoirs could be acceptable considering multiple performance objectives of the Nile stakeholders. The studies can help to facilitate the ongoing Nile basin country efforts to explore possible reservoir designs, their coordinated management and investment strategies (e.g., joint investments and power-sharing from the proposed reservoirs). Many of the approaches proposed are applicable to other transboundary water resource development problems and other multi-stakeholder system planning problems outside the water resources planning discipline.

Acknowledgments

I would like to express my sincere gratitude to my supervisor, Prof. Julien Harou, for his supervision, guidance, and advice. His dedication to water resources development, and inspiring enthusiasm to understand and tackle limitations in the real world is gratefully appreciated.

I am grateful for the financial support from the Engineering and Physical Sciences Research Council (EPSRC) and University College London. I am thankful to the British Government and taxpayers for enabling this study.

I would like to thank my parents Tilaye Geressu and Asnakech Dersso for their dedicated support throughout my studies. I am grateful to Ms. Haleluwya Kamal, whose love and support made life away from my home country Ethiopia bearable.

Many thanks to my former teachers Dr. Yilma Seleshi, Dr. Semu Moges, Dr. Dereje Asfaw and Mr. Ramesh Babu. I am grateful for their help, advice, and inspiration at various points in my career. I thank my former colleagues at NBI-ENTRO, Mr. Mulugeta Tadesse, Dr. Yosif Ibrahim and Ms. Fatima Taha for their help during my time there and for encouraging me to take on bigger challenges. I am grateful to Dr. Nagaraja Rao Harshadeep, whose efforts on capacity building for wider use of water resources modelling, and optimization in water systems decision making inspired me.

Many thanks to Ms. Sarah Davis Postgraduate Research Manager at UCL, Dr. Silvia Padula and Dr. Yohannes Subagadis whose kindness and help during my Ph.D study are highly appreciated.

Additional contributions

Evgenii Matrosov renewed the IRAS model used in this research: IRAS-2010 [*Matrosov et al.*, 2011] and Anthony Hurford provided training on its use. Ivana Huskova, coded the C++ wrapper to link the IRAS-2010 simulation model to the multi-objective evolutionary algorithm and provided training on its use [*Hurford et al.*, 2014]. Charles Rouge contributed formulation advice on the adaptive operating rule chapter.

Contents

List of Figures

List of Tables

1 Introduction

This section gives background information on the water resource development planning problems that motivate the work. This will be followed by a description of the research questions and an outline of the rest of the thesis.

1.1. General background

Sufficient and reliable energy supplies are a pre-requisite for attracting investments and bolstering industry in developing countries [*Dunkerley and Ramsay*, 1982; *Bartle*, 2002; *Javadi et al.*, 2013; *Kenfack et al.*, 2014; *Zhu et al.*, 2014]. However, many developing countries are ill-equipped to meet growing energy demands and suffer from frequent service interruptions [*Alfaro and Miller*, 2014; *Dugoua and Urpelainen*, 2014]. Energy security is therefore at the forefront of development agendas of many governments [*Bartle*, 2002; *Kaygusuz*, 2004; *Amer et al.*, 2005; *Porrua et al.*, 2009]. Despite its high cost, and its vulnerability to variability of climate, hydropower is an attractive source of energy for many regions around the world [*Bartle*, 2002; *Yüksel*, 2009; *Seeger*, 2010; *Tortajada*, 2015; *Zarfl et al.*, 2015] and is increasingly advocated as an alternative green energy that helps combat climate change.

New reservoirs can significantly alter hydro-physical processes given how they regulate flows of water, sediments, nutrients and the economic benefits associated with human water use [*Tilmant et al.*, 2014; *Wada et al.*, 2014; *Wild and Loucks*, 2014; *Latrubesse et al.*, 2017]. The engineering, social, environmental, economic, and political impacts of large hydro dams can be significant. New reservoirs are frequently challenged also for their high costs [*Ansar et al.*, 2014] or inappropriately balanced benefits [*Bird and Wallace*, 2001; *Sneddon and Fox*, 2008]. The World Commission on Dams reports poorly designed dams and multi-reservoir systems led to large societal opportunity costs [*World Commission on Dams*, 2000].

Dams may reduce the availability and alter the timing of water deliveries for some water using sectors such as irrigated agriculture (food security under threat) and the environment (threat of socio-ecological damage). This is a reason why hydropower development projects can cause concern for downstream riparians who fear the potential negative consequences of modified flow regimes [*Sneddon and Fox*, 2008; *Räsänen et al.*, 2012; *Wu et al.*, 2013; *Gebreluel*, 2014]. The impact of large reservoirs can be contentious as evidenced by water disputes in some of the world's large river basins [*Block and Strzepek*, 2010; *Dinar*, 2012; *Räsänen et al.*, 2012]. However, despite a large opposition to dams, dam building and planning has sharply increased in recent years; with an estimated 3,700 dams either planned or in construction worldwide [*Zarfl et al.*, 2015].

Most infrastructure developments concern multiple stakeholders with potentially conflicting interests, differing perception of risk and opportunity. In this context promoting consensus-based decision-making requires catering for both the interests and concerns of different stakeholders. Accommodating different partys' needs is necessary in a transboundary context to reduce conflict [*Swain*, 2011; *Anghileri et al.*, 2013; *Sadoff et al.*, 2013]. The fact that water, land, energy and financial resources are distributed unevenly in many transboundary basins can incentivise cooperation – the coordinated use of resources [*Conway et al.*, 1996; *Wichelns et al.*, 2003; *Conway*, 2005; *Tafesse*, 2005; *Dinar*, 2006; *Cascao*, 2008; *Vaughn et al.*, 2009]. Resource pooling such as sharing expertise, cost sharing or facilitation of loans can enhance individual and shared benefit of cooperation [*Whittington and McClelland*, 1992; *Wichelns et al.*, 2003], yielding gains that can be greater than the value of the disputed water itself to the users. However, significant challenges in assessing, designing and negotiating the implementation and management of water systems remain. These include the lack of adequate knowledge base needed for decision making, difficulty to consider multiple issues in the design problems and incorporate the views of stakeholders in multi-stakeholder problems.

To achieve development targets, system planners should consider the impact of new developments on existing uses and how overall benefits could be enhanced. Negotiated introduction of new dams and coordinating their implementation and use could help achieve consensus among stakeholders and reduce chances of conflict. For this, new approaches are needed to improve the design, financing, and management of dams to meet local, national and regional development needs, goals and preferences.

The thesis proposes and applies new formulations of the multi-objective and multi-stakeholder reservoir system design, management, and negotiation planning problem using many objective optimization algorithms (MOEAs) [*Vemuri*, 1974; *Hernandez-Diaz et al.*, 2007; *Hadka and Reed*, 2013; *Maier et al.*, 2014a] and visual analytics tools [*Keim et al.*, 2008; *Vitiello et al.*, 2012; *Woodruff et al.*, 2013].

1.2. Research Questions

How can designs of new or extended reservoir systems consider the impacts on the performance of existing and future water users?

Does joined up consideration of the sizing, scheduling and operating rules of reservoirs improve system performance?

Given sensitivity of performance metrics to uncertain future parameters, how can multi-objective evolutionary algorithms be used to compare performance of alternative infrastructure options?

Can the performance of reservoirs be improved by using operating strategies that adapt to recent system performance?

How can the benefits of multi-stakeholder cooperation be considered, along with performance trade-offs, in the negotiated design of infrastructure systems and their management?

1.3. Thesis outline

This work first reviews the literature (Chapter 2) to identify knowledge gaps in the planning, negotiation, and implementation of reservoir systems and their management. The proposed Blue Nile reservoirs are used as a case study (Chapter 3) to test problem formulations of increasing complexity (please see Figure 1) using the many objective optimization and visual analysis approach to help with better infrastructure and operating rule designs, scheduling of system expansions, presentation of complex water system design and assessment of results and negotiation approaches. Chapter 4 describes the overall method used in the study. The next two chapters focus on the design of new multi-reservoir systems. The methods consider the potential contribution of each existing and proposed component of a water system to a coordinated management to suggest best designs (i.e., the selection, size and operating rules given in Chapter 5) and their scheduling (Chapter 6) considering the flexibility of reservoir operating policies as the reservoir system expands.

These will be followed by Chapter 7 and 8 which use new formulations of the many objective optimization approach to help identify robust designs and allow stakeholders visualise and compare pre-identified options (even when dominated) with non-dominated options.

Chapter 9 demonstrates an adaptive reservoir operation to prioritize the multi-purpose use of reservoirs in a range of hydrological conditions (e.g., droughts of different magnitudes and lengths). These are followed by (in Chapter 10) a hybrid multi-objective optimization and multi-criteria weighing approach to support the negotiated design of water systems considering resource-sharing mechanisms (e.g., power-trade and/or cost sharing). Chapter 11 summarizes the findings, while Chapter 12 presents the limitations of the study and proposed future works.

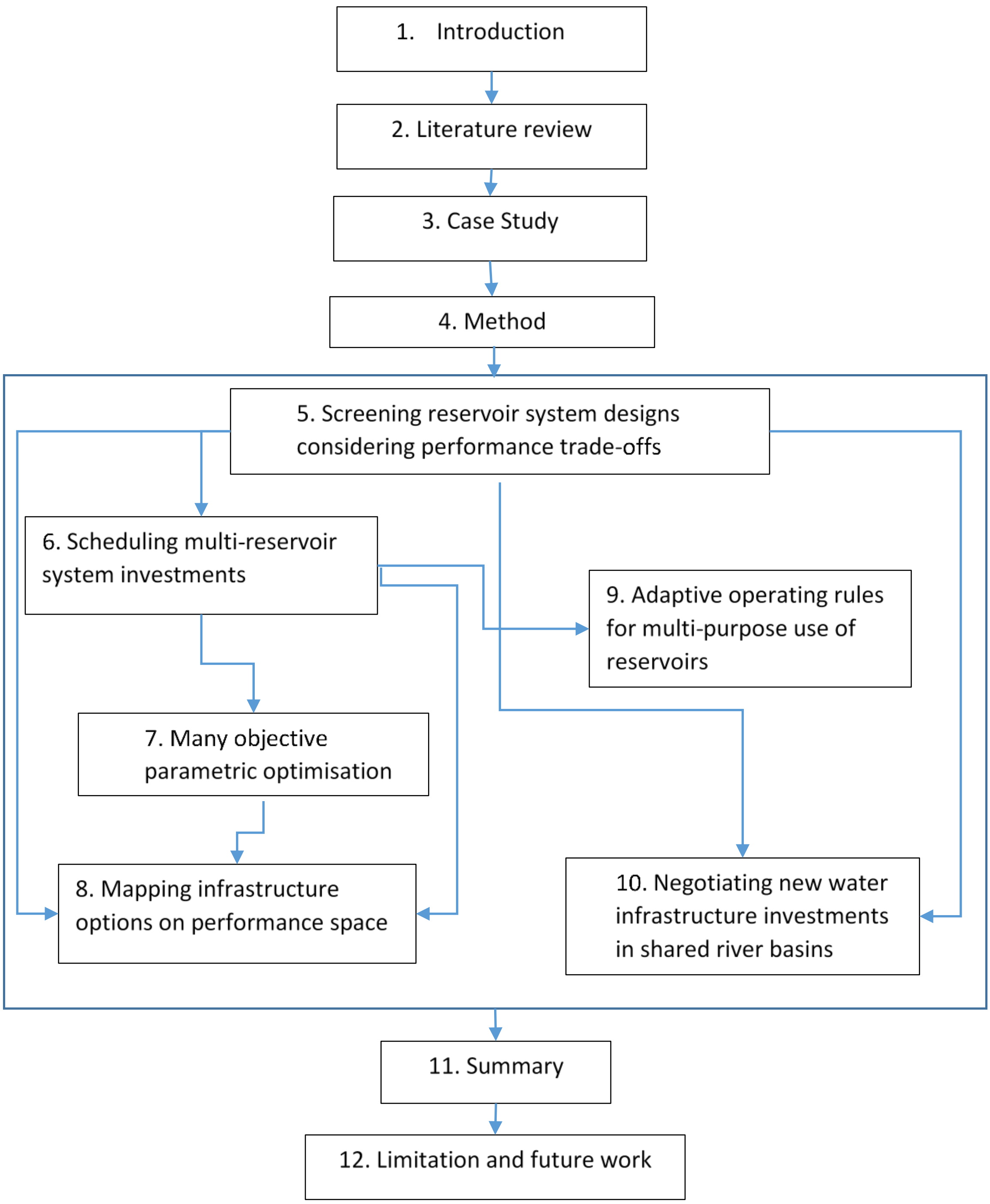


Figure 1 Thesis flow diagram (conceptual interdependence of the chapters in this report)

2 Literature review

Reservoir system designs (e.g., selecting among options, sizing), their management and the timing of system expansions is an important decision consideration in many water resources planning problems that involve multiple stakeholders with potentially diverging interests. This chapter reviews the literature on reservoir system design in particular and the design, decision support and negotiation support approaches in the general water resources planning management literature to take stock of the historical development, account for the latest conceptual, algorithmic and methodological developments and to identify knowledge gaps.

2.1 Water resources system modeling

Computer models are employed extensively in water resource planning to help decision makers understand the impacts of alternative management options on water resources systems; the majority being simulation models. Water resources planning problems are often complex; and are difficult to handle with conventional simulation modelling because invariably too many possible combinations of assets and their coordinated operation rules need to be considered [Khaliquzzaman and Chander, 1997], in such contexts, optimization models are more appropriate [Harou et al., 2009].

Optimization models provide insight into best management practices to maximize benefits [Afshar et al., 1991; Askew, 1974; J Harou, 2010; Revelle and Kirby, 1970]. Problem formulation used in simulation and optimization assessments can affect the predictions of the consequences of alternative solutions and consequently which solutions are considered ‘‘optimal’’ [*Roy*, 1991; *Kasprzyk et al.*, 2009]. Quinn et al. [2017] suggest a ‘rival-framings’ framework to interrogate multiple competing hypotheses of how complex water management problems should be formulated. Moreover, various optimization approaches have important limitations. For example, many hydro-economic models assume water systems are composed of entities that have perfect information, are perfectly rational and would subscribe to the views of an omniscient central planner who makes investment and policy choices to maximize system benefit [*J J Harou et al.*, 2009]. Although the optimal allocation of resources in shared water systems - as would be prescribed by hydro-economic optimization models - can maximize overall system benefit, it is not always possible due to various political and historical reasons [*Bendor*, 1988; *Jeuland et al.*, 2014; *Madani*, 2010; *Read et al.*, 2014].

Optimization algorithms that adopt reduced gradient method (e.g., CONOPT, MINOS) can solve large problems with nonlinear objective by reducing the number of variables and linearizing the nonlinear constraints [Drud, 1985]. The use of linear programming solvers, which are used extensively, requires significant simplification for large water resource systems. This is sometimes justified as simulating a water system with optimization methods allow bypassing the complex set of rules that would be required in simulation model of the systems.

2.1.1 Linked simulation optimization

Water resource model functions are often characterized with discontinuity, non-convexity, non-linearity, and high dimensionality which makes them difficult to model with some optimization models [*Labadie*, 2004]. Approaches that link simulation models with heuristic global search methods such as evolutionary algorithms [*Deb et al.*, 2002; *Coello Coello et al.*, 2007] are well suited to handle non-linearity associated with operating rule design [*Thorne et al.*, 2003; *Sechi and Sulis*, 2009; *Vamvakeridou-Lyroudia et al.*, 2010; *Hurford and Harou*, 2014]. Multi-objective evolutionary algorithms [*Nicklow et al.*, 2010; *Maier et al.*, 2014a] evolve approximations to the Pareto optimal set through search processes that exploit global probabilistic search operators for mating, mutation, and selection. Evolutionary algorithms have been demonstrated to be effective for water resources optimization involving non-convex and discontinuous functions [*Nicklow et al.*, 2010; *Hadka and Reed*, 2013; *Maier et al.*, 2014a]. Anghileri *et al.* [2013], Arena *et al.* [2010] and Giuliani *et al.* [2014] used multi-objective evolutionary algorithms to refine operating policies of reservoir systems. Relying on simulation models linked -with optimization [*Sechi and Sulis*, 2007] avoids simplifying assumptions [*Wurbs*, 1993; *Giuliani et al.*, 2014] and allows for the inclusion of complex risk-based performance metrics in the objective function [*Hashimoto et al.*, 1982].

2.1.2 Many objective optimization and Visual Analytics

An assumptions that water users sharing a basin will subscribe to the views of omniscient central planner who makes investment and policy choices to maximize system benefit [J J Harou et al., 2009] can be unrealistic in many system as rational decision makers often prefer to maximize their individual benefit. These limitations in coordination should be represented in the design, valuation of benefits and cost of new system to evaluate alternative plans. Many objective optimization and visual analysis of trade-offs allows the tracking the individual benefits of multiple stakeholders and the benefit trade-offs for each group of stakeholders involved; including the benefit trade-offs of individual stakeholders with the system benefit.

Single objective optimizations, which mostly consisted of minimizing the cost of providing services relied heavily on commensurating or monetizing different goals. By using single objective optimization, decision makers could inadvertently ignore important decision alternatives. Solutions suggested by low dimensional problem formulations can also only reinforce their presumptions, preventing new insight [*Chang et al.*, 1982]. Moreover, stakeholders may not know what is possible before seeing the full set of possibilities, considering many-objectives explicitly and simultaneously can help avoid this cognitive myopia [*Hogarth*, 1981].

Many objective optimization and visual analytics for trade-offs analysis have gained popularity in recent years for assessing development options based on multiple criteria [*Fu et al.*, 2013; *Kasprzyk et al.*, 2013a; *Geressu and Harou*, 2015; *Matrosov et al.*, 2015; *Huskova et al.*, 2016]. However, while the many objective optimization and visual analytics approach is an improvement over single objective optimization [*Brill et al.*, 1982; *Coello Coello et al.*, 2007], decision making based on Pareto-optimality alone may not be possible in multi-stakeholder problems. This occurs when competing stakeholders objectives result in different stakeholders preferring different system designs [*Geressu and Harou*, 2015]. Also, water resources management and design problems often involve political, societal, and other subjective goals that could be difficult to represent mathematically [*Nicklow et al.*, 2010].

Techniques in the literature that help identify potential solutions outside the optimality measure to find alternatives that may be sub-optimal but those that stakeholders may find acceptable include near-optimal analysis [e.g., *Rosenberg*, 2015], threshold detection [*Brown et al.*, 2012] and agent based modelling [*van Oel et al.*, 2010; e.g., *Wang et al.*, 2013; *Bristow et al.*, 2014].

2.1.3 Multi-stakeholder Negotiation

Given that risks associated with water resource planning require political considerations [*Dore and Lebel*, 2010], the search for a consensus solution in a multi-party system requires explicitly considering subjective preferences of the different parties [Anderson et al., 2003]. Stakeholders could have conflicting preferences on the designs and use of water infrastructures. Where the necessary mechanisms to enforce coordination strategies are impractical, optimal designs may be unsatisfactory at local or system-wide scales [*Madani and Hipel*, 2011; *Jeuland and Whittington*, 2014].

Computer-based support for negotiation and conflict resolution in water resources management include Graph Model for Conflict Resolution [*Kilgour et al.*, 1987, 1996; *Hipel et al.*, 1997], Adjusted Winner [*Massoud*, 2000], and the works of [*Nkomo and van der Zaag*, 2004; *Borowski and Hare*, 2007, etc.]. Institutional mechanisms to manage shared resources and resolve disputes have achieved some success [*Song and Whittington*, 2004; *Vieira Getirana et al.*, 2008; *Abitbol and Schoenfeld*, 2009; *Andreu et al.*, 2009; *Carmona et al.*, 2013]. However, despite wide acceptance of the need for rigorous, all-inclusive decision making [*X M Cai et al.*, 2004; *Herman et al.*, 2014; *Hipel et al.*, 1993; *Hummel et al.*, 2014] and economic benefit of cooperation [*J J Harou et al.*, 2009; *Howe et al.*, 1986; *Lund et al.*, 2006], many water systems are planned and managed in suboptimal coordination levels [*Elhance*, 1999; *Jeuland et al.*, 2014].

Many objective optimization and trade-off analysis [*Vemuri*, 1974; *Brill et al.*, 1982; *Mavrotas*, 2009; *Kasprzyk et al.*, 2013a] can assist in achieving designs approved by groups with varying interests by establishing a reduced set of efficient alternatives worthy of further deliberation. However, an optimal or Pareto-optimal solution for one set of users may not be perceived as such for other group of stakeholders [*Reed and Kasprzyk*, 2009]. *Fitzgerald and Ross* [2015] argue the traditional approach of multi-objective analysis cannot readily be used for multi-stakeholder tradespace exploration and suggest framing of the problem so that multi-stakeholder visualization can reduce fixation on the individual cost-benefit Pareto front.

2.2 **Multi-reservoir system design**

2.2.1 Infrastructure screening

Various methods have been used for designing (i.e., selecting among plausible reservoir sites, their capacities, and operating rules) cost-effective reservoir system interventions in the last decades. Klemes [1979], Lall and Miller [1988], Eastman and Revelle [1973] contributed early methods for design of single-purpose standalone reservoirs. Often reservoirs are planned jointly in multi-reservoir system design. This task is difficult to handle with conventional simulation modeling because invariably too many possible combinations of assets and their coordinated operation rules need to be considered [*Khaliquzzaman and Chander*, 1997]. This led researchers early on to attempt using optimization to search for good multi-reservoir system designs [*Houck and Cohon*, 1978; *Lall and Miller*, 1988; *Sinha and Bischof*, 1998]. Stedinger *et al.* [1983] review different early optimization-based reservoir screening models.

2.2.2 Operating rules

One important factor in reservoir system benefit and impact trade-off levels are the operating rules of reservoirs. Water researchers have considered the optimization of reservoir operating rules in an extensive literature. Operating rule parameters can be found from deterministic optimization models using fitting methods [*Koutsoyiannis and Economou*, 2003a]. Regression techniques have been used to infer reservoir release rules as functions of presently knowable conditions such as storage [*Young*, 1967; *Bhaskar and Whitlatch*, 1980] . *Lund and Ferreira* [1996] illustrate the limitations of applying deterministic optimization to development of strategic operating rules for large-scale water resource systems

In Direct Policy Search (DPS) [*Giuliani et al.*, 2014], also called parameterization-simulation-optimization approaches [*Guariso et al.*, 1986; *Oliveira and Loucks*, 1997; *Koutsoyiannis and Economou*, 2003a; *Celeste and Billib*, 2009; *Rani and Moreira*, 2010], the operating policy is assigned a functional form (e.g., linear or piecewise linear) and then parameters are optimised to meet one or more objectives. The approach is helpful and estimated performace is verifiable (i.e., using simulation modeling) as operating rules can be expressed such that they are usable by operators who have limited foresight of the future [*Li et al.*, 2014].

Development of optimal operational policies for large water resources systems is a complicated process because of the numerous objectives that may exist [*Ko et al.*, 1992]. Operating rules generated by single objective and insufficiently constrained optimization may maximize total benefits, but they are likely to be impractical or unsatisfactory at local or system-wide scales. This is because single objective economic engineering optimization models tend to ignore non-commensurate objectives that cannot be monetized [*Ko et al.*, 1992]. Many researchers have focused on how to operate hydropower reservoirs to meet multiple objectives including ecological ones, e.g.,[*Petersson et al.*, 2007; *Jager and Smith*, 2008; *Renofalt et al.*, 2010; *Mirumachi and Torriti*, 2012].

2.2.3 Scheduling capacity expansion

Infrastructure capacity expansion planning involves identifying schedules of interventions (new assets or demand management efforts) in supply-demand systems that meet service provision goals and other criteria [*Hall and Buras*, 1961; *Mortazavi-Naeini et al.*, 2014]. While the scheduling of water supply system infrastructure investments has traditionally been driven by minimizing total discounted costs [*Lund*, 1987; *Mousavi and Ramamurthy*, 2000; *Luss*, 2010; *Padula et al.*, 2013], the importance of environmental and economic downstream impacts of reservoirs is increasingly recognised [*The World Bank*, 2009; *Galaz et al.*, 2012; *Beh et al.*, 2014; *King et al.*, 2014; *Sandoval-Solis and McKinney*, 2014; *Sahin et al.*, 2016].

Additions of new reservoirs in an expanding system can significantly reduce performance temporarily (for several years) depending on the scale and relative position of assets. Hence, planning the expansion of multi-reservoir systems requirs attention to the impacts of alternative development and management options on the existing systems. Multi-reservoir system design should also consider the potential for coordinated operation of reservoirs to improve the overall system performance [*Labadie*, 2004]. Hence, rigorous analysis and re-assignment of operation rules to reservoirs in different physical system designs is essential to estimate potential benefits and downstream impacts of water resources expansion plans.

2.3 **Uncertainty**

Uncertainties associated with natural variability of river flows, climate change, economic and enegineering performance pose various levels of risk to water users [*Milly et al.*, 2008; *Velpuri and Senay*, 2012; *King and Block*, 2014]. These could lead to costly, inadequate or unsatisfactory decisions with unnacceptable negative impacts. Considering uncertainity help predict the likelihood of success and failure and select among alternative options based on the decision makers' view of acceptable trade-offs between risk and opportunity. Hence, decision makers are required to consider various uncertainties due to hydrologic stochasticity, climate change, and future water demands [*Block and Strzepek*, 2010; *Conway et al.*, 1996; *A King and Block*, 2014; *Swain*, 1997; 2011].

2.3.1 Natural variability

Two of the most popular approaches to deal with the natural variabilities in water resource problems are the explicit and implicit stochastic optimization approaches. Explicit stochastic optimization [*Braga et al.*, 1991; *Tejadaguibert et al.*, 1995] is designed to operate directly on probabilistic descriptions of random streamflow processes without the presumption of perfect foreknowledge of future events. Feasible combinations of state variables grow exponentially for large systems making the approach computational burdensome for many systems [*Roefs and Bodin*, 1970; *Labadie*, 2004; *Giuliani et al.*, 2014].

Implicit stochastic models are convenient in model representation and computationally. When applied in gradient-based optimization algorithms, the approach involves performing deterministic optimization on long historical or stochastically generated inflow sequences. Operating rules are then inferred from the optimal storage and release solutions by applying multiple regression analysis. However, it is difficult to know apriori whether or not these inference processes will provide satisfactory operating rules requiring extensive trial and error processes. Moreover, the deterministic representation of variability makes optimization algorithms assume that decision-makers would have full knowledge of future inflows. Because this misrepresents real water managers (who have limited foresight) as being capable of making efficient choices that maximize the long-term benefits, implicit stochastic optimization lead to overestimation of benefits [*Labadie*, 2004; *Philbrick and Kitanidis*, 1999; *Rani and Moreira*, 2010; *Satti et al.*, 2015].

2.3.2 Deep Uncertainty

The assumptions that future conditions can be extrapolated from the past has been central to water system analysis. However, depending on past observation in planning for future management can be risky due scarcity of hydrological data (which don't allow us to look at the sufficiently long history of hydrological variability) and significant environmental changes in many places. Non-stationarity of environmental conditions [Galloway, 2011; Lins and Cohn, 2011] and conflicting climate-change impact projections also make it hard for different stakeholder groups to agree on the likelihood of future condition [Knight, 1921]. Deep uncertainty is where historical data cannot be used to quantify the likelihood of future scenarios and hence probability based assessment is inappropriate [Groves and Lempert, 2007; Milly et al., 2008]. Policies that can be adapted over time in response to how the uncertainties resolve have been suggested to improve performance in the presence of deep uncertainty [Lempert et al., 1996; Kwakkel et al., 2013; e.g., Werners et al., 2013]. Robust decision making (RDM) approach identifies and selects strategies that meet threshold performance criteria across plausible scenarios without presumption of any one scenario being more likely than another [Lempert et al., 2006]. Info-gap theory identifies the solutions that meet threshold performance criteria for each uncertainty set by developing increasingly large multidimensional uncertainty sets [Ben-Haim, 2006]. Other recent studies, particularly under non-stationary conditions with deep uncertainty, propose an adaptive approach [Walker et al., 2010; Haasnoot et al., 2013] with optimisation formulations which are explicitly adaptive [Beh et al., 2015; Kwakkel et al., 2015; Zeff et al., 2016; Erfani et al., 2018]. Adaptive management works by taking into account changes in external factors in a proactive manner and adjusting a decision that is implemented in stages [Huntjens et al., 2011]. This requires problem formulations that are designed such that decisions evolve in response to new information" [Lempert et al., 2003].

Studies that address the trade-off between economies of scale (with large projects) and management of the uncertain future which may benefit from the flexible implementation of smaller ones staged over the planning period include the works of Braga et al. [1985], Mahmoud [2006], Chang and Chang [2009] .

However, economic and financial uncertainty could be more relevant for stakeholders in some planning problems. Gaudard et al. [2016] show that greenhouse gas scenarios represent a low source of uncertainty compared to electricity prices for a hydropower case study in Switzerland.

2.3.3 Set based uncertainty

Some uncertainty forms are set-based (i.e., they take any value from a set of possible parameter realizations) [*Jin and Branke*, 2005; *Bertsimas et al.*, 2011; *Fliege and Werner*, 2014]. An example is discount rate used in investment planning. Discounting benefits over time takes into account the time value of money and the uncertainty about future societal demands and technologies [*Fisher*, 1930; *Koopmans*, 1960]. The discount rate used in cost-benefit analysis will influence the outcome of the investment options assessment [*Van Liedekerke*, 2004] yet setting it is a subjective or political decision [*Pearce et al.*, 2003; *Hahn and Dudley*, 2008]. Hence, evaluating or optimising infrastructure investment decisions with different benefit horizons, scales and purposes (e.g., energy generation, flood mitigation, irrigation water supply) under a single discount rate assumption could introduce a decision-bias which would limit the quality of decision-making [*Lopez*, 2008]. The sensitivity of decision-making assessment to discount rates has led some researchers to avoid its use altogether [e.g., *Rubinstein and Ortolano*, 1984; *Dziegielewski et al.*, 1992; *Cai et al.*, 2002; *Yang et al.*, 2007; *Mortazavi-Naeini et al.*, 2014]. An improvement would be to consider (or optimise in our case) investments under a range of discount rate values in the hope of identifying options who's value are robust (relatively less sensitive) to the discount rate. In this case the decision to invest in a particular intervention would remain efficient over a range of discount rates, a sign of a robust rather than brittle decision.

Smalley et al. [2000] propose combining a noisy genetic algorithm (that uses sampling from parameter distributions to assess the performance of candidate designs) with a number of models to predict risk simultaneously and proposes cost-effective options for reducing risk. *Gopalakrishnan et al.* [2003] found the noisy genetic algorithm, that uses a type of noisy fitness function, to be efficient compared to Monte Carlo simulation modeling.

Ehrgott *et al.* [2014] extended the concept of minmax robustness Ben-Tal *et al.* [2009] to multi-objective optimization and called this extension robust efficiency for uncertain multi-objective optimization problems. Fliege & Werner [2014] introduce a robust counterpart to a multi-objective programming and demonstrate that robust, efficient frontiers can be found by standard methods of robust and multi-objective programming under commonly made assumptions on the uncertainty. The approach works for convex parametric multi-objective optimization problem under data uncertainty.

In reality, multiple parameter uncertainties simultaneously affect performance. Considering uncertainty due to various factors independently may not reveal the overall impact and accumulated uncertainty [*Gaudard et al.*, 2016]. *Kasprzyk et al.* [2009] use Monte Carlo sampling to evaluate objective function values for each solution in successive generations of evolutionary search to help find the robust solutions given uncertainty from estimates of the reservoir mass balance, amount of water available for consumers, fluctuations in lease pricing and volumetric water demand.

In many situations, the computational requirement of robustness analysis could be foreboding. Because of this, robustness analysis over set based uncertainity such as uncertainity on the discount rate of future benefits, energy prices etc. is ignored in many water planning reports in the literature.

2.4 **Knowledge gaps in the literature**

Given the large number of alternative infrastructure and management options in many water planning problems, optimization techniques can help identify best performing designs for further deliberation. However, due to limited resources to analyze complex river systems, simplifying assumptions in formulating planning problems are frequently made [*Kim and Yeh*, 1986; *Takeda and Papalambros*, 2012; *Beh et al.*, 2014; *Galelli et al.*, 2014]. Labadie [2004] and Rogers and Fiering [1986] cite lack of confidence in the assumptions and structure of many water resource optimization models for their relatively modest real-world use. Stalled negotiations in participatory decision-making processes are prevalent, during which stakeholders preferences cannot begin to converge toward an appropriate decision [*Kaner et al.*, 2007].

A review of literature for this study found the following gaps which will be addressed in this thesis.

2.4.1 Sizing of Reservoirs

Upstream reservoirs can change the variability of inflow to downstream reservoirs. Hence, the assumption of variability used for sizing of the downstream reservoirs could be violated when new dams come online. Given that the change in hydrological variability to the downstream reservoirs will depend both on the size, and operating rule of the upstream reservoir and that coordinated use of the reservoirs can improve their overall performance, the design (i.e., size and operating rule) of each reservoir in a multi-reservoir system on a river reach should consider the design of all other reservoirs in the system. However, multi-reservoir system designs in the literature ignore this complexity in lieu of a simplified assumption where an optimal size and operating rule of each as a standalone reservoir would be good enough for when the reservoir is operated in a multi-reservoir system. This could lead to unnecessarily large reservoirs or systems performing below capacity.

2.4.2 Sequencing of Reservoirs

Related to the above, assessing the scheduling of reservoirs ignoring the flexibility of their operating rules to evolve as the reservoir system expands can underestimate reservoir system performance. However, in multi-reservoir system planning, the ability to change operating rules as the system expands is typically ignored. Moreover, expansion decision points are often constrained (e.g., 5 years [*Beh et al.*, 2014; *Jeuland and Whittington*, 2014], 7 years [*Block and Strzepek*, 2010], decadal [*Mortazavi-Naeini et al.*, 2014]). Fixing the time between interventions could bias recommendations as sequenced bundles that work well together (i.e., interfering least with each other's performance) are not considered.

The filling periods of large reservoir are a key factor in their planning and can be contentious because of the diminished performance during this period, However, the transient period performance, their trade-off and the link between infrastructure sequence choice with the flexibility to operate reservoirs to achieve more desirable balance of performance at different expansion stages is not reported in reservoir system scheduling literature.

2.4.3 Adaptivity of Reservoir operating rules

Reservoir operators either abandon or deviate from standard operating guidelines when necessary to use various sources of information on different time scales [Hejazi et al., 2008]; with the values that these different sources of information have depending on the system objective [Tejadaguibert et al., 1995]. Reservoir operating rules generally associate lower releases to lower storage levels. Traditional operating rules to deal with droughts are potentially ill-suited in this situation, since they are centred around water supply hedging which assumes a limited storage capacity should lead to further reductions in releases [Bayazit and Ünal, 1990; Lund and Ferreira, 1996; Tu et al., 2003; You and Cai, 2008]. The inability to mathematically formulate and optimise adaptive operating rules in assessing the impacts of alternative reservoir management strategies could lead to sub optimal results.

2.4.4 Parameter Uncertainty

Performance of systems is often affected by multiple parameter uncertainties simultaneously. Multi-stakeholder decision support could require representation of multiple uncertainty sources such as variability, climate change but also the approperiate value for the discount rate of future benefits, possible construction cost overruns, and delay. Informed dialog and negotiations could be hindered by differences in opinion on these deeply uncertain factors because these could potentially influence design choices. Hence, water resources system expansion planning decision/ negotiation support involving multiple stakeholders could benefit from the representation of multiple scenarios for the uncertain parameters and the best plans for these scenarios. However, water systems are typically assessed assuming key parameter values such as costs, prices and discount rate of future cash flows deterministically.

2.4.5 Inability to compare full set of alternative options

Several modern Decision Making Under Uncertainty methods use many objective optimisation (MOO) [Vemuri, 1974; Mavrotas, 2009; Kasprzyk et al., 2013b] to assist in many objective or multi stakeholder problems by establishing a reduced set of efficient alternatives where any objective cannot be further improved without simultaneously harming one or more other objectives [Arena et al., 2010; Kasprzyk et al., 2013a; Woodruff et al., 2013]. Given the dependence of infrastructure performance on its operating policies (e.g., reservoir release rules), evaluating alternative infrastructure options requires exploring how each option would perform under a variety of operating policies. When using MOO methods, the Pareto-front does not discriminate between infrastructure and management choices, thus ignoring that assets are relatively unchangeable, while policies can be changed with relatively less political and financial cost).

In practice most regions in need of development have a series of options that have been considered - sometimes for decades (e.g., on the Nile and Rufiji basins in Africa [Block and Strzepek, 2010; Duvail et al., 2014]) and may have been through site selection, pre-feasibility study and preliminary environmental impact assessment processes. This puts them in the public consciousness and means they should be at least represented within stakeholder driven design processes. Moreover, some stakeholders might stand to gain from local development and may disagree to forfeit local benefits for designs that perform slightly better in aggregated regional or national assessments. Conventional trade-off analysis retains only high performing intervention options and drops those with lower performance objectives [Coello Coello, 2006; Reed et al., 2013]. This can be problematic where evaluation of certain development options with existing constituencies need to be included in planning exercises to allow their performance comparison and maintain stake-holder confidence in the decision support system.

2.4.6 Negotiated system design and coordinated use of resources

New reservoirs could negatively affect benefit of existing users; making system changes difficult to agree upon. Considering cost and benefit sharing strategies (e.g., payments or access to energy trade) could facilitate agreement as this could make system changes more acceptable to all parties.

The literature identifies tying benefit sharing to the negotiation [*Mumpower and Rohrbaugh*, 1996; *Wu and Whittington*, 2006; *Arjoon et al.*, 2016] as a possible enhancement to complex multi-party environmental resource system development problems. However, agreeing on project selection among many alternatives is challenging given the multitude of stakeholders and their diverse preferences. Many decision support tools (e.g., Tchebycheff algorithm, game theory) for participatory decision-making processes require all stakeholders to interact with the decision support tools for multiple iterations in order to narrow down the alternatives [*Thiessen and Loucks*, 1992; *Cai et al.*, 2004; *Keller et al.*, 2010]. Given that concessions are not always an attractive proposition, the inability to agree on one or few system designs to start negotiating on can stall negotiations [*Mumpower and Rohrbaugh*, 1996]. In addition to the possibility of stalled negotiations due to disagreements on valuation of impacts and benefits, problem formulation and priority for various system performance attributes, the sequencing of decisions on system design and benefit and cost sharing could lead to sub-optimal results. It is not clear from the literature how starting points for negotiation among multiple alternative designs will affect the ability of stakeholders a consensus solution.

The gaps identified above in 2.4.1, 2.4.2, 2.4.3, and 2.4.6 the could overestimate the cost of compromises in negotiation, tempting stakeholders to opt for unilateral implementation of projects. These could exacerbate environmental impact and impact on downstream users and lead to under or inefficiently exploited potential. The gaps described in sections 2.4.4, 2.4.5, and 2.4.6 also hinder negotiated system design and implementation as stakeholder may have differing perceptions of risk and opportunity and may not agree on the assumptions used for finding the optimised system designs and their predicted performance.

The study addresses these gaps using the Blue Nile case study described in the following section for demonstration.

3 Case study

3.1 The Nile Basin

The Nile basin is a culturally and socio-economically diverse river basin home to more than 250 million inhabitants in 11 riparian countries [*Nile Basin Initiative*, 2016]. The basin is characterized by large differences in income, uneven resource allocation between its riparian countries [*Whittington and McClelland*, 1992; *Küng*, 2003; *Arsano and Tamrat*, 2005], poverty of its inhabitants and rapid watershed degradation [*Hurni et al.*, 2005; *Awulachew et al.*, 2010]. The growing population numbers, the associated increase in demand for agricultural, domestic and industrial water supply requires a reliable supply of water beyond which current storage arrangement on the Nile can deliver [*Conway et al.*, 1996; *Swain*, 2011].

3.2 The Blue Nile

The Blue Nile River is the largest of the four major tributaries of the Nile River; contributing more than half of the annual flow. The river emanates from the central highlands of Ethiopia and is joined by a number of large tributaries before it crosses into Sudan. The Blue Nile is one of the largest basins in Ethiopia, covering 35% of its landmass. The basin receives an average 1000 mm/year of rainfall in summer monsoon season, with highest totals in the June-September months [*Conway*, 2000]. The river is highly seasonal and annually variable [*Block and Rajagopalan*, 2007] with frequent flooding (affecting population centers near its origin around Lake Tana in Ethiopia and in the Sudan including it capital Khartoum) and occasional droughts.

In Sudan, Roseires and Sennar dams enable irrigation of large sways of land along with small hydropower generation. In contrast, only a scant irrigable land has been developed in the Ethiopian part of the Blue Nile. The cooler climate and narrow gorges in upstream parts of the basin provide potential locations for new dams [*Sadek et al.*, 2004; *El-Kady and Moustafa*, 2005; *Swain*, 2011], with large potential for hydropower production in Ethiopia. Physiographic characteristics of the Blue Nile in Sudan is not suited for large reservoirs for overyear storage capacity to supply irrigation and reduce the reoccurring flood damage. The deep and narrow gorges in the upper part of the Blue Nile presents a better choice for storage in addition to its large hydropower potential generating system-wide, multipurpose benefits [Blackmore and Whittington, 2009].

Successive Ethiopian governments sought to construct and utilise the opportunity presented by the Blue Nile cascade dams which were first identified as far back as 1963 with the help of the United States Bureau of Reclamations (USBR) [*Blackmore and Whittington*, 2008]. The downstream countries Egypt and Sudan had been wary of new upstream infrastructure which could reduce the amount of water reaching them and give control of the water supply to Ethiopia [*Cascao*, 2008; *Allan*, 2009; *Swain*, 2011; *Rahman*, 2012; *Tawfik*, 2016; *Yihdego et al.*, 2016].

Ethiopia argues the energy is much needed domestically; in addition, the Blue Nile dam will benefit both Sudan and Egypt through increased availability of cheaper hydropower in the region [*Habteyes et al.*, 2015]. Others also point to the benefit of upstream regulation by the GERD in enhancing low flows to improve downstream water security

[*Blackmore and Whittington*, 2008]. Unable to self-fund the mega projects or secure international funding for the construction of the dams, these resources had until recently laid untapped [*Arsano and Tamrat*, 2005; *Hefny and El-Din Amer*, 2005; *Cascao*, 2008].

Ethiopia is currently constructing the Grand Ethiopian Renaissance Dam (GERD) which will create a large reservoir with 1.5 the annual flow of the Blue Nile near its border with Sudan. The GERD will inundate the site of the proposed Mandaya dam, forcing its relocation to an upstream site with an alternative design named 'Upper Mandaya.' A smaller GERD design with 620 masl full supply level (see Table 1) would allow the implementation of Mandaya dam. Farther upstream, the Beko Abo High can be implemented instead of the upstream-proposed dam site Karadobi and Beko Abo Low.

The challenge to finance the projects and the wisdom in Ethiopia's self-financing such a mega project (considering alternative uses of the large capital) is a subject of ongoing dialog [*Arsano and Tamrat*, 2005; *Block and Strzepek*, 2010; *Whittington et al.*, 2014]. Some argue against building the downstream most of the proposed Blue Nile dams first because of the impact that filling the rest of the proposed Blue Nile reservoirs would have on the GERD.

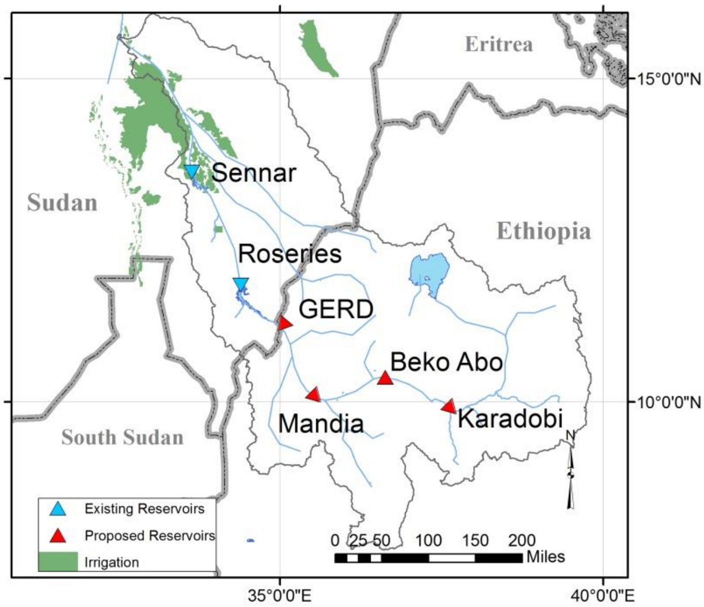


Figure 2 Locations of proposed reservoirs in Ethiopia and existing dams in downstream Sudan

Table 1 Proposed Blue Nile reservoirs

Reservoir	Mutually exclusive with	Maximum storage (MCM)	Installed Capacity (MW)	Cost estimate (MUSD)	Estimated construction length (years)

Beko Abo High	Karadobi, Beko Abo Low	31692	1940	3213	4
Beko Abo Low	Beko Abo High	1751	935	1208	3
GERD (FSL 620 m)	GERD (FSL640 m)	34970	6000	3800	5
GERD (FSL 640 m)	GERD (FSL620 m)	72000	6000	4630	8
Karadobi	Beko Abo High	40200	1600	2044	5
Mandaya	GERD (FSL640 m), Upper Mandaya	48088	2000	3408	6
Upper Mandaya	Mandaya	27702	1700	2183	4

The need for coordination for efficient use of resources on the Nile has long been recognised [*Whittington and McClelland*, 1992; *Wichelns et al.*, 2003; *Wu and Whittington*, 2006]. *Wu and Whittington* [2006] examined the incentive structure of cooperative and non-cooperative strategies for different Nile riparian countries when assessing possible sub-coalitions of the Nile countries to maximise their individual benefits.

Various studies investigated the feasibility of proposed reservoirs [*Jeuland and Whittington*, 2014], their transboundary impact on downstream use [*Sreenath et al.*, 2002; *El-Kady and Moustafa*, 2005; *Goor et al.*, 2010; *Whittington et al.*, 2014], the socio-economic, political and ecological impacts [Amer et al., 2005; Cascão, 2009; Nicol and Cascao, 2011], and the opportunities for cooperation on basin scale [Whittington and McClelland, 1992; Wichelns et al., 2003; Wu and Whittington, 2006].

Several water resources models have been developed to help understand basin wide implications of development alternatives on the Nile. Whittington and McClelland [1992] used an optimization model to estimate potential annual gross economic benefits of Nile under perfect collaboration. They estimated the value of collaboration on the Nile to be from 4-5 billion US dollars annually using hydro - economic optimization model. Block and Strzepek [2010] used a deterministic perfect foresight model of the upper Blue Nile basin to assess effects of reservoir filling, construction staggering and climate change on the benefits of the proposed Blue Nile dams. Goor et al. [2010] assessed planning and management options of Nile water resources using a stochastic dual dynamic programming formulation. They concluded coordinated reservoir operation would save water, increase annual energy generation and enable an increase in irrigated area in downstream Sudan.

Jeuland and Whittington [2014] attempted the problem of Selection, Sizing and Sequencing of New Dams on the Blue Nile considering sensitivity of economic outcomes of investments to climate change. Optimal filling and operation rules which maximise the hydropower generation in both Mandaya and Roseires reservoirs was synthesized using simulation and multi-objective optimization [Hassaballah et al., 2012].

Driven by robust demographic growth, projected energy demand will make new infrastructure necessary to ensure the continued reliability of the water supply and energy services [*Conway et al.*, 1996; *Swain*, 2011]. Increasing demand for energy coupled with high cost of fossil fuel makes the cheaper hydropower alternative from these potential investments attractive.

The three Easter Nile riparian countries Egypt, Ethiopia, and the Sudan, signed an agreement in 2015 to develop the Nile water resources while avoiding significant harm to any of the countries. The agreement could allow joint development of the Blue Nile reservoir to meet agricultural water and energy supply for their fast-growing populations which are expected to double in the next 30 years. Various development options of the proposed Blue Nile dams and their management policies present different mixes of benefits, impacts, and vulnerabilities.

The Eastern Nile countries have differing views on what equitable or fair water use could be and differing beliefs and perceptions on the legality of existing water use allocations [*Amer et al.*, 2005; *Dumont*, 2009; *Hamouda et al.*, 2009; *Zeitoun et al.*, 2010; *Swain*, 2011]. The historical background, differences in economic and development policy directions could also translate into how each will view the potential benefit and impacts of new developments. These challenges are confounded by imperfect knowledge of system function, and lack of sufficient dialogue and trust between the countries [*Cascao*, 2008]. However, despite these challenges, participatory assessment and planning could help identify potentially acceptable benefit distributions among the Nile riparian countries.

3.3 The gaps in the literature

The literature on the Nile fails to quantify the sectoral and multi-country benefit trade-off associated with new developments in the Blue Nile. Studies that assess multi-reservoirs system designs do not consider the flexibility of operating rules to evolve as the multi-reservoir system expands or how reservoir systems can be managed for multi-purpose use. This gap is a missed opportunity to address concerns of impact from upstream dams and potential to improve downstream benefits. Moreover, this could dramatise the perceived impact of new developments on downstream system performance. The reliance on few deterministic assumptions which can be contested by stakeholders (e.g., energy price, discount rate, etc..) used in studies in the literature also affects stakeholders' perceptions of system capacity, performance trade-off, and financial feasibility of development options. Hence, existing planning and assessment approaches on the Nile fail to facilitate negotiations on system design and coordinated resource use on this multi-country multi-issue planning problem.

This work proposes a design, management, assessment, and negotiation framework that address the identified gaps in the Nile water resource management literature and allows the Nile basin countries to explore possible designs and resource coordination strategies (e.g., joint investments and power-sharing from the proposed reservoirs).

3.4 Case study research questions

How does impacts of the dam system (including some downstream impacts) depend on design parameters of the Ethiopian dams?. Does ignoring reliability metrics, as a number of studies on the Nile do, affect multi-reservoir system composition recommendation by decision support systems? What are the optimal storage sizes of the Blue Nile reservoirs in a potential multi-reservoir system?

What are the best options (choice or reservoirs, the timing of their activation, and their operating rules that adapt to system expansion) for various balances of benefit from new reservoirs and their downstream impacts.

What are the robust infrastructure choices considering dam construction delay and cost overrun scenarios, and under various assumption of discount rates for future financial benefits (energy price).

How does considering the coordinated use of resources (e.g., cost sharing and energy interconnection) affect the preference of Nile riparians for system designs? Does the pre-selection of system designs to negotiate on affect the satisfaction of stakeholders? How can the negotiation on system design selection (infrastructure and their operating rule management) be facilitated?

The approach is applied to a proof of concept evaluation of proposed Blue Nile reservoirs in Ethiopia. Results of this study are intended to demonstrate the method but not to be taken as prescriptive recommendations.

4 Method

The proposed approaches are applied to assess which infrastructure designs (i.e., combinations, sizes, etc.) and management (operating rules) and the multi-country shared uses of new Blue Nile reservoirs are most efficient and what the relevant trade-offs between system goals are. 'Efficient' is used in a Pareto-optimality sense (the set of solutions which cannot be further improved in any one metric without simultaneously reducing performance in others) rather than a monetised sense where multiple performance objectives would need to be commensurable.

4.1 Many objective optimization

A heuristic optimization approach is employed where a search algorithm [*Kollat and Reed*, 2006; *Reed et al.,* 2013] is coupled with a simulation model of the water resources system via a wrapper code. The optimization is conducted using a many-objective evolutionary algorithm (MOEA) which have proved popular in water system applications [*Labadie*, 2004; *Reed et al.*, 2013].

The Epsilon-Dominance Non-dominated Sorted Genetic Algorithm II (ε-NSGAII) [*Kollat and Reed,* 2006; *Tang et al.,* 2006] generates its initial random population of decision variables by exploiting uniform random sampling within the user-specified ranges. These variables are then passed as input variables to the water resources simulator which evaluates the performance of the system. The performance information is passed back to the ε-NSGAII algorithm which evaluates the fitness of the decision variables to produce the next generation of decision variables. To ensure the final solutions are not influenced by the randomly generated initial populations, the algorithm is run a number of times depending on the problem formulation and its complexity with different seed values. The results from each run are then sorted together to provide the best overall reference set [*Kollat et al.*, 2008].

The multi-objective system design analysis provides Pareto-approximate sets of designs for which no objective can be further improved without deterioration in at least one other objective [*Reed et al.*, 2013] (i.e., the 'non-dominated' set of infrastructure portfolios). Heuristic search results cannot be mathematically proven to be Pareto-optimal hence the term 'Pareto-approximate' [*Datta et al.*, 2008]. Visual analytic trade-off plots [*Vitiello et al.*, 2012; *Reed and Kollat*, 2013; *Woodruff et al.*, 2013] are used to present the results.

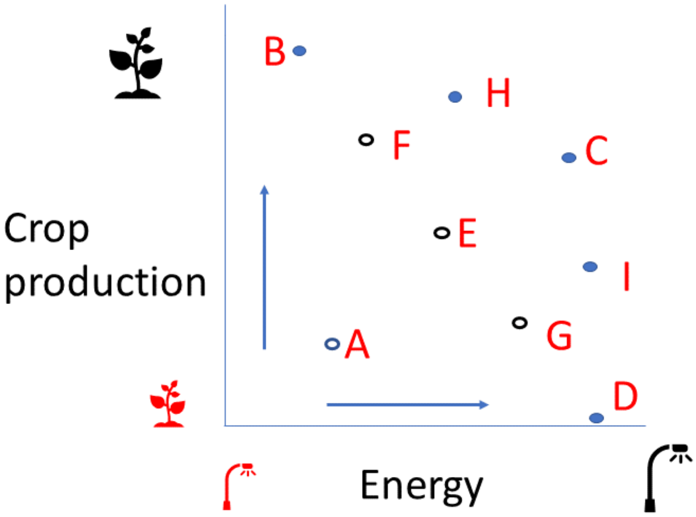


Figure 3 Pareto optimal solution set (shown with filled circles) for a hypothetical design problem where the performance objectives are maximizing crop production from irrigation and maximizing hydropower generation only.

Designs shown with hollow circles on Figure 3 are ignored as alternative options on the Pareto-front exist which score better in both energy and crop production objectives. The performance of any of the Pareto-optimal designs 'B','H','C','I','D' cannot be improved in both energy and crop production simultaneously as a further improvement in one performance leads to a deterioration in the other. The pareto-optimal designs can be equally useful to inform decision and the best amongst them can be selected considering preference of the decision maker which could be subjective.

The shape of the Pareto-front can vary depending on the decision problem. Visualizing the rate of sacrifice necessary in one performance objective to gain in another can help identify relatively more acceptable compromises.

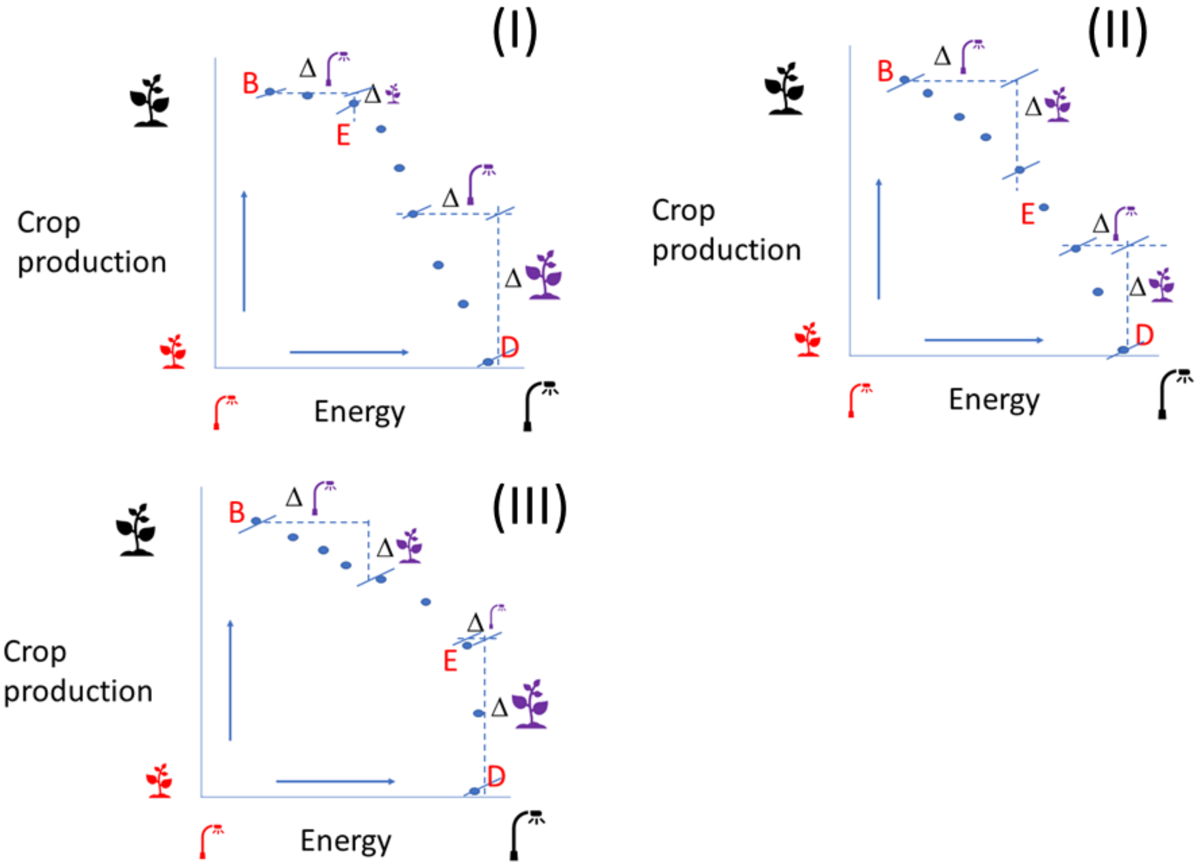


Figure 4 Panel I show a small sacrifice in crop production can allow higher gain in energy generation when moving from design B to E. Panel II also shows a case where sacrifice in energy generation for a gain in a unit measure of the crop production is uniform throughout the Pareto-front. Panel III represents the revers where a large increase in crop production is possible with a small energy sacrifice (moving from designs D to design E. This opportunity is not available for other parts of the Pareto-front in Panel I or the other two Panels which represent different problems.

4.2 Interactive River-Aquifer Simulation 2010

The water system simulation model representing the Blue Nile includes 3 irrigation demand nodes, 9 reservoir nodes and 16 junction nodes and 13 links representing river reaches. The system model was built using the interactive river-aquifer simulation system 2010 ('IRAS-2010') described by *Matrosov et al.*, [2011].

IRAS 2010 is a generalised water resource system simulation model. The IRAS-2010 model represents a water management system as a network composed of various nodes and links. Nodes represent natural lakes, reservoirs, aquifers, and gauge sites with time-series of inflows, demand sites, consumption sites and confluence or divergence sites.

The simulation model calculates surface and groundwater storage, flows, consumption and energy generation throughout water resource network. Input data necessary include hydrological inflows, evaporation rates, water allocation and reservoir release rules, consumptive water demands and minimum environmental flows. Streamflow routing, regional groundwater flow, ecological flows, hydropower, pumping and other features can also be represented where necessary.

The IRAS-2010 is selected for this study for its computational efficiency in running models that require multiple runs and its simple programming structure which enables easier changes to existing code.

4.3 Visual presentations

Many-objective optimization allows planners to visually assess important trade-offs where stakeholder preferences are evolving. Learning and exploring the benefits and negative impacts of new investments help different parties assess new designs, compromise on their benefit distribution and hopefully agree upon an acceptable way forward. The mapping of assets in performance space helps to summarise which asset combinations achieve what performance; providing valuable insights to system planners [*Fu et al.*, 2013; *Reed and Kollat*, 2013; *Woodruff et al.*, 2013]. Interactive multi-criteria performance plots can play a valuable role in understanding the implications of development within complex systems [*Kollat and Reed*, 2007; *Woodruff et al.*, 2013]. Visual interaction with results allows stakeholders to introduce minimum performance requirements (by filtering or 'brushing' results) [*Reed and Kollat*, 2013].

A mix of the scatter and parallel plots is used in this study to efficiently communicate the Pareto-optimal designs. This section demonstrates how considering multiple goals and their trade-offs explicitly and simultaneously in system planning can provide valuable assistance in the decision-making process using a simple hypothetical basin as example (shown in Figure 5).

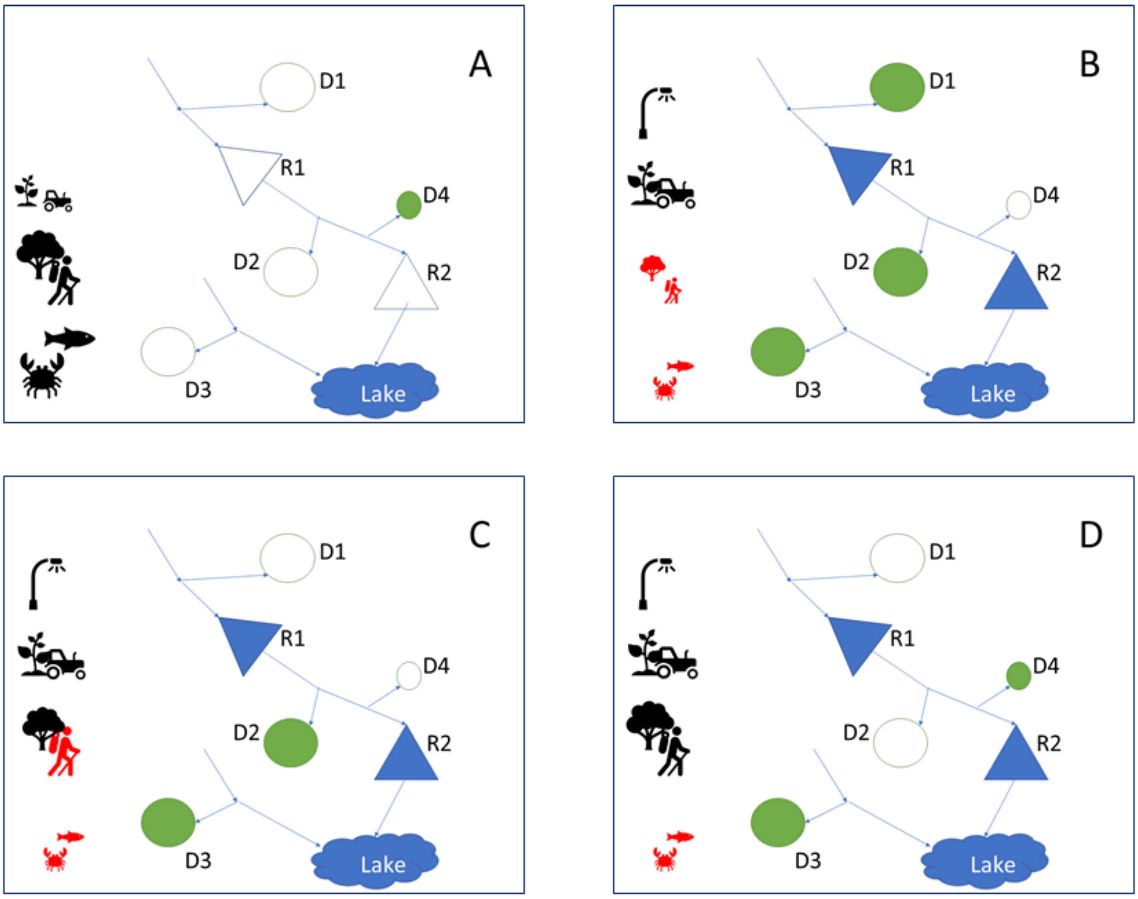


Figure 5 Alternative designs for a hypothetical basin. Panel A shows the status quo with minimal irrigation development, no reservoirs and pristine environment with tourism and undisturbed ecosystem. Panel B prioritises irrigation use for maximizing crop production. In this case the reservoirs could be used to maximise the reliability of water supply to downstream irrigation sites. Panel C shows intermediate development balancing irrigation and hydropower use. Panel B shows a design prioritizing energy development.

Presentation techniques inspired by the Parallel axis plots [*Inselberg*, 2009; *Steed et al.*, 2012] are also used to efficiently communicate the relationship (i.e., trade-offs or synergy) and also performance of each Pareto optimal design. Figure 6 shows how the use of scatter plots and parallel plots are related by showing the same 4 designs on the two different plots.

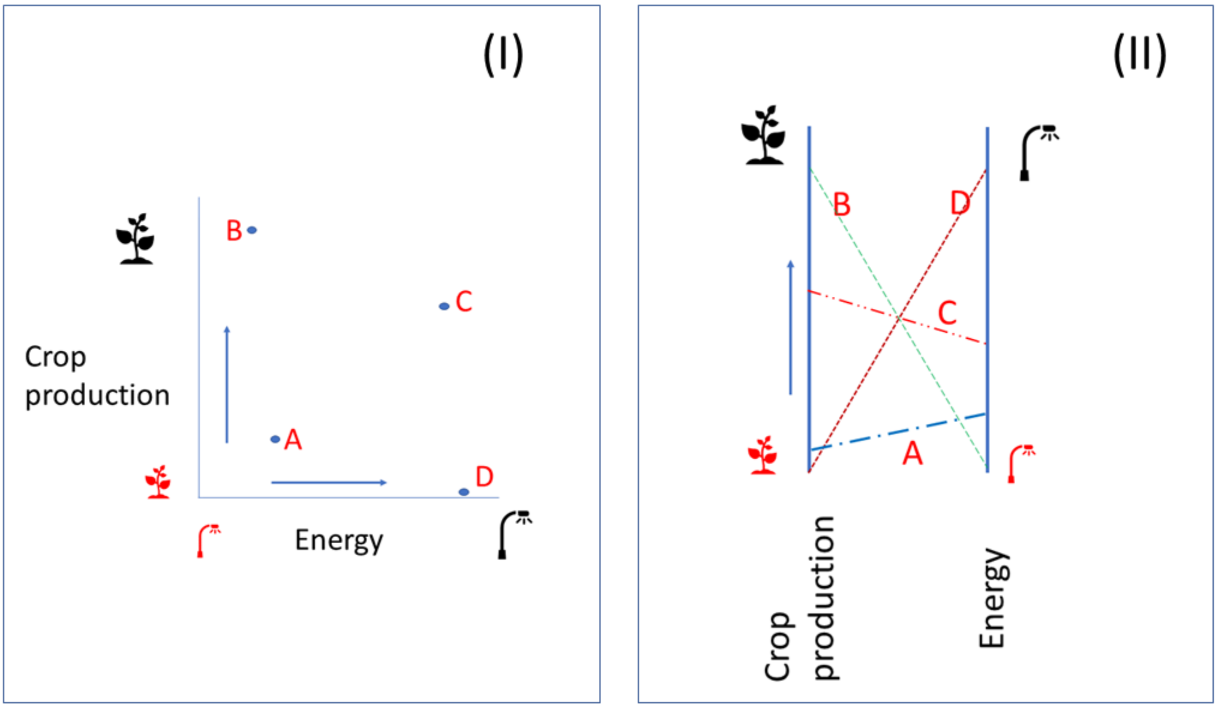


Figure 6 Crop production and energy performance of designs shown in figure in Scatter plot Panel I) and Parallel axis (Panel II) formats.

The number of axes in a parallel axis plots can be extended to show the relationship of several performance objectives simultaneously. The points in Panel A could also replaced by shapes or characterised by different size or colours to show how the design represented by each point differes from the other and also to show the relationhip of particular system designs that are optimal for the performance shown. Similary, the line in the parallel plots can be caractersise by line type (‘-‘,’..’,’-.’, etc), colour, line width, etc.

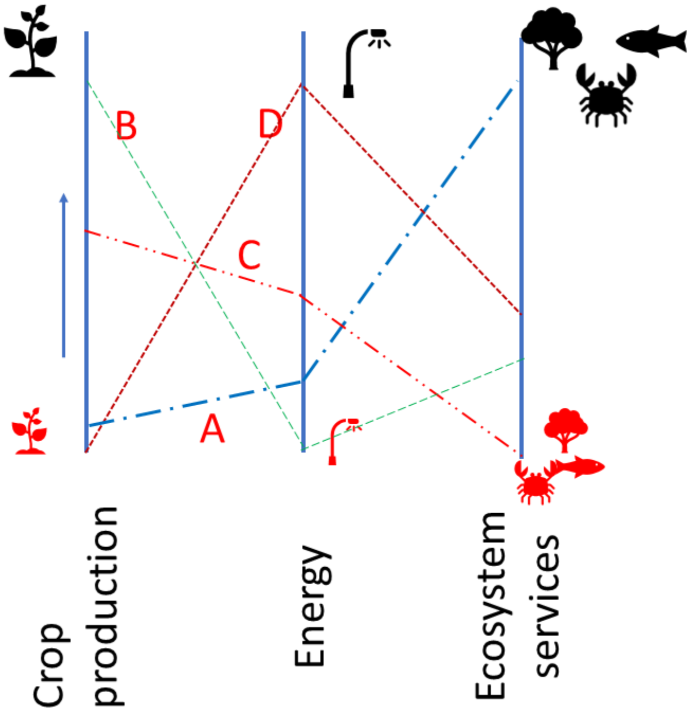


Figure 7 The axis on the right shows the impact of the designs (A, B, C and D first shown on Figure 5) on ecosystem service in addition to the crop production and energy performance.

5 Screening reservoir system

5.1 Introduction

Multi-reservoir system design should consider the potential for coordinated operation of reservoirs. *Mortazavi et al.* [2013] identify the failure to optimize operating rules jointly with infrastructure options as a limitation of existing design methods. Moreover, upstream reservoirs can change the variability of inflow to downstream reservoirs; violating the assumption of variability used for sizing of the downstream reservoirs (if the upstream dams come online later or if their hydrological effect not considered). Given that the change in hydrological variability to the downstream reservoirs will depend both on the size, and operating rule of the upstream reservoir and that coordinated use of the reservoirs can improve their overall performance, the design (i.e., size and operating rule) of each reservoir in a multi-reservoir system on a river reach should consider the design of all other reservoirs in the system.

The approach proposed here screens designs by considering the interdependency of infrastructure and its operation. The asset selection, size (capacity) and reservoir operating rules are simultaneously optimized to balance multiple objectives. The method suggests the required increase in reservoir capacities for gaining an increase in benefits (i.e., energy, reliability, irrigation water supply). The approach fulfills decision-makers' desire to see the critical factors that affect various performance objectives. In transboundary systems where full coordination may not be feasible, selecting designs that lead to acceptable downstream benefits while being operated to maximize upstream benefits is desirable.

This section explores what combinations of new Ethiopian reservoirs, their storage sizes, and operating rules, would perform best considering several performance metrics. What new reservoir system designs, optimized for Ethiopian benefits, would most benefit Sudan irrigation and hydropower interests are also investigated.

The proposed approach is applied to suggest which combinations of new Ethiopian Blue Nile reservoirs, are most efficient and what the relevant trade-offs between system goals are. 'Efficient' is used in a Pareto-optimality sense (the set of solutions which cannot be further improved in any one metric without simultaneously reducing performance in others) rather than a monetized sense where multiple performance objectives would need to be commensurable.

5.2 Problem formulation 1

The problem is formulated as a seven-objective optimization problem with 2 existing reservoirs and 7 proposed reservoir designs. The objectives are evaluated by simulating the system monthly using 50 years of monthly historical flow data. The objectives include minimizing the storage size of new infrastructures, maximizing firm monthly and average annual energy generation from the proposed dams and maximizing energy generation and minimizing water supply deficit for irrigation served from the existing 2 reservoir system. Minimizing the number of reservoirs is also included as an objective to consider possible preferences for a simpler system design. Decision variables include the activation of new reservoirs, their storage capacity, and reservoir release rule parameters. The multi-objective problem is formulated as:

Minimize $F_X = \left(-f_{Sc}, -f_{FEE}, -f_{AAE}, -f_{AAS}, f_{IDS}, -f_{No\,Re\,S}\right)$ (1)

$\forall x \in \Omega$

$X = (Y_i, Cap_i, Op_i, Op_j)$ (2)

$Y_i = \{0,1\} \forall i \in RES$

Subject to $Y_i + Y_k < 2 \forall i,k \in m_t$

Where RES is the set of all reservoirs given in Table 1, $m_t \in RES$ are the sets of mutually exclusive designs given in rows in Table 1.

Where

F_x	=		Target function
f_{SC}	=	$\sum_{1}^{i=No\,Re\,s} Scap_i$	Aggregate storage capacity of reservoirs in the multi-reservoir system
f_{FEE}	=	$quantile_{i\in(1,\ldots,SimYearx12)}\{E_t, 0.95\}$	Reliability of the monthly energy output, measured as the monthly energy generation exceeded 95% of the time. The objective is to maximize the minimum monthly energy generation from all time steps (months) in the simulation.
f_{AAE}	=	$\sum_{i=1}^{i=NoRES}(\sum_{1}^{SimYear}\sum_{1}^{12} P_{t,f}\,t)/SimYear$	The average annual energy generation from the combined Blue Nile dams in Ethiopia
f_{AAS}	=	$\sum_{i=1}^{i=2}(\sum_{1}^{SimYear}\sum_{1}^{12} P_{t,f}\,t)/SimYear$	Average annual energy generation from the Roseires and Sennar dams combined
f_{IDS}	=	$\sum_{1}^{SimYear}\sum_{m=1}^{12}(S_m - D_m)/SimYear$	Average annual Irrigation water supply deficit in the Blue Nile schemes in Sudan
$f_{No\,Re\,s}$	=		Number of reservoirs
m_t			Sets of mutually exclusive designs (columns 1 and 2 in Table 1) over which logical constraints are set.

i, j	Notations refereeing to proposed and existing dams respectively
Y_i	Decision to activate reservoir i
Cap_i	Storage capacity of reservoir i
Op_i, Op_j	Operation rule parameters of proposed and existing reservoirs respectively
$p_t = \rho h_t q_t$	Energy generation at month t, with $h_t q_t$ referring to height and discharge and ρ a constant that considers length of time, gravity and efficiency.

This section aims to answer the question, what combinations of assets perform well for the historical flow record. The storage capacity (*S_{cap}*) varies between maximum storage (*S_{Max}*) and storage corresponding to the minimum operating level of the hydropower generators (*S_{Mol}*). The study does not consider the future progression of time, and discounting is not used. The storage size is used as a rough proxy for capital costs.

Because upstream reservoirs alter flow regimes, downstream reservoirs operating rules may need to change if dams are built upstream. With simultaneous design and operating rule optimization, the selection of reservoirs and their release rules are jointly considered by the search algorithm to increase performance. The proposed approach identifies high performing designs of multi-reservoir systems assuming optimally coordinated operations formulated as a piecewise linear curve for each reservoir (Figure 8). Reservoir designs where the storage sizes are optimized are compared with those for which the storage sizes are assumed fixed to demonstrate the impact of concurrent optimization in achieving efficient investment portfolios.

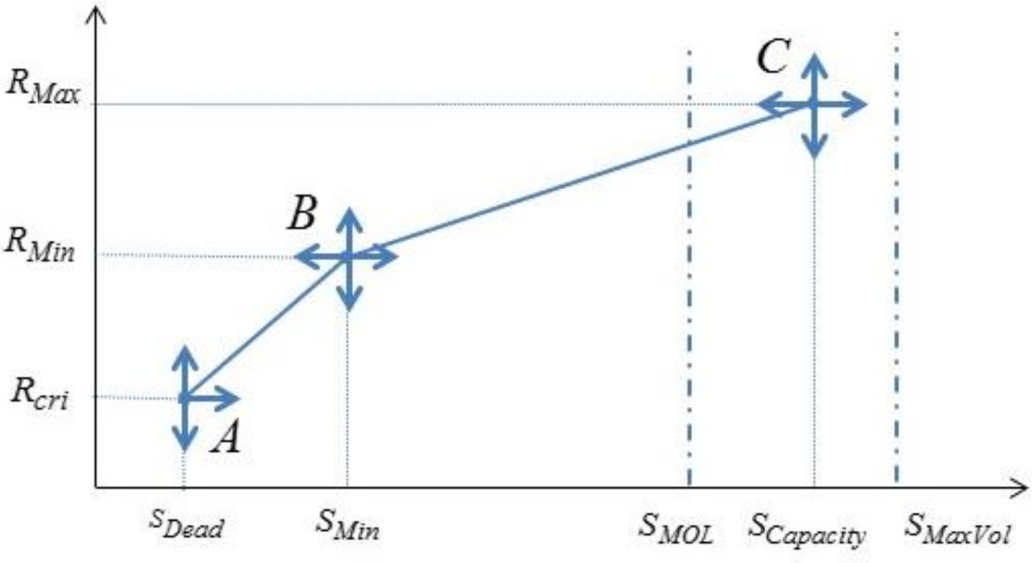


Figure 8 Operating rule curve as represented in the water resource simulation model adapted from (Hurford *et al.*, 2014). $R_{cri,}$, R_{Min}, R_{Max}: release values corresponding to the dead storage required for siltation (S_{Dead}), the storage level beyond which hedging is employed (S_{Min}) and the storage capacity $S_{Capacity}$ respectively. The storage capacity itself varies between maximum storage (S_{Max}) and storage corresponding to the minimum operating level of the hydropower generators (S_{Mol}). Arrows indicate allowed directions of search for the optimized decision rules (the coordinates of points A, B and C).

5.3 **Results**

Analysis results consist of trade-off curves built of Pareto-approximate designs; each design consists of existing reservoirs and one or more new reservoirs, their storage capacities, and operating rules. The 'efficient' designs cannot be further improved in any dimension without deterioration of at least one other objective [*Olenik and Haimes*, 1979; *Mavrotas and Florios*, 2013].

In the following sections, we present non-dominated designs of proposed individual new reservoirs (Section 5.3.1) and of multi-reservoir system designs (5.3.2) considering multiple performance metrics. Reservoir operating rules for the different Pareto-approximate reservoir configurations are discussed in Section 5.3.3. Finally, Section 5.3.4 investigates the downstream impact of designs that are Pareto-approximate in upstream objectives.

5.3.1 Single Dam Strategy

This section presents performance of non-dominated designs of single new dams using different operational strategies, e.g., maximizing average annual energy or firm monthly energy generation.

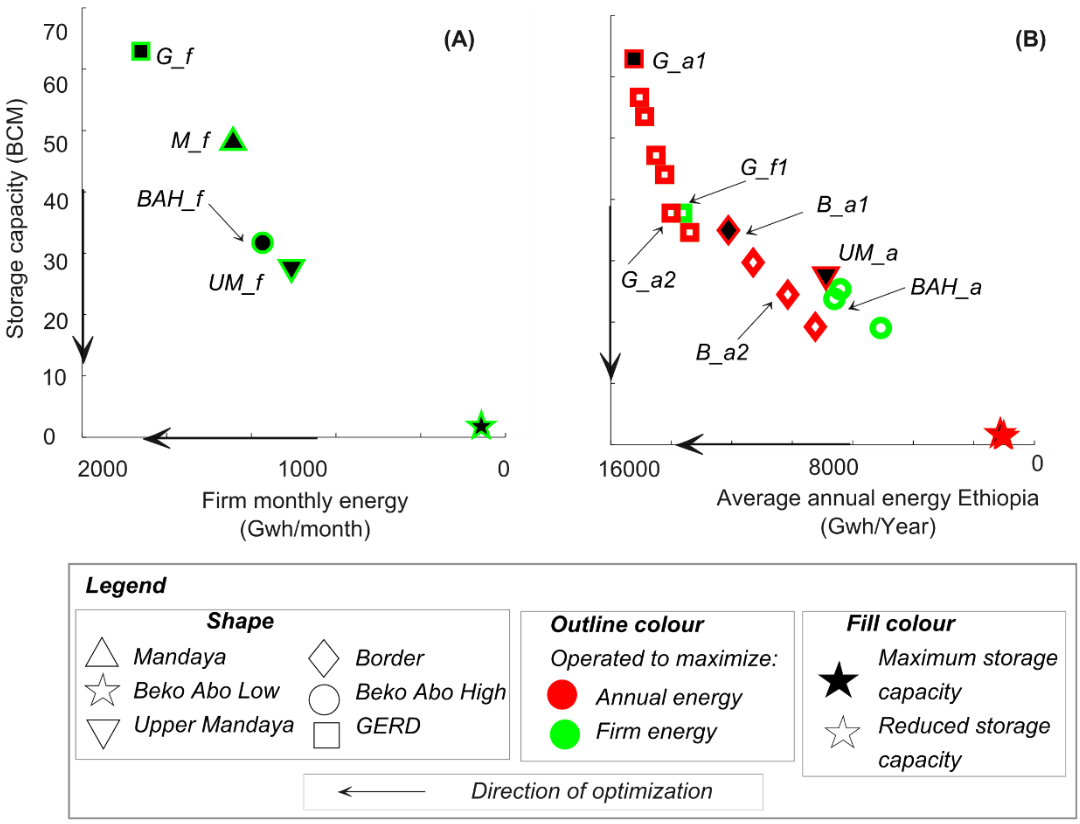


Figure 9 Performance of efficient non-dominated strategies that build only one new reservoir as seen in the storage capacity vs. firm energy (panel A) and storage capacity vs. average annual energy (panel B) two-dimensional trade-off spaces. Panel B also shows the performance of Pareto-optimal designs operated for maximizing firm energy (green) in comparison with Pareto-optimal designs for maximizing annual energy (red). Some designs such as Mandaya ('M_f' and 'BAH_f') , which are Pareto-approximate for maximizing firm energy (Panel A) are not Pareto-approximate for maximizing annual energy. Optimizing storage size of designs (shown with hollow shapes) achieves better performance (e.g., 'B_a2') compared to where the storage size of reservoirs is assumed fixed (shown with dark fills e.g., 'UM_a').

The points with darkened fills in Figure 9 show performance of proposed reservoirs without storage capacity optimization, i.e., $Cap_i = CapMax_i$. For a reservoir with a given storage capacity, operating rule parameters (which are decision variables) can be chosen to maximize the firm energy (panel A) at a cost of the average annual energy (red colored shapes in Figure 9 panel B) and vice-versa.

Figure 9 Panel B shows that when operating rule parameters are chosen to maximize annual energy, the GERD works well over a wide range of capacities. Although a GERD design with intermediate storage capacity performs better when maximizing annual energy (in panel B), it is inferior to Mandaya and Beko Abo High dam designs (in panel A) if the objective is to maximize firm energy. Therefore, if firm energy is preferred and a storage capacity of

48 or 30 BCM are chosen for other reasons as the upper storage limit, Mandaya and Beko Abo High dam respectively would be better choices than the GERD.

5.3.2 Multi-Reservoir Systems

Figure 10 shows designs that include more than one reservoir on the firm energy vs. the total combined storage capacity (Panel A) and energy generation vs. total combined storage capacity trade-off (Panel B).

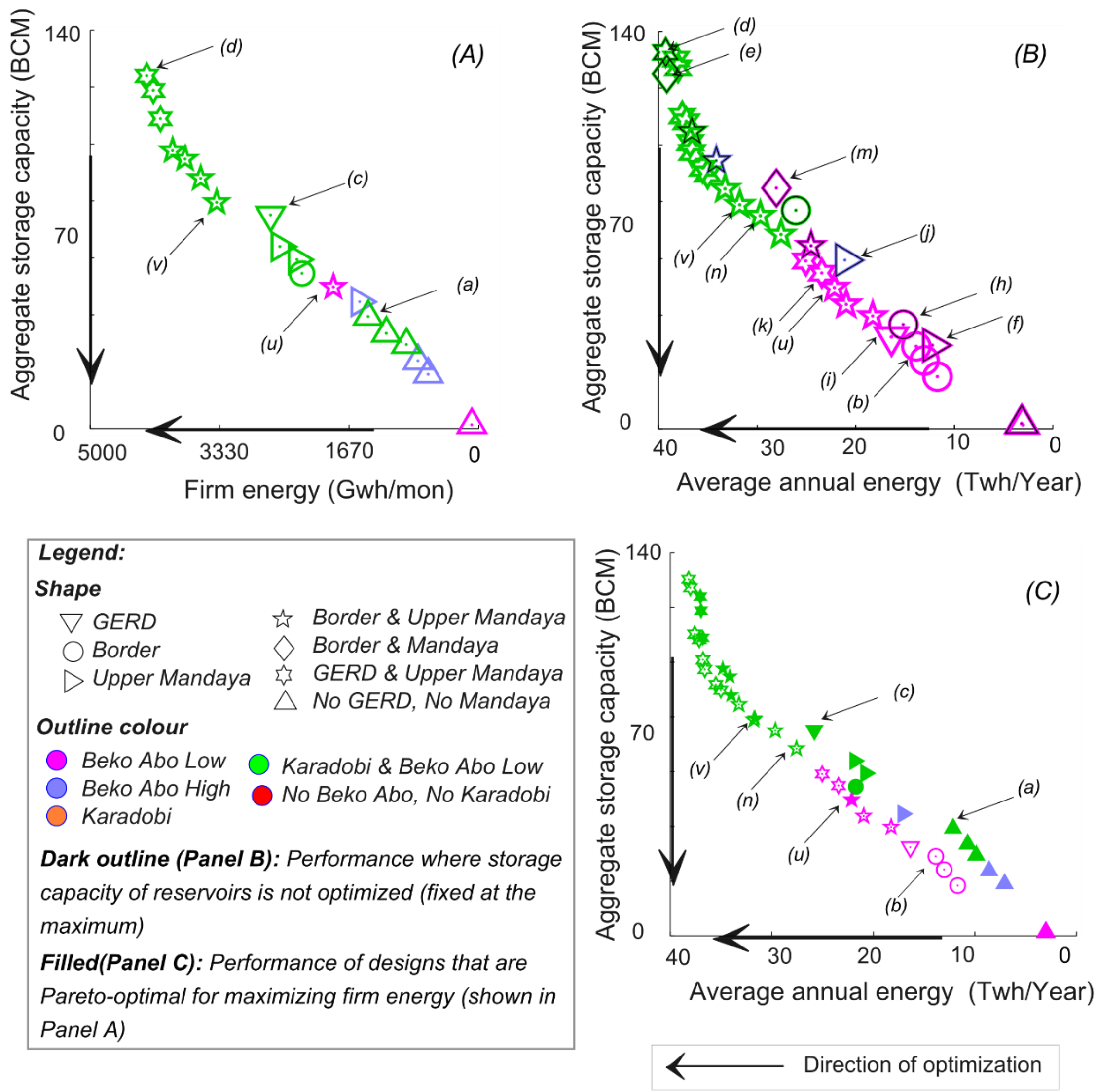


Figure 10 Performance of non-dominated reservoir portfolios that maximize firm energy (panel A) and annual energy (panel B) and minimize aggregate storage (y-axis on both panels). Letter labels assigned to portfolios are the same in each panel. Panel B shows that designs for which storage capacity is optimized achieve better performance in minimizing aggregate storage size in some ranges of the trade-off space (between 8 and 35 TWh/year) compared to when the storage size of reservoirs is not optimized (Dark edged shapes). The plot reveals what system designs are

most efficient as total system storage capacity is decreased. Panel C show the reduction in annual energy (panel B) if firm energy is preferred by overlaying the annual energy performance of designs that are Pareto-approximate for maximizing firm energy (filled shapes) and minimizing aggregate storage size. Overall, this plot shows that for high energy producing systems (left hand side of each panel) that achieve a relatively small overall system storage, the portfolios with the Border and Mandaya (star shape e.g.,'n' and 'k') reservoirs are most efficient.

A 4-reservoir system of GERD, UpperMandaya, Karadobi and Beko Abo Low ('d' in panel B) achieve the highest average annual energy generation capacity of more than 39 TWh/year, an alternative 4-reservoir system with Border dam, Mandaya, Karadobi and Beko Abo Low ('e') being the next best. Labels 'c' and 'n' in Figure 10 show alternative designs recommended (for similar aggregate storage sizes) when maximizing firm energy (label 'c') and for maximizing annual energy (label 'n'). Some portfolios (e.g. designs 'u' and 'v') do well in both annual energy and firm energy whereas other designs (e.g. labelled 'a', 'b, 'c') only do well in one of these.

Stakeholders may prefer reservoir systems with smaller aggregate storage capacity as these would leave lower local environmental footprint and could translate to a lower cost. Fewer reservoirs could also be preferable (e.g. easier to implement, quicker onset of benefits). Pareto approximate portfolios that minimize the number of reservoirs are shown in Figure 11.

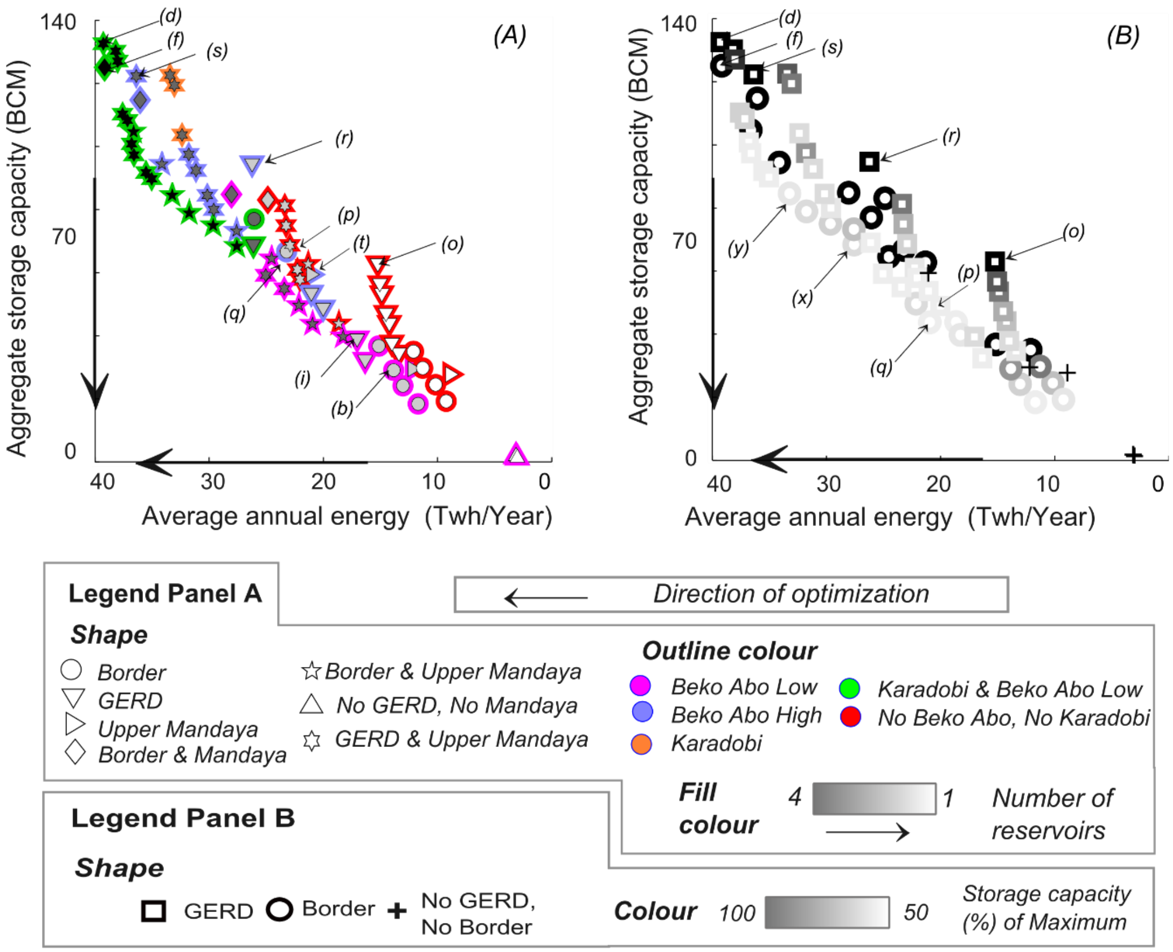


Figure 11 contains the same Pareto-optimal portfolios as Figure 10 Panel B but with an additional objective: minimising the number of new reservoirs. Panel A shows the performance reduction as the number of reservoirs (shown with inside fill color gradient) are minimized. Panel B shows the optimal size of the Border Dam (Circles) and GERD (squares) relative to their maximum storage (shown with color gradient). The plot shows that the Border dam with reduced storage size is Pareto-approximate in most combinations (lighter circles) that don't limit the number of reservoirs.

Figure 11 shows the relationship of the optimal sizes of the alternative Border and GERD dams (circles and squares respectively in panel B) with the overall energy generation capacity of the system. The plots show Border dam with reduced storage size is Pareto-approximate in most combinations (lighter circles) that don't constrain the number of reservoirs. The optimal size of the Border dam depends on which upstream reservoirs are implemented, with reductions to its size improving overall performance (i.e., lighter colored circles approach the ideal solution, e.g. 'q', 'x', 'y'). The GERD designs with current storage size (Figure 11 label 'o') is dominated by two ('p') or three reservoirs ('q') i.e., with less aggregate storage size and higher energy generation. However, the current design of the GERD (with 100% of its stated storage size) is Pareto-approximate for plans that aim to minimize number of reservoirs such as in one ('o'), two ('r'), three ('s') and four ('d') reservoir systems.

5.3.3 Operating Rules

In this section we show how optimized reservoir operating rules change depending on system configurations using GERD as an example. Figure 12 panel A displays storage and release relationships over the full simulation period for GERD reservoir.

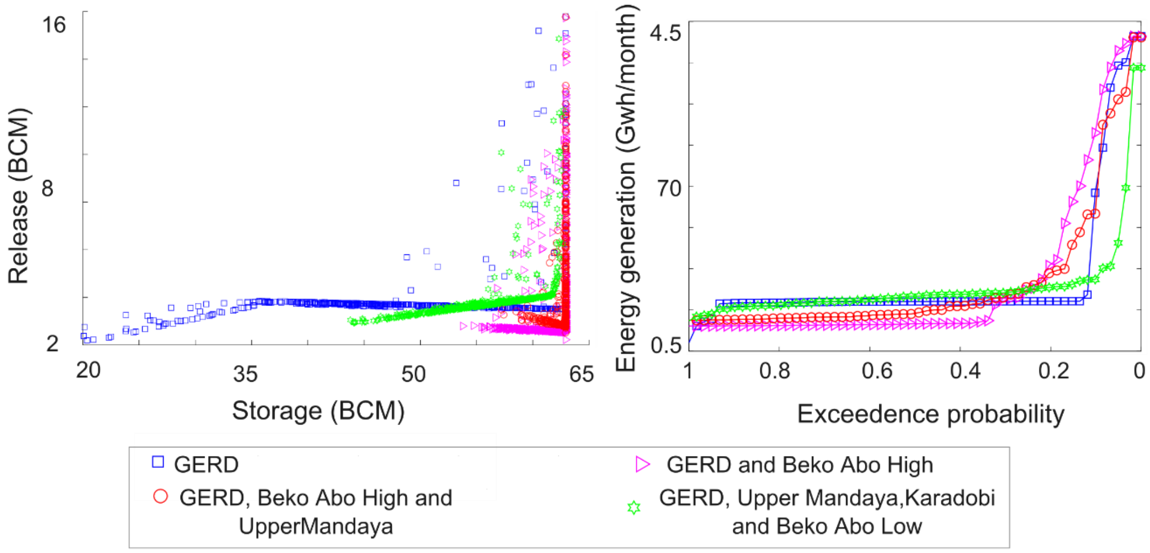


Figure 12 storage vs. release (Scatter plot panel A) and monthly energy generation exceedance probability (Panel B) from GERD. Exceedance probability (on the X axis of the right panel) shows how often the energy generation (on the Y axis of the right panel) the monthly energy generation is exceeded in the simulation period. The plots compare optimal operating rules and monthly energy outputs for annual energy maximizing operations of a standalone GERD (blue squares) and in GERD operated in coordination with upstream dams ('r','s', and 'd' in Figure 11)

Upstream regulation when reservoirs are added (e.g., Beko Abo High, Upper Mandaya) allows the GERD to function with less variation and a high storage level (green star, orang circle and magenta triangle) compared to the standalone GERD (blue square in Figure 12 Panel A).

Figure 12 panel B shows monthly energy generation from GERD for annual energy maximizing operations as a standalone (blue squares) and in coordinated operation with upstream dams ('r', 's', and 'd' in Figure 11). Both the minimum energy that may be required to be guaranteed as firm energy (to be generated close to 95-100% of the time) and the highest monthly energy (available only 5 to 20% of the time) are improved with addition of upstream reservoirs.

5.3.4 Downstream impact of proposed reservoirs

In this section, the impact of upstream Pareto-approximate designs identified in Figure 9 on the Sudanese system are investigated. Figure 13 shows the highest achievable performance of the two existing Sudanese reservoirs with designs (i.e., reservoirs, storage capacity and operating rules) that are Pareto-approximate for Ethiopian objectives of maximizing firm and annual energy at least storage capacity.

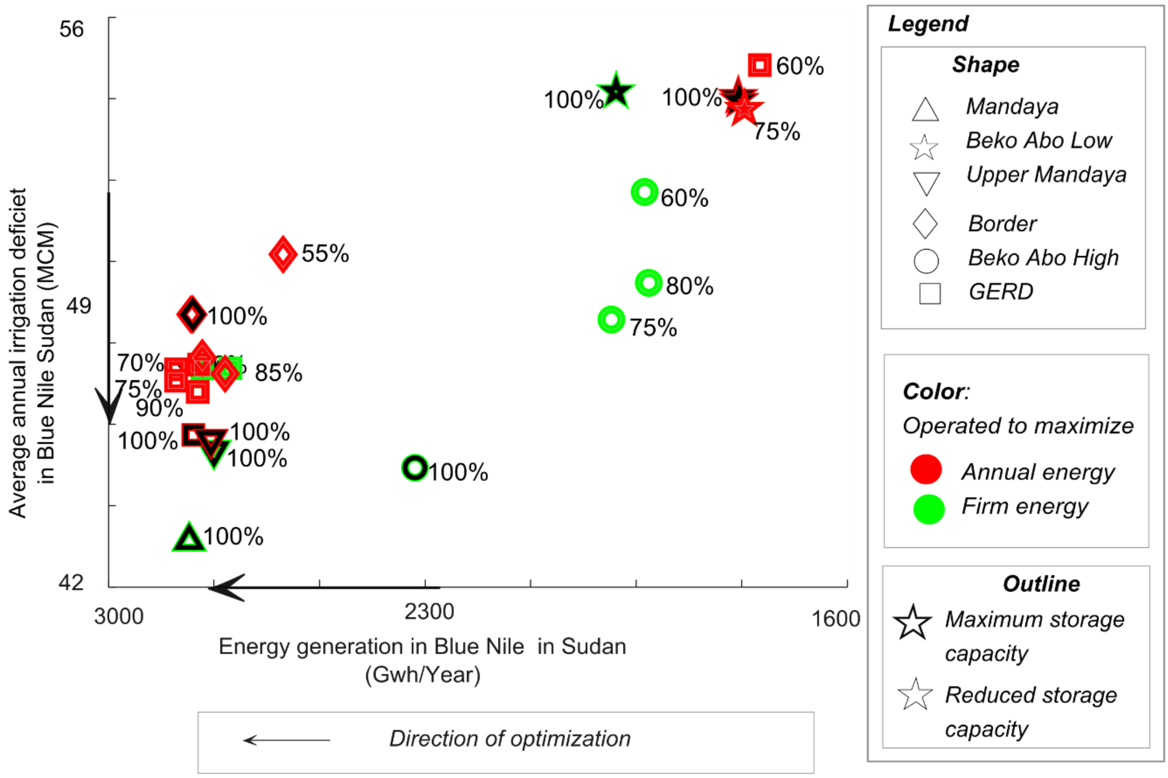


Figure 13 key Sudanese system metrics for upstream Pareto-optimal designs limited to a single upstream dam (same designs considered in Figure 9). Shapes show which single dam achieves the performance; optimized storage capacities are given with labels as percentage of maximum storage capacity. Green coloured shapes show downstream system performance for upstream reservoirs operated to maximize firm energy; red coloured ones show designs where upstream annual energy was maximized. The plot shows Mandaya and GERD (green upright triangle and square respectively near origin) with large (%) of their maximum storage capacity operated for firm energy and Upper Mandaya operated to maximize annual energy (red triangle pointing downwards) are the most favorable designs when considering Sudanese irrigation and energy generation objectives. Note: Sudanese objectives displayed on the plot axes above were not optimized for in the model formulation described in this chapter.

Figure 13 shows the average irrigation water supply deficit for a simulation period of 50 years. Downstream system performance (in Sudan) is affected by what single reservoir is built upstream (shown with shapes), its size (labels) and its operating strategy (color). For each portfolio plotted in Figure 13, the operating rules of the two Sudanese reservoirs, Roseires and Sennar, are optimized to adjust to the new hydrologic conditions each upstream system design implies. Although the downstream system performance is improved under most designs, a large storage (shown with % of maximums storage capacity), Mandaya and GERD operated for firm energy (green upright triangle and square respectively near origin) and Upper Mandaya operated to maximize annual energy (red triangle pointing downwards near origin of Figure 13) are most favorable to Sudanese system performance.

5.4 **Discussion of the application 1**

5.4.1 Screening new reservoirs within the Blue Nile multi-reservoir system

A multi-criteria approach to screening proposed new reservoirs within multi-reservoir systems is proposed and applied to the Blue Nile multi-reservoir portfolio design problem. The method reveals the trade-offs in management objectives that the most promising (Pareto-approximate) system designs (incorporating new and existing dams, their sizes and their operating rules) imply. High performing designs which achieve the most efficient trade-offs between conflicting objectives are revealed visually. The mapping of assets in performance space, e.g., figures 3, 4 and 5, summarize which asset combinations achieve what performance providing valuable insights to system planners.

The results show the combinations of assets that work best together vary throughout the performance space. Figure 9 and Figure 10 were used to assess which subset of designs are Pareto-approximate revealing how certain assets do well under several sets of objectives (e.g. designs ‘u’ and ’v’ in Figure 10,) whilst others not as well (e.g. design ‘a’, ‘b, ‘c in Figure 10).

Reliability measures for hydropower systems can be difficult to commensurate with cost and benefit measures. Designs that have the highest average annual and firm monthly energy generating capacity are in general desirable. However, those efficient in maximizing annual energy do not necessarily perform best for maximizing firm energy output. Incorporating energy reliability, a non-monetary metric of interest to system planners, shows how multi-objective analysis helps reveal practical designs with complex combinations monetary and non-monetary benefits.

Investment costs and costs associated with the downstream impact of projects often are accrued by different stakeholders. Due to ongoing disputes over Nile water use rights, selecting designs on the aggregated net benefits, i.e., total benefits estimated from energy generation, capital costs and costs incurred by downstream users (reduction in benefits due to upstream intervention) may be difficult. In reservoir systems required to meet a number of conflicting objectives held by upstream and downstream system owners, explicit consideration of all major stakeholder objectives help identify potential compromise designs and the trade-offs in benefits these designs imply. Visual assessment of trade-offs can facilitate stakeholder deliberations post optimization, meaning weights are not required as in ‘apriori’ multi-criteria analysis. Many-objective optimization as shown here allows planners to visually assess important trade-offs where stakeholder preferences are evolving. Learning and exploring about benefits and negative impacts of new investments help different parties assess new designs, compromise on their benefit distribution and hopefully agree upon an acceptable way forward. Considering multiple goals and their trade-offs explicitly and simultaneously in system planning can provide valuable assistance in the decision making process [*Kasprzyk et al.*, 2009].

Figure 10 shows jointly optimizing reservoir capacities and operating rules achieves better performing designs than only optimizing the coordination of rules. Figure 11 and Figure 12 demonstrated that optimal storage size and optimal operating rules for a reservoir depend on the portfolio of reservoirs included in any particular design. Plots like Figure 11 and Figure 13 that show the performance trade-offs of new dams as their storage capacity is reduced could be of interest to those arguing for larger or smaller reservoirs. Results show assessing new reservoirs considering their coordination with existing and other new assets enables effective screening of new reservoir designs.

5.4.2 Implications for Blue Nile infrastructure development

Given the current data and modelling assumptions, results argue that multiple reservoirs achieve better results at lower aggregate storage capacity. The current GERD design is not Pareto-approximate for maximizing energy generation for the least storage capacity possible (Figure 10 panel B) but it is Pareto-approximate with regard to maximizing energy generation while minimizing number of reservoirs (Figure 11 panel A). GERD only requires one dam to achieve the benefits rather than two or three as the nearby more efficient portfolios do. If several dams could be built at once, it would be advantageous to build a combination of reservoirs rather than a single reservoir with equivalent storage size, if not, GERD is an efficient alternative for the benefits considered in this study.

Storage-size-optimized designs (hollow shapes in Figure 10) perform better in energy generation compared to those at maximum capacity for which only operating rules are optimized (shapes with dark outline in Figure 10) in some ranges of the trade-off space. Results show if constructing more than one dam was possible at the same time and Border dam were to be selected, less than its maximal storage would have been efficient up to 35 TWh/Yr (e.g., ‘k’ on panel B in Figure 10). Outside of this range, the maximum storage size designs of each reservoir are most efficient. Figure 11 panel B presents system designs for which storage size of the downstream most reservoirs GERD and Border dam are optimized (shown with color and shape). The maximum storage size of the GERD is efficient in all ranges where the number of reservoirs is purposely limited. Although reducing the storage size of GERD leads to Pareto-approximate designs (e.g., labels ‘b’, ’q’ in Figure 11 panel B) at lower ranges of energy generation capacity. This would limit future expansion potential (e.g., ‘d’,’f’,’s’ in Figure 11) and performance in designs aiming to minimize the number of reservoirs as it would involve, for example, constructing the GERD and the Beko Abo High (‘p’) with reduced storage size.

Figure 12 panels B shows that the reliability of energy output from the GERD will be improved with addition of upstream reservoirs. Figure 13 showed downstream irrigation deficits and hydropower production in Sudan given different optimized standalone Ethiopian reservoirs. Sudan’s benefits depend on upstream reservoir storage capacities and operations (i.e., whether they maximize firm or total annual energy). Figure 13 showed the Mandaya design would perform better than all alternative single dam designs from the Sudanese perspective including Border dam if it was to be operated for firm energy. The current GERD design performs best if it is to be operated to maximize annual energy. The results also show reducing the storage size of the GERD reduces the irrigation water supply performance. Coordinated multi-purpose operation of Ethiopian reservoirs could potentially further improve performance of the downstream system. However, the potential collaborative use of the Ethiopian and Sudanese and other downstream reservoirs is out of scope for this study which limits itself to predicting the best performance achievable in Sudan when the Ethiopian system is operated to either maximize annual or firm energy.

Study limitations are discussed below and in Chapter12 and they strongly impact the results this study can offer which aim mostly to describe a proposed approach to multi-reservoir system design. At it currently stands, the analysis results can be summarized as follows. A four-reservoir system, either with GERD or Border dam, can generate more than 39 TWh/year. If a total energy generation capacity of less than 35 TWh/yr is acceptable, Border dam is in the efficient asset mix in lieu of GERD. Although once it has been filled a two-reservoir system (e.g., GERD and Beko Abo High) achieves higher energy production with a lesser aggregate storage capacity than a standalone GERD, the current GERD-only design is the best possible one-reservoir system design given the objectives and assumptions considered in this study. Furthermore, if operated to maximize annual energy, the current GERD design (with 95 to 100% of the proposed storage capacity) enables the highest levels of downstream Sudanese benefits assuming Sudan would change its reservoir operations to adapt to the new upstream development.

5.5 **Limitations**

This chapter focused on a trade-off analysis of alternative designs and leaves the consideration of uncertainty of filling periods and the long-term impacts of climate change or other supply/demand changes for future work. The study is deterministic, the assets are evaluated over one hydrological time-series (the historical one) rather than multiple plausible future futures as is done by other authors using similar optimization methods [*Arena et al.*, 2010; *Anghileri et al.*, 2013; *Hurford et al.*, 2014]. Also, as discussed in section 5.2, this chapter does not consider possible inter-country collaboration; all plots maximize benefits from the country where the dams are located (in this case Ethiopia). This study only modeled Blue Nile impacts.

The study assesses the storage size requirements assuming fixed installed power capacities. An aggregate net benefit maximizing objective considering variation in cost and installed power capacities with storage size, peaking power demand and the cost of delay in onset of benefits could provide more decision relevant information. The study uses monthly time steps. The firm energy metric used in this study represents the seasonal and inter annual variation of monthly energy generated. Incorporating other short-term performance metrics such as energy supply reliability considering the daily and hourly demand distribution which are of interest to system planners could reveal more insights on the design problem.

Only benefits along the Blue Nile and for few major irrigation sites in Sudan are considered. The impact/benefit of regulation on other important dams on the Main Nile (Merowe and Aswan) and impacts of Ethiopian dams on Egypt are not assessed in this proof of concept study. The study also ignores possible changes of cropping patterns in Sudan, i.e., the change in magnitude and/or timing of seasonal irrigation demand with the availability of more regulated flow from Ethiopian dams. Finally in this study reservoirs use one operating policy, the standard linear operating policy. The operating rules are assumed to be fixed throughout the time horizon and do not vary when basin conditions change as they might with real operators. More complex rules that change with environmental conditions could likely attain better performance and hence might change the systems designs recommended within this study.

6 Scheduling reservoir investments

6.1 Introduction

Chapter 5 demonstrated performance increase when storage size and operating rule parameters are optimized simultaneously. For large structures, such as the proposed Blue Nile multi-reservoirs, system expansion may need to be staggered rather than concurrent to minimize continuous negative impact on downstream storage structures from reduced downstream flow resulting from filling the new reservoirs upstream. Given the impact of the new reservoirs on each other (i.e., filling of newer upstream reservoirs could affect performance of downstream reservoirs if those are built earlier), selecting components of the multi-reservoir system and sequencing their construction should consider the filling period performance of alternative investment schedules in addition to their overall long-term performance.

In water resources systems with interdependence such as multi-reservoir systems on a single stretch of a river ('dams in series'), the performance reduction when new reservoirs are filling can be substantial. The filling of the new Blue Nile dams could be subject to minimum downstream release requirements to minimise downstream impact in Sudan and Egypt which are downstream. Slower filling to meet such requirements could delay benefits from the new dams and potentially affect their financial viability [*Block and Strzepek*, 2010].

Figure 14shows a typical problem when a new multi-reservoir system is to be implemented upstream of an existing water system. The filling of new reservoirs affects the performance of both the existing system and planned one.

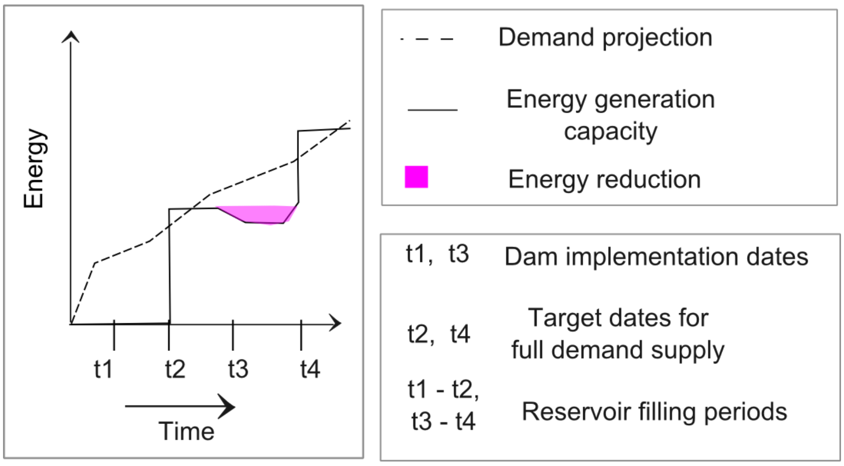


Figure 14 sketch showing a demand projection, multi-reservoir system performance and impact levels at different stages of expansion. Meeting demand during periods 't2' and 't4' requires interventions at times 't1' and 't3' respectively. Addition of a new dam upstream at 't3' could reduce energy generation from the existing system (during period from 't3' to 't4').

This chapter investigates how considering downstream release requirements and energy generation performance in filling periods could improve overall performance and system design recommendations and their scheduling over time. The chapter also examines the extent to which allowing for the evolution of operating rules in an optimised multi-reservoir system design impacts the trade-offs of benefits obtained from reservoir systems and impacts their optimised schedules. We compare the results of the multi-reservoir scheduled designs under different degrees of evolving operating rules (different levels of responsiveness of operating changes to system expansion).

The current chapter considers the trade-offs in energy generation and environmental benefits (maximizing releases to minimise downstream impacts during reservoir filling periods) with economic (discounted NPV) performance goals. The NPV metric measures the difference between time discounted future benefits (from energy production) and discounted capital costs. System designs are evaluated by the heuristic search algorithm using 30 realizations of a hydrologic series statistically resembling historically observed flows. The case-study shows the importance (impact on NPV and on system design and scheduling) of considering changing operating rules during the filling periods of new large dams in multi-reservoir system expansion planning.

6.2 **Problem formulation 2**

Here we describe the multi-reservoir system scheduling problem and the proposed approach.

6.2.1 Many objective planning problem formulation

In order to search for high value designs and their sequencing for this problem, we propose to use many objective optimization. Visual analysis of trade-offs helps with the discovery of alternative designs which present acceptable performance trade-offs [*Kollat and Reed*, 2007; *Kasprzyk et al.*, 2009; *Woodruff et al.*, 2013]. The general problem formulation is the minimization/maximization of multiple performance objectives (eq. 1) which guides the search algorithm to look through the decision space (eq. 2) subject to any constraints such as water balance, mutual exclusivity of dam options etc.:

$$\text{Minimise } Fx = (f_i) \tag{1}$$

$$\forall x \in \Omega \tag{2}$$

Fx	Target function
f_i	Performance metrics such as Net present value of investments, average energy, etc.

The decision variables include choice of reservoir portfolios, the timing of their implementation and their management (e.g., coordinates of storage-based release rules). To investigate the impact of simplifying assumption on quality of the infrastructure investment decision, we compare the optimised performance of the multi-reservoir scheduled designs under different levels of operating rule responsiveness to system expansion. Operating rules responsiveness levels include (A) rules optimised for individual reservoirs then fixed in a second stage many objective optimization that sequences the pre-defined investments; (B) rules are optimised jointly with dam selections but the rules are changed only once, and (C) rules of each reservoir are optimised for each unique system expansion stage. These levels of responsiveness in reservoir operation optimization, Schemes A, B and C, are displayed graphically in Figure 15using panel letters with the same letter.

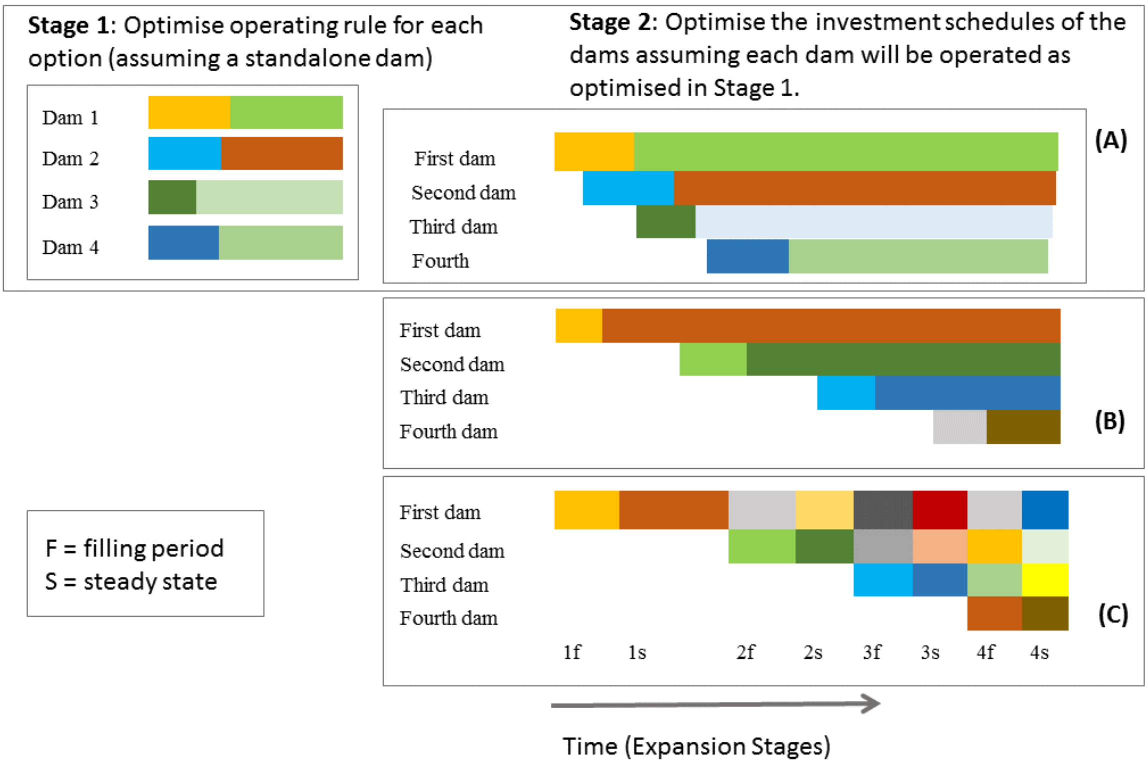


Figure 15 Three schemes with varying levels of responsiveness for the optimization of operating rules in multi-reservoir system capacity expansion. Colour patches represent time periods when an optimised operating rule is applied for an individual dam. Stage 1 in Panel A shows the operating rules of each of the dam options is optimised (ignoring possible impact of other dam in the future). Stage 2 uses these operating rules while searching for the best combination and timing of new reservoirs. Panels B and C designate designs where the operating rule designs and infrastructure choices are optimised simultaneously. Panel B assumes the operating rules of the dams change only once at the end of filling while Panel C considers changing operating rules for each of the reservoirs as the reservoir system expands.

6.2.2 Operating rules

Like *Giuliani et al.* [2014] we apply direct policy search, where the operating policy is first parameterised within a given family of functions and then the parameters optimised with respect to the operating objectives. We parameterise the control policies using gaussian radial basis function (RBF) [*Giuliani et al.*, 2014]. Radial basis function have been used to map the reservoir storage and time index into release decisions [*Giuliani et al.*, 2014; *Zatarain Salazar et al.*, 2017] and take the form of

$$\varphi_i(z_t) = \sum_{i=1}^{n} w_i \exp(-\sum_{j=1}^{m} \frac{(z_{t,j} - c_{i,j})^2}{b^2{}_{i,j}}) \qquad (3)$$

Following [*Maier et al.*, 2014b; *Zatarain Salazar et al.*, 2017], we use n = 4 RBFs where m is the number of input variables (two) - the storage in the reservoir and time of year are used as input to the release rule. The Inputs in Z_t are uniformed on [0,1] while the centres and radii take value in $c_{i,j} \in [-1,1]$ $b_{i,j} \in [0,1]$ $w_{i,j} \in [0,1]$ $\sum_{i=1}^{n} w_i = 1$.

Each of the multi reservoir expansion stage represented with distinct colour in Figure 15 require a separate operating rule. Each reservoir is allocated a unique release rule based on its own storage level and time of the year. We set the number of RBFs equal to one more than the sum of the number of inputs (2) and outputs (1). Each RBF has associated with it 4 weights and 4x2=8 centres and 4x2=8 radii that need to be optimized. A total of 21 variables need to be optimized considering the further one variable which will be multiplied with the result of RBF storage and time function (which is normalized on [0,1]) to give the actual release magnitude. The optimal value of this variable can take a value from 0 to maximum release capacity of the dam. Hence a Radial basis function based operating rule for a four-reservoir system that is expanding could require up to (21x20=420) decision variables (i.e., for the most detailed operating rule representation in Figure 15 Panel C). While, increased degrees of freedom for the operating rule of reservoirs could improve performance, it could lead to higher stochasticity of results in problems where decision variables are interdependent; resulting in high computational cost. The increase in computational requirements with increased responsiveness of the operating rule is compared.

The storage targets of a large reservoir are typically varied during its filling period of several years length. The Radial basis function based operating rule considers varying storage targets at various points in the filling period time-span of each reservoir (which could be more than a year) in contrast to the after-filling period where an optimised operating rule specifies storage targets for a typical year.

For the Blue Nile, the amount of reliable downstream flow are of concern as are the financial feasibility and energy generation capacity of new developments. The performance objectives considered in this study include maximizing the average and lower quartile net present value of future benefits ($fAveNPV, fNPV_{25}$), maximizing final (once reservoirs have filled) average annual, firm annual and firm monthly energy generation $fAveAE, fMinFAE, fMinFME$ respectively and the reliable 3-year cumulative downstream releases($fMin3R$). The simulation period length is set at 80 years to accommodate the assumptions that each dam will have a project life of 50 years.

$$\text{Maximise} \quad Fx = (fAveNPV,\ fNPV_{25},\ fAveAE,\ fMinFAE,\ fMinFME,\ fMin3R) \qquad (4)$$

$$\forall x \in \Omega$$

$$x = (Y_i, T_i, Op_{i,s}, Fop_{i,s}, FL_s)$$

$$Y_i = \{0,1\} \qquad \forall i \in M$$

Subject to $Y_i + Y_j < 2 \qquad \forall i, j \in m_k$

The decision variables include the activation of new reservoirs (Table 1), their implementation dates, their reservoir release rule parameters at various multi-reservoir system expansion stages (i.e., first, second, third, etc… filling and steady state operating periods).

Where 'm' is the set of all possible reservoir options while $m_k \in M$ are the sets of mutually exclusive designs given as rows in the Table 1. The performance of water resources infrastructure is dependent on several uncertain factors including hydrologic variability, climate change, future water demands and evolving institutions [*Conway et al.*, 1996; *Block and Strzepek*, 2010; *Swain*, 2011]; in this application, only the first source of uncertainty is considered.

Fx	Target function	
$fAveNPV =$	$quantile_{i\in(1,...,F)}\{Npv, 0.5\}$	Average net present value of benefits,i.e., present worth of benefits from energy generation minus present worth of capital cost of reservoirs
$fNPV_{25} =$	$quantile_{i\in(1,...,F)}\{Npv, 0.25\}$	75% exceeded net present value of benefits,
$fAveAE =$	$quantile_{i\in(1,...,F),\, j\in(tL,...,Es)}, \{... Eannl_{i,j}, 0.5$	Average energy generation in regular operating periods after all dams are implemented and filled (i.e., 'tL' to the end of simulation 'Es')
$fMinFAE =$	$quantile_{i\in(tL,...,Es),\, j\in(1,....,F)}\{... Eannl_{i,j}, 0.95\}$	95% exceeded (near minimum) annual energy generation of the reservoir system in the last steady state (i.e. after all dams are implemented and the last filling periods.
$fMinFME =$	$quantile_{i\in(1,...,F),\, j\in(tL,..,Es)}\{... Em_{i,j}, 0.99\}$	95% exceeded (near minimum) monthly energy generation of the reservoir system in the last steady state (i.e. after all dams are implemented and the last filling periods.
$fMinR3yr =$	$quantile_{i\in(1,...,Ts),\, j\in(1,...,F)}\{ R3_{i,j}, 0.95\}$	99% exceeded (near minimum) cumulative releases over a 3-year consecutive period. The maximization of cumulative release in consecutive years is considered as a proxy for Egyptian interests in reducing the impact of filling of Ethiopian reservoirs on the High Aswan reservoir.

$E_t =$	$\rho h_t q_t$	Energy generation at month t; a function of head and discharge and a constant that depends on gravity and length of month
$Eannl_y =$	$sum(E_t, t \in y)$	The sum of monthly energy generations in the year 'y'
$R3_t$	$\sum_{t-36}^{t} R_t$	Cumulative release of past 36 months at time t
$NPV_{Benefits} =$	$\dfrac{\sum_{y=1}^{80} Eval \times Eannl_y}{(1+d)^y}$	Time discounted economic returns from energy generation
$NPV_{Costs} =$	$\dfrac{\sum_{1}^{NoRES} \sum_{1}^{LenCons} Cost_i}{LenCons_i \times (1+d)^{(IMP_i + T_{i,c})}}$	Time discounted cost of infrastructure
$NPV =$	$NPV_{Benefits} - NPV_{Costs}$	Time discounted net present value
$LenCons_i$		Length of construction of dam i
IMP_i		Implementation date of dam i
$T_{i,c}$		Construction year (between 1 and max length of construction period of dam i (see Table 1)
d		Discount rate (assumed at 10%)
$Cost_i$		Capital cost of reservoir i
i		Dam notation
s		Expansion stage
Y_i		Decision to activate Storage option i
T_i		Implementation date for reservoir number i
$Op_{i,s}$		Steady state operation rule coordinates of reservoir i in period s
$Fo_{i,s}$		Filling period operation rule of reservoir i in period s
FL_s		Length of filling period at stage s
$Eval$		Value of energy per kWh

6.3 **Results**

Next, and for our simplified system representation, we present the proposed Blue Nile reservoirs' potential and the trade-offs among different performance objectives under operating rules increasingly adapted to the new system as it expands. Section 6.3.1 examines the trade-offs between the average net present value (NPV) and the reliable downstream flow from the Blue Nile at the Ethiopia-Sudan border for a one reservoir design. The NPV metric measures the difference between time discounted future benefits (from energy sales) and immediate and future (for reservoirs planned to be build in the future) capital costs. Section 6.3.2 compares estimated performance of the multi-reservoir system as operating rules are increasingly refined to address each unique stage of system expansion. Section 6.3.3 examines the Pareto-optimal dam investment schedules across multiple metrics of performance for operating rule Scheme C (Figure 1).

6.3.1 Single reservoir design

This section considers the performance trade-offs implied by a range of operating rules for the simplified case where only one reservoir is to be built. To quickly meet their design potential and generate benefits, new reservoirs are ideally filled quickly and operated at full energy generation capacity. However, rapid filling of reservoirs can adversely affect existing downstream water uses. This trade-off between loss of new dam performance and downstream impact will depend on the location, size and filling strategy of the new dam. Figure 16 shows the trade-off between the reliable (99% exceeded) 3-year cumulative releases and the average NPV for a single new reservoir operated with one optimised rule during filling and another after filling (i.e., as per stage 1 of Figure 15 Panel A). Each marker represents an optimal filling and steady state operating strategy in addition to a dam selection choice.

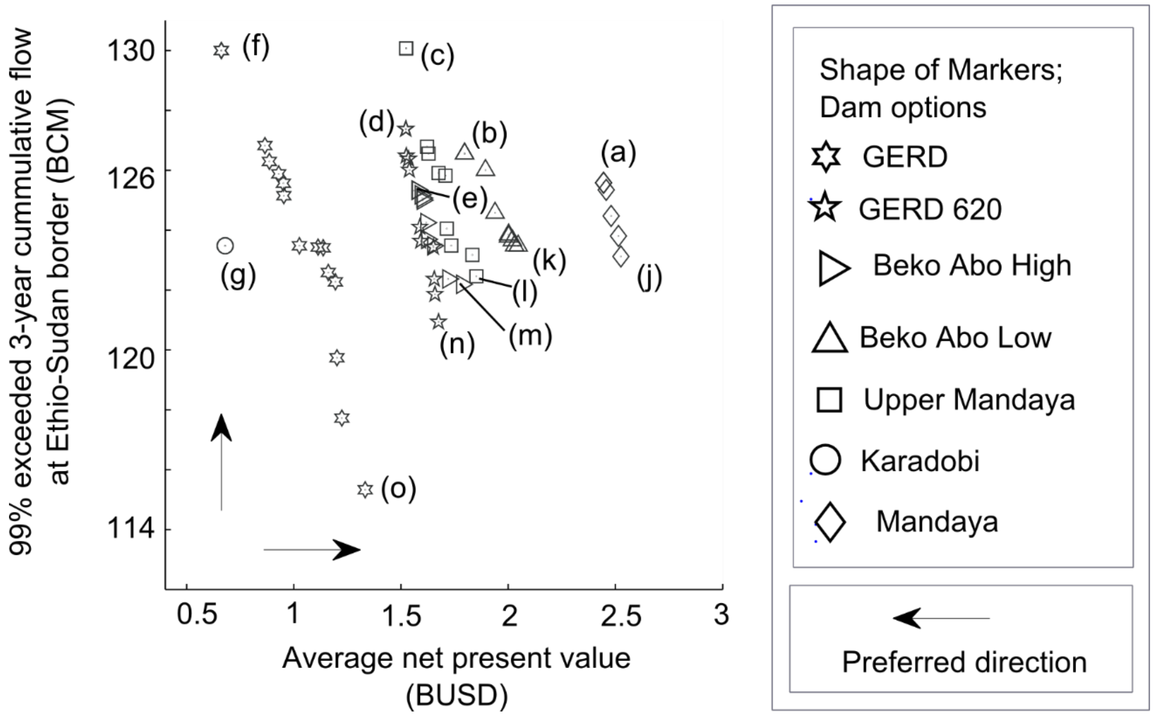


Figure 16 Efficient trade-offs between the average net present value of benefits and 99% exceeded 3-year downstream flow at the Ethio-Sudan border for standalone reservoir options. The Pareto-fronts when each of the reservoirs is assessed separately is shown with similar markers e.g., designs between ‘a’ and ‘j’, and between ‘b’ and ‘k’.

6.3.2 Comparison of performance as operating rules adapt to new system designs

This section considers the case of a two -reservoir system and assesses the gains in performance when using an operating rule set which is increasingly responsive to the system’s expansion. We compare the two responsive schemes (B and C of Figure 15) with ‘static’ rules that are not changed when the reservoir system expands, i.e., the operating rules are optimised for each dam regardless of other dams (i.e., ’a’, ..., ‘o’ ofFigure 16).

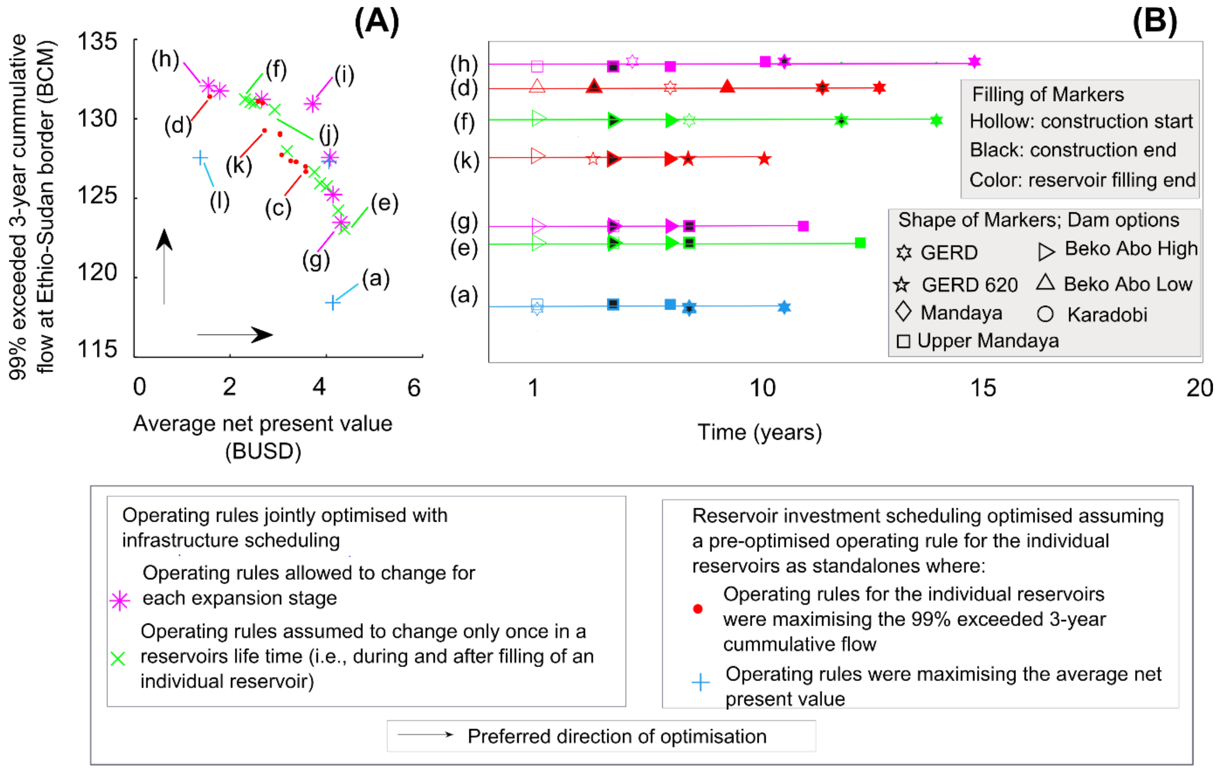


Figure 17 Pareto optimal reservoir system designs with optimised operating rules under differing levels of responsiveness to system expansion. Investment schedules that seek to maximise financial benefit while assuming unresponsive operating rules disproportionately impact downstream system (e.g., 'a') compared to the responsive operating rule formulations (e.g. 'e', 'g'). Less responsive operating rules lead to lower performance (e.g., 'j', 'k' and 'l' presents lower net present value in billions of US dollars (BUSD) compared to 'i' for similar release requirements).

Figure 17 shows the difference in the average net present worth of investments estimated under the different rules (i.e., 'a', 'e', and 'g') is less than 5% when there is no downstream release requirement (low performance on the y-axis). However, differences in net present value increase with higher requirements in downstream flow performance. For the two-reservoir system design, the average net present value for similar reliable releases requirements varies by more than $1 billion US dollars (BUSD) when the release requirement is high (e.g., comparing designs labelled 'k' and 'i'); showing the value of considering the responsiveness of reservoir operating rules to dam system expansion. Figure 17 Panel B shows how recommended dam schedules (selection of reservoirs, and gap between their implementations) change (e.g., compare designs 'h', 'd' and 'f') under differing levels of operating rule responsiveness to system expansion.

Efficient designs in Figure 16 and Figure 17 showed the trade-off between two performance objectives. However, stakeholders are likely to track multiple objectives simultaneously. Results in Section 6.3.3will show how Pareto-optimal designs can address other important criteria.

6.3.3 Performance trade-offs across multi-reservoir expansion stages

In this section, only the designs optimised under the most responsive ‘Scheme C’ optimised operating rules (Figure 15 Panel C) are considered. Parallel axis plots [*Inselberg*, 2009; *Steed et al.*, 2012] are used here to show multiple objectives. The right-most panel ‘III’ allow to visually represent dam scheduling over time.

Figure 18 shows the trade-offs between multiple performance goals and corresponding design parameters of Pareto-optimal investment schedules. The figure includes 9 Panels, I through III from left to right and A-C from top to bottom. Panel I shows performance related to the net present value and annual energy generation capacity. The net present value tracks the difference between time discounted future benefits and costs. The energy metrics report performance in steady state (after filling of all dams). Panel II shows the 99% exceeded 3-year cumulative downstream release including in the filling period. Panel III shows the optimal sequencing of reservoirs over time via the x-axis.

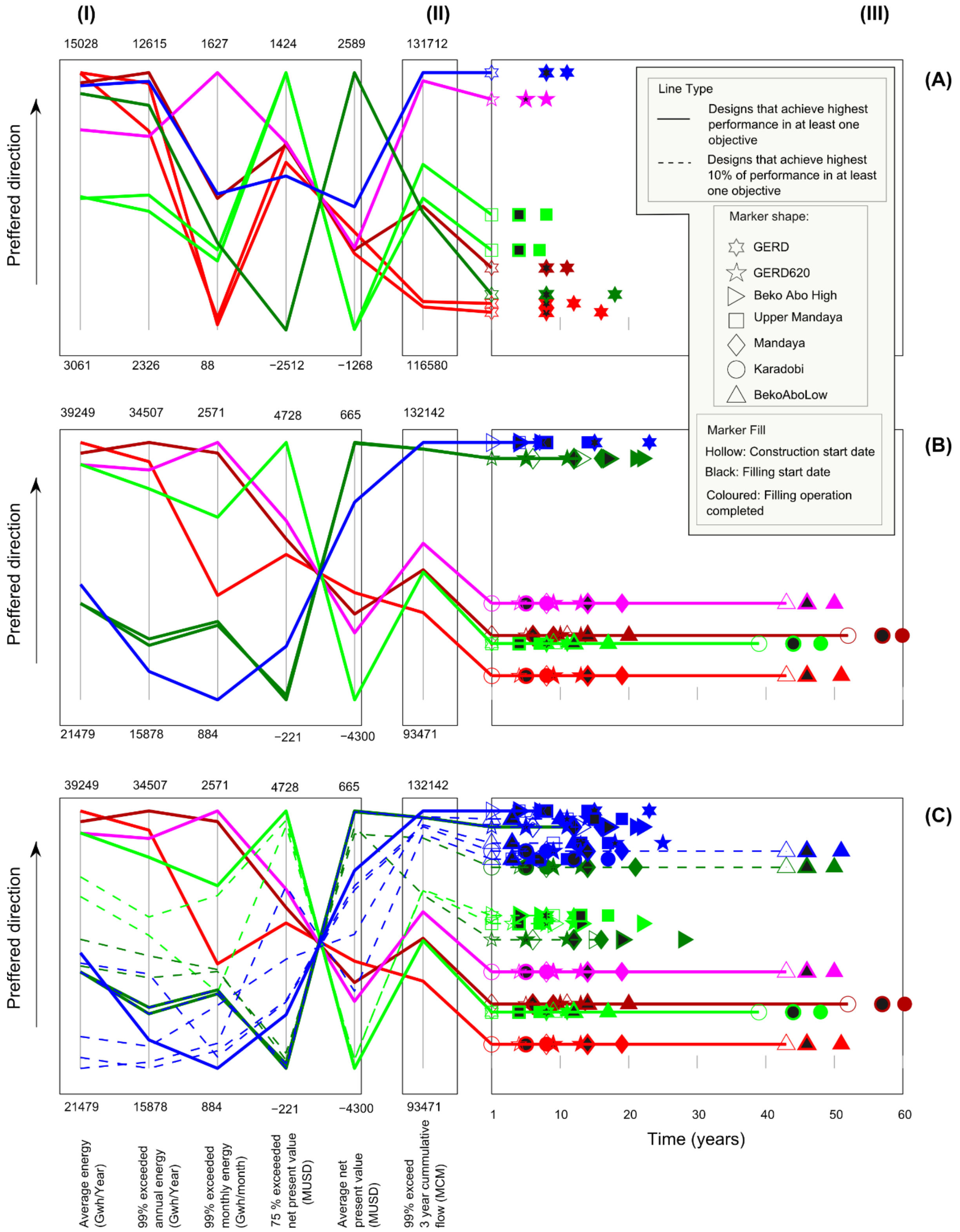


Figure 18 Parallel axis plot showing trade-offs between multiple performance metrics. Panel A shows result for a single reservoir formulation. Designs that achieve maximum performance in one of the performance objectives is shown with the same colour. Panels B and C correspond to unconstrained multi-reservoir scheduling. Panels A and B show designs which achieve highest performance in at least one of the objectives. Panel C includes (shown with

dashed lines) the designs that achieve the top 10% in at least one of the performance objectives for a multi-reservoir system. Panel III shows schedule of reservoir portfolios for the different balances of performance shown in Panels I (Ethiopian interests) and Panel II (Egyptian interest).

Portfolios schedules with different numbers of reservoirs (represented by marker shapes) are recommended as optimal for differing balances of the conflicting performance objectives (i.e., downstream release, energy generation and net present value). The majority of designs that seek to maximise the financial benefit and minimise downstream impact (e.g., green and blue lines in Panels B and C) suggest implementing the first 3 designs in the first 20 years and delaying the fourth one. Up to 60 years could be needed to implement all the Blue Nile reservoirs with these optimised development programs.

The Blue Nile multi-reservoir system has a potential to generate up to 39 Twh/Year of which 34.5 Twh/Year is the reliable energy (i.e., which can be meet 99 out of 100 years). Despite this relatively high potential for energy generation, the cost of the reservoirs and time taken to construct and fill the reservoir limits their financial potential (i.e., net present worth) to an average of less than 5 Billion USD. Moreover, the reliability of financial success of the dams is low with trade-offs between the average net present worth and lower quartile net present value measure. The maximum average net present value (4.7 BUSD) can be achieved if 3 dams with GERD and Upper Manday and Beko Abo High are implemented within the first 20 years followed by the Karadobi dam after an additional 20 years (Green solid line in Figure 18). However, such decision also implies an acceptance of up-to 4.3 billion USD net present value in losses. While the average net present worth has a trade-off with the downstream flow performance objective, the lower quartile net present value performance measure and the downstream flow performance have synergy; indicating where Ethiopia and downstream country Egypt could potentially find a consensus solution. The designs that constitute low financial opportunity for Ethiopia and low risk to downstream countries include reservoir options with smaller sizes and which are located more upstream while designs that maximise the average net present value recommend the larger dams (e.g., Mandaya, GERD and Upper Mandaya) as the initial reservoirs.

Comparing compromise designs (dashed lines in Figure 18 Panel C) shows different first reservoir options could achieve close performance levels. Demonstrating that the sequence of reservoir implementation is not the only factor, but that operating policies of reservoirs also determine the performance and benefit trade-offs to the Nile stakeholders.

Reservoir designs with energy generation capacity of up to 25 Twh/Year (Beko Abo High, Upper Manday and GERD shown with solid Blue line in Figure 18) are possible while also meeting the highest possible downstream flow reliability. While the reliable downstream flow trades-off with the average net present value, it does not have a clear trade-off with the potential average annual energy generation. This is also shown by how relaxing the downstream release requirement from the maximum possible (solid line) to 90% does not improve the average annual energy generation performance. The results show regulation from Blue Nile dams can also improve the reliability of downstream flows.

Infrastructure decisions that are best to meet a certain balance of objective (e.g., maximizing average net present worth) for a single reservoir differ for a multi-reservoir system. The Beko Abo Low followed by Upper Mandaya and GERD would make the best scheduling for minimal downstream impact (Blue solid line in Figure 18) for a 3-reservoir system. While the GERD can do well in minimizing downstream impact for a single reservoir system. Similarly, a Smaller GERD (GERD 620 meters above sea level) design followed by Mandaya and Beko Abo Low would be best to maximise the 75% exceeded net present value (dark green solid line) for a multi-reservoir system while the GERD is the best of the first dam designs if only one reservoir is to be implemented. Given the uncertainty about how many of the potential dams will be implemented, how they will be managed in their filling and steady states, and when the next dam will be implemented, it is not possible to assess the current decision by Ethiopia to select GERD as the first investment. The rate of filling and its management is still being negotiated among the thee Eastern Nile countries Egypt, Ethiopia and Sudan, Figure 18 Panel A shows the GERD could be a compromise decision as it can meet a number of performance objectives (i.e., maximizing the average and reliable annual energy, red and dark red solid lines, and maximizing the minimum net present value) under various management strategies.

6.4 Discussion

A multi-criteria multi-reservoir capacity expansion scheduling approach is proposed and applied to the possible Blue Nile multi-reservoir system components. We use visual analytic techniques to present alternative Pareto optimal designs given many objectives (6). Results show the performance trade-offs and optimised schedule of infrastructure depend on the degree of responsiveness of operating policies to system changes (i.e. a change in the optimization formulation). The approach helps stakeholders visualise trade-offs between multiple performance goals and helps identify the best infrastructure and operating rule design choices under various social, environmental and downstream performance requirements.

The Nile water allocation and how the filling of the Blue Nile reservoirs will be managed is yet to be negotiated among the Nile riparian countries. The modeling approach demonstrated in this study helps explore the trade-offs implied in alternative plans for Blue Nile reservoir development (including selection of reservoirs, scheduling, and filling & steady-state operating policies).

A decision-making approach seeking to maximise a single measure of performance identifies one plan as best. Explicit consideration of competing goals helps identify potential compromise designs. Parallel axis plots such as Figure 18 are best used interactively allowing decision makers to internalise how designs choices lead to performance trade-offs.

Results demonstrate that low dimensional optimization (i.e., one or few objectives) could over-estimate the benefit of some designs by ignoring large reductions in filling period benefits (e.g. Designs labelled ‘a’,’e’,’g’ inFigure 17). The results also show not considering responsiveness of operating rules to system expansion leads to overestimating the cost of compromises (e.g., from ‘a’ to ‘l’ instead of ‘e’ to ‘i’ in Figure 17 Panel A), thereby overemphasising the trade-offs and perpetrating the perception of the intractability of Nile development challenge. Hence excessively simple assumptions on the number of reservoirs, their implementation gap and rigid operating rules in Nile development assessment can lead to excessively optimistic or pesimistic performance estimates (overstate trade-offs and bias estimates of performance) for various stakeholders.

6.4.1 Limitations

The study contains several limitations that could be addressed in future work. Firstly, the current study considers the flexibility of reservoir operating policies to change at different stages of system expansion, but operating rules are assumed fixed throughout the period for which they are optimised and do not vary based on hydrologic conditions. In practice, when dam operators find themselves in a particular hydrologic or demand conditions; they typically adapt rules to current conditions (e.g., change priorities between filling reservoirs and releasing in cases of prolonged droughts). Considering operating rules that change based on hydrologic conditions (e.g., in recent years) would likely attain more efficient trade-offs and change which investment schedules are deemed Pareto-optimal. Other limitations include that the study considers a limited number of performance objectives and ignores the financial potential of peak power energy sales. Finally, although the sizing of reservoirs can also be optimised within the proposed approach as in *Geressu and Harou* [2015], this was not done here to help simplify results.

Including performance measures such as internal rate of return (IRR) or revenue self-sufficiency conditions in future studies could suggest designs with a more desirable cashflow (e.g., where the revenue from initial investments could cover part of the cost of subsequent dams); alternatively access to capital could be constrained in the search formulation

In this study we focus on the benefits of dam investment planning that considers changing (adapting) operating policies as the reservoir system configuration changes. The method produces a scheduled sequence of optimised dam system upgrades. We do not consider the flexibility to change or abandon plans in future when more information is available. Other recent studies, particularly under non-stationary conditions with deep uncertainty, propose an adaptive approach [*Walker et al.*, 2010; *Haasnoot et al.*, 2013], some of which use optimisation formulations which are explicitly adaptive [*Beh et al.*, 2015; *Kwakkel et al.*, 2015; *Zeff et al.*, 2016; *Erfani et al.*, 2018]. These approaches are promising, but we consider them outside the scope of this particular study which, in a first instance, considers the case of stationary conditions without deep uncertainties in supply or demand. Given climate change trends for Eastern Africa aren't clearly wetting or drying [*Conway*, 2017], and that energy demands are largely unmet [*Arsano and Tamrat*, 2005; *Block and Strzepek*, 2012], this may be an acceptable initial simplifying planning assumption.

By using 10 hydrologic realizations we are assuming this ensemble is sufficiently large to represent uniformly distributed peaks and droughts that do not bias the investment scheduling. Optimization over larger numbers of streamflow time-series could better represent the plausible hydrologic variability at different periods of the simulated period. The computational requirements of the simulation-optimization approach make it difficult to apply the multi-objective optimization on a large number of streamflow realizations. Also, uncertainty due to climate change can be an important for long-term assets [*Block and Strzepek*, 2010; *Jeuland and Whittington*, 2014] but is not considered in our study which assumes climate stationarity. Moreover, because information on methods used for filling gaps in the observed streamflow series and estimating flow in ungauged catchments is not accessible [*Block and Strzepek*, 2010; *Alan*, 2012; *NBI-ENTRO*, 2015], results are only indicative and intended to demonstrate the methodology but should not to be taken as prescriptive recommendations. Given the uncertainties and shortcomings in the current study we recognise the limitations of the results and do not claim our results should directly impact current decision-making.

Despite the limitations of the computational infrastructure available for this study, we are able to show initial results to demonstrate the formulation works and has the potential to be solved satisfactorily for large problems.

7 Sensitivity analysis

7.1 Introduction

Financial feasibility of resource system investments is a salient consideration for many governments who struggle to meet increasing demand with scarce financial resources. Investment decisions in human developed natural resource systems are typically made despite various uncertainties and therefore robust options that perform acceptably over a range of plausible futures are desirable. However, evaluating robust portfolios of interventions is computationally challenging for resource systems where multiple sources of stochastic, deep and set-based uncertainty create a large future impact space. Chapter 6 showed how the recommended reservoir system composition and sequence changes for various balances of performance. However the results (i,e., net present value performance, and recommended best designs) are reliant on the assumptions of energy price, cost of infrastructure and discount rate. The high initial capital investments, delayed benefits and economic uncertainties make large infrastructure development risky. Reliance on deterministic assumptions, which are actually uncertain and likely to be contested by stakeholders (e.g., energy price, discount rate, etc..) could affect the perception of Nile riparian countries on the system capacity, performance trade-off, financial feasibility. Also, given that attractiveness of cooperative developments or energy trade deals will depend on the relative price of hydropower energy from the Ethiopian dams when compared to the cost of traditional sources of energy for Egypt and Sudan (e.g., hydrocarbon), the financial feasibility assessment of different options should consider a range of energy prices.

In this chapter we propose a use of an automated ‘robustness mapping’ process (using multi-objective robust optimization) that reveals efficient interventions and their performance over multi-dimensional set-based system parameter uncertainties; for which a probability distribution cannot be assumed but take a value in a given range. This chapter assesses the financial feasibility of the proposed Blue Nile reservoirs under a range of energy prices (0.07-0.11 USD/Kwh), and under various assumption (7-11%) of discount rates for future financial benefits. The many objective parametric optimization is demonstrated on a stylized problem: selecting one of the proposed new Blue Nile hydropower reservoirs. The method suggested here identifies robust infrastructure choices for a range of uncertain parameters and demonstrate the ability of many objective evolutionary algorithms to reveal system performance over multi-dimensional set-based uncertainties and the fitness of interventions. Visual analytics [*Vitiello et al.*, 2012; *Fu et al.*, 2013; *Reed and Kollat*, 2013] is used to identify which of the infrastructure choices are robust for a range of the uncertain parameters. The results allows decision makers to visualise the performance trade-off simultaneously with the sensitivity of the performance measures to uncertain parameters.

7.2 Method

To explain the application of the many objective parametric optimization approach to sensitivity analysis (i.e., when the exact system parameter is not known but its minimum and maximum range is known), consider putting the uncertain parameters as decision variables in a many objective evolutionary algorithms (MOEA). The MOEA result will be biased as the final solution set will pick the most favorable value of the uncertain variable. To mitigate this problem, and allow dominated options (with unfavorable values of the uncertain parameter) to survive until the end of the evolution, the proposed approach is to add dummy performance metrics (that are not directly of interest for the decision-making process) that pulls the solution set in the opposite direction. This is possible by formulating the many-optimization problem (eq. 1) such that a conflicting functions of the uncertain input parameter (e.g., *p*) are included as performance metrics (e.g., $f_3(p)= p$ and $f_4(p)= -p$).

This allows evaluation of the sensitivity of other objective functions (e.g., f_1 in Eq. 1 which can for example be net present value metric) that depend on parameter *p* over the range [p_{min} , p_{max}] at minimum intervals determined by the epsilon (f_{Eps}). The formulation can be extended to sensitivity analysis of solutions with multiple uncertain parameters.

Minimise $$F_x = (f_1, f_2, f_3, f_4) \quad (1)$$

$$f_3(p) = p \quad (2)$$

$$f_4(p) = -1xp \quad (3)$$

To prove the method works, we use a simple problem where a function (which can also be solved allergically) is required to be evaluated at a set of integer values.

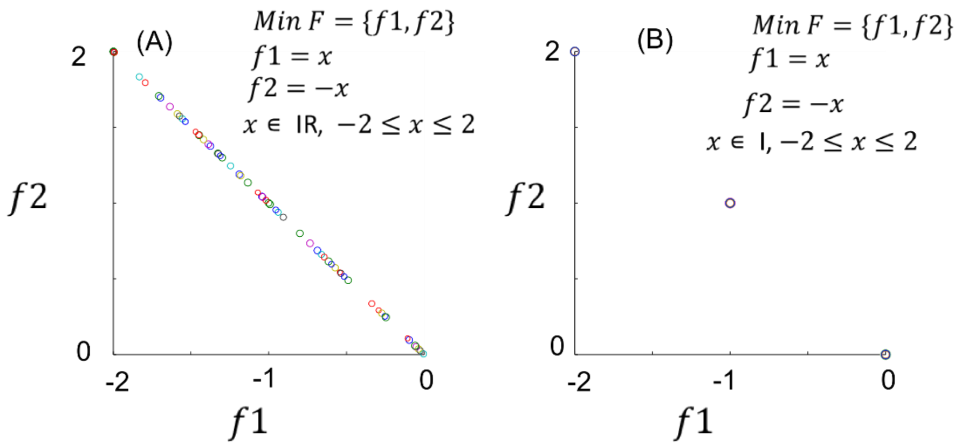


Figure 19 Solution of a two-objective optimization problem Minimize F (*f1*, *f2*), where *f1* = x and *f2* = -x and real value (Panel B) and integer value (Panel B) are allowed. Points with different colours in Panel A show solutions sets from multiple optimization runs. The difference emanates from random generation of variables used in genetic algorithms; resulting in stochasticity of the solutions set. However, each of the solution sets are pareto-optima for the considered objectives.

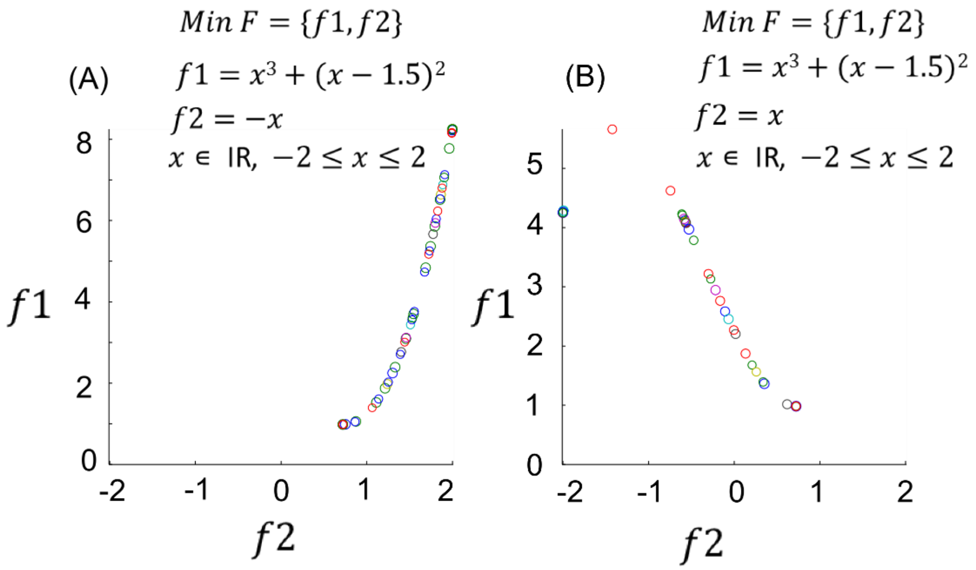


Figure 20 Solution of a two-objective optimization problem where real value are allowed. Panel A shows solutions for Minimize F (*f1*, *f2*), where *f1* = x and *f2* = (x-1.5)2+x3. Panel B shows solutions for Minimize F (*f1*, *f2*), with *f1* = -x and *f2* = (x-1.5)2+x3. Points with different colours show solutions sets from multiple optimization runs.

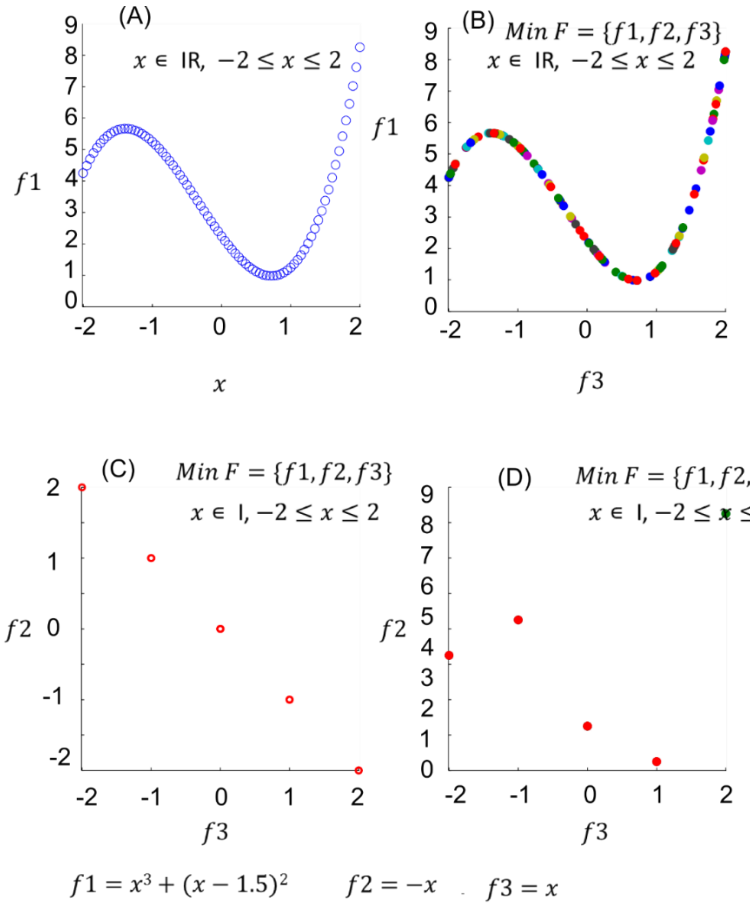


Figure 21 Panel A and B show the values of *f1* function for x taking a real number in the range -2 and 2 calculated using algebraic and many objective optimization respectively. Panel C and Panel D show the function values of *f1*,

f2 and *f3* as evaluated by a many objective optimization for x taking integer values only. Points with different colours in Panel B show solutions sets from multiple optimization runs. The difference is due to random generation of variables used in genetic algorithms; resulting in stochasticity of the solutions set.

7.2.1 Problem formulation 3

To demonstrate the approach, the problem is formulated with objectives of maximizing the net present worth of investments and opposing function of the discount rate 'd' (i.e., f1 =d and f2= -d)

For the Blue Nile, the amount of reliable downstream flow are of concern as are the financial feasibility and energy generation capacity of new developments. The performance objectives considered in this multi-objective planning exercise include maximizing the average net present value of future monetary benefits ($fAveNPV$), maximizing final (once reservoirs have filled) average annual energy generation $fAveAE$ respectively and the reliable 3-year cumulative downstream releases($fMin3R$).

The sensitivity of performance to multiple factors (both exogenous uncertainties and decision-relevant parameters) are assessed by including them in the objective function.

Maximize $$F_x = \left(fNPB, fEnergy, fR, [fDis, fDis^*, fEval, fEval^*] \right) \quad (3)$$

$$\forall x \in \Omega$$

The Decision variable here will be limited to the filling and steady state reservoir release rule parameters of one reservoir.

$$x = (Y_i, Op_{s,i}, Fop_{s,i})$$

$$Y_i = \{0,1\} \qquad \forall i \in R$$

$$\sum_{i=1}^{7} Y_i < 2 \qquad \forall i \in R$$

The decision variables include the activation of a new reservoir (Table 1), its reservoir release rule parameters for filling and steady state operating periods.

The term in the bracket in (eq. 3) is used to assess the sensitivity of the net worth of investments to discount rate of future benefits and energy price. The sensitivity analysis requires setting the ranges of the uncertain parameters over which the search is conducted. The uncertain parameters in our application were assumed to have the range given in Table 2.

Table 2 Uncertain parameter range in this case study

Parameters	Min	Max
Discount rate	7%	11%
Price of energy	7 USD cents/Kwh	11 USD cents/Kwh

The simulation period is set to 80 years so that it accommodates the construction period (a maximum of 8 years), a potentially long filling period (up to 20 years), and for the steady state operation of the reservoirs (considering a service life of 50 years).

$fAveNPV$	=	$quantile_{i\in(1,\ldots,F)}\{Npv_i, 0.5\}$	Average net present value of benefits, i.e., present worth of benefits from energy generation minus present worth of capital cost of reservoir
$fAveAE$	=	$quantile_{i\in(1,\ldots,Ts),\, j\in(1,\ldots,F)}\{\ldots Eannl_{i,j}, 0.5\}$	Average energy generation in regular operating period
$fMinR3yr$	=	$quantile_{i\in(1,\ldots,Ts),\, j\in(1,\ldots,F)}\{\ldots R3_{i,j}, 0.95\}$	95% exceeded (near minimum) cumulative releases over a 3-year consecutive period. The maximization of cumulative release in consecutive years is considered as a proxy for Egyptian interests in reducing the impact of filling of Ethiopian reservoirs on the High Aswan reservoir.
$fEval$	=	$Eval$	energy price maximizing and minimizing functions respectively
$fEval*$	=	$-Eval$	
$fDis$	=	d	Discount rate minimizing objectives respectively
$fDis*$	=	$-d$	Discount rate maximizing objectives respectively
E_t	=	$\rho h_t q_t$	Energy generation at month t; a function of head and discharge and a constant that depends on gravity and length of month

$Eannl_y$	=	$sum(E_t, t \in y)$	The sum of monthly energy generations in the year 'y'
$R3_t$	=	$\sum_{t-36}^{t} R_t$	Cumulative release of past 36 months at time t
$NPV_{Benefits}$	=	$\dfrac{\sum_{y=1}^{80} Eval \times Eannl_y}{(1+d)^y}$	Time discounted economic returns from energy generation
NPV_{Costs}	=	$\dfrac{\sum_{1}^{LenCons} Cost_i}{LenCons_i \times (1+d)^{(IT_{i,c})}}$	Time discounted cost of infrastructure
NPV	=	$NPV_{Benefits} - NPV_{Costs}$	Time discounted net present value

Notation

i	Dam notation
t	Time (month)
R_t	Release at time t
Y_i	Decision to activate Storage option i
IMP_i	Implementation date of dam i
$Cost_i$	Capital cost of reservoir i
$Egen_y$	Energy generated in year y
$LenCons_i$	Length of construction of dam i
$T_{i,c}$	Construction year (between 1 and max length of construction period of dam i (see Table 1)
Op_i	Steady state operation rule coordinates of reservoir i
Fo_i	Filling period operation rule of reservoir i
FL_s	Length of filling period
Ts	Length of steady state use (total life minus length of filling period)
F	Number of synthetic hydrologic realizations

7.3 Results

This section presents the application of the proposed approach to the stylized Blue Nile case study. We first present the performance of the proposed reservoir designs whilst varying the discount rate and energy price. Figure 22 shows the sensitivity of the average net present value metric to energy price and discount rate variables when uncertainty in one parameter is considered at a time.

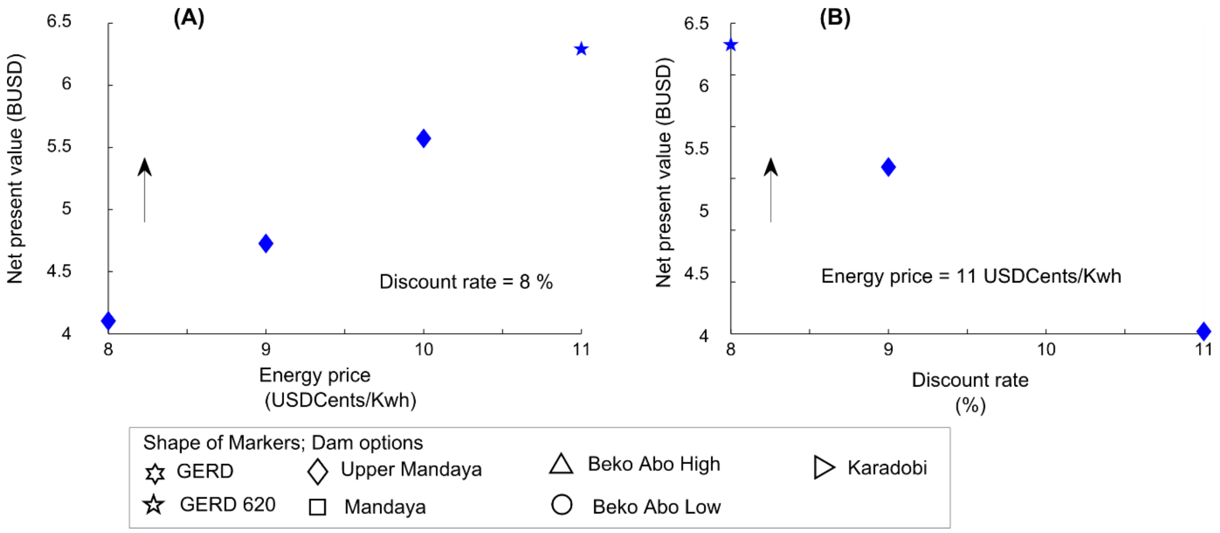


Figure 22. Panels A and B show sensitivity of the average net present value metric when variation in one parameter is considered at a time. Markers show the best infrastructure choice for the given energy price and discount rate.

Only Mandaya and GERD 620 are shown here as they are the designs that achieve the highest average net present value for the given scenarios and performance criteria (i.e., no constraints on the minimum energy generation capacity and downstream flow).

Figure 23 presents the sensitivity of the average net present value when uncertainty in the two parameters is considered simultaneously, as per the proposed approach.

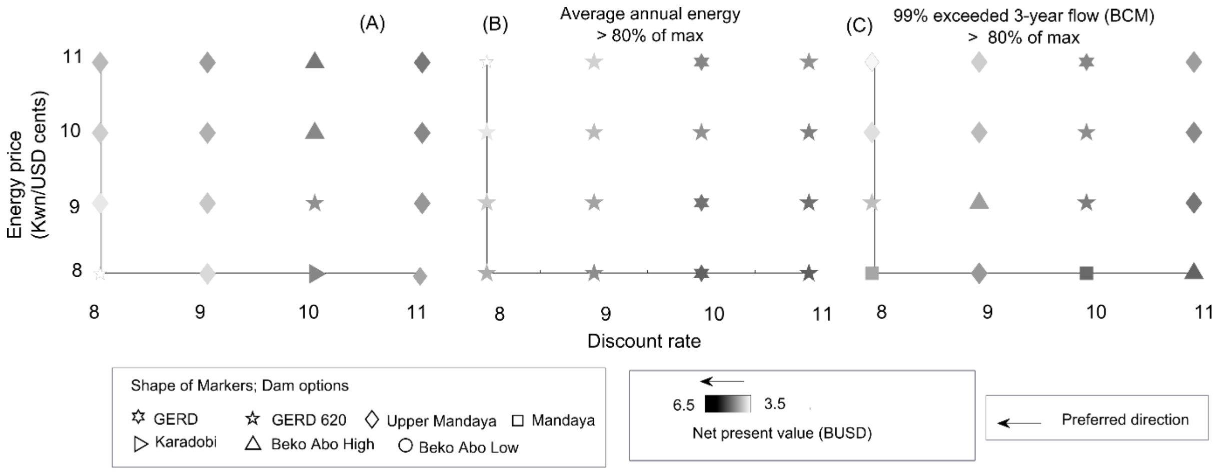


Figure 23 The Net present value (shown with filling of markers) as it varies with discount rate and energy price without restriction in other performance requirements (Panel A) and with restrictions of at least 80% of the potential average annual energy and 80% of the maximum 99% exceeded 3-year cumulative flow at Ethio-Sudan border (Panel B and C respectively). Markers show the best infrastructure choice for the given energy price and discount rate.

Figure 22 and Figure 23 Panel A show sensitivity of one performance metric (the net present value) ignoring energy generation capacity and downstream release performance requirements. Figure 23 Panels B and C show the best designs for meeting different performance criteria under a range of discount rate and energy price scenarios.

In addition to the uncertainties, identifying plans that achieve an acceptable balance of conflicting benefits is aided by considering trade-offs between the many objectives. For a given set of energy price and discount rate settings, the efficient solution identified here is the one where any objective cannot be further improved without simultaneously harming one or more other objectives (e.g., in a scenarios of a discount rate of 9% and energy price of 11USDcents/Kwh, the green makers on Figure 24).

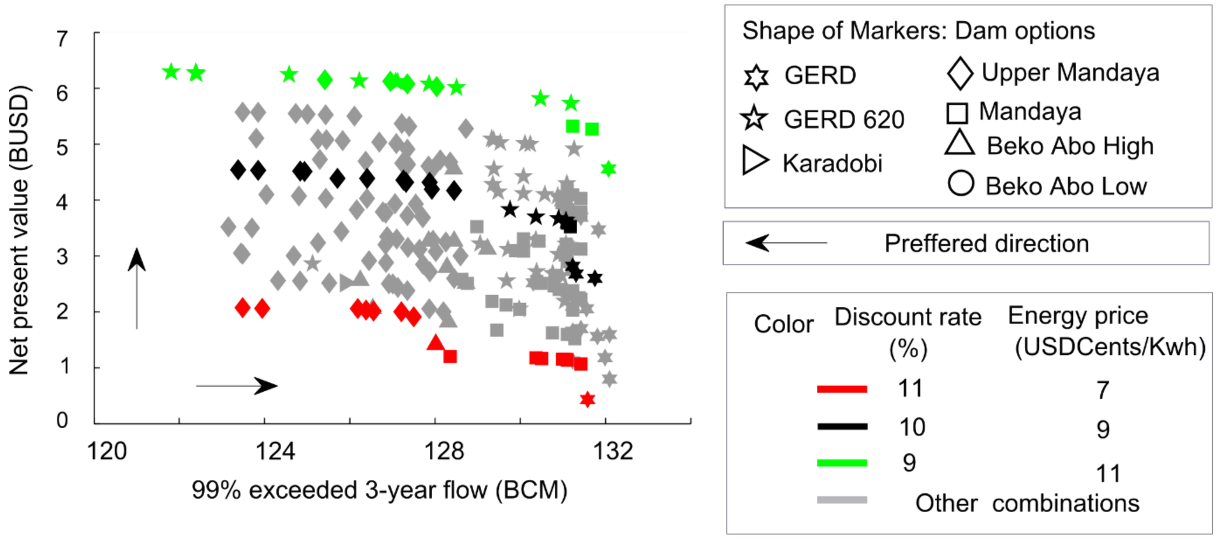


Figure 24 shows a shifting Pareto-front as uncertain parameters vary. The dark black Markers show the Pareto-front for discount rate and energy price values of 10% and 0.09 USD/kwh respectively. The red and the green show results at the extremes of the ranges considered while the grey markers show performance for intermediate system parameters.

Figure 24 shows shifts in the Pareto-front between conflicting performance metrics of average net present value and reliable 3-year cumulative downstream flow as the two uncertain parameters (discount rates, energy prices) change. For combinations of the uncertain parameters (e.g., the 11% discount rate and 7 USDcents/Kwh shown with red colour), the points reveal what infrastructure selection were most efficient for different balances of average net present value and 99% exceeded 3-year cumulative release.

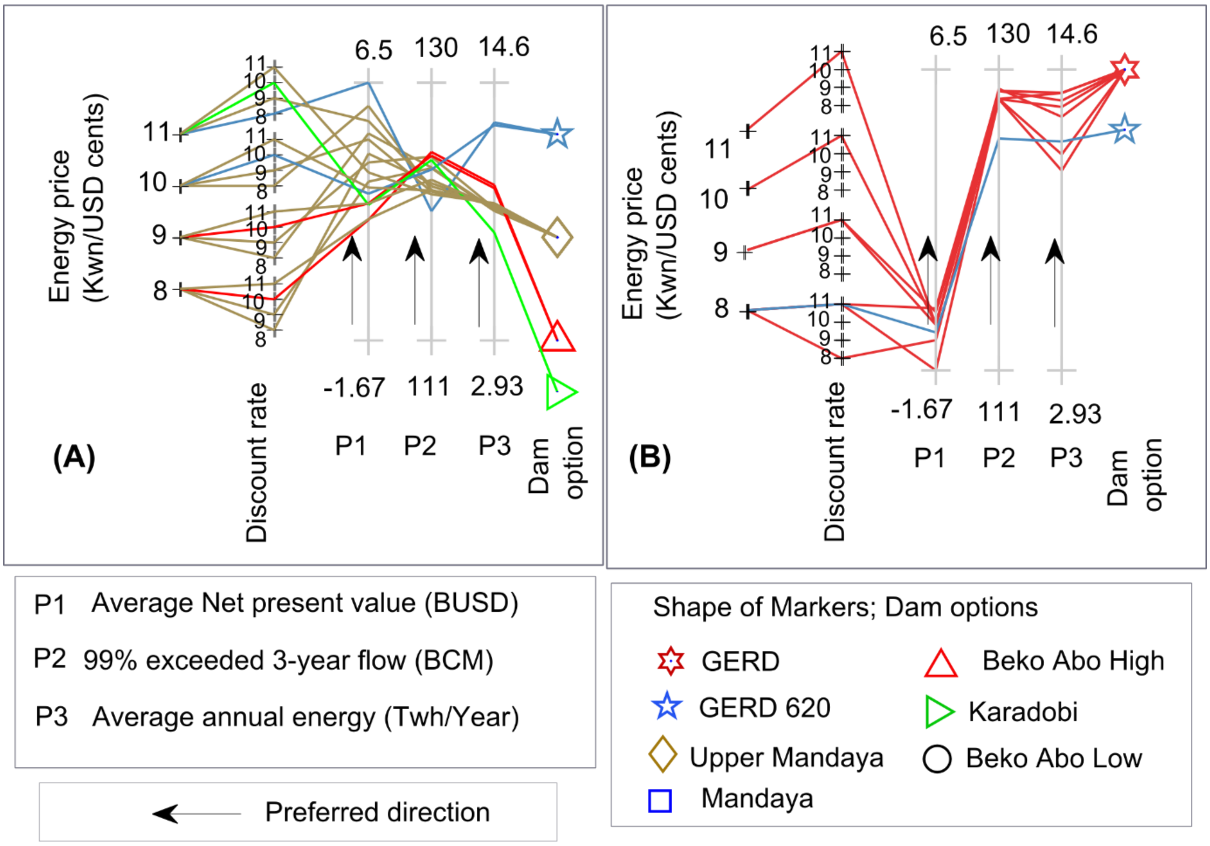


Figure 25 Panel A shows designs that achieve the highest average net present value, average annual energy and 99% exceeded 3-year cumulative downstream release under each combination of energy price and discount rate value. Panel B shows the combination of scenarios (discount rate and energy price) and performance requirements (downstream flow requirement that make some of the designs (shown with markers) financially infeasible (average net present value below zero). Colours have the same meaning as marker shapes and are included for ease of visualisation and do not provide new information. The tree structure part of the plots allows visualizing discrete scenarios while the parallel plot part on the right shows the relationship between multiple performance metrics.

Figure 25 Panel A shows 4 of the potential 7 dam options could be the best options to maximize net present value in different energy price and discount rate scenarios. The smaller dam options of Beko Abo High and Karadobi achieve less average net present value while the larger GERD620 and Upper Mandaya score the highest net present value under the range of the uncertain parameters. Figure 25 Panel B shows only the GERD and GERD620 with high 99% exceeded downstream release requirement and some of the discount rate and energy price scenarios can become financially infeasible. The GERD becomes financially unviable under the entire range of energy prices for the high discount rate assumption (11%). The GERD620 option can also become financially unviable under 11% discount rate and low energy price (0.08 USD/Kwh). Other infrastructure options, while financially feasible under the considered range of discount rate and energy prices, result in lower average annual energy.

7.4 **Discussion**

This chapter proposes and demonstrates a method for using multi-objective optimization to assist with infrastructure investment selection problems under multiple uncertainties. The method reveals a robust set of alternatives, those that meet multiple performance criteria under various uncertainties, including in our study energy prices, discount rate and hydrological uncertainty. The proposed formulation of many objective infrastructure selection problems for Robust optimization was demonstrated on the proposed dams of the Blue Nile multi-reservoir system for 8-11 USD cents/Kwh energy price and 8-11% discount rate range at intervals of 1 USD/Kwh and 1% discount rate (considering a total of 4x4 discrete scenarios).

Figure 23 showed which of the proposed Blue Nile reservoirs were most robust for energy prices 8 to 11 USD cents/Kwh, discount rates between 8 and 11% and energy and downstream release performance requirements. Some infrastructure options were demonstrated to be robust over multiple scenarios (e.g., Mandaya is robust over discount rates 8 and 9% under all considered energy futures (8-11 USD cents/Kwh) when there are no downstream release and minimum energy generation constraints. Larger dam options (e.g. GERD620, GERD) are best only when energy generation and downstream release requirements are introduced (Figure 23 Panel B and C)

For the proposed Blue Nile dams considered here, the recommended efficient dam choice can change for as little as a 10% change in the assumed discount rate and energy price. The financial feasibility of the dams in our study however is only affected by a combination of the discount rate, energy price and downstream release requirement and not by any of these factors individually. This analysis revealed the GERD under construction in Ethiopia could be financially unattractive for assumptions of a 11% discount rate and a high 3-year release requirement.

Given that up to 10 conflicting objective can be modelled in MOEA [*Reed et al.*, 2013]. [*Teytaud*, 2007], up to 4 uncertain variables can be considered simultaneously with the proposed approach (if evaluating one or two performance metrics when two dummy performance metrics need to be introduced for each uncertain system parameter). The number of uncertainity variable can however be increased to 8 when one dummy performance objective is sufficient which is when the uncertainity parameters have a direct conflict with one of the performance objective and visualizing the performance associated with favourable scenarios is not necessary (e.g., in problems with objective of maximizing the net present and uncertainties on construction period, delay on implementation of the second reservoir in multi-reservoir system expansion scheduling)

The use of evolutionary algorithms to optimise interventions in complex system can rapidly become computationally prohibitive if the system is large with many objectives and possible interventions. The minimum number of function evaluations and number of random-seed analysis that achieve the highest possible hypervolume metric [*Knowles and Corne*, 2002; *Zitzler et al.*, 2003] should be sought as the use of many objective evolutionary algorithms is computationally intensive. In this section we compare the computational resources required for a conventional trade-off analysis with the proposed robustness mapping under uncertainty.

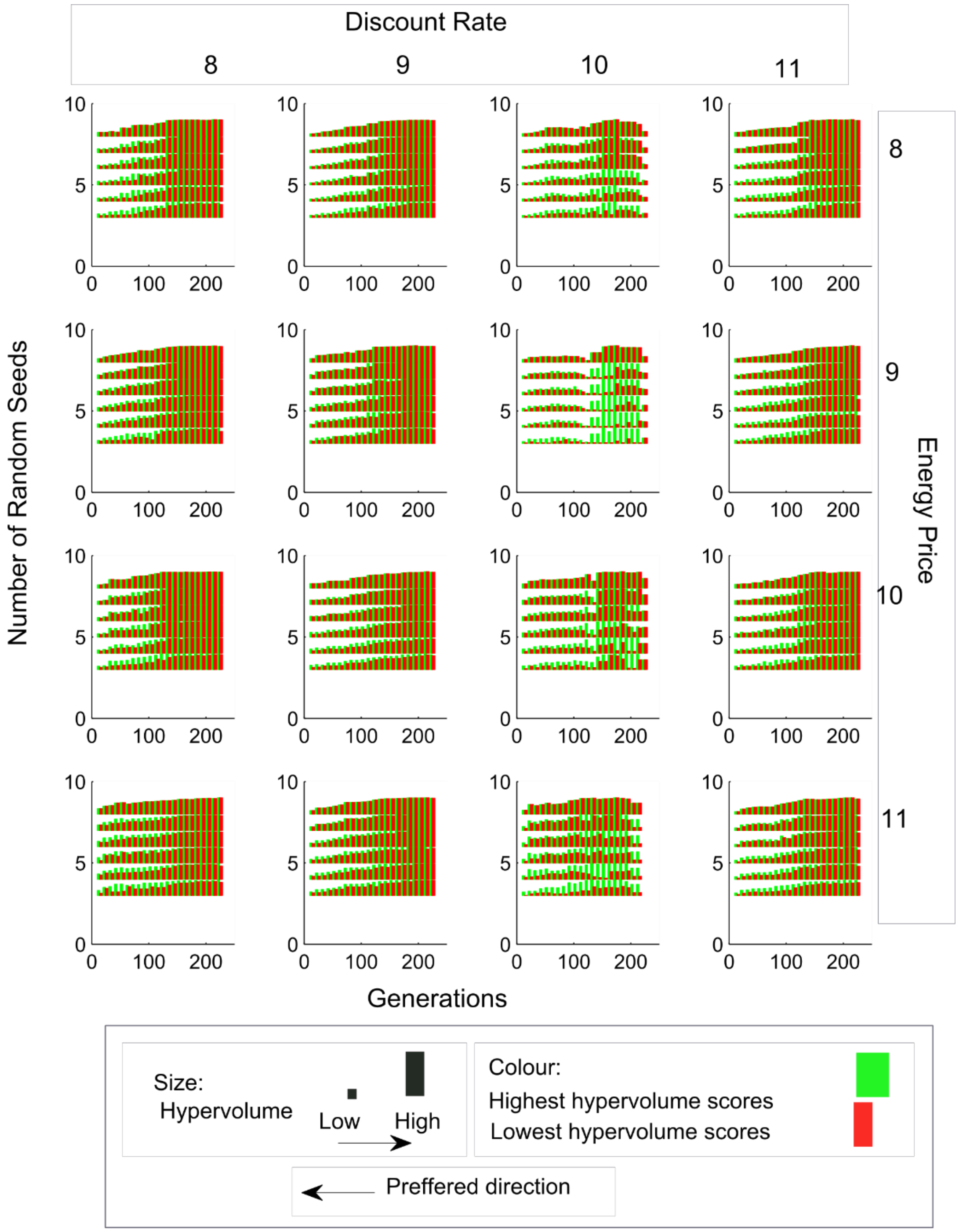


Figure 26 evolution of hypervolume indicator with number of function evaluations (x-axis of each panel) Pareto-sorted across a number of runs with randomly seeded initial points (y-axis in each panel) for solutions under range of combinations of energy price (row of Panels) and discount rate parameters (column of Panels).

Figure 26 show the differing number of function evaluations and random seed analysis required to approximate the solution to the true (but unknown) many objective Pareto-front. The absence of improvement in the Hypervolume metric and its robustness with additional generations and number of random seeded runs is taken as an optimization stopping criterion.

To compare the computational requirement of the proposed re-formulation with a conventional MOEA approach where each discount rate and energy price combination would be optimized, we propose using the least number of random seeds and function evaluations needed to achieve the 95,99 and 100% of the maximum Hypervolume with 99% confidence as an indicator. For the case study problem, the proposed re-formulation requires a maximum of 70,400 function evaluations (FE) under 12 random seeds (RS) or 844,800 FE in total to achieve convergence (with the stated criteria above). A test deterministic MOEA run assuming 10% discount rate and 0.1 USD/Kwh energy price is conducted to measure it computational requirements. The test needed a maximum length of 49,920 FE and 11 RS, a total of 549,120 FE to get similar convergence criteria. While this represents an increase of 35% in computational requirement when doing the robustness mapping over deterministic (single scenario) analysis, the approach provides a reduction of 90% in computational time requirement considering using a conventional MOEA formulation for robustness analysis over the 16 scenarios would require a total of 8,785,920 FE and 176 RS.

7.4.1 Limitations

The number of uncertain parameters, and the resolution of the sensitivity investigation in this study was limited. Future studies could include uncertainty in construction cost, construction delays, inflation and others. This is a proof-of-concept study on a simplified form of a subset of relevant performance objectives for the Nile infrastructure investment assessment problem. We assume a problem formulation with only one dam being selected of the potential 4 reservoir system. The formulation also includes only a few of the relevant performance metrics (e.g., it ignores peak power, and firm monthly and annual energy requirements and could include more downstream impact metrics). Decision-makers could be comparing between different technologies with different likelihoods of cost overruns. By using 30 hydrologic realizations of 80 years each we are assuming this ensemble is sufficiently large to represent historical variability of the Blue Nile river flow. Uncertainty due to climate change can be an important for long-term assets [*Block and Strzepek*, 2010; *Jeuland and Whittington*, 2014] but is not considered in our study which assumes climate stationarity. Moreover, because information on methods used for filling gaps in the observed streamflow series and estimating flow in ungauged catchments is not accessible [*Block and Strzepek*, 2010; *Alan*, 2012; *NBI-ENTRO*, 2015], results of this case study are only indicative and intended to demonstrate the methodology but should not to be taken as prescriptive recommendations.

8 Mapping options on performance space

8.1 Introduction

This chapter considers problems where visualizing the Pareto-fronts of individual infrastructure options (i.e., even when dominated), in addition to the Pareto front that considers the entire feasible decision space, can be useful to decision support. This is relevant when the ability to change the balance of benefits via policy changes, or where the extent to which management changes could increase robustness to uncertainty is valued. Other problem contexts where the proposed application could be useful include when some infrastructure options are preferred for unmodeled reasons like equity or socio-political reasons, or where information on how management policies impacts the adaptability of different infrastructure options is useful. We propose a problem reformulation approach to demonstrate the ability of many objective evolutionary algorithms to tackle such problems efficiently. The approach is applied to evaluate the Grand Ethiopian Renaissance Dam (GERD) vs. other possible Blue Nile hydropower options given multiple performance criteria.

8.2 Method

This section explain the proposed many objective parametric optimization approach to reveal the performance (and allow the comparison of) of all binary decisions (i.e., that can be represented with binary variable (1 for on 0 for off)).

Consider an infrastructure selection problem with mutually exclusive options *a,b,c,d* where each option can be implemented with a management decision unique to the selected infrastructure option to maximize conflicting system performance objectives f_1 and f_2. Direct policy search (DPS) approach [*Guariso et al.*, 1986; *Koutsoyiannis and Economou*, 2003b; *Giuliani et al.*, 2014] where the operating policy is first parameterized within a given family of functions (e.g., linear, piecewise linear or Gaussian Radial Basis function) can be applied and then the parameters optimized with respect to the operating objectives to identify management options best for various balances of conflicting performance objectives. Say for example, a many objective optimization that considers all possible options simultaneously identifies a performance front (a1, c1, c2, c3 in Figure 27). The pareto fronts for infrastructure and management options for individual options a, b, and c which work with management options can be identified in separate optimization runs as (a1,a2,a3,a4), (b1,b2,b3), (c1,c2,c3) and (d1,d2 on Figure 27) respectively.

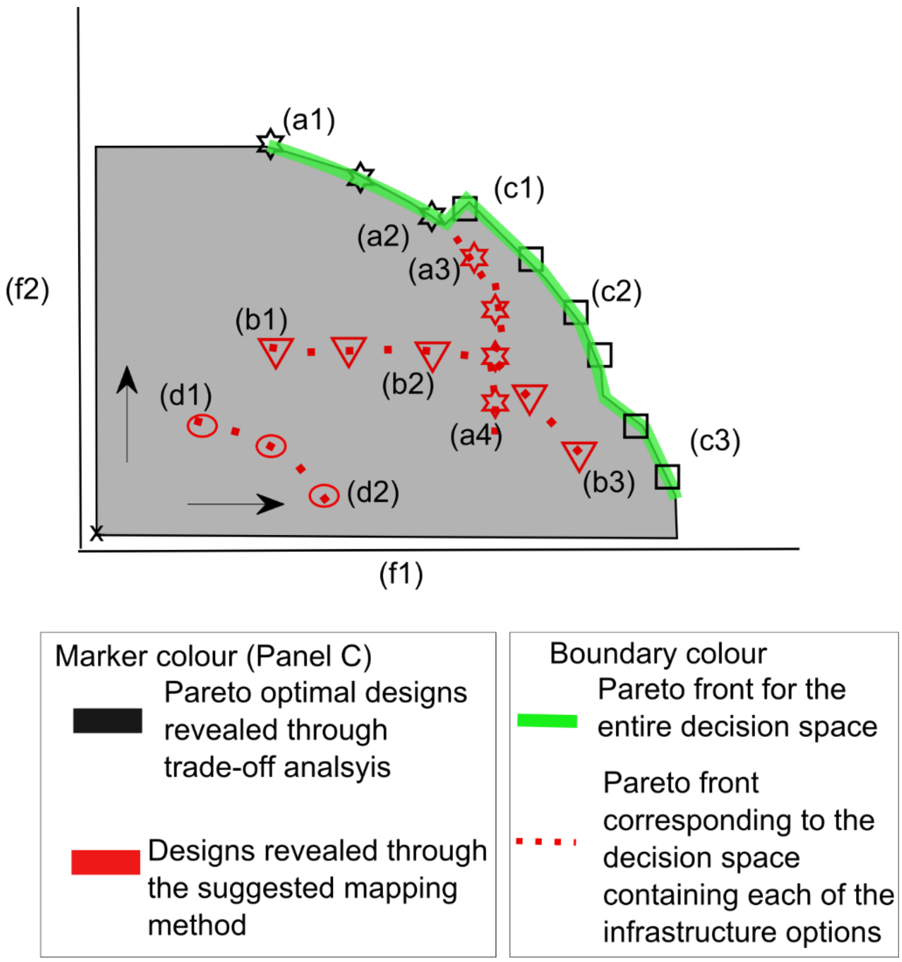


Figure 27 The propose mapping approach differentiates near-optimal solutions that vary as a result of discrete choice element of the decision space (e.g., infrastructure selection shown with red markers) from those that are different from the Pareto optimal solutions because of management decision (Grey coloured space show the overall dominated space when all options are considered simultaneously.).

The proposed performance mapping approach generates more decision relevant information than visualizing only the Pareto-front provides on 1) the extent of performance possible under each option e.g., (a1,a2, a3 and a4) instead of only a1 and a2 2) possibility of alternative infrastructure and management designs with close performance as the Pareto optimal option e.g., a3 (instead of c1) which could be more preferable for unmodeled reasons such as security of its location, invigorating local economy of impoverished area or helping with equitable development of regions. 3) the performance regrets when alternative performance criteria are adopted in the future once an irreversible or costly infrastructure decision is made and implemented. Assume f1 and f2 refer to performance under futures 1 and 2 respectively, option ‘b’ which is inferior compared to ‘a’ in some performance ranges such as ‘a1’ to ‘a3’ might be preferable to avoid large regret of f1(c3)-f1(a4) in leu of a smaller regret f1(c3)-f1(b3) in a future 1 scenario if the regret of f2(a1)-f2(b1) is considered tolerable when future 2 materializes.

Many objective evolutionary algorithms (MOEA) generates its initial random population of decision variables by exploiting uniform random sampling within the user-specified ranges of decision variables. These variables are then passed as input variables to a function evaluator, in our case a water resources system simulator, which evaluates the performance. This information is passed back to the MOEA, which evaluates the fitness of decision variables to produce the next generation of decision variables. MOEAs work by evolving solution sets of system alternatives with high fitness functions and 'forgetting' solutions with low fitness score in search of better performing solutions for a given set of performance objectives [*Coello Coello et al.*, 2007; *Reed et al.*, 2013].

Retaining dominated discrete options along with the non-dominated solutions requires a variation of the conventional many objective optimization and trade-off analysis approach reported in the literature [*Geressu and Harou*, 2015; *Huskova et al.*, 2016]. For example, in Chapter 5, the decision variables representing the inclusion or exclusion of a reservoir option in a multi-reservoir system design are binary (take a value of either 0 or 1). Evaluation of binary options (e.g., whether a certain known dam proposal should go ahead or not) even when it is a dominated option means that these options are represented in the set of solutions at the end of evolution.

Given that the evolutionary algorithms use uniform random generation, representing the distribution of the pre-defined options in an evolving population set is possible using a single decision variable to track them. Consider a variable 'n' that takes integer values for indexing the a number of predefined options with integer numbers (e.g., a value of 0 represents first option, 1 for section option etc…). This means the first options will be on if the variable 'n' is 0 while the other options will be off simultaneously; similarly, second option will be on if the variable 'n' is 1, etc...

Dummy performance objectives that drive the indexing variable in the opposite direction (e.g. fX_3=n and fX_4= -n) where $N = 0,1,2, MaxIndex$ can then be used to keep the options in the evolving population of solutions.

Minimise $$F_x = (f_1, f_2, f_3, f_4) \tag{1}$$

$$f_3(n) = n \tag{2}$$

$$f_4(n) = -1xn \tag{3}$$

The binary variables (that tell the simulator whether the options are on or off while simulating the system are then calculated based on the indexing variable 'n' and treated as a dependent variable (not directly represented in the optimizer but derived in the wrapper please see Figure 50).

To demonstrate the method, we first use a simple hypothetical example. The decision problem is an infrastructure selection among 5 options of which only one can be selected. Each option has two parameters (x and y) that are related to the two performance objectives $F1(x,y) = x^2 + 0.5y^2$ and $F2(x,y) = x + y^3$ which are required to be maximized.

Table 3 Parameters of the 5 options for the hypothetical infrastructure selection problem

	Parameters				
Option	x	y	Index	F1(x,y)	F2(x,y)
a	2	3	1	5.5	26
b	4	5.5	2	18.75	164.875
c	3	5	3	11.5	123
d	3	6	4	12	213
e	5	3	5	26.5	29

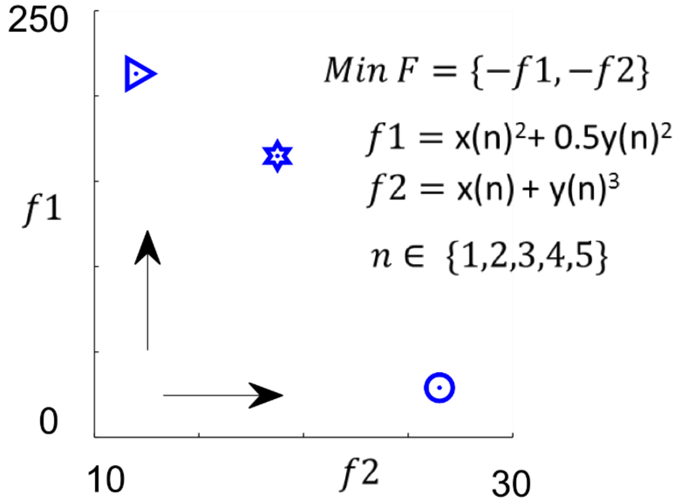
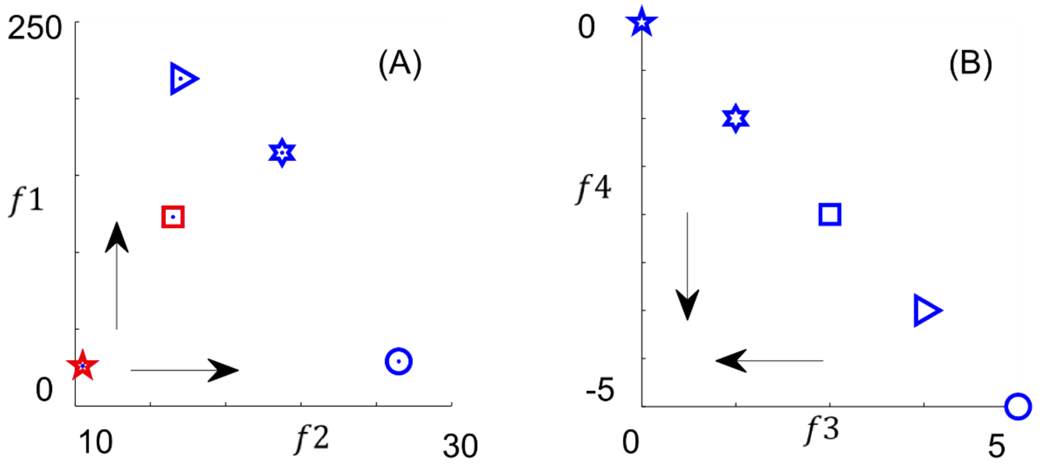


Figure 28 Pareto optimal designs for the two objectives f1 and f2 which are desired to be high (in the direction of the arrows). Only 3 of the 5 options, which are Pareto optimal for the performance objective considered are shown in this conventional trade-off analysis. hence, comparing the performance of the dominated options is not possible.



$Min\ F = \{-f1, -f2, f3, f4\}$ $\quad f1 = x(n)^2 + 0.5y(n)^2 \quad f3 = n$

$n \in \{1,2,3,4,5\}$ $\quad f2 = x(n) + y(n)^3 \quad f4 = -n$

Figure 29 Blue markers in Panel A show the Pareto optimal designs for the two objectives *f1* and *f2*. Red markers on Panel A show the two dominated options, allowing their performance comparison with the Pareto-optimal choices. The dominated options survived the heuristic search because they are non-dominate for the additional performance objectives *f3* and *f4* (as shown in Panel B).

8.2.1 Problem formulation 4

Explicitly considering trade-offs between key objectives elucidates the interdependences between scheme selection and its benefits and can be helpful in defining acceptable compromise plans [*Richter and Thomas*, 2007; *Kasprzyk et al.*, 2009; *Woodruff et al.*, 2013; *Hurford et al.*, 2014]. For the Blue Nile, the amount of reliable downstream flow are of concern as are the financial feasibility and energy generation capacity of new developments. The performance objectives considered in this study include maximizing the average and lower quartile net present value of future benefits ($fAveNPV$, $fNPV_{25}$), maximizing final (once reservoirs have filled) average annual, firm annual and firm monthly energy generation $fAveAE, fMinFAE, fMinFME$ respectively and the reliable 3-year cumulative downstream releases ($fMinR\_3$).

The performance of all discrete intervention options is assessed by adding dummy performance objectives that force the many objective optimization to keep all options till the end of evolution. for this purpose, the many-objective problem is re-formulated as:

Maximize $$F_X = (AveNPV, fNPV_{25}, fAveAE, fMinFAE, fMinFME, fMin3R, fopt, fopt^*)$$ (2)

$$\forall x \in \Omega$$

The decision variables include the activation of one new reservoir (Table 1) and its filling and steady state reservoir release rule parameters.

$$X = (Y_i, T_i, Op_i, Fop_i)$$

$$Y_i = \{0,1\}$$

$$Y_i = \{0,1\} \quad \forall i \in R, \ \sum_{i=1}^{7} Y_i < 2$$ assuming only one dam will be built

$fAveNPV$	=	$quantile_{i\in(1,\ldots,F)}\{Npv, 0.5\}$	Average net present value of benefits, i.e., present worth of benefits from energy generation minus present worth of capital cost of reservoir
$fNPV_{25}$	=	$quantile_{i\in(1,\ldots,F)}\{Npv, 0.5\}$	75% exceeded net present value of benefits
$fAveAE$	=	$quantile_{i\in(1,\ldots,Ts), i\in(1,\ldots,F)}\{\ldots Eannl_{i,j}, 0.5\}$	Average energy generation in regular operating period
$fMinFAE$	=	$quantile_{i\in(1,\ldots,Ts), j\in(1,\ldots,F)}\{\ldots Eannl_{i,j}, 0.5\}$	95% exceeded (near minimum) annual energy generation of the reservoir in steady state (i.e. after the filling period.
$fMinFME$	=	$quantile_{i\in(1,\ldots,Ts\times 12), i\in(1,\ldots,F)}\{\ldots Emon_{i,j}, 0.95\}$	95% exceeded (near minimum) monthly energy generation in steady state.
$fMinR3yr$	=	$quantile_{i\in(1,\ldots,Ts), j\in(1,\ldots,F)}\{\ldots R3_{i,j}, 0.95\}$	95% exceeded (near minimum) cumulative releases over a 3-year consecutive period. The maximization of cumulative release in consecutive years is considered as a proxy for Egyptian interests in reducing the impact of filling of Ethiopian reservoirs on the High Aswan reservoir.
$fopt$	=	n	dummy performance metrics 1
$fopt*$	=	$-n$	dummy performance metrics 2

E_t	=	$\rho h_t q_t$	Energy generation at month t; a function of head and discharge and a constant that depends on gravity and length of month
$Eannl_y$	=	$sum(E_t, t \in y)$	The sum of monthly energy generations in the year 'y'
$R3_t =$	=	$\sum_{t-36}^{t} R_t$	Rolling 3-year cumulative flow
$NPV_{Benefits}$	=	$\dfrac{\sum_{y=1}^{80} Eval \times Eannl_y}{(1+d)^y}$	Time discounted economic returns from energy generation
NPV_{Costs}	=	$\dfrac{\sum_{1}^{LenCons} Cost_i}{LenCons_i \times (1+d)^{(T_{i,c})}}$	Time discounted cost of infrastructure
NPV	=	$NPV_{Benefits} - NPV_{Costs}$	Time discounted net present value

i	Dam notation
t	Time (month)
R_t	Release at time t
Y_i	Decision to activate Storage option i
$Cost_i$	Capital cost of reservoir i
$Egen_y$	Energy generated in year y
$LenCons_i$	Length of construction of dam i
$T_{i,c}$	Construction year (between 1 and max length of construction period of dam i (see Table 1)
Op_i	Steady state operation rule coordinates of reservoir i
Fo_i	Filling period operation rule of reservoir i
FL_i	Length of filling period
$Eval$	Value of energy per kWh
d	Discount rate (assumed at 10%)
Ts	Length of steady state use (total life minus length of filling period)
F	Number of synthetic hydrologic realizations

The simulation period is set such as the operation of the reservoirs is modeled throughout their service life (50 years).

8.3 Computational details

The system model was built using the interactive river-aquifer simulation system 2010 ('IRAS-2010') described by [*Matrosov et al.*, 2011]. The water system simulation model representing the Blue Nile includes 7 reservoir nodes and 10 junction nodes and 6 links representing river reaches.

We follow *Giuliani et al.* [2014] in applying direct policy search, where the operating policy is first parameterized within a given family of functions (e.g., Radial basis function or piecewise linear) and then the parameters optimized with respect to the operating objectives. Water researchers have considered the optimization of reservoir operating rules in an extensive literature, for example using parameterization-simulation-optimization [*Guariso et al.*, 1986; *Oliveira and Loucks*, 1997; *Koutsoyiannis and Economou*, 2003a] also known as Direct Policy Search (DPS) [*Giuliani et al.*, 2014]. The decision space for most system designs contains few infrastructure choices and many management alternatives. We parameterize the control policies using radial basis function[*Giuliani et al.*, 2014]. Radial basis function have been used to map the reservoir storage and time index into release decisions [*Giuliani et al.*, 2014; *Zatarain Salazar et al.*, 2017] and take the form of

$$\varphi_i(z_t) = \sum_{i=1}^{n} w_i \exp\left(-\sum_{j=1}^{m} \frac{(z_{t,j} - c_{i,j})^2}{b^2{}_{i,j}}\right) \tag{12}$$

Following [*Maier et al.*, 2014b; *Zatarain Salazar et al.*, 2017], we use n = 4 RBFs. The Inputs in Z_t are uniformed on [0,1], while $c_{i,j} \in [-1,1]$ $b_{i,j} \in [0,1]$ $w_{i,j} \in [0,1]$ $\sum_{i=1}^{n} w_i = 1$ Where m is the number of input variables which would be 2 (only reservoir storage and time of the year). Each RBF has associated with it 4 weights and 4x2=8 centres and 4x2=8 radii that need to be optimized. A total of 21 variables need to be optimized considering the further one variable which will be multiplied with the result of RBF storage and time function (which is normalized on [0,1]) to give the release magnitude. The optimal value of this variable can take a value from 0 to maximum release capacity of the dam.

The storage targets of a large reservoir are typically varied during its filling period of several years, the Radial basis function based operating rule (i.e., which take storage and time inputs) for filling period will consider varying storage targets at various points in the filling period in contrast to the after-filling period where an optimized operating rule specifies storage targets for a typical year (i.e., seasonally). The maximum annual filling rate for large reservoirs is assumed to be one-third of their maximum storage volume considering construction quality monitoring requirements.

We employ a heuristic optimization approach where a search algorithm [*Kollat and Reed*, 2006; *P. M. Reed et al.*, 2012] is coupled with a simulation model of the water resources system. The objectives are evaluated by simulating the system monthly using 60 years of stochastically generated monthly flow data. We use implicit stochastic optimization approach to assess the probabilities of benefits and impacts given the inflow variability. The system model is tested for a number of stream flow realizations statistically resembling historical conditions.

The many objective optimization is counducted with up to 30 runs with different initial points (random seeds) where each is allowed to last for up to 100,000 function evaluations. The results from each run are then sorted together to provide the best overall reference set [*Kollat et al.*, 2008]. Given the high computational cost associated with increasing either of the number of random seeds or the length of evolutions, balancing both with computational resources is required while ensuring fidelity of the results. We assess the computational performance of the conventional trade-off analysis and that of the proposed mapping problem formulations under various number of random seeds and lengths of evolutions by using Monte-Carlo combination of run with randomly seeded starting points. Heuristic search results cannot be mathematically proven to be Pareto-optimal hence the term 'Pareto-approximate' [*Datta et al.*, 2008] but we refer to them as Pareto-optimal hereafter to simplify communication.

8.4 **Results**

This section presents the performance of the proposed Blue Nile reservoirs and discusses the information revealed when the many objective optimization is conducted for each infrastructure option separately in comparison to when all options are considered jointly.

Red markers on Figure 30 show the pareto optimal designs when considering the conflicting performance objectives of maximizing the average net present value and the 99% exceeded downstream flow at the Ethio-Sudan border. The shape of markers presents the highest performance in the two performance metrics under each infrastructure option (i.e., with the best possible management rules not shown here).

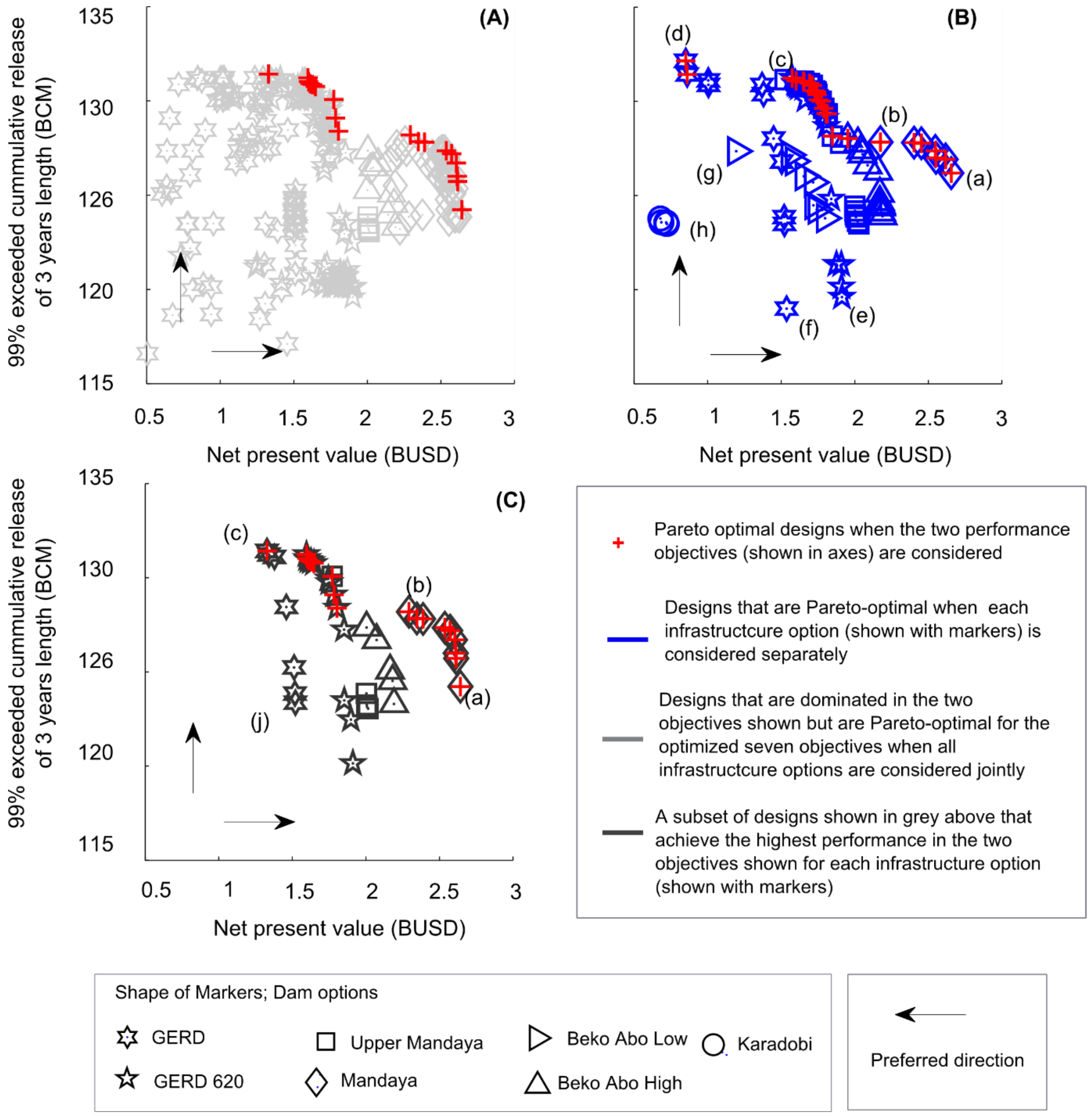


Figure 30 Red markers shows the Pareto-optimal set of infrastructure options (with associated management rules not shown here) that do best for different balances of the average net present value and 99% exceeded 3-year cumulative flow performance. The shape of the markers shows the reservoir choices. Black markers (in Panel C) show the highest 2-dimensional performance under infrastructure options extracted from the Pareto optimal solutions set (shown with Grey makers in Panel A) of a 7-objective problem. Blue Markers shows performance extent of all infrastructure options when each infrastructure option is considered separately in the many objective optimization and performance information is visualised jointly.

Grey markers in Figure 30 show designs that are Pareto optimal for the original seven objective problem but dominated for the two performance goals. The solution set for the seven objective problem is Pareto-sorted for the two performance goals to produce the pareto optimal solutions shown in red color.

Figure 30 Panel A shows the efficient trade-offs between the reliable (99% exceeded) 3-year cumulative downstream release at the Ethio-Sudan border and the average net present value. This approach could show only some of the potential options on the Pareto-front (e.g., GERD, GERD620 and Mandaya). Because of this, stakeholders who may be interested in other infrastructure options (say Karadobi) will not be able to see how the performance of their preferred infrastructure choice would compare with the ones shown as Pareto-optimal and other infrastructure options. Figure 30 Panel B shows how the infrastructure choices compare (with the best management designs not shown in the figure) to maximize the two performance objectives. In conventional many objective optimization, this would require conducting the experiment for each infrastructure option separately and merging the solution set to performance.

Figure 31 shows a comparison of designs identified through standard many objective optimisation analysis (red lines) and designs identified through the proposed mapping approach (green lines) considering larger number of performance goals.

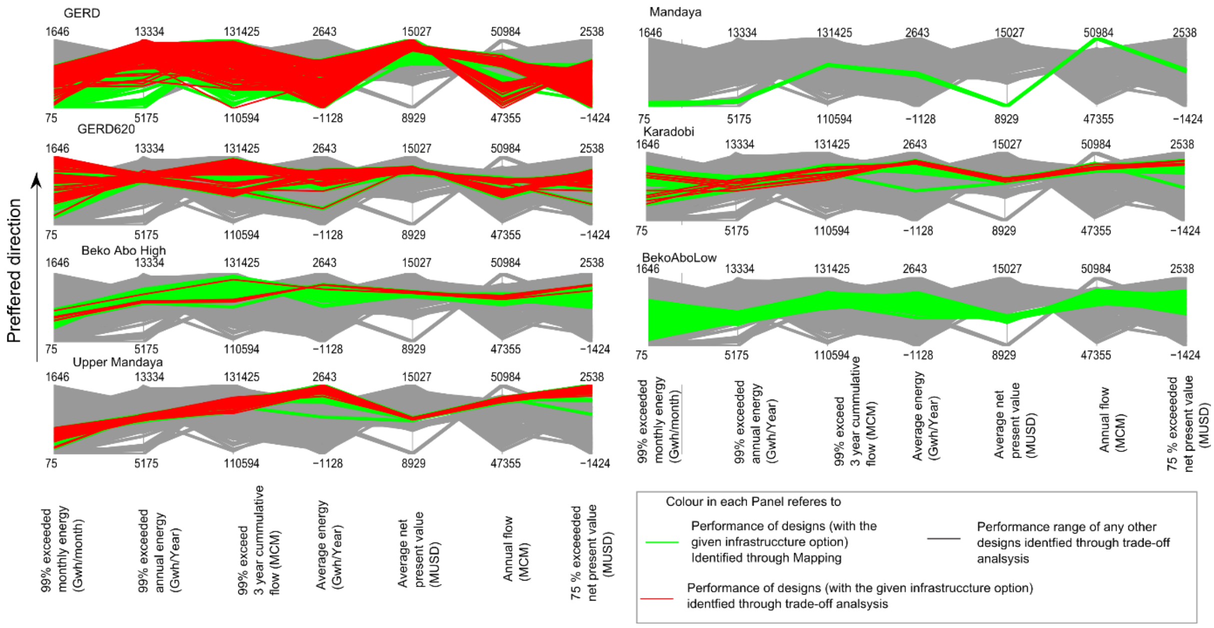


Figure 31 management designs for each of the infrastructure options (Panel name) identified through traditional many objective optimisations (red lines) overlaid over designs identified through the proposed approach of mapping management options (green lines). Green space in each panel show the performance space not explored by visualizing the solutions set generated through the conventional many objective optimization. Grey space is the entire performance space containing all infrastructure options and their possible management.

While some performance goals (downstream release goals) can be achieved with multiple infrastructure options, a decision on some infrastructure options could imply an irreversible loss in some performance goals (e.g., a decision to build GERD comes with a lost performance in possible net present value). Figure 32 summarizes the performance regret when committing for any one of the infrastructure options compared to what would have been possible under any of the other infrastructure options.

The GERD has zero regret in both firm annual, average annual and downstream flow metrics. However, it is associated with regret in the average and 75% exceeded net present value which would have been topped by a Mandaya dam choice (Maganta line). All designs show low regret in downstream flow metrics (i.e., 99% exceeded 3-year flow and average annual flow) because the downstream impacts are least dependent on infrastructure choice.

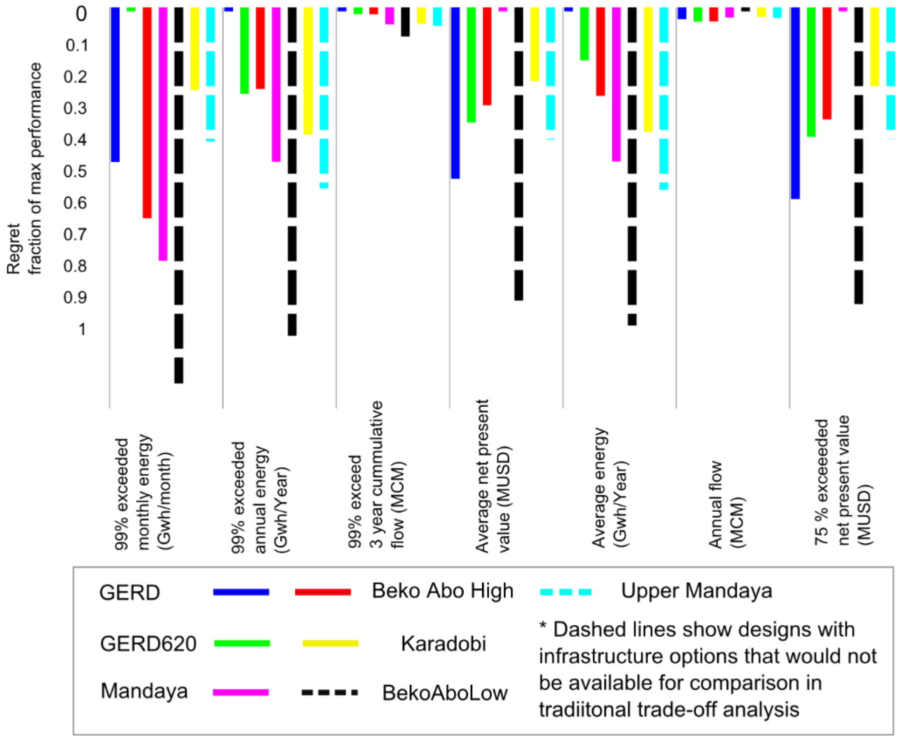


Figure 32 Highest performance possible under each of the infrastructure decision options (Shown with line colour) for the different performance metrics (columns).

Figure 33 uses the regret information of Figure 32 to evaluate the ranking of infrastructure options considering flexibility in management decision (e.g., in a build first and negotiate management later decision making approach). Say the GERD design is selected for providing high average annual energy potential than any other infrastructure. Figure 33 Panel A shows the GERD management alternatives with annual energy level higher than what is possible with the next best infrastructure option (GERD 620) for average annual energy generation. Similarly, if Mandaya had been selected for its financial feasibility performance, the Maganta performance space (Figure 33 Panel B) shows the performance possible under Manday with net present value higher than net present value possible with the next best infrastructure option (Karadobi). The dashed lines (red for GERD and Green for Mandaya) show designs which would performance less than the next best infrastructure option for the stated performance goals (i.e., violating the rational for their selection).

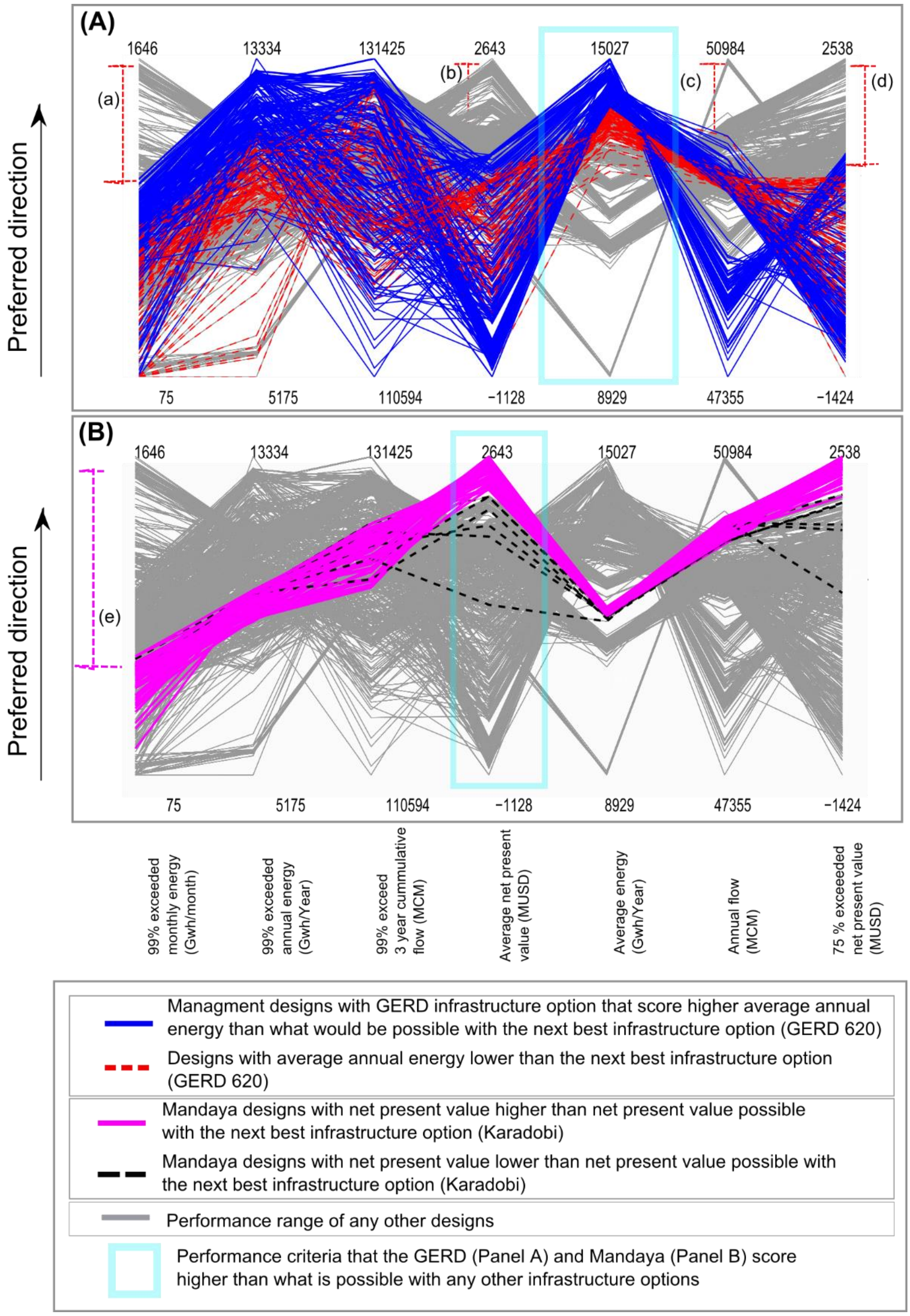


Figure 33 exploring performance regrets attached with infrastructure options. Lines coloured Blue (GERD) and Maganta (Mandaya) show management decision space that provide performance criteria of average annual energy and net present value being above the next best infrastructure decision. Red and Green coloured lines show where the performance is below the next best infrastructure. justifying criteria

For contexts where either the GERD or Manadaya infrastructure decision have been committed to for providing highest average annual energy and highest average net present value respectively. The Blue space shows the decision space left for negotiation with downstream countries which won't violate its justifying criteria for building GERD. Other related management designs (e.g., Red and Green lines) while possible, would potentially disqualify the infrastructure decisions in retrospect. By committing to the GERD infrastructure option Ethiopia has lost the performance opportunity a (firm monthly energy), b (average net present value), c (average annual flow) and d (75% exceeded net present value) that would have been available through other single reservoir options. If it had constructed the Mandaya however, a different set of regret - inducing the ability to generate energy and regulating the 3-year cumulative flow would have resulted (e.g., e).

8.5 **Discussion**

In this chapter we propose a computationally efficient approach that uses many objective evolutionary algorithms to allow performance comparison of all/selected set of dominated infrastructure options (when considered with their best possible management) with non-dominated (Pareto-optimal design) options. The many objective optimization and performance mapping approach is demonstrated on the proposed Blue Nile multi-reservoir system.

In many objective optimization, the best designs are shown as 'efficient' designs where any of the objectives cannot be further improved without deterioration on at least one other objective [*Olenik and Haimes*, 1979; *Mavrotas and Florios*, 2013; *Reed et al.*, 2013; *Woodruff et al.*, 2013]. Results show traditional trade-off analysis (e.g., Figure 30 Panel A) could fail to show how important alternatives (that would be preferred by stakeholders for unmodeled reasons) compare with the Pareto-optimal designs; In this case the GERD which is already under construction in Ethiopia. Mapping the extent of performance possible under each infrastructure option also shows more decision relevant information such as how a dominated infrastructure could be more suited to extend capability of the system in one or more performance metrics. The GERD designs ('f' in Figure 30 Panel A) is dominated for downstream flow and average net present value maximizing objectives and can do only as much as the Upper Mandaya option to maximize the 99% exceeded 3-year cumulative flow, however it does better than the Mandaya, GERD620 and other dam options which can explained by how larger storage size allows more regulation of flows.

The approach reveals the loss implied by selecting the next best dominated alternatives instead of the better performing non-dominated choices). Another use of the mapping approach is to visualise regrets involved with committing to infrastructure option while leaving their management (which could be dominant in affecting the balance of conflicting performance) to be negotiated later. For example, if maximizing the average net present value while ensuring at least 125 BCM was the decision criteria then design 'c' in Figure 30 would be the preferred choice of the Pareto optimal options. However, if the downstream release requirement is relaxed after the infrastructure is implemented then the regret will be npv(a)-npv(k) and not npv(b)-npv(c) as would be perceived from a conventional trade-offs analysis.

By implementing the GERD, Ethiopia availed itself flexibly to maximize several of the conflicting objectives including the average and firm annual energy and the 3-year cumulative downstream flow compared to what was possible with the other infrastructure options. However, opportunities to maximize the firm monthly energy the average net present value, average annual flow, and the 75% exceeded net present value that would have been available through other single reservoir options are lost. The downstream impact are strongly related to its management while the large capital cost and hence the financial benefits are results of an infrastructure choice which is already made.

Visualizing the performance dominated is possible because the dominated options are non-dominated for the dummy performance metrics (fopt,nfopt) that are modelled but not shown in the two-dimensional trade-off curve. The Pareto optimal solutions for the nine objective problem is first sorted for the four objectives (fAveNPV, fMinR_3, fopt, nfopt) then the resulting subset of Pareto-optimal designs visualised in 2 dimensions (net present value and downstream release in filling periods).

Many-objective optimization visual analytics facilitates a continual learning process wherein decision-makers come to understand a problem while seeking its solution and emphasizes learning through problem reformulation [e.g., *Woodruff et al.*, 2013]. By availing better representation of alternative infrastructure options to the ones identiefied as Pareto-optimal and their proximity to the the Pareto front, the mapping approach could avoid the potential bias that could result from decision making under a narrow definition of optimality. Moreover, failure to include popular interventions in systematic design assessments could affect stakeholder's confidence in the planning processes [*Lund and Palmer*, 1997; *Langsdale et al.*, 2013] and ultimately the success of multi-stakeholder group decision making. The results show the method to be computationally efficient for mapping performance of infrastructure options compared to the alternative where the many-objective optimization would need to be computed individually for all mutually exclusive discrete interventions options of interest.

The literature provides a rich set of examples where Pareto-optimality may not be sufficient for decision support. The need for 'soft systems paradigm analysis' approach for wicked, ill-structured or difficult to define problems to find solutions that are not necessarily optimal, but which are acceptable on separate dimensions without requiring explicit trade-offs has been recognised for several decades now [see *Mendoza and Martins*, 2006].

This includes problems with socio-economic or political facets that stakeholders may not be able to quantify and include in the multi-criteria assessment [*Nicklow et al.*, 2010; *Jeuland and Whittington*, 2014; *Rosenberg*, 2015]. Hence, focusing only on Pareto-optimal solutions may miss potentially important near optimal alternatives that may be attractive to stakeholders [*Madani et al.*, 2014; *Rosenberg*, 2015]. Techniques to identify potential solutions outside of the optimality measure include modelling to generate alternatives (MGA) which identifies promising solutions that perform within a specified tolerance of the optimal solution [*Brill et al.*, 1982; *Chang et al.*, 1982; *Gunalay et al.*, 2012]; and threshold detection to identify the range or points where changes in solutions matter

[*Brown et al.*, 2012]. Rosenberg [2015] proposes blended tools to generate, visualise, and interactively explore the near-optimal region of an optimised design problem. The approach involves first generating one or numerous alternatives, then the user guides further generation and visualization until reaching an acceptable end point. Some of the limitations in near-optimal approaches in the literature include the need to use iterative procedures which can be computationally intensive, and the need for human input which can be difficult in problems with large number of infrastructure options. Unlike the conventional near-optimal solution discovery methods, the approach differentiates discrete choice element of the decision space (e.g., infrastructure selection) from the management decision space; constraining the generated near optimal designs to decision relevant ones such as those that lead to a different infrastructure choice and hence potentially affect unmodeled socio-economic and political factors.

Other application of the method, which generates information on the extent to which management options can be adopted under each of the infrastructure options, could be in problem contexts where 1) minimizing regrets when alternative performance criteria are adopted in the future once an irreversible or costly infrastructure decision is made and implemented is important and 2) ensuring flexibility to deal with deeply uncertain future supply, demand and performance balance requirement.

Decisions are typically made despite various uncertainties; requiring robust plans which perform acceptably over a range of plausible futures. The recognition of deep uncertainty in planning for the future has given rise to a range of methods for decision-making, such as Robust-Decision Making and Dynamic Adaptive Policy Pathways that share emphasizing the multi objective nature of all water investments among their principles to encourage decisions that performs acceptably well under a wide range of plausible future conditions [*Matrosov et al.*, 2013; *Moody and Brown*, 2013; *Herman et al.*, 2014a]. Future studies should investigate how the application of the mapping approach to Many Objective Robust Decision Making [*Kasprzyk et al.*, 2013a] and Adaptive Decision Making approaches [*Walker et al.*, 2010; *Haasnoot et al.*, 2013] which use Many objective evolutionary search to generate alternatives for complex planning problems.

Recent studies indicate greater likelihood of increased Nile flow accompanied by higher variability, there is no concensus on how climate chage will affect the water availability and performance of exiting and proposed infrastructures. While the impact of filling of the new reservoirs is an immediate concern to downstream countries especially Egypt, given the growing population number and hence demand, no or insufficient storage infrastructure will leave the region vulnurable to impacts of variability without the option of adopting upstream reservoirs to augment downstream water availability in critical conditions. Future studies applying the mapping of management flexibility under each infrastructure portfolio approach could provide insight on the extent to which upstream dams can be adopted within the rational decision space.

MOEA search seeks to generate Pareto-optimal sets that both converge to the true Pareto front and are diverse (i.e., capture the geometry and extent of tradeoffs). The formulation for the mapping approach requires addition of at least two dummy performance objectives that could increase the computational requirement. Below we compare the computational requirements of the suggested mapping approach compared to the conventional many objective optimization approach. We use hypervolume [*Knowles and Corne*, 2002; *Zitzler et al.*, 2003] a metric that captures both diversity and proximity, to track how well the proposed problem formulation captures the performance of alternative options in a single MOEA search.

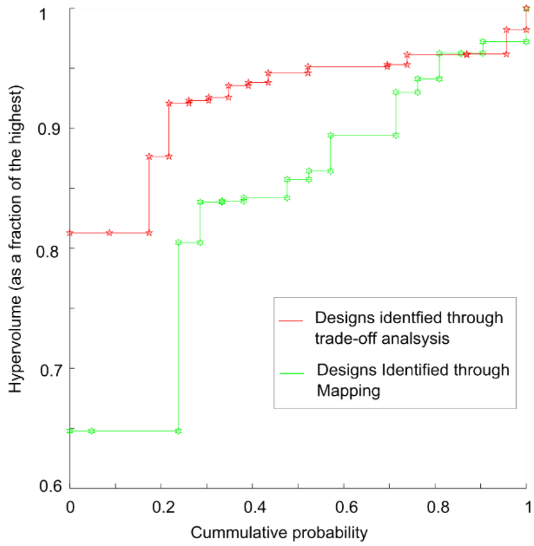


Figure 34 The cumulative distribution function of the hypervolume achieved under each run (as a fraction of highest Hypervolume) for conventional trade-off analysis (red colour) and under the proposed Mapping formulation (green). Here the hypervolume metric is tracking the overall dominated space in both the conventional and mapping formulation.

Figure 34 shows the cumulative probability distribution of the relative hypervolume scores of the performance frontier under the Mapping method approach (green) and that of the conventional trade-off analysis method (red) as the number of runs increases.

The performance of MOEA algorithms (i.e., whether a run approximates the true Pareto-front) can be affected by the initial conditions. Hence, Pareto-sorting of solutions from different random seeded runs is required to better approximate the true-Pareto front and provide the best overall reference set [*Kollat et al.*, 2008]. Given the high computational requirement of MOEA optimizations, the minimum number of function evaluations and number of random-seed analysis is usually sought that achieve highest possible hypervolume metric. The absence of improvement in the Hypervolume metric with additional generations and number of random seeds is taken as a proof of convergence.

Figure 35 presents a comparison of the computational requirement of the proposed mapping formulation and that of optimizing for each infrastructure options separately; which generate similar information.

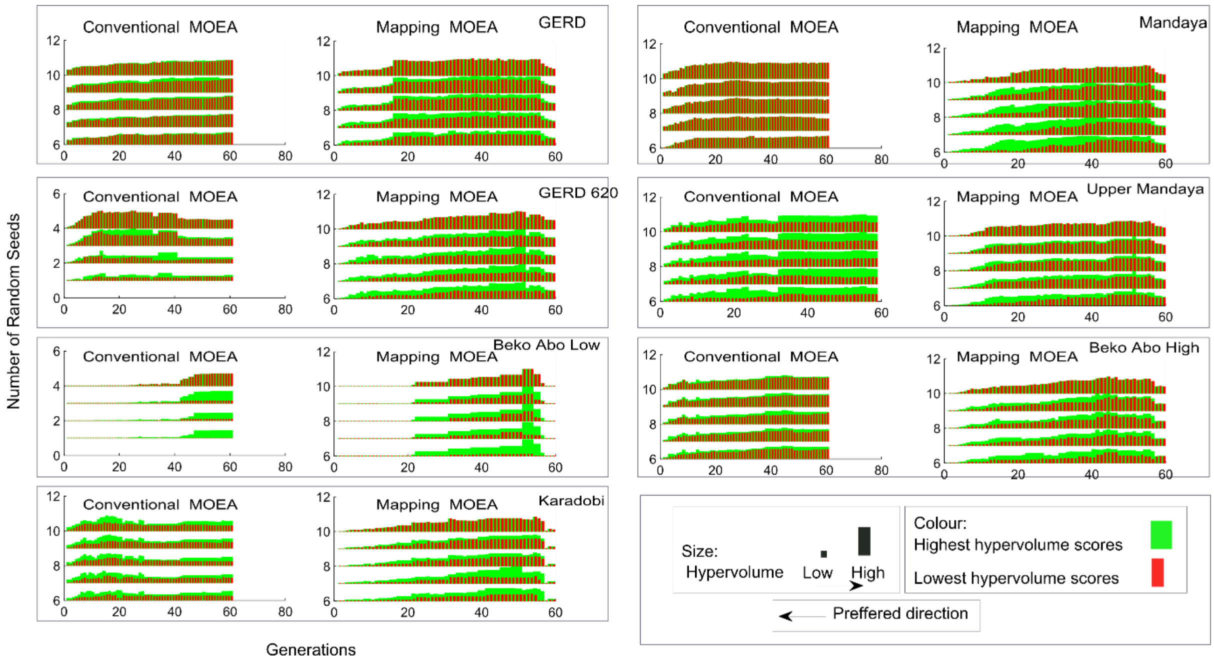


Figure 35 Each Panel show the hypervolume progression for the proposed the Blue Nile reservoirs under conventional MOEAs search and under the proposed Mapping formulation. Differing number of function evaluations (generations length) and random seed analysis is required to approximate the solution to the true (but unknown) many objective Pareto-front in the conventional MOEA formulation. The solution set achieve a monotonic improvement in convergence and diversity metric (the hypervolume) under the mapping formulation than in the conventional MOEA search for all dams.

Figure 35 shows the number of function evaluations (generations length) and random seed analysis required to approximate the solution to the true (but unknown) many objective Pareto-front in conventional trade-offs analysis and the proposed mapping approach. The solution set converges with fewer number of function evaluation and random seed analysis for some of the options (e.g., GERD, Mandaya, GERD 620 and Beko abo High) compared to the rest of the options. This indicates the number of function evaluation and random seed analysis required to achieve convergence to the true Pareto front and diversity among solutions (high hypervolume metric) vary depending on the input to a particular problem (i.e., reservoir characteristics, hydrologic variability) even under similar problem formulation.

To compare the computational requirement of the proposed re-formulation with a conventional MOEA approach where a separate optimization for each dam would be computed, we use the least number of random seeds and generations needed to achieve 100% of the maximum Hypervolume with 99% confidence as an indicator. For the case study, a maximum of 81 generations with upto 15 random seeds was required for the 7 dams. In contrast the proposed mapping approach provides the equivalent information with a maximum of 51 generations and 9 random seeds. Hence the approach provides a reduction of up to ((91x7)-51)/ (91x7) = 92% in number of generation and ((15x7)-9)/ (15x7) = 91% in number of random seeds needed. The computational requirement of the Mapping approach could be reduced by up to (91-51)/ 91 = 44% in number of generations and increase by (9-7)/ 9 = 22% in random seeds compared to that of the conventional trade-off analysis.

8.5.1 Limitations

In this study, we focus on reservoir operators' flexibility to change operating policies only for the purpose of reservoir fillings. Considering operating rules that change based on hydrologic conditions (e.g., in recent years) would likely attain more efficient trade-offs and change which investment schedules are deemed Pareto-optimal. Other limitations include that the study considers limited number performance objectives and ignores peak power, and firm monthly and annual energy requirements. Considering uncertainty associated with inflation and variation of installed power capacities with storage size could provide more decision relevant information.

9 Adaptive operating rule

9.1 Introduction

Release rules help manage reservoirs under variable inflows and should represent the ability of reservoir operators to incorporate information from various sources. However, simplicity of use and computational convenience are often the overriding factors for the type of reservoir operating rules adopted. Chapter 5 and Chapter 6 demonstrated the performance increase when flexibility of reservoir operating rules are considered in the search for best composition of multi-reservoir system and their investment scheduling analysis. However, the change in operating rule are assumed to be affected only by a change in the infrastructure state of the system. Recent literature on reservoir operating rule advocate using adaptive rules to mitigate the negative impacts of changing environmental conditions. Feng et al. [2017] derive adaptive operating rules as explicit functions of changing hydrologic factors. They use a deterministic optimization model to obtain optimal water releases, which are then used as input in the reservoir simulation model. Herman and Giuliani [2018] propose a framework where policies are formulated as binary trees, using a simulation-optimization approach. In their study candidate operating rules are generated across an ensemble of climate scenarios, incorporating indicator variables describing longer-term climate shifts to investigate opportunities for adaptation. These applications attempt to forecast future states of the water system.

This chapter proposes to use pluri-annual information on recent reservoir management to design adaptive multi-year reservoir operating rules that balance the benefits of a large reservoir with its downstream impacts. The approach is illustrated with the Grand Ethiopian Renaissance Dam (GERD). The problem is formulated as a many objective problem whose decision variables are the design of the alternative rules and the conditions (triggers) under which they should be used. Downstream impacts are evaluated via the reliable (99% exceeded) 1-, 2- and 3-year cumulative releases. Upstream performance measures are the average and 99% exceeded statistical measures of annual and monthly hydropower production. Performance and computational implications of the adaptive versions of the Radial basis function and piece-wise linear operating rule are discussed.

This chapter investigates the potential of multi-year adaptive operating rules for balancing the primary purposes of a large reservoir (or reservoir system) with the interests of downstream users. In addition to traditional information sources on the state of a reservoir system (i.e., storage level, inflow and time of the year), the suggested approach integrates explicit information on recent releases going back several years to base current release requirements.

Given the implication of operating rule forms on performance and computational tractability, the viability of two widely used operating rule structures (i.e., Radial Basis function and Piece-wise linear) for adaptive management formulation are teste.

9.2 **Multi-year adaptive operating rules**

9.2.1 Definition

An operating rule is a map of release decisions as a function of available information. In formal terms, reservoir operations are generally modeled in discrete time steps, so the release decision R_t corresponds to the total quantity of water required to flow downstream during that time step. R_t is expressed as a function of the vector α of variables that contain information that is relevant to the decision:

$$\mathrm{R}_t = \mathrm{f}_t(\alpha) \quad (1)$$

where the function $f_t(.)$ is in fact the release rule. It could differ throughout a year depending on the seasonal variability of inflows, release demands, and storage capacity.

To adapt operating rules to events from the past few years, we adopt the adaptation glossary proposed by Haasnoot *et al.* [2013] . *Signposts* are the variables to watch in order to decide which course of action to take, and *triggers* are the threshold values of these variables beyond (or below) which adaptive action must be undertaken. In the context of multi-year adaptive rules in large reservoirs or cascades of reservoirs, signposts refer to variables that reflect inflows and operations from the last few years; in the case of a single reservoir for instance, cumulative release from the past year carries information on both inflows and reservoir operations.

Therefore, a multi-year adaptive release rule is defined by *M* signposts $(\beta_t^m)_{1\le m\le M}$ and many associated triggers $(\gamma_t^m)_{1\le m\le M}$:

$$\mathrm{R}_t = \mathrm{f}_t(\alpha, \beta_t^1, \beta_t^m, \ldots, \beta_t^M, \gamma_t^1, \gamma_t^m, \ldots, \gamma_t^M) \quad (2)$$

9.2.2 Example

Consider a simple piece-wise linear operating rules (Figure 36) of the form:

$$, \qquad R_{St} = \frac{R\max - R\min}{S\max - S\min}(Storage) + R_{\min} \quad (3)$$

Such rules have been used in past studies where operation rules are determined by evolutionary algorithms [*Oliveira and Loucks*, 1994; *Otero et al.*, 1995; *Arena et al.*, 2010; *Hurford and Harou*, 2014; *Geressu and Harou*, 2015]. Decision variables are the coordinates of the extremities of the segments that define the release rules (e.g. A, B, C inFigure 36, totalling 6 variables).

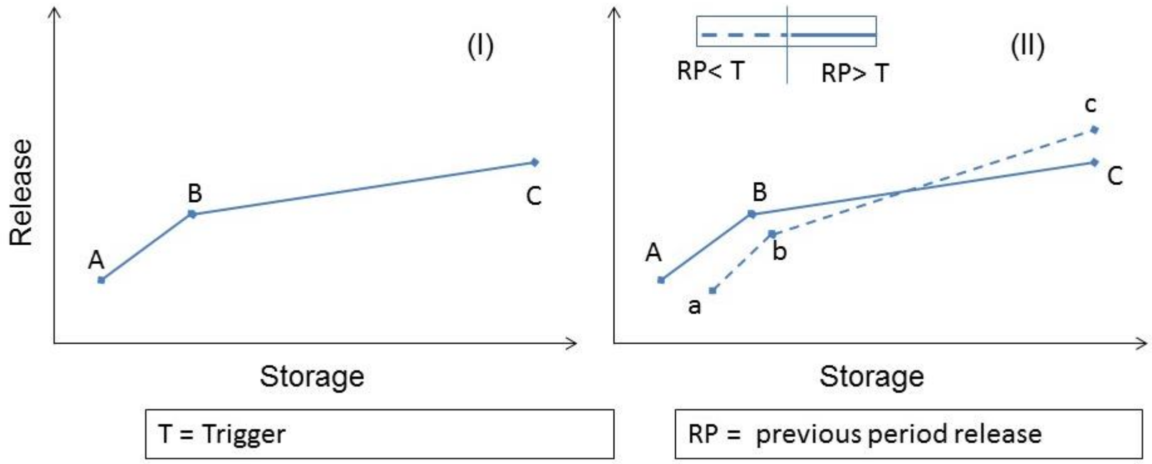


Figure 36 Static storage based release rule (Panel I) and Adaptive operating rule (Panel II) with a single signpost. If the variable is below a trigger (threshold value), then the adaptive rule (dashed line) is used instead of the original rule (continuous line).

Let us assume that release is determined adaptively using total release over the previous calendar year as a signpost. Then noting θ January of the current year, signpost β_t reads as follows, assuming a monthly time step:

$$\forall t \in [\theta, \theta + 11], \beta_t = \sum_{\alpha=\theta-12}^{\theta-1} R_\alpha \qquad (4)$$

and the associated trigger is a threshold value on the signpost. For instance, if release is below the threshold T on Figure 1, then an alternative release rule is triggered. Designing multi-year adaptive rules is more complex than standard rules, because one has to design a new rule (6 decision variables on Figure 1) if a threshold (an additional decision variable) is crossed. Other examples of signpost include total release over the past two calendar years, or any other indicator aggregating past releases.

9.2.3 Many-objective search for adaptive rules

Multi-year adaptive operating rules are designed to balance reservoir objectives with downstream needs. Formulating this design problem as a many-objective search problem enables managers to understand the trade-offs between potentially conflicting objectives – if they exist.

A many-objective problem consists in finding a vector x of decision variables that maximises a vector of n objectives $F(x)$, and that satisfies to equality and inequality constraints (e.g., Kaspryczk et al., 2013):

$$\underset{f \in \Omega}{Max} F(x) = (O_1, O_2, ..., O_n) s.t \begin{cases} c_i(x) = 0 \forall i \in [1, q] \\ c_j(x) = 0 \forall j \in [1, r] \end{cases} \quad (5)$$

where Ω is the decision space Ω_k are the individual objectives, and q and r are the numbers of equality and inequality constraints, respectively. When it comes to specifying operating rules, **x** is a vector of parameters that enable the determination of the release rules at different times during a year (see Section 9.2).

Such problems are classically solved using multi-objective search techniques where an MOEA [*Kollat and Reed*, 2006; *Reed et al.*, 2012] is coupled with a simulation model of the water resources system, e.g., [*Matrosov et al.*, 2011]. Visual analytic trade-off plots can then be used to present analysis results [*Reed and Kollat*, 2013; *Vitiello et al.*, 2012]. Heuristic search results cannot be mathematically proven to be Pareto-optimal hence the term 'Pareto-approximate' [*Datta et al.*, 2008].

9.3 Problem formulation 5

The problem is formulated as a 7-objective optimization problem aimed at finding the parameters **x** defining the operating rule.

$$Maximize \quad F_x = (fR_1, fR_2, fR_3, fEave, fEave_{Min}, fE_{Min}, fEm_{Min})$$

(6)

$$\forall x \in \Omega$$

Where F_X is the target function, and these objectives are:

fR_1	=	$quantile_{i \in (1,...,Ts), j \in (1,...,F)} \{R1_{i,j}, 0.99\}$	99% exceeded annual release
fR_2	=	$quantile_{i \in (1,...,Ts), j \in (1,...,F)} \{R2_{i,j}, 0.99\}$	99% exceeded 2-year cumulative flow
fR_3	=	$quantile_{i \in (1,...,Ts)\, j \in (1,...,F)} \{R3_{i,j}, 0.99\}$	99% exceeded 3-year cumulative flow
fE_{Ave}	=	$quantile_{i \in (1,...,Ts)\, j \in (1,...,F)} \{Eannl_{i,j}, 0.5\}$	Average annual energy generation
$fEAve_{Min}$	=	$quantile_{i \in (1,...,F)} \{... (quantile_{j \in (1,...,Ts)} \{Eannl_{i,j}, 0.5\}),... 0.99\}$	99% exceeded average annual energy generation of the dam in its life time from across the 30 hydrologic traces
fE_{Min}	=	$quantile_{i \in (1,...,F), j \in (1,...,Ts)} \{Eannl_{i,j}, 0.99\}$	99% exceeded annual energy generation
fEm_{Min}	=	$quantile_{i \in (1,...,F), j \in (1,...,Ts)} \{Em_{i,j}, 0.99\}$	99% exceeded monthly energy generation

E_t	=	$\rho h_t q_t$	Energy generation at month t; a function of head and discharge and a constant that depends on gravity and length of month
$Eannl_y$	=	$sum(E_t, t \in y)$	The sum of monthly energy generations in the year 'y'
$R1_t$	=	$\sum_{t-12}^{t} R_t$	Cumulative release of past 12 months at time t
$R2_t$	=	$\sum_{t-24}^{t} R_t$	Cumulative release of past 24 months at time t
$R3_t$	=	$\sum_{t-36}^{t} R_t$	Cumulative release of past 36 months at time t

F	Number of synthetic hydrologic realizations

Performance metrics are computed over 30 hydrologic traces of inflow time series and in a time window that is 10 years to 80 years from the start of the simulation. This is to ensure the performance are not affected by the filling period performance of the dam; which this study does not deal with. Decision variables are the design parameters of the operating policy (static or adaptive); they have been enumerated in the previous section.

9.4 **Results**

The goal of this chapter is to propose and demonstrate a multi-year reservoir operating strategy that is explicitly responsive to recent hydrologic conditions.

We assess the reservoir performance under seasonal operating rules that are invariant from year to year in comparision to multi-year reservoir operating strategies with responsiveness to recent hydrologic conditions. This section first presents performance comparison between static and adaptive Radial Basis function (RBFS, RBFA respectively) and static and adaptive Piece-wise linear (PWLS, PWLA respectively) storage based operating rules (Section 9.4.1). The best operating rule designs under each formulation are shown as 'efficient' designs where any of the objectives cannot be further improved without deterioration on at least one other objective [*Olenik and Haimes*, 1979; *Nicklow et al.*, 2010; *Mavrotas and Florios*, 2013]. This will be followed by storage time-series details of the static operating rules and the proposed adaptive operating rule (Section 9.4.2). Section 9.4.3 presents the computational requirements of the MOEA searches.

9.4.1 Performance comparison under standard and adaptive operating strategies

Figure 37 shows comparison of performance under the four operating rule formulations when one of the multiple performance objectives is to be prioretised.

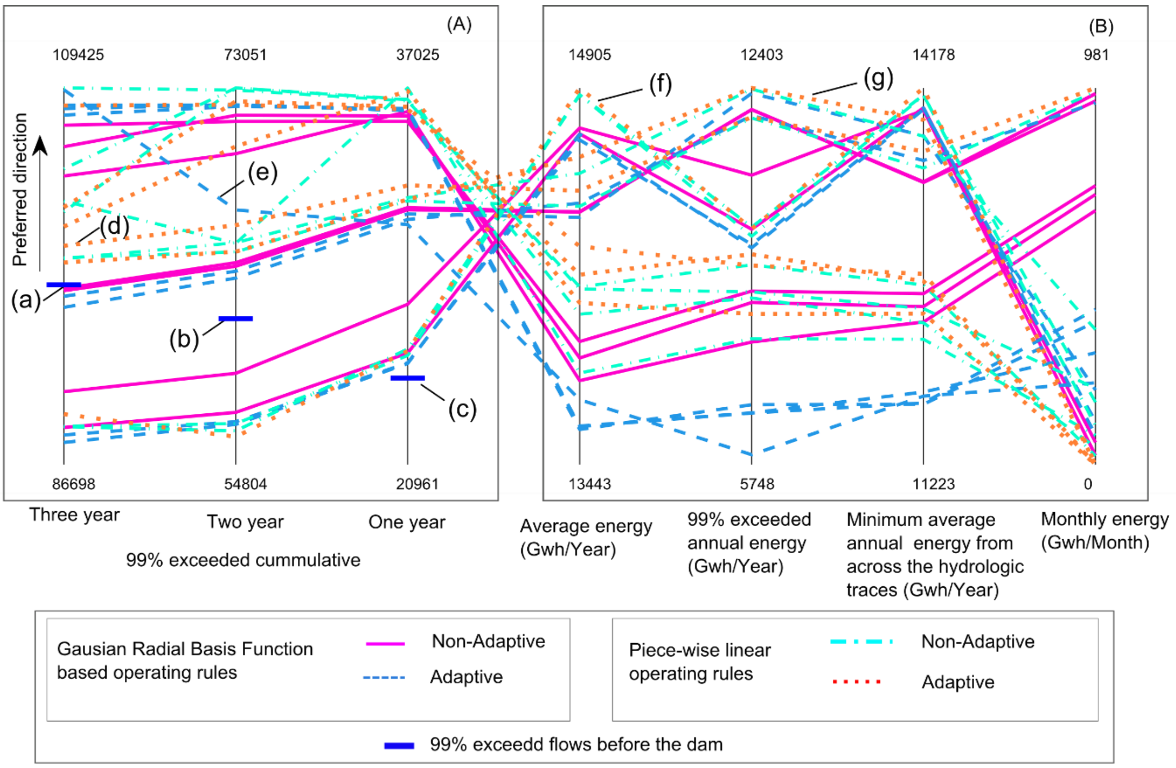


Figure 37 The adaptive piece-wise linear operating strategy can maximise all the energy generation metrics (Panel B). An adaptive radial basis function based operating rule (-) are best for maximizing the reliable three year downstream flow. The non-adaptive piece-wise linear version can perform higher in maximizing the reliable one and two year flows.

Figure 37 compares performance of the GERD under different operating rule formulations where one performance goal is prioritised over the others. In both the static and adaptive operating strategies, the performance objectives of interest to Egypt (Figure 37 Panel A) and Ethiopia (Panel B) are conflicting; with an increase to one resulting in a reduction of the other. Of the performance objectives of interest to Ethiopia (Panel B), management options that maximise the firm monthly ('d'), and firm annual energy generation ('g') enhance downstream benefits (i.e., the reliable 1,2 and 3-year cumulative releases) the most compared to the ones that maximises the average annual energy generation. Maximizing the average annual energy leads to only minimal improvements of one and two-year cumulative releases and also reduces the reliability of the annual and monthly energy generation.

An adaptive radial basis function based operating strategy achieves the highest reliable cumulative 3-year release the energy performance (design 'e' on Figure 37) compared to a static radial basis function and both static and adaptive piece-wise linear operating rule forms. However, this will be accompanied by low upstream benefits; with the reliable annual energy generation being affected the most.

Figure 38 show the implication of the operating rule formulation on the benefit trade-offs when compromise between selected two performance objectives at a time is sought.

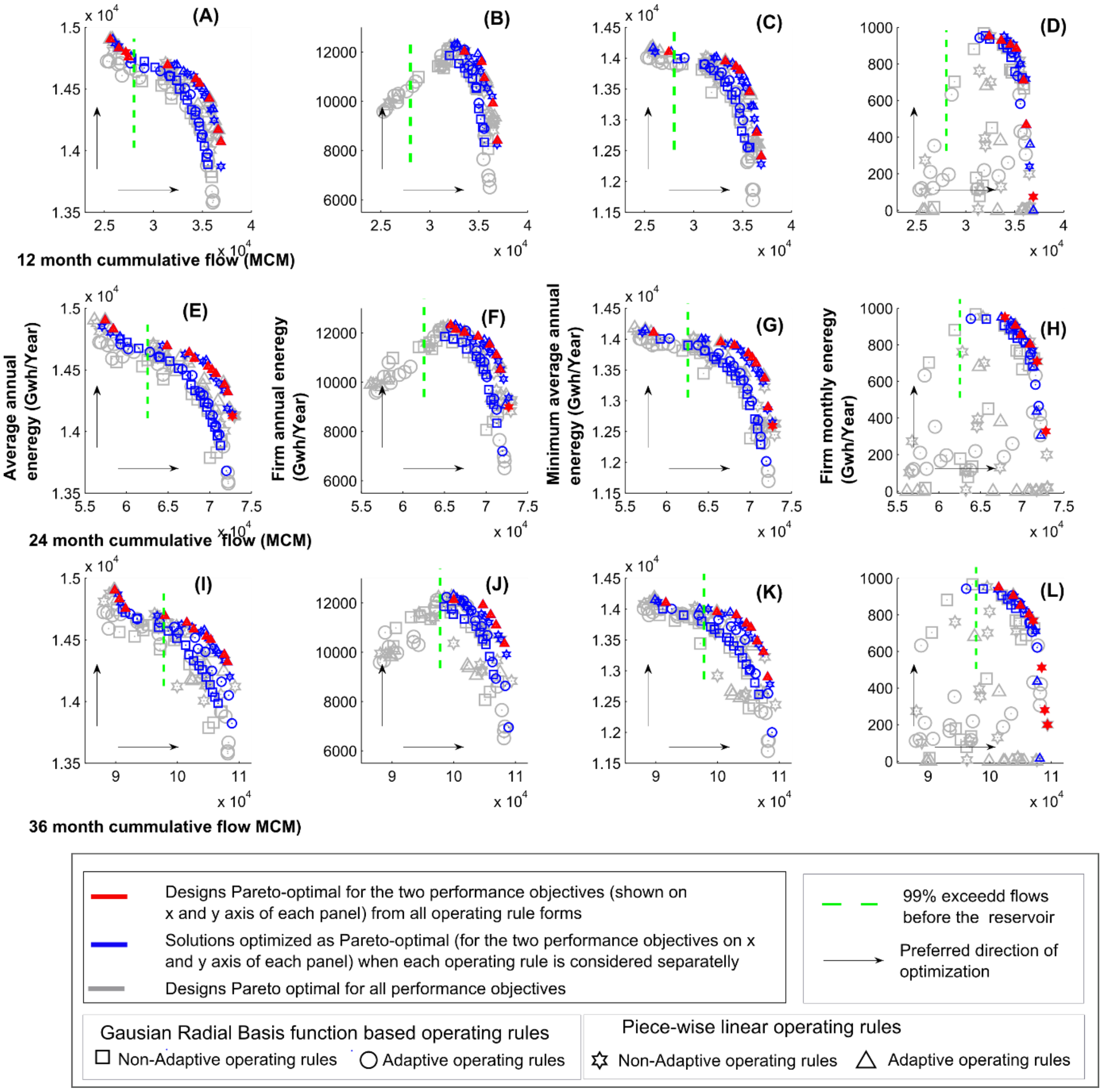


Figure 38 efficient trade-offs when two performance objectives are considered at a time. For both Radial basis function based and piece-wise linear operating rules performance improvement of adaptive operating strategy over the static operating rules is less than 1%. The piece-wise linear operating rules (both static and adaptive) can improve the minimum downstream release with less sacrifice in energy generation than would be imposed by the radial basis function based operating strategy.

9.4.2 Storage requirement implied by operating rule forms

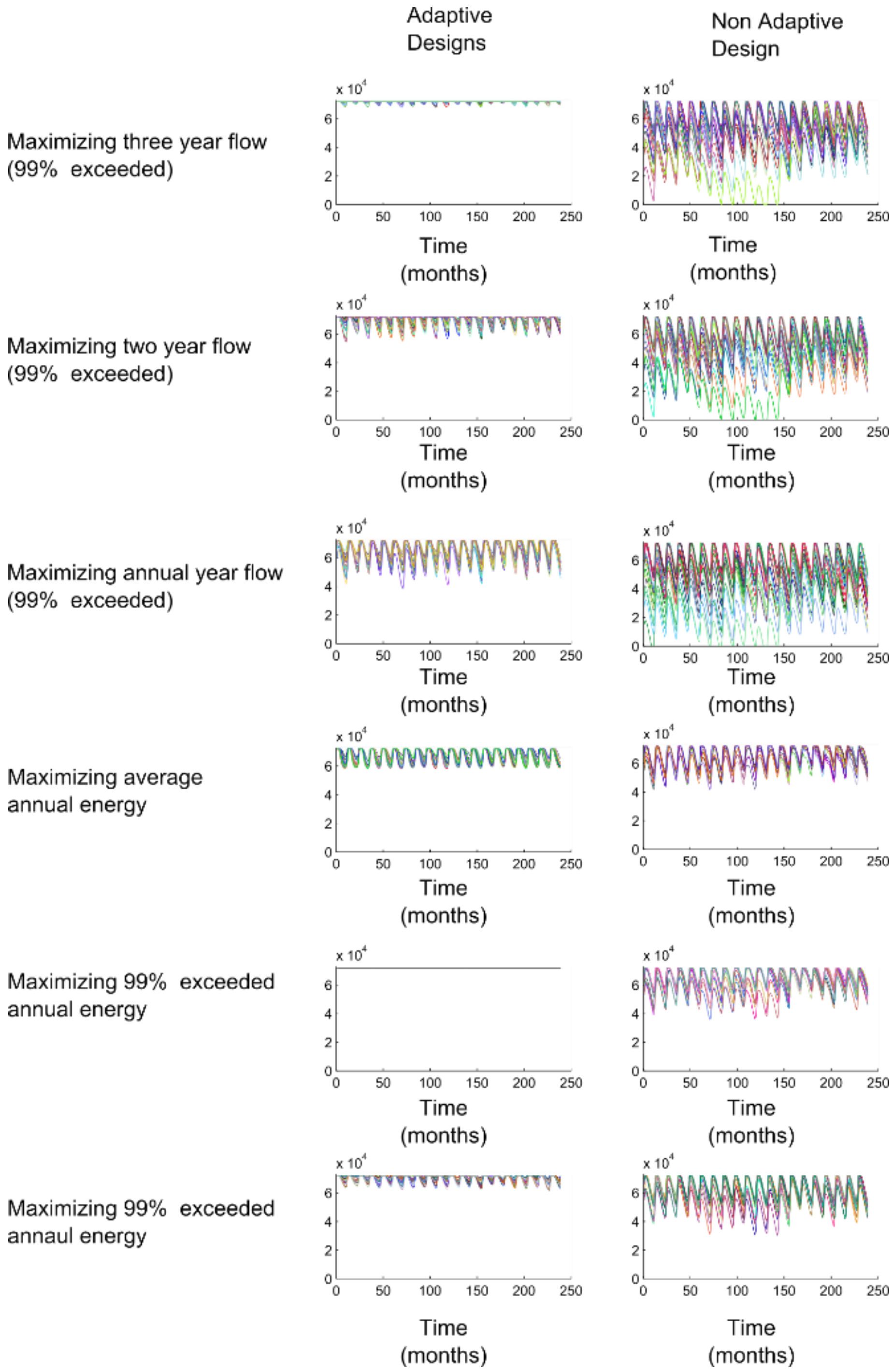


Figure 39 Projected storage under various management strategies and traces of inflow hydrology in the steady state operation (20 years after filling period of dams). Adaptive operating strategies (shown in Panel A) allow the storage level to be maintained higher compared to static operating strategies (Panel B). conventional static operating strategies could result in high fluctuation of the GERD storage level while adaptive operating rules suggest (enable) maintaining a high storage level.

9.4.3 Comparison of computation requirements

Performance of many objective evolutionary algorithms is stochastic, with no guarantee that the true (but unknown) Pareto front will be achieved [*Zatarain Salazar et al.*, 2017]. Multiple runs with randomly seeded initial points are required to ensure solutions are not affected by their initial populations. The hypervolume metric has been popular for assessing the convergence and diversity of populations in many objective optimizations runs. The absence of improvement in the Hypervolume metric with additional generations and number of random seeds is taken as a proof of convergence.

Section 9.4.1 showed how the solutions sets under different operating rule formulations achieve differing levels of performance. The diversity of solutions also depends on the operating rule formulation and could be uncorrelated to the performance. For example, the adaptive piece-wise linear operating rule designs (‘a’ to ‘c’ on Panel E on Figure 38) achieve higher performance but low diversity compared to the radial basis function based operating rule (‘b’ to ‘d’ Panel E on Figure 38). Hence comparing of the hypervolume score of different formulation is not sufficient to select the best among them.

Figure 40 shows the runtime hypervolume dynamics for each of the operating rule formulations. The adaptive operating rules using Radial basis function, which has larger number of decision variables and inter-dependence between decision variables, require more function evaluations and Pareto-sorting among a larger number of random-seeded runs to achieve convergence. The static Piece-wise linear operating rule and adaptive Radial basis function show a monotonic improvement of hypervolume with number of generations and higher reliability of runs achieving the ideal high hypervolume. The absence of improvement (Blue boxes in Figure 40) in the hypervolume indicator is taken as a proof of convergence.

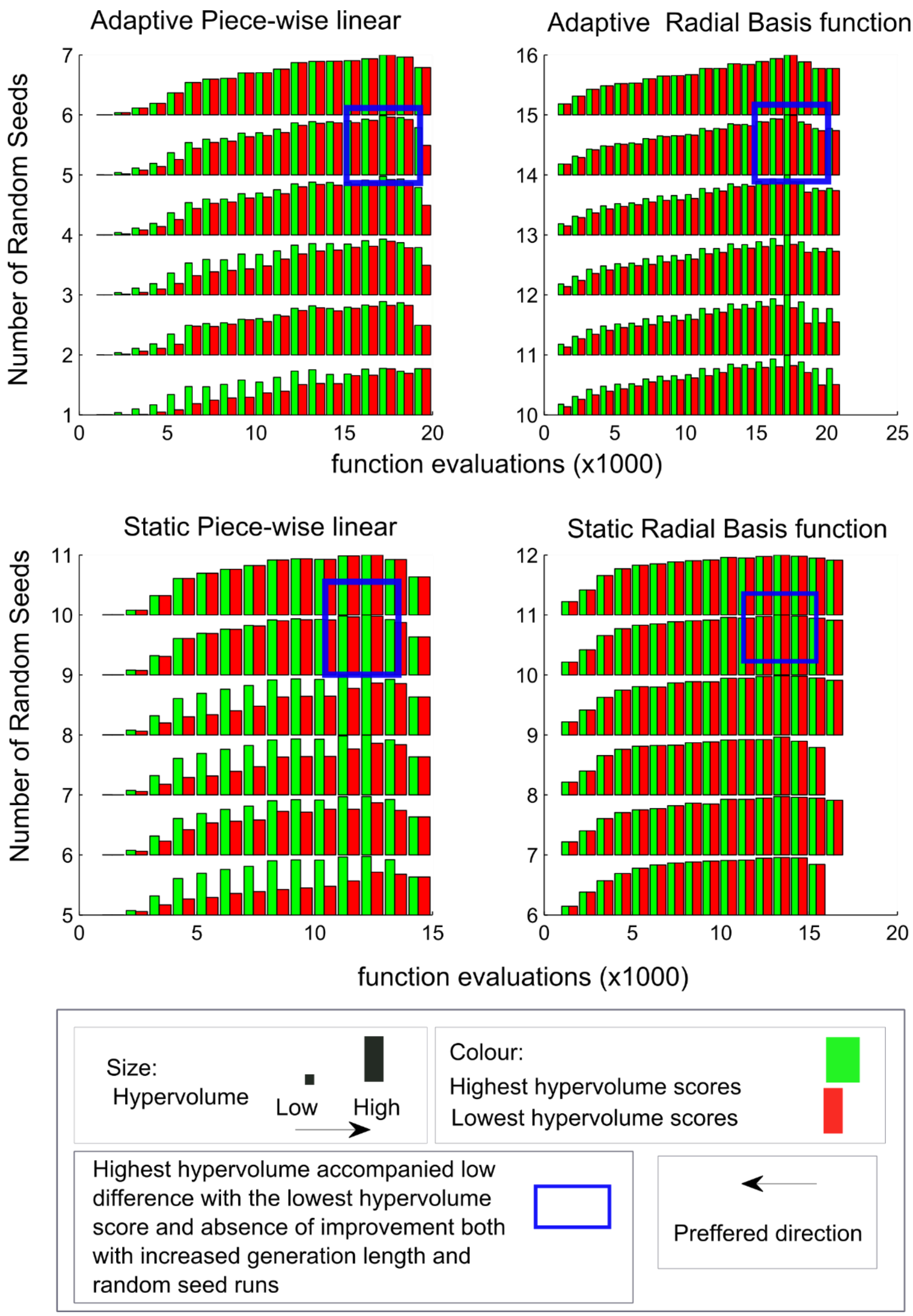


Figure 40 Runtime hypervolume dynamics for each of the operating rule formulations. The minimum function evaluations and number of random-seed analysis (shown in blue boxes) that achieve highest possible (shown with size of green boxes) and lowest (shown with red colour) hypervolume metric are taken as a stopping criterion.

9.5 Discussion

We investigate the application of adaptivity (the inclusion of explicit information on recent past performance) on the two widely used operating rule structures in the reservoir operating rules literature (i.e., Radial Basis function and Piece-wise linear) and discuss the implication on performance and their computational tractability.

The results show the GERD can produce an average of 14.9 Twh/year ('f' in Figure 37). The side benefit of regulation by the reservoir (if design that prioritises firm monthly energy 'd' in Figure 37 is selected) will be an increase in annual, two and three-year cumulative releases by 8, 3 and 2BCM respectively. The results show, compared to radial basis function based operating rules, piece-wise linear (standard operating rules) allow better performance if reliability of downstream flow is prioritised. The piece-wise linear operating rules are also more parsimonious (i.e., require less parameters) and hence require less computational resources to optimise.

Figure 37 and Figure 38 shows the trade-off between maximizing the average annual energy and maximizing the reliable monthly energy; with monthly energy generation under a management design that seeks to maximise the average annual energy (design 'f' in Figure 37) having low monthly energy reliability. Seeking high reliable monthly generation and in the process improving the reliable downstream cumulative flows of one to three years requires a sacrifice in the average annual energy generation of 500 Gwh/year from the maximum possible of 14900 Gwh/year (a change from 'f' to 'd'). Figure 37 and Figure 38 shows the standard piece-wise linear operating strategy can improve the energy generation and downstream release performance simultaneously compared to performance under Radial basis function based operating rules. If the dam was to be operated with maximizing downstream benefits as a priority, the one, two and three year reliable flows could be enhanced by 8, 10 and 16 BCM, which will come with the sacrifice of 5% in average annual and 25% in firm annual energy generations.

Figure 39 showed the storage level under various management designs; with some designs maintaining high storage levels throughout the year and others allowing it to fluctuate. These differences are important as the steady state storage requirement impacts the amount of water needed to fill the reservoir; and could be substantial. This chapter assesses the relevance of adaptive operating rules that use explicit information of recent past performance as an indicator of the continuing hydrological state of the water system.

The results show the Radial basis based adaptive operating rules are computationally intensive compared to all other forms of operating rules. The recommended operating forms will depend on the balance of performance sought after consultation with stakeholder and available computational resources. Comparison of the Radial basis function and piece-wise linear storage based operating rule imply the need to consider alternative operating rule formulations for reservoir system but do not recommend any one over the other as the dominance of once over the other could be problem specific.

9.5.1 Limitations

This work focused on steady-state reservoir management for inter-annual variability. Climate change impact and economic uncertainty could be factors for adaptive reservoir system expansion and management [*Eriksson and Weber*, 2008; *Giuliani et al.*, 2016]. Future work could include considering the adaptivity in reservoir operating rules when screening among alternative storage designs and their schedule of implementation. The impact of various management strategies of the GERD on existing reservoirs in the downstream system such as the High Aswan Dam will depend re-operations of the reservoir in Sudan and Egypt and demand management strategies adopted in the countries[*Wheeler et al.*, 2016]. A number of downstream decision levers such as reduction of the irrigation abstraction and a change in seasonal pattern of irrigation demand in Sudan and Egypt will also need to be investigated. The performance metrics (i.e., energy generation and cumulative downstream releases for one, two and three years) used here relate to stakeholders who have conflicting interests and dispute each-others water share claims. Hence, while these can be informative of likely compromises. The study does not purport to recommend a particular design as best.

10 Negotiation

10.1 Introduction

Chapters 5 , 6, and 9 demonstrated the performance increase when the reservoir system design (e.g., multi-reservoir composition, sizing), investment scheduling and management are considered simultaneously; and the efficient trade-offs for multi country performance metrics. Chapter 5 showed the use of many objective optimization and visual analytics in finding the efficient trade-off between multiple conflicting objectives and filtering the best designs that achieve various balances among the many objectives. All plots in Chapter 5 maximise benefits from the country where the dams are located (in this case Ethiopia). Here we consider the whole decision space for inter-country collaboration (i.e., with dams in once country being possibly designed and managed to maximise performance in another country). These can help stakeholders to understand the trade-offs between various performance objectives, and also to work out a compromise amongst themselves [*Kasprzyk et al.*, 2013a; *Hurford et al.*, 2014; *Geressu and Harou*, 2015].

However, negotiations on water systems shared by various groups may not be limited to compromises in the physical parameters (e.g., type, location and size of reservoirs) or management of the system (e.g., Chapter 9) but may need to consider coordinated use of resources (e.g., cost or power sharing) in finding a compromise solutions. Such multi-stakeholder negotiations could require cost and benefit sharing and hence identifying the relative cost and benefit of various options to the different countries.

However, agreeing on the relative value of water and its services to different countries could be difficult. A more practical approach could be to allow each country to independently evaluate the benefit and impacts of system designs and coordination strategies as they see fit. The other challenge is the fact that a negotiation on coordinated use or resources has to rely on a pre-selected system design. Because the selection of a system design to start negotiation on will affect or is perceived to affect the benefit distribution for the negotiating parties, agreeing on a particular system design to start negotiation on can be difficult. In these contexts, a negotiation support mechanism that could incorporate multiple performance metrics of interest and the relative country preferences for these could help identify consensus solutions.

To address these challenges, this chapter proposes a negotiation support framework for new infrastructure investments in shared river basins by combining the many objective optimization and visual analytic approach with the multi-criteria selection. A post optimization weighing of performance objectives is used to represent stakeholders' value judgments in subsequent automated searches. This is done after the initial many objective optimization that establishes the efficient trade-offs and identifies the Pareto-optimal designs.

Stakeholder preferences are represented in the automated searches as a remedy to the challenge of stakeholder fatigue with iterative procedures in negotiations that consider many alternative system designs and coordination strategies.

The proposed negotiation framework allows stakeholders to provide their own criteria weights for performance objectives, without having to agree on weights a priori with competing negotiators.

Given the challenge in capturing the exact preference information (value judgment of stakeholders), and sensitivity of multi-criteria analysis results to criteria weights, the suggested approach includes robustness analyses. This chapter builds on the results of Chapter 5 (as it is simpler to use compared to subsequent chapters) in a proof-of concept demonstration of the relatively complex method. This chapter demonstrates the usability of common many-objective optimization and visual analysis techniques to help with various stages of the negotiation process (i.e., preference elicitation, automated search for acceptable solution and robustness analysis) in addition to the knowledge generation aspects demonstrated in previous chapters.

10.2 **Method**

The approach follows 5 steps qualified as 1. Problem formulation 2. Search & deliberation, 3. Preference elicitation, 4. Search & negotiation and 5. sensitivity analysis; we summarise them in section 2.1 and in more detail in subsequent sections.

10.2.1 Proposed 5-step infrastructure negotiation framework

1. The first step consists formulating the problem (e.g., identifying performance metrics relevant to stakeholders', system constraints, alternative interventions and exogenous scenarios). Agreeing on a single problem formulation could be difficult in multi-stakeholder problems [e.g., *Di Matteo et al.*, 2017]. Problem formulation affects the predictions of the consequences of alternative solutions and consequently which solutions are considered 'optimal' [*Roy*, 1991; *Kasprzyk et al.*, 2009]. Quinn et al. [2017] suggest a 'rival-framings' framework that helps mitigate inherent biases of alternative problem formulations by interrogating multiple competing hypotheses of how complex water management problems should be formulated. [*Piscopo et al.*, 2015] suggest an iterative optimization approach where problem formulation is updated based on the results of prior rounds of optimization. Wu et al. [2016] introduced a framework for including stakeholder input in multi-objective water resource optimization problems.

2. A stakeholder-trusted system impact simulation model help evaluate system outcomes of any particular system design. The impact model is linked to a many objective search algorithm [*Reed et al.*, 2013] to help find efficient designs given multiple criteria. The first many-objective optimization generates approximately Pareto-optimal designs for performance measures of interest to stakeholders (Section 10.3.1). The generated efficient designs are displayed in interactive visual analytic plots that show the performance and their trade-offs implied by alternative designs. At this stage, stakeholders would be able to see possible coordination options and what infrastructure and management designs would allow that. However, it's unlikely for different groups to select the same asset bundles for development, the framework has 3 further steps.

3. Next, each of the stakeholders is asked to articulate their priorities between objectives (i.e., weigh the performance metrics) including those made possible only through coordination with other stakeholders. The purpose of eliciting

preference information is to document stakeholders value judgments coherently so that it can be used to represent their preferences in automated searches in later stages; avoiding user fatigue.

Two approaches can be used for this purpose. The first is to elicit a number array representing how the stakeholders weight the performance objectives directly. Information on how each of the stakeholders prioritises (weigh) the performance objectives can be used to generate an aggregate multi-criteria score for each system design allowing them to rank the system designs. The weight elicitation process can be supported by visual analytics tools using the performance trade-off information generated in Step 2 so that stakeholders could iteratively select criteria weights which reflect how they would rank the system designs (Section 10.3.2). Optionally, each stakeholder groups may be asked to rank all or a subset of Pareto-optimal options (infrastructure designs and their management options identified in step 2) along with another subset of the Pareto-optimal options bundled with coordination options. The criteria weights can be inferred (e.g., through regression) from the ranking information. The constructed set should be diverse enough to reflect the system performance trade-off and allow the decrypting of the value judgment of stakeholders once they indicate how they would rank the elements of the set. How stakeholders rank alternative system design-coordination options or alternatively weight the performance metrics indicate their priorities and the performance trade-off they are willing to accept.

In a competitive setting, agreement can be reached only if all stakeholders consider at least one combination of infrastructure-management and coordination bundle achieve at least as much performance (e.g., multi-criteria score) as the next best alternative. By the end of Step 3, the information on how the stakeholders would rank (multi-criteria score) the possible system designs and coordination bundles will be available.

4. In the absence of a single system design ranked best by all, a second many-objective search (Section 10.3.3) aims to find a particular system design (an infrastructure and management option combination identified in Step 2) which will have the highest multi-criteria scores for each negotiating group by allocating sharable performance attributes (e.g., cost, energy, etc.) among them. System designs combined with coordination strategies are the alternative investment portfolios referred to hereafter as ‘bundles’.

5. Sensitivity analysis of solutions will be used to 1, check the criteria weights represent stakeholders value judgments and 2, the robustness of solutions around the criteria weights 3, to identify which one of the stakeholders’ preferences prevents finding a consensus solution.

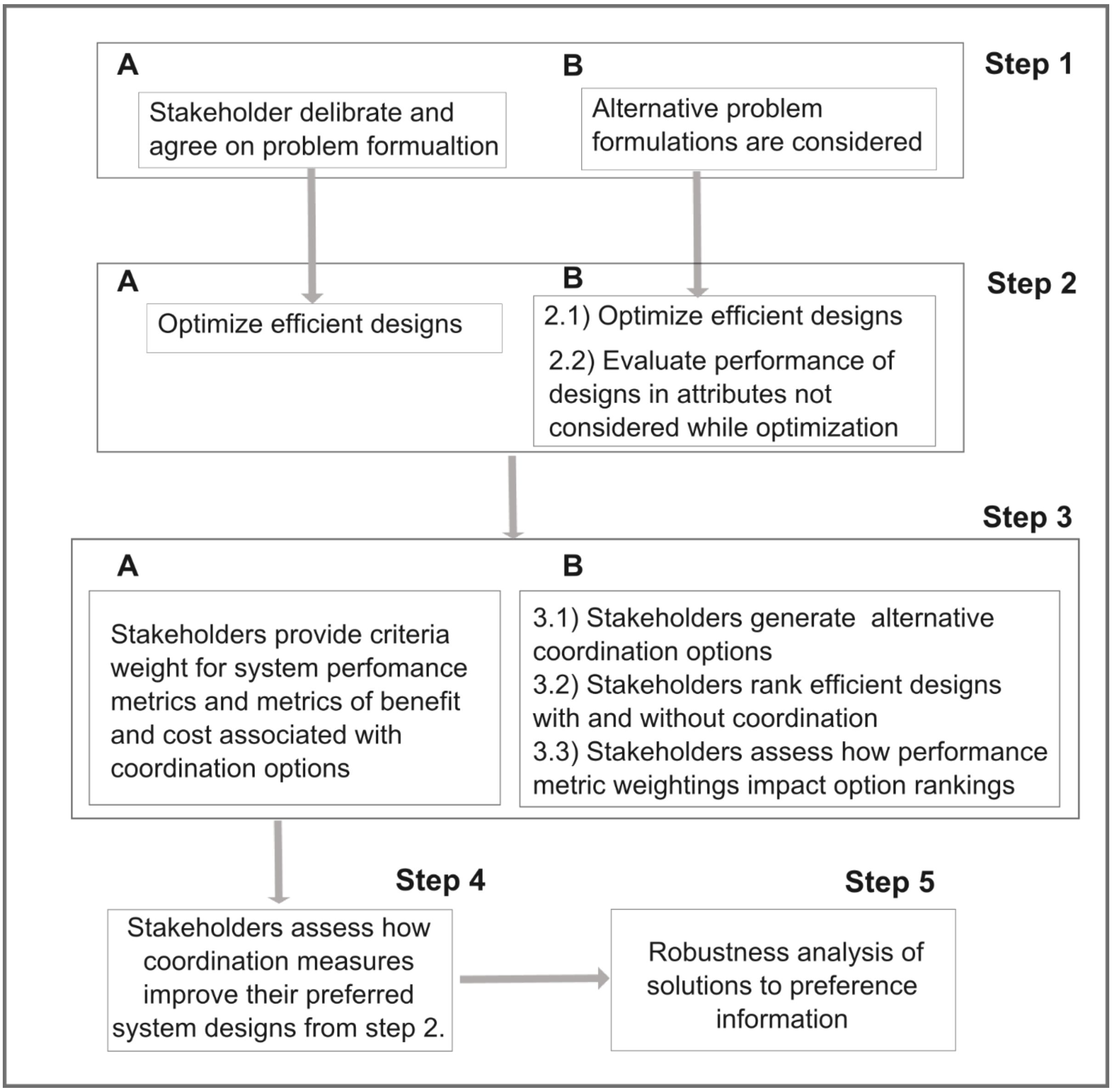


Figure 41. Visual representation of the proposed framework for supporting infrastructure system design negotiation. Panels A and B in each step describe alternative implementations based on problem context. In Step 1 stakeholders formulate the decision problem (i.e., identify performance requirements, constraints and possible decision alternatives). Regardless of stakeholder ability to agree on a single problem formulation, system simulation and many-objective optimization is used in Step 2 to assess the performance trade-offs of different system interventions. In the case that stakeholders were not able to agree on a single problem formulation, the Pareto-optimal designs are evaluated for performance metrics for which they were not optimised for (i.e., tracked metrics). Mapping the identified system designs from multiple formulations (Step 2) on the performance space allows stakeholders learn how interventions impact performance. In Step 3 each stakeholder group iteratively chooses weights for performance metrics such that the different intervention options and a representative and diverse set of plausible bundles of infrastructure, management and coordination alternative can be ranked from their perspective. In Step 4 a second many objective search is conducted to maximise the aggregate performance measure of system designs, now referred

to as intervention bundles (including both new infrastructure investments plus associated coordination mechanisms). Step 5 assesses the robustness of results to stakeholder provided preference information (from Step 3).

10.2.2 Many objective optimization of infrastructure system designs

For the Step 2 optimization, we link a search algorithm to a simulation model of the infrastructure system. The optimization is conducted using many-objective search which have proved popular in water system applications [*Labadie*, 2004; *Reed et al.*, 2013]. The many objective evolutionary algorithm (MOEA) is linked to the water system impact model. Repeated simulations are made until the search algorithm can no longer improve performance in one metric without simultaneously having to reduce performance in one or more other metrics.

$$\text{Maximise} \qquad F_x = (f_1, f_2, \ldots) \qquad (1)$$

Where $f_1, f_2 \ldots f_n$ n= 1,2,3… represent performance metrics of interest

The approximately Pareto-optimal set produced with multi-objective optimization consists of a range of designs i.e., combinations of physical system parameters and operating rules. Like *Giuliani et al.* [2014] we apply direct policy search.

The decision variables include the activation of new reservoirs and their reservoir release rule parameters (see Figure 8 in Appendix). The operating policy is first parameterised within a given family of functions (piecewise linear) and then the parameters optimised with respect to the operating objectives. The operating rules are formulated as annual piecewise linear storage vs. release curves for each reservoir [*Geressu and Harou*, 2015]. The location and size of reservoirs and their release rules are jointly considered to identify high performing reservoir system designs.

$$X = (Y_i, Op_{i,s}) \qquad (2)$$

$$Y_i = \{0,1\} \qquad \forall i \in M \qquad (3)$$

10.2.3 Multi-criteria scoring of alternatives

Distance measure techniques (e.g., Compromise Programming, Topsis, etc…) [*Merigo*, 2013; *Zhou et al.*, 2013; *Merigó et al.*, 2017] can be used to compare the alternatives with some ideal results; With the alternative closest to the ideal result being the best one [*Merigó and Casanovas*, 2010].

We adopt the Weighted sum model (WSM) [Peter C. Fishburn, 1967] for its simple conceptual structure and with good performance comparable with more sophisticated methods [Chang and Yeh, 2001]. The reader is referred to [Kabir et al., 2014]for literature on various type of multi-criteria decision analysis techniques and their appropriateness for different problems settings.

The multi-criteria scoring [*Kornbluth and Steuer*, 1981; *Hipel et al.*, 1993; *Goedhart and Spronk*, 1995; *Despotis*, 1996; *Mendoza and Martins*, 2006; *Wallenius et al.*, 2008; *Ke et al.*, 2012] of the Pareto-approximate designs (i.e., generated in Section10.2.2) is done using a post-optimization multi-criteria analysis using (eq. 7).

$$Agg_{i,c} = \sum_f W_{f,c} \times F_{f,i} \tag{7}$$

$$F_{f,i} = \frac{f_{f,i} - \min(f_f)}{\max(f_f) - \min(f_f)} \tag{8}$$

$$F_{f,i} = 1 + \frac{f_{f,i} - \min(f_f)}{\max(f_f) - \min(f_f)} \tag{9}$$

Where $f_{f,i}$, $F_{f,i}$, $W_{f,c}$ are performance scores, partial failure values of system performance and preference criteria weights respectively. The partial failure function is calculated depending on the direction of optimization with (eq.8) for performance scores that are maximised and (eq.9) for minimization.

$Agg_{i,c}$ in (eq. 7) represents the aggregate score of each bundle *i* based on preference information $W_{f,c}$ for each performance attributes *f* and stakeholder group *c*. $Agg_{i,c}$ measures the weighted distance of a bundle's performance from its performance target.

10.2.4 Evaluating system alternatives under coordinated use

In the absence of a single system design ranked best by all, stakeholders could be expected to pick one design alternative and negotiate on sharing benefits.

In a typical negotiation, stakeholder would pick one of the system design alternative and then apply coordination (eq., 10 and 11). The value of coordinated performance for the uncoordinated alternative is calculated by using a factor of 1 or 0 for each stakeholder (i.e., 1 for the other in a two stakeholder negotiation if the first got 0 and vise versa), while the coordinated performance for coordinated alternative is calculated using a fraction 't' between 0 and 1. This can then be evaluated with the rest of the alternatives to which no coordination is applied.

$$CoordPerf1 = t \times Perf1 \tag{10}$$

$$CoordPerf2 = (1-t) \times Perf1 \tag{11}$$

For a case where stakeholders are negotiating to divide a resources, the partial failure function of a coordinated performance is calculated in relation to the range of performance. For example if the coordinated performance is derived from performance metric 1 the partial failure function of the coordinated alternative is calculated as in (eq. 12).

$$F_{cordj} = \frac{f_{coord,j} - \min(f_1)}{\max(f_1) - \min(f_1)} \tag{12}$$

10.2.5 Optimizing coordination

Both the performance of the system design to be implemented and how its cost and benefits are distributed among stakeholders impact the satisfaction of negotiators [*Winter*, 1997; *Inderst*, 2000]. The Step 4 optimization aims to find a design-coordination strategy combination with the maximum aggregate multi-criteria score from the perspective of each negotiating party. The optimization consists of at least as many objectives as the number of stakeholders, where the objective optimised is the multi-criteria score of the design-coordination strategy for each stakeholder. Ideally, the selected system design alternative and coordination would be scored the highest from the perspective of each of the negotiators ($\Delta MCA_d = Max(MCA_c) - MCA_{d,c} = 0$).

$$\text{Minimise} \qquad F_x = (\Delta MCA_{Selected,c}) \qquad \forall c \in C \qquad (13)$$

Where *c* represents each stakeholder in the group of stakeholders C

Decision variables include the infrastructure system design and coordination levels (e.g., cost-sharing, power/energy sharing).

10.2.6 Preference elicitation

Techniques for choosing weights include direct rating, indifference trade-off and the analytical hierarchy process [*Hobbs et al.*, 1992]. These methods require posing a complex set of questions to the stakeholders to elicit their relative preferences [Larichev, 1992]. Here we show how many-objective optimization and visual analytics can be used to iteratively generate weights that reflect stakeholders' ranking of alternatives (see Step 3 panel of Figure 1). We follow the conjoint procedures (Green and Srinivasan, 1990) that involve decision maker ranking or rating alternatives followed by the derivation of weights that best fit the alternatives' evaluations. The metrics (i..e, $f_{RankDis}$) is used as distance measure between stakeholder ranking of alternatives and the ranks of alternatives implied by weights.

$$\text{Minimise} \qquad F_x = (f_{RankDis}) \qquad (4)$$

$$\text{Where} \quad f_{RankDis_n} = \sum_{i=1}^{n} (Rank_{i,u} - Rank_{i,w})^2 \qquad (5)$$

Fx		Target function
$f_{RankDis}$		A distance measure between user assigned ranks of alternatives and their rank as calculated using weights
$Rank_{i,u}, Rank_{i,w}$		Ranks of alternative 'I' provided by a stakeholder and implied by weight respectively

The result is an array of numbers W_j with the range of [0, 100] which can then be converted to an array of weights (eq. 6) that closely imitate the stakeholder's ranking of alternatives. The range [0, 100] is selected as it allows weights from 0 to 1 (i.e., when an attribute's relative preference is given close 100 while other attributes is kept close to 0) to be generated while being a reasonably small space to explore using heuristic algorithms. The exercise should be iterative to ensure consistency of the ranking of alternatives.

$$w_j = \frac{W_j}{\sum_{j=1}^{t} W_j} \tag{6}$$

10.2.7 Robustness of weights

The many objective optimization formulation (eq. 13) can be adopted as (eq. 14) to see how the solution (Pareto-front of the multi-criteria score) could shift for marginal changes in the relative value of stakeholders' weights. This formulation shows both how the solution set changes, and to which of the performance preference weights 'j' the solution is most sensitive to.

Minimise $$F_x = (\Delta MCA_{Selected,c}, \Delta W_{j,c}) \qquad \forall c \in C \tag{14}$$

Where c represents each stakeholder in the group of stakeholders C

Decision variables include the infrastructure system design, coordination levels (e.g., cost-sharing, power/energy sharing), the change in the value of a relative weight, and which of the performance 'j' and stakeholder 'c' the weight would be changed for.

10.3 **Results**

This section summarises the results of the proposed approach applied to our case-study. Non-dominated designs of proposed reservoirs are presented in Section10.3.1. These include alternative designs (i.e., selection of a reservoir, its storage capacity, and operating policy) that most efficiently balance the different system goals. The multi-criteria weight elicitation from different stakeholder's perspectives is demonstrated in Section 10.3.2. Section10.3.2presents the optimised coordination levels that could allow the countries to agree on a single design in our synthetic negotiation example. Sections 10.3.4present validation of the proposed approach and Section 10.3.5 deals with a demonstration of the sensitivity analysis of results to preference information uncertainty.

10.3.1 Performance of designs

This section presents the many objective assessment of efficient infrastructure options. Results consist of trade-off curves built of Pareto-approximate designs; each design consists of existing reservoirs and one new reservoir, its storage capacity, and operating rules of the new and existing reservoirs.

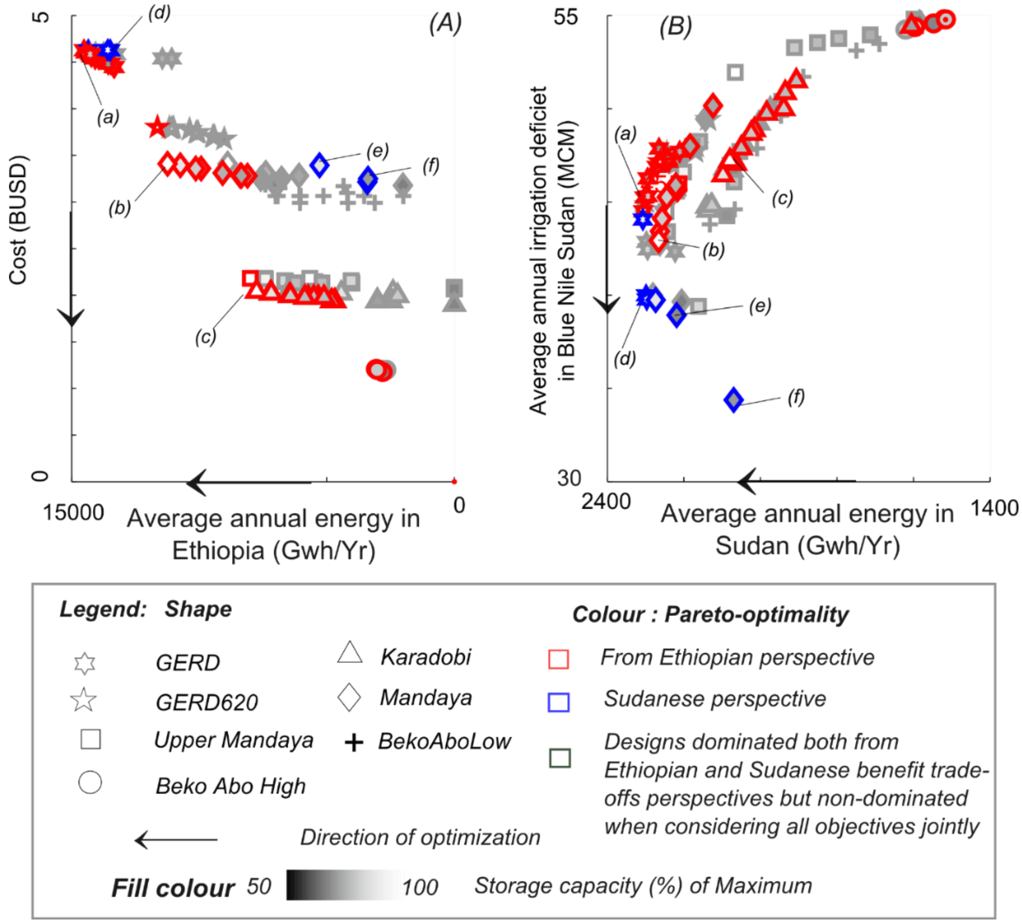


Figure 42. Results of the first many-objective optimization (Step 1 in Figure 1). The plots show performance of designs that are Pareto-optimal for Ethiopia (red) or Sudan (blue markers). Grey colored markers are not Pareto-optimal when considering the Ethiopian and Sudanese objectives separately but are non-dominated when all objectives are optimised together. The figure shows how efficient designs for one group of stakeholders (e.g., designs 'b','c' on Panel A) could be sub-optimal for others (e.g., for Sudan as shown on Panel B).

Figure 3 Panel A shows how the reservoir designs map onto the optimised annual energy/cost trade-off space compared to the ideal performance of highest energy and lowest cost for Ethiopia. Panel B shows the performance of designs from the Sudanese perspective. Red and Blue colored markers show designs (i.e., reservoirs, storage capacity and operating rules) that are non-dominated when considering Ethiopian and Sudanese objectives respectively. Downstream system performance (in Sudan) is affected by which single reservoir is built upstream (shown with shapes), its size (fill color) and its operating strategy. For each performance shown in Figure 42, the operating rules of the two Sudanese reservoirs, Roseires and Sennar, are optimised to adjust to the new hydrologic conditions brought about by the new upstream dam [*Geressu and Harou*, 2015].

Infrastructure designs and operating policies that achieve best energy generation and irrigation water supply in Sudan shown with Blue Markers (e.g., point 'd', 'e', 'f') near the ideal solution in Panel B are far from ideal from the Ethiopian perspective (seeking the highest annual energy generation at least cost) as shown in Panel A (where markers 'a', 'b', 'c' show an example of a desirable design). The performance of Blue markers (i.e., show the highest achievable performance of the two existing Sudanese reservoirs) assumes upstream reservoirs are designed and operated primarily to maximise downstream objectives.

Grey markers show designs that are not Pareto-optimal for either of the countries Ethiopia or Sudan but are Pareto-optimal when all objectives are included simultaneously in the optimization. Figure 3 show the performance trade-offs implied by each non-dominated design. Each of the designs is non-inferior hence the plots cannot recommend any one of the designs as 'best'. Designs such as 'a','b' and 'c' represent different balances of conflicting objectives which will be perceived differently by decision makers. It is likely negotiating country representatives would choose different designs (blue or red) rather than compromise (grey), so this motivates moving to the rest of the Steps of the proposed approach.

10.3.2 Preference elicitation

In Step 3 of the proposed framework, stakeholders are asked for their preference through weighing performance criteria. The purpose of eliciting preference information is to document users value judgments. In this section, we demonstrate how the efficient trade-offs identified (e.g., shown in Figure 3) can be used for preference elicitation from stakeholders in an interactive setting which shows them how criteria weight they chose affect the ranking of the Pareto-optimal designs identified in Step 2 (please see Table 4 and Figure 43).

Table 4 Example preference information (criteria weights) used for proof of concept demonstration

Preference set	**Stakeholder**	**Annual energy generation from new dams**	**Cost of project**	**Energy from existing reservoirs**	**Annual irrigation deficit in Blue Nile Sudan**	**Energy for Ethiopian domestic use**	**Energy shared to Sudan from Ethiopian dams**	**Cost to be covered by Ethiopia**	**Cost to be covered by Sudan**
1	Ethiopia	0.166667	0.333333	0	0	0.333333	0	0.166667	0
	Sudan	0	0	0.4	0.2	0	0.2	0	0.2
2	Ethiopia	0.333333	0.166667	0	0	0.333333	0	0.166667	0
	Sudan	0	0	0.4	0.2	0	0.2	0	0.2
3	Ethiopia	0.5	0.1	0	0	0.1	0	0.3	0
	Sudan	0	0	0.1	0.4	0	0.4	0	0.1

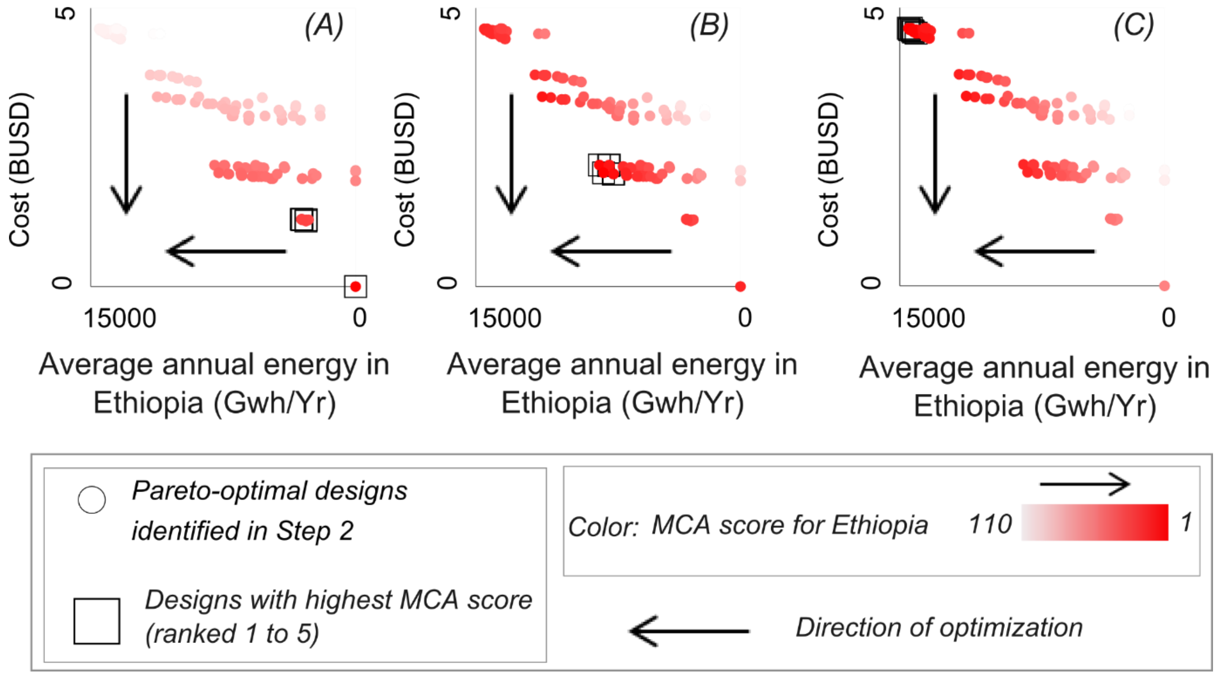


Figure 43 Trial and error weight elicitation from stakeholders guided by visual analytics. Users will see how the relation between the array of criteria weight they provide (e.g., Table 2) and how the highest ranked designs map on the performance space per the weights.

Color of markers in Figure 43 shows the ranking of designs (according to multi-criteria scoring for Ethiopia). Square markers show the location of best ranked designs on the performance trade-off plot for user specified criteria weights. Observing how the best ranked system designs map on the performance space indicates what trade-offs the stakeholders are willing to accept. Each of the stakeholder groups can separately use the weight elicitation technique which is demoed here only for Ethiopia as an example.

The weight elicitation is iterative where each stakeholder group provides a set of criteria weights and visualises the implication of the provided criteria weight on performance trade-off until the user is satisfied that the criteria weight reflects their value judgments. Criteria weights should reflect the willingness of the stakeholders to exchange parts of these various system benefit forms some of which could be shared (e.g., cost of implementing a system designs, energy generated from dams owned by one stakeholder can be shared across borders). Hence, the trial and error approach demonstrated in Table 4 and Figure 43 for criteria weight elicitation would not be sufficient to elicit information on stakeholder's preference of coordination options. This is because the performance metrics that are optimised for in the first many objective optimization in Step 2, and for which the trade-off information is available by this stage, only track water system benefit and not how it should be allocated among negotiators according to their preferences.

The criteria weights can be inferred from how each of the stakeholders would rank a set of alternative system-design and coordination options. Evolutionary algorithm can be used to find a set of criteria weights that would result in the same ranking as the stakeholders' through regression (see eq. 4). Below we use an example set of possible coordination strategies to demonstrate the approach.

Table 5 Example performance mixes with assumed ranking by one of stakeholders (Ethiopia). The set of criteria weights that express its preference for various performance attributes can be inferred from the ranking of the mix of options.

Stakeholder given rank (	Annual energy generation from new dams	Cost of project	Energy from existing reservoirs in Sudan	Annual irrigation deficit in Blue Nile Sudan	Energy for Ethiopian domestic use	Energy shared to Sudan from Ethiopian dams	Cost to be covered by Ethiopia	Cost to be covered by Sudan
1	13583	4630	2297	39768.3	7991	5592	2179.85	2450.15
2	13583	4630	2297	39768.3	10787	2796	3404.925	1225.075
3	5284	3392.12	2274	39735.6	5284	2707	3392.12	1212.27
4	5284	3392.12	2274	39735.6	6637.5	1353.5	2785.985	606.135

Table 6 An optimization result to find a set of weights that best fit user specified ranking of bundles.

Preference set	**Stakeholder**	**Annual energy generation from new dams**	**Cost of project**	**Energy from existing reservoirs**	**Annual irrigation deficit in Blue Nile Sudan**	**Energy for Ethiopian domestic use**	**Energy shared to Sudan from Ethiopian dams**	**Cost to be covered by Ethiopia**	**Cost to be covered by Sudan**
1	Ethiopia	0.915	0.000	0.000	0.000	0.000	0.000	0.084	0.000

The multi-criteria ranking of designs implied by the weights derived from the optimization (e.g., Table 6) can be visualised as in Figure 43 to ensure stakeholders are satisfied by the ranking. This makes it possible for stakeholders to see if they would rank the performance mix differently after learning the implication of their previous choice of performance criteria weights on the ranking of alternative designs. The weight elicitation should be iterative where each stakeholder group provides an array of best ranked design and coordination bundles, derives weights, compare their ranking of bundles and weights-implied ranking of bundles until they are satisfied with how the criteria weights reflect the ranking of the bundles from their individual perspective.

At this stage, each stakeholder would be able to identify their most preferred system design and coordination option which will be the alternative with highest multi-criteria score. The ultimate goal in the negotiation is to get one common best-ranked design (a bundle of infrastructure and management choice and coordination level) for all stakeholders. However, given that each of the stakeholders would choose the infrastructure and management options that maximise their individual benefits, there could be a stalemate.

This negotiation framework aims to help stakeholders find more acceptable system design and coordination bundles such that one or more of the stakeholder groups would feel sufficiently compensated (with benefits from coordination) to agree to an alternative system design to their choice. For demonstration of the approach, we will test the approach for two preference scenarios (i.e., preference sets '2' and '3' given in Table 4 as arrays of weights) . In a real application this would be replaced with result of step 3.

10.3.3 Optimal coordination strategies

In the fourth Step, an optimised selection of a system design and coordination levels is sought to simultaneously improve the satisfaction level of stakeholders. Note the satisfaction level is represented by the multi-criteria score that each stakeholder group assigns to the optimised selection of the system designs-coordination bundle. Ideally, the optimization would reveal a single best bundle that all stakeholders could agree on because each of them cannot find any other alternative bundles with a higher MC score. However, this is dependent on the problem context (i.e., preference structure of the stakeholders as it relates to the system performance); where in some problems no or only partial improvement in resolving the conflict is possible. An example is where the approach finds a bundle that provide simultaneously higher multi-criteria score to competing stakeholders compared to intervention options without any coordination but where for a given solution at least one of the stakeholders could find an alternative bundle with higher MC score.

Each possible system design and coordination bundle is evaluated by comparing its multi-criteria score with the set of the system designs without coordination (i.e., Pareto optimal set of infrastructure and management designs identified in Step 2). A measure of the distance of an individual system design-coordination bundle (b) score for a stakeholder group (c) from a the maximum score in the whole set (i.e,, the bundle and the rest of system designs with no coordination) is designated by $\Delta MCA_{b,c}$.

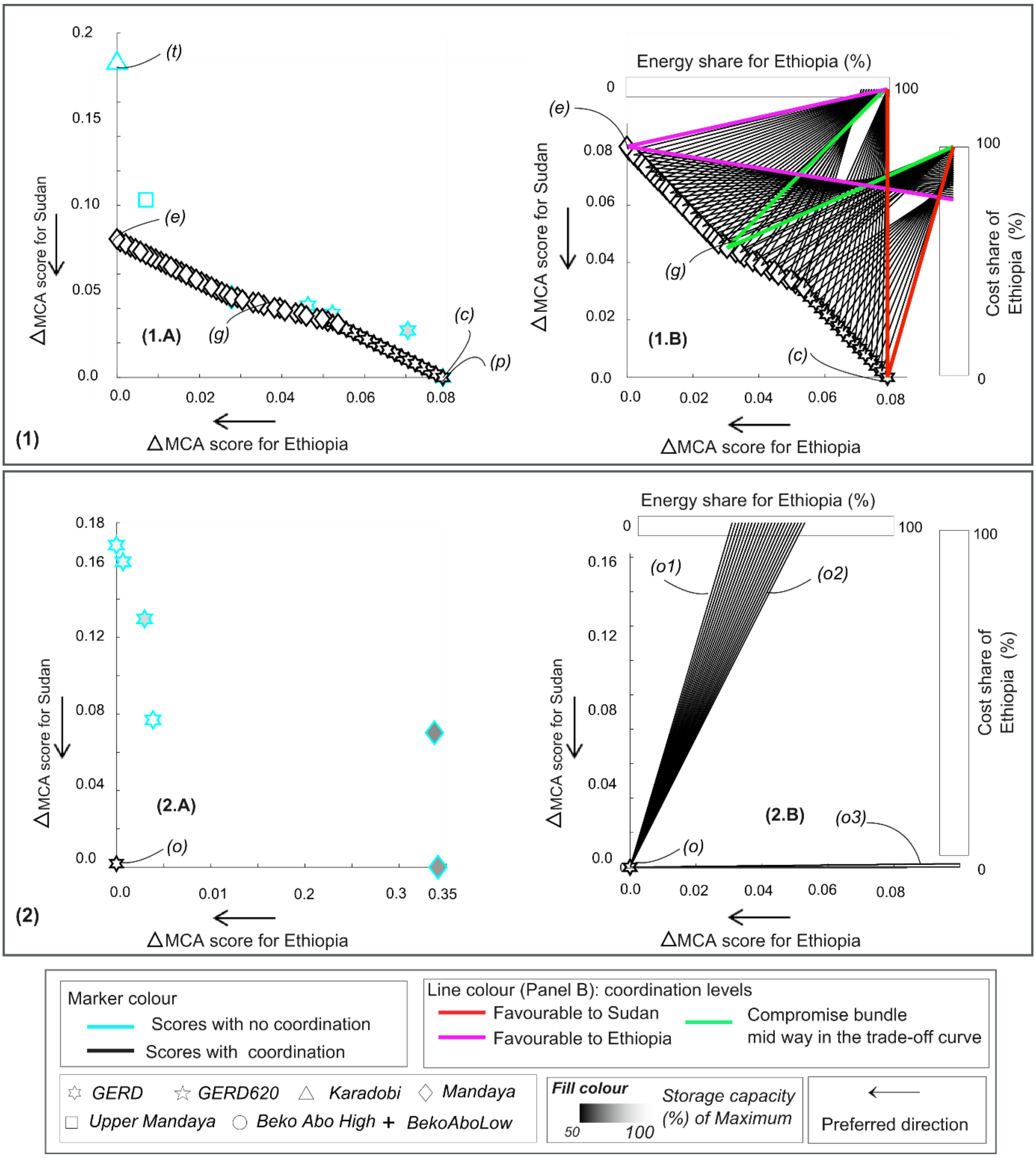


Figure 44 Comparison of systems designs without coordination (Cyan colors) and system designs with optimised coordination (black colors). Panels 1 and 2 correspond to results where stakeholder preferences are given by criteria weights in row 1 and row 3 in Table 4 respectively. The results in Panel 1 show, for the given set of preference information, while coordinated use of selected designs (e.g., designs 'c', 'g', and 'e') can improve performance for competing stakeholders simultaneously, no single design-coordination bundle can simultaneously satisfy both stakeholders more than would be with at least one of the system designs without coordination. Panel 2 shows a single design 'o' - with a range of coordination strategies (e.g., o1,o2, and o3 in Panel B) could be found

as best by both countries. In both cases system design and coordination bundles achieve higher satisfaction measures for stakeholder compared to designs without coordination.

Figure 44 Panel 1 shows that optimal coordination (i.e., energy use and cost sharing) can improve the satisfaction of users (when the preference information for the two counties is as in row 1 Table 4). However, the best solutions for Ethiopia and Sudan, both in unilateral and coordinated use, are ranked low by the other; implying compromise will have to be reached. A preference of the two counties as in row 3 of Table 4 would allow finding a single system design and coordination bundle that results in the countries agreeing on at least one system design and coordination bundle (one of 'o1,'o2','o3' in Figure 44 Panel 2) as these designs are ranked better than all system designs without coordination. Figure 45 allows visualizing additional information for stakeholders to further evaluate the system design coordination bundles.

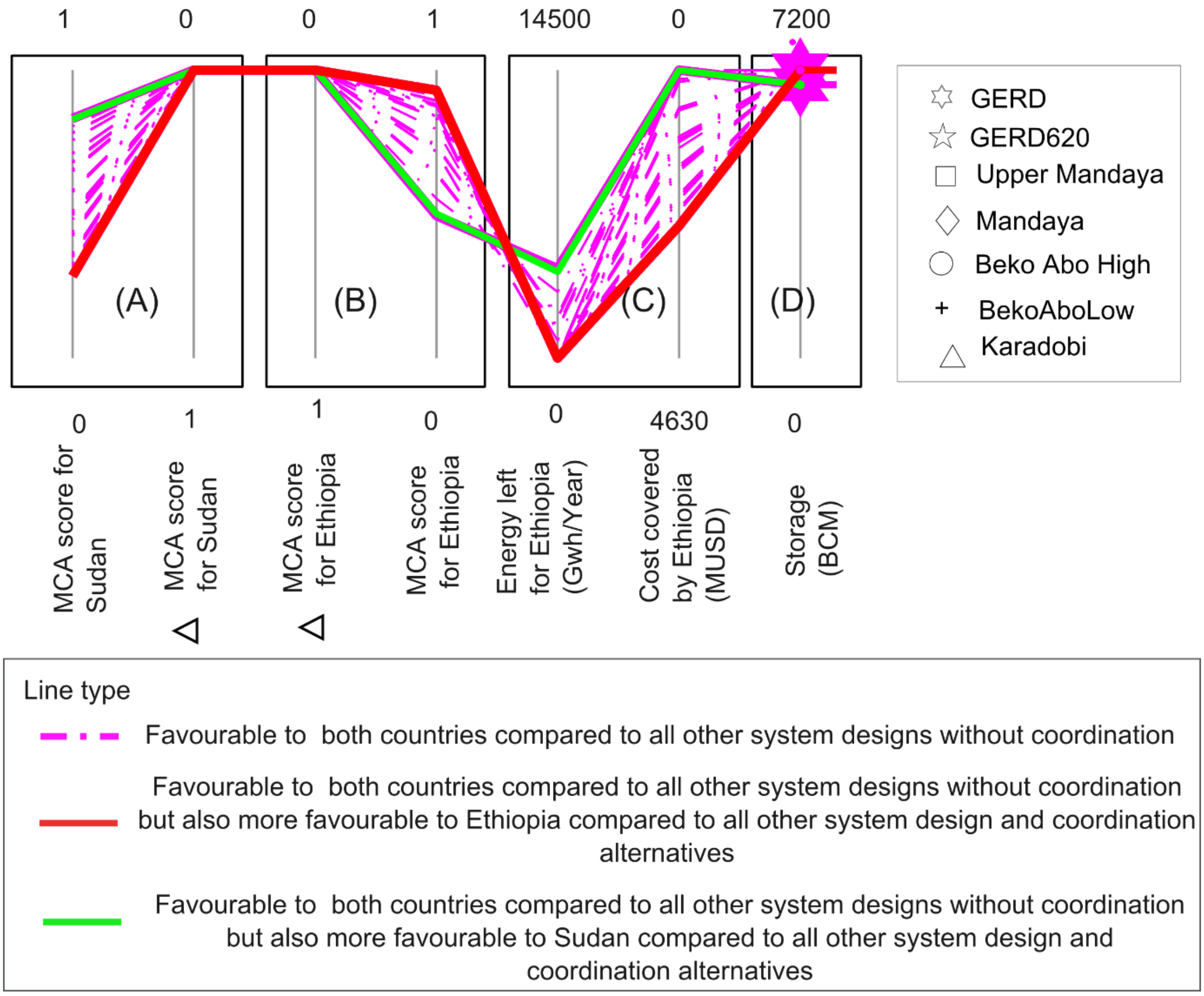


Figure 45 Multi-criteria scores of designs in coordinated use of resources. system design-coordination bundles that are simultaneously better than a no coordination option for both countries where stakeholder preferences are given by criteria weights in row 3 in Table 4.

10.3.4 Validation

This section investigates how the selection of a system design to start negotiation on will affect the search for a consensus solution (i.e., one that all stakeholders would find with higher multi-criteria score). From a particular stakeholder's perspective, a reasonable starting point for negotiating on coordinated use of resources is the design that does best for them without negotiation (i.e., designs 't' and 'p' for Ethiopia and Sudan respectively).

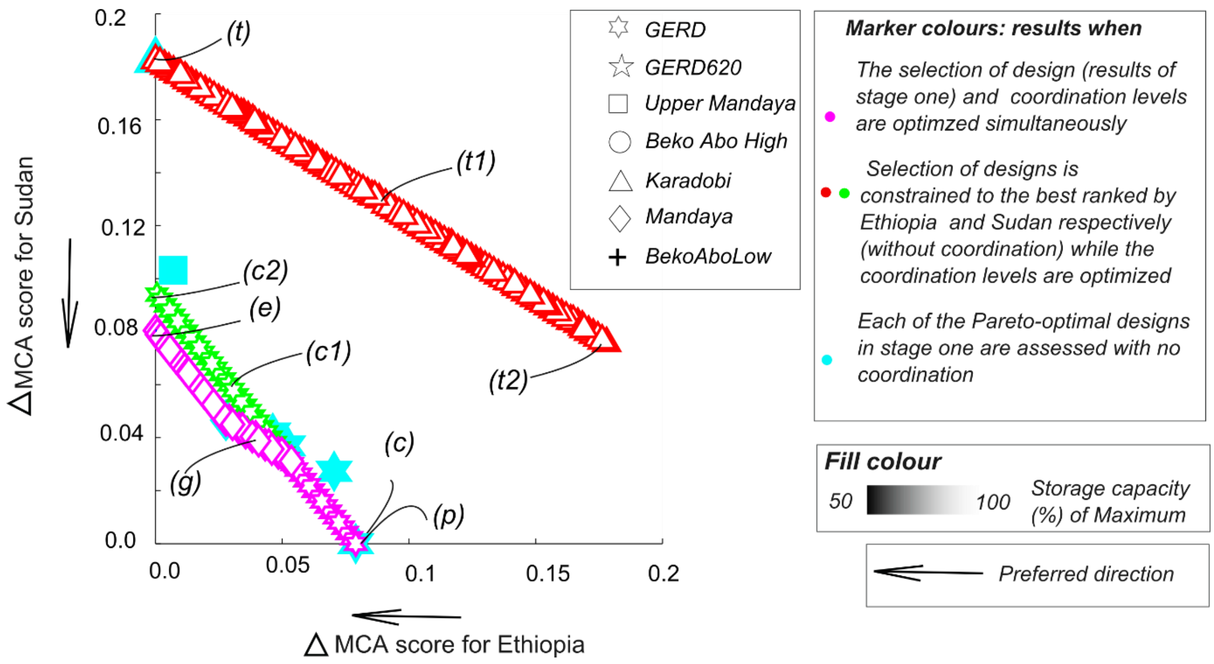


Figure 46. Comparison of results under different search approaches for coordinated use. Optimization where the selection of design and coordination levels are done jointly (i.e. Magenta coloured bundles such as 'e' and 'g') achieve better measures of satisfaction performance compared to search results where the designs best ranked without coordination for Ethiopia ('t') and Sudan ('c') respectively are fixed while optimizing for coordination (e.g., t1, t2, c1, c2). 'Cyan' (light blue) markers show results of search where each design is assessed with null coordination levels.

The figure shows how the simultaneous search for design choices and coordination levels can enhance the satisfaction (higher multi-criteria score) of competing negotiators compared to where the designs choice is pre-fixed while searching for coordination.

10.3.5 Sensitivity analysis

Sensitivity analyses of solutions to assumed criteria weights is needed to explore the robustness of the obtained results. Where a single best solution cannot be picked by the stakeholders, sensitivity analysis can reveal which of the criteria's is detrimental to achieving a "perfect" solution, (i.e., where all stakeholders choose a single design-coordination bundle), the analysis reveals the likely best solutions if criteria weights were marginally different to what is specified. Figure 47 shows sensitivity of results assuming only one of set of performance criteria can be misrepresented at a time. The method can be extended to finding the sensitivity of results to a combination of criteria weights by changing (eq. 13 in Section 10.2.4 to eq. 14 in Section 10.2.7). The sensitivity analysis approach can also be used to assess the robustness of an ideal solution (i.e., where a single infrastructure, management and coordination level is scored as best by all stakeholders) to criteria weights.

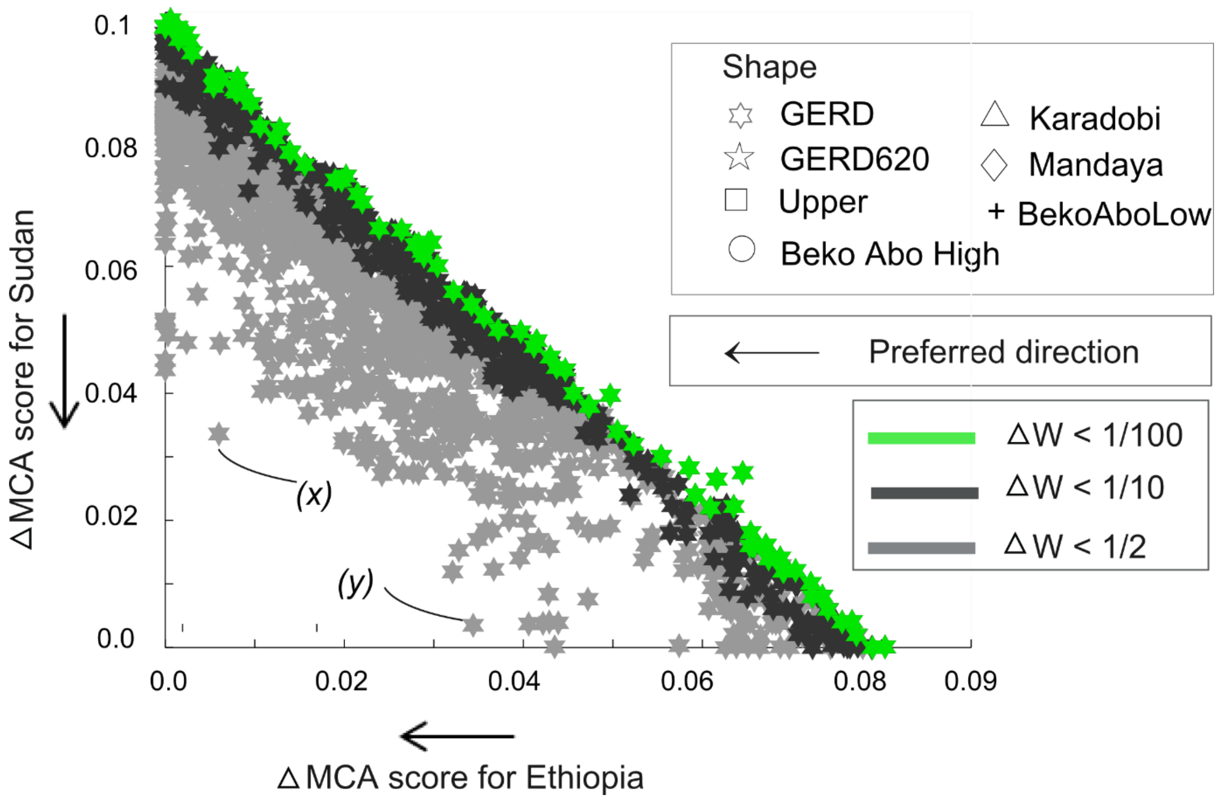


Figure 47 Sensitivity analysis of solutions to uncertainty in relative weight given to performance by two stakeholders to two different criteria. (Panel A) shows a region of uncertainty where the true value of two performance criteria may be located. Green, Cyan and Grey markers show solutions if the actual criteria weights were within 1, 10 and 50% margin of the ones provided by stakeholders respectively.

Figure 47 shows the many-objective optimization generated solutions that approximate a multi-dimensional space formed by one or more uncertain parameters.

Table 7 Example sensitivity analysis results ('x' and 'y' in Figure 47).

Solution	Stakeholder	Changed weight	Change factor (ΔW	Original weight	New Relative	New weight $w_j = W_j \Big/ \sum_{j=1}^{t} W_j$

					weight (W)	
‘x’ in Figure 47	1	2	0.732	0.333	0.122	0.128
	2	3	1.1936	0.400	0.244	0.47744
‘y’ in Figure 47	1	7	1.194	0.400	0.244	0.477
	2	3	0.511	0.000	0.000	0.000

Table 8 example re-calculation of criteria weights for the case of solution (‘x’ inFigure 47) for stakeholder 1.

S.no	remark	Annual energy generation from new dams	Cost of project	Energy from existing reservoirs	Annual irrigation deficit in Blue Nile Sudan	Energy for Ethiopian domestic use	Energy shared to Sudan from Ethiopian dams	Cost to be covered by Ethiopia	Cost to be covered by Sudan	Sum
1	original	0.167	0.333	0.000	0.000	0.333	0.000	0.167	0.000	1.000
2	W	0.167	0.243789	0	0	0.333	0	0.167	0	0.910789
3	w	0.183357	0.267668	0	0	0.365617	0	0.183357	0	1

10.4 **Discussion of application 6**

A framework for designing and negotiating the multipurpose development of infrastructure systems among diverse stakeholders is proposed. The search process and its formulation is similar to the one in *Geressu and Harou* [2015] but here we consider the process of negotiating trade-offs between complex competing interests and the role of coordination strategies (e.g. cost and power sharing) in selecting system designs. The framework enables considering the explicit preference information of users and use of multi-criteria scoring (through weighing method) for tracking the satisfaction of stakeholders. An application to a simplified Blue Nile dam development problem helped us demonstrate the approach and the type of insights and processes it could facilitate.

10.4.1 Discussion of results

Results showed that, in the absence of coordination mechanisms to incentivise consensus building in the Blue Nile problem, one country's Pareto optimal designs are inferior when considering the other country's interests. Figure 42 showed the country implications of changes in reservoir design, i.e., changing the size, operating rules or location of a dam [*Geressu and Harou*, 2015]. Figure 43 showed how the most efficient designs would be ranked (colors of markers) for a stakeholder's different criteria weights (proposed in Table 4). The 'best design' for each of the countries individually performs poorly for the other. Benefit trade-offs that the proposed hydropower systems imply (as implied by a fictitious preference information) for upstream and downstream users were presented in Figure 44 using aggregate multi-criteria scores. Multi-criteria scoring of designs was done based on their weighted distance from target performance levels.

The evolutionary algorithms explore the range of each decision variable using random generation of values in uniform distribution. To minimise number of evolution needed, we optimise for intermediate decision variables which have a range [0, 100] which are then converted to an array of weights using eq. 6 (please see section 10.2.6). Normalizing by the sum of the array ensures they always add up to unity. This avoids the need to discard set of criteria weights that do not add up to unity. The range [0, 100] for the intermediate variables is considered sufficient to approximate the lowest and highest possible value that each weight can have (i.e., 0 to 1).

A large number of sets of intermediate decision variables could result in one set of normalised criteria weights that can emulate the ranking of alternatives. While this is not a problem by itself, this could result in longer run times for the evolutionary algorithm as it will end up exploring larger decision space than necessary. Fixing the value of one or few of the elements of the array reduces the decision space as the optimiser will concentrate in finding the value of the rest of criteria weights that work well with the fixed value.

Negotiators could try to maximise their individual and collective satisfaction by adding 'coordination strategies' (in our case exchanges of funds and energy) to the deal. The Pareto-optimal designs in Figure 42 or the best ranked designs for the stakeholder countries from Figure 43 are not ideal system designs to start negotiations because they always benefit one country over the other.

Section 10.3.3 presented the results of a second search showing the best design-coordination bundles (i.e., with highest multi-criteria score) for example preferences of stakeholders as expressed by criteria weights (rows 1 and 3 in Table 4). Figure 44 showed how coordination strategies improve benefits (measured by the aggregate multi-criteria score of designs) compared to without coordination (see for example how design 'e' beat 't' in Panel 1.A). An ideal solution is a design-coordination bundle that would be ranked better than the unilateral best designs for each of the stakeholders simultaneously (Figure 44 Panel 2). Finding such solutions by trial and error could be arduous. Even if one did find some, there could be many solutions that meet this requirement and one would need a systematic way of evaluating them. The is achieved by the Step 4 search of the proposed process.

Results show the satisfaction that stakeholders could get from each alternative water system design under unilateral implementation could be surpassed by several system designs when including coordination. Figure 46shows the implications of alternative starting points (system design choices) of negotiation. The results validate the need for simultaneous optimization of system design and coordination levels to find better performing system design and coordination bundles.

10.4.2 Visual analytics and the interactive negotiation process

Interactive multi-criteria performance plots can play a valuable role in understanding the implications of development within complex systems [*Reed and Kollat*, 2013; *Woodruff et al.*, 2013]. The use of visual analytics [*Kollat and Reed*, 2007; *Keim et al.*, 2008] is an integral part of the proposed negotiation framework for four reasons. First, given that choosing multi-criteria weights for different performance goals is a difficult task [*Mimi and Sawalhi*, 2003; *Mendoza and Martins*, 2006], visual analytics facilitates weights (preference) elicitation from stakeholders. This can be done through interactive learning, i.e., stakeholders progressively assimilate the implication of weighing their goals by instant visual inspection (Figure 43) of its impacts on system performance, trade-offs, and (if allowed) on infrastructure portfolio composition. This iterative prioritization exercise using a linked weight elicitation and visualization tool would continue until stakeholders are satisfied with their criteria weights. Secondly, visual interaction with results allows stakeholders to introduce minimum performance requirements (by filtering or 'brushing' results) [*Reed and Kollat*, 2013]. In this way parts of the performance space can be excluded post the first many objective optimization when eliciting preferences from stakeholders. Such flexibility and customization could help increase stakeholders' trust in the control they have over the negotiation process. Thirdly, visual analytics helps communicate through intuitive visual summaries and record and document results of the assessment and negotiation process. Finally, by adopting a generate-first-choose-later approach [*Herman et al.*, 2014b] enabled by visual analytics, a large decision space is considered at all stages of decision making with full insight on the performance trade-offs. Hence, the results are not limited by the stakeholders' and analyst's assumption of acceptable coordination levels among the negotiators. This could be helpful in politically sensitive negotiations where participants are reticent to reveal (admit) concessions they might make [*Fearon*, 1998].

10.5 **Limitations**

The approach demonstrated on the Blue Nile problem in this chapter relies on the assumptions that any loss in performance from one objective can be compensated by an increase in another or others. This could be invalid for some real-life application where, for example, stakeholder don not feel that a financial gain may not compensate reduced energy service levels. Such relations may not be accurately represented with the use of weights for preference elicitation.

This study does not aim to answer the question "what the acceptable downstream benefits are or what performance objectives can be traded-off by which country?". These can and should only be answered by stakeholders through negotiation coupled with extensive studies on system goals and needs in each country. A real-world application would involve iterative deliberation among multi-disciplinary groups within and among the countries about the performance objectives to consider and the preference information that describe how stakeholders value each performance target in relation to other targets. The objectives and assumptions presented here are changeable. The criteria weights used in this study are hypothetical and are meant for demonstration purposes.

This is a proof-of-concept study on a simplified form of a subset of the Nile problem. The method is demonstrated using few objectives and limit the geographical scope to the Blue Nile (excluding Egyptian interests). The suggested framework could accommodate other players in the basin such as Egypt and development partners which could contribute financing in exchange for coordinated development (e.g., managing filling of reservoirs and energy trade). Future work could benefit from considering the impacts of filling of new dams and including more Nile countries.

11 Summary

Meeting growing food and energy demands in many regions will require the expansion of water resources infrastructure [*Spiertz and Ewert*, 2009; *Bieker et al.*, 2010; *Qu et al.*, 2013]. Given that water system developments can help alleviate poverty and spur growth in regions such as the Nile, new reservoirs will be built within existing multi-reservoir systems. Interventions change the distribution of system benefits to stakeholders with differences in preferences; which explains why the multi-reservoir planning problem is a difficult one to solve.

Accommodating different parties' needs is necessary in a transboundary context to avoid major conflicts [*Swain*, 2011; *Anghileri et al.*, 2013; *Sadoff et al.*, 2013]. Evaluating future designs based on aggregating all system benefits will not be helpful in situations where the intervention impacts different sectors and geographical areas. It is more helpful for planners to quantify stakeholder defined goals thereby tracking the implications of various infrastructure investments on these. However, this task is difficult due to the limited cognitive capacity of humans to understand complex systems and the tendency of stakeholders to maximise their individual benefits in group decision making.

The water resources planning and management literature has advanced the design and management of complex water systems in the last several decades. This work identified some gaps in the literature and sought to address them. The suggested approaches for reservoir system sizing, scheduling, and management considering multiple objectives and multi-stakeholder negotiation work by linking a water resource system simulator to a multi-criteria heuristic search optimization algorithm. The approach works for any number of objectives that are ideally defined through consultation with stakeholders and decision-makers to ensure appropriate performance criteria are used. Outputs include the set of approximately Pareto-optimal systems designs which can be viewed in customised plots showing how different objectives trade-off for the most efficient designs (e.g.. sizes, sequence, implementation dates, and operating rules of reservoirs at various expansion stages). Customised plots are used for creating communicative displays.

The approaches are designed such that they can serve a single organization's planning or potentially aid negotiations on future reservoir development between different stakeholder groups (e.g., upstream and downstream).

In Chapter 5, a screening method is proposed that simultaneously optimises the operation and sizing of reservoirs when searching for promising multi-reservoir system configurations. Proposed system designs were obtained via minimizing aggregate storage capacity while maximizing monthly firm energy and total energy production. The method was used to identify those Ethiopian reservoirs and their capacities that achieve the greatest firm or total annual energy production at least aggregate system storage.

The proposed approach for screening efficient system designs allows the analyst to present decision makers with a wide range of designs and the trade-offs they imply to inform deliberation on many environmental and societal goals in addition to economic and financial objectives without having to first agree on their monetization. The study in Chapter 6 proposed a many-objective optimization and visual analytics approach to help decision makers consider multiple objectives when deliberating reservoir system expansion scheduling. The approach screens designs by considering the optimally coordinated operation of infrastructures and flexibility of reservoir operation at different expansion stages. Results show that assessing the scheduling of reservoirs assuming their operating rules as fixed overestimates the compromises required in negotiations between stakeholders that argue for or against quicker dam filling. The proposed scheduling approach enables planning without having to depend on initial assumptions about filling rate, operating rules, sequence of implementations and future priorities (how reservoirs may be operated in future). Optimizing operating rules for each reservoir and for each unique system expansion stage ensures that impacts of scheduling designs are de-linked from the infrastructure choices; revealing the best compromise designs (i.e., whether a change in physical or operating rule design is needed to minimise impact and maximise benefits).

In this first-order analysis, not considering new reservoir operating policies for the different system expansion stages is shown to underestimate the net worth of the Blue Nile reservoirs by up to 6 BUSD. Coordinated use of multiple reservoirs achieves higher performance. Failure to consider these, not only under-estimates benefits but could also lead to sub-optimal designs being recommended.

Decision makers often consider equity and other political considerations that might be difficult to model and that are subjective, the comparison of performance between all development (e.g., dams, irrigation schemes, etc.) options could be important in decision support in general and group decision support in particular. The many objective optimization and visual analysis approaches used in Chapter 5 and 6 show only the non-dominated solutions for considered performance objectives. This results in the performance of some infrastructure options (i.e., that are dominated) not being able to be compared with the non-dominated ones. For some stakeholders, who may have vested interest in some options, this might be unsatisfactory and even unacceptable; potentially discouraging them from participatory analysis and negotiations. Also, given that the performance metrics are dependent on deterministic assumption of some parameters that could be disputed, the set of Pareto-optimal options could be unsatisfactory.

Chapter 7 proposed a many-objective optimization and visual analytics approach to help decision makers consider multiple sources of uncertainty in deliberations for water resource system planning. The results produce a database of efficient designs which decision makers can query through various what-if scenarios they feel are likely. By adopting robust optimization, the technique reveals more decision-relevant information than post-optimization sensitivity analysis; showing possible robust plans that may work satisfactorily in a wide range of future conditions. Given that stakeholder could find agreeing on the likelihood of future economic conditions and risks difficult this could help facilitate negotiations by allowing stakeholders with differing attitudes towards risk and opportunity argue for a consensus solution based on their separate assessments.

The approach proposed in Chapter 8 allows stakeholders to visualise the performance of both the efficient and dominated intervention options (e.g., dam sites, irrigation schemes, water transfer, power interconnection options).

Chapter 9 demonstrates adaptive operating policies can improve long period performance (e.g., annual or multi-year minimum release goal) by considering past performance (i.e., previous month's releases). The approach relies on monitoring/accounting of the recent past conditions to prioritise among multiple management goals. This enables a realistic assessment of reservoir system performance, as it is not reliant on forecast skills, while also meeting a range of release requirements to minimise impact/ increase downstream benefit. The results show adaptive operating strategies can minimise the trade-offs in benefit between the Nile riparian countries. By minimizing the trade-offs between multiple, conflicting performance goals of different lengths, the proposed adaptive operating strategy reveals low-risk-high-benefit management options compared to traditional operating strategies which are static.

Finally, Chapter 10 proposed a 5-step approach allowing for the benefit of coordination and explicit preference information of users to be considered in the negotiated design of infrastructure and their management. The study identifies, for a given set of performance metrics and multiple stakeholders' preference information, the infrastructure, operating rules and coordination strategies that offer viable and attractive balances of benefits.

12 Limitations and future work

The problem formulations proposed in this thesis and applied to the Nile dam planning problem show that a many objective optimization approach can be used to study a range of transboundary water resources issues. While it is crucial to ensure adequate representation of stakeholder in planning water systems, opportunities for official stakeholder interaction in our studies were limited due to the diplomatic tensions between the Nile countries concerning the Grand Ethiopian Renaissance Dam (GERD).

This thesis contains proof of concept studies on the Blue Nile including only some of the possible performance metrics that could be relevant to Nile stakeholders. The limitations of the case study recommendations in this thesis emanates from the fact that each chapter deals with a subset of the complex Blue Nile problem and is intended to be a proof-of-concept application. This was essential to demonstrate the proposed methods succinctly and to avoid excessive detail. Real world decision support for this NIle would need to incorporate and combine the approaches demonstrated and performance metrics used in chapter 5 through chapter 10 and additional proposed studies described at the end of this section and shown in Figure 48.

The problem formulations ignore the demand dynamics; this is justified given the shortage of electricity in the region and the possibility of power trade among several countries in the region which is already being explored. The fact that unmet electricity demand is higher than the supply capacity of the proposed dams is why the demand dynamics or uncertainty is not considered in this study.

Several other points (e.g., displaced population, floods, etc.) matter for decision making. However, this chapter focuses on the downstream impact of the proposed Blue Nile reservoirs, especially during their filling period. The impact of filling the large dams on downstream water use is a major concern and could be the biggest hindrance to rapid development even in the presence of agreement. Other studies on Nile development [e.g., Whittington et al., 2005; Blackmore and Whittington, 2008; Block et al., 2008; Goor et al., 2010; Jeuland and Whittington, 2014] consider the filling period performance and its trade-off with financial feasibility of the investments as a pressing issue for Nile development.

Block and Strzepek [2012] find while a changing climate may pose a challenge to meeting expected targets from the Blue Nile dams, energy development utilizing hydropower appears economically reasonable (but benefit cost ratio as low as 1.1) . They opine that “this development is desperately needed, independent of future climate change trends, with the hope of appreciably reducing vulnerability to variability". More recently van der Zwaan et al.[2018] suggest while a changing climate may impose costs of US$2–4 billion compared with a no climate change scenario, energy development utilizing hydropower is economically reasonable.

A decision support for a negotiated multi-reservoir design would involve multiple stakeholder countries with conflicting performance objective and hence various designs would likely be considered. The Nile riparian countries, through the Nile Basin Initiative have been engaged in building a shared vision model to aid with decision support for a consensus development plans.

It would be difficult to optimise all the decision levers that can be applied in the management of the Nile (in downstream countries) without making controversial assumptions of what the downstream countries would find unacceptable. Moreover, realistically estimating the costs and benefits for all Nile countries is difficult as there is no single source of such information in the Nile. Moreover, the countries are unlikely to agree on the cost and benefits of alternative management options (e.g., the price of energy, the cost of energy reduction to each of the countries' economy, the appropriate discount rate, etc…). Including different parts of the system would have complicated the study considerably.

The study adopted a parsimonious approach - simulating as little of the whole system as necessary to make a case for the methodological contribution presented here. The formulation includes explicit accounting of the downstream releases in different filling periods to represent downstream countries' interests, such as Egypt's. The downstream releases are considered as an effective proxy for a range of more specific performance measures that downstream countries could be interested in. It allows downstream stakeholders to estimate the impact of a particular infrastructure and management decision. For example, it would be conceptually straightforward for an interested party to investigate the implications of the policies developed in this chapter on the High Aswan dam.

The GERD620 dam design is not actively being considered [Jeuland and Whittington, 2014] but it is included here to demonstrate the proposed approaches. An aggregate net benefit maximizing objective considering variation in cost and installed power capacities with storage size, and peaking power demand could provide more decision-relevant information. The firm energy metric used in this study represents the seasonal and interannual variation of monthly energy generated. Incorporating other short-term performance metrics such as energy supply reliability considering the daily and hourly demand distribution which are of interest to system planners could reveal more insights on the design problem.

The study also ignores possible changes of cropping patterns in Sudan, i.e., the change in magnitude and timing of seasonal irrigation demand with the availability of more regulated flow from Ethiopian dams.

Uncertainty due to climate change can be an important consideration for long-term assets but is not considered in this work which assumes climate stationarity. Recent papers explore climate change impacts on the economic feasibility of the projects and the impact on the downstream system that filling and operating of these reservoirs entails [*Block and Strzepek*, 2010; *Jeuland and Whittington*, 2014].

The work in chapter 9 is on reservoir system management for inter-annual variability. Climate change impact and economic uncertainty could potentially be addressed for adaptive reservoir system expansion and management [*Eriksson and Weber*, 2008; *Giuliani et al.*, 2016]. The study focused on the steady-state management of the GERD reservoir. Future work could include considering the adaptivity in reservoir operating rules when screening among alternative storage designs and their schedule of implementation.

Water resource assessment approaches traditionally assumed future actions as static while in fact they are typically reviewed based on recurrently updated information. A typical assumption in the assessment of system interventions is that the interaction of decision-makers and the system plan is a one-off. The multi-reservoir scheduling approach in chapter 6 includes this limitation. This under-estimates decision makers' abilities to incorporate information from across the basin and over time (e.g., adapting operating rules and delaying or abandoning investments). For many decision problems, failure to adequately represent (model) the inter-dependency of the natural, infrastructure and human systems perpetuate the perception of intractability by overdramatizing the trade-offs between conflicting objectives and among stakeholders' benefits.

In addition to potential benefits of regulation, upstream reservoirs can increase foresight (predicting future flows) if monitoring of storage levels is possible. For example, in highly seasonal basins, where the dry season flow is low compared to the wet season flows, the water availability downstream of a reservoir throughout the year can be predicted with information on the end of flood season storage level if the operating policy of the reservoir is known. However, most simulation modelling applications assume demands and supply (inflows) as independent. This assumption could be misleading where water demand is at least partially dependent on its supply [*Faber and Frenken*, 2009; *Jeuland*, 2010]. An adaptive agricultural decision making that resembles seasonal flow forecasts, but that which, instead of prediction being solely based on observed correlations between precipitation or river flows and various weather variables in global climate system [*Seleshi and Demaree*, 1995; *Berhane et al.*, 2014], considers spatially and temporally varied artificial interventions in water systems to predict water availability could be useful and necessary to understand the true impacts of new upstream storage structures.

Given the uncertainties and shortcomings in the current study as listed in the previous paragraphs, the author recognises the limitations of the results and does not claim the results should impact current Nile decision-making directly. Results are indicative and intended to demonstrate the methodology but should not to be taken as prescriptive recommendations.

From the lessons learned in this study, and to address some of the limitations described above, future research directions (Figure 48) are suggested to provide more decision-relevant information on the Blue Nile reservoirs.

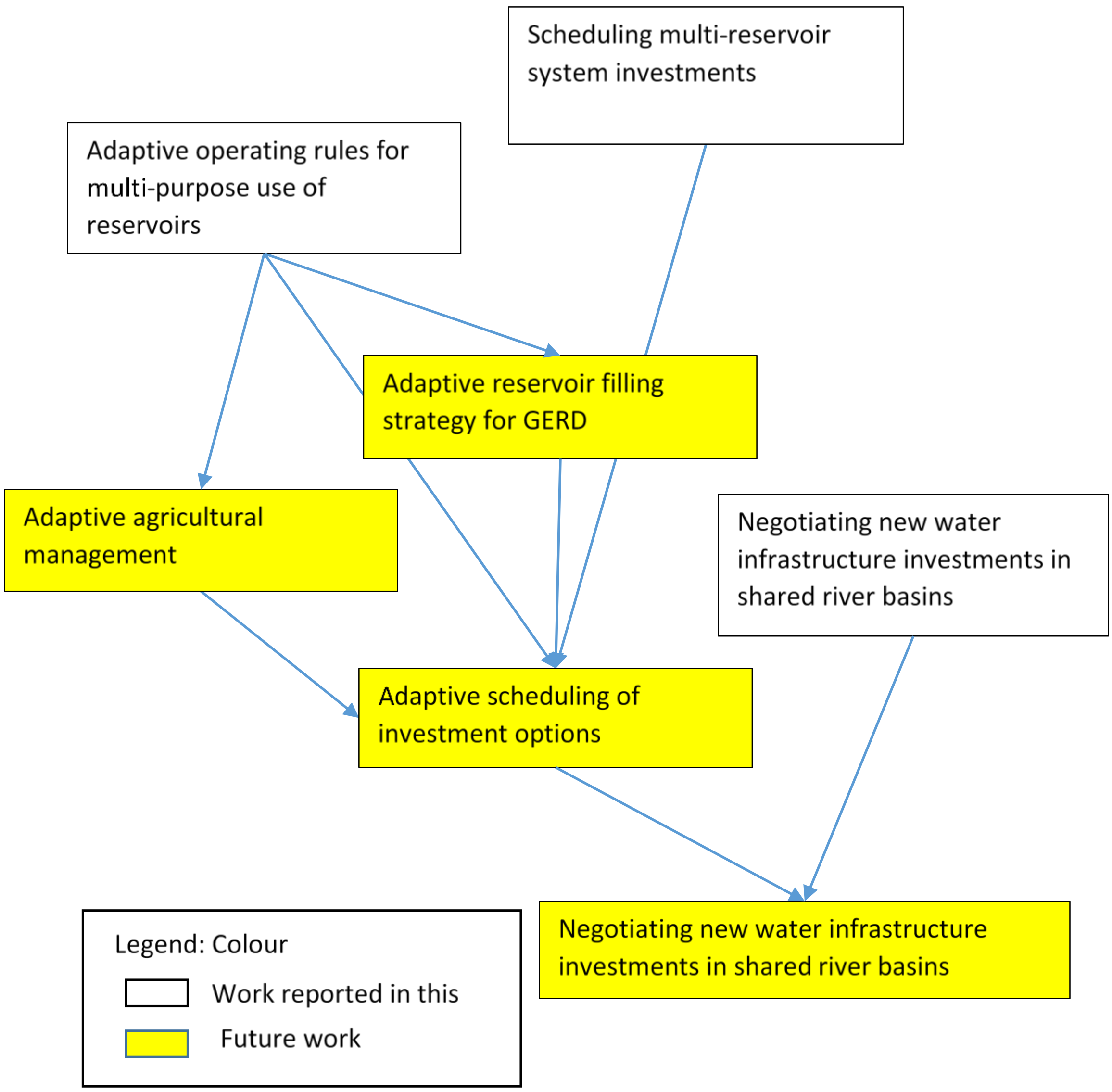


Figure 48 Proposed future research

13 Appendix

13.1 **Appendix A:**

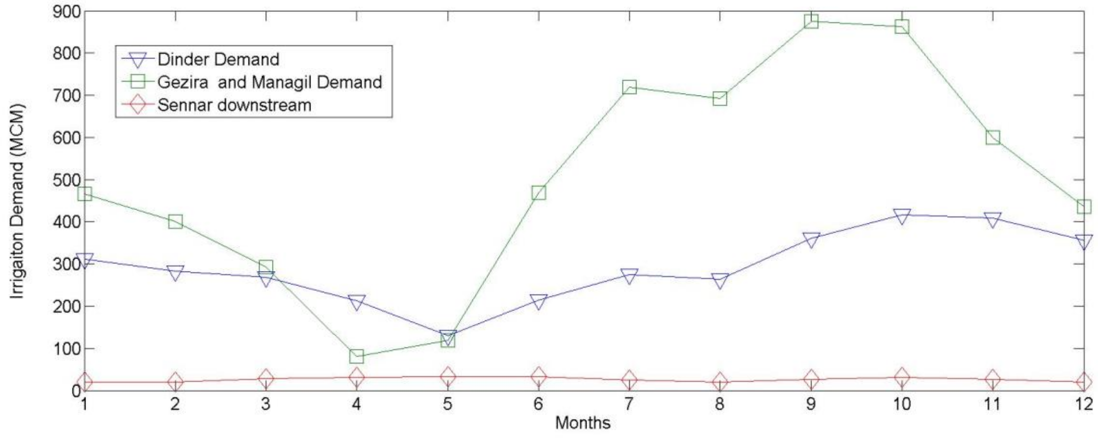


Figure 49 Seasonal distribution of irrigation water demand for sites served by Sennar and Roseires reservoirs in Blue Nile Sudan.

13.2 **Appendix B:**

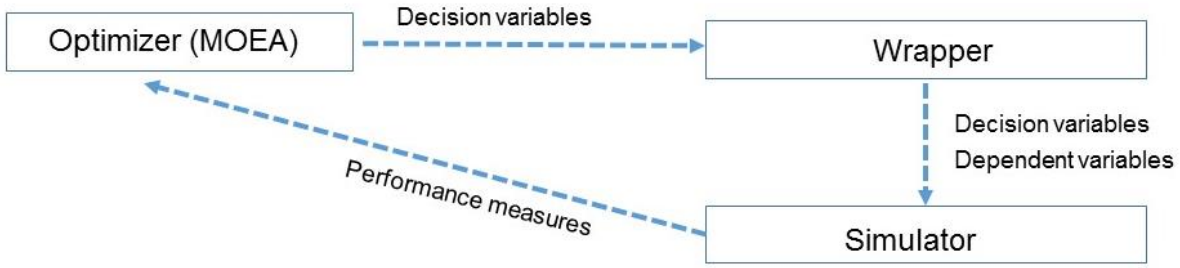


Figure 50 Computational framework

13.3 **Appendix C:**

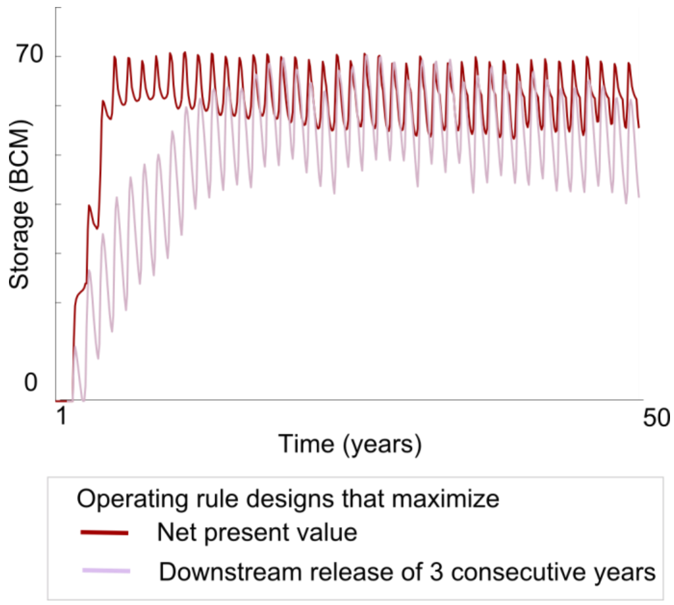


Figure 51 Time series of storage (averaged over 10 hydrological traces) for example designs (f' and 'o' in Figure 16, i.e., when the GERD dam is operated to maximise the 99% exceeded 3-year cumulative downstream flow and net present value respectively). The figure shows that maximizing reliable downstream releases requires filling the reservoir over a longer period compared to operating designs that maximise the net present worth.

13.4 **Appendix D:**

This section compares computational requirements as the operating rules of the multi-reservoir system scheduling problem is formulated with increasing degrees of responsiveness in Chapter 6.

Performance of many objective evolutionary algorithms is stochastic, with no guarantee that a particular single optimization run will achieve close performance levels as the true (but unknown) Pareto-front. Whether a run approximates the true Pareto-front can be affected by the initial conditions. Solutions from different optimization runs can also occupy (or approximate) various parts of the true Pareto-front. Hence, Pareto-sorting of solutions from different random seeded runs could better approximate the extent of the true-Pareto front. often, multiple runs with randomly seeded initial populations are required to approximate the Pareto-front [*Zatarain Salazar et al.*, 2017].

Figure 52 provides an illustrative example of how hypervolume is computed for a 2-objective problem [*Zatarain Salazar et al.*, 2017]. A reference point is chosen based on the bounds of the approximation set plus an additional delta; the delta ensures the boundary points contribute positive volume to the overall hypervolume.

A large hypervolume will correspond to approximation sets that dominate more space, indicating high quality approximation sets (i.e., proximity and diversity). The most dominant alternatives score higher hypervolume.

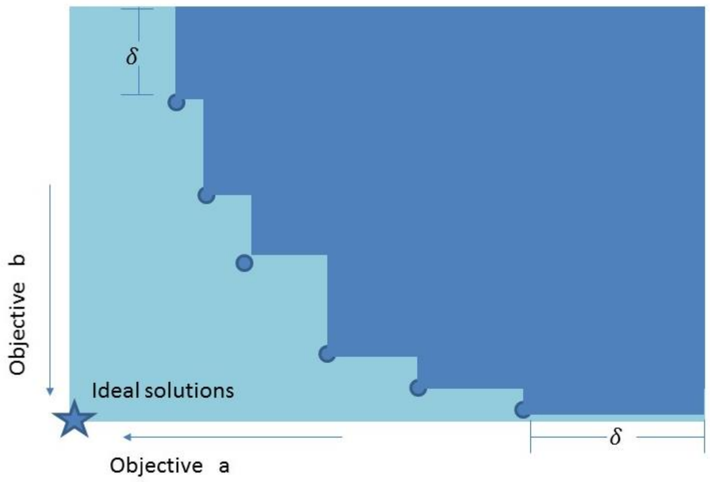


Figure 52 Schematic of the hypervolume indicator in a 2D projection. The bounds of the reference approximation set are used to calculate the reference point; this calculation typically adds a delta (δ), so that the boundary points contribute positive hypervolume.

The many objective optimization is counducted with up to 30 runs with different initial points (random seeds) where each is allowed to last for up to 100,000 function evaluations. The results from each run are then sorted together to provide the best overall reference set [*Kollat et al.*, 2008].

Given the high computational cost associated with increasing either the number of random seeds or the length of evolutions (which is correlated with higher performance), balancing both with computational resources is required while ensuring fidelity of the results. We present the computational performance of the different problem formulations under various number of randomly seeded runs and lengths of evolutions. The absence of improvement in the Hypervolume metric (i.e., an indicator for convergence and diversity of solutions) [*Kollat and Reed*, 2006; *Beume*, 2009] with additional function evaluations and number of random seeds is understood as evidence of convergence.

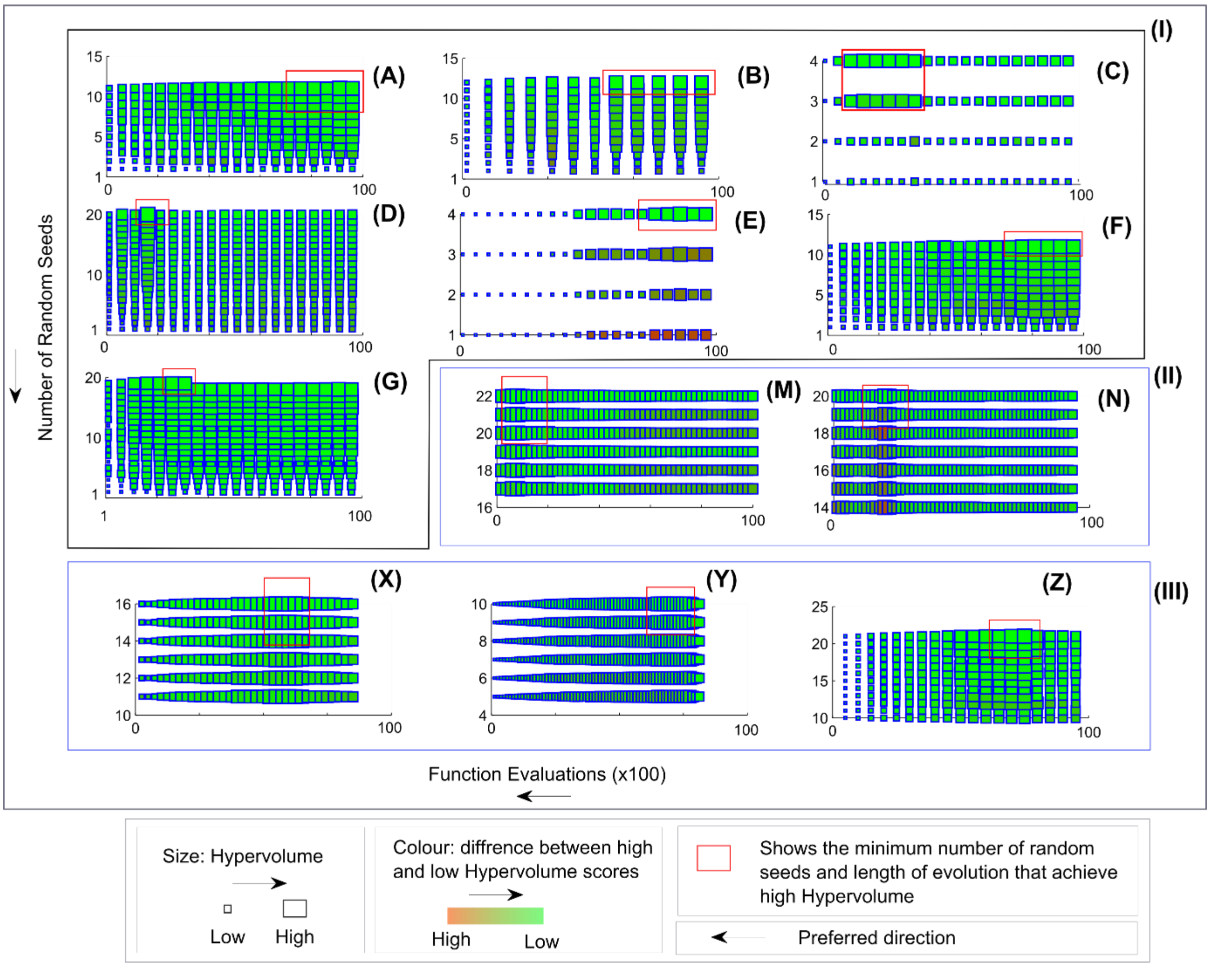


Figure 53 The minimum function evaluations and number of random-seed analysis (shown in red boxes) that achieve highest possible hypervolume metric (shown with size of boxes) and robustness (shown with colour). Panels (A-G) show the hypervolume progression for each of the proposed Blue Nile reservoirs (53 decision variables). Panels M and N show a multi-reservoir scheduling formulation that assumes a fixed pre-optimised operating rule for each reservoir (11 decision variables). Panels X and Y correspond to a two-reservoir investment scheduling with semi-responsive and highly responsive operating rule designs (95 and 137 number of decision variables) respectively. Panel Z shows the hypervolume progress for a four-reservoir problem with highly responsive operating rules (a total of 431 decision variables).

Problem formulations with larger number of decision variables and inter-dependence between decision variables (e.g. Panels X, Y and Z) require Pareto-sorting among a larger number of random-seeded runs to achieve convergence compared to simpler ones (i.e., Panel M and Panel N).

14 Bibliography

Abitbol, E., and S. Schoenfeld (2009), Constructing An Adaptive Regional Vision of Water, in *The Jordan River and Dead Sea Basin: Cooperation Amid Conflict*, edited by C. Lipchin, D. Sandler, and E. Cushman, pp. 297–316.

Alan, B. (2012), *Strategic perspectives and options assessment of Blue Nile multiPorpose development*, Nile Basin Initiative - Eastern Nile Technical Regional Office, Addis Ababa, Ethiopia.

Alfaro, J., and S. Miller (2014), Satisfying the rural residential demand in Liberia with decentralized renewable energy schemes, *Renew. Sustain. Energy Rev.*, *30*, 903–911, doi:10.1016/j.rser.2013.11.017.

Allan, J. A. (2009), Nile Basin Asymmetries : A Closed Fresh Water Resource , Soil Water Potential , the Political Economy and Nile Transboundary, in *The Nile*, vol. 89, edited by H. J. Dumont, pp. 749–770.

Amer, S. E., Y. Arsano, A. El-Battahani, O. E. Hamad, M. A. E. Hefny, I. Tamrat, and S. Mason (2005), Sustainable development and international cooperation in the Eastern Nile Basin, *Aquat. Sci.*, *67*(1), 3–14, doi:10.1007/s00027-004-0764-z.

Anderson, R. M., B. F. Hobbs, and M. L. Bell (2003), Multi–objective Decision–making in Negotiation and conflict resolution, *Encycl. Life Support Syst.*, 1–27.

Andreu, J., M. A. Perez, J. Paredes, and A. Solera (2009), Participatory analysis of the Jucar-Vinalopo (Spain) water conflict using a Decision Support System, *18th World Imacs Congr. Modsim09 Int. Congr. Model. Simul. Interfacing Model. Simul. with Math. Comput. Sci.*, 3230–3236.

Anghileri, D., A. Castelletti, F. Pianosi, R. Soncini-Sessa, and E. Weber (2013), Optimizing Watershed Management by Coordinated Operation of Storing Facilities, *J. Water Resour. Plan. Manag.*, *139*(5), 492–500, doi:10.1061/(ASCE)WR.1943-5452.0000313.

Ansar, A., B. Flyvbjerg, A. Budzier, and D. Lunn (2014), Should we build more large dams? The actual costs of hydropower megaproject development, *Energy Policy*, *69*, 43–56, doi:10.1016/j.enpol.2013.10.069.

Arena, C., M. R. Mazzola, and G. Scordo (2010), A simulation/optimization model for selecting infrastructure alternatives in complex water resource systems, *Water Sci. Technol.*, *61*(12), 3050–3060, doi:10.2166/wst.2010.220.

Arjoon, D., A. Tilmant, and M. Herrmann (2016), Sharing water and benefits in transboundary river basins, *Hydrol. Earth Syst. Sci.*, *20*(6), 2135–2150, doi:10.5194/hess-20-2135-2016.

Arsano, Y., and I. Tamrat (2005), Ethiopia and the Eastern Nile Basin, in *Aquatic Sciences*, vol. 67, pp. 15–27.

Awulachew, S., L.-M. Rebelo, and D. Molden (2010), The Nile Basin: tapping the unmet agricultural potential of Nile waters, *Water Int.*, *35*(5), 623–654, doi:10.1080/02508060.2010.513091.

Bartle, A. (2002), Hydropower potential and development activities, *Energy Policy*, *30*(14), 1231–1239, doi:10.1016/s0301-4215(02)00084-8.

Bayazit, M., and N. E. Ünal (1990), Effects of hedging on reservoir performance, *Water Resour. Res.*, *26*(4), 713–719, doi:10.1029/WR026i004p00713.

Beh, E. H. Y., G. C. Dandy, H. R. Maier, and F. L. Paton (2014), Optimal sequencing of water supply options at the regional scale incorporating alternative water supply sources and multiple objectives, *Environ. Model. Softw.*, *53*, 137–153, doi:10.1016/j.envsoft.2013.11.004.

Beh, E. H. Y., H. R. Maier, and G. C. Dandy (2015), Adaptive, multiobjective optimal sequencing approach for urban water supply augmentation under deep uncertainty, *Water Resour. Res.*, *51*(3), 1529–1551, doi:10.1002/2014WR016254.

Ben-Haim, Y. (2006), *Info-gap decision theory: decisions under severe uncertainty*.

Ben-Tal, A., L. El Ghaoui, and A. Nemirowski (2009), *Robust optimization*, Princeton University Press, Princeton, New Jersey.

Berhane, F., B. Zaitchik, and A. Dezfuli (2014), Subseasonal Analysis of Precipitation Variability in the Blue Nile River Basin, *J. Clim.*, *27*(1), 325–344, doi:10.1175/jcli-d-13-00094.1.

Bertsimas, D., D. B. Brown, and C. Caramanis (2011), Theory and Applications of Robust Optimization, *SIAM Rev.*, *53*(3), 464–501, doi:doi:10.1137/080734510.

Beume, N. (2009), S-metric calculation by considering dominated hypervolume as Klee's measure problem, *Evol. Comput.*, *17*(4), 477–492, doi:10.1162/evco.2009.17.4.17402.

Bhaskar, N. R., and E. E. Whitlatch (1980), Derivation of monthly reservoir release policies, *Water Resour. Res.*, *16*(6), 987–993, doi:10.1029/WR016i006p00987.

Bieker, S., P. Cornel, and M. Wagner (2010), Semicentralised supply and treatment systems: Integrated infrastructure solutions for fast growing urban areas, *Water Sci. Technol.*, *61*(11), 2905–2913, doi:10.2166/wst.2010.189.

Bird, J., and P. Wallace (2001), Dams and development - An insight to the report of the World Commission on Dams, *Irrig. Drain.*, *50*(1), 53–64, doi:10.1002/ird.11.

Blackmore, D., and D. Whittington (2008), Opportunities for cooperative water resources development on the eastern Nile: Risks and rewards, *Rep. to East. Counc. Minist. Entebbe*, (October).

Block, P., and B. Rajagopalan (2007), Interannual Variability and Ensemble Forecast of Upper Blue Nile Basin Kiremt Season Precipitation., *J. Hydrometeorol.*, *8*(3), 327–343, doi:10.1175/JHM580.1.

Block, P., and K. Strzepek (2010), Economic Analysis of Large-Scale Upstream River Basin Development on the

Blue Nile in Ethiopia Considering Transient Conditions, Climate Variability, and Climate Change, *J. Water Resour. Plan. Manag.*, *136*(2), 156–166, doi:10.1061/(asce)wr.1943-5452.0000022.

Block, P., and K. Strzepek (2012), Power Ahead: Meeting Ethiopia's Energy Needs Under a Changing Climate, *Rev. Dev. Econ.*, *16*(3), 476–488, doi:10.1111/j.1467-9361.2012.00675.x.

Block, P. J., K. Strzepek, M. W. Rosegrant, and X. Diao (2008), Impacts of considering climate variability on investment decisions in Ethiopia, *Agric. Econ.*, *39*(2), 171–181, doi:10.1111/j.1574-0862.2008.00322.x.

Borowski, I., and M. Hare (2007), Exploring the gap between water managers and researchers: Difficulties of model-based tools to support practical water management, *Water Resour. Manag.*, *21*(7), 1049–1074, doi:10.1007/s11269-006-9098-z.

Braga, B. P. F., J. G. L. Conejo, L. Becker, and W. W. G. Yeh (1985), CAPACITY EXPANSION OF SAO-PAULO WATER-SUPPLY, *J. Water Resour. Plan. Manag.*, *111*(2), 238–252.

Brill, E. D., S.-Y. Chang, and L. D. Hopkins (1982), Modeling to generate alternatives: the HSJ approach and an illustration using a problem in land use planning, *Manage. Sci.*, *28*(3), 221–235, doi:10.1287/mnsc.28.3.221.

Bristow, M., L. Fang, and K. W. Hipel (2014), Agent-Based Modeling of Competitive and Cooperative Behavior Under Conflict, *Ieee Trans. Syst. Man Cybern.*, *44*(7), 834–850, doi:10.1109/tsmc.2013.2282314.

Brown, C., Y. Ghile, M. Laverty, and K. Li (2012), Decision scaling: Linking bottom-up vulnerability analysis with climate projections in the water sector, *Water Resour. Res.*, *48*, 12, doi:10.1029/2011wr011212.

Cai, X., D. C. McKinney, and L. S. Lasdon (2002), A framework for sustainability analysis in water resources management and application to the Syr Darya Basin, *Water Resour. Res.*, *38*(6), 1085–1098, doi:10.1029/2001WR000214.

Cai, X., L. Lasdon, and A. M. Michelsen (2004), Group Decision Making in Water Resources Planning Using Multiple Objective Analysis, *J. Water Resour. Plan. Manag.*, *130*(1), 4–14, doi:10.1061/(ASCE)0733-9496(2004)130:1(4).

Carmona, G., C. Varela-Ortega, and J. Bromley (2013), Participatory modelling to support decision making in water management under uncertainty: Two comparative case studies in the Guadiana river basin, Spain, *J. Environ. Manage.*, *128*, 400–412, doi:10.1016/j.jenvman.2013.05.019.

Cascao, A. E. (2008), Ethiopia - Challenges to Egyptian hegemony in the Nile Basin, *Water Policy*, *10*, 13–28, doi:10.2166/wp.2008.206.

Cascão, A. E. (2009), Changing power relations in the Nile river basin: Unilateralism vs. cooperation?, *Water Altern.*, *2*(2), 245–268.

Celeste, A. B., and M. Billib (2009), Evaluation of stochastic reservoir operation optimization models, *Adv. Water Resour.*, *32*(9), 1429–1443, doi:10.1016/j.advwatres.2009.06.008.

Chang, L. C., and F. J. Chang (2009), Multi-objective evolutionary algorithm for operating parallel reservoir system, *J. Hydrol.*, *377*(1–2), 12–20, doi:10.1016/j.jhydrol.2009.07.061.

Chang, S.-Y., E. D. Brill, and L. D. Hopkins (1982), Use of mathematical models to generate alternative solutions to water resources planning problems, *Water Resour. Res.*, *18*(1), 58–64, doi:10.1029/WR018i001p00058.

Chang, Y. H., and C. H. Yeh (2001), Evaluating airline competitiveness using multiattribute decision making, *Omega*, *29*(5), 405–415, doi:10.1016/S0305-0483(01)00032-9.

Coello Coello, C. A. (2006), Evolutionary Multi-Objective Optimization: A Historical View of the Field, *IEEE Comput. Intell. Mag.*, *1*(1), 28–36, doi:10.1109/MCI.2006.1597059.

Coello Coello, C. A., G. B. Lamont, and D. a Van Veldhuizen (2007), *Evolutionary algorithms for solving multi-objective problems*, edited by G. Lamont, Springer-Verlag, New York.

Conway, D. (2000), The climate and hydrology of the Upper Blue Nile river, *Geogr. J.*, *166*, 49–62, doi:10.1111/j.1475-4959.2000.tb00006.x.

Conway, D. (2005), From headwater tributaries to international river: Observing and adapting to climate variability and change in the Nile basin, *Glob. Environ. Chang.*, *15*(2), 99–114, doi:10.1016/j.gloenvcha.2005.01.003.

Conway, D. (2017), Water resources: Future Nile river flows, *Nat. Clim. Chang.*, *7*(5), 319–320, doi:10.1038/nclimate3285.

Conway, D., M. Krol, J. Alcamo, and M. Hulme (1996), Future availability of water in Egypt: The interaction of global, regional, and basin scale driving forces in the Nile Basin, *Ambio*, *25*(5), 336–342.

Datta, D., C. M. Fonseca, and K. Deb (2008), A multi-objective evolutionary algorithm to exploit the similarities of resource allocation problems, *J. Sched.*, *11*(6), 405–419, doi:10.1007/s10951-008-0073-9.

Deb, K., A. Pratap, S. Agarwal, and T. Meyarivan (2002), A fast and elitist multiobjective genetic algorithm: NSGA-II, *IEEE Trans. Evol. Comput.*, *6*(2), 182–197, doi:10.1109/4235.996017.

Despotis, D. K. (1996), Fractional minmax goal programming: A unified approach to priority estimation and preference analysis in MCDM, *J. Oper. Res. Soc.*, *47*(8), 989–999, doi:10.1057/jors.1996.126.

Dinar, S. (2006), Assessing side-payment and cost-sharing patterns in international water agreements: The geographic and economic connection, *Polit. Geogr.*, *25*(4), 412–437, doi:10.1016/j.polgeo.2006.03.007.

Dinar, S. (2012), The Geographical Dimensions of Hydro-politics: International Freshwater in the Middle East, North Africa, and Central Asia, *Eurasian Geogr. Econ.*, *53*(1), 115–142, doi:10.2747/1539-7216.53.1.115.

Dore, J., and L. Lebel (2010), Deliberation and scale in mekong region water governance, *Environ. Manage.*, *46*(1), 60–80, doi:10.1007/s00267-010-9527-x.

Dugoua, E., and J. Urpelainen (2014), Relative deprivation and energy poverty: When does unequal access to electricity cause dissatisfaction?, *Int. J. Energy Res.*, *38*(13), 1727–1740, doi:10.1002/er.3200.

Dumont, H. J. (2009), A Description of the Nile Basin, and a Synopsis of Its History, Ecology, Biogeography, Hydrology, and Natural Resources, *Nile Orig. Environ. Limnol. Hum. Use*, *89*, 1–21.

Dunkerley, J., and W. Ramsay (1982), Energy and the oil-importing developing-countries, *Science (80-.).*, *216*(4546), 590–595, doi:10.1126/science.216.4546.590.

Duvail, S., A. B. Mwakalinga, A. Eijkelenburg, O. Hamerlynck, K. Kindinda, and A. Majule (2014), Jointly thinking the post-dam future: exchange of local and scientific knowledge on the lakes of the Lower Rufiji, Tanzania, *Hydrol. Sci. J.*, *59*(3–4), 713–730, doi:10.1080/02626667.2013.827792.

Dziegielewski, B., W. R. Mee, and K. R. Larson (1992), Developing a Long-Term Drought Plan for Phoenix, *J. Am. Water Work. Assoc.*, *84*(10), 46–51.

Eastman, J., and C. ReVelle (1973), Linear decision rule in reservoir management and design: 3. Direct capacity determination and intraseasonal constraints, *Water Resour. Res.*, *9*(1), 29–42, doi:10.1029/WR009i001p00029.

Ehrgott, M., J. Ide, and A. Schöbel (2014), Minmax robustness for multi-objective optimization problems, *Eur. J. Oper. Res.*, *239*(1), 17–31, doi:10.1016/j.ejor.2014.03.013.

El-Kady, M., and M. Moustafa (2005), The Nile River Basin: Development Research Priorities for Water Security and Management across Borders, *Proc. 2nd Int. Yellow River Forum Keep. Heal. Life River*, *Vol I*, 261–272.

Erfani, T., K. Pachos, and J. J. Harou (2018), Real-options water supply planning : Multistage scenario trees for adaptive and flexible capacity expansion under probabilistic climate change uncertainty, *Water Resour. Res.*, 1–46, doi:10.1029/2017WR021803.

Eriksson, E. A., and K. M. Weber (2008), Adaptive Foresight: Navigating the complex landscape of policy strategies, *Technol. Forecast. Soc. Change*, *75*(4), 462–482, doi:10.1016/j.techfore.2008.02.006.

Faber, A., and K. Frenken (2009), Models in evolutionary economics and environmental policy: Towards an evolutionary environmental economics, *Technol. Forecast. Soc. Change*, *76*(4), 462–470, doi:10.1016/j.techfore.2008.04.009.

Fearon, J. D. (1998), Bargaining, Enforcement, and International Cooperation, *Int. Organ.*, *52*(02), 269–305, doi:10.1162/002081898753162820.

Feng, M., P. Liu, S. Guo, L. Shi, C. Deng, and B. Ming (2017), Deriving adaptive operating rules of hydropower reservoirs using time-varying parameters generated by the EnKF, *Water Resour. Res.*, 6885–6907, doi:10.1002/2016WR020180.

Fisher, I. (1930), The Theory of Interest., *J. R. Stat. Soc.*, doi:10.2307/2342072.

Fitzgerald, M. E., and A. M. Ross (2015), Effects of enhanced multi-party tradespace visualization on a two-person negotiation, in *Procedia Computer Science*, vol. 44, pp. 466–475.

Fliege, J., and R. Werner (2014), Robust multiobjective optimization & applications in portfolio optimization, *Eur. J. Oper. Res.*, *234*(2), 422–433, doi:10.1016/j.ejor.2013.10.028.

Fu, G., Z. Kapelan, J. R. Kasprzyk, P. Reed, and M. Asce (2013), Optimal design of water distribution systems using many-objective visual analytics, *J. Water Resour. Plan. Manag.*, *139*(December), 624–633, doi:10.1061/(ASCE)WR.1943-5452.0000311.

Galaz, V., F. Biermann, C. Folke, M. Nilsson, and P. Olsson (2012), Global environmental governance and planetary boundaries: An introduction, *Ecol. Econ.*, *81*, 1–3, doi:10.1016/j.ecolecon.2012.02.023.

Galelli, S., G. B. Humphrey, H. R. Maier, A. Castelletti, G. C. Dandy, and M. S. Gibbs (2014), An evaluation framework for input variable selection algorithms for environmental data-driven models, *Environ. Model. Softw.*, doi:10.1016/j.envsoft.2014.08.015.

Galloway, G. E. (2011), If Stationarity is Dead, What Do We Do Now?, *J. Am. Water Resour. Assoc.*, *47*(3), 563–570, doi:10.1111/j.1752-1688.2011.00550.x.

Gaudard, L., J. Gabbi, A. Bauder, and F. Romerio (2016), Long-term Uncertainty of Hydropower Revenue Due to Climate Change and Electricity Prices, *Water Resour. Manag.*, *30*(4), 1325–1343, doi:10.1007/s11269-015-1216-3.

Gebreluel, G. (2014), Ethiopia's Grand Renaissance Dam: Ending Africa's Oldest Geopolitical Rivalry?, *Wash. Q.*, *37*(2), 25–37, doi:10.1080/0163660X.2014.926207.

Geressu, R. T., and J. J. Harou (2015), Screening reservoir systems by considering the efficient trade-offs - Informing infrastructure investment decisions on the Blue Nile, *Environ. Res. Lett.*, *10*(12), 125008, doi:10.1088/1748-9326/10/12/125008.

Giuliani, M., J. D. Herman, A. Castelletti, and P. Reed (2014), Many-objective reservoir policy identification and refinement to reduce policy inertia and myopia in water management, *Water Resour. Res.*, *50*(4), 3355–3377, doi:10.1002/2013WR014700.

Giuliani, M., D. Anghileri, A. Castelletti, P. N. Vu, and R. Soncini-Sessa (2016), Large storage operations under climate change: expanding uncertainties and evolving tradeoffs, *Environ. Res. Lett.*, *11*(3), 035009, doi:10.1088/1748-9326/11/3/035009.

Goedhart, M. H., and J. Spronk (1995), Financial-planning with fractional goals, *Eur. J. Oper. Res.*, *82*(1), 111–124, doi:10.1016/0377-2217(94)00034-a.

Goor, Q., C. Halleux, Y. Mohamed, and A. Tilmant (2010), Optimal operation of a multipurpose multireservoir system in the Eastern Nile River Basin, *Hydrol. Earth Syst. Sci.*, *14*(10), 1895–1908, doi:10.5194/hess-14-1895-2010.

Gopalakrishnan, G., B. Minsker, and D. E. Goldberg (2003), Optimal Sampling in a Noisy Genetic Algorithm for Risk-Based Remediation Design, *J. Hydroinformatics*, *5*, 11–25, doi:10.1061/40569(2001)94.

Groves, D. G., and R. J. Lempert (2007), A new analytic method for finding policy-relevant scenarios, *Glob. Environ. Chang. Policy Dimens.*, *17*(1), 73–85, doi:10.1016/j.gloenvcha.2006.11.006.

Guariso, G., S. Rinaldi, and R. Soncini-Sessa (1986), The Management of Lake Como: A Multiobjective Analysis, *Water Resour. Res.*, *22*(2), 109–120, doi:10.1029/WR022i002p00109.

Gunalay, Y., J. S. Yeomans, and G. H. Huang (2012), Modelling to generate alternative policies in highly uncertain environments: An application to municipal solid waste management planning, *J. Environ. Informatics*, *19*(2), 58–69, doi:10.3808/jei.201200209.

Haasnoot, M., J. H. Kwakkel, W. E. Walker, and J. ter Maat (2013), Dynamic adaptive policy pathways: A method for crafting robust decisions for a deeply uncertain world, *Glob. Environ. Chang. Policy Dimens.*, *23*(2), 485–498, doi:10.1016/j.gloenvcha.2012.12.006.

Habteyes, B. G., H. A. E. H. El-Bardisy, S. A. Amer, V. R. Schneider, and F. A. Ward (2015), Mutually beneficial and sustainable management of Ethiopian and Egyptian dams in the Nile Basin, *J. Hydrol.*, *529*, 1235–1246, doi:10.1016/j.jhydrol.2015.09.017.

Hadka, D., and P. Reed (2013), Borg: An Auto-Adaptive Many-Objective Evolutionary Computing Framework, *Evol. Comput.*, *21*(2), 231–259.

Hahn, R. W., and P. M. Dudley (2008), *How Well Does the U.S. Government Do Benefit-Cost Analysis?*

Hall, W. A., and N. Buras (1961), The dynamic programming approach to water-resources development, *J. Geophys. Res.*, *66*(2), 517, doi:10.1029/JZ066i002p00517.

Hamouda, M. A., M. M. N. El-Din, and F. I. Moursy (2009), Vulnerability Assessment of Water Resources Systems in the Eastern Nile Basin, *Water Resour. Manag.*, *23*(13), 2697–2725, doi:10.1007/s11269-009-9404-7.

Harou, J. J., M. Pulido-Velazquez, D. E. Rosenberg, J. Medellín-Azuara, J. R. Lund, and R. E. Howitt (2009), Hydro-economic models: Concepts, design, applications, and future prospects, *J. Hydrol.*, *375*(3–4), 627–643, doi:10.1016/j.jhydrol.2009.06.037.

Hashimoto, T., J. R. Stedinger, and D. P. Loucks (1982), Reliability, resiliency, and vulnerability criteria for water resource system performance evaluation, *Water Resour. Res.*, *18*(1), 14–20, doi:10.1029/WR018i001p00014.

Hassaballah, K., A. Jonoski, I. Popescu, and D. P. Solomatine (2012), Model-Based Optimization of Downstream Impact during Filling of a New Reservoir: Case Study of Mandaya/Roseires Reservoirs on the Blue Nile River, *Water Resour. Manag.*, *26*(2), 273–293, doi:10.1007/s11269-011-9917-8.

Hefny, M., and S. El-Din Amer (2005), Egypt and the Nile Basin, in *Aquatic Sciences*, vol. 67, pp. 42–50.

Hejazi, M. I., X. Cai, and B. L. Ruddell (2008), The role of hydrologic information in reservoir operation - Learning from historical releases, *Adv. Water Resour.*, *31*(12), 1636–1650, doi:10.1016/j.advwatres.2008.07.013.

Herman, J. D., and M. Giuliani (2018), Policy tree optimization for threshold-based water resources management over multiple timescales, *Environ. Model. Softw.*, *99*, 39–51, doi:10.1016/j.envsoft.2017.09.016.

Herman, J. D., H. B. Zeff, P. M. Reed, and G. W. Characklis (2014a), Beyond optimality: Multistakeholder robustness tradeoffs for regional water portfolio planning under deep uncertainty, *Water Resour. Res.*, *50*(10), 7692–7713, doi:10.1002/2014wr015338.

Herman, J. D., H. B. Zeff, P. M. Reed, and G. W. Characklis (2014b), Beyond optimality: Multistakeholder robustness tradeoffs for regional water portfolio planning under deep uncertainty, *Water Resour. Res.*, *50*(10), 7692–7713, doi:10.1002/2014wr015338.

Hernandez-Diaz, A. G., L. V Santana-Quintero, C. A. C. Coello, and J. Molina (2007), Pareto-adaptive epsilon-dominance, *Evol. Comput.*, *15*(4), 493–517, doi:10.1162/evco.2007.15.4.493.

Hipel, K. W., K. J. Radford, and L. P. Fang (1993), Multiple participant - multiple criteria decision - making, *Ieee Trans. Syst. Man Cybern.*, *23*(4), 1184–1189, doi:10.1109/21.247900.

Hipel, K. W., D. M. Kilgour, L. P. Fang, and X. Y. Peng (1997), The decision support system GMCR in environmental conflict management, *Appl. Math. Comput.*, *83*(2–3), 117–152, doi:10.1016/s0096-3003(96)00170-1.

Hobbs, B. F., V. Chankong, W. Hamadeh, and E. Z. Stakhiv (1992), Does choice of multicriteria method matter? An experiment in water resources planning, *Water Resour. Res.*, *28*(7), 1767–1779, doi:10.1029/92WR00712.

Hogarth, R. M. (1981), BEYOND DISCRETE BIASES - FUNCTIONAL AND DYSFUNCTIONAL ASPECTS OF JUDGMENTAL HEURISTICS, *Psychol. Bull.*, *90*(2), 197–217, doi:10.1037//0033-2909.90.2.197.

Houck, M. H., and J. L. Cohon (1978), Sequential explicitly stochastic linear-programming models - proposed method for design and management of multipurpose reservoir systems, *Water Resour. Res.*, *14*(2), 161–169.

Huntjens, P., C. Pahl-Wostl, B. Rihoux, M. Schlüter, Z. Flachner, S. Neto, R. Koskova, C. Dickens, and I. N. Kiti (2011), Adaptive water management and policy learning in a changing climate: A formal comparative analysis of eight water management regimes in Europe, Africa and Asia, *Environ. Policy Gov.*, doi:10.1002/eet.571.

Hurford, A. P., and J. J. Harou (2014), Balancing ecosystem services with energy and food security - Assessing trade-offs from reservoir operation and irrigation investments in Kenya's Tana Basin, *Hydrol. Earth Syst. Sci.*, *18*(8), 3259–3277, doi:10.5194/hess-18-3259-2014.

Hurford, A. P., I. Huskova, and J. J. Harou (2014), Using many-objective trade-off analysis to help dams promote economic development, protect the poor and enhance ecological health, *Environ. Sci. Policy*, *38*, 72–86, doi:10.1016/j.envsci.2013.10.003.

Hurni, H., K. Tato, and G. Zeleke (2005), The implications of changes in population, land use, and land management for surface runoff in the upper Nile Basin area of Ethiopia, *Mt. Res. Dev.*, *25*(2), 147–154, doi:10.1659/0276-4741(2005)025[0147:tiocip]2.0.co;2.

Huskova, I., E. S. Matrosov, J. J. Harou, J. R. Kasprzyk, and C. Lambert (2016), Screening robust water infrastructure investments and their trade-offs under global change: A London example, *Glob. Environ. Chang.*, *41*, 216–227, doi:10.1016/j.gloenvcha.2016.10.007.

Inderst, R. (2000), Multi-issue Bargaining with Endogenous Agenda, *Games Econ. Behav.*, *30*(1), 64–82, doi:10.1006/game.1999.0710.

Inselberg, A. (2009), Parallel Coordinates: Interactive Visualization for High Dimensions, in *Trends in Interactive Visualization: State-of-the-Art Survey*, edited by E. ZudilovaSeinstra, T. Adriaansen, and R. VanLiere, pp. 49–78.

Jager, H. I., and B. T. Smith (2008), Sustainable reservoir operation: Can we generate hydropower and preserve ecosystem values?, *River Res. Appl.*, *24*(3), 340–352, doi:10.1002/rra.1069.

Javadi, F. S., B. Rismanchi, M. Sarraf, O. Afshar, R. Saidur, H. W. Ping, and N. A. Rahim (2013), Global policy of rural electrification, *Renew. Sustain. Energy Rev.*, *19*, 402–416, doi:10.1016/j.rser.2012.11.053.

Jeuland, M. (2010), Economic implications of climate change for infrastructure planning in transboundary water systems: An example from the Blue Nile, *Water Resour. Res.*, *46*(11), doi:10.1029/2010WR009428.

Jeuland, M., and D. Whittington (2014), Water resources planning under climate change: Assessing the robustness of real options for the Blue Nile, *Water Resour. Res.*, *50*(3), 2086–2107, doi:10.1002/2013wr013705.

Jin, Y. J. Y., and J. Branke (2005), Evolutionary optimization in uncertain environments-a survey, *IEEE Trans. Evol. Comput.*, *9*(3), 303–317, doi:10.1109/TEVC.2005.846356.

Kabir, G., R. Sadiq, and S. Tesfamariam (2014), A review of multi-criteria decision-making methods for infrastructure management, *Struct. Infrastruct. Eng.*, *10*(9), 1176–1210, doi:10.1080/15732479.2013.795978.

Kaner, S., L. Lind, C. Toldi, S. Fisk, and D. Berger (2007), *Facilitator 's guide to participatory decision making*.

Kasprzyk, J. R., P. M. Reed, B. R. Kirsch, and G. W. Characklis (2009), Managing population and drought risks using many-objective water portfolio planning under uncertainty, *Water Resour. Res.*, *45*, doi:10.1029/2009wr008121.

Kasprzyk, J. R., S. Nataraj, P. M. Reed, and R. J. Lempert (2013a), Many objective robust decision making for complex environmental systems undergoing change, *Environ. Model. Softw.*, *42*, 55–71, doi:10.1016/j.envsoft.2012.12.007.

Kasprzyk, J. R., S. Nataraj, P. M. Reed, and R. J. Lempert (2013b), Many objective robust decision making for complex environmental systems undergoing change, *Environ. Model. Softw.*, *42*, 55–71, doi:10.1016/j.envsoft.2012.12.007.

Kaygusuz, K. (2004), Hydropower and the world's energy future, *Energy Sources*, *26*(3), 215–224, doi:10.1080/00908310490256572.

Ke, G. Y., K. W. Li, and K. W. Hipel (2012), An integrated multiple criteria preference ranking approach to the Canadian west coast port congestion conflict, *Expert Syst. Appl.*, *39*(10), 9181–9190, doi:10.1016/j.eswa.2012.02.086.

Keim, D., G. Andrienko, J. D. Fekete, C. G??rg, J. Kohlhammer, and G. Melan??on (2008), Visual analytics: Definition, process, and challenges, in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 4950 LNCS, pp. 154–175.

Keller, L. R., C. W. Kirkwood, and N. S. Jones (2010), Assessing stakeholder evaluation concerns: An application to the Central Arizona water resources system, *Syst. Eng.*, *13*(1), 58–71, doi:10.1002/sys.20132.

Kenfack, J., O. V. Bossou, J. Voufo, and S. Djom (2014), Addressing the current remote area electrification problems with solar and microhydro systems in Central Africa, *Renew. Energy*, *67*, 10–19, doi:10.1016/j.renene.2013.11.044.

Khaliquzzaman, and S. Chander (1997), Network flow programming model for multireservoir sizing, *J. Water Resour. Plan. Manag.*, *123*(1), 15–25, doi:10.1061/(asce)0733-9496(1997)123:1(15).

Kilgour, D. M., K. W. Hipel, and L. P. Fang (1987), THE GRAPH MODEL FOR CONFLICTS, *Automatica*, *23*(1), 41–55, doi:10.1016/0005-1098(87)90117-8.

Kilgour, D. M., L. P. Fang, and K. W. Hipel (1996), Negotiation support using the decision support system GMCR, *Gr. Decis. Negot.*, *5*(4–6), 371–383.

Kim, S. K., and W. W. Yeh (1986), A Heuristic Solution Procedure for Expansion Sequencing Problems, , *22*(8), 1197–1206.

King, A., and P. Block (2014), An assessment of reservoir filling policies for the Grand Ethiopian Renaissance Dam, *J. Water Clim. Chang.*, *5*(2), 233–243, doi:10.2166/wcc.2014.043.

King, J., H. Beuster, C. Brown, and A. Joubert (2014), Pro-active management: the role of environmental flows in transboundary cooperative planning for the Okavango River system, *Hydrol. Sci. Journal-Journal Des Sci. Hydrol.*, *59*(3–4), 786–800, doi:10.1080/02626667.2014.888069.

Klemeš, V. (1979), Storage mass???curve analysis in a systems???analytic perspective, *Water Resour. Res.*, *15*(2), 359–370, doi:10.1029/WR015i002p00359.

Knight, F. (1921), *Risk, Uncertainty, and Profit*, Houghton Mifflin, Boston.

Knowles, J., and D. Corne (2002), On metrics for comparing nondominated sets, in *Proceedings of the 2002*

Congress on Evolutionary Computation, CEC 2002, vol. 1, pp. 711–716.

Ko, S. K., D. G. Fontane, and J. W. Labadie (1992), Multi objective optimization of reservoir systems operation, *Water Resour. Bull.*, *28*(1), 111–127.

Kollat, J. B., and P. Reed (2007), A framework for Visually Interactive Decision-making and Design using Evolutionary Multi-objective Optimization (VIDEO), *Environ. Model. Softw.*, *22*(12), 1691–1704, doi:10.1016/j.envsoft.2007.02.001.

Kollat, J. B., and P. M. Reed (2006), Comparing state-of-the-art evolutionary multi-objective algorithms for long-term groundwater monitoring design, *Adv. Water Resour.*, *29*(6), 792–807, doi:10.1016/j.advwatres.2005.07.010.

Kollat, J. B., P. M. Reed, and J. R. Kasprzyk (2008), A new epsilon-dominance hierarchical Bayesian optimization algorithm for large multiobjective monitoring network design problems, *Adv. Water Resour.*, *31*(5), 828–845, doi:10.1016/j.advwatres.2008.01.017.

Koopmans, T. C. (1960), Stationary Ordinal Utility and Impatience, *Econometrica*, doi:10.2307/1907722.

Kornbluth, J. S. H., and R. E. Steuer (1981), Goal programming with linear fractional criteria, *Eur. J. Oper. Res.*, *8*(1), 58–65, doi:10.1016/0377-2217(81)90029-1.

Koutsoyiannis, D., and A. Economou (2003a), Evaluation of the parameterization-simulation-optimization approach for the control of reservoir systems, *Water Resour. Res.*, *39*(6), n/a-n/a, doi:10.1029/2003WR002148.

Koutsoyiannis, D., and A. Economou (2003b), Evaluation of the parameterization-simulation-optimization approach for the control of reservoir systems, *Water Resour. Res.*, *39*(6), doi:10.1029/2003wr002148.

Küng, R. (2003), Addressing the dimensions of transboundary water use - The Nile basin initiative, *Mt. Res. Dev.*, *23*(1), 4–6, doi:10.1659/0276-4741(2003)023[0004:ATDOTW]2.0.CO;2.

Kwakkel, J. H., W. L. Auping, and E. Pruyt (2013), Dynamic scenario discovery under deep uncertainty: The future of copper, *Technol. Forecast. Soc. Change*, *80*(4), 789–800, doi:10.1016/j.techfore.2012.09.012.

Kwakkel, J. H., M. Haasnoot, and W. E. Walker (2015), Developing dynamic adaptive policy pathways: a computer-assisted approach for developing adaptive strategies for a deeply uncertain world, *Clim. Change*, doi:10.1007/s10584-014-1210-4.

Labadie, J. W. (2004), Optimal Operation of Multireservoir Systems: State-of-the-Art Review, *J. Water Resour. Plan. Manag.*, *130*(2), 93–111, doi:10.1061/(ASCE)0733-9496(2004)130:2(93).

Lall, U., and C. W. Miller (1988), An optimization model for screening multipurpose reservoir systems, *Water Resour. Res.*, *24*(7), 953–968, doi:10.1029/WR024i007p00953.

Langsdale, S., A. Beall, E. Bourget, E. Hagen, S. Kudlas, R. Palmer, D. Tate, and W. Werick (2013), Collaborative

Modeling for Decision Support in Water Resources: Principles and Best Practices, *J. Am. Water Resour. Assoc.*, *49*(3), 629–638, doi:10.1111/jawr.12065.

Larichev, O. I. (1992), Cognitive validity in design of decision???aiding techniques, *J. Multi???Criteria Decis. Anal.*, *1*(3), 127–138, doi:10.1002/mcda.4020010303.

Latrubesse, E. M. et al. (2017), Damming the rivers of the Amazon basin, *Nature*, *546*(7658), 363–369, doi:10.1038/nature22333.

Lempert, R. J., M. E. Schlesinger, and S. C. Bankes (1996), When we don't know the costs or the benefits: Adaptive strategies for abating climate change, *Clim. Change*, *33*(2), 235–274, doi:10.1007/bf00140248.

Lempert, R. J., S. W. Popper, and S. C. Bankes (2003), *Shaping the Next One Hundred Years: New Methods for Quantitative, Long-term Policy Analysis*, RAND, Santa Monica, CA.

Lempert, R. J., D. G. Groves, S. W. Popper, and S. C. Bankes (2006), A general, analytic method for generating robust strategies and narrative scenarios, *Manage. Sci.*, *52*(4), 514–528, doi:10.1287/mnsc.1050.0472.

Li, L. P., P. Liu, D. E. Rheinheimer, C. Deng, and Y. L. Zhou (2014), Identifying Explicit Formulation of Operating Rules for Multi-Reservoir Systems Using Genetic Programming, *Water Resour. Manag.*, *28*(6), 1545–1565, doi:10.1007/s11269-014-0563-9.

Van Liedekerke, L. (2004), Discounting the Future: John Rawls and Derek Parfit's Critique of the Discount Rate, *Ethical Perspect.*, doi:10.2143/EP.11.1.504781.

Lins, H. F., and T. A. Cohn (2011), Stationarity: Wanted Dead or Alive?, *J. Am. Water Resour. Assoc.*, *47*(3), 475–480, doi:10.1111/j.1752-1688.2011.00542.x.

Lopez, H. (2008), *The Social Discount Rate: Estimates for Nine Latin American Countries*.

Lund, J. R. (1987), Evaluation and Scheduling of Water Conservation, *J. Water Resour. Plan. Manag.*, *113*(5), 696–708.

Lund, J. R., and I. Ferreira (1996), Operating Rule Optimization for Missouri River Reservoir System, *J. Water Resour. Plan. Manag.*, *122*(4), 287–295, doi:10.1061/(ASCE)0733-9496(1996)122:4(287).

Lund, J. R., and R. N. Palmer (1997), Water Resource System Modeling for Conflict Resolution, *Water Resour. Updat.*, doi:10.1016/S0377-2217(01)00319-8.

Luss, H. (2010), Operations Research and Capacity Expansion Problems: A Survey, *Oper. Res.*, *30*(5), 907–947, doi:10.1287/opre.30.5.907.

Madani, K., and K. W. Hipel (2011), Non-Cooperative Stability Definitions for Strategic Analysis of Generic Water Resources Conflicts, *Water Resour. Manag.*, *25*(8), 1949–1977, doi:10.1007/s11269-011-9783-4.

Madani, K., L. Read, and L. Shalikarian (2014), Voting Under Uncertainty: A Stochastic Framework for Analyzing

Group Decision Making Problems, *Water Resour. Manag.*, *28*(7), 1839–1856, doi:10.1007/s11269-014-0556-8.

Mahmoud, M. R. (2006), High dimension dynamic programming model for water resources expansion projects, *Eng. Optim.*, *38*(3), 371–389, doi:10.1080/03052150600593218.

Maier, H. R. et al. (2014a), Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions, *Environ. Model. Softw.*, *62*(0), 271–299, doi:10.1016/j.envsoft.2014.09.013.

Maier, H. R. et al. (2014b), Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions, *Environ. Model. Softw.*, *62*, 271–299, doi:10.1016/j.envsoft.2014.09.013.

Massoud, T. G. (2000), Fair division, Adjusted Winner procedure (AW), and the Israeli-Palestinian conflict, *J. Conflict Resolut.*, *44*(3), 333–358, doi:10.1177/0022002700044003003.

Matrosov, E. S., J. J. Harou, and D. P. Loucks (2011), A computationally efficient open-source water resource system simulator - Application to London and the Thames Basin, *Environ. Model. Softw.*, *26*(12), 1599–1610, doi:10.1016/j.envsoft.2011.07.013.

Matrosov, E. S., A. M. Woods, and J. J. Harou (2013), Robust Decision Making and Info-Gap Decision Theory for water resource system planning, *J. Hydrol.*, *494*, 43–58, doi:10.1016/j.jhydrol.2013.03.006.

Matrosov, E. S., I. Huskova, J. R. Kasprzyk, J. J. Harou, C. Lambert, and P. M. Reed (2015), Many-objective optimization and visual analytics reveal key trade-offs for London's water supply, *J. Hydrol.*, *531*, 1040–1053, doi:10.1016/j.jhydrol.2015.11.003.

Di Matteo, M., G. C. Dandy, and H. R. Maier (2017), A multi-stakeholder portfolio optimization framework applied to stormwater best management practice (BMP) selection, *Environ. Model. Softw.*, *97*, 16–31, doi:10.1016/j.envsoft.2017.07.012.

Mavrotas, G. (2009), Effective implementation of the epsilon-constraint method in Multi-Objective Mathematical Programming problems, *Appl. Math. Comput.*, *213*(2), 455–465, doi:10.1016/j.amc.2009.03.037.

Mavrotas, G., and K. Florios (2013), An improved version of the augmented epsilon-constraint method (AUGMECON2) for finding the exact pareto set in multi-objective integer programming problems, *Appl. Math. Comput.*, *219*(18), 9652–9669, doi:10.1016/j.amc.2013.03.002.

Mendoza, G. A., and H. Martins (2006), Multi-criteria decision analysis in natural resource management: A critical review of methods and new modelling paradigms, *For. Ecol. Manage.*, *230*(1–3), 1–22, doi:10.1016/j.foreco.2006.03.023.

Merigo, J. M. (2013), The probabilistic weighted averaging distance and its application in group decision making, *Kybernetes*, *42*(5), 686–697, doi:10.1108/K-06-2013-0107.

Merigó, J. M., and M. Casanovas (2010), Decision making with distance measures and linguistic aggregation 0operators, *Int. J. Fuzzy Syst.*, *12*(3), 190–198.

Merigó, J. M., D. Palacios-Marqués, and P. Soto-Acosta (2017), Distance measures, weighted averages, OWA operators and Bonferroni means, *Appl. Soft Comput. J.*, *50*, 356–366, doi:10.1016/j.asoc.2016.11.024.

Milly, P. C. D., J. Betancourt, M. Falkenmark, R. M. Hirsch, Z. W. Kundzewicz, D. P. Lettenmaier, and R. J. Stouffer (2008), Climate change - Stationarity is dead: Whither water management?, *Science (80-.).*, *319*(5863), 573–574, doi:10.1126/science.1151915.

Mimi, Z. A., and B. I. Sawalhi (2003), A decision tool for allocating the waters of the Jordan River basin between all riparian parties, *Water Resour. Manag.*, *17*(6), 447–461, doi:10.1023/B:WARM.0000004959.90022.ba.

Mirumachi, N., and J. Torriti (2012), The use of public participation and economic appraisal for public involvement in large-scale hydropower projects: Case study of the Nam Theun 2 Hydropower Project, *Energy Policy*, *47*, 125–132, doi:10.1016/j.enpol.2012.04.034.

Moody, P., and C. Brown (2013), Robustness indicators for evaluation under climate change: Application to the upper Great Lakes, *Water Resour. Res.*, *49*(6), 3576–3588, doi:10.1002/wrcr.20228.

Mortazavi-Naeini, M., G. Kuczera, and L. Cui (2014), Application of multiobjective optimization to scheduling capacity expansion of urban water resource systems, *Water Resour. Res.*, *50*(6), 4624–4642, doi:10.1002/2013WR014569.

Mortazavi, M., G. Kuczera, and L. Cui (2013), How flexibility in urban water resource decisions helps to manage uncertainty?, *Considering Hydrol. Chang. Reserv. Plan. Manag.*, *362*, 49–56.

Mousavi, H., and A. S. Ramamurthy (2000), Optimal design of multi-reservoir systems for water supply, *Adv. Water Resour.*, *23*(6), 613–624, doi:10.1016/S0309-1708(99)00053-6.

Mumpower, J. L., and J. Rohrbaugh (1996), Negotiation and design: Supporting resource allocation decisions through analytical mediation, *Gr. Decis. Negot.*, *5*(4–6), 385–409, doi:10.1007/BF02404642.

NBI-ENTRO (2015), Eastern Nile Power Toolkit,

Nicklow, J. et al. (2010), State of the Art for Genetic Algorithms and Beyond in Water Resources Planning and Management, *J. Water Resour. Plan. Manag.*, *136*(4), 412–432, doi:10.1061/(asce)wr.1943-5452.0000053.

Nicol, A., and A. E. Cascao (2011), Against the flow - new power dynamics and upstream mobilisation in the Nile Basin, *Rev. Afr. Polit. Econ.*, *38*(128), 317–325, doi:10.1080/03056244.2011.582767.

Nile Basin Initiative (2016), Nile Basin Water Resources Atlas, , *The Socio-*.

Nkomo, S., and P. van der Zaag (2004), Equitable water allocation in a heavily committed international catchment area: The case of the Komati Catchment, *Phys. Chem. Earth*, *29*(15–18 SPEC.ISS.), 1309–1317, doi:10.1016/j.pce.2004.09.022.

van Oel, P. R., M. S. Krol, A. Y. Hoekstra, and R. R. Taddei (2010), Feedback mechanisms between water availability and water use in a semi-arid river basin: A spatially explicit multi-agent simulation approach, *Environ. Model. Softw.*, *25*(4), 433–443, doi:10.1016/j.envsoft.2009.10.018.

Olenik, S. C., and Y. Y. Haimes (1979), A hierarchical multiobjective framework for water resources planning, *IEEE Trans. Syst. Man Cybern.*, *9*(9), 534–544, doi:10.1109/TSMC.1979.4310278.

Oliveira, R., and D. P. Loucks (1994), *DERIVATION OF OPERATING POLICIES FOR MULTI-RESERVOIR SYSTEMS BY GENETIC ALGORITHMS*, edited by G. Tsakiris and M. A. Santos.

Oliveira, R., and D. P. Loucks (1997), Operating rules for multireservoir systems, *Water Resour. Res.*, *33*(4), 839, doi:10.1029/96WR03745.

Otero, J. M., J. W. Labadie, D. E. Haunert, and M. S. Daron (1995), Optimization of managed runoff to the St. Lucie Estuary, *Int. Water Resour. Eng. Conf. - Proc.*, *2*, 1506–1510.

Padula, S., J. J. Harou, L. G. Papageorgiou, Y. Ji, M. Ahmad, and N. Hepworth (2013), Least Economic Cost Regional Water Supply Planning - Optimising Infrastructure Investments and Demand Management for South East England’s 17.6 Million People, *Water Resour. Manag.*, *27*(15), 5017–5044, doi:10.1007/s11269-013-0437-6.

Pearce, D., B. Groom, C. Hepburn, and P. Koundouri (2003), Valuing the future: recent advances in social discounting, *World Econ.*, doi:10.1.1.121.130.

Peter C. Fishburn (1967), Additive Utilities With Incomplete Product Sets: Application To Priorities and Assignments, *Oper. Res.*, *15*(3), 537–542, doi:10.1287/opre.15.3.537.

Petersson, E., C. Giupponi, and J. Feas (2007), Decision support for strategic water management: Mdss in the large dam context, *Water Int.*, *32*(2), 265–279.

Piscopo, A. N., J. R. Kasprzyk, and R. M. Neupauer (2015), An iterative approach to multi-objective engineering design: Optimization of engineered injection and extraction for enhanced groundwater remediation, *Environ. Model. Softw.*, *69*, 253–261, doi:10.1016/j.envsoft.2014.08.030.

Porrua, F., R. Chabar, L. M. Thome, L. A. Barroso, M. Pereira, and Ieee (2009), Incorporating Large-Scale Renewable to the Transmission Grid: Technical and Regulatory Issues, *2009 Ieee Power Energy Soc. Gen. Meet. Vols 1-8*, 2811–2817.

Qu, X., J. Brame, Q. Li, and P. J. J. Alvarez (2013), Nanotechnology for a safe and sustainable water supply: Enabling integrated water treatment and reuse, *Acc. Chem. Res.*, *46*(3), 834–843, doi:10.1021/ar300029v.

Rahman, M. a. (2012), Water Security: Ethiopia-Egypt Transboundary Challenges over the Nile River Basin, *J.*

Asian Afr. Stud., *48*(1), 35–46, doi:10.1177/0021909612438517.

Rani, D., and M. M. Moreira (2010), Simulation-Optimization Modeling: A Survey and Potential Application in Reservoir Systems Operation, *Water Resour. Manag.*, *24*(6), 1107–1138, doi:10.1007/s11269-009-9488-0.

Räsänen, T. A., J. Koponen, H. Lauri, and M. Kummu (2012), Downstream Hydrological Impacts of Hydropower Development in the Upper Mekong Basin, *Water Resour. Manag.*, *26*(12), 3495–3513, doi:10.1007/s11269-012-0087-0.

Reed, P. M., and J. Kasprzyk (2009), Water Resources Management: The Myth, the Wicked, and the Future, *J. Water Resour. Plan. Manag.*, *135*(6), 411–413.

Reed, P. M., and J. B. Kollat (2013), Visual analytics clarify the scalability and effectiveness of massively parallel many-objective optimization: A groundwater monitoring design example, *Adv. Water Resour.*, *56*, 1–13, doi:10.1016/j.advwatres.2013.01.011.

Reed, P. M., D. Hadka, J. D. Herman, J. R. Kasprzyk, and J. B. Kollat (2013), Evolutionary multiobjective optimization in water resources: The past, present, and future, *Adv. Water Resour.*, *51*, 438–456, doi:10.1016/j.advwatres.2012.01.005.

Renofalt, B. M., R. Jansson, and C. Nilsson (2010), Effects of hydropower generation and opportunities for environmental flow management in Swedish riverine ecosystems, *Freshw. Biol.*, *55*(1), 49–67, doi:10.1111/j.1365-2427.2009.02241.x.

Richter, B. D., and G. A. Thomas (2007), Restoring environmental flows by modifying dam operations, *Ecol. Soc.*, *12*(1), doi:12.

Roefs, T. G., and L. D. Bodin (1970), MULTIRESERVOIR OPERATION STUDIES, *Water Resour. Res.*, *6*(2), 410-, doi:10.1029/WR006i002p00410.

Rogers, P. P., and M. B. Fiering (1986), Use of Systems-Analysis in Water Management, *Water Resour. Res.*, *22*(9), S146–S158, doi:10.1029/WR022i09Sp0146S.

Rosenberg, D. E. (2015), Blended near-optimal alternative generation, visualization, and interaction for water resources decision making, *Water Resour. Res.*, *51*(4), 2047–2063, doi:10.1002/2013WR014667.

Roy, B. (1991), The outranking approach and the foundations of electre methods, *Theory Decis.*, *31*(1), 49–73, doi:10.1007/BF00134132.

Rubinstein, J., and L. Ortolano (1984), Water Conservation and Capacity Expansion, *J. Water Resour. Plan. Manag.*, *110*(2), 220–237, doi:10.1061/(ASCE)0733-9496(1984)110:2(220).

Sadek, N., K. Attia, and A. Fahmy (2004), Highlights on high flood effects on river Nile, *Proc. Ninth Int. Symp. River Sedimentation, Vols 1-4*, 524–531.

Sadoff, C., N. R. Harshadeep, D. Blackmore, X. Wu, A. O'Donnell, M. Jeuland, S. Lee, and D. Whittington (2013), Ten fundamental questions for water resources development in the Ganges: myths and realities, *Water Policy*, *15*, 147–164, doi:10.2166/wp.2013.006.

Sahin, O., R. S. Siems, R. A. Stewart, and M. G. Porter (2016), Paradigm shift to enhanced water supply planning through augmented grids, scarcity pricing and adaptive factory water: A system dynamics approach, *Environ. Model. Softw.*, *75*, 348–361, doi:10.1016/j.envsoft.2014.05.018.

Sandoval-Solis, S., and D. C. McKinney (2014), Integrated Water Management for Environmental Flows in the Rio Grande, *J. Water Resour. Plan. Manag.*, *140*(3), 355–364, doi:10.1061/(asce)wr.1943-5452.0000331.

Sechi, G. M., and A. Sulis (2007), Mixed simulation-optimization technique for complex water resource system analysis under drought conditions, in *Methods and Tools for Drought Analysis and Management*, vol. 62, edited by G. Rossi, T. Vega, and B. Bonaccorso, pp. 217–237.

Sechi, G. M., and A. Sulis (2009), Water System Management through a Mixed Optimization-Simulation Approach, *J. Water Resour. Plan. Manag.*, *135*(3), 160–170, doi:10.1061/(asce)0733-9496(2009)135:3(160).

Seeger, C. (2010), Sustainable Hydropower-10 years after WCD, *Wasserwirtschaft*, *100*(4), 56–58.

Seleshi, Y., and G. R. Demaree (1995), Rainfall variability in the Ethiopian and Eritrean highlands and its links with the Southern Oscillation Index, *J. Biogeogr.*, *22*(4–5), 945–952, doi:10.2307/2845995.

Sinha, A. K., and C. H. Bischof (1998), Application of Automatic Differentiation to Reservoir Design Models, *J. Water Resour. Plan. Manag.*, *124*(3), 162–167, doi:10.1061/(ASCE)0733-9496(1998)124:3(162).

Smalley, J. B., B. S. Minsker, and D. E. Goldberg (2000), Risk-based in situ bioremediation design using a noisy genetic algorithm, *Water Resour. Res.*, *36*(10), 3043–3052, doi:10.1029/2000WR900191.

Sneddon, C., and C. Fox (2008), Struggles over dams as struggles for justice: The World Commission on Dams (WCD) and anti-dam campaigns in Thailand and Mozambique, *Soc. Nat. Resour.*, *21*(7), 625–640, doi:10.1080/08941920701744231.

Song, J., and D. Whittington (2004), Why have some countries on international rivers been successful negotiating treaties? A global perspective, *Water Resour. Res.*, *40*(5), doi:10.1029/2003wr002536.

Spiertz, J. H. J., and F. Ewert (2009), Crop production and resource use to meet the growing demand for food, feed and fuel: Opportunities and constraints, *NJAS - Wageningen J. Life Sci.*, *56*(4), 281–300, doi:10.1016/S1573-5214(09)80001-8.

Sreenath, S. N., A. M. Vali, and G. Susiarjo (2002), The Nile River Problematique - An integrated look at the future of Egypt and Ethiopia, *Water Int.*, *27*(4), 517–531.

Stedinger, J. R., B. F. Sule, and D. Pei (1983), Multiple reservoir system screening models, *Water Resour. Res.*, *19*(6), 1383–1393, doi:10.1029/WR019i006p01383.

Steed, C. A., G. Shipman, P. Thornton, D. Ricciuto, D. Erickson, and M. Branstetter (2012), Practical application of parallel coordinates for climate model analysis, *Procedia Comput. Sci.*, *9*, 877–886, doi:10.1016/j.procs.2012.04.094.

Swain, A. (2011), Challenges for water sharing in the Nile basin: changing geo-politics and changing climate, *Hydrol. Sci. Journal-Journal Des Sci. Hydrol.*, *56*(4), 687–702, doi:10.1080/02626667.2011.577037.

Tafesse, T. (2005), An Appraisal of Shared Water Dispute Resolution Mechanisms in the Nile Basin, *Proc. 2nd Int. Yellow River Forum Keep. Heal. Life River*, *Vol V*, 350–361.

Takeda, N., and P. Y. Papalambros (2012), A heuristic sequencing procedure for sequential solution of decomposed optimal design problems, *Struct. Multidiscip. Optim.*, *45*(1), 1–20, doi:10.1007/s00158-011-0664-5.

Tang, Y., P. Reed, and T. Wagener (2006), How effective and efficient are multiobjective evolutionary algorithms at hydrologic model calibration?, *Hydrol. Earth Syst. Sci.*, *10*(2), 289–307.

Tawfik, R. (2016), Reconsidering counter-hegemonic dam projects: The case of the Grand Ethiopian Renaissance Dam, *Water Policy*, *18*(5), 1033–1052, doi:10.2166/wp.2016.162.

Tejadaguibert, J. A., S. A. Johnson, and J. R. Stedinger (1995), THE VALUE OF HYDROLOGIC INFORMATION IN STOCHASTIC DYNAMIC-PROGRAMMING MODELS OF A MULTIRESERVOIR SYSTEM, *Water Resour. Res.*, *31*(10), 2571–2579, doi:10.1029/95wr02172.

Teytaud, O. (2007), On the hardness of offline multi-objective optimization, *Evol. Comput.*, *15*(4), 475–491, doi:10.1162/evco.2007.15.4.475.

The World Bank (2009), *World Development Report 2009 - Reshaping Economic Geography*.

Thiessen, E. M., and D. P. Loucks (1992), Computer-assisted negotiations of water resources conflicts, *JAWRA J. Am. Water Resour. Assoc.*, *28*(1), 163–177, doi:10.1111/j.1752-1688.1992.tb03162.x.

Thorne, J. M., D. A. Savic, and A. Weston (2003), Optimised conjunctive control rules for a system of water supply sources: Roadford Reservoir System (UK), *Water Resour. Manag.*, *17*(3), 183–196, doi:10.1023/a:1024157210054.

Tilmant, A. and A. D. and M. G., D. Arjoon, and G. F. Marques (2014), Economic Value of Storage in Multireservoir Systems, *J. Water Resour. Plan. Manag.*, *140*(3), 375–383, doi:10.1061/(ASCE)WR.1943-5452.0000335.

Tortajada, C. (2015), Dams: An Essential Component of Development, *J. Hydrol. Eng.*, *20*(1), doi:10.1061/(asce)he.1943-5584.0000919.

Tu, M. Y., N. S. Hsu, and W. W. G. Yeh (2003), Optimization of reservoir management and operation with hedging rules, *J. Water Resour. Plan. Manag.*, *129*(2), 86–97, doi:10.1061/(asce)0733-9496(2003)129:2(286).

Vamvakeridou-Lyroudia, L. S., M. S. Morley, J. Bicik, C. Green, M. Smith, and D. A. Savic (2010), AquatorGA:

Integrated optimisation for reservoir operation using multiobjective genetic algorithms, *Integr. Water Syst.*, 493–500.

Vaughn, E. J. C., A. Mirchi, D. Watkins, and K. Madani (2009), Modeling for Watershed Planning , Management , and Decision Making, *WatershedsManagement, Restor. Environ.*, 1–25.

Velpuri, N. M., and G. B. Senay (2012), Assessing the potential hydrological impact of the Gibe III Dam on Lake Turkana water level using multi-source satellite data, *Hydrol. Earth Syst. Sci.*, *16*(10), 3561–3578, doi:10.5194/hess-16-3561-2012.

Vemuri, V. (1974), Multi-Objective Planning of Water-Resource Systems, *Trans. Geophys. Union*, *55*(12), 1121.

Vieira Getirana, A. C., V. de F. Malta, and J. P. Soares de Azevedo (2008), Decision process in a water use conflict in Brazil, *Water Resour. Manag.*, *22*(1), 103–118, doi:10.1007/s11269-006-9146-8.

Vitiello, P. F., R. S. Kalawsky, and Ieee (2012), Visual Analytics: A Sensemaking Framework for Systems Thinking in Systems Engineering, *2012 Ieee Int. Syst. Conf.*, 8–13.

Wada, Y., D. Wisser, and M. F. P. Bierkens (2014), Global modeling of withdrawal, allocation and consumptive use of surface water and groundwater resources, *Earth Syst. Dyn.*, *5*(1), 15–40, doi:10.5194/esd-5-15-2014.

Walker, W. E., V. A. W. J. Marchau, and D. Swanson (2010), Addressing deep uncertainty using adaptive policies: Introduction to section 2, *Technol. Forecast. Soc. Change*, *77*(6), 917–923, doi:10.1016/j.techfore.2010.04.004.

Wallenius, J., J. S. Dyer, P. C. Fishburn, R. E. Steuer, S. Zionts, and K. Deb (2008), Multiple criteria decision making, multiattribute utility theory: Recent accomplishments and what lies ahead, *Manage. Sci.*, *54*(7), 1336–1349, doi:10.1287/mnsc.1070.0838.

Wang, P., M. D. Gerst, and M. E. Borsuk (2013), Exploring Energy and Economic Futures Using Agent-Based Modeling and Scenario Discovery, in *Energy Policy Modeling in the 21st Century*, edited by H. QudratUllah, pp. 251–269.

Werners, S. E., S. Pfenninger, E. van Slobbe, M. Haasnoot, J. H. Kwakkel, and R. J. Swart (2013), Thresholds, tipping and turning points for sustainability under climate change, *Curr. Opin. Environ. Sustain.*, *5*(3–4), 334–340, doi:10.1016/j.cosust.2013.06.005.

Wheeler, K. G., M. Basheer, Z. T. Mekonnen, S. O. Eltoum, A. Mersha, G. M. Abdo, E. A. Zagona, J. W. Hall, and S. J. Dadson (2016), Cooperative filling approaches for the Grand Ethiopian Renaissance Dam, *Water Int.*, *8060*(May), 1–24, doi:10.1080/02508060.2016.1177698.

Whittington, D., and E. McClelland (1992), Opportunities for Regional and International Cooperation in the Nile Basin, *Water Int.*, *17*(3), 144–155, doi:10.1080/02508069208686134.

Whittington, D., X. Wu, and C. Sadoff (2005), Water resources management in the Nile basin: The economic value of cooperation, *Water Policy*, *7*(3), 227–252.

Whittington, D., J. Waterbury, and M. Jeuland (2014), The grand renaissance dam and prospects for cooperation on the eastern nile, *Water Policy*, *16*(4), 595–608, doi:10.2166/wp.2014.011.

Wichelns, D., J. Barry, M. Muller, M. Nakao, L. D. Philo, and A. Zitello (2003), Co-operation regarding water and other resources will enhance economic development in Egypt, Sudan, Ethiopia and Eritrea, *Int. J. Water Resour. Dev.*, *19*(4), 535–552, doi:10.1080/0790062032000161355.

Wild, T. B., and D. P. Loucks (2014), Managing flow, sediment, and hydropower regimes in the Sre Pok, Se San, and Se Kong rivers of the Mekong Basin, *Water Resour. Res.*, *50*(6), 5141–5157, doi:10.1002/2014WR015457.

Winter, E. (1997), Negotiations in multi-issue committees, *J. Public Econ.*, *65*(3), 323–342, doi:10.1016/S0047-2727(96)01627-1.

Woodruff, M. J., P. M. Reed, and T. W. Simpson (2013), Many objective visual analytics: Rethinking the design of complex engineered systems, *Struct. Multidiscip. Optim.*, *48*(1), 201–219, doi:10.1007/s00158-013-0891-z.

World Commission on Dams (2000), *Dams and development: a new framework for decision-making : the report of the World Commission on Dams*.

Wu, W., H. R. Maier, G. C. Dandy, R. Leonard, K. Bellette, S. Cuddy, and S. Maheepala (2016), Including stakeholder input in formulating and solving real-world optimisation problems: Generic framework and case study, *Environ. Model. Softw.*, *79*, 197–213, doi:10.1016/j.envsoft.2016.02.012.

Wu, X., and D. Whittington (2006), Incentive compatibility and conflict resolution in international river basins: A case study of the Nile basin, *Water Resour. Res.*, *42*(2), doi:10.1029/2005WR004238.

Wu, X., M. Jeuland, C. Sadoff, and D. Whittington (2013), Interdependence in water resource development in the Ganges: an economic analysis, *Water Policy*, *15*, 89–108, doi:10.2166/wp.2013.003.

Wurbs, R. A. (1993), Reservoir-System Simulation and Optimization Models, *J. Water Resour. Plan. Manag.*, *119*(4), 455–472, doi:10.1061/(ASCE)0733-9496(1993)119:4(455).

Yang, C.-C., L.-C. Chang, C.-H. Yeh, and C.-S. Chen (2007), Multiobjective planning of surface water resources by multiobjective genetic algorithm with constrained differential dynamic programming, *J. Water Resour. Plan. Manag.*, *133*(6), 499–508, doi:10.1061/(asce)0733-9496(2007)133:6(499).

Yihdego, Z., A. Rieu-Clarke, and A. E. Cascão (2016), How has the Grand Ethiopian Renaissance Dam changed the legal, political, economic and scientific dynamics in the Nile Basin?, *Water Int.*, *41*(4), 503–511, doi:10.1080/02508060.2016.1209008.

You, J. Y., and X. M. Cai (2008), Hedging rule for reservoir operations: 1. A theoretical analysis, *Water Resour. Res.*, *44*(1), doi:10.1029/2006wr005481.

Young, G. (1967), Finding reservoir operating rules, *J. Hydraul. Div.*, *93*(6), 297–321.

Yüksel, I. (2009), Dams and Hydropower for Sustainable Development, *Energy Sources, Part B Econ. Planning, Policy*, *4*(1), 100–110, doi:10.1080/15567240701425808.

Zarfl, C., A. E. Lumsdon, J. Berlekamp, L. Tydecks, and K. Tockner (2015), A global boom in hydropower dam construction, *Aquat. Sci.*, *77*(1), 161–170, doi:10.1007/s00027-014-0377-0.

Zatarain Salazar, J., P. M. Reed, J. D. Quinn, M. Giuliani, and A. Castelletti (2017), Balancing exploration, uncertainty and computational demands in many objective reservoir optimization, *Adv. Water Resour.*, *109*, 196–210, doi:10.1016/j.advwatres.2017.09.014.

Zeff, H. B., J. D. Herman, P. M. Reed, and G. W. Characklis (2016), Cooperative drought adaptation: Integrating infrastructure development, conservation, and water transfers into adaptive policy pathways, *Water Resour. Res.*, *52*(9), 7327–7346, doi:10.1002/2016WR018771.

Zeitoun, M., J. A. Allan, and Y. Mohieldeen (2010), Virtual water "flows" of the Nile Basin, 1998-2004: A first approximation and implications for water security, *Glob. Environ. Chang. Policy Dimens.*, *20*(2), 229–242, doi:10.1016/j.gloenvcha.2009.11.003.

Zhou, L., H. Chen, and J. Liu (2013), Continuous Ordered Weighted Distance Measure and Its Application to Multiple Attribute Group Decision Making, *Gr. Decis. Negot.*, *22*(4), 739–758, doi:10.1007/s10726-012-9289-3.

Zhu, X. L., G. Y. Zhuang, and N. Xiong (2014), A review of China's approaches toward a sustainable energy future: the period since 1990, *Wiley Interdiscip. Rev. Environ.*, *3*(5), 409–423, doi:10.1002/wene.101.

Zitzler, E., L. Thiele, M. Laumanns, C. M. Fonseca, and V. G. Da Fonseca (2003), Performance assessment of multiobjective optimizers: An analysis and review, *IEEE Trans. Evol. Comput.*, *7*(2), 117–132, doi:10.1109/TEVC.2003.810758.

van der Zwaan, B., A. Boccalon, and F. Dalla Longa (2018), Prospects for hydropower in Ethiopia: An energy-water nexus analysis, *Energy Strateg. Rev.*, *19*, 19–30, doi:10.1016/j.esr.2017.11.001.