Incorporating Deeply Uncertain Factors into the Many Objective Search Process to Improve Adaptation to Environmental Change

by

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B.S., Virginia Tech, 2012

A thesis submitted to the

Faculty of the Graduate School of the

University of Colorado in partial fulfillment

of the requirements for the degree of

Master of Science

Department of Civil, Environmental, and Architectural Engineering

2015

This thesis entitled:
Incorporating Deeply Uncertain Factors into the Many Objective Search Process to Improve Adaptation to Environmental Change
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Incorporating Deeply Uncertain Factors into the Many Objective Search Process to Improve Adaptation to Environmental Change

Thesis directed by Prof. Joseph R. Kasprzyk

Deep uncertainty refers to situations in which decision makers or stakeholders do not know, or cannot fully agree upon, the full suite of risk factors within a planning problem. This phenomenon is especially important when considering scenarios of future environmental change, since there exist multiple trajectories of environmental forcings (e.g., streamflow timing and magnitude) and socioeconomic factors (e.g., population growth). This thesis first reviews frameworks that have been proposed to plan for systems under deep uncertainty. One recently introduced framework is Many Objective Robust Decision Making (MORDM). MORDM combines two techniques: evolutionary algorithm search is used to optimize planning alternatives and robust decision making methods are used to sample performance over a large range of plausible factors and subsequently choose a robust solution.

However, MORDM does not incorporate the deeply uncertain scenario information into the search process itself. In this thesis, we present a methodology for doing so, that focuses on modifying the suite of uncertain data selected within the search process. Using a case study of water planning in the Lower Rio Grande Valley (LRGV) in Texas, this research uses several visualization techniques to assess the performance of optimized alternatives across five different deeply uncertain scenarios to answer two major questions: (1) How do the deeply uncertain scenarios impact the tradeoffs and decisions? and (2) What is the impact of experiencing futures unlike the optimized conditions? Ultimately, the results compare baseline optimization with new solution sets that examine optimal management strategies under scenarios that mimic possible scenarios of water management under environmental change.

Dedication

To my parents, Kathy and Gary Watson. Thank you for always encouraging me to put forth my best effort.

Acknowledgements

I would like to thank my advisor, Professor Kasprzyk. Through our countless meetings, phone calls, and my freak outs, Joe remained patient, flexible, and supportive. My technical, analytical, and writing skills have improved immensely under his guidance, and I am forever grateful.

I would also like to acknowledge the the Hydrology, Water Resources & Environmental Fluid Mechanics group professors. I know that my coursework has thoroughly prepared me to serve the public and protect the environment as a water resources engineer. Thank you to Professor Balaji and Professor Zagona for serving on my committee and reading this (rather verbose) manuscript. I would like to thank Professor Neupauer for her mentorship over the past two years. Roseanna instilled the confidence I needed to complete my degree and start my career.

Not only did Liz Houle and Mark Schutte brave late nights of homework and studying with me, but they have also become wonderful friends. I would like to thank Liz for pushing me out of my comfort zone over the last two years, which has helped me grow as a person and love my life here in Colorado.

This thesis would not have been possible without the Janus supercomputer, which is supported by the National Science Foundation (award number CNS-0821794) and the University of Colorado Boulder. The Janus supercomputer is a joint effort of the University of Colorado - Boulder, the University of Colorado - Denver and the National Center for Atmospheric Research. Janus stuck with me through hours and hours and hours of computing. Thank you, Janus.

Contents

Chapter

1 Introduction 1

2 Background 3

2.1 Motivation . . . 3

2.2 Optimization . . . 4

2.2.1 Deterministic Programming . . . 5

2.2.2 Probabilistic Programming . . . 7

2.2.3 Multi-Objective Evolutionary Algorithms . . . 12

2.3 Decision Making Under Deep Uncertainty . . . 16

2.3.1 Robust Decision Making . . . 16

2.3.2 Many Objective Robust Decision Making . . . 18

2.3.3 Adaptive Robust Design . . . 22

2.3.4 Multi-Objective Adaptive Robust Design . . . 24

2.3.5 Benefits and Limitations of Decision Making Under Uncertainty Frameworks 26

3 Case Study and Methods 29

3.1 Case Study . . . 29

3.2 Lower Rio Grande Valley Simulation Model . . . 32

3.3 Problem Formulation . . . 36

3.3.1 Uncertainties . . . 36

3.3.2 Decision Levers, Relationships, and Measures 39
3.3.3 Many Objective Problem Formulation 43
3.4 Computational Experiment 44
3.4.1 Phase I: How do the scenarios impact the tradeoffs? 45
3.4.2 Phase II: What is the impact of experiencing futures unlike the optimized conditions? 48

4 Results 50
4.1 Phase I 50
4.2 Phase II 58

5 Discussion, Conclusion, and Future Work 69
5.1 Discussion and Conclusion 69
5.2 Future Work 72

Bibliography 74

Appendix

A Supporting Figures and Tables 84

Tables

Table

3.1 Deep uncertainties 38

3.2 Decision levers 39

3.3 Uncertain scenarios 46

3.4 Decision lever bounds 46

3.5 ϵ resolution used with the Borg MOEA for each objective 47

4.1 Decision levers of highlighted solutions [1] 56

4.2 Performance of highlighted solutions 62

A.1 Default Borg parametrization (includes simulated binary crossover (SBX), differential evolution (DE), parent centric mating (PCX), simplex crossover (SPX), uniform normally distributed crossover (UNDX), uniform mutation (UM), and polynomial mutation (PM) operators) [Woodruff et al., 2013; Zeff et al., 2014] 84

Figures

Figure

2.1 Integration of a multi-objective evolutionary algorithm with a generic simulation model 13
2.2 Many Objective Robust Decision Making framework [Kasprzyk et al., 2013] 18
2.3 Adaptive Policymaking Process [Walker et al., 2001] 22
2.4 Adaptive Robust Design Process, adapted from Hamarat et al. [2013] 23

3.1 Logic behind α and β strategic decision variables 34
3.2 Model mass balance 35

4.1 Non-dominated tradeoffs optimized under each of the five scenarios. Each cone represents a water portfolio solution. The spatial position indicates each solution's performance with respect to 10-year cost, number of leases, and surplus water. . . . 51
4.2 Decision levers and non-dominated tradeoffs optimized under each of the five scenarios. Each line represents a water portfolio solution. The vertical position on each axis represents the value of that decision lever or objective. 53
4.3 Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, with a solution per scenario highlighted. The color of the highlighted solution refers to the color of its optimization scenario set. The black solution is the robust solution from the prior study. 55

4.4 Non-dominated tradeoffs optimized under each of the five scenarios. The robust solution as well as five additional solutions are selected for further exploration in Phase II. 57

4.5 The effect of optimized scenario on 10-year cost when evaluated under each scenario. Each plot contains the optimized set of a single scenario, with the permanent rights decision lever shown. Solution point color refers to the scenario the solutions were evaluated under. 59

4.6 The effect of optimized scenario on dropped transfers when evaluated under each scenario. Each plot contains the optimized set of a single scenario, with the permanent rights decision lever shown. Solution point color refers to the scenario the solutions were evaluated under. 61

4.7 Non-dominated tradeoffs optimized under each of the five scenarios and evaluated under Scenario 1. The highlighted solutions correspond to the solutions discussed in Section 4.1. The dark circles show the general location of the highlighted solutions within the solution cluster. 64

4.8 Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, all evaluated under Scenario 1. Highlighted solutions correspond to the solutions identified in Phase I. The color of the highlighted solution refers to the color of its scenario set. The black solution is the robust solution from the prior study. 65

4.9 Non-dominated tradeoffs optimized under each of the five scenarios and evaluated under Scenario 5. The highlighted solutions correspond to the solutions discussed in Section 4.1. 66

4.10 Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, all evaluated under Scenario 5. Highlighted solutions correspond to the solutions identified in Phase I. The color of the highlighted solution refers to the color of its scenario set. The black solution is the robust solution from the prior study. 67

A.1 Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, with the Scenario 1 (baseline) solutions highlighted atop the four other scenarios. Each line represents a water portfolio solution. The vertical position on each axis represents the value of that decision lever or objective. 85

A.2 Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, with the Scenario 2 (moderate) solutions highlighted atop the four other scenarios. Each line represents a water portfolio solution. The vertical position on each axis represents the value of that decision lever or objective. 86

A.3 Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, with the Scenario 3 (cost) solutions highlighted atop the four other scenarios. Each line represents a water portfolio solution. The vertical position on each axis represents the value of that decision lever or objective. 87

A.4 Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, with the Scenario 4 (reliability) solutions highlighted atop the four other scenarios. Each line represents a water portfolio solution. The vertical position on each axis represents the value of that decision lever or objective. 88

A.5 The effect of optimized scenario on dropped transfers when evaluated under each scenario. Each plot contains the optimized set of a single scenario, with the $\alpha_{May-Dec}$ decision lever shown. Solution point color refers to the scenario the solutions were evaluated under. 89

A.6 The effect of optimized scenario on 10-year cost when evaluated under each scenario. Each plot contains the optimized set of a single scenario, with the $\alpha_{May-Dec}$ decision lever shown. Solution point color refers to the scenario the solutions were evaluated under. 89

A.7 Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, all evaluated under Scenario 2. Highlighted solutions correspond to the solutions identified in Phase I. The color of the highlighted solution refers to the color of its scenario set. The black solution is the "robust" solution from the prior study. 90

A.8 Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, all evaluated under Scenario 3. Highlighted solutions correspond to the solutions identified in Phase I. The color of the highlighted solution refers to the color of its scenario set. The black solution is the "robust" solution from the prior study. 91

A.9 Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, all evaluated under Scenario 4. Highlighted solutions correspond to the solutions identified in Phase I. The color of the highlighted solution refers to the color of its scenario set. The black solution is the "robust" solution from the prior study. 92

Chapter 1

Introduction

The global water resources supply is threatened by uncertainties such as impending extreme weather events driven by climate change and land use change from population growth and migration. Uncertainty is defined as limited knowledge about future, past, or current events [Walker et al., 2013b]. However, these factors extend beyond the concept of uncertainty into deep uncertainty. Deep uncertainty characterizes components of a planning problem in which decision makers cannot agree upon the full set of risks to a system or their associated probabilities [Knight, 1921; Langlois and Cosgel, 1993; Lempert, 2002, 2003; Kasprzyk et al., 2013]. Decision making in the context of deep uncertainty is necessary to cope with and adapt to environmental change, which broadly captures both human-induced and natural changes to the physical, biological, chemical, and geological environment [*Foresight: Migration and Global Environmental Change*, 2011]. In fact, a recent World Bank white paper urges decision makers to develop plans that adapt to and mitigate the innate uncertainty that surrounds climate change to avoid global consequences [Kalra et al., 2014].

In this thesis, we incorporate deep uncertainties into the development of water resources management strategies, providing an alternative method to manage resources in the context of environmental change. Specifically, we adjust the likelihood of hydrological and demand extremes in the input of a simulation model linked with a multi-objective evolutionary algorithm (MOEA), allowing the MOEA to search under varying conditions of uncertainty. We present and test our methodology by generating alternative water supply management strategies that utilize permanent water rights and market instruments to meet demands of a hypothetical city in the Lower Rio

Grande Valley (LRGV) of Texas. This research serves as an extension of prior work surrounding the integration of the LRGV case study with multi-objective optimization [Kasprzyk et al., 2009, 2012, 2013].

There are several questions driving this study. First, how does incorporating deep uncertainty within the search process of an MOEA impact the performance of water supply management strategy decisions? For the LRGV case study, we measure the performance of water supply management strategies using objectives of efficiency, risk, and market use. Second, what is the impact on water supply management strategy decisions? Essentially, we want to explore whether deviations from expected hydrological and demand model input conditions result in a different suite of alternative management strategies. Lastly, how do water supply management strategies optimized under particular conditions of uncertainty perform under different conditions of uncertainty? In answering this question, we illustrate how a water supply management strategy within a specific optimized solution set performs when the city experiences other unplanned conditions.

Before exploring these questions, Chapter 2 provides further motivation for this work. Within this section, a review of traditional and modern optimization strategies provides a foundation for the optimization methodology used in this work. Additionally, decision making frameworks designed to handle uncertainty are briefly reviewed to identify gaps in the current literature that our work can close. Chapter 3 discusses the LRGV case study and simulation model. We also lay out the problem formulation inherited from prior work and the computational experiment contributed by this thesis. Chapter 4 presents the results in two separate phases to answer the motivational questions discussed previously. Chapter 5 discusses the results, presents conclusions, and identifies avenues for future work. This thesis is being adapted into a journal manuscript for *Environmental Modelling & Software*.

Chapter 2

Background

2.1 Motivation

Water management systems have been designed, developed, and operated under assumptions of stationarity [Milly et al., 2008]. Stationarity considers the mean and variance of processes constant over time, allowing historic data to represent future conditions. However, there is increased variability of streamflow, precipitation, and evaporation resulting from anthropogenic causes [Milly et al., 2008; Parry and IPCC, 2007; Solomon and IPCC, 2007; Seager and Vecchi, 2010]. For example, in the Western United States, there were shifts in precipitation, snowmelt, and streamflow from 1950 to 1999 in response to increased greenhouse gas concentrations and aerosol use [Barnett et al., 2008]. This hydrologic variability coupled with uncertain population and land use changes indicate that future conditions are uncertain. In result, Milly et al. [2008] issue a call to plan and assess risk of water management systems under these changing hydrological and socioeconomic conditions. Robust planning is one approach to plan in the presence of uncertainty in which planning strategies and policies are developed to withstand many plausible trajectories or scenarios of future conditions [Schindler and Hilborn, 2015].

This thesis presents and tests a framework to plan under uncertainty using the robust planning approach. The resulting framework has footings in traditional and modern optimization and decision making methods. This chapter provides a background of these methods and their applications in water resources literature.

2.2 Optimization

Optimization refers to the process of searching for the maximum or minimum of one or more response functions [Wehrens and Buydens, 2006] as a means of finding the most ideal solution. An optimization problem in its general form follows below [Deb, 2008].

$$\begin{aligned} &\text{Maximize} && f_m(X), && m = 1, 2, \ldots, M; \\ &\text{Subject to:} && g_j(X) \leq 0, && j = 1, 2, \ldots, J; \\ & && h_k(X) = 0, && h = 1, 2, \ldots, H; \\ & && x_i^{(L)} \leq x_i \leq x_i^{(U)}, && i = 1, 2, \ldots, I; \end{aligned} \tag{2.1}$$

Equation (2.1) represents either a single-objective optimization problem where the number of objective functions, M, is one, or a multi-objective optimization problem, where M is greater than 1. The formulation above presents the optimization problem as a maximization problem, but it is also acceptable to minimize the objective function. The X vector is composed of decision variables, quantities that are solved for to optimize the objective function. The remaining components of the optimization problem are constraints, or equations to be satisfied to ensure a realistic optimal solution. $g_j(X)$ and $h_k(X)$ denote inequality and equality constraints, respectively. The final constraint restricts decision variables between an upper and lower bound, creating a decision space. A solution is feasible if it satisfies all of the constraints.

It is difficult to define the functions and constraints to find an optimal solution for a real system that has many stakeholders and complexities [Rosenhead, 1996; Hitch, 1960; Tsoukias, 2008]. This is especially true in water resources planning problems, which could be characterized as "wicked." Reed and Kasprzyk [2009] summarize Liebman [1976] and Rittel and Webber [1973] by describing wicked problems as ill-defined due to their risks and uncertainties. Additionally, water resources planning problems are wicked because they involve society as a whole; therefore, they are difficult to solve and are continuously re-solved over time [Reed and Kasprzyk, 2009; Rittel and Webber, 1973]. Liebman [1976] argues that the optimization process may be used to learn about wicked problems, where the desired end solution may be initially unknown. To do so, optimization

should be used to formulate and understand alternative solutions. In this light, optimization is a tool to find and present alternative solutions to decision makers, thus providing the insights needed to make an informed decision. It is in this context that we present our work.

In the remainder of this section we expand upon different types of optimization and their uses in water resources planning. Specifically, we discuss deterministic mathematical programming, probabilistic mathematical programming, and multi-objective evolutionary algorithms.

2.2.1 Deterministic Programming

Deterministic programming frames optimization problems by assuming all parameters are known *a priori*. Linear programming and dynamic programming are examples of classical deterministic optimization methods that have been applied in water resources problems. A key challenge with classical optimization problems is that the number of variables to solve can grow very large when an analyst considers multiple factors within the optimization problem. For example, water resources systems can be composed of physical infrastructure; regulations, rights, and laws; ecological and biological concerns; human demands; and hydrological and climatic inputs. A linear program may be utilized to solve a water allocation problem where the decision variables would be set as quantities of water to allocate to different purposes. The constraints would ensure the preservation of mass balance, and the objective function would maximize some benefit that is a function of the volumes of water allocated. A linear program follows the generalized formulation of Equation (2.1); however, the objective function(s) and all constraints are linear, as shown in Equation (2.2).

$$\begin{aligned} \text{Maximize} \quad & Z = c_1 x_1 + c_2 x_2 + ... + c_m x_m \\ \text{Subject to:} \quad & a_{11} x_1 + a_{12} x_2 + ... + a_{1m} x_m \leq b_1 \\ & \vdots \qquad\qquad \vdots \\ & a_{j1} x_1 + a_{j2} x_2 + ... + a_{jm} x_m \leq b_j \\ & x_h \geq 0 \end{aligned} \tag{2.2}$$

Equation (2.2) is an instance of Equation (2.1) and consists of an objective function, Z, and constraint functions. The c and b vectors are known quantities that are payoffs for the respective decision variables in the objective function and right hand side limits on the constraints. The a matrix contains coefficients on the decision variables in the constraints. The final constraint is a non-negativity constraint for all activities.

This optimization methodology provides an intentionally simplified representation of a problem [Dreyfus, 1956] due to the linearity requirement. However, linear programming approaches have been efficiently and adequately employed to solve complex water resources problems in which non-linear processes were approximated [Loucks et al., 2005]. Drobny [1971] provides a thorough review of linear programming applications in the field of water resources in the late 1960s, when this field was growing in popularity. Some notable examples include reservoir operating policy with conflicting hydropower and irrigation objectives [Thomas and Revelle, 1966] and water allocation to meet both tangible (e.g., agricultural uses) and intangible (e.g., fish and wildlife preservation) objectives using economic criteria [Heaney, 1968].

Dynamic programming builds upon linear programming, but offers a framework for breaking larger optimization problems into smaller sub-problems to be solved. In our discussion of optimization, dynamic programming introduces the concept of multi-stage problem solving in which there are sequential decisions in stages where a decision in one stage impacts the following stage. Often, multi-stage programming provides the capability for optimization over time; however, multi-stage decisions may be beneficial in many situations. There are many notable uses of dynamic programming in solving water resource problems, such as branching sewer design [Mays and Wenzel, 1976] and maintenance of river dissolved oxygen levels [Chang and Yeh, 1973]. Yakowitz [1982] provides a comprehensive review of water resources problems analyzed and solved using dynamic programming.

While linear programming and dynamic programming are efficient and readily employable with modern computing power, there are many limitations. Linear programming often oversimpli-

fies problems by linearly approximating all functions.[1] The decision variables must be proportional to their levels of use and the objective function must be equal to the sum of the individual parts. It is also difficult to include all levels of complexity of a water resources problem with respect to all stakeholders within a linear or dynamic program. For this reason, linear programming is frequently used to initially screen a problem or reduce alternatives [Loucks et al., 2005]. Dynamic programming offers some additional flexibility by readily handling nonlinearity and integer problems [Buongiorno, 2003], but it requires custom development since the approach is more general [Labadie, 2004]. These methods are traditionally used for problems that estimate values for the many uncertainties found in water resource planning problems. Above all, these methods, as they are defined here, are designed to optimize with respect to a single objective. It should be noted that this review has only compared two types of deterministic programming; however, there exist other frameworks such as non-linear programming, integer programming, and quadratic programming that can be applied in water resources problems. These other existing frameworks and newer optimization methodologies are used in practice and research to overcome the highlighted weaknesses of linear and dynamic programming.

2.2.2 Probabilistic Programming

Uncertainty is inherent in real-world problems, especially in the field of water resources which depends on hydrologic and climate variables, such as runoff and precipitation, that may be acknowledged as random phenomena. Stochastic and robust optimization are mathematical programming frameworks that incorporate uncertainty with probabilistic representations of parameters. These uncertainties are deemed classical uncertainties.

Stochastic programs follow the general optimization formulation provided by Equation (2.1), typically optimizing the expected value, allowing some or all of the data incorporated in the objective function and constraints to be uncertain. Uncertain parameters are assumed as random variables and characterized by known or estimated probability distributions. A reasonable ap-

[1] Both proportionality and additivity must be satisfied in linear programs.

proach to incorporating uncertainty may be optimizing to find a solution that is feasible across all possible parameter values [Shapiro and Philpott, 2007]. However, stochastic programs capitalize on the likelihood of parameter values despite the inherent uncertainty. Linear and dynamic programs can adopt stochastic formulations. It is standard to solve stochastic programs across multiple realizations of uncertainty referred to as scenarios [Shapiro and Philpott, 2007].

Various types of stochastic programs, such as two-stage recourse, multi-stage recourse, and chance-constrained problems, offer flexibility in how to incorporate uncertainty [Birge, 1997]. Two-stage recourse linear programs are the most common stochastic programming formulation [Shapiro and Philpott, 2007], with water resources implementations beginning in the 1960s [Huang and Loucks, 2000]. Both two-stage and multi-stage recourse models include decisions that are made prior to and after uncertainty is realized in the problem [Birge, 1997]. Essentially, a decision or action is taken in the first stage then the system is subjected to a random event consisting of uncertain parameters. In the recourse stage or stages, the decision maker may make decisions responding to the possibly negative outcomes resulting from the uninformed prior decision or decisions [Shapiro and Philpott, 2007] and may allow infeasibilities with a penalty [Sahinidis, 2004]. Huang and Loucks [2000] take advantage of the power of two-stage linear programs to handle more ambiguous uncertain parameters that cannot be represented by probability distributions, illustrating one of the advantages of stochastic programming. The study presents a hypothetical inexact two-stage stochastic programming problem that optimizes the economic activity in a water supply in which available water is modeled as a random variable.

In two-stage or multiple-stage recourse models, however, it is difficult to prevent constraint violations since decisions are made before randomness or uncertainty is realized. Chance-constrained stochastic programming introduces probabilistic constraints, meaning that optimization constraints must hold with a certain probability [Birge, 1997; Henrion, n.d.]. In essence, these probabilistic constraints allow the optimization to meet feasibility under uncertainty [Sahinidis, 2004]. There are three general methods for implementing chance-constrained programming: maximizing an expected value function subject to chance constraints; minimizing the variance subject to chance constraints;

and maximize the likelihood of satisfying the chance constraints [Olson and Wu, 2010; Charnes and Cooper, 1959]. In the field of water resources, this type of mathematical programming formulation helps capture the uncertainty in constraints on water quantity and quality parameters, which are naturally non-deterministic.

Stochastic programming is useful when seeking decisions with average performance across many possible scenarios [Shapiro and Philpott, 2007]. Satisfactory operations under a range of hydrologic and demand possibilities is an essential characteristic of water resources systems [Hashimoto et al., 1982], meaning that it may be deficient to design a system that may operate successfully under some plausible scenarios and fail under other plausible scenarios. To overcome this risk of failure, the Robust Optimization (RO) framework may be applied. RO, developed by Mulvey et al. [1995], is a mathematical programming framework designed to find robust solutions to water resources problems by integrating goal programming with scenarios or realizations of uncertainties [Watkins and McKinney, 1997; Mulvey et al., 1995]. The resulting robust solutions perform well relative to alternative solutions over a wide range of plausible futures under uncertainty [Lempert, 2003; Morgan, 2009].

RO is a hybrid framework, bridging stochastic programming with multi-objective analysis [Watkins and McKinney, 1997]. The basis of the multi-objective component of RO is goal programming. Goal programming, originally an extension of linear programming, aims to simultaneously consider and prioritize several objectives, which differs from the deterministic programs discussed in Section 2.2.1. Generally, goal programming formulations seek to minimize the summation of undesired deviations between goals, or target values, and achievements [Lee, 1973]. Essentially, the constraints are reformulated as objectives that are to be met "as closely as possible," allowing for constraint violation unlike other programming frameworks [Charnes et al., 1955]. To complete the RO formulation, scenario-based analysis is coupled with goal programming. Essentially, the mathematical programming formulation is subjected to a series of scenarios, or combinations of values for uncertain parameters. Scenario-based analysis is introduced to develop solutions that are less sensitive to perturbations or uncertainties [Mulvey et al., 1995]; thus, providing the ability

to both estimate and control the risks of sub-optimality [Watkins and McKinney, 1997].

A robust optimization problem formulation is shown in Equation (2.3) [Mulvey et al., 1995; Watkins and McKinney, 1997].

$$\begin{aligned} \text{Minimize} \quad & \sigma(x, y_1, ..., y_s) + \omega\rho(z_1, ..., z_s) \\ \text{Subject to:} \quad & Ax = b \\ & B_s x + C_s y_s + z_s = e_s \quad \text{for all } s \in \Omega \\ & x \geq 0, y_s \geq 0 \quad \text{for all } s \in \Omega \end{aligned} \tag{2.3}$$

The x and y vectors consist of decision variables. The x vector contains design decision variables, which are determined independent of uncertainty realizations, whereas the y vector contains control decision variables, which are subjected to uncertainty realizations. The first term in the objective function is itself an aggregate objective function that could be used to compute the mean, conduct a worst-case analysis, or represent an alternative utility function, depending on the intent of the optimization. This term determines how "close" the solutions are to optimality. The second term is the feasibility penalty function, which penalizes constraint violations. This term measures the feasibility of the solutions, and it is weighted, similar to many goal programming formulations, to indicate the acceptability of solution infeasibilities. The model is subjected to a set of scenarios, Ω, each with a different probability of occurance, p. Lastly, the set of z error variables measures the infeasibility of the control decision vectors. This formulation allows a decision maker to evaluate and understand the tradeoffs between optimality and feasibility.

With the formulation demonstrated by Equation (2.3), it is evident that this framework is not simply a reactive sensitivity analysis tool [Bertsimas et al., 2011]. The scenario-based analysis component finds solutions that are less sensitive to perturbations or uncertainties proactively [Mulvey et al., 1995], which provides the ability to both estimate and control the risks of sub-optimality [Watkins and McKinney, 1997]. An explicit comparison between traditional stochastic programming approaches and RO is illustrated by Watkins and McKinney [1997] through two water resources examples adapted from prior literature – water supply planning under various scenarios of

water supply and demand events (adapted from Lund and Israel [1995]) and groundwater contaminant plume containment under many hydraulic conductivity realizations (adapted from Gorelick [1987]; Wagner et al. [1992]; Morgan et al. [1993]; Chan [1994]). In both examples, Watkins and McKinney [1997] demonstrate that RO formulations allow the decision maker to incorporate risk or robustness along with other objectives in evaluating system tradeoffs.

While the RO framework is flexible, there are disadvantages, one of which being the issue of "overconservatism," which refers to the requirement for robustness across all uncertainties despite their individual probabilities [Gabrel et al., 2014]. Alternative RO formulations have been presented to control the degree of conservatism of resulting solutions, thereby alleviating this limitation. Chung et al. [2009] demonstrate a formulation presented by Bertsimas and Sim [2004] in a hypothetical water supply management optimization in which uncertainties of future demand and supply are considered. To minimize system costs of a hypothetical water supply system that includes groundwater, surface water, and transferred water inputs, Chung et al. [2009] introduce a set of parameters that control the degree of uncertainty of the system. For the purposes of their problem, the overall level of system reliability was controlled, resulting in new constraint formulations for uncertain precipitation, availability of water for import, and water demand. Solving this problem formulation demonstrated that uncertainties in future demands (agricultural and domestic) dominate the system, controlling system costs. These results showed a tradeoff between system reliability, denoted as probability of constraint violation, total system costs, and amount of water imported.

To conclude, solutions derived from a deterministic mathematical problem formulation can often result in sub-optimality or infeasibility when uncertainty impacts the system [Watkins and McKinney, 1997; Dantzig, 1955; Bertsimas et al., 2011]. Both traditional stochastic programming and RO frameworks overcome this inability of deterministic programming to consider uncertainty inherent in real-world problems. Stochastic programming is beneficial when the system uncertainties may be quantified probabilistically; however, in situations when the decision maker desires a robust system that remains feasible under any value of uncertainty, Robust Optimization is pre-

ferred.

2.2.3 Multi-Objective Evolutionary Algorithms

The simplifying assumptions required for the deterministic and probabilistic formulations discussed previously are often unrealistic when trying to solve real-world water resources problems. These problems are typically characterized by multiple, conflicting objectives such as economic goals, water demand obligations, and regulatory requirements. Furthermore, the problems often encompass large decision spaces, include nonlinearities, or have multimodal behavior. Multi-objective evolutionary algorithms (MOEAs) are heuristic search algorithms that mimic evolutionary processes to approximate the optimal set of solutions to optimization problems. MOEAs have the capability to solve real-world problems whereas deterministic methods may not be suited or even fail [Nicklow et al., 2010].

A multi-objective evolutionary algorithm may be integrated with a simulation model, as shown in Figure 2.1, in which the algorithm feeds decisions to the model as inputs and, consequently, outputs are used to compute objective functions. This process is called simulation optimization. In the framework of an MOEA, each alternative solution, which may be a different policy, design, or project [Basdekas, 2014], is represented by a set of decisions, or a decision vector. As stated by Nicklow et al. [2010], these algorithms are characterized by several elements. There is a random initial generation of a population of candidate solutions. Objective functions are used to assess the fitness of each potential solution. When optimizing using an MOEA, objective functions are not required to share the same units of measure [Deb, 2001]. A selection operator determines which solutions are deemed "parent" solutions, used to generate "offspring" solutions. A variation operator alters the selected solutions to ensure diversity and prevent premature convergence. Variation operators include mating and mutation operators. Mating combines the genetic material of two parent solutions to generate offspring whereas a mutation operator alters the genetic material of a single solution to create a new solution or solutions. The process begins with the initial random candidate set of solutions, which are fed into a simulation model, and repeats with offspring popu-

lations iteratively until stopping criteria is met, with the final surviving solutions representing the Pareto approximate set. The reader is encouraged to refer to Deb [2001] and Coello et al. [2002] for an in-depth review of multi-objective optimization and evolutionary algorithms.

This class of algorithms has grown in popularity, in part, because they are population-based, determining a population of solutions in a single run of the algorithm [Coello et al., 2002]. The concept of Pareto optimality is used in MOEAs since there is not a single optimal solution. A solution within the population is deemed Pareto optimal (non-dominated) if no other solution within the population exhibits improvement in an objective without sacrificing performance in another objective. Pareto optimal solutions form the Pareto optimal set and represent tradeoffs between objectives because it is impossible to simultaneously maximize or minimize conflicting objectives in multi-objective problems [Van Veldhuizen and Lamont, 2000].

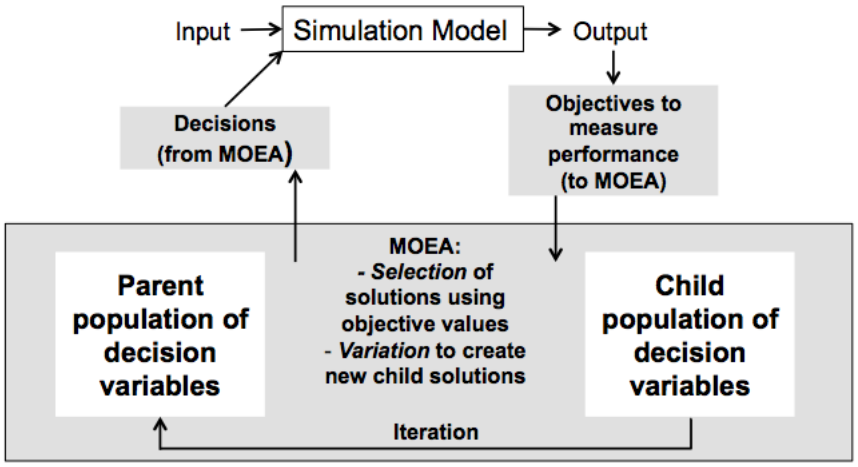

Figure 2.1: Integration of a multi-objective evolutionary algorithm with a generic simulation model

Applications of MOEAs in water resources are growing rapidly. One notable example, Smith et al. [In Review], linked an MOEA with RiverWare, an object-oriented simulation model used to model river systems, to determine optimal pumping strategies and reservoir balancing rules for a water supply utility, Tarrant Regional Water District, in Texas. Basdekas [2014] demonstrates

practitioner use of MOEAs in a drought policy study for the Colorado Springs Utilities, using conflicting objectives of demand reliability, demand vulnerability, storage reliability, and storage resilience. In addition to the previous examples of water resources planning problems, MOEAs have also been utilized in groundwater applications, such as long-term groundwater monitoring (LTM) design. In this specific design problem, the placement of sampling wells is optimized to sample a groundwater contaminant plume. This design problem has been leveraged to further understanding of how problem size affects MOEA effectiveness as well as issue a comparison between the performance of different MOEAs [Kollat and Reed, 2007; Kollat et al., 2008].

This thesis extends a series of studies that have utilized MOEAs to optimize water supply management strategies for the Lower Rio Grande Valley (LRGV) case study. The LRGV case study is of a hypothetical city in Texas that uses permanent water rights and water marketing instruments (i.e., spot leases and adaptive options contracts) to ensure adequate water supply for city demands. A simulation model of the case study has been used in conjunction with MOEAs to generate alternative water management strategies composed of the three water supply instruments. The case study and associated simulation model are discussed further in Sections 3.1 and 3.2, respectively. The first study in this series of studies introduced many (three or more) objective optimization using the epsilon Nondominated Sorting Genetic Algorithm II (ϵ-NSGAII) [Kollat and Reed, 2006] to the case study [Kasprzyk et al., 2009]. Kasprzyk et al. [2009] presents four different cases to understand how introducing new water supply instruments increases flexibility in water supply management strategies. Case A represents typical water utility planning in which permanent water rights are the sole source of water supply. Case B introduces water leasing, Case C adds both leases and adaptive options contracts, and Case D represents a highly constrained Case C that ensures a certain level of reliability. By incorporating many objectives using an MOEA, this study demonstrated that water marketing lowers costs, increases reliability, and improves efficiency of water supply management strategies. Kasprzyk et al. [2012] contributed the sensitivity-informed *de Novo* planning framework that continually updates objectives, decisions, and constraints based on knowledge gained while solving the problem. This framework is inspired by the *de Novo* planning

paradigm developed by M. Zeleny [Zeleny, 1981, 2005]. In this application, a sensitivity analysis is performed on the initial problem formulation to inform new many-objective problem formulations. Once the formulations are optimized using an MOEA, the preferred optimized problem formulation set may be selected to see how deviations from the expected assumptions impact the performance of alternative management strategies. By incorporating this framework with the LRGV case study, Kasprzyk et al. [2012] demonstrated that a moderately complex problem formulation is sufficient to develop efficient, reliable water supply management strategies. Building upon the results from the *de Novo* study, Kasprzyk et al. [2013] introduced a new planning framework termed Many Objective Robust Decision Making that assesses the robustness of alternative management strategies and studies what conditions of uncertainty impact robustness. This framework is discussed in detail in Section 2.3.2.

The LRGV case study has also been used in two different diagnostic studies of MOEAs. Reed et al. [2013] assessed the effectiveness, reliability, controllability, and efficiency of ten different MOEAs including the Borg MOEA [Hadka and Reed, 2013]. The LRGV case study served as a reasonable diagnostic test because it is highly constrained, representing the only test case in the study with explicit constraints within the problem formulation, and non-deterministic, which makes this case a challenging search test for the MOEAs compared in the study. In result, this case study proved to be the most difficult test problem to solve, with the Borg MOEA and the OMOPSO MOEA [Sierra and Coello, 2005] being the top performing algorithms for this problem. Kasprzyk et al. [In-Press] explored the impact of aggregate objective functions and reduced decision variable formulations on the search of an MOEA using the LRGV case study. This study investigated Arrow's Paradox, a theorem introduced by Arrow [1950] stating that it is impossible to create a weighting function to simultaneously and fairly consider multiple stakeholder preferences between three or more alternatives. Using four different problem formulations, Kasprzyk et al. [In-Press] showed that the solution sets emerge as a result of Arrow's Paradox, with aggregate formulations biased towards solutions that primarily utilize permanent water rights rather than water marketing mechanisms, for example. For the LRGV case study, this study also found that a larger number

of objectives resulted in a more controllable, reliable, efficient, and effective MOEA search. In conclusion, these research studies demonstrated the ability for MOEAs to solve the complex LRGV case study problem that is featured in this thesis.

2.3 Decision Making Under Deep Uncertainty

Recall that frameworks for decision making in the presence of deep uncertainty are continuously emerging. Deep uncertainty refers to components of a planning or management problem where decision makers cannot agree upon the full set of risks to a system or their associated probabilities [Knight, 1921; Langlois and Cosgel, 1993; Lempert, 2002, 2003; Kasprzyk et al., 2013]. Several of these decision making frameworks for complex systems include Robust Decision Making [Lempert et al., 2010], Many Objective Robust Decision Making [Kasprzyk et al., 2013], Adaptive Robust Design [Hamarat et al., 2013], Adaptive Policymaking [Walker et al., 2001], Info-Gap Decision Theory [Ben-Haim, 2006], and Dynamic Adaptive Pathways [Haasnoot et al., 2013]. Ultimately, these frameworks aim to eliminate failures caused by excluding uncertainty in policy or strategy development [Lempert, 2003; Hamarat et al., 2013]. Some of these frameworks focus on developing robust planning strategies or policies, that is strategies that perform well across many different assumptions regarding the deeply uncertain factors [Lempert, 2002; Hine and Hall, 2010; Brown et al., 2011]. Other frameworks hone in on adaptivity, the ability to adapt to changing future conditions [Haasnoot et al., 2011; Walker et al., 2013a].

This section provides a non-comprehensive review of these frameworks, highlighting Robust Decision Making, Many Objective Robust Decision Making, Adaptive Robust Design, and Multi-Objective Adaptive Robust Design, to provide an adequate background relevant to the methods used in this thesis.

2.3.1 Robust Decision Making

Robust Decision Making (RDM), a product of the RAND corporation, is a framework designed to evaluate policy or strategy options in the presence of uncertainty [Lempert et al., 2010].

RDM is a framework for decision making in which solutions (policy or strategy options) are assessed across a range of plausible futures, similar to the scenario-based approach of RO (discussed in Section 2.2.2), thereby abandoning the approach of incorporating uncertainty by assuming a single joint probability distribution applied in stochastic methods [Matrosov et al., 2013]. RDM improves upon RO, however, with an iterative approach that capitalizes on computing power to continuously simulate over many deeply uncertain possibilities to finalize an appropriate strategy. This component of the framework formalizes the natural inclination for humans to test theories and plans with "what if" scenarios [Lempert et al., 2010]. Additionally, this framework extends beyond the human capability to pose futures by generating futures that are not simply based on past trends and intuition [Lempert et al., 2010]. Hall et al. [2012] presents example uses of RDM, such as using RDM to develop policies adaptive to climate change for the Inland Empire Utilities Agency in California [Lempert and Groves, 2010].

The first step of RDM is to select a candidate solution or policy. Second, a scenario discovery process, discussed in more detail in Section 2.3.2, finds combinations of uncertain parameters that cause the candidate solution to perform poorly. A new candidate solution is then developed from the original solution to hedge against vulnerabilities found in the scenario discovery step. These steps are repeated until a seemingly robust strategy is found [Matrosov et al., 2013].

RDM is advantageous because it overcomes the limitations of traditional optimization methods that rely on best estimates and probability distributions of parameters input into simulation models. RDM has the ability to help develop adaptive strategies that evolve over time as new information becomes available. This framework uses two measures of robustness: (1) sacrifice of optimality to increase insensitivity over many possible futures and (2) reasonable performance relative to alternatives over many possible futures [Hall et al., 2012]. These measures circumvent the conservation strictness of other methodologies such as RO. Additionally, these measures of robustness coupled with RDM's ability to identify vulnerabilities of potential planning strategies [Hall et al., 2012] allow the planner greater flexibility relative to RO. While this framework provides a systematic process for selecting robust alternatives or strategies [Lempert et al., 2006], it lacks

the ability to help the decision maker generate strategies to test within the framework [Kasprzyk, 2013].

2.3.2 Many Objective Robust Decision Making

The many objective robust decision making framework (MORDM) is a planning framework for complex environmental systems that integrates MOEA optimization with the RDM framework to optimize and select planning strategies under conditions of deep uncertainty. This framework emphasizes the importance of decision maker involvement and feedback with an iterative approach that leverages interactive visual analytics in several forms to inform problem formulation. MOEAs are employed to generate alternative planning strategies subject to decision maker-defined system constraints measured by many (four or more) objectives. To ultimately find a robust planning strategy that performs well regardless of future external conditions, MORDM capitalizes on several strengths of RDM: discovering combinations and values of uncertainties that cause system vulnerabilities and evaluating the robustness of candidate planning strategy alternatives. MORDM was developed and first demonstrated by Kasprzyk et al. [2013]. The research presented in this thesis is based on the MORDM framework.

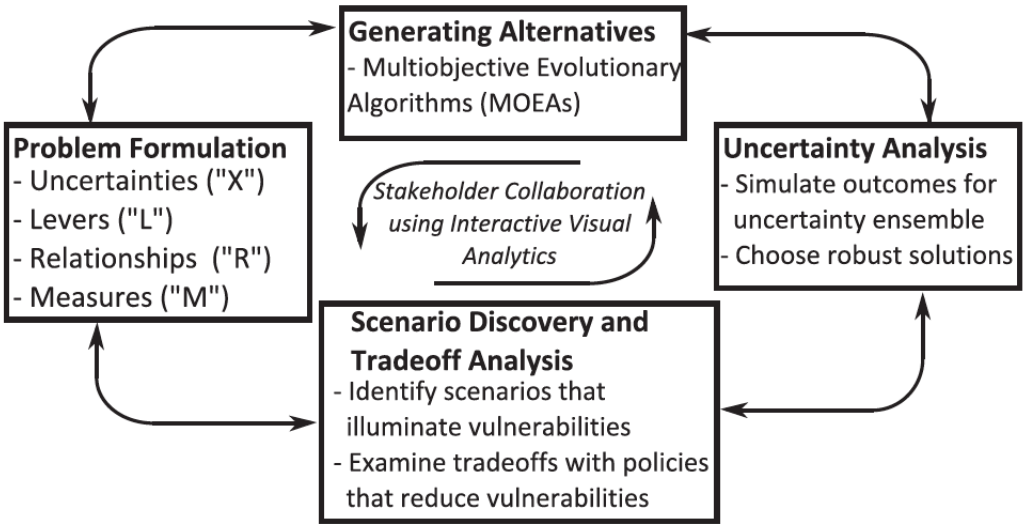

Figure 2.2: Many Objective Robust Decision Making framework [Kasprzyk et al., 2013]

As shown in Figure 2.2, the following steps compose the MORDM framework: (1) problem formulation, (2) generating alternatives, (3) uncertainty analysis, and (4) scenario discovery and tradeoff analysis. The first step is carried out in conjunction with the decision maker and stakeholders to determine what system elements and decisions are important. The problem formulation step is divided into four components denoted as X, L, R, and M, inspired by the RDM framework [Lempert, 2003; Lempert et al., 2006]. Uncertainties (X), are exogenous (i.e., external) factors represented by assumed values or probability distributions. These uncertainties are beyond the control of the decision maker and, therefore, could dramatically impact the system if assumed values and distributions misrepresent future conditions. Decisions (L) are actions the decision maker can take to interact with the system. The relationship (R) is a simulation model linked to an MOEA that maps actions to outcomes. Performance measures (M) are objectives used to measure the success of different planning strategies. These individual components are open to re-formulation as more is learned about the problem through iteration of the MORDM framework [Liebman, 1976; Reed and Kasprzyk, 2009; Kasprzyk et al., 2013; Herman et al., 2014, 2015].

Planning strategy alternatives composed of the decisions and evaluated by the performance metrics determined in the problem formulation step are generated using an MOEA. This is unprecedented in the RDM framework before the introduction of MORDM. The Pareto approximate solutions representing planning strategies are developed based on assumed best-estimate values and probability distributions for X, which, for the remainder of this section, are termed baseline conditions.

Uncertainty analysis is performed to expose the Pareto approximate set of solutions to a range of plausible values for uncertainties. Latin Hypercube Sampling (LHS) [McKay et al., 1979][2] is used to sample deep uncertainties within set ranges to generate an ensemble of plausible States of the World (SOWs). The Pareto approximate set is subjected to these SOWs, allowing for a robust solution to be selected based on performance thresholds chosen by the decision maker. The

[2] Latin Hypercube Sampling is a multi-dimensional sampling technique that divides the sampling space into an evenly-spaced grid then randomly selects one sample for each row and each column.

implementation of MORDM in Kasprzyk et al. [2013] demonstrates a regret robustness metric, in which the percent deviation between the performance metric values under the most extreme ten percent of the SOWs and the baseline performance values is computed, assuming that if a solution performs "well" in the most extreme SOWs, then it is a robust solution. Herman et al. [2014] employs the MORDM framework on the Research Triangle, a region in North Carolina that includes a network of four water utilities threatened by drought and growing demand. In this demonstration, a different robustness metric is used to find a solution that performs well relative to alternatives across a wide range of SOWs [Lempert and Collins, 2007; Hall et al., 2012]. Specifically, a robust solution was found based on the fraction of SOWs in which all performance metric thresholds were met. These two implementations illustrate the importance of robustness metric selection based on the purpose of the decision making and present two opposing metrics of regret, defined as the performance cost of choosing incorrectly [Herman et al., 2015], and satisficing, meeting one or more performance thresholds at a potential sacrifice of optimality [Simon, 1959; Herman et al., 2015]. MORDM provides the framework for evaluating robustness; however, the modeler in conjunction with the decision maker are responsible for choosing a sensible robustness metric for the system of interest.

An RDM scenario discovery process is carried out to determine combinations of uncertainties that cause the seemingly robust solution to perform poorly or fail. First, it is necessary to set thresholds on performance metrics considering decision maker needs that characterize acceptable (i.e., performance metric thresholds are not violated) versus vulnerable (i.e., performance metric thresholds are violated) performance. The scenario discovery process itself is a statistical clustering analysis that identifies the acceptable versus vulnerable solutions in which the Patient Rule Induction Method (PRIM) [Friedman and Fisher, 1999] is applied to find the combinations of exogenous uncertain factors and their value ranges that cause vulnerability of the robust solution. PRIM essentially identifies multi-dimensional "boxes" in which layers of uncertainty space are "peeled" and "pasted" until each box represents the ranges of uncertainties likely to induce failure.

This framework stresses the importance of interactive visualization of decisions, performance

metrics, and robustness of the solution set. Kasprzyk et al. [2013] utilizes glyph plots, three-dimensional plots that use point shape, size, color, and transparency to communicate up to seven dimensions, and parallel coordinate plots, plots that illustrate a pairwise comparison between performance metrics with no limit on the number of dimensions shown [Inselberg, 1985; Wegman, 1990; Fleming et al., 2005; Kasprzyk et al., 2013]. These plotting techniques may be used to learn about the problem and results of the problem formulation throughout the MORDM steps, allowing the modeler and the decision maker ample opportunity to experiment with different problem formulations.

As mentioned in Section 2.2.3, Kasprzyk et al. [2013] demonstrated the MORDM framework using the LRGV case study. Kasprzyk et al. [2013] developed four different problem formulations termed cases, each composed with a different combination of decision variables (i.e., variables that represent permanent water rights, adaptive options contracts, and leases which compose water management strategies). Each case was optimized using the ϵ-NSGAII [Kollat and Reed, 2006], and the resulting solution sets were then subjected to $10,000$ SOWs. These SOWs were made up of different values of uncertain inputs such as inflows and demands. To understand how performance across the solution sets changed under uncertainty, the percent deviation from the baseline performance value and the performance in the 10% most extreme SOWs was taken. Using visual analytics and the uncertainty analysis results, a robust solution was selected from the simplest problem formulation. This problem formulation is made up of permanent water rights, a single-volume non-adaptive options contract, and a variable that determines "when" and "how much" water to obtain using the options contract. In the scenario discovery step, the robust solution was found to be vulnerable under values that scale the input probability distributions of inflows, losses, and demands and parameter values of the initial rights, demand growth, and initial reservoir volume. Specifically, three scenarios were found that caused high costs, low reliability, and high market use of the robust solution. This thesis is based on these discovered scenarios. In this thesis, we demonstrate how optimizing under these discovered conditions of uncertainty impact the water supply management strategies for the LRGV case study. Our approach is discussed in Chapter 3.

2.3.3 Adaptive Robust Design

Adaptive Robust Design (ARD) is an iterative and quantitative framework for adaptive policymaking or decision making, the design of policies or plans that adapt to changing conditions [Hamarat et al., 2013]. This approach combines Adaptive Policymaking (APM) [Walker et al., 2001], Exploratory Modeling and Analysis (EMA) [Kwakkel and Pruyt, 2013; Bankes, 1993], and elements of RDM [Lempert et al., 2010] to move from a conceptual framework of adaptive policymaking to an operational tool.

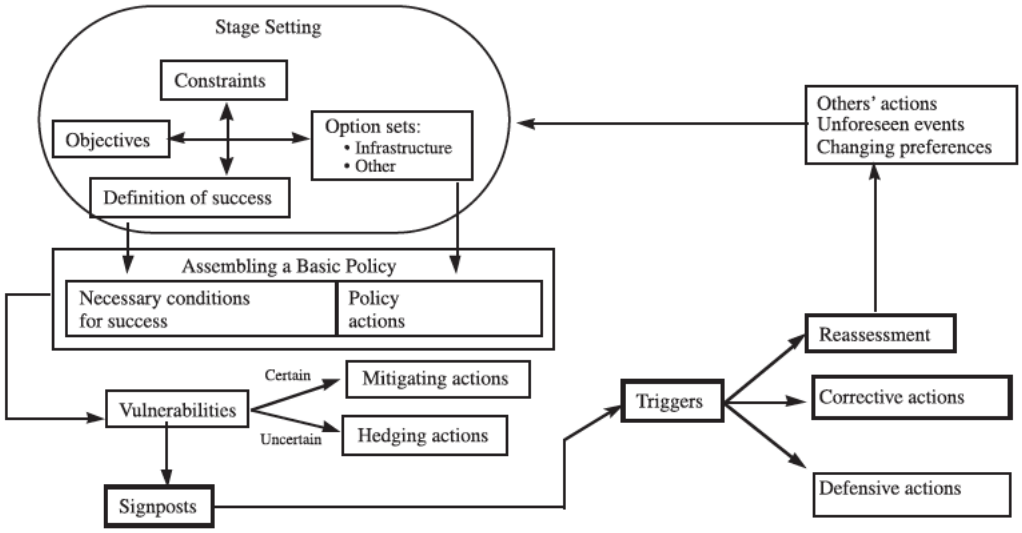

Figure 2.3: Adaptive Policymaking Process [Walker et al., 2001]

APM is a conceptual framework aimed toward designing long-term policies under uncertainty [Walker et al., 2001, 2013a]. There are two major phases of the framework: (1) design or thinking phase and (2) implementation phase. The first phase involves developing the basic policy, identifying uncertainties, forming future actions to modify the policy, and establishing a monitoring system. The devised future actions are categorized as mitigating, hedging, defensive, and corrective. Mitigating and hedging actions are enacted to prevent certain and possible, respectively, adverse effects of a policy whereas defensive actions occur after a policy problem occurs. Corrective actions provide adjustments to the policy over time. The monitoring system consists of signposts and triggers.

Signposts are specified information that should be tracked throughout the implementation of the policy to measure success while triggers are critical values of signpost that indicate when additional policy-modifying actions should be taken. The monitoring system is a key component of APM and is present in the ARD framework. In the implementation phase, the policy is enacted, signposts are tracked, and adaptive actions are put in motion when triggers are met. A more in-depth review of this decision making framework is shown in Figure 2.3.

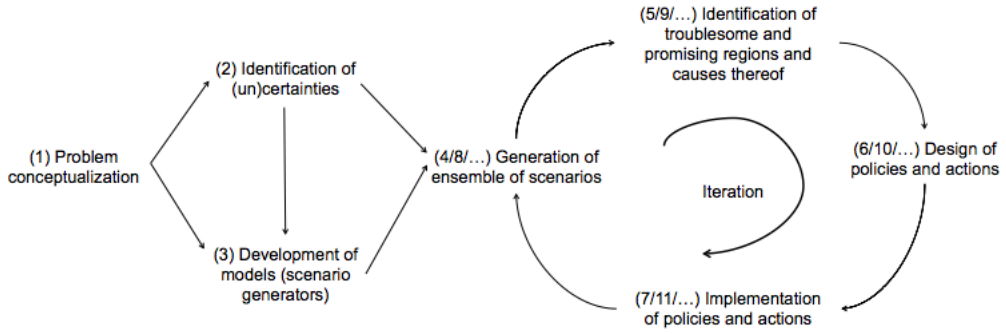

Figure 2.4: Adaptive Robust Design Process, adapted from Hamarat et al. [2013]

ARD builds upon this APM structure with EMA, model-based support developed by the RAND Corporation that uses computational experiments to generate plausible scenarios used to understand the effect of uncertainty on modeled systems [Kwakkel and Pruyt, 2013]. The resulting ARD framework is composed of nine steps: (1) problem conceptualization; (2) uncertainty and certainty identification; (3) development of models used to generate scenarios; (4) generation of a large ensemble of scenarios; (5) scenario discovery on ensemble of scenarios [Bryant and Lempert, 2010]; (6) design of adaptive policies to overcome issues identified by the scenario discovery process; (7) implementation of candidate policies in models; (8) generation of all plausible scenarios in the case of the candidate policies; and (9) exploration and analysis of the scenarios generated [Hamarat et al., 2013, 2014]. This process is illustrated in Figure 2.4.

Similarly to Kasprzyk et al. [2013], PRIM is used in the scenario discovery step. However, Hamarat et al. [2013] employs PRIM to find both troublesome and promising regions of the

uncertainty space to find combinations of uncertainties that result in negative as well as positive effects in the modeled system. This framework is also designed to be an iterative process, like RDM and MORDM, allowing the decision maker or policy maker to realize the effects of a plan or policy then alter decisions to improve outcomes. ARD is demonstrated in a case study of the transition from a fossil fuel driven energy sector to more sustainable energy generation technologies [Hamarat et al., 2013]. In this application, the transition is dependent on the development and improvement of sustainable technologies for actionable use and the subsequent adoption by society, both highly uncertain. Hamarat et al. [2013] used LHS to generate an ensemble of scenarios for this case study, marking another comparable component between the ARD and MORDM frameworks.

2.3.4 Multi-Objective Adaptive Robust Design

A recently introduced framework by Hamarat et al. [2014] integrates Adaptive Robust Design [Hamarat et al., 2013] with MOEAs to develop adaptable policy strategies that cope with deep uncertainty. Recall that deep uncertainty is defined as the inability of decision makers and stakeholders to agree on or enumerate all of the uncertainties within a planning problem. In the context of this policymaking approach, deep uncertainty also involves decisions that change over time [Hallegatte et al., 2012; Hamarat et al., 2014]. Within this framework, ARD is used to understand the problem, develop scenarios, create adaptive policies, and test adaptive policies while MOEAs are employed to determine robust and optimal values of trigger points to initiate future actions in the adaptable policies. The ultimate goal of this new approach is to determine and balance the appropriate timing, represented by trigger points, to adapt policies that meet the objectives of multiple stakeholders, which is a current gap in existing frameworks [Walker et al., 2010; Hamarat et al., 2013, 2014].

The steps outlined in Section 2.3.3 are followed in this approach, with several adjustments. First, to conduct the scenario discovery step, the uncertain input data are pre-processed using Principal Component Analysis (PCA) [Dalal et al., 2013], a data transformation procedure that rotates the coordinate system of the uncertainties to perpendicularly align with the scenario boundaries.

Second, simulation optimization using an MOEA is used to determine values for triggers, declared as decision variables, subject to constraints. Hamarat et al. [2014] elect to embed uncertainty directly within the optimization by using robust objective functions that decrease sensitivity and simultaneously increase the expected outcomes of the policy or plan. The authors suggest a robustness metric inspired by the signal-to-noise ratio [Brub and Wu, 2000], where the mean is divided by the standard variation for maximized objectives and the mean is multiplied by the standard deviation for minimized objectives. This metric maximizes the expected value and minimizes the standard deviation, or variance, which are indicative of more robust decisions.

The demonstrating case study in Hamarat et al. [2014] best illustrates how this complex framework unfolds. The European Emissions Trading Scheme (ETS) policy aims to reduce carbon emissions and increase use of renewable energy technologies to meet European Union targets for the year 2020 by enforcing a cap-and-trade principle, which places a restriction on greenhouse gas emissions while allowing trading of allowances for emissions. This policy has been ineffective in reducing carbon emissions, which makes it an ideal case study. A simulation model of the EU's power sector is used to simulate 10,000 plausible futures based on Latin Hypercube Sampling of 46 different uncertainties such as economic growth, battery storage of renewable technologies, and price-demand elasticity. Scenario discovery is conducted on the simulations to find vulnerabilities and opportunities of the present ETS policy, which were utilized to determine three future policy adaptation actions: (1) phasing-out of non-renewable energy technologies; (2) introducing a subsidy fraction on the marginal costs of investing in renewable energy technologies; and (3) decommissioning of non-renewable energy technologies based on a desired fraction of renewable technologies. The same model simulations were re-run with these actions included in the policy, and showed improvement with respect to several objectives of average total cost, carbon emissions reduction fraction, and fraction of renewable energy technologies.

To find a robust and approximately optimal set of triggers to enact these future actions, the simulation model was linked with the Nondominated Sorting Genetic Algorithm-II (NSGA-II) [Deb et al., 2002]. The three objectives used to measure policy performance were transformed into

the previously discussed robustness metrics (e.g., maximizing the mean of the fraction of carbon emission reduction divided by the standard division of the fraction of carbon emission reduction). Each of the three actions are made up of several decisions (e.g., the first action is made up of two decisions: desired fraction of renewable technologies and additional fraction of non-renewable technologies to be decommissioned). The robustness metrics are computed across 500 runs of the simulation optimization where each run is representative of a different plausible future developed using LHS across the 46 uncertainties again. The resulting solutions, each representing different values for the the three action triggers, show a tradeoff between the average cost objective and the fraction of reduced carbon emissions.

Through this case study, it is evident that this methodology may be used to develop adaptive policies with specified triggers for actionable use. The incorporation of uncertainty into the actual optimization using a robustness metric based on mean and standard deviation ensures that resulting decisions perform well across a number of plausible scenarios.

2.3.5 Benefits and Limitations of Decision Making Under Uncertainty Frameworks

The frameworks discussed here provide a sample of decision making tools used to develop water resources planning strategies. Two of these frameworks, MORDM and Multi-Objective Adaptive Robust Design, incorporate optimization techniques, specifically MOEAs, within their frameworks. MORDM integrates multi-objective optimization into the RDM framework, capitalizing on the scenario discovery process of RDM, whereas the Multi-Objective Adaptive Robust Design framework appends ARD and APM. However, MORDM and Multi-Objective Adaptive Robust Design utilize MOEAs for different purposes. Within MORDM, a many objective problem formulation is determined where the planning strategy composed of decision variables is optimized according to many objectives of importance to the decision maker. In the Multi-Objective Adaptive Robust Design framework, an MOEA is used to optimize trigger points, which enact future adjustments to a planning strategy or policy when appropriate to adapt to changing conditions.

The varying uses of MOEAs within these two frameworks highlights another important dif-

ference - the robustness measure. Within MORDM, robustness is measured after the planning strategy is optimized. Thus, the alternative solutions, each representing a different set of values for decision variables, are optimized under baseline conditions, ignoring any future deeply uncertain trajectories. The robustness measure determines how susceptible each solution is to the deep uncertainties, allowing the decision maker to select an approximately optimal solution according to present baseline conditions that holds up against various futures. This methodology is useful because deeply uncertain trajectories are unknown, thus it is sensible to optimize under expected baseline conditions based on historical data. Essentially, MORDM guarantees a solution that is "optimal" with respect to these conditions. However, if one of the extreme futures were to occur, the robust solution may sacrifice an acceptable (as determined by the decision maker) amount of performance in one or several objectives.

Within the Multi-Objective Adaptive Robust Design framework, the robustness of triggers is optimized using an evolutionary algorithm. With this methodology, the strategy or policy is optimized to adapt in a robust way, ensuring that the future actions are robust across a wide range of futures. The robustness metrics between the two frameworks differ as well. MORDM uses a percent deviation metric that deems solutions that perform well in extreme futures as robust. Contrary to MORDM, Multi-Objective Adaptive Robust Design measures robustness as the ratio of the expected value to the standard deviation of three particular performance measures, using optimization across many different futures to increase the expected value and decrease the spread of values. While Hamarat et al. [2014] includes deep uncertainty within the optimization search by optimizing across many futures, the framework as it stands does not allow the decision maker to consider other objectives of importance to design an adaptable planning strategy.

Both of these frameworks seek to overcome the static limitations of traditional approaches [van Drunen et al., 2009; Walker et al., 2013a]. The Multi-Objective Adaptive Robust Design builds in the ability to adapt to future changes with future actions and triggers. MORDM's coping and adapting flexibility is implicit in the iterative nature of the framework. When a planning strategy becomes unsuitable, the problem may be reformulated and the framework may be applied to develop

a fitting strategy. Additionally, both of these frameworks realize robust planning strategies or policies across many different plausible futures, contrary to a select few futures.

To conclude, both of these recently introduced frameworks aid in the design of sustainable plans, which must both be robust and adaptable [Walker et al., 2013a]. These frameworks also demonstrate the use of optimization in decision making for water resources applications. Ultimately, however, these frameworks do not ensure that a planning strategy or policy will perform successfully (without loss of performance) under any one particular extreme future. This gap motivates the point of departure of this thesis. In this thesis, we extend the MORDM framework to consider deeply uncertain factors directly within the MOEA search itself. In doing so, we explore two research questions: (1) how optimizing under conditions of deep uncertainty, specifically conditions that may cause poor performance of a seemingly robust solution, impacts the design of a planning strategy? and (2) how does this design of a planning strategy cope with futures unlike the conditions of the optimization?

Chapter 3

Case Study and Methods

This thesis builds upon the optimization techniques and frameworks presented in Chapter 2 using a case study of the Lower Rio Grande Valley water market to demonstrate how to optimize while incorporating deep uncertainty within the search process of an MOEA. Section 3.1 discusses the case study, including general information about the region and the water supply tools. Section 3.2 discusses the simulation model representation of the case study used in conjunction with an MOEA for this research. This simulation model is inherited from prior work [Kasprzyk et al., 2009, 2012, 2013]. The problem formulation from Kasprzyk et al. [2013] is presented in Section 3.3. The computational experiment contributed by this thesis is outlined in Section 3.4.

3.1 Case Study

This thesis explores the impact of deep uncertainty on water management planning decisions for a hypothetical city located in the Lower Rio Grande Valley (LRGV) region of Texas. The case study is adapted from and expands upon prior work of Characklis et al. [2006], Kirsch et al. [2009], and Kasprzyk et al. [2013]. This chapter provides a brief background of the LRGV region and accompanying water market.

The LRGV basin is at the southernmost tip of Texas. The primary water source, shared by the United States and Mexico, is the lower portion of Rio Grande River. Its shared use is governed by the 1944 International Water Treaty between the United States and Mexico [Schoolmaster, 1991]. Diversions are stored in the Amistad and Falcon reservoirs, with a combined storage volume of 7.2

billion cubic meters (bcm), excluding a flood storage volume of 2.6 bcm [Characklis et al., 2006]. Diversions and consequent storage from the Rio Grande River provide 99% of water for all uses as groundwater reserves lack adequate water quantity and quality [Schoolmaster, 1991]. In general, water management in Texas must prepare for likely extended drought conditions [Wurbs, 2014], while providing for municipal, industrial, and agricultural demands. Economically, the LRGV is an agricultural community, producing cotton and citrus fruits [Levine, 2007]. As of 1999, irrigation accounted for 85% of regional water use [Characklis et al., 1999]. However, the recent growth in the urban sector has lead to changes in water use distribution.

The water scarcity issues and constrained water use in this region are illustrative examples of issues and uses in the western United States. However, the water rights and water market structure found in the LRGV are unique to the region. Historically, water ownership was dictated exclusively by riparian water rights[3] until a "dual system" was adopted in the late 1800s to ensure water resource sustainability in more arid regions of the LRGV [Stubbs et al., 2003]. This dual system mandated that land acquired after 1895 would no longer retain riparian water rights, instead the rights were appropriated according to a set of new Texas state procedures [Stubbs et al., 2003]. Water was overallocated through this dual system since prior riparian rights were still observed while new landowners were also appropriated water. The water appropriation system in the LRGV continued to evolve in 1967 to a system of State licensing of water rights, removing all prior riparian rights [Stubbs et al., 2003; Wurbs, 2014]. In Texas, these licensed water rights are akin to property rights, in which they may be sold, transferred, or leased under a specific set of rules Schoolmaster, 1991; Kaiser, 1987]. Furthermore, there are two surface water State licensing systems, one applying to the the Lower and Middle Rio Grande below the Amistad Dam, which includes the LRGV [Stubbs et al., 2003; Wurbs, 2014]. The remaining portion of Texas above the Amistad Dam abides by a different State licensing system [Stubbs et al., 2003].

Presently, in the LRGV region, the majority of permanent water rights are held by irriga-

[3] Riparian rights govern water as common property, where users may decide when and how to use water under ownership [Dellapenna, 2011], contrary to the "first in time, first in right" basis of a prior appropriation system.

tors. A rapidly growing population, fueled by immigration [Leidner et al., 2011], in the region is diversifying and further stressing water use [Levine, 2007; Wurbs, 2014], resulting in complex use of the water market among and between willing sellers in "marginal value" agriculture sectors and "willing buyers" in municipal sectors in the region [4] [Schoolmaster, 1991]. The water market use is in part a result of the growing demand, providing ample economic motive for irrigators to sell their rights to municipal buyers [Characklis et al., 2006]. This increased competition for water between agricultural and municipal users has lead to active water market use in the LRGV region of Texas [Levine, 2007; Schoolmaster, 1991].

While this case study is modeled after the LRGV, the water supply management strategies developed are widely applicable to other cities and countries that utilize water market structures to control and distribute water. The relevance of this study is likely to increase as the prevalence of water marketing also increases, where water scarce regions across the globe may turn to markets as an adaptation mechanism [Wheeler et al., 2014]. One important constraint on adaptation capability in these systems is the regulatory environment. In the western United States, water is distributed according to prior appropriation doctrine, which serves as the basis for water markets that allow the sale or transfer of rights within and out of basins [Donohew, 2009; Wheeler et al., 2014]. Specifically, the South Platte Basin in Colorado is one of the most active markets in the United States, developed to support irrigation needs [Libecap et al., 2009]. Internationally, many countries use private water markets, with Australia as a prominent example. In general, Australia's water marketing structure includes eight main water trading mechanisms [Tisdell, 2011], which is more expansive than the number of water instruments in this study. In particular, the water market in the southern Murray-Darling Basin is one of the most active markets in the world based on number of transactions [Grafton et al., 2010; Wheeler et al., 2014]. Due to the prevalence of these active water markets throughout the world, there is an audience that justifies the development of water supply management strategies based on multi-objective tradeoffs.

[4] Within the simulation model implementation of this case study, the city is not guaranteed water rights as stated here. Within the model, there is a pro rata allocation of water rights, described in Section 3.2

3.2 Lower Rio Grande Valley Simulation Model

In this thesis, we use an existing simulation model of the LRGV, which models a hypothetical city with usage based on Brownsville, Texas. This model is a hydrologic-market supply simulation model, developed by Kasprzyk et al. [2009, 2013] as an adaptation from Kirsch et al. [2009], used to develop water management planning portfolios, which are water supply management strategies consisting of both non-market and market tools.[5] The LRGV model explores hypothetical forms of water policy instruments, similar to a screening-level analysis as discussed in the policy literature (e.g., Walker and Veen [1987]). Although the form of the supply instruments is not exactly the same as in the real LRGV system, the model can potentially help planners discover new forms of instruments and risk assessment under uncertainty, especially in the context of drought planning [Kasprzyk et al., 2009].

The model obeys a reservoir mass balance and requires input parameters characterized by both single scalar value and random values sampled from probability distributions. Specifically, the model exploits historical hydrological (e.g., inflows, reservoir losses, and variation in reservoir volume) and socio-economic (e.g., population projections, water supply demands, and spot lease pricing) data from the region of interest. A 10-year simulation and single-year severe drought simulation are performed at a monthly time step.

There are three distinct water supply instruments represented in the model: permanent rights, adaptive options contracts, and spot leases. Permanent water rights may be held by a person, corporation, or city [Schoolmaster, 1991]. In the LRGV model, the permanent rights belong to the hypothetical city. In the LRGV system, permanent rights are given priority; however, in the LRGV model, permanent water rights are allocated as a function of reservoir inflows [Characklis et al., 1999]. The permanent rights decision variable is represented by the volume N_R. These rights grant allocations by a *pro rata* basis in the form of a percentage of water inflow to the rights

[5] Although the model does not directly describe real water management in the LRGV, its development was designed to help researchers explore alternative water marketing mechanisms, such as having a market augment permanent rights, which are based on reservoir inflow only.

holder each month. Essentially, if the city owns 5% of total regional water rights, determined by the ratio of N_R to total rights water volume, then the city is allocated 5% of inflows each month. Water from permanent rights allocations may be used in any subsequent month. Permanent rights are considered constant annually because transfer of rights is a time-consuming regulatory action [Characklis et al., 2006]. The annualized cost, denoted by p_R, is \$22.50 per af [Kirsch et al., 2009].

The spot market lease is a temporary flexible water supply instrument that has formed in response to changes in the water market with respect to increased demand and seasonal influences, such as drought [Characklis et al., 2006]. Spot market leasing allows for "wet" water to be transferred from the agricultural sector to the municipal sector within a few days, which makes it an attractive alternative to transfers of permanent water rights. Similarly to permanent rights, spot market leasing transactions occur at the end of the month, allowing the holder to use the water in any subsequent month. For the modeled city, lease water volume, represented by N_l, purchase cost is sampled from historical pricing distributions. There are two pricing distributions dependent on reservoir level where decreased reservoir levels correspond to increased purchase prices [Characklis et al., 2006]. Purchase cost as a price per cubic foot is expressed as $\hat{p}_l$.

Options contracts enable a user to purchase lease rights to a volume of water, N_O, at the beginning of the year and may be "exercised" during a specified month, reminiscent of a European call stock option [Characklis et al., 2006]. During the exercise month, the user may purchase a portion of or all of the agreed upon volume of water at a fixed price. In this study, adaptive options contracts with June as the exercise month are available. The adaptive options contract provides greater flexibility to the city than a traditional options contract by allowing the city to choose between a high and low options contract volume at time of purchase based on the city's present and anticipated water supply volume. The adaptive options contract cost at the beginning of the year is \$5.30 per ac-ft multiplied by N_O, where N_O is determined at the beginning of the year based on the ratio of the city's volume of current water supply, N_{r_o}, to volume of permanent rights. Equation 3.1 shows that the value of this ratio relative to a threshold of ξ allows the city to choose the high-volume ($N_{O_{\text{high}}}$) or low-volume ($N_{O_{\text{low}}}$) options contract volume.

$$N_O = \begin{cases} N_{O_{\text{low}}} & \text{if } \frac{N_{r_o}}{N_R} \geq \xi \\ N_{O_{\text{high}}} & \text{if } \frac{N_{r_o}}{N_R} < \xi \end{cases} \tag{3.1}$$

The initial water supply volume for each model simulation is equal to a fraction of permanent rights. The initial water volume is an adjustable parameter, allowing for assessment of water portfolio performance across an array of initial conditions. The demand is represented as a set of 12 monthly normal distributions developed by parameter estimation from historical data [Kasprzyk et al., 2013]. The demand growth rate over multiple years of simulation is initially set at 2.3% per year based on expected population growth determined by [Characklis et al., 1999]. The α_k and β_k decision variables are thresholds that determine "when" and "how much" water should be acquired, respectively, in time period k using adaptive options contracts and spot leases. As shown in Figure 3.1, if the α_k threshold is greater than the ratio of the expected supply to the expected demand for a given month, then water must be purchased. The model includes two sets of these variables, a set for both the January through April period and the May through December period. The lease prices are compared to the adaptive option prices during the options month to determine which supply instrument is more cost-effective. There is no restriction of using both options and leases during the exercise month to obtain sufficient supply. The model tracks lease pricing and municipal demand for each simulation month. As stated previously, a reservoir mass balance, shown in Figure 3.2, is satisfied at the end of each simulation month and depends on

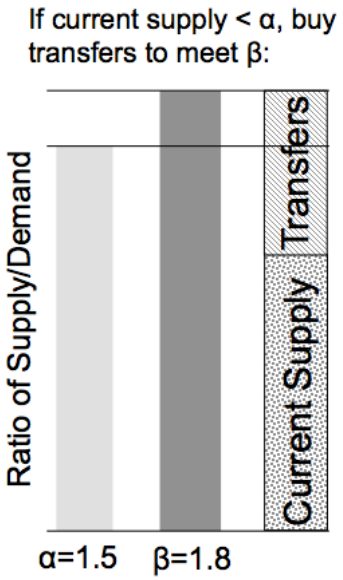

Figure 3.1: Logic behind α and β strategic decision variables

the total reservoir volume in the previous month, monthly inflow, and reservoir variation. Reservoir variation represents evaporative losses and other users' outflows and diversions.

A Monte Carlo simulation samples the historical input data to develop distributions of random variables. The LRGV simulation model assumes all variables are independent, and a set of analyses in prior work showed that this assumption was valid. Specifically, Characklis et al. [2006] conducted the Pearson test for serial independence for the inflow input variable and showed weak autocorrelation. The authors contribute this weak autocorrelation to the large time step (monthly) and the dry climate of the region. A series of additional tests showed the weak correlation between input variables [Characklis et al., 2006]. In result, random independent samples from each monthly distribution are reasonable. The Monte Carlo simulation is the consideration of uncertainty within the simulation model. The inclusion of deep uncertainty occurs when the framework contributed by this thesis is employed.

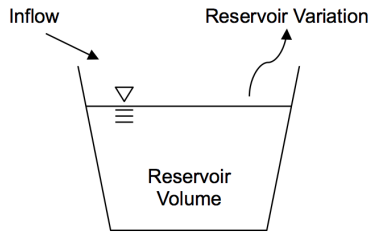

Figure 3.2: Model mass balance

To conclude, the LRGV model is subject to assumptions made by Characklis et al. [2006] and Kirsch et al. [2009]. The number of permanent rights owned by and options contracts acquired by the city are established before each year begins. Water from permanent rights is expressed as a percentage of reservoir inflows. It is assumed that there is always water available for spot market leases and options contracts. Lease pricing distributions and demand growth rate are assumed constant throughout the simulation period. In the real system, water transfers are limited to occur between similar user types; however, it is likely that transfers between sectors will be legal in the future. Therefore, the lease pricing in this simulation is derived from the agricultural market and represents lease pricing between agricultural and municipal users. The reader is encouraged to explore Characklis et al. [2006], Kirsch et al. [2009], and Kasprzyk et al. [2009] for a more in-depth review of this model and underlying assumptions.

3.3 Problem Formulation

The problem formulation in this thesis is from Kasprzyk et al. [2013] and consists of uncertainties (X), decision levers (L), relationships (R), and measures (M). Section 3.3.1 discusses the treatment of uncertainties in the MORDM study and this thesis. Sections 3.3.2 and 3.3.3 describe the remaining components of the problem formulation

3.3.1 Uncertainties

Classical and deep uncertainty are included within this exploration. As discussed previously, classical uncertainty is considered within the simulation model through a Monte Carlo simulation with a sample size $5,000$ that samples historical hydrology (inflow, losses, and reservoir variation), demand, and lease pricing. Inflows and losses are modeled as empirical monthly distributions based on historical data. The difference between the sampled inflow and loss for each month represents the volume of water available for allocation. The demand is sampled from a set of 12 monthly distributions. These distributions are based on historical data and are normally distributed with estimated mean and standard deviation parameters. The demand distribution is subject to a demand growth rate, which is treated as a fixed value. From analysis of a prior study, Characklis et al. [2006], the lease pricing is partitioned into two empirical monthly distributions based on reservoir volume. There are distributions corresponding to reservoir volumes greater and less than 1.76 bcm, respectively. The reservoir variation distribution is based on historical data and represents the change in volume of the stored water in the reservoir from external forcings such as precipitation and evaporation.

Recall that this thesis focuses on understanding how optimizing under conditions of uncertainty impact water supply planning; therefore, we are interested in deep uncertainties in the computational experiment. Specifically, this study is interested in the values of the deeply uncertain parameters that caused a promising robust solution to perform poorly in the prior MORDM study presented by Kasprzyk et al. [2013].[6] The prior study investigated two types of deep uncertainties

[6] Kasprzyk et al. [2013] uses the percentage deviation between the performance metric values under the most

as discussed below and summarized in Table 3.1 [Kasprzyk et al., 2013].

(1) *Parameters represented by baseline probability distributions sampled in the Monte Carlo simulation*

To understand how deviations from baseline conditions impacted the performance of the highlighted robust solution, the prior study scaled the deeply uncertain parameters based on a methodology presented in Dixon et al. [2008]. The parameters defined by probability distributions were renormalized to emphasize the extremes in the distributions. To increase the likelihood of either the lowest or highest 25% of the distribution, an integer scaling factor between 1 and 10 was sampled to reweight the tails, thus forcing the extremes to be between 1 and 10 times more likely. The resulting distributions represent low inflow, high loss, high demand, high lease price, and loss in reservoir storage cases. Low inflows and high losses, for example, correspond to renormalization of the lowest 25% and highest 25% of the respective probability distributions. The losses in reservoir storage refers to the renormalization of the lowest 25% of the reservoir variation distribution. The reader is encouraged to refer to Kasprzyk [2013] and Kasprzyk et al. [2013] for an in-depth reasoning behind the chosen renormalized extremes.

(2) *Parameters treated as fixed scalar values in the Monte Carlo simulation*

These parameter values represent the baseline conditions for the initial permanent water rights (i.e., initial condition designating the amount of water available to the city in the first month of the simulation), demand growth rate, and the initial reservoir volume. To re-define parameters set as fixed values in the Monte Carlo simulation, a lower and upper bound for sampling each parameter value was determined. For the initial rights parameter, a lower bound of 0 corresponds to zero water availability and a higher bound of 0.4 corresponded to a volume that is 40% of the city's total water rights volume. The demand growth rate

extreme ten percent of the SOWs and the baseline performance values to determine the robust solution. The assumption is that if a solution performs well in the most extreme SOWs, then it is a robust solution. While the selected solution is "robust," there are specific combinations of uncertainties that will cause this solution to perform poorly, which is determined in the scenario discovery process.

parameter was bounded 1.1% and 2.3%, and the initial reservoir volume was bounded between 987 million cubic meters and 2,714 million cubic meters. LHS was applied to generate 10,000 SOWs by sampling the scaling weights and values for the fixed single-valued parameters between the upper and lower bounds.

Table 3.1: Deep uncertainties

	Uncertainty Input Variable	*Description*	*Scaling factor*		*Reweighting*
			Lower Bound	*Upper Bound*	
Probability Distribution	Inflows	empirical monthly distribution	1	10	Lowest 25%
	Losses	empirical monthly distribution	1	10	Highest 25%
	Demands	normal distribution with parameters estimated using historic data	1	10	Highest 25%
	Lease pricing	two empirical monthly distributions	1	10	Highest 25%
	Reservoir variation	empirical monthly distribution	1	10	Lowest 25% of the reservoir variation distribution
	Uncertainty Input Variable	*Description*	*Parameter value*		*Sampling*
			Lower Bound	*Upper Bound*	
Scalar Parameter	Initial rights	initial condition representing amount of water available in first month of simulation	0	0.4	0 to 40% of permanent rights volume
	Demand growth rate [%]	projected growth of demand in LRGV region	1.1	2.3	1.1% to 2.3% growth rate
	Initial reservoir level [10^6 m^3]	initial volume of reservoir; impacts lease pricing	987	2,714	987x10^6 m^3 to 2,714x10^6 m^3

The robust solution was subjected to the 10,000 SOWs and the scenario discovery process (discussed in Section 2.3.2) to determine ranges of the deeply uncertain parameter scaling factors and fixed values that cause that specific solution to perform poorly with respect to previously defined thresholds of performance. These ranges define the starting point of the computational experiment and are detailed in Section 3.4.

3.3.2 Decision Levers, Relationships, and Measures

The decision levers, relationship, and measures for the LRGV case study are from Kasprzyk et al. [2013]. A full description and equations of these components of the problem formulation is found in Kasprzyk et al. [2013] and Kasprzyk et al. [2012]. The decision levers compose the water supply portfolio instruments discussed in Section 3.2. The three water supply portfolio instruments include permanent rights, spot leases, and adaptive options contracts. The decision levers are tabulated below.

Table 3.2: Decision levers

Decision Lever		*Units*	*Description*
Permanent Rights Volume	N_R	[m^3]	Non-market instrument allocating an annual percentage of inflows to the city
Adaptive Options Contracts Volume	N_{Olow} N_{Ohigh}	[m^3]	Market instrument used to purchase lease rights to either a low or high volume of water at the beginning of the year at a fixed price as determined by an anticipatory threshold
Adaptive Options Contract Threshold	ξ	[-]	
Transfer Thresholds	α	[-]	Market variable issuing "when" water should be acquired through adaptive options contracts and spot leases
	β	[-]	Market variable issuing "how much" water should be acquired through adaptive options contracts and spot leases

The LRGV Simulation Model described in Section 3.2 defines the "relationship" for the problem formulation. The simulation model employs a 10-year expected performance Monte Carlo simulation and single year drought simulation. There are three groups of metrics to measure the performance of the decision levers in the simulation model. Efficiency metrics measure costs and volumes of water throughout the simulation. Risk indicator metrics assess success, failure, and recovery of water supply planning portfolio decisions. Market use metrics evaluate the dependence on water marketing instruments.

The performance measures include both objectives and constraints. The general notation

for these measures includes i for planning year, j for month within planning year, and T for total simulation time period, which is 10 years for the long-term planning simulation and 1 year for the drought simulation. The expected value across M Monte Carlo samples is represented by $E[\ ]_i$. The vector of decision levers is denoted by $\boldsymbol{x}$.

3.3.2.1 Efficiency Metrics

Cost: The cost objective is calculated as an expected value of the sum of annual costs from permanent rights, initial purchasing cost of the adaptive options contract, subsequent exercise cost of options, and purchased leases. Total cost is minimized in the optimization.

$$f_{\text{annual cost}}(\mathbf{x})_i = \mathrm{E}\left[N_R p_R + N_{O_i} p_O + N_{x_i} p_x + \sum_{j=1}^{12}\left(N_{l_{i,j}} \hat{p}_{l_{i,j}}\right)\right]_i \tag{3.2}$$

$$f_{\text{cost}}(\mathbf{x}) = \sum_{i=1}^{T} f_{\text{annual cost}_i} \tag{3.3}$$

Equation (3.2) shows the summation of individual expenses in a given year and Equation (3.3) computes the total cost in the simulation, with all variables defined previously. As shown here, the permanent rights volume is constant across all years in the simulation. Leases may be purchased at any month within each planning year at an associated sampled price.

Surplus Water: Conceptually, the surplus water objective is the volume of water held by the city at the end of each planning year. Shown in Equation (3.4), surplus water is computed as the average across the simulation duration of the expected value of surplus water volumes, measured in the last month (12) of each planning year.

$$f_{\text{surplus}}(\mathbf{x}) = \sum_{i=1}^{T} \frac{1}{T}\left(\mathrm{E}[S_j]_i\right),\ j = 12 \tag{3.4}$$

The S_j variable denotes the water supply of the city, composed of volumes from permanent rights, the options contract, and leases. This objective is minimized in the optimization because minimiz-

ing the single city's surplus water could ostensibly free water for other regional users (not modeled in this case study) to use.

Dropped Transfers: The dropped transfers objective quantifies unused water from options contracts and leases. The variable a represents the "age" in months of water in the city's supply account. Since leases and exercised options expire after one year of non-use, dropped transfer volume accumulates when $a > 12$. Equation (3.5) calculates this metric as the summation over the simulation duration of the expected value of total transfer volume when the age is greater than 12 months.

$$f_{\text{dropped}}(\mathbf{x}) = \sum_{i=1}^{T} \left(\mathrm{E}\left[\{N_{x_i} : \mathrm{a} > 12\} + \sum_{j=1}^{12} \{N_{l_{i,j}} : \mathrm{a} > 12\} \right] \right) \tag{3.5}$$

It is noteworthy to mention that the simulation allows fractional use of lease acquisitions. Thus, if a portion of a lease is utilized, and the remaining portion expires, then that expired portion of water will count as a "dropped transfer." This objective is minimized.

Cost Variability: The cost variability metric is based on the concept of the contingent value at risk (CVAR), which measures the risks of incurring high costs. This metric quantifies the variance in the cost distribution that results from the Monte Carlo sampling of options and leases. CVAR is computed as the ratio of the mean of the costs falling above the 95^{th} percentile, and the cost variability is computed as the CVAR value corresponding to the year with the maximum CVAR divided by the expected average annual cost (Equation (3.6)).

$$f_{\text{costvar}}(\mathbf{x}) = \frac{\max_{i \in [1,T]} \mathrm{CVAR}_i}{f_{\text{annual cost}_i}} \tag{3.6}$$

This computation ensures that the greatest variability throughout the simulation duration is captured. Previous work [Characklis et al., 2006] showed that the cost variability metric adds greater value as a constraint to limit low probability high costs in the LRGV case study.

Drought Transfers Cost: The drought transfers cost is calculated as the sum of the cost of exercising of leases and options and excludes the one-time costs of permanent rights and upfront adaptive options contracts.

$$f_{\text{dr trans cost}}(\mathbf{x})_i = N_{x_i} p_x + \sum_{j=1}^{12} \left(N_{l_{i,j}} \hat{p}_{l_{i,j}} \right) \tag{3.7}$$

These costs are incurred during a single year of drought conditions. Drought scenario conditions include: (1) monthly demand set as the maximum demand of the normal distribution from the 10 year long term planning simulation and (2) monthly inflows and water available for allocation from the driest calendar year of the historical hydrologic data. This objective is minimized.

3.3.2.2 Risk Indicator Metrics

Reliability: Reliability measures the probability of successfully meeting the city's water demands using both non-market and market supply instruments. Equation (3.8) [Characklis et al., 2006] illustrates how reliability in a year i is calculated in the simulation model.

$$r_i = 1 - \frac{\mathrm{E}[n_{\text{fail}}]_i}{12} \tag{3.8}$$

Reliability considers the expected number of monthly failures in each planning year, where failure occurs when the city supply (S) is less than demand (d) in a month, defined by Equation (3.9).

$$S_j < d_j \tag{3.9}$$

The overall reliability metric is calculated as the minimum yearly reliability in the simulation duration to ensure that the reliability represents the lowest reliability of the planning strategy.

$$f_{\text{rel}}(\mathbf{x}) = \min_{i \in [1,T]} (r_i) \tag{3.10}$$

Reliability is included as a constraint in the optimization to encourage successful planning portfolio performance.

Critical Reliability: Critical reliability also measures the probability of successfully meeting the city's water demands. Contrary to the reliability metric, however, critical reliability quantifies failure as supply unable to meet 60% of the demand [Characklis et al., 2006]. Equations (3.8) and (3.10) are applied in the calculation of critical reliability with the new definition of failure. Critical reliability is included in the optimization as both an objective and a constraint.

3.3.2.3 Market Use Metrics

Number of Leases: This objective captures the number of leases to be purchased by the city in all months of the simulation. Since this metric sums number of leases rather than lease volume, this metric serves as a proxy for transactions costs. Number of leases is calculated as the sum of the expected number of leases in a planning year over the simulation duration.

$$f_{\text{num. leases}}(\mathbf{x}_k) = \sum_{i=1}^{T} \left(\mathrm{E}\left[\sum_{j=1}^{12} \phi_{i,j} \right] \right) \tag{3.11}$$

The variable ϕ accounts for whether a lease is required based on a non-zero lease volume, N_l.

$$\phi_{i,j} = \begin{cases} 1 & \text{if } N_{l_{i,j}} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{3.12}$$

The number of leases is minimized in the optimization.

3.3.3 Many Objective Problem Formulation

The complete many objective problem formulation from Kasprzyk et al. [2013] is shown below. The subscripts on the objectives identify whether the objective is computed for the 10 year long term planning simulation or the drought simulation. All objectives are minimized with the

exception of $f_{10\text{ yr crit rel}}$, which is maximized.

$$\begin{aligned}
\mathbf{F}(\mathbf{x}) &= (f_{10\text{ yr cost}}, f_{10\text{ yr surplus}}, f_{10\text{ yr crit rel}}, \\
&\quad f_{10\text{ yr dropped}}, f_{10\text{ yr num leases}}, f_{\text{dr trans cost}}) && (3.13)\\
&\quad \forall \mathbf{x} \in \Omega && (3.14)\\
\mathbf{x} &= (N_R, N_{O_{\text{low}}}, N_{O_{\text{high}}}, \xi, \\
&\quad \alpha_{\text{Jan}-\text{Apr}}, \beta_{\text{Jan}-\text{Apr}}, \alpha_{\text{May}-\text{Dec}}, \beta_{\text{May}-\text{Dec}})
\end{aligned}$$

$$\begin{aligned}
\text{Subject to} : c_{\text{rel}} : &\quad f_{\text{rel}} \geq 0.98 && (3.15)\\
c_{\text{crit rel}} : &\quad f_{\text{crit rel}} \geq 0.99 && (3.16)\\
c_{\text{costvar}} : &\quad f_{\text{costvar}} \leq 1.2 && (3.17)\\
c_{\text{dr vuln}} : &\quad f_{\text{dr vuln}} = 0 \\
& && (3.18)
\end{aligned}$$

The inclusion of constraints in the problem formulation reduces the number of solutions and restricts solutions to meet realistic needs of a decision maker. The reliability (c_{rel}) and critical reliability ($c_{\text{crit rel}}$) constraints, however, ensure surviving solutions have a high reliability in comparison to real water utility planning [Kasprzyk et al., 2013]. The cost variability (c_{costvar}) constraint guarantees that unlikely high costs are not significantly greater than the average cost in a planning year of the 10 year simulation. The drought vulnerability ($c_{\text{dr vuln}}$) constraint assures that there are no failures in any month during the drought simulation, where failure occurs when the monthly demand exceeds the monthly supply in the city's account.

3.4 Computational Experiment

The prior study [Kasprzyk et al., 2013] followed the MORDM procedure. As a brief review, first, optimization was performed under the baseline scenario, and each resulting tradeoff solution was subjected to a large ensemble of possible values for the deeply uncertain factors. The solutions

deviation from baseline performance was used to choose a single robust solution. This robust solution was subjected to a scenario discovery procedure that revealed values of the uncertain factors that caused that solution to perform poorly. In summary, the exploration of the deeply uncertain scenarios was done after all MOEA optimization runs were completed.

The point of departure of this study is that the discovered scenarios of MORDM are used directly within the MOEA search. This approach builds on recent work that includes robustness objectives in the search itself [Hamarat et al., 2014], but it differs because multiple scenarios are determined that are based on a full MORDM procedure that preceded the analysis.

There are two phases of the computational experiment. The methods for each phase are described in the following sections. In Phase I we aim to understand how optimizing under different conditions impacts the optimized alternatives and their tradeoffs. Consequently, in Phase II we evaluate each scenario's optimized decision levers under the other four scenarios to analyze the loss or gain in performance. Both phases of the computational experiment were completed on the University of Colorado - Boulder Janus supercomputer.[7]

3.4.1 Phase I: How do the scenarios impact the tradeoffs?

The prior study determined ranges of uncertainty scaling factors and uncertain parameters that resulted in vulnerable performance[8] of a robust solution. In this phase, we identified five scenarios based on these ranges of vulnerability, shown in Table 3.3. For simplicity, we chose to focus on the parameters represented by probability distributions. Scenario 1, also termed as the baseline scenario, does not alter the uncertain inputs into the LRGV model. Scenario 2 represents a moderate scenario in which all uncertain distributions are scaled by a factor of two. Scenarios 3, 4, and 5 were derived directly from the minimum values of the scaling factor ranges identified in the MORDM study. Each of these three scenarios represent violations of different sets of performance

[7] Janus is composed of 1368 compute nodes, each with 12 cores. Each node contains two hex-core 2.8Ghz Intel Westmere processors. There is 32TB total system RAM and roughly 800TB of high performance storage accessible through the Lustre filesystem.

[8] Vulnerable performance indicates violation of performance measure thresholds set according to reasonable decision maker preferences.

metrics.

Table 3.3: Uncertain scenarios

Scenario	*Uncertainty*	*Scaling Factor*	*Description*
1: Baseline	No scaling factor adjustment		Baseline probability distributions and model parameter value estimates for uncertainties
2: Moderate	Low Inflows	2	Extremes twice as likely
	High Losses	2	
	Losses in Reservoir Storage	2	
	High Lease Prices	2	
	High Demands	2	
3: Cost	Low Inflows	4	Scaled uncertainty combination that incurred high cost and cost variability for the robust solution
	High Losses	2	
	High Demands	4	
4: Reliability	Low Inflows	7	Scaled uncertainty combination that resulted in low reliability, critical reliability, and drought reliability for the robust solution
	High Losses	2	
	High Demands	6	
5: Market	Low Inflows	8	Scaled uncertainty combination that caused the city to use a high number of leases for the robust solution
	High Losses	4	
	High Demands	7	

Table 3.4: Decision lever bounds

Decision	*Lower Bound*		*Upper Bound*	
Lever	*Borg*	*Transformed*	*Borg*	*Transformed*
N_R	0	37,004,455 m^3	1	74,008,910 m^3
N_{Olow}	0	0 m^3	1	24,669,637 m^3
N_{Ohigh}	0	N_{Olow}	1	$2N_{Olow}$
ξ	0.1	0.1	0.4	0.4
$\alpha_{\text{May-Dec}}$	0	0	3	3
$\beta_{\text{May-Dec}}$	0	$\alpha_{\text{May-Dec}}$	1	3
$\alpha_{\text{Jan-Apr}}$	0	0	3	3
$\beta_{\text{Jan-Apr}}$	0	$\alpha_{\text{Jan-Apr}}$	1	3

The MORDM study optimized the LRGV case study problem under Scenario 1 (baseline) conditions. To incorporate uncertainty into the generation of water supply planning portfolio options, we optimized under all five scenarios separately, meaning that the the extremes of the uncertain parameters are more likely (as determined by the scaling factors) in the Monte Carlo simulation. This

Table 3.5: ϵ resolution used with the Borg MOEA for each objective

Objective	*Value*
Cost	\$300,000
Surplus water	1233 m^3
Dropped transfers	2467 m^3
Drought transactions cost	\$10,000
Critical reliability	0.002
Number of leases	0.3

scenario analysis was inspired by the Robust Optimization programming framework [Mulvey et al., 1995; Watkins and McKinney, 1997], which subjects a problem formulation to a series of scenarios to develop solutions that are insensitive to uncertain parameters. To generate solutions under the severity of extremes in this research, the the upper limit of the cost variability (c_{costvar}) constraint was increased to 1.2 in this research from the prior MORDM problem formulation ($c_{\text{costvar}} \leq 1.1$) .

We employ the Borg MOEA to generate alternatives in this study [Hadka and Reed, 2013]. This state-of-the-art algorithm includes features such as ϵ-dominance, adaptive population sizing, and adaptive operator selection. The first feature, ϵ-dominance, relies on the concept of dominance. A solution is said to "dominate" another solution if it is no worse in any objective and strictly better in at least one objective [Deb, 2001]. ϵ-dominance [Laumanns, 2002] issues a user-defined tolerance (ϵ) that sets an acceptable improvement in performance needed for a solution to dominate another solution. This feature ensures both diversity and convergence of the solution set. The concept of ϵ-dominance is extended to another feature called ϵ-progress that ensures solutions improve by ϵ throughout the search process, otherwise a restart or termination of the algorithm is issued. ϵ-progress avoids preconvergence to a local optima. Adaptive population sizing adapts the search population size to be proportional to the archive size. Borg uses a variety of evolutionary operators including simulated binary crossover (SBX), differential evolution (DE), parent-centric recombination (PCX), unimodal normal distribution crossover (UNDX), simplex crossover (SPX), polynomial mutation (PM) and uniform mutation (UM) operators. The adaptive operator selection

increases the number of offspring an operator can produce based on the success of previous offspring generated by that operator, which allows Borg to auto-adapt to the problem it is solving. In a series of diagnostic tests across a range of problem formulations, Reed et al. [2013] demonstrates the superior, consistent performance of Borg relative to other state-of-the-art MOEAs. Additionally, the Borg MOEA successfully has been implemented to optimize this particular case study problem in parallel [Reed and Hadka, 2014].

Based on the consistent performance of Borg shown by Reed et al. [2013], the default Borg parametrization (Appendix A) is used in this research. The algorithm was run for $75,000$ function evaluations. We leveraged the AeroVis software package to visualize the evolution of the Pareto front throughout the $75,000$ function evaluations to ensure convergence. Additionally, the algorithm was run for ten random optimization trials to guarantee that the final approximately optimal solution sets were not a product of artifacts of random seed generation (i.e., the initial random population of solutions and the search operators). The upper and lower bounds of each of the decision levers are provided in Table 3.4. The Borg values are algorithm variables that must fall between 0 and 1. The transformed values are transformed values of the algorithm variables for input into the simulation model. The transformation between these two variable types allows the interface between the MOEA and the simulation model. Table 3.5 shows the ϵ resolution values for each objective used in both the search process of the MOEA and the sorting process to develop the final Pareto front.

3.4.2 Phase II: What is the impact of experiencing futures unlike the optimized conditions?

The first phase resulted in a set of optimized decisions for each of the five scenarios. In Phase II, the optimized decisions levers for each scenario are evaluated under the other four scenarios. This analysis was completed by feeding each set of the the optimized decisions into the LRGV simulation model for each evaluation scenario (referring to the scenarios unlike that of the optimized decisions). In each iteration of this process, the Monte Carlo sampling with a sample size of $5,000$

within the LRGV simulation model samples the scaled uncertain parameter sets that correspond to the scenario the decisions are being evaluated under. This phase resulted in 25 sets of objectives corresponding to 5 sets of decision levers, which also includes an evaluation of each scenario under its optimized conditions.

Similarly to the prior MORDM study, visual analytics play a major role in the analysis of the multi-objective decisions and tradeoffs of this research. In this study, we take advantage of several different plotting techniques to understand the implications of experiencing futures unlike that of the optimized conditions. We use the AeroVis software to generate three-dimensional glyph plots to understand the tradeoffs and differences between objectives and decisions, respectively, across scenarios and evaluations. Recall from Section 2.3.2 that these plots can display up to seven dimensions. We generate parallel plots [Inselberg, 1985] to visually connect the decisions to the resulting objectives to encourage a better understanding of how trends in decisions vary across scenarios and their resulting objectives across evaluations. Lastly, we demonstrate relationships between two variables using two-dimensional plots that are intuitive to readers.

Chapter 4

Results

4.1 Phase I

The LRGV case study problem was optimized under five different combinations of uncertainty scaling factors. Each combination of values of uncertainty factors is termed a scenario, as discussed in Section 3. Scenario 1 optimized under the baseline conditions, consistent with the prior MORDM study, in which all uncertain inputs are sampled according to their defined probability distributions. Scenario 2 is the moderate scenario, with extremes of uncertain parameters set as twice as likely in the Monte Carlo simulation relative to the baseline scenario. Scenarios 3, 4, and 5 are more severe scenarios that increase the probability of particular uncertainties.

The multi-objective tradeoffs optimized using Borg for each of the five scenarios are shown in Figure 4.1. In this glyph plot, each cone is a water portfolio solution. A solution consists of eight decision lever values with six associated objective values that measure the performance of the decisions. The color of the cone indicates the scenario the solution was optimized and evaluated under (i.e., the blue cones are solutions optimized under Scenario 1 conditions then evaluated under Scenario 1 conditions). To understand how the scenarios impact the tradeoffs, the spatial coordinates show the cost in the 10-year simulation ($f_{\text{10 yr cost}}$), number of leases ($f_{\text{10 yr num leases}}$), and surplus water ($f_{\text{10 yr surplus}}$) of each solution. The orientation of the cone corresponds to dropped transfers ($f_{\text{10 yr dropped}}$), and the size of the cone corresponds to transfer costs in the drought simulation ($f_{\text{dr trans cost}}$). The arrows along the axes and shown in the legend indicate the direction of increasing preference, depending on whether the objective was minimized or maximized.

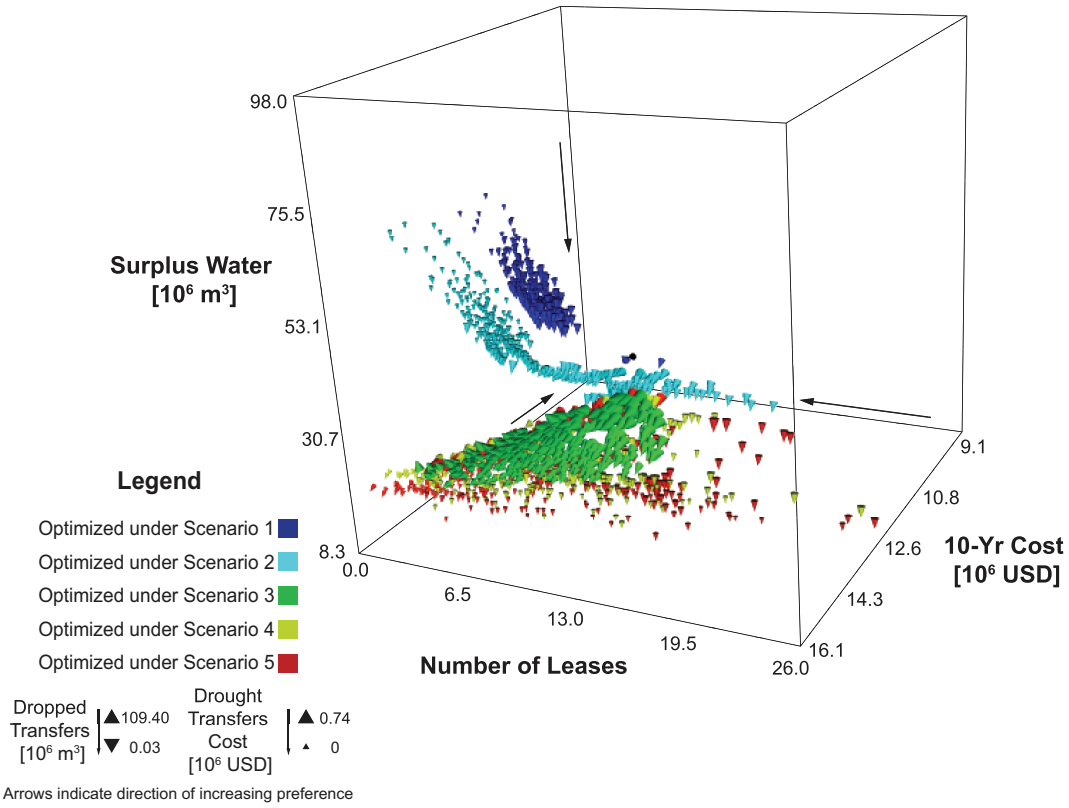

Figure 4.1: Non-dominated tradeoffs optimized under each of the five scenarios. Each cone represents a water portfolio solution. The spatial position indicates each solution's performance with respect to 10-year cost, number of leases, and surplus water.

Across the scenarios, the baseline scenario resulted in the fewest number of alternatives at 241 solutions. The Scenario 5 optimization produced the largest number of alternatives at 446 solutions. This result demonstrates that the severity of the scenario does not necessarily limit the number of alternatives generated in the multi-objective optimization.

From Figure 4.1, there is a distinctive divide between the optimized set under each scenario. The baseline (Scenario 1) and moderate (Scenario 2) scenarios outperform the other three scenarios in the cost objective, with relatively low volumes of dropped transfers. Essentially, these solution sets have a lower expected value of total costs of rights, options contracts, and leases with lower volumes of dropped transfers. As a general trend, the expected number of leases decreases as ex-

pected surplus volume and cost increase. The second group contains the more severe scenarios: Scenario 3, Scenario 4, and Scenario 5. This group exhibits a similar trend in tradeoffs between the three objectives plotted on the spatial axes, with a smaller average expected value of surplus water. As a reminder, the surplus water objective measures the expected volume of water retained by the city at the end of each planning year. In this problem formulation, this objective is minimized (meaning that a lower volume is preferred) since the city is the only represented user in the simulation; therefore, this objective serves as a proxy for other users. Scenario 3 exhibits higher drought transfers costs, which is the cost of exercising options and purchasing leases in the single-year drought simulation. Broadly, this scenario comprises solutions that result in a higher volume of dropped transfers, suggesting inefficient use of the water market instruments under these conditions. The most severe scenarios, Scenarios 4 and 5, yielded solutions that use a higher number of leases relative to the other scenarios, characterizing higher market use. This finding corresponds to the prior study, in which the robust solution acquired more leases when experiencing Scenario 5 conditions. Generally, there are higher costs seen in this group of scenarios, which aligns with high cost felt by the robust solution under Scenario 3 conditions.

These results indicate that the different combinations of scaled uncertainties within the scenarios impact the performance of the optimized water portfolios. In other words, even when the severe scenario information is exposed to the Borg MOEA during the search process, the best possible objective function values are sometimes lower due to the severe conditions. A notable indicator is the difference between the two groups of scenarios in surplus water performance. Scenarios 3, 4, and 5 outperform the baseline and moderate scenarios with respect to the surplus water objective, meaning that the city has less water in its supply account at the end of each planning year. However, this improvement in this objective across the severe scenarios may not be considered favorable by some water managers because it indicates stressed conditions. These severe scenarios also caused these portfolios to acquire a higher number of leases, another indicator of less water within the city's supply account. Overall, it is clear that the scenarios have an impact on the tradeoffs between the conflicting objectives in this case study.

The impact of the scenarios on the objectives poses a secondary question: how do the scenarios impact the decision levers? To explore this question, a parallel coordinate plot in Figure 4.2 presents the trends in decision levers values across the scenarios. Each colored line represents a water portfolio alternative, composed of the eight decision levers discussed in Section 3. To refresh, the permanent water rights (N_R) decision is a non-market instrument. The low and high adaptive options exercise volume ($N_{O_{\text{low}}}$ and $N_{O_{\text{high}}}$) decisions are determined according to a decision threshold of ξ. The anticipatory α and β strategy rule decisions are used to establish market use (i.e., exercise options and acquire leases) at the beginning and end of the year. This figure also visually connects these decision levers with the corresponding objective performance, illustrating how the decisions perform in that scenario's conditions. This is an advantage over the glyph plot shown in

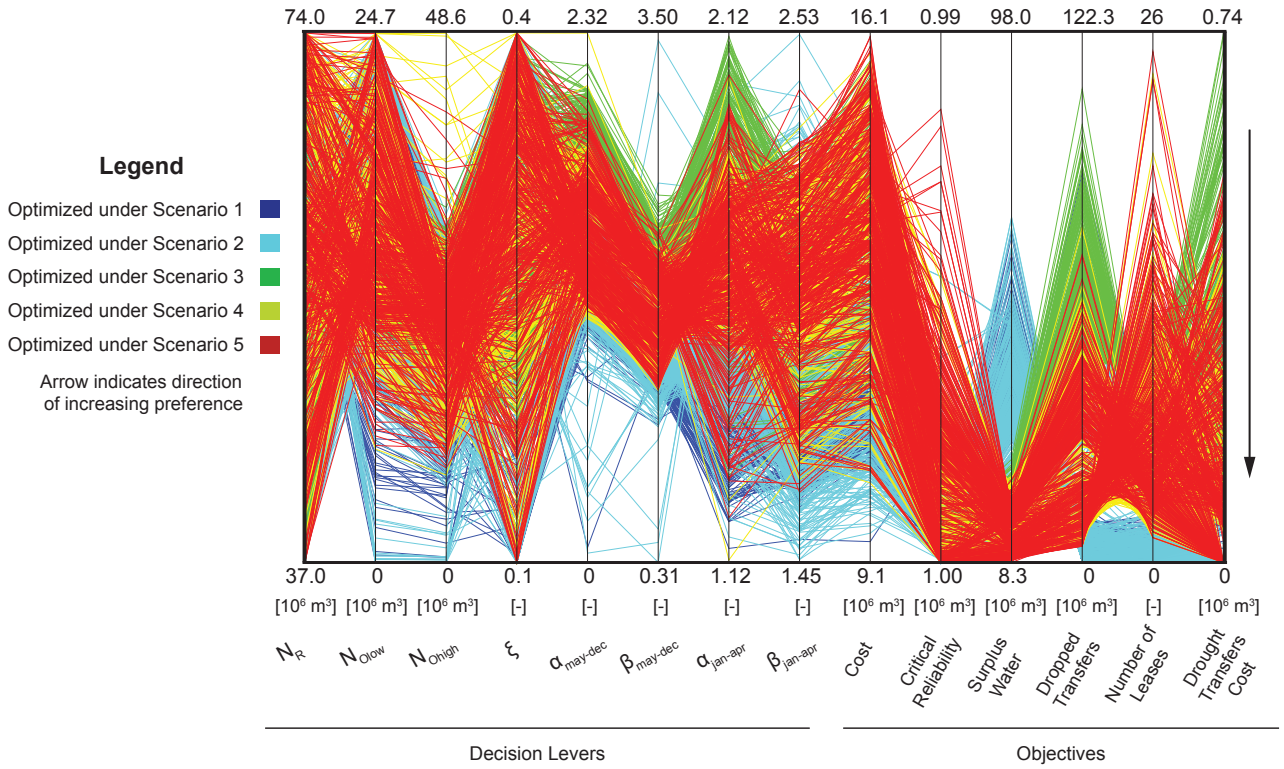

Figure 4.2: Decision levers and non-dominated tradeoffs optimized under each of the five scenarios. Each line represents a water portfolio solution. The vertical position on each axis represents the value of that decision lever or objective.

Figure 4.1. Similarly to the glyph plot, the arrow points in the direction of increasing preference for the objectives, which are shown on the last six vertical axes. Since there is no designated preference of decision lever values, the ideal water portfolio would result in a flat line across the bottom axis along the objectives.

There is a difference in use of water marketing, which includes exercising adaptive options and purchasing water leases, between the two groups of solutions defined previously (i.e., group 1: Scenarios 1 and 2; and group 2: Scenarios 3, 4, and 5). The second group of scenarios with more probable extremes require greater market use to meet the city's needs. This is in part evident by the larger volumes of both low and high options contracts seen in Figure 4.2 for these three scenarios. Interestingly, it is clear that in these scenarios, particularly Scenarios 4 and 5, large volumes of permanent rights do not indicate low volumes of options. Scenarios 1 and 2 provide solutions that utilize a large volume of rights or a large volume of options. Accordingly, these three severe scenarios have trends of higher α and β variables, which indicates a higher use of the market through both exercising options and purchasing leases to meet demands. Despite this similar trend between the three severe scenarios, the combination of uncertainty scaling factors used in Scenario 3 lead to alternative portfolios that have a significantly higher expected volume of dropped transfers. In the drought simulation, the Scenario 3 alternatives are the most costly as well. Ultimately, more severe scenarios require the market and may incur higher costs to meet the city demands. Please refer to Figures A.1, A.2, A.3, and A.4 in Appendix A to view the parallel coordinates with Scenarios 1, 2, 3, and 4 as the prominent scenario, like Scenario 5 is shown in Figure 4.2.

From this analysis, the baseline conditions result in a general trend of decisions; however, the values of the decision levers from the tradeoff set change when planning for extremes of uncertain inputs. To provide better insight on the different trends of decisions across the scenarios, several solutions have been highlighted. The robust solution identified in the prior study has also been selected. Figure 4.3 and Table 4.1 highlight these solutions across the suite of scenarios to bridge the gap between decisions and objectives. For spatial context, Figure 4.4 identifies the solutions on the same glyph plot as Figure 4.1. In this plot, the double-headed arrows in dark brown point to

the solutions.

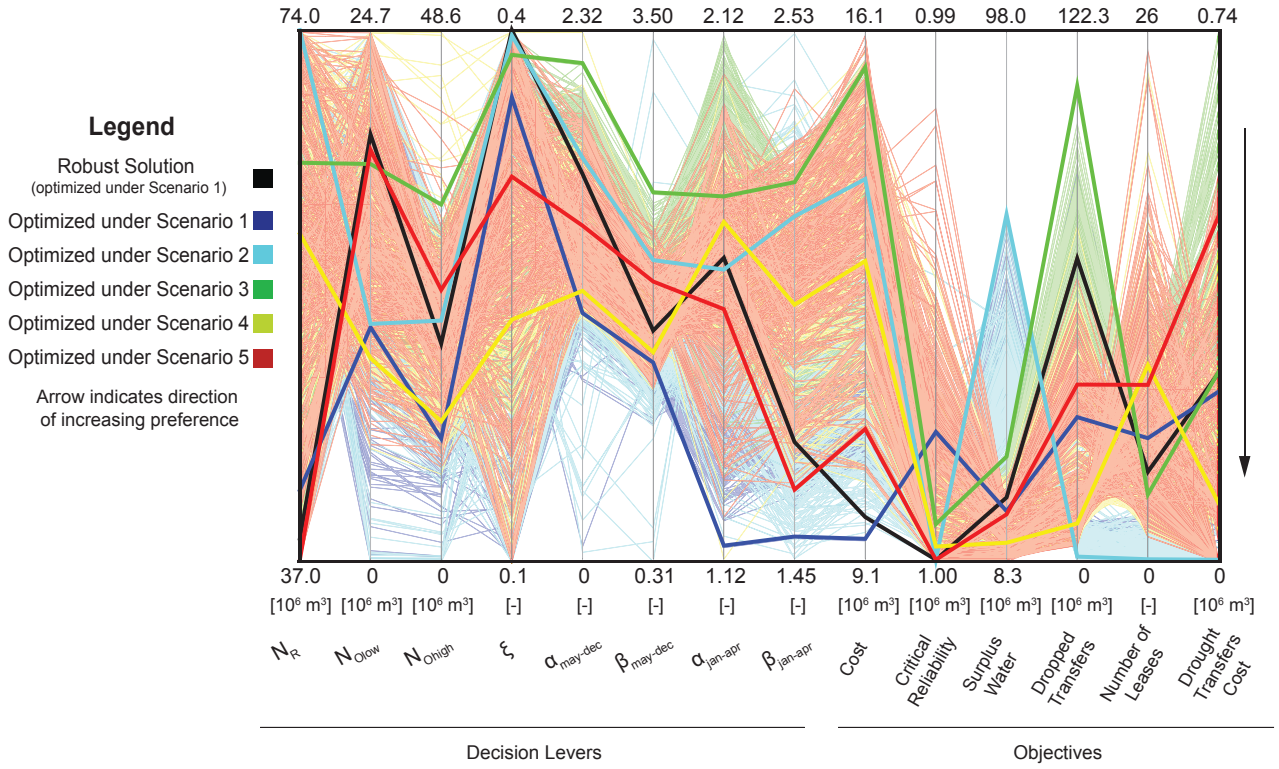

Figure 4.3: Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, with a solution per scenario highlighted. The color of the highlighted solution refers to the color of its optimization scenario set. The black solution is the robust solution from the prior study.

The decisions and objectives of each of the six solutions are explained below. As mentioned previously, the robust solution was optimized under baseline conditions. This solution is termed Solution 0 and is highlighted in black in Figure 4.3. Solution 0 requires the expected supply to be 1.69 times greater than the expected demand in the city in all months of the 10-year simulation, based on the strategy variable values in Table 4.1. The volume of permanent rights is less than the other other highlighted solutions. This robust water supply portfolio ensures adequate water supply by using both options and leases. Solution 1 is the blue solution, selected from the Scenario 1 set because it exhibits the lowest cost of all of the Scenario 1 solutions. The volume of permanent rights acquired for this solution is comparable to the robust solution. However, the remaining decisions

Table 4.1: Decision levers of highlighted solutions [9]

Solution	*Description*	*Decisions*							
		N_R [10^6 m^3]	N_{Olow} [10^6 m^3]	N_{Ohigh} [10^6 m^3]	ξ [-]	$\alpha_{May\text{-}Dec}$ [-]	$\beta_{May\text{-}Dec}$ [-]	$\alpha_{Jan\text{-}Apr}$ [-]	$\beta_{Jan\text{-}Apr}$ [-]
0	Robust solution from prior study marked by a low volume of permanent rights and market use	38.48	19.84	19.84	-	1.69	1.69	1.69	1.69
1	Low volume of permanent rights and low use of market in late year planning period	41.87	10.84	11.11	0.36	1.08	1.50	1.15	1.50
2	High volume of permanent rights and high options threshold (i.e., current supply equal to 40% of permanent rights)	74.01	11.00	21.94	0.40	1.76	2.11	1.67	2.15
3	Greatest market use marked by highest for α and β for both planning periods	64.74	18.46	32.60	0.39	2.18	2.52	1.81	2.22
4	Mid-ranged permanent rights volume and low options threshold (i.e., current supply equal to 24% of permanent rights)	59.77	9.40	12.70	0.24	1.18	1.56	1.76	1.97
5	Low volume of permanent rights, using the market to supplement water supply	37.00	19.11	24.76	0.32	1.46	1.99	1.59	1.59

differ, resulting in the low cost. Both sets of strategy planning variables, α and β are lower, meaning that less expected supply relative to expected demand is required so market instruments are not triggered as easily. Contrary to the two highlighted solutions under baseline conditions, Solution 2 obtains a substantially larger volume of permanent rights. This solution also exhibits high market use based on the options volumes and α and β values. Solution 2 also has a high threshold values for options contracts, meaning that if the current supply is equal to 40% or more of the permanent rights volume, then a low volume options contract is exercised, else a high volume options contract is exercised. Although Solution 2 performs poorly in the surplus water objective, evident by Figure 4.3 and Figure 4.4, it performs well relative to alternative solutions across all sets in critical reliability, dropped transfers, number of leases, and drought transfers costs.

[9] Please note that the robust solution was optimized under a simplified problem formulation made up of three decision levers: permanent rights, a single-volume non-adaptive options contract, and a single strategy variable to determine both "when" and "how much" water to acquire using market instruments. A more detailed description of this problem formulation may be found in Kasprzyk et al. [2013].

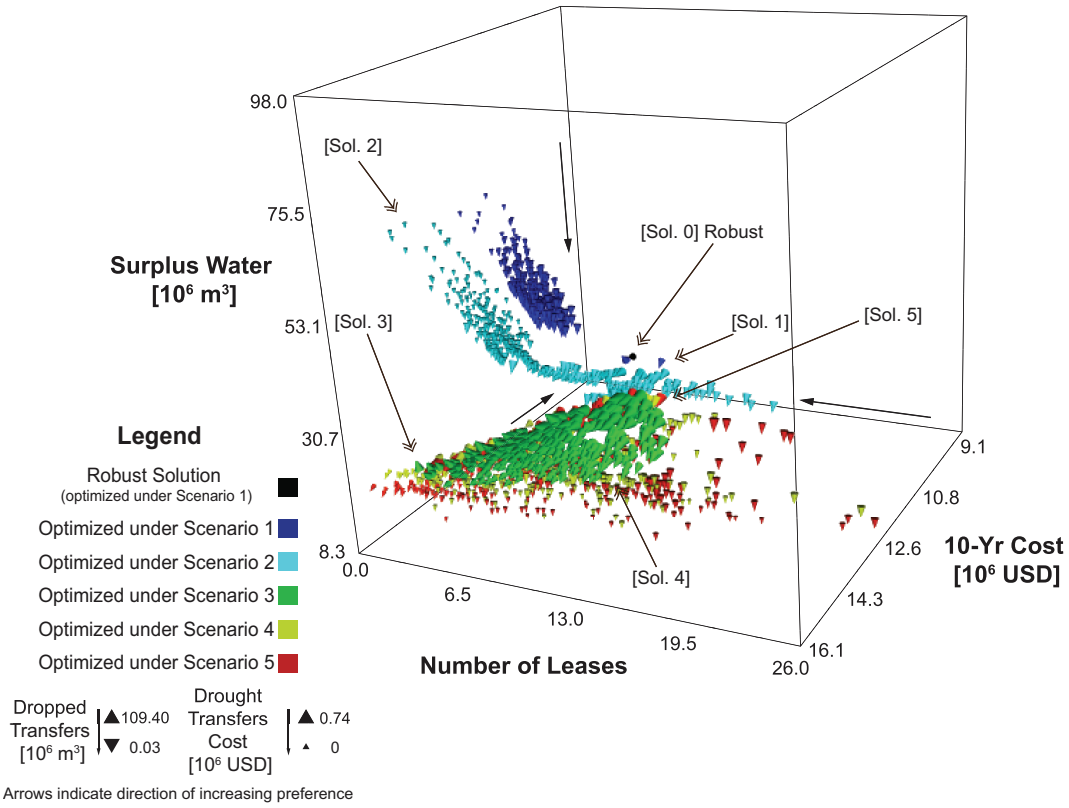

Figure 4.4: Non-dominated tradeoffs optimized under each of the five scenarios. The robust solution as well as five additional solutions are selected for further exploration in Phase II.

Solution 3 corresponds to Scenario 3, which is subjected to higher probability low inflows, high losses, and high demands. In response, this portfolio has more conservative strategies that indicate it would use the market more than highlighted Solutions 4 and 5. The high α variables in both time periods require the city to maintain a higher expected supply relative to expected demand, and the β variables require the city to purchase a greater amount of water relative to the expected demand. Interestingly, Solution 3 has the highest cost of the selected solutions, corresponding to the expected result as this scenario's conditions caused the robust solution to have high costs. Solutions 4 and 5 correspond to Scenarios 4 and 5, respectively. In general, Solution 4 relies more on permanent rights than Solution 5. Based on the α and β variable values, Solution 4 requires the market more in the early planning period whereas Solution 5 requires the market more in the late

planning period. Solution 3 water portfolio was highlighted because of the high volume of dropped transfers. Solution 4 marks a "compromise" solution between objectives of cost, surplus water, and dropped transfers. The decision levers in Solution 5 lead to a lower cost relative to the majority of the Scenario 5 solution set, apparent on Figure 4.4.

In summary, we demonstrated the effect of optimizing under varying conditions of uncertainty. Generally, the decisions and objectives correspond to the severity of the scenario, with less extreme scenarios incurring lower costs and lower market use and more extreme scenarios exhibiting lower volumes of surplus water and higher market use. The highlighted solutions map decisions to objectives and illustrate the variety of decisions that emerge from optimizing under these different scenarios. These highlighted solutions will serve as bases for comparison in Phase II. These results uncover a weakness in the MORDM framework that this study is built upon. Ultimately, we demonstrate that optimizing under extreme scenarios provides a different suite of decisions for the city to consider, providing opportunities outside of the portfolio alternatives that arise from optimizing under baseline conditions only. The prior study searches for a robust solution within the baseline optimized set, Scenario 1, however, there may exist a potentially more robust solution within a set optimized under different conditions of uncertainty. This point is explored in Phase II of this study.

4.2 Phase II

In Phase II, each optimized solution set was evaluated under the opposing scenarios to determine how the decision levers perform under different plausible future conditions. For example, solutions that resulted from optimizing under Scenario 1 were then evaluated under Scenarios 2, 3, 4, and 5. Essentially, this phase served as a series of "stress" tests to understand how the city responds to conditions other than those planned for in the optimization. We imposed the constraint set ($f_{\text{rel}} \geq 0.98$, $f_{\text{crit rel}} \geq 0.99$, $f_{\text{costvar}} \leq 1.2$, and $f_{\text{dr vuln}} = 0$) *a posteriori* to retain and present solutions that comply with decision maker requirements.

For a general overview, Figures 4.5 and 4.6 show how the optimized sets perform under each

scenario. The individual plots on the figures refer to the optimized sets, and the point colors correspond to the scenario the set was evaluated under. Each point represents a solution consisting of decision lever values and objective values. Consequently, each individual plot contains one or more solution points marked by same decision lever values, depending on the feasibility of each optimized solution in the evaluation scenarios. Each solution point, however, has a different objective function performance based on the evaluation. On these plots, a decision variable is plotted on the y-axis and an objective is plotted on the x-axis. In doing so, the range of values for the decision lever of interest for each optimized set is visible, and the change in horizontal position of each solution point between the colored sets quantifies the change in performance.

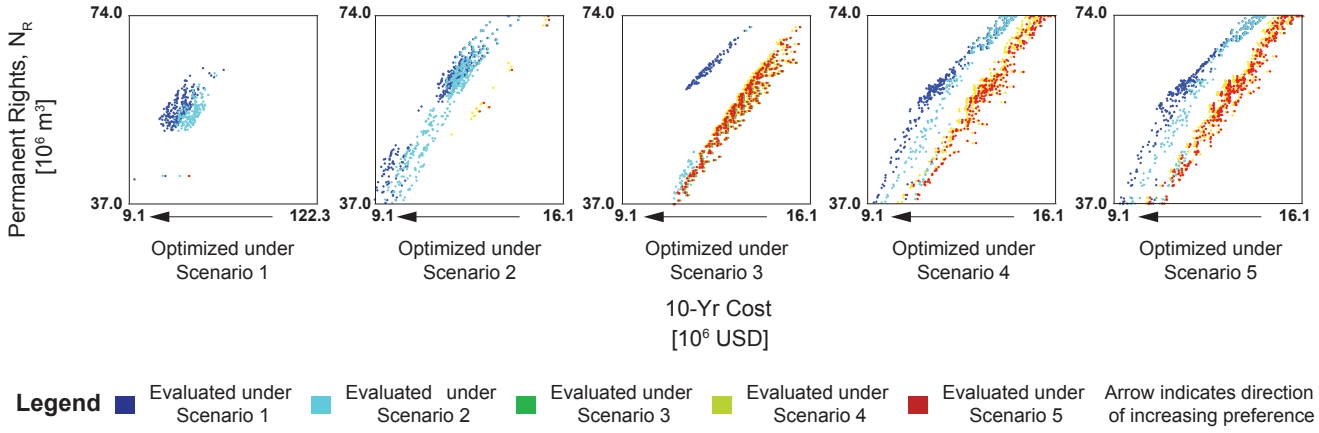

Figure 4.5: The effect of optimized scenario on 10-year cost when evaluated under each scenario. Each plot contains the optimized set of a single scenario, with the permanent rights decision lever shown. Solution point color refers to the scenario the solutions were evaluated under.

Figure 4.5 displays permanent rights on the y-axis and 10-year cost on the x-axis. This visualization shows the relative volume of the non-market water supply between the optimizations. Through observation of the cluster of dark blue solutions in the first plot, the permanent rights for Scenario 1 all lie in the mid-range of the permanent rights values. Conversely, the other four optimized scenarios consist of solutions that lie along the entire range of the permanent rights decision lever values. Thus, the baseline solutions typically rely on similar volumes of permanent

rights, leveraging the market for supplemental water. However, the other solution sets include portfolios that depend on lower volumes of permanent rights and high market use or higher volumes of permanent rights with supplemental market use. This visualization brings attention to the variety of solutions that exist outside of the set optimized under conservative baseline conditions.

While the decision lever values remain constant, there is a change in performance of the objectives across the evaluation scenarios shown by the shift of solution clusters in each plot. The solutions optimized under Scenario 1 invariably cost the city more when evaluated under Scenario 2 conditions. In other words, if the city selects a seemingly favorable solution from the Scenario 1 set, but experiences extremes (of the model inputs) twice as often, the costs will be higher than the estimated performance under Scenario 1.

Figure 4.5 also shows the influence of the constraints in this analysis. Evident by the red and yellow solution points in first plot, there is only one solution within the entire set of 241 solutions that remains feasible under Scenario 4 and Scenario 5 conditions, and there are no solutions that remain feasible under Scenario 3 conditions. The same limitation appears in the set optimized under Scenario 2 conditions. There are substantially fewer solutions that survive under Scenarios 4 and 5 relative to those that survive under baseline conditions. The solutions optimized under Scenarios 4 and 5 conditions are generally more robust because most of the solutions survive under all scenarios with the exception of Scenario 3. This analysis also demonstrates that selecting a solution optimized under these severe conditions may benefit the city in the 10-year cost objective. When increasingly amenable conditions are experienced, the cost of these solutions decrease. Ultimately, this figure exposes the difficulty of the city to cope with Scenario 3 conditions. Very few solutions optimized under the other scenarios survive under Scenario 3 conditions. Thus, it may be advantageous to plan for these conditions since there are Scenario 3 solutions that are feasible under the other four scenarios.

Figure 4.6 shows the same set of solutions as Figure 4.5 against the dropped transfers objective shown on the x-axis. Transfers from options and leases expire after 12 months of non-use, so the dropped transfers objective calculates the volume of un-used transfers. Decreasing volumes of

dropped transfers demonstrates improvement in the performance of portfolio solutions. Unlike Figure 4.5 the objective performance of the decisions under less severe scenarios does not show a clear trend of improvement. This is very clear in the set of solutions optimized under Scenario 3 conditions. When the Scenario 3 solutions are evaluated under Scenarios 4 and 5, there is improvement in the dropped transfers objective. This outcome highlights the stressed hydrologic conditions experienced under Scenario 4 and 5 conditions, showing that more of the water obtained through the market may be used rather than dropped. However, the most successful portfolio performance occurs under Scenario 1 conditions, where several solutions have no dropped transfer volume. Within the set optimized under Scenario 3 conditions, the city suffers in this objective when experiencing Scenario 2 conditions. For another perspective of these solutions, Appendix A contains Figures A.5 and A.6 that show the $\alpha_{May-Dec}$ decision lever.

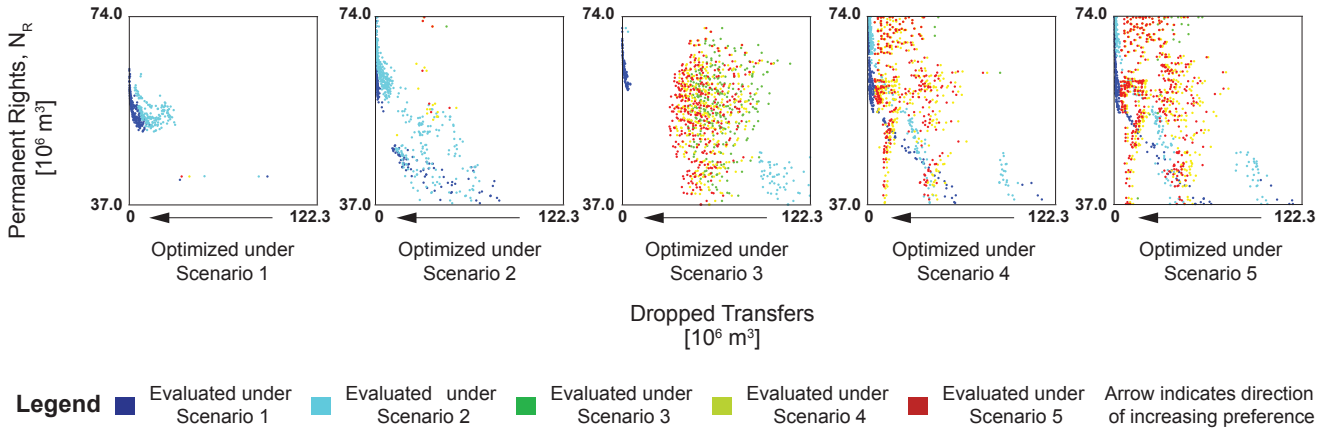

Figure 4.6: The effect of optimized scenario on dropped transfers when evaluated under each scenario. Each plot contains the optimized set of a single scenario, with the permanent rights decision lever shown. Solution point color refers to the scenario the solutions were evaluated under.

From Figures 4.5 and 4.6, we gained insight on how the city fares under conditions unlike that of the optimized conditions. To explore further, the performance of the highlighted solutions from Phase I has been tracked across all evaluation scenarios, shown in Table 4.2. Recall that Solution 0 and Solution 1 were optimized under baseline conditions. Solutions 2, 3, 4, and 5 were

optimized under Scenarios 2, 3, 4, and 5, respectively.

Table 4.2: Performance of highlighted solutions

Solution	*Description*	*Evaluation Scenario*	*Performance Measures*					
			10-Yr Simulation					*Drought Simulation*
			Cost	*Critical Reliability*	*Surplus Water*	*Dropped Transfers*	*Number of Leases*	*Transfers Cost*
			[10^6 USD]	[-]	[10^6 m^3]	[10^6 m^3]	[-]	[10^6 USD]
0	Robust solution from prior study	**1**	9.65	1.00	18.82	69.54	4.32	0.26
		2	9.90	1.00	16.30	52.79	6.27	0.26
		3	Constraint Violation: f_{rel}=0.97					
		4	10.38	1.00	11.41	15.68	13.48	0.26
		5	10.45	1.00	10.95	13.07	14.52	0.26
1	Exhibits low 10-year cost under Scenario 1	**1**	9.36	1.00	16.50	32.95	5.97	0.23
		2	Constraint Violation: f_{rel}=0.97					
		3	Constraint Violation: f_{rel}=0.90, $f_{crit\ rel}$=0.98, $f_{costvar}$=1.21					
		4	Constraint Violation: f_{rel}=0.91, $f_{crit\ rel}$=0.98, $f_{costvar}$=1.21					
		5	Constraint Violation: f_{rel}=0.90, $f_{crit\ rel}$=0.98, $f_{costvar}$=1.21					
2	Exhibits high volume of surplus water under Scenario 2	1	14.05	1.00	97.05	0.00	0.00	0.00
		2	14.10	1.00	66.76	0.72	0.02	0.00
		3	Constraint Violation: f_{rel}=0.97					
		4	15.40	1.00	22.19	31.08	1.35	0.00
		5	15.54	1.00	20.34	31.46	1.53	0.00
3	Exhibits high volume of dropped transfers under Scenario 3	1	12.71	1.00	68.05	1.99	0.05	0.15
		2	Constraint Violation: $f_{costvar}$=1.33					
		3	15.57	1.00	25.74	109.40	3.20	0.26
		4	15.41	1.00	25.01	98.34	2.55	0.15
		5	15.53	1.00	24.09	97.01	2.49	0.15
4	Compromise between 10-year cost, surplus water, and dropped transfers objectives under Scenario 4	1	Constraint Violation: f_{rel}=0.97					
		2	Constraint Violation: $f_{costvar}$=1.33					
		3	Constraint Violation: f_{rel}=0.96, $f_{dr\ vuln}$>0					
		4	13.02	1.00	11.15	8.37	9.55	0.08
		5	Constraint Violation: f_{rel}=0.97					
5	Exhibits low 10-year cost under Scenario 5	1	10.38	1.00	23.42	114.25	7.52	0.48
		2	10.71	1.00	21.15	95.85	8.09	0.48
		3	Constraint Violation: f_{rel}=0.97					
		4	10.80	1.00	16.43	45.80	8.41	0.48
		5	10.80	1.00	15.96	40.48	8.58	0.48

According to Table 4.2, the robust solution from the prior study is feasible in all scenarios with the exception of Scenario 3. From the table, we see that the changes in this solution across evaluation scenarios follow those identified in both Phase I and Phase II of this study. As discussed

in Phase I, the surplus water objective decreases in harsher conditions. While we strictly looked at the optimized sets in Phase I, this trend highlights the claim that this objective is in part a relic of the conditions.[10] The portfolio results in higher costs in more severe scenarios while the dropped transfers decrease, showing improved efficiency, in more severe scenarios. Based on the findings from Figures 4.5 and 4.6, it is not surprising that Solution 1 does not survive in any of the evaluations other than Scenario 1. Solution 1 violates the reliability constraint across all evaluations other than under Scenario 1. When evaluated under the more severe scenarios, the critical reliability and cost variability constraints are also violated, with even lower levels of reliability. Note that we consider a constraint violation of any magnitude to cause a solution to be infeasible in the evaluated scenario. Similarly to Solution 1, Solution 4 does not remain feasible across the other scenarios. Within the set of highlighted solutions, Solution 4 is the only solution that violates the drought vulnerability constraint, which indicates that failure (supply $<$ demand) occurs in the drought year simulation. The selection of Solution 4 illustrates the importance of decision maker consideration of other plausible futures before selecting an optimized set of decision levers.

To visualize the change in performance of the highlighted solutions, Figures 4.7 and 4.8 present the tradeoffs and decisions of the highlighted solutions, all evaluated under Scenario 1. The colors in both figures represent the scenario the solutions were optimized under.

In Figure 4.7, all of the surviving solutions converge along a single front. Due to the tightness of the front, the general location of two of the highlighted solutions, Solution 0 and Solution 3, are shown by the dark circles. The robust solution, Solution 0, optimized under the baseline conditions, costs less and has a lower expected value of surplus water relative to Solution 3. However, Solution 3 outperforms Solution 0 in dropped transfers, number of leases, and drought transfer costs objectives. Despite the finding from Phase I that the Scenario 3 solutions generally exhibit higher volumes of dropped transfers and higher drought transfers costs, we see that by evaluating under the baseline

[10] Recall that the city aims to minimize the surplus water objective to free water for other uses, so a smaller objective value is preferable. In Phase I, the surplus water objective decreased under the severe scenario optimizations, revealing that the surplus water objective value reflects the reduced water input into the city. Therefore, it is important to consider the conditions of optimization and evaluation before claiming improvement or degradation in this objective.

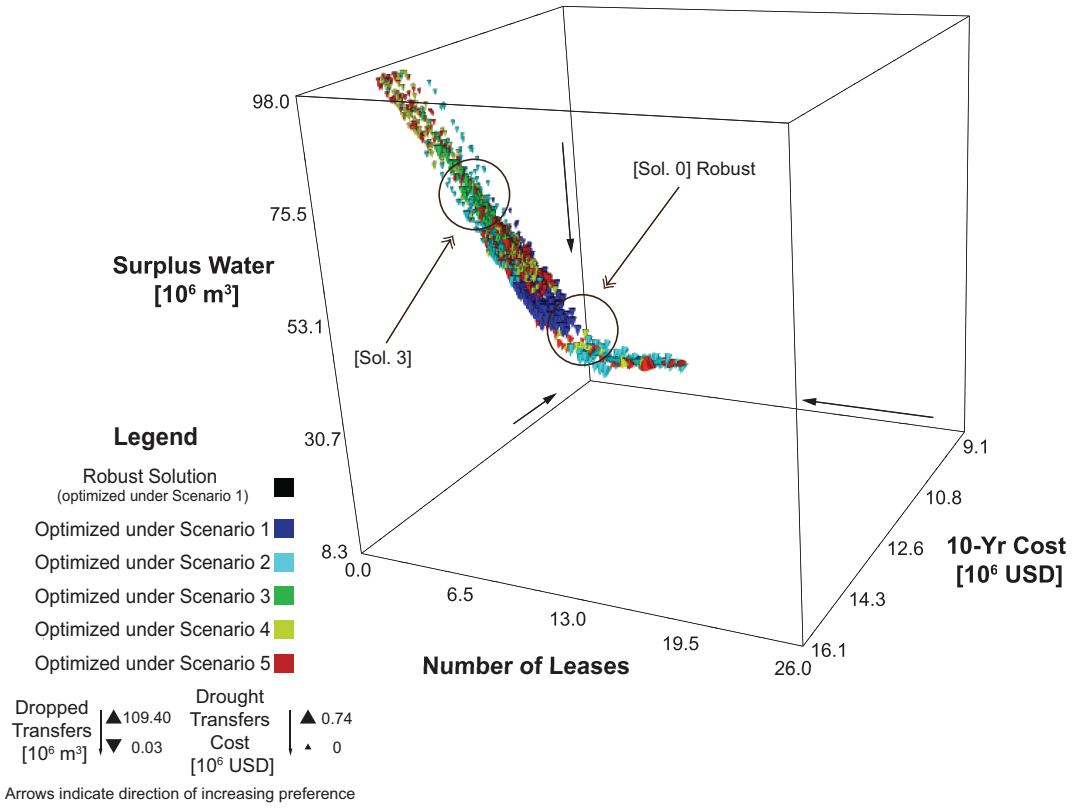

Figure 4.7: Non-dominated tradeoffs optimized under each of the five scenarios and evaluated under Scenario 1. The highlighted solutions correspond to the solutions discussed in Section 4.1. The dark circles show the general location of the highlighted solutions within the solution cluster.

conditions, these solutions actually perform better than select solutions optimized under baseline conditions.

Figure 4.8 provides a view of the tradeoffs of all of the highlighted solutions across all objectives when evaluated under Scenario 1. Although the solutions optimized under baseline conditions, Solutions 0 and 1, are better than the other highlighted solutions in objectives of 10-year cost and surplus water, it is evident that solutions from other optimized sets are viable and preferable with respect to some objectives.

Similarly to the previous two plots, Figures 4.9 and 4.10 show the highlighted solutions in a spatial setting using a glyph plot and as side-by-side comparisons using a parallel plot. These

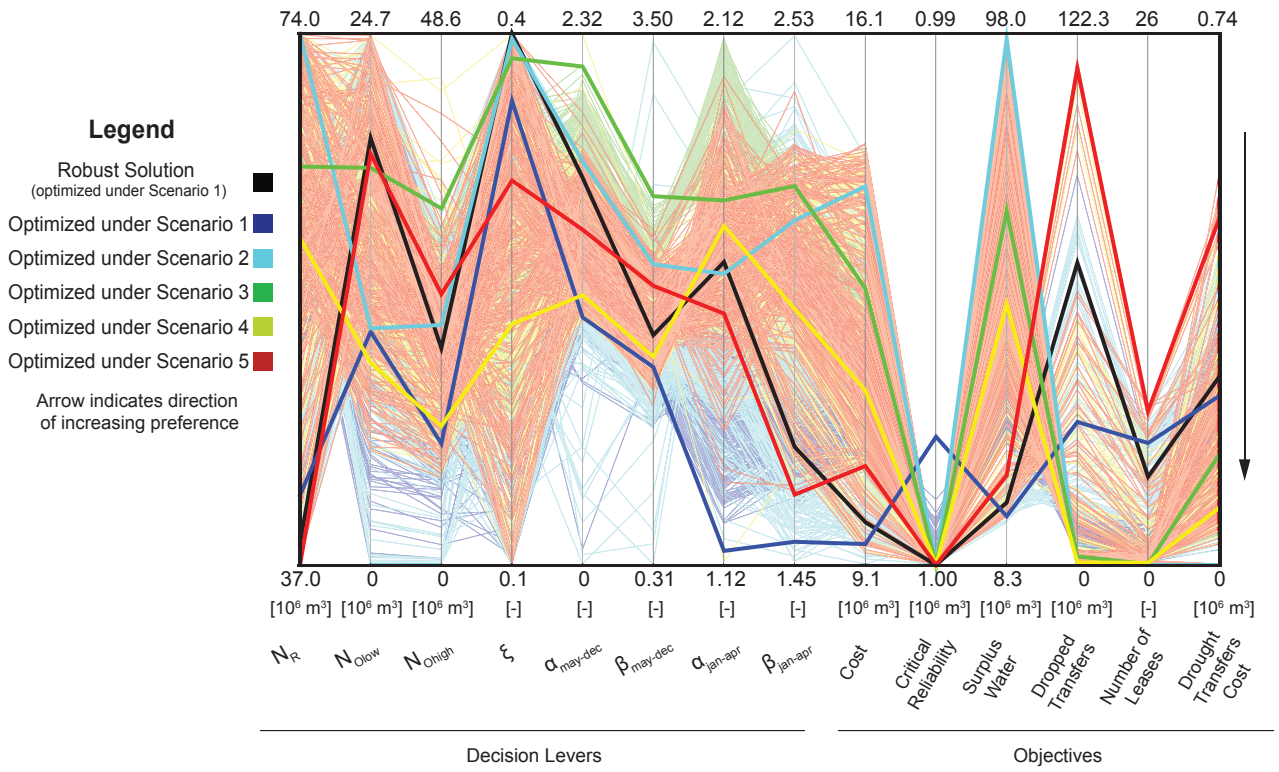

Figure 4.8: Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, all evaluated under Scenario 1. Highlighted solutions correspond to the solutions identified in Phase I. The color of the highlighted solution refers to the color of its scenario set. The black solution is the robust solution from the prior study.

figures show the evaluation of the highlighted solutions under Scenario 5.

The shape and composition of the converged front in Figure 4.9 is different compared to the evaluation under Scenario 1 shown in Figure 4.7. Overall, there are smaller volumes of surplus water in the surviving solutions, and there is greater spread along the number of leases and 10-year cost objectives. The surviving solutions are primarily from the Scenario 3, Scenario 4, and Scenario 5 solution sets. The two highlighted solutions, Solutions 0 and 3, have similar relative performance when evaluated under Scenario 5 compared to the Scenario 1 evaluation. The robust solution, Solution 0, experiences lower 10-year costs and surplus water, similar to the previous analysis. However, Solution 0 outperforms Solution 3 in the dropped transfers objective, aligning

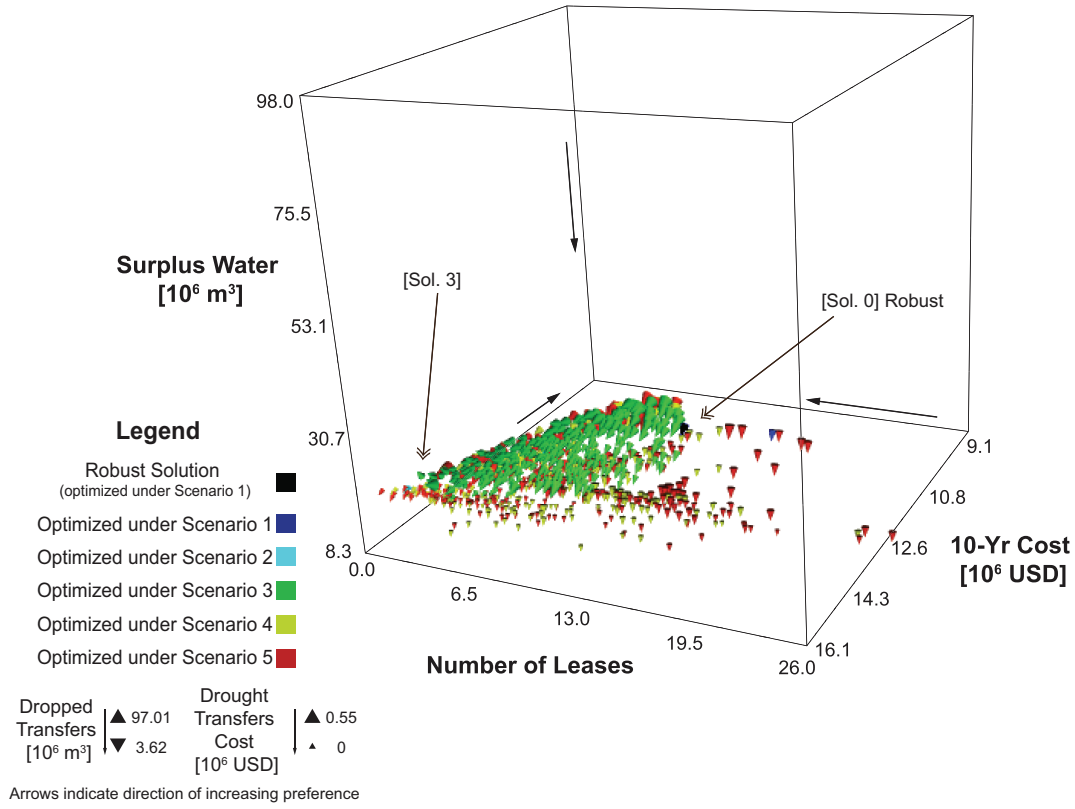

Figure 4.9: Non-dominated tradeoffs optimized under each of the five scenarios and evaluated under Scenario 5. The highlighted solutions correspond to the solutions discussed in Section 4.1.

with the characterization of higher dropped transfer volumes in the Scenario 3 optimization. The city obtains fewer leases and lower drought transfer costs under the decisions of Solution 3 when experiencing these harsher conditions.

Figure 4.10 displays the highlighted solutions that remain feasible under Scenario 5 conditions. Comparing this figure to Figure 4.8, the success of the Scenario 5 solution, Solution 5, under its own conditions is evident in the dropped transfers and surplus water objectives. However, while this solution was optimized under these evaluation conditions, Solution 5 is not the best performing solution in all objectives. To view the success of the highlighted solutions under Scenarios 2, 3, and 4, please refer to Figures A.7, A.8, and A.9 in Appendix A.

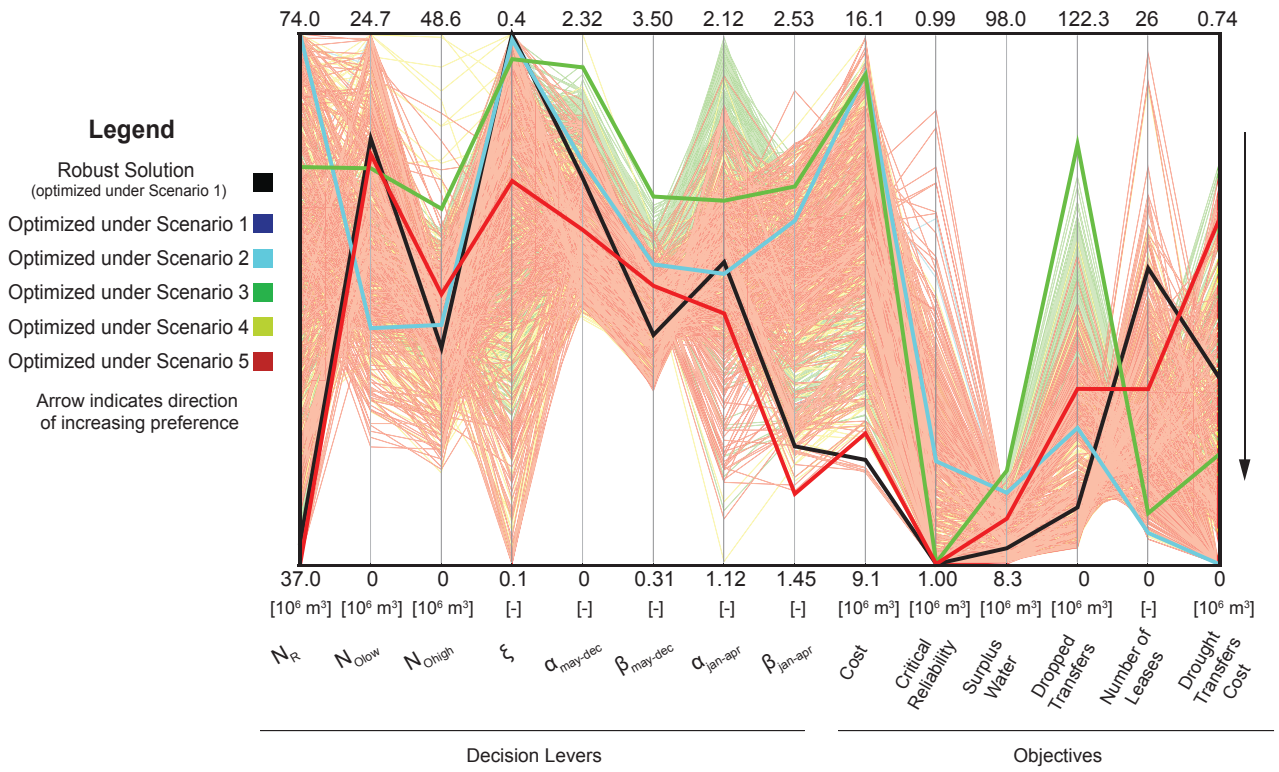

Figure 4.10: Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, all evaluated under Scenario 5. Highlighted solutions correspond to the solutions identified in Phase I. The color of the highlighted solution refers to the color of its scenario set. The black solution is the robust solution from the prior study.

To conclude, this analysis demonstrated portfolio limitations due to the constraint set and impacts of evaluating under varying conditions. First, by enforcing the constraints in the evaluations of each optimized set, the number of viable solutions decreased when experiencing conditions unlike the optimized conditions. This was clear in Figures 4.5 and 4.6 which showed that the baseline (Scenario 1) solutions are the most limited when evaluated under the other four scenarios. Second, the performance of the decisions does change under different conditions. The shape and location of the fronts in Figures 4.7 and 4.9 highlight this finding by showing that the same solutions (with the same decision lever values) have very different objective values under different conditions. The analysis also revealed that solutions optimized under the evaluation conditions are not necessarily

the top performing solutions in that evaluation. Overall, these results suggest that optimizing under different conditions of uncertainty can lead to finding a solution that is robust across may plausible futures.

Chapter 5

Discussion, Conclusion, and Future Work

5.1 Discussion and Conclusion

The results of this study shed light on all of the questions that motivated this thesis. First, we show that preparing for plausible extreme futures that may result from a multitude of causes, namely climate change, land use changes, and population growth, by optimizing under those conditions generates new sets of tradeoffs and decisions. This is evident in Phase I of the study. Each optimized set was clustered differently in the glyph plots and the parallel plots. We learned that despite preparing for extremes (i.e., Scenarios 3, 4, and 5), the city still experiences higher "costs" across the objectives. However, in doing so, the city knows about the performance of the decisions and can prepare accordingly. For example, Scenario 3 conditions cause the city to spend more in a drought year and drop larger volumes of leased water relative to solutions optimized under the other scenario conditions. We also learned that the decisions prepare for the uncertain conditions differently across the scenarios. Under the severe scenarios, higher α and β decision lever values indicate greater use of the market.

Second, in Phase II, we demonstrate the importance of evaluating the optimized decisions under different conditions of uncertainty. From this analysis, we found that the number of viable solutions is significantly decreased due to constraint violations. This was very clear in the evaluation of Scenario 1 solutions across the other scenarios. Additionally, the performance of the decisions changes under different conditions of hydrology and demand. The more severe scenarios, for example, incurred lower costs when evaluated under the baseline conditions. These results

provide a starting point to select a robust solution that is viable and successful (i.e., meets desired level of performance) across the scenarios.

For the LRGV case study, these results can be used to select robust decision values for a variety of planning purposes. First, the city may select robust decision values from the severe optimization sets that adequately meet needs for both short-term and long-term forecasting of streamflow, precipitation, and evapotranspiration. Since forecasting is uncertain in nature, the selection of robust values leverages forecasting predictability without a dependence on accuracy. In this case study, for example, robust values for market decisions, such as the α and β variables, would ensure that the market could provide adequate water supply if flows were lower than forecasted. While it may seem contradictory to develop robust plans for short-term forecasting, many decisions cannot be changed quickly enough to respond to evolving forecasts. For the LRGV region, the purchase and sale of permanent water rights is a timely process; therefore, it is beneficial to ensure that the value of this decision variable is appropriate for short-term and long-term planning. Second, this study illustrates a shift to a market-based water supply system in the LRGV under more severe conditions. In the event the city would like to plan for severe conditions resulting from future population growth (as projected for the region) and climate change, our results provide a suite of alternative market-based water supply portfolios. The advantage of our results and methodology is that the city may select several of these market-based portfolios planning for harsh conditions and evaluate their performances under expected conditions, ensuring that the final selected portfolio is not overly conservative in the likely conditions.

In addition to the specific results found in our work, we offered a new methodology to manage deep uncertainty that provides insight on robust decision making that cannot be uncovered in existing frameworks. Contrary to traditional optimization, we allowed the MOEA to design *how* to use the water supply instruments to respond to different hydrological and demand conditions. Traditional methods optimize under a single set of hydrological and demand conditions subject to a likely prediction. By conducting multiple optimizations under different conditions, our methodology generates new and robust ways to use water supply instruments to meet changing needs. In addition

to generating robust decisions, our framework promotes the selection of appropriate robust decisions by evaluating under multiple future conditions. In doing so, this framework reduces some the decision making obstacles that result from disagreement among predictions.

The treatment of deep uncertainty in this thesis also differs from modern frameworks. MORDM, the framework we expanded upon, presents an application of traditional methods by optimizing under baseline conditions, but then subjects the alternatives to an exhaustive number of alternative states of the world to find a robust solution. While the MORDM framework can aid a decision maker in the actual selection of a solution, there are many solutions that are not even considered because solutions are generated under one set of expected conditions. The framework introduced by Hamarat et al. [2014], Multi-Objective Adaptive Robust Design, also uses MOEAs to design solutions that respond to uncertainty. The Multi-Objective Adaptive Robust Design framework incorporates robustness into the search process of the MOEA using objective functions that reduce the variance in the performance of decisions across many plausible futures. While the method developed by Hamarat et al. [2014] ensures robustness, the results could be overly conservative. We allow for exploration of decisions that could arise from considering uncertainty in the development of solutions, which could lead to solutions that are robust in addition to other benefits (i.e., successful performance across multiple objectives unrelated to robustness).

To conclude, this research demonstrates that the optimization process can be leveraged in new ways to develop solutions for water planning that currently exist outside of the scope of traditional planning. We provide a methodology that overcomes some weaknesses of other recently introduced frameworks by incorporating uncertainty into the search process of an MOEA. We also show the importance of exploring how solutions perform under different conditions because many solutions may become infeasible or result in poor performance. This thesis lays the groundwork for a whole new perspective on water resources planning under uncertainty.

5.2 Future Work

There are several avenues to expand upon the research presented in this thesis. First, it would be beneficial to apply our methodology to a different planning problem or several planning problems to compare results. While we showed that optimizing under varying conditions of uncertainty resulted new sets of decisions and objectives for the LRGV case study, we do not know if this methodology will shed light on possibly opportune decisions for different planning problems. For example, applying our methodology to a water stressed basin in the western United States to optimize water marketing instruments under scenarios of increasing demand, continued drought, and variable conservation would be a relevant planning problem that could be fairly compared to this study. Similarly, a problem that establishes conditions to enact new policies, such as conservation measures, could leverage our methodology. The use of transfer mechanisms could be optimized at a monthly scale under various scenarios to reveal combinations of uncertainties that cause the system to utilize all allowable transfers and require conservation procedures. In this type of optimization, it would be necessary to set constraints on annual transfer volumes and seasonal use of transfer volumes.

Another potential opportunity to build upon this work lies in the actually optimization process of the MOEA. Specifically, characterizing and quantifying the difficulty of solving increasingly more severe problems using MOEAs would allow for intelligent development of problem formulations and scenarios. In this study, the cost variability constraint was loosened to generate solutions across all scenarios. The resulting optimizations under the newly defined constraint set produced fewer solutions in the baseline scenario relative to the other four scenarios that we anticipated would be more difficult to solve. Overall, it would be very helpful to know the impact of increasing the probability of extremes in the inputs on the MOEA search process to understand when to loosen constraints or adjust the problem formulation to guarantee solution generation.

Lastly, we see great potential for developing a quantitative framework to formally compare solutions optimized under different scenarios and, consequently, aid a decision maker in selecting a

robust solution. While the second phase of this study demonstrated how the optimized solutions under each scenario performed across the suite of scenarios, there is a need for a step-by-step approach to compare solutions based on their change in performance across evaluations. This framework is especially important for understanding when "improvement" in certain objectives corresponds to the stressed conditions so that a decision maker does not select a solution based purely on objective performance without understanding this caveat. Ultimately, with a formal framework, a solution that withstands many other plausible futures may be selected. This framework could combine concepts from both the prior MORDM study and work we have contributed in this thesis.

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Appendix A

Supporting Figures and Tables

Table A.1: Default Borg parametrization (includes simulated binary crossover (SBX), differential evolution (DE), parent centric mating (PCX), simplex crossover (SPX), uniform normally distributed crossover (UNDX), uniform mutation (UM), and polynomial mutation (PM) operators) [Woodruff et al., 2013; Zeff et al., 2014]

Parameter	*Value*
Initial population size	100
Tournament selection size	2
SBX rate	1.0
SBX distribution index	15.0
DE crossover rate	1.0
DE step size	0.5
PCX parents	3
PCX offspring	2
PCX eta	0.1
PCX zeta	0.1
SPX parents	3
SPX offspring	2
SPX epsilon	2
UNDX parents	3
UNDX offspring	2
UNDX eta	0.5
UNDX zeta	0.5
UM rate	$\frac{1}{27} = \frac{1}{\text{number of DV}}$
PM rate	$\frac{1}{27} = \frac{1}{\text{number of DV}}$
PM distribution index	20

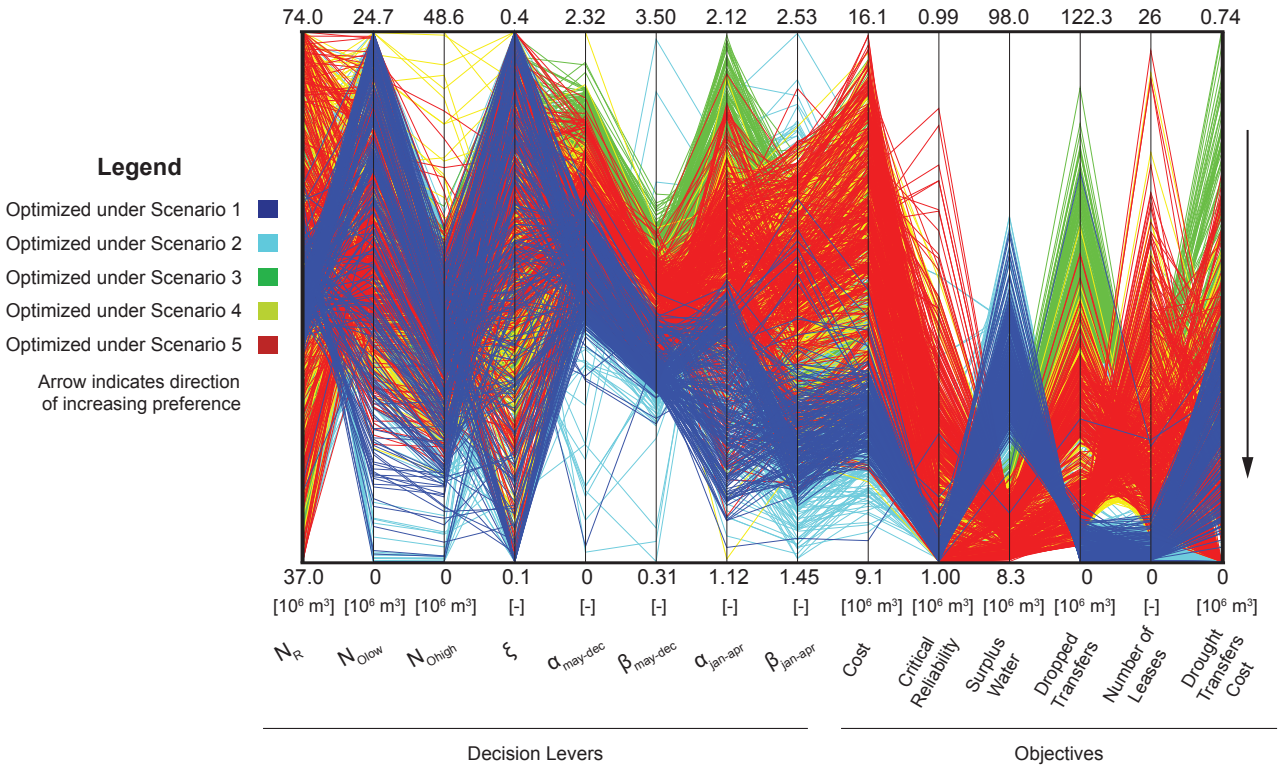

Figure A.1: Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, with the Scenario 1 (baseline) solutions highlighted atop the four other scenarios. Each line represents a water portfolio solution. The vertical position on each axis represents the value of that decision lever or objective.

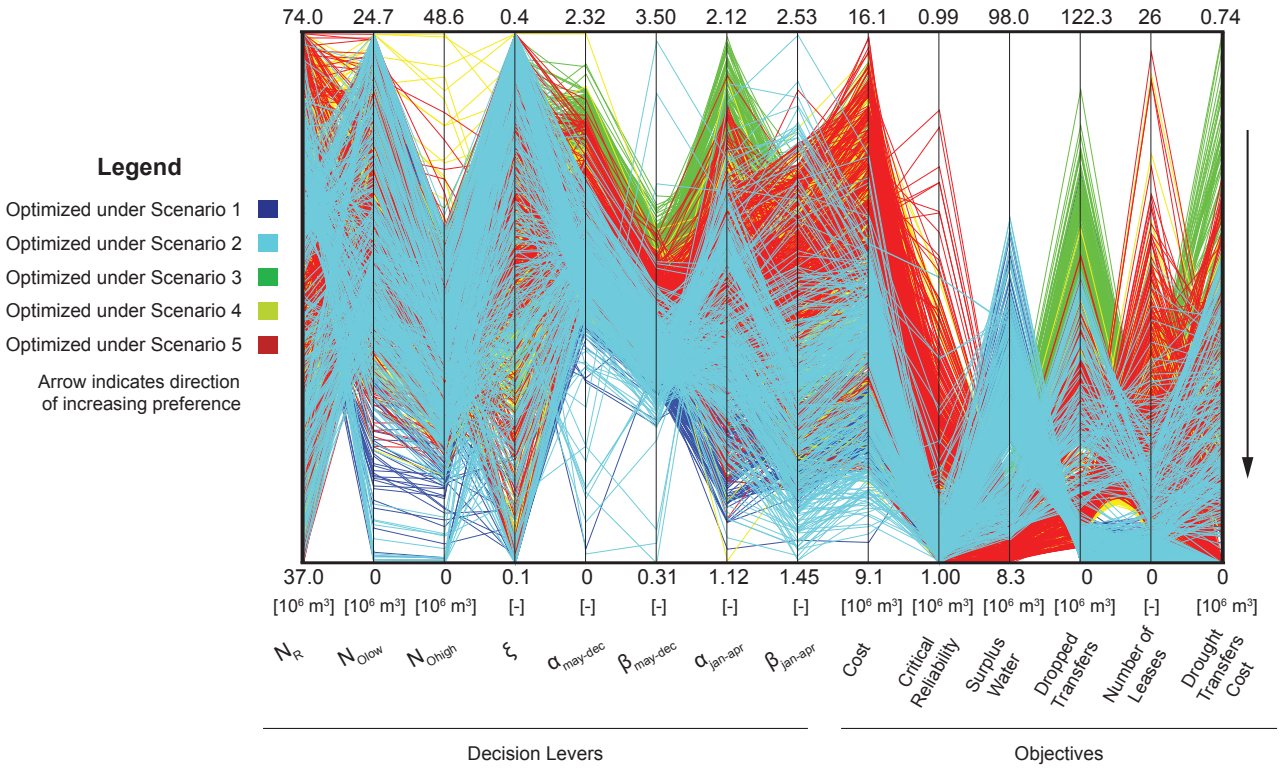

Figure A.2: Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, with the Scenario 2 (moderate) solutions highlighted atop the four other scenarios. Each line represents a water portfolio solution. The vertical position on each axis represents the value of that decision lever or objective.

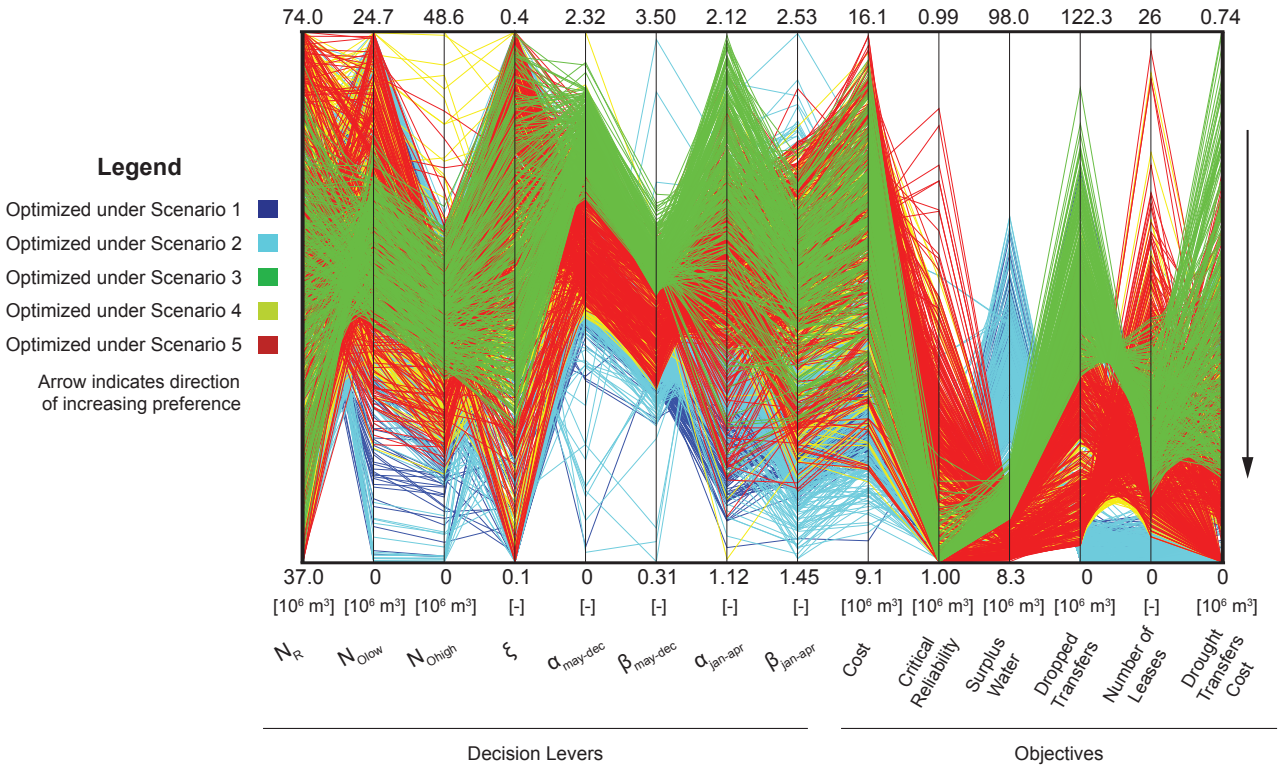

Figure A.3: Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, with the Scenario 3 (cost) solutions highlighted atop the four other scenarios. Each line represents a water portfolio solution. The vertical position on each axis represents the value of that decision lever or objective.

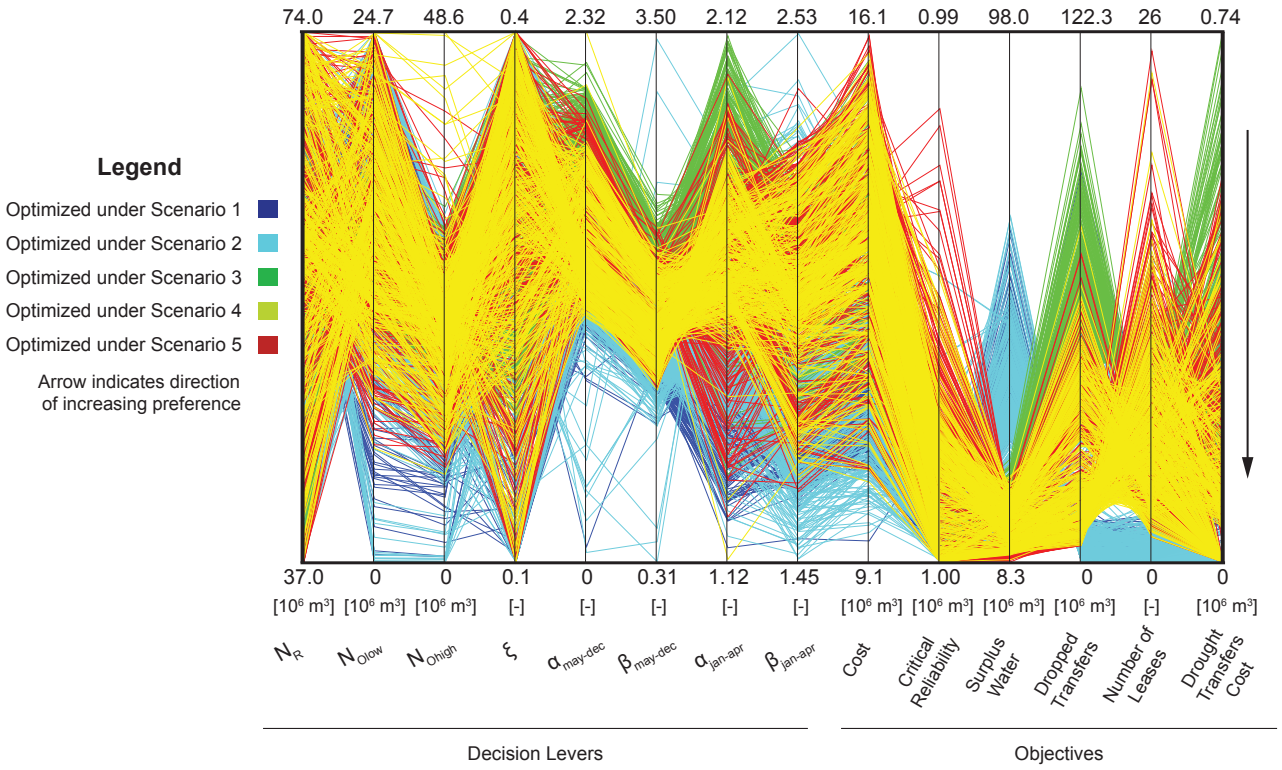

Figure A.4: Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, with the Scenario 4 (reliability) solutions highlighted atop the four other scenarios. Each line represents a water portfolio solution. The vertical position on each axis represents the value of that decision lever or objective.

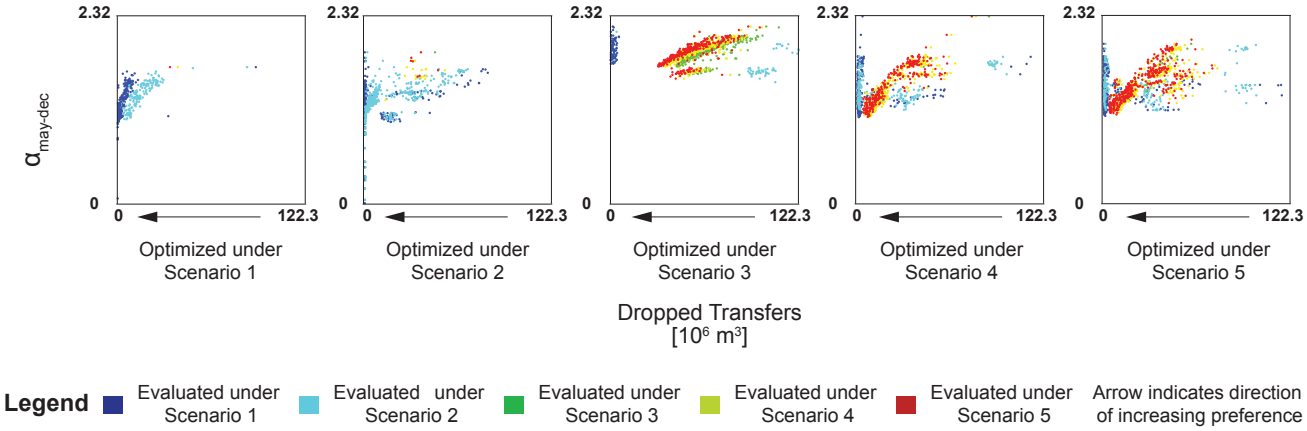

Figure A.5: The effect of optimized scenario on dropped transfers when evaluated under each scenario. Each plot contains the optimized set of a single scenario, with the $\alpha_{May-Dec}$ decision lever shown. Solution point color refers to the scenario the solutions were evaluated under.

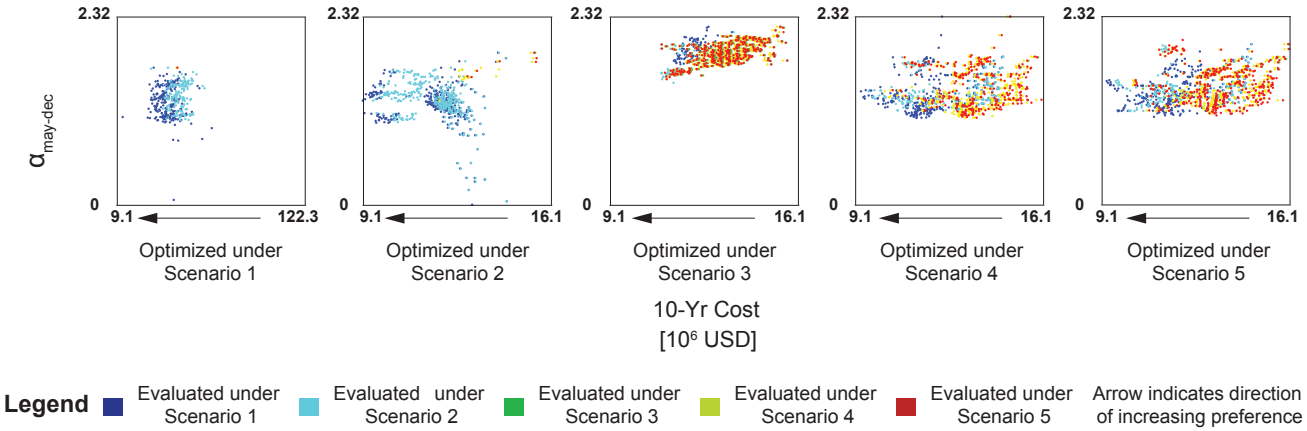

Figure A.6: The effect of optimized scenario on 10-year cost when evaluated under each scenario. Each plot contains the optimized set of a single scenario, with the $\alpha_{May-Dec}$ decision lever shown. Solution point color refers to the scenario the solutions were evaluated under.

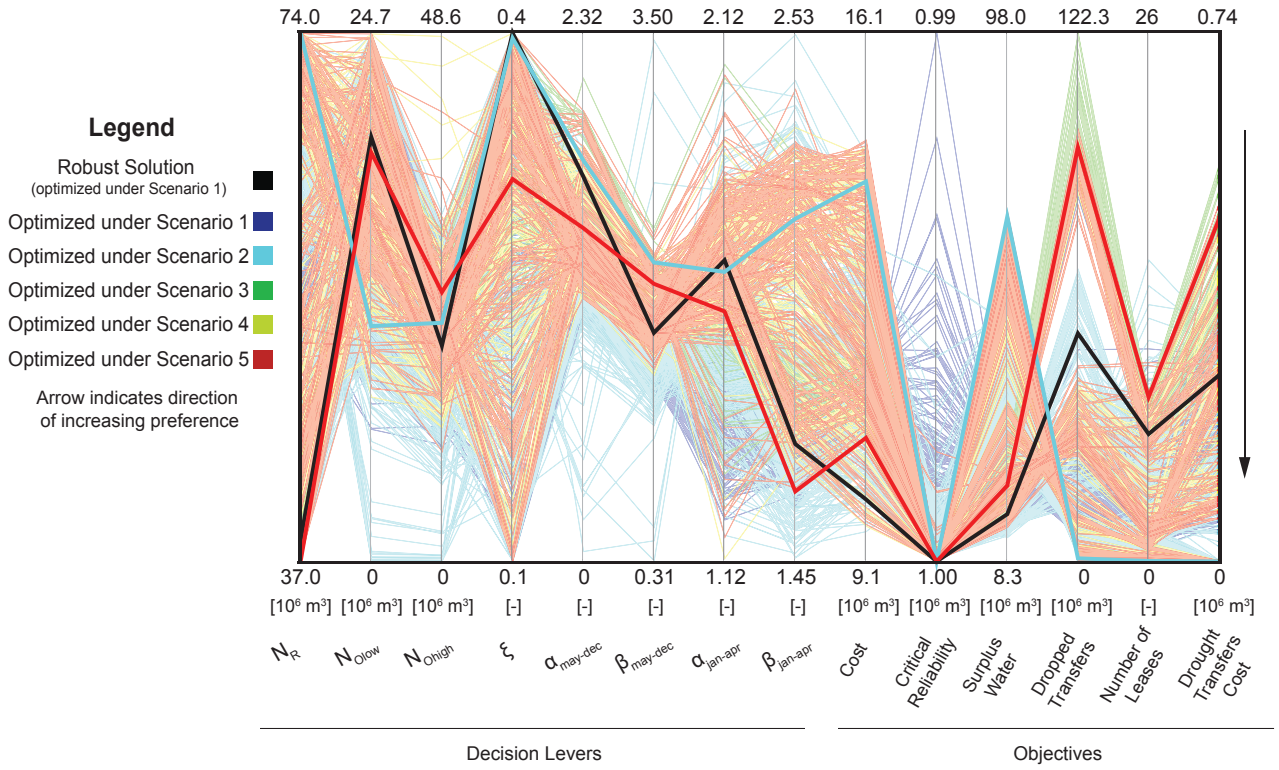

Figure A.7: Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, all evaluated under Scenario 2. Highlighted solutions correspond to the solutions identified in Phase I. The color of the highlighted solution refers to the color of its scenario set. The black solution is the "robust" solution from the prior study.

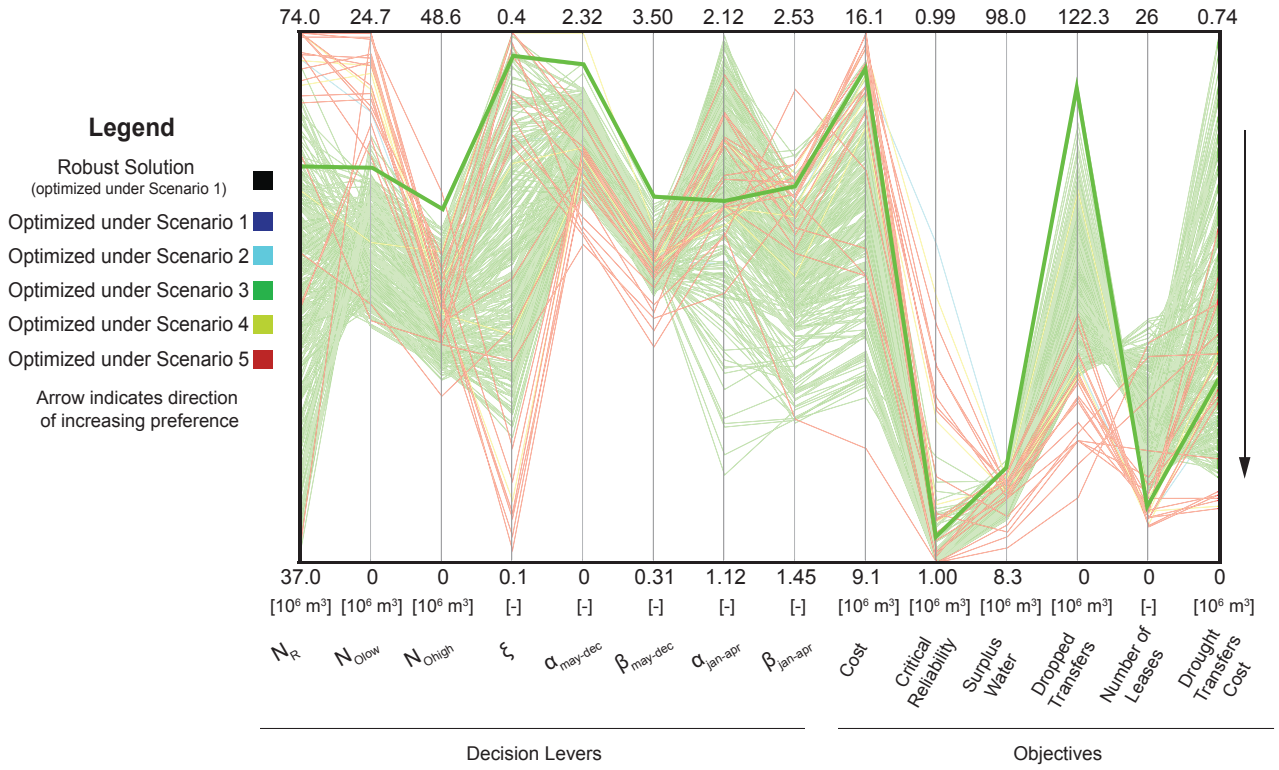

Figure A.8: Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, all evaluated under Scenario 3. Highlighted solutions correspond to the solutions identified in Phase I. The color of the highlighted solution refers to the color of its scenario set. The black solution is the "robust" solution from the prior study.

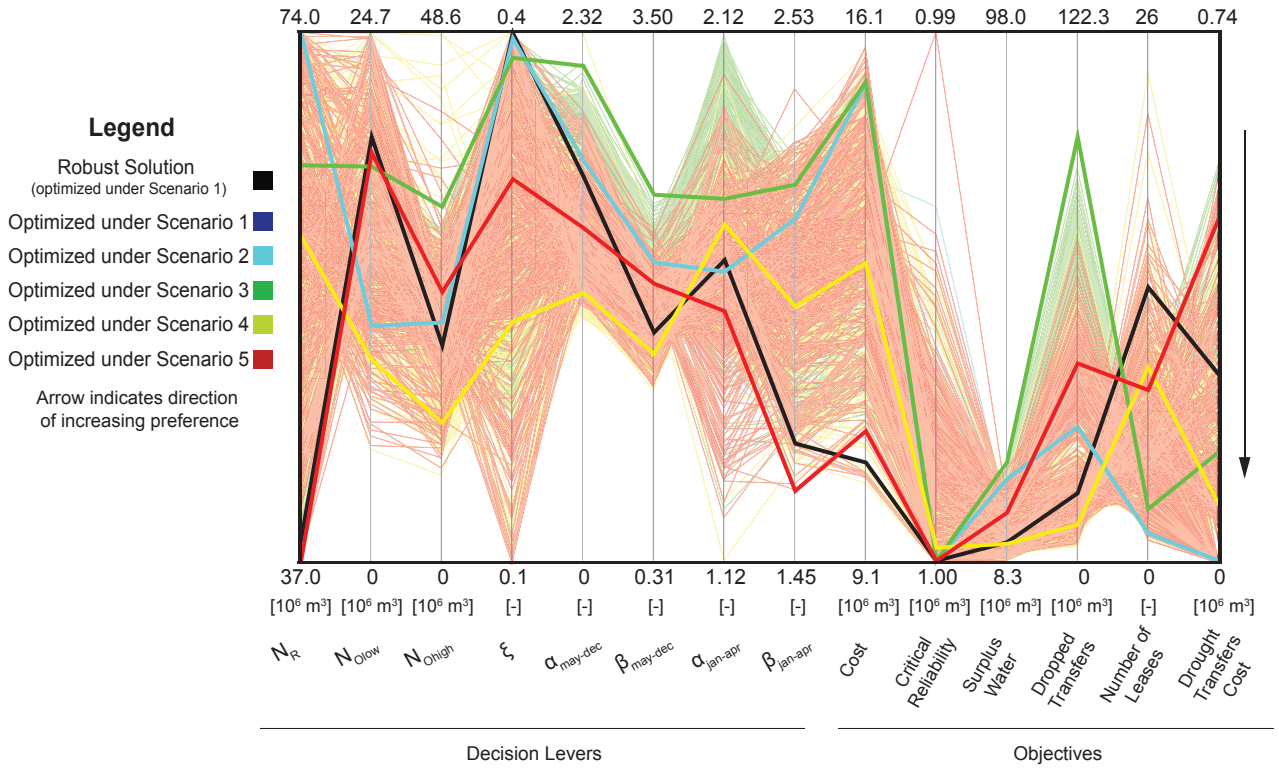

Figure A.9: Decision levers and non-dominated tradeoffs optimized under each of the five scenarios, all evaluated under Scenario 4. Highlighted solutions correspond to the solutions identified in Phase I. The color of the highlighted solution refers to the color of its scenario set. The black solution is the "robust" solution from the prior study.