The Pennsylvania State University
The Graduate School

MANAGING POPULATION AND DROUGHT RISKS USING MANY-OBJECTIVE WATER PORTFOLIO PLANNING UNDER UNCERTAINTY

A Thesis in
Civil Engineering
by
Joseph Robert Kasprzyk

© 2009 Joseph Robert Kasprzyk

Submitted in Partial Fulfillment
of the Requirements
for the Degree of

Master of Science

May 2009

The thesis of Joseph Robert Kasprzyk was reviewed and approved* by the following:

Patrick M. Reed
Associate Professor of Civil Engineering
Thesis Advisor

Thorsten Wagener
Assistant Professor of Civil Engineering

Michael N. Gooseff
Assistant Professor of Civil Engineering

William D. Burgos
Associate Professor of Environmental Engineering
Graduate Officer of the Department of Civil and Environmental Engineering

---

*Signatures are on file in the Graduate School.

Abstract

This study contributes a many-objective analysis of the tradeoffs associated with using the portfolio planning approach for managing the urban water supply risks posed by growing population demands and droughts. The analysis focuses on four supply portfolio strategies: (1) portfolios with permanent rights to reservoir inflows, (2) adaptive options contracts added to the permanent rights, (3) rights, options, and leases, and (4) rights, options, and leases subject to a critical reliability constraint used to represent a maximally risk averse case. The portfolio planning strategies were evaluated using a Monte Carlo planning simulation model for a city in the Lower Rio Grande Valley (LRGV) within Texas, USA. Our solution sets provide the tradeoff surfaces between portfolios' expected values for cost, cost variability, reliability, surplus water, frequency of using leases, and dropped (or unused) transfers of water. Using a severe drought scenario, this work shows that leases and options can reduce the potential for critical supply failures when urban supply systems must contend with unexpected and severe extremes in both demand and water scarcity. In summary, this thesis contributes a framework that couples interactive visualization and many-objective optimization to innovate urban water portfolio planning under uncertainty. Many-objective analysis of the LRGV case study shows that effective water portfolio planning can simultaneously improve the costs, the efficiency, the reliability, the adaptability and the resiliency of urban water supplies.

Table of Contents

List of Figures **vi**

List of Tables **ix**

Acknowledgments **x**

Chapter 1
Introduction **1**

Chapter 2
Lower Rio Grande Case Study **6**

Chapter 3
Methods **15**
3.1 Problem Formulation 15
3.1.1 Planning Objectives 18
3.1.2 Constraints 22
3.2 Multiobjective Evolutionary Algorithms 23
3.3 Computational Experiment 26
3.3.1 Parameterization of Multiobjective Search 26
3.3.2 Constraint Handling in Search 29
3.3.3 Evaluation of Portfolio Performance Using Drought Scenarios 30

Chapter 4
Results **31**
4.1 Multiobjective Tradeoffs 31
4.1.1 Case A: Permanent Rights Only 31
4.1.2 Case B: Permanent Rights and Adaptive Options Contracts 34
4.1.3 Case C: Permanent Rights, Options, and Leases 37
4.1.4 Case D: Portfolio Planning Under A Critical Reliability Constraint 41

4.2 Drought Scenario Performance 44

Chapter 5
Discussion **49**
5.1 The Value of Water Portfolios 49
5.2 The Value of Many-Objective Planning 51
5.3 The Value of Constructive Decision Aiding 52

Chapter 6
Conclusion **53**

Chapter 7
Future Work **55**

Bibliography **57**

List of Figures

1.1 The solution shown in figure 1a minimizes a single-objective formulation. The same solution when plotted with respect to a two-objective formulation often maps to an inferior value assuming that objective 1 does not strongly dominate decision preferences. Adapted from [33] 4

2.1 Boxplots of monthly historical data for Demand and New Water measured in acre feet (af). The median is shown with a horizontal line in each plot. The boxes show quartiles, while whiskers show data within 1.5 of the interquartile range (IQR), and outliers beyond 1.5 times the IQR are shown for each data set with crosses at each data point. 11

2.2 Illustration of the simulation-optimization framework used in this paper. A parent population of N candidate solutions is input into the multiobjective evolutionary algorithm (MOEA). The MOEA first evaluates each solution, and this process is shown in the upper box. The decision variables are coupled with an ensemble of M input data to the model. The model then creates an ensemble of M results that are used to calculate objective functions and possible constraint violations that are fed back to the MOEA. The MOEA uses these objectives and constraints to sort and select the best solutions, upon which variation is used to generate a new child population. The process repeats until termination. 13

3.1 A two-objective minimization problem illustrating the concept of epsilon dominance. The user-specified epsilon resolution is shown with dashed grid lines. The algorithm eliminates redundant solutions in each grid block (solution C dominates solution D), as well as performs sorting with respect to whole grid blocks (solution B block-dominates A). Note that solutions B, C, and E block-dominate the intersecting gray shaded areas. 24

4.1 Tradeoff for Case A, determined by enumerating discrete integer values of permanent rights volumes. Each cone represents a portfolio planning strategy (a volume of rights). The axes of the figure plot cost, reliability, and surplus water objectives and the color plots the volume of permanent rights: low volumes in blue to high volumes in red. Solution 1 is the high-cost solution in Case A. . . . 32
4.2 Tradeoff for Case B determined by using an MOEA to find nondominated solutions that mix permanent rights and options. Each cone represents a portfolio planning strategy. The axes of the figure plot cost, reliability, and surplus water objectives and the color plots the volume of permanent rights: low volumes in blue to high volumes in red. Additionally, the orientation of the cones plots the exercised options (down to up representing low to high exercised options). Solution 2 is a representative Case B low permanent rights solution. 35
4.3 Tradeoff for Case C determined by using an MOEA to find nondominated solutions that mix permanent rights, options, and leases. Each cone represents a portfolio planning strategy. The axes of the figure plot cost, reliability, and surplus water objectives and the color plots the volume of permanent rights: low volumes in blue to high volumes in red. Additionally, the orientation of the cones plots the exercised options (down to up representing low to high exercised options) and the size of the cones plots the expected volume of leases (small representing zero leases to large representing the most leases acquired). 38
4.4 Parallel plot of the epsilon-nondominated Pareto approximation of Case C. Each solution is represented by a line in this figure, with the color of each line representing the volume of permanent rights held by each solution portfolio, and the vertical position of the line vertices representing the relative value of the solution's given objective function value. The objective function values for cost, reliability, surplus water, dropped transfers, cost variability, and number of leases are shown. Note the distribution of solutions with high permanent rights (red and yellow solutions) versus the lower permanent rights solutions (blue and cyan solutions). 39

4.5 Tradeoff for Case D determined by using an MOEA to find nondominated solutions that mix permanent rights, options, and leases subject to the critical reliability constraint. Each cone represents a portfolio planning strategy. The axes of the figure plot cost, reliability, and surplus water objectives and the color plots the volume of permanent rights: low volumes in blue to high volumes in red. Additionally, the orientation of the cones plots the exercised options (down to up representing low to high exercised options) and the size of the cones plots the expected volume of leases (small representing zero leases to large representing the most leases acquired). Solutions 3 - 6 from the figure are selected for further analysis. . . . 43
4.6 Monthly water balance for selected portfolios evaluated during the drought scenario. The dark gray bars indicate initial condition water (in January) and water carried over from the previous month. Allocations to rights are shown with hashed lines, and light gray bars indicate leases. Exercised options are shown with white bars, and the projected demand is shown with dots. The actual demand is shown with the x symbol, and a failure occurs when the ordinate of the demand (x) is higher than the bar graph. Objective function values from the ten-year simulation are shown for each solution, with reliability omitted due to its near-100% value for each solution. For the objective function values, cost is in millions of USD while surplus and dropped water is given in acre ft. 46

List of Tables

2.1 Model Decision Variables 9

3.1 Problem Formulations: Cases A, B, C, and D 17
3.2 Parameters for this study 27

4.1 Selected Solutions' Performance in 10-Year Model 45

Acknowledgments

My experience in graduate school was made complete by the kind support of many people. Firstly, I would like to thank Dr. Patrick Reed for his continued support from my honors work at Penn State through the research presented in this thesis. I appreciate his kind assistance and mentorship, and I fondly remember the enjoyable travels we had discussing this work at Tufts University and at AGU in San Francisco. I would also like to thank my committee members Dr. Thorsten Wagener and Dr. Michael Gooseff for their helpful comments and discussion. In addition to their help, this project could not have been possible without the fruitful collaboration of Brian Kirsch and Dr. Greg Characklis at the University of North Carolina. Brian was especially patient during my numerous phone calls discussing this model, and he never even hung up on me! I would also like to thank two other patient people, Joshua Kollat and Ruchit Shah, who put up with my crazy ideas in our cubicle and had some nice conversations with me, especially related to creative ways for performing this analysis and presenting the work. Life is a pleasant experience in Sackett Building, and I would like to acknowledge Keith Sawicz, Christa Kelleher, Adam Ward, Mukesh Kumar, George Holmes for their friendship and support.

I would like to give special thanks to Emil Laftchiev, Melissa Long, and Brian Thomson, who have been close and dear friends who have made the graduate school experience really great. I look forward to continuing this journey with them in the years to come. I also express sincere appreciation and love to my parents for providing me the opportunity and gracious support to pursue my dreams.

Dedication

To my parents.

Chapter 1

Introduction

Milly et al. clearly capture the growing concern over the risks posed to our water supply systems by growing population demands and climate change [1]. The Intergovernmental Panel on Climate Change (IPCC) has highlighted that these risks and the associated vulnerabilities of water resources systems emphasizes the need for improved water management through non-structural adaptation strategies. Specifically, the IPCC report highlights that water marketing and portfolio-based management strategies should be used to reduce water supply vulnerabilities and avoid the environmental and fiscal burdens associated with structural increases to the water supply (new reservoirs, etc.) [2]. Although the climate change context brings these issues to the forefront [3–5], water scarcity has long motivated interest in the use of water markets to confront the uncertainties, risks, and growing demands on urban water supplies [6–16]. Water markets seek to allocate water resources to their "highest-value use" [17–20] by transferring volumes of water across regions [19] or user sectors [21]. As noted in [22], droughts have been the dominant factor that has motivated the emergence of water markets as well as innovations in the types of transfers considered in water portfolio planning such as spot market leases [23] or adaptive options contracts [24, 25].

Spot market leases are a very flexible water supply portfolio planning instrument, where short-term transfers of water are purchased for prices that vary substantially subject to supply and demand conditions. Options provide a mechanism for reducing the price volatility associated with leases. An options contract allows water portfolio planners to reserve a fixed price for a set quantity of water, all or some of which can be used later in the year to purchase water transfers (i.e., "exercise" the option). Beyond price volatility, options also provide the added benefit of allowing planners to delay transfer purchase decisions until they have a better understanding of the state of their water supply systems. Several studies have shown that water portfolio planning with both options and leases can reduce the costs associated with maintaining reliable urban water supplies [11–13, 26–28]. These prior studies have used a range of deterministic and stochastic single-objective planning formulations to minimize the expected costs of reliably meeting urban water demand. In this thesis, we build on this body of work to contribute a "many-objective" [29, 30] exploration of the tradeoffs inherent to the portfolio planning problem. The term many-objective refers specifically to the consideration of 3 or more planning objectives in management problems.

This study explores the uncertainty and tradeoffs associated with up to six conflicting water portfolio planning objectives over a ten-year planning horizon for a single city in the Lower Rio Grande Valley (LRGV) in Texas, USA. Our work distinguishes four cases, Case A: permanent rights to reservoir inflows as the sole source of supply, Case B: permanent rights and adaptive options, Case C: a combination of permanent rights, adaptive options, and leases, and Case D: a critically constrained (or highly risk averse) version of Case C (see Table 3.1). The problems have been explored using a linked chain of multiobjective formulations, meaning that Case A is a sub-space of Case B, Case B is a sub-space of the six objective formulation of Case C, and Case D is a highly constrained version of Case C. Our solution sets provide the tradeoff surfaces between portfolios' expected values for cost, cost variability, reliability, surplus water, frequency of using leases, and dropped (or unused) transfers of water. This work contributes clear evidence that options and leases have a dramatic impact on the marginal costs associated with improving the efficiency and reliability of urban water supplies. Moreover, our many-objective analysis permits the discovery of a broad range of high quality portfolio strategies. In addition to identifying tradeoff sets, this thesis draws from recommendations in [1], by using scenario analysis [31] to illustrate how leases and options can reduce the potential for critical failures when urban supply systems must contend with unexpected and severe extremes in both demands and water scarcity.

Our drought scenario analysis highlights that the severe risk aversion that typifies water supply planning problems yields significant mathematical challenges, especially when considering growing uncertainties from environmental and socioeconomic variability and limitations in predicting future conditions. Our analysis demonstrates that severe risk aversion and uncertainties can cause the emergence of highly discrete and discontinuous “feasibility islands” for the portfolio planning problem. Our use of the term feasibility island in this study refers to portions of the portfolio planning problem’s solution space where small, discontinuous clusters of feasible solutions reside. These types of spaces are of concern because often they indicate that optimal solutions’ performance may degrade rapidly with small changes in decisions. Traditional deterministic optimization methods could fail to identify these discontinuous solution clusters or in the worst case identify critically sensitive water supply optima that could actually increase water supply failure risks. These challenges were addressed in this work using many-objective problem formulations, multi-objective evolutionary algorithms (MOEAs), and interactive high-dimensional tradeoff visualizations. The water resources community has commonly recognized challenges associated with “nonstationarity” in hydrologic systems’ forcing and response due to change, as well as modifications in land cover and the impact of built systems that effect the hydrologic cycle. However, there is an additional challenge regarding the “nonstationarity” in how we define water management problems. Given the increasingly severe uncertainties, dependencies and decision tradeoffs for complex urban water supply systems, design paradigms must evolve to better elucidate the consequences, compromises, and hypotheses that emerge with new information and knowledge. Broadly, a new design paradigm is needed that better accounts for the structural uncertainty and nonstationarity of the mathematical spaces (or topologies) that define water management tradeoff analysis. These spaces are nonstationary in the sense that as designers make new discoveries about system properties or planning objective conflicts, they are likely to form new hypotheses that represent human-guided structural changes in their mathematical formulations (i.e., the definition of optimality changes) [32]. We have used our “chain” of formulations in Cases A-D to demonstrate the importance and value of exploring the structural (or topological) nonstationarity in management problem formulations.

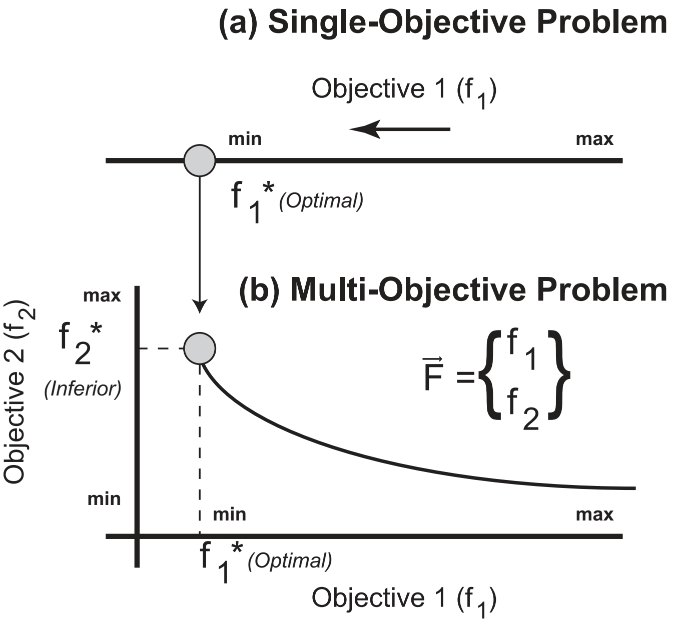

Figure 1.1. The solution shown in figure 1a minimizes a single-objective formulation. The same solution when plotted with respect to a two-objective formulation often maps to an inferior value assuming that objective 1 does not strongly dominate decision preferences. Adapted from [33]

The idea of adding human-guided structural changes to evolving management formulations relates directly to the body of knowledge that has emerged from the "joint cognitive systems" literature [34]. The motivating question is: how should we combine human intelligence and the expanding explorative power of computers in a complementary manner that enhances decision quality, promotes design discoveries, and expands the complexity of the systems that can be addressed effectively? Formally, two challenging issues must be considered. Initial design preconceptions can strongly bias and limit human-guided search. Gettys and Fisher termed this phenomenon "cognitive hysteresis" where decision makers seek alternatives that confirm their initial problem knowledge, which consequently limits experts from making new discoveries and generating (or falsifying) key hypotheses on system performance [35]. The second issue addresses spatial (or dimensional) limits as a key concern for engineering problem formulations. Brill et al. [33] clearly highlight that for complex systems with ill-defined evaluative criteria and quantitative objectives, solutions classified as being optimal in lower dimensions (i.e., using fewer criteria) are often considered inferior by decision makers if new criteria are added for their analysis (see Figure 1.1). Topologically, a lower dimensional problem structure causes a form of "cognitive myopia" [36] where decision quality decreases as a consequence of a too narrowly focused problem analysis. As the complexity of urban water supply problems increases, more modeled and unmodeled criteria will emerge as being important for testing system performance hypotheses and for generating design innovations [33–39]. We demonstrate in this thesis that coupling interactive tradeoff visualizations and many-objective optimization has a strong potential for overcoming cognitive challenges in decision making under uncertainty and for facilitating the discovery of innovative design compromises for improving the long-term sustainability of our urban water supplies.

This thesis is adapted from a paper submitted to *Water Resources Research* coauthored by Patrick Reed, Brian Kirsch, and Gregory Characklis submitted in April 2009. In the remainder of this thesis, chapter 2 provides a detailed overview of the Lower Rio Grande water market case study and the Monte Carlo simulation used to evaluate water supply portfolio alternatives. Chapter 3 provides a detailed description of the many-objective problem formulations, the MOEA solution tool, and the computational experiment used to generate our portfolio planning tradeoff results. Chapters 4 and 5 present the results and discuss their implications for improving urban water portfolio planning given the growing concerns over severe droughts. Chapter 6 presents the conclusions, and chapter 7 suggests future work that can be undertaken as an extension of this study.

Chapter 2

Lower Rio Grande Case Study

This study examines water marketing in the Lower Rio Grande Valley (LRGV) in southern Texas, USA. An overview of the market is given in [18], [40], and [41]. Because of limited groundwater reserves in the region, the primary stores of water in the LRGV are the Falcon and Amistad reservoirs in which the reservoirs' water is governed by a 1944 treaty between the United States and Mexico. The region's water resources are primarily used by agriculture, constituting 85% of the total regional use.

While water marketing in the LRGV may help municipalities effectively alleviate drought conditions, efficient use of the market poses planning challenges to the region's water managers. For example, Characklis et al. observed that municipalities tend to acquire a significant surplus of water rights due to their risk aversion associated with supply failures [40]. Improvements in water portfolio planning strategies have the potential to help municipalities lower their required water surplus while maintaining high levels of supply reliability. This blend between lowered surplus and improved supply reliability can then facilitate water availability for other non-urban water uses, such as the maintenance of ecological flows as noted by [42] and [8].

The case study presented in this thesis focuses on a single city and creates planning goals that attempt to maximize the efficiency of the city's water supply, while reducing its supply costs and maximizing its reliability. The case study represents a hypothetical city with an average water use of 21,000 acre feet (af) per year in the LRGV, participating in a water market that allows transfers from the agricultural sector to municipal water supply. The planning goals developed and evaluated in this study help the city alleviate risks from growing population demands and drought conditions. In the LRGV case study, we analyze efficiency in two ways. First, we consider volumetric efficiency by quantifying the surplus water held by the city including excess transfers of water from the market that expire from non-use. Secondly, we analyze the city's logistical efficiency defined in terms of transactions costs [43] and the city's exposure to cost variability that may result from use of market-based augmentations to its water supply. Regionally, concerns over the decreasing flow from Mexican tributaries into the LRGV's reservoir system [41] motivate the importance of improving the efficiency of water supply portfolios, in order to help mitigate the risks posed by regional decreases in reservoir storage.

The population in the LRGV is projected to grow by a factor of three from 1990 - 2050 [40]. The associated increase in urban water demands with growing population requires a flexible planning strategy that addresses the risks posed by uncertain demand projections [44]. The cascading uncertainties of growing population demand, variable hydrologic inputs, and market pricing distributions are addressed in this work by evaluating supply portfolios within a probabilistic framework. Previous studies have presented supply reliability from the consumer's standpoint [26,45], and this work extends this treatment by addressing how uncertainty affects the probability of shortfalls using a Monte Carlo simulation of the LRGV.

The Monte Carlo simulation evaluates how supply strategies exploit the water market to meet the city's planning goals for efficiency and reliability. The model is governed by anticipatory planning strategies that use risk-based thresholds for supply decisions, and Monte Carlo draws of historical data to develop distributions of plausible futures for the city. The historical data and computational model are adapted from a multi-year planning scenario developed in a study by Kirsch et al. [28].

Historical data from the LRGV drives this study's water supply model. Monthly draws are performed that simulate 10 years of water supply decisions, such that a reservoir mass balance, municipal demand, lease pricing distribution, and portfolio performance is tracked for each of the 120 simulation months. In a given month t, the city's supply is denoted by S_t and the city's expected supply, based on historical averages for permanent rights allocation, is denoted by S_{E_t}. The initial condition in the model specifies a starting reservoir volume and volume of water for the city's supply, N_{r_o}. In this study, the initial condition for the water supply N_{r_o} was set to 0.3 times the city's permanent rights, consistent with [28]. In effect, this initial condition assumes that the city will always have thirty percent of its permanent rights in the account at the beginning of the simulation. For the multi-year planning scenario, N_{r_o} also represents the water that the city has in its supply account in the beginning of each subsequent simulation year. Reservoir water is allocated to the city from a simulated reservoir balance, where the total reservoir volume R_t in a month t is related to the previous month's level, simulated inflow (i_t), outflow (o_t), and reservoir losses (l_t) (as shown in equation 2.1).

$$R_t = R_{t-1} + i_t - o_t - l_t \tag{2.1}$$

The reservoir mass balance is calculated at each month to determine whether or not there is sufficient water available to allocate a volume to the city's municipal supply. The reservoir level also impacts lease pricing consistent with [27]. The initial condition for the reservoir level in this work is set to 0.8 million acre-feet (af), representing a restrictive and disadvantageous situation for the city following the prior assumptions of Characklis et al. [27].

The city's water supply portfolio consists of three supply instruments: permanent rights to reservoir inflows, an adaptive options contract that guarantees a fixed price for water acquisitions at a specified point in the year, and spot leases acquired at any month in the year with a variable price. The decision variables relating to each of the supply instruments are summarized in Table 2.1.

The city's permanent rights, denoted by N_R, are allocated as a percentage of the total reservoir inflow, so that if the city owns 10% of the total regional water rights, the city will be allocated 10% of the reservoir's inflow for the month (after accounting for evaporative and conveyance losses). This pro rata nature of reservoir allocations means that the specified volume of rights held by the city is not always allocated its full volume, with a volume of 0.725 af of water allocated on average per 1 af of the city's permanent rights [27]. An important aspect of

Table 2.1. Model Decision Variables

Decision Variable	Range	Cases	Description
N_R	30,000 - 60,000	A, B, C and D	Volume of Permanent Rights [af]
$N_{O_{\text{low}}}$	0 - 20,000	B, C and D	Low-Volume Options Contract Alternative [af]
$N_{O_{\text{high}}}$	$N_{O_{\text{low}}}$ - $2.0N_{O_{\text{low}}}$	B and C	High-Volume Options Contract Alternative (af)
ξ	0.1 - 0.4	B, C and D	Low to High Options Threshold
$\alpha_{\text{May}-\text{Dec}}$	0.0 - 3.0	B, C and D	Lease/Options Strategy for May-Dec. ("when to acquire?")
$\beta_{\text{May}-\text{Dec}}$	α_2 - 3.0	B, C and D	Lease/Options Strategy for May-Dec. ("how much to acquire?")
$\alpha_{\text{Jan}-\text{Apr}}$	0.0 - 3.0	C and D	Lease Strategy for Jan.-Apr. ("when to acquire?")
$\beta_{\text{Jan}-\text{Apr}}$	α - 3.0	C and D	Lease Strategy for Jan.-Apr. ("how much to acquire?")

the permanent rights implementation in this thesis is that permanent rights are constrained here to always be greater than the average yearly water demand for the city. A lower-bound permanent rights volume of 30,000 af as shown in table 2.1 should be allocated at least the 21,000 af of average demand. The permanent rights have a fixed price per acre foot, p_R, equal to \$22.60 per af [28]. Each of the prices, p, in this chapter are reported as a price per acre foot of water.

The second water supply instrument, the adaptive options contract, is analogous to a European call stock option, in which the city pays an up-front fee for the right to later acquire water at a set exercise price. Examples of existing options contracts in water markets are provided in [22] and [25]. In this model, a single adaptive options contract is agreed upon by the city for the entire planning period. The consistent ten year options contract used in this work reflects the trend that long-term water transfers are becoming more popular in water markets [46]. The adaptive options contract identifies either a high-volume ($N_{O_{\text{high}}}$) or low-volume ($N_{O_{\text{low}}}$) option purchase building on [28]. The choice between exercising the high-volume or low-volume option is determined using a threshold, ξ, that compares the volume of water in the city's account at the beginning of a simulation year, N_{r_o}, to the percentage of the city's permanent rights (as shown in equation 2.2 below).

$$N_O = \begin{cases} N_{O_{\text{low}}} & \text{if } \frac{N_{r_o}}{N_R} > \xi \\ N_{O_{\text{high}}} & \text{if } \frac{N_{r_o}}{N_R} < \xi \end{cases} \tag{2.2}$$

If city's available supply is higher than this threshold, the city uses the low-volume alternative in the contract, and if it is lower than the threshold, the high-volume alternative is available to the city. The options contract has two associated prices, the up-front cost paid, p_O, set at \$5.30 per af, and the option exercise price, p_x, of \$15.00 per af. An options contract provides some security against high lease prices, since the lease pricing can fluctuate with demand. The city pays the up-front cost equal to either the high-volume or low-volume of optioned water as determined by the threshold, multiplied by p_O, to have the right to exercise water from the contract during the planning year. In the options exercise month, set to May for this study, the city has the ability to exercise all or part of the volume of water in the contract, paying a price of p_x. The initial options price, p_O, was set according to Black-Sholes option pricing theory [47] relative to the options exercise price p_x; a more thorough discussion of the options pricing in the model is presented in [27].

The third water supply instrument in the city's portfolio is a spot lease of water, which represents a volume of water that can be acquired at the end of any month and is transferred to the city for use in the following month. Lease pricing is a random variable $\hat{p}_l$ drawn from the Monte Carlo distribution. The lease prices are based on distributions for each month, reflecting actual lease prices obtained from the LRGV watermaster's office from 1994-2003. One distribution of lease prices exists when the reservoir level is high, and another distribution exists for a low reservoir level, stemming from previous work where regional water pricing was correlated to reservoir levels (see [27]).

In the LRGV management simulation, the decisions to exercise water in the options contract or purchase leases is made using an anticipatory strategy of ratios between supply and demand. The value for α_k in planning period k is used for the city to decide "when" to purchase leases and exercise options, while the decision on "how much" to purchase or exercise is governed by β_k. The following equation relates the expected supply and demand in the $t + 1$st month to the α_k and β_k

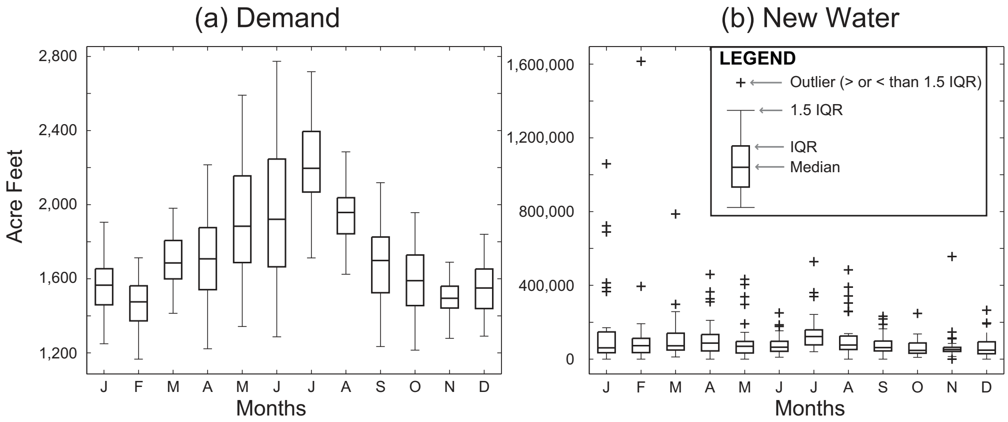

Figure 2.1. Boxplots of monthly historical data for Demand and New Water measured in acre feet (af). The median is shown with a horizontal line in each plot. The boxes show quartiles, while whiskers show data within 1.5 of the interquartile range (IQR), and outliers beyond 1.5 times the IQR are shown for each data set with crosses at each data point.

planning decisions:

$$\begin{aligned} \text{If}: \quad & \frac{S_{E_{t+1}}}{\sum_{j=t+1}^{12} \bar{d}_j} < \alpha_k \\ \text{Purchase transfers, s.t.}: \quad & S_{E_{t+1}} = \beta_k \sum_{j=t+1}^{12} \bar{d}_j \end{aligned} \tag{2.3}$$

where $S_{E_{t+1}}$ is the city's expected water supply in month $t+1$, and $\bar{d}_j$ is the historical average demand for the jth month. First, the ratio of expected supply to expected demand is compared to the alpha threshold. If the supply to demand ratio is lower than specified by the α_k decision variable, the city purchases leases and exercises options such that the month's expected supply is equal to the β_k ratio (as indicated in equation 2.3). Consistent with previous work, this study constrains β_k decision variables to be greater than or equal to the associated α_k variable.

This work creates two sets of alpha and beta planning variables. The variables $\alpha_{\text{Jan-Apr}}$ and $\beta_{\text{Jan-Apr}}$ represent the thresholds for January through April, and $\alpha_{\text{May-Dec}}$ and $\beta_{\text{May-Dec}}$ represent May (the options exercise month) through the end of the year. Two sets of alpha and beta ratios represent a simple anticipatory model, but the approach can be adapted to more complex models or situations.

Figure 2.1 shows an example of the input data that drives the LRGV case study's model. Figure 2.1a shows the distribution of monthly demand in the historical record. The demands were modeled using unique normal distributions for each month of the year, which were developed based on historical data for the region. Figure 2.1b gives the historical distributions of the volume of water that can be allocated to the total region's water rights in each month. The figure illustrates the out-of-phase timing in the water system; when the water demand tends to be highest, the available "new water" for allocation tends to be low. The anticipatory portfolio planning approach used in this work allows urban water planners to efficiently blend leasing and options to augment permanent rights allocations in months that tend to have supply shortfalls and higher demand. A schematic of the optimization and simulation framework is provided in figure 2.2. The figure illustrates that the model evaluations are embedded in a multiobjective evolutionary algorithm (MOEA) that evolves a population of solutions to have improved objective function performance. Note that each solution evaluation involves an independent ensemble of M Monte Carlo samples; each Monte Carlo sample contains 120 months of hydrology, demands, and lease pricing data used to evaluate the planning strategies.

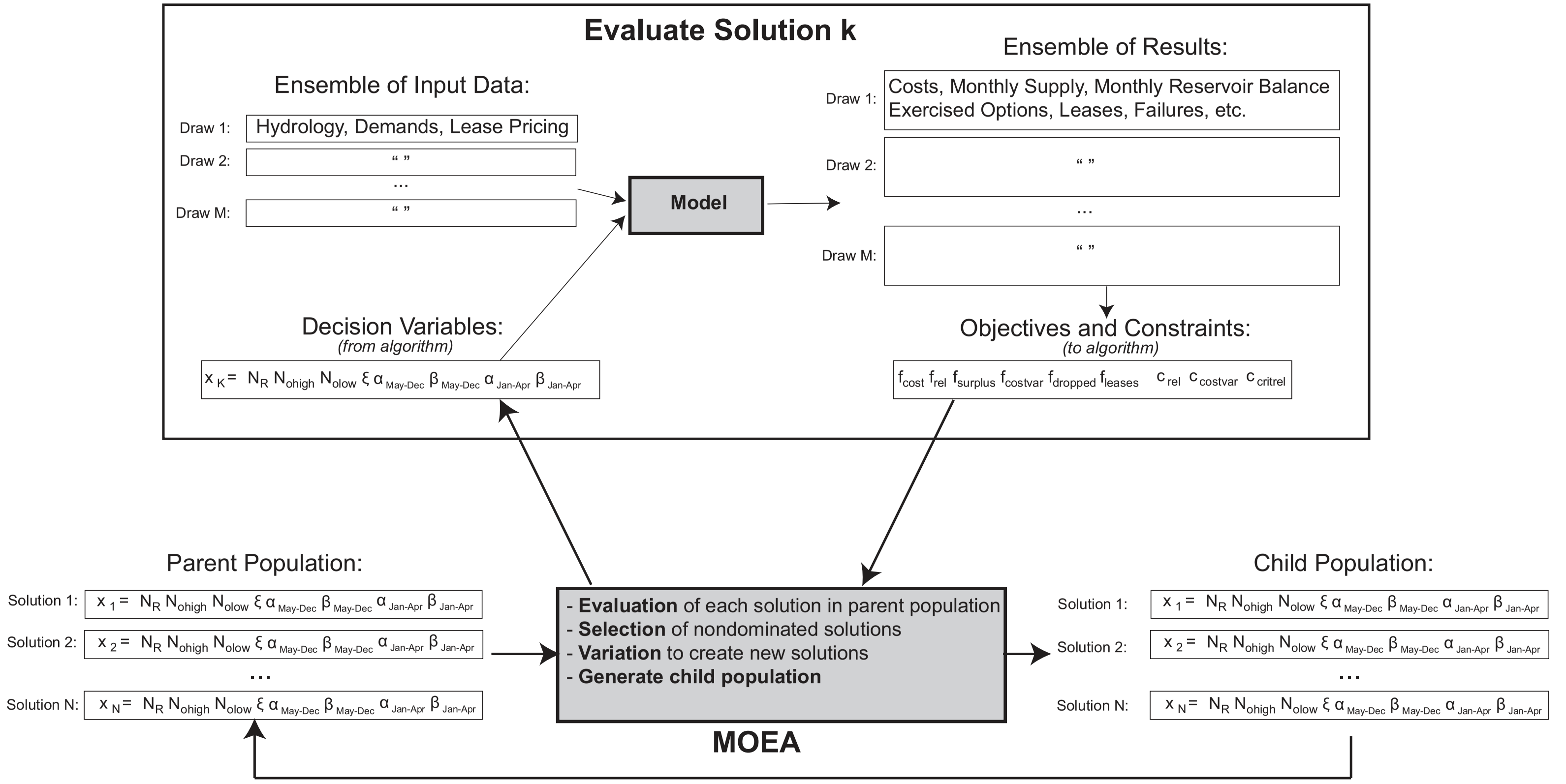
Evaluate Solution k
Ensemble of Input Data:
Draw 1: Hydrology, Demands, Lease Pricing
Draw 2: “ ”
…
Draw M: “ ”
Model
Ensemble of Results:
Draw 1: Costs, Monthly Supply, Monthly Reservoir Balance Exercised Options, Leases, Failures, etc.
Draw 2: “ ”
…
Draw M: “ ”
Decision Variables:
(from algorithm)
$x_K = N_R\ N_{ohigh}\ N_{olow}\ \xi\ \alpha_{May\text{-}Dec}\ \beta_{May\text{-}Dec}\ \alpha_{Jan\text{-}Apr}\ \beta_{Jan\text{-}Apr}$
Objectives and Constraints:
(to algorithm)
$f_{cost}\ f_{rel}\ f_{surplus}\ f_{costvar}\ f_{dropped}\ f_{leases}\ \ c_{rel}\ c_{costvar}\ c_{critrel}$
Parent Population:
Solution 1: $x_1 = N_R\ N_{ohigh}\ N_{olow}\ \xi\ \alpha_{May\text{-}Dec}\ \beta_{May\text{-}Dec}\ \alpha_{Jan\text{-}Apr}\ \beta_{Jan\text{-}Apr}$
Solution 2: $x_2 = N_R\ N_{ohigh}\ N_{olow}\ \xi\ \alpha_{May\text{-}Dec}\ \beta_{May\text{-}Dec}\ \alpha_{Jan\text{-}Apr}\ \beta_{Jan\text{-}Apr}$
…
Solution N: $x_N = N_R\ N_{ohigh}\ N_{olow}\ \xi\ \alpha_{May\text{-}Dec}\ \beta_{May\text{-}Dec}\ \alpha_{Jan\text{-}Apr}\ \beta_{Jan\text{-}Apr}$
- Evaluation of each solution in parent population
- Selection of nondominated solutions
- Variation to create new solutions
- Generate child population
MOEA
Child Population:
Solution 1: $x_1 = N_R\ N_{ohigh}\ N_{olow}\ \xi\ \alpha_{May\text{-}Dec}\ \beta_{May\text{-}Dec}\ \alpha_{Jan\text{-}Apr}\ \beta_{Jan\text{-}Apr}$
Solution 2: $x_2 = N_R\ N_{ohigh}\ N_{olow}\ \xi\ \alpha_{May\text{-}Dec}\ \beta_{May\text{-}Dec}\ \alpha_{Jan\text{-}Apr}\ \beta_{Jan\text{-}Apr}$
…
Solution N: $x_N = N_R\ N_{ohigh}\ N_{olow}\ \xi\ \alpha_{May\text{-}Dec}\ \beta_{May\text{-}Dec}\ \alpha_{Jan\text{-}Apr}\ \beta_{Jan\text{-}Apr}$

Figure 2.2. Illustration of the simulation-optimization framework used in this paper. A parent population of N candidate solutions is input into the multiobjective evolutionary algorithm (MOEA). The MOEA first evaluates each solution, and this process is shown in the upper box. The decision variables are coupled with an ensemble of M input data to the model. The model then creates an ensemble of M results that are used to calculate objective functions and possible constraint violations that are fed back to the MOEA. The MOEA uses these objectives and constraints to sort and select the best solutions, upon which variation is used to generate a new child population. The process repeats until termination.

Our use of the LRGV case study model in this thesis is subject to several assumptions that have an impact on the results of our analysis. Characklis et al. [27] and Kirsch et al. [28] outline many of these assumptions and should be consulted for further information. The first set of assumptions has to do with how the market operates. We model an active market in which there is always water available for the city to use, both with the options contract and with spot leasing. The city has the ability to purchase an options contract within the range given in table 2.1, with the largest possible contract having a 20,000 af low-volume alternative and a 40,000 af high-volume alternative. There is no upper limit on the volume of leases the city can acquire, but the city is constrained to keep at least 30,000 af of permanent rights per year. The city's use of the market is subject to the assumption that the city exerts no influence on water pricing in the market; it must accept the quoted price for any volume of water it purchases. Another set of assumptions addresses the input data to the model. An analysis in Characklis et al. [27] showed that there are only weak correlations between inflow, reservoir storage, and reservoir outflow. Following this analysis and consistent with previous work, Monte Carlo draws of the different input variables are independently performed from each historical monthly distribution. An implicit assumption of the anticipatory strategies used in the work is that the historical average supply and demand predictions are appropriate for acquiring supply (i.e., there is no trend in the data that is used in the portfolio strategies). Modifications in the relative magnitude of the alpha and beta strategy variables, though, can represent the city's assumption on the likelihood of a higher demand or lower supply than would be expected. That is, a more conservative set of alpha/beta variables can account for the simplistic nature of predictions based on the average data.

Chapter 3

Methods

This thesis analyzes the LRGV case study using four alternative problem formulations that successively increase the number of modeled supply instruments, planning objectives, and system constraints. Section 3.1.1 gives specific details on the objective formulations. Section 3.1.2 discusses the supply constraints used in our study. Section 3.2 provides a summary of the multiobjective evolutionary algorithm (MOEA) used to solve all of the multiobjective problem formulations considered in this thesis. Section 3.3 provides a detailed discussion of the MOEA's parameterization (section 3.3.1), constraint handling (section 3.3.2) and the drought scenarios used to rigorously test the performance of potential water portfolio alternatives (section 3.3.3).

3.1 Problem Formulation

Table 3.1 illustrates our use of four problem formulations labeled Cases A, B, C, and D to distinguish how adding potential supply instruments, planning objectives, and formulation constraints impacts the LRGV city's portfolio planning alternatives. Cases A - C focus on the effects of the adding new alternative supply instruments, using three- to six-objective problem formulations. Case D extends this analysis by adding a restrictive constraint to the full set of instruments in Case C to analyze the dynamics of these instruments during a highly risk-averse planning scenario. This full complexity formulation, Case D, is summarized in the following equations; note that cases A - C are subsets of this full formulation.

$$\begin{aligned}
\mathbf{F}(\mathbf{x}) &= (f_{\text{cost}}, f_{\text{rel}}, f_{\text{surplus}}, \\
&\quad f_{\text{costvar}}, f_{\text{dropped}}, f_{\text{leases}}) \qquad (3.1)\\
&\quad \forall \mathbf{x} \in \Omega \\
\mathbf{x} &= (N_R, N_{O_{\text{low}}}, N_{O_{\text{high}}}, \xi, \\
&\quad \alpha_{\text{Jan-Apr}}, \beta_{\text{Jan-Apr}}, \\
&\quad \alpha_{\text{May-Dec}}, \beta_{\text{May-Dec}}) \\
\text{Subject to} : c_{\text{rel}} &: \quad f_{\text{rel}} > 0.98 \qquad (3.2)\\
c_{\text{costvar}} &: \quad f_{\text{costvar}} < 1.1 \qquad (3.3)\\
c_{\text{critrel}} &: \quad \Pr[S_{i,j} > 0.6 d_{i,j}] = 1.0 \\
&\quad \forall i \in [1, T] \text{ and } j \in [1, 12] \qquad (3.4)
\end{aligned}$$

In case A, the city is restricted to using permanent rights to fulfill its water supply. Portfolios in Case A have a single decision variable, the volume of permanent rights (N_R) and are evaluated with respect to total supply cost (f_{cost}), reliability (f_{rel}), and average volume of surplus water at the end of each simulation year (f_{surplus}).

Case B adds adaptive options contracting in addition to the permanent rights planning decision. The city may utilize the options contract to exercise water at a fixed price in May of each simulation year. In addition to the permanent rights decision, Case B adds decision variables for the low-volume alternative in the options contract, $N_{O_{\text{low}}}$, the high-volume options alternative, $N_{O_{\text{high}}}$, and the threshold to decide between the two alternatives, ξ. The risk-based decision variables $\alpha_{\text{May-Dec}}$ and $\beta_{\text{May-Dec}}$ governing how options are exercised are also considered in Case B. For Case B, the first three objectives from Case A are maintained, and additional objectives are added to minimize cost variability (f_{costvar}) and minimize dropped transfers (the exercised options-contract water that expires after one year of nonuse, f_{dropped}).

Case C represents a fully flexible portfolio planning formulation, with permanent rights supplemented by the adaptive options contract and spot leasing in any of the 120 months of the simulation. For Case C, the decision variables from Case

Table 3.1. Problem Formulations: Cases A, B, C, and D

Case	Supply Instruments	Objectives	Constraints
A	rights	$f_{\text{cost}}, f_{\text{rel}}, f_{\text{surplus}}$	c_{rel}
B	rights, options	$f_{\text{cost}}, f_{\text{rel}}, f_{\text{surplus}},$ $f_{\text{costvar}}, f_{\text{dropped}}$	$c_{\text{rel}}, c_{\text{costvar}}$
C	rights, options, leases	$f_{\text{cost}}, f_{\text{rel}}, f_{\text{surplus}},$ $f_{\text{costvar}}, f_{\text{dropped}}, f_{\text{leases}}$	$c_{\text{rel}}, c_{\text{costvar}}$
D	rights, options, leases	$f_{\text{cost}}, f_{\text{rel}}, f_{\text{surplus}},$ $f_{\text{costvar}}, f_{\text{dropped}}, f_{\text{leases}}$	$c_{\text{rel}}, c_{\text{costvar}}, c_{\text{critrel}}$

B are maintained, with the $\alpha_{\text{May}-\text{Dec}}$ and $\beta_{\text{May}-\text{Dec}}$ controlling lease acquisitions in addition to how options are exercised from May to December. For lease decisions made in January through April, a second set of variables is introduced, $\alpha_{\text{Jan}-\text{Apr}}$ and $\beta_{\text{Jan}-\text{Apr}}$. These decision variables allow planners to account for differences in early year versus late year hydrologic inputs and demands. A sixth objective is added in Case C, which minimizes the number of leases purchased on the spot market (f_{leases}) as a proxy for transactions costs. Note that f_{dropped} for Case C also includes expired transfers from leased water in addition to water from exercised options.

Case A is subject to a single constraint, c_{rel}. This constraint denotes that the portfolios' reliability, f_{rel}, must be higher than 98%. Cases B and C are also subject to the c_{costvar} constraint that limits the the cost variability objective, f_{costvar} to be less than 1.1 (see equation 3.3 and table 3.1). Case D modifies the formulation from Cases A - C by employing the critical reliability constraint c_{critrel} in equation 3.4. The goal of Case D is to identify how critical failures affect water portfolio alternatives. Small failures could be mitigated by water conservation or other practices, but larger failures present a greater challenge to the municipality. Critical failures, as defined in [27], occur in any month when the city fails to meet more than 60% of their required demand with their available supply. Equation 3.4 therefore requires the supply $S_{i,j}$ to fulfill at least 60% of the simulated demand, $d_{i,j}$ for a month i in the year j. The constraint then forces this inequality for all 120 months in the simulation. The definition ensures that even if failures occur, the failures occurring in Case D will not be critical. The purpose of Case D is to demonstrate that many-objective analysis can help overcome the severe search challenges that emerge when accounting for the extreme risk aversion that typifies urban water supply problems.

3.1.1 Planning Objectives

This section provides a detailed description of the individual planning objectives listed in equation 3.1. Recall that our LRGV case study objectives are evaluated under uncertainty using a Monte Carlo simulation ensemble of regionally-derived hydrology, demand, and lease pricing data. The supply strategies developed are evaluated for a planning period of T years. The planning horizon T used in this study is 10 years, and in the following equations the index i runs from year 1 through year 10. In this section, we use the expectation notation $E[]_i$ to denote the average value for a variable of interest with respect to all the Monte Carlo samples used to simulate the ith year. Planning decisions are evaluated with a monthly timestep using index j, which starts at 1 in the month of January.

COST. The cost function for each candidate solution is defined as a sum of the expected values of cost for each simulation year. In each Case A through D, the cost objective is defined as:

$$\begin{aligned}\text{Minimize}: \quad f_{\text{cost}}(\mathbf{x}) &= \sum_{i=1}^{T} \mathrm{E}\Bigg[N_R p_R + N_{O_i} p_O \\ &\quad + N_{x_i} p_x + \sum_{j=1}^{12} \left(N_{l_{i,j}} \hat{p}_{l_{i,j}} \right) \Bigg]_i \end{aligned} \tag{3.5}$$

The city's water supply cost has four components. The first component charges the city a set price per acre foot, p_R, for the entire volume of its permanent rights, N_R. This component is the only cost for Case A and is included for cases A - D. In cases B through D, the city is also charged for the upfront options cost p_O regardless of the actual volume exercised. The value of p_O used in this cost calculation fluctuates based on the percentage of Monte Carlo draws that caused the city to use the high-volume or low-volume alternatives in their options contract (see equation 2.2). The third component, also used in cases B through D, quantifies the costs when exercised options are added to the city's supply at the fixed strike price, p_x. Finally, cases C and D account for the costs associated with the monthly volume of leases acquired by the city. Spot leases of water are assigned a random variable lease price $\hat{p}_l$ from a Monte Carlo draw multiplied by the individual lease volume, $N_{l_{i,j}}$ specific to month j in the ith year.

RELIABILITY. In a year i, portfolio reliability r_i is defined following the formulation of [27] (see equation 3.6):

$$r_i = 1 - \frac{n_{\text{fail}_i}}{12} \tag{3.6}$$

where n_{fail_i} represents the expected number of monthly failures in the year i. For example, a reliability of 98% is equivalent to a failure occurring in 2% of the Monte Carlo simulations for year i. Therefore, if the performance of year i continued, an operator could expect a failure at a rate of every 4.2 years. A failure here is defined as a city's supply falling short of the simulated demand in a given month t:

$$S_t < d_t \tag{3.7}$$

where S_t is the total supply in the city's account in a month t and d_t is simulated demand from a Monte Carlo draw for the month t. Note that calculation of f_{rel} does not account for the severity of the failure, but the c_{critrel} constraint will address the severity of failures later in this thesis.

The reliability objective, for all cases A-D, is given in equation 3.8:

$$\text{Maximize}: \quad f_{\text{rel}}(\mathbf{x}) = \min_{i \in [1,T]} (E[r_i]_i) \tag{3.8}$$

Equation 3.8 maximizes the lowest expected reliability, r_i in the ith year of the T year planning period. This max-min formulation ensures that water portfolio alternatives will perform as well or better than the representative worst year while also maximizing the worst year's performance. The max-min formulation attempts to avoid choosing alternatives that show adequate average performance over the full planning period but may yield lower reliability in individual years.

SURPLUS WATER. The third objective common to Cases A, B, C and D minimizes the water held by the city at the end of each simulation year. This volume of water, which includes volumes of water from permanent rights, options, and leases, is minimized in this study to free water for other uses (such as ecological flows), as discussed in [27]. Formally, the objective takes an average for the T years of the simulation, by taking an average of the annual expected surplus water volumes:

$$\text{Minimize :} \quad f_{\text{surplus}}(\mathbf{x}) = \sum_{i=1}^{T} \frac{1}{T} \Big(\mathrm{E}[S_t]_i \Big), \; t = 12 \tag{3.9}$$

Recall that the city's water supply is denoted with the variable S_t, so that this objective is minimizing the expected supply at the end of each year, in the month of December. The purpose of this objective is to reduce the surplus water carried over from year to year.

COST VARIABILITY. Case A represents a deterministic cost structure, since the price of permanent rights is known and the volume of permanent rights purchased does not change during the simulation. However, cost variability in cases B through D stems from fluctuations in the volume of options and leases acquired as well as uncertainties associated with lease pricing. To analyze this variability, the objective calculation uses the Contingent Value at Risk (CVAR), defined as the average of costs in the Monte Carlo simulation above the 95th percentile. That is, if there were 1,000 Monte Carlo members, this cost would equal the average of the most expensive 50 samples in a given simulation year [28]. The cost variability objective for Cases B - D is then measured with the following equation:

$$\text{Minimize :} \quad f_{\text{costvar}}(\mathbf{x}) = \max_{i \in [1,T]} \left[\frac{\text{CVAR}_i}{f_{\text{avg. yearly cost}_i}} \right] \tag{3.10}$$

This equation minimizes cost variation for the year with the highest variability (i.e., the highest value of CVAR) in the overall planning period. This min-max objective formulation ensures that the remaining years in the full planning period will have a lower average cost variability than the worst performing year. The CVAR cost is normalized by the average yearly cost, $f_{\text{avg. yearly cost}_i}$, which is similar to the cost objective presented in equation 3.5 evaluated for a given year i. The purpose of normalization is to ensure that years with high costs and years with lower magnitudes of cost have their variability evaluated evenly.

DROPPED TRANSFERS. Since the leases and exercised options in this study expire after a year of non-use (one year without being used to fulfill the city's demand), we quantify the city's loss of this water using the "dropped" transfers objective. To illustrate how the transferred water expires, consider a large spot lease purchased in April of the first simulation year. Starting in May, the city considers this volume of water as part of its expected supply to fulfill demand through the rest of the year. The city attempts to fulfill May's demand with water from its permanent rights first. If the permanent rights water was insufficient to fill monthly demand, it will use the water in its leases and options account that was acquired first. Our hypothetical spot lease will expire when subsequent monthly demand is not high enough to trigger water use from the options and leases account – from May of the first simulation year to April of the second simulation year. We define the variable a as the age of the water in this account, so that when $a > 12$, the water has not been used for 12 months and therefore expires.

The dropped transfers objective, for Cases B through D, is computed as the sum of the annual expected volume of dropped transfers.

$$\text{Minimize}: \quad f_{\text{drop}}(\mathbf{x}) = \sum_{i=1}^{T} \Bigg(\mathrm{E}\Bigg[\{N_{x_i} : \mathrm{a} > 12\} + \sum_{j=1}^{12} \{N_{l_{i,j}} : \mathrm{a} > 12\} \Bigg] \Bigg) \tag{3.11}$$

Equation 3.11 takes a sum of the expected volume of dropped transfers for all T simulation years. This volume of dropped transfers has two components, a volume of water from exercised options (one value in the ith year, N_{x_i}) and leased water (acquired in the jth month of year i, $N_{l_{i,j}}$). An important note here is that a partial volume of an acquired lease or exercised option can be considered in the dropped transfers objective; if the city purchases a 1,000 af lease and only uses 300 af, for example, the lapsed volume of 700 af will be counted in the calculation of equation 3.11.

NUMBER OF LEASES. Cases C and D allow for leases to be added to the city's supply portfolio, which can be purchased in any month of the 120 month planning period. An inherent hypothesis when generating a model that uses anticipatory strategies for lease acquisitions is that an efficient strategy would require the city to purchase several leases in critical months as a way of efficiently augmenting supply in specific months within a drought. To further examine this idea, we minimize the number of times the city would be required to go to the spot market to obtain leases, as a function of the anticipatory decision variables from the city's supply portfolio. Minimizing transfers in this manner can be seen as a proxy for the transactions costs associated with acquiring leases, as noted in section 2. The leases objective is shown in equations 3.12 and 3.13 below:

$$\text{Minimize :} \qquad f_{\text{leases}}(\mathbf{x}) = \sum_{i=1}^{T} \left(\mathrm{E}\left[\sum_{j=1}^{12} \phi_{i,j} \right] \right) \tag{3.12}$$

$$\phi_{i,j} = \begin{cases} 1 & \text{if } N_{l_{i,j}} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{3.13}$$

Here, ϕ accounts for whether or not a lease was acquired, regardless of its volume. There is a 0 or 1 value for each month j in every simulation year i. Similar to other objectives in this study that take a sum over all of the T planning years, expectations are first calculated for each simulation year independently and then summed to compute the final objective value.

3.1.2 Constraints

The reliability constraint c_{rel} (equation 3.2) requires that the reliability of candidate portfolios, f_{rel} must be higher than 98%, consistent with previous work [27,28]. It is utilized in each of the cases A through D. While the reliability constraint was explored in prior work, a contribution of the many-objective approach presented here is that our analysis explicitly quantifies multivariate tradeoffs for a range of portfolio reliabilities from the constrained minimum (i.e., 98%) to the potential maximum of 100%. These reliability tradeoffs are generated without having to specify multiple constrained single objective formulations, through use of the MOEA described in chapter 3.2.

The cost variability constraint c_{costvar} (equation 3.3) is employed in Cases B through D and limits cost variability for the worst-case simulation year to be no more than 10% of the portfolio's total cost in that simulation year. In Case D, portfolios must fulfill the reliability constraint (c_{rel}), the cost variability constraint (c_{costvar}), and a critical reliability constraint denoted by c_{critrel}. As shown in equation 3.4, the c_{critrel} constraint forces the monthly supply to always fulfill at least 60% of simulated demand. The probability of occurrence of a critical failure (when supply reaches a shortfall under this limit) in any ensemble member of the Monte Carlo simulation must effectively be zero, to enforce a "critical" portfolio reliability of 100%.

3.2 Multiobjective Evolutionary Algorithms

Quantitative tradeoffs for the objectives and constraints presented in section 3.1 are developed in this study using a state-of-the-art multiobjective evolutionary algorithm (MOEA), the epsilon Non-Dominated Sorting Genetic Algorithm II (ε-NSGAII) [48,49]. This section will introduce how nondominated sorting is used to generate alternatives that satisfy each of the planning objectives.

The objectives that characterize water resources planning problems often conflict with each other. The tradeoffs between these conflicting objectives can be complex and reveal surprising interactions, even between different measures of quality that would not be expected to conflict [50, 51]. The concept of Pareto optimality is used to define multiobjective tradeoffs for a system. A solution x_1 is Pareto optimal (or non-dominated) if no other solution x in the solution space gives a better value for one objective without also having degraded performance in at least one other objective. MOEAs are heuristic search algorithms that evolve an approximation to the Pareto optimal set using operators such as crossover, selection, and mutation that mimic natural selection in populations of organisms in nature. The evolutionary algorithm search process is an iterative process of selection, which preserves and reproduces high-quality solutions, and variation, to introduce innovation in order to improve the population of solutions. There are many examples of MOEAs used to solve complex non-linear and non-convex multiobjective problems (a detailed review is given in [52]). Examples of application areas in water resources engineering include groundwater monitoring design [29,48,53,54]; groundwater remediation [55–57]; and water resources systems management [42].

The ε-NSGAII represents an improvement to the original NSGA-II developed in [58] by incorporating epsilon-dominance archiving [59] and adaptive population sizing [60]. Epsilon-dominance archiving helps reduce the computational demand

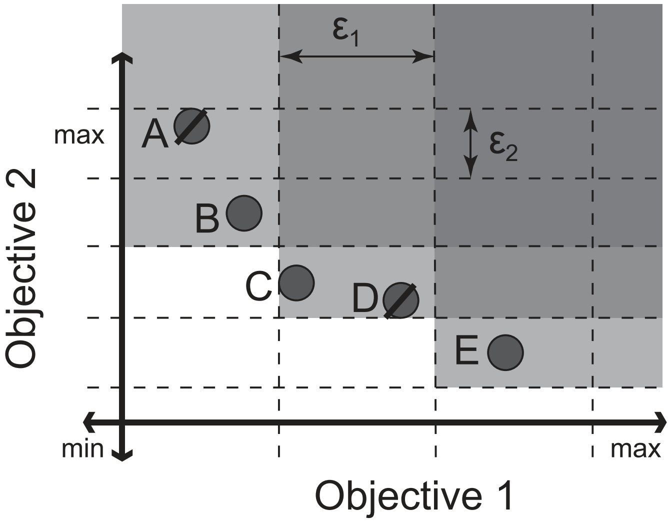

Figure 3.1. A two-objective minimization problem illustrating the concept of epsilon dominance. The user-specified epsilon resolution is shown with dashed grid lines. The algorithm eliminates redundant solutions in each grid block (solution C dominates solution D), as well as performs sorting with respect to whole grid blocks (solution B block-dominates A). Note that solutions B, C, and E block-dominate the intersecting gray shaded areas.

of solving high-dimensional optimization problems [49] by allowing the user to control the resolution at which the objectives are evaluated and ranked. Figure 3.1 illustrates this process. Solutions A through E are shown in a simple two-objective minimization example. Note that since both objectives are being minimized, preferred solutions are located toward the lower left hand corner of the figure. Each gray circle represents objective function values for a solution to the hypothetical optimization problem. First, the user specifies values for ε_1 and ε_2 that represent an objective resolution to be used in evaluations (these epsilon values represent a significant precision for solution ranking). Next, redundant solutions in each grid block are eliminated. For example, solution D is eliminated since solution C is closer than solution D to the lower left hand corner of the block containing both solutions. Finally, nondominated sorting is performed with respect to entire grid blocks. Solution A is eliminated (or epsilon block-dominated) since the grid block containing solution B dominates the entire shaded area. The gray shading in figure 3.1 reflects this block dominance, showing that the block containing solution B will dominate each of the blocks directly above it, or directly to the right of it. The successive shaded areas in the figure illustrate that the final epsilon-nondominated set would include solutions B, C, and E. Our use of epsilon-dominance is important from a theoretical perspective when solving many-objective applications. Evaluations of dominance using epsilon blocks ensures finite solution set sizes, direct user control of computational demands, and improved diversity in search [49, 59].

A large population size in evolutionary algorithms can provide enough new candidate solutions for populations to generate high-quality solutions, but this also increases the computational demand of using the algorithm. The adaptive population sizing approach used in the ε-NSGAII automatically increases or decreases this population size through a series of "connected runs", changing population size in accordance with problem difficulty. The population size is increased by injecting new randomly generated candidate solutions into a population that contains solutions from an epsilon-dominance archive of high-quality solutions. This reduces the number of parameters that the user must set in order to properly use the MOEA, and introduces new candidate solutions to aid further search (i.e., a time continuation operator as recommended by [61]).

Another benefit of using MOEAs for this problem formulation is their known efficacy at solving problems under uncertainty. Robust evolutionary algorithm optimization is discussed in [62], where robustness is defined as the insensitivity of objective function performance to small perturbations in uncertain decision variables. In addition to decision variable uncertainty, the uncertainty in characterizing natural or built system parameters has been explored using single and multiobjective evolutionary algorithm approaches [55, 56, 63, 64]. Each study uses a very small number of Monte Carlo draws to effectively generate solutions to risk-based water resources applications. For the current study, uncertainty stems from our estimates of the reservoir mass balance and available water to the city on a monthly basis, as well as fluctuations in lease pricing and volumetric water demand. Independent Monte Carlo sampling is used here to help find the most robust solutions, with a large enough sample size to lower the oscillations (or uncertainty) in design objective evaluations. The evolutionary analogy is appropriate for optimization under uncertainty since good solutions must robustly perform for exponentially increasing numbers of MC samples during the search process. In successive iterations (generations) of evolutionary search new, independent Monte

Carlo draws are used to evaluate objective function values for each solution. Therefore, if a solution makes it to the final generation, it has already been evaluated for an exponentially increasing number of realizations based on its ability to survive and propagate in the search population [65].

3.3 Computational Experiment

3.3.1 Parameterization of Multiobjective Search

The first phase of the analysis presented in this thesis is to generate the multiobjective tradeoffs for Cases A through D. By generating these tradeoffs, this thesis will show the interactions between planning objectives and decisions to provide decision makers a broader understanding of the potential implications of using the adaptive water portfolio management approach to cope with rising population demands and drought risks.

We enumerated the tradeoff for Case A by calculating the values for each of the three planning objectives for candidate solutions with each discrete integer value of N_R ranging from 30,000 af to 60,000 af in 1 af increments. Recall that the lower bound of 30,000 af represents a constraint that the volume of permanent rights will be adequate to meet the city's average annual demand. Each candidate solution was evaluated for 5,000 independent Monte Carlo samples from the historical or assumed data distributions. While the cost objective f_{cost} for Case A is deterministic, the values for the reliability objective, f_{rel}, and the surplus water objective, f_{surplus}, are based on the results of this Monte Carlo sample. A nondominated sort was performed on the set of 30,000 candidate solutions in order to obtain the Pareto optimal set of solutions with respect to the three planning objectives specified for Case A (see table 3.1).

The ε-NSGAII was used to generate high-quality approximations to the Pareto sets for Cases B through D. Table 3.2 summarizes the algorithm's parameters used in this study. Similar to the calculations for Case A, each potential portfolio is evaluated with 5,000 Monte Carlo samples. Because of the large Monte Carlo sample size, the objective function calculations are strongly representative of their expected values. A smaller sample size, though, could also generate useful results,

Table 3.2. Parameters for this study

Symbol	Value	Description
MC	5,000	Monte Carlo Sample Size
T	10	Planning Period [years]
p_m (Case B)	1/6	Probability of mutation (Case B)
p_m (Case C)	1/8	Probability of mutation (Cases C and D)
p_c	1.0	Probability of crossover
η_c	15	Distribution index (crossover)
η_m	20	Distribution index (mutation)
$\varepsilon_{\text{cost}}$	0.0001	Epsilon Resolution: cost
ε_{rel}	0.0001	Epsilon Resolution: rel
$\varepsilon_{\text{surplus}}$	0.0001	Epsilon Resolution: surplus
$\varepsilon_{\text{costvar}}$	0.001	Epsilon Resolution: costvar
$\varepsilon_{\text{dropped}}$	0.0001	Epsilon Resolution: dropped
$\varepsilon_{\text{leases}}$	0.001	Epsilon Resolution: leases

especially when coupled with variance reduction techniques as in [28]. We were highly conservative in this study with the number of Monte Carlo samples used per portfolio evaluation because we had sufficient parallel computational resources to do so. Moreover we wanted to rigorously explore the mathematical complexities that arise when accounting for the severe risk aversion that typifies water planning problems.

Epsilon dominance is used to set the resolution of the planning objectives in the following manner. Each of the objectives is first scaled to the range 0 to 1 for use in the MOEA. The epsilon resolution used in ε-NSGAII for the kth objective, denoted by ε_k, reflects this transformation. The value of $\varepsilon_{\text{cost}}$ is set to 0.0001, equivalent to a cost resolution in actual dollars of \$10,000. A resolution for the reliability objective, $\varepsilon_{\text{rel}} = 0.0001$, represents scaling of the reliability in increments of 0.01 percent. The values for $\varepsilon_{\text{surplus}}$ and $\varepsilon_{\text{dropped}}$ are set to 0.0001, representing a resolution of 100 af for each objective. The cost variability objective is set to an epsilon resolution, $\varepsilon_{\text{costvar}}$, of 0.001, representing 0.01 of the cost variability index reported in this work (for example, 1.1 compared to 1.2). The resolution of the leases objective represents a difference of 0.1 in the expected value of leases ($\varepsilon_{\text{leases}} = 0.001$).

The operators within ε-NSGAII are parameterized following the recommendations of [49], [48], and [66]. The crossover probability, p_c is set to 1.0 [67]. The mutation probability is set as a function of the number of decision variables being searched [68]. Case B has 6 decision variables and the probability of mutation was set to $p_m = \frac{1}{6}$ and Cases C and D (with 8 decision variables) have $p_m = \frac{1}{8}$. The crossover distribution index η_c is set to 15 and the mutation distribution index, η_m, is set to 20. The adaptive population sizing framework begins each algorithm run with an initial population of 12 individuals. Each connected run is performed for 250 generations, with randomly generated population members introduced after every run at a ratio of 4 random members to every 1 archive member (the adaptive population sizing ratios were set according to recommendations in [69]). Connected runs with this adaptive population sizing are performed for cases B through D for a total of 100,000 function evaluations across the generations of search. Recall that each function evaluation constitutes a Monte Carlo ensemble of 5,000 members. Cases B through D, therefore, each used 500 million simulations of the LRGV case study per single random trial (or initialization seed).

As a population-based search technique, MOEAs require generation of an initial random population of candidate solutions, and the adaptive population sizing with ε-NSGAII also requires input of new random solutions. In addition, the operators used within the algorithm are probabilistic and require random numbers at each iteration. The collection of solutions at the end of an algorithm run therefore depends on the random numbers generated during the search process; that is, the search process will yield different results for successive trials of the same algorithm parameters. To reduce these effects, we used 50 trial runs to rigorously generate reference sets for the tradeoffs presented in Cases B-D. An example of the 50-seed reference set generation technique is provided in [66]. A non-dominated sorting routine is then used to compare results across different random seed trial runs. The tradeoffs represent our best approximation to the true Pareto-optimal set using 50 random trials for each problem subset (i.e., 50 seeds with 500 million simulations per seed yields 2.5×10^{10} simulations per case). Our goal is to very carefully explore the high dimensional spaces of Cases B-D. Again our computational experiment is very conservative and good approximations can be attained using single trial runs with smaller Monte Carlo samples. We were conservative in our analysis because of our expectation that Case D's critical reliability constraint would promote discrete feasibility islands that pose a significant search challenge.

3.3.2 Constraint Handling in Search

This section introduces the constraint handling approach used in this thesis; for more detail, please refer to [58]. During the binary tournament selection used in the ε-NSGAII, two solutions are evaluated to see which has better objective function performance. The approach used in the thesis handles constraints by modifying the definition of domination. Since constraints determine whether or not a solution is feasible (that is, whether or not it violates a constraint), Deb et al. define three cases for when a solution a dominates a second solution denoted by b [58]. In the first instance a is feasible but b is not (regardless of the objective values of a). The second is that both a and b are infeasible but the magnitude of the constraint violation of a is lower than b. The third is that both a and b are feasible but a dominates b (comparing objective function values using the traditional concept of nondomination).

As an example of calculating a constraint violation, consider the reliability constraint c_{rel}, which requires a solution's reliability to be higher than a certain threshold. The constraint violation, v_k associated with a constraint c_k is defined in equation 3.14.

$$v_k = \min\left(\frac{y_k}{y_{\mathrm{constr}_k}} - 1.0, 0\right) \tag{3.14}$$

A value of interest for constraint c_k is given by y_k. In our example, y_k equals the portfolio reliability, f_{rel}. This value is divided by the constraint threshold y_{constr_k}. For the reliability constraint, $y_{\mathrm{constr}_{\mathrm{rel}}}$ is set to 0.98. If this ratio is less than one, subtracting 1.0 yields a negative value for v. Otherwise, the constraint is met and v is set to zero.

In a formulation with multiple constraints, the values for each of the constraint violations are added together. The benefit of this constraint handling approach is that feasible solutions are always preferred over infeasible solutions, but the method allows infeasible solutions to be modified through variation operators to become feasible in subsequent generations during the search process. The method also requires no a priori knowledge of how much to penalize solutions or manually modify them to meet the constraints.

3.3.3 Evaluation of Portfolio Performance Using Drought Scenarios

The second phase of this work evaluates individual water supply portfolios under a severe drought scenario. Four candidate solutions from the highly-constrained Case D representing different portfolio types had their performances independently tested for the driest calendar year on record in the LRGV. We coupled this year with the highest possible demand for each month, adjusted for population growth to reflect the tenth year of the multi-year planning scenario. The drought scenario proposed in this section is a very severe test and statistically unlikely. By assuming maximum monthly demands, the scenario maximizes predictive errors in demand projections based on Monte Carlo sampling. The reservoir inflows that constitute the driest calendar year are also unlikely to be selected from a probabilistic standpoint, and the existence of this year in the historical record shows that it could realistically happen in a similar manner in the future. The scenario created here severely tests the adaptive power of the anticipatory rules used in the evolved portfolios, since the rules for exercising options and purchasing leases are based on assumptions of average demand and reservoir allocations.

Chapter 4

Results

This chapter presents the results of our many-objective analysis of the LRGV case study. Section 4.1 presents the multiobjective tradeoffs for each of the problem formulations while section 4.2 presents results from the drought study, in which an extreme drought scenario was used to test the performance of representative portfolio planning solutions.

4.1 Multiobjective Tradeoffs

This section presents the solution sets for Case A (figure 4.1), Case B (figure 4.2), and Case C (figure 4.3). These results focus on how permanent rights, options, and leasing supply instruments affect the city's water supply tradeoffs.

4.1.1 Case A: Permanent Rights Only

Case A begins with the city using solely permanent rights for the water supply where all potential portfolio solutions have permanent rights volumes (N_R) ranging from 30,000 af to 60,000 af. The tradeoff shown in figure 4.1 was attained by enumerating all 30,000 designs using 1 af increments. Each candidate portfolio was evaluated with respect to its cost (f_{cost}), reliability (f_{rel}), and surplus water (f_{surplus}) planning objectives. The concept of epsilon-dominance was then used to determine the epsilon-nondominated set for Case A, presented in figure 4.1. Note that while we evaluated 30,000 alternatives, we present only those solutions within

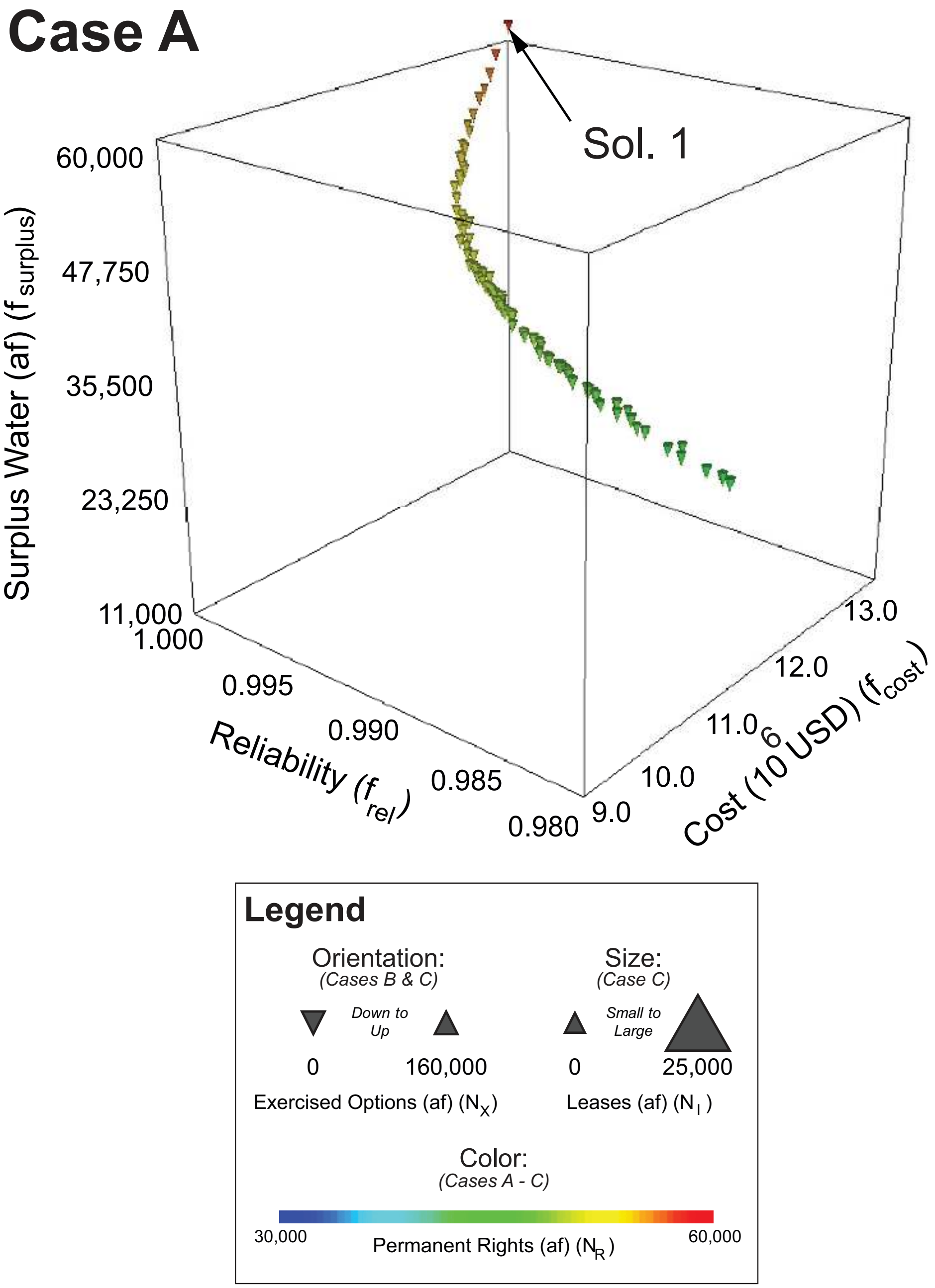

Figure 4.1. Tradeoff for Case A, determined by enumerating discrete integer values of permanent rights volumes. Each cone represents a portfolio planning strategy (a volume of rights). The axes of the figure plot cost, reliability, and surplus water objectives and the color plots the volume of permanent rights: low volumes in blue to high volumes in red. Solution 1 is the high-cost solution in Case A.

the constrained range of reliability (98% to 100%) that are epsilon-nondominated. The reliability (f_{rel}), cost (f_{cost}, from 9 million USD to 13 million USD) and surplus water (f_{surplus}, from 10,000 af to 60,000 af) are plotted on the primary axes. Each of the figures 4.1 through 4.3 have uniform plotting ranges. The coordinates of each solution represent its relative objective function value. The color of each cone in the figures represents the volume of permanent rights from blue (low permanent rights) to red (high permanent rights), indicated with the colorbar in the figures' legend. Using color in this manner has been shown to be an effective way to represent trends in plotted data [51, 70]. Furthermore, visualizing formal objective values simultaneously with decision variables or model output can be helpful for decision makers who often view these analysis components as being interchangeable [71]. This also allows analysts to examine trends or concerns that were not reflected in the original model formulation [72]. The goal is to elucidate the balance between the objectives as a function of the increasing volume of permanent rights. A unique contribution of this work is the ability to move beyond the traditional cost-reliability analysis [73, 74] and consider a broader suite of design objectives.

Solutions in Case A with low permanent rights generally started with a sufficient surplus in the beginning of the simulation to meet demand requirements. As the simulation continued, though, the volume of surplus water would decrease, indicating that failures and shortages were diminishing the city's water supply. Sixty percent of the solutions that were enumerated did not have adequate supply to meet the c_{rel} reliability constraint. The solutions that were able to meet the constraint (with volumes of permanent rights greater than 48,000 af) did so with a large surplus that increased as a function of the simulation year. Solution 1 exemplifies this trend and is plotted in figure 4.1 and summarized in table 4.1. For near-100% reliability, the portfolio had a cost of $13 million and a surplus water objective function value of 61,471 af (the average yearly surplus volume). Its associated volume of end-of-year water is 29,965 af at the end of year one, but 87,099 af in year 10. This large increasing reserve of surplus water has negative implications for the region's other water demands (e.g., water available for environmental flow requirements). Examining the full range of solutions shown in figure 4.1 shows that the marginal cost of increasing reliability increases dramatically for achieving reliabilities near 100%.

4.1.2 Case B: Permanent Rights and Adaptive Options Contracts

Case B adds adaptive options contracting to the permanent rights supply approach used in Case A. The additional decision variables include the low-volume options contract alternative, $N_{O_{\text{low}}}$, the high-volume options contract alternative, $N_{O_{\text{high}}}$, and the contract threshold, ξ (see equation 2.2). The Case B formulation also adds the risk-based decision variables $\alpha_{\text{May}-\text{Dec}}$ and $\beta_{\text{May}-\text{Dec}}$ for options exercising. Table 3.1 shows that Case B adds the dropped transfers objective f_{dropped} and the cost variability objective f_{costvar} with an additional constraint on cost variability, c_{costvar}. Prior work has shown that adding temporary transfers such as options and leases can reduce the city's supply cost while maintaining high reliability [27, 28]. The purpose of this section is to provide a broader understanding of the cost effectiveness and efficiencies provided by the adaptive options contract. The objectives are visualized simultaneously with volumetric permanent rights and exercised options variables to relate objective function performance with the relative volumes of each supply instrument specified by the portfolio's strategy.

Figure 4.2 maintains the spatial plotting axes and color plotting with the ranges of figure 4.1 but additionally plots the expected volume of exercised options, N_x, by using the orientation of each cone. Cones pointing downward indicate a low volume of exercised options (0 af) and cones oriented upwards indicate a high volume of exercised options (160,000 af) cumulatively over the ten year planning period. The value of N_x plotted here represents a sum of the yearly expected values of exercised options for the 10-year simulation for each candidate solution. This value is dependent on the monthly Monte Carlo simulation of inflow and demand, as well as the available water in the city's supply account due to its permanent rights.

Similar to Case A, the high cost solutions near 100% reliability for case B require high volumes of permanent rights (greater than 50,000 af) with costs of approximately 12 to 12.7 million USD. These portfolios lower the volume of permanent rights required to achieve near 100% reliability by exercising options in a small number of the Monte Carlo draws. While these solutions have minimal volumes of dropped transfers, their values for surplus water are still quite high as

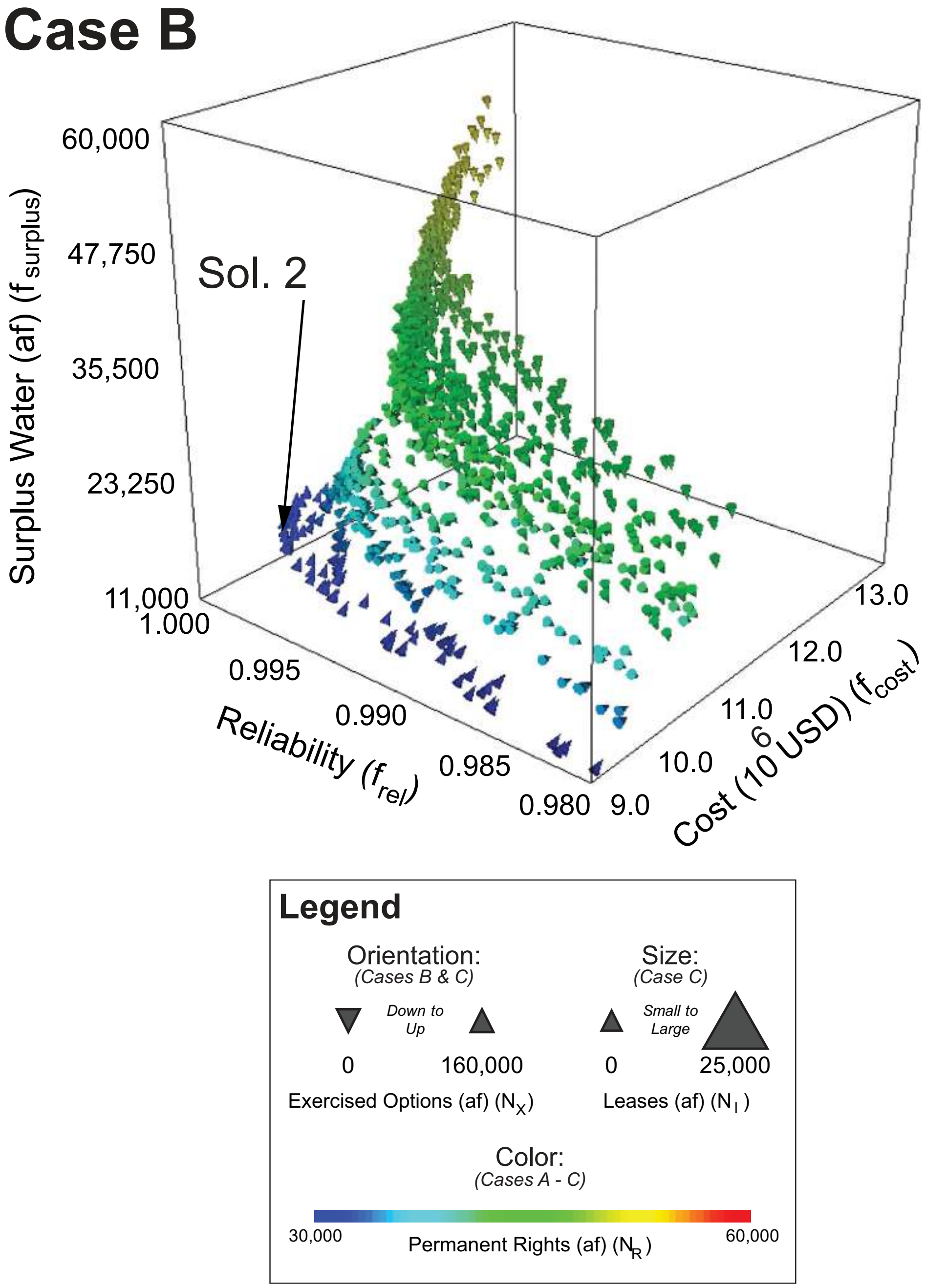

Figure 4.2. Tradeoff for Case B determined by using an MOEA to find nondominated solutions that mix permanent rights and options. Each cone represents a portfolio planning strategy. The axes of the figure plot cost, reliability, and surplus water objectives and the color plots the volume of permanent rights: low volumes in blue to high volumes in red. Additionally, the orientation of the cones plots the exercised options (down to up representing low to high exercised options). Solution 2 is a representative Case B low permanent rights solution.

shown in figure 4.2. The permanent rights-dominated portfolios (shown as green to yellow solutions) have high costs and require high volumes of surplus water. Overall, exercised options lower the cost and surplus water associated with every level of reliability compared to the Case A results in figure 4.1. The blue solutions between 9 and 11 million USD cost also have a lower marginal cost of reliability in addition to the surplus water savings.

Solution 2 is a representative solution for Case B (see table 4.1). The cost objective has a value of 10 million USD, with a cost variability of 1.02 and a surplus water objective value of 16,171 af. For this portfolio, the city had a permanent rights volume of 30,089 af. Its adaptive options contract specifies a low volume alternative of 18,666 af with the high volume alternative of 20,533 af, and the ξ threshold set to 0.25 for choosing which alternative to use. The specified value obligates the city to choose the high-volume alternative in its options contract when its available supply at the beginning of a simulation year is less than 25% of its permanent rights (see equation 2.2). Carryover of water from the options contract led to the city almost always choosing the low-volume options contract (it only chose the high-volume alternative in 1.1% of the Monte Carlo simulations in an average simulation year). However, an average of 4931 Monte Carlo draws per year (out of a possible 5000) resulted in exercising options from the contract in Solution 2. This led to a total expected value of 147,237 af in exercised options over the ten-year planning horizon (see figure 4.2). The consistent exercising of options provides stability from a planning standpoint (i.e., low cost variability), but the strategy also resulted in a value of 71,756 af for the dropped transfers objective. This tradeoff shows that the city consistently exercises a volume of water that exceeds their demand needs to limit their risks. Interestingly, the consistent level of optioned water that expires at a periodic rate leads to a minimized surplus water objective. An interesting result of the Case B tradeoff is the emergence of diverse and distinctly different portfolio strategies. One set of strategies, identified by dark blue solutions, is described by minimal permanent rights and high exercised options. Cyan solutions represent an increase in permanent rights and moderate volumes of options. The remaining solutions have higher permanent rights and low options yielding higher costs to achieve near-100% reliability.

4.1.3 Case C: Permanent Rights, Options, and Leases

The problem formulation for Case C adds leases to the city's water portfolio yielding a total of eight decision variables: the volume of permanent rights (N_R), the low and high alternatives in the options contract ($N_{O_{\text{low}}}$ and $N_{O_{\text{high}}}$) with the high-low contract threshold (ξ), and two sets of alpha/beta variables for the beginning and end of the year ($\alpha_{\text{Jan-Apr}}, \beta_{\text{Jan-Apr}}, \alpha_{\text{May-Dec}}, \beta_{\text{May-Dec}}$). The anticipatory alpha and beta rules are used to exercise options and acquire leases based on Monte Carlo forecasts of the expected ratios of supply to demand. More details on the decision variables used in each formulation can be referenced in table 2.1 and equations 2.2 and 2.3.

Figure 4.3 is formatted similarly to figures 4.1 and 4.2, where the plot axes show values of reliability (f_{rel}), cost (f_{cost}), and surplus water (f_{surplus}). Again the color of the cones represents the volume of permanent rights, N_R, and the orientation of the cones represents the volume of exercised options. An additional plotting mechanism for this tradeoff shows the expected volume of acquired leases with cone size. Small cones represent 0 af of leases while the largest cones represent 25,000 af for the entire simulation. The visualization in figure 4.3 demonstrates how leases dramatically transform the portfolios' performance. Recall that the Case C formulation was solved for a total of six objectives with two constraints (see table 3.1).

At first glance, the tradeoff for Case C shares some similarity with the results of Cases A and B. High permanent rights solutions still exist that have both high reliabilities and the highest costs. The yellow and green solutions figure 4.3 used a very limited number of leases and exercised options (less than 3000 af exercised options and 1700 af leases, as shown visually with each of the solutions pointing downwards and having a small size). Note that even a small number of leases and options significantly lowers the volume of permanent rights (and cost) required to maintain reliability. For example, a solution with 49,514 af of permanent rights achieved 99.96% reliability with $f_{\text{leases}} = 0.3$ (less than one lease during the whole 120 month planning period). Volumetrically, this solution exhibited expected values of acquired leases of 796 af, with 527 af of exercised options on average. In contrast to these yellow and green high-permanent rights solutions, we also see blue and cyan solutions that have similar properties to Case B, with the damp-

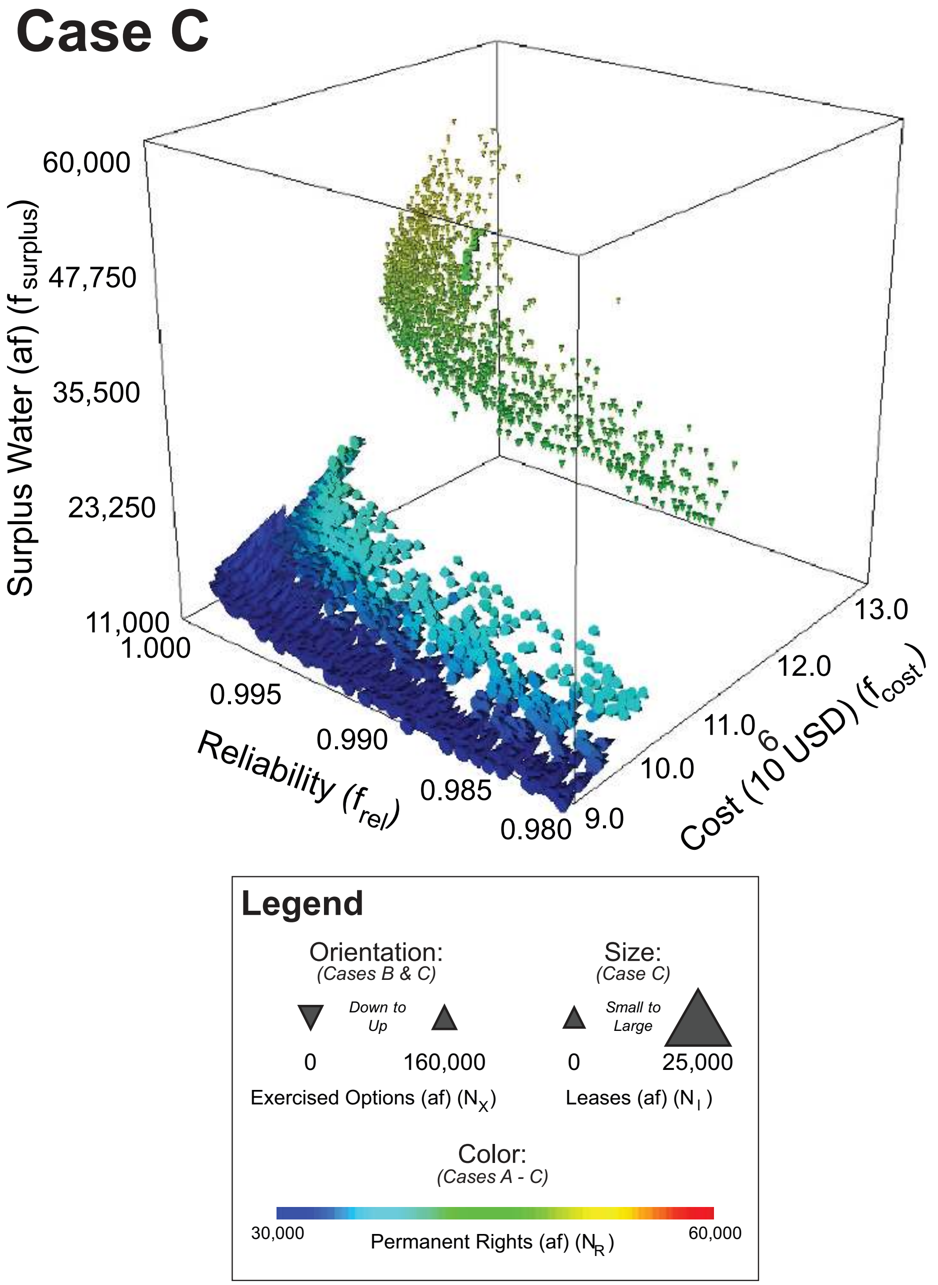

Figure 4.3. Tradeoff for Case C determined by using an MOEA to find nondominated solutions that mix permanent rights, options, and leases. Each cone represents a portfolio planning strategy. The axes of the figure plot cost, reliability, and surplus water objectives and the color plots the volume of permanent rights: low volumes in blue to high volumes in red. Additionally, the orientation of the cones plots the exercised options (down to up representing low to high exercised options) and the size of the cones plots the expected volume of leases (small representing zero leases to large representing the most leases acquired).

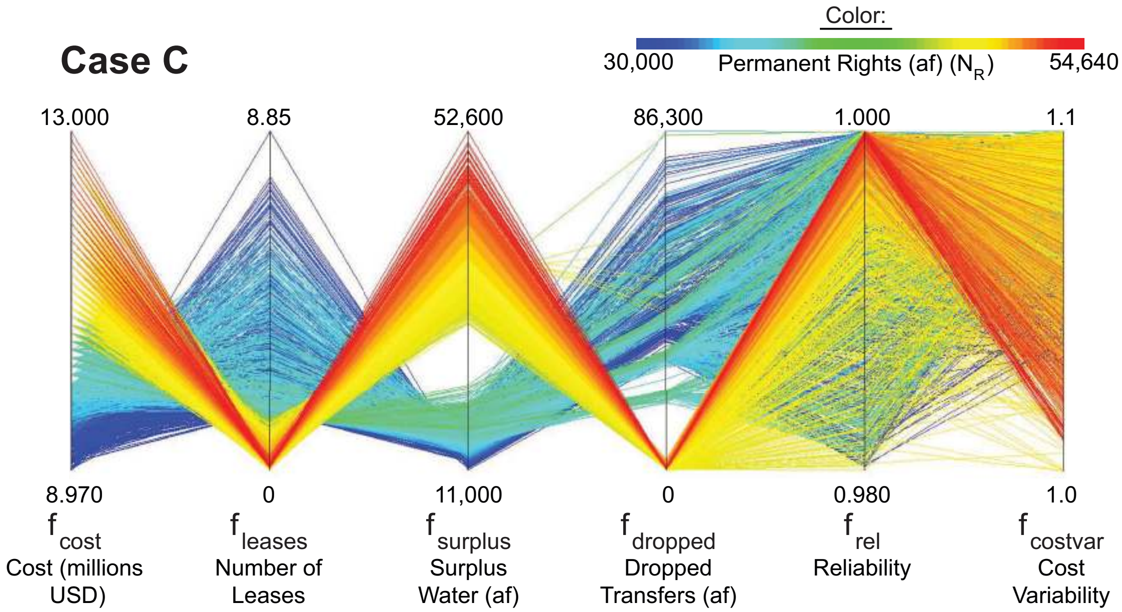

Figure 4.4. Parallel plot of the epsilon-nondominated Pareto approximation of Case C. Each solution is represented by a line in this figure, with the color of each line representing the volume of permanent rights held by each solution portfolio, and the vertical position of the line vertices representing the relative value of the solution's given objective function value. The objective function values for cost, reliability, surplus water, dropped transfers, cost variability, and number of leases are shown. Note the distribution of solutions with high permanent rights (red and yellow solutions) versus the lower permanent rights solutions (blue and cyan solutions).

ened marginal cost of increasing reliability and low volumes of surplus water.

There are significant trends, however, that are unique to case C and are not found with solely permanent rights and options portfolios. Note that there is a distinct break (in terms of cost and surplus water) between the blue and cyan solutions with higher leases and options and the aforementioned yellow and green high-permanent rights solutions. This break does not represent a search failure. It demonstrates a potential discovery of the dramatic influence of leasing on the actual geometry of the objective tradeoffs, not known a priori in our formulation of Case C. Such a break occurs due to the difference between a discrete decision to purchase permanent rights and exercise options at the beginning of the year versus the monthly flexibility of acquiring leases. Relative to Case B (figure 4.2), many portfolios in Case C have dramatically lower costs and surplus water. Leases help the city avoid acquiring excess exercised options to maintain reliability. In fact, the only way that the city can achieve near 100% reliability in Case B is to plan for having a large ratio of exercised options water for 12-month periods to meet excess demand when allocations are low (see the timing lag in the summer months of figure 2.1). In case C, though, the city can acquire leases closer to when the water is actually needed. The complexities of this monthly augmentation strategy motivate looking at all six of the planning objectives simultaneously (figure 4.4).

Figure 4.4 presents a parallel line plot, which is helpful for viewing all of the Case C portfolios' six objectives simultaneously. The parallel line plotting technique has been demonstrated as an effective way to view multiple variables [30, 75, 76]. Each line represents a solution to the planning problem (equivalent to the cones in figure 4.3). The lines are colored similar to the tradeoff figure, but with the permanent rights range scaled from 30,000 af to the highest permanent rights existing in the epsilon-nondominated Case C set, 54,000 af. Therefore, low permanent rights solutions are still blue in color and they transition to high permanent rights solutions in green, yellow, and red.

Conflicts and interdependency between the objectives can be readily explored using parallel line plots [30]. For example, consider the two minimization objectives surplus water (f_{surplus}) and dropped transfers (f_{dropped}) where the objectives are plotted with optimal values near the bottom of the plot. If a conflict did not exist between these objectives, a solution with optimal values for both objectives would have a horizontal line near the bottom of the plot. However, we can observe a conflict between the objectives, in which minimal surplus water cannot be achieved without having a higher value for dropped transfers. This is an interesting result for water managers who may assume that purchasing leases and exercising options that tend to expire is wasteful. The result presented in figure 4.4 shows that red (high permanent rights solutions) tend to have high costs with minimal numbers of leases, but maximize surplus water while minimizing their dropped transfers. We can see that there are low permanent rights solutions that minimize cost and surplus water, but do so by having higher values for the number of leases and dropped transfers objectives. Moving from the dropped transfers objective to reliability and cost variability, we note that in high permanent rights solutions, small decreases in permanent rights at high reliability require a slightly higher cost variability, due to those portfolios' reliance on options and leases to meet their demand requirements. It should be noted that on average over the full 120-month planning period fewer than 9 leases would be expected to be used across all of the nondominated solutions. Figure 4.4 also highlights that many-objective analysis can falsify preconceptions on system performance. Operationally it would seem intuitive to minimize dropping transfers of water but in reality this could maximize costs and supply shortfall risks.

Using the parallel line plot, we find that the presence of more than three objectives can highlight groups of planning goals that represent tradeoffs between different system operating heuristics and conceptions about how to best operate the system. At a high level of reliability, we see that there is a set of objectives that captures risk aversion (having near optimal values for dropped transfers, cost variability, and leases but allowing inferior performance in cost and surplus water) and a set of objectives that captures a more flexible approach by having near optimal performance with respect to cost and surplus water while trading off degradations in performance with respect to dropped transfers, cost variability, and the number of leases. The visualization of figure 4.4 provides a direct feedback, therefore, in furthering system understanding and allowing the decision maker to modify their problem formulation and conceptual understanding of the system.

4.1.4 Case D: Portfolio Planning Under A Critical Reliability Constraint

The Case D problem formulation maintains the supply instruments, evaluative performance objectives and constraints of Case C but adds the restrictive c_{critrel} constraint (see table 3.1). Equation 3.4 requires that the "critical" reliability of candidate portfolios is 100%, equivalent to ensuring that the supply in each month of the 120 month simulation is at least 60% of the simulated demand. This requirement mathematically abstracts severe risk aversion and is challenging given the large Monte Carlo ensemble size used in this study. The portfolio strategies are required to be robust enough to have supply even when low reservoir inflows are coupled with high water demand. Of the set shown in figure 4.5, the lowest reliability identified was 99.5%, indicating that the lower reliabilities (between

98% and 99.5%) would often yield a nonzero probability of having a critical failure during the simulation. We recognize that in reality there will always be some nonzero likelihood of a critical failure; our analysis in this section seeks to explore only the most extreme reliability alternatives.

The limited range of reliability identified in Case D motivated different plotting axes for the tradeoff. Two of the primary axes, plotting cost (f_{cost}) and surplus water (f_{surplus}), are similar to figures 4.1, 4.2 and 4.2. The key difference is that the dropped transfers objective (f_{dropped}) from 0 af to 80,000 af has been plotted on the remaining axis. Recall that the dropped transfers objective is calculated as a sum of the expected value of dropped transfers in each simulation year. Solutions 3 through 6 exemplify the different regions of this objective tradeoff and capture the maximally different alternatives [33] for satisfying extreme risk aversion.

Similar to figure 4.3, a distinct break in terms of surplus water and cost is seen between yellow and green solutions (the groups that contain solutions 3 and 4) and the blue and cyan solution group (that contains solutions 5 and 6). The figure also indicates a similar discontinuity with respect to the dropped transfers objective. While Case D's tradeoff behavior is similar to the Case C portfolios' objective value performance, an important result for the Case D analysis is that we identified many high-quality solutions with very high reliability in the reduced permanent rights region (blue and cyan solutions). These solutions each have near 100% reliability while maintaining the same relative volume of surplus water. In this region of the objective space, we find that at a given volume of dropped transfers, increasing the permanent rights represents a cost increase, and a gradual increase in surplus water commensurate with the increase in N_R. The level of dropped transfers can be controlled by the adaptive strategy for a given portfolio, as the city uses temporary transfers in place of permanent rights to manage shortfalls. This result shows that there is a certain level of dropped transfers that are required to fulfill the critical reliability constraint for the water planners, but the cost savings and surplus water savings to do so are significant and worthwhile. It is also interesting to note that the discrete spacing of the different portfolio types mathematically represents isolated islands of feasible solutions that would be difficult to discover using one-at-time single objective analysis and more narrowly-defined views of “optimality”.

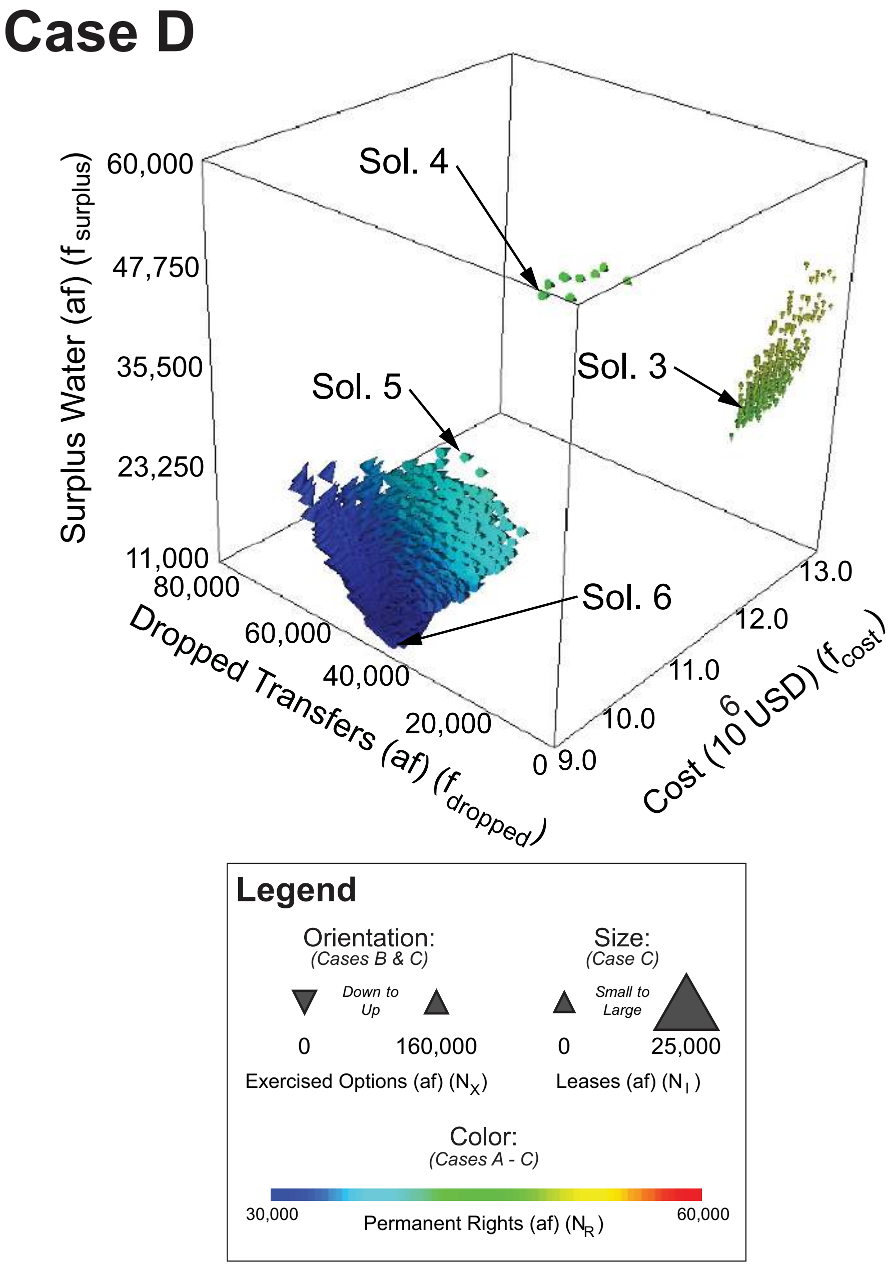

Figure 4.5. Tradeoff for Case D determined by using an MOEA to find nondominated solutions that mix permanent rights, options, and leases subject to the critical reliability constraint. Each cone represents a portfolio planning strategy. The axes of the figure plot cost, reliability, and surplus water objectives and the color plots the volume of permanent rights: low volumes in blue to high volumes in red. Additionally, the orientation of the cones plots the exercised options (down to up representing low to high exercised options) and the size of the cones plots the expected volume of leases (small representing zero leases to large representing the most leases acquired). Solutions 3 - 6 from the figure are selected for further analysis.

4.2 Drought Scenario Performance

An important assumption of the anticipatory planning approach used in our LRGV case study model is that the ratio of expected supply to expected demand is used when planning augmentations to the city's water supply through options and leases. This rule is analogous to many traditional planning approaches in water management that assume stationarity in future performance with respect to the historical record [1]. We identified the solutions based on their objective performance in the 10-year problem formulation described in section 3.1, with values shown in table 4.1. However, by changing the supply and demand scenario, we will test the generality of the portfolio strategies and whether or not the planning alternatives identified in the prior sections are appropriate given an independent performance test based on a plausible but extremely unlikely scenario according to the LRGV historical data and demand assumptions. Testing planning strategies is important as municipalities seek a risk management approach to coping with drought, as discussed in [77]. As described in section 3.3.3, this section uses the driest calendar year on record coupled with the largest feasible demand in every month's assumed distribution that accounts for maximum population growth as modeled in the 10th year of the Monte Carlo simulation.

We chose four solutions from Case D for the drought analysis. Table 4.1 summarizes the decision variables, objective function performance, and model output from these solutions (including the example solutions discussed in Cases A and B). The primary question to be answered is: how will the identified long-term high performance portfolios perform during an extreme drought event? Generally, this question tests the validity of an optimization model that uses mean behavior as a predictor of future challenges for water management. Recall that our portfolio strategies specify the supply decisions for a single city. This section will briefly discuss the solutions' performance in the 10-year simulation model and we will compare this performance to the drought scenario we specified. Solution 3 was selected from the high permanent rights group. With 49,289 af of permanent rights, the city supplemented its supply in this portfolio with 1,259 af of leases on average and exercised its options contract in only 0.9% of the Monte Carlo draws on average. Note that even the small volume of leases and options in this port-

Table 4.1. Selected Solutions' Performance in 10-Year Model

Solution	1	2	3	4	5	6
Case	A	B	D	D	D	D
$f_{\text{cost}}(10^6\ \$)$	13.0	10.0	11.5	12.5	11.0	9.2
$f_{\text{rel}}(\%)$	99.99	99.97	99.99	100.00	99.99	99.56
f_{surplus} (af)	61,471	16,170	37,038	33,858	21,031	12,271
f_{dropped} (af)	0	71,756	598	60,892	54,025	37,713
f_{costvar}	1.00	1.02	1.10	1.05	1.09	1.10
f_{leases}	0.0	0.0	0.5	0.7	1.1	4.8
N_R	57,696	30,089	49,289	45,737	39,851	30,011
ξ	N/A	0.25	0.15	0.30	0.10	0.15
$N_{O_{\text{low}}}$	N/A	18,666	5,615	19,450	16,363	14,644
$N_{O_{\text{high}}}$	N/A	20,533	7,861	38,900	22,908	19,037
$\alpha_{\text{May}-\text{Dec}}$	N/A	1.6	1.1	2.1	1.6	1.5
$\beta_{\text{May}-\text{Dec}}$	N/A	1.8	1.3	2.8	2.0	1.5
$\alpha_{\text{Jan}-\text{Apr}}$	N/A	N/A	1.8	1.8	1.6	1.5
$\beta_{\text{Jan}-\text{Apr}}$	N/A	N/A	2.0	1.8	1.7	1.5
$\%\ N_{O_{\text{high}}}$	N/A	1.1	1.4	10.9	0	0
$\%\ N_x$	N/A	98.624	0.9	38.3	56.7	82.7
N_x (af)	0	147,237	264	59,074	66,562	90,125
N_l (af)	0	0	1,259	11,772	12,672	18,966

folio was able to save the city 1.5 million dollars throughout the 10-year scenario versus the high-cost, permanent-rights supply portfolio in Case A. Solution 4 is characterized by high permanent rights and high leases and was chosen from the group of isolated solutions in the top region of figure 4.5. This compromise region was not artifically created but is a result of the non-dominated ranking in our many-objective analysis, since these solutions have lower values of cost variability than each of the other identified Case D solutions, allowing them to survive in the evolutionary search. Solutions 5 and 6 are from the low permanent rights region. Solution 5 represents the cyan region where lower options and an increased use of permanent rights are used to meet the critical reliability constraint. Alternatively solution 6 uses an increased volume of exercised options and reduced permanent rights.

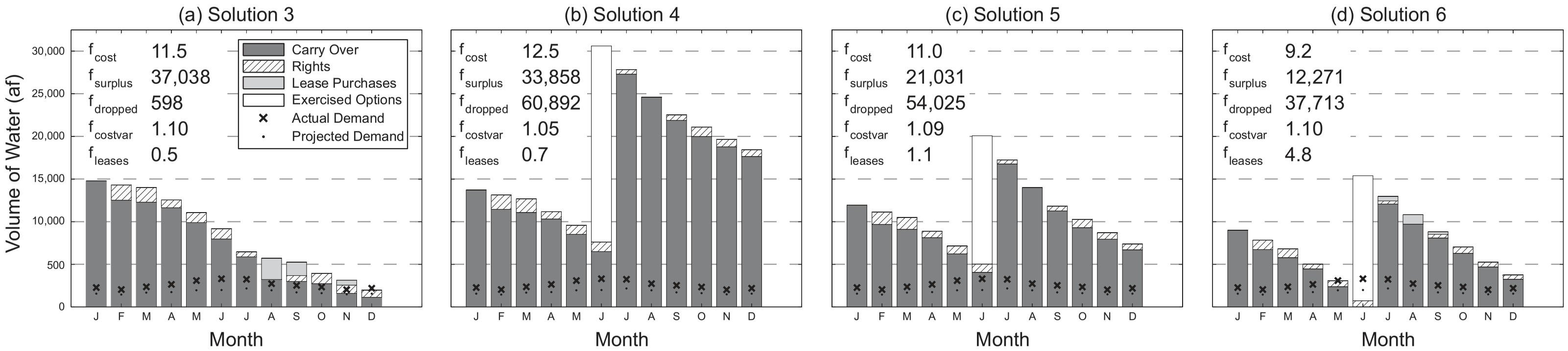

Figure 4.6. Monthly water balance for selected portfolios evaluated during the drought scenario. The dark gray bars indicate initial condition water (in January) and water carried over from the previous month. Allocations to rights are shown with hashed lines, and light gray bars indicate leases. Exercised options are shown with white bars, and the projected demand is shown with dots. The actual demand is shown with the x symbol, and a failure occurs when the ordinate of the demand (x) is higher than the bar graph. Objective function values from the ten-year simulation are shown for each solution, with reliability omitted due to its near-100% value for each solution. For the objective function values, cost is in millions of USD while surplus and dropped water is given in acre ft.

Figure 4.6 presents the results from each of the solutions during the drought year. The bar charts represent a water balance for the city's water supply in each month of the simulation. In January, the city begins with the modeled initial condition of S_{Jan} equal to 30% of the portfolio's permanent rights, as a surrogate for the water that is often left in the city's water supply account from the previous year. This water is indicated as "carry over" water in the figure and shaded dark gray. In February through December, the hashed lines represent water allocated to the city's permanent rights in the previous month available for use in the current month. Similarly, the light gray and white boxes represent leased and optioned water purchased by the city in the previous month and available for use in the current month. The Monte Carlo prediction of demand (based on the historical average) is shown with a circle symbol in each month. The "true" or scenario's maximum demands are designated with an x symbol. Note we are degrading the predictive value of the Monte Carlo projections used in the risk-based alpha/beta calculation for lease acquisition and options exercising. A failure happens, then, when the demand (x symbol) falls higher than the supply (of carried over water, rights allocations, options, and leases) indicated by the bar. Due to the nature of the adaptive planning strategies, the city cannot forecast the drought conditions and only allocates water according to the ratio of expected supply and expected demand for a given month.

Figure 4.6a shows that Solution 3 would be typically forced to rely on a large volume of surplus water, or water carried over in its account, to fulfill supply. In years with high permanent rights allocations, this would be sufficient to build a level of water that would be adequate to meet demand, similar to the volume that it begins with in January. However, in this scenario the allocations to permanent rights are low, and the city specifies lease purchases for the months of August, September, and November. These allocations are insufficient to avoid a small failure in the month of December. Examining the portfolio strategy summarized in table 4.1, we see that this failure was partially due to the relatively low values of alpha and beta in this strategy. Interestingly, water from the options contract was also not exercised here due to the high volume of water the city initially had in its account as a function of the initial condition.

Solution 4 specified a large volume of rights, options, and leases in the multiyear scenario with the high values for alpha and beta as well. An interesting consequence of the problem formulation identified in this work is that some portfolios with low cost variability would also have high average costs, since cities that purchase high volumes of options consistently would have a low level of variability in their costs. This conservative strategy was a success here, with no failure occurring and a large quantity of water at the end of the year due to the large volume of options exercised in this scenario.

Solutions 5 and 6 use a combination of leases and options to cope with the drought, with a slightly higher initial condition for solution 5 due to its higher permanent rights. The lower initial condition for solution 6 triggered some lease purchases for the months of July, August, and September, but these purchases were not enough to avoid the small shortfall in May. For each of the solutions, no leases were purchased until after the options exercising in May due to the initial condition related to the permanent rights in this scenario. The benefit of solution 6, though, was that its supply strategy exhibited resilience by providing adequate supply after the failure in May. This demonstrated flexibility is important since this solution had low cost and surplus water in the ten-year scenario as well as good performance during the drought scenario.

Chapter 5

Discussion

The discussion in this chapter focuses on three major themes: the value of water portfolio planning (section 5.1), the value of many objective analysis (section 5.2), and the value of the constructive decision aiding paradigm (section 5.3).

5.1 The Value of Water Portfolios

The LRGV case study presented in this work demonstrates the efficiency and effectiveness of water supply portfolio planning using adaptive options contracting and spot leases. This flexible approach is helpful for municipalities like those in the LRGV that face rising supply development costs under increasing hydrologic uncertainty [1]. The addition of leases and options had a dramatic effect on the range of portfolios and alternatives identified. Leasing and adaptive options supply instruments can significantly lower water supply costs and improve reliability while enhancing the overall efficiency of alternatives (both logistically and volumetrically). The work confirmed the cost savings at high reliability suggested in prior studies [27, 28]. Our "many-objective" analysis shows that cost savings appeared even in portfolios that followed a more conservative water supply approach by using leases and options sparingly as a supplement to the city's permanent rights. This work moves beyond the standard cost-reliability analysis by using volumetric and logistical metrics to measure the city's efficiency in using leases and options. Reductions in permanent rights with increases in leases and options yielded decreases in surplus water and dramatic cost savings. The demonstrated logistic efficiency of these portfolios can help to alleviate some concerns over transactions costs in using a portfolio approach, since the portfolio with the highest number of leases specified less than 9 leases in a 120 month planning scenario. Beyond the benefits of leases and options, the many-objective analysis has a strong potential for providing decision makers with feedbacks on limitations in their intuitive heuristic planning rules and system preconceptions [36–38]. For example, we modeled temporary transfers of water in this study to expire after 12 months of nonuse. The costs associated with dropped transfers analyzed in Cases C and D are negligible compared to their benefits in overall cost-savings, reduced surplus water, and system reliability. These benefits could be lost by a water manager's hesitancy to purchase these "wasted" transfers.

Historically, many water management applications focusing on deterministic, least cost analysis have noted the "flat" or well behaved solution spaces for planning problems [78]. The six-objective, critical risk analysis in Case D of this study does not support this view. The inclusion of severe risk aversion for critical failures in Case D showed that many of the failures of Case C were in fact critical failures. This is a clear example of the systems planning risk of "standing on the point of a needle", meaning that shifts towards extreme system states [1] may severely degrade the forecasted behavior of deterministic optima, exposing water managers to severe failures.

Our modeling of extreme risk aversion and portfolio performance for an extreme drought scenario is an important contribution of this work. The scenario limited the predictive power of the city's planning strategy, creating an unexpected supply shortfall under conditions of extreme demand. We found that the leases and options provided a way for the city to cope with the drought even in portfolios that had minimal use of these temporary instruments during the multiyear planning scenario. Solution 3, identified in case D (see figure 4.5a) with high permanent rights and low expected number of leases, specified that the city purchase three leases in the drought year. So in fact a decision maker heuristic of seeking to minimize dependence on transfers would inadvertently make their system critically dependent on several leases for extreme system states (i.e., timid use of the market and inaccurate forecasts of the success of reservoir storage, see [79]). Solutions 4 - 6, which represented portfolios that relied more heavily on leases and options, provided a more resilient performance during the scenario, ironically using fewer leases than solution 3 in the drought scenario year. This portion of our analysis shows that managers should be cognizant of the risk management decision heuristics inherent in their portfolio planning to ensure robustness in unexpected and extreme situations.

5.2 The Value of Many-Objective Planning

Our analysis identified interesting relationships between planning objectives that were not previously known, such as minimizing dropped (or wasted) transfers can dramatically increase costs and risks for supply failures. Adding objectives can prove that the “optimal” solution to a single objective problem can appear in the inferior region with respect to broader problem formulations [33]. Using many objectives suggests a paradigm of discovery and negotiation, in which decision makers can learn about the structure of the problem itself, challenge preconceptions used in their decision making, and “shop” for solutions that can allow them to learn more about their planning problem.

By specifying six objectives in case C or D, we are solving more than 60 problems simultaneously in each case, including the six single objective problems, fifteen two objective problems, twenty three-objective problems, and so on. It would be difficult to specify each of these combinations a priori, but with proper visualization the decision maker can identify clear trends and relationships between the objectives in the whole space of the problem or any of its subspaces. This study builds on the visualization analysis in [51] and contributes an understanding of the relationship between volumetric water supply instruments and evaluative water supply planning objectives. After probing the solution sets created with the evolutionary algorithm, we chose several representative solutions to be analyzed under the drought scenario, as has been successfully demonstrated in prior studies [29, 51, 70]. Our visualization combined with many-objective analysis can provide decision heuristic feedbacks and reduce the potential for cognitive myopia [36] that may result from narrowly-defined delineations among decision variables, objectives, constraints, and other metrics. Moreover, we have solved a linked chain of formulations as an example of how to account for the nonstationarity of management problem formulations [32] and as a tool to reduce cognitive hysteresis in decision making [35].

5.3 The Value of Constructive Decision Aiding

Our combination of optimization, visualization, and explorative analysis of interesting solutions represents a direct attempt to demonstrate the constructive decision aiding paradigm [80] for a water resources management application. Roy highlights that objectives, decisions, and preferences of decision makers are rarely well-defined at the beginning of analysis [80]. This study has presented a flexible approach in which an evolving "chain" of problem formulations helps planners understand the dynamics of their system and planning problem. The problem formulations we identified were each a subset of the most complex formulation, but the stepwise approach in this thesis helps shed light on the relative contribution of options independent of leases, and the effect of adding a restrictive critical reliability constraint. An important feedback between the analysis and visualization exists where the trends learned in visualization of the many objective analysis inform future analyses and promote new problem formulations. This result highlights the importance of management model structural uncertainties [81] that can only be dealt with using diverse hypotheses and problem views to reduce the risks associated with decision-making errors. By combining a flexible, evolving approach to the problem structure (i.e. multiple formulations) we were able to evolve planning strategies that proved robust even when evaluated through metrics that were not originally included in the analysis [72].

Chapter 6

Conclusion

Water markets seek to allocate water resources to their highest value use and provide a mechanism for water planners to improve the reliability of urban water supply. The increasing risks posed by drought have encouraged a broader range of market-based supply management tools being made available to water portfolio planners including mixtures of permanent rights to fixed percentages of uncertain reservoir inflows, spot market leases, and adaptive options contracts. Spot market leases offer a highly flexible, but potentially price volatile supply instrument for short term water transfers. Options address the price volatility of leases by allowing planners to reserve a fixed price for a set volume of water that may be transferred later in a planning year. Beyond reducing price volatility, options also provide planners with more time to assess the state of their system before exercising options and transferring water into their systems. The flexibility of these supply instruments when used to augment traditional permanent rights is both a challenge and an opportunity for effective water resources planning and management under the risks posed by growing population demands and climate change.

This thesis contributes the first "many-objective" analysis of how to manage the flexibility, uncertainty, and risks inherent in water portfolio planning from a city's perspective within a Lower Rio Grande Valley case study. All supply alternatives were evaluated in this work using regional data and Monte Carlo simulation of demands, pricing, and supply variability in the LRGV. This work contributes a unique example of how to "chain" or evolve problem formulations to clearly demonstrate the impacts of permanent rights, options, and leasing on a broad array of performance metrics. Tradeoff surfaces are both quantified and visualized that capture the impacts of up to six objectives. These surfaces clarify the dependency structure of each portfolio's cost, cost variability, reliability, surplus water volumes, frequency of leasing, and dropped (or wasted) transfers. Drawing on growing concerns of the nonstationarity in forcing characteristics and response of hydrologic systems, this study uses a severe drought scenario to demonstrate that leases and options dramatically reduce the costs associated with avoiding critical failures in urban water supply systems when confronted with unexpected and severe extremes in both water demands and water scarcity.

Our drought scenario analysis demonstrates that the combination of severe risk aversion typical of urban water supply planners and the potential for growing uncertainties yields significant mathematical challenges for water portfolio planning using traditional tools. In this study, these challenges manifested themselves in the form of complex discontinuities in the search problem and the potential for severe supply failures. These challenges were overcome in this work by combining multi-objective evolutionary optimization, interactive high-dimensional tradeoff visualization, and evolving problem formulations. Additionally, as noted above, severe drought scenario analysis was used to verify the adaptability, cost-effectiveness, reliability, and resilience of a diverse suite of portfolio planning strategies identified in our results. Another unique contribution of this work is the exploration of nonstationarity in how we define and solve water management problems. This stems from the dynamic nature of water management problems; as designers make new discoveries, they can create new hypotheses and subsequently introduce structural changes in their mathematical formulations. The structural nonstationarity (or uncertainty) is both a challenge and an opportunity for innovating how we conceptualize and solve future water management problems. In this thesis, we demonstrate that evolving many-objective problem formulations and interactive tradeoff visualization has strong potential for confronting many of the cognitive challenges posed by decision making under uncertainty while facilitating both discoveries and negotiation in water planning problems.

Chapter 7

Future Work

This study represented an effective way to analyze the tradeoffs and uncertainties associated with a single city's water supply portfolio strategies. Future work can continue to address the challenges that a single city would face under growing population demands and increasing hydrologic variability. In this thesis, the sensitivity of the adaptive planning strategies to changes in the hydrologic forcing (i.e., an extreme drought scenario) demonstrated the need for improved planning strategies for municipalities to use water markets. These new strategies could help the city to augment its supply even when historical data does not provide sufficient predictive power [1] and extreme conditions warrant a more diversified portfolio strategy to provide reliable supply. An extension of this framework would be to incorporate the interactivity in the optimization process itself, adding interactive decision steering [82] to guide the generation of alternatives in real-time or using visualization as an a posteriori analysis tool as demonstrated in [29, 51]. In either case, this interactive visualization involves the decision maker in the planning process by facilitating new hypotheses and examining interesting potential solutions. The modular framework would allow further modifications in the problem structure such as new assumptions about drought or population pressure to the system in order to test the robustness of selected solutions and decision making heuristics.

These advanced tools for single-city planning will ultimately need to be extended to a regional approach to improve the sustainability of water supply at larger scales [6]. Regional environmental concerns such as the degradation of ecosystems coupled with myriad conflicting uses for our water resources magnify the socioeconomic and climate change factors that threaten our engineering systems. Future work extending from this thesis will need to address regulatory issues associated with these water resources conflicts. In particular, we need to formulate hypotheses on how changes in understanding of our environmental systems (see [83] for an interesting discussion) impact the built system that sustains economic growth. The evolving chain of problem formulations suggested in this thesis could be extended to test hypotheses about increasing model complexity and its effect on our ability to predict risks to water supply, water allocation, and environmental sustainability.

Bibliography

[1] Milly, P. C. D., J. Betancourt, M. Falkenmark, R. Hirsch, Z. W. Kundzewicz, D. P. Lettenmaier, and R. J. Stouffer (2008) "Stationarity is Dead: Whither Water Management?" *Science*, **319**, pp. 573–574.

[2] Kundzewicz, Z., L. Mata, N. Arnell, P. Doll, P. Kabat, B. Jimenez, K. A. Miller, T. Oki, Z. Sen, and I. Shiklomanov (2007) "Freshwater resources and their management," in *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* (M. Parry, O. Canziani, J. Palutikof, P. J. van der Linden, and C. E. Hanson, eds.), Cambridge University Press, Cambridge, pp. 173–210.

[3] Frederick, K. D. and G. Schwarz (1999) "Socioeconomic Impacts of Climate Change on U.S. Water Supplies," *Journal of the American Water Resources Association*, **35**(6), pp. 1563–1583.

[4] Lane, M. E., P. H. Kirshen, and R. M. Vogel (1999) "Indicators of Impacts of Global Climate Change on U.S. Water Resources," *Journal of Water Resources Planning and Management*, **125**(4), pp. 194–204.

[5] Barnett, T., R. Malone, W. Pennell, D. Stammer, B. Semtner, and W. Washington (2004) "The Effects of Climate Change on Water Resources in the West," *Climactic Change*, **62**, pp. 1–11.

[6] Vaux Jr., H. J. and R. E. Howitt (1984) "Managing Water Scarcity: An Evaluation of Interregional Transfers," *Water Resources Research*, **20**(7), pp. 785–792.

[7] Saliba, B. C. (1987) "Do Water Markets Work? Market Transfers and Trade-Offs in the Southwestern States," *Water Resources Research*, **23**(7), pp. 1113–1122.

[8] Colby, B. G., M. A. McGinnis, and K. A. Rait (1991) "Mitigating Environmental Externalities Through Voluntary and Involuntary Water Reallocation: Nevada's Truckee-Carson River Basin," *Natural Resources Journal*, **31**(4), pp. 757–783.

[9] Lund, J. R. and M. Israel (1995) "Water transfers in water resource systems," *Journal of Water Resources Planning and Management*, **121**(2), pp. 193–205.

[10] Kaiser, R. A. and M. McFarland (1997) "A Bibliographic Pathfinder on Water Marketing," *Natural Resources Journal*, **37**(4), pp. 881–908.

[11] Wilchfort, O. and J. R. Lund (1997) "Shortage Management Modeling for Urban Water Supply Systems," *Journal of the American Water Resources Association*, **123**(4), pp. 250–258.

[12] Watkins Jr., D. W. and D. C. McKinney (1999) "Screening Water Supply Options for the Edwards Aquifer Region in Central Texas," *Journal of Water Resources Planning and Management*, **125**(1), pp. 14–24.

[13] Jenkins, M. W. and J. R. Lund (2000) "Integrating Yield and Shortage Management under Multiple Uncertainties," *Journal of the American Water Resources Association*, **126**(5), pp. 288–297.

[14] Howe, C. W. and C. Goemans (2003) "Water Transfers and their Impacts: Lessons from Three Colorado Water Markets," *Journal of the American Water Resources Association*, **39**(5), pp. 1055–1065.

[15] Bauer, C. J. (2004) "Results of Chilean water markets: Empirical research since 1990," *Water Resources Research*, **40**(W09S06, doi:10.1029/2003WR002838).

[16] Nieuwoudt, W. L. and R. M. Armitage (2004) "Water market transfers in South Africa: Two case studies," *Water Resources Research*, **40**(W09S05, doi:10.1029/2003WR002840).

[17] Frederick, K. D. and D. C. Gibbons (eds.) (1986) *Scarce Water and Institutional Change*, Resources for the Future, Inc., Washington, D.C.

[18] Schoolmaster, F. A. (1991) "Water Marketing and Water Rights Transfers in the Lower Rio Grande Valley, Texas," *Professional Geographer*, **43**(3), pp. 292–304.

[19] Israel, M. and J. R. Lund (1995) "Recent California Water Transfers: Implications for Water Management," *Natural Resources Journal*, **35**(1), pp. 1–32.

[20] Anderson, T. L. and P. J. Hill (eds.) (1997) *Water Marketing: The Next Generation*, The Political Economy Forum, Rowman and Littlefield, Lanham.

[21] Hadjigeorgalis, E. (2008) "Managing Drought Through Water Markets: Farmer Preferences in the Rio Grande Basin," *Journal of the American Water Resources Association*, **44**(3), pp. 594–605.

[22] Howitt, R. E. (1998) "Spot Prices, Option Prices, and Water Markets: An Analysis of Emerging Markets in California," in *Markets for Water: Potential and Performance* (K. W. Easter, M. W. Rosegrant, and A. Dinar, eds.), Kluwer Academic Publishers, Boston, pp. 119–140.

[23] Ranjan, R. (2008) "Predicting Participation in Spot and Options Markets for Water," Http://works.bepress.com/ram_ranjan/11/.

[24] Michelsen, A. M. and R. A. Young (1993) "Optioning Agricultural Water Rights for Urban Water Supplies during Drought," *American Journal of Agricultural Economics*, **75**(4), pp. 1010–1020.

[25] Villinski, M. T. (2004) "Valuing Multiple-Exercise Option Contracts: Methodology and Application to Water Markets," in *American Agricultural Economics Association Annual Meeting*, Denver, Colorado.

[26] Lund, J. R. (1995) "Derived estimation of willingness to pay to avoid probabilistic shortage," *Water Resources Research*, **31**(5), pp. 1367–1372.

[27] Characklis, G., B. R. Kirsch, J. Ramsey, K. Dillard, and C. T. Kelley (2006) "Developing portfolios of water supply transfers," *Water Resources Research*, **42**(W05403, doi:10.1029/2005WR004424).

[28] Kirsch, B. R., G. W. Characklis, K. Dillard, and C. T. Kelley (2009) "More efficient optimization of long-term water supply portfolios," *Water Resources Research*, **45**(W03414, doi:10.1029/2008WR007018).

[29] Reed, P. M. and B. S. Minsker (2004) "Striking the Balance: Long-Term Groundwater Monitoring Design for Conflicting Objectives," *Journal of Water Resources Planning and Management*, **130**(2), pp. 140–149.

[30] Fleming, P. J., R. C. Purshouse, and R. J. Lygoe (2005) "Many-Objective Optimization: An Engineering Design Perspective," in *EMO 2005: The Third International Conference On Evolutionary Multi-Criterion Optimization* (C. Coello Coello, A. Aguirre, and E. Zitzler, eds.), no. 3410 in Lecture Notes in Computer Science, Springer Verlag, pp. 14–32.

[31] Farber, D., M. Pietrucha, and A. Lakhtakia (2008) "Systems and scenarios for a philosophy of engineering," *Interdisciplinary Science Reviews*, **33**(3), pp. 214–225.

[32] Zeleny, M. (2005) "The Evolution of Optimality: De Novo Programming," in *EMO 2005: The Third International Conference On Evolutionary Multi-Criterion Optimization* (C. Coello Coello, A. Aguirre, and E. Zitzler, eds.), no. 3410 in Lecture Notes in Computer Science, Springer Verlag, pp. 1–13.

[33] Brill, E. D., J. M. Flach, L. D. Hopkins, and S. Ranjithan (1990) "MGA: A Decision Support System for Complex, Incompletely Defined Problems," *IEEE Transactions on Systems, Man, Cybernetics*, **20**(4), pp. 745–757.

[34] Woods, D. (1986) "Paradigms for intelligent decision support," in *Intelligent Decision Support in Process Environments* (E. Hollnagel, G. Mancini, and D. Woods, eds.), Springer-Verlag, New York, pp. 153–173.

[35] Gettys, C. and S. Fisher (1979) "Hypothesis plausibility and hypothesis generation," *Organizational Behavior and Human Performance*, **24**(1), pp. 93–110.

[36] Hogarth, R. M. (1981) "Beyond Discrete Biases: Functional and Dysfunctional Aspects of Judgemental Heuristics," *Psychological Bulletin*, **90**(2), pp. 197–217.

[37] Wason, P. C. (1960) "On the Failure to Eliminate Hypotheses in a Conceptual Task," *Quarterly Journal of Experimental Psychology*, **12**(3), pp. 129–140.

[38] Tversky, A. and D. Kahneman (1974) "Judgement Under Uncertainty: Heuristics and Biases," *Science*, **185**, pp. 1124–1131.

[39] Lund, J. and R. Palmer (1997) "Water Resources System Modeling for Conflict Resolution," *Water Resources Update: University Council on Water Resources*, **108**, pp. 70–82.

[40] Characklis, G. W., R. C. Griffin, and P. B. Bedient (1999) "Improving the ability of a water market to efficiently manage drought," *Water Resources Research*, **35**(3), pp. 823–831.

[41] Levine, G. (2007) "The Lower Rio Grande Valley: a case study of a water market area," *Paddy and Water Environment*, **5**(4), pp. 279–284.

[42] Suen, J.-P. and J. W. Eheart (2006) "Reservoir management to balance ecosystem and human needs: Incorporating the paradigm of the ecological flow regime," *Water Resources Research*, **42**(W03417, doi:10.1029/2005WR004314).

[43] Livingston, M. L. (1995) "Designing Water Institutions: Market Failures and Institutional Response," *Water Resources Management*, **9**(3), pp. 203–220.

[44] Ng, W. S. and G. Kuczera (1993) “Incorporating demand uncertainty in water supply headworks simulation,” *Water Resources Research*, **29**(2), pp. 469–477.

[45] Griffin, R. C. and J. W. Mjelde (2000) “Valuing Water Supply Reliability,” *American Journal of Agricultural Economics*, **82**(2), pp. 414–426.

[46] Brewer, J., R. Glennon, A. Ker, and G. Libecap (2008) “2006 Presidential Address: Water Markets in the West: Prices, Trading, and Contractual Forms,” *Economic Inquiry*, **46**(2), pp. 91–112.

[47] Black, F. and M. Scholes (1973) “The Pricing of Options and Corporate Liabilities,” *The Journal of Political Economy*, **81**(3), pp. 637–654.

[48] Kollat, J. B. and P. M. Reed (2006) “Comparing state-of-the-art evolutionary multi-objective algorithms for long-term groundwater monitoring design,” *Advances in Water Resources*, **29**(6), pp. 792–807.

[49] ——— (2007) “A Computational Scaling Analysis of Multiobjective Evolutionary Algorithms in Long-Term Groundwater Monitoring Applications,” *Advances in Water Resources*, **30**(3), pp. 335–353.

[50] Tang, Y., P. Reed, and T. Wagener (2006) “How effective and efficient are multiobjective evolutionary algorithms at hydrologic model calibration?” *Hydrology and Earth System Science*, **10**, pp. 289–307.

[51] Kollat, J. B. and P. M. Reed (2007) “A Framework for Visually Interactive Decision-making and Design using Evolutionary Multiobjective Optimization (VIDEO),” *Environmental Modelling & Software*, **22**(12), pp. 1691–1704.

[52] Coello Coello, C. A., G. B. Lamont, and D. A. Van Veldhuizen (eds.) (2007) *Evolutionary Algorithms for Solving Multi-Objective Problems*, Genetic and Evolutionary Computation, 2 ed., Springer, New York.

[53] Cieniawski, S., J. W. Eheart, and S. Ranjithan (1995) “Using genetic algorithms to solve a multiobjective groundwater monitoring problem,” *Water Resources Research*, **31**(2), pp. 399–409.

[54] Wu, J., C. Zheng, C. C. Chien, and L. Zheng (2005) “A comparative study of Monte Carlo simple genetic algorithm and noisy genetic algorithm for cost-effective sampling network design under uncertainty,” *Advances in Water Resources*, **29**(6), pp. 899–911.

[55] Beckford, O., A. B. Chan Hilton, and X. Liu (2003) “Development of an Enhanced Multi-Objective Robust Genetic Algorithm for Groundwater Remediation Design Under Uncertainty,” in *World Water Congress 2003* (P. Bizier and P. Debarry, eds.), ASCE.

[56] Chan Hilton, A. B. and T. B. Culver (2005) "Groundwater Remediation Design under Uncertainty with Genetic Algorithms," *Journal of Water Resources Planning and Management*, **131**(1), pp. 25–34.

[57] Singh, A. and B. S. Minsker (2008) "Uncertainty-based multiobjective optimization of groundwater remediation design," *Water Resources Research*, **44**(W02404, doi:10.1029/2005WR004436).

[58] Deb, K., A. Pratap, S. Agarwal, and T. Meyarivan (2002) "A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II," *IEEE Transactions on Evolutionary Computation*, **6**(2), pp. 182–197.

[59] Laumanns, M. (2002) "Combining Convergence and Diversity in Evolutionary Multiobjective Optimization," *Evolutionary Computation*, **10**(3), pp. 263–282.

[60] Harik, G., E. Cantu-Paz, D. Goldberg, and B. Miller (1997) "The gambler's ruin problem, genetic algorithms, and the sizing of populations," in *IEEE International Conference on Evolutionary Computation*, pp. 7–12.

[61] Goldberg, D. E. (2002) *The Design of Innovation: Lessons from and for Competant Genetic Algorithms*, Kluwer Academic Publishers, Boston.

[62] Deb, K. and H. Gupta (2006) "Introducing Robustness in Multi-Objective Optimization," *Evolutionary Computation*, **14**(4), pp. 463–494.

[63] Smalley, J. B., B. S. Minsker, and D. E. Goldberg (2000) "Risk-based in situ bioremediation design using a noisy genetic algorithm," *Water Resources Research*, **36**(10), pp. 3043–3052.

[64] Kapelan, Z. S., D. A. Savic, and G. A. Walters (2005) "Multiobjective design of water distribution systems under uncertainty," *Water Resources Research*, **41**(W11407, doi:10.1029/2004WR003787).

[65] Miller, B. L. and D. E. Goldberg (1996) "Optimal sampling for genetic algorithms," in *Intelligent Engineering Systems Through Artifical Neural Networks* (C. H. Dagli, ed.), ASME, pp. 291–297.

[66] Kollat, J. B., P. M. Reed, and J. R. Kasprzyk (2008) "A New Epsilon-Dominance Hierarchical Bayesian Optimziation Algorithm for Large Multi-Objective Monitoring Network Design Problems," *Advances in Water Resources*, **31**(5), pp. 828–845.

[67] Deb, K. and R. B. Agrawal (1994) *Simulated binary crossover for continuous search space, Tech. Rep. IITK/ME/SMD-94027*, Indian Institute of Technology, Kanpur.

[68] Deb, K. (2001) *Multi-objective Optimization Using Evolutionary Algorithms*, John Wiley, New York.

[69] Kollat, J. B. and P. M. Reed (2005) "The Value of Online Adaptive Search: A Performance Comparison of NSGAII, epsilon-NSGAII and epsilon-MOEA," in *EMO 2005: The Third International Conference On Evolutionary Multi-Criterion Optimization* (C. Coello Coello, A. Aguirre, and E. Zitzler, eds.), no. 3410 in Lecture Notes in Computer Science, Springer Verlag, pp. 386–398.

[70] Stump, G. M., M. Yukish, T. W. Simpson, and E. N. Harris (2003) "Design Space Visualization and its Application to a Design by Shopping Paradigm," in *Proceedings of the ASME 2003 Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, ASME.

[71] Tsoukias, A. (2008) "From decision theory to decision aiding methodology," *European Journal of Operational Research*, **187**(1), pp. 138–161.

[72] Loughlin, D. H., S. R. Ranjithan, E. D. Brill, and J. W. Baugh (2001) "Genetic Algorithm Approaches for Addressing Unmodeled Objectives in Optimization," *Engineering Optimization*, **33**(5), pp. 549–569.

[73] Cohon, J. L., R. L. Church, and D. P. Sheer (1979) "Generating Multiobjective Trade-Offs: An Algorithm for Bicriterion Problems," *Water Resources Research*, **15**(5), pp. 1001–1010.

[74] Farmani, R., G. A. Walters, and D. A. Savic (2005) "Trade-off between Total Cost and Reliability for Anytown Water Distribution Network," *Journal of Water Resources Planning and Management*, **131**(3), pp. 161–171.

[75] Inselberg, A. (1985) "The Plane with Parallel Coordinates," *The Visual Computer*, **1**, pp. 69–91.

[76] Wegman, E. J. (1990) "Hyperdimensional Data Analysis Using Parallel Coordinates," *Journal of the American Statistical Assocation*, **85**(41), pp. 664–675.

[77] Knutson, C. L. (2008) "The role of water conservation in drought planning," *Journal of Soil and Water Conservation*, **63**(5), pp. 154A–160A.

[78] Loucks, D. P. and E. van Beek (2005) *Water Resources Systems Planning and Management: An Introduction to Methods, Models, and Applications*, United Nations Educational, Scientific and Cultural Organization.

[79] Kahneman, D. and D. Lovallo (1993) “Timid Choices and Bold Forecasts: A Cognitive Perspective on Risk-Taking,” *Management Science*, **39**, pp. 17–31.

[80] Roy, B. (1999) “Decision-aiding today: What should we expect?” in *Multicriteria Decision Making: Advances in MCDM Models, Algorithms, Theory, and Applications* (T. Gal, T. Stewart, and T. Hanne, eds.), chap. 1, Kluwer, Dordrecht, pp. 1–35.

[81] Liebman, J. C. (1976) “Some Simple-Minded Observations on the Role of Optimization in Public Systems Decision-Making,” *Interfaces*, **6**(4), pp. 102–108.

[82] Winer, E. and C. L. Bloebaum (2002) “Development of visual design steering as an aid in large-scale multidisciplinary design optimization. Part 1: method development,” *Structural and Multidisciplinary Optimization*, **23**(6), pp. 412–424.

[83] Maxwell, R. and S. Kollet (2008) “Interdependence of groundwater dynamics and land-energy feedbacks under climate change,” *Nature Geoscience*, **1**, pp. 665–669.