Many-Objective de Novo Water Supply Portfolio Planning Under Deep Uncertainty

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Abstract

This paper proposes and demonstrates a new interactive framework for sensitivity-informed de Novo planning to confront the deep uncertainty within water management problems. The framework couples global sensitivity analysis using Sobol’ variance decomposition with multiobjective evolutionary algorithms (MOEAs) to generate planning alternatives and test their robustness to new modeling assumptions and scenarios. We explore these issues within the context of a risk-based water supply management problem, where a city seeks the most efficient use of a water market. The case study examines a single city’s water supply in the Lower Rio Grande Valley (LRGV) in Texas, using a suite of 6-objective problem formulations that have increasing decision complexity for both a 10-year planning horizon and an extreme single-year drought scenario. The de Novo planning framework demonstrated illustrates how to adaptively improve the value and robustness of our problem formulations by evolving our definition of optimality while discovering key tradeoffs.

Key words:

1. Introduction

Climate change, population growth, and increased urbanization pose serious challenges to urban water supply management (Frederick and Schwarz, 1999; Lane et al., 1999; Vorosmarty et al., 2000; Milly et al., 2008; Brekke et al., 2009). These changes lead to increased water demands and amplified hydrologic variability, subsequently leading to higher risks for water supply failures (Kundzewicz et al., 2007). The severe costs associated with structural adaptations such as building new reservoirs motivate the need for innovative
nonstructural adaptation techniques such as water marketing (Anderson and Hill, 1997). A water market seeks to allocate water to its “highest value use” through transfers between regions (Israel and Lund, 1995) or different user sectors (Hadjigeorgalis, 2008). The presence of a water market, though, does not imply that the city knows how to develop the most efficient water supply portfolio that fulfills all of its planning goals (Kasprzyk et al., 2009). This difficulty can be attributed to severe uncertainties within water supply portfolio planning, including future supply and demand (Ng and Kuczera, 1993), the form of economic instruments within the water market itself (Williamson et al., 2008), and the quantitative model that relates decision making within the market to decision maker’s utility and preferences.

Many of these uncertainties can be characterized as deep (Lempert et al., 2006) or Knightian (Knight, 1921) in nature, since it may not be straightforward (or even possible) to construct a probability model of likely vulnerabilities for these systems. Since the seminal work by Knight, there has been much discussion on the proper definition of deep uncertainty (Ellsberg, 1961; LeRoy and Singell, Jr., 1987; Langlois and Cosgel, 1993; Runde, 1998). According to Langlois and Cosgel (1993), the most prevalent interpretation is exemplified by Friedman (1976), who states that Knight’s risk describes events that can be characterized by a “knowable” probability distribution while deep uncertainty describes events where it is not possible to characterize a probability distribution. Our interpretation follows Langlois and Cosgel (1993), where deep uncertainty refers to decision makers’ limitations in conceptualizing the full range of possible types of risk in addition to quantitative probabilities of those risks. This paper explores the deep uncertainty in water portfolio planning by rigorously testing alternative formulations of a city’s decision strategies and carefully exploring the effect of modeling assumptions by constructing challenging planning scenarios. The goal of this analysis is to develop robust solutions that have good performance under many different modeling conditions (Lempert, 2002) and aid decision makers in understanding the effects of their use of estimated probabilities (Savage, 1972) on the planning process.

To explore the deep uncertainties of water portfolio planning, we present an adaptive decision-making framework termed the sensitivity-informed de Novo planning framework. The framework continually updates planning objectives, constraints, and decision variables with the goal of aiding the decision maker in rigorously attaining a more complete understanding of their planning problem (Zeleny, 1989). Our work is an extension of the de Novo
programming paradigm developed by Zeleny, in which the formulation of resource allocation problems is modified to avoid squandered resources (Zeleny, 1981, 2005). While recent studies have acknowledged the “statistical nonstationarity” of historical data (Milly et al., 2008), we posit that there is a more general mathematical nonstationarity in how water management problems are actually defined. This nonstationarity lies in the definition of “optimality” itself and reflects that knowledge gained in solving a problem will lead to iterative changes in the definitions of planning objectives, decisions, and constraints (i.e., a nonstationary problem topology because the definition of optimality is changing). Our work builds on the growing body of work in the area of constructive decision aiding (Roy, 1990; Lund and Palmer, 1997; Roy, 1999; Castelletti and Soncini-Sessa, 2006), which emphasizes the role of quantitative environmental policy models as a means of promoting and improving problem understanding rather than strictly focusing on providing a single definitive answer (Liebman, 1976).

This paper uses a case study of a single city’s use of market-based transfers to augment its water supply in the Lower Rio Grande Valley (LRGV) of Texas, USA (Characklis et al., 2006; Kirsch et al., 2009; Kasprzyk et al., 2009). The case study is used to demonstrate the planning framework with the goal of promoting improved problem understanding of water marketing within the LRGV. Each step in the framework (presented in figure 1)
uses the concept of many-objective (Reed and Minsker, 2004; Fleming et al., 2005) tradeoffs of three or more objectives. Solutions in the tradeoffs are found using the concept of nondomination or Pareto optimality; solutions in the tradeoff set are better than all other solutions in at least one objective.

Step 1 begins with an \textit{a priori} problem formulation that represents planners’ initial conception of the problem through a quantitative model, decision variables that control strategies within the model, and objectives and constraints that measure strategies’ performance. In step 2, the framework diagnoses the effect of decision variables and model parameters using Sobol’ variance decomposition (Sobol’, 1993). The illustration in figure 1 shows that different variables can have a wide range of sensitivity performance across different evaluative metrics. Step 3 uses insights from the sensitivity analysis to construct a new many-objective planning problem. Objectives and constraints can be removed or added depending on their sensitivity structure or insights learned from previous iterations of the framework. Additionally, a suite of decision variable formulations of increasing complexity are used to explore the implications of the sensitivity analysis results. This framework seeks a balance between the complexity and effectiveness of a planning formulation.

Step 4 solves the \textit{de Novo} formulations using a multi-objective evolutionary algorithm (MOEA) (Coello Coello et al., 2007; Nicklow et al., 2010). After a quantitative tradeoff comparing performance across decision variable formulations is developed, step 5 uses interactive visual analytics (Keim et al., 2006; Thomas and Cook, 2006; Thomas and Kielman, 2009; Andrienko et al., 2010) to view the tradeoffs interactively when evaluating the competing decision variable formulations. Exploration of decision variables’ impact on many-objective tradeoffs has been successfully demonstrated in prior work (van Werkhoven et al., 2009). Use of interactive visual analytics represents \textit{a posteriori} decision making, where decision makers explore our approximate Pareto-optimal sets to negotiate a choice of alternative as a final decision (Stump et al., 2003; Kollat and Reed, 2007b; Lotov, 2007; Castelletti et al., 2010). A major benefit to this approach is that it allows the decision makers to modify their preferences and perform experiments through setting thresholds on objective function values and adding unmodeled objectives (Loughlin et al., 2001) to their analysis. Within step 5, the planners can choose the decision variable formulation that provides preferred performance compared to the other formulations. In this manner, formulations themselves can be considered non-dominated with respect to each other if they provide non-dominated solutions of interest to the decision maker and/or increase
the diversity of alternatives that can be considered (Brill et al., 1990). This focus on finding the non-dominated problem formulation (as compared to the classical focus on non-dominated solutions within a single static formulation) is a unique contribution of this work. Selected solutions within this preferred formulation are also used to further interrogate the effect of deeply uncertain model assumptions on the solutions’ performance. Step 6 shows how deviations in model assumptions can change the performance of the selected solutions. For our case study, we use modifications of model assumptions within a drought scenario. Note that this process is iterative, and further improvements can be made to the problem formulation after this scenario analysis (i.e., the formulation from step 6 becomes a new \textit{a priori} formulation for the next investigation). Overall, the \textit{de Novo} planning framework seeks to facilitate learning and innovation in decision making problems solved under deep uncertainty.

2. Lower Rio Grande Case Study

The case study used to demonstrate our \textit{de Novo} planning framework focuses on water marketing (Anderson and Hill, 1997) in the Lower Rio Grande Valley (LRGV) of Texas, USA. The LRGV’s water market is described in Schoolmaster (1991), Characklis et al. (1999) and Levine (2007). Due to limited regional groundwater storage, the primary sources of water in the LRGV are the Falcon and Amistad reservoirs, in which the water supply is shared between the United States and Mexico (Schoolmaster, 1991). The reservoirs have an estimated combined storage of 7.2 cubic km (5.8 million acre feet), with 2.6 cubic km (2.1 million acre feet) reserved for flood protection (Characklis et al., 2006).

Prior work has shown that many-objective planning within the LRGV water market has a strong potential for improving the efficiency of urban water supplies while maintaining resiliency and adaptability to risks posed by population growth and droughts (Kasprzyk et al., 2009). In the LRGV, the presence of a water market does not imply that urban water planners can easily ascertain how to maintain high levels of reliability while also seeking to minimize a city’s water surplus. This complex risk management problem requires flexible planning frameworks that can incorporate new knowledge and evaluate strategies rigorously for their complexity and effectiveness given the deep uncertainties associated with the long-term sustainability of the LRGV’s water supply.
Our work focuses on a hypothetical city in the LRGV modeled after Brownsville, Texas, USA (Characklis et al., 2006). The modeled city has an average annual water use of 26 million cubic meters (21,000 acre feet) and participates in a water market in which water is transferred from the agricultural sector. Regional agricultural use contributes mostly to irrigation of low-valued crops such as cotton and accounts for 85 percent of regional water use. In this study, the volume of water needed for the city’s municipal supply is relatively small compared to the other demands from the reservoir, and the rapidly increasing population demands motivate economic incentives for the irrigators to transfer water using the market from irrigation to municipal supply (Characklis et al., 2006). Water portfolio planning strategies are evaluated using both a ten year expected performance evaluation as well as a single year severe drought scenario, both using a monthly time step. This section provides a brief introduction to the quantitative model used to simulate the city’s use of the market, and the reader is encouraged to refer to Kasprzyk et al. (2009) and Kirsch et al. (2009) for more details.

Three types of water supply instruments are considered in our case study. The first is permanent rights, where users are allocated a percentage of reservoir inflows every month. The second instrument is the options contract (Michelsen and Young, 1993), in which users pay a small up-front fee at the beginning of each year for the right to exercise all or some of the options contract at a fixed price. Options contracts in this study are similar to a European call stock option, where the contract can only be exercised at a set month (June) every year. The third instrument is spot leasing (Characklis et al., 1999), in which the user can purchase a variable amount of water in any month at the market price. Note that the options contract provides some reduction in cost volatility compared to the spot leasing market, but the restriction of exercising only at one time reduces the options’ flexibility.

A Monte Carlo simulation model samples historical hydrology, water pricing, and projections for the region’s rapidly growing population demands and is used to evaluate the performance of the city’s water supply portfolio (Characklis et al., 2006; Kirsch et al., 2009; Kasprzyk et al., 2009). The portfolio is comprised of anticipatory risk-based water purchasing rules that control how the city’s acquires spot leases and exercises its options contracts. The rules are formulated to trigger alternative strategies for purchasing water transfers given uncertain forecasts of the city’s supply and demands. This work seeks to carefully formulate these risk-based rules to be as simple as possible for guiding the city’s use of the LRGV water market while providing
decisions that are robust to potentially severe droughts.

The city’s water supply portfolio planning is represented using a suite of decision variables for each of the supply instruments. The city’s permanent rights are specified by a volume, $N_R$. In each month, water is allocated to the permanent rights on a *pro rata* basis using the ratio of $N_R$ to the volume of total regional water rights. If the city had 10 percent of the regional rights, therefore, it would be allocated 10 percent of the available inflows in each month. The rights have an annualized price, $p_R$, set to $1.82$ per 100 cubic meters ($22.50$ per acre-foot) (Kirsch et al., 2009). The city’s options contract dictates a volume of water $N_O$ that represents the maximum amount that can be exercised in the exercise month. In this study, a single exercise month is used, with decisions made at the end of May (with water available for use starting in June). This volume of water also influences the up-front cost for holding the contract, set to the volume of options multiplied by the fixed options price $p_O$ of $0.43$ per 100 cubic meters ($5.30$ per acre foot). An adaptive options contract introduced in recent work (Kirsch et al., 2009; Kasprzyk et al., 2009) provides more flexibility to the city’s use of the options contract. The adaptive contract allows the city to reduce its contract volume when it anticipates that it has a sufficient volume of water in its supply account. In each simulation year, the city chooses between a high ($N_{O_{high}}$) and low-volume ($N_{O_{low}}$) options alternative based on the ratio of its current supply at the beginning of the year ($N_{ro}$) to its permanent rights. An additional decision variable, $\xi$, sets this threshold (see equation 1).

$$N_O = \begin{cases} N_{O_{low}} & \text{if } \frac{N_{ro}}{N_R} \geq \xi \\ N_{O_{high}} & \text{if } \frac{N_{ro}}{N_R} < \xi \end{cases}$$ (1)

The third instrument, leases, is denoted by $N_l$. The city is charged a price per cubic foot for acquired leases, $\hat{p}_l$, drawn randomly from the lease price distribution. Following Characklis et al. (2006), there are two distributions of historical lease pricing based on the reservoir level, with higher prices corresponding to a lower reservoir level.

Each model run for either the ten-year scenario or the drought begins with a volume of water expressed as a percentage of the city’s permanent rights, such that the initial volume of water $N_{ro}$ relates to the rights according to equation 2:

$$N_{ro} = i_{fr}N_R$$ (2)

where $i_{fr}$ is fraction of the initial rights given to the city to begin the sim-
ulation. Additionally, regional demand growth is modeled in the study as exponential growth with a compounded percentage change, $dm$, in each year. Both the initial fraction $i_{fr}$ and the demand growth $dm$ are explored in our sensitivity-informed framework to diagnose their effect on the water supply portfolios’ performance.

The volume of water acquired from the options contract and leases is determined by two types of anticipatory thresholds. In time period $k$, the $\alpha_k$ variable determines “when” the city purchases water, by comparing the ratio of expected supply to expected demand and comparing it to the alpha value. If the amount of water is less than the threshold, the city must purchase water on the market. The actual volume of water purchased (i.e., “how much” water) is dictated by $\beta_k$. For example, if $\alpha_k$ is 1.5 and $\beta_k$ is 2.0, the city will purchase water if their expected supply to demand ratio is lower than 1.5. When the city purchases this water on the market, it purchases a sufficient volume such that their supply is 2.0 times their expected demand forecast. In all months except the options exercise month, these market purchases are made using spot leases. In the options exercise month, the city first meets its required market acquisition volume by exercising their options at the fixed price $p_X$ ($1.22 per 100 cubic meters) if this price is lower than that month’s sampled lease price. Conversely, if the leases have a lower price, leases are used instead of options. Additionally, the city can augment its options purchase in the exercise month with extra leases if the volume of their options contract is not large enough to meet the amount of water that the $\beta_k$ value requires.

Two sets of $\alpha$ and $\beta$ strategy variables were used in prior work: the first from January to April, and the second from May to December (including the options exercise month) (Kasprzyk et al., 2009). Also, in each period $k$, $\beta_k$ was always constrained to be greater than or equal to $\alpha_k$. Note that the use of the market could be controlled by fewer variables (i.e., one threshold for both “when” and “how much”, regardless of time of year), or more variables (as many as one unique value per month, with distinct $\alpha_k$ and $\beta_k$). The goal of our de Novo planning framework is to specifically clarify the balance between the complexity of the risk-based rules for water purchases and their effectiveness across a broad range of performance objectives.
3. Methods

3.1. Performance Metrics

The three categories of performance metrics considered in this work are presented in Table 1. Efficiency metrics evaluate costs and the volumes of water carried over or not used for supply, risk indicators focus on water portfolios’ modes of failure and recovery, and market use metrics quantify the extent to which portfolios rely on the water market to provide supply. Full descriptions of the equations used to calculate these metrics are given in the appendix, section A.

3.2. A Priori Problem Formulation

In Kasprzyk et al. (2009), successively higher-dimensional objective formulations distinguished the impact of adding market-based water supply instruments for urban water portfolio planning within the LRGV. This paper builds on those results and shifts our focus to evaluating the appropriate level of decision variable complexity to yield simple and effective risk-based rules to guide the city’s market use. The a priori decision variable formulation was first defined in Kasprzyk et al. (2009) and is presented in equation 3.

\[
\mathbf{x}_{\text{a priori}} = (N_R, N_{O_{low}}, N_{O_{high}}, \xi, \\
\alpha_{\text{Jan-Apr}}, \beta_{\text{Jan-Apr}}, \\
\alpha_{\text{May-Dec}}, \beta_{\text{May-Dec}})
\]  

Equation 3 states that the city’s water supply portfolio is determined by volumetric variables for permanent rights \((N_R)\) and the adaptive options contract (low volume alternative \(N_{O_{low}}\) and high volume alternative \(N_{O_{high}}\)). The risk-based thresholds are \(\xi\), which the city uses to decide between its high and low options alternatives in every year, and the alpha and beta variables that control options exercising and lease acquisitions. Equations 4 through 7 present the objectives and constraints used in the a priori problem formulation.

\[
\mathbf{F}_{\text{a priori}}(\mathbf{x}_{\text{a priori}}) = (f_{\text{cost}}, f_{\text{rel}}, f_{\text{surplus}}, f_{\text{cost var}}, \\
\quad f_{\text{dropped}}, f_{\text{leases}}) \\
\forall \mathbf{x} \in \Omega
\]

Subject to: \(c_{\text{rel}}\) \(f_{\text{rel}} \geq 0.98\)  

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Table 1: Planning Metrics

<table>
<thead>
<tr>
<th>Name</th>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Efficiency</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cost</td>
<td>$f_{\text{cost}}$</td>
<td>Cost of rights, options, leases</td>
</tr>
<tr>
<td>Surplus Water</td>
<td>$f_{\text{surplus}}$</td>
<td>Water held at end of year</td>
</tr>
<tr>
<td>Cost Variability</td>
<td>$f_{\text{costvar}}$</td>
<td>High tail of cost distribution</td>
</tr>
<tr>
<td>Dropped Transfers</td>
<td>$f_{\text{dropped}}$</td>
<td>Volume of expired transfers</td>
</tr>
<tr>
<td><strong>Risk Indicators</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reliability</td>
<td>$f_{\text{rel}}$</td>
<td>Probability of successfully meeting demands</td>
</tr>
<tr>
<td>Critical Reliability</td>
<td>$f_{\text{crit. rel}}$</td>
<td>Probability of avoiding critical failures (supply less than 60% of demand)</td>
</tr>
<tr>
<td>Resilience</td>
<td>$f_{\text{resil}}$</td>
<td>How quickly the system recovers after a failure</td>
</tr>
<tr>
<td>Vulnerability</td>
<td>$f_{\text{vuln}}$</td>
<td>Volume of most severe failure</td>
</tr>
<tr>
<td><strong>Market Use</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Leases</td>
<td>$f_{\text{num. leases}}$</td>
<td>Number of leases regardless of volume</td>
</tr>
<tr>
<td>Volume of Leases</td>
<td>$f_{\text{vol. leases}}$</td>
<td>Volume of purchased leases</td>
</tr>
<tr>
<td>Volume of Exercised Options</td>
<td>$f_{\text{vol. ex. options}}$</td>
<td>Volume of exercised options</td>
</tr>
<tr>
<td>Cost Percentage Leases</td>
<td>$f_{\text{cost per. leases}}$</td>
<td>Contribution of leases to total cost</td>
</tr>
<tr>
<td>Cost Percentage Options</td>
<td>$f_{\text{cost per. options}}$</td>
<td>Contribution of options to total cost</td>
</tr>
</tbody>
</table>
\[ c_{\text{costvar}} : \quad f_{\text{costvar}} \leq 1.1 \quad (6) \]
\[ c_{\text{critrel}} : \quad f_{\text{crit}, \text{rel}} = 1.0 \quad (7) \]

In the above equations, \( \mathbf{F}_{\text{a priori}}(\mathbf{x}_{\text{a priori}}) \) represents the vector-valued objective function for the \textit{a priori} formulation with components as described previously in section 3.1. The \( \Omega \) represents the space of feasible values of \( \mathbf{x}_{\text{a priori}} \), and \( c \) variables represent constraints. In this formulation, each of the objectives in the vector-valued objective function are minimized except for reliability, \( f_{\text{rel}} \), which is maximized. Also note that each term in the formulation refers to the ten year scenario, with the metrics explicitly defined in the appendix, section A. Constraint values for equations 5 and 6 represent preferred ranges for the objectives and reflect values set in prior work. The critical reliability constraint set to 1.0 reflects a highly risk-averse planning problem developed in (Kasprzyk et al., 2009) in which no simulations have a critical failure where supply is less than 60% of demand.

### 3.3. Sobol’ Sensitivity Analysis

Global sensitivity analysis is used in this study to determine the relative importance of the decision variables controlling the city’s use of the water market, the initial condition model parameter \( i_f \) (the city’s initial supply fraction), and the demand growth rate \( dm \) for the suite of output metrics discussed in section 3.1. A variety of sensitivity analysis approaches are available (Saltelli et al., 2000), ranging from local methods that vary a single parameter at a time to global methods that sample the entire parameter space and are more appropriate for complex non-linear models (Tang et al., 2007; Saltelli and Annoni, 2010). This study uses the global method termed the Sobol’ variance decomposition (Sobol’, 1993) due to prior work that has rigorously evaluated its effectiveness compared to other global sensitivity analysis approaches (Tang et al., 2007).

Our study focuses total-order sensitivity indices, which measure the impact of a variable \( X_i \) acting individually and as a result of all of its interactions with other variables. The total sensitivity index \( S_i^T \) is calculated using equation 8.

\[
S_i^T = 1 - \frac{V[E[Y|X_{\sim i}]]}{V[Y]} \quad (8)
\]

where \( X_{\sim i} \) denotes the set of all variable inputs not including \( X_i \). The upper term, \( V[E[Y|X_{\sim i}]] \) represents the amount of variance in the output \( Y \).
that would be reduced if one set all other variables in the analysis constant, allowing only \( X_i \) to vary over its range (Hasofer, 2009).

The computational technique for calculating the total-order sensitivity indices is fully described in Saltelli et al. (2008) and demonstrated in Tang et al. (2007). For this study all our Monte Carlo samples of the parameter space were generated using Sobol’ quasi-random sequence sampling (Sobol’, 1967) using a sample size denoted by \( q \). Our computations utilize the recommendations of Saltelli (2002) to calculate the first-order (individual effects), second-order, and total order indices using \( q \times (2p + 2) \) runs. Following the recommendation of Sobol’ (1967), the sample size was explored using values of \( q = 2^k \), where \( k \) is an integer. An additional diagnostic tool in our analysis was the assessment of the convergence and uncertainty of the Sobol’ indices using the moment method for bootstrapping the sensitivity index estimates (Archer et al., 1997; Tang et al., 2007) to attain the 95% confidence intervals on the magnitudes of the sensitivity indices.

3.4. Multiobjective Evolutionary Algorithms

Water resources planning problems are often characterized by multiple conflicting objectives, in which improvement in one objective cannot be obtained without degradation in other objectives (for example, minimizing cost of a system at the expense of its performance). The concept of Pareto optimality, or nondomination, is used to define tradeoffs for the system; a solution \( x_1 \) is nondominated if no solution \( x \) in the feasible solution space \( \Omega \) is better in all objectives. This work uses a multiobjective evolutionary algorithm (MOEA) to develop approximations to the Pareto optimal solution sets for the LRGV management problem. MOEAs are heuristic search algorithms that use an iterative process of selection of good candidate solutions and variation on those solutions to evolve a high-quality approximation to the true Pareto set (see Coello Coello et al., 2007; Nicklow et al., 2010, for extensive reviews). To develop the tradeoff sets, this study uses a MOEA termed the epsilon Non-Dominated Sorting Genetic Algorithm, abbreviated \( \varepsilon\text{-NSGAII} \) (Kollat and Reed, 2006, 2007a; Reed et al., 2007). The \( \varepsilon\text{-NSGAII} \) was used due to its demonstrated effectiveness compared to other state-of-the-art MOEAS (Kollat and Reed, 2006; Tang et al., 2006).

The \( \varepsilon\text{-NSGAII} \) extends the original NSGA-II (Deb et al., 2002) by adding epsilon-dominance archiving (Laumanns, 2002) and adaptive population sizing (Harik et al., 1997). Epsilon-dominance archiving divides the objective space into user-sized blocks allowing the algorithm’s precision to change with
user preferences or computational constraints (Kollat and Reed, 2007a), and subsequent use of the term “nondominated sorting” in this paper refers to this epsilon-nondominated sorting technique.

Uncertainty in objective function calculations provides an additional challenge to using MOEAs. The major sources of uncertainty in the objective function calculations for the LRGV case study result from sampling distributions of hydrologic conditions, water demands, and lease pricing. The uncertainty is problematic since the nondomination ranking procedure may preserve solutions in which a different ensemble of sampled data in the Monte Carlo simulation would have caused them to be dominated by another solution. We address this issue by using a novel application of epsilon dominance; the epsilon resolution is set to minimize the likelihood that solutions are mistakenly added to the epsilon nondominance archive due to uncertainty or noise in their mean-based objective rankings. Figure 2 illustrates the approach on a two objective problem. An epsilon non-dominated approximation to the Pareto set is illustrated with four solutions labeled A-D. The solutions’ error bars indicate the noise or range of each solution’s mean values for objectives 1 and 2, and the circle illustrates an example instance of the mean. Epsilon values control the ranking calculation and determine the solutions that will remain in the set; the values are set to a fine resolution in figure 2a and adjusted for noise in figure 2b. The dotted lines indicate the range of epsilon blocks into which draws of each solution would fall.

Within the MOEA’s search process, multiple copies of decision variable vectors are made and evaluated with a new ensemble sample of input data. Copies of solutions that fall in the light grey blocks would be falsely classified as being epsilon non-dominated with respect to the solution’s uncertain mean value and would remain in the Pareto approximation set. Copies that fall in the darker grey boxes would dominate the mean and replace it in the set, and copies that fall elsewhere would be dominated by the existing instance of the mean. Using the fine resolution in figure 2a yields a high likelihood that copies of already existing solutions (i.e. with identical values of the decision variables) may erroneously survive in the reference set. In figure 2b, we size the epsilon blocks to be equal to the largest sampled range or uncertainty in the means of any solution on a given objective. This reduces the chance that a solution’s copies will be replicated in the Pareto approximation set, because draws of the solutions are more likely to be made within the same epsilon block and would be eliminated within the sorting procedure. In figure 2b, only solution C has the possibility of its copy dominating the
Figure 2: Consequences of epsilon resolution settings for an example two-objective minimization under uncertainty. The Pareto set consists of 4 solutions in each panel with the circle indicating mean objective value performance and the error bars showing the range of objective function values. Panel A has a fine epsilon resolution while panel B’s resolution is more coarse. The black dotted line shows the range of epsilon blocks into which a draw of each solution could fall. Dark gray blocks indicate that a draw in this block would dominate the mean objective value, lighter gray blocks indicate that a draw in this block would be nondominated with respect to the mean value. Draws in the gray blocks would result in copies of the same decision vector maintained in the Pareto set with different objective values. However, the reduced resolution of panel B reduces the likelihood of those copies being made.
mean, and situations such as this would become less frequent as the number of dimensions increases. The approach summarized in figure 2 increases the competition among solutions to stay epsilon-nondominated within each large block. In a many-objective problem as in Kasprzyk et al. (2009), it is very unlikely that the noise would bias a solution to be falsely non-dominated in all objectives. Robust solutions will have to repeatedly beat other candidates by stably controlling their epsilon box (i.e., the means for all objectives are nondominated).

The approach presented in figure 2 is advantageous because it requires no modification of the algorithm itself and it is valid within high-dimensional problems with no closed-form analytical representations of the probability distributions of objectives. The approach is similar to the ranking methodology of Teich (2001) but requires no a priori assumption of the shape of the uncertainty distribution. To obtain the noise-adjusted epsilon values for search, a representative set of solutions is evaluated for several independent identically distributed random draws to develop an uncertainty estimate for each objective’s Monte Carlo based estimate of its mean. The epsilon blocks are then sized to be equal to the largest sampled range of uncertainty across the set of selected solutions. Sampling different types of solutions is helpful in determining if they exhibit varied probabilistic behavior depending on the decisions. While there is some computational cost in performing the initial Monte Carlo sampling necessary to create these settings, the resulting search problem that uses the noise-adjusted epsilon values yields a smaller Pareto approximation set size than with the fine resolution epsilon settings, maintains diversity throughout the objective space, and reduces overall computational time (Kollat and Reed, 2007a). The noise-adjusted epsilon values increase the robustness of solutions, since the uncertain solutions face increased competition to survive in successive generations in larger grid blocks (Deb and Gupta, 2006).

3.5. Drought Scenarios

The drought scenario tests how alternative LRGV water supply portfolios perform in a single year with statistically unlikely low allocation volumes and maximally high demands. Inclusion of this drought scenario reflects deep uncertainty in planning for multi-year severe droughts. Following the treatment of Knightian or deep uncertainty in Langlois and Cosgel (1993), extreme droughts are an example condition where a planner cannot fully conceptualize the possible risks to their system. The city begins the scenario
with a percentage of their permanent rights, $i_{fr}$, similar to the beginning of the ten year scenario. In each month, the city must meet the maximum value of the Gaussian distribution of demand adjusted for the tenth year of the multi-year simulation. These maximally high demands are coupled with monthly inflows and allocations from the driest calendar year identified from our input hydrologic data. The 19th year in the record was chosen because it represents the lowest observed inflows and allocation volumes in almost every month. The drought scenario tests the portfolios’ performance when the expected value estimates of water allocations are violated (i.e. low inflows and high demands in every month). Since the anticipatory thresholds used for market transfers are based on expected values of the historical inflows and demands, the drought scenario tests how robust the thresholds are to changing assumptions. This shift between the assumed conditions of the ten year planning scenario to a single dry year focuses on supporting robust decision making by exposing vulnerabilities of planning strategies that arise due to model assumptions (Groves and Lempert, 2007). Moreover, if failures occur from a historically-observed drought, then the system vulnerability is potentially more severe than assumed in the Monte Carlo probabilistic model due to deep uncertainties associated with the potential climate change impacts and population demands that could impact the LRGV (Milly et al., 2008; Lempert, 2002). The drought scenario is used in this study as an exploratory tool for evaluating the robustness of solutions in the many objective tradeoff set.

3.6. Computational Experiment
3.6.1. Sensitivity Analysis

Our analysis first performs global sensitivity analysis of the a priori decision variable formulation (see section 3.2) using the variance decomposition method of Sobol’. Table 2 presents the variables explored in the Sobol’ analysis with their respective ranges. The ranges for the decision variables in table 2 follow Kasprzyk et al. (2009), and the reader can consult this reference for more information. The Sobol’ analysis also includes the yearly demand growth $dm$ and the initial rights $i_{fr}$ to further explore the effect of model parameters in addition to the decision variables. The range for $dm$ was chosen based on reports of national water use released every five years from the U.S. Geological Survey (U.S.G.S.) (Kenny et al., 2009), focusing on Cameron County, Texas. This county in the LRGV includes Brownsville, the city upon which our hypothetical case study is based. Using the published
Table 2: Variables for Sobol’ analysis

<table>
<thead>
<tr>
<th>Decision Variable</th>
<th>Range</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_R$</td>
<td>37 - 74</td>
<td>Volume of Permanent Rights $[10^6 \text{ cubic m}]$</td>
</tr>
<tr>
<td>$N_{O_{\text{low}}}$</td>
<td>0 - 24.7</td>
<td>Low-Volume Options</td>
</tr>
<tr>
<td>$N_{O_{\text{high}}}$</td>
<td>$1.1N_{O_{\text{low}}} - 2.0N_{O_{\text{low}}}$</td>
<td>High-Volume Options Contract Alternative $[10^6 \text{ cubic m}]$</td>
</tr>
<tr>
<td>$\xi$</td>
<td>0.1 - 0.4</td>
<td>Low to High Options Threshold</td>
</tr>
<tr>
<td>$\alpha_{\text{May- Dec}}$</td>
<td>0.0 - 3.0</td>
<td>Lease/Options Strategy for May- Dec. (“when to acquire?”)</td>
</tr>
<tr>
<td>$\beta_{\text{May- Dec}}$</td>
<td>$\alpha_{\text{May- Dec}} - 3.0$</td>
<td>Lease/Options Strategy for May- Dec. (“how much to acquire?”)</td>
</tr>
<tr>
<td>$\alpha_{\text{Jan- Apr}}$</td>
<td>0.0 - 3.0</td>
<td>Lease Strategy for Jan- Apr. (“when to acquire?”)</td>
</tr>
<tr>
<td>$\beta_{\text{Jan- Apr}}$</td>
<td>$\alpha_{\text{Jan- Apr}} - 3.0$</td>
<td>Lease Strategy for Jan- Apr. (“how much to acquire?”)</td>
</tr>
<tr>
<td>$dm$</td>
<td>0.011 - 0.023</td>
<td>Demand growth (exponential rate)</td>
</tr>
<tr>
<td>$i_{fr}$</td>
<td>0.0 - 1.0</td>
<td>Fraction of initial rights</td>
</tr>
</tbody>
</table>
data from 1985-2005, the five-year trends in water use suggest a yearly exponential growth rate of between 1.1% and 2.3%, which is the range for $dm$ used in this study. For the $i_{fr}$ parameter, the Sobol’ analysis uses the parameter’s full range, from 0.0 representing a failure before the planning period began, to 1.0 representing water supply portfolios that keep a large volume of water in their supply account and consequently end the ten year simulation with a volume of supply approximately equal to their entire permanent rights volume.

Two runs of the Sobol’ analysis were performed, the first using the ten-year planning horizon and the second run using the one-year drought scenario. All metrics described in section 3.1 are valid for the drought except for cost variability and dropped transfers (the number of years is $T = 1$ and a single draw is performed with characteristics described in section 3.5). For both tests, a sample size of $q = 2^{13}$ was used, based on initial tests that showed convergence for this sample size, using an approach similar to Tang et al. (2007).

The sensitivity analysis ensemble comprises $q \times (2p + 2)$ simulations of the LRGV management model, each with a randomly generated set of decision variables, demand growth factor, and initial rights. For each of these $q \times (2p + 2)$ simulations, an identical Monte Carlo simulation of 5,000 draws of the historical hydrology, demands, and lease pricing is used. This ensemble size was chosen to coincide with the number of Monte Carlo draws in each function evaluation of the optimization (Kasprzyk et al., 2009). Furthermore, an identical sample of draws is used for each generated parameter set to reduce the likelihood that our reported variable sensitivity is artificially caused by differences in draws of the input data between runs.

### 3.6.2. Parameterizing Multiobjective Search and Handling Uncertainty

The $\varepsilon$-NSGAII is used to create the Pareto approximate tradeoffs for each problem formulation considered. The algorithm’s parameters used in this study are given in table 3 and were set following recommendations of previous work (Kollat and Reed, 2007a, 2006; Kollat et al., 2008; Kasprzyk et al., 2009).

The $\varepsilon$-NSGAII utilizes an adaptive population sizing approach that resizes the algorithm’s population based on how many archive solutions have been found. Parameters for the adaptive population sizing were set according to Kollat and Reed (2005). Each MOEA run lasts for 500,000 function evaluations, with each function evaluation comprising $M$ independent Monte
Table 3: Parameters for this study

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( M )</td>
<td>5,000</td>
<td>Monte Carlo Sample Size</td>
</tr>
<tr>
<td>( T )</td>
<td>10</td>
<td>Planning Period [years]</td>
</tr>
<tr>
<td>( p_m )</td>
<td>( 1/p )</td>
<td>Probability of mutation (( p ): num. of model param.)</td>
</tr>
<tr>
<td>( p_c )</td>
<td>1.0</td>
<td>Probability of crossover</td>
</tr>
<tr>
<td>( \eta_c )</td>
<td>15</td>
<td>Distribution index (crossover)</td>
</tr>
<tr>
<td>( \eta_m )</td>
<td>20</td>
<td>Distribution index (mutation)</td>
</tr>
<tr>
<td>( NFE )</td>
<td>500,000</td>
<td>Number of function evaluations</td>
</tr>
</tbody>
</table>

Carlo simulations of the water management model. This termination criterion was deemed appropriate by consulting visualizations of preliminary tests that showed very few solutions being added to the archive at this number of function evaluations.

The reference set presented in this work is generated by sorting each model case’s final approximated Pareto optimal set together to compare the case’s performance against each other. Each case was evaluated using a set of 50 random seed trials per case, to reduce the influence of random effects within the probabilistic search operators and generation of initial random populations. The reference set generation process occurs as follows. In step 1, we perform a sort using the objective values obtained during search (each function call in the algorithm had a unique set of Monte Carlo draws). Step 2 evaluates each solution in this set with an identical large sample of 100,000 draws of the historical data. The rigorous sample used in Step 2 uses an identical ensemble of input data for each evaluation to minimize the likelihood that variance in objective function values for different solutions are an artifact of their uncertain input data. Step 3 enforces constraints with respect to the new objective values found in Step 2. This test of robustness eliminates solutions that were feasible in the algorithm’s evaluation, but infeasible in the new larger sample. Step 4 sorts the remaining solutions with respect to the new objective values (from the large sample). The tradeoff presented in this paper reflects the results of this final sort in Step 4. All simulations for both the sensitivity analysis and many-objective search were completed using Penn State’s CyberSTAR infrastructure, a computing cluster with quad-core AMD Shanghai Processors at 2.7 ghz and Intel Nehalem processors at 2.66
3.6.3. Solution Exploration

Interactive visual analytics (Keim et al., 2006; Thomas and Cook, 2006; Thomas and Kielman, 2009; Andrienko et al., 2010) are used in this study to explore the many-objective tradeoffs and identify promising candidate solutions. Visualization of the high-dimensional tradeoffs demonstrates the “joint cognitive systems” (Woods, 1986; Woods and Hollnagel, 2006) approach that couples human innovation with the expanding exploratory power of computers to aid decision making under uncertainty. By combining human decision makers with computer-aided decision support, the approach enhances decision quality, promotes design discoveries, and expands the complexity of the systems that can be addressed effectively. It also helps address the cognitive challenge of initial design preconceptions biasing search toward solutions that confirm these assumptions. Gettys and Fisher termed this phenomenon “cognitive hysteresis” where decision makers seek alternatives that confirm their initial problem knowledge, limiting experts from making new discoveries and generating (or falsifying) key hypotheses on system performance (Gettys and Fisher, 1979). Furthermore, our exploration approach considers a large number of problem dimensions (both in optimization objectives and other performance metrics) to fully capture decision maker preferences and maximize the amount of available information. Topologically, this avoids lower dimensional problem structures that can cause a form of “cognitive myopia” (Hogarth, 1981) where decision quality decreases as a consequence of a too narrowly-focused problem analysis.

The approach used in this paper follows the method of Kollat and Reed (2007b) by visualizing tradeoff solutions both in the objective space (i.e., the quantitative values for performance metrics) and the decision space (the values that define the city’s supply portfolio). Parallel coordinates (Inselberg, 1985) are also used to visualize the objectives simultaneously and identify conflicts between objectives (Fleming et al., 2005). By selecting promising solutions and modifying the model assumptions and parameters, we also interrogate the effectiveness of our search on unmodeled objectives (Loughlin et al., 2001) and further inform problem modifications for future work.
4. Results

4.1. Sobol Sensitivity Indices

This section presents the results from our Sobol’ sensitivity analysis of the a priori problem formulation. The goal of the sensitivity analysis is to identify the relative importance of decision variables controlling the city’s water supply portfolio, the demand growth parameter, and the city’s initial water supply on groups of output performance metrics. Figure 3 summarizes the total sensitivity for the ten-year scenario (figure 3a) and the drought (figure 3b). Each row represents a different evaluation metric, with the metrics grouped into efficiency, risk indicators, and market use. Each column represents a variable studied within the Sobol’ Analysis, with the darkness of a block indicating the variable’s value for the Sobol’ total sensitivity index (equation 8), from white representing zero and black representing greater than or equal to 0.6. Recall that the total order indices represent the percentage of the ensemble variance controlled by a parameter’s impacts by itself as well as all of its higher order interactions with other parameters.

4.1.1. Ten Year Sensitivity

Figure 3a presents sensitivity analysis results from the ten year planning period. To compile these results, each set of values for the ten variables in table 2 was run within an identical Monte Carlo sample of 5,000 draws for the planning period of ten years with a monthly time step. The columns in the figure show that permanent rights ($N_R$), the initial fraction of rights ($i_{fr}$), and the May-December alpha variable ($\alpha_{May-Dec}$) were sensitive for almost all metrics. The January-April alpha variable $\alpha_{Jan-Apr}$ was also sensitive across many metrics. In contrast, some variables are insensitive across almost all metrics, including the high-volume options alternative ($N_{O_{high}}$), the low-high options threshold ($\xi$), and the beta variables ($\beta_{May-Dec}$ and $\beta_{Jan-Apr}$). This result generally suggests that these variables are not as important in determining the values for the city’s planning metrics. The sensitivity across metrics is most similar when the metrics are within the same group. For example, the same set of variables ($N_R$, $\alpha_{May-Dec}$, $\alpha_{Jan-Apr}$, and $i_{fr}$) is sensitive for each metric in the risk indicator group. Therefore, permanent rights, the threshold for “when” the market is used, and the initial volume of water in the city’s account are the largest determinants of its risk-based performance. While the low-volume options volume $N_{O_{low}}$ was not significant in the risk indicator group, it is a significant control on each many metrics in the market
Figure 3: Sobol results for the two scenarios. The groups of rows represent groups of decision metrics, with each row a single metric. The columns represent variables, both decision variables and model parameters. The color of each block represents the magnitude of the total Sobol sensitivity index.
use group, with the rights, alpha variables, and initial rights also having an
effect. When comparing the sensitivity structure across groups, however, we
see slightly different behavior, such as the alpha variables having a larger in-
fluence on the risk indicators than on the efficiency and market use metrics.
Similarly, the January-April beta variable $\beta_{\text{Jan-Apr}}$ is only sensitive in the
efficiency group (cost and cost variability) and not in the others.

The sensitivity analysis results show some surprising trends that would run counter to typical problem preconceptions. The relative importance of the permanent rights ($N_R$) is surprising; the sensitivity analysis suggests that rights are more important than the market-use alpha and beta variables on controlling the volume of leases. Portfolios that have high permanent rights rely on allocations to these rights to fulfill their supply, rendering the market-use variables relatively unimportant for determining the aggregate volume of leases. Permanent rights are also important for the city’s efficiency metrics; the surplus water is only sensitive to changes in the permanent rights and initial fraction of rights. Additionally, the insensitivity of the beta variables suggests that these variables do not contribute much to the city’s use of the market, apart from influencing cost and cost variability. Using only the most sensitive variables from this section would yield a decision variable formulation that focuses mainly on rights, a single options contract, and the alpha variables for determining market use (omitting beta and the adaptive options contracting).

4.1.2. Drought Sensitivity

Figure 3b presents results from the Sobol’ sensitivity analysis for the drought scenario. Note that each of the metrics in section 3.1 is valid for the drought except for the cost variability and the dropped transfers, which are omitted in the figure. The variables identified as being most sensitive across all the metrics in the ten year analysis are also important in the drought (the rights, alpha variables, and initial rights). There are however some strong differences between the average 10 year planning sensitivities and those attained for the drought scenario. Unlike in the ten year sensitivity results, the high-volume options contract ($N_{O_{\text{high}}}$) influenced the cost percentage for options, and the beta variables influenced the number of leases, cost, and surplus water. Furthermore, the demand growth parameter $dm$ had an influence on resilience and the number of leases. Some of these effects may be due to the single-year nature of the drought. In a single year, the adaptive options contract decision between the high and low volume options alterna-
tive is made only once, providing a clearer signal to the sensitivity analysis than in the ten year scenario.

Another contrast to the ten year analysis is in the relative importance of some variables. Every metric is very sensitive to the initial fraction of rights, since a high or low initial fraction of rights in the drought scenario drastically affects the city’s supply decisions. If the city has a large volume of water in its supply account (due to a high initial rights), it may not need to perform as many mitigating actions in the drought as when it has little to no water (i.e. in a multi year drought occurring before our hypothetical single year drought begins). The May-Dec alpha variable $\alpha_{\text{May-Dec}}$ is also very important in the drought, since the city’s risk-based thresholds need to be high to counteract the drought’s low inflows relative to expected conditions. Permanent rights are less important than in the ten year scenario, since portfolios with high volumes of permanent rights become exposed to failures in the drought’s statistically low permanent rights allocations in every month. The contrasts between the drought and the ten year analysis provide further evidence that its inclusion in the planning framework yields a different set of controls on supply portfolio performance that can improve the portfolio’s robustness to new conditions.

4.2. Sensitivity-Informed Problem Modifications

The second phase of our analysis uses the results from the sensitivity analysis and insights from prior work (Kasprzyk et al., 2009) to inform our de Novo many-objective analysis. In support of this analysis we have defined a suite of decision variable formulations of increasing complexity, termed “model cases”. The set of model cases is designed to begin with a model that uses only the most sensitive decision variables across all metrics, with subsequent decision variables being added to represent more complex risk-based rules for portfolios. The final, most complex formulation in the set tests the a priori decision variable formulation described in section 3.2. The analysis therefore attempts to distinguish when reductions in the complexity of our proposed decision rules is warranted within a many-objective decision making framework. Furthermore, the multiple model cases allow us to explore sorting at the problem formulation level, to determine which formulations are “non-dominated” in the many-objective analysis.

Table 4 presents the model cases explored in this study. Model case I builds a water supply portfolio using three decision variables: the volume of permanent rights ($N_R$), the volume of options ($N_O$) and the threshold
that controls both “when” the city uses the market and also “how much”
water it acquires, $\alpha$. Case II retains the permanent rights and single-volume
options contract of Case I but uses two variables to guide the city’s market
use. $\alpha_{\text{Jan-Apr}}$ controls the city’s acquisition of leases in January through
April, and $\alpha_{\text{May-Dec}}$ controls the city’s use of options and lease acquisitions
for the rest of the year. Case II was created to explore the effectiveness
of the January-April market threshold; this variable was not as sensitive
as the May-December threshold in the sensitivity analysis. Furthermore,
this added flexibility relative to case I may be useful for the city, in that
it allows the city to emphasize a more conservative strategy in one part of
the year in order to anticipate the summer drought period. Case III also
retains the single-volume options contract but uses both beta and alpha
variables for the city’s market use. Similar to Kasprzyk et al. (2009), the
beta variables are constrained to always be greater than or equal to alpha
and control the volume of water acquired after the city decides to use the
market. As described in section 2, setting beta greater than alpha could lead
to the city using the market less frequently because it is purchasing larger
volumes. While the beta variables were not sensitive for many metrics in the
Sobol’ analysis, we add them here to isolate the individual effects of groups
decision variables as effectively as possible. Adding betas at this step also
serves as a multiobjective evaluation of our Sobol’ results, which are limited
to uniform, independent sampling of beta and single metric impacts (i.e.,
they do not inform the decision maker of a decision variable’s impact on a
portfolio’s nondomination across all objectives).

Model cases I-III exploit the most sensitive variables to explore whether
or not the city could meet its water demands effectively with fewer decision
variables than the most complex a priori formulation. To provide a com-
plete test of how reductions in model complexity affect the decision making
problem, the a priori formulation is included as model case IV. Model case
IV introduces the adaptive options contract in which the city chooses be-
tween the low-volume ($N_{O_{\text{low}}}$) and high-volume ($N_{O_{\text{high}}}$) options alternatives
based on a threshold decision variable ($\xi$, see equation 1). By comparing
the a priori decision variable formulation with the reduced-complexity de-
cision variable formulations, our analysis can determine when reductions in
the complexity of decision variable formulations greatly change our many-
objective tradeoffs and inform choice of the simplest yet most effective rules
to guide the city’s use of the water market.

Cases I - IV are tested within a many objective problem formulation
Table 4: Model Cases

<table>
<thead>
<tr>
<th>Case</th>
<th>Volumetric Strategy</th>
<th>Decisions</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>$N_R, N_O$</td>
<td>$\alpha$</td>
<td>Single opt. contract, one alpha controls “when” and “how much”</td>
</tr>
<tr>
<td>II</td>
<td>$N_R, N_O$</td>
<td>$\alpha_{\text{May-Dec}}, \alpha_{\text{Jan-Apr}}$</td>
<td>Single opt. contract, two alphas control “when” and “how much”</td>
</tr>
<tr>
<td>III</td>
<td>$N_R, N_O$</td>
<td>$\alpha_{\text{May-Dec}}, \alpha_{\text{Jan-Apr}}, \beta_{\text{May-Dec}}, \beta_{\text{Jan-Apr}}$</td>
<td>Single opt. contract, alphas control “when”, betas control “how much”</td>
</tr>
<tr>
<td>IV</td>
<td>$N_R, N_{O_{\text{low}}}, N_{O_{\text{high}}}$</td>
<td>$\xi, \alpha_{\text{May-Dec}}, \alpha_{\text{Jan-Apr}}, \beta_{\text{May-Dec}}, \beta_{\text{Jan-Apr}}$</td>
<td>Adaptive opt. contract, a priori formulation</td>
</tr>
</tbody>
</table>

that was formulated to exploit the diagnostic information provided in the sensitivity analysis as well as insights from prior work. Equations 9 through 13 present the formulation for model case $k$ using the metric definitions of section 3.1. The formulation combines analysis components from the ten year analysis (abbreviated “10 yr.”) and the drought (abbreviated “dr.”).

$$F(x_k) = (f_{10 \text{ yr. cost}}, f_{10 \text{ yr. surplus}}, f_{10 \text{ yr. crit. rel}}, f_{10 \text{ yr dropped}}, f_{10 \text{ yr num. leases}}, f_{\text{dr. trans. cost}})$$

$$\forall x_k \in \Omega$$

Subject to:

$$c_{10 \text{ yr. rel}} : f_{10 \text{ yr. rel}} \geq 0.98$$

$$c_{10 \text{ yr. costvar}} : f_{10 \text{ yr costvar}} \leq 1.1$$

$$c_{10 \text{ yr. crit. rel}} : f_{10 \text{ yr. crit. rel}} \geq 0.99$$

$$c_{\text{dr. vuln.}} : f_{\text{dr. vuln}} = 0$$

In this formulation, each objective is minimized except for critical reliability $f_{10 \text{ yr. crit. rel.}}$, which is maximized. The drought transactions cost objective $f_{\text{dr. trans. cost}}$ is the portion of the cost resulting from acquisition of options and exercising of leases (i.e., the permanent rights cost and up-front options costs are omitted).

The objectives of cost, surplus water, dropped transfers, and number of leases were retained from the a priori formulation due to their interesting tradeoff structures that guided our analysis in prior work (Kasprzyk et al., 2009). Our formulation transitions from the reliability objective to a critical reliability objective to more accurately capture the risk aversion in the
system. Also, the cost variability objective was removed because it shared a similar sensitivity structure to the cost and it did not provide much information beyond its inclusion as a constraint ($c_{10\ yr\ .\ crit\ .\ rel}$). Finally, the drought transfers cost objective was added to the formulation due to the drought’s differing sensitivity structure from then ten year scenario, to explore the tradeoff between long-term cost savings in the ten-year scenario and added costs during the drought.

Two constraints were retained from the a priori formulation: the reliability constraint ($c_{10\ yr\ .\ rel}$) and the cost variability constraint ($c_{10\ yr\ .\ costvar}$). The magnitude of the cost variability constraint was introduced in prior work (Characklis et al., 2006) and ensures that the city’s cost variability (a statistical measure of high magnitude, low probability costs) is not significantly higher than their average cost in each planning year. Cost variability is effective as a constraint, but adding it as an objective would not contribute to the analysis since our prior work found that its tradeoffs have limited planning power. The constraint on critical reliability $c_{10\ yr\ .\ crit\ .\ rel}$ was modified to $f_{10\ yr\ .\ crit\ .\ rel} \geq 0.99$ to capture a wide range of objective performance while still allowing a sufficient level of high performance for the portfolios. Recall that the reliability and critical reliability are calculated using the expected number of failures in the scenario. Levels of the reliability constraints in this work reflect a very high reliability relative to typical planning by water utilities. Finally, the drought vulnerability constraint $c_{dr\ .\ vuln}$ was added to ensure that no candidate portfolios had any failures in the drought to capture the severe risk aversion that characterizes urban water planning. Note that our alternative formulations all represent severely challenging, highly constrained explorations of stochastic decision spaces. It is a major advancement in this work to be able to approximate the many-objective tradeoffs for these alternative problem formulations.

Data from the reference set for the most conservative formulation in Kasprzyk et al. (2009) (equivalent to the a priori formulation here) were used to determine typical values for the initial rights for portfolios. After beginning the simulation with an $i_{fr}$ of 0.3, the portfolios maintained a ratio of their surplus water to permanent rights at approximately 0.4. We fit a normal distribution to the first simulation year of these results with a mean of 0.4118 and a standard deviation of 0.0285. The initial rights $i_{fr}$ in the ten year scenario were then sampled from this distribution in each Monte Carlo draw. The city also began the single year in the drought scenario with a $i_{fr}$ of 0.4118 to maintain continuity with the ten year scenario. In both
scenarios, the demand growth parameter $d_m$ was set to 0.023, the largest value in its feasible range based on our analysis of the USGS data.

The $\varepsilon$-NSGAII was used to generate solution sets using the sensitivity-informed problem formulations for the model cases. As introduced in section 3.6.2, the noise in calculations of the mean objective function values is used to parameterize the epsilon dominance settings within the algorithm. To capture a representative sample across model cases and solution types, a set of 20 nondominated solutions was chosen from preliminary algorithm runs.

For each solution, we performed 50 draws of the model, using a new set of 5,000 Monte Carlo draws of the input data in each sample. The CDFs in figure 4 reflect the deviation of each solution’s objective function calculations about the mean, calculated across these 50 draws. The figure shows variations in the 50 replicate ensemble mean calculations using the ten year model for cost (figure 4a), surplus water (figure 4b), critical reliability (figure 4c), number of leases (figure 4d), and dropped transfers (figure 4e). Note that the drought transfers cost is not sampled because this objective is calculated deterministically within the single drought scenario. Each solution is shown

Figure 4: Cumulative distribution plots of objective function performance for 20 selected solutions. Each CDF was constructed from an ensemble of 50 calls of the noisy objective function.
Table 5: Objectives’ Epsilon Settings

<table>
<thead>
<tr>
<th>Objective</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>10-yr Cost</td>
<td>$30,000</td>
</tr>
<tr>
<td>10-yr Surplus Water</td>
<td>1,233 cubic m</td>
</tr>
<tr>
<td>10-yr Critical Reliability</td>
<td>0.002</td>
</tr>
<tr>
<td>10-yr Drops</td>
<td>2,467 cubic m</td>
</tr>
<tr>
<td>10-yr Number of Leases</td>
<td>0.3</td>
</tr>
<tr>
<td>Drought Trans. Cost</td>
<td>$10,000</td>
</tr>
</tbody>
</table>

with a light gray line, while the solution with the largest range is shown with a bold black line. Table 5 summarizes the noise-filtering epsilon settings that result from this analysis. These larger epsilons provide two major benefits for the MOEA search: (1) they enhance the robustness of solutions identified in search and (2) they reduce the computational demands of search by reducing the size of the Pareto-approximate solution sets attained for each model case. The noise adjusted epsilons serve to coarsen the resolution of the non-dominated set and for formulations with small objective counts it is important to confirm that a sufficient representation of tradeoffs is attained. As the number of objectives increases, this issue reduces as a concern because of the rapid growth rates of Pareto optimal sets with objective count.

4.3. Multiobjective Tradeoffs

This section presents the multiobjective solution set for model cases I-IV using the sensitivity-informed de Novo problem formulation developed in this work. Figure 5 shows the model cases sorted together, to directly compare the objective function performance of the cases relative to each other. In the figure, each cone represents one alternative supply portfolio, with the cone’s coordinates plotting each portfolio’s cost ($f_{10\text{ yr. cost}}$), number of leases ($f_{10\text{ yr. num. leases}}$), and surplus water ($f_{10\text{ yr. surplus}}$). The orientation of each cone represents the percentage of cost due to market transfers (the sum of the cost percentages of options and leases). Cones oriented vertically along the surplus water axis and pointing toward the lowest value of surplus water (i.e. pointing downward) represent portfolios with limited market use, whereas cones pointed toward the highest value of surplus water have up to 31 percent of their cost in market transfers. The size of the cones plots the portfolios’ critical reliability, with small cones indicating $f_{10\text{ yr. rel}} = 0.99$ and the largest cones indicating a value of 1.0 for this objective. The color of
the cones indicates each model case: cones for case I are navy blue, case II is shown in cyan, case III’s cones are yellow, and case IV is shown using red cones. The ε-NSGAII was run for 50 random seed trials for each model case. After these runs, the model cases were combined together to create a final reference set using the four step approach outlined in section 3.6.2.

Of the 447 solutions in the total set, model case I contributed 108 solutions (24 percent of the total), model case II contributed 18 solutions (4 percent), model case III contributed 196 solutions (44 percent), and model case IV contributed 125 solutions (28 percent). Two distinct groups of solutions emerge. The first set has high values for cost and surplus water with low percentages of their costs in the market and are hereafter referred to as “permanent rights-dominated solutions” (see highlight (i) in the figure). The rest of the solutions, termed market-dominated solutions and shown in area (ii) of the figure, are typified by lower costs and surplus water values and a range of values for the number of leases objective. The blue arrows in the figure indicate the preferred direction within the tradeoff (minimum values for the three spatial objectives).

Model case I is the simplest decision variable configuration, with the city’s market use determined by three decision variables: \(N_R\) for rights, \(N_O\) for the volume of the options contract, and \(\alpha\) controlling all lease acquisitions and options exercising. The market-dominated solutions from this case in figure 5 are able to achieve efficient performance relative to the permanent rights-dominated solutions, but the other cases have preferred performance in the spatial axes relative to case I. For example, the added flexibility in model case II (a different \(\alpha\) in the beginning of the year than in the end) yields more diversity in the tradeoff (i.e. a larger objective value range). The large size of solutions in cases I and II shows that they exhibit good performance with respect to the reliability objective. The solutions from these cases have better costs, number of leases, and surplus water performance relative to I and II. Interestingly, these solutions also do so by using less of their cost in the market (i.e. they are oriented pointing downwards relative to solutions in cases I and II). These results suggest that solutions in these cases can achieve high reliability using fewer leases on average than I and II (due to the betas being higher than alphas). The solutions from Cases III and IV span a wide range of the spatial objectives in figure 5. Examining the spatial axes in the figure, it is difficult to ascertain the difference between the objective value performance of cases III and IV.

Based on results of figure 5, the final stage of our analysis focuses on the
Figure 5: Approximations of the Pareto set for model cases sorted together. The spatial axes plot surplus water, number of leases, and cost objectives. The color of the cones indicates the model case. The orientation of the cones represents the percentage of total cost due to market transfers, whereas the size of the cones represents each portfolio's critical reliability. Model case III is shown opaque with other cases shown with transparency for the purpose of highlighting the contribution of case III.
contributions of model case III to this final reference set, because it represents a simple and effective formulation of the planning problem. This case had the largest number of solutions in the reference set, and its contribution to the reference set featured solutions from both the permanent-rights dominated solutions and the market-dominated solutions. Figure 6 presents a parallel line plot of case III’s contribution to the total reference set. Each line in this plot represents the objective function values for a single solution. The values on each axis are plotted such that the position on the vertical numberlines represents the relative magnitude of each objective, and the direction of increasing preference for each objective is pointing downward. Because of this plotting convention, conflicts between objectives can be seen when the lines cross (Fleming et al., 2005). Color represents the percent of the total cost due to market use, similar to the reference sets figure, ranging from 2.0 percent in blue to 27.5 percent in maroon.

Market-dominated solutions (yellow and red solutions that spend more of their supply costs in the market) exhibit low costs and surplus water, with higher values for the dropped transfers $f_{10 \text{ yr. drop}}$ and number of leases $f_{10 \text{ yr. num. leases}}$ objectives. Solutions with higher percentages of their cost in the market actually have lower values for their 10 year aggregate $f_{10 \text{ yr. cost}}$ objective. A prominent conflict exists between the cost ($f_{10 \text{ yr. cost}}$) and the drought market transfers cost ($f_{\text{dr. trans. cost}}$) objectives. Portfolios that exhibit high cost in the long-term scenario have cost savings in the drought. This result, though, is contingent on our assumption of constant initial rights in the drought. The assumption is equivalent to assuming that a drought would occur after a “typical” year with the city holding a sufficient amount of water in its supply account. As a further exploration of solution performance, the next section will explore the impact of this initial condition on several selected water supply portfolios.

Table 6 and the annotations in figures 5 and 6 show three solutions selected for further analysis. In table 6, the $\%N_x$ metric is defined as percentage of Monte Carlo draws in which the city exercises their options (calculated as an average across the 10 simulation years). All other metrics are as defined previously, and each measures performance in the ten year scenario except as noted. Solution 1 is termed “Low 10 Yr. Cost.” It has preferred cost and surplus water objective performance, and exhibits the highest market use of any of the selected solutions. Note in table 6 that there is a distinct difference in this solution’s $\alpha$ and $\beta$ values; in May-December, the beta is 1.53 whereas the alpha is 1.29. This separation would not have been possible
Figure 6: Parallel line plot for model case III’s contribution to the reference set. Each solution is represented by a line, with the color of the line representing the percent contribution of market transfers to the solution’s planning period cost, and the vertical position of the line representing the relative objective function value for each respective objective. Solutions 1 - 3 are picked for further analysis and are shown with bold lines.
in the simpler decision variable formulations of cases I and II. For solution 1, 25.1 percent of its cost is from market use, with 77.1 percent of the Monte Carlo draws resulting in an exercised option. Solution 2 is termed “High 10 Yr. Cost.” It has higher costs and surplus water relative to solution 1 but its low market use and tendency to store large volumes of surplus water yields preferred performance with respect to solution 1 in several other objectives. Solution 2 also has very low drought transfers costs, due to the fact that the high volume of water carried over at the beginning of the drought allowed the city to avoid high volumes of market transfers in the drought scenario. Solution 2’s $\alpha_{\text{Jan-Apr}}$ and $\beta_{\text{Jan-Apr}}$ values are very low, indicating that this solution would never have had to buy leases in these months. Solution 3 is termed the “Compromise” solution. Each of its objective function values falls between the magnitude of the other solutions’ objective function values. The solution has relatively high volumes for both the permanent rights $N_R$ and the options contract $N_O$, and it exhibits some separation between $\alpha$ and $\beta$ values. Examining the market use metrics in the third part of table 6 shows that solution 3’s market use is lower than solution 1’s, and that solution 3 exercised its options fewer times than solution 1 did. Additionally, its critical reliability $f_{10\text{ yr. critrel}}$ is higher than in solution 1. In general, the high cost solution 2 represents how utilities typically plan, whereas the solution 1 could be implemented by a utility that was highly tolerant of risk. Solution 3, though, is a reasonable amount of market use for a risk averse utility that has high potential to lower costs while maintaining high reliability through using the market.

4.3.1. Exploration of Solutions through the Drought Scenario

Recall that the drought scenario is a single statistically dry year coupled with the highest simulated demands. This section explores the effect of changing the initial volume of water available to the city at the beginning of the scenario, to show how deeply uncertain model assumptions about water availability or timing of drought can affect the city’s water portfolio performance. The three solutions chosen for further analysis each had good objective function performance across all six objectives considered in the many-objective problem formulation. The different values for the initial condition in this section serve as a proxy for simulating when a severe drought occurs. The first test, $i_{fr} = 0.4$, tests how the city’s supply portfolio would perform if a drought occurred after a year with average supply on hand. The value used is slightly lower than what was used in the optimization, and this
Table 6: Selected Solutions’ Performance

<table>
<thead>
<tr>
<th>Solution Name</th>
<th>Low 10 Yr.</th>
<th>High 10 Yr.</th>
<th>Compromise</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_{10\text{ yr. cost}} \ (10^6 \text{ $})$</td>
<td>9.05</td>
<td>11.12</td>
<td>10.19</td>
</tr>
<tr>
<td>$f_{10\text{ yr. surplus}} \ (10^6 \text{ m}^3)$</td>
<td>15.2</td>
<td>50.6</td>
<td>19.8</td>
</tr>
<tr>
<td>$f_{10\text{ yr. critrel}} \ (%)$</td>
<td>99.8</td>
<td>99.9</td>
<td>99.9</td>
</tr>
<tr>
<td>$f_{10\text{ yr. dropped}} \ (10^6 \text{ m}^3)$</td>
<td>44.0</td>
<td>0.365</td>
<td>32.8</td>
</tr>
<tr>
<td>$f_{10\text{ yr. numleases}}$</td>
<td>2.74</td>
<td>0.404</td>
<td>1.78</td>
</tr>
<tr>
<td>$f_{\text{dr. trans. cost}} \ (10^6 \text{ $})$</td>
<td>0.189</td>
<td>0.00975</td>
<td>0.119</td>
</tr>
<tr>
<td>$N_R \ (10^6 \text{ m}^3)$</td>
<td>37.0</td>
<td>60.8</td>
<td>46.0</td>
</tr>
<tr>
<td>$N_O \ (10^6 \text{ m}^3)$</td>
<td>17.2</td>
<td>0.0049</td>
<td>21.0</td>
</tr>
<tr>
<td>$\alpha_{\text{May–Dec}}$</td>
<td>1.29</td>
<td>1.29</td>
<td>1.24</td>
</tr>
<tr>
<td>$\beta_{\text{May–Dec}}$</td>
<td>1.53</td>
<td>1.34</td>
<td>1.60</td>
</tr>
<tr>
<td>$\alpha_{\text{Jan–Apr}}$</td>
<td>1.20</td>
<td>0.06</td>
<td>1.39</td>
</tr>
<tr>
<td>$\beta_{\text{Jan–Apr}}$</td>
<td>1.28</td>
<td>0.09</td>
<td>1.39</td>
</tr>
<tr>
<td>$f_{\text{cost per. rights}} \ (%)$</td>
<td>74.9</td>
<td>99.8</td>
<td>82.7</td>
</tr>
<tr>
<td>$f_{\text{cost per. options}} \ (%)$</td>
<td>22.7</td>
<td>0.00</td>
<td>16.0</td>
</tr>
<tr>
<td>$f_{\text{cost per. leases}} \ (%)$</td>
<td>2.4</td>
<td>0.18</td>
<td>1.34</td>
</tr>
<tr>
<td>$%N_z$</td>
<td>77.1</td>
<td>1.53</td>
<td>44.6</td>
</tr>
<tr>
<td>$N_z \ (10^6 \text{ m}^3)$</td>
<td>10.8</td>
<td>0.0</td>
<td>5.95</td>
</tr>
<tr>
<td>$N_l \ (10^6 \text{ m}^3)$</td>
<td>2.19</td>
<td>0.110</td>
<td>1.30</td>
</tr>
</tbody>
</table>
Figure 7: Drought scenario analysis results. The bars show the amount of water in the city’s supply account in each month. The scenario demand is shown with an x, and the projected or mean demand is shown with a circle. Failures occur when the ordinate of the demand is higher than the city’s supply. The columns represent different selected solutions, and the rows represent different assumptions of initial rights that begin the scenarios. Risk indicators are shown in the upper right hand corner, with “Rel.” representing reliability, “C.Rel.” representing critical reliability, and “Resil.” representing resilience.
small perturbation is well within the uncertainty on how much the city would have to hold from year to year. The second test has $i_{fr} = 0.2$, which will greatly limit the amount of water in the beginning of the drought simulation and trigger different behavior for market utilization. Lower initial conditions will specifically test the January-April market utilization variables, since the city will be more vulnerable in those months than on average. The final test has $i_{fr} = 0$. An equivalent situation to this test would be a multi-year drought in which the city experiences a failure in the month before our drought scenario begins.

Figure 7 presents the results of these tests, with each solution’s decision variable values shown above the bar charts, and each panel showing the city’s equivalent reliability (“Rel.”), critical reliability (“C. Rel.”) and resilience (“Resil.”) for that test. The first row is for the initial condition at 40 percent of the portfolio’s permanent rights (i.e., $i_{fr} = 0.4$), the second row shows 20 percent, and the third row shows 0 percent (no water carried over). The three columns each represent the three selected solutions. The vertical axis on each bar chart shows a water balance for the city’s water supply in each month of the simulation, with each bar representing one of the 12 months of the year starting in January. The initial conditions for each test are defined using equation 2, where the city is granted a starting volume of water commensurate with its volume of permanent rights $N_R$. Recall that this initial condition is considered a surrogate for the water that is often left in the city’s water supply account from the previous year.

After January where the initial condition water begins the simulation, the city’s water from the previous months that is not used is indicated as “carry over” water and shaded dark gray. For the months of February through December, allocations to the city’s permanent rights are shown using hashed lines, purchased leases are shown in light gray, and exercised options are shown in white. The demand volume used in the anticipatory thresholds (i.e. the expected value demand) is shown with a circle. However, the drought scenario’s maximal demand that the city must actually meet is shown with an x. Failures occur when the demand (shown with an x) falls higher than the supply (of carried over water, rights allocations, options, and leases) indicated by the bar. Note that for each of these tests, our drought scenario examines what would happen if the city used the market in the exact manner that the evolved portfolios dictated. Our goal here is to examine the solutions’ performance as if the decision rules were codified such that it would be exceedingly difficult to change the regulations even in an emergency.
Panels (a)-(c) of figure 7 show the tests when the initial condition was 40 percent, slightly lower than what was used in the optimization. All three solutions had no failures in this test, but each leaves December with much less water than its starting volume. Solutions 2 and 3, in particular, had barely enough supply to meet its December demand, and in the subsequent year they would start with a condition similar to the 0 percent initial condition shown in panels (g)-(i). Another consequence of this test is that the large volume of initial condition water in panel (b) for solution 2 quickly degrades with the low allocations and high demands of this drought scenario. This result highlights that while portfolios may be able to rely on carry-over water for supply in typical conditions, violating these assumptions may expose the city to severe risks for supply failures.

Transitioning to panels (d)-(f), the city has a lower percentage of its rights available as an initial condition. Market decisions triggered by lower volumes of water supply in the first months of the year before May will be determined by the January-April $\alpha$ and $\beta$ variables. Even though solution 1 in panel (d) has fairly high values for these variables, the moderate volume of water available is enough to not trigger the thresholds until the end of April into May, when a small lease is not enough to prevent a failure in May. After the option exercise month, the city has sufficient volumes of water to avoid failure. Solution 3 exhibits a similar behavior in panel (f), with the same performance metric values without having to purchase a lease due to higher initial conditions and different strategy variables. Note also that one of the failures of solution 1 in panel (d) was critical (i.e. the city could provide less than 60 percent of its total demands), whereas the failure for solution 3 in panel (f) was not critical. A combination of the carry-over water and multiple leases allowed solution 2 to avoid any failures in this test. An interesting aspect of this test, though, was that the city is forced to rely on many leases to avoid failures here, whereas it only purchased 0.404 leases on average in the 10-year scenario.

Panels (g)-(i) show the test in which the city has no water in its account before the drought scenario begins. Recall that portfolios that have very low water (or a failure) in the last month of the other drought scenario tests would be forced to confront a test such as this in the subsequent year (i.e. there is no water available and the drought continues). The adaptivity of the market-dominated solutions 1 and 3 in panels (g) and (i) allowed both portfolios to purchase leases in January, April, and May, with an additional purchase by
solution 1 in August. Both solutions had one critical failure, but exhibited resilient performance in that there were no failures in the month after the shortage. Solution 2 in panel (h), however, had failures in six out of the twelve months. The low $\alpha$ and $\beta$ variables in the first five months paralyzed the city’s water supply, with failures in January through June (many of which were critical failures). After the option exercise month, the city’s market use variables allowed it to purchase several leases and it had reliable supply until the end of the year.

The results show the importance of having sufficient values for the volumetric variables ($N_R$ and $N_O$) as well as risk-based triggers that are conservative enough such that the city uses the market at appropriate times. Portfolios that had their $\beta$ values higher than $\alpha$ tended to use the market less frequently for larger volumes which can increase supply security. The comparative analysis done in this section also focuses our attention on the difference between early and late year patterns (i.e. in the months before and after the option exercise month); across different initial conditions, the pattern in the early or late months are the same. Thus, the initial conditions have less of an effect for some portfolios after the options exercise month. Another important result is that even the safest portfolios had a low amount of water at the end of the year, but the compromise solution has the highest volume left on average. These insights can inform further problem modifications in subsequent iterations of the problem. For example, the assumptions of initial conditions or the appropriate planning time scale (short term versus long term) can be critically important for developing effective water supply portfolios.

5. Conclusion

This work supports the view that decision variable and objective formulations are constantly changing and being improved by new learning or decision maker preferences (Zeleny, 1989). Typical environmental planning problems are solved within a static formulation using a quantitative model with a fixed set of decision variables that determine the planning strategy. The sensitivity analysis using Sobol’ variance decomposition, however, showed that several variables were insensitive across many candidate planning metrics considered in the work. Our sensitivity-informed changes to our formulation (“de Novo planning”) removed the variables that did not contribute to the variance of key water supply evaluation metrics. Changes to our planning problem
formulation also included the addition of a drought cost objective because drought year sensitivities were significantly different than average year controls. The full diagnostic value of these changes was not seen, though, until interactive visual analytics were used to review the MOEA-generated tradeoffs. Visualization of the alternative formulations’ many-objective tradeoffs showed that a decision variable formulation of moderate complexity (model case III) was sufficient to develop portfolios that exhibited improved efficiency with respect to surplus water, balanced market use, and reduced water supply risks.

This study shows the effectiveness of combining multiple tools for increasing the robustness of environmental planning. The framework demonstrates the value of global sensitivity analysis, many-objective optimization, and interactive visual analytics to promote problem understanding and incorporate stakeholder learning into the planning process. This study also contributes computational advances in solving noisy multiobjective problems by introducing the concept of noise-adjusted epsilon dominance settings to filter solutions that are highly uncertain and lack robustness with respect to planning objectives.

The robustness of planning solutions is further explored in this study using the concept of deep uncertainty, which is characterized by decision makers not being able to predict accurately the categories of risk to which their systems are vulnerable. In addition to the average year planning horizon, the extreme drought scenario showed how market use can help cities avoid catastrophic failures in times of low water availability. Our exploration of deep uncertainty in the drought scenario indicated that solutions that depended on large volumes of “carry-over” water for supply would be left exposed to critical water shortages after twelve months of low water supply (i.e., a drought that extends beyond a single calendar year). Resolving this challenge requires a compromise between high market use and high permanent rights use to minimize the impacts of sustained drought while simultaneously reducing a city’s long term planning costs and surplus water capacity in non-drought years.

A. Detailed Performance Metric Descriptions

The following notational definitions refer to our Monte Carlo simulation ensemble, with the variable $M$ representing the number of Monte Carlo samples taken. The simulation is run for $T$ planning years where $T = 10$ for our
long-term analysis and $T = 1$ in the drought. The index $i$ is used below to indicate the planning year, and the index $j$ denotes the month within that year. The notation $E[.]$, denotes an expectation over the $M$ Monte Carlo samples of the $i$th year. The notation $x_k$ represents the vector of decision variables that describes the city’s water supply portfolio. The subscript $k$ denotes the form of the decision variable vector used.

A.1. Efficiency Metrics

**COST** The cost of each portfolio comprises costs from permanent rights, an up-front fee for the options contract, the exercised options, and purchased leases. The cost metric (equation 15) is a sum of the annual costs (equation 14) calculated as follows,

\[
f_{\text{annual cost}}(x_k)_i = E \left[ N_{RP} + N_{OP} \sum_{j=1}^{12} \left( N_{l,j} \hat{p}_{l,i,j} \right)_i \right]
\]

with terms as defined previously. The permanent rights volume is constant for all $T$ simulation years. The decision to exercise options is made once per year, denoted by the subscript $i$. If the adaptive options contract is used, the volume of options available ($N_{O}$) is determined by the city’s initial water supply in each year according to equation 1. Leases incur cost when purchased in each of the 12 months of the $T$ simulation years, with each lease purchase subject to a uniquely sampled price, $\hat{p}_{l,i,j}$, in the $j$th month of the $i$th year.

**SURPLUS WATER** The surplus water metric quantifies 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, has been minimized in previous work (Kasprzyk et al., 2009) to free water for other uses (such as ecological flows). Formally, the metric calculates an average of the annual expected surplus water volumes:

\[
f_{\text{surplus}}(x_k) = \sum_{i=1}^{T} \frac{1}{T} \left( E[S_j]_i \right), \quad j = 12
\]
where the variable $S_j$ denotes the city’s water supply (comprising rights, options, and leases) in month $j$.

**COST VARIABILITY** Variance in the distribution of costs for each portfolio is introduced by the anticipatory rules for exercising options and purchasing leases, since each draw in the Monte Carlo ensemble has different volumes of options and leases acquired. The Contingent Value of Risk (CVAR) captures this variability, defined as the mean of costs falling above the 95th percentile (Kirsch et al., 2009). Following our previous work (Kasprzyk et al., 2009), the metric captures the year with the highest cost variability, to ensure that the rest of the simulation years have a lower amount of variability (see equation 17),

$$f_{\text{costvar}}(x_k) = \frac{\max_{i \in [1,T]} \text{CVAR}_i}{f_{\text{annual cost}_i}}$$

where the index $i$ denotes the year with the highest CVAR cost, and $f_{\text{annual cost}_i}$ is expected annual cost in that year.

**DROPPED TRANSFERS** The dropped transfers metric stems from the fact that leases and exercised options in this study expire after a year of non-use. The variable $a$ describes the “age” of the water in the city’s supply account, so that when $a > 12$, the water has not been used for 12 months after its acquisition and therefore expires (it is no longer considered available to meet demand). This metric is important since water managers would prefer portfolios that avoid transfers that result in large volumes of water being dropped. The dropped transfers objective is computed as the sum of the annual expected volume of dropped transfers (see equation 18).

$$f_{\text{dropped}}(x_k) = \sum_{i=1}^{T} \left( \mathbb{E}\left\{ N_{x_i} : a > 12 \right\} + \sum_{j=1}^{12} \left\{ N_{l_{i,j}} : a > 12 \right\} \right)$$

Note that the metric measures two components: a volume of water from exercised options (one value in the $i$th year, $N_{x_i}$) and leased water (acquired in the $j$th month of year $i$, $N_{l_{i,j}}$). In calculating the metric, both entire lease acquisitions and portions of lease acquisitions that are unused are considered. For example, if the city purchases 1,000 cubic meters and only 300 cubic meters are used, 700 cubic meters are said to be dropped.

### A.2. Risk Indicator Metrics

Drawing from Hashimoto et al. (1982), the concepts of resilience, reliability, and vulnerability are used to quantify the risk-based performance of portfolio planning strategies.
RELIABILITY The reliability of a portfolio captures the probability of successfully supplying the city’s water demands (i.e., how often the city avoids failure). A portfolio’s reliability \( r(x) \) is initially defined following the formulation of Characklis et al. (2006).

\[
r(x_k) = 1 - \frac{E[n_{fail}]}{12}
\]

(19)

where \( E[n_{fail}] \) represents the expected number of monthly failures in the year \( i \). These failure events are defined as the city’s supply \( (S_j) \) falling strictly short of the simulated demand \( (d_j) \) regardless of the shortfall volume, according to equation 20.

\[
S_j < d_j
\]

(20)

The aggregate reliability metric \( f_{rel} \) calculates the lowest expected reliability of any year in the planning period.

\[
f_{rel}(x_k) = \min_{i \in [1,T]} (r_i)
\]

(21)

When used in the optimization, \( f_{rel} \) is maximized to ensure that each planning year has performance at least as high as this lower bound.

CRITICAL RELIABILITY Critical reliability, \( f_{crit\_rel} \), is calculated in the same manner as reliability (see equations 19 and 21), but the definition of failure is set to the city not being able to meet at least 60% of its simulated demand (Characklis et al., 2006), given in equation 22.

\[
S_j < 0.6d_j
\]

(22)

RESILIENCE Resilience measures “...how quickly [a water resource system] returns to a satisfactory state once a failure has occurred” (Hashimoto et al., 1982). Following the notation of Fowler et al. (2003), the set of “satisfactory” states represents the condition where the monthly supply is strictly greater than the simulated demand (see equation 20). An “unsatisfactory” state consequently represents a failure in that month. In this study, resilience is function of a portfolio’s performance during the whole simulation regardless of simulation year. The index \( t \) is used such that the simulation begins at \( t = 1 \) and ends at \( t = 12T \), where \( T \) is the number of years in the simulation. This convention accounts for failure periods that span more than one calendar year, from December of one simulation year through January of the next simulation year, for example. Let \( Z_t \) equal 1 if there is no failure in a
month \( t \). This relationship is expressed using the notation for the supply in month \( t \) \((S_t)\) and the demand in month \( t \) \((d_t)\) as follows:

\[
\text{if } S_t > d_t \text{ then } Z_t = 1 \\
\text{else } Z_t = 0
\]  

(23)

Since resilience considers transitions between satisfactory and unsatisfactory states, the variable \( W_t \) is introduced to indicate a transition into failure in timestep \( t + 1 \) after an observed failure at time step \( t \) (equation 24).

\[
W_t = \begin{cases} 
1 & \text{if } Z_t = 1 \text{ and } Z_{t+1} = 0 \\
0 & \text{otherwise}
\end{cases}
\]  

(24)

Using the above definitions, equation 25 defines resilience for the \( m \)th Monte Carlo realization, denoted by \( r_{sm} \).

\[
r_{sm} = \begin{cases} 
1.0 & \text{if } Z_t = 0 \forall t \in [1, T] \\
\frac{\sum_{t=1}^{T} W_t}{\sum_{t=1}^{T} Z_t} & \text{otherwise}
\end{cases}
\]  

(25)

In equation 25, the resilience is 1.0 if there are no failures. In the presence of failures, resilience is the ratio of the number of transitions into a failure state to the number of failure time steps. If there is the same number of failures as the number of transitions into the unsatisfactory state, this means that the system quickly “rebounds” from a failure and does not spend more than one step in the unsatisfactory state. Across all \( M \) Monte Carlo realizations, the resilience metric is defined using an expected value in equation 26:

\[
f_{\text{resil}}(x_k) = \sum_{m=1}^{M} \frac{1}{M} r_{sm}
\]  

(26)

**VULNERABILITY** Vulnerability measures the most severe failure period, defined as a set of failures with the largest differential between the volume of supply, \( S_t \), relative to the demand, \( d_t \). Using the notation of Fowler et al. (2003), let the number of failure periods of one or more timestep be denoted by \( G \). Also, let \( J_g \) be the set of timesteps representing the \( g \)th transition from the satisfactory state, to the unsatisfactory state, and back. For example, if the 3rd and 4th months represented the first time the system went into a failure, then \( J_1 = \{3, 4\} \). If the 5th month was satisfactory, the 6th month contained a failure, and the 7th month was satisfactory, then
$J_2 = \{6\}$. Equation $vn_m$ denotes a measure of vulnerability for the $m$th realization (i.e. a single time series similar to equation 25).

$$vn_m = \max_{g \in \{1, G\}} \left( \sum_{t \in J_g} (d_t - S_t) \right) \quad (27)$$

Each period of failures is examined in the time series, with the period with the most severe failure recorded as a volume, $vn_m$. Similar to the resilience metric shown above, the vulnerability metric calculates an expectation across all $M$ Monte Carlo realizations (equation 28).

$$f_{vuln}(x_k)i = \sum_{m=1}^{M} \frac{1}{M} vn_m \quad (28)$$

A.3. Market Use Metrics

**NUMBER OF LEASES** Since leases can be purchased in any month, some portfolios may specify a large number of leases to be purchased, which may imply a large transactions cost for the city. The number of leases metric attempts to quantify this by explicitly counting the number of leases regardless of volume, according to equations 30 and 29 below:

$$\phi_{i,j} = \begin{cases} 1 & \text{if } N_{i,j} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (29)$$

$$f_{num.\; leases}(x_k) = \sum_{i=1}^{T} \left( E \left[ \sum_{j=1}^{12} \phi_{i,j} \right] \right) \quad (30)$$

where $\phi$ accounts for whether or not a lease was acquired, regardless of its volume.

**VOLUME OF LEASES** The volume of leases metric calculates the average annual expected volume of leases for a given portfolio. This metric was included in the analysis since the anticipatory risk-based rules that govern options and leases do not provide a deterministic amount of market use but rather provide a strategy for the city to use the market based on the amount of supply and demand that is forecasted in future decision periods. Equation 31 calculates a sum of lease volumes across the 12 months of the $i$th year for each Monte Carlo simulation, and take the expected value across all Monte Carlo simulations. Using the $T$ values for the expected annual volume
of leases, a planning period average is calculated from each of these annual values.

\[ f_{\text{vol. leases}}(x_k) = \sum_{i=1}^{T} \frac{1}{T} E\left[ \sum_{j=1}^{12} (N_{i,j}) \right] \tag{31} \]

**VOLUME OF EXERCISED OPTIONS** Similar to the volume of leases metric, this metric provides a calculation of the average volume of exercised options for a given portfolio. Equation 32 first uses the Monte Carlo simulation to calculate an expected value of the exercised options \((N_{x_i})\) in year \(i\). An average volume of exercised options is then calculated by averaging these \(T\) annual values.

\[ f_{\text{vol. ex. options}}(x_k)_i = \sum_{i=1}^{T} \frac{1}{T} E[N_{x_i}] \tag{32} \]

**COST PERCENTAGE LEASES** The following cost percentage metrics seek to quantify the contribution of market use to the total cost. To calculate the cost percentages of leases metric, the portion of the total cost that was due to lease acquisitions is divided by the total cost.

\[ f_{\text{cost per. leases}}(x_k) = \frac{\sum_{i=1}^{T} E\left[ \sum_{j=1}^{12} (N_{i,j} \hat{p}_{i,j}) \right]}{f_{\text{cost}}} \tag{33} \]

where \(f_{\text{cost}}\) is the cost metric presented in equation 15.

**COST PERCENTAGE OPTIONS** Similar to the previous metric, the cost percentage of options metric quantifies the contribution of the up-front options and exercised options to the portfolio’s total cost. The metric is calculated using equation 34:

\[ f_{\text{cost per. options}}(x_k) = \frac{\sum_{i=1}^{T} E\left[ N_{O_i} p_O + N_{x_i} p_x \right]}{f_{\text{cost}}} \tag{34} \]

where the up-front options cost is calculated in the first term and the exercised options cost is calculated in the second term in the numerator. With the adaptive options contract, each year \(i\) has a distinct \(N_{O_i}\) (see equation 1); if the adaptive contract is not used, every year has the same value for \(N_{O_i}\).
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