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Searching for a Robust Operation of Lake Mead

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SEARCHING FOR A ROBUST OPERATION OF LAKE MEAD

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Searching for a Robust Operation of Lake Mead

Thesis directed by Professor Joseph Kasprzyk

The Colorado River spans seven US states and Mexico and is an important cultural, economic, and natural resource for 35 - 40 million people. Its complex operating policy is based on the "Law of the River," which has evolved since the Colorado River Compact in 1922. Operational guidelines were negotiated in 2007 to address shortage reductions and coordinated operations of Lakes Powell and Mead. These interim guidelines – in effect until 2026 - were ultimately agreed on after manually exploring hundreds of alternatives. The Colorado River Basin's projected water delivery reliability has continued to degrade since 2007, primarily due to a persistent drought causing a lower supply and secondarily from a growing demand. The magnitude of the future supply-demand imbalance is challenging to predict since the most likely realizations of future water demand and hydrology are unknown, nor are the uncertainties quantifiable. Hence, these future conditions can be described as deeply uncertain. Negotiations for the new 2026 guidelines will need to consider deep uncertainty when searching for and evaluating operational alternatives.

This research explores innovative planning approaches that are appropriate for conditions of deep uncertainty and then demonstrates an application of a method called Many Objective Robust Decision Making (MORDM). This MORDM application couples a multi-objective evolutionary algorithm (MOEA) with the Colorado River Simulation System (CRSS) model to generate and evaluate thousands of new operating policies for Lake Mead. The MOEA-generated policies are then re-simulated across multiple future water supply and water demand scenarios testing each policy's performance across a wide range of plausible future uncertainty. This

research identified multiple robust operating policies through applying a satisficing analysis to the set of MOEA-generated policies. The operational similarities between the identified robust policies may shed light on how Lake Mead's operation could be formulated to be more robust to a wide range of future hydrologic and water demand conditions. This research provides a realistic application of an MOEA to one of the largest most complex river basins that has been optimized using an MOEA to date.

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Chapter 1 Introduction

Traditional decision making methods have aided water managers in selecting an optimal water management plan where the primary focus is maximizing system performance. These methods are often classified as "top-down" methods where the analysis starts with projecting the most likely future condition and ends with identifying actions to guarantee optimal performance for the most likely projection. These projections are based on past records, expert knowledge, or a combination of the two (Dittrich et al., 2016). A historical example of "top-down" planning in the Colorado River Basin (CRB) is the allocation of Colorado River water to neighboring US states and Mexico during the signing of the Colorado River Compact (Compact) in 1922. The Compact allocations were decided during a period (1905 - 1922) of abnormally high streamflow conditions where the annual average flow at Lees Ferry was 16.4 million acre-feet (National Research Council, 2007).

The streamflow conditions during this period were thought to be the expected conditions in the CRB and the decision makers thought this estimate of annual flow would most likely be the future streamflow condition. However, recent streamflow reconstruction studies have concluded that the long-term annual average streamflow at Lees Ferry is closer to 14.3 million acre-feet, which is significantly less than the expected conditions during the signing of the Compact (Woodhouse et al., 2006). The decisions made in the Compact led to over-allocating the water in the CRB due to not considering a wider range of possible hydrologic conditions than had been observed at the time - conditions of severe or deep uncertainty.

The term “deep uncertainty” describes an uncertain condition that is unquantifiable, for which the most likely realization of the future is unknown (Knight, 1921). Therefore, deep uncertainty is a critical challenge for “top-down” approaches that assume known future conditions. A growing body of research suggests that under such circumstances, plans should be designed to be *robust* rather than optimal. Specifically, planning for robustness focuses on having satisfactory performance in many projections of uncertain future conditions instead of focusing on having optimal performance for the “expected” future (Lempert & Collins, 2007). Therefore, a new class of methods termed "bottom-up" methods focuses on simulating plans across many plausible states of the world rather than assigning likelihoods to future conditions as in “top-down” methods. For clarification, the term “states of the world” means plausible projections of future uncertain factors that impact the planning system. Examples of uncertain factors in water resource management include future streamflow projections, water demand scenarios, or greenhouse gas concentration trajectories.

Reclamation incorporated "bottom-up" planning in the Colorado River Supply and Demand Study (Basin Study) in which Robust Decision Making[1] was explored to identify vulnerable conditions that could impact the water delivery reliability in the CRB (Groves et al., 2013). The CRB’s projected water delivery reliability has continued to degrade since the 2012 Basin Study, due to the imbalance of growing demand and dwindling supply. The magnitude of this imbalance is challenging to predict due to the deep uncertainty of future water demand and hydrology. Moreover, the projected demand-supply imbalance may stress the previously negotiated

[1] Robust Decision Making is a bottom-up decision making technique that will be discussed further in Chapter 2 of this thesis.

operational guidelines, motivating changes to the existing planning to consider conditions of deep uncertainty when searching and evaluating operational alternatives.

This thesis explores a different approach to formulate new reservoir operating policies. Specifically, this research demonstrates a bottom-up planning approach that couples a multi-objective evolutionary algorithm (MOEA) with the Colorado River Simulation System (CRSS) model to generate and evaluate thousands of new operating policies for Lake Mead. The MOEA-generated policies are then re-simulated across multiple future water supply and water demand scenarios testing each policy's performance across a wide range of plausible future uncertainty. The ultimate goal is to discover robust policies for new operating guidelines for Lake Mead that manage the CRB efficiently and have satisfactory performance across wide ranging projections of future conditions.

The following three research questions will be used to help structure the discussion in this thesis. First, can an MOEA generate comparable policies to those negotiated in the 2007 Interim Guidelines? To evaluate the performance of the MOEA-generated policies, we use the previously negotiated policies as performance benchmarks. Second, are the MOEA-generated policies robust to a wide range of plausible future hydrologic and water demand conditions? Specifically, we measure the robustness of a generated policy by its ability to maintain a satisfactory level of performance across a broad range of future conditions. Third, which attributes of a Lake Mead operating policy lead to robust performance? To address this question, we utilize a series of interactive visuals to identify operational similarities between robust policies.

The organization of this thesis in the four additional chapters is as follows. Chapter 2 provides an overview of multiple state-of-the-art planning frameworks that are appropriate for conditions of deep uncertainty. Moreover, this chapter selects a planning framework to be considered in this research of exploring robust reservoir operation in the CRB. Chapter 3 discusses MOEAs, the simulation model employed, and the methodological steps that the selected planning framework requires. Additionally, this chapter provides a section describing the computational experiments that were conducted in this research. Chapter 4 highlights findings through providing analysis of the results. Chapter 5 provides a further discussion of the results, presents conclusions, and outlines areas of future work. Preliminary results from the MOEA-search portion of this research were presented at the American Geophysical Union Fall Meeting 2017 (Alexander et al., 2017) and at the Environmental & Water Resources Institute's Water Resources Congress in Spring 2018 (Alexander et al., 2018). The findings from this thesis will be adapted into a journal article.

Chapter 2 Background

2.1. Introduction

This chapter starts off reviewing state-of-the-art bottom-up planning frameworks and then ends with the selection of a bottom-up framework that best addresses the needs of the CRB planning context of discovering robust reservoir operating policies.

2.2. Overview of Bottom-Up Planning Frameworks

As mentioned previously, bottom-up planning frameworks are designed to aid decision makers in making policy choices when confronted with deep future uncertainty. Bottom-up frameworks can be broadly categorized by the extent to which they include plans changing in time. Adaptive frameworks generally focus on devising plans that can adapt to changing uncertain future conditions (Walker et al., 2013). These methods include: Adaptive Policy Pathways (Haasnoot et al., 2013) and Adaptive Policymaking (Walker et al., 2001). A second class of methods uses a static analysis to develop plans that are considered to be unchanging (though the plans can have thresholds or trigger points that allow actions to adapt within time). These methods include: Information Gap Decision Theory (Ben-Haim, 2004), Robust Decision Making (Lempert et al., 2003), and Many Objective Robust Decision Making (Kasprzyk et al., 2013). In general, all bottom-up frameworks seek robust plans that exhibit satisfactory performance regardless of the uncertain future condition.

Although adaptive planning frameworks have had interesting theoretical contributions in recent literature, the focus of our CRB planning is on a static analysis that would generate new operating plans that are transparent and agreed upon for a long time horizon. Therefore, we choose to focus the remainder of this chapter on the static class of methods. The remainder of this chapter will provide a non-exhaustive literature review of three bottom-up frameworks that construct static robust plans including: Information Gap Decision Theory (IGDT), Robust Decision Making (RDM), and Many Objective Robust Decision Making (MORDM).

All bottom-up planning methods can be categorized by how they identify alternatives, how they identify states of the world, the types of robustness measures they use, and how they identify controls on robustness. Figure 2.1, adapted from Herman et al. (2015), illustrates these methodological differences. The first of these differences begins with identification of management alternatives to be considered in the planning study. Alternatives can be pre-specified by decision makers, similar to traditional engineering alternatives analysis. In contrast, a bottom-up framework can instead use an optimization algorithm to automatically generate many candidate alternatives that could be considered. The second difference is how the bottom-up framework identifies states of the world that will be used as inputs to the simulation of the management policies. The most basic delineation of states of the world is a scenario analysis with a small number of states of the world that are hand selected; other approaches use statistical designs of experiments to generate the states of the world. The third difference is how a bottom-up framework measures robustness. The selected frameworks identify robust alternatives through their ability to use either a single or multiple formulation of robustness measures. The final methodological difference is a bottom-up framework's ability or inability to conduct a sensitivity analysis to determine the range of uncertain factors that control (or limit) the robustness of each

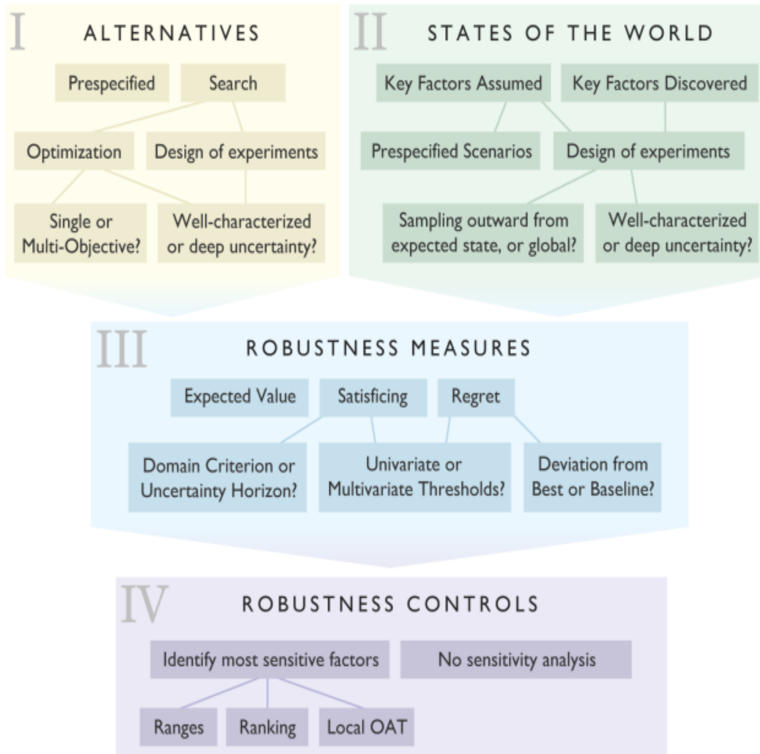

Figure 2.1. A bottom-up framework taxonomy developed by Herman et al. (2015).

alternative. This chapter will use the Herman framework and specifically point out the differences between the three bottom-up planning frameworks. Subsequent subsections will provide brief descriptions of the three bottom-up frameworks, culminating in a discussion of a final chosen bottom-up framework for CRB planning.

2.2.1. Information Gap Decision Theory

Information Gap Decision Theory (IGDT) was developed by Ben-Haim (2004) as a method to evaluate the robustness of plans through simulating alternatives across nested sets of uncertainty. This method measures robustness as the maximum range of uncertainty over which an alternative achieves a prescribed level of performance. Figure 2.2 illustrates the specific methodological choices for IGDT.

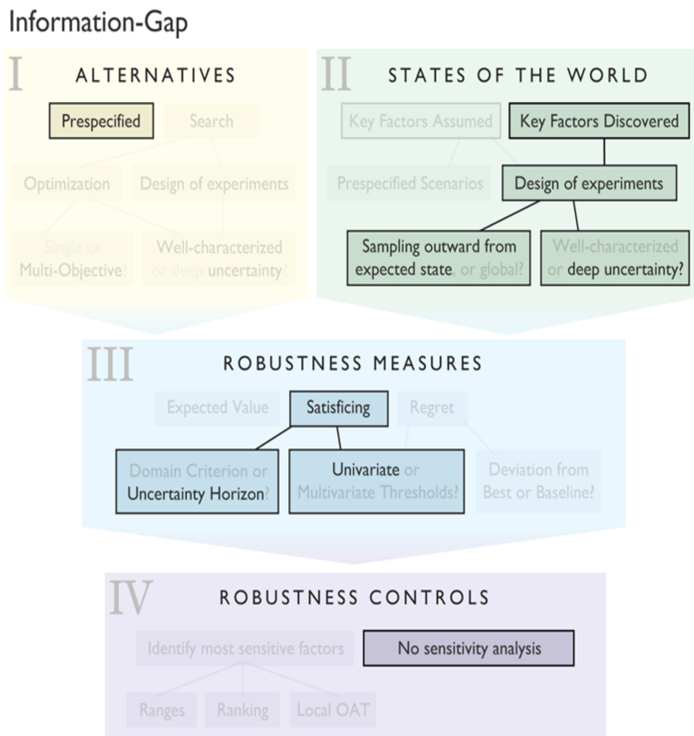

Figure 2.2. Bottom-up framework taxonomy developed by Herman et al. (2015) outlined for IGDT.

Planning alternatives are typically prespecified within IGDT. Once the alternatives are formulated by the decision makers, IGDT requires an uncertainty model to evaluate the robustness of each alternative. The uncertainty model requires a best future estimate, written as $\tilde{u}$, of the future uncertain factor u, that affects the system in question. The range of uncertainty, or future states of the world, is then represented as sampling radially outward at equal horizons of uncertainty, written as $\alpha: \alpha \geq 0$ (Hall et al., 2012). Therefore, the IGDT uncertainty model is written as a nested set of $U(\alpha, \tilde{u})$. Refer to Figure 2.3 for a visual representation of a two-dimensional IGDT uncertainty model. The size and number of horizons of uncertainty $[\alpha]$ in the IGDT uncertainty model determine the extent of the uncertain future states of the world evaluated. Once the uncertainty model is established, the management alternatives are run through a simulation model that calculates system performance at each horizon of uncertainty. The robustness of a management alternative is quantified as the number

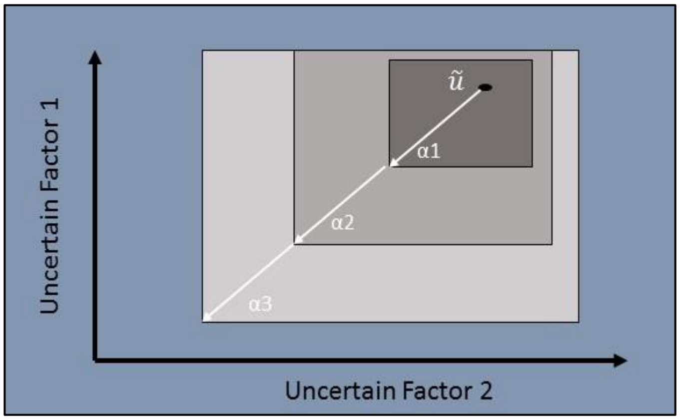

Figure 2.3. A 2-dimensional representation of IGDT uncertainty model.

of horizons of uncertainty [α] before a performance metric (i.e. water supply reliability) drops below a critical performance threshold (Matrosov et al., 2013). Based on how robustness is calculated, IGDT can determine for which performance criterion a management alternative first fails, which makes this bottom-up framework unique. This informs the decision maker of which specific performance metric threshold is constraining the planning problem.

Applications of IGDT include: supporting the management of invasive species (Yemshanov et al., 2010), recommending a water supply expansion in the Thames Basin (Matrosov et al., 2013), and supporting a flood risk management decision in the UK (Hine & Hall, 2010). However, several shortcomings of IGDT limit its effectiveness for real-world planning problems. The first two limitations have to do with how IGDT samples the uncertain states of the world. IGDT evaluates a management alternative's robustness at discrete horizons of uncertainty, which restricts IGDT to a local robustness analysis around the best estimate, $\tilde{u}$. In the Matrosov et al. (2013) IGDT implementation, a poor estimate of the uncertain factor ($\widetilde{u}$) began measuring alternatives' robustness under severe uncertain conditions before considering more favorable uncertain conditions. Due to this poor estimate of $\widetilde{u}$, the IGDT analysis recommended a management alternative that performed better only in severe future conditions.

Another consequence of selecting a poor estimate of $\tilde{u}$ is that the IGDT robustness analysis will miss out on plausible ranges of uncertain factors that can affect the system. Moreover, Herman et al. (2015) highlighted that IGDT lacks a sensitivity analysis that determines the controls on robustness, see Figure 2.2 (IV). A sensitivity analysis is a useful component of a bottom-up framework because it provides the decision maker the ranges of uncertain factors that are responsible for systemic vulnerabilities.

2.2.2. Robust Decision Making

Robust Decision Making (RDM) was developed by Lempert et al. (2003) as a method to iteratively evaluate the robustness of plans through sampling of states of the world and utilizing various robustness measures. Figure 2.4 illustrates the specific methodological choices for RDM. Unlike IGDT, RDM methods design experiments on the states of the world instead of assuming that they are arranged as horizons around a best estimate of uncertainty. RDM analyses have

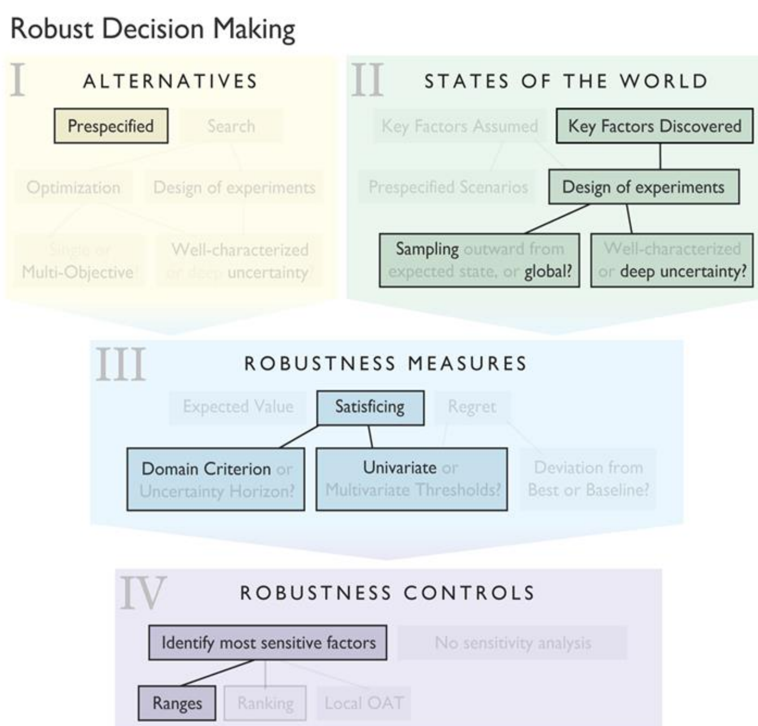

Figure 2.4. Bottom-up taxonomy developed by Herman et al. (2015) for RDM.

utilized several measures of robustness which include: measuring the deviation of an alternatives' performance from a benchmark level of performance (*regret*) or performing reasonably well over a wide range of plausible future states of the world (*satisficing*) (Hall et al., 2012). This bottom-up framework is often embedded in a process of participatory stakeholder engagement and utilizes interactive visual analytics. The term interactive visual analytics describes an analytical approach that enables planners to obtain system insights and explore performance tradeoffs through a visual exploration of abundant simulation data (Woodruff et al., 2013).

As in IGDT, RDM falls under the class of bottom-up frameworks that requires decision makers' input to prespecify management alternatives, Figure 2.4 (I). The first step of RDM requires specifying management alternatives and formulating the planning problem using a framework termed XLRM to define terminology for the problem being considered, Figure 2.5. The range of future uncertain factors are defined (X), changeable components of a management alternative are identified (L), a simulation model is made to simulate future condition (R), and performance metrics (M) are defined that will be used to evaluate the simulated performance of a management alternative (Groves et al., 2013). The next step of RDM involves a global sampling of future states of the world in which alternatives are simulated across an expansive range of uncertain factors. This step results in an extensive dataset that documents how an alternative's

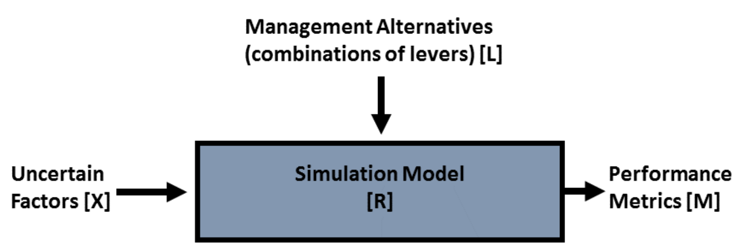

Figure 2.5. A schematic displaying each XLRM component in the problem formulation step.

performance varies across the future states of the world. Each alternative's robustness can be quantified using the dataset obtained from its simulation across all states of the world. Candidate alternatives are then selected by choosing alternatives with favorable measures of robustness. The formulation of the robustness measure should reflect how the decision makers define robustness in the planning study since the candidate alternatives' selections are dependent on their robustness formulation. The third step of RDM is a sensitivity analysis that characterizes the range of future uncertain factors (X), that prevents a candidate alternative from meeting a performance metric (M) requirement. This RDM step utilizes a cluster finding algorithm to identify an alternative's vulnerability. A common cluster finding algorithm used in RDM studies is the Patient Rule Induction Method (PRIM) (Friedman & Fisher, 1999). The fourth and final step of RDM is a trade-off analysis where interactive visual analytics are used to compare candidate alternatives and select robust solutions for the planning problem.

Applications of RDM include: supporting the Colorado River Basin Water Supply and Demand Study by identifying future vulnerable conditions that could lead to water delivery shortages (Groves et al., 2013); assisting Inland Empire Utilities in identifying climate change vulnerabilities to develop a robust integrated water resource plan (Lempert & Groves, 2010); and aiding the development of an energy policy (Popper et al., 2009). As the RDM applications suggest, RDM provides information to decision makers on what aspects of the system to monitor to determine if a vulnerable condition is approaching. Another benefit of RDM's sensitivity analysis is that the added information can be utilized by the decision makers to create additional alternatives to mitigate the vulnerabilities uncovered, thus starting another iteration of a RDM analysis. The RDM framework has added capabilities compared to IGDT which include: ability to globally sample future states of the world, flexibility to use multiple robustness measures, and the ability to perform a sensitivity analysis on results. RDM's added capabilities provide a more complete analysis than IGDT; however, its requirement to prespecify management alternatives could lead to decision makers inadvertently ignoring key aspects of the problem and therefore missing out on robust solutions.

2.2.3. Many Objective Robust Decision Making

Many Objective Robust Decision Making (MORDM) was developed by Kasprzyk et al. (2013) as a decision making framework that adds to the RDM approach by using a multi-objective evolutionary algorithm to *generate* planning alternatives and focusing on using multiple metrics to evaluate the performance of alternatives. This is especially applicable in complex systems where it can be difficult to prespecify alternatives that perform well under deep uncertainties. Figure 2.6 illustrates the specific methodological choices for MORDM.

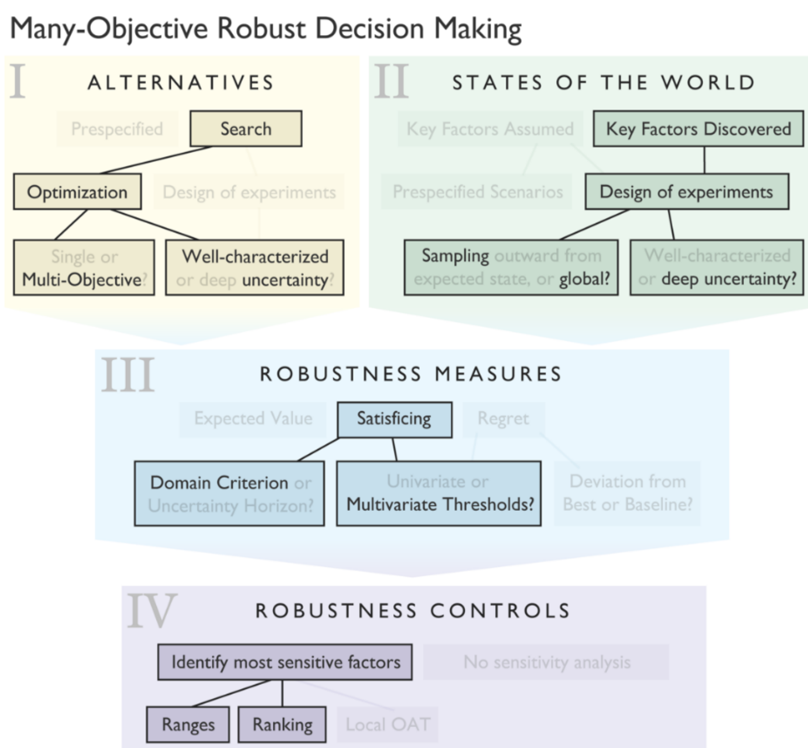

Figure 2.6. Bottom-up taxonomy developed by Herman et al. (2015) for MORDM.

MORDM starts off structuring the problem formulation where the decision makers define the XLRM components, Figure 2.5. An important aspect of MORDM is to formulate physical actions (levers, L) that decision makers can take to interact with the system in a simulation model (relationship, R). The decision levers within MORDM are often also called decision variables or policy variables. When formulating the problem, it is important to code these variables in such a way that the optimization algorithm can automatically change these variables. A management alternative consists of a unique set of the decision variables. Lastly, the optimization algorithm in MORDM requires the decision makers to formulate multiple planning objectives (measures of system performance, M) that an alternative will be optimized to meet.

The second step of MORDM is the generation of a suite of management alternatives that covers a diverse range of tradeoffs between planning objectives. This is important within MORDM because of its focus on using optimization to *generate* the alternatives as compared to them being prespecified, as shown in Figure 2.6. The second step utilizes a multi-objective evolutionary algorithm (MOEA) to modify values of decision variables in order to improve multiple planning objectives (Watson & Kasprzyk, 2017). The result of an MOEA optimization is a diverse set of management alternatives, from which a planner can choose. This set of alternatives is an approximation to the Pareto optimal solution set to the problem; solutions are Pareto optimal if their performance cannot improve with respect to one objective without degrading performance in another objective. Note that MOEAs and Pareto optimality will be discussed further in Chapter 3, Section 3.2.1 of this thesis. MORDM first generates its alternatives using a baseline best estimate of future conditions, and then uses methods derived from RDM to interrogate the generated solution across multiple states of the world. In the third step of MORDM, the set of management alternatives discovered by the MOEA is re-simulated across a wide range of uncertain future states of the world, Figure 2.6 (II). After these simulations are complete, multiple measures of robustness are used to help decision makers choose one or more robust alternatives. The ability for MORDM to utilize multiple measures of robustness is an improvement over the IGDT framework. Once a few robust candidate alternatives are selected, MORDM continues with identifying the controls on robustness for these selected alternatives. This MORDM step is identical to RDM's sensitivity analysis where a cluster analysis provides valuable information to decision makers on which ranges of uncertain factors lead to systemic vulnerabilities. Robust solutions to the planning problem are negotiated through exploring performance and robustness tradeoffs of candidate alternatives.

Applications of MORDM include: generating and evaluating pollution control strategies for an a urban lake problem (Hadka et al., 2015), identifying robust water management portfolios to supplement the Lower Rio Grande Valley's traditional reservoir based supply (Kasprzyk et al., 2013), and evaluating water management portfolio's robustness for a regional urban water supply study in North Carolina (Herman et al., 2014). Since MORDM includes RDM analysis, the benefits described in the RDM Section 2.2.2 are similar for MORDM. Generation of alternatives using an MOEA reduces decision biases in the analysis and provides an exploratory search revealing solutions that could remain hidden under IGDT and RDM analyses. In addition to generating alternatives, incorporating an MOEA provides the concept of Pareto optimality that can mathematically prove a management alternative is superior in terms of the planning objectives outlined by the decision makers. MORDM and RDM also set themselves apart from other bottom-up frameworks through utilizing interactive visuals in each stage of the analysis (Kasprzyk et al., 2013). This naturally facilitates decision makers' discussion of decision variables, planning objectives, and measures of robustness for each management alternative, and provides a conduit to iteratively learn and improve the planning study formulation.

2.3. Selection of a Bottom-up Framework

Each of the bottom-up frameworks reviewed have distinguishing attributes; however, each method shares the primary purpose of seeking robust management alternatives. IGDT provides useful information to decision makers regarding discrete sets of uncertain factors; yet the absence of a sensitivity analysis limits this method. RDM is a more complete approach (compared to IGDT) for developing management alternatives that are robust under conditions of deep uncertainty; however, this method's reliance on specifying alternatives could lead to decision makers inadvertently ignoring key aspects of the planning problem. MORDM distinguishes itself from the other bottom-up frameworks mentioned by complementing the decision maker’s capability to *generate* new management alternatives, interactively explore performance and robustness tradeoffs, and obtain valuable system insights in a single, iterative planning framework.

MORDM is proposed as the bottom-up framework to be considered in this research of exploring robust reservoir operations in the Colorado River Basin. Water from the Colorado River is an important cultural, economic, and natural resource for 35 – 40 million people located in the southwestern United States and United Mexican States (Bureau of Reclamation, 2015). The interest of the multiple services that Colorado River water provide is represented by a diverse group of Basin States, Federal, Environmental, and Tribal stakeholders. Handcrafting new reservoir operating policies that satisfy the multiple conflicting interests of the CRB stakeholders is a challenging task. Not to mention, these handcrafted reservoir operating policies might fail to accommodate multiple planning objectives under future supply and demand scenarios that “stress” the CRB. MORDM’s ability to *generate* policies that are robust to deep future uncertainty (including conditions that "stress" the CRB) and interactively explore performance and robustness tradeoffs between policies would enhance Reclamation’s policy analysis to determine future reservoir guidelines with the stakeholders in the CRB.

Chapter 3 Methods

3.1. Introduction

As described in Chapter 2, Many Objective Robust Decision Making (MORDM) is the selected bottom-up framework to be considered in this research of exploring robust planning and policy analysis in the CRB. This chapter starts with a general overview of multi-objective evolutionary algorithms (MOEAs) and then provides a detailed description of the three methodological steps of the MORDM application in the CRB.

These steps include: 1) Formulate the decision variables, multiple planning objectives, and uncertain conditions considered during the optimization and the simulation model that will be used by the MOEA to generate new operating policies for Lake Mead. 2) Describe the range of uncertain future water supply and water demand scenarios across which the generated policies are re-simulated. 3) Discuss how the robustness of the generated policies is evaluated. The chapter concludes with a section on the details of the computational experiments required for each of the three components of the MORDM analysis. The MORDM application presented in this thesis does not conduct the last methodological step of MORDM (a sensitivity analysis); however the requirements to conduct this step is described in the future work section of Chapter 5.

3.2. Multi-Objective Evolutionary Algorithms

Unlike single objective optimization that tests for optimality using a single objective function to decide the one “best” solution, multiple objective optimization uses the concepts of dominance and Pareto optimality to define performance. A solution is considered non-dominated if its objective performance is not exceeded by any other feasible solutions in all objectives. The non-domination operator can be used on any set of feasible solutions to an optimization problem. A special case of non-domination is when all feasible solutions to the optimization problem are considered, and the Pareto optimal set is the set of solutions that are non-dominated with respect to *any* feasible solution. Importantly, in the presence of conflicts among objectives, there will be multiple Pareto optimal points, not just one in the case of single objective optimization.

Multi-objective evolutionary algorithms (MOEAs) are state-of-the-art tools that provide an approximation to the Pareto optimal set for planning problems by efficiently generating and evaluating hundreds to thousands of candidate solutions to a problem. MOEAs use a process similar to natural selection to heuristically search for the Pareto optimal solutions (Coello Coello et al., 2007). Because it is computationally intractable to search the entire solution space, MOEAs do not necessarily find the true Pareto optimal set but rather a high-quality approximation to the set. Therefore, in the remainder of the thesis, the final set from the MOEA search will be termed the non-dominated set rather than the Pareto optimal set.

MOEAs are gaining prominence in solving challenging water resources planning problems in the water utility sector (Basdekas, 2014) and in various research applications (Kasprzyk et al., 2013; Maier et al., 2014; Reed et al., 2013; Smith et al., 2016). This research applies an MOEA to one of the largest water systems that has been optimized using an MOEA to date. We employ an MOEA to generate new operating policies for Lake Mead to balance the conflicting operational aims of multiple water supply performance metrics. Therefore, in the specific context of this study, a candidate "solution" in the optimization is equivalent to an operating policy, and thus the terms are used interchangeably.

The MOEA utilized in this research is the Borg MOEA (Hadka & Reed, 2012). The Borg MOEA has demonstrated superior performance on a suite of test problems relative to other competitive MOEAs (Reed et al., 2013; Ward et al., 2015; Zatarain Salazar et al., 2016). This improvement in performance is attributed to Borg's epsilon-dominance, epsilon-progress, and adaptive operator selection features. The Borg MOEA exploits epsilon-dominance to determine when significant improvement in objective values have been achieved. This feature is useful because it allows an analyst to set a desired precision for objective function values, ensuring the algorithm does not waste time in trying to achieve insignificant improvements in performance. Moreover, Borg maintains an epsilon-dominance archive of the best solutions during search, which helps to preserve diversity and convergence of the MOEA-generated solution set (Laumanns et al., 2002). Additionally, Borg has a feature termed epsilon-progress, which periodically checks if the MOEA is generating at least one solution in new regions of the objective space, defined by the epsilon resolution, to avoid search stagnation (Hadka & Reed, 2012).

The Borg MOEA uses a combination of seven separate search operators, meaning it has seven different methods to modify the composition of strong performing solutions to create new solutions (called offspring). These seven search operators include: simulated binary crossover (SBX), differential evolution (DE), parent-centric crossover (PCX), unimodal normal distribution crossover (UNDX), simplex crossover (SPX), uniform mutation (UM), and polynomial mutation (PM). The adaptive operator selection feature is a feedback mechanism that rewards search operators with successful offspring (Hadka & Reed, 2012). Search operators are rewarded by increasing the number offspring an operator produces in each successive iteration of the search, thus allowing Borg to auto-adapt to the multi-objective problem it is solving.

3.3. Generating New Operating Policies for Lake Mead

When framing the problem formulation for this study, a goal was to be able to recreate Lake Mead operating policies as negotiated in the 2007 Interim Shortage Guidelines (Bureau of Reclamation, 2007). This section will describe three Lake Mead operating policies that were previously considered in the 2007 Interim Guidelines and then we will use these policies to explain the operational elements that drive Lake Mead's reservoir operations.

The Water Supply Alternative (WSA), the Reservoir Storage Alternative (RSA), and the Preferred Alternative (PA) are three Lake Mead operating policies from the 2007 Interim Guidelines. The WSA prioritizes water deliveries, the RSA prioritizes storing water for future use, and the PA is how Lake Mead is currently operated. The policies' operating structures are visualized in Figure 3.1. Each color block indicates a separate operating tier and the horizontal reference lines shows Lake Mead's pool elevation. Lake Mead's operation is determined for a given year (starting in January) based on the previous year's December reservoir pool elevation. Thus, different types of operations are triggered if the December pool elevation falls within different colored tiers. The blue shaded tiers trigger surplus operations; the grey tiers trigger normal operation; and the yellow to red shaded tiers trigger discrete shortage reduction tiers. The operational differences of these policies, as observed in Figure 3.1, align with storylines used in

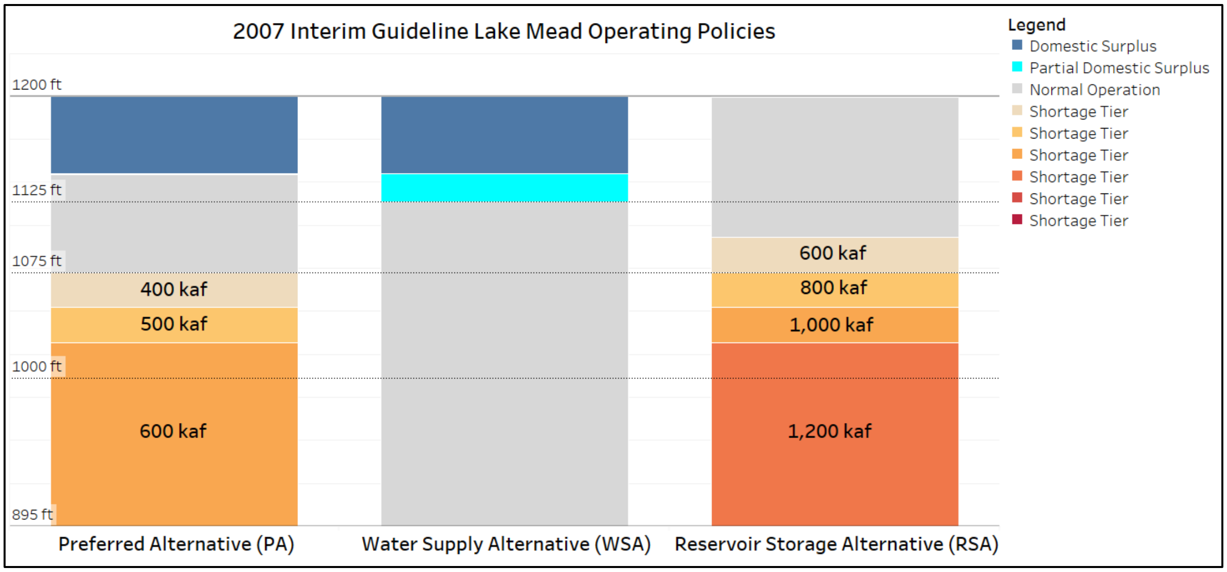

Figure 3.1. Three Lake Mead operating policies from the 2007 Interim Guidelines.

their creation. The WSA maximizes water deliveries by providing water users their normal allocation (normal operation) even in low Lake Mead pool elevations. In contrast, the RSA maximizes keeping water stored in Lakes Powell and Mead through imposing reductions (amounts in kaf) from the water users' normal allocations starting at pool elevation 1,100 feet. The PA is a compromise between the two by imposing more moderate shortage reductions than the RSA and waiting until a lower pool elevation of 1,075 feet to trigger shortage operations. The next section will describe the formulation of the decision variables that are used to "build" a Lake Mead operating policy structure.

3.3.1. Building New Lake Mead Operations: Policy Variables

In this study, policy variables[2] modify Lake Mead's operating policy structure. As seen in Table 3.1, the policy variables correspond to operational elements in Lake Mead that drive the

[2] Following the terminology of Smith et al. (2016), policy variable is used to contrast with the typical use of "decision variable" in water resources optimization problems, which often refers to quantities of water that are allocated with an optimization model. Instead, the policy variable defines the components of the reservoir's operating policy.

Table 3.1. List of 14 policy variables, their physical limits, and values to recreate the Preferred Operation of Lake Mead.

Category	Policy Variable	Lower Limit	Upper Limit	Preferred Alternative
Lake Mead Surplus Operation (*Surplus Distance*) [Units = Feet]	d_1	0	75	55
	d_2	0	75	0
Lake Mead Shortage Operation (*Shortage Elevation*) [Units = Feet]	e_1	895	1,100	1,075
	e_2	895	1,100	1,050
	e_3	895	1,100	1,025
	e_4	895	1,100	895
	e_5	895	1,100	895
	e_6	895	1,100	895
Lake Mead Shortage Operation (*Shortage Volume*) [Units = KAF]	V_1	0	2,400	600
	V_2	0	2,400	600
	V_3	0	2,400	600
	V_4	0	2,400	600
	V_5	0	2,400	500
	V_6	0	2,400	400

implementation of various shortage and release policies, their upper and lower limits, and values to recreate the PA. Each new Lake Mead operating policy is defined by its unique combination of the 14 policy variables, and this operating policy remains constant for the entire simulation horizon. Refer to Figure 3.2 later in this section for a visual representation of the policy variables recreating Lake Mead's PA and a new Lake Mead's pool elevation tiered operating policy. In the following sections, each variable is described in more detail.

3.3.1.1. Surplus Distance

Surplus distance variables (d_{1-2}) are the distances downward from Lake Mead pool elevation 1,200 feet to the bottom of the surplus operational zone and are used to set Domestic and Partial Domestic surplus operational tiers for Lake Mead. These variables have an upper limit of 75 feet and a lower limit of zero feet, therefore surplus operation has the potential to be triggered starting at Lake Mead pool elevation 1,125 feet to pool elevation 1,200 feet. The surplus operation assumptions include: the surplus distance policy variables start at Lake Mead pool elevation 1,200 feet, ensuring that a flood control operation is present in each management alternative. If surplus distances d_1 and d_2 equate to the same value or if d_2 equals a value of zero, then there is only a single Domestic Surplus tier, and the rounding precision of this variable is 5 feet.

3.3.1.2. Shortage Elevation

Shortage elevation variables ($e_{1\text{-}6}$) determine the sizes and number of shortage reduction tiers having the potential to set up to 6 distinct shortage tiers. These variables have an upper limit of 1,100 feet and a lower limit of 895 feet; therefore a shortage operation has the potential to be triggered starting at Lake Mead pool elevation 1,100 feet to the reservoir's dead pool elevation of 895 feet. There are three assumptions for the shortage elevation: the distance between the lowest surplus pool elevation trigger and the highest shortage pool elevation trigger will consist of normal operation of Lake Mead; the shortage elevation variables are formulated so that shortage operation can be "turned off" to be replaced with normal operation; and the rounding precision of this variable is 5 feet.

3.3.1.3. Shortage Volume

Shortage volume variables ($V_{1\text{-}6}$) determine the quantity of water reduced to US Lower Basin States' and United Mexican States' normal allocation for each shortage operational tier created by the shortage elevation variables. These variables have an upper limit of 2,400,000 acre-feet and a lower limit of zero acre-feet, therefore these variables are formulated such that if all volumes are zero acre-feet shortage operation can be "turned off" to be replaced with normal operation. The shortage volume assumptions include: these variables are formulated so shortage reduction volumes have the highest volume at the lowest shortage tier and decreases in quantity as Lake Mead pool elevation increases; shortage volume is an aggregate reduction volume that is distributed between Arizona, Nevada, United Mexican States following the 2007 Interim Guidelines Record of Decision; and the rounding precision of this variable is 25,000 acre-feet.

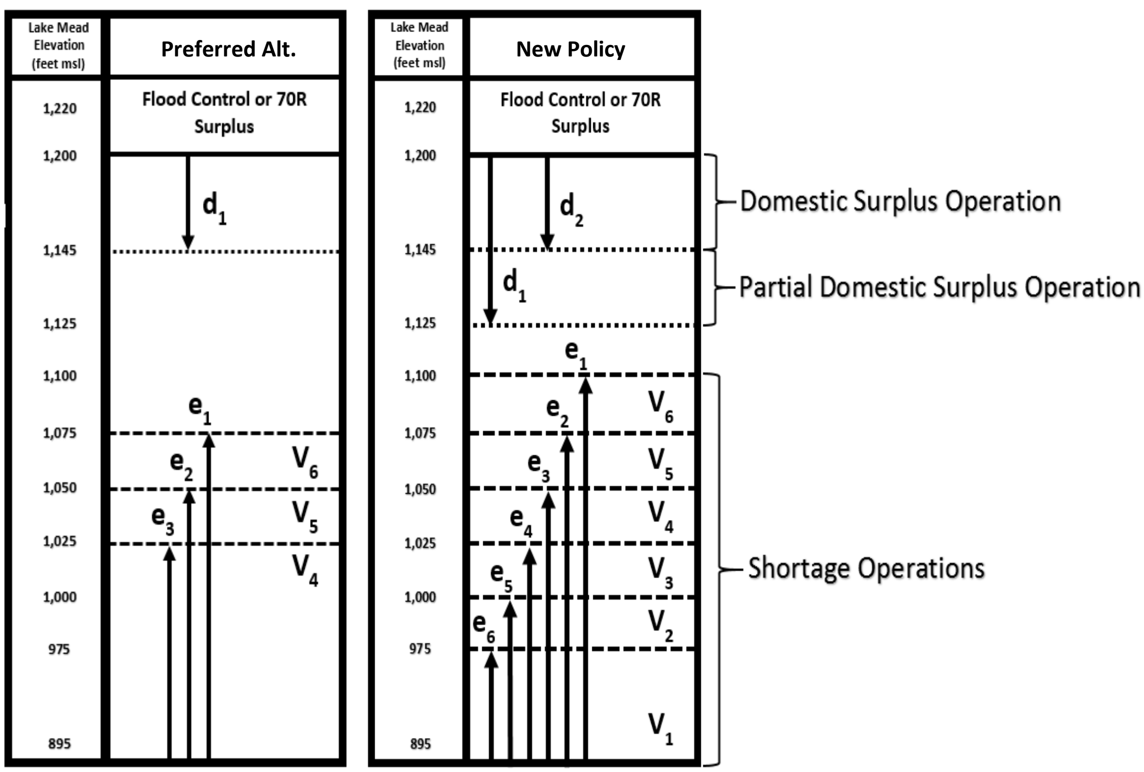

Figure 3.2. Diagram showing how the 14 policy variables construct the Preferred Alternative and a new operating policy.

3.3.1.4. Recreating Lake Mead's Preferred Alternative

The policy variables for this study were designed to create a wide array of potential operational alternatives for Lake Mead. One test of the efficacy of these variables is to use them to recreate important existing alternatives for the system; specifically, this section will walk through the formulation of Lake Mead's Preferred Alternative. A visual representation of Lake Mead's Preferred Alternative is displayed in Figure 3.2 and the policy variables used to recreate this tiered structure are provided in Table 3.1.

The process of recreating the PA is as follows. Values of the surplus distance variables of d_1 = 55 feet and d_2 = 0 feet creates a single Domestic Surplus operating tier ranging from pool elevation 1,200 feet to 1,145 feet. The shortage elevation values e_1 = 1,075 feet, e_2 = 1,050 feet, e_3 = 1,025 feet, e_4 = 895 feet, e_5 = 895 feet, and e_6 = 895 feet set shortage operations starting at pool elevation 1,075 feet and ending at Lake Mead's dead pool elevation of 895 feet. These policy variable values create 3 separate shortage tiers, where the first shortage tier ranges from pool elevation 1,075 feet to 1,050 feet, the second tier from pool elevation 1,050 feet to 1,025 feet, and the third tier from pool elevation 1,025 feet to 895 feet. The repeating values of 895 feet for $e_{4\text{-}6}$ indicate that this policy variable hits the lower limit, restricting the variable from structuring additional tiers below Lake Mead's dead pool elevation. Since there is no surplus operation or shortage operation in the pool elevation zone between 1,145 feet and 1,075 feet, this range of pool elevations is reserved for normal operations where diversions receive their normal water allocation. The shortage volume values V_1 = 600 kaf, V_2 = 600 kaf, V_3 = 600 kaf, V_4 = 600 kaf, V_5 = 500 kaf, and V_6 = 400 kaf set the shortage reduction volumes for the three shortage tiers created by the shortage elevation variables. As described above, the shortage volume is formulated to assign the highest volume at the tier closest to Lake Mead's dead pool elevation and assign shortage volumes in decreasing quantity for tiers above the lowest tier. The largest shortage volume of 600 kaf is assigned to the shortage tier from pool elevation 1,025 feet to 895 feet. Next, the second largest shortage volume of 500 kaf is assigned for the above shortage tier from pool elevation 1,050 feet to 1,025 feet. Lastly, the smallest shortage volume of 400 kaf is assigned for the top shortage tier from pool elevation 1,075 feet to 1,050 feet. Subsequent subsections describe how these operating alternatives are evaluated within the optimization framework.

3.3.2. Future Uncertainty Considered During the MOEA Search

A collection of input data is used to provide realistic future conditions under which to evaluate the operating policies. Specifically, the simulation model requires input traces of both future CRB hydrology and water demand. The future hydrology considered in the MOEA search is a subset of the Direct Natural Flow (DNF) ensemble (Bureau of Reclamation, 2007). The full DNF ensemble has 107 hydrologic traces or 107 plausible future hydrologic conditions. Each trace within the Direct Natural Flow ensemble is a repeat of the historical natural streamflow record (from 1906 to 2013) with a different starting year and the record wrapping around at the ending year 2013 (i.e., 2013, 1906, 1907) (Bureau of Reclamation, 2007). The term natural streamflow means subtracting anthropogenic influences, such as reservoir regulation and depletions, from the observed streamflow record.

Although it is likely that considering the entire DNF ensemble during the optimization would increase the precision of the MOEA generated policies by exposing them to more possible hydrologic traces, the computational limitations (discussed in Section 3.6.1) favor the use of a subset of the DNF ensemble during the MOEA search. For the subset, twelve traces from the DNF ensemble were chosen randomly using the uniform distribution. Comparison of the hydrologic characteristics of the full DNF ensemble to the subset from the ensemble is displayed in Figure 3.3. This plot shows a flow duration curve for annual natural flow above Lees Ferry where the blue dots are annual exceedance measurements from the DNF 107 traces ensemble and the red are from the randomly selected DNF 12 traces ensemble. As seen in Figure 3.3, the shape of these flow duration curves is nearly identical even in the high and low annual exceedance regions. Since the distributional characteristics of the subset ensemble matched the full DNF 107

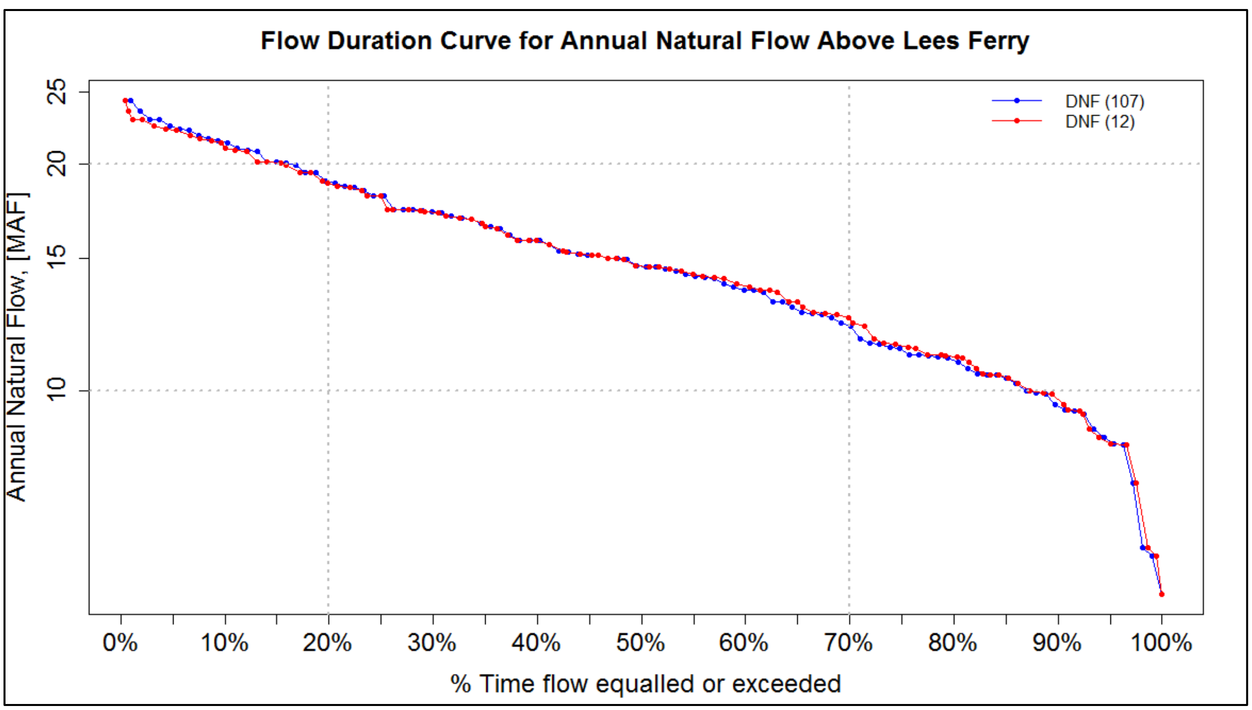

Figure 3.3. Flow duration curves based on annual natural flow above Lees Ferry, Arizona for a subset (shown in red) and the full DNF hydrologic ensemble (shown in blue).

traces ensemble, the randomly selected DNF 12 traces ensemble is deemed adequate for the future hydrology considered in the MOEA search.

The future water demand projections considered in the MOEA search is a combination of Upper Basin demands and Lower Basin demands. The Upper Basin demands are per the 2007 Upper Colorado River Commission future depletion schedule and the Lower Basin demands are per the Colorado River Interim Guidelines Final Environmental Impact Statement (Bureau of Reclamation, 2007; Upper Colorado River Commission, 2007). The future hydrology and demand traces considered in the MOEA search are viewed as the baseline estimates of future conditions in MORDM terms.

3.3.3. Colorado River Simulation System

The Colorado River Simulation System (CRSS) is a simulation model that Reclamation uses for long-term planning in the Colorado River Basin at a monthly timestep. This model simulates water supply, flood control, hydropower and salinity, and incorporates realistic reservoir operating rules that capture Colorado River Basin policy. CRSS models reservoir operations for 12 reservoirs in the Colorado River Basin and is implemented in RiverWare (Zagona et al., 2001). For this research, a simplified version of the official CRSS model was created to compare a multitude of Lake Mead operational policies at a lower computational expense compared to the official CRSS model. The modifications to the CRSS model include simplifying the simulation in the Upper Basin and turning off Intentionally Created Surplus (ICS) in the model (Bureau of Reclamation, 2007). These simplifications were made to decrease simulation time and to create a more direct system response of unfavorable hydrology to lower water delivery reliability. The simulation period of this study is from January 2017 to December

2060, resulting in a planning horizon of 44 years. The model is initialized with observed 2016 end-of-calendar-year reservoir conditions.

3.3.4. Evaluating Performance: Objectives

After a generated policy is run through CRSS, its model output needs to be formulated into objective values before the MOEA can evaluate the quality of the generated policy. This multi-objective problem formulation considers eight conflicting basin-wide water supply performance metrics that are treated as objectives, as seen in Table 3.2. The objectives are closely tied to system performance through incorporating critical reservoir pool elevations, duration, frequency and quantity of Lower Basin (LB) shortage reductions from CRSS model output. Several of these objectives are based on Water Delivery and Electric Power indicator metrics developed during the Colorado River Basin Water Supply and Demand Study (Bureau of Reclamation, 2012).

Table 3.2. Set of 8 objectives that represent aspects of water supply performance spanning both the Upper and Lower Colorado River Basin.

Lower Basin Objectives		
Mead 1000	1	Minimize % of time that monthly Lake Mead Pool Elevation is < 1,000'
LB Max Consecutive Shortage Duration	2	Minimize the maximum amount of consecutive years in shortage operation
LB Shortage Frequency	3	Minimize % of time that the system is in an annual shortage operation
LB Shortage Volume	4	Minimize the cumulative average annual Lower Basin total shortage volume
Max Annual LB Shortage	5	Minimize the maximum annual Lower Basin policy shortage volume
Upper Basin Objectives		
Powell 3490	6	Minimize % of time that monthly Lake Powell Pool Elevation is less than 3,490'
Powell WY Release	7	Minimize cumulative average annual Water Year release from Lake Powell
Lee Ferry Deficit	8	Minimize % of time that annual 10 year compact volume falls below 75 maf

These objectives are formulated in the CRSS RiverWare model as eight individual scalar slots with expressions in a Data Object. Simulating a policy in CRSS for a single input trace returns a single value for each of the eight objectives. Since there are twelve hydrologic and one demand trace considered in the MOEA search, simulating a policy returns twelve values for each of the eight objectives. The twelve values for each objective are then aggregated to single values for each objective so the MOEA can evaluate the quality of a generated policy. The aggregation technique is the same for all eight objectives - we use the average value of the objectives across the twelve hydrologic traces. A benefit of using the average values is that it will return a unique objective value to enable the comparison of objective performance between Lake Mead operating policies. Refer to Appendix A for further explanation of how the objectives and their corresponding expressions are formulated in RiverWare. All objectives are minimized, meaning lower values indicate superior performance. The objectives are described further in the following sections.

3.3.4.1. Lower Basin Objectives

Two objectives were formulated to compute the frequency of critical events in Lake Mead - ***Mead 1000*** and ***LB Shortage Frequency***. ***Mead 1000*** measures the percentage of time that monthly Lake Mead pool elevation is less than 1,000 feet. This objective is indicative of the health of the Lower Basin since the reliability of water deliveries is closely tied to Lake Mead pool elevation (Groves et al., 2013). ***LB Shortage Frequency*** measures the percentage of years that a shortage condition is imposed in the Lower Basin. The resilience or the ability of the CRB to “bounce back” from imposing shortage reductions is formulated as the ***LB Max Consecutive Shortage Duration*** objective. ***LB Max Consecutive Shortage Duration*** measures the maximum number of consecutive years that the CRB is in a shortage condition, and lower values indicate a more resilient Lake Mead operating policy. The final two Lower Basin objectives are ***Max Annual LB Shortage*** and ***LB Shortage Volume,*** which measure the maximum annual shortage reduction volume imposed during simulation and the average annual shortage volume imposed for a given operating policy.

3.3.4.2. Upper Basin Objectives

Two objectives were formulated to compute the frequency of critical events in the Upper Basin. These include ***Powell 3490*** and ***Lee Ferry Deficit***. The significance of ***Powell 3490*** is to minimize the frequency that Lake Powell falls below the minimum power pool elevation of 3,490 feet for Glen Canyon Dam. This protects a vital economic and renewable energy source for the southwestern US. ***Lee Ferry Deficit*** measures the percentage of time that the running ten-year sum of Upper Basin deliveries to the Lower Basin falls below 75,000,000 acre-feet. This objective is indicative of the health of the Upper Basin and is a measure of Upper Basin water delivery reliability (Groves et al., 2013). The last Upper Basin objective is ***Powell WY Release***, which measures the cumulative average annual water year release from Lake Powell throughout the simulation period.

3.3.5. Coupling CRSS with Borg MOEA

The coupling between an MOEA and a RiverWare simulation model was first accomplished in Smith et al. (2016) where the Borg MOEA suggested reservoir balancing strategies within a multiple reservoir RiverWare model. Our research employs the Borg MOEA to search for Lake Mead operating policies and simulates these policies in the CRSS RiverWare model. The simplified CRSS RiverWare model is embedded within the Borg MOEA search loop via a software wrapper that feeds operating policies generated by Borg MOEA to RiverWare and delivers objective values from RiverWare back to Borg MOEA. This software wrapper (Borg-RW.exe) was first developed by the Center for Advanced Decision Support for Water and Environmental Systems (CADSWES) staff for the coupling of an MOEA and a RiverWare model in Smith et al. (2016) and enhanced for later applications. To aid the explanation of the

Borg MOEA search loop, following is a narrative of each step of the MOEA search loop referencing Figure 3.4.

In the first step of the search loop, the Borg MOEA generates an initial random population of operating policies (highlight A). Each policy is run within in the CRSS RiverWare model (highlight B). The performance of each MOEA-generated operating policy is quantified through calculating eight objectives using the CRSS model output (highlight C). The Borg MOEA then exploits epsilon-dominance to determine which operating policies are non-dominated based on the epsilon values for each objective. The Borg MOEA archives the non-dominated policies, which concludes the first iteration of the MOEA search loop (highlight D). Note that Borg maintains two separate sets of solutions within its search – the archive of the best solutions found so far, and the population of solutions that is used to provide new material to evolve better solutions as the search progresses.

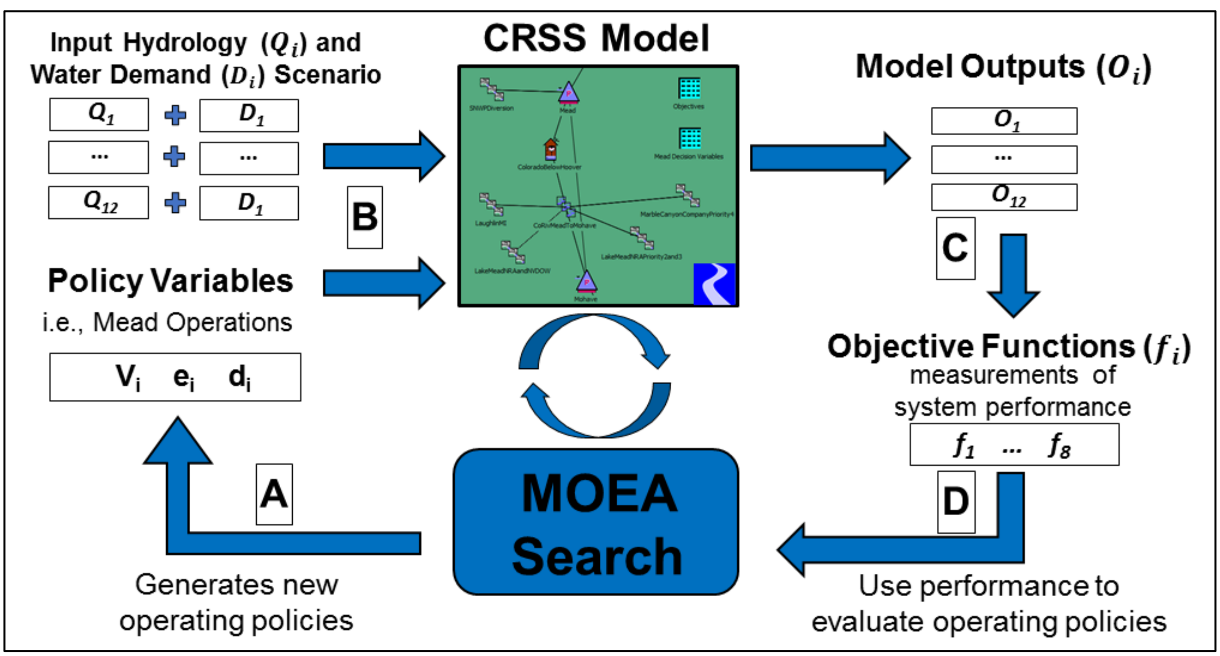

Figure 3.4. A schematic of the Borg MOEA search loop which generates and evaluates alternate Lake Mead operations.

The second iteration of the search loop commences with the Borg MOEA employing its variation operators. In doing so, one or more solutions from the population is combined with the archive, with one of the variation operators employed to generate a new candidate solution whose performance is quantified with the objectives from CRSS. If the solution dominates solutions in the archive, it replaces those solutions in the archive. This search loop iterates thousands of times, with the archive progressively improving as new solutions are generated and evaluated, and replace poorer performing solutions. The result of the search loop is a set of non-dominated operating policies that can be compared with respect to their tradeoffs in multiple objectives.

3.4. Re-Simulating the Generated Policies Across Many States of the World

Recall that a key component of MORDM is the evaluation of candidate policies over a large number of states of the world. Figure 3.5 displays the components that make up this

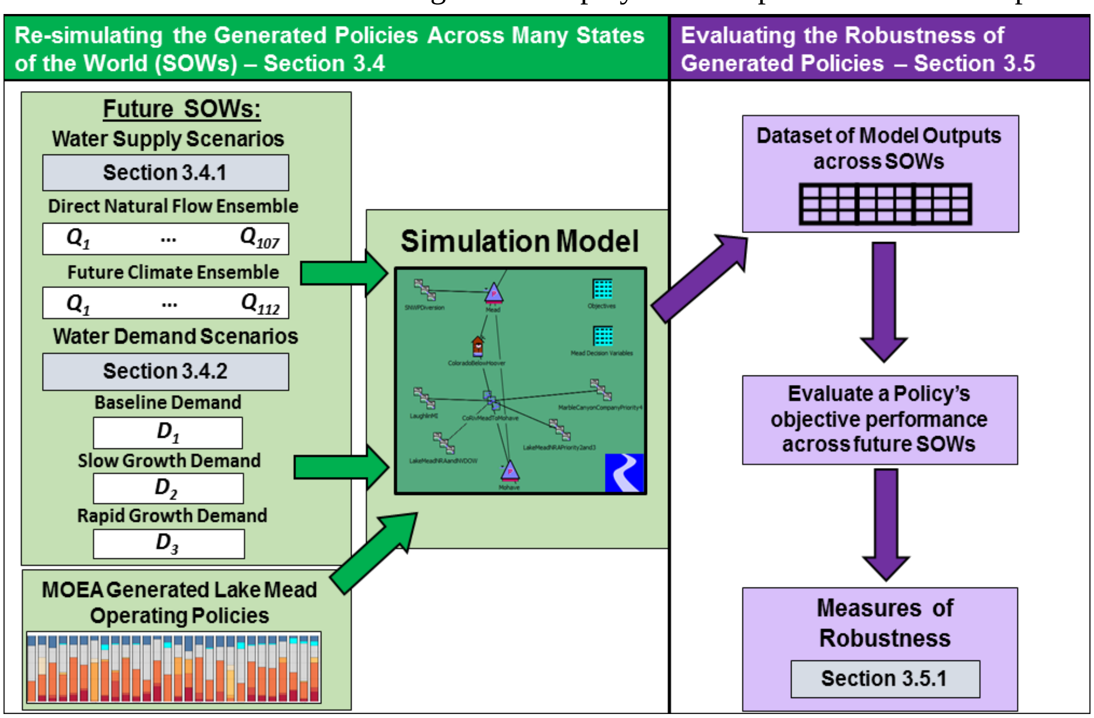

Figure 3.5. Schematic displaying the second and third methodological steps of the MORDM application in the CRB.

methodological step. This section first describes the future water supply scenarios and then the future water demand scenarios considered in this MORDM step.

3.4.1. States of the World: Future Water Supply Scenarios

Water supply scenarios come from two sources. First, we use the DNF ensemble described previously but now include the entire 107 hydrologic traces ensemble. Second, we utilize the Future Climate scenario which consists of downscaled streamflow projections from 112 climate projections used in the Intergovernmental Panel on Climate Change Fourth Assessment Report (Intergovernmental Panel on Climate Change, 2008). The 112 climate projections are derived from 16 general circulation models (GCMs) and three global carbon emissions projections and were statistically downscaled then run through the Variable Infiltration Capacity (VIC) hydrologic model to obtain 112 future hydrologic traces (Bureau of Reclamation, 2012). Each of these water supply scenarios consists of naturalized streamflow ensembles all with the same timeseries from 2017 to 2060.

Figure 3.6 displays the range of projected annual flows for the Colorado River at Lees Ferry, Arizona for the two water supply scenarios using boxplots. These boxplots display 44 annual natural flow values for each trace in the ensemble resulting in 4,708 values for the DNF scenario and 4,928 values for the Future Climate scenario. The top and bottom whiskers display the 90^{th} and 10^{th} percentiles of annual natural flow values and the top and bottom of the box display the 75^{th} and 25^{th} percentiles. The middle black line represents the median and the red

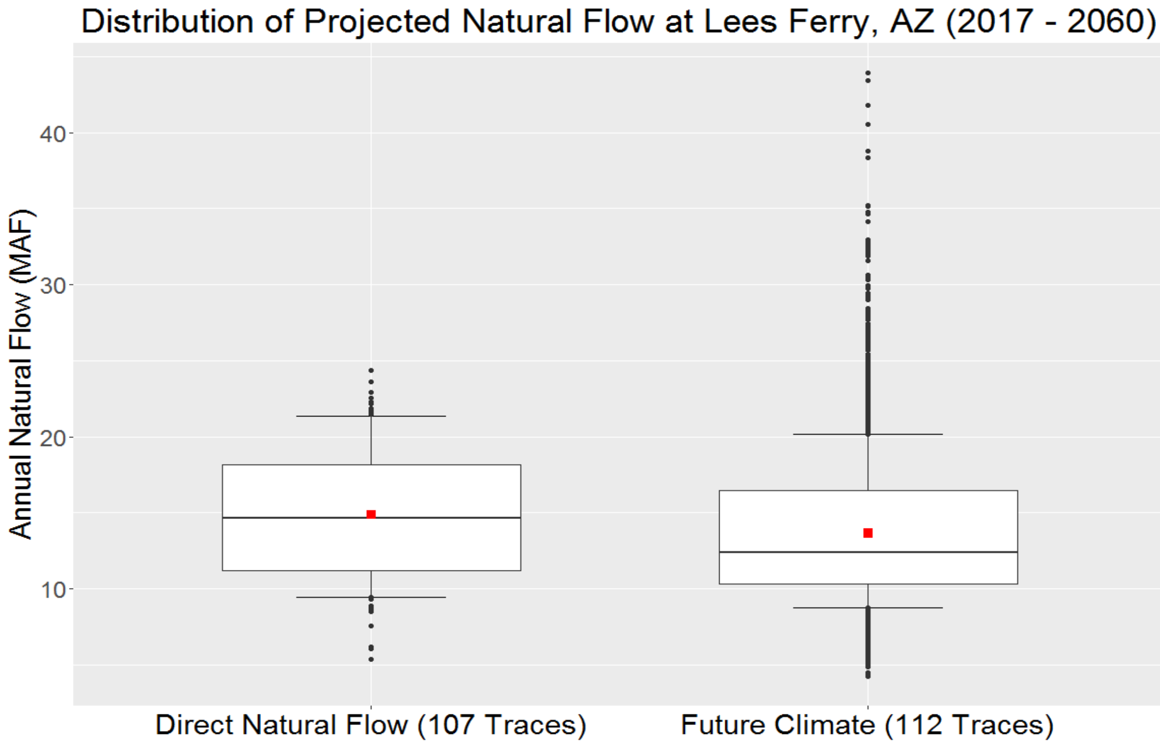

Figure 3.6. Boxplots of two future water supply scenarios displaying the variability of annual streamflow at Lees Ferry, Arizona.

boxes display the mean of the annual natural flow values for both water supply scenarios. Figure 3.6 demonstrates that the Future Climate scenario has a lower median annual flow and a higher annual variability compared to the DNF scenario. Re-simulating the generated Lake Mead policies across the Future Climate scenario along with the DNF scenario adequately captures an expansive range of plausible future CRB water supply conditions.

3.4.2. States of the World: Future Water Demand Scenarios

This section describes the range of future water demand scenarios used in the re-simulation process. As mentioned in Section 3.3.2, the future water demand scenario considered in the MOEA search is a combination of Upper Basin demands developed by the Upper Colorado River Commission and Lower Basin demands that are in accordance with the Colorado River Interim Guidelines Final Environmental Impact Statement. The combination of these Upper

Basin and Lower Basin demand projections is referred to as the Baseline Demand scenario. Two additional future water demand scenarios are introduced to test the generated policies' performance against more severe and more benign future water demand compared to the Baseline Demand scenario, Figure 3.7.

The two additional demand scenarios are the Slow Growth (B) and Rapid Growth (C1) scenarios from the Colorado River Basin Water Supply and Demand Study (Bureau of Reclamation, 2012). The Slow Growth Demand scenario has a storyline of a slow population growth in the CRB (2060 population of 49.3 million) and has an emphasis on water use efficiency in the municipal and industrial sectors. The Rapid Growth Demand scenario has a

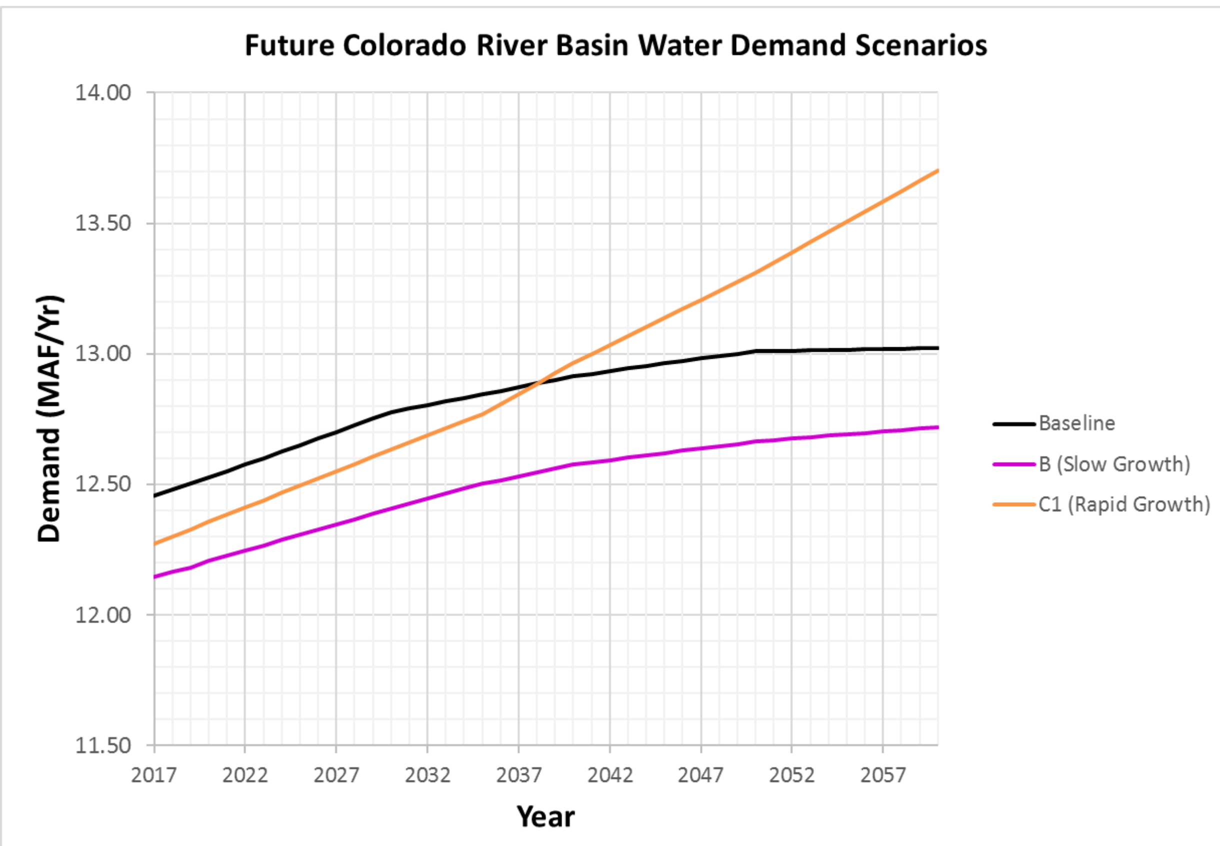

Figure 3.7. Timeseries of three future water demand scenarios displaying the rate of future growth of water demand in the Colorado River water.

higher projection of population growth in the CRB (2060 population of 76.5 million) and has a slower adoption of water use efficiency technology. Figure 3.7 displays the CRB total (Upper and Lower Basin states) annual water demand in maf for the three future water demand scenarios. The scenarios listed from highest to lowest average projected water demand are as follows: the Rapid Growth scenario (orange) with 13.03 maf, the Baseline scenario (black) with 12.92 maf, and lastly the Slow Growth scenario (purple) with 12.59 maf. As seen in Figure 3.7, the Rapid Growth scenario starts off with lower annual water demand than the Baseline scenario; however, in 2038, the Rapid Growth scenario exponentially surpasses the Baseline future water demand. Incorporating the two future water demand scenarios from the Basin Study in addition to the Baseline Demand scenario in this step adequately captures the range in future water demand of Colorado River water.

3.5. Evaluating the Robustness of the Generated Policies

The third methodological step of the MORDM application uses robustness calculations to quantify how the generated policies perform across the future states of the world, see Figure 3.5. This section first provides a brief overview of different measures of robustness and then formulates study-specific requirements to develop a definition of robustness for this planning study.

3.5.1. Measures of Robustness

There are numerous classes of robustness measures since there are numerous ways of quantifying an operating policy’s objective performance across a set of future states of the world (SOWs). This section provides an overview of regret and satisficing robustness measures, which are two common classes of robustness measures (Lempert & Collins, 2007). For a comprehensive review of different classes of robustness measures, the reader is encouraged to read McPhail et al. (2018).

3.5.1.1. Regret Based Measures of Robustness

As described in Section 2.2.2, regret measures the deviation of an operating policy's objective performance from a benchmark level of performance. Following Herman et al. (2015), there are two categories of regret based robustness measures depending on what is used as the benchmark level of performance. The first category is Regret Type A, which measures the deviation ($\boldsymbol{D}$) of a policy's performance in a given future SOW from the policy's performance in the baseline future SOW (Kasprzyk et al., 2013; Lempert & Collins, 2007). For this study, a given future SOW is a combination of a trace from a water supply scenario (i.e. trace 1 from the DNF ensemble) and a future water demand scenario (i.e. Rapid Growth demand). Regret Type A is defined in the below equation:

Equation 3.1

$$\boldsymbol{Regret\ Type\ A}\ (\boldsymbol{D_{i,j}}) = \frac{|F(\boldsymbol{x_m})_{i,j} - base\ F(\boldsymbol{x_m})_i|}{base\ F(\boldsymbol{x_m})_i}$$

where x_m is an MOEA-generated operating policy; $F(\boldsymbol{x_m})_{i,j}$ is the policy's ith objective performance in SOW j; and $base\ F(\boldsymbol{x_m})_i$ is a policy's ith objective performance in the baseline SOW. Regret Type A's deviation ($\boldsymbol{D}$) is normalized by the policy's performance in the baseline SOW; thus, a robust operating policy would have minimal deviations ($\boldsymbol{D_{i,j} = 0}$) from the baseline performance across all tested SOWs.

The second category is Regret Type B, which measures the deviation ($\boldsymbol{D}$) of an operating policy's performance in a given future SOW from the best performing operating policy in that same future SOW (Herman, et al., 2015). This is represented mathematically as

Equation 3.2

$$\boldsymbol{Regret\ Type\ B}\ (\boldsymbol{D_{i,j}}) = \frac{|F(\boldsymbol{x_m})_{i,j} - best\ F(\boldsymbol{x_m})_{i,j}|}{F(\boldsymbol{x_m})_{i,j}}$$

where $best\ F(\boldsymbol{x_m})_{i,j}$ is the best value of the i^{th} objective in SOW j. Regret Type B's deviation ($\boldsymbol{D}$) is normalized by the objective values since the best value often approaches zero in minimization optimizations formulations. Therefore, a robust operating policy for Regret Type B would have low deviations from all the best objective performance values across all tested SOWs. These regret formulations also require additional aggregation (i.e. applying the mean or taking the 90th percentile) of the deviations across all SOWs and a way to handle multiple objectives, since all robustness measures require a single value to quantify the robustness of an operating policy.

3.5.1.2. Satisficing Based Measures of Robustness

Satisficing measures the ability of an operating policy to meet decision makers' performance requirement(s) across many future SOWs (Herman et al., 2015). The formulation of a satisficing based measure is rooted in the domain criterion (Starr, 1962) and calculates the percentage of future SOWs where an operating policy satisfies one or more performance threshold prescribed by the decision makers. This is represented mathematically as

Equation 3.3

$$\boldsymbol{Satisficing} = \frac{1}{N}\sum_{j=1}^{N} S_{i\epsilon I}\{\,F(\boldsymbol{x_m})_{i,j}\}$$

where *N* is the total number of future SOWs; *j* is a future SOW; *i* is a counter in the set of *I* objectives; $F(\boldsymbol{x_m})_{i,j}$ is the ith objective performance in SOW *j*; and $S_{i\epsilon I}$ is an indicator function that returns a value of $S_i = 1$ if operating policy $\boldsymbol{x_m}$ meets the ith objective performance threshold in SOW *j* and $S_i = 0$ otherwise. These indicator function values are summed and then divided by the total number of future SOWs *N*. Therefore, a robust operating policy would meet a decision maker's minimum objective performance requirement(s) in a high percentage of all SOWs tested.

3.5.2. Defining Robustness

Choosing a robustness measure and its formulation should consider the needs of the planning context. In the context of determining new operating guidelines for Lake Mead, a robustness measure should be formulated across multiple planning objectives (as considered in the MOEA-search) and be easy to comprehend. A computational experiment is described in Section 3.6.3 in which formulations of both regret (Equations 3.1 and 3.2) and satisficing (Equation 3.3) based measures are tested to see which measure best fits these requirements.

3.6. Computational Experiments

This section provides detail on the computational requirements and experiments of the three methodological steps of the MORDM application in the CRB.

3.6.1. Generating New Operating Policies for Lake Mead: Computational Experiment

As discussed in Section 3.3, the CRSS simulation model is embedded with the Borg MOEA search loop to generate and evaluate new operating policies for Lake Mead. This MOEA search loop was set up on a computer with 32 GB of RAM and 12-cores operating at 2.6 GHz. The simplifications to the CRSS official model described in Section 3.3.3, along with implementing other RiverWare efficiency customizations, helped reduce the simulation time to test a Lake Mead operating policy for 528 monthly timesteps. A single operating policy is simulated with a single input trace (e.g. $Q_1 + D_1$ in Figure 3.4) and evaluated by these steps: (1) import the policy variable values generated by the MOEA into slots in the RiverWare model; (2) convert these values into a pool elevation based operating tiers table for Lake Mead; (3) simulate future operations of the 12 CRB reservoirs; and (4) evaluate eight water-supply objectives using model output. These steps for a single operating policy and a single input trace took the computer 120 seconds to execute. RiverWare has the functionality to simulate a single model across multiple cores of a computer. This allows a single operating policy to be simultaneously simulated across 12 input traces, since we are using a 12-core computer. Because an MOEA search usually requires testing thousands of operating policies to generate the non-dominated set, this study was designed to use a limited set of 12 hydrologic inputs to CRSS and shorter (relative to other MOEA applications) number of functional evaluations (NFE) for the MOEA search. These computational decisions facilitate the ability to perform an MOEA search using a comprehensive model of the CRB on a 12-core computer.

In order to determine the proper number of function evaluations, a series of test search trials was run. Within these trials, we visualized the non-dominated set at certain snapshots of the search process and determined a point of diminishing return where the search was not significantly improving. As a result of these trials, all search runs used 7,500 function evaluations. In addition to setting the maximum NFE, a Borg MOEA search requires additional Borg MOEA search parameters and objective epsilon values, which are listed in Table 3.3. The default values of the Borg MOEA parameters were used in this study, due to the Borg MOEA's consistent performance in a set of diagnostic studies that showed how the algorithm was insensitive to choice of its parameters (Reed et al., 2013; Ward et al., 2015; Zatarain Salazar et al., 2016). After a 2-week computational duration, the coupled CRSS – Borg MOEA search with 7,500 maximum NFE finished executing on the 12-core computer. This MOEA search discovered 751 non-dominated Lake Mead operating policies with varying performance in the eight objectives considered in the multi-objective optimization. The next section will explain the computational requirements for the second methodological step of this MORDM application in which the 751 non-dominated Lake Mead operating policies are re-simulated across many states of the world.

Table 3.3. Parameter values for the Borg MOEA search and objective epsilon settings for computational experiment.

Parameter	Value
Initial population size	100
Number of function evaluations (NFE)	7,500
Number of objectives	8
Number of policy variables	14
Objective Epsilons	**Value**
Objective 1 (Mead 1000), ε	1%
Objective 2 (LB Max Cons Short Duration), ε	1 year
Objective 3 (LB Shortage Frequency), ε	3%
Objective 4 (LB Shortage Volume), ε	50 KAF/Y
Objective 5 (Max Annual LB Shortage), ε	50 KAF
Objective 6 (Powell 3490), ε	1%
Objective 7 (Powell WY Release), ε	50 KAF/Y
Objective 8 (Lee Ferry Deficit), ε	3%

Table 3.4. Experimental design for the re-simulation of non-dominated policies across many states of the world.

Supply Scenarios	Hydrologic Traces		Demand Scenarios		Operating Policies		Simulations
Direct Natural Flow	107	x	3	x	751	=	241,071
Future Climate	112	x	3	x	751	=	252,336
Total	**219**	**x**	**3**	**x**	**751**	**=**	**493,407**

3.6.2. Re-Simulating the Generated Policies Across Many States of the World: Computational Experiment

The ranges of future water supply and water demand scenarios that make up the future states of the world (SOWs) are explained in detail in Section 3.4. This section first provides details on the experimental design of SOWs and operating policies combinations, then explains the software tool utilized for the re-simulation of the non-dominated policies. As seen in Table 3.4, the re-simulation of 751 unique Lake Mead operating policies across 219 plausible hydrologic traces and three future water demand scenarios results in 493,407 individual CRSS model simulations.

The expansive set of RiverWare simulations required in this analysis prompted the use of the RiverSMART (http://riverware.org/RiverSmart/RiverSmartSoftwareSuiteHelp.html) software tool. RiverSMART was developed at CADSWES and it has the capabilities to automatically execute and archive results from numerous RiverWare model runs. With these capabilities in mind, a RiverSMART study (as seen in Figure 3.8) was created to handle the re-simulation of the 751 non-dominated operating policies across the future SOWs. This RiverSMART study took two months of continuous simulation on the 12-core computer described in the preceding section. Furthermore, this step results with an extensive dataset (over

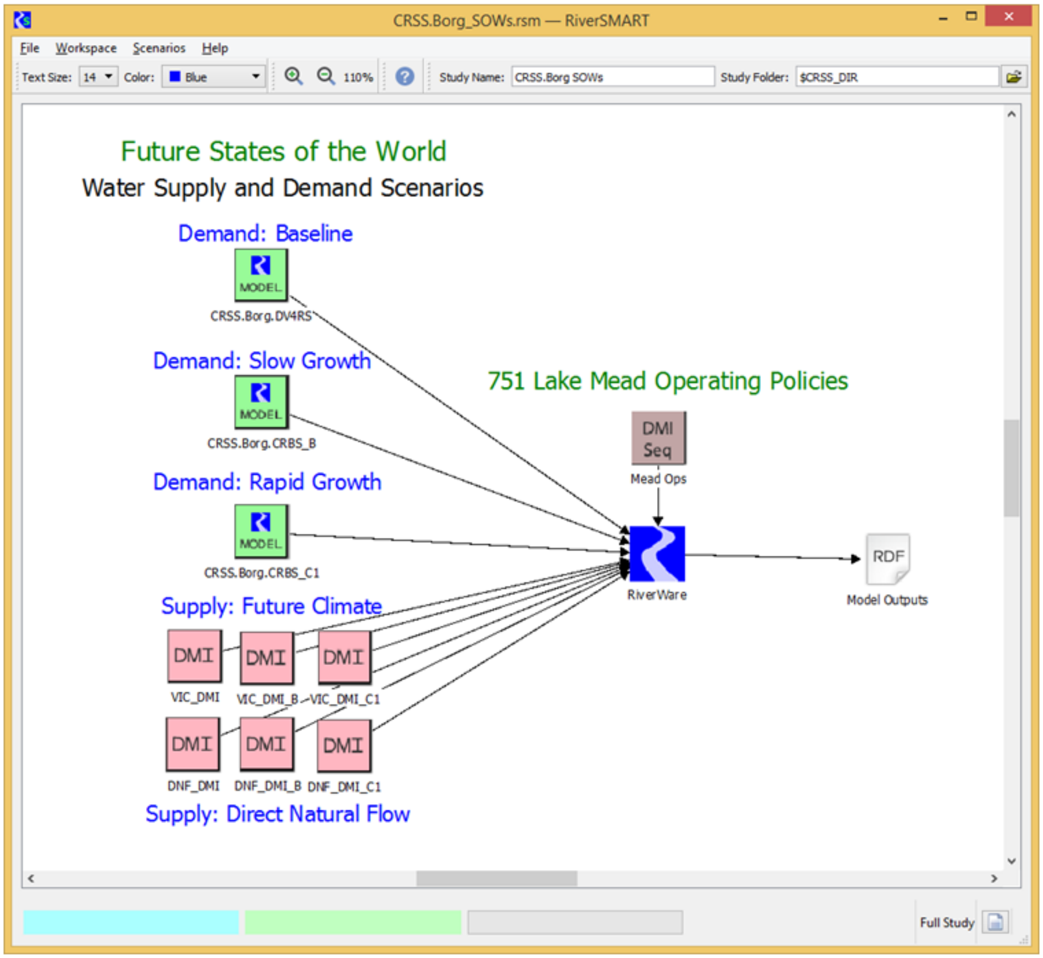

Figure 3.8. A screenshot of the RiverSMART study used in this research.

250 GBs of model output) that documents how a policy's performance varies across the future SOWs.

3.6.3. Evaluating the Robustness of the Generated Policies: Computational Experiment

Multiple formulations of satisficing and regret based robustness measures were computed for each operating policy using the dataset obtained from the re-simulation of the 751 non-dominated operating policies across the future SOWs. The purpose of this computational experiment is to test these two classes of robustness measures to see which measure best fits the requirements as prescribed in Section 3.5.2.

Regret Type A (Equation 3.1) and Type B (Equation 3.2) robustness measures were calculated for each of the 751 policies using multiple objectives (from the set of eight). The recommendations from Matrosov et al. (2013) and Herman et al. (2015) on how to aggregate regret measures across multiple objectives were utilized in these calculations. The results of these regret based calculations were extremely sensitive to the method used to aggregate regret measures across the multiple objectives. Even after refining the aggregation techniques and testing different sub-groups of the eight objectives (calculated across objective 1, 4, 8, etc.), a dependable formulation of a regret measure across multiple objectives was not achieved in this planning study.

Similarly, the satisficing (Equation 3.3) robustness measure was calculated for each of the 751 policies using multiple groups of objectives (from the set of eight) and using ranges of minimum performance requirements for the groups of objectives considered. An important note is that a compound formulation of satisficing was employed to consider multiple groups of objectives. For example, when considering a group of 3 objectives ($I = 3$) the satisficing indicator function ($S_{i\epsilon I}$) will only return a value of one if the minimum level of performance is met in *all* the separate objectives considered in the calculation. The results of these satisficing based calculations were sensitive to the selection of sub-groups from the set of objectives and were also sensitive to the minimum level of performance prescribed. However, satisficing's flexibility to change the minimum level of performance on an objective by objective basis enabled us to fine tune a formulation across multiple objectives. This flexibility also enables satisficing to account for performance requirements in objectives that interest decision makers the most. Furthermore, the presentation of CRB system performance as percent of traces in the bi-annual official CRSS runs is very similar to how satisficing formulates robustness as percentage of future SOWs where an operating policy meets minimum performance requirements.

Regret based measures were relatively easy to comprehend and straightforward to implement; however, their inability to be dependably formulated across multiple objectives deemed them inadequate for use in this research. Satisficing better fit the study specific requirements compared to regret for achieving a dependable formulation across multiple planning objectives and being easy to comprehend since satisficing presents robustness in a similar form that CRB decision makers are used to viewing CRB system performance. Since the satisficing robustness measure (Equation 3.3) meets all the requirements, it is the selected measure of robustness implemented in this research.

Chapter 4 Results

4.1. Introduction

This chapter presents selected results from the computational experiments, Section 3.6, of the MORDM application in the CRB. First, the performances of the Interim Guidelines policies are presented, then the performance of the MOEA-generated policies is explored; lastly the results from the robustness analysis are provided at the end of the chapter. Results in this chapter are visualized using different graphical techniques to aid the interpretation of tradeoffs in multiple objectives and robustness values.

4.2. Performance of the 2007 Interim Guideline Policies

This section uses parallel coordinate plots to display the objective values from the 2007 Interim Guideline operating policies, as discussed in Section 3.3. Parallel coordinate plots provide a systematic way to visualize the tradeoffs between multiple performance objectives by showing connected polylines that can show tradeoffs in more than three dimensions simultaneously (Fleming et al., 2005; Inselberg, 1985). To help frame the performance of the MOEA-generated operating policies, we first provide an explanation of parallel coordinate plots using objective values from the three previously negotiated policies and then in the next section we present the full set of results using parallel coordinate plots.

To refresh, the Water Supply Alternative (WSA) prioritizes water deliveries; the Reservoir Storage Alternative (RSA) prioritizes storing water for future demand; and the Preferred Alternative (PA) is a compromise between the two alternatives. All three of these Interim

Guidelines Lake Mead operating policies were simulated in CRSS using the same future CRB hydrology and water demand scenarios as considered in the MOEA search obtaining objective values for each policy; the first major research question of this study is whether or not the MOEA can generate comparable policies to these previously generated ones.

Figure 4.1 displays the performance (for two planning objectives) of the previously negotiated policies using both a Cartesian coordinates plot (a) and a parallel coordinates plot (b). Both plots display the tradeoff between a policy's ability to keep Lake Mead's pool elevation above 1,000 feet (Objective 1) and reduce the maximum annual LB policy shortage imposed during the simulation (Objective 5). In Figure 4.1 (a) each point represents a different Lake Mead operating policy, and the x and y axes show the range of values for each objective. Alternatively, in Figure 4.1 (b) each line represents a different operating policy and each column represents a different objective. All objective values displayed were individually re-scaled so the minimum objective value in the set of solutions (MOEA-generated & the previously negotiated policies) is zero and the maximum value is one. Thus, an ideal performance in the planning

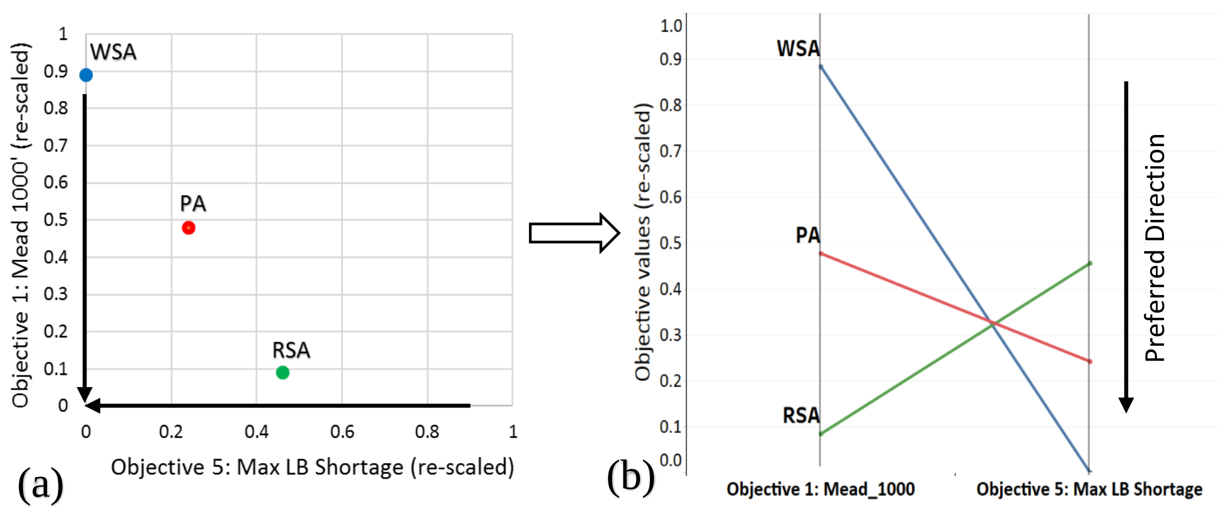

Figure 4.1. Translation of points between Cartesian coordinates (a) and parallel coordinates (b) of objectives 1 and 5 values for the previously negotiated policies.

objectives is plotted at zero and is indicated in Figure 4.1 as the directional arrows along both plots' axes. Where the line crosses the column in Figure 4.1 (b) represents the performance value for that given objective. Thus, the tradeoff between a policy's ability to keep Lake Mead's pool elevation above 1,000 feet and reduce the maximum annual LB policy shortage imposed can be visualized by the crossing lines in Figure 4.1 (b). The usefulness of visualizing performance tradeoffs with the Cartesian coordinate system is limited when considering more than three planning objectives (Fleming et al., 2005); therefore, this research visualizes tradeoffs using parallel coordinates since there are eight planning objectives considered in the MOEA search.

Figure 4.2 illustrates the tradeoffs in performance in the eight planning objectives of the three Interim Guideline Lake Mead operating policies using an 8-dimensional parallel coordinate

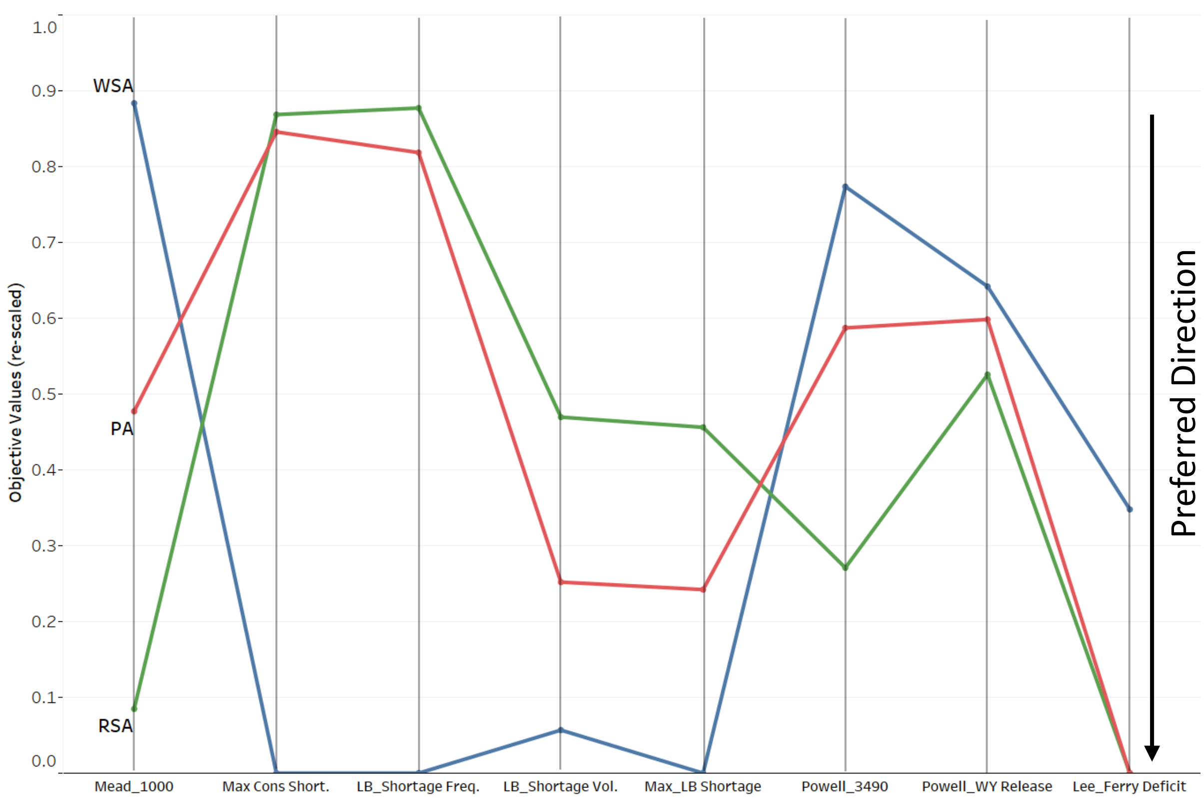

Figure 4.2. A parallel coordinate plot displaying the multi-objective performance of the three previously negotiated Lake Mead operating policies.

plot. The WSA, the blue line in Figure 4.2, achieves favorable performance in the shortage focused objectives (columns 2 through 5) while achieving unfavorable performance in objectives focused on keeping water levels above critical pool elevations in Lakes Mead and Powell (columns 1 and 6). The absence of shortage operating tiers in WSA’s operating policy explains the performance tradeoffs of achieving the best-found values in the shortage focused objectives at the expense of retaining water for future use.

4.3. Performance of MOEA-Generated Policies

As mentioned in Section 3.6.1, the MOEA search discovered 751 non-dominated Lake Mead operating policies with varying operating policy structures and a diverse range of performance in the eight planning objectives. Figure 4.3 displays a parallel coordinate plot of the objective performance of the 751 non-dominated operating policies (in grey) along with the three previously negotiated operating policies overlaid with the same colors used in Figure 4.1. Each line represents a different Lake Mead operating policy, which consists of different combinations of policy variables set by the MOEA. The eight columns in Figure 4.3 represents the eight planning objectives, and the location of where a line crosses each column represents the policy's performance in that objectives. The numbers on the limits of each column represents the maximum (top) and the minimum (bottom) objective value in the set of MOEA-generated and Interim Guideline policies considered. Since all eight objectives were minimized during the multi-objective optimization, an ideal operating policy would be represented as a horizontal line across the bottom of the columns.

As demonstrated in Figure 4.3, the MOEA generated a diverse set of 751 policies that demonstrate interesting tradeoffs in policies’ ability to minimize frequency, duration, and

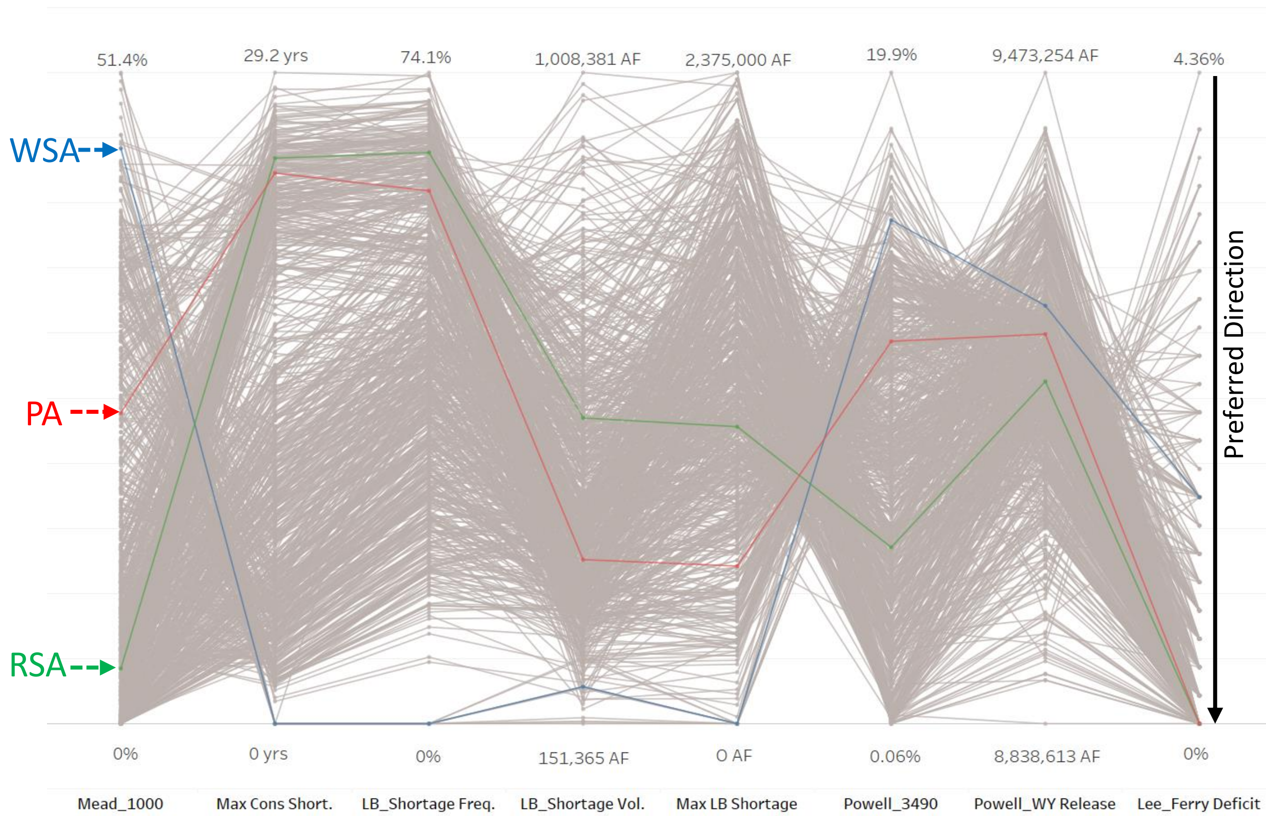

Figure 4.3. A parallel coordinate plot of the non-dominated set of MOEA-generated operating policies (in grey) along with the three previously negotiated Lake Mead operating policies overlaid (in color).

quantity of shortages reductions imposed while maximizing storage in Lakes Powell and Mead. A finding from this research is that the MOEA-generated operating policies explore a wider range of the solution space than the three previously negotiated policies, which were thought to be adequate bounds of the planning problem in 2007.

4.4. Identifying Robust Policies

The second part of the analysis measures the robustness of the generated policies using the concept of *satisficing* — the percentage of future SOWs in which the operating policy satisfies multiple performance requirements. As previously described, SOWs are plausible combinations of factors that could cause performance issues for the system in the future. Specifically, we use two future supply scenarios and three future water demand scenarios as was described in Section 3.4. This research considers three satisficing criteria that are based on performance thresholds in three planning objective functions. The criteria that define a robust Lake Mead operating policy include: maintaining a Lake Mead pool elevation above 1,000 feet in 90% of the months simulated (Mead 1000 $\leq$ 10%), imposing a cumulative average annual Lower Basin shortage reduction less than or equal to 600 kaf throughout the simulation horizon (LB Shortage Volume $\leq$ 600 kaf), and maintaining a Lake Powell pool elevation above 3,490 feet in 95% of the months simulated (Powell 3490 $\leq$ 5%). These three satisficing criteria were decided upon using a combination of interactive visual analytics and scoped through a series of project meetings where representatives from Reclamation articulated the performance requirements of CRB stakeholders. A policy's performance is considered robust if all three satisficing criteria are met in the tested future SOW.

The ranked robustness bar plot, first presented in Herman et al. (2014), provides a straightforward visualization of the relative robustness of a set of planning alternatives, ranking them from most robust to least according to a given metric. The ranked bar plot for the 751 operating policies generated in this thesis is shown in Figure 4.4. The operating policies are plotted (x-axis) in descending order based on their robustness values (y-axis). Robustness values range from 0% to 100%. If a policy meets the satisficing criteria in all SOWs tested, then that policy would have a 100% robustness value. Figure 4.4 shows the range of robustness achieved by all the policies, which ranges from policies meeting the satisficing criteria in as low as 17%

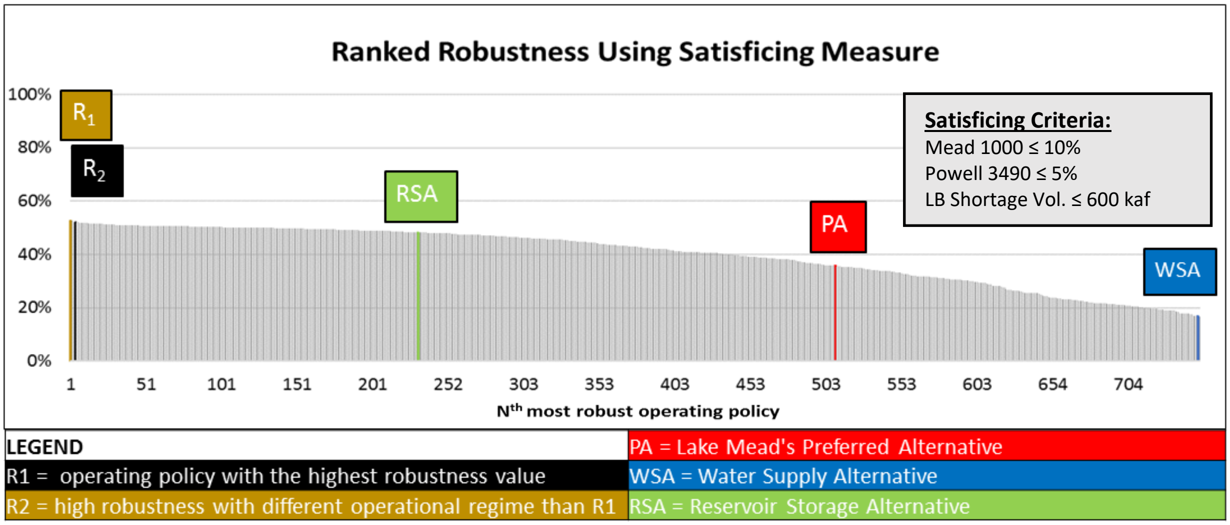

Figure 4.4. Ranked robustness tradeoffs of 751 non-dominated operating policies (grey bars) and the three previously negotiated policies (colored bars).

and as high as 53% of the SOWs tested. This satisficing analysis provides a flexible way to rank and identify robust policies from the large set of MOEA-generated policies.

The highlighted solutions include the previously negotiated policies with the same colors as were used in Figure 4.3 and two chosen operating policies that are termed “robust”. The operating policy that achieved the highest robustness is labeled R1, and R2 is a policy that also achieved high robustness but has a different operational composition than R1. The results also suggest that the RSA achieves a higher robustness than the PA. This improvement in robustness can be attributed to RSA’s operating policy of imposing greater shortage reductions at a higher starting pool elevation when compared to the PA’s operating policy, shown in Figure 3.1. It is also important to note that the WSA is among the policies with the least amount of robustness to future water supply and demand uncertainty. This low robustness can be attributed to the WSA’s absence of shortage operating tiers. This highlights that the policy variables that structure Lake Mead's shortage tiers are crucial to achieve incremental improvements in robustness. Learning how the R1 and R2 policies achieved the highest robustness values will potentially suggest new alternative operating policies that are more robust to future water supply and demand uncertainty. R1 and R2 policies' operating policy composition will be explored in the next section.

4.5. Recognizing Robust Lake Mead Operating Structures

This section first presents a parallel coordinate plot using color to display the policies' robustness values, then the same parallel coordinate plot is displayed but the highlighted policies from Section 4.4 are selected along with a visualization of their corresponding Lake Mead operating policy structures. Figure 4.5 presents a parallel coordinate plot displaying the robustness values of all the MOEA-generated policies using color and the same satisficing

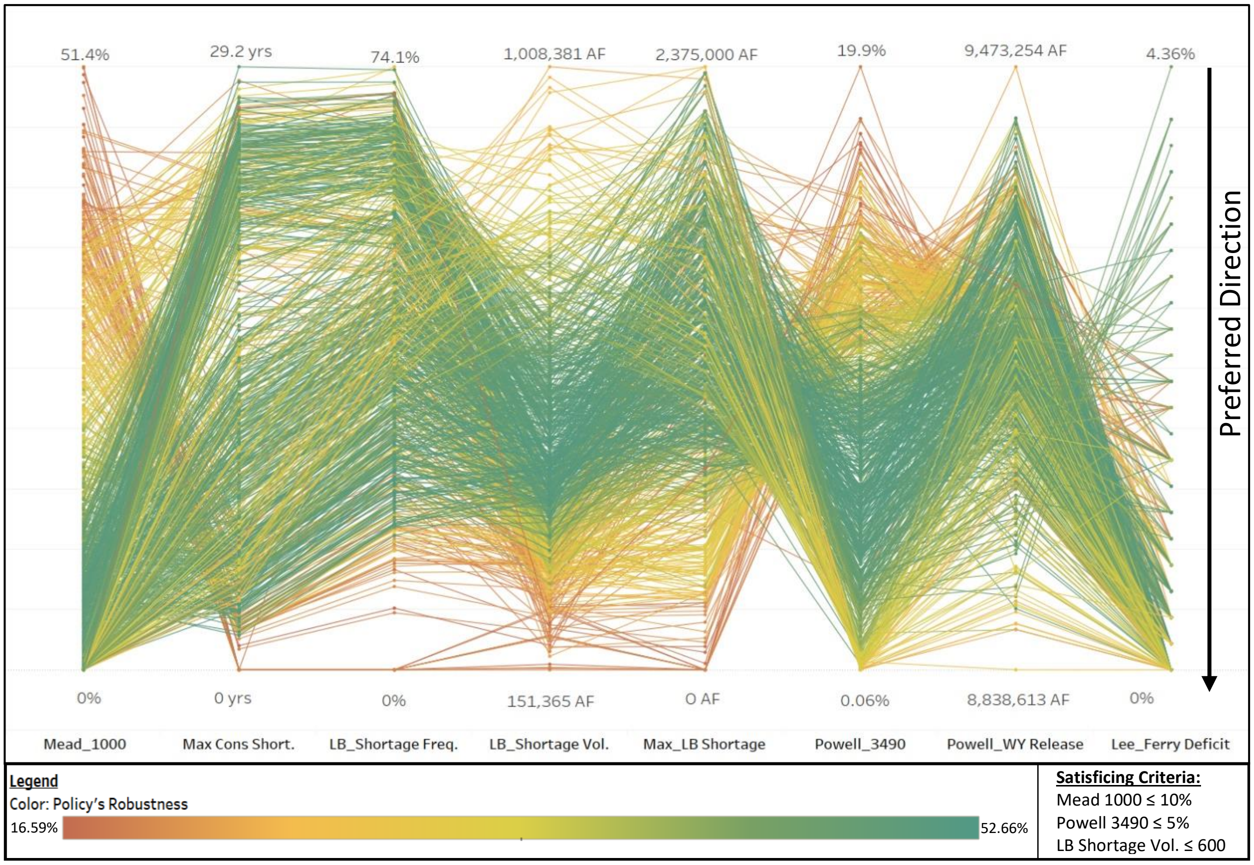

Figure 4.5. Parallel coordinate plot displaying the policies' performance from the multi-objective optimization (line location) and robustness values (color).

criteria as in the previous section. This plot superimposes a red-green color gradient to distinguish low robust policies (red) from high robust policies (green). It retains the same orientation of the lines as Figure 4.3, thus, where the lines cross the axes indicates the policies' objective performance for each objective. The operating policies with favorable performance in each of the *individual* objectives considered in the satisficing criteria (*Mead 1000*, *LB Shortage Volume*, and *Powell 3490*) were revealed to have low robustness values (yellow to orange in color). The most robust policies (group of dark green lines) achieved favorable performance in *all* objectives considered in the satisficing criteria.

This figure was created using Tableau Software which has the functionality to interactively select an operating policy and see multiple attributes of that policy in a single plotting interface (Jones, 2014). Figure 4.6 was created through interactively selecting the most robust (R1 and R2) and the previously negotiated policies (PA, WSA, and RSA). Visualizing a policy's multi-objective optimization performance (line location), robustness values (color) and operating policy structure contiguously is a powerful approach that enables us to learn which operational attributes led to robust performance. We begin to understand how the R1 policy achieved high robustness through taking a closer look at its Lake Mead operating policy structure, Figure 4.6 (b). The R1 policy imposes a shortage reduction volume of 1,875 kaf at pool elevation 1,030 feet and then at pool elevation 915 feet imposes a higher shortage reduction volume of 2,400 kaf. It is somewhat surprising that this policy maintained an average shortage reduction volume less than

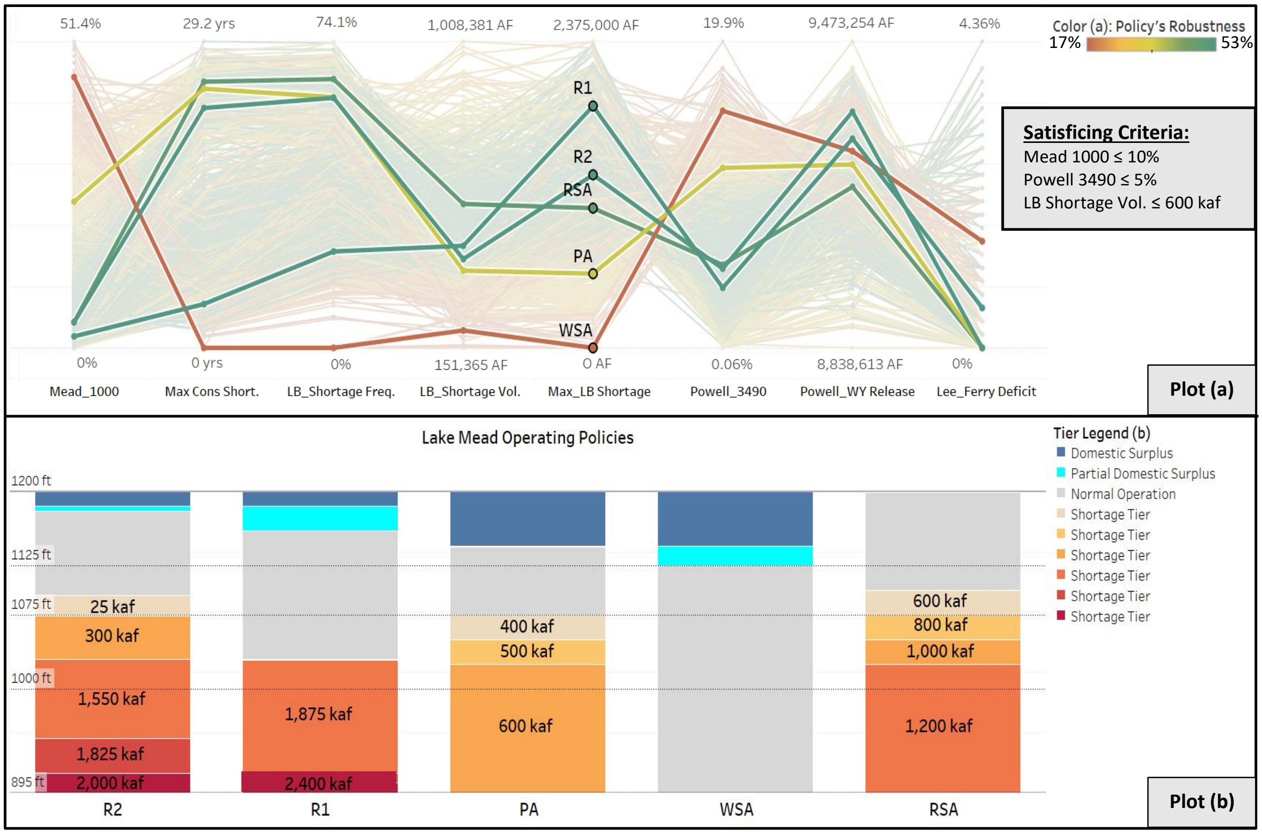

Figure 4.6. Parallel coordinate plot (plot a) displaying the previously negotiated and selected robust policies' performance from the multi-objective optimization (line location) and robustness values (color). Each selected policy's corresponding Lake Mead operating policy structure is also presented below (plot b).

or equal to 600 kaf in the majority of SOWs tested. However, imposing a high shortage reduction at a relatively low pool elevation could be just enough for the system to bounce back from a stressed hydrologic and water demand condition.

R2's operating policy has a different operational structure than R1, as seen in Figure 4.6 (b). This policy imposes a low shortage reduction volume of 25 kaf at pool elevation 1,095 feet, then a moderate shortage volume of 300 kaf at 1,075 feet, ramping up the shortage volume to 1,550 kaf at 1,030 feet, increasing the shortage volume to 1,825 kaf at 950 feet, and again increasing the shortage volume to 2,000 kaf at 915 feet. It is important to note that R2 and RSA have similar shortage operation tier locations and their reduction volumes are similar, except that R2 has a high shortage volume below 950 feet, which explains RSA's high robustness value.

Also, that R2 starts its shortage operation at pool elevation 1,095 feet explains why R2 has a higher frequency and duration of shortage when compared to R1. Both R1 and R2 impose their first major shortage reduction at pool elevation 1,030 feet and a higher shortage reduction at pool elevation 915 feet. The similarities between the robust operating policies may shed some light on how Lake Mead's current operation can be refined to be more robust to future water supply and demand uncertainty.

Chapter 5 Discussion, Conclusion, and Future Work

5.1. Introduction

This research provides an innovative approach to generate and identify robust Lake Mead reservoir operating policies using the Many Objective Robust Decision Making (MORDM) planning framework. The MORDM framework was selected because it distinguished itself from other bottom-up frameworks by its capability to *generate* new operating policies, interactively explore performance and robustness tradeoffs, and obtain valuable system insights in a single, iterative planning framework. This chapter provides a further discussion of the contributions of this MORDM application and is organized into the following sections. The discussion section further analyzes the results while addressing all the research questions posed in the first chapter. Afterwards, concluding thoughts will be provided to encapsulate the research conducted. This chapter will end with a future work section where next steps of this research will be outlined.

5.2. Discussion and Conclusion

The results presented in Chapter 4 answered each research question posed in this thesis. First, can a multi-objective evolutionary algorithm (MOEA) generate comparable policies to those negotiated in the 2007 Interim Guidelines? The MOEA-search discovered 751 non-dominated operating policies with comparable operating policy structures and multi-objective performance to that of the previously negotiated policies. The policy variables were structured to be able to set two additional shortage tiers and impose twice as much shortage volume as the operating policies considered in the 2007 Interim Guidelines. This enabled the MOEA-generated policies to explore a wider range of the solution space than the three previously negotiated policies, as shown by the grey lines in Figure 4.3. We also learned that it was beneficial to have the ability to simulate realistic CRB operating policies (PA, RSA, and WSA) in the same MOEA framework used to generate new policies. This enabled us to see how the previously identified policies meet each of the planning objectives. Each of the previously identified policies have significantly different operating policy structures and performance in the objectives. Therefore, the ability to compare the multi-objective values of the generated policies to that of the previous identified policies enabled us to further understand the tradeoffs in performance of different operating policy compositions. In addition, the MOEA-generated policies have multi-objective values that are comparable to previously identified operating policies, which gives confidence in the policies suggested by the MOEA.

Second, are the MOEA-generated policies robust to a wide range of plausible future hydrologic and water demand conditions? Through testing the MOEA-generated policies across an expansive range of future hydrologic and water demand conditions we found that the policies achieved a range of robustness values depending on their ability to meet the satisficing criteria. Each policy's robustness value is sensitive to the specific performance requirements considered in the satisficing criteria. However, analyzing the relative ranges of all the robustness values revealed operational insights and details regarding the future states of the world (SOWs) considered in this research. Operating policies with the lowest robustness values most likely meet the robustness criteria only in "favorable" SOWs made up of hydrologic traces from the Direct Natural Flow or Future Climate ensemble with higher than normal annual flow paired with the Slow Growth water demand scenario. In these favorable SOWs, undesirable operating policies that impose high shortage reductions starting at Lake Mead pool elevation around 1,100 feet and policies with no shortage operating tiers (including the WSA) still satisfy all the robustness criteria. This reveals that there are SOWs in which robust performance can be achieved regardless of an operating policy's composition. The policies with the highest robustness (R1 and R2) meet the robustness criteria in the majority of the SOWs tested, as seen in Figure 4.4. The fact that these operating policies achieved robust performance in approximately half of the SOWs tested may reveal that there are SOWs in which robust performance cannot be achieved. To test this claim, it may warrant the need to further adjust the performance requirements in the satisficing criteria or to consider a wide range of hydrologic traces (including traces outside the range of the observed record) in the MOEA-search similar to robust optimization studies (Trindade et al., 2017; Watson & Kasprzyk, 2017).

Lastly, which attributes of a Lake Mead operating policy lead to robust performance? The operational similarities between the candidate robust policies (R1 and R2) were uncovered through further analyzing the MOEA-generated policies. We experienced the utility of interactive visual analytics through being able to analyze multiple attributes (multi-objective values, robustness values, and policy structures) of 751 operating policies in a single plotting interface. This interactive plotting interface allowed us to highlight policies based on their robustness values, which revealed two different Lake Mead operating policy compositions with high robustness, which we called the R1 and R2 policies. The R1 and R2 policies have identical pool elevations that trigger two shortage operating tiers with similar shortage volumes. The first similar operating tier has a high shortage volume (1,550 - 1,875 kaf) starting at 1,030 feet pool elevation and the second similar operating tier has even higher shortage volume (2,000 - 2,400 kaf) at 915 feet pool elevation. The similar attributes of the R1 and R2 policies are a significant finding from this research. This finding is important because these attributes could be used to refine Lake Mead's current operation to be more robust. In addition, it would have been difficult to make a similar discovery only using static images, since it would be difficult to associate 751 images of the separate operating policies to their corresponding robustness values.

In conclusion, we demonstrated that coupling an MOEA with CRSS is an effective tool to generate and evaluate thousands of new Lake Mead operating policies. This research identified multiple robust operating policies through applying a satisficing analysis to the set of MOEA-generated policies. The operational similarities between the identified robust policies may shed light on how Lake Mead's operation could be formulated to be more robust to a wide range of future hydrologic and water demand conditions. We provide a realistic application of an MOEA to one of the largest, most complex river basins that has been optimized using an MOEA to date.

5.3. Future Work

This section suggests both near and long-term pragmatic future actions to explore. As mentioned in Chapter 2, the last methodological step of MORDM is a sensitivity analysis to isolate uncertainties that control the robustness of the candidate policies. Conducting a sensitivity analysis using the R1 and R2 robust candidate policies is the first near-term action that is suggested. The sensitivity analysis requires distilling information about the ranges of both uncertain future hydrologic and water demand conditions, so each future states of the world can be characterized by a single hydrologic or water demand attribute. Monthly inflow to Lake Powell is a function of both the future supply and demand scenario considered and is an input into the simplified CRSS model. For these reasons, a distilled form of monthly inflow to Lake Powell time series could be the first characterization of uncertainty tested in the sensitivity analysis. After multiple characterization of both hydrologic and water demand uncertainties are selected, then a cluster finding algorithm can be employed to identify ranges of the uncertain conditions which causes a candidate policy to fail the satisficing criteria (Bryant & Lempert, 2010). Revealing the controls on the robustness of candidate alternatives could be useful to understand ranges of future hydrologic and water demand conditions that degrade a policy's robustness.

The current operation of the CRB considers a coordinated operation of Lakes Powell and Mead. Another near-term extension of the project would be to set up the Borg MOEA to suggest alternative Lake Powell operating policies, in addition to suggesting the alternative policies for Lake Mead. We have mathematically formulated additional policy variables that would change Lake Powell's operating policy structure. These additional policy variables would change Lake Powell's operating tier size and release volumes. However, additional work is required to restructure Lake Powell's operating rules in the RiverWare model to be influenced by different combinations and values of Lake Powell policy variables. The added capability to generate and evaluate new Lake Powell operating policies (in addition to Lake Mead policies) would enable this research to holistically assist in future Reclamation CRB policy analysis.

An additional area of future work is to refine the precision of the epsilon values for each planning objective considered in the MOEA search. It was revealed through interactive visual analytics that some of the MOEA-generated policies had very similar Lake Mead operating structures. One potential explanation for this result is that the epsilon precision for objectives was too fine, causing policies to survive the non-dominated sorting within the search although their objective values were very similar. Therefore, an additional computational experiment is proposed to run a series of MOEA searches testing different epsilon values to improve the diversity of the MOEA-generated policies.

A long-term area of future work is to build on the lessons learned from this MORDM application to refine the composition of the policy variables. These refinements would require a series of workshops inviting a diverse group of CRB stakeholders and analysts. A goal of these workshops would be to refine limits on the policy variables to directly reflect the stakeholders' preferences in operating policy structure and to brainstorm new policy variable formulations. Additional policy variable formulations could include more influential surplus operation formulations or different degrees of conservation measures.

References

Alexander, E., Kasprzyk, J., Zagona, E., Prairie, J., Jerla, C., & Butler, A. (2017). *Using Multi-Objective Optimization to Explore Robust Policies in the Colorado River Basin*. Poster Presentation presented at the AGU Fall Meeting, New Orleans.

Alexander, E., Kasprzyk, J., Zagona, E., Prairie, J., Jerla, C., & Butler, A. (2018). *Using Multi-Objective Optimization to Explore Robust Policies in the Colorado River Basin*. Oral Presentation presented at the Environmental & Water Resources Institute Water Congress, Minneapolis.

Basdekas, L. (2014). Is Multiobjective Optimization Ready for Water Resources Practitioners? Utility's Drought Policy Investigation. *Journal of Water Resources Planning and Management*, *140*(3), 275–276. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000415

Ben-Haim, Y. (2004). Uncertainty, probability and information-gaps. *Reliability Engineering & System Safety*, *85*(1), 249–266. https://doi.org/10.1016/j.ress.2004.03.015

Bryant, B. P., & Lempert, R. J. (2010). Thinking inside the box: A participatory, computer-assisted approach to scenario discovery. *Technological Forecasting and Social Change*, *77*(1), 34–49. https://doi.org/10.1016/j.techfore.2009.08.002

Bureau of Reclamation. (2007). *Colorado River Interim Guidelines for Lower Basin Shortage and Coordinated Operations for Lake Powell and Mead - Final Environmental Impact Statement*. U.S. Department of the Interior.

Bureau of Reclamation. (2012). *Colorado River Basin Water Supply and Demand Study*. U.S. Department of the Interior.

Bureau of Reclamation. (2015). *Colorado River Basin Stakeholders Moving Forward to Address Challenges Identified in the Colorado River Basin Water Supply and Demand Study*. U.S. Department of the Interior.

Coello Coello, C. A., Lamont, G. B., & Van Veldhuizen, D. (2007). *Evolutionary Algorithms for Solving Multi-Objective Problems* (Second). New York: Springer.

Dittrich, R., Wreford, A., & Moran, D. (2016). A survey of decision-making approaches for climate change adaptation: Are robust methods the way forward? *Ecological Economics*, *122*, 79–89. https://doi.org/10.1016/j.ecolecon.2015.12.006

Fleming, P. J., Purshouse, R. C., & Lygoe, R. J. (2005). Many-Objective Optimization: An Engineering Design Perspective (pp. 14–32). Presented at the International Conference on Evolutionary Multi-Criterion Optimization, Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-31880-4_2

Friedman, J. H., & Fisher, N. I. (1999). Bump hunting in high-dimensional data. *Statistics and Computing*, *9*(2), 123–143. https://doi.org/10.1023/A:1008894516817

Groves, D. G., Fischbach, J. R., Bloom, E., Knopman, D., & Keefe, R. (2013). Adapting to a Changing Colorado River [Product Page]. Retrieved March 12, 2018, from https://www.rand.org/pubs/research_reports/RR242.html

Haasnoot, M., Kwakkel, J. H., Walker, W. E., & ter Maat, J. (2013). Dynamic adaptive policy pathways: A method for crafting robust decisions for a deeply uncertain world. *Global Environmental Change*, *23*(2), 485–498. https://doi.org/10.1016/j.gloenvcha.2012.12.006

Hadka, D., & Reed, P. (2012). Borg: An Auto-Adaptive Many-Objective Evolutionary Computing Framework. *Evolutionary Computation*, *21*(2), 231–259. https://doi.org/10.1162/EVCO_a_00075

Hadka, D., Herman, J., Reed, P., & Keller, K. (2015). An open source framework for many-objective robust decision making. *Environmental Modelling & Software*, *74*, 114–129. https://doi.org/10.1016/j.envsoft.2015.07.014

Hall, J. W., Lempert, R. J., Keller, K., Hackbarth, A., Mijere, C., & McInerney, D. J. (2012). Robust Climate Policies Under Uncertainty: A Comparison of Robust Decision Making and Info-Gap Methods. *Risk Analysis*, *32*(10), 1657–1672. https://doi.org/10.1111/j.1539-6924.2012.01802.x

Herman, J. D., Zeff, H. B., Reed, P. M., & Characklis, G. W. (2014). Beyond optimality: Multistakeholder robustness tradeoffs for regional water portfolio planning under deep uncertainty. *Water Resources Research*, *50*(10), 7692–7713. https://doi.org/10.1002/2014WR015338

Herman, J. D., Reed, P. M., Zeff, H. B., & Characklis, G. W. (2015). How Should Robustness Be Defined for Water Systems Planning under Change? *Journal of Water Resources Planning and Management*, *141*(10), 04015012. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000509

Hine, D., & Hall, J. W. (2010). Information gap analysis of flood model uncertainties and regional frequency analysis. *Water Resources Research*, *46*(1), W01514. https://doi.org/10.1029/2008WR007620

Inselberg, A. (1985). The plane with parallel coordinates. *The Visual Computer*, *1*(2), 69–91. https://doi.org/10.1007/BF01898350

Intergovernmental Panel on Climate Change. (2008). *Climate Change 2007: Synthesis Report* (Contribution of Working Groups I, II, and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change.). Retrieved from https://www.ipcc.ch/pdf/assessment-report/ar4/syr/ar4_syr_full_report.pdf

Jones, B. (2014). *Communicating Data with Tableau: Designing, Developing, and Delivering Data Visualizations.* Sebastopol, CA: O'Reilly Media, Inc.

Kasprzyk, J. R., Nataraj, S., Reed, P. M., & Lempert, R. J. (2013). Many objective robust decision making for complex environmental systems undergoing change. *Environmental Modelling & Software*, *42*, 55–71. https://doi.org/10.1016/j.envsoft.2012.12.007

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

Laumanns, M., Thiele, L., Deb, K., & Zitzler, E. (2002). Combining Convergence and Diversity in Evolutionary Multiobjective Optimization. *Evolutionary Computation*, *10*(3), 263–282. https://doi.org/10.1162/106365602760234108

Lempert, R. J., & Collins, M. T. (2007). Managing the Risk of Uncertain Threshold Responses: Comparison of Robust, Optimum, and Precautionary Approaches. *Risk Analysis*, *27*(4), 1009–1026. https://doi.org/10.1111/j.1539-6924.2007.00940.x

Lempert, R. J., & Groves, D. G. (2010). Identifying and evaluating robust adaptive policy responses to climate change for water management agencies in the American west.

Technological Forecasting and Social Change, *77*(6), 960–974. https://doi.org/10.1016/j.techfore.2010.04.007

Lempert, R. J., Popper, S. W., & Bankes, S. C. (2003). *Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis* (Product Page). RAND Corporation. Retrieved from https://www.rand.org/pubs/monograph_reports/MR1626.html

Maier, H. R., Kapelan, Z., Kasprzyk, J., Kollat, J., Matott, L. S., Cunha, M. C., et al. (2014). Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions. *Environmental Modelling & Software*, *62*(Supplement C), 271–299. https://doi.org/10.1016/j.envsoft.2014.09.013

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

McPhail, C., Maier, H. R., Kwakkel, J. H., Giuliani, M., Castelletti, A., & Westra, S. (2018). Robustness Metrics: How Are They Calculated, When Should They Be Used and Why Do They Give Different Results? *Earth's Future*, *6*(2), 169–191. https://doi.org/10.1002/2017EF000649

National Research Council. (2007). *Colorado River Basin Water Management: Evaluating and Adjusting to Hydroclimatic Variability*. https://doi.org/10.17226/11857

Popper, S. W., Berrebi, C., Griffin, J., Light, T., Daehner, E. M., & Crane, K. (2009). Natural Gas and Israel's Energy Future [Product Page]. Retrieved March 12, 2018, from https://www.rand.org/pubs/monographs/MG927.html

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

Smith, R., Kasprzyk, J., & Zagona, E. (2016). Many-Objective Analysis to Optimize Pumping and Releases in Multireservoir Water Supply Network. *Journal of Water Resources Planning and Management*, *142*(2), 04015049. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000576

Starr, M. K. (1962). *Product design and decision theory*. Englewood Cliffs, N.J.: Prentice-Hall.

Trindade, B. C., Reed, P. M., Herman, J. D., Zeff, H. B., & Characklis, G. W. (2017). Reducing regional drought vulnerabilities and multi-city robustness conflicts using many-objective optimization under deep uncertainty. *Advances in Water Resources*, *104*, 195–209. https://doi.org/10.1016/j.advwatres.2017.03.023

Upper Colorado River Commission. (2007, December). Upper Colorado River Division States Current and Future Depletion Demand Schedule UPPER BASIN TOTALS.

Walker, W. E., Rahman, S. A., & Cave, J. (2001). Adaptive policies, policy analysis, and policy-making. *European Journal of Operational Research*, *128*(2), 282–289. https://doi.org/10.1016/S0377-2217(00)00071-0

Walker, W. E., Haasnoot, M., & Kwakkel, J. H. (2013). Adapt or Perish: A Review of Planning Approaches for Adaptation under Deep Uncertainty. *Sustainability*, *5*(3), 955–979. https://doi.org/10.3390/su5030955

Ward, V. L., Singh, R., Reed, P. M., & Keller, K. (2015). Confronting tipping points: Can multi-objective evolutionary algorithms discover pollution control tradeoffs given environmental thresholds? *Environmental Modelling & Software*, *73*, 27–43. https://doi.org/10.1016/j.envsoft.2015.07.020

Watson, A. A., & Kasprzyk, J. R. (2017). Incorporating deeply uncertain factors into the many objective search process. *Environmental Modelling & Software*, *89*, 159–171. https://doi.org/10.1016/j.envsoft.2016.12.001

Woodhouse, C. A., Gray, S. T., & Meko, D. M. (2006). Updated streamflow reconstructions for the Upper Colorado River Basin. *Water Resources Research*, *42*(5). https://doi.org/10.1029/2005WR004455

Woodruff, M. J., Reed, P. M., & Simpson, T. W. (2013). Many objective visual analytics: rethinking the design of complex engineered systems. *Structural and Multidisciplinary Optimization*, *48*(1), 201–219. https://doi.org/10.1007/s00158-013-0891-z

Yemshanov, D., Koch, F. H., Ben-Haim, Y., & Smith, W. D. (2010). Robustness of risk maps and survey networks to knowledge gaps about a new invasive pest. *Risk Analysis: An Official Publication of the Society for Risk Analysis*, *30*(2), 261–276. https://doi.org/10.1111/j.1539-6924.2009.01284.x

Zagona, E. A., Fulp, T. J., Shane, R., Magee, T., & Goranflo, H. M. (2001). Riverware: A Generalized Tool for Complex Reservoir System Modeling1. *JAWRA Journal of the American Water Resources Association*, *37*(4), 913–929. https://doi.org/10.1111/j.1752-1688.2001.tb05522.x

Zatarain Salazar, J., Reed, P. M., Herman, J. D., Giuliani, M., & Castelletti, A. (2016). A diagnostic assessment of evolutionary algorithms for multi-objective surface water reservoir control. *Advances in Water Resources*, *92*, 172–185. https://doi.org/10.1016/j.advwatres.2016.04.006

Appendix A: Formulating Objectives in RiverWare

Lower Basin Objectives & Corresponding Expressions Functions

Objective: Mead 1000

Slot Type: Scalar Slot with Expression

Units: Percentage (%)

Arguments: (Objectives.Mead 1000 indicator function, @" Start Timestep", and @" Finish Timestep")

Argument time-step: Monthly

Expression:

$$\left(\frac{\text{SumSlot(Objectives. Mead 1000 indicator function, @ "Start Timestep", @"Finish Timestep")}}{\text{LENGTH @ "Start Timestep" TO @ "Finish Timestep"}}\right) * 100.00$$

Notes: This monthly objective quantifies the percentage of time that monthly Mead Pool Elevation is less than 1,000 feet MSL.

Mead 1000 Indicator Function

Slot Type: Series Slot with Expression

Units: NONE

Arguments: (Mead.Pool Elevation)

Argument time-step: Monthly

Expression:

$$\text{IF(Mead. Pool Elevation [ ]} < \text{1,000.0000 "ft") THEN}$$

1.0000

ELSE

0.0000

END IF

Notes: This expression returns a 1 when Mead. Pool Elevation is less than 1,000 feet.

Objective: LB Max Consecutive Shortage Duration

Slot Type: Scalar Slot with Expression

Units: Years

Arguments: (Objectives.Consecutive Shortage Counter)

Argument time-step: Annual

Expression:

$$\text{MaxItem}\left(\begin{array}{c}\text{GetSlotVals(Objectives. Consecutive Shortage Counter,} \\ \text{@ "24:00:00 December 31, 2017",} \\ \text{@ "24:00:00 December 31, 2060")}\end{array}\right)$$

Notes: This annual objective quantifies the maximum amount of consecutive years that the system is in shortage operation.

Consecutive Shortage Counter

Slot Type: Series Slot with Expression

Units: Years

Arguments: (Objectives.LB Shortage indicator function)

Argument time-step: Annual

Expression:

$\text{IF (@t} == \text{@"24:00:00 December 31, Current Year") THEN}$

$\text{IF(@t} == \text{@"24:00:00 December 31, 2017")THEN}$

$\text{IF(Objectives. LB Shortage indicator function [ ]} == 0.0000\text{)THEN}$

0.0000

ELSE

$\text{Objectives. LB Shortage indicator function [ ]}$

END IF

ELSE

$\text{IF}(\text{Objectives. LB Shortage indicator function } [\,] == 0.0000)\text{THEN}$

0.0000

ELSE

$\text{Objectives. LB Shortage indicator function } [@\text{"t}-1\text{" }] +$
$\text{Objectives. LB Shortage indicator function } [\,]$

END IF

END IF
END IF

Notes: This expression slot determines if the system is in shortage operation and if it is this expression slot will begin counting the duration of shortage. The logic is also set up to stop counting once the shortage operation (begins normal operation for that year) ends meaning that this expression only considers consecutive shortages.

<u>LB Shortage indicator function</u>

Slot Type: Series Slot with Expression

Units: NONE

Arguments: (LBHydrologicShortage.AnnualPolicyShortage)

Argument time-step: Annual

Expression:

$\text{IF } (@\text{t} == @\text{"24: 00: 00 December 31, Current Year"}) \text{ THEN}$

$\text{IF(LBHydrologicShortage. AnnualPolicyShortage } [\,] > 0.00000009 \text{ "}acre -$
$ft\text{")THEN}$

1.0000

ELSE

0.0000

END IF
END IF

Notes: The slot used in the corresponding objective function is in an annual time-step; therefore this function will return a one if the LBHydrologicShortage.AnnualPolicyShortage is greater than zero or if it equal to zero it will return a zero.

Year Counter

Slot Type: Series Slot with Expression

Units: NONE

Arguments: (@ “t”)

Argument time-step: Monthly

Expression:

$$\text{IF } (@t == @\text{"24:00:00 December 31, Current Year"}) \text{ THEN}$$

1.0000

ELSE

0.0000

END IF

Notes: Expression returns a one for every December simulated and which can be summed up to get how many years were simulated.

Objective: LB Shortage Frequency

Slot Type: Scalar Slot with Expression

Units: Percentage (%)

Arguments: (Objectives.LB Shortage indicator function, @” Start Timestep”, and @”Finish Timestep”)

Argument time-step: Annual

Expression:

$$\left(\frac{\begin{array}{c}\text{SumSlot(Objectives. LB Shortage indicator function,}\\ \text{@ "24:00:00 December 31, 2017",}\\ \text{@ "24:00:00 December 31, 2060")}\end{array}}{\text{SumSlot(Objectives. Year Counter, @ "Start Timestep", @"Finish Timestep")}}\right) * 100.0$$

Notes: This annual objective quantifies the annual percentage of time that the system is in shortage operation.

Objective: LB Shortage Volume

Slot Type: Scalar Slot with Expression

Units: Volume (acre-feet)

Arguments: (LBHydrologicShortage.AnnualTotalShortage, @"Start Timestep", and @"Finish Timestep")

Argument time-step: Annual

Expression:

$$\left(\frac{\begin{array}{c}\text{SumSlot(LBHydrologicShortage. AnnualTotalShortage,}\\ \text{@ "24:00:00 December 31, 2017",}\\ \text{@ "24:00:00 December 31, 2060")}\end{array}}{\text{SumSlot(Objectives. Year Counter, @ "Start Timestep", @"Finish Timestep")}}\right)$$

Notes: This annual objective quantifies the cumulative average annual Lower Basin total shortage volume throughout the modeling period. This expression includes both hydrologic and policy shortages.

Objective: Max Annual LB Shortage

Slot Type: Scalar Slot with Expression

Units: Volume (acre-feet)

Arguments: (LBHydrologicShortage.AnnualPolicyShortage

Argument time-step: Annual

Expression:

$$\text{MaxItem}\left(\begin{matrix}\text{GetSlotVals}(\text{LBHydrologicShortage. AnnualPolicyShortage,}\\ \text{@ "24:00:00 December 31, 2017",}\\ \text{@ "24:00:00 December 31, 2060")}\end{matrix}\right)$$

Notes: This annual objective quantifies the maximum annual Lower Basin Policy shortage volume throughout the modeling period.

Upper Basin Objectives & Corresponding Expressions Functions

Objective: Powell 3490

Slot Type: Scalar Slot with Expression

Units: Percentage (%)

Arguments: (Objectives.Powell 3490 indicator function, @"Start Timestep", and @"Finish Timestep")

Argument time-step: Monthly

Expression:

$$\left(\frac{\text{SumSlot(Objectives. Powell 3490 indicator function, @ "Start Timestep", @"Finish Timestep")}}{\text{LENGTH @ "Start Timestep" TO @ "Finish Timestep"}}\right) * 100.00$$

Notes: This monthly objective quantifies the percentage of time that monthly Powell Pool Elevation is less than 3,490 feet MSL.

Powell 3490 Indicator Function

Slot Type: Series Slot with Expression

Units: NONE

Arguments: (Powell.Pool Elevation)

Argument time-step: Monthly

Expression:

$$\text{IF(Powell. Pool Elevation [ ] } < \text{ 3,490.0000 "ft") THEN}$$

1.0000

ELSE

0.0000

END IF

Notes: This expression returns a 1 when Powell.Pool Elevation is less than 3490 feet.

Objective: Powell WY Release

Slot Type: Scalar Slot with Expression

Units: acre-feet

Arguments: (PowellOperation.PowellWYRelease, Objectives. Year Counter, @"Start Timestep", and @"Finish Timestep")

Argument time-step: Annual

Expression:

$$\frac{\text{SumSlot(Powell. Operation. PowellWYRelease, @"Start Timestep", "Finish Timestep")}}{\text{SumSlot(Objectives. Year Counter , @"Start Timestep", @"Finish Timestep")}}$$

Notes: Cumulative average annual Water Year release from Powell throughout the modeling period.

Objectives: Lee Ferry Deficit

Slot Type: Scalar Slot with Expression

Units: Percentage (%)

Arguments: (Objectives.Lee Ferry Deficit indicator function, Objectives. Year Counter, @"Start Timestep", and @"Finish Timestep")

Argument time-step: Annual

Expression:

$$\left(\frac{\begin{array}{c}\text{SumSlot(Objectives. Lee Ferry Deficit indicator function,} \\ \text{@ "24:00:00 December 31, 2017",} \\ \text{@ "24:00:00 December 31, 2060")}\end{array}}{\text{SumSlot(Objectives. Year Counter , @"Start Timestep", @"Finish Timestep")}} \right) * 100.000$$

Lee Ferry Deficit indicator function

Slot Type: Series Slot with Expression

Units: NONE

Arguments: (PowellOperation.10 Year Compact Volume and @"t")

Argument time-step: Annual

Expression:

```
IF (@t = = @"24: 00: 00 December 31, Current Year") THEN
    IF(PowellOperation. 10 Year Compact Volume [ ] < 75,000,000 "acre-feet")THEN
  1.0000
    ELSE
  0.0000
    END IF
END IF
```

Notes: The slot used in the corresponding objective function is in an annual time-step; therefore this function will return a one if the PowellOperation.10 Year Compact Volume is less than 75 maf or if it is greater than 75 maf it will return a zero on the December timestep. It will return an NaN on all timesteps other than December.