

**Co-production with Water Managers to Evaluate Multiobjective Evolutionary
Algorithm (MOEA)-assisted Optimization for Long Term Water Utility
Planning and Shape Future Research Agendas**

By

Rebecca M. Smith

B.S., University of Alabama in Huntsville, 2011

M.S., University of Colorado, 2014

A thesis submitted to the
Faculty of the Graduate School of the
University of Colorado in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
Department of Civil, Environmental and Architectural Engineering
2017

This thesis entitled:
Co-production with Water Managers to Evaluate Multiobjective Evolutionary Algorithm (MOEA)-
assisted Optimization for Long Term Water Utility Planning and Shape Future Research Agendas
written by Rebecca M. Smith
has been approved for the Department of Civil, Environmental and Architectural Engineering

Dr. Joseph Kasprzyk

Dr. Lisa Dilling

Dr. Leon Basdekas

Dr. Edith Zagona

Dr. Balaji Rajagopalan

Date _____

The final copy of this thesis has been examined by the signatories, and we
find that both the content and the form meet acceptable presentation standards
of scholarly work in the above mentioned discipline.

IRB protocol # 14-0687

Smith, Rebecca M (Ph.D., Civil Engineering)

Co-production with Water Managers to Evaluate Multiobjective Evolutionary Algorithm (MOEA)-

assisted Optimization for Long Term Water Utility Planning and Shape Future Research Agendas

Thesis directed by Dr. Joseph Kasprzyk

Many promising tools and methods developed in water resources systems analysis research have seen little uptake outside of academia. This may be due to a lack of effective communication about the research to water managers, or it may be because the tools are not ultimately useful or usable in practice. Current predominant research frameworks do not provide insight into these issues or facilitate the incorporation of industry needs into research agendas.

This dissertation introduces a structured research approach called the Participatory Framework for Assessment and Improvement of Tools (ParFAIT) that formally connects researchers and water managers in purposeful, iterative exercises to educate about promising tools, evaluate their usefulness and usability, and draw practitioner feedback into academic agendas. The process is founded on co-production concepts and involves two workshops which are designed to ultimately result in: a broadly relatable vehicle to demonstrate the tool (a testbed), practitioner feedback about the tool resulting from hands-on workshop experience, tool-specific as well as more general industry context, and definitive suggestions for increasing the relevance of future research.

ParFAIT is demonstrated by testing Multiobjective Evolutionary Algorithm (MOEA)-assisted optimization for long term water utility planning with a group of Front Range, Colorado, water managers. The first workshop informed the creation of the Eldorado Utility Planning Model, a complex but hypothetical testbed designed to be widely relatable to participants. MOEA-assisted optimization was performed on the testbed using workshop-informed formulations of planning decisions, objectives, constraints, and planning scenarios. The optimization results formed the basis of a second workshop at which managers worked directly with testbed output in structured activities and discussions

This ParFAIT study found that practitioners consider the information provided by MOEA-assisted optimization to be useful for several aspects of their long term planning processes, but that there are

important considerations for ensuring usability of the tool itself and its output. One important consideration is the interpretation of complex MOEA results. Based on this feedback, this work presents a novel application of Multivariate Regression Tree analysis to extract system insights from MOEA-assisted optimization results.

Dedication

For Chris.

Acknowledgements

First and foremost, I thank my committee members, who have each contributed greatly to my graduate school growth and success. As my primary adviser, Joseph Kasprzyk has been a stellar mentor, providing four years of dedicated, enthusiastic, and encouraging research guidance and support. Edith Zagona has been instrumental in *all* phases of my experience at the University of Colorado. Lisa Dilling brought new dimensions to my PhD research that will inform all of my work going forward. Leon Basdekas offered irreplaceable time, expertise, and creative contributions to this research. Balaji Rajagopalan has always been a positive and supportive professor and department chair. I am excited and grateful that I get to continue seeing and working with all of you during my career.

This work would not have been possible without the support of the Center for Advanced Decision Support for Water and Environmental Systems (CADSWES) and the Western Water Assessment (WWA). The kind staff at CADSWES contributed innumerable hours of modeling, programming, technical, and administrative support. The positive practitioner relationships developed by WWA and the expertise and workshop support offered by their scientists were integral to this study.

I thank the Front Range, Colorado, water utilities who contributed their time and expertise to this research: City of Aurora, City of Boulder, Colorado Springs Utilities, Denver Water, City of Fort Collins, and Northern Water. I especially thank Laurna Kaatz of Denver Water for her enthusiastic contributions to the design and implementation of this study, as well as her inclusiveness in many other water management venues that broadened my knowledge and network.

I gratefully acknowledge my two funding sources: NOAA's Sectoral Applications Research Program (SARP), grant # NA14OAR4310251; and a Doctoral Assistantship for Excellence Award from the University of Colorado's Civil, Environmental and Architectural Engineering Department.

Contents

Chapter 1: Introduction	1
1.1 Motivation.....	1
1.2 Background	2
1.2.1 Water Utility Planning	2
1.2.2 Multiobjective Evolutionary Algorithms (MOEAs) for Water Utility Planning	3
1.2.3 Push, Pull, and Co-production of Science.....	8
1.2.4 Participatory Modeling	9
1.3 Overview of Work	10
1.4 Organization of Dissertation	11
Chapter 2: Participatory Framework for Assessment and Improvement of Tools (ParFAIT): increasing the impact and relevance of water management decision support research	13
2.1 Introduction.....	13
2.2 Participatory Framework for Assessment and Improvement of Tools	18
2.3 Application of the Participatory Framework for Assessment and Improvement of Tools	22
2.3.1 Front Range, Colorado, Background	23
2.3.2 MOEA-assisted Optimization	24
2.4 Workshop 1 Results	30
2.4.1 Water Management Challenges	31
2.4.2 Decision Levers.....	35
2.4.3 Objectives	39

2.4.4	Constraints	41
2.4.5	Modeling	42
2.4.6	Scenarios	44
2.5	Synthesis of Results	45
2.6	Conclusion	49
Chapter 3: Multiobjective optimization of long term planning portfolios on the Front Range of Colorado		
	52
3.1	Introduction.....	52
3.2	Background.....	56
3.2.1	MOEA-assisted Optimization.....	56
3.2.2	Practitioner Input on Model and Problem Formulation.....	57
3.2.3	The Front Range of Colorado.....	58
3.3	Eldorado Utility Planning Model.....	60
3.3.1	Hydrologic Model Inputs.....	63
3.3.2	Eldorado Utility.....	63
3.3.3	Other model features.....	65
3.3.4	Planning for Eldorado’s Future Population while considering Potential Impacts of Climate Change	66
3.4	Optimization Configuration.....	68
3.4.1	Decision Levers.....	68
3.4.2	Performance Objectives and Constraint.....	71
3.4.3	Streamflow Ensemble	78

3.4.4	Computational Experiment	79
3.5	Results.....	80
3.5.1	Exploration of Full Tradeoff Set.....	80
3.5.2	Further Exploration of Results using Comparisons of Individual Portfolios.....	83
3.6	Conclusion	92
Chapter 4: A multiobjective tradeoff charrette to engage with Colorado water managers about long term		
	planning	95
4.1	Introduction.....	95
4.2	Background.....	98
4.2.1	MOEA-assisted optimization for long term water utility planning.....	98
4.2.2	Participatory Framework for Assessment and Improvement of Tools (ParFAIT).....	100
4.2.3	Background summary	108
4.3	Methods.....	108
4.3.1	Interactive tradeoff visualization workbooks.....	108
4.3.2	MOEA research charrette: June, 2016	112
4.4	Results.....	120
4.4.1	Managers' usage of tradeoffs.....	120
4.4.2	Opportunities and challenges to using MOEA-assisted optimization.....	129
4.4.3	Adoption of new tools.....	132
4.4.4	Real-world planning and decision making context.....	133
4.5	Conclusions.....	134

Chapter 5: Combining Multivariate Regression Trees and multiobjective tradeoff sets to reveal fundamental insights about water resources systems.....	136
5.1 Introduction.....	136
5.2 Methods.....	140
5.2.1 Regression trees	140
5.2.2 Multiobjective Evolutionary Algorithm (MOEA)-assisted optimization	143
5.3 Case study	144
5.3.1 Front Range, Colorado.....	144
5.3.2 Eldorado Utility Planning Model.....	145
5.3.3 Problem formulation	148
5.3.4 Scenarios	152
5.3.5 Computational experiment.....	153
5.3.6 Eldorado optimization tradeoffs.....	154
5.4 Results.....	157
5.4.1 MRT for 1°C-perturbed tradeoff set	158
5.4.2 MRT for 4°C-perturbed tradeoff set	164
5.4.3 Comparing MRTs	166
5.5 Conclusion	168
Chapter 6: Concluding Remarks	170
6.1 Summary.....	170
6.2 Conclusions.....	171
6.3 Contributions.....	172

6.4 Future Work..... 173

6.4.1 Workshops 173

6.4.2 Technical Studies 174

Bibliography 176

Tables

Table 2-1. Full list of challenges described by water managers at Workshop 1.....	33
Table 2-2. Supply levers proposed by researchers and water managers at Workshop 1.	37
Table 2-3. Demand levers proposed by researchers and water managers at workshop 1.	39
Table 2-4. Objectives proposed by researchers and water managers at workshop 1.	41
Table 2-5. Constraints proposed by water managers at Workshop 1.....	42
Table 2-6. Important hypothetical water supply network features as suggested by water managers at Workshop 1.....	44
Table 3-1. List of geographic locations, data sources, and historic magnitudes of the streamflow inputs used in the model.	63
Table 3-2. Information about Eldorado’s historic consumption, projected demands, and system yield. ...	67
Table 3-3. Description of Eldorado’s three restriction levels and their estimated demand reductions.....	67
Table 3-4. Summary of decision levers available to Eldorado..	71
Table 3-5. Storage-based triggers for restriction levels.	73
Table 3-6. Summary of performance objectives that Eldorado seeks to optimize.....	78
Table 3-7. Decision lever and objective values for Selections 1 and 2.....	86
Table 3-8. Decision lever and objective values for Selections 3 and 4.....	91
Table 4-1. Summary of performance objectives.	105
Table 4-2. List of decision levers.....	107
Table 4-3. Summary of charrette activities.	119
Table 4-4. Results of post-charrette survey.	130
Table 5-1. Detail for water users in Eldorado Utility Planning Model.....	147
Table 5-2. Summary of Eldorado Utility decision levers.	150
Table 5-3. Summary of Eldorado Utility performance objectives.	152

Figures

Figure 1-1. Example of multiobjective tradeoffs using a simplified grocery list planning problem.	5
Figure 2-1. Participatory Framework for Assessment and Improvement of Tools (ParFAIT).....	18
Figure 2-2. MOEA optimization loop and how its components were informed by water managers.....	26
Figure 2-3. Glyph plot of the results from a multi-reservoir MOEA optimization study.	29
Figure 2-4. Parallel plot of the results from Figure 2-3 adapted from Smith et al. (2015)..	30
Figure 3-1. Diagram of the Eldorado Utility Planning Model’s regional water supply network.....	62
Figure 3-2. Plot of the average regional monthly flows for the 1950 – 2005 historic record and the 4°C- perturbed regional flows.	79
Figure 3-3. Parallel plots of the full set of nondominated portfolios.	81
Figure 3-4 Parallel plots of two highlighted solutions.	85
Figure 3-5. Comparison of the non-Wholesaler storage volumes over time for Selections 1 and 2.....	87
Figure 3-6. Parallel plots of two highlighted solutions.	90
Figure 4-1. A screenshot of a Tableau worksheet that corresponds closely with what participants used in the charrette.....	110
Figure 4-2. Diagram of the Eldorado Utility Planning Model given to charrette participants.....	115
Figure 4-3. Screenshot of manager B3’s portfolio selections for Activity 2, Exercise 1.....	122
Figure 4-4. Screenshot of manager B4’s portfolio selections for Activity 2, Exercise 1.....	123
Figure 4-5. Screenshot of manager B2’s portfolio selections for Activity 2, Exercise 2.....	125
Figure 5-1. Schematic of the Eldorado Utility Planning Model.	146
Figure 5-2. Average annual regional hydrographs for the historic record and two climate change scenarios.....	153
Figure 5-3. Parallel plots of the tradeoff set resulting from optimizing the Eldorado Utility Planning Model under 1°C-warmer hydrology.	155
Figure 5-4. Multivariate regression tree generated from the Eldorado Utility 1°C optimization.	159
Figure 5-5. Comparison of two leaves from the 1°C MRT.....	161

Figure 5-6. Parallel plots from the 1°C Eldorado Utility tradeoff set	163
Figure 5-7. Multivariate regression tree generated from the Eldorado Utility 4°C optimization tradeoffs.	165
Figure 5-8. Comparison of Leaf 2 from the 1°C MRT and Leaf 1 from the 4°C MRT.	167
Figure 5-9. Comparison of Leaf 5 from the 1°C MRT and Leaf 3 from the 4°C MRT.	167

Chapter 1

Introduction

1.1 Motivation

Water resources planning in many parts of the world has become increasingly complicated as populations grow and new water supply options become scarcer and more difficult to execute (Gleick, 2002). Uncertainties stemming from climate change and predictions of future demands and regulations exacerbate the impending imbalances (Milly et al., 2008; Roberson and Aubuchon, 2013; Smith et al., 2017). Municipal water providers are on the front lines of responding to these challenges; they must work within regulatory, funding, hydrologic, technological, and societal constraints to provide sufficient quantity and quality of water to meet customers' demands.

Recently there has been increasing awareness among practitioners and government agencies of the need for advanced decision support tools to meet the compounding challenges described above (Jacobs, 2002; Means et al., 2010; National Research Council, 2009). While demand for new ways of approaching planning has become more urgent, the concept of water management innovation is not new; Water Resources Systems Analysis (WRSAs) researchers have been developing tools and methods intended to improve water resources decision making since the 1950s (Maass et al., 1962), with some examples of successful incorporation into practice. However, the combination of increasingly technical tools and limited interaction between researchers and practitioners has resulted in a lack of evidence that new tools are useful in practice or implemented successfully (Asefa, 2015; Brown et al., 2015; Moser, 2009).

WRSAs researchers often have engineering education and training. In society, engineers are relied upon to use science to design systems that meet specified goals while considering practical limitations. Because WRSAs researchers integrate engineering principles with the pursuit of knowledge, we posit that their charge is to advance water management practice and improve planning outcomes. To do so, they must make intentional, formal effort to understand how WRSAs research can respond to the needs of water

utilities and effectively educate practitioners about new tools (Cosgrove and Loucks, 2015). Existing research paradigms either do not involve practitioners at all, consult them for application-specific information, or transform researchers into analysts of real-world projects. To increase the likelihood that innovations will diffuse into practice and hone future WRSA research, a co-production research model, in which both researchers and practitioners are integral to creating knowledge and setting research agendas, is needed (Lemos and Morehouse, 2005; Smits, 2002).

This dissertation demonstrates a co-production approach that brings together academics and practitioners to generate tool-specific knowledge and inform future WRSA research. The study centers on the prospects for Multiobjective Evolutionary Algorithm (MOEA)-assisted optimization to enhance water utility planning, and improves understanding of the real-world context that shapes the potential for existing and future decision support tools. We focus on MOEAs because of their mature body of research and inherent relevance to modern water resources planning. Support for these assertions is provided in the following section.

1.2 Background

1.2.1 Water Utility Planning

Municipal water providers are subject to a vast range of geographical, climatological, and cultural circumstances, but all must strategically manage water supplies to meet current and future demands. Long term planning to meet growing demands entails supplementing an existing system with new sources and management policies. A long term plan is a defined set of actions and policies that emerges from several possible combinations of options.

Water supply and conveyance networks are often extensive and complex. Utilities invest large amounts of time and expertise to develop simulation models that capture the components and dynamics of these systems, and rely heavily on them to answer “what if” questions (Labadie, 2004). One line of questioning these models support is how new water sources, infrastructure, and policies will perform

under future supply and demand scenarios. Using models to try different combinations of actions, or portfolios, is the technical foundation of long term planning.

In recent decades, growing momentum for environmental stewardship as well as transparency and public participation have changed societies' expectations of water utilities' planning processes and outcomes (Elkington, 2004; Kenway et al., 2007). In the past, utilities' plans were primarily driven by meeting target demand reliability at minimum financial cost; now they must directly consider social and environmental costs as well, which are often in tension with minimizing financial investment. For example, a high-yield reservoir at a structurally and geographically convenient site that damages a scenic area and/or displaces residents may be subject to wide-ranging opposition despite its potential to ensure future water security (Tolchin, 1990; Woods, 1994).

The inclusion of objectives beyond yield and cost increases the complexity of developing and evaluating planning portfolios. Furthermore, utilities must become more creative in light of hydrologic challenges and limited opportunities for conventional infrastructure solutions. To navigate the tradeoffs between financial, social, and environmental performance, a greater variety of combinations of actions needs to be simulated and evaluated based on multiple objectives. Utilities have traditionally designed a relatively small number of portfolios by hand using expert system knowledge and subjective variations of portfolio decisions to accommodate social and environmental concerns. This approach limits the information on which decision makers and the public can express preferences, and the few modeled portfolios may not capture the full performance potential of the system.

1.2.2 Multiobjective Evolutionary Algorithms (MOEAs) for Water Utility Planning

As described above, water utility planning is characterized by multiple conflicting performance objectives, potentially many thousands of possible combinations of decisions that make up portfolios, and the need for creative approaches to meet current and future supply, demand, and regulatory challenges. For these reasons, WRSA researchers have studied and advanced the science of applying Multiobjective

Evolutionary Algorithms (MOEAs) to a variety of water resources planning problems (Maier et al., 2014).

MOEAs are optimization algorithms that efficiently generate portfolios of decisions, feed the portfolios to embedded simulation models, and evaluate them based on translating model output into multiple user-defined objectives. Several aspects of MOEA-assisted optimization make it an attractive method for water resources planning. The first is that any simulation model can be embedded into the algorithm search loop, so there is no need to simplify a system model in order to use the optimization method. Another benefit is that the algorithm evaluates performance on multiple objectives separately, so each objective can maintain its native units, there is no need for a priori weighting schemes, and performance in each objective is explicit rather than obscured within a single objective function. Finally, MOEA search uses the concept of evolution to create successive generations of solutions based on earlier high-performing portfolios, meaning that the search is intelligent and can efficiently find feasible, high quality portfolios.

Because there is no single optimal solution to a problem with multiple conflicting objectives, the result of performing MOEA-assisted optimization is a set of non-dominated (approximately Pareto-optimal) portfolios (Pareto, 1896), where every portfolio is better than another in at least one objective but not all objectives. The set of portfolios quantitatively describes the tradeoffs between objectives by showing exactly how much performance a user must sacrifice in one objective to achieve improvements in another. The results also reveal approximately how well a system *can* perform, and help users understand what impacts their preferences have across multiple types of system performance measures.

To demonstrate the concept of tradeoffs and how they may be visualized, we present a stylized grocery planning problem. You are going shopping and can create a “portfolio” of food items consisting of varying amounts of apples, beef, bread, carrots, celery, chicken, chips, eggs, hummus, ice cream, and peanut butter. Each of these items has a monetary cost, and you have also given each of them a score for nutrition and pleasure where 1 = little nutrition/pleasure and 10 = high nutrition/pleasure. When making

your list, you would ideally minimize cost while maximizing nutrition and pleasure, but (at least for the sake of this example), these objectives conflict. If you plotted a set of six possible grocery lists, they may look like Figure 1-1.

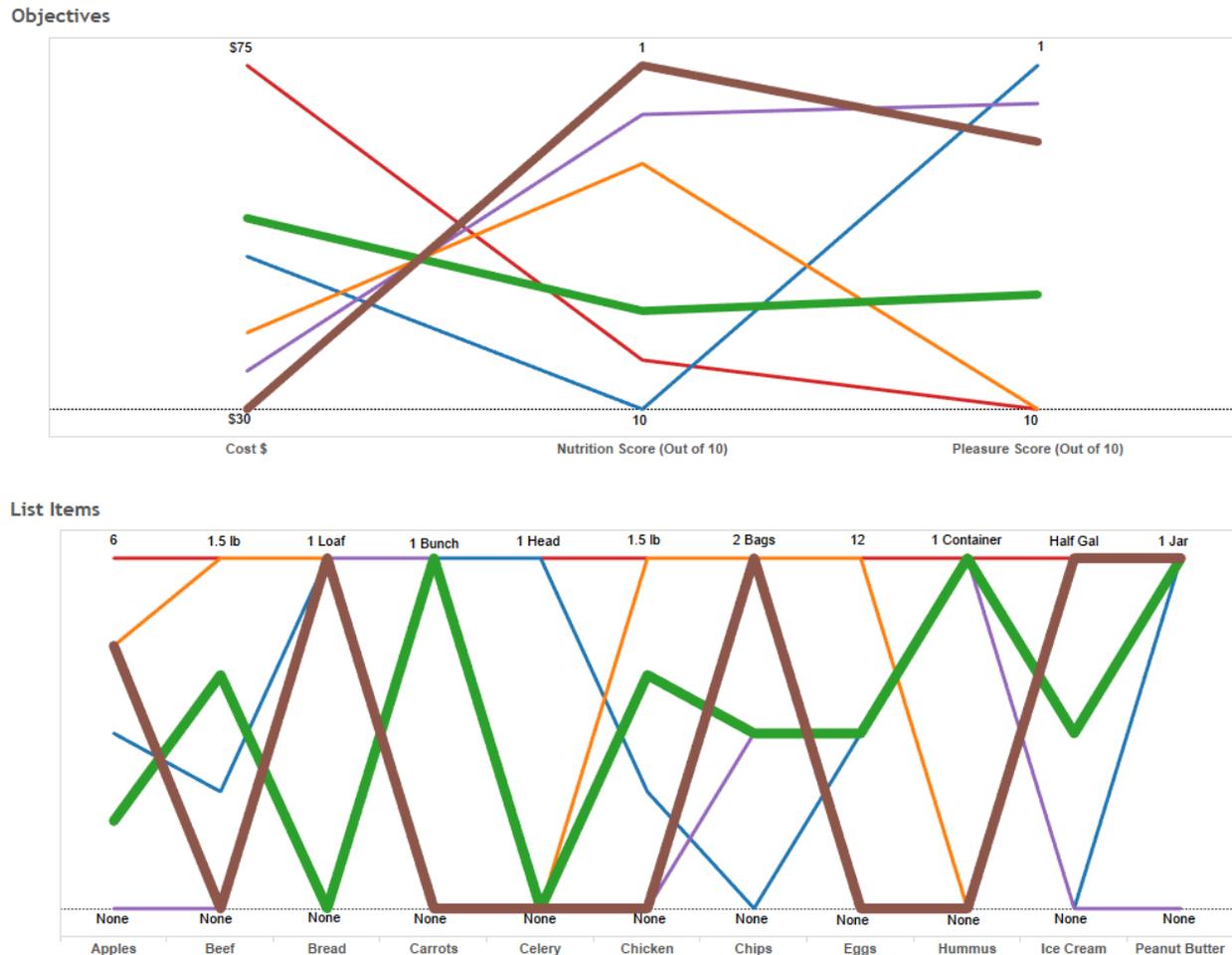


Figure 1-1. Example of multiobjective tradeoffs using a simplified grocery list planning problem.

The top plot shows performance in the three objectives, where each is represented by a vertical axis. Each individual grocery list is represented by a colored line that connects across the axes, where the height at which the line crosses an axis denotes its score in that objective. The lower a list line crosses an axis, the better its performance, so a straight line across the bottom would be the ideal list but it doesn't exist because the objectives conflict. The bottom plot shows the items incorporated into each list, where each item has a vertical axis and the list is depicted by a colored line that matches the color of the

corresponding list in the top plot. The lower the list line crosses an item axis, the less of that item is included in the list.

Examining the top plot, you can see that lists which have very low costs tend to have poor nutrition, both because less nutritious foods are often less expensive but also because lists with fewer items have lower cost and less nutrition. These considerations present a tradeoff, which is visually represented by the crossing lines between the first and second axes. The brown list has the lowest cost, which from the bottom plot you can see includes only five items, two of which are chips and ice cream. If you wanted to compromise between all three objectives, you might choose the green list, which has nine items and includes moderate amounts of non-nutritious (but pleasurable) chips and ice cream.

This highly simplified grocery example shows how combinations of decisions impact performance in objectives that you care about and that visualizing the sets of decisions and their performance can quickly convey system dynamics and provide a canvas on which to apply preferences. Water supply systems are of course infinitely more complex than grocery lists in terms of dynamics, number of possible portfolios of decisions, and performance criteria and preferences; this is why MOEAs test thousands of portfolios to meaningfully quantify tradeoffs between user-defined objectives and explore how well the system can perform in each of them.

In the context of a broader water utility planning process, both the process of incorporating an MOEA and the results it produces should be considered potential enhancements, not replacements for existing analyses and human judgement. Because MOEAs offer the benefit of optimizing across many objectives, utilities may expand their thinking about what types of system performance they care about and how to quantify those objectives. Once the optimization is finished, the first use of the tradeoffs may be to determine whether the dynamics they reveal confirm previous system understanding (e.g. the importance of a large new reservoir) or reveal new information (e.g. a combination of new water sources and demand conservation are more effective than the reservoir). Any surprises may be investigated using additional simulation analyses; there is no assumption of blind trust in the results. There is also no

requirement that a final plan be one that was produced by the optimization; in depth analysis and engagement with decision makers and the public should be integrated with MOEA results. The ultimate power of MOEA tradeoffs is the ability to efficiently find a diverse set of planning portfolios that show how well a system can perform, see relationships between different objectives, confirm or improve understanding of the system, and increase confidence in a final plan.

There are many examples of research studies applying MOEAs to water resources problems, but here we present a few notable contributions. After decades of extensive development in primarily groundwater management applications (Nicklow et al., 2010), Kasprzyk et al (2009) applied an MOEA to a problem which modeled a single reservoir and the use of a water market in the Lower Rio Grande Valley to balance six objectives including cost, reliability, and surplus water. Mortazavi et al (2012a) used an MOEA to optimize infrastructure and operations decisions in consideration of three objectives for a simplified model of Sydney's multireservoir network. Zeff et al (2014) expanded the use of MOEAs to a regional multi-utility, multireservoir model to demonstrate that cooperation resulted in financial benefits and improved reliability for all utilities. Finally, Smith et al (2016) demonstrated MOEA-assisted optimization using the full-complexity multireservoir legacy model of a Texas utility. This last application used the sophisticated RiverWare modeling software and an off-the-shelf desktop computer, unlike most previous studies which used less complex modeling software and supercomputing.

Many factors suggest that this method can be successfully used by practitioners: industry recognition of need for advanced decision support tools, utilities' widespread reliance on simulation modeling, access to computing resources either through powerful desktop machines or the cloud (Mathew and Varia, 2014), and successful research development of MOEAs to be adaptive to many problems (Hadka and Reed, 2013). Despite the opportunity described throughout this introduction, MOEAs for water resources planning have seen little use outside of academia. With the notable exceptions of Colorado Springs Utilities' drought vulnerability study (Basdekas, 2014) and integrated water resources

plan (CSU, 2017a), there have not been any other real-world water management applications of MOEA-assisted optimization.

1.2.3 Push, Pull, and Co-production of Science

Based on descriptions from Dilling and Lemos (2011), research performed in the WRSA field generally follows either the “push” or “pull” model of science production. In the push model, tools and methods are developed without input from water practitioners about what is needed or desired, assuming the fruits of research efforts will find their way into practice (or not). Even when practitioners are incorporated into research, it is often in a consultative role to assist researchers in their ongoing agendas (Matrosov et al., 2015; Smith et al., 2016). In the pull model, agencies commission researchers to help them solve specific problems, resulting in researchers-as-analysts case studies, e.g. Lempert and Groves (2010), which may not be seen as providing fundamental insight that can be applied to other water management contexts (Brown et al., 2015).

Research on the uptake of science by practitioners finds that uptake potential is partially determined by the usefulness and usability of the information. Useful science “improves... decision-making by expanding alternatives, clarifying choices and enabling decision makers to achieve desired outcomes” (McNie, 2007). Usable science is that which “fits decision-making processes and decision environments in practice” (Lemos and Rood, 2010). Achieving and ascertaining both usefulness and usability of science to potential users is most likely to occur through researchers’ intentional, iterative engagement with target audiences (Dilling and Lemos, 2011). This process is the co-production model of research, where the research agenda is shaped by both producers of knowledge and users (Lemos and Morehouse, 2005).

Co-production is often carried out with the help of boundary organizations. Boundary organizations are entities that actively facilitate coordination between practitioners and researchers (Cash et al., 2003). Notable examples are the Center for Decision Support for Water and Environmental Systems (CADSWES) and the Western Water Assessment (WWA), which is a NOAA Regional Integrated

Sciences and Assessment (RISA) team, which are both housed at the University of Colorado and contributed to this work. Other examples of boundary organizations are the Water Utility Climate Alliance (WUCA), which is a group of water utilities from around the country who engage with a variety of scientists, and the eight regional USGS Climate Science Centers. However, the relationships supported by these organizations are the exception, not the rule. More deliberate effort to supplement WRSA's "push" research activities with co-production could increase the likelihood of practitioners using tools like MOEAs and also help direct the tools' future research developments toward an agenda responsive to practitioner feedback.

1.2.4 Participatory Modeling

The co-production research paradigm guided the development of this study. A team of water managers, engineering researchers, social scientists, and climate scientists developed questions, goals, and an agenda to create knowledge that would be beneficial to both practitioners and academics. To carry out the research, we employed techniques used in participatory modeling. Participatory modeling brings together researchers and stakeholders in structured settings for the specific purpose of co-developing a model to improve the framing or actions taken by society to solve a particular (usually) environmental problem (Voinov and Bousquet, 2010).

Our study differs from traditional participatory modeling in that the purpose is to educate practitioners about an existing tool, generate feedback about the tool, and fold that feedback into future research. However, because our sequence of steps does involve formal sessions where practitioners provide input to a model and then evaluate output from that model, we are firmly situated in this literature and simply expand its scope of application.

Please note the distinction between co-production and participatory modeling. Our use of a co-production mode of research (in contrast with science "push" or "pull") means that we incorporated

practitioner input directly into our research agenda via two water manager principal investigators¹. Our use of participatory modeling refers to the fact that we used practitioner input to build and evaluate a simulation model.

1.3 Overview of Work

The overall goal of this dissertation is to demonstrate how co-production can improve understanding of an individual water resources decision support tool as well as influence the broader WRSA research agenda for the benefit of both researchers and practitioners. The research activities undertaken to achieve this goal were driven by four objectives.

The first objective was to develop a research framework that combined the expertise of practitioners and academics to evaluate the potential for MOEA-assisted optimization to contribute to long term utility planning, and generate feedback that could be incorporated into future research. This objective was met through our design of the Participatory Framework for Assessment and Improvement of Tools (ParFAIT). ParFAIT is a generalizable sequence of steps that includes a workshop through which practitioners' input influences the development of a representative application of the tool (a testbed) and a second workshop at which practitioners interact with testbed output to gain experience with and provide feedback about the tool.

The second objective was to learn about aspects of real-world water management that researchers should account for when proposing and performing research. This objective was addressed through both ParFAIT workshops: in the first, we learned about water utilities' challenges, management objectives, and the actions they can take to ready their systems to meet growing demands with uncertain supplies and future conditions (or states of the world); in the second workshop, we learned about the long term planning process itself, including the phases, players, and roles of different types of information.

¹ Laurina Kaatz of Denver Water and Leon Basdekas of Black & Veatch, formerly of Colorado Springs Utilities

The third objective – to understand practitioners’ perceptions of MOEAs and their potential to impact long term utility planning – was built into the ParFAIT process as the main purpose of the second workshop. Specific activities and feedback structures at the workshop enabled us to develop knowledge about how the practitioners interacted with MOEA tradeoffs themselves, and how that tradeoff information could be useful to their agencies.

The fourth objective was to determine and undertake additional research to address practitioner feedback from the second ParFAIT workshop. Practitioners’ responses to MOEA tradeoffs shaped our study of how the information contained within tradeoff sets can be mined to enhance the usefulness of MOEAs and help utilities understand the impacts that specific combinations of decisions could have on their planning objectives.

1.4 Organization of Dissertation

This dissertation is structured as follows:

Chapter 2 is the journal article “Participatory Framework for Assessment and Improvement of Tools (ParFAIT): increasing the impact and relevance of water management decision support research,” published in *Environmental Modelling and Software* with co-authors Joseph Kasprzyk and Lisa Dilling (Smith et al., 2017). It describes ParFAIT, its theoretical foundation, and the format and results from the first ParFAIT workshop that informed the model, problem formulation, and planning scenarios of our MOEA testbed.

Chapter 3 is the journal article “Multiobjective optimization of long term planning portfolios on the Front Range of Colorado,” which is in review at the *Journal of Water Resources Planning and Management* and co-authored by Joseph Kasprzyk and Leon Basdekas. It describes the MOEA testbed informed by practitioner input from workshop 1, including the simulation model, MOEA problem formulation, optimization scenario, and some tradeoff results. We show that a generic model built around

the hypothetical Eldorado Utility and its regional context can produce results that credibly represent tradeoffs faced by real Front Range, Colorado, utilities.

Chapter 4 is the journal article “A multiobjective tradeoff charrette to engage with Colorado water managers about long term planning,” which is in preparation for submission to *Environmental Modelling and Software* and is co-authored by Joseph Kasprzyk and Lisa Dilling. Here we connect our second ParFAIT workshop to the concept of a charrette. In the context of research, “charrette” is a term used by construction management researchers to denote a focus group during which practitioners provide direct feedback and input about existing and proposed research tools and agendas. The chapter describes the methods and activities we incorporated into our charrette to generate both structured and un-structured practitioner feedback and discusses findings relevant to MOEAs specifically as well as the needs of utilities more broadly.

Chapter 5 is the journal article “Combining Multivariate Regression Trees and multiobjective tradeoff sets to reveal fundamental insights about water resources systems,” which is co-authored by Joseph Kasprzyk and Balaji Rajagopalan and is in preparation for submission to *Water Resources Research*. This chapter applies a multivariate regression tree data mining technique to tradeoffs produced by the Eldorado Utility model to learn how specific decisions or combinations of decisions lead to different performance outcomes. The ability to access this information directly addresses the interest expressed by practitioners during the charrette to understand the relationships between decisions and objectives.

Chapter 6 presents the conclusions and contributions of this research and proposes avenues of future work.

Chapter 2

Participatory Framework for Assessment and Improvement of Tools (ParFAIT): increasing the impact and relevance of water management decision support research

This chapter proposes the Participatory Framework for Assessment and Improvement of Tools (ParFAIT) as a way to address low uptake of Water Resources Systems Optimization (WRSO) tools. ParFAIT is a transdisciplinary process conducted in five stages, two of which are participatory modeling (PM) exercises. Herein we describe the framework, introduce our candidate tool- Multiobjective Evolutionary Algorithm (MOEA)-assisted optimization, and present the results of our first PM workshop. MOEA-assisted optimization has been put forth as a planning and decision making aid for utilities facing a large number of decisions and highly uncertain futures. The PM workshop, designed to solicit input on a tool testbed, was held in February 2015 with representatives from six Front Range, Colorado, water utilities. Our results include an expanded characterization of the decision making landscape, feedback on water utility decisions and performance goals commonly employed in WRSO studies, and new questions that warrant future investigation by researchers.

2.1 Introduction

Since its inception during the Harvard Water Project (Maass et al., 1962), water resources systems analysis (WRS) research has sought to bring about improved processes and outcomes in the water management industry. Many WRS “tools”- any software or method intended to facilitate resource management activities- have achieved prominence in industry, e.g. simulation modeling (Jakeman and Letcher, 2003; Loucks et al., 1981; Loucks and van Beek, 2005) and stochastic hydrology (Linsley Jr et al., 1975; Rajagopalan et al., 2006). However, the field still faces challenges when attempting to implement tools in real-world contexts, particularly in the area of systems optimization (hereafter referred to as WRSO- Water Resources Systems Optimization) (Brown et al., 2015; Junier and Mostert, 2014; Kok et al., 2008; Maier et al., 2014; McIntosh et al., 2005, 2011; Rogers and Fiering, 1986). WRSO involves using one or more computerized tools to automatically generate candidate solutions

(combinations of actions and/or policies) to complex water management problems, especially in the context of long term planning and decision making.

Three reasons for this disjunction between WRSO research and water management practice are 1) practitioners' lack of exposure to promising research; 2) barriers to adoption within water management agencies; and 3) academia's failure to produce relevant tools. Lack of exposure is primarily due to the differences between research and water agency agendas (Borowski and Hare, 2006; Jacobs, 2002; McNie, 2007). Researchers are incentivized to publish in scientific journals that are often behind paywalls, and they write in language that may be unfamiliar to practitioners (Cvitanovic et al., 2015). Adding to this, water managers have many duties and may not have time or expertise to engage with research (Brown and Farrelly, 2009).

Even if water managers were able to regularly review WRSO literature, there are many complicated factors that impact adoption of research into water management (Dilling and Lemos, 2011). One is that water utilities are risk-averse, and unlikely to experiment (Farrelly and Brown, 2011). Another is that incorporating a new tool or method could require the backing of high level managers, necessitating a "champion" within the utility to advocate for the change and sustain its development (Farrelly and Brown, 2011; Taylor, 2009). Though efforts by researchers cannot overcome all barriers to adoption, addressing the lack of exposure would substantially reduce one of them. If managers do not have backgrounds in recent advanced techniques and are not exposed to promising research, one of the major predictors for adoption (a champion within the utility) is unlikely to arise. The result of this is that tools produced by WRSO research have little chance of being adopted by practitioners (Díez and McIntosh, 2009).

Funtowicz and Ravetz (1993) contend that in an age of great uncertainty and high stakes, improving the quality of scientific inputs to decisions requires an expansion of traditional boundaries, including meaningfully incorporating the experiences and values of previously un- or under-represented

stakeholder communities. However, because of disincentives in academia for working with practitioners and across disciplinary lines, and the lack of accessibility of academic journals for many practitioners, there is often a disconnect between researchers and the target audience for their tools. According to the National Research Council (2009), “decision support strategies should be built on an understanding of decision makers’ values and priorities”. This calls for direct, two-way communication between researchers and practitioners, without which WRSO researchers may lack crucial understanding of how information and technology are acquired and used by water management agencies (Díez and McIntosh, 2009). While consultants could provide one route for research to be informed by and inform decision making, because they are focused on near-term applications demanded by clients, they may not often have the capacity to provide a conduit or pathway between new tools developed by academic research and practitioners themselves.

There has been a period of rapid technical development in WRSO research, but attention to research relevance and knowledge transmission warrant equal attention (Cosgrove and Loucks, 2015; Lawrence and Després, 2004; Sahota and Jeffrey, 2005; Smajgl and Ward, 2013; Thompson Klein, 2004; Voinov et al., 2014; Wen et al., 2015). In order to produce usable tools and methods, WRSO must avoid oversimplification of complex decision making environments and recognize political and social constraints (Allan, 1999; Asefa, 2015). Similarly to WRSO research, climate science has historically not seen widespread application in practice. Analysis of that field’s challenges has shown that usability is the product of iterative interactions between producers and users, achieved through intentional engagement between researchers and practitioners (Dilling and Lemos, 2011), and there are groups that have been engaging in such practices for many years (e.g. NOAA’s Regional Integrated Sciences and Assessments program). Other fields can benefit from the lessons learned by climate science; based on the dearth of evidence that WRSO research is influencing water management planning and decision making (Brown et al., 2015; Rogers and Fiering, 1986), it is likely that WRSO research may be lacking in this engagement

and intentionality. Indeed, studies have shown that innovations in general are most successful when they result from close negotiations between developers and users (Díez and McIntosh, 2009; Smits, 2002).

Transdisciplinarity, especially as applied in participatory research, can be used to combat two of the three challenges for disseminating WRSO efforts- lack of exposure and low relevance (Lawrence and Després, 2004; Ruiz et al., 2015). Transdisciplinary research is collaboratively designed and executed by researchers and stakeholders to solve complex problems, often at the human-environment interface, incorporating methodological iteration and evolution, and with an emphasis on extended learning (Hadorn, 2008; Lawrence and Després, 2004; Thompson Klein, 2004; Wickson et al., 2006). One form of transdisciplinarity is participatory modeling (PM). The foundational precept of PM is stakeholder involvement in modeling as the major tool for decision making (Voinov and Bousquet, 2010). We posit that the definition of stakeholders for analysis of WRSO tools includes water management practitioners who are one of the target user groups. Researchers may use PM for anything from developing a decision support model, (e.g. Argent and Grayson, 2003), to creating a platform to facilitate mutual understanding between disparate stakeholders, e.g. (Eeten et al., 2002). Some examples of recent applications of PM are: participatory development of a model to solve persistent pollution problems in St. Albans Bay (Gaddis et al., 2010); participatory development of an integrated socio-ecological model to enable stakeholders in Reichraming, Austria, to understand the interactions between local policies, human behavior, and the environment (Gaube et al., 2009); and a workshop to assess water managers' perceptions of the output from a previously-developed water quality model in northeast Mexico (Robles-Morua et al., 2014). In light of the fact that government-funded research programs increasingly emphasize practicality and applicability (National Research Council, 2009), participatory research efforts, especially those aimed at evaluating existing tools, are likely to become more important for WRSO research (Voinov et al., 2016). Thus, explicitly bringing PM concepts to bear in a structured way to advance the WRSO field is an important undertaking.

The purpose of this chapter is to present a novel participatory framework and the first stage of our results from its application. The Participatory Framework for Assessment and Improvement of Tools (ParFAIT) is designed to obtain feedback on emerging WRSO tools while directly addressing the exposure and relevance challenges that inhibit WRSO research impacts. The core of ParFAIT is the use of two PM workshops. The first combines the expertise of researchers and practitioners to design a generic demonstration case study, or testbed, that captures broadly relatable management context. The second PM workshop assesses whether the *nature* of the information produced by the tool is seen as valuable to managers as they engage with the testbed. As described above, applications of PM have traditionally centered on pre-defined decisions or resource management projects. However, if a series of PM exercises is applied as laid out in ParFAIT, the purpose can be broadened to hone future applications of a tool, enhance its impact, and increase the relevance of WRSO research.

We developed ParFAIT shown in Figure 1 through the contributions of a transdisciplinary team made up of water managers, engineering researchers, climate scientists, and social scientists. In our application of the framework, we explore the use Multiobjective Evolutionary Algorithms (MOEAs) for long term water utility planning, and solicit participation from water managers through two workshops. The purpose of the first workshop was to co-design an experimental MOEA testbed, which will be used to generate representative MOEA output (further explained in Section 3). A second workshop will assess how the type of information provided by the MOEA testbed results might contribute to water managers' decision processes in the context of long term utility planning.

In Section 2 we provide a detailed description of the elements of our framework. In Section 3 we introduce the MOEA research tool we will subject to our assessment framework, as well as the water management agencies participating in our study. Sections 4 and 5 will present the results of Workshop 1 and synthesize the insights they contribute to WRSO research. Section 6 will provide concluding remarks.

2.2 Participatory Framework for Assessment and Improvement of Tools

Several studies that reflect on forms and functions of participatory research agree that emphasis on a process, template, or framework is an important early consideration in any PM undertaking; it improves the chances that roles of actors and purpose(s) of different phases of the project are clearly defined (Seidl, 2015). This conclusion underscores the value of defining and implementing the sequence of steps in the Participatory Framework for Assessment and Improvement of Tools (ParFAIT). Going forward, we will refer to specific steps as depicted in the diagram in Figure 2-1.

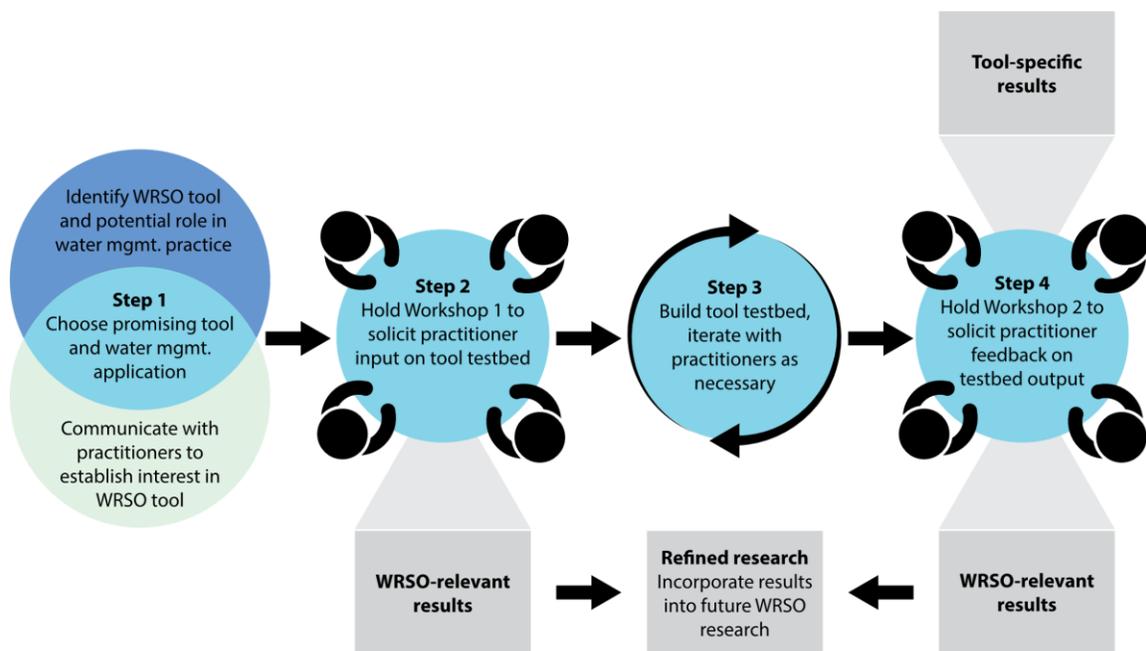


Figure 2-1. Participatory Framework for Assessment and Improvement of Tools (ParFAIT).

Step 1 of ParFAIT is to identify a promising tool and a proposed use for the tool. An appropriate combination of tool and purpose should be informed by two factors. The first is the maturity of the tool. Has it been applied to multiple problems? Has it been systematically evaluated? The second factor is whether or not the tool has a ripe opportunity to be useful for water management practice. Tool maturity can be confirmed through knowledge of WRSO literature, but opportunity for practical application should be based on practitioners' experiences and input.

Purposeful interaction with practitioners about their needs and capabilities is the ideal way to design a ParFAIT study, and is a fundamental aspect of transdisciplinarity (Hadorn, 2008; Lang et al., 2012). Working with managers to assess the state of practice and identify their goals or interests (i.e. formulate the research goal) results in *substantive* contributions from water managers- the practitioners' involvement is necessary to ensure the quality of both the project and the knowledge it produces. Their continued involvement throughout the project also serves *normative* goals- to demonstrate the value of soliciting feedback about promising research tools as well as real-world context from intended users (Fiorino, 1990).

There are several avenues by which researchers can identify and recruit practitioners for the framework, such as exploiting existing relationships or surveying local managers who might be interested in contributing to a research project. The particular approach to identifying and recruiting practitioners is beyond the scope of this paper. Some useful resources for engaging practitioners in research are research foundations and professional societies such as the Regional Integrated Sciences and Assessments (RISAs) (<http://cpo.noaa.gov/ClimateDivisions/ClimateandSocietalInteractions/RISAProgram.aspx>), Climate Science Centers (<https://nccwsc.usgs.gov>), the Water Utility Climate Alliance (<https://www.wucaonline.org>), or the Water Research Foundation (<http://www.waterrf.org>).

The choice of tool and purpose will determine the elements of a “testbed”, or generic, representative platform that serves as a vehicle for communicating a tool’s capabilities to practitioners. These testbed elements are general categories of components, e.g. hydrologic data, models, and analytical tools. The rest of the framework is structured around the particular components needed to demonstrate the tool for the purpose.

During the framework’s first workshop, Step 2, managers play a consultative role (Pretty, 1995); in-depth, substantive input from water managers is elicited to inform the foundation of the testbed and define the “problem” the tool will analyze (Reed and Kasprzyk, 2009). When planning this workshop, researchers and the workshop participants must decide what type of testbed to work on – the specific

system of an agency (i.e., choose one city upon which to perform optimization) or create a generic testbed. When a tool is demonstrated via a case study using a specific agency's system, the modeling and forcing data are intrinsically relevant to a single utility. It may be difficult to engage a utility in experimental applications, however, because of risk aversion and data sensitivity (Farrelly and Brown, 2011), and the resulting insights may not be accepted as fundamentally valuable beyond the sponsoring agency (Brown et al., 2015). Therefore, our suggestion for achieving broad relatability and eliminating the need for any agency to commit to a new technology is to demonstrate a tool on a hypothetical, yet realistic, testbed. To produce a credible hypothetical testbed that captures important but generalized dynamics, input from practitioners is crucial (Jakeman et al., 2006).

The first workshop is intended to have a relatively low level of structure, or formalization, compared to the second workshop. Formalization refers to how researchers design the mechanisms for interaction, and therefore how open the design is to receiving unanticipated input. More formal structure includes mechanisms such as closed-ended questionnaires or pre-determined modeling exercises. In contrast, less formal mechanisms might include interviews or discussion groups where the conversations may be initiated from a specific question but allowed to generate responses in a more open, unrestricted manner (Newig et al., 2008). Since structure within a workshop acts as a filter, designing this workshop to be less structured meets the goal of casting a wide net around topics that are relevant to the construction of a testbed. We recommend open-ended questions or prompts to initialize brainstorming and discussions. Note that while limiting workshop structure to capture nuance and context for subject matter is desirable, researchers should take steps to ensure that they hear from all participants (e.g. actively facilitating discussions).

This workshop is an example of a co-learning, or social learning process wherein parties with different perspectives collaborate to develop a product but also achieve a better understanding of a problem (Mostert et al., 2008; Pahl-Wostl and Hare, 2004). Previous studies suggest that the results of co-learning experiences are valuable (McNie, 2007; Thompson Klein, 2004), and publishing the content can

contribute to more relevant WRSO tools by informing a scientific agenda that is better able to reconcile supply and demand for the tools (Sarewitz and Pielke, 2007). Additionally, the results presented in this paper significantly shape the evolution of the project, and warrant full discussion apart from the results of Workshop 2.

The first workshop is designed to not only brainstorm direct responses about testbed components (e.g. modeling platform preferences and physical supply infrastructure to be modeled), but also to generate discussion and commentary on the real-world context of those components. In Step 3, researchers translate the participants' input from Step 2 into the hypothetical testbed on which the tool will be demonstrated. This enables researchers to convert the potentially diverse experiences and concerns of the managers into a coherent set of testbed components that a large group of participants will be able to connect with. The specific mechanics of the tool in question will dictate the testbed components. Regardless of tool or components, the process of building the testbed should include informal iteration with one or more practitioners to ensure proper scope, conceptual validity, and appropriate data and assumptions (Jakeman et al., 2006).

Step 4 is a second workshop with the same participants as the workshop in Step 2 (or at least significant overlap and participants with similar backgrounds to the original attendees), during which the managers again play a consultative role (Pretty, 1995). In this second PM exercise, attendees should have direct interaction with output from the testbed's representative tool output², with researchers, and with each other. This type of exercise is similar to previous studies such as Gaddis et al. (2010) and Smajgl and Ward (2013) in that participants interact with results. However, in our study, the purpose is not to use the results to make a decision, evaluate the testbed itself, or give feedback on the particulars of the output (though such feedback would be welcome). Rather, the workshop's purpose is to assess the usefulness of

² "Representative tool output" means a relatable but generic example of similar output that could result from adoption of the tool by participants' agencies. The meaning of representative tool output could vary in the application of ParFAIT – some applications could focus more specifically on creating a usable tool for agencies compared to a hypothetical tool. Regardless of the application, the goal of Step 4 is to have an interactive workshop.

the *nature* of the information provided by the tool and the practicality of using it. In other words, through a combination of hands-on exercises and feedback, water managers can share how the type of information provided by the tool may or may not influence their utilities' planning or decision making approaches. For this workshop, using highly structured activities results in participation and responses that are more focused than those sought in Workshop 1 (Newig et al., 2008).

The second workshop is designed to address two challenges- lack of exposure and low relevance- that have inhibited the ability of WRSO tools to impact real-world decisions. The participants are exposed to a promising tool and they interact with representative tool output that is directly relevant to their management concerns. The use of the hypothetical water supply system allows them to react candidly because they are not responding to sensitive real-world decisions. This low-pressure interaction can provide the type of information that a water manager in search of planning solutions needs in order to begin petitioning for the tool's use in her/his agency. The data collected from practitioners' activity responses and discussions will be directly applicable to future development or application of the tool in question, and also broadly useful to WRSO researchers in their future innovations.

2.3 Application of the Participatory Framework for Assessment and Improvement of Tools

Although ParFAIT can be applied to a number of different WRSO tools, we provide an illustrative example here on a specific tool and its proposed use in practice. WRSO researchers have paid great attention to the call for decision support tools to help water providers develop long term plans for highly uncertain future conditions (Cosgrove and Loucks, 2015; Hallegatte, 2011; Ray and Brown, 2015; Reed and Kasprzyk, 2009; Sahota and Jeffrey, 2005). A tool that has been gaining prominence in academic long term planning studies in the past decade is Multiobjective Evolutionary Algorithm (MOEA)-assisted optimization. To confirm industry opportunity and practitioner openness to the tool, we built upon relationships that the Western Water Assessment (WWA) RISA has been developing since 1999 (<http://wwa.colorado.edu/>), and in the design of the study we consulted closely with two Colorado water

managers³ who are champions of innovation. Thus, the literature review and practitioner consultation for Step 1 of our ParFAIT application resulted in the goal of testing MOEA-assisted optimization for long term water utility planning.

Our geographic focus is the Front Range region of Colorado, USA. In the following section, we will describe the broad planning challenges faced by water utilities in this region, recognizing that many areas, especially in the Western U.S., face similar adverse conditions. After briefly introducing our participating utilities, we will present the tool choice we made in Step 1: Multiobjective Evolutionary Algorithm (MOEA)-assisted optimization. We describe the necessary components of an MOEA testbed that informed not only how we conducted our Step 2 workshop, but also how we structured the results presented in this document.

2.3.1 Front Range, Colorado, Background

The Front Range region is an urban corridor located just east of the Rocky Mountains that includes several large and many small cities. The region is projected to experience a 70% population increase by 2050 (State of Colorado, 2017), and since at least 1900 there have more claims on local water sources than can be met in most years (Eschner et al., 1983). Colorado experiences great seasonal and interannual precipitation and streamflow variability; over half of the state's precipitation falls as snow that runs off from about mid-April to mid-July (National Climatic Data Center, 2015), and annual streamflows can vary by up to 600% between lowest flow years and highest (Lukas et al., 2014). As the impacts of climate change intensify in the coming decades, Colorado will face anywhere from a 1.4 °C to a 3.6°C temperature increase by 2050 relative to the 1970-2000 baseline (Lukas et al., 2014). The projected changes in precipitation are less clear, though; under a medium-low emissions scenario, the state could see anywhere from -15% to +25% change in precipitation, depending on hydrologic region and time of

³ Leon Basdekas, a consultant with Black & Veatch (who worked for Colorado Springs Utilities at the time of this study) and Laurina Kaatz of Denver Water contributed to the design of this research.

year (Lukas et al., 2014). Given these substantial supply and demand challenges and uncertainties, water providers on the Front Range are highly motivated to pursue careful, adaptive, and innovative planning.

The Front Range utilities participating in this project are: Aurora Water, the City of Boulder, Colorado Springs Utilities, Denver Water, the City of Fort Collins, and Northern Colorado Water Conservancy District. All are operating under the same regulatory, population growth, and climatic circumstances, but they are diverse in their size, infrastructure, and water rights. The number of customers served ranges from about 113,000 (Boulder) to over 1.3 million (Denver) (City of Boulder and MWH, 2009; Denver Water, 2015a). The amount of storage controlled by each utility ranges from over 1.3 billion cubic meters (bcm) (Northern) to under 0.017 bcm (Fort Collins) (AMEC Environment and Infrastructure, 2014; Northern Water, 2015), and all have varying portfolios of storage, direct flow, and groundwater rights. All six utilities use water from the Colorado River and South Platte River basins and two also have Arkansas River basin resources (Aurora and Colorado Springs). Their current broad goals include balancing sources, increasing flexibility, or developing more storage (City of Boulder et al., 2009; Denver Water, 2015b; Gertig, 2015).

2.3.2 MOEA-assisted Optimization

This section presents our chosen WRSO tool, its research background, and the components necessary to apply it. The tool we have chosen to test is Multiobjective Evolutionary Algorithm (MOEA)-assisted optimization. Both workshops, as well as the testbed development, are structured around the attributes and purposes of the targeted tool, so it is important to explain the elements of our test case that inform our application of the framework. Later sections will present contrasts between previous approaches to MOEA applications and what we learned at our workshop.

MOEA-assisted optimization consists of four parts: the evolutionary algorithm, the problem formulation, a water supply simulation model, and visualizations of tradeoffs. The MOEA is a search technology that finds solutions to optimization problems. The problem formulation is a set of structured

concepts that define the “problem” or system to be optimized. The water supply simulation model is used to evaluate the performance of potential sets of actions. The output from the tool is a set of tradeoffs that quantitatively demonstrate the relationships between conflicting system performance objectives, which can require creative visualization approaches to enable effective analysis of the results. The following three sub-sections will describe evolutionary algorithms, problem formulations, and simulation modeling. The problem formulation and modeling sections describe two aspects of our testbed that are informed by water managers in the Step 3 workshop.

2.3.2.1 Multiobjective Evolutionary Algorithms

MOEAs are engines used to perform simulation-optimization: the MOEA search intelligently finds new planning or operations alternatives for a system, and those alternatives are evaluated by the algorithm based on user defined output from a simulation model. In the context of balancing water system objectives, the output of MOEA search is a set of portfolios that together demonstrate how improvement in one objective impacts performance in another. This quantified objective tradeoff information lends itself to visual analytics (discussed in Section 3.2.4).

Since the early 1990s, MOEAs have been used in research settings to explore objective tradeoffs in a variety of water management problems, including groundwater pollution (Ritzel et al., 1994), monitoring (Cieniawski et al., 1995; Reed and Minsker, 2004), and remediation (Erickson et al., 2002; Piscopo et al., 2013); water distribution (Farmani et al., 2005; Walters et al., 1999a); planning and operation for multiple reservoirs (Labadie, 2004; Smith et al., 2015; Zeff et al., 2014); watershed management (Muleta and Nicklow, 2005), and water marketing for drought management (Kasprzyk et al., 2009). Notably, prior work by two co-authors of this paper contributed an application of MOEA-assisted decision support using a Texas utility’s complex and sophisticated multireservoir supply model (Smith et al., 2015), and Basdekas (2014) offered his utility’s use of an MOEA as proof of their readiness for industry application. However, the most prominent use of MOEAs in WRSO has been in the context of

research. The success of MOEAs in research settings warrants conducting a structured study to investigate their potential for broader application by practitioners.

2.3.2.2 Problem Formulation

The problem formulation is a structured characterization of a real-world management problem, which instructs the MOEA on how to construct candidate solutions and judge the solutions' performances. MOEA problem formulations have three components: decision levers, objectives, and constraints. Figure 2 provides a schematic of how the elements interact within an MOEA search loop.

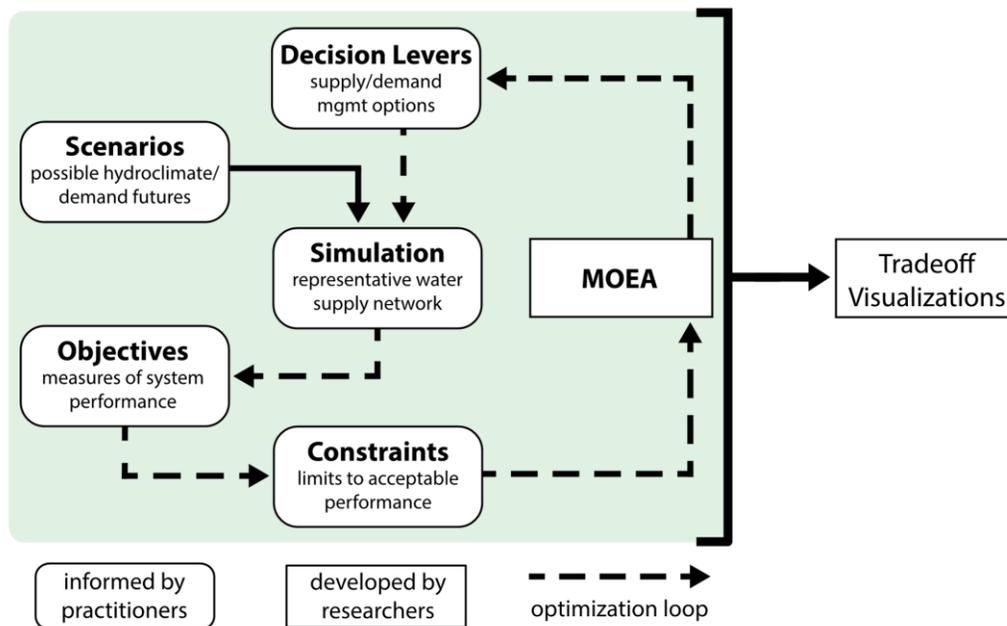


Figure 2-2. MOEA optimization loop and how its components were informed by water managers. The MOEA automatically generates combinations of user-defined decision levers which are fed to a simulation model. The simulation runs in one or more supply and demand scenarios, and outputs values for user-specified system metrics that are translated into objectives. The MOEA evaluates the portfolios of decisions and recombines “traits” of high-performing portfolios to produce new generations of portfolios.

Decision levers are the set of all options at a utility’s disposal to meet its performance goals. A decision lever can take different forms. For example, a binary decision lever might have values that are either “on” or “off”, such as a decision of whether or not to build some infrastructure. A real-valued decision lever may have many different potential values, such as the capacity of a new reservoir, or the

amount of new water supply to obtain. The set of enacted decisions makes up a portfolio. The levers relevant to this particular study range from estimated water savings from conservation education campaigns to new reservoirs, and the act of cataloguing and quantifying them is a useful undertaking in itself (Girard et al., 2015; Miller and Belton, 2014). Within the MOEA problem formulation, the utility's planning goals are represented with a set of quantitative variables termed *objectives*. Defining objectives requires a utility to translate goals into quantifiable metrics that intelligently and comprehensively represent those goals. It is informative for water managers to separate objectives from *constraints*, or limits to acceptable performance. A solution satisfies a constraint if it meets a particular criterion (e.g., reliability being over a given numerical threshold). As long as the solution meets this performance, the solution is considered feasible. An objective, on the other hand, is a quantity that is minimized or maximized, and a decision maker *does* care about the relative magnitude of a solution's performance in an objective. In other words, the difference between these categories, objectives and constraints, is the difference between "we *want* to..." and "we *have* to..." achieve a particular goal. Because the problem formulation is one quarter of the MOEA-assisted optimization tool, defining the problem formulation is a critical, often iterative process through which new system insights and evolving goals are revealed (Piscopo et al., 2014; Smith et al., 2015). It is most beneficial for both the optimization results and the parties seeking information through optimization if the process involves stakeholders (Hitch, 1960; Liebman, 1976).

2.3.2.3 Simulation Model and Scenarios

To represent the system that is being optimized, a water supply simulation model is embedded into the search loop of the MOEA. Simulation models play an increasingly important role in utilities' planning and management (Labadie, 2004). Though many different approaches and platforms are used, they all seek to provide detailed representations of water collection and delivery infrastructure to help managers quantify system performance under "what if" scenarios. In the MOEA-assisted optimization process, a solution from the MOEA represents a particular operations and/or infrastructure scheme, fully

defined by values of decision levers. This solution is loaded into the simulation model, which simulates multiple time steps until the end of the time horizon. At the end of simulation, the model returns values to the algorithm that describe how the model (i.e. the water supply system) performed using that solution; the values could be timeseries of system performance or scalar quantities (e.g., average pumping rate, total volume spilled). These values are translated into user defined objective values, and the MOEA assesses the solutions' performances based on those objectives.

With advances in modeling software and computing power, simulation models have improved in detail and fidelity to real systems, increasing water managers' trust in the simulations (Rani and Moreira, 2010). Because these models are becoming more trustworthy and ubiquitous, optimization tools that use them to search for promising solutions should become more appealing. However, system models developed within utilities, or "legacy" models, have rarely been coupled with MOEAs, and this fact suggests an investigation into the applicability and relevance of MOEA-assisted optimization is warranted.

Using simulation models in water resources planning requires hydrology and demand inputs that reflect plausible states of the world. Multiple scenarios can be useful for utilities since their systems face substantial uncertainty in future demand trajectories (Black et al., 2014; Mahmoud et al., 2011), as well as uncertainties introduced by climate variability and change (Means et al., 2010; van der Keur et al., 2010). These multiple scenarios can also contribute to MOEA studies, since their use within optimization can help identify management strategies that are robust (Hamarat et al., 2013; Herman et al., 2014; Kasprzyk et al., 2013; Smith et al., 2015).

2.3.2.4 Tradeoff Visualizations

MOEA-assisted optimization produces performance information about multiple objectives, often with three or more objectives. In order to fully appreciate the complicated tradeoffs between different objectives, many objectives must be shown simultaneously. Previous MOEA studies have used glyph

plots that can show up to seven dimensions at once (see Figure 2-3) or parallel coordinates plots that can represent one objective per vertical axis, with no limit on the number of axes (see Figure 2-4) (Kasprzyk et al., 2013; Smith et al., 2015; Zeff et al., 2014). These visualizations, when interactive, can greatly enhance the ability to work with the tradeoffs and enable users to apply subjective criteria to reduce the often large sets of portfolios down to a more manageable number of solutions (Kollat and Reed, 2007; Wu et al., 2016a).

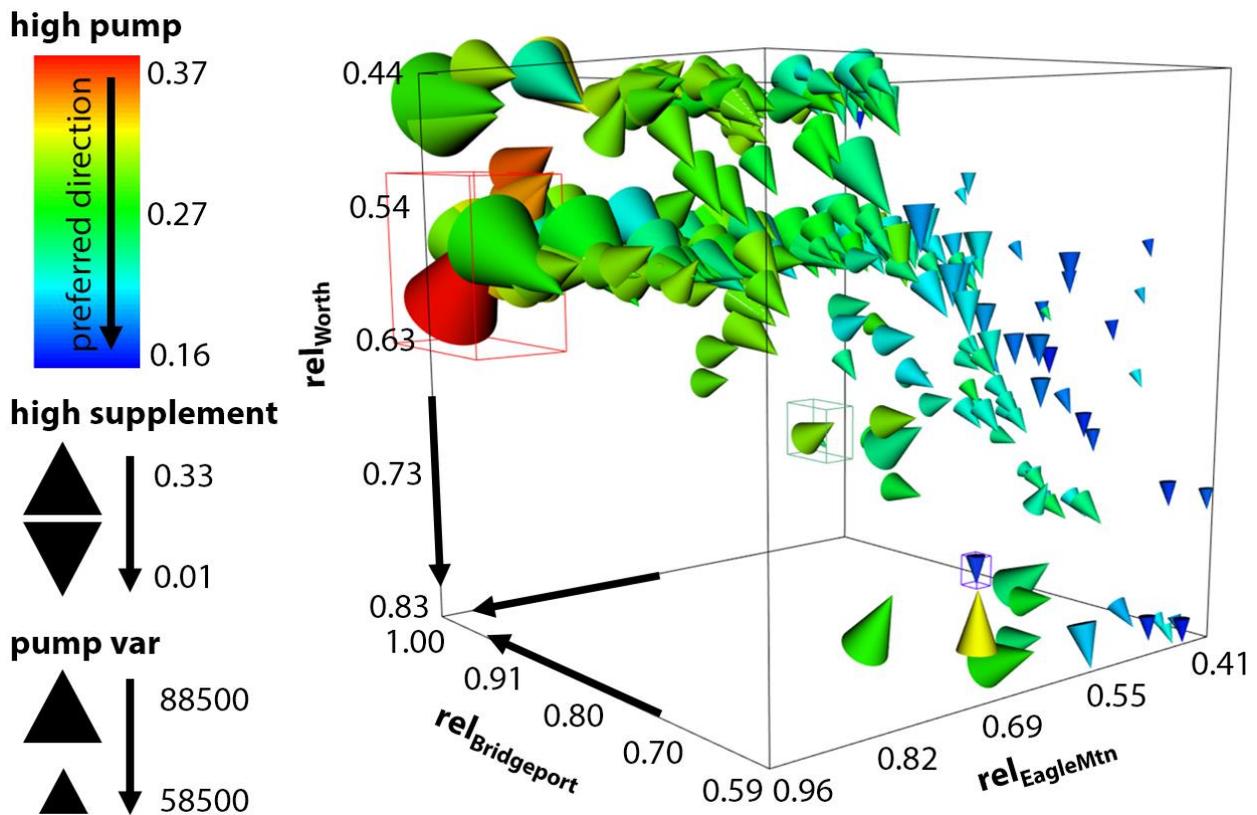


Figure 2-3. Glyph plot of the results from a multi-reservoir MOEA optimization study, adapted from Smith et al. (2015). It is presented here to illustrate how to use three-dimensional plots to show MOEA results. The optimized portfolios are shown in six dimensions (for six objectives), and three solutions have colored boxes around them to call attention to different management approaches. These boxed solutions are also highlighted in Figure 2-4.

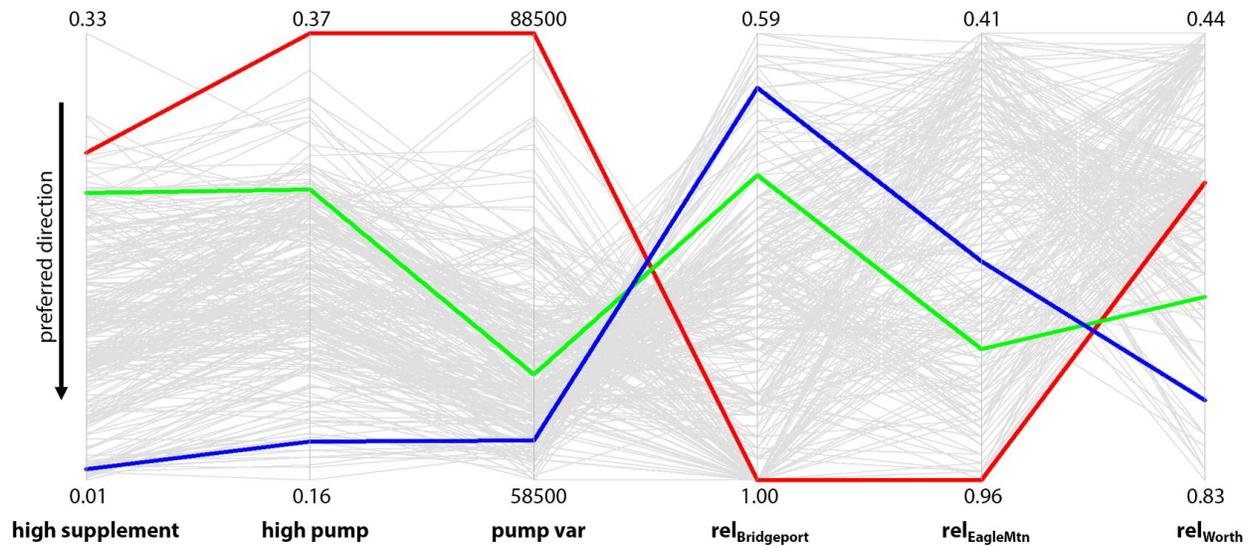


Figure 2-4. Parallel plot of the results from Figure 2-3 adapted from Smith et al. (2015). The results are presented again to demonstrate another visualization approach where each of six objectives is represented by a vertical axis. The full set of optimized solutions is shown in grey lines, while the highlighted solutions are representative of the different management strategies highlighted in Figure 2-3.

In accordance with components presented in Section 3, our first workshop included educating participants about MOEAs, and eliciting input on 1) specific challenges they faced in planning and managing water supply; 2) decisions, objectives, and constraints to inform problem formulations; 3) preferred simulation software; 4) critical infrastructure and management dynamics to include in our testbed model; and 5) supply and demand scenarios of interest. We did not consult the participants about visualization techniques.

2.4 Workshop 1 Results

We focus in this paper on presenting the results from Steps 1 and 2 of the framework, including the first workshop. Workshop 1 was a participatory modeling exercise used to elicit practitioner input on the MOEA testbed, extract relevant water management context, and co-learn for a better understanding of water utility planning. We begin by briefly describing how the workshop was designed and carried out. The remainder of the section is devoted to presenting and discussing the findings from the workshop that will influence the production of our MOEA testbed as well as contribute to improved understanding of

real-world water management context for future WRSO research: water management challenges, decision levers, objectives, constraints, modeling considerations, and scenarios.

Effective PM workshops involve preparatory activities (Stave, 2002). After identifying and establishing contact with our participant group with the help of WWA, we consulted with a subset of managers several months prior to the workshop to develop a workshop agenda. We also emailed an “Introduction to MOEAs” background document and short survey to all participants three weeks beforehand in order to make efficient use of workshop time.

The workshop was held on 3 February 2015 at the University of Colorado Boulder (CU) and lasted six hours. Twelve water managers from six agencies attended, along with seven researchers from different departments and organizations associated with CU. Throughout the workshop, the facilitator and researchers encouraged all water managers to share their experiences through direct conversation and individual prompts. These efforts, along with the pre-workshop survey, ensured that every utility was represented on fundamental topics (e.g. relevant decisions and objectives, scenarios of interest, etc.). Discussion developed as a result of questions from researchers to water managers as well as through interactions between water managers. Our workshop program consisted mainly of open-ended prompts to discuss testbed components, creating space in order to gather a wide range of information from participants (Newig et al., 2008). To promote discussion and brainstorming, researchers presented examples of decisions levers, objectives, and modeling considerations that were subsequently updated throughout the workshop as participants shared ideas and feedback. Please note that the content included below is summarized from across the six utilities, and was produced in a research context; it is not reflective of any one utility’s position or intentions.

2.4.1 Water Management Challenges

One of the fundamental areas WRSO researchers should understand is the decision making landscape in which managers operate. Greater appreciation for the complexities of decision making will

help researchers recognize the limitations of technical contributions, spur creative approaches to address problems that may not be well-characterized in previous literature, and gain insight into the ultimate usability of research (Dilling and Lemos 2011). Therefore, we began our workshop by asking participants to discuss the management challenges they face both within and outside their organizations. Because we laid this foundation, we were better able to understand the later discussions about specific testbed elements and ask more relevant follow-up questions. Presenting this information here provides context for the content in subsequent sections of the results.

The first concept we established was that water managers face management challenges that are different depending on the time scale. The development of WRSO tools, and their demonstrative applications, should be aware of how these challenges operate across timescales and which ones might be important to the development of new tools and their testbeds. Our participants identified challenges in the following time ranges: operational, <1 year; short term, 1-5 years; mid term, 5-20 years; long term, >20 years. A complete list of the challenges brought up during the workshop can be found in Table 2-1, but below we will discuss some of the responses that were particularly important. Not all of these challenges can be addressed through the use of better decision support tools of course, but understanding the larger context for water management helps to identify the opportunities for innovation and advancing decision support as well as the limits that might be anticipated.

Table 2-1. Full list of challenges described by water managers at Workshop 1.

<p>Short Term (1-5 years)</p> <p>Politics- lack of continuity on city councils/utility boards; Prioritizing capital development projects; Lack of reliable hydrologic forecasting; Wildfires; Floods; Budgets; Conflicting objectives- conservation that reduces revenues vs. maintaining financial ability to invest in system adaptability; De facto rate ceilings due to public fatigue; Incorporating lessons learned from crises; Drought restrictions</p>
<p>Mid Term (5-20 years)</p> <p>Capital planning; Budgets; Population growth; Changes in water use & population density; Lack of conjunctive land/water use planning; Social values; Extremes (floods/droughts); Aging infrastructure; Increasing uncertainty (in every arena); Regulatory/governance changes; Major ecosystem shifts; Renegotiation of Upper and Lower Colorado Basin dynamics; Costs of compliance with Endangered Species Act (ESA), National Environmental Policy Act (NEPA)</p>
<p>Long Term (>20 years)</p> <p>*Everything from mid term category but with increased uncertainty; Climate change; Opportunity hardening (for new supply); Lack of clarity on the State of Colorado's response to potential Colorado River shortages; Impact of increased reuse on return flows; Regional responsibilities between utilities; Unforeseen takeovers of neighboring utilities/changes to buildout expectations; Ecosystem management</p>

All of the utilities agreed that the biggest challenge they face is “politics”, and it was mentioned for all time periods. Politics, from the level of utility boards all the way to interstate negotiations, have major implications for their water planning (Blomquist and Schlager, 2005; Cocklin and Blunden, 1998). In the short term, water managers felt they generally had answers to looming problems, but political will could prevent them from moving quickly enough to address them. For short and mid terms, participants noted that councils and boards change, often triggering a shift in support for a planning direction or various projects, tools, and policies (especially if there is not a mandate from local citizens). Regardless of any particular administration continuity or lack thereof, the planning perspective of water utilities is 10 or 15 years further into the future than that of any board member or politician, and it can be a major hurdle to get sustained support to achieve acceptable water management outcomes. On a longer timescale, lack of certainty about how the state of Colorado will respond to potential future shortages in the Colorado River Basin is considered a major factor in these utilities’ plans (they all rely heavily on water from Colorado River tributaries). Furthermore, renegotiation of Interim Guidelines for shortage sharing

between Lakes Powell and Mead will begin around 2020, and the outcomes could have major implications for utilities across the western United States (U.S. Bureau of Reclamation, 2007).

Another issue that researchers had not considered, which is related to politics, is the importance of “buildout” conditions and the uncertainty around them. Every utility is planning toward a future with specific parameters related to which land will be within their service area and the expected population density and water use. Several utilities expressed some doubts about whether they could expect the future to play out as delineated, but they are prevented by sensitive political circumstances from including other possibilities in their plans. In reality, most of the participating utilities are surrounded by smaller providers and there could very well be a future where changes to development or tax codes (which currently prohibit annexations) lead to the exploitation of economies of scale, meaning service areas would combine and increase the responsibilities of our participating utilities.

Federal regulations, local control, and social and environmental stewardship greatly impact utility planning and decision making. Managers said that their organizations “think hard” before pursuing a project that requires a lengthy and expensive NEPA permitting process with uncertain outcomes. In Colorado, utilities must also contend with the requirement to satisfy the concerns of county governments who may legally block a project that does not adequately address the impacts of the project on their communities (Stengel, 2009). These regulations hold utilities accountable for environmental and social impacts, but utilities are increasingly taking proactive steps to gain more local acceptance in recognition that negotiating directly with community and environmental stakeholders contributes to good will and more equitable sharing of costs and benefits as growing cities pursue new water supplies and infrastructure. One recent successful example of this new dynamic is the Colorado River Cooperative Agreement between Denver Water and 17 regional stakeholders (“Colorado River Cooperative Agreement,” 2012).

Finally, participants brought up the fundamentally conflicting nature of several of the expectations placed on municipal utilities. For instance, in this water-scarce region, conservation is advocated by many groups, and water utilities are generally held responsible for promoting conservation; however, conservation may result in revenue reductions, making it difficult to meet fixed costs and maintenance needs, and thus impacting the ability of water utilities to build adaptable systems without unpopular rate increases.

In WRSO research, these realities are often not acknowledged due to the fact that they are not strictly engineering problems. Some of the feedback directly informs the technical work in this study, e.g. modeling a Lower Colorado River demand. Other information, e.g. buildout demand, helps us understand the motivations for certain planning scenarios over others. Such context is important, and our results strengthen recent arguments for greater integration of engineering research with social sciences to ensure a more comprehensive approach to difficult water management problems (Lund, 2015; Rosenberg and Madani, 2014).

2.4.2 Decision Levers

Water utilities must have infrastructure and operations in place to react to potential supply and demand imbalances. In order to be prepared for challenging times, they take actions to either increase supply or reduce demand; these actions are called decision levers. There is no “right” answer or perfect decision combination to insure a utility against all possible futures. In the workshop, Front Range water providers described a complicated water management context with many independent actors and discussed using a wide range of decision levers to try to maintain or increase future security.

The discussions of decision levers were separated into two subtopics: supply and demand levers. Supply levers included any decisions a utility might make to increase the amount of water available to them overall, improve the security or quality of their existing supplies, or manage their supplies to account for various supply situations. In advance of the workshop, researchers used their previous

experience, literature findings, and knowledge of the region to create the list of examples found at the top of Table 2-2⁴. Participants agreed that all of the suggestions provided were relevant decisions that their agencies would consider, and they provided additional ideas, listed below in Table 2. One action that researchers found particularly interesting was deliberate watershed management, which could serve both to increase the security of supply (several of the utilities obtain water from basins that were impacted by recent forest fires) as well as to promote environmental stewardship. A participant compared watersheds to other types of infrastructure and noted that they needed to be maintained just as are pipes, pumps, and dams. Decisions about maintaining infrastructure were considered very important. Thus, it would be helpful to incorporate maintenance in this and future optimization studies. A participant noted that there was a substantial difference between levers that increase yield and those that prevent failure/increase resilience, and that an exploration of which category of levers is more important to achieving good objective performance in different scenarios would be interesting. Some participants also suggested that levers could be ranked according to various criteria such as social acceptability, cost, length of time to results, and probability of successful permitting and achieving expected yield.

⁴ Because the participating utilities all operate under similar social, regulatory, and hydrologic conditions, there was general consensus around acceptance or rejection researchers' suggestions. This consensus, developed through discussion, is reflected in the tables below. Wherever we encountered opposing views, we explore those in the text.

Table 2-2. Supply levers proposed by researchers and water managers at Workshop 1.

Supply Levers Suggested by Researchers	Managers' Response
Buy agricultural rights	Agreed and expanded
Exercise dry year options/other interruptible supply options	Agreed and expanded
Buy shares from water wholesalers	Agreed
Develop new transmountain water	Agreed
Develop groundwater	Disagreed
Build/expand reservoir	Agreed and expanded
Maintain more carryover storage	Agreed
Negotiate temporary contractual storage	Agreed
Additional Levers Proposed by Water Managers	
Buy <i>any</i> senior water rights (not just agricultural)	
Lease water from agriculture	
Watershed management	
Add redundancy to facilitate maintenance	
Develop reuse- indirect or direct, potable or non-potable	
Build any type of storage- aquifer, gravel pit, on channel, off channel	
Increase efficiency- e.g. line canals, enlarge pipes	
Cloud seeding	

Both researchers and participants found it difficult to come up with more than a handful of demand levers; the “appropriate” level of municipal water use is a social, political, and environmental issue, and water utilities have a first priority of simply meeting demands, whatever they may be. Managers emphasized the fact that utilities are limited both legally and socially in the influence they have over customer behavior and future demand growth; their rates must be based on their cost of service, and they are not involved in the land use planning decisions made by separate agencies or departments. Despite these limitations, it was clear that the participating utilities take seriously their duty to promote responsible water use in a region where water is a very sensitive issue.

Managers rejected several of the demand levers suggested by researchers (see the top of Table 2-3). Rate changes were roundly dismissed as a lever; though utilities *do* use a tiered pricing structure to

encourage low water use (Bonbright et al., 1988; OECD, 1999), our participating utilities do not implement price increases to lower demand. Even the phrasing “temporary rate increases” was deemed too broad; participants said that although pricing has substantial impact on their customers’ use, a potential supply shortfall is not a socially or politically acceptable reason for increasing rates, even temporarily. These utilities only temporarily increase their water prices to recover lost revenue *after* a period of restrictions by enacting “drought surcharges”. Other demand levers were already being implemented regularly and thus seen as standard operating procedure in this region: non-drought conservation, education campaigns, and appliance rebates.

For modeling purposes, the utilities seemed to agree that representation of a utility’s influence on demand was commonly undertaken in a lumped and bracketed fashion. That is, the utilities’ demand management actions are lumped together into a single percentage reduction in demand. Then, uncertainty about the impacts is incorporated by creating high and low estimates around the reduced demand, where it would be desirable to meet the higher estimate. Example scenarios around these brackets are developed, more as conceptual description as example of how savings might be achievable.

Table 2-3. Demand levers proposed by researchers and water managers at workshop 1.

Demand Levers Suggested by Researchers	Managers' Response
Non-drought conservation	Disagreed (already standard procedure)
Rate changes	Disagreed
Change triggers for various restriction levels	Agreed
Temporary rate increases	Disagreed (rephrased)
Education campaigns	Disagreed (already standard procedure)
System improvements- e.g. fix leaks	Agreed
“Behavioral water efficiency” (e.g. smiley faces on bills)	Disagreed (already standard procedure)
Additional Levers Proposed by Water Managers	
Drought surcharges	
Encourage xeriscaping/lawn replacement	
Change building codes	
Provide incentives for appliance updates	
Land use planning (politically difficult; rare and informal)	

2.4.3 Objectives

Water suppliers seek to provide water responsibly and efficiently. In order to evaluate their system’s ability to meet these broad goals, a utility must define quantitative ways to measure how well their system is performing, or how well proposed system modifications will perform. For MOEA-assisted optimization, these measures are called objectives.

During our objectives section, we learned that “reliability” is by far the most important objective for all utilities. In WRSO literature, reliability has a specific meaning: the frequency of a metric being in a satisfactory state, which is defined by a failure threshold. For example, a reservoir that must stay above a certain elevation for its outlets to work would be considered 99% reliable if it fell below that elevation threshold for 1 day out of 100. Researchers developed this definition to help characterize system performance that varies over time (Hashimoto et al., 1982). Since its formal definition, reliability has figured prominently in optimization research as an objective that is maximized (Herman et al., 2014;

Karamouz and Nazif, 2013; Kasprzyk et al., 2013; McMahon et al., 2006; Moy et al., 1986; Paton et al., 2014)

We found that the utilities use the term “reliability” to refer to the ability of their system to satisfy customer demands. As the participants explained in the workshop, they treat the achievement of a reliable system as more important than any other performance measure. One participant commented that reliability was so important that it trumped the marginal costs (not necessarily monetary) of not meeting other goals. In other words, reliability may not be considered an objective where, through multiple simulations, various outcomes of the objective function are compared (e.g., 98% vs. 99%). This finding challenges some previous conceptions of optimization problem formulations that presumed that water suppliers might sacrifice reliability performance once the benefits of doing so were quantified. Additionally, each utility has a different definition for reliability: one considers their system to be reliable if they can meet 100% of average annual demand through a 1-in-50 drought event without going into restriction; another uses a threshold of maintaining at least 1.0 years’ worth of annual demand in storage at all times; several utilities used definitions of reliability that refer to different levels of drought restrictions.

Other objectives were offered over the course of the discussion (see the bottom of Table 3 for the full list): minimizing spills (and flooding, though not much detail was provided on this), minimizing pumping (one utility has a mandate to minimize greenhouse gas emissions), and minimizing uncollected water (complicated water rights schemes and spatial limitations of infrastructure make it a challenge to move water around a system to take full advantage of spring runoff). We had an interesting discussion about how realistic it is to minimize costs in the mid- to long-term; many aspects of costs, whether they are associated with new infrastructure, pumping, or other activities, are very uncertain. Though the managers confirmed that it is a critical consideration in any plan or decision, a participant noted that including cost as an objective may unjustifiably affect the results produced in multiobjective optimization. In response, another participant noted that other aspects of planning, such as population density affecting

peak demand and sizing of water treatment plants or distribution pipes, were also uncertain. This discussion helped researchers recognize that accounting for supply and demand uncertainty through simulation scenarios can partially address some types of uncertainty, but that the scenarios that affect cost may not be adequately represented in most simulation models. In light of this, care should be taken before including cost in a problem formulation. A final interesting note on the objectives discussion is that only one utility referenced resilience and vulnerability, or speed of recovery after a failure and severity of failure (Hashimoto et al., 1982). These are well-established objective definitions in optimization literature, but seem not to have been widely adopted by practitioners at our workshop. It is unclear whether this is due to a failure of knowledge transfer or if the objectives do not translate well in practice.

Table 2-4. Objectives proposed by researchers and water managers at workshop 1.

Objectives Suggested by Researchers	Managers' Response
Minimize time spent in restriction	Agreed
Minimize costs	Agreed (with caution)
Maximize total year-end storage	Agreed
Maximize time a reservoir spends above a given elevation	Agreed
Additional Objectives Proposed by Water Managers	
Meet reliability criteria (various)	
Minimize spills	
Maximize hydropower production	
Minimize pumping	
Minimize greenhouse gas emissions	
Maximize resiliency	
Minimize vulnerability	

2.4.4 Constraints

In optimization studies, constraints can be used for many purposes, such as physical infrastructure limitations, limits for decision variables, or preserving mass balance restrictions, which may be especially important in classical optimization methods (Rani and Moreira, 2010). However, when an analyst sets up an MOEA to be linked to a sophisticated simulation model, physical feasibility constraints may be

handled internally within the simulation model itself (Smith et al., 2015). Therefore, at our workshop, the discussion of constraints was oriented toward the managers' ideas for acceptable management outcomes.

Past studies have used performance constraints such as maintaining 98% supply reliability (Kasprzyk et al., 2009) or 99% reservoir elevation reliability (Zeff et al., 2014). Because we anticipated that there would be a fairly limited number of constraints, we opted not to provide examples and instead let the managers lead. They widely agreed on the absolute requirement to meet 100% of *indoor* demand no matter what, as well as meeting environmental flow agreements. Refer to Table 2-5 for the complete list of managers' suggestions.

Table 2-5. Constraints proposed by water managers at Workshop 1.

Constraints Proposed by Water Managers
Meet 100% of indoor demand
Meet environmental flow requirements
Do not strand assets- e.g. pursue projects that fail permitting process, acquire unusable water rights

2.4.5 Modeling

Utilities build simulation models in order to simulate how their systems will react to different internal and/or external circumstances. Models are useful for exploring a range of future supply and demand scenarios and for evaluating new infrastructure or operations schemes. The nature of the “what if” questions being asked will dictate modeling choices.

We discussed four issues related to modeling during the workshop: time horizon (length of simulation), timestep, modeling platform, and network features. No participants voiced a strong preference for any particular time horizon, but they were interested to compare optimization results from shorter simulations (10-25 years) with optimization over a longer period. There were also no strong

feelings about using a daily versus monthly timestep, but it was pointed out that changes in snowmelt timing on the order of days or weeks could not be captured by a model that used a monthly timestep.

To inform the discussion of choosing a modeling platform, researchers began by presenting some important things to consider when choosing software to be part of an MOEA search loop: simulation time, ease of linking to the MOEA, and ease of defining levers and objectives. A complex water supply network on a sophisticated platform with advanced, intricate features such as MODSIM (Labadie and Baldo, 2000) or RiverWare (Zagona et al., 2001) will enable out-of-the-box, in-depth investigation into properties of solutions but may entail a longer simulation time that leads to compromises on scenarios and simulation horizons. A platform with minimal or no graphical user interface (GUI) and fewer pre-packaged features, like the Central Resource Allocation Model (CRAM) or StateMod (Brendecke et al., 1989; Parsons and Bennet, 2006) could mean a streamlined MOEA link and fast simulation time but potentially limit a user's ability to explore the implications of solutions in detail. Having performance information that was not officially recorded in the problem formulation, e.g. a timeseries of reservoir elevations, readily available was shown to be useful in Smith et al (2015). The attendees generally agreed that the specific platform was not important, as long as relevant model structure and levers were well represented.

This study's simulation model is a representation of a hypothetical water supply network designed to resemble the systems of participating utilities. Though it may have been possible to use a specific model of one participating utility, we deliberately chose to create a hypothetical, more generic model to increase the generalizability of our findings. Brown, et al, recently asserted that the prevalence of context-specific models has impaired the water resources systems analysis community's ability to provide fundamental insights (2015).

In order for the hypothetical network to be engaging and capture a reasonable amount of the complexity of Front Range water management dynamics, we asked workshop participants for a list of

important water supply system features. We recognize that no model can fully capture the complex interactions within a built system or between different users, nor the impacts that utility decisions have on water and environmental quality. Our intention is to capture our participating agencies' current approach to long term modeling even though the systems represented are incomplete (Glynn, 2015). The structure of the network will be informed by the feedback on levers, objectives, and features, as well as take into account the real systems of the participating utilities. The feature list is located in Table 2-6.

Table 2-6. Important hypothetical water supply network features as suggested by water managers at Workshop 1.

Network Features Proposed by Water Managers
Complicated water exchanges
Priority system with suites of rights that vary by seniority and season
Significant reuse
Downstream requirements- e.g. competing rights, environmental flows
Multiple water sources
Return flows
Alter use of groundwater (but no new groundwater sources)
Water-type tracking (for reuse purposes)
Alternative transfer methods, e.g. dry-year options
Leased water to and from agriculture

2.4.6 Scenarios

Planning for climate change and climate variability via scenarios is an important part of the modeling process within the MOEA Testbed. Fortunately for our study, the participating utilities were very familiar with the concept of climate change scenarios through their involvement in a 2012 project called the Joint Front Range Climate Change Vulnerability Study (JFRCCVS). In that study, the utilities' feedback was used to develop a methodology and set of hydrologic traces that incorporated for downscaled GCM output (Woodbury et al., 2012). The JFRCCVS used output from CMIP3 (Meehl et al.,

2007) to develop temperature and precipitation offsets with which to calculate streamflows at important points around Colorado, encompassing five temperature and precipitation scenarios applied to two different time horizons (2040 and 2070). During our study's workshop, attendees expressed that this previously developed approach to incorporating climate change was acceptable, and that it was unnecessary to update the offsets using CMIP5 output (Taylor et al., 2011). Along with climate change scenarios, participants asked that this study incorporate scenarios not necessarily related to climate change as well. They felt strongly that the historic hydrology should be included, as well as a resequencing of the record to develop more challenging droughts that still resemble what they have experienced. Of particular importance was the sequence from 2000 through 2002 which can be roughly summarized as a very dry year followed by a moderately dry year and culminating in an extremely dry 2002 that resulted in severe regional supply challenges (Pielke et al., 2005). Other scenarios, such as wild fires and infrastructure failures were also considered important.

2.5 Synthesis of Results

Typically, research in water resources decision support has relied on modeling and methods created without input from those who might use the insights or findings (Lund, 2015; Voinov and Bousquet, 2010). However, a wide range of sources suggest that it is critical to work with water management practitioners when conceptualizing and developing WRSO tools (Jacobs, 2002; Liu et al., 2008; McNie, 2007; Melillo et al., 2014; Tsoukias, 2008). To that end, ParFAIT is applied as a process for researchers and practitioners to engage directly over the design and assessment of an MOEA testbed. By using a less formal structure for Workshop 1, we were able to take advantage of the diverse knowledge and experience of attendees to efficiently hone in on ideas that will improve the relevance of the testbed and future research (Newig et al., 2008). Specifically, the managers very readily compiled a list of model features that reflect the attributes they consider important in their systems that will feed into the hypothetical supply systems designed in Step 4. Also, the managers added to and refined our potential decision levers and objectives, increasing the pertinence of our problem formulations. Workshop 1

revealed some of our faulty assumptions. For example, we overestimated the role that groundwater will play in improving future supply outlook, and underestimated the prominence of different types of reuse. We had made the assumption that non-drought conservation was a lever, but the managers roundly agreed that on the Front Range there is a culture of water conscientiousness regardless of drought status. Finally, throughout the workshop, but especially during the Challenges section, we gained substantial insight into the *context* of water management in the region. The influence of water politics and regular politics on management decisions is hard to overstate. Utilities must be respectful of geographical and sectoral sensitivities (for example, a utility may consider enacting restrictions before supply shortfalls require it if its neighbors are forced to cut back). They must also navigate changing local, regional, state, and interstate political agendas while maintaining or increasing their future water security.

During the Objectives section of the workshop, several issues arose which have not formally been addressed in multiobjective optimization research to date. First, each utility has a different set of criteria to define the achievement of a reliable system. There were two broad categories of definitions: storage-based and restrictions-based. An example of storage-based criteria is requiring a minimum of 100% of average annual unrestricted demand in storage at all times. An example of restrictions-based criteria for establishing that a system is reliable is not exceeding a Level 1 restrictions frequency of 13 times in 350⁵ years, not exceeding a Level 2 restrictions frequency of 7 times in 350 years, and so on (where increasing restriction Levels correspond to greater water use reductions). Most of our utilities use a combination of both types of reliability, but note that if both types were individually incorporated as objectives into a multiobjective problem formulation, they could conflict. The variety of reliability definitions prompts several questions:

1. How do the two reliability categories impact performance in other objectives?
2. Is one category sufficient, and if so, is one or the other more useful?

⁵ Water management agencies sometimes use tree ring data to extend their hydrologic records and expand the range of conditions for which they can test their modeled systems. See <http://www.treeflow.info/applications>.

3. If a composite definition of reliability is warranted, are there any general insights to be gained about how it should be constructed?

Future optimization research that investigates these interactions may yield information that improves utilities' approaches to defining system-wide reliability.

Though the deficiencies of the concept of reliability have been noted (Brown, 2010), it appears to be alive and well in the water management industry. The participants overwhelmingly focused on system-wide demand reliability as *the most important* planning goal, but seemed to discuss it in a way that suggests it should be represented as a constraint in the problem formulation, and not as an objective that could have varying levels of performance. One manager said that degraded performance in other objectives is always warranted in pursuit of achieving a policy-specified level of system reliability. As a general statement about the priorities of water utilities, this makes sense, but if managers were presented with quantified information about how other objectives benefit from minor reduction of the value (magnitude) of their reliability objective (one that is likely to be defined very conservatively), would they consider making small sacrifices to reliability? In other words, if managers *perceive* a particular level of reliability as inviolable, can tradeoff information change their minds? This is especially relevant in the context of uncertainty in defining reliability in these simulations, since changes in the input data or assumed scenarios could lead to different values of a reliability output. It was evident from workshop discussions that, in practice, utilities do end up violating their 100% reliability standard. The discrepancy between stated priorities and practical experience creates ambiguity around whether the optimization problem formulation reflect the utilities' ideals and define reliability as a constraint or reveal tradeoffs by defining it as an objective?

Throughout WRSO research history, cost has been a prominent metric by which water management options are evaluated (Cui and Kuczera, 2003; Kasprzyk et al., 2009; Maass et al., 1962; Watkins and McKinney, 1997; Zhu et al., 2015); indeed, monetized costs and benefits have often been the

most influential factors in making project decisions (Arnold, 1988; Maass, 1966). Some reasons to optimize using direct project costs (not necessarily monetized estimates of the costs of other impacts) are readily apparent- funds are limited, public funds must be used responsibly, etc. However, the calculation of project costs is highly sensitive to the chosen discount rate, among other assumptions (Hallegatte, 2011), and there is a long history of over-budget projects to suggest that predicting costs is a very uncertain endeavor (Liu and Frangopol, 2005). During our workshop, a participant noted that although cost considerations would influence plan adoption during later phases of planning, allowing the MOEA to evaluate a solution based on such an uncertain calculation may prevent ultimately preferable (to decision makers) solutions from surviving the optimization. Another participant pointed out that if utilities did not consider cost, they would build (or the algorithm would suggest) completely drought-proof systems that could meet demands in any scenarios, but they do not. In considering this exchange, we find another reason that cost is frequently used as an objective in optimization literature: unless there is an objective that penalizes solutions that require more resources than other solutions, an algorithm will prefer solutions that bring all resources to bear in order to improve, for example, reliability objectives. The larger point being made by the first participant was that cost is not the most important consideration when searching for solutions to very challenging potential supply shortfalls. For researchers, it is worthwhile to examine how including or excluding cost in a problem formulation can impact optimization results, and possibly investigate avenues other than highly uncertain cost calculations to penalize the incorporation of expensive projects. For example, one potential alternative to cost is to give each decision lever a complexity score. This could capture the relative challenges inherent to different projects, thereby signaling a cost-like preference to the algorithm, since the algorithm would be less likely to select portfolios that would be too complex to implement.

Research applications of MOEAs have shown them to be useful for efficiently suggesting innovative solutions, promoting learning about a system via iterative problem formulation, and quantifying objective tradeoffs, (Kasprzyk et al., 2009; Paton et al., 2014; Smith et al., 2015; Zechman

and Ranjithan, 2007), but we recognize that many issues that influence water utility decision making cannot be addressed by application of the MOEA-assisted decision support tool. Consider uncertainty, for example; using an MOEA method can incorporate, but not reduce, hydroclimate and demand uncertainties. Similarly, when planning under a challenging political climate, considered to be the greatest challenge for our participants, MOEAs can generate innovative solutions that may lead to more politically palatable management options, or provide quantitative tradeoff information to help justify politically challenging decisions, but they cannot shield water utilities from changing political agendas.

2.6 Conclusion

Rogers and Fiering (1986) noted several reasons that WRSO research tools had not played a more prominent role in water management decision making. Among them were the existence of conflicting objectives, a focus on finding a single optimal solution, the challenge of high dimensionality in water resources problems (i.e. many system variables and performance metrics), and the oversimplification of system representations. Many of these shortcomings have been addressed through technical advancements such as greater access to computing power and the advent of tools like MOEAs that incorporate a full-complexity model and generate many solutions that capture performance across conflicting objectives.

Despite these developments, however, there are still fewer examples of successful WRSO tool adoption than might be expected by researchers and practitioners familiar with the field (Asefa, 2015; Brown et al., 2015; Maier et al., 2014). We posit that there are three main challenges that account for the discrepancy: water managers' lack of exposure to promising tools; institutional and cultural adoption barriers within water management agencies; and low relevance of WRSO tools. The Participatory Framework for Assessment and Improvement of Tools (ParFAIT) contributes a formal approach, anchored by two participatory modeling workshops, through which researchers and practitioners can work together to overcome the exposure and relevance challenges. The results discussed here demonstrate that the early steps of this framework are particularly important for improving the relevance WRSO research as a whole.

By integrating practitioner experience, social science concepts and methods, and engineering innovations, ParFAIT may increase the impact of a specific tool by exposing practitioners to the tool in an in-depth but risk-free way that inspires new thinking about the tool and empowers managers to consider whether the resulting information can help them. Furthermore, their feedback may improve the tools itself. Additionally, as demonstrated in this paper, the framework provides a channel through which researchers can elicit information from practitioners about their management context and the needs of water supply agencies. Here, we report the direct feedback on our suggestions for decision levers and objectives for use with MOEAs. This information was constructive not only for building our testbed but also in reshaping our understanding of the roles that modeling and optimization can play in what are ultimately political decisions. We have also provided direct input from managers about ideas they have for future studies: comparing the effects of actions that increase supply yield (e.g. building a reservoir) to those that help prevent failures (e.g. managing watersheds to lower the risk of forest fires); methods to determine how long term planning outcomes interact with shorter term decision making; and how the introduction of subjective decision lever assessments would affect quantitative optimization.

In this study, we demonstrate the application of ParFAIT to assess MOEA-assisted optimization for long term water utility planning, but the framework is much more broadly valuable. The field of WRSA could greatly benefit from similar evaluations of other tools, e.g. agent-based modeling (Zechman Burgland, 2015) and hydroeconomic modeling (Harou et al., 2009). ParFAIT can test water resources systems *methods* (i.e. not necessarily highly-technical tools themselves), e.g. info gap (Hipel and Ben-Haim, 1999) and dynamic adaptive policy pathways (Haasnoot et al., 2013). Furthermore, other fields with emerging but under-utilized tools and methods can easily adopt this research approach.

Ultimately, we hope that the further use of this methodology can help to impact WRSA research agendas at small and large scales, thereby improving the relevance of tools intended for use by practitioners. The framework and subsequent results demonstrated here represent a new approach that can be followed to deliberately engage water managers so that the interaction and collaboration necessary for

more usable decision support tools can be “built in.” The dialogue facilitated by an intentional, less formal workshop approach designed to elicit more open input and responses was critical to researchers selecting the most relevant elements of the problem formulation, which increased the chances of building a suitable and usable tool testbed. While this framework requires additional time and resources to implement, we believe in the end it results in a more effective method for shaping WRSO tools. As WRSA research increasingly seeks to improve “real-world” outcomes in water management, ParFAIT may provide a useful path to that future.

Chapter 3

Multiobjective optimization of long term planning portfolios on the Front Range of Colorado

A variety of studies using Multiobjective Evolutionary Algorithms (MOEAs) have shown these tools to be useful for quantifying performance tradeoffs that enhance utilities' pursuit of balanced long term planning portfolios. To enable exploration of multi-reservoir planning in the western U.S. and support experimentation in MOEA applications, this study contributes the Eldorado Utility Planning Model. The hypothetical but complex model demonstrates the potential for MOEAs to help utilities navigate the challenges associated with highly-regulated and tightly-constrained supply, rapidly growing demand, and regional sensitivities. Because it generically captures relevant water management context, the model is a useful platform for MOEA innovation; it is not bound to any specific agency's needs or political sensitivities. Here, this advantage is demonstrated through an innovative set of planning objectives that provide an alternative to optimizing with cost projections and reveal performance tradeoffs through which utilities can express fundamental policy preferences. The results of this study capture the western U.S.'s tradeoffs between pursuit of major infrastructure and acquisition of regional agricultural water.

3.1 Introduction

This paper contributes a realistic multireservoir case study that explores long term water utility planning in Colorado and the western U.S. in order to experiment with, and communicate, the use of Multiobjective Evolutionary Algorithms (MOEAs). Utilities often refer to a general set of performance metrics for long term water sustainability as the "triple bottom line" – a framework through which they try to assess social, financial, and environmental impacts (Elkington, 2004). The potential conflicts inherent in these goals are especially dramatic in Colorado and other water-limited areas because utilities' decisions are made within strictly-regulated and constrained systems of complex physical, temporal, legal, and cultural dynamics; in other words, the decisions are likely to have broad regional impacts.

MOEAs are tools that generate thousands of decision portfolios to discover tradeoffs between objectives that represent these conflicting performance goals, and can inject valuable information into utility planning processes as agencies navigate the tradeoffs. The model presented here is a platform through which researchers can innovate with MOEAs while producing results that are realistic and generic enough to be communicated to a wide range of water managers in Colorado and beyond.

Since the 1990s, MOEAs have gained prominence in Water Resources Systems Optimization (WRSO) research (Nicklow et al., 2010). They have been applied to many types of water supply problems, including planning and operation for multiple reservoirs (Labadie, 2004; Smith et al., 2016), regional groundwater aquifer management (Siegfried et al., 2009), and water marketing for drought management (Kasprzyk et al., 2009). One particularly active area of MOEA research is optimization of long term water supply portfolios. Encouragingly, several recent studies have applied MOEAs to models that are based on real systems, using input from water managers at the respective real-world agencies: the Lower Hunter region of New South Wales (Mortazavi et al., 2013); Adelaide in South Australia (Wu et al., 2016b); London supply in the Thames Basin (Matrosov et al., 2015); and the Research Triangle of North Carolina (Zeff et al., 2014). In summary, MOEA applications to long term planning have benefited from a mature body of research, increasing frequency of studies, and, recently, an application by Colorado Springs Utilities (Basdekas, 2014; CSU, 2017a).

Given this ripe opportunity for MOEA applications in the field, there is a need to develop more guidance on best practices for agencies seeking to use MOEAs (Maier et al., 2014). Though there is a wide spectrum of case studies to date, they are limited in their ability to facilitate experimentation that leads to practical insights and reliable results. On one end of the spectrum are the studies using highly simplified models that may not represent the complexity of real-world decision spaces or tradeoffs recognizable to practitioners. On the other end of the spectrum are studies that use real-world systems. Though more complex and reliable, these real-world studies can have drawbacks. First, they produce results that may be politically sensitive and use difficult-to-obtain data. The second drawback relates to

defining the MOEA problem formulations. The problem formulations are informed by the agencies' existing practices, but directly translating existing practices into MOEA search can be problematic because it limits the space of solutions that can be suggested by the MOEA (Mortazavi et al., 2013).

Two examples of ways that an agency's direct influence on a problem formulation can potentially limit MOEA results are the use of existing reliability definitions and the inclusion of cost as an objective. Water utilities have supply reliability policies that they use to evaluate their current systems and future plans; these policies are based on historic climate conditions and possibly outdated social perspectives, and may arbitrarily constrain their systems' performance potential. In other words, using different performance metrics associated with reliability in an MOEA search could yield better plans overall. Another example is using cost as a measure of performance for long term planning portfolios, which is common in MOEA research. While it is true that the financial cost of a plan is an important consideration for water suppliers, calculating a portfolio's cost is problematic because it involves choosing an uncertain discount rate, estimating project life-cycle costs, and combining cost estimates of projects that are in different phases of study (EU Framework, 1998; Maheepala et al., 2014; Newell and Pizer, 2001; Walski, 2001). Use of uncertain portfolio costs with an advanced optimization tool can inappropriately preference certain projects, contribute to the continuation of traditional planning mindsets, and obscure opportunities for MOEA innovation. Both research and real-world MOEA applications can benefit from exploring new ways to formulate planning objectives.

One way to develop new techniques that can contribute practical MOEA guidance is to experiment with generic case studies. An example of the power of a generic case study to transform a field is the Anytown, U.S.A. water distribution system model. Originally developed for use in a "battle" of optimization techniques in 1985, Anytown was devised as a realistic platform that could bring together researchers and practicing engineers to compare approaches to solving pipe-sizing problems (Walski et al., 1987). Over the years, a variety of researchers have used the case study to demonstrate new techniques, often adding complexity without changing the fundamental nature of the problem (Farmani et

al., 2005; Murphy et al., 1994; Walters et al., 1999b). Continued relevance and evolution are testaments to the initial proposal and design of the model. To this day, Anytown remains a vehicle for WRSO innovation, including being used in a recent six-objective MOEA study (Fu et al., 2013).

Another example of a generic case study supporting MOEA experimentation is “the lake problem”, which models the dynamics associated with lake eutrophication and was originally introduced in 1999 (Carpenter et al., 1999). In the model, a city must make a series of decisions about how much phosphorous to discharge into a shallow lake in light of conflicting management priorities. The problem is interesting and broadly relevant because it demonstrates the implications of interdependent decisions over time, multiple equilibria, and performance thresholds that often arise at the interface of human activity and ecological systems (Grüne et al., 2005). It has recently been used to: demonstrate Many-Objective Robust Decision Making (MORDM) (Singh et al., 2015); explore the implications of constraints on MOEA search behavior (Clarkin et al., In Review); and combine direct policy search with the concept of environmental tipping points (Julianne D. Quinn et al., 2017).

Anytown and the lake problem provide researchers the ability to develop and combine WRSO tools and techniques for water distribution and environmental water quality with complete creative freedom. The benefits that come with this license have not been realized for multireservoir supply systems, though, because there is no generic case study. Multireservoir supply planning problems offer particularly rich opportunities for WRSO research to enhance traditional processes and outcomes because they are spatially distributed and often involve multiple sources of water, competing uses, and complex interactions within the system and with external actors and regulations (Labadie, 2004).

This chapter introduces the Eldorado Utility Planning Model, a generic case study that focuses on the long term planning of one utility within a regional context and is based on conditions on the Front Range of Colorado. Like many areas of the southwestern and western U.S., the Front Range is projecting vigorous population growth in the coming decades (State of Colorado, 2017). Also like much of the southwestern U.S., it is water supply-limited and highly dependent on snow pack to meet demands

(Rajagopalan et al., 2009). Climate change is expected to increase regional temperatures but the impacts of those increases and the altered precipitation patterns on timing and magnitude of streamflow are unclear (Lukas et al., 2014). On top of seasonal and interannual variability, uncertain climate change impacts, and growing demands, the Front Range operates within a strict regulatory environment. The supply and management decisions that Front Range water providers face are extremely complex and highly interdependent on each other as well as on future streamflows. These are the types of planning conditions in which the insights provided by MOEA-derived analyses may prove critical to better understanding of current and future water security issues.

The major elements of this case study – the model and the MOEA problem formulation (explained in the *MOEA-assisted Optimization* section) – were developed through direct, structured input from 11 Front Range water managers (Smith et al., 2017) as well as iterative feedback from a subset of those managers. This process produced relatable results that are communicable to a broad practitioner audience and avoids limiting the configuration and output to a specific utility’s interests. Thus, this case study extends MOEA-assisted optimization to a new geographic region while facilitating innovation and dissemination of MOEA research. In short, development and use of the Eldorado Utility Planning Model represent a new paradigm for extending multireservoir WRSO research within academia and beyond.

3.2 Background

3.2.1 MOEA-assisted Optimization

Multiobjective Evolutionary Algorithm (MOEA)-assisted optimization is a technique that employs a search algorithm to explore how portfolios of inter-related decisions impact conflicting performance objectives in complex systems. There are four components of the technique: the MOEA, a simulation model, a problem formulation, and visualization of results. There are several choices for state-of-the-art MOEAs; this study uses the Borg algorithm (Hadka and Reed, 2013) which has been shown to perform favorably on challenging problems (Reed et al., 2013; Zatarain Salazar et al., 2016).

The problem formulation consists of a set of decision levers, objectives, and constraints. Decision levers are the set of options available to a water utility to improve its current supply system or operations, e.g. building a reservoir or enacting conservation. Objectives are measures of performance that quantify the utility's planning goals, e.g. minimizing frequency of restrictions. Constraints are limits to acceptable performance, e.g. maintaining at least 90% of annual demand in storage.

The MOEA intelligently searches for portfolios (sets of decision levers) that perform well across all objectives by feeding portfolios to an embedded simulation model and evaluating output from the model based on the user-defined objectives and constraints. The search process produces a set of non-dominated portfolios (in which every portfolio performs better than another in at least one objective, but no portfolio performs better than another in all objectives) that together quantify the tradeoffs between conflicting objectives. MOEA results are high-dimensional in that there are many relationships between decisions and objectives that are best understood when viewed together, and this fact prompts the use of visual analytics such as interactive parallel plots (Fleming et al., 2005; Jones, 2014) or glyph plots (Kollat, 2015; Kollat and Reed, 2007).

3.2.2 Practitioner Input on Model and Problem Formulation

The Eldorado Utility case study was created as part of a larger participatory research effort. That process, termed the Participatory Framework for the Assessment and Improvement of Tools (ParFAIT), engaged Front Range water managers from six utilities to evaluate whether MOEAs would be useful to their agencies and identify future research avenues to increase their value to practitioners. Details beyond the brief content below can be found in Smith et al (2017).

In February, 2015, researchers held a workshop with 11 Front Range water managers to solicit their input on the Eldorado problem formulation and model features. It is widely recognized that defining the problem formulation is a critical aspect of using an MOEA (Kasprzyk et al., 2012; Loughlin et al., 2001; Reed and Kasprzyk, 2009), and researchers increasingly incorporate practitioner input into the process (Mortazavi et al., 2013; Wu et al., 2016b). For each element of the problem formulation,

researchers and practitioners engaged in open-ended discussion and brainstorming to determine a variety of decision levers, objectives, and constraints that combined their individual utilities' experiences as well as their shared wisdom. Their ideas, mixed with some novel research concepts, are incorporated in this study's problem formulation, described in the *Optimization Configuration* section.

To produce reliable, relevant optimization results, the simulation model embedded in MOEA search must credibly represent reality, even when the model is hypothetical. At the workshop, the group of managers suggested aspects of their systems and their regional management context that would need to be represented for them to be able to engage with optimization results at a second workshop. Almost all of these features are represented in the model description in the *Eldorado Utility Planning Model* section.

3.2.3 The Front Range of Colorado

The Front Range region of Colorado is an urban corridor located just east of the Rocky Mountains that encompasses several mid-sized cities and many smaller communities. The mountain range runs north and south, forming the continental divide, and is a significant physical, hydrologic, and political demarcation within the state. Like other regions in the Western U.S., Colorado is experiencing rapid population growth; the number of residents on the Front Range is forecasted to increase by 70% by 2050 (State of Colorado, 2017). Currently, 80% of the state's population lives on the East Slope of the mountains, with only 30% of the surface water supplies (State of Colorado, 2015). Since the early 1900s there have been more claims on the East Slope rivers than can be met in most years (Caulfield Jr. et al., 1987; P. O. Abbott, 1985). A result of this disparity is that around 72% of the water used by Front Range cities comes from transmountain diversions (TMDs), or water imported from basins on the West Slope through large infrastructure projects or water wholesalers ("Colorado Springs Utilities 2014 Water Tour," 2014).

All of Colorado's major rivers begin in the Rocky Mountains, above 8000 feet, and are primarily fed by snow that falls from October through May. Because the water provided by snowpack melts within a two-month window, users in Colorado (as in many Western U.S. states) depend heavily on storage in

both snowpack and reservoirs to meet demands throughout the year (Rajagopalan et al., 2009). On top of the seasonal precipitation variability, the region experiences high inter-annual streamflow variability, making reservoirs even more crucial to ensuring water availability for economic, agricultural, and ecosystem health (Doesken, 2014).

Impacts of climate change in Colorado could result in anywhere from 1.4 to 3.6°C temperature increase by 2050 relative to the 1970-2000 baseline. The projected changes in precipitation are less clear; under a medium-low emissions scenario, Colorado could see anywhere from -15% to +25% change in precipitation depending on hydrologic region and time of year (Lukas et al., 2014). However, increases in precipitation may not fully offset increases in temperature; more evapotranspiration and lower soil moisture may result in decreased streamflow despite more precipitation (Udall and Overpeck, 2017; Woodbury et al., 2012).

In Colorado, as in most of the western U.S., water use is tightly regulated by the prior appropriation doctrine (Hobbs, 2004). The right to use water is granted to entities by the state based on the date of first use; is for finite amount of water; and is legally bound to a specified purpose and location. The earlier in time that a right was granted, the more senior it is, and senior users take the full amount of their right before juniors can take any water. This means that, except in high streamflow years, many junior rights in Colorado do not receive their full allotment (i.e. a water right does not guarantee a specific yield). Water rights can be granted for diversion from the stream for direct application to their purpose (a specified flow rate), they can be storage rights (with a maximum annual volume of storage), or they can be instream rights, where a designated flow rate must be present at a specified point in the river. In Colorado, agricultural users own the vast majority of senior water rights.

As their populations increase and streamflow potentially decreases, municipal water utilities in Colorado are seeking to increase their supplies and manage growing demands. Building new storage may offer inter-annual security (if it can be filled), but it is also very expensive, difficult to permit, environmentally disruptive, and potentially socially unpopular. Buying senior water rights from other

users (e.g. farmers) could greatly increase supplies, but without storage, the timing or location of their availability may not be practical, and transferring water away from other users can cause social, economic, and environmental hardship in their communities. Conservation is an important tool for balancing supply and demand, but it can reduce utility revenues and lead to rate increases or reduced adaptation capacity (Leurig, 2010). Given the challenging regulatory environment, complex interactions between decisions, and broader impacts of utilities' choices, innovative decision support tools could greatly advance long term water planning in Colorado.

3.3 Eldorado Utility Planning Model

In order to represent the reality that most Front Range water suppliers draw water from multiple basins and through multiple mechanisms, the Eldorado Utility Planning Model is regional in scope. It has two major basins, one on the western slope of a mountain range and one on the eastern slope. Each of these basins is made up of sub basins that have multiple types of competing users (agricultural, municipal, industrial, and instream flow) and infrastructure. Each user has one or more priority dates that dictate their places in line to divert or store water (or maintain instream flow). Each diverter or reservoir also has a specific location in the basin that its unconsumed water (return flows) or releases re-enter the stream system. The spatial distribution of diversions, storage, and return flows as well as the temporal distribution of water right priority dates are critical for capturing the extremely complex implications of making long term water supply decisions on the Front Range.

Because the spatial and temporal relationships are so intricate, this case study uses the RiverWare modeling platform (Zagona et al., 2001). RiverWare is a generalized river system modeling tool with advanced features and a graphical user interface (GUI) to facilitate organization and analysis of model relationships and performance. Critically, RiverWare uses a policy language that allows modelers to create customized operating and ownership rules to capture complex system dynamics. Equally important are the platform's advanced accounting functions which can allocate limited available water to different users based on priority dates, and also keep track of which return flows are reusable. Reusable water

sources are a critical component of Colorado water management; their potential yields are greater than single-use sources, but they also present spatial and temporal complexities that drive decision making and thus reusability must be carefully modeled. Finally, RiverWare is an example of the type of sophisticated decision support tools used by many water utilities. Smith et al. (2016) linked an MOEA with the legacy RiverWare model of a Texas utility to improve the operations of a large multireservoir system. This study builds on the work of Smith et al. but uses the Eldorado Utility Planning Model to generically capture Front Range, Colorado, water management context and demonstrate techniques that are broadly applicable to other systems.

Going forward, the schematic in Figure 3-1 will be a reference point to describe the Eldorado Utility system, as well as other model features and their significance in more detail.

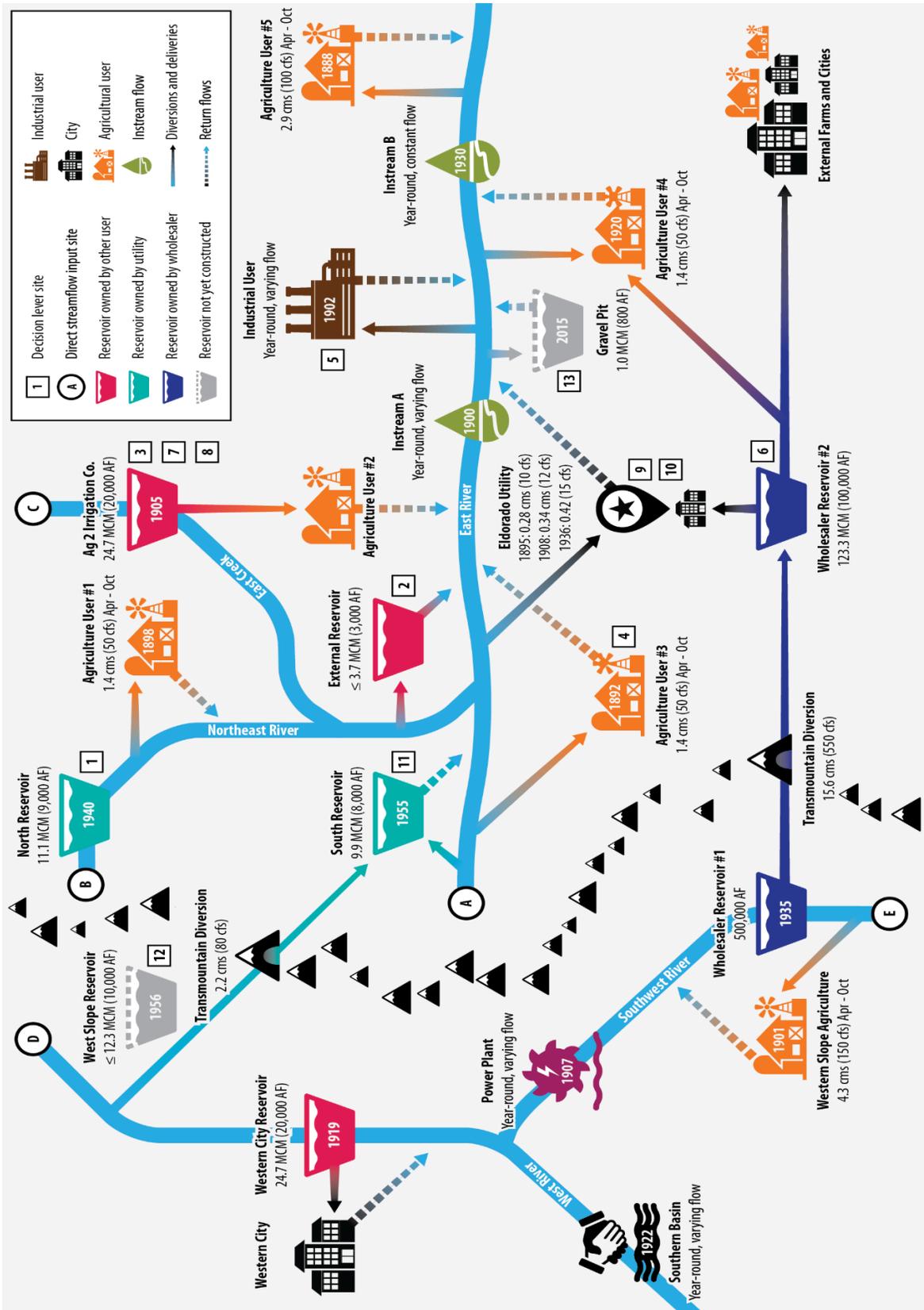


Figure 3-1. Diagram of the Eldorado Utility Planning Model's regional water supply network.

3.3.1 Hydrologic Model Inputs

The model runs at a monthly timestep and has five headwater streamflow input sites, represented by white circles in Figure 3-1. Streamflow in Colorado is primarily snowmelt-dependent, and different watersheds across a region often exhibit strong relationships because of similar annual snow volumes and runoff patterns. Therefore, streamflow inputs needed to be temporally and spatially correlated. To achieve this for synthetic flow sequences, natural historic monthly flows at five Colorado headwaters sites were summed to annual and then regional flows (Lins, 2012; Woodbury et al., 2012). Historic regional annual flow volumes were sampled using a Lag1 K-NN bootstrap technique (Lall and Sharma, 1996), then disaggregated spatially and then temporally to monthly flow at each site via Nowak's proportions method (2010).

Table 3-1. List of geographic locations, data sources, and historic magnitudes of the streamflow inputs used in the model.

Site Name	Model Site (Figure 1 label)	Data Source	USGS Gage #	1950 – 2005 Mean Annual Natural Flow
Boulder Creek near Orodell	East River (A)	Woodbury et al (2012)	06727000	87.8 MCM (71,169 AF)
Middle Boulder Creek at Nederland	Northeast River (B)	Lins (2012)	06725500	49.3 MCM (39,970 AF)
Bear Creek at Morrison	East Creek (C)	Lins (2012)	06710500	42.9 MCM (34,753 AF)
Fraser River at Granby	West River (D)	Woodbury et al (2012)	09034000	187.4 MCM (151,963 AF)
Upper Colorado River at Granby	Southwest River (E)	Woodbury et al (2012)	09019500	334.3 MCM (270,989 AF)

3.3.2 Eldorado Utility

The Eldorado Utility is a small eastern slope municipal water provider for a hypothetical city whose system features and demands are based loosely on real cities. It currently serves 100,000 customers with an average customer use of 550 liters per capita per day (Lpcd) (145 gallons per capita per day – gpcd). This use translates to approximately 20 million cubic meters (MCM) (or 16,200 acre feet – AF) of annual demand if no use restrictions are imposed. The predominant demand pattern is single family

residential, so demand increases substantially during summer months for outdoor ornamental landscape irrigation (31% of total annual use serves these outdoor purposes). The model differentiates between indoor and outdoor use when calculating actual water consumption, where 95% of indoor use returns to the stream and 15% of outdoor use returns to the stream.

To meet current demands, Eldorado owns three eastern slope direct streamflow diversion rights, one transmountain diversion right (transferred under the mountains from the western slope to the eastern slope), two eastern slope reservoirs, and 10,000 wholesaler shares (shares are a term for fixed yields of water provided through the infrastructure and management of an entity other than Eldorado). All diversion and storage water used by the utility is taken from the stream just below the confluence of the Northeast River and the East River. The three diversion rights for 0.28, 0.37, and 0.42 cubic meters per second (cms) (10, 12, and 15 cubic feet per second, cfs) have a range of seniority, from the third most senior date of 1895 to the fourth most junior date of 1936, all from the East River. The 1956 transmountain diversion (TMD) right is the most junior right and brings water from the West River under the mountains to be stored in the South Reservoir (SouthRes), which is owned by Eldorado. SouthRes can hold up to 9.87 MCM (8,000 AF) of eastern or western slope water, and collects East River water in offstream storage with a 1955 priority date. The two sources for this reservoir compete for space, limiting the yields of both rights. Eldorado's North Reservoir (NorthRes) is an 11.1 MCM (9,000 AF) onstream reservoir that stores Northeast River water with a 1940 priority date. The Wholesaler shares are collected on the western slope and stored on both slopes, and Eldorado draws its shares directly from the eastern slope Wholesale Reservoir.

TMD water is Eldorado's only current source of reusable water; whenever the utility uses this water to meet demands, the resulting unconsumed return flows can be re-used to extinction either by some form of direct reuse, storage for later use, or an exchange mechanism as long as no intervening senior rights are injured. However, with no downstream ability to capture the reusable flows or any

upstream location to store this water, the exchanged reuse must occur concurrently with the return flows. Such conditions are rarely met, so this reusable source is underutilized.

3.3.3 Other model features

Including the utility, there are nine different water users on the eastern slope of the mountains. The diversion and return flow points for the other water rights holders are often disadvantageous for Eldorado. Eldorado's two reservoirs are the farthest upstream water rights, and also the most junior, so eight other senior users draw water away from them for much of the year. For example, Agriculture User #1 is located directly downstream of NorthRes on the Northeast River; the farmer has a growing season diversion right (April 1 through October 31) that draws water down the river that Eldorado wants to store. Another example is Agriculture User #3, who during the growing season diverts water immediately downstream of SouthRes on the East River. This user also has a return point that is inconvenient for the utility; it is just downstream of Eldorado's diversion point, meaning the farmer's unconsumed water cannot increase streamflow at a location that benefits the utility's opportunity to divert its junior rights. Similarly, Eldorado's return flow point is just downstream of the 1900 priority date instream flow right, so the utility's unconsumed water does not help to meet that flow requirement. All of the other users' priority dates and diversion and return flow points create additional complicated stream dynamics and challenge Eldorado's ability to access the limited water supply.

Because Eldorado also gets water from the western slope via its TMD and Wholesaler shares, the model is designed to constrain those sources as well. The Eldorado TMD and the Wholesaler's collection reservoir are junior to all of the other water rights on the western slope; these storage, diversion, and instream flow requirement rights limit the yields of the utility's sources. The details of all water users are shown in Figure 3-1.

Between the two slopes of the model, Eldorado has access to 5 different watersheds and competes with 12 other users (some of which are also represented in the *Decision Levers* section as potential supply sharing partners for the utility). Flow magnitudes shrink and grow at various points along the streams'

lengths, and the hydrology varies by basin, season, and year. The priority system, not only physical availability, dictates which users get water and when. Though scaled down, these model characteristics are representative of the conditions faced by many utilities on the Front Range and around the western U.S. The model was inspired by input from water managers at a workshop as well as real utilities' systems, and the complexity was necessary to make it credible to participants in an MOEA assessment workshop built around the Eldorado Utility case study. Future MOEA-practitioner studies may also take advantage of this credibility.

3.3.4 Planning for Eldorado's Future Population while considering Potential Impacts of Climate Change

The water supply system described above is deliberately designed to provide more than enough water in most years to meet Eldorado Utility's current demands under historic hydrology. With an average use of 550 Lpcd (145 gpcd) and 100,000 customers, the utility's current unrestricted demands are 20 MCM (16,200 AF) per year. However, Eldorado is a desirable place to live with a strong economy and has projected a 40% population increase by 2050, after which the population is expected to level off (it will have reached projected buildout conditions). If per capita use stays constant, 140,000 people would use 28 MCM (22,700 AF) per year. The firm yield of Eldorado's current supplies is only 22 MCM (17,800 AF) per year given historic hydrologic conditions, so the utility needs to start taking action to secure future water supplies now if it wants to have enough for its buildout population.

Climate change is already increasing regional temperatures. While the impacts of climate change on streamflows are uncertain, the increased temperatures will result in higher evaporation from reservoirs and greater lawn irrigation demands. Exploring long term plans designed for historic streamflow and demands will not provide adequate information for future system performance, so Eldorado is using perturbed supply and demand conditions from a 4°C -warmer future to bound and inform scenario development. Front Range climate change studies have shown this to be a plausible future (Woodbury et al., 2012). The utility estimates that this future would cause a 10% increase in per-capita demand (a new

average of 606 Lpcd (160 gpcd)), resulting in an unrestricted annual demand of 31 MCM (25,000 AF). Evaluation of Eldorado's current system using hydrology perturbed by a 4°C temperature increase shows a firm yield of 19.9 MCM (16,100 AF) per year. Table 3-2 summarizes the system statistics.

Table 3-2. Information about Eldorado's historic consumption, projected demands, and system yield.

Hydrologic Scenario	Historic	+4°C
Avg per capita Use w/o Conservation	550 Lpcd (145 gpcd)	606 Lpcd (160 gpcd)
Unrestricted Annual Current Demand (pop. = 100K)	20 MCM (16200 AF)	---
Unrestricted Annual Buildout Demand (pop. = 140K)	28 MCM (22700 AF)	31 MCM (25000 AF)
Current System Annual Firm Yield	22 MCM (17800 AF)	19.9 MCM (16100 AF)

Eldorado has three levels of drought response that restrict outdoor water use. The different levels of restrictions are triggered by a storage-to-long term demand relationship (see Equation 3-4). The impacts of the three levels of restrictions are given in Table 3-3.

Table 3-3. Description of Eldorado's three restriction levels and their estimated demand reductions.

Restriction Level	Resulting Indoor Use	Resulting Outdoor Use
1	100%	80%
2	100%	50%
3	100%	0%

Eldorado's governing board has determined that the utility must meet certain supply reliability criteria (i.e. they must meet demands at a certain level). The criteria are:

1. Eldorado must not go into Level 1 Restrictions more than 5 times in 25 years;
2. Eldorado must not go into Level 2 restrictions more than 1 time in 25 years;
3. Eldorado must never go into Level 3 restrictions.

The planning problem described in this section is generic but representative of the context of many western U.S. cities. Using traditional planning methods, they would likely pursue a few options that simply *meet* the criteria. However, now that MOEAs have made substantial gains in research applications and seen successful applications by Colorado utilities, researchers should explore how to effectively

formulate multiobjective optimization problems in light of future real-world users. The following section defines the problem formulation developed with input from Front Range water managers (Smith et al., 2017).

3.4 Optimization Configuration

Recall from the *Background* section that the problem formulation is one of the four major components of MOEA-assisted optimization. Carefully defining the set of decision levers, objectives, and constraints, is as important as the simulation model to producing useful results.

3.4.1 Decision Levers

Eldorado has 13 decision levers available to address its looming water supply gap. The levers fall into three categories: Enhancing Operations, Acquiring Supply, and Building Storage. The levers described below and their complex interactions with each other were incorporated in response to workshop input from water managers and are directly comparable to the decision spaces that real Front Range utilities operate within (Smith et al., 2017). Table 3-4 summarizes the levers described below.

3.4.1.1 Enhancing Operations

This category includes levers that increase Eldorado's operational flexibility. The first lever is *Exchange*, which, when chosen, gives Eldorado the legal right to trade its reusable return flows from their downstream return location to an upstream reservoir. The *Exchange* can only operate when the trade will not injure other water rights holders. To facilitate the trading, Eldorado can lease firm (designated) space in an existing reservoir belonging to an unmodeled external user, through a lever called $LeaseVol_{XRes}$. XRes is located halfway upstream between Eldorado's return point and NorthRes, and, importantly, downstream of Agriculture User #1. When this farmer's right is in priority, Eldorado can store reusable water in XRes until there is opportunity to trade it up to NorthRes. The amount of XRes storage space available is determined by the volume specified by the $LeaseVol_{XRes}$ lever. Another place Eldorado can choose to store reusable return flows is in the Ag2 Irrigation Company reservoir (Ag2Res). If $Lease_{Ag2Res}$

is turned on, Eldorado has access to available space in Ag2Res. This is not a fixed volume; it is subject to availability.

3.4.1.2 Increasing Supply

These levers are non-infrastructure actions that Eldorado can take to increase the amount of water available to put toward meeting demand. The utility can choose to buy water from Agriculture User #3 (Ag3) using the lever $Rights_{Ag3}$. Ag3 has a high-seniority right just below SouthRes on East River. Eldorado can buy up to 20% of this 1.4 cubic meters per second (cms) (or 50 cubic feet per second- cfs) right and store it in SouthRes (after preserving the historic return flow patterns of the farmer's original usage). Eldorado can also choose to buy up to 20% of Industrial User's downstream, mid-seniority right through the $Rights_{Industrial}$ lever. After preserving Industrial's historic return flow patterns, Eldorado may divert the rest of the water directly from the stream. Both of these sources are reusable.

In addition to water rights, Eldorado may also acquire shares of other user's water. The utility may add up to 6,000 additional Wholesaler shares to its current stock of 10,000 via $Shares_{Wholesaler}$. Each share yields approximately 863 cubic meters (0.7 AF) per year, and due to Wholesaler policies, this water is not reusable. The Ag2 Irrigation Co. also operates based on shares; currently they are all owned by Ag2 farmers, but Eldorado may purchase up to 10,000, each of which yields approximately 617 cubic meters (0.5 AF) per year. That yield is reduced by the amount of water necessary to preserve the farmers' historic return flow patterns, but the water is reusable. Another supply mechanism to help Eldorado recover from droughts is temporarily leasing additional shares from Ag2 Irrigation Co. These shares are "interruptible" because the utility may activate them in any given year when facing low storage conditions. The $Shares_{Interruptible}$ lever may option up to 10,000 shares.

Two other levers Eldorado may use to increase available supply are to conserve water and to increase distribution efficiency. Long term conservation measures free up water that would have otherwise not been available to meet future demand, so it is a way to increase supply. $ConsFactor$ may be set to no conservation, moderate, or aggressive conservation. Increasing distribution efficiency by, e.g.,

improving metering or fixing leaks, also reclaims previously-unavailable water. *DistEff* is currently at 90%, but may increase to up to 93% depending on the value of the lever.

3.4.1.3 Building Storage

Eldorado has three possibilities for adding permanent storage to its system. It may expand SouthRes from 9.87 MCM (8,000 AF) to up to 12.3 MCM (10,000 AF), so *ExpandVol_{SouthRes}* may be 0 – 2.47 MCM (0 – 2,000 AF). Adding this volume would create more space to store the 1955 East River right, the TMD right, and, potentially, the Ag3 right; all of these sources compete for space in SouthRes. Eldorado can also choose to build a West Slope reservoir (WestSlopeRes), which would store the TMD right on the western slope until it could be stored locally in SouthRes or used to meet demands. *BuildVol_{WestSlopeRes}* may be 0 – 12.3 MCM (0 – 10,000 AF). Finally, Eldorado can choose to develop gravel pits located downstream of its return point. When *GP* is on, the utility has 0.99 MCM (800 AF) in which to store reusable return flows that can help to meet historic return flow patterns or be exchanged upstream.

Table 3-4. Summary of decision levers available to Eldorado. The numbers in “Figure 1 Label” refer to numbered features in Figure 3-1 to orient readers to decision lever locations.

Figure 1 Label	Decision	Description	Units	Range
Enhancing Operations				
1	Exchange	Acquire right to exchange reusable return flows to NorthRes	---	0 - 1
2	LeaseVol _{XRes}	Pay owners of XRes to lease dedicated space that can facilitate Exchange	MCM (AF)	0 – 3.7 (0 - 3,000)
3	Lease _{Ag2Res}	Pay Ag2 Irrigation Co. to store water in any available unused space; 0 = off, 1 = on	---	0 - 1
Increasing Supply				
4	Rights _{Ag3}	Purchase a portion of Ag3’s senior diversion right	%	0 - 20
5	Rights _{Industrial}	Purchase a portion of Industrial user’s mid-seniority diversion right	%	0 - 20
6	Shares _{Wholesaler}	Purchase additional shares of Wholesaler water	shares	0 - 6,000
7	Shares _{Ag2}	Purchase shares of Ag2 Irrigation Co. water	shares	0 - 10,000
8	Shares _{Interruptible}	Negotiate agreement with Ag2 Irrigation Co. for optional supply leases	shares	0 - 10,000
9	ConsFactor	Reduce starting per capita demand through conservation measures; 0 = no change, 1 = 10% reduction, 2 = 20% reduction	---	0 - 2
10	DistEff	Improve distribution efficiency by reducing unaccounted-for water (e.g. fixing leaks, improving metering, etc.)	%	90 - 93
Building Storage				
11	ExpandVol _{SouthRes}	Expand SouthRes	MCM (AF)	0 – 2.47 (0 – 2,000)
12	BuildVol _{WestSlopeRes}	Build WestSlopeRes	MCM (AF)	0 – 12.3 (0 - 10,000)
13	GP	Develop gravel pits to store reusable return flows downstream of the city; 0 = not developed, 1 = developed	---	0 - 1

3.4.2 Performance Objectives and Constraint

The multiobjective optimization process involves evaluating an objective function, $\mathbf{F}(\mathbf{x})$, vector. Each value in the vector is calculated from a different performance objective, $f_{objective}$. The result of performing multiobjective optimization is a set of Pareto-optimal solutions (Pareto, 1896), where every solution is better than another solution in at least one objective (or, conversely, within the set, performance improvement in one objective is only possible by sacrificing performance in another). In this

optimization study, \mathbf{x} is the vector of values that define implementation levels of decision levers within Ω , the space of feasible lever values. Formally,

Equation 3-1

$$\mathbf{F}(\mathbf{x}) = (f_{RestLev1}, f_{RestLev2}, f_{RestLev3}, f_{MissedOpp}, f_{NewSupply}, f_{April1Storage}, f_{NewStorage},)$$

$$\forall \mathbf{x} \in \Omega$$

Equation 3-2

$$\mathbf{x} = \text{Exchange}, \text{LeaseVol}_{XRes}, \text{Lease}_{Ag2Res}, \text{Rights}_{Ag3}, \text{Rights}_{Industrial}, \text{Shares}_{Wholesaler}, \text{Shares}_{Ag2}, \\ \text{Shares}_{Interruptible}, \text{ConsFactor}, \text{DistEff}, \text{ExpandVol}_{SouthRes}, \text{BuildVol}_{WestSlopeRes}, \text{GP}$$

Subject to

Equation 3-3

$$c_{UnmetDemand} = 0$$

The only performance constraint in this optimization problem formulation, $c_{UnmetDemand}$, is that all planning portfolios must meet 100% of indoor demands. This requirement is intuitive because indoor water use is the highest priority type of demand, and the constraint was suggested by managers at the 2015 workshop from the first phase of this study (Smith et al., 2017).

Note that several of the objectives described below directly reflect managers' input from the above-mentioned workshop; performance objectives related to utilities' reliability criteria were considered most important, with utilities reporting a mixture of storage-based and restrictions-based measures. Cost was also emphasized, but the best way to use this highly uncertain measure within a strict mathematical optimization process was the subject of an interesting discussion (Smith et al., 2017). Further exploration of this topic can be found below the description of $f_{NewStorage}$.

The first three objectives, $f_{RestLev1}$, $f_{RestLev2}$, and $f_{RestLev3}$ are restrictions-based measures. As described in the *Eldorado Utility Planning Model* section, Eldorado has reliability criteria that are defined

by frequencies of three different levels of restrictions. The restriction level is determined by storage levels on April 1 of every year. Because Colorado has primarily a snowmelt-dominated system, a utility can reasonably predict the status of its resources for the upcoming year based on existing storage levels and snowpack on April 1. Year-long restriction determinations are standard practice in Colorado because going in and out of restrictions is undesirable due to numerous implementation difficulties and negative customer impacts.

Table 3-5 summarizes Eldorado’s restriction levels and the triggering storage thresholds:

Table 3-5. Storage-based triggers for restriction levels.

Current Storage-to-Long Term Avg Annual Demand	Restriction Level
$\geq 75\%$	0
$< 75\%$	1
$< 50\%$	2
$< 25\%$	3

where “Current Storage-to-Long Term Avg Annual Demand” is defined as

Equation 3-4

$$RestLev = \frac{\text{Total Water in Storage on April 1}}{\text{Long Term Unrestricted Annual Utility Demand}} \times 100$$

The three restrictions objectives are calculated as follows:

Minimize the number of years that Eldorado spends in Level 1 Restrictions:

Equation 3-5

$$f_{RestLev1}(\mathbf{x}) = E \left[\sum_{i=1}^Y y_{RestLev=1} \right]_t$$

Minimize the number of years that Eldorado spends in Level 2 Restrictions:

Equation 3-6

$$f_{RestLev2}(\mathbf{x}) = E \left[\sum_{i=1}^Y y_{RestLev=2} \right]_t$$

Minimize the number of years that Eldorado spends in Level 3 Restrictions:

Equation 3-7

$$f_{RestLev3}(\mathbf{x}) = E \left[\sum_{i=1}^Y y_{RestLev=3} \right]_t$$

where Y is the number of years simulated per t traces in the hydrologic ensemble. Expectation notation, $E[\]$, denotes that the average across the traces was used, and this aggregation method was used for all seven objectives. For the three restrictions-based objectives, once the average is taken, the values are rounded to the nearest integer with halves rounding up. This approach was taken in order to return whole numbers of years for frequencies of restrictions. \mathbf{x} is the vector of values that describe the set of decisions incorporated in the portfolio.

The fourth objective, $f_{MissedOpp}$, is a measure of how efficiently Eldorado's supplies and system components operate to meet demands. It is affected by whether the utility can capitalize on reusable water and also whether Eldorado acquires an overabundance of shares. As mentioned in the model description, in Colorado, some water can legally be reused to extinction. Recall that much of the water diverted by Eldorado (or any municipality) is not fully consumed. The rule of thumb used by one Front Range utility is that for every 1.23 thousand cubic meters (1 AF) of reusable water they have, they can get 2.46 thousand cubic meters (2 AF) of use out of it. Thus, acquiring reusable water is desirable, but it can only be taken advantage of with adequate infrastructure that can: capture it in strategic storage locations for exchange upstream in the system; control the timing of its release downstream (e.g. from a gravel pit

below a utility's return point); or make it available for specific applications such as non-potable irrigation. Additionally, some types of water options available to Eldorado are "use it or lose it". Though there are different operational implications for capitalizing on "use it or lose it" water sources versus reusable return flows, here they are combined for an overall system objective. To pursue efficient water usage and sourcing, Eldorado seeks to minimize the average annual volume of water that Eldorado had available but did not use:

Equation 3-8

$$f_{MissedOpp}(\mathbf{x}) = E \left[\frac{1}{Y} \sum_{i=1}^Y (Unused\ Shares_{Wholesaler_i} + Unused\ Shares_{Interruptible_i} + Lost\ Reusable\ Return\ Flows_i) \right]_t$$

Objective five, $f_{NewSupply}$, quantifies the amount of water that the utility obtains through acquisitions. It is a measure of how efficiently Eldorado meets its demands. The increasing population requires that the utility seek new supply and possibly mitigate the effects of a growing population by enacting conservation measures. Taking all possible acquisition and demand reduction actions would likely result in minimizing frequency of restrictions. However, there are several factors that influence utilities to not take every possible acquisition decision they can make, including limited funds, engaged communities, and environmental awareness (i.e. triple bottom line considerations). To represent Eldorado's desire to acquire water intelligently and avoid onerous demand management measures or efficiency efforts (which reduce utility revenue), Eldorado seeks to minimize the average annual volume of water "created" through: acquisition of water rights or shares, enactment of conservation, and pursuit of distribution efficiencies:

Equation 3-9

$$f_{NewSupply}(\mathbf{x}) = E \left[\frac{1}{Y} \sum_{i=1}^Y \text{(yield from: } Rights_{Ag3}, Rights_{Industrial}, Shares_{Wholesaler}, Shares_{Ag2}, ConsFactor, DistEff) \right]_t$$

The sixth objective, $f_{April1Storage}$, measures the amount of water Eldorado has in storage on April 1 of every year. This is a second reliability measure that emphasizes long term performance more so than the restrictions-based objectives which favor immediate performance of the system. Year-to-year carryover storage is critical for utilities in areas like the Front Range that have high interannual snowpack variability; they may seek to maintain, e.g., a year's worth of demand in storage in case of an upcoming drought of unknown duration. Reservoirs fill in spring when melting snow increases streamflow, and the stored water is used to meet demands over the winter when streamflow is low. In Colorado, April 1 is used as the approximate date of lowest reservoir volumes, so Eldorado wants to maximize the minimum April 1 storage-to-demand ratio over the course of a planning period:

Equation 3-10

$$f_{April1Storage}(\mathbf{x}) = E \left[y_{min} \left(\frac{Total\ Eldorado\ April\ 1\ Storage\ Vol}{Avg\ Long\ Term\ Annual\ Demand} \right) \times 100 \right]_t$$

The seventh and final objective, $f_{NewStorage}$, seeks to minimize the volume of storage built by Eldorado. Storage projects are difficult and expensive to permit, expensive to build with highly uncertain construction and operations and maintenance costs (at the conceptual phase typically used in long term planning), environmentally impactful, and can be socially controversial. For all of these reasons, limiting the amount of new storage in Eldorado's portfolio is desirable. Thus, Eldorado wants to minimize total volume of new storage:

Equation 3-11

$$f_{NewStorage}(\mathbf{x}) = \sum [ExpandVol_{SouthRes}, BuildVol_{WestSlopeRes}, (GP * 0.99 MCM)]$$

Note that GP is multiplied by 0.99 MCM (800 AF) because the GP lever is on/off or 1/0, but the volume added is 0.99 MCM (800 AF).

Using an approach informed by the work of Colorado Springs Utilities (Basdekas, 2014; CSU, 2017b), the combined effects of objectives five and seven are a surrogate for using monetary cost as a performance objective to measure the magnitude of infrastructure investments. There are several complications that accompany cost as an objective: choice of discount rate, confidence in the final lifecycle cost estimates of fully-planned projects, and cost comparisons of projects that are in different phases of study. This third issue is especially problematic; allowing projects to compete within the optimization based on essentially incomparable cost estimates could inappropriately disadvantage one or more projects because the algorithm cannot tell the difference between firm cost projections and those that are less refined. In any long term planning exercise, the infrastructure options being considered will almost certainly have different study-completion statuses.

Of course, cost *is* an important consideration for water utility planning; when combined with, e.g., a reliability objective, the optimization is trying to answer the question of whether one or more actions is “worth it”. In long term planning, that question can be answered indirectly, though, avoiding the problematic assumptions associated with defining and comparing monetary costs. The supply-demand imbalance has to be resolved in some way, likely through a mixture of non-infrastructure and infrastructure actions. This problem formulation allows the algorithm to differentiate these two types of levers by separating them into two objectives: minimizing supply created without new infrastructure and minimizing newly-built storage. This distinction provides a cost-like signal to the MOEA and can also lead to a more holistic exploration of system responses. The results of the optimization of *volume of storage* vs. *volume of supply* can be interpreted by human reasoning in a more nuanced assessment than the perspective of doing as few expensive projects as possible. Estimating lifecycle costs is a critical

component of any planning process and can be included as part of a portfolio evaluation and selection process at the same time that triple bottom line assessments are being weighed. Examples of this can be found in the *Results* section.

Table 3-6. Summary of performance objectives that Eldorado seeks to optimize.

Objective	Description	Impactful Levers
<i>RestLev1</i>	Minimize frequency of Level 1 restrictions over 25 years	all
<i>RestLev2</i>	Minimize frequency of Level 2 restrictions over 25 years	all
<i>RestLev3</i>	Minimize frequency of Level 3 restrictions over 25 years	all
<i>MissedOpp</i>	Minimize average annual volume of the sum of: return flows that Eldorado could have captured and reused, foregone Wholesaler shares, and foregone Ag2 and Interruptible shares	Exchange, LeaseVol _{XRes} , Lease _{Ag2Res} , Rights _{Ag3} , Rights _{Industrial} , Shares _{Wholesaler} , Shares _{Ag2} , Shares _{Interruptible}
<i>NewSupply</i>	Minimize average annual new water created by either conserving or acquiring rights and shares	Rights _{Ag3} , Rights _{Industrial} , Shares _{Wholesaler} , Shares _{Ag2} , Shares _{Interruptible} , ConsFactor, DistEff
<i>AprilStorage</i>	Maximize the lowest April 1 st storage-to-annual demand ratio during the 25-year simulation	all
<i>NewStorage</i>	Minimize the volume of newly-built storage in a portfolio	ExpandVol _{SouthRes} , BuildVol _{WestSlopeRes} , GP

3.4.3 Streamflow Ensemble

To stress the Eldorado Utility's supply system, synthetic hydrology was generated that incorporated streamflow impacts that could result from a 4°C warmer future. In 2012, the Joint Front Range Climate Change Vulnerability Study used downscaled CMIP3 temperature and precipitation projections from five General Circulation Models (GCMs) in hydrologic models to simulate the impact of the projections on Colorado streamflows. The results of the study were sets of monthly streamflow percentage change deltas for multiple sites in the state (Meehl et al., 2007; Woodbury et al., 2012). In that study, researchers applied the deltas from Sacramento Soil Moisture Accounting (SAC-SMA) modeling to historic monthly records from the five direct streamflow sites and then used the method described in the *Figure 3-1. Diagram* of the Eldorado Utility Planning Model's regional water supply network.

Hydrologic Model Inputs section to generate spatially and temporally correlated sequences with the perturbed monthly flows. Of the 100 sequences of monthly streamflow produced, each 25 years long, 10 were randomly chosen to be included in this study. A comparison of the historic and perturbed regional monthly average flow volumes is shown in Figure 3-2.

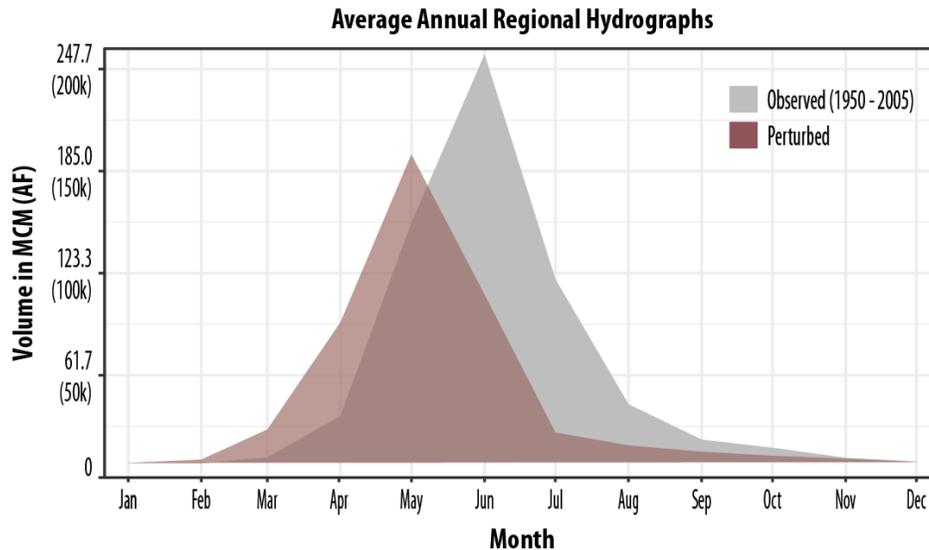


Figure 3-2. Plot of the average regional monthly flows for the 1950 – 2005 historic record and the 4°C-perturbed regional flows.

3.4.4 Computational Experiment

The RiverWare Eldorado Utility Planning Model was embedded within the search loop of the Borg MOEA (Hadka and Reed, 2013). Model runtime is approximately 20 seconds to simulate 25 years at a monthly timestep, during which 150 custom operating policies that support complex interactions between objects, accounts, and water types are iteratively applied. Each portfolio proposed by Borg was evaluated over the course of the 25 years as a fully-implemented configuration of Eldorado’s system (i.e. the utility’s system did not change over time). The performance of each portfolio was averaged across ten hydrologic traces which were distributed to 10 computing cores using RiverWare’s concurrent multiple run management functionality.

Optimization was performed using Amazon Web Services’ Elastic Compute Cloud (EC2) computing tier (Mathew and Varia, 2014). Based on the model’s long simulation time (relative to other

MOEA research applications) and a previous Borg-RiverWare study (Smith et al., 2016), researchers determined that 5,000 function evaluations would be sufficient to produce interesting and informative tradeoffs. Each optimization run took approximately 36 hours. This application of Borg made use of default settings for all parameters except for initial population size, which was changed from 100 to 50 so that evolutionary search would commence more quickly (Hadka et al., 2012; Reed et al., 2013).

3.5 Results

3.5.1 Exploration of Full Tradeoff Set

This study uses parallel axis plotting (Fleming et al., 2005) to present the nondominated solutions produced by optimizing the Eldorado Utility's system in a 4°C future. Parallel axis plots are useful for communicating high-dimensional data, and have been used in several recent optimization studies (CSU, 2017a; Herman et al., 2014; Rosenberg, 2015; Watson and Kasprzyk, 2017a). Viewing all nondominated portfolios together, in all objectives, makes it possible to see tradeoff relationships between the objectives. Showing all of the decisions that make up the portfolios along with the objectives' relationships further informs the viewer about how specific decisions, or combinations of decisions, affect performance. The utility of using visual analytics is demonstrated below.

Figure 3-3 (a) shows performance in seven objectives, each of which has a vertical axis. Each portfolio is represented by a line that connects across all of the axes, crossing each axis at the level of performance in that objective. In all objectives plots in this paper, lower positioning on an axis denotes better performance. Crossing lines between adjacent axes indicate conflicts, or tradeoffs, in those objectives. Each axis has a transparent "violin" that represents the distribution of portfolios' performances in the objective.

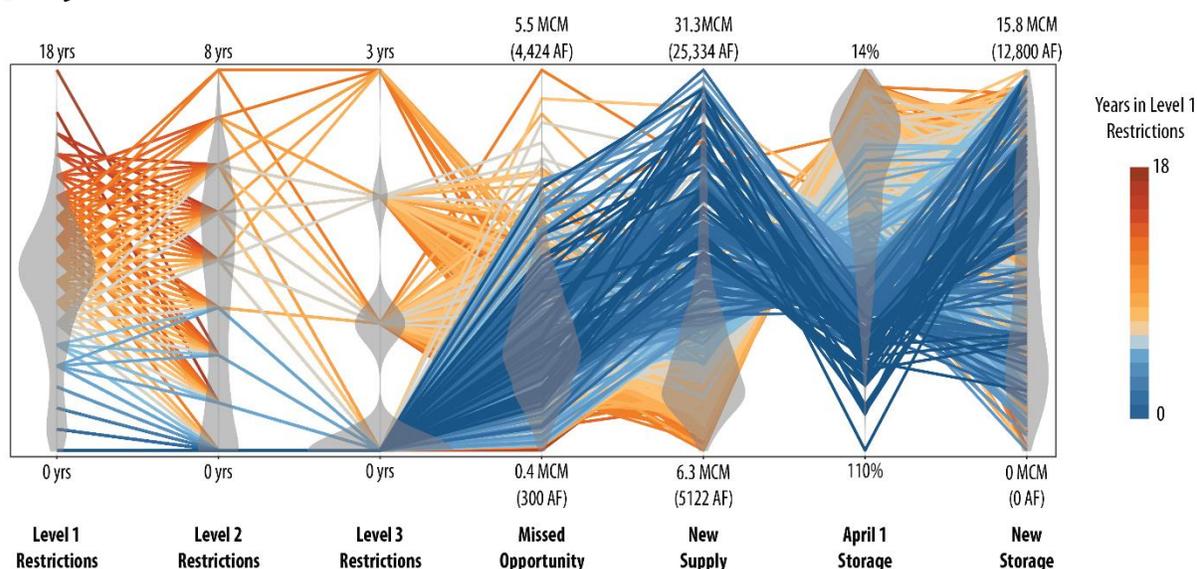
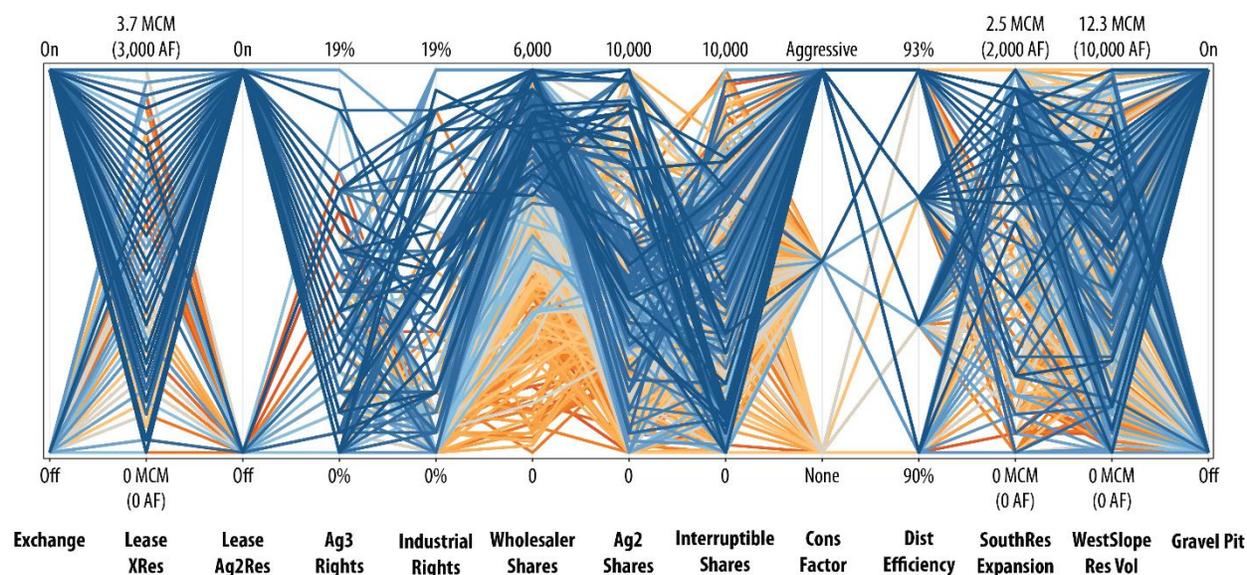
(a) Objectives**(b) Decision Levers**

Figure 3-3. Parallel plots of the full set of nondominated portfolios. In plot (a), vertical axes represent the 7 performance objectives, and a line for each portfolio connects across each axis to denote its performance (lower is better); transparent “violins” on each axis convey distribution of performance in each objective. In plot (b), vertical axes represent the 13 decision levers, and a line for each portfolio connects across each axis to denote the level to which each decision was incorporated (lower means “less” of a decision lever). Color corresponds to the number of years the portfolios entered Level 1 restrictions (performance in the leftmost objective).

Figure 3-3 (b) is configured similarly to Figure 3-3 (a) but the vertical axes now represent each of the 13 decision levers. The decision axes are in the same order as they were presented in Table 3-4: the

first three are operations-related, the next seven are supply-related, and the last three are storage-related. Again, each portfolio is represented by a line connecting across the axes, and the position at which the line crosses an axis denotes “how much” of that decision is included in the portfolio. For all decisions plots, the lower a line crosses an axis, the “less” of that lever is in the portfolio. Each portfolio line in Figure 3-3 (b) has a corresponding line characterizing its performance in Figure 3-3 (a).

In Figure 3-3 (a) and (b), color corresponds to the average number of years across all traces that a portfolio enacted Level 1 restrictions (the same performance that is represented on the leftmost axis); using color this way helps to identify major trends in the results. Portfolios that are dark blue have 0 years in Level 1 restrictions and dark red lines have 18 years. Given Eldorado’s current reliability criteria, which allow up to five years in Level 1, one year in Level 2, and zero years in Level 3 restrictions, all solutions that are a shade of blue are satisfactory.

Recall that Eldorado seeks to minimize its acquisition of New Supply, which is affected by levers that buy rights or shares, or conserve or increase distribution efficiency (which “free up” new water). In Figure 3-3 (a), the color gradient reveals a significant relationship between low frequency of Level 1 restrictions and the New Supply objective: the blue-colored portfolios are almost exclusively found between the middle to top end of the New Supply axis. In contrast, the large span of blue lines on the right-most axis indicates that there is not a strong relationship between minimizing restrictions and minimizing New Storage. These two results suggest that Eldorado may meet its reliability criteria without building *any* new storage, but must acquire at least 12.6 MCM per year (10,250 AF per year) of New Supply to be compliant. There is a tradeoff between New Supply and New Storage, though – portfolios that have less New Storage tend to make up for it with more New Supply, and vice versa.

The April 1 Storage objective which seeks to maintain long term storage levels does not conflict with Level 1 restrictions, but the crisscrossing lines between this objective and New Supply in Figure 3-3 (a) reveal a conflict; minimal New Supply will result in very poor performance in April 1 Storage regardless of the amount of storage added to the system. The grouping of orange lines on the bottom of

the New Supply axis vs at the top of the April 1 Storage axis also reflect this relationship. Conversely, the lines between April 1 Storage and New Storage do not always cross – long term storage reliability is possible for Eldorado even with small infrastructure investments as long as adequate New Supply is in place. In fact, portfolios with the maximum amount of New Storage (orange, at the top of the New Storage axis) but only medium levels of New Supply do not meet restrictions reliability criteria.

Several major characteristics of highly-reliable portfolios are apparent from Figure 3-3 (b). Refer to the *ConsFactor* axis, fifth from the right. In the plot, all blue lines are either in the moderate or aggressive category of conservation, so meeting reliability criteria requires conservation. A closer analysis that is not fully visible from the figure reveals that 232 of the 246 restrictions-compliant portfolios include aggressive conservation. Conserved water is counted as New Supply and can “create” over 6.17 MCM (5,000 AF) of new water per year. The other prominent attribute of highly-reliable portfolios is that they all include moderate to large numbers of Wholesaler shares; the clustering of blue lines on this decision axis (sixth from the right) shows that to meet reliability criteria, a portfolio must acquire at least 2,200 shares. Another finding is that all compliant portfolios selected one or more decisions to store reusable water. Though not visible in Figure 3-3 (b), detailed examination of the results reflects that portfolios use NorthRes and Xres (axes 1 and 2), or Ag2Res (axis 3), or both. This finding underscores the fact that improving system operations has a noticeable impact on long term planning performance.

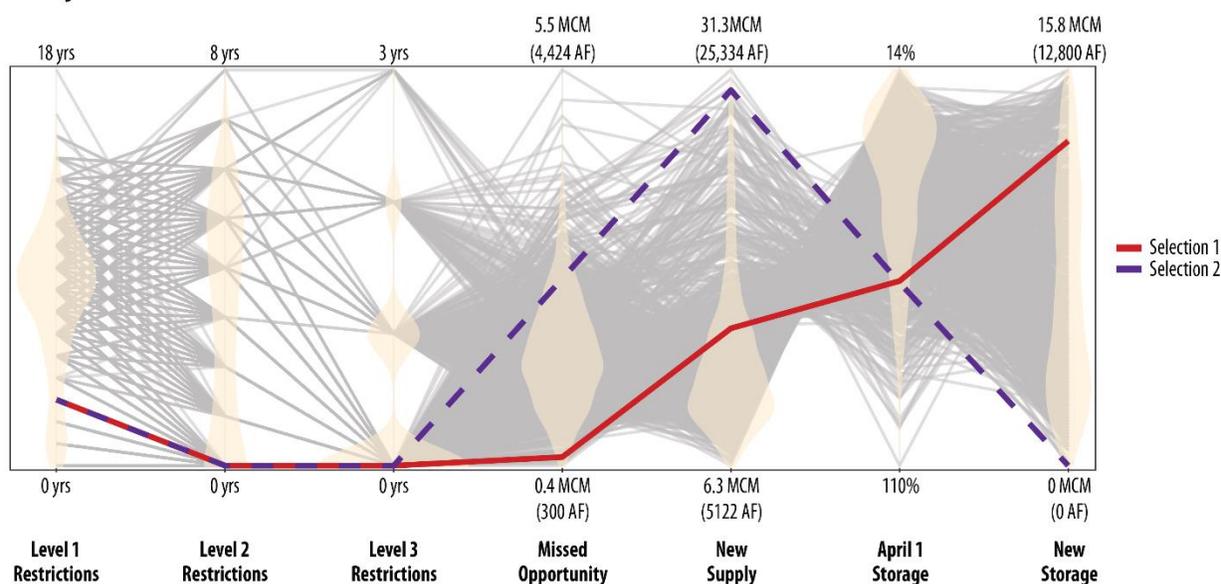
3.5.2 Further Exploration of Results using Comparisons of Individual Portfolios

Visualizing a full set of nondominated portfolios helps to reveal ranges of performance that are possible, relationships between objectives, and general decision lever trends. Examining individual portfolios and comparing them provides a more in-depth understanding of underlying system dynamics and an opportunity to combine human judgement with optimization search results. The next two sections will present two such examples.

3.5.2.1 Similar Reliability, Divergent Decisions

Figure 3-4 (a) and (b) show two highlighted portfolios in the format explained for Figure 3-3: performance tradeoffs in the top plot and decision characteristics on the bottom. Figure 3-4 (a) shows that Selection 1 (red) and Selection 2 (purple) have identical restrictions-based and storage-based reliability performance (see Table 3-7 for exact values) while in Missed Opportunity, New Supply, and New Storage they have very different performance. In Figure 3-4 (b), the two highlighted lines have very different patterns, signaling divergent decision lever values. With no difference in reliability, managers may use these two portfolios to explore preferences in other non-reliability objectives, as well as analyze the strategic and policy implications that the two different sets of decisions portfolios have for their systems.

(a) Objectives



(b) Decision Levers

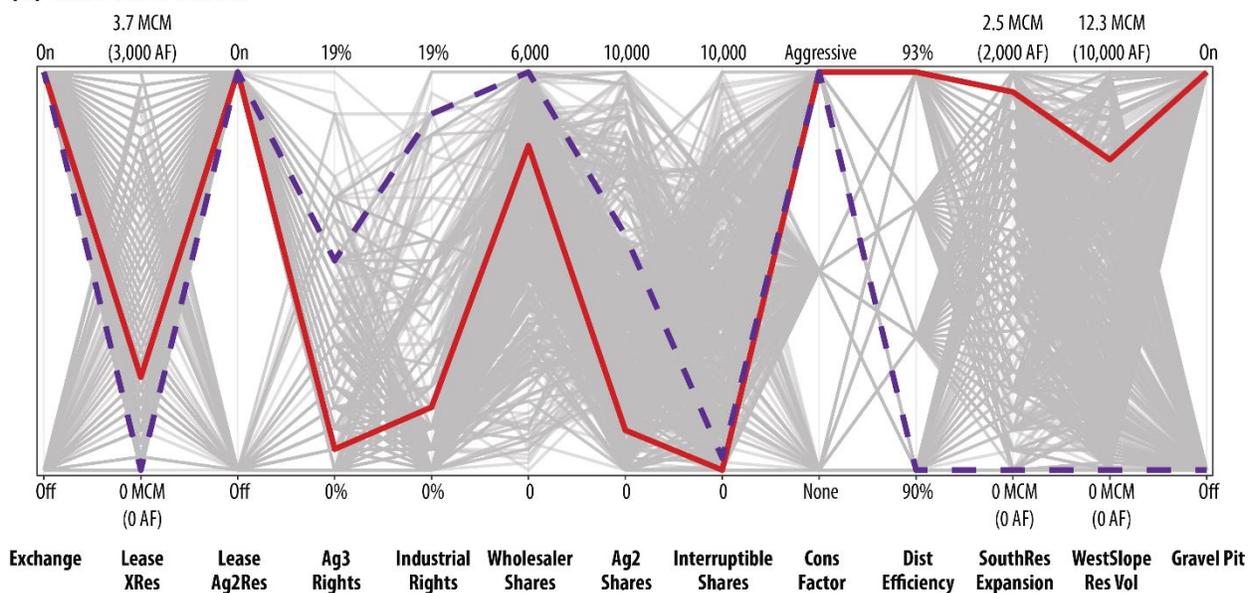


Figure 3-4 Parallel plots of two highlighted solutions. Plot (a) shows portfolio performance in the 7 objectives, and plot (b) depicts levels of the 13 decisions that make up each portfolio. The highlighted portfolios have similar reliability performance but divergent decisions that impact the three non-reliability objectives.

Table 3-7. Decision lever and objective values for Selections 1 and 2.

	Selection 1	Selection 2
Decision Levers		
Exchange	on	on
LeaseVol _{XRes}	0.86 MCM (700 AF)	0
Lease _{Ag2Res}	on	on
Rights _{Ag3}	1%	10%
Rights _{Industrial}	3%	17%
Shares _{Wholesaler}	4,890	6,000
Shares _{Ag2}	1,000	5,900
Shares _{Interruptible}	0	300
ConsFactor	aggressive	aggressive
DistEff	93%	90%
ExpandVol _{SouthRes}	2.34 MCM (1,900 AF)	0
BuildVol _{WestSlopeRes}	9.62 MCM (7,800 AF)	0
GP	on	off
Objectives		
<i>RestLev1</i>	3 yrs	3 yrs
<i>RestLev2</i>	0	0
<i>RestLev3</i>	0	0
<i>MissedOpp</i>	0.48 MCM (389 AF)	2.77 MCM (2,249 AF)
<i>NewSupply</i>	14.97 MCM (12,136 AF)	30.0 MCM (24,306 AF)
<i>AprilStorage</i>	65%	65%
<i>NewStorage</i>	12.95 MCM (10,500 AF)	0

Selections 1 and 2 demonstrate several Front Range performance and decision tradeoffs well. For example, some Front Range utilities have a positive view of new storage; they aren't trying to avoid infrastructure because storage that they own outright provides more security than other types of decision levers. Selection 1 would be promising for a utility with a pro-storage strategy because it incorporates a large WestSlopeRes and a large expansion of SouthRes. Relative to Selection 2, it relies less on Wholesaler shares, and much less on Ag2 shares and Industrial rights. This relatively large volume of New Storage and smaller volume of New Supply are reflected in the performance in Figure 3-4 (a).

Conversely, minimizing New Storage represents a distinct policy or strategy to avoid relying on costly and potentially contentious infrastructure to meet reliability criteria. Selection 2, which adds no new infrastructure, may be appealing from a monetary cost perspective. However, Selection 2 requires purchasing large amounts of shares and Industrial rights. The avoidance of infrastructure necessitates drawing more water away from nearby agriculture and industry, which will likely adversely impact those communities (thus incurring a high social cost). Additionally, in the case of Selection 2, less New Storage and more reusable New Supply results in a greater volume of Missed Opportunity water; this combination of decisions may not result in the most efficient use of resources.

Comparing the performances and decisions of Selections 1 and 2 shows that Eldorado has a wide range of paths toward achieving supply reliability. Drilling down to examine how the two portfolios behave within the simulation can offer more system response information. Figure 3-5 contains three plots: (a), (b), and (c) compare the two selections' non-Wholesaler storage volumes through time in three different hydrologic traces. As before, Selection 1 is shown in red and Selection 2 is shown in green.

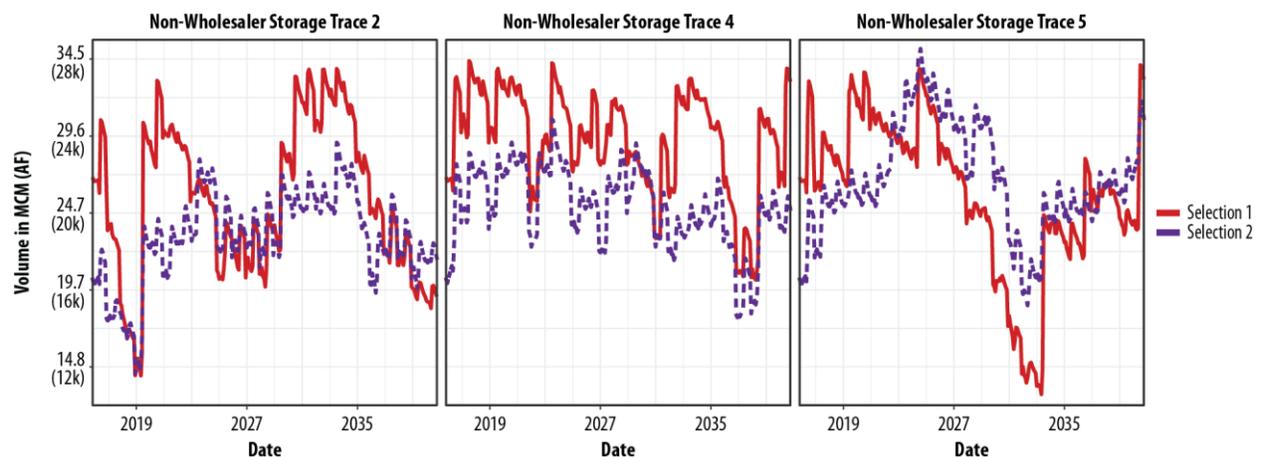


Figure 3-5. Comparison of the non-Wholesaler storage volumes over time for Selections 1 and 2. Plot (a) is the timeseries resulting from the simulation of hydrologic Trace 2, plot (b) is from Trace 4, and plot (c) is from Trace 5. Comparing the relative storage values of the two selections across the three traces shows that different sets of decisions can be more or less advantageous depending on hydrology and geography.

Despite Selection 1 building 12.95 MCM (10,500 AF) of new storage while Selection 2 builds none, the non-Wholesaler storage volumes do not always reflect the difference. In Figure 3-5 (a),

Selection 1 has for several periods approximately 9.87 MCM (8,000 AF) more water in storage than Selection 2, but for much of the 25 years the storage volumes are similar. Additionally, Selection 1's expanded storage does not prevent Eldorado from dipping far down into reserves during a multiyear drought beginning in 2017. In Figure 3-5 (b), however, Selection 1 frequently has at least 4.93 MCM (4,000 AF) more water in storage than does Selection 2. Then, in Figure 3-5 (c), storage volumes are similar again, with a nine-year span during which Selection 2 has more water in storage; indeed, in 2033, despite having approximately 60% more storage capacity than Selection 2, Selection 1 reaches a much lower minimum volume. This is because with the Selection 1 portfolio, Eldorado would rely more heavily on stored water to meet demand rather than shares and rights that contribute annually (even if their yields are reduced in dry years).

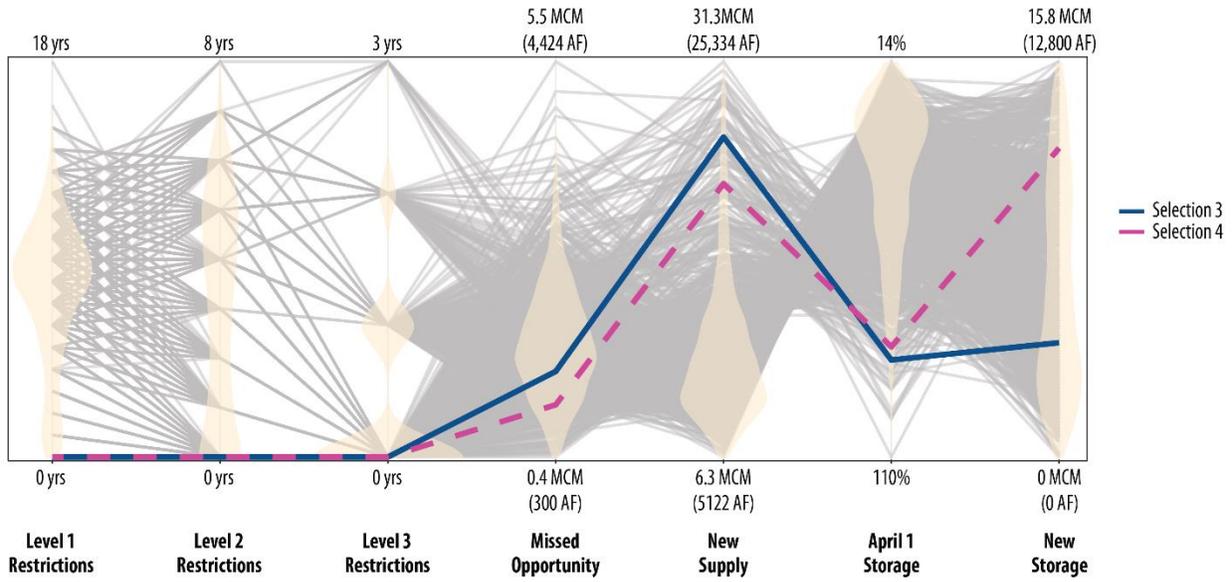
Though the 2 selected portfolios have identical average minimum storage levels across the 10 traces used in the optimization, being able to see the variation in the storage relationships between the two portfolios tells more of the story. On top of substantial interannual hydrologic variability in Colorado, Front Range water managers must also consider the fact that, despite frequent spatial correlation, basins do sometimes exhibit different patterns of relative abundance or scarcity of streamflow. Selection 1 builds storage that enables Eldorado to take greater advantage of its western slope water right (both WestSlopeRes and SouthRes can store that water). Selection 2 instead buys a large number of Ag2 shares (stored in Ag2 Res) and Industrial rights, so it has greater supply from East River and East Creek. The fact that these two approaches have similar reliability performance shows that either basin can provide secure supply, but the storage timeseries in Figure 3-5 suggest that a geographically-balanced approach to planning may offer the most consistent overall water supply.

3.5.2.2 Learning Through Objectives that go Beyond Cost and Reliability

The advantages gained by optimizing with non-traditional objectives can be demonstrated by comparing the two portfolios highlighted in Figure 3-6, which is oriented identically to Figure 3-4. In Figure 3-6 (a), Selection 3 (blue) and Selection 4 (purple) both result in zero years in all levels of

restrictions. Selection 3 has slightly higher April 1 Storage reliability than Selection 4, with a minimum 25-year storage-to-annual demand level of 86% vs. 83%. Selection 3 performs far better at minimizing New Storage: 4.56 MCM (3,700 AF) of newly-built storage versus 12.3 MCM (10,000 AF) in Selection 4. Based on this analysis, Selection 3, which has far less New Storage and slightly better reliability, would dominate Selection 4 in a strict cost versus reliability optimization. It is only the inclusion of minimizing Missed Opportunity Water and New Supply, where Selection 4 outperforms Selection 3, that enables the algorithm to find a portfolio with very similar reliability but a different portfolio approach and likely different policy implications. The tradeoff generated by minimizing New Supply and New Storage separately is especially significant because it explicitly directs the algorithm to search for portfolios tied to distinct policy approaches. Decision lever and performance attributes for these selections are presented Table 3-8.

(a) Objectives



(b) Decision Levers

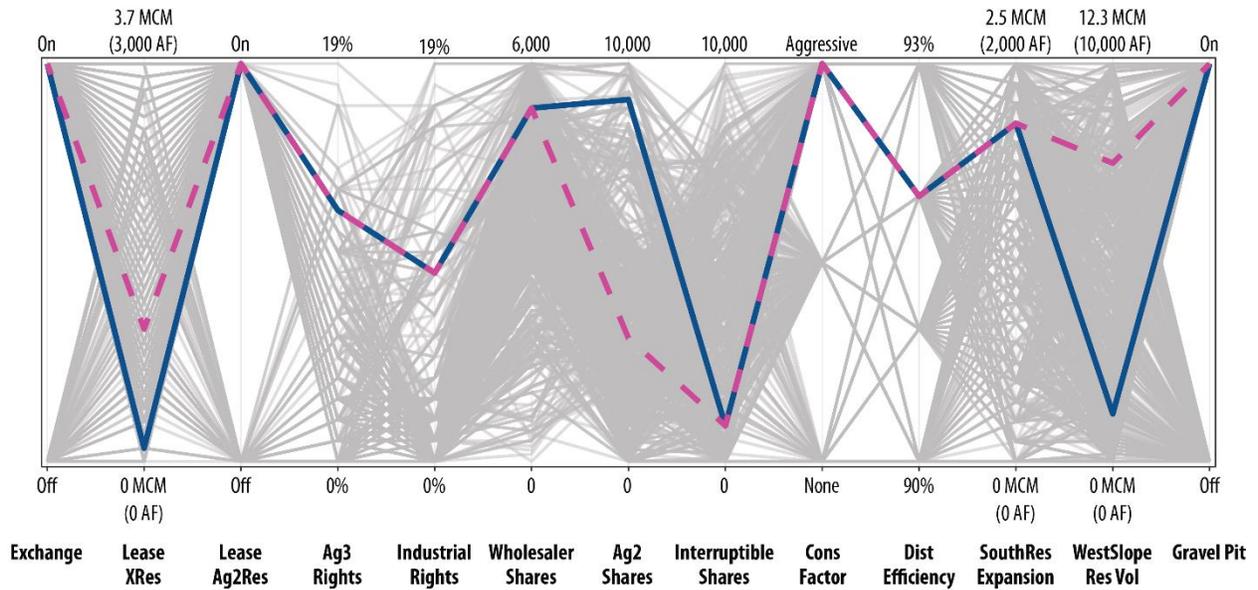


Figure 3-6. Parallel plots of two highlighted solutions. Plot (a) shows portfolio performance in the 7 objectives, and plot (b) depicts levels of the 13 decisions that make up each portfolio. In plot (a), the highlighted portfolios have very similar performance in all but the rightmost New Storage objective. Examination of plot (b) shows that only 3 out of 13 decisions are different between the two. This suggests that 7.77 MCM (6,300 AF) more West Slope reservoir storage and 1.11 MCM (900 af) more leased XRes exchange volume (Selection 4) result in similar performance to 6,000 more Ag2 shares (Selection 3).

Table 3-8. Decision lever and objective values for Selections 3 and 4.

	Selection 3	Selection 4
Decision Levers		
Exchange	on	on
LeaseVol _{XRes}	0.12 MCM (100 AF)	1.23 MCM (1000 AF)
Lease _{Ag2Res}	on	on
Rights _{Ag3}	12%	12%
Rights _{Industrial}	9%	9%
Shares _{Wholesaler}	5,330	5,330
Shares _{Ag2}	9,100	3,100
Shares _{Interruptible}	900	900
ConsFactor	aggressive	aggressive
DistEff	92%	92%
ExpandVol _{SouthRes}	2.1 MCM (1,700 AF)	2.1 MCM (1,700 AF)
BuildVol _{WestSlopeRes}	1.48 MCM (1,200 AF)	9.25 MCM (7,500 AF)
GP	0	0
Objectives		
<i>RestLev1</i>	1 yrs	1 yrs
<i>RestLev2</i>	0	0
<i>RestLev3</i>	0	0
<i>MissedOpp</i>	1.47 MCM (1,193 AF)	1.04 MCM (845 AF)
<i>NewSupply</i>	26.5 MCM (21,477 AF)	23.55 MCM (19,095 AF)
<i>AprilStorage</i>	86%	83%
<i>NewStorage</i>	4.56 MCM (3,700 AF)	12.3 MCM (10,000 AF)

Examination of Figure 3-6 (b) reveals interesting information about certain decision levers. The fact that, for the majority of the decisions, only one line is visible means that the set of decisions in each portfolio is almost identical. Just three decision levers are different in these portfolios: Selection 4 builds a 9.25 MCM (7,500 AF) West Slope Reservoir, while Selection 3 builds a 1.48 MCM (1,200 AF) reservoir; Selection 4 acquires 3,100 Ag2 shares while Selection 3 acquires 9,100 shares; Selection 4 leases 1.23 MCM (1000 AF) of XRes space, while Selection 3 only leases 0.12 MCM (100 AF). Or, put into a policy-distinguishing context, Selection 4 takes more action to capitalize on the western slope water right while Selection 4 takes more water out of agriculture production on the eastern slope. In terms of long and short term reliability, these two actions are virtually identical, and the algorithm was able to

quantify this subtle system response because of the explicit tradeoff between two distinct types of decisions: New Supply and New Storage. Presenting managers with the opportunity to express preferences for different types of portfolios enables MOEA-assisted optimization to support utilities' human-based value judgements.

3.6 Conclusion

The Eldorado Utility Planning Model is unique in WRSA literature in that it represents a generic utility's planning problem but incorporates three important facets that, in combination, provide an effective vehicle for advancing the ability of MOEA research to support real-world applications of the algorithms. First, it was created with the explicit input of eleven Front Range, Colorado, water managers using their structured feedback about important decisions, objectives, constraints, and system features (Smith et al., 2017). Further, it incorporated close, iterative input from a subset of those managers throughout model development. Second, the model captures both the dynamics of a single utility's decisions within a complex regulatory environment as well as the context of those actions on a regional scale by including multiple actors within the model. Finally, the case study is modeled using sophisticated RiverWare decision support software; in contrast to many research applications of MOEAs which use generic programming to create models that run in fractions of seconds, using RiverWare connects MOEA research to the computational capabilities and types of modeling that many water management agencies use today (Labadie, 2004).

Results produced by the Eldorado Utility Planning Model and this study's problem formulation demonstrate that it captures real-world-relevant and relatable Front Range and western U.S. water management context. Through optimization of seven objectives, the MOEA developed informative tradeoffs and found relationships between decisions and objectives that reveal fundamental planning insights, e.g. the elevated importance of acquiring moderate to high volumes of New Supply, and the effectiveness of purchasing Wholesaler shares. A major contribution of this work is a set of objectives that simultaneously avoid use of problematic cost projections (EU Framework, 1998; Maheepala et al.,

2014; Newell and Pizer, 2001; Walski, 2001) and enable water utilities to explore their planning values in a more fundamental way. Trading off minimization of New Supply with minimization of New Storage tells the MOEA to distinguish between different types of decision levers whose prevalence or absence within portfolios aligns with different planning strategies. The resulting set of diverse portfolios can favor New Supply, or New Storage, or balance between the two. Using these results, utilities can explicitly decide whether they want to pursue actions that draw water away from other regional users by acquiring rights and shares, or build costly, uncertain, potentially controversial infrastructure.

Literal cost versus reliability optimization is intuitive, but because of the many complexities that go into adopting a long term plan, may ultimately not be the best way for water providers to incorporate MOEA-assisted optimization into their processes. As framed by Basdekas (2014) and applied by Colorado Springs Utilities, MOEAs can help users effectively and efficiently move away from the inferior decision space. The results of the optimization then form the foundation on which utility experts evaluate additional important system and policy considerations. The plan ultimately adopted by a utility may not be contained within the set of Pareto-optimal portfolios, but the information provided by the set is very valuable for supporting utilities' triple bottom line assessments. This post-optimization analysis is an appropriate time to consider life cycle costs in a way that incorporates the human reasoning required to turn MOEA tradeoffs into a long term plan. Furthermore, continued focus on cost versus reliability does not capitalize on the opportunity offered by MOEAs to disaggregate performance measures and apply preferences *a posteriori* (Coello et al., 2007; Kasprzyk et al., 2013; Lempert, 2002).

The ubiquity and variety of WRSA studies performed on the Anytown, U.S.A. water distribution model (Walski et al., 1987) and the environmental water quality Lake Problem model (Carpenter et al., 1999) prove the creative value of having generic experimental case studies. Using the Eldorado Utility Planning Model, researchers can similarly innovate, expand, advance, and combine analysis techniques for long term water supply systems without the need to represent or protect a real agency's interests. Furthermore, the complexity of this case study and the broad real-world relatability provide a platform

through which researchers can more easily communicate their findings to a wide range of practitioners.

The success of this design goal was confirmed in a 2016 workshop as part of an application of the Participatory Framework for Assessment and Improvement of Tools (ParFAIT) (Smith et al., 2017).

Chapter 4

A multiobjective tradeoff charrette to engage with Colorado water managers about long term planning

Multiobjective Evolutionary Algorithms (MOEAs) generate quantitative information about performance relationships between a system's potentially conflicting objectives (termed tradeoffs). Research applications have suggested that tradeoffs can enhance long term water utility planning, but no studies have formally engaged with practitioners to assess their perceptions of the proposed contributions. This chapter examines how practitioners themselves interact with MOEA tradeoffs and reports their ideas for how their agencies could use MOEA results. We hosted a group of Colorado water managers at a charrette, or structured investigatory workshop, where they directly interacted with tradeoffs, discussed how they used the information, and linked their workshop experiences to opportunities for MOEAs to enhance their agencies' planning processes. We found that while managers approached tradeoff analyses differently, they all sought to understand relationships between decisions and performance. Managers' feedback about processing tradeoffs as well as opportunities and challenges for real-world applications suggest promising future research directions.

4.1 Introduction

Decision making, whether by an individual or a group, is a process; in contrast with the compulsory or involuntary, when an agent desires an outcome and is able to take action, deliberation will occur (Aristotle, 1920). In most decision making processes, preferences are constructed based on problem framing, previous experience, and available information, time, and resources (Payne et al., 1992; Roy, 1999; Slovic, 1995; Tsoukias, 2008). In combination, these factors help decision makers develop what Montgomery (1983) terms a "dominance structure", which is necessary when there is no strictly-optimal option. The dominance structure is iteratively built up in stages using mechanisms that help decision makers assess relative merits of alternatives and/or alter their internal representations of situations until one alternative becomes dominant. This process of creating arguments for and against alternatives

develops a justification, or basis for reasoning that can be conveyed to others. Justifiability is a cornerstone of deliberate human decision making (Connolly and Reb, 2012; Payne et al., 1992; Slovic, 1975; Tversky, 1972).

Multiobjective Evolutionary Algorithms (MOEAs) have been researched and applied as tools to aid decision making processes concerning complex systems for which there are multiple conflicting performance measures. MOEAs seek to optimize system performance in multiple performance objectives, efficiently searching through thousands of alternatives to develop a set that quantitatively characterizes the best tradeoffs between those objectives. Quantified tradeoffs reveal how much performance in one objective must be forfeited to get better performance in another. In the context of choosing a long term water resources plan, MOEAs test thousands of alternative portfolios of new sources, new infrastructure, and new operations in order to balance between performance objectives such as maximizing supply reliability and minimizing environmental impact.

Several studies have applied MOEAs to long term water resources planning problems. Long term plans are essentially overarching decisions about pursuing a set of actions. Three recent academic examples are Matrosov et al's use of an MOEA to develop long term planning portfolios for London, balancing cost, energy use, resilience and environmental objectives (2015); Zeff et al (2016) optimize long and short term risk triggers to develop adaptation strategies and support regional cooperation between utilities in North Carolina; and Wu et al apply multiobjective optimization to identify portfolios of traditional and alternative water sources for Adelaide in consideration of cost, emissions, reliability, and the environmental impacts of water and wastewater reuse (2017). These studies demonstrate that MOEAs can produce informative tradeoffs for multiple aspects of planning in a variety of geographic contexts which could inform agencies' planning decisions. However, none of these examples have undertaken a structured exploration of how a practitioner or agency employing an MOEA would interact with or perceive tradeoffs, and thus have not determined whether or how they actually aid decision making.

To study whether MOEA tradeoffs contribute to the creation of dominance structures that help water managers construct preferences and justify decisions, researchers need to be able to observe, interrogate, and analyze practitioners' usage of tradeoffs. Efficiently producing and capturing this information necessitates an interface between practitioners and researchers designed specifically around the type of information that results from MOEA-assisted optimization. Here, we can draw on an approach called a "charrette" which, in non-academic settings, is used to achieve a high level of public awareness and input on the design or vision of a community project or plan (US EPA, 2014). Charrettes are also used by researchers in the fields of construction management and safety. Research charrettes are structured workshops that bring together industry professionals and academics in a relatively short but intensely-productive session in order to generate discussion and feedback about newly-created products or practices intended for industry use (Gibson and Whittington, 2010). Charrettes combine the advantages of surveys, interviews, and focus groups in an accelerated time frame, overcoming the difficulties of undertaking these methods individually (e.g. low response rates, time commitments from both researchers and practitioners, access to data, etc.). Results from applying these mixed methods to technical research topics have shown that charrettes can offer both short and long term benefits to participating industry professionals and improved validity and reliability of research outcomes (Abowitz and Toole, 2010; Green et al., 2010).

This paper presents the content, methods, and results of a research charrette through which our transdisciplinary research team engaged with Front Range, Colorado, water managers over the use of MOEA tradeoff information for long term water utility planning. The workshop was designed to discover how practitioners used tradeoff information to make decisions, and whether and how the managers perceived the information to be useful in their agencies' planning processes. The goals of the workshop were to expose practitioners to an emerging tool and use the collected data to hone future MOEA research agendas and target new applications.

The charrette is the culmination of a larger study that introduced and applied the Participatory Framework for Assessment and Improvement of Tools (ParFAIT) (Smith et al., 2017). The following section briefly presents work from the previous phases of our application of ParFAIT to MOEA-assisted optimization for long term utility planning, as well as the contributions of those efforts to this final step in the framework. In Section 4.3, we describe the methods and content from our workshop. Next we describe the results, and in Section 4.5 offer concluding remarks.

4.2 Background

4.2.1 MOEA-assisted optimization for long term water utility planning

For water utilities, planning for long term, sustainable water security is a critical task and a major undertaking. Many utilities are required to update their long term plans at regular intervals, e.g. every five or six years (MWD, 2015; SPU, 2012). The planning process involves technical tasks such as analyzing potential supply and demand futures, identifying system vulnerabilities to climate change, policies, and laws, and using models to develop portfolios of decisions that achieve satisfactory system performance (CSU, 2017a; Kaatz and Waage, 2011). Technical staff review alternative strategies and discuss broad goals and needs with board- or council-level decision makers (CSU, 2017a; MWD, 2015), and public involvement in the process is now a high priority (WUCA, 2015). Developing and approving a final plan takes several years because each edition involves multiple iterations of the technical, board, and public participation components. On top of the process complexity, planning is inherently difficult because utilities face deeply uncertain futures (Knight, 1921; Lempert, 2002), and because there is no perfect plan due to the conflicts between financial, social, and environmental factors that utilities must navigate (Elkington, 2004). The ultimate goal of planning is for utilities to make smart, responsible, and justifiable decisions that allow their systems to meet the communities' chosen demand reliability policies in combination with community values.

Multiobjective Evolutionary Algorithm (MOEA)-assisted optimization has been studied (Matrosov et al., 2015; Mortazavi et al., 2012b; Smith et al., In Review; Wu et al., 2016a) and applied (Basdekas, 2014; CSU, 2017a) as a method to help utilities develop long term plans. While a traditional planning process compares the performance of a handful of planning portfolios, the MOEA efficiently designs and tests many potential portfolios, eventually characterizing how well a utility's system *can* perform in light of conflicting performance objectives and future supply and demand conditions. Researchers have proposed that the resulting quantified performance tradeoffs could provide information that is useful for utility planning. To carry out MOEA-assisted optimization, a utility would link the MOEA to a simulation model of their system via a problem formulation, allow the MOEA to search through thousands of portfolios of actions to optimize across multiple performance objectives, and then analyze the resulting set of portfolios by visualizing tradeoffs. More detail about this process is provided below.

A utility's system simulation model captures important dynamics and allows managers to quantify system performance under "what if" scenarios. The simulation is also the vehicle that contains elements of the problem formulation. A problem formulation consists of a set of decision levers, objectives, and constraints that define "the problem" being optimized. Decision levers are a utility's options to modify its system to meet performance goals, e.g. building a reservoir or enacting conservation. The set of chosen decisions levers makes up a portfolio. Objectives are measures of system performance that are quantified representations of a system's goals or purposes, e.g. minimizing frequency of lawn watering restrictions or maximizing water in storage. Constraints are numeric limits to acceptable performance, e.g. if a portfolio cannot meet 100% of indoor demand at all times it is not considered a valid planning approach.

The problem formulation is the set of directions that tells the MOEA how to construct candidate solutions (portfolios of actions) and how to evaluate their performance (via objectives and constraints). The MOEA automatically generates a portfolio which is loaded into the simulation model. At the end of

the simulation, values for objectives and constraints are reported back to the MOEA. This loop iterates thousands of times, during which the MOEA produces new populations of portfolios based on actions that performed well in previous generations. The results of using MOEA-assisted optimization are a set of portfolios that quantitatively characterize tradeoffs between objectives and form a Pareto-optimal set (Pareto, 1896). This means that each portfolio performs better than at least one other portfolio in at least one objective, but not better in all objectives. Within this nondominated set, performance improvement in one objective is only achieved by sacrificing performance in another, so the portfolios “trade” levels of performance. Analyzing the tradeoffs requires careful analysis including visualization techniques, and these are the final component of MOEA-assisted optimization. More information about tradeoff visualization is presented in Section 4.3.1.

Water utility planning is a complex process which may benefit from new technologies. Increased public scrutiny, greater mandates to protect social and environmental interests, and heightened awareness of future uncertainty all suggest that extensive portfolio search and explicit performance tradeoff information would be useful to the agencies. Building on existing technical analyses, MOEA-assisted optimization has the potential to enhance utilities’ decision making processes and increase confidence in final plans.

4.2.2 Participatory Framework for Assessment and Improvement of Tools (ParFAIT)

Many research applications of MOEA-assisted optimization have established the ability of MOEAs to generate tradeoff information about water supply systems and produce innovative portfolios that can outperform plans developed with human expertise or previously-established operational approaches (Maier et al., 2014; Nicklow et al., 2010). However, to date there have been few examples of this promising research tool being applied in real-world settings. To understand and potentially overcome the limited uptake of MOEA-assisted optimization, researchers must consider the factors that lead industries to adopt tools and consciously seek to create usable science. That is, researchers must

undertake intentional, iterative interaction with practitioners to understand their needs, transmit research, and co-produce relevant future research directions (Díez and McIntosh, 2009; Dilling and Lemos, 2011; Sarewitz and Pielke, 2007; Smits, 2002).

The Participatory Framework for Assessment and Improvement of Tools (ParFAIT) is a research process designed to bring academics and practitioners together in a structured way (Smith et al., 2017). Though demonstrated in this and the previously-cited paper as a way to bridge the gap between MOEA researchers and water utilities, the framework is generic and the sequence of steps may be carried out in any field, for any tool. ParFAIT is a four-phase research sequence that can be summarized as follows:

Step 1: Choose a promising research tool and a practical use for it that is supported by academic literature and knowledge of the proposed industry;

Step 2: Hold Workshop 1 to solicit input from practitioners that will inform development of a tool testbed. (A testbed is a platform on which the tool can be demonstrated to practitioners.);

Step 3: Build the tool testbed, iterating with practitioners as necessary to ensure reliability and relevance to real-world tool application context;

Step 4: Hold Workshop 2, a research charrette, to solicit practitioner feedback on the testbed results (i.e. results representative of what they could expect if their agencies adopted the tool).

For in-depth discussion of the basis for developing ParFAIT and the supporting theory behind both the process as a whole and the particular steps, please refer to Smith et al (2017).

4.2.2.1 ParFAIT Workshop 1

Workshop 1 of our ParFAIT process took place in February, 2015. It brought together water managers from six Front Range, Colorado, utilities⁶ and our research team was made up of engineering, social science, and climate science researchers as well as water utility practitioners. Through targeted but free-form group discussions, managers shared their experiences of Front Range management challenges, and provided feedback and suggestions to inform the elements needed to create an MOEA-assisted optimization testbed: supply and demand decision levers, performance objectives and constraints, future supply and demand scenarios, and important features for a generic but relevant hypothetical water supply simulation model (Smith et al., 2017).

Creating a relatable testbed is crucial for the successful application of ParFAIT because it is the basis for generating representative results, and also because its components must be recognizable to participants in the second ParFAIT workshop. This enables them to quickly grasp the testbed and focus on engaging with the results. Based on the information we generated through Workshop 1 and iteration with practitioners on our research team, we developed the problem formulation (decision levers, objectives, and constraints) and water supply simulation model that make up the hypothetical Eldorado Utility Planning Model testbed.

4.2.2.2 ParFAIT testbed: The Eldorado Utility Planning Model and case study

The Eldorado Utility Planning Model and case study generically capture management context relevant to utilities on the Front Range of Colorado as well as other regions in the western U.S. A hypothetical utility embarking on a long term planning process provides the narrative and technical vehicle for demonstrating MOEA-assisted optimization.

⁶ City of Aurora, City of Boulder, Colorado Springs Utilities, Denver Water, City of Fort Collins, and Northern Colorado Water Conservancy District

The Eldorado Utility is a relatively small water provider currently serving 100,000 customers and, like much of the western U.S., is expecting rapid population growth (a 40% increase by 2050) (State of Colorado, 2017). The rest of this section will describe Eldorado's supply system and problem formulation, the model, and minimal pertinent Front Range context. The focus of this chapter is on development and results from our MOEA charrettes, so the description below is tailored to information that enables understanding of the workshop. For more Front Range context, refer to Chapter 2 or Smith et al. (2017), and for more detail on the model and case study results, refer to Chapter 3 or Smith et al (In Review).

Much of the western U.S. is severely water-limited and tightly regulated by the prior appropriation legal doctrine, or "first in time, first in right" (Hobbs, 2004). One practical outcome of these factors is that, as cities grow, they obtain a variety of types of water rights (e.g. storage rights and streamflow diversion rights), each with different temporal priorities, and which may be sourced from multiple geographic locations. As such, the hypothetical city of Eldorado's system includes: two reservoirs on two different rivers with junior priority dates; three direct diversion streamflow rights on a nearby river – one senior, one mid-seniority, and one junior; one junior diversion right on a distant river that requires the diverted water to be conveyed under a mountain range in order to be stored closer to the utility; and 10,000 shares of a water wholesale company that Eldorado takes directly from a reservoir owned and operated by the wholesaler.

In many years, junior rights do not all get their full allotments (Caulfield Jr. et al., 1987; P. O. Abbott, 1985); e.g., a reservoir does not necessarily fill or a streamflow right does not always get to divert. Streamflow and competition for water on different rivers varies, however, and this means that utilities' water supplies strategically span entire regions. The Eldorado Utility Planning Model encompasses 5 basins and 12 water users besides Eldorado. The other users with senior water rights often limit the yields from most of Eldorado's sources. Some also offer opportunities for the utility to acquire more water, though, and the decision levers to do so are presented below.

The problem formulation describing Eldorado's long-term planning optimization includes 5 objectives⁷ used to characterize the performance of portfolios of 13 decision levers. Formally,

Equation 4-1

$$\mathbf{F}(\mathbf{x}) = (f_{RestLev1}, f_{MissedOpp}, f_{NewSupply}, f_{NewStorage}, f_{April1Storage})$$

$$\forall \mathbf{x} \in \Omega$$

Equation 4-2

$$\mathbf{x} = \text{Exchange}, \text{LeaseVol}_{XRes}, \text{Lease}_{Ag2Res}, \text{Rights}_{Ag3}, \text{Rights}_{Industrial}, \text{Shares}_{Wholesaler}, \text{Shares}_{Ag2}, \\ \text{Shares}_{Interruptible}, \text{ConsFactor}, \text{DistEff}, \text{ExpandVol}_{SouthRes}, \text{BuildVol}_{WestSlopeRes}, \text{GP}$$

Subject to

Equation 4-3

$$c_{UnmetDemand} = 0$$

Equation 4-1 describes Eldorado's five performance objectives. The first, $f_{RestLev1}$, measures the frequency with which Eldorado goes into Level 1 restrictions, which occurs when the utility's storage drops below 75% of average annual demand⁸. Eldorado's reliability policy dictates that the utility should not enact these restrictions more than 5 times in 25 years. There are two higher restriction levels, but satisfying the Level 1 objective satisfies the policies for those as well, and they are therefore unnecessary

⁷ Chapter 3 and Smith et al (In Review) described in detail the Eldorado Utility Planning Model and case study. The full problem formulation included seven objectives, but we chose to limit our charrette activities to only five objectives for ease of visualization and interpretation. As such, only the five incorporated in the charrette are presented here.

⁸ When storage drops below 50% of annual demand more severe restrictions are triggered but those are not pertinent to this problem formulation.

for the purposes of this chapter. $f_{RestLev1}$ is minimized. $f_{MissedOpp}$ measures how much of certain types of water that Eldorado had access to but could not use due to incompatible demand timing, lack of storage, etc. The inability to use the water means these are “missed opportunities”, and Eldorado wants to minimize the average annual volume of MissedOpp water. $f_{NewSupply}$ tracks the average annual volume of water over the course of the simulation that Eldorado acquires through decisions such as buying rights or shares, or conserving water (i.e. freeing up water to meet new demands). While Eldorado does need more water for a growing population, drawing more water than necessary away from other users creates social and economic disruption in their communities, so this objective is minimized. Another way to evaluate reliability is by measuring how much water is left in storage at the end of the winter drawdown season; $f_{April1Storage}$ seeks to maximize the lowest April 1st storage volume over the course of the simulation. Finally, $f_{NewStorage}$ minimizes the volume of newly-built storage within a portfolio because adding infrastructure is expensive, uncertain, and environmentally problematic. These objectives are summarized in Table 4-1 and explained in more detail in Chapter 3 and Smith et al (In Review). The only constraint on system performance is that portfolios must meet 100% of indoor demands (Equation 4-3).

Table 4-1. Summary of performance objectives.

Objective	Description
RestLev1	Minimize frequency of Level 1 restrictions over 25 years
MissedOpp	Minimize average annual volume of the sum of: return flows that Eldorado could have captured and reused, forfeited Wholesaler shares, and forfeited Ag2 shares
NewSupply	Minimize average annual new water created by either conserving or acquiring right and shares
NewStorage	Minimize the volume of newly-built storage in a portfolio
April1Storage	Maximize the lowest April 1 st storage-to-annual demand ratio during the 25-year simulation

Eldorado’s long-term planning portfolio will consist of values for the 13 decision levers presented in Equation 4-2. The levers fall into three general categories, and will be very briefly described below in the context of those categories.

Exchange, *LeaseVol_{XRes}*, and *Lease_{Ag2Res}* are all options that Eldorado can use to alter how its system manages reusable water. Exchange can be on or off and determines whether Eldorado has the right to store reusable return flows in an upstream reservoir; *LeaseVol_{XRes}* and *Lease_{Ag2Res}* are both volumes of storage that Eldorado can lease (rather than build). These are all minimally invasive “soft path” options (Gleick, 2002).

Rights_{Ag3}, *Rights_{Industrial}*, *Share_{SWholesaler}*, *Share_{SAg2}*, *Share_{SInterruptible}*, *ConsFactor*, and *DistEff* are all sources of “new” water. Eldorado can buy rights from an agricultural user and an industrial user, the utility can buy shares from farmers in an agriculture cooperative or a wholesaler, or they can purchase “interruptible” shares from the agriculture cooperative. Enacting long term conservation measures and increasing distribution efficiency (by, e.g., fixing leaks or improving metering) are ways that Eldorado can “create” water to be put toward growing demands. *ConsFactor* can be none, moderate, or aggressive conservation. *DistEff* can increase efficiency from 90% to 91, 92, or 93% (or not increase at all).

ExpandVol_{SouthRes}, *BuildVol_{WestSlopeRes}*, and *GP* are all options for building new storage. *ExpandVol_{SouthRes}* is the volume of storage added to an existing eastern slope reservoir. *BuildVol_{WestSlopeRes}* is the volume of a newly-built western slope reservoir, and *GP* is an on or off decision to build or not build gravel pits downstream of the utility to enable it to capture more reusable return flows. Table 4-2 summarizes all 13 decisions. MCM abbreviates millions of cubic meters; AF abbreviates acre-feet. Water management in the western U.S. is inextricably tied to units of AF, so they are presented alongside metric units.

Table 4-2. List of decision levers.

Figure 1 Label	Decision	Description	Units	Range
Enhancing Operations				
1	Exchange	Acquire right to exchange reusable return flows to NorthRes	---	0 – 1
2	LeaseVol _{XRes}	Pay owners of XRes to lease dedicated storage space that can facilitate Exchange	MCM (AF)	0 – 3.7 (0 – 3,000)
3	Lease _{Ag2Res}	Pay Ag2 Irrigation Co. to store water in any available unused space; 0 = off, 1 = on	---	0 – 1
Increasing Supply				
4	Rights _{Ag3}	Purchase a portion of Ag3's senior diversion right	%	0 – 20
5	Rights _{Industrial}	Purchase a portion of Industrial user's mid-seniority diversion right	%	0 – 20
6	Shares _{Wholesaler}	Purchase additional shares of Wholesaler water	shares	0 – 6,000
7	Shares _{Ag2}	Purchase shares of Ag2 Irrigation Co. water	shares	0 – 10,000
8	Shares _{Interruptible}	Negotiate agreement with Ag2 Irrigation Co. for optional supply leases	shares	0 – 10,000
9	ConsFactor	Reduce starting per capita demand through conservation measures; 0 = no change, 1 = 10% reduction, 2 = 20% reduction	---	0 – 2
10	DistEff	Improve distribution efficiency by reducing unaccounted-for water (e.g. fixing leaks, improving metering, etc.)	%	90 – 93
Building Storage				
11	ExpandVol _{SouthRes}	Expand SouthRes	MCM (AF)	0 – 2.47 (0 – 2,000)
12	BuildVol _{WestSlopeRes}	Build WestSlopeRes	MCM (AF)	0 – 12.3 (0 – 10,000)
13	GP	Develop gravel pits to store reusable return flows downstream of the city; 0 = not developed, 1 = developed	---	0 – 1

The Eldorado Utility and regional system are modeled using the generalized, sophisticated RiverWare platform (Zagona et al., 2001). The optimization was performed on a 25-year simulation horizon with monthly timestep. We used the Borg MOEA (Hadka and Reed, 2013), which performs similarly to or better than other MOEAs in difficult benchmark problems (Reed et al., 2013; Zatarain Salazar et al., 2016). Optimizations were performed in three different hydrologic scenarios: historic,

streamflow resulting from a 1°C-perturbed future, and streamflow resulting from a 4°C-perturbed future. More information about the choice of these scenarios can be found in Chapter 3 or Smith et al (In Review) and Woodbury et al (2012) and a description of their generation is in Chapter 3 and Smith et al (In Review). The historic optimization run was stochastic, and objective values were reported as the average of 10 hydrologic traces. The 1°C and 4°C runs were performed using a single trace for each in order to more clearly convey to workshop participants the impacts of the future scenario.

4.2.3 Background summary

This research was undertaken to study how managers respond to tradeoff information produced through MOEA-assisted optimization, learn from them if and how it could enhance their long term planning processes, and determine future research directions. The novelty of the tool and the type of information it provides necessitated a strategic process to ensure that our research team could present a broadly-relatable MOEA testbed. Our application of ParFAIT solicited practitioner feedback at a February, 2015, workshop which informed the construction of our MOEA testbed – the hypothetical Eldorado Utility Planning Model and problem formulation. We used the testbed to generate multiple tradeoff sets of long term planning portfolios for use in our second ParFAIT workshop. This workshop, or charrette, was designed to engage managers over hands-on experience in analyzing MOEA tradeoffs. To create the experience, we developed charrette content, engagement mechanisms, and activities. The methods we applied are described below.

4.3 Methods

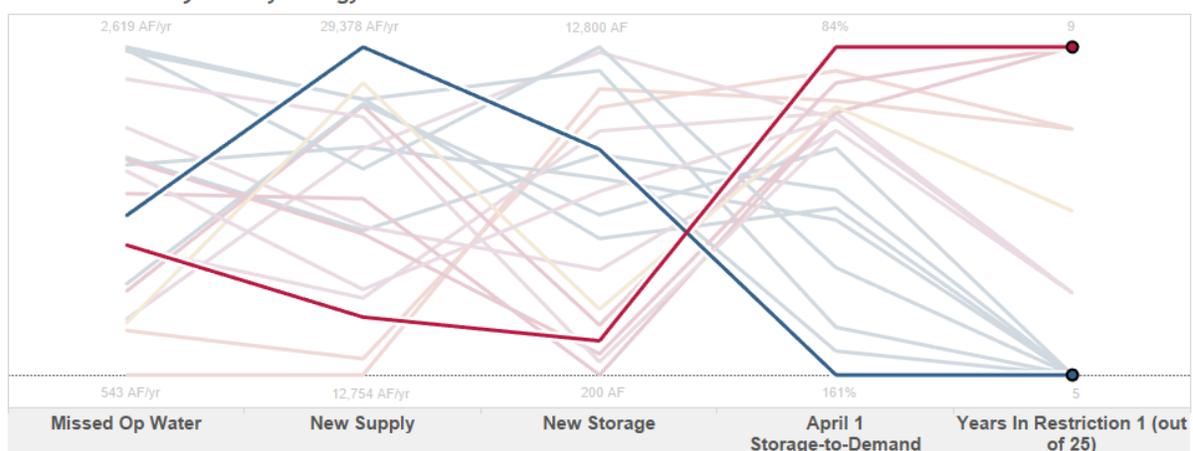
4.3.1 Interactive tradeoff visualization workbooks

To explore and understand the quantitative tradeoffs contained within a set of nondominated portfolios produced by MOEA-assisted optimization, users need to be able to see the complex relationships between the portfolios. This is facilitated by visualizing multiple portfolios at a time in several objectives, or dimensions. Being able to see relationships across all dimensions simultaneously provides the greatest opportunity to see tradeoffs, since only seeing a subset of the objectives can obscure

higher-dimensional relationships (Kollat and Reed, 2007). Understanding and exploring a large dataset in many dimensions requires advanced visualization techniques called visual analytics (Keim et al., 2006; Liu et al., 2017; Thomas and Cook, 2006; Woodruff et al., 2013).

Parallel axis plotting is a visual analytics technique frequently used in MOEA studies. The plots use a series of vertical axes to represent as many dimensions as desired (Fleming et al., 2005; Herman et al., 2014; Inselberg, 1985; Watson and Kasprzyk, 2017b). This study also uses parallel axis plots, and example results from optimizing the Eldorado Utility case study are presented in Figure 4-1. Briefly discussing the example results will facilitate readers' understanding of the information that water managers used during the charrette.

Performance in *Very Hot* Hydrology



Decision Levers

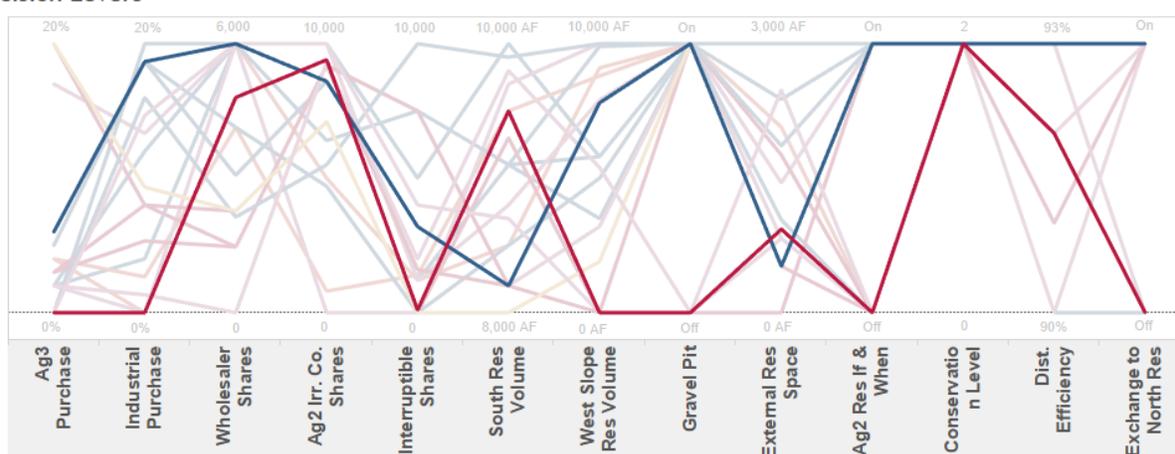


Figure 4-1. A screenshot of a Tableau worksheet that corresponds closely with what participants used in the charrette (the only differences are that here we use color to enhance the clarity of a static picture and there is no pane to record portfolio selections). The top half of the figure shows Eldorado system performance in five objectives, where each objective has a vertical axis. Each line represents the performance a portfolio of decisions across each objective and the lower on an axis a line crosses the better a portfolio has performed in that objective. The bottom half of the figure is a plot of decision levers and has 13 axes- one for each lever. A portfolio is depicted as a line connected across all of the axes, where crossing position denotes “how much” of that lever is included in the portfolio (lower means less). Two portfolios are highlighted to demonstrate tradeoffs.

The plots in Figure 4-1 show 20 portfolios⁹ that resulted from optimizing the Eldorado Utility case study using hydrology generated for a 4°C-warmer future. The top plot has five vertical axes- one for each performance objective. Each of the lines connecting the axes is a portfolio. The vertical position at

⁹ The full tradeoff sets produced by the Eldorado Utility optimizations included approximately 1000 portfolios each (Smith et al., In Review). In order to make the most of limited workshop activity time, we only showed participants 20 alternatives that were hand-selected to represent performance tradeoffs.

which a portfolio line crosses an objective axis denotes its performance, where lower intersection is better. The portfolios are colored based on how many years of Level 1 restrictions they produced (i.e. the performance on the rightmost axis); blue lines all have five years in restriction, red lines all have nine years. Two portfolios are highlighted to demonstrate the tradeoffs presented in the plot. The blue portfolio has the best possible performance in April 1 Storage-to-Demand and Years in Restriction 1, has medium-poor performance in New Storage and Missed Op Water, and the worst possible performance in New Supply. These levels indicate the tradeoffs between reliability measures on the right two axes and other system performance considerations. Conversely, the red portfolio performs the worst in April 1 Storage-to-Demand and Years in Restriction 1 but better, sometimes much better, than the blue portfolio in the other three objectives. Depending on Eldorado's preferences and priorities, they might choose portfolios with different performance characteristics.

The bottom plot shows decision lever attributes using a vertical axis for each of the 13 levers. As in the objectives plot, the lines connecting across axes are portfolios, and the position at which they intersect an axis denotes "how much" of a decision is included in the portfolio. The lower a portfolio line crosses, the "less" of that lever is present. Each portfolio line in the objectives plot has a corresponding line in the decision levers plot, so we can compare a few of the decisions led to the contrasting performance of the two highlighted alternatives described above. Looking at the second axis from the left, we see that the blue portfolio pursued a far larger share of the Industrial rights than the red portfolio; continuing rightward across the plot, another divergent decision lever was the size of the West Slope Res each portfolio built- the red portfolio did not build any reservoir and the blue portfolio built a relatively large one. Examining the rest of the axes shows there are many small and large differences between the decisions in each portfolio. We showed workshop participants the objectives and decisions together to provide all information about the portfolios and enable them to evaluate tradeoffs between different objectives and also express decision preferences.

Studies have shown that if parallel plots are interactive, first-time users can learn to use them effectively with 5-10 minutes of training (Johansson and Forsell, 2016; Siirtola and Rähä, 2006). Previous research has assessed whether users can evaluate multiple dimensions to complete a closed-form task with the plots, e.g. “Which one of the cars manufactured in 1982 has the slowest acceleration?” (Siirtola and Rähä, 2006). Our workshop differs in that we asked participants to use the information from the plots to make their own choices, so our results will reflect on how practitioners used parallel plots to weigh tradeoffs and make judgements.

To enable the water managers to use parallel plots for subjective analyses, we created plots that supported extensive browsing, multiple selections, and comparisons between portfolios and across workshop activities (described in Section 4.3.2.3). We used Tableau, a commercially-available business analytics program (Jones, 2014), to create a series of interactive worksheets on which participants could: hover over portfolios to get full decision and performance information, select one or more portfolios to highlight them, and enter portfolio IDs that changed the colors of those portfolios to register their choices for the activities described below. Critically, the workbooks allowed us to save their choices which both recorded them for later research analysis as well as allowed us to show managers how their choices changed (or did not change) over the course of the workshop. We provided each participant a laptop pre-loaded with the workbooks.

4.3.2 MOEA research charrette: June, 2016

Step four of our application of ParFAIT, a research charrette, provided water managers with hands-on experience with MOEA-assisted optimization results. Our goals for the workshop were to:

1. provide exposure for the emerging tool;
2. observe managers’ analyses of tradeoff information;
3. understand how managers relate the tradeoff information to their current needs and practices;
4. get feedback about what potential uses and barriers managers see in the tool;
5. learn about the general process of utilities adopting a new tool; and

6. report any opportunities for future research to meet the needs of practice.

4.3.2.1 Participation

Nine total participants from six Front Range utilities attended the workshop. The utilities capture a wide range of system sizes, and the individuals themselves also represented a range of experience levels: 4 managers had over 16 years of experience in Front Range water management; 1 had between 11 and 15 years; 1 had between 6 and 10 years; and 3 had 0 to 5 years of experience. We also had participants with different roles within their respective agencies: four were at a management level and five were technical staff. This variety was helpful in getting different perspectives, and the presence of both technical and managerial practitioners was especially encouraging since having advocates at multiple levels of administration increases the likelihood of innovation uptake (Daniell et al., 2014).

4.3.2.2 Supporting materials

In order for participants to fully engage in the workshop and provide researchers with thoughtful, relevant feedback about using the tool, they needed to be able to

1. understand why MOEA-assisted optimization has been proposed as a useful tool for water planning;
2. understand the concept of performance tradeoff sets;
3. have sufficient understanding and acceptance of the hypothetical utility, its supply and demand context, and its policies to be able to focus on tradeoffs;
4. understand and relate to the problem formulation and planning scenarios; and
5. effectively operate the Tableau workbooks and interact with parallel plots.

We covered these topics in a 90-minute introductory presentation. After explaining and taking questions about MOEAs and the testbed (content similar to that found in the Background section of this chapter), we held an interactive parallel plot training session.

In order to introduce parallel plots and tradeoff analysis, we created a simple multiobjective grocery shopping problem. Each participant used a Tableau worksheet set up identically to those that they would see in later activities that showed plots of performance and decision levers. We defined three conflicting objectives – minimize cost, maximize nutrition, and maximize pleasure – through which to optimize a set of eleven potential shopping items such as apples, ice cream, eggs, etc. As a group, we went through closed-form exercises finding the shopping lists that found the least expensive list, the most nutritious list, etc. The exercises required participants to analyze the plots and learn their interactive functions.

To support the managers in the day's activities, we gave them printed packets that included a diagram of the Eldorado Utility Planning Model, current and future utility demands, utility policies, descriptions of the decision levers and objectives, and descriptions of the different hydrologic scenarios. The diagram, reproduced in Figure 4-2, conveys the spatial and temporal complexity of the system using icons, colors, dates, and arrows.

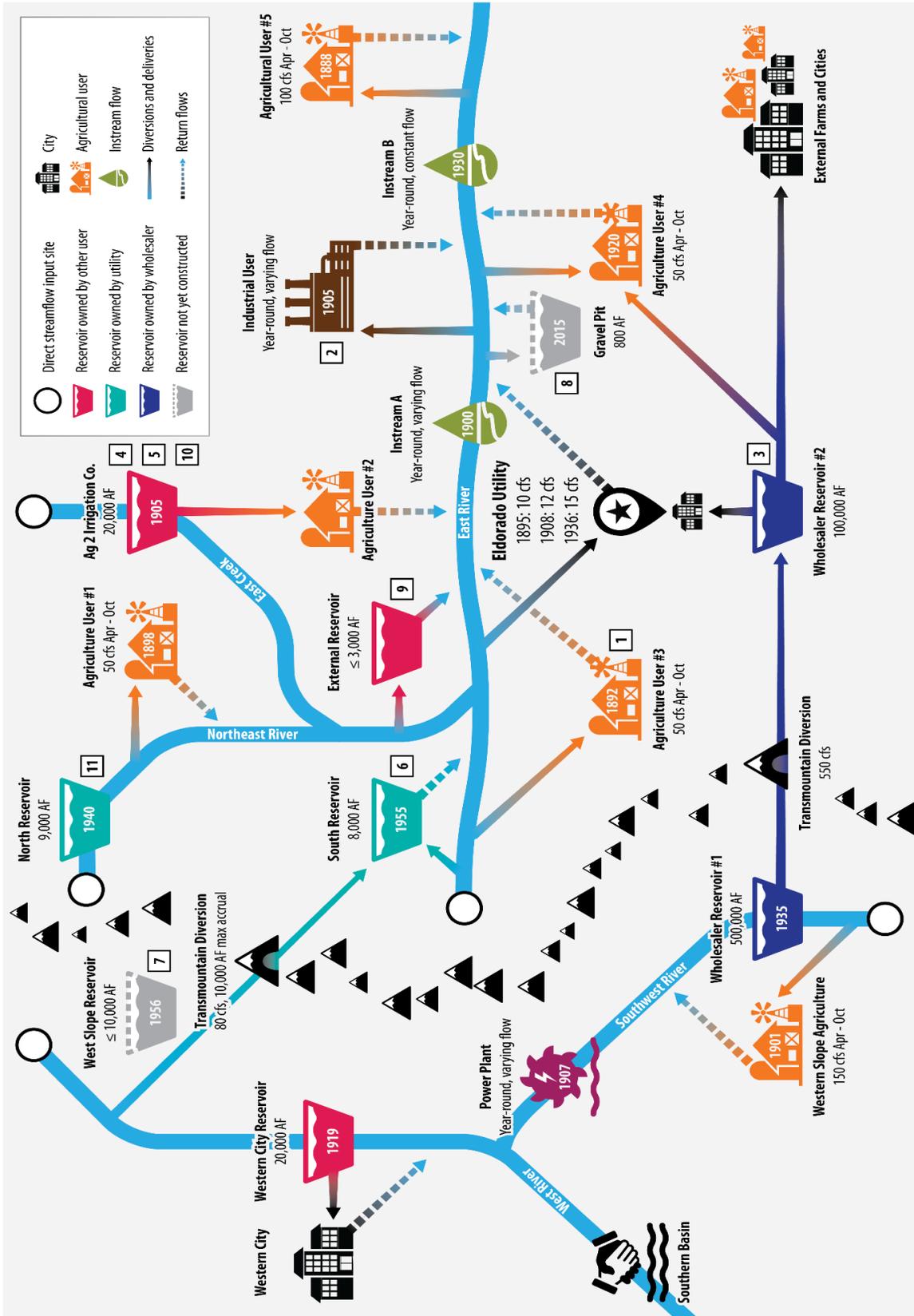


Figure 4-2. Diagram of the Eldorado Utility Planning Model given to charrette participants.

4.3.2.3 Charrette design

The majority of the charrette was spent on a series of activities during which we presented participants with tradeoffs and asked them to make two portfolio choices after approximately 15 minutes of independent analysis. Managers were free to use any logic (or dominance structure) they wanted to make the choices, and in fact understanding their logic was an intention of the workshop. In groups of three, participants completed a series of decision-making activities and engaged in facilitated small-group discussion that were led by facilitators and based on specific questions. We designed the activities and questions to prompt participants to consider specific multiobjective optimization concepts, generate insights about how they used the tradeoffs, and lay the foundation for an end-of-day discussion. Intense preparation and attention to charrette form, function, and sequencing made it possible for both participants and our team to approach the actual experience as a fun day of learning.

As described above, this workshop used a detailed format, custom computer workbooks, and concrete tasks associated with the activities, all of which guided information flows between participants and researchers. Compared to our first ParFAIT workshop, which relied on free-form discussions about targeted topics, this workshop was a relatively formal participation mechanism (Newig et al., 2008; Smith et al., 2017). However, the facilitated small group discussion sessions built into each activity captured less-filtered impressions from participants and allowed us to access subtleties of how utilities plan and operate and how managers relate to their systems. After the workshop we electronically surveyed participants about their perceptions of MOEA usefulness. This mixture of methods is fundamental to the success of charrettes (Gibson and Whittington, 2010). The incorporation of focus group-type activities and discussions was particularly useful for bridging the gap between researchers and practitioners because the interactions “provide a clear view of how others think and talk” (Morgan, 1993).

To provide context for the results presented in Section 4.4, brief descriptions of workshop activities and their purposes are necessary. The sequencing is especially relevant because of the complex

and, for most participants, novel quantitative tradeoff information that was the focus of this study. Table 4-3 summarizes the content below.

The purpose of Activity 1 was to establish initial preferences and create a basis for managers to compare decision making with and without tradeoff information. The participants chose one of three portfolios developed heuristically by an expert “consultant” (researcher familiar with the model and case study). Each portfolio was characterized by its constituent decisions and its firm yield in historic hydrology, but no performance tradeoff information was offered. The chosen portfolios from this activity were brought back in Activity 4.

The Activity 2 sequence was designed to ease the managers into evaluating tradeoffs in complex plots, to create space for analyzing tradeoffs without the dominant influence of reliability (Smith et al., 2017), to have managers be able to explicitly compare their usage of different amounts of information, and to do all of this without considering the likelihood or implications of climate change on Front Range supplies. In Activity 2, Exercise 1, participants were shown performance of 20 algorithm-optimized portfolios in a two-objective tradeoff (along with a plot of all of the portfolios’ decisions) and asked to select two “portfolios of interest.” The portfolios resulted from optimizing for historic hydrology, and were constrained to meet Eldorado’s restrictions-based reliability policy. This was made clear to managers so they knew they did not have to worry about reliability in this first activity. In Activity 2, Exercise 2, managers were shown the same set of 20 portfolios as in Exercise 1, but now were given performance information in a four-objective tradeoff plot (along with the decisions plot). In Activity 2, Exercise 3, participants were shown the choices they made from Exercises 1 and 2 in one plot to compare the preferences they expressed with different amounts of tradeoff information.

Activity 3 introduced the *frequency of Level 1 restrictions* objective and perturbed hydrology. The exercises allowed researchers to probe how the presence of the Level 1 restrictions objective influenced participants’ perceptions of other tradeoffs and added hydrologic challenges to their decision calculations. In Exercise 1, participants were shown 20 algorithm-optimized portfolios that resulted from

optimizing in a 1°C warmer future. To understand the implications of the different hydrology, managers referred to the informational packets where plots showing a slightly lower magnitude of peak runoff, slightly earlier peak timing, and similar regional flow variability. They were again asked to choose two portfolios and had to directly trade off reliability policy performance with the other four objectives from Activity 2. Exercise 2 was identical to Exercise 1 except that the 20 portfolios were from a set produced by optimizing for a 4°C warmer future. This scenario had a much lower peak runoff magnitude, much earlier peak timing, and lower variability due to lower magnitude high-flow years.

Activity 4 was designed to emphasize to participants that portfolios developed for or optimized under specific futures may not be acceptable if the future is different than they planned for. Managers saw the exact same set of portfolios from Activity 3, Exercise 2, but now their performance in a set of *varied* hydrologic traces was shown (i.e., in a supply scenario that they were not optimized for). The set of 10 traces were drawn from all other scenarios, so performance reflected the portfolios' average performances in a wide set of futures. They were again asked to make two choices from this set, and while making the choices they could see how each portfolio performed in varied as well as 4°C hydrology (so they had two parallel plots of objectives and one plot of decision levers). Managers were also shown how their hand-

crafted solution from Activity 1 performed in both scenarios and asked to reflect on how they felt about those portfolios, which were developed using historic hydrology.

Table 4-3. Summary of charrette activities.

Exercise	# Objectives	Hydrology	Description
Activity 1	0	Historic	Choose 1 of 3 handmade portfolios
Activity 2, Exercise 1	2	Historic	Choose 2 portfolios based on 2 objectives
Activity 2, Exercise 2	4	Historic	Choose 2 portfolios based on 4 objectives
Activity 2, Exercise 3	4	Historic	Compare choices from 2- and 4-tradeoff exercises
Activity 3, Exercise 1	5	1°C	Choose 2 portfolios while evaluating explicit tradeoffs between reliability and other objectives
Activity 3, Exercise 2	5	4°C	Choose 2 portfolios while evaluating explicit tradeoffs between reliability and other objectives
Activity 4	5	Varied, 4°C	Choose 2 portfolios with knowledge of how they perform in both varied and extreme (4°C) hydrology; reflect on choices from Activity 1.

At the workshop, the managers played the roles of engineers at the hypothetical Eldorado Utility who were evaluating a new tool for its potential to enhance their upcoming long term planning process. Asking them to play a fictional role and use hypothetical (but realistic) tradeoff results helped participants to engage more candidly by distancing them from physical, social, and political pressures of their own systems. Similarly, for each activity, we asked the managers to choose two portfolios “to subject to further analysis” to avoid comparisons with the real-world, complex process that a utility undertakes to actually decide on one plan. It was important, however, to ask them to make individual choices; this forced them to really grapple with tradeoffs and to use some logical process, and thus created a more defined experience for them to discuss with researchers and each other.

For each exercise (except for Activity 2, Exercise 3 during which participants just compared two sets of portfolio choices), small group facilitators asked three main questions to prompt discussion:

- A. What objective performances or tradeoffs made the two portfolios you chose interesting to you?
- B. What decision lever attributes made the solutions interesting to you?

- C. Based on the objectives' performance, as a manager at your utility, do you think you would have chosen the same solutions to investigate further? Why or why not?

Questions A and B were designed to separate the ways that performance and decision levers impacted choices, and question C was designed to emphasize that we wanted the managers to choose freely but also provide as much real-world decision making context as they could.

Data from this workshop includes the portfolio choices that managers made as well as discussions about the MOEA testbed tradeoffs, managers' analytical processes, utilities' planning approaches, tool adoption, potential for MOEAs overall, and workshop content. As such, we made sure to capture participants' portfolio choices but also took audio recordings and notes of each small group of managers. Having three types of information allowed us to ensure accuracy and produce results that synthesized both qualitative and quantitative responses. Additionally, post-workshop surveys recorded participants' overall perceptions of the usefulness of MOEA-assisted optimization.

4.4 Results

Throughout the day managers engaged with tradeoffs, facilitators, and each other. They took the purposes of the workshop seriously and combined openness to the activities with reflections about their own agencies' planning contexts. As we prompted them with specific concepts, they each interpreted and applied them differently. A result of this was that, across nine managers, the portfolio selections often varied widely and sometimes the processes they used to make them also varied significantly. Rather than report each individual's choices and processes, below is a description of common themes and examples of how logic changed over the course of the day.

4.4.1 Managers' usage of tradeoffs

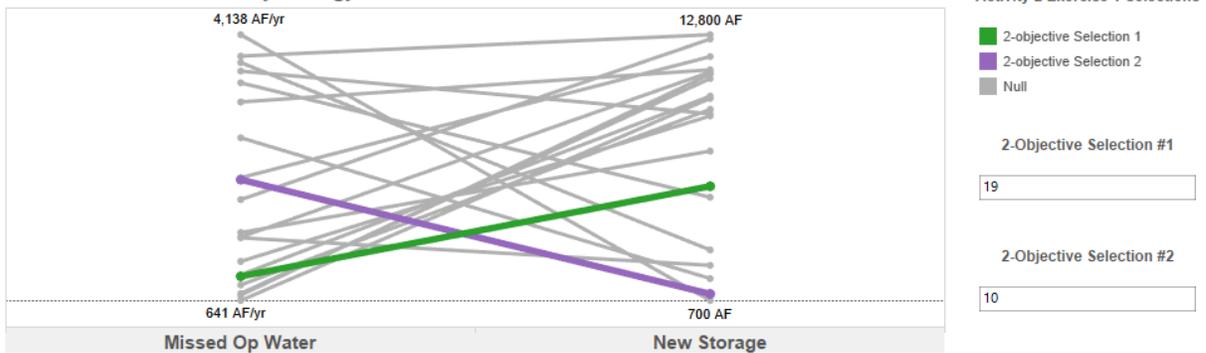
Within this section about how managers used tradeoff information, there are four subsections. The first discusses findings from Activity 2, which presented managers with first two, then four objectives to analyze. The second subsection of results is based on Activity 3, which introduced a fifth

objective (Level 1 restrictions) and two new, more challenging, hydrologies. Subsections three and four present findings that emerged throughout all four activities.

4.4.1.1 Tradeoffs in two objectives vs. in four objectives

In Activity 2, Exercise 1, where participants saw tradeoffs in two objectives, three general strategies emerged for choosing portfolios of interest. Five managers weighted performance in the objectives equally, two performed cost-benefit analyses between the two objectives, and two managers prioritized performance in one objective over the other. For example, Figure 4-3 shows the results of Manager B3's process. After spending time analyzing how different sets of decisions affected performance and which levers were more common, the manager ultimately chose two solutions that were relatively good across both objectives but allowed each choice to prioritize one of the objectives: the green portfolio is lower (better) on the Missed Op axis but not as low as possible because the portfolios that perform the best in this objective only achieve this by building medium-high to high volumes of storage; the purple portfolio is nearly at the bottom of the New Storage axis (i.e. almost the best performer) but this manager chose to add a very small volume of storage (relative to the smallest amount possible at the very bottom of the right axis) to greatly reduce the amount of Missed Op water from the maximum amount that would have occurred with the least-storage portfolio.

Performance in *Historic Hydrology*



Decision Levers

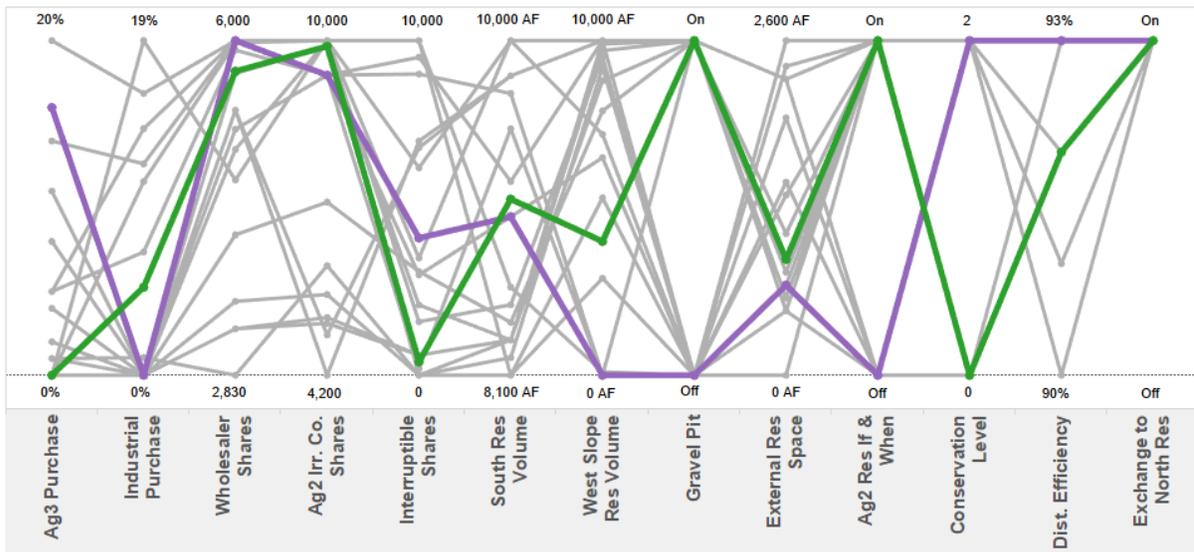
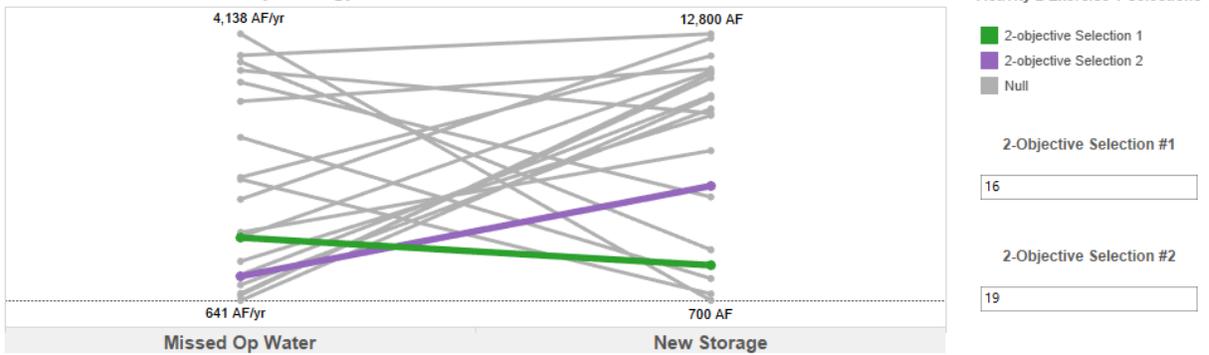


Figure 4-3. Screenshot of manager B3’s portfolio selections for Activity 2, Exercise 1.

Figure 4-4 (below) shows the results of Manager B4’s cost-benefit analysis. The manager started by picking the portfolio with the least storage, then worked incrementally up the New Storage axis to find out how much better the performance in Missed Op could get. The manager ultimately tried to find the portfolios where the tradeoff was “reasonable”- where the sacrifice in one objective came with a worthwhile gain in the other. Consider Selection 1, in green: the manager started at the bottom of the right axis with the minimum possible New Storage, and, finding that this portfolio had the worst possible Missed Op performance, chose to allow incrementally more New Storage and evaluate the improvement in Missed Op. Ultimately the manager was satisfied with the tradeoff of 2.0 million cubic meters (MCM) (1,600 acre feet (AF)) more of New Storage to reduce Missed Op by 3.3 MCM (2,672 AF) per year.

Selection 2, in purple, was the result of the same process, but it started at the bottom of the left axis with the minimum amount of Missed Op water. The two next-best performing portfolios (in terms of Missed Op) did not come with significant improvements in New Storage, but the next portfolio did reduce required storage by 4.9 MCM (4,000 AF) and only resulted in 0.4 MCM (318 AF) more Missed Op water. The strategies used by managers B3 and B4 demonstrate how practitioners could use optimization results to find solutions that achieve balanced performance and how quantified tradeoffs allow users to calculate how much performance they are willing to give up in one objective to improve in another.

Performance in *Historic Hydrology*



Decision Levers

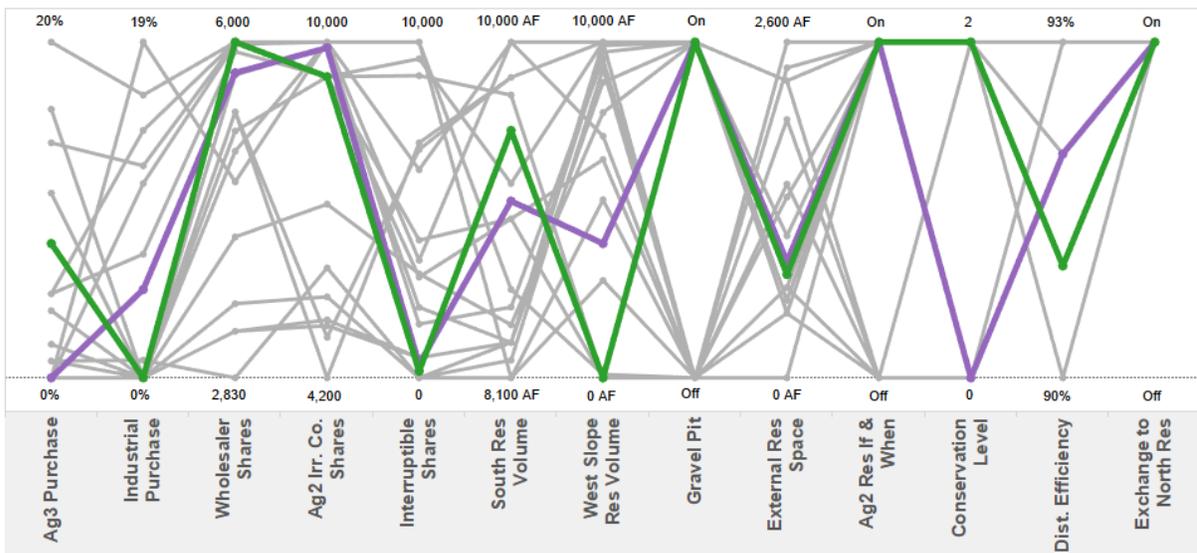


Figure 4-4. Screenshot of manager B4’s portfolio selections for Activity 2, Exercise 1.

In Activity 2, Exercise 2, managers were asked to make two selections from the same set of portfolios that they saw in Exercise 1, but they did so with performance tradeoffs in four objectives

instead of just two (so it was possible to choose the same portfolios in both exercises). Indeed, two managers chose the exact same portfolios as they did in Exercise 1, three managers chose one matching portfolio, and the other four participants chose two new solutions when presented with more tradeoff information. In Activity 2, Exercise 3, where managers were shown the two sets of choices they made, the managers who had identical sets of choices said that they used the same criteria in the second exercise as they did first. For example, Manager C2 did pay attention to portfolios' performances in the New Supply objective that had been added to the screen in Exercise 2, but ultimately focused on decision levers that maxed out conservation and turned on the exchange of reusable water (two "soft path" options) while balancing the initial two objectives from Exercise 1. This is a good reminder that new tools and new information do not necessarily result in changed preferences or different choices; tools may also provide value by reinforcing understanding and increasing confidence in decisions.

For the seven managers who chose at least one new portfolio in Exercise 2, they tended to balance their two choices against each other. For example, if they chose one portfolio that was "middle of the road" across the objectives (i.e. balanced), they allowed themselves to choose a second portfolio that prioritized one objective regardless of whether it performed poorly in another. Figure 4-5 is the result of Manager B2's first choice to balance, and second choice to disregard Missed Op and focus on New Storage: Selection 1, in blue, has middling performance in all four objectives, indicating that no objective was prioritized; Selection 2, in maroon, achieved the best possible performance in New Storage but exhibited moderately-poor to poor performance in the other three objectives. When discussing the process used to make choices with two tradeoffs versus four, this manager said "More objectives is better in terms of understanding the system and its performance. I assume that at some point it gets too noisy, but I definitely see value in going from two to four. Even if I end up prioritizing one or two objectives, it helps to see the implications that has on the others."



Figure 4-5. Screenshot of manager B2's portfolio selections for Activity 2, Exercise 2.

4.4.1.2 Use of the Level 1 Restrictions objective

The tradeoff analyses from Activity 2 included only portfolios that complied with Eldorado's restrictions-based reliability criteria (defined as not exceeding 5 years in Level 1 restrictions over the 25-year simulation). This condition was explicitly conveyed to participants, and they were not presented with an objective that measured restrictions performance. By omitting an objective about restrictions performance, the participants were able to consider their performance and decision preferences without directly grappling with level-of-service or policy consequences. Once frequency of restrictions was introduced as the fifth objective in Activity 3, all participants used it as their initial screening criterion. Additionally, both exercises in this activity used a climate change-perturbed hydrology: the portfolios in

Exercise 1 resulted from a 1°C warmer scenario, and portfolios in Exercise 2 resulted from a 4°C warmer scenario.

Though they had many options that resulted in only two years of restrictions, five of nine managers considered portfolios that exhibited from three to five years in Level 1 Restriction in Activity 3, Exercise 1. However, only two managers ended up choosing portfolios with three or more years in restriction because the other managers did not find that the performance gains in other objectives warranted the extra years. Seven of nine participants expressed satisfaction with the balances they were able to strike, while two expressed concerns that their decision preferences seemed less effective in the warmer scenario.

While all managers chose to outperform Eldorado's reliability requirement in Exercise 1, it was difficult to even meet the criteria in Exercise 2; there were no portfolios that had fewer than five years in Level 1 restrictions (the maximum allowed by Eldorado's policy). All portfolios that met the criteria required great sacrifices in at least two other objectives. For the three participants who stayed within the criteria, two focused on performance in one other objective and one tried to balance three other objectives within the compliant portfolios. Of the six other managers, four determined that one or two extra years in restrictions was worth the gains in other objectives, noting that this thinking would trigger policy discussions with their decision making boards- "this tool would be really useful in demonstrating just how much service we would have to give up in order to avoid unpopular storage or supply decisions." Two managers felt that once the climate had warmed by 4°C, norms would have changed, lawns would have disappeared, and people wouldn't expect the same levels of service that they had seen in the past, so they chose portfolios with nine years in restrictions and were able to avoid big storage projects. So, given difficult tradeoffs, three managers made painful concessions to comply with restrictions policy, four bargained (relatively) small policy deviations thinking that the trade could become the focus of broader negotiations, and two managers reframed the problem in order to justify alternative(s) that they considered superior.

4.4.1.3 More information, divergent choices

In analyzing all managers' specific portfolio choices over the course of the day, we found that as more information was added and tradeoff experience increased, the group's choices started to diverge. Three participants made identical choices to one another in Activity 2, Exercise 1; the same was true in Activity 2, Exercise 2. The sets of participants and the choices were different, though, and there were no correlations with experience level of the participants or size of utility. Overall, seven different portfolios were chosen in Exercise 1 and five different portfolios were chosen in Exercise 2 (out of 18 total choices made per exercise: 2 choices for each of 9 participants). There were no sets of identical choices in Activities 3 and 4. In Activity 3, Exercises 1 and 2, 10 and 12 different portfolios were chosen, respectively, out of 18 total choices that were made for each exercise. Finally, 12 different portfolios were chosen in Activity 4.

Adding the Level 1 Restrictions objective and using more challenging hydrology resulted in more divergent choices than those in historic hydrology with only two or four objectives in play. The finding that more information can lead to a wider variety of choices is perhaps not surprising because there are more avenues for creating dominance structure. However, it is worth considering how increasing information and greater divergence would affect a real-world planning process that involves several levels of scrutiny by many employees, decision makers, and the public.

4.4.1.4 Using objectives vs. decisions to make choices

For all participants, objective performance was the main focus when choosing portfolios of interest. Whether they tried to balance across all objectives or prioritized a subset of them, managers tended to structure preferences primarily around performance. From the subset of portfolios that had satisfactory performance, they would sometimes try to find the ones that had decisions they preferred. This secondary screening based on decision levers almost always centered on avoidance or pursuit of certain types of storage and/or moderate or aggressive use of soft path options (e.g. interruptible shares or conservation). One manager who was focusing on portfolios that minimized New Storage was also

concerned that some portfolios that performed relatively well in this objective could actually be hard to pursue because they had small amounts of storage in multiple locations (i.e. a medium expansion of SouthRes and building a small WestSlopeRes). Another manager noted that they were all “starting with performance and then looking at the levers. We want to see the results first and then work backwards. That’s not how a lot of things are done in reality; normally we look at sets of levers and then model outcomes.” Another reflected that “if you pick totally on performance and ignore decision levers, you pick solutions that you wouldn't have chosen just based on decisions; conversely, if you pick based on decisions first, you'll probably be surprised about their poor performance.”

Use of decision levers to make choices varied throughout the day. In the first exercise with two objectives, four of nine participants considered decision levers, while only three of nine did so in the four-objective exercise and the 1°C warming exercise. This slight drop off may at least partially be due to the fact that complexity was added via number of tradeoffs and (in the case of the 1°C exercise) new hydrology. These changes may have taken up some extra cognitive bandwidth for participants, as suggested by one manager: “How many objectives is too many? What can we handle versus what do you miss if you don't include all of the objectives?” In the 4°C scenario, seven of nine participants looked at decision levers while making choices. One reason for this could be the fact that only hydrology changed between 1°C and 4°C. Besides participants’ greater comfort with the complex data visualizations, the increased consideration of decision levers in 4°C was related to the fact that limiting the number of years in restrictions required large sacrifices in New Storage and/or New Supply. In coming to terms with this tradeoff, managers tried to reduce reliance on storage or permanent agriculture dry-up, but ended up having to weigh this tradeoff against meeting reliability criteria.

Whether or not they used decision lever characteristics to choose portfolios of interest, all participants expressed surprise and curiosity about the relationships between decisions and performance. Comments like the ones below came up frequently throughout the day:

- Why do the decisions change so much but give me similar performance?

- Why do very similar portfolios perform so differently?
- Why didn't this certain lever ever get turned on in the portfolios I was focusing on?
- Why can't I have this performance but with more conservation?
- What are the differences in decisions with these two extremes in performance?
- Why aren't these levers ever turned on? Are they not effective?

One participant wondered: "Is the impact that subtle changes in decisions can have on performance something that utilities miss in the way we currently do things?"

4.4.2 Opportunities and challenges to using MOEA-assisted optimization

4.4.2.1 Opportunities

Over the course of the exercises, as well as during the large group discussion, participants noted how the type of information produced by MOEA-assisted optimization could be used to enhance their utilities' long term planning processes. Managers proposed two uses that support the technical foundations of planning: to help staff understand complex dynamics of their supply sources and infrastructure interactions, and to use surprising dynamics to interrogate the accuracy of their planning models. One manager focused on the public participation aspect of planning, suggesting the results could be used to show community members how much service they would have to give up (via more frequent restrictions) in order to avoid unpopular and expensive infrastructure projects. Another manager brought up the council-level component of planning when considering how the tradeoffs could help make the case for changing reliability policy to decision makers or board members.

One participant had ideas to tie the tool to two common water utility planning concepts: triple bottom line assessments (Elkington, 2004) and robust decisions. Regarding the triple bottom line, the manager wondered whether each lever could be scored by knowledgeable utility staff based on its economic, social, and environmental costs. These scores could then be used as objectives, minimized by the MOEA. Although this scoring would be somewhat qualitative, subjective, and may possibly under- or overestimate costs of specific projects that have not been thoroughly studied, connecting tradeoffs directly

to fundamental utility planning concepts may prove useful. Utilities are also concerned with elucidating robust decisions, or those that support good system performance in a wide range of climatic futures. The manager suggested that finding specific decisions that featured prominently in portfolios that achieved desired performance balance in multiple planning scenarios could mean that they are robust.

One participant thought it might be useful to give each portfolio an area under the curve score based on the objectives as a way to objectively compare portfolios. Another reflected that with the current trend of relying on algorithms make choices based on a priori weighting, this application of optimization was appealing because it still focuses on human decision making but with extra information.

Table 4-4 below shows the results of a post-workshop survey that asked participants two questions:

1. How useful do you think the quantitative tradeoff information produced by the MOEA would be for learning about your utility's system?
2. How useful do you think the quantitative tradeoff information produced by the MOEA would be for enhancing your utility's approach to long term planning?

The scale for responses was from 1 (not useful) to 5 (very useful).

Table 4-4. Results of post-charrette survey.

Score	Count	
	Useful for system learning	Useful for planning
1.0	0	0
2.0	0	0
3.0	4	2
3.5	0	2
4.0	4	3
5.0	1	2
Average	3.7	3.9

There were no response patterns based on either length of career or size of utility. The only notable correlation was that the two managers who responded that they thought the tool was “very useful” for planning both came from utilities who had recently used the tool in their long term planning processes.

4.4.2.2 Challenges

The challenges brought up by participants fall into three general categories: modeling, personnel, and conveying process and results. A manager from a utility that had just used MOEA-assisted optimization in their planning asked a simple question: “How much do you trust your model?” When the participant’s agency was confronted with surprising tradeoff results, in some cases the results provided verifiable, novel system understanding; in other cases, they were the product of model errors. This issue was exacerbated when existing models were run in extreme hydrologic and portfolio combinations, and underscored the importance of having system and project experts review portfolios. On the topic of modeling, other managers noted that you have to have the right kind of planning model- one that provides a useful timestep resolution, an appropriate level of internal system detail and external context, and that can run reasonably quickly.

Managers from the two utilities that had MOEA experience agreed that training staff to understand the tradeoff results and maintaining those skills was a struggle. Understanding and interacting with tradeoffs requires a particular cognitive approach, and the managers reported that for many members of their teams, seeing results from their consultants once a month required a review at each appointment. Furthermore, to continue to see benefits from using the tool, one or more staff members would need to maintain proficiency with the results and potentially be able to produce new optimization runs. The managers also said that when technical staff who had often spent years developing certain projects were confronted with portfolios that performed well but did not incorporate their projects, discussions and negotiations could become difficult.

The inner workings of the MOEA, the process of employing one, and the results it produces are complex. In order for a utility to use one, one or more staff would have to make considerable effort to build understanding about the tool within the agency. Because the results are so complex, technical staff also must simplify the message to decision makers without sacrificing confidence in the tool or alienating their audience. Managers with and without MOEA experience agreed that this is a difficult task. A critical

component of understanding, simplifying, and conveying the results is having visualizations that are as easy as possible to understand. A manager suggested that this is so important that it may be worth consulting someone with training in data visualization for input.

4.4.3 Adoption of new tools

Researchers asked participants to discuss their utilities' experiences with the process of adopting new tools. The process starts when technical staff become aware of new tools. According to these managers, the water management industry is bombarded with great ideas and they have to sift through them and think about what they can apply. Sometimes the ideas come from consultants, e.g. through Integrated Water Resources Plan (IWRP) requests-for-proposals, and sometimes the ideas come from conferences, workshops, and/or co-production with researchers. They agreed that case studies of real-world applications are helpful for opening utilities up to new tools, and the cases are especially influential when they involve neighboring utilities. Managers from one of the utilities that had used an MOEA said it took sustained effort to convince upper management to become that case study.

Once a tool is being considered by a utility, many conditions must be met before it can be adopted. Managers report that getting broad acceptance is very challenging; it can take years, and requires at least one champion within the agency, but preferably two because this lends credibility and force to the proposal. Ultimately, upper managers and boards trust technical staff to do analyses once they have boiled down the details and shown need for, and potential benefit from, the tool. However, in order for staff to buy in, they need to understand the background and "guts" of using the new tool, they need to be heavily involved in developing and integrating it, and they need to have access to technical assistance once they are using it.

One manager offered a distilled version of the above: "We need proof that the tool works, trust in the people proposing it, and we need evidence that it is useful and usable." In other words, the tool needs to be credible, legitimate, and salient (Cash et al., 2003).

4.4.4 Real-world planning and decision making context

During small group discussions, participants answered the specific questions posed by facilitators, but also had discussions among themselves that provided insight into how utilities think about difficult planning questions. One such conversation was around level of service versus customer billing rates. If utilities try to avoid costly infrastructure as much as possible, rates don't have to go up to pay for it. But, in the long term future when Colorado utilities will potentially be even more dependent on wet years to recover system storage, the only way to take advantage of that is to have adequate capacity. If avoiding infrastructure means greater frequency of restrictions that can lead to long term reduced utility revenues, rates may slowly creep up anyway. Once rates increase, they will never go back down, so how do customers want to experience this? "Where do you want the pain to be in your system- low reliability or high rates?"

Another group discussed the drawbacks of conservation and demand hardening. For smaller service areas, conservation has very little impact compared to the yield of new supply, and may only displace the need for new supply in the short term. Conservation is really most effective at saving water used on lawns in wetter years; in dry years, watering is already reduced via restrictions. Once conservation sets off demand hardening or years of restrictions creates a "drought shadow" (persistence of lower demand than pre-drought levels), restrictions don't produce as much savings and deeper, more invasive restrictions become necessary.

We also learned about some practical realities of how utilities make decisions. Managers noted that opportunism plays a big role in determining which projects go forward and when; e.g., if a cable company is ripping up a road, a utility will go ahead and fix leaks in the nearby pipes. Another major factor for whether utilities take on a project is whether it involves federal permitting; agencies strongly prefer not to undertake this process which commonly takes more than 10 years, millions of dollars, and relies on highly uncertain outcomes. Sunk costs also motivate utility decision making; any projects that have already seen some investment may be pursued regardless of optimization results.

In the large group discussion at the end of the day, several managers lamented the realities of planning at five-year intervals. Long term planning has become such an undertaking that the preparation involved in creating a plan can take many months, after which the planning process itself is so arduous that staff need time to recuperate. Once normal staff functioning resumes, it may be time to start thinking about the next plan. Researchers should consider how existing their current expertise or future research can contribute tools or processes that support sustained planning.

4.5 Conclusions

In the charrette tradeoffs often, but not always, influenced managers' construction of preferences. It was clear that the ability to directly compare alternatives across several dimensions helped managers reason out a dominance structure; sometimes they iterated until they found a satisfying alternative and sometimes they worked backward to justify a choice. In a few responses, though, managers simply applied their preferences to the set of options they were given and chose, e.g., the portfolio with the least new storage. This suggests that the other objectives were not compelling enough to warrant compromises, and/or that additional information does not always affect core priorities. On another level, managers often used the opportunity to make two selections to balance their indecision and actually seemed to trade performance between their two choices.

Beyond using tradeoffs to justify their own selections, managers came up with ways that tradeoff sets could bring justification to broader aspects of the utility planning process. They suggested that the tradeoffs could support policy negotiations with boards or councils as well as communications with the public. If the tradeoffs revealed that a minor relaxation of reliability criteria could drastically reduce reliance on new storage, that information could be a valuable point of discussion. Similarly, if a community opposed a specific project, tradeoffs could explicitly show sacrifices that would be necessary to avoid it. This feedback from the participants clearly points to how MOEAs can enhance many aspects and phases of planning.

Though there are challenges to incorporating MOEAs, e.g. appropriate and trustworthy modeling, maintaining tradeoff fluency, and securing technical support, many managers found their distinct capabilities appealing. They appreciated the ability to see relationships between objectives. We heard that it was refreshing to be able to combine an optimization tool with human reasoning- that the tradeoffs empowered managers instead of diminishing their input.

The results from this charrette suggest to us at least two promising avenues for further research to support MOEAs for long term water utility planning. We draw the first from what we heard about the relationships between decision levers and objectives and how each traditionally influence planning. Generally, utilities devise portfolios to see how they perform; in the workshop, a manager pointed out that they were choosing performance and then seeing which levers that entailed. This shift prompted many questions about what influence one or more levers had on performance. Future research that quantifies relationships between levers and performance could increase the value of tradeoff sets to the agencies that use MOEAs.

The other avenue is to begin exploring the role that MOEA tradeoff sets can play in sustained planning. Can the system information attained through the tradeoffs and the large set of potential portfolios form the basis of adaptation? As supply or demand information solidifies or infrastructure projects do or do not come to fruition, can future actions be informed by tradeoffs and portfolios that have already been generated, thus reducing the burden of planning cycles?

The MOEA research charrette was an effective approach to engaging with water managers about the potential for MOEAs to enhance long term water utility planning. Through the workshop we exchanged and created new knowledge with our participants. This success was possible through the application of the Participatory Framework for Assessment and Improvement of Tools (ParFAIT), which created a roadmap for research activities and structured the relationships with our practitioner partners. This transdisciplinary, participatory venture resulted in deeper understanding of water management context, inspired future research directions, and forged new links between academia and industry.

Chapter 5

Combining Multivariate Regression Trees and multiobjective tradeoff sets to reveal fundamental insights about water resources systems

This chapter presents a data mining method to reveal fundamental system information contained within Multiobjective Evolutionary Algorithm (MOEA)-generated tradeoff sets, and demonstrates its value on a long term water utility planning problem. MOEA-assisted optimization produces a large set of non-dominated solutions, each of which represents an observation of how multiple independent variables (decision levers) impact performance in multiple response variables (objectives). Multivariate Regression Trees (MRTs) succinctly reveal how a small number of decisions produce large variations in performance. Unlike other decision tree methods, MRTs accommodate multiple response variables, and can thus preserve the performance relationships found in multiobjective tradeoff sets during splitting. We generate an MRT for each set of tradeoffs that resulted from optimizing the Eldorado Utility long term planning problem under two climate change scenarios. A single MRT can be a vehicle for determining core planning decisions, e.g. reservoir size or demand conservation level, that lead to preferred performance; it can also demonstrate how decision preferences may impact performance in such objectives as minimizing restrictions and maximizing long term storage. Comparing MRTs from two optimization scenarios allows managers to identify decisions that are common across scenarios, i.e. robust. The information provided by MRTs can help technical managers and decision makers understand large, high-dimensional tradeoff sets. This work is part of an ongoing research agenda informed by practitioner feedback obtained during a hands-on MOEA workshop.

5.1 Introduction

Increasing access to digital storage and computing power has expanded the scope and capabilities of water resources management practice and research. As data volume and availability have grown, so too has the potential for the field to employ data mining techniques to gain value from the stores (Babovic, 2005; Loucks et al., 2005; Velickov and Solomatine, 2000). While the term “data mining” is often used

interchangeably with terms like knowledge discovery or information harvesting, here we use it to refer to an automated process of extracting new, useful, and, ideally, comprehensible knowledge hidden within a large data set (Fayyad et al., 1996; Hand et al., 2001). The earliest and most frequent examples of water resources data mining applications have been in hydrology (Jain and Srinivasulu, 2004; Lohani and Loganathan, 1997; Nasser et al., 2013; Wei and Watkins, 2011) and reservoir operations (Bessler et al., 2003; Wei and Hsu, 2008; Yang et al., 2016) due to the volume of records that had already been building for decades.

More recently, Water Resources Systems Analysis (WRSA) research has begun incorporating analytical methodologies that produce large data sets for the purpose of using data mining techniques to gain valuable information. For water providers seeking portfolios of policies and actions that are likely to perform well in a wide range of futures (i.e. are robust), evaluating one or more portfolios under thousands of possible future conditions can help them learn under which subset of future conditions a portfolio may fail. A prominent approach to this is scenario discovery using the Patient Rule Induction Method (PRIM) data mining algorithm (Friedman and Fisher, 1999; Lempert et al., 2006), which seeks to define a small number of conditions that strongly predict plan failure. PRIM has seen many successful applications in WRSA literature, e.g. (Groves and Lempert, 2007; Herman et al., 2015; Kasprzyk et al., 2013; Lempert and Groves, 2010). Similarly, if water providers want to know to which external uncertainties their systems are most vulnerable, they might perform a Sobol' global sensitivity analysis. By subjecting a system model to a large number of variations of external forcings, Sobol' sensitivity analysis identifies the relative contributions of each of the uncertain factors to variations in system performance. This data mining method has been applied in several recent water resources planning studies, e.g. (Beh et al., 2015; Herman et al., 2015; Kasprzyk et al., 2012).

Another eminent method in WRSA that produces large data sets is Multiobjective Evolutionary Algorithm (MOEA)-assisted optimization. Water resources systems generally strive to meet conflicting performance goals, and planning for the future of these systems to achieve good performance in those

conflicting objectives involves making many decisions which themselves exhibit complex interactions and dynamics. MOEAs are search engines that efficiently generate and evaluate thousands of portfolios of decisions to try to optimize across the multiple conflicting objectives. The optimization process results in a set of nondominated, or Pareto-optimal portfolios (Pareto, 1896), where performance in one objective is only possible through sacrifice in another, conflicting, objective; the set of portfolios enumerates performance tradeoffs.

These Pareto tradeoff sets consist of hundreds and often thousands of portfolios that contain hidden information about the water resources system and the optimization problem. To date, WRSA research applications of MOEAs have mostly relied on visual analytics (Kasprzyk et al., 2009; Kollat and Reed, 2007; Matrosov et al., 2015; Smith et al., 2016), or Cartesian plots (Mortazavi et al., 2012a; Wu et al., 2017) for insights, performing relatively subjective assessments on the tradeoffs to frame assertions of different performance priorities. In several studies previously mentioned, MOEA results have also formed the bases for performing scenario discovery (Kasprzyk et al., 2013), or sensitivity analyses (Beh et al., 2015), or both (Herman et al., 2015).

However, studies combining multiobjective Pareto sets and data mining *have* been conducted in other fields, particularly frequently in the areas of product and industrial design and optimizing production systems. Here we briefly discuss some specific examples. For a thorough treatment and comparison of the many ways that knowledge can be extracted from multiobjective optimization sets (not just automated data mining), see the survey by Bandaru et al (2017a).

Early applications of data mining methods to product design were problematic; either they did not relate decisions to objectives or used very complex mining algorithms that did not produce easily understandable information: Ulrich et al (2008) used dendrograms on the classical knapsack problem to group portfolios in decision space; Obayashi and Sasaki (2003) and Obayashi et al (2005) applied self-organizing maps (SOM) to the decision spaces of supersonic wing and wing-fuselage design problems and then translated the decision maps to objective space; and Oyama et al (2010) used proper orthogonal

decomposition to characterize how a few decisions affected three categories of performance in the optimization of transonic airfoil shapes. Deb and Srinivasan (2006), early proponents of mining MOEA results, coined the term “innovization” for the process of learning *innovative* design principles from *optimization* results; however, the first automated version of their concept still required user intervention; in Bandaru and Deb’s (2011) demonstration of innovization on the design of trusses and welded beams, the researchers had to pre-specify basis functions before the automated process analyzed the set for design rules.

The results of more recent efforts to apply data mining to Pareto sets are easier to understand, at least in part due to expansion of methods. Ulrich (2013) used an MOEA to optimize clustering of bridge designs in objective space vs. decision space so that the results of different sets of clusters were themselves tradeoffs between describing sets of similar decision variables or similar performance. Sugimura et al (2010) used the optimization results of a two-objective centrifugal impeller design problem to mine decision trees, producing a straightforward tree for each objective. Dudas et al (2011) and (2014) also used decision tree mining on a three-objective automotive manufacturing problem; in 2011 they produced a tree for each objective, and in 2014 they created portfolio clusters in objective space and generated a tree for each cluster. The growth of studies combining Pareto sets and data mining seems to be gaining momentum: Bandaru et al (2017b) developed and compared four new methods, including classification trees, on three different production system problems.

Decision trees (which can be classification or regression trees and are further described in Section 5.2.1) are desirable data mining techniques because the resulting diagram clearly relates the inputs or decisions of an optimization problem to outputs or objectives via simple rules. However, Sugimura et al (2010), Dudas et al (2011) and (2014), and Bandaru et al (2017b) were all limited to producing trees one objective at a time or developing innovative ways to reduce multiobjective optimization results to a single output variable; in doing so, they necessarily lost explicit information about relationships between objectives, which is one of the benefits of performing multiobjective optimization.

Our study overcomes the limitations of applying single-objective decision tree data mining to multiobjective optimization Pareto sets through the use of Multivariate Regression Tree (MRT) analysis (De'Ath, 2002; Larsen and Speckman, 2004). MRTs are a variation of decision tree that develops data splits using information about how sets of decision inputs affect all objective outputs simultaneously. Furthermore, we introduce the benefits of data mining to applications of MOEA-assisted optimization in the WRSA field through the use of a complex long term water resources planning study called the Eldorado Utility Planning Model.

5.2 Methods

5.2.1 Regression trees

5.2.1.1 Classification and Regression Tree (CART)

The Classification and Regression Tree (CART) is a data mining technique that builds a predictive or descriptive model based on relationships between one or more predictor variables and a single response variable (Breiman et al., 1984). The algorithm recursively partitions data into two mutually-exclusive sets using successive values of predictor variables in order to create groups of similar values of the response variable. Classification trees are built for qualitative or categorical data; here we will only discuss regression trees, which are produced from quantitative data sets.

Starting with the full data set, or root, all possible splits in values of all predictor variables are analyzed to find the one that produces the greatest reduction in deviance in the response variable. Deviance within a group of observations is equal to the sum of squared distances to the mean value of the response variable (the sum of squared errors).

For each of these subsets, another split occurs using the value of any predictor variable that attains the maximum reduction in response error from its parent node. Branching continues until some stopping criterion is met. There are multiple ways to define stopping criterion; one is to specify that if a subsequent partition does not result in subsets that reduce error by at least 1% of the total original (root) error, a branch will not split. For example, if the total root error was 300, each split would have to reduce

the error within the subgroup by a value of at least 3 or there would be no split. When a branch can no longer split because the next split does not comply with the criterion, that node becomes a leaf.

Once a tree is completely grown (and possibly pruned to provide an interpretable amount of information), it reports: the number of observations at each leaf; the constituent partition rules (or decisions) to arrive at the leaf; and the predicted value (mean) of the response variable.

Regression trees are versatile and easy to interpret. The partitioning process does not assume any relationships between predictors and response, and can uncover hidden structures and interactions between hierarchical and nonlinear variables (Prasad et al., 2006; Verbyla, 1987). Among many predictor variables, the method can determine which have the greatest influence on response (Lawrence and Wright, 2001). The binary rules are clear; those who are not experts (either in statistics or the problem domain) can understand the decisions that lead from the root node to a leaf. Finally, the decision tree structure itself is an intuitive way to visualize a model.

5.2.1.2 Multivariate Regression Tree (MRT)

The Multivariate Regression Tree (MRT) is a data mining technique derived from CART. The method was originally developed for ecologists to analyze data sets describing assemblages of multiple species and their observed habitat characteristics (De'Ath, 2002; Larsen and Speckman, 2004). Importantly for De'Ath, the MRT made no assumptions about the underlying relationships (e.g. co-occurrence or aversion) between the different species (the response variables). And, as with univariate regression trees, there were also no assumptions about the relationships between species and environmental characteristics (predictor variables).

The extension from CART to MRT is straightforward: instead of the univariate response, MRT considers a multivariate response. Error calculations are the summed squares of observations' distances from all response means; in geometric terms, the Euclidian distances of all points from the centroid. Thus,

the best split will use the value of a single predictor variable that minimizes the multivariate error of the resulting two subsets:

Equation 5-1

$$\text{minimize } \sum_{k=1}^2 \sum_{i=1}^n \sum_{j=1}^m (y_{ij(k)} - \bar{y}_{j(k)})^2$$

where y is an observed value of the response variable, \bar{y} is the mean value of the subset's response variable, k = the subset formed by the split, n = the number of observations in a subset, and m = the number of response variables.

The resulting distinctions in response variables between branches may come from a large reduction in error in one response variable (where the two subsets have very different means in that variable) or smaller differences in means in multiple response variables. That is, the error reduction may be concentrated in one variable or dispersed across several.

Total tree error across all leaves is given by:

Equation 5-2

$$\sum_{l=1}^L \sum_{i=1}^n \sum_{j=1}^m (y_{ij(k)} - \bar{y}_{j(k)})^2$$

And explanatory power of the tree model is defined as:

$$\frac{\sum_{l=1}^L \sum_{i=1}^n \sum_{j=1}^m (y_{ij(k)} - \bar{y}_{j(k)})^2}{\sum_{i=1}^N \sum_{j=1}^m (y_{ij} - \bar{y}_{j(N)})^2}$$

Where a CART regression tree reports the univariate response mean of the group of observations within each leaf, MRT typically reports the within-group mean for each response variable (as described in Section 5.4, our MRT application reports the distributions instead of just the means). The benefits of CART – versatility and interpretability – are also realized with MRT.

5.2.2 Multiobjective Evolutionary Algorithm (MOEA)-assisted optimization

Multiobjective Evolutionary Algorithms (MOEAs) are a search technology used to efficiently generate and evaluate alternative solutions to systems whose conflicting performance objectives are impacted by many decisions that exhibit complex interactions. In MOEA-assisted optimization, a system is represented by a model which is embedded within the search loop of the MOEA. The MOEA interacts with the system model by feeding it portfolios of decision levers and evaluating the performance of each portfolio based on simulation outputs that produce values for objectives and constraints. This loop iterates thousands of times during which the MOEA tries to optimize the multiple, possibly conflicting, objectives by producing new generations of portfolios based on traits (decision lever values) of previously-evaluated portfolios with good performance; hence, the search is evolutionary. When objectives conflict there is no universally optimal portfolio, so the result of MOEA-assisted optimization is a set of nondominated portfolios in which improvement in one objective is only possible through sacrifice in another (i.e. the set is approximately Pareto-optimal (Pareto, 1896)).

The set of decision levers, objectives, and constraints make up the MOEA problem formulation. In water resources planning, the problem formulation would include decision levers such as how many water rights to purchase, how much to conserve, or what size reservoir to build; examples of objectives

are maximizing water demand reliability or minimizing incidence of reservoir levels below a certain elevation; a constraint could be a measure such as ensuring delivery of 100% of indoor municipal demand. An MOEA would try thousands of combinations of supply and demand decisions and produce a set of portfolios that quantitatively describe the tradeoffs between objectives defined by an agency seeking to balance economic, social, and environmental system goals (Elkington, 2004).

Each portfolio within the nondominated set produced by MOEA-assisted optimization is an observation of how multiple independent predictor variables (decision levers) affect a system's performance in multiple response variables (objectives). We propose applying MRT analysis to tradeoff sets as a way to discover relationships between multiple decision levers and between levers and objectives that are not readily apparent via visual inspection and which are not necessarily revealed by sorting and filtering on pre-determined dimensions-of-interest. The branches of the resulting trees can clearly communicate decision lever paths that lead to different leaves of performance outcomes, connecting subsets of high-impact decisions with different tradeoff regions.

5.3 Case study

5.3.1 Front Range, Colorado

The Front Range of Colorado is an urban corridor on the eastern slope of the Rocky Mountains that encompasses several mid-sized cities and many smaller communities. Water providers in the region rely heavily on runoff from highly variable annual mountain snowpack, so storage is critical for weathering intra- and interannual water supply fluctuations (Doesken, 2014; Rajagopalan et al., 2009). The long term impact that climate change will have on Colorado's hydrology is unclear; temperatures are expected to continue increasing, but precipitation could increase or decrease (Lukas et al., 2014). Recent studies have shown that none of the potential precipitation increases in current climate projections would offset the higher temperatures, however, so there is likely to be less water available in the future (Udall and Overpeck, 2017; Woodbury et al., 2012). In addition to the natural supply variability and uncertainty

from climate change, the Front Range is experiencing the compounding challenge of rapid population growth; the regional population is projected to increase by 40% by 2050 (State of Colorado, 2017).

Water management in Colorado is further complicated by the prior appropriation doctrine, a legal framework that bases the succession of streamflow access on date of first use (“first in time, first in right”) (Hobbs, 2004). Farmers and energy companies own the vast majority of senior water rights in the state, and by 1900 most of the water in eastern slope rivers was fully appropriated (Eschner et al., 1983). This means that as cities grew, they collected a mixture of supplies from multiple locations (including the western slope of the Rockies) by acquiring junior streamflow diversion rights, building junior reservoirs, buying senior diversion rights from agriculture, or buying shares in other water companies. All long term utility planning involves making many decisions and balancing conflicting objectives; on the Front Range, these inherent difficulties are exacerbated by rapidly increasing demand, highly uncertain impacts of climate change, complex regulations, and contentious social and environmental issues. This context is the basis of our MOEA case study, briefly described in the next section.

5.3.2 Eldorado Utility Planning Model

The Eldorado Utility Planning Model was designed based on input from 11 Front Range water managers to generically capture important regional management features and challenges (Smith et al., 2017). It encompasses the region surrounding a small municipal water provider called the Eldorado Utility. Eldorado is located on the eastern slope of a mountain range along with eight other water users that directly compete with the utility to divert and store water. Eldorado has mostly junior diversion rights, junior storage rights in two reservoirs that it owns, and also has shares in a water wholesale company that it takes out of a reservoir owned by that entity. One of Eldorado’s diversion rights comes from the western slope, where an additional four users impede the utility’s access to water.

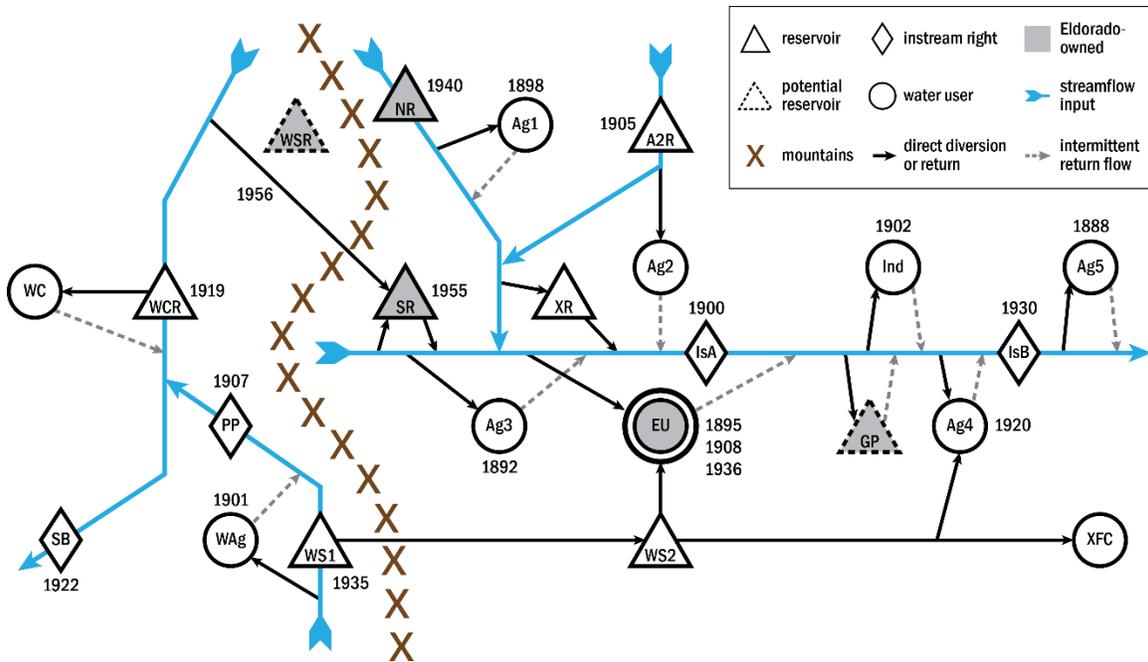


Figure 5-1. Schematic of the Eldorado Utility Planning Model. Many different users on both slopes of the mountain range impact Eldorado’s ability to collect and divert water via their priority dates, the locations of their diversions, and the locations of their return flows (precise diversion and return flow locations are indicated by arrows). The Eldorado Utility is represented by a green star on the eastern slope. Shapes and colors represent different types of rights and different types of users- see the key within the diagram and the details in Table 5-1. Each user in the diagram has a priority date associated with it where applicable.

Table 5-1. Detail for water users in Eldorado Utility Planning Model. Abbreviations refer to those found in Figure 5-1. The order of users going down each table column corresponds approximately to reading left-to-right on the diagram. Bolded users are particularly relevant to the results presented in Section 5.4. Superscripts in the table are defined as follows: ^ARes = Reservoir; ^BMCM = million cubic meters; ^CKAF = thousand acre feet; ^DAg = Agriculture; ^Ecms = cubic meters per second; ^Fcfs = cubic feet per second.

Abbr.	Name	Magnitude of Rights	Abbr.	Name	Magnitude of Rights
SB	Southern Basin	varying flow	A2R	Ag2 Irrigation Co. Res	24.7 MCM (20 KAF)
WC	Western City	n/a	Ag2	Ag2 User	n/a
WCR	Western City Res ^A	24.7 MCM ^B (20 KAF ^C)	EU	Eldorado Utility	0.28 cms (10 cfs); 0.34 cms (12 cfs); 0.42 cms (15 cfs)
WAg	Western Ag ^D User	4.3 cms ^E (150 cfs ^F) seasonal	WS2	Wholesaler Res 2	123.3 MCM (100 KAF)
PP	Power Plant	varying flow	IsA	Instream Flow A	varying flow
WSR	West Slope Res	varying vol; 2.2 cms (80 cfs)	GP	Gravel Pit	1.0 MCM (800 AF)
WS1	Wholesaler Res1	616.7 MCM (500 KAF)	Ind	Industrial User	varying flow
NR	North Res	11.1 MCM (9 KAF)	Ag4	Ag User 4	1.4 cms (50 cfs) seasonal
SR	South Res	9.9 MCM (8 KAF)	IsB	Instream Flow B	0.42 cms (15 cfs)
Ag3	Ag User 3	1.4 cms (50 cfs) seasonal	XFC	External Farms & Cities	n/a
Ag1	Ag User 1	1.4 cms (50 cfs) seasonal	Ag5	Ag User 5	2.9 cms (100 cfs) seasonal
XR	External Res	varying vol			

The model incorporates a wide range of water rights dates to capture the temporal complexity created by prior appropriation. It also has great spatial complexity to reflect the fact that in Colorado, water is constantly being diverted from and returned to the stream. Overall, there are five distinct basins in the model, each with a streamflow input site at its headwaters. The model was designed such that, under historic hydrology, Eldorado's existing system and sources could meet 100% of current demands with only rare need for restrictions. Different future streamflow scenarios that alter timing and volume of streamflow require the utility to take action in order to meet growing demands. These scenarios and demands are described in Section 5.3.4. For more detailed model information refer to Chapter 3 or Smith et al (In Review).

The Eldorado Utility Planning Model was built using the RiverWare modeling software (Zagona et al., 2001). RiverWare’s advanced capabilities facilitated our use of prior appropriation water allocation and enabled us to manage ownership of water through its accounting functionality. The model uses over 150 custom rules to operate the intricate relationships between objects, users, and accounts, and is an example of the kind of complex decision support system that many utilities have incorporated into their planning (Labadie, 2004).

5.3.3 Problem formulation

5.3.3.1 Decision Levers

Eldorado Utility has a total of 13 decision levers available to enable it to meet growing demands with potentially more challenging streamflow conditions. Some increase the system’s operational flexibility, some involve acquiring or freeing up water, and some develop new storage. They are briefly described below and summarized in Table 5-2. Where applicable, lever descriptions include a reference to the relevant user in figure 5-1.

5.3.3.1.1 Enhancing operations

Certain water sources in Colorado are reusable; cities carefully monitor their return flows from unconsumed water so that they can re-divert reusable return flows to meet demands. This is only possible by legally acquiring the right to exchange the water from downstream to upstream and only works well with strategic storage options. Three levers help Eldorado take advantage of reusable return flows: *Exchange* determines whether the legal right is acquired to store reusable water in a reservoir owned by Eldorado; *LeaseVol_{XRes}* determines the amount of dedicated exchange storage space Eldorado rent in the External Res (XR); and *Lease_{Ag2Res}* determines whether Eldorado is allowed to use available space in Ag2 Irrigation Co. Res (A2R) to store reusable water.

5.3.3.1.2 Increasing supply

There are three ways that Eldorado can gain access to “new” supplies. The utility can acquire portions of water rights of other users in the model, it can buy shares of water companies in the model,

and it can create water through conservation or increasing distribution efficiency. Eldorado may purchase up to 20% of the rights of Ag3 User (Ag3) ($Rights_{Ag3}$) and Industrial User (Ind) ($Rights_{Industrial}$). Ag3 rights are very senior and may be stored but are not available year-round; Industrial rights are mid-seniority and must be directly diverted from the stream, but are available year-round. Eldorado may buy shares from either Wholesaler (WS1, WS2) ($Shares_{Wholesaler}$) or Ag2 Irrigation Co. (A2R) ($Shares_{Ag2}$). Through $Share_{Interruptible}$ the utility may also execute a contract for access to A2R shares that is triggered when Eldorado's storage is severely depleted. Acquiring water from any of these sources will draw water away from regional agriculture and industry and potentially disrupt those communities. Finally, Eldorado may enact none, moderate, or aggressive conservation measures (ConsFactor) or increase distribution efficiency ($DistEff$) by up to 3%.

5.3.3.1.3 Building storage

There are three opportunities for Eldorado to increase the amount of storage it owns. The utility may expand the existing South Res (SR) to help store both existing and new eastern slope and western slope water ($ExpandVol_{SouthRes}$). Eldorado can build a new West Slope Res (WSR) to store its existing western slope diversion right ($BuildVol_{WestSlopeRes}$); this is a very challenging proposition because of regulatory, social, and environmental considerations. Lastly, the utility can develop gravel pits (GP) downstream of its return point to capture reusable flows (GP).

Table 5-2. Summary of Eldorado Utility decision levers.

Figure 1 Label	Decision	Description	Units	Range
Enhancing Operations				
1	<i>Exchange</i>	Acquire right to exchange reusable return flows to NorthRes	---	0 - 1
2	<i>LeaseVol_{XRes}</i>	Pay owners of XRes to lease dedicated space that can facilitate Exchange	MCM (AF)	0 – 3.7 (0 - 3,000)
3	<i>Lease_{Ag2Res}</i>	Pay Ag2 Irrigation Co. to store water in any available unused space; 0 = off, 1 = on	---	0 - 1
Increasing Supply				
4	<i>Rights_{Ag3}</i>	Purchase a portion of Ag3's senior diversion right	%	0 - 20
5	<i>Right_{Industrial}</i>	Purchase a portion of Industrial user's mid-seniority diversion right	%	0 - 20
6	<i>Share_{Wholesaler}</i>	Purchase additional shares of Wholesaler water	shares	0 - 6,000
7	<i>Share_{SAg2}</i>	Purchase shares of Ag2 Irrigation Co. water	shares	0 - 10,000
8	<i>Share_{Interruptible}</i>	Negotiate agreement with Ag2 Irrigation Co. for optional supply leases	shares	0 - 10,000
9	<i>ConsFactor</i>	Reduce starting per capita demand through conservation measures; 0 = no change, 1 = 10% reduction, 2 = 20% reduction	---	0 - 2
10	<i>DistEff</i>	Improve distribution efficiency by reducing unaccounted-for water (e.g. fixing leaks, improving metering, etc.)	%	90 - 93
Building Storage				
11	<i>ExpandVol_{SouthRes}</i>	Expand SouthRes	MCM (AF)	0 – 2.47 (0 – 2,000)
12	<i>BuildVol_{WestSlopeRes}</i>	Build West Slope Res	MCM (AF)	0 – 12.3 (0 - 10,000)
13	<i>GP</i>	Develop gravel pits to store reusable return flows downstream of the city; 0 = not developed, 1 = developed	---	0 - 1

5.3.3.2 Objectives

The problem formulation includes seven objectives which are briefly described here and summarized in Table 5-3. For more detail and discussion about the problem formulation, see Chapter 3 or Smith et al (In Review). The first three, *RestLev1*, *RestLev2*, and *RestLev3*, seek to minimize the total number of years (within the 25-year simulation) that Eldorado goes into the three different, increasingly

invasive, levels of restriction. To comply with Eldorado’s current reliability policy, the utility can only go into each level 5, 1, and 0 years out of 25, respectively.

The fourth objective, *MissedOpp*, minimizes the average annual volume of water that the utility “misses”, i.e. when timing of demand or availability of storage space prevent Eldorado from capitalizing on the full amount of its water rights. Optimizing how efficiently Eldorado uses the water it has helps prevent wasteful acquisitions.

Objective five, *New Supply*, seeks to minimize the average annual volume of water Eldorado uses from new sources. Though the utility does need to acquire or create new water to meet growing demands, they do not want to take more than they need for future water security.

The sixth objective, *AprilStorage*, maximizes carryover storage of the lowest storage-to-annual demand percentage recorded during the 25-year simulation. April 1 is the approximate date when reservoirs would be at their lowest levels before spring runoff begins to fill them again. Compared with the restrictions-based objectives, this captures a longer term reliability signal.

Finally, *NewStorage* minimizes the volume of newly-built storage within each portfolio. Because storage is difficult to permit and socially and environmentally contentious, Eldorado seeks to carefully consider the number and size of storage projects it pursues. The combination of this and the *NewSupply* objective provide a cost-like signal and allow the utility to consider planning policy on a broader level (Smith et al., In Review).

Formally, the optimization problem is defined as

Equation 5-4

$$\mathbf{F}(\mathbf{x}) = (f_{RestLev1}, f_{RestLev2}, f_{RestLev3}, f_{MissedOpp}, f_{NewSupply}, f_{April1Storage}, f_{NewStorage},)$$

$$\forall \mathbf{x} \in \Omega$$

Equation 5-5

$$\mathbf{x} = \text{Exchange}, \text{LeaseVol}_{XRes}, \text{Lease}_{Ag2Res}, \text{Rights}_{Ag3}, \text{Rights}_{Industrial}, \text{Shares}_{Wholesaler}, \text{Shares}_{Ag2}, \\ \text{Shares}_{Interruption}, \text{ConsFactor}, \text{DistEff}, \text{ExpandVol}_{SouthRes}, \text{BuildVol}_{WestSlopeRes}, \text{GP}$$

Performance was subjected to a single constraint, which is that all planning portfolios must meet 100% of indoor demands.

Equation 5-6

$$C_{UnmetDemand} = 0$$

Table 5-3. Summary of Eldorado Utility performance objectives.

Objective	Description
RestLev1	Minimize frequency of Level 1 restrictions over 25 years
MissedOpp	Minimize average annual volume of the sum of: return flows that Eldorado could have captured and reused, forfeited Wholesaler shares, and forfeited Ag2 shares
NewSupply	Minimize average annual new water created by either conserving or acquiring right and shares
NewStorage	Minimize the volume of newly-built storage in a portfolio
April1Storage	Maximize the lowest April 1 st storage-to-annual demand ratio during the 25-year simulation

5.3.4 Scenarios

The optimization runs using the Eldorado Utility Planning Model assumed a buildout demand based on a 40% population increase by 2050, when the simulation time horizon starts. The demands exhibit single family residential patterns, i.e. use increases substantially during summer months when lawns are irrigated. The irrigation demands go up slightly during dry years and are affected by conservation and distribution efficiency levers, but the baseline population demand does not change throughout the simulation.

Because future streamflow in Colorado is highly uncertain, the set of studies associated with this model use several hydrologic scenarios. The scenarios relevant to this chapter are the 1°C- and 4°C-

warmer futures, which were chosen based on a Front Range climate change study (Woodbury et al., 2012). The perturbed hydrology used monthly deltas from that study and generated sets of stochastic headwater streamflow input for the model using KNN resampling (Lall and Sharma, 1996) and proportional disaggregation (Nowak et al., 2010). See Chapter 3 or Smith et al (In Review) for more detail. Figure 5-2 shows a comparison of the average annual regional hydrographs for the two scenarios plus the historic record; the differences in timing and magnitude of flows summarize the relationships between the three scenarios.

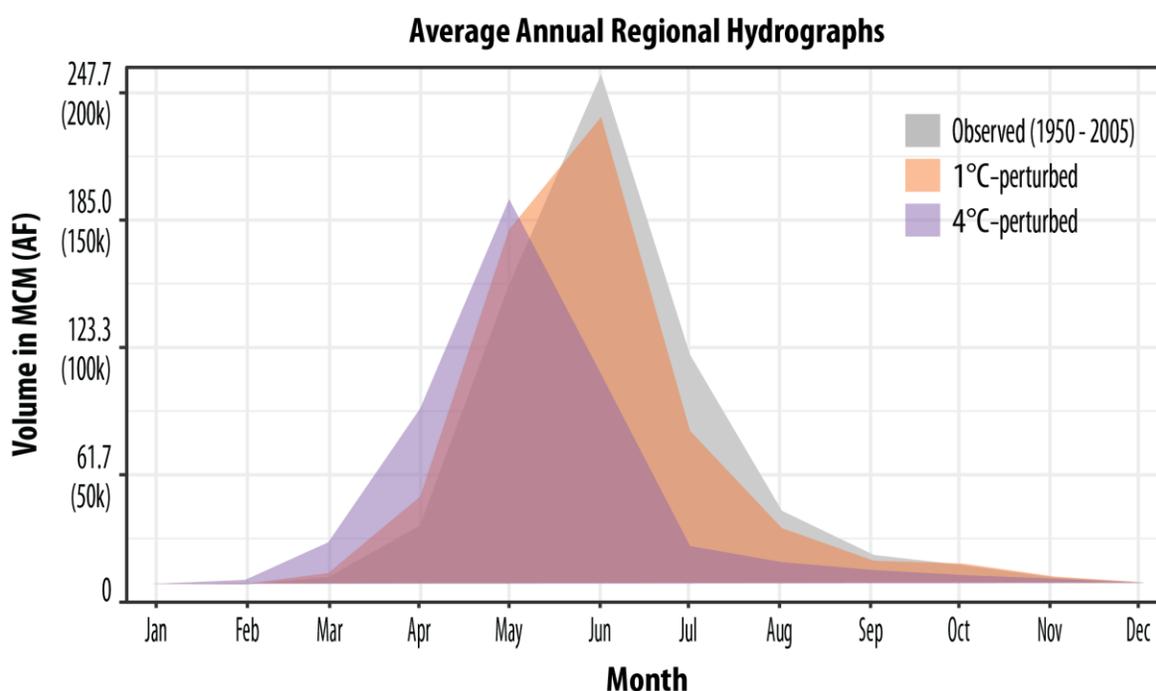


Figure 5-2. Average annual regional hydrographs for the historic record and two climate change scenarios.

5.3.5 Computational experiment

We used the Borg MOEA for this study (Hadka and Reed, 2013), which tests have shown to perform similarly or favorably compared to other state-of-the-art algorithms on difficult benchmark problems (Reed et al., 2013; Zatarain Salazar et al., 2016). The RiverWare model embedded in the search loop simulates the supply and usage dynamics of Eldorado Utility and other regional water users over 25

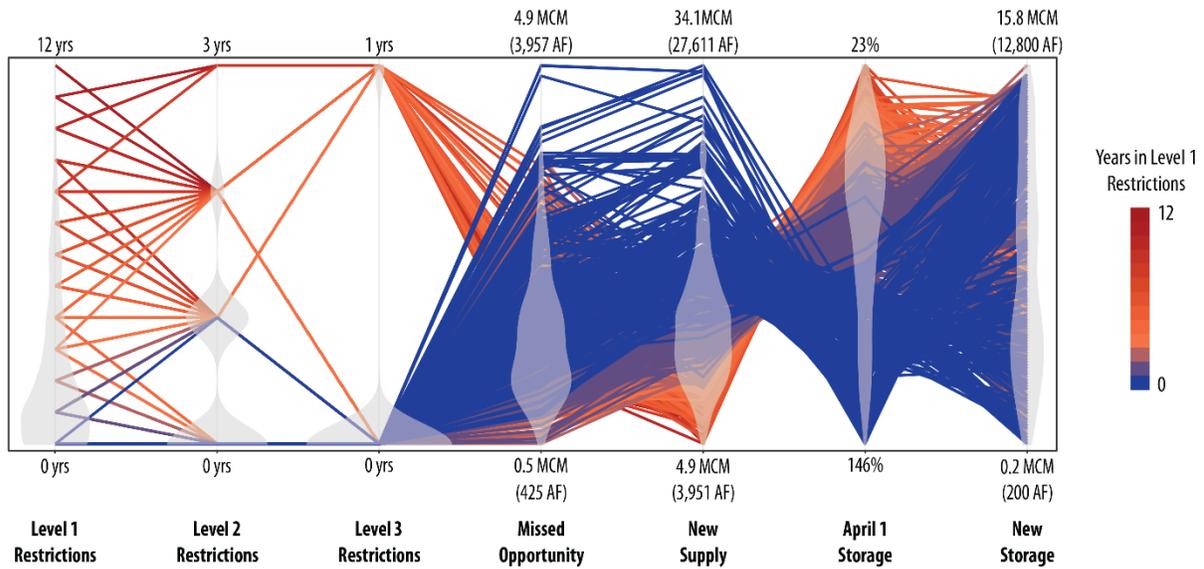
years (from 2050 to 2075) at a monthly timestep. Portfolios were tested as fully-implemented configurations of Eldorado's system.

Performance of each portfolio was evaluated across ten hydrologic traces, each distributed to a separate computing core of an Amazon Web Services Elastic Compute Cloud (EC2) instance (Mathew and Varia, 2014). Each distributed simulation took approximately 20 seconds. This relatively long simulation time prompted us to limit search to 5,000 function evaluations, a number shown to produce sufficiently-diverse tradeoff sets in previous work (Smith et al., 2016). We used the default Borg settings except for changing initial population size from 100 to 50 (Hadka and Reed, 2012; Reed et al., 2013).

5.3.6 Eldorado optimization tradeoffs

To facilitate readers' understanding of how MOEA tradeoffs sets, the Eldorado Utility Planning Model, and the Front Range of Colorado are all captured in the MRT results in the next section, here we present and briefly describe a set of Eldorado Pareto-optimal portfolios from a 1°C-perturbed optimization run. The performance and decision tradeoffs of the set of 961 portfolios are presented using parallel axis plots, which are a visual analytics technique commonly used in multiobjective optimization studies (Herman et al., 2014; Kasprzyk et al., 2013; Watson and Kasprzyk, 2017a).

(a) Objectives



(b) Decision Levers

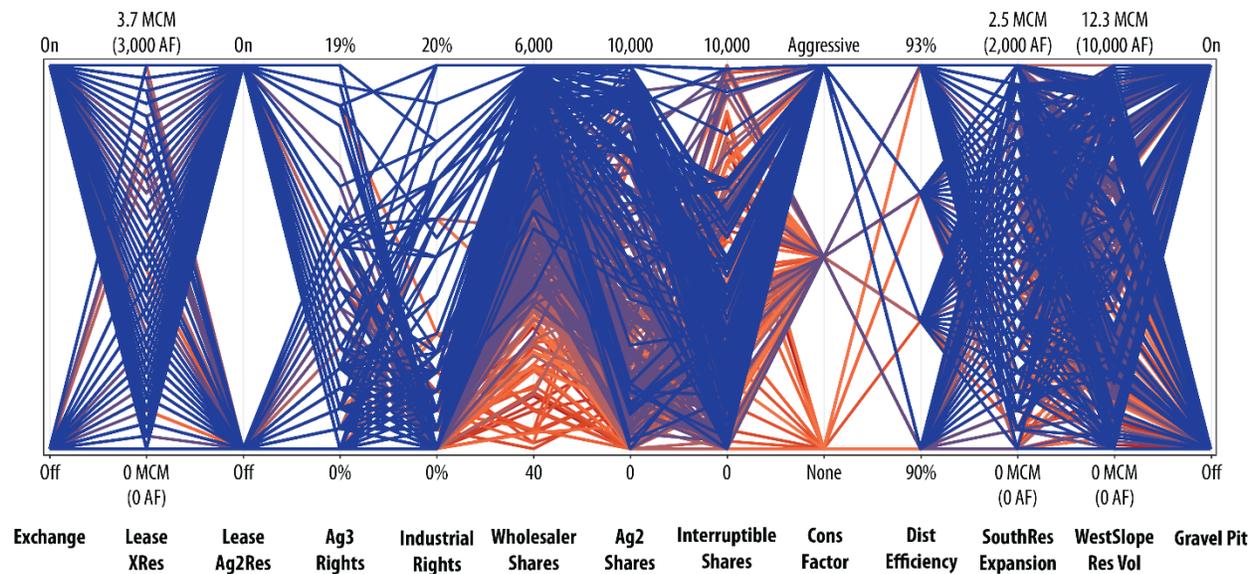


Figure 5-3. Parallel plots of the tradeoff set resulting from optimizing the Eldorado Utility Planning Model under 1°C-warmer hydrology. Plot (a) shows the relationships between different performance objectives, with color indicating performance in Level 1 Restrictions. Plot (b) shows the portfolios of decisions that resulted in the performance from plot (a).

In Figure 5-3a, each of the seven performance objectives is represented by a vertical axis. Each of the 961 portfolios is represented by a segmented line that crosses each axis at the level of performance it achieves in that objective, where crossing lower on an axis denotes better performance. The portfolio lines are colored based on the number of years they were in Level 1 restrictions, with dark blue

corresponding to zero years at the bottom of the leftmost axis. Presenting the set of portfolios as a group and in many dimensions is advantageous for seeing broad tradeoff patterns that are not necessarily perceivable in lower dimensions (Kollat and Reed, 2007). A disadvantage of this is that it can be difficult to discern trends within each objective because of the overlapping lines; the “violins” on the axes assist with this by showing the portfolio densities. Figure 5-3b is oriented identically to Figure 5-3a except that there are 13 axes – one for each decision lever. Every portfolio line in Figure 5-3a has a corresponding line in Figure 5-3b that conveys the amounts or levels of all of the decisions within the portfolio. The lower a line crosses an axis in Figure 5-3b, the less of that decision has been chosen.

In Figure 5-3a we can see relationships between the objectives. Color enables us to tell that all of the dark blue portfolios with zero years in Level 1 restrictions have medium to high levels of New Supply (fifth axis from the left), medium to high levels of April 1 carryover storage¹⁰, but may have anywhere from 0.2 to 15.4 MCM (200 to 12,500 AF) of New Storage (rightmost axis). This means that to minimize years in Level 1 restrictions, it is imperative that Eldorado attain new water sources but may choose to build or avoid large amounts of new reservoir storage. However, portfolios that do not build much New Storage perform more poorly in April 1 Storage and tend to require greater volumes of New Supply. This shows an important tradeoff within the Eldorado model as well as on the Front Range: utilities often have to choose between meeting growing demands with new supplies that come from conservation and other users’ shares and rights, which may be socially and economically disruptive to communities, and relying on contentious, expensive infrastructure that is difficult to permit. For further discussion on this topic, refer to Chapter 3 or Smith et al (In Review).

Looking at Figure 5-3b we can see several trends relating decisions to performance by using color as a guide. All of the portfolios with zero years in Level 1 restrictions are plotted at the top of the ConsFactor axis (fifth from the right), denoting that they all include aggressive conservation (ConsFactor

¹⁰ April 1 Storage is the only maximization objective, so even though higher levels of storage are better, that is still represented by lower positioning on the axis.

= 2). It is possible to achieve acceptable reliability performance (fewer than five years in Level 1 restrictions) with only moderate conservation, but aggressive conservation is an overwhelmingly promising strategy. We also see that portfolios with few years in Level 1 restrictions tend to have medium to high numbers of Wholesaler Shares (sixth axis from right). Beyond these two visible trends, no other insights are readily apparent.

Interactive parallel plots are known to be helpful when working with this type of high-dimensional data (Johansson and Forsell, 2016; Siirtola and Rähä, 2006). However, while shown to be useful in finding or choosing a specific portfolio (Siirtola and Rähä, 2006; Smith et al., In Review), the large number of ways to manipulate the visualizations (e.g. through reordering axes, changing colors, filtering, etc.) may impede unbiased understanding about the problem itself.

MOEA tradeoff sets contain information about relationships between decision levers and objectives as well as interactions between groups of decisions. In any optimization problem with many complex decisions, some levers are going to be more consequential, and some will be more flexible. In the context of water resources planning, this information could indicate which water sources or infrastructure projects are more core to a reliable system and which are more peripheral contributors. As we demonstrate in the next section, large data sets produced by MOEA-assisted optimization offer an opportunity for water providers to gain this information through data mining.

5.4 Results

A Multivariate Regression Tree (MRT) generated from a set of MOEA-produced Pareto-optimal portfolios relates independent predictor variables (decision levers) to observations of response variables (performance objectives). Because the objectives used in MOEA-assisted optimization of a water resources system are often measured in different units with different scales, it is necessary to scale the observations in each objective to a range of zero to one; otherwise, the objective with the largest range and units would dominate the regression splits and the decision levers' impacts on an objective with a smaller range and small units would have very little impact in reducing error. Values of decision levers

are not scaled. Another consideration when generating the trees is specifying the stopping criterion that tell the tree when to stop splitting. Requiring at least a 1% reduction in error compared to the root error is common; here, we used a 1.6% reduction to grow trees that provide good explanatory power but also fit on a page. Alternatively, you could grow a very large tree and prune it by hand.

We used the *mypart* R package (De'Ath, 2002, 2014; R Core Team, 2016), which is archived but still functional. The *mypart* package generates a set of bar plots for the mean objective values at each leaf, but we replace the bars with boxplots to give more information.

For every set of tradeoffs produced by an optimization run we produced a tree. Below, we introduce the results of an MRT with the tree from the 1°C-perturbed portfolios described in the previous section, and we follow that discussion with a tree from a tradeoff set produced by a 4°C-perturbed run. Comparing trees from different optimization scenarios results in additional problem and system understanding.

5.4.1 MRT for 1°C-perturbed tradeoff set

Figure 5-4 presents the MRT generated from the 961 portfolios in the 1°C-perturbed tradeoff set described in Section 5.3.6. We will first orient the reader to the features of the tree and then discuss different approaches to interpretation and insights from it.

Multivariate Regression Tree, 1°C-perturbed Hydrology

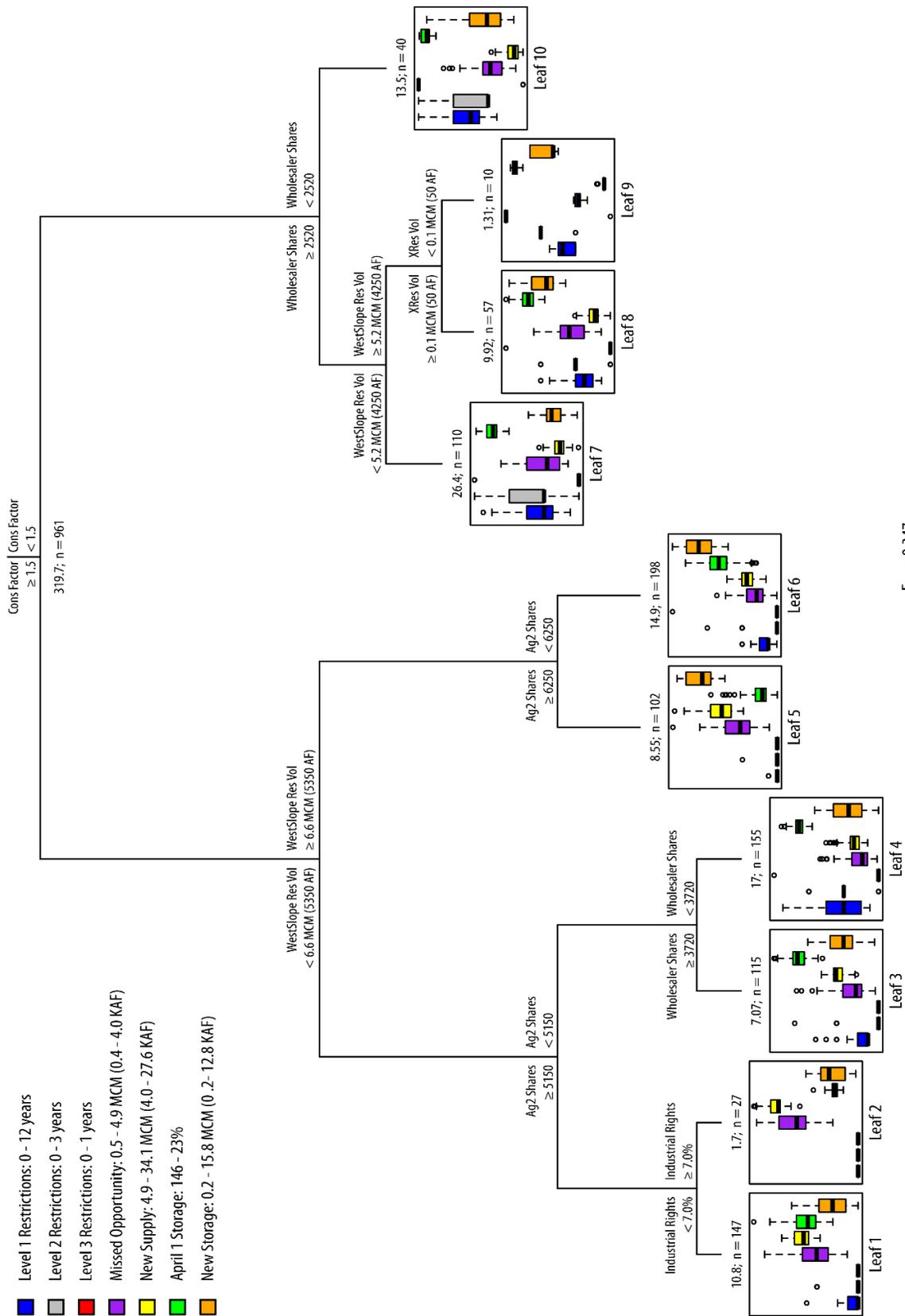


Figure 5-4. Multivariate regression tree generated from the Eldorado Utility 1°C optimization tradeoffs.

5.4.1.1 Features of an MRT

At the top of the tree is the root node, where the information about number of portfolios and total root error are presented. Here we also see that the first split is based on the conservation level incorporated into each portfolio. No conservation is $\text{ConsFactor} = 0$, moderate conservation is $\text{ConsFactor} = 1$, and aggressive conservation is $\text{ConsFactor} = 2$. The left branch includes portfolios where ConsFactor is greater than or equal to 1.5, i.e. portfolios that have aggressive conservation. The split value reported is the average between the levels of decision above and below the split. As another example, following the left branch, the next split is on the volume of West Slope Res. To the left are portfolios that have reservoirs up to 6.5 MCM (5300 AF), and to the right go the portfolios that have reservoir volumes starting at 6.7 MCM (5400 AF). The granularity of the split value depends on the discretization of a decision lever (i.e. some levers are continuous, while other levers increase by steps of, e.g., 10).

Following splits down to the leaves, we find that each leaf has a set of boxplots. There is a boxplot for each of the seven objectives, each with a color denoted in the legend. The ranges for each objective can also be found in the legend (the same ranges in Figure 5-3a). The order of the boxplots is the same as the order in which the objectives were first described, which is also their order in Figure 5-3a. And, like the parallel plots, the lower a boxplot is positioned within the plot area, the better the performances of the portfolios within the leaf.

Also located at each leaf is the number of portfolios contained within the leaf and the total error across all objectives within the leaf. Notice that leaves with larger numbers of portfolios tend to have higher error because there are more errors to sum, and also that leaves that have a large distribution of performance in one or more objectives (i.e. large boxplot ranges) will also have higher in-leaf error; this makes sense because when a group has a wide distribution in one or more objectives, the portfolios contained in the leaf have objective values that are further from the objective mean(s), and error is a measure of these distances. Finally, the error number reported at the bottom of the tree is the amount of error leftover after growing the tree. It is equal to the sum of all within-leaf errors divided by the root

error. The remaining error for this tree is 0.347, so the tree explains 65.3% of the performance objective variance within the data set. This can be understood as a measure of how well the tree was able to organize the set of portfolios into groups of similar performance characteristics, where this tree reduced the disorganization from 100% to 34.7%.

5.4.1.2 Interpreting the tree: leaves-first

One way to use the information contained within the tree is to start at the leaves, consider the ranges of performance for the objectives, assert a set of priorities to direct focus on a single leaf, and then follow the branches up to the root to see what decision rules produced that leaf. For example, Eldorado Utility managers may want to prioritize reliability-related objectives (Smith et al., In Review). Given that criteria, leaves that have boxplots that are very low with small ranges in the first three objectives (blue, grey, and red) would contain portfolios of interest. Examining the leaves shows that there are three that meet that boxplot configuration- leaves 1, 2, and 5. Focusing on leaves 2 and 5, which are superior to Leaf 1 in years in Level 1 Restrictions, will help illustrate the value of MRTs and connect them to recognizable tradeoffs. Figure 5-5 provides a close up comparison of the two sets of boxplots.

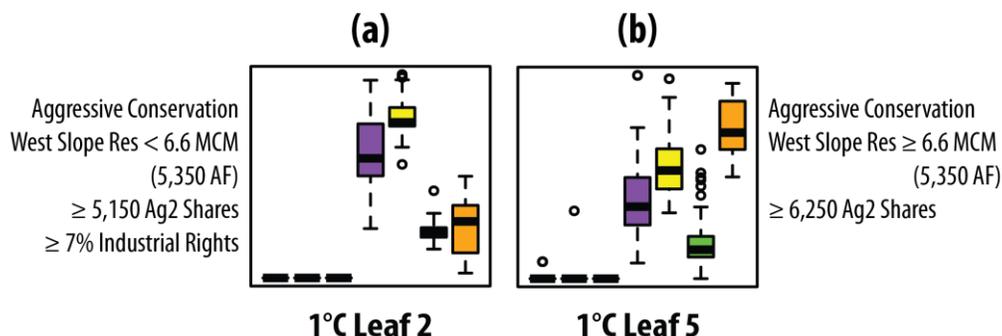


Figure 5-5. Comparison of two leaves from the 1°C MRT. Note that both leaves incorporate Aggressive Conservation and have very similar amounts of Ag2 Shares.

The decision rules that lead to Leaf 2 are: aggressive conservation; a West Slope Res smaller than 6.6 MCM (5350 AF); 5,200 or more shares of the Ag2 Irrigation Co.; and at least 8% of Industrial User's water rights. None of the portfolios have any incidence of any level of restrictions, they have moderate to high volumes of MissedOpp water, a very high range of NewSupply (the highest range of all the leaves),

medium-high April 1 carryover storage, and moderate to low volumes of NewStorage. Despite having zero years in restrictions, the April 1 carryover storage objective is not as high (i.e. positioned a low) as might be expected because the portfolios within the leaf have relatively low amounts of NewStorage.

The path to Leaf 5 includes aggressive storage, a West Slope Res 6.6 MCM (5350 AF) or larger, and at least 6300 Ag2 Shares. The performance ranges in Leaf 5 are notably different than in Leaf 2. Among the portfolios in Leaf 5, there is one occurrence of Level 1 restrictions and 1 occurrence of Level 2 restrictions, moderate volume of MissedOpp water, moderate to high NewSupply, high to moderate volumes of April 1 carryover storage, and high to very high volume of NewStorage. Incorporating the larger West Slope Res reduced Leaf 5's reliance on NewSupply (e.g. via the Industrial Rights required in Leaf 2), but the portfolios are therefore more likely to have large amounts of NewStorage. The comparison of the two leaves confirms the tradeoff between NewSupply and NewStorage discussed for the parallel plot in Figure 5-3a, and also confirms that even with large storage volumes, moderate NewSupply is still required for high reliability. We also note that the correspondence of two decisions- ConsFactor and Ag2S Shares- underscores that these are promising decision levers.

Emphasizing leaves 2 and 5 as superior to others in reliability objectives does not preclude other leaves and other sets of decisions from containing portfolios that match Eldorado's performance priorities. The leaves simply indicate that after sequentially splitting the portfolios based on all of the relationships within the tradeoff set, these particular sets of decision levers are most likely to result in appealing portfolios. Furthermore, the decisions in the paths to highly reliable leaves must still be accompanied by actions in the other decision levers; there is just more flexibility in the values for these levers. Figure 5-6 shows revisits the parallel plots presented in Figure 5-3 but now emphasizes the 27 portfolios in Leaf 2.

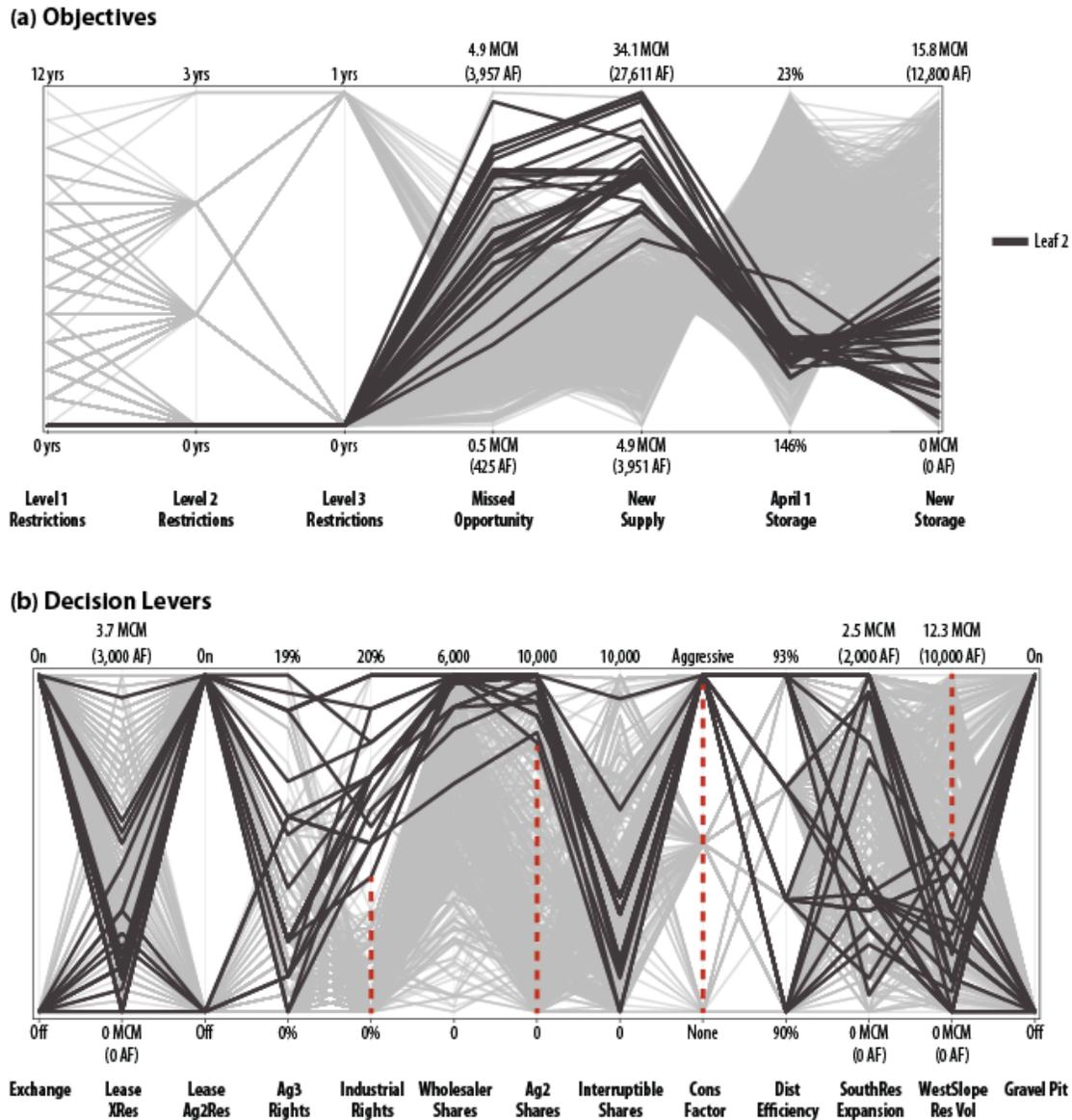


Figure 5-6. Parallel plots from the 1°C Eldorado Utility tradeoff set, with the portfolios contained within Leaf 2 of the 1°C MRT darkened. Plot (a) shows performance tradeoffs. Plot (b) shows constituent decisions and uses red dashed axes to highlight the four decisions from the branches that lead to Leaf 2.

Figure 5-6a and Figure 5-6b are oriented almost exactly like the plots in Figure 5-3: the 7 objectives all have axes in Figure 5-6a and the 13 decisions all have axes in Figure 5-6b. The only difference is that in this figure, color is used to distinguish the set of 27 portfolios from Leaf 2. In Figure 5-6a, the pattern and ranges of the portfolios’ performance across the seven objectives matches the boxplots from Figure 5-5a. The ranges of ConsFactor, West Slope Res, Ag2Shares, and Industrial Rights in the decision levers in Figure 5-6b also reflect the decision rules, and red dashed axis lines highlight the

restricted ranges of those decisions. In eight of the remaining nine decision dimensions, there is considerable variety in potential values to accompany the constrained decisions. The levels of Wholesaler Shares are almost universally very high, though, so this decision lever correlated closely with one of the other decision rules that produced a split.

5.4.1.3 Interpreting the tree: root-first

Approaching the tree from the leaves up means asserting *performance* preferences and learning which decisions are likely to lead to good performance. Starting from the root and working down allows users to learn how their *decision* preferences impact performance.

Using the tree in Figure 5-4, we can simulate the path an Eldorado manager might take down the tree. At the first split, a manager may choose to go to the right because even though conservation is a part of any serious long term plan, she or he does not want to have to rely on *aggressive* conservation to meet performance goals. At the next split, a manager may choose to go left because Wholesaler Shares are a reliable water source that do not require infrastructure. At the next split, a manager may want to avoid a large West Slope Res because of cost, permitting, etc., so would go left and end up at Leaf 7. The boxplots in Leaf 7 reveal that these decisions will likely result in good performance in NewSupply and NewStorage but poor to terrible performance in the other objectives. This manager would have learned that the combination of decisions in this path will likely result in non-preferable performance regardless of the other 10 decisions in the portfolio.

5.4.2 MRT for 4°C-perturbed tradeoff set

All previous discussions of tradeoffs, portfolios, and trees have referred to a set of portfolios generated from optimizing for a 1°C-warmer future. Planning in consideration of multiple possible future scenarios is beneficial in and of itself, and it also increases the impact of MOEA-based MRTs. Below we present an MRT generated from a set of portfolios optimized for 4°C-perturbed hydrology. After briefly describing a few features specific to this tree, we discuss findings from comparing the 1°C and 4°C trees.

The root error and total number of portfolios are given at the root node of the MRT in Figure 5-7. Splits, leaves, boxplots, colors, and objective ranges are all oriented the same as in Figure 5-4, but note that the objective ranges are different. This is especially relevant in the first three objectives (years in levels of restrictions); the more challenging hydrology resulted in more frequent restrictions and fewer portfolios with low incidence. The final error for this tree, located at the bottom, is 0.341, so it explains 65.9% of the performance variance found within the tradeoff set.

If we repeat the same leaf-first exercise from the 1°C tree, where we determined that the performance preference was to have minimal years in all three levels of restrictions, that criteria reduces viable leaves down to two: Leaf 1 and Leaf3. The decision path to Leaf 1 includes aggressive conservation, at least 4060 Wholesaler Shares, a West Slope Res less than 4.3 MCM (4350 AF), and at least 7% of Industrial Users rights. The decision rules for Leaf 3 are, like Leaf 1, aggressive conservation and at least 4060 Wholesaler Shares, but then instead of a small West Slope Res and a percentage of Industrial rights, Leaf 2 includes a West Slope Res at least 5.4 MCM (4350 AF) in volume. A comparison of the two leaves shows that they exhibit the same NewSupply-NewStorage tradeoff seen in the 1°C MRT and the original parallel plots of the 1°C tradeoffs.

5.4.3 Comparing MRTs

Comparing the broad characteristics of the two trees provides valuable information. First, we note that the decisions on which splits occur are very similar across both trees: ConsFactor, West Slope Res, and Industrial Rights are prominent in both trees. In the 1°C tree, Ag2 Shares are more important while in the 4°C tree, Wholesaler Shares are more important. Since Wholesaler Shares are a western slope source and Ag2 Shares are eastern slope, this may be indicative of a shift in basin yields with warmer temperatures. The general agreement in splits suggests that these decisions are the most influential factors in a portfolio in either scenario, and this is a fundamental insight about the Eldorado system.

We can expand on this general decision lever agreement by comparing sets of leaves from the two trees. First we will compare Leaf 2 from the 1°C tree and Leaf 1 from the 4°C tree, as shown in

Figure 5-8. The decisions that lead to these leaves with very similar objective patterns include three nearly identical splits: aggressive conservation, a medium or smaller West Slope Res, and approximately 7% or more of the Industrial rights. Ag2 Shares in 1°C are traded for Wholesaler Shares in 4°C.

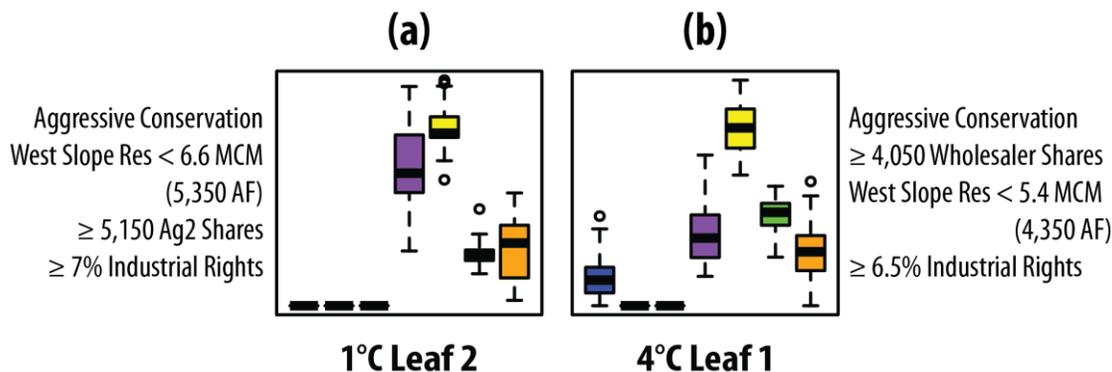


Figure 5-8. Comparison of Leaf 2 from the 1°C MRT and Leaf 1 from the 4°C MRT. Note that Aggressive Conservation, West Slope Res, and Industrial Rights have identical or similar values in both leaves.

Now compare Leaf 5 from the 1°C tree and Leaf 3 from the 4°C tree in Figure 5-9. Like the previous comparison, the patterns of objective performances are similar, and they share two almost identical splits: aggressive conservation and medium to large West Slope Res. Again, Ag2 Shares in 1°C are replaced by Wholesaler Shares in 4°C.

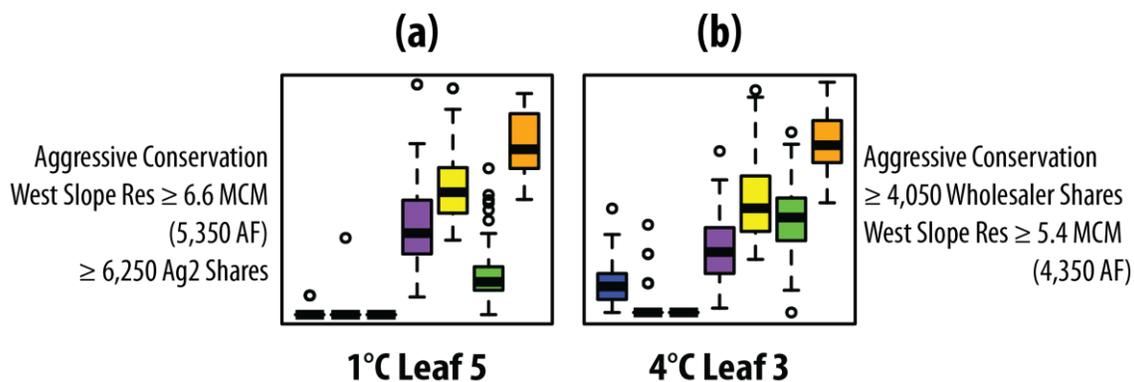


Figure 5-9. Comparison of Leaf 5 from the 1°C MRT and Leaf 3 from the 4°C MRT. Note that these leaves both incorporate Aggressive Conservation and a moderate-to-large West Slope Res.

Recall from Figure 5-2 that the 1°C- and 4°C-perturbed hydrologies are substantially different in runoff timing and magnitude and overall hydrograph shape. The overlap in the two sets of leaves suggests

that when seeking portfolios with high reliability, there is a fundamental strategy for preferring to minimize NewStorage at the cost of more NewSupply (leaves 2 and 1 in Figure 5-8) and a fundamental strategy for preferring to prioritize minimizing NewSupply instead of NewStorage (leaves 5 and 3 in Figure 5-9). As discussed in Chapter 3 and Smith et al (In Review), these strategies may map to broader planning policies agreed upon within a utility.

5.5 Conclusion

Large MOEA tradeoff sets are valuable sources of hidden system information that data mining can efficiently access. MRTs can relate performance variations within and across multiple objectives to distinct subsets of specific decisions, providing users with information about the most consequential decisions and their most productive ranges. Once MOEA tradeoffs are on hand, MRTs are very simple to generate and present easily comprehensible insights.

The trees generated for the Eldorado Utility long term planning case study clearly demonstrate how the combination of MOEAs and MRTs can benefit a water provider. Within one tree, a user can start at a leaf and learn which few decisions, that, when included in a broader plan, would likely result in preferred (e.g. reliable) system performance. Because the ultimate success of any given decision is itself uncertain, prioritizing outcomes in the core, consequential decisions could allow for greater flexibility in the remaining decisions. Furthermore, as uncertainty in decision outcomes lessens over the course of implementing a plan, alternative values of the flexible decisions could be exchanged. Reading an MRT from top to bottom can also help managers or, equally importantly, high level decision makers, quickly understand what types of performance would likely materialize if their decision preferences were to shape a plan. Comparing leaves and decisions across trees generated from very different optimization scenarios can shed light on decisions that will result in good performance in a wide range of futures, i.e. decisions that are robust. Whether or not a utility chooses a specific portfolio from within one of the leaves (or one generated directly by the MOEA at all), the information offered by MRTs can quickly and objectively

organize system understanding for the many technical staff and decision makers who must work together to devise and adopt a plan.

The method presented in this chapter was developed in response to direct feedback from a group of Front Range water utility managers. In 2016, we held a hands-on MOEA charrette at which we presented managers with multiple sets of tradeoffs generated from the Eldorado Utility optimization case study (Smith et al., In Review). Over the course of the day-long workshop, nine managers remarked frequently that they would like to understand how decisions were affecting performance – information that was difficult to deduce from interactive parallel plots alone. The managers' responses highlighted the need to undertake research that could help agencies make practical sense of the voluminous, high-dimensional results of performing MOEA-assisted optimization for long term water utility planning. In keeping with the philosophy developed over an extended participatory study, we hope this area of research further develops with continued practitioner input.

Chapter 6

Concluding Remarks

6.1 Summary

This dissertation presented a participatory framework designed to explore the usefulness and usability of research-developed tools, learn about industry context directly from practitioners, and develop future research avenues based on tool-specific as well as general feedback from participants. We demonstrated the Participatory Framework for Assessment and Improvement of Tools (ParFAIT) on Multiobjective Evolutionary Algorithm (MOEA)-assisted optimization for long term water utility planning with water managers from six Front Range water provider partners. The introduction of this document established the reasons for carrying out the framework on this tool and application; it described the ripe opportunity for MOEA-assisted optimization based on a growing number research case studies, utilities' reliance on simulation models, access to computing power, and the interest expressed by practitioners. This is the first step of ParFAIT.

Our processes and results from performing the remaining steps were described in subsequent chapters of this dissertation. Step 2, to hold a workshop with practitioners to elicit planning context and solicit their input on a tool testbed, was presented in Chapter 2; we described how a structured set of topics organized free-form discussions between practitioners and researchers. The workshop resulted in ideas for decision levers, objectives, constraints, modeling, and scenarios to inform our MOEA testbed, and also expanded our understanding of Front Range water utilities' challenges. Chapter 3, corresponding with ParFAIT step 3, introduced the testbed we created – the Eldorado Utility Planning Model – and presented MOEA optimization results and analysis demonstrating its ability to capture Front Range management complexity and relevant planning tradeoffs. Chapter 4, i.e. step 4, detailed the careful design and content of our second workshop (or charrette), and reported practitioners' responses to tradeoff analysis activities and discussion prompts about their broader planning processes. Finally, Chapter 5

introduced Multivariate Regression Trees (MRTs) to reveal fundamental system information contained within MOEA tradeoff sets.

6.2 Conclusions

Throughout this document, we provide evidence of the efficacy of ParFAIT. The structured process allowed practitioners make the case *to us* that MOEA-assisted optimization could be useful in their planning processes. In the second workshop, managers found the tradeoffs beneficial in identifying and justifying planning strategies, and they reported that the tradeoffs could also support policy discussions with decision makers and help to achieve plan buy-in from the public. Discussions at the workshop also resulted in insights about important usability considerations, e.g. the importance of having the right type of model and appropriate visualization techniques. Furthermore, workshop 2 successfully generated actionable feedback about MOEA-assisted optimization that has already begun to shape our research agenda via the application of MRTs; this data mining method can shed light on the types of questions about decisions vs. objectives that came up frequently for workshop 2 participants.

Besides the benefits of the structured process of the framework, we also recognize that using a specific tool as the main organizing concept helped ParFAIT in its other goal: to draw information about important water utility planning context into Water Resources Systems Analysis (WRSAs) literature. The pre-defined topics relevant to performing MOEA-assisted optimization led to nuance that may not have come out if we asked more general questions; for example, asking utilities in the first workshop to give examples of planning objectives as they related to an MOEA problem formulation resulted in a revealing discussion about different ways of defining reliability and its relationship to other types of objectives. In workshop 2 we heard a discussion between managers about the tradeoff between increasing rates now to pay for new infrastructure vs. slowly increasing them to balance the reduced demand that would result from frequent restrictions or aggressive conservation measures.

A final conclusion is that investing time and effort into soliciting direct input from practitioners and then iterating with practitioner PIs can result in a valuable testbed simulation model. As with other

models designed for research purposes, the Eldorado Utility Planning Model comes with the freedom to experiment, but it advances the art by bringing in far greater complexity than previous WRSA research simulations. Knowing which types of complexity to incorporate, e.g. water ownership and intricate return flow patterns, was only possible because of interactions with water managers. Additionally, the necessity of testing our modeling and problem formulations with managers at workshop 2 provided important motivation and feedback.

6.3 Contributions

This study contributes the ParFAIT framework itself. Though demonstrated here on MOEA-assisted optimization for long term water utility planning, it can be used by any research field for any tool and any proposed purpose to ascertain usefulness and usability of a tool and inform future research agendas. Through published and in-preparation articles, we have shown that the work is publishable, and thus not a diversion from an important traditional research motivation. Ideas for research that respond directly to input from practitioners provide greater confidence in WRSA research within the academic community and among practitioners, and building relationships that span the boundary between academia and practice can result in greater long term water resources sustainability. Finally, practitioners benefit by getting hands-on experience with an emerging tool, which may also increase the likelihood that the tool is (more widely) adopted in practice.

Through two workshops, this study has drawn into academic literature important insights about water utilities' experiences, challenges, planning processes, decision levers, and objectives. Importantly, we present them clearly and for the explicit purpose of informing future WRSA research rather than framing them as byproducts or inferences. We hope that these can broadly impact future work and that this effort will encourage future studies that incorporate practitioners to do the same.

We contribute the complex, credible, relatable, and practitioner-tested Eldorado Utility Planning Model. Through this model, future MOEA research can be conducted in consideration of challenges that

more closely resemble real-world context than previously-developed models. This advantage can facilitate communication of results and new techniques to a practitioner audience.

Finally, this research contributes a novel application of MRTs to mine MOEA tradeoffs. This is a contribution relevant not only to WRSA research but also to other fields that use MOEA-assisted optimization. While we learned that MOEA tradeoffs are perceived as useful and usable, we also realized that techniques which support the interpretation of the tradeoffs are needed. MRTs offer a way to connect multiobjective performance to individual and groups of decisions, providing fundamental system information and potentially offering guidance in formulating robust long term water utility plans.

6.4 Future Work

6.4.1 Workshops

The success of our second workshop, where practitioners were able to work with MOEA tradeoffs and provide thoughtful feedback, suggests that additional workshops addressing different aspects of MOEA-assisted optimization would be fruitful. One logical extension, and an idea we heard during the workshop, is to design exercises to investigate how tradeoffs can support group decision making. This could focus on either building group understanding, negotiating around different priorities, or both. Recent research using MOEAs for transboundary operations in the Nile River basin suggests that developing and testing approaches to this in a hypothetical application could benefit future real world efforts (Wheeler et al., In Review). Another workshop idea would be to follow up with Front Range managers to determine how the information provided by MRTs could enhance the usefulness of tradeoffs and what role the trees could play. Finally, we have determined that practitioners see potential for MOEA tradeoffs in the context of long term planning, but evaluating the tool in the context of optimizing short term operational policies is a different proposition and would be an interesting iteration of the ParFAIT approach.

6.4.2 Technical Studies

Our inaugural application of MRTs to MOEA tradeoffs can be a starting point for several different research directions. First, the standard partitioning method for the trees is to minimize deviance, but other partitioning algorithms could produce different results. Development and comparison of partitioning techniques could potentially improve on this first effort. Another useful avenue would be to test the efficacy of MRTs on tradeoff sets from operations-scale MOEA studies; this would ask whether, e.g., identifying a small number of core rule curve elevations or releases would be meaningful for reservoir operation. Finally, MRTs should be only the beginning of applying data mining to WRSA tradeoff sets. Other data mining techniques should be tested on these troves of system information.

MRTs could be useful for identifying vulnerabilities in a planning portfolio, similarly to how the Patient Rule Induction Method (PRIM) is used to hunt for a small number of comprehensible conditions that lead to plan failure. If traces are characterized by dimensions such as lowest 10-year average flow, or longest span of annual flow below X acre feet, the MRT algorithm could determine splits in those dimensions (the independent variables) that produce different types of portfolio performance across multiple objectives (the response variables). Lempert et al (2008) recognized the potential of both tree algorithms and PRIM for scenario discovery, and found that Classification and Regression Tree (CART) performed comparably to PRIM, though the two methods had different strengths and weaknesses.

Two weaknesses of PRIM are that it only accounts for success or failure to meet a user-defined threshold (i.e. it can only be used for binary classifications), and it struggles when there are both categorical and continuous dimensions of uncertainty. Kwakkel and Jaxa-Rozen (2016) recently tested avenues of addressing these shortcomings, including incorporating elements of CART. Considering that there are multiple measures of performance for any plan, and quantitative performance information could be desirable for assessing performance, MRTs should be explored in the context of scenario discovery.

A fundamental MOEA research need is to develop more guidance on how objective calculations should be aggregated across multiple traces. Academic studies have commonly minimized the mean

performance, or maximized performance in the worst trace, but aside from Quinn et al (2017), which compared the robustness of minimizing either the single worst trace, the worst first percentile trace, or the mean, there has been little study of the most appropriate aggregation functions. Other conceivable functions such as the median or geometric mean should be considered. Researchers need to develop a formal framework that any user can apply which accounts for: the number of hydrologic traces (or traces of other uncertain factors) used, the range of those traces (i.e. are there extremes?), the type of objective in question, and a process for assessing how that objective can vary under different scenarios.

Bibliography

- Abowitz, D.A., Toole, 2010. Mixed Method Research: Fundamental Issues of Design, Validity, and Reliability in Construction Research. *J. Constr. Eng. Manag.* 136, 108–116. [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0000026](https://doi.org/10.1061/(ASCE)CO.1943-7862.0000026)
- Allan, T., 1999. Productive efficiency and allocative efficiency: why better water management may not solve the problem. *Agric. Water Manag.* 40, 71–75. [https://doi.org/10.1016/S0378-3774\(98\)00106-1](https://doi.org/10.1016/S0378-3774(98)00106-1)
- AMEC Environment and Infrastructure, 2014. Fort Collins Water Supply and Demand Management Policy Revision Report. City of Fort Collins, Boulder, Colorado.
- Argent, R.M., Grayson, R.B., 2003. A modelling shell for participatory assessment and management of natural resources. *Environ. Model. Softw., Applying Computer Research to Environmental Problems* 18, 541–551. [https://doi.org/10.1016/S1364-8152\(03\)00029-X](https://doi.org/10.1016/S1364-8152(03)00029-X)
- Aristotle, 1920. *Ethica Nicomachea*, Oxford Classical Texts. Oxford University Press, Oxford, New York.
- Arnold, J.L., 1988. The Evolution of the 1936 Flood Control Act. U.S. Army Corps of Engineers, Washington.
- Asefa, T., 2015. Innovative Systems-Based Decision Support: Tales for the Real World. *J. Water Resour. Plan. Manag.* 01815001. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000565](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000565)
- Babovic, V., 2005. Data mining in hydrology. *Hydrol. Process.* 19, 1511–1515. <https://doi.org/10.1002/hyp.5862>
- Bandaru, S., Deb, K., 2011. Automated Innovization for Simultaneous Discovery of Multiple Rules in Bi-objective Problems, in: *Evolutionary Multi-Criterion Optimization, Lecture Notes in Computer Science*. Presented at the International Conference on Evolutionary Multi-Criterion Optimization, Springer, Berlin, Heidelberg, pp. 1–15. https://doi.org/10.1007/978-3-642-19893-9_1
- Bandaru, S., Ng, A.H.C., Deb, K., 2017a. Data mining methods for knowledge discovery in multi-objective optimization: Part A - Survey. *Expert Syst. Appl.* 70, 139–159. <https://doi.org/10.1016/j.eswa.2016.10.015>
- Bandaru, S., Ng, A.H.C., Deb, K., 2017b. Data mining methods for knowledge discovery in multi-objective optimization: Part B - New developments and applications. *Expert Syst. Appl.* 70, 119–138. <https://doi.org/10.1016/j.eswa.2016.10.016>
- Basdekas, L., 2014. Is Multiobjective Optimization Ready for Water Resources Practitioners? Utility's Drought Policy Investigation. *J. Water Resour. Plan. Manag.* 140, 275–276. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000415](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000415)
- Beh, E.H.Y., Maier, H.R., Dandy, G.C., 2015. Scenario driven optimal sequencing under deep uncertainty. *Environ. Model. Softw.* 68, 181–195. <https://doi.org/10.1016/j.envsoft.2015.02.006>
- Bessler, F.T., Savic, D.A., Walters, G.A., 2003. Water reservoir control with data mining. *J. Water Resour. Plan. Manag.* 129, 26–34.
- Black, D.C., Wallbrink, P.J., Jordan, P.W., 2014. Towards best practice implementation and application of models for analysis of water resources management scenarios. *Environ. Model. Softw.* 52, 136–148. <https://doi.org/10.1016/j.envsoft.2013.10.023>
- Blomquist, W., Schlager, E., 2005. Political Pitfalls of Integrated Watershed Management. *Soc. Nat. Resour.* 18, 101–117. <https://doi.org/10.1080/08941920590894435>
- Bonbright, J.C., Danielson, A.L., Kamerschen, D.R., 1988. *Principles of Public Utility Rates*, 2nd ed. Public Utilities Reports, Arlington, Virginia.
- Borowski, I., Hare, M., 2006. Exploring the Gap Between Water Managers and Researchers: Difficulties of Model-Based Tools to Support Practical Water Management. *Water Resour. Manag.* 21, 1049–1074. <https://doi.org/10.1007/s11269-006-9098-z>

- Breiman, L., Friedman, J., Olshen, R., Stone, C., 1984. *Classification and Regression Trees*, Wadsworth Statistics/Probability. Chapman and Hall/CRC.
- Brendecke, C.M., DeOreo, W.B., Payton, E.A., Rozaklis, L.T., 1989. Network models of water rights and system operations. *J. Water Resour. Plan. Manag.* 115, 684–696.
- Brown, C., 2010. The End of Reliability. *J. Water Resour. Plan. Manag.* 136.
- Brown, C.M., Lund, J.R., Cai, X., Reed, P.M., Zagona, E.A., Ostfeld, A., Hall, J., Characklis, G.W., Yu, W., Brekke, L., 2015. The future of water resources systems analysis: Toward a scientific framework for sustainable water management. *Water Resour. Res.* 51, 6110–6124. <https://doi.org/10.1002/2015WR017114>
- Brown, R.R., Farrelly, M.A., 2009. Delivering sustainable urban water management: a review of the hurdles we face. *Water Sci. Technol.* 59, 839. <https://doi.org/10.2166/wst.2009.028>
- Carpenter, S.R., Ludwig, D., Brock, W.A., 1999. Management of Eutrophication for Lakes Subject to Potentially Irreversible Change. *Ecol. Appl.* 9, 751–771. <https://doi.org/10.2307/2641327>
- Cash, D.W., Clark, W.C., Alcock, F., Dickson, N.M., Eckley, N., Guston, D.H., Jäger, J., Mitchell, R.B., 2003. Knowledge systems for sustainable development. *Proc. Natl. Acad. Sci.* 100, 8086–8091. <https://doi.org/10.1073/pnas.1231332100>
- Caulfield Jr., H.C., Evans, N., Flack, J.E., Grigg, N., Hendricks, D., Labadie, J., McWhorter, D., Morel-Seytoux, H., Raley, W., Young, R., Milliken, J.G., 1987. *Voluntary Basinwide Water Management South Platte River Basin* (No. 133). Colorado Water Resources Research Institute, Fort Collins, Colorado.
- Cieniawski, S.E., Eheart, J.W., Ranjithan, S., 1995. Using Genetic Algorithms to Solve a Multiobjective Groundwater Monitoring Problem. *Water Resour. Res.* 31, 399–409. <https://doi.org/10.1029/94WR02039>
- City of Boulder, MWH, 2009. *Boulder Water Utility Master Plan Volume 1: Executive Summary*. City of Boulder, Boulder, CO.
- City of Boulder, MWH, AMEC, 2009. *City of Boulder Source Water Master Plan Volume 2: Detailed Plan*. City of Boulder, Boulder, CO.
- Clarkin, T., Raseman, W., Kasprzyk, J., Herman, J., In Review. Diagnostic Assessment of Constraints in Multiobjective Evolutionary Algorithms for Water Resources. *J. Water Resour. Plan. Manag.*
- Cocklin, C., Blunden, G., 1998. Sustainability, water resources and regulation. *Geoforum* 29, 51–68. [https://doi.org/10.1016/S0016-7185\(97\)00017-1](https://doi.org/10.1016/S0016-7185(97)00017-1)
- Coello, C.A.C., Lamont, G.B., Veldhuizen, D.A.V. (Eds.), 2007. *Evolutionary Algorithms for Solving Multi-Objective Problems*, 2nd ed, Genetic and Evolutionary Computation. Springer, New York.
- Colorado River Cooperative Agreement, 2012.
- Colorado Springs Utilities 2014 Water Tour, 2014.
- Connolly, T., Reb, J., 2012. Regret aversion in reason-based choice. *Theory Decis.* 73, 35–51. <https://doi.org/10.1007/s11238-011-9269-0>
- Cosgrove, W.J., Loucks, D.P., 2015. Water management: Current and future challenges and research directions. *Water Resour. Res.* <https://doi.org/10.1002/2014WR016869>
- CSU, 2017a. *Integrated Water Resources Plan Final Report*. Colorado Springs Utilities, Colorado Springs.
- CSU, 2017b. *Integrated Water Resources Plan Technical Memo 21: Portfolio Development and Evaluation*. Colorado Springs Utilities, Colorado Springs.
- Cui, L.-J., Kuczera, G., 2003. Optimizing Urban Water Supply Headworks Using Probabilistic Search Methods. *J. Water Resour. Plan. Manag.* 129, 380–387.
- Cvitanovic, C., Hobday, A.J., van Kerkhoff, L., Wilson, S.K., Dobbs, K., Marshall, N.A., 2015. Improving knowledge exchange among scientists and decision-makers to facilitate the adaptive governance of marine resources: A review of knowledge and research needs. *Ocean Coast. Manag.* 112, 25–35. <https://doi.org/10.1016/j.ocecoaman.2015.05.002>
- Daniell, K.A., Coombes, P.J., White, I., 2014. Politics of innovation in multi-level water governance systems. *J. Hydrol.* 519, 2415–2435. <https://doi.org/10.1016/j.jhydrol.2014.08.058>

- De'Ath, G., 2014. mvpart.
- De'Ath, G., 2002. Multivariate regression trees: a new technique for modeling species–environment relationships. *Ecology* 83, 1105–1117.
- Deb, K., Srinivasan, A., 2006. Innovization: Innovating design principles through optimization. Presented at the 8th Annual Genetic and Evolutionary Computation Conference 2006.
- Denver Water, 2015a. Denver Water Population vs. Water Use [WWW Document]. Denver Water. URL <http://www.denverwater.org/SupplyPlanning/WaterUse/Population/> (accessed 7.7.15).
- Denver Water, 2015b. Denver Water Gross Reservoir Expansion Project [WWW Document]. Denver Water. URL <http://www.denverwater.org/SupplyPlanning/WaterSupplyProjects/Moffat/> (accessed 7.10.15).
- Díez, E., McIntosh, B.S., 2009. A review of the factors which influence the use and usefulness of information systems. *Environ. Model. Softw.* 24, 588–602. <https://doi.org/10.1016/j.envsoft.2008.10.009>
- Dilling, L., Lemos, M.C., 2011. Creating usable science: Opportunities and constraints for climate knowledge use and their implications for science policy. *Glob. Environ. Change* 21, 680–689. <https://doi.org/10.1016/j.gloenvcha.2010.11.006>
- Doesken, N., 2014. Colorado Climate Update.
- Dudas, C., Frantzen, M., Ng, A.H.C., 2011. A synergy of multi-objective optimization and data mining for the analysis of a flexible flow shop. *Robot. Comput.-Integr. Manuf.*, Conference papers of Flexible Automation and Intelligent Manufacturing 27, 687–695. <https://doi.org/10.1016/j.rcim.2010.12.005>
- Dudas, C., Ng, A.H.C., Pehrsson, L., Boström, H., 2014. Integration of data mining and multi-objective optimisation for decision support in production systems development. *Int. J. Comput. Integr. Manuf.* 27, 824–839. <https://doi.org/10.1080/0951192X.2013.834481>
- Eeten, M.J.G. van, Loucks, D.P., Roe, E., 2002. Bringing actors together around large-scale water systems: Participatory modeling and other innovations. *Knowl. Technol. Policy* 14, 94–108. <https://doi.org/10.1007/s12130-002-1017-x>
- Elkington, J., 2004. Enter the Triple Bottom Line, in: Henriques, A., Richardson, J. (Eds.), *The Triple Bottom Line: Does It All Add Up*. Earthscan, London, pp. 1–16.
- Erickson, M., Mayer, A., Horn, J., 2002. Multi-objective optimal design of groundwater remediation systems: application of the niched Pareto genetic algorithm (NPGA). *Adv. Water Resour.* 25, 51–65. [https://doi.org/10.1016/S0309-1708\(01\)00020-3](https://doi.org/10.1016/S0309-1708(01)00020-3)
- Eschner, T., Hadley, R., Crowley, K., 1983. Hydrologic and Morphologic Changes in Channels of the Platte River Basin in Colorado, Wyoming, and Nebraska: A Historical Perspective, in: *Hydrologic and Geomorphic Studies of the Platte River Basin*, Geological Survey Professional Paper 1277. United States Department of the Interior, Washington.
- EU Framework, 1998. *Understanding and Monitoring the Cost-Determining Factors of Infrastructure Projects: A User's Guide*, Guidance Document. European Commission.
- Farmani, R., Walters, G.A., Savic, D.A., 2005. Trade-off between total cost and reliability for Anytown water distribution network. *J. Water Resour. Plan. Manag.* 131, 161–171.
- Farrelly, M., Brown, R., 2011. Rethinking urban water management: Experimentation as a way forward? *Glob. Environ. Change*, Special Issue on The Politics and Policy of Carbon Capture and Storage 21, 721–732. <https://doi.org/10.1016/j.gloenvcha.2011.01.007>
- Fayyad, U.M., Piatetsky-Shapiro, G., Smyth, P., 1996. From Data Mining to Knowledge Discovery in Databases. *AI Mag.* 17.
- Fiorino, D.J., 1990. Citizen Participation and Environmental Risk: A Survey of Institutional Mechanisms. *Sci. Technol. Hum. Values* 15, 226–243. <https://doi.org/10.1177/016224399001500204>
- Fleming, P.J., Purshouse, R.C., Lygoe, R.J., 2005. Many-Objective Optimization: An Engineering Design Perspective, in: Coello, C.A.C., Aguirre, A.H., Zitzler, E. (Eds.), *Lecture Notes in Computer Science*. Springer Verlag, pp. 14–32.

- Friedman, J.H., Fisher, N.I., 1999. Bump hunting in high-dimensional data. *Stat. Comput.* 9, 123–143. <https://doi.org/10.1023/A:1008894516817>
- Fu, G., Kapelan, Z., Kasprzyk, J., Reed, P., 2013. Optimal Design of Water Distribution Systems Using Many-Objective Visual Analytics. *J. Water Resour. Plan. Manag.* 139, 624–633. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000311](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000311)
- Funtowicz, S.O., Ravetz, J.R., 1993. Science for the post-normal age. *Futures* 25, 739–755. [https://doi.org/10.1016/0016-3287\(93\)90022-L](https://doi.org/10.1016/0016-3287(93)90022-L)
- Gaddis, E.J.B., Falk, H.H., Ginger, C., Voinov, A., 2010. Effectiveness of a participatory modeling effort to identify and advance community water resource goals in St. Albans, Vermont. *Environ. Model. Softw.*, Thematic Issue - Modelling with Stakeholders 25, 1428–1438. <https://doi.org/10.1016/j.envsoft.2009.06.004>
- Gaube, V., Kaiser, C., Wildenberg, M., Adensam, H., Fleissner, P., Kobler, J., Lutz, J., Schaumberger, A., Schaumberger, J., Smetschka, B., Wolf, A., Richter, A., Haberl, H., 2009. Combining agent-based and stock-flow modelling approaches in a participative analysis of the integrated land system in Reichraming, Austria. *Landsc. Ecol.* 24, 1149–1165. <https://doi.org/10.1007/s10980-009-9356-6>
- Gertig, K., 2015. In the City: Planning for Fort Collins' future water needs [WWW Document]. Coloradoan. URL <http://www.coloradoan.com/story/news/local/2015/03/08/city-planning-fort-collins-future-water-needs/24620819/> (accessed 7.10.15).
- Gibson, E.G., Whittington, D.A., 2010. Charrettes as a Method for Engaging Industry in Best Practices Research. *J. Constr. Eng. Manag.* 136, 66–75. [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0000079](https://doi.org/10.1061/(ASCE)CO.1943-7862.0000079)
- Girard, C., Rinaudo, J.-D., Pulido-Velazquez, M., Caballero, Y., 2015. An interdisciplinary modelling framework for selecting adaptation measures at the river basin scale in a global change scenario. *Environ. Model. Softw.* 69, 42–54. <https://doi.org/10.1016/j.envsoft.2015.02.023>
- Gleick, P.H., 2002. Soft water paths. *Nature* 418, 373.
- Glynn, P.D., 2015. Integrated Environmental Modelling: human decisions, human challenges. *Geol. Soc. Spec. Publ.* 408, 22. <https://doi.org/10.1144/SP408.9>
- Green, S.D., Chung-Chin, K., Larsen, G.D., 2010. Contextualist Research: Iterating between Methods While Following an Empirically Grounded Approach. *J. Constr. Eng. Manag.* 136, 117–126. [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0000027](https://doi.org/10.1061/(ASCE)CO.1943-7862.0000027)
- Groves, D.G., Lempert, R.J., 2007. A new analytic method for finding policy-relevant scenarios. *Glob. Environ. Change* 17, 73–85.
- Grüne, L., Kato, M., Semmler, W., 2005. Solving ecological management problems using dynamic programming. *J. Econ. Behav. Organ.*, Multiple Equilibria, Thresholds and Policy Choices 57, 448–473. <https://doi.org/10.1016/j.jebo.2005.04.002>
- 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. *Glob. Environ. Change* 23, 485–498. <https://doi.org/10.1016/j.gloenvcha.2012.12.006>
- Hadka, D., Reed, P., 2013. Borg: An Auto-Adaptive Many-Objective Evolutionary Computing Framework. *Evol. Comput.* 21, 231–259. https://doi.org/doi:10.1162/EVCO_a_00075
- Hadka, D., Reed, P., 2012. Diagnostic Assessment of Search Controls and Failure Modes in Many-Objective Evolutionary Optimization. *Evol. Comput.* 20, 423–452. https://doi.org/10.1162/EVCO_a_00053
- Hadka, D., Reed, P.M., Simpson, T.W., 2012. Diagnostic Assessment of the Borg MOEA for Many-Objective Product Family Design Problems, in: *Evolutionary Computation (CEC), 2012 IEEE Congress*. Brisbane. <https://doi.org/10.1109/CEC.2012.6256466>
- Hadorn, G.H. (Ed.), 2008. *Handbook of transdisciplinary research*. Springer, Dordrecht ; London.
- Hallegatte, S., 2011. Uncertainties in the Cost-Benefit Analysis of Adaptation Measures, and Consequences for Decision Making, in: Linkov, I., Bridges, T.S. (Eds.), *Climate, NATO Science for Peace and Security Series C: Environmental Security*. Springer Netherlands, pp. 169–192.

- Hamarat, C., Kwakkel, J.H., Pruyt, E., 2013. Adaptive Robust Design under deep uncertainty. *Technol. Forecast. Soc. Change, Future-Oriented Technology Analysis* 80, 408–418.
<https://doi.org/10.1016/j.techfore.2012.10.004>
- Hand, D.J., Mannila, H., Smyth, P., 2001. *Principles of Data Mining*. The MIT Press.
- Harou, J.J., Pulido-Velazquez, M., Rosenberg, D.E., Medellin-Azuara, J., Lund, J.R., Howitt, R.E., 2009. Hydro-economic models: Concepts, design, applications, and future prospects. *J. Hydrol.* 375, 627–643.
- Hashimoto, T., Stedinger, J.R., Loucks, D.P., 1982. Reliability, Resiliency and Vulnerability Criteria for Water Resource System Performance Evaluation. *Water Resour. Res.* 18, 14–20.
- Herman, J.D., Reed, P.M., Zeff, H.B., Characklis, G.W., 2015. How Should Robustness Be Defined for Water Systems Planning under Change? *J. Water Resour. Plan. Manag.* 141, 04015012.
[https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000509](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000509)
- 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 Resour. Res.* 50, 7692–7713. <https://doi.org/10.1002/2014WR015338>
- Hipel, K.W., Ben-Haim, Y., 1999. Decision making in an uncertain world: information-gap modeling in water resources management. *IEEE Trans. Syst. Man Cybern. Part C Appl. Rev.* 29, 506–517.
<https://doi.org/10.1109/5326.798765>
- Hitch, C.J., 1960. On the Choice of Objectives in Systems Studies (No. P-1955). The RAND Corporation.
- Hobbs, G.J., 2004. *Citizen's Guide to Colorado Water Law*, 2nd ed. Colorado Foundation for Water Education, Denver, Colorado.
- Inselberg, A., 1985. The Plane with Parallel Coordinates. *Vis. Comput.* 1, 69–91.
- Jacobs, K., 2002. *Connecting Science, Policy, and Decision-making: A Handbook for Researchers and Science Agencies*. National Oceanic and Atmospheric Administration, Office of Global Programs, Silver Spring, MD.
- Jain, A., Srinivasulu, S., 2004. Development of effective and efficient rainfall-runoff models using integration of deterministic, real-coded genetic algorithms and artificial neural network techniques. *Water Resour. Res.* 40, W04302. <https://doi.org/10.1029/2003WR002355>
- Jakeman, A.J., Letcher, R.A., 2003. Integrated assessment and modelling: features, principles and examples for catchment management. *Environ. Model. Softw., Applying Computer Research to Environmental Problems* 18, 491–501. [https://doi.org/10.1016/S1364-8152\(03\)00024-0](https://doi.org/10.1016/S1364-8152(03)00024-0)
- Jakeman, A.J., Letcher, R.A., Norton, J.P., 2006. Ten iterative steps in development and evaluation of environmental models. *Environ. Model. Softw.* 21, 602–614.
<https://doi.org/10.1016/j.envsoft.2006.01.004>
- Johansson, J., Forsell, C., 2016. Evaluation of Parallel Coordinates: Overview, Categorization and Guidelines for Future Research. *IEEE Trans. Vis. Comput. Graph.* 22, 579–588.
<https://doi.org/10.1109/TVCG.2015.2466992>
- Jones, B., 2014. *Communicating Data with Tableau: Designing, Developing, and Delivering Data Visualizations*. O'Reilly Media, Inc.
- Junier, S., Mostert, E., 2014. A decision support system for the implementation of the Water Framework Directive in the Netherlands: Process, validity and useful information. *Environ. Sci. Policy* 40, 49–56. <https://doi.org/10.1016/j.envsci.2014.04.004>
- Kaatz, L., Waage, M., 2011. Denver Water's approach to planning for climate change. *Water Resour. IMPACT* 13.
- Karamouz, M., Nazif, S., 2013. Reliability-Based Flood Management in Urban Watersheds Considering Climate Change Impacts. *J. Water Resour. Plan. Manag.* 139, 520–533.
[https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000345](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000345)
- Kasprzyk, J.R., Nataraj, S., Reed, P.M., Lempert, R.J., 2013. Many Objective Robust Decision Making for Complex Environmental Systems Undergoing Change. *Environ. Model. Softw.* 42, 55–71.
<https://doi.org/10.1016/j.envsoft.2012.12.007>

- Kasprzyk, J.R., Reed, P.M., Characklis, G.W., Kirsch, B.R., 2012. Many-objective de Novo water supply portfolio planning under deep uncertainty. *Environ. Model. Softw.* 34, 87–104. <https://doi.org/10.1016/j.envsoft.2011.04.003>
- Kasprzyk, J.R., Reed, P.M., Kirsch, B.R., Characklis, G.W., 2009. Managing population and drought risks using many-objective water portfolio planning under uncertainty. *Water Resour. Res.* 45. <https://doi.org/10.1029/2009WR008121>
- Keim, D.A., Mansmann, F., Schneidewind, J., Ziegler, H., 2006. *Challenges in Visual Data Analysis*. IEEE Computer Society, London, UK, pp. 9–16.
- Kenway, S., Howe, C., Maheepala, S., 2007. Triple Bottom Line Reporting of Sustainable Water Utility Performance. American Water Works Assn.
- Knight, F.H., 1921. *Risk, Uncertainty, and Profit*. Houghton Mifflin, Boston, MA.
- Kok, J.-L. de, Kofalk, S., Berlekamp, J., Hahn, B., Wind, H., 2008. From Design to Application of a Decision-support System for Integrated River-basin Management. *Water Resour. Manag.* 23, 1781–1811. <https://doi.org/10.1007/s11269-008-9352-7>
- Kollat, J., 2015. DiscoveryDV. DecisionVis, LLC, State College, Pennsylvania.
- Kollat, J.B., Reed, P.M., 2007. A Framework for Visually Interactive Decision-making and Design using Evolutionary Multiobjective Optimization (VIDEO). *Environ. Model. Softw.* 22, 1691–1704.
- Kwakkel, J.H., Jaxa-Rozen, M., 2016. Improving scenario discovery for handling heterogeneous uncertainties and multinomial classified outcomes. *Environ. Model. Softw.* 79, 311–321. <https://doi.org/10.1016/j.envsoft.2015.11.020>
- Labadie, J.W., 2004. Optimal Operation of Multireservoir Systems: State-of-the-Art Review. *J. Water Resour. Plan. Manag.* 130, 93–111.
- Labadie, J.W., Baldo, M.L., 2000. MODSIM: decision support system for river basin management: Documentation and user manual.
- Lall, U., Sharma, A., 1996. A nearest neighbor bootstrap for resampling hydrologic time series. *Water Resour. Res.* 32, 679–693.
- Lang, D.J., Wiek, A., Bergmann, M., Stauffacher, M., Martens, P., Moll, P., Swilling, M., Thomas, C.J., 2012. Transdisciplinary research in sustainability science: practice, principles, and challenges. *Sustain. Sci.* 7, 25–43. <https://doi.org/10.1007/s11625-011-0149-x>
- Larsen, D.R., Speckman, P.L., 2004. Multivariate Regression Trees for Analysis of Abundance Data. *Biometrics* 60, 543–549. <https://doi.org/10.1111/j.0006-341X.2004.00202.x>
- Lawrence, R.J., Després, C., 2004. Futures of Transdisciplinarity. *Futures, Transdisciplinarity* 36, 397–405. <https://doi.org/10.1016/j.futures.2003.10.005>
- Lawrence, R.L., Wright, A., 2001. Rule-based classification systems using classification and regression tree (CART) analysis. *Photogramm. Eng. Remote Sens.* 67, 1137–1142.
- Lemos, M.C., Morehouse, B.J., 2005. The co-production of science and policy in integrated climate assessments. *Glob. Environ. Change* 15, 57–68. <https://doi.org/10.1016/j.gloenvcha.2004.09.004>
- Lemos, M.C., Rood, R.B., 2010. Climate projections and their impact on policy and practice. *Wiley Interdiscip. Rev. Clim. Change* 1, 670–682. <https://doi.org/10.1002/wcc.71>
- Lempert, R.J., 2002. A new decision sciences for complex systems. *Proc. Natl. Acad. Sci.* 99, 7309–7313.
- Lempert, R.J., Bryant, B.P., Bankes, S.C., 2008. Comparing Algorithms for Scenario Discovery (No. WR-557-NSF). RAND.
- 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. *Technol. Forecast. Soc. Change* 77, 960–974.
- Lempert, R.J., Groves, D.G., Popper, S.W., Bankes, S.C., 2006. A General, Analytic Method for Generating Robust Strategies and Narrative Scenarios. *Manag. Sci.* 52, 514–528.
- Leurig, S., 2010. *The Ripple Effect: Water Risk in the Municipal Bond Market*. Ceres, Boston, MA.
- Liebman, J.C., 1976. Some Simple-Minded Observations on the Role of Optimization in Public Systems Decision-Making. *Interfaces* 6, 102–108.

- Lins, H.F., 2012. USGS hydro-climatic data network 2009 (HCDN-2009). US Geol. Surv. Fact Sheet 3047.
- Linsley Jr, R.K., Kohler, M.A., Paulhus, J.L.H., 1975. Hydrology for engineers.
- Liu, M., Frangopol, D.M., 2005. Bridge Annual Maintenance Prioritization under Uncertainty by Multiobjective Combinatorial Optimization. *Comput.-Aided Civ. Infrastruct. Eng.* 20, 343–353.
- Liu, S., Maljovec, D., Wang, B., Bremer, P.T., Pascucci, V., 2017. Visualizing High-Dimensional Data: Advances in the Past Decade. *IEEE Trans. Vis. Comput. Graph.* 23, 1249–1268. <https://doi.org/10.1109/TVCG.2016.2640960>
- Liu, Y., Gupta, H., Springer, E., Wagener, T., 2008. Linking science with environmental decision making: Experiences from an integrated modeling approach to supporting sustainable water resources management. *Environ. Model. Softw.* 23, 846–858. <https://doi.org/10.1016/j.envsoft.2007.10.007>
- Lohani, V.K., Loganathan, G.V., 1997. An Early Warning System for Drought Management Using the Palmer Drought Index. *JAWRA J. Am. Water Resour. Assoc.* 33, 1375–1386. <https://doi.org/10.1111/j.1752-1688.1997.tb03560.x>
- Loucks, D.P., Stedinger, J.R., Haith, D.A., 1981. *Water Resource Systems Planning and Analysis*. Prentice-Hall, Inc., Englewood Cliffs, N.J.
- Loucks, D.P., van Beek, E., 2005. *Water Resources Systems Planning and Management: An Introduction to Methods, Models, and Applications*. United Nations Educational, Scientific and Cultural Organization.
- Loucks, D.P., van Beek, E., Stedinger, J.R., Dijkman, J.P.M., Villars, M.T., 2005. *Water Resources Systems Planning and Management: An Introduction to Methods, Models and Applications*. Paris : UNESCO.
- Loughlin, D.H., Ranjithan, S.R., Brill, E.D., Baugh, J.W., 2001. Genetic Algorithm Approaches for Addressing Unmodeled Objectives in Optimization. *Eng. Optim.* 33, 549–569.
- Lukas, J., Barsugli, J., Doesken, N., Rangwala, I., Wolter, K., 2014. *Climate Change in Colorado: A Synthesis to Support Water Resources Management and Adaptation*. Western Water Assessment, Boulder, CO.
- Lund, J.R., 2015. Integrating social and physical sciences in water management. *Water Resour. Res.* 51. <https://doi.org/10.1002/2015WR017125>
- Maass, A., 1966. Benefit-Cost Analysis: Its Relevance to Public Investment Decisions. *Q. J. Econ.* 80, 208–226.
- Maass, A., Hufschmidt, M.M., Dorfman, R., Jr, H.A.T., Marglin, S.A., Fair, G.M., 1962. *Design of Water-Resource Systems: New Techniques for Relating Economic Objectives, Engineering Analysis, and Governmental Planning*. Harvard University Press, Cambridge.
- Maheepala, S., Dandy, G., Marchi, A., Mirza, F., Wu, W., Daly, R., Hewa, G., Neumann, L., Maier, H., He, Y., others, 2014. *A Decision Support Framework for identifying optimal water supply portfolios: Metropolitan Adelaide Case Study: Volume 1 Main Report*. Goyder Inst. Water Res. Tech. Rep. Ser.
- Mahmoud, M.I., Gupta, H.V., Rajagopal, S., 2011. Scenario development for water resources planning and watershed management: Methodology and semi-arid region case study. *Environ. Model. Softw.* 26, 873–885. <https://doi.org/10.1016/j.envsoft.2011.02.003>
- Maier, H.R., Kapelan, Z., Kasprzyk, J., Kollat, J., Matott, L.S., Cunha, M.C., Dandy, G.C., Gibbs, M.S., Keedwell, E., Marchi, A., Ostfeld, A., Savic, D., Solomatine, D.P., Vrugt, J.A., Zecchin, A.C., Minsker, B.S., Barbour, E.J., Kuczera, G., Pasha, F., Castelletti, A., Giuliani, M., Reed, P.M., 2014. Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions. *Environ. Model. Softw.* 62, 271–299. <https://doi.org/10.1016/j.envsoft.2014.09.013>
- Mathew, S., Varia, J., 2014. Overview of amazon web services. Amaz. Whitepapers.

- Matrosov, E.S., Huskova, I., Kasprzyk, J.R., Harou, J.J., Lambert, C., Reed, P.M., 2015. Many-objective optimization and visual analytics reveal key trade-offs for London's water supply. *J. Hydrol.* 531, Part 3, 1040–1053. <https://doi.org/10.1016/j.jhydrol.2015.11.003>
- McIntosh, B.S., Ascough II, J.C., Twery, M., Chew, J., Elmahdi, A., Haase, D., Harou, J.J., Hepting, D., Cuddy, S., Jakeman, A.J., Chen, S., Kassahun, A., Lautenbach, S., Matthews, K., Merritt, W., Quinn, N.W.T., Rodriguez-Roda, I., Sieber, S., Stavenga, M., Sulis, A., Ticehurst, J., Volk, M., Wrobel, M., van Delden, H., El-Sawah, S., Rizzoli, A., Voinov, A., 2011. Environmental decision support systems (EDSS) development – Challenges and best practices. *Environ. Model. Softw.* 26, 1389–1402. <https://doi.org/10.1016/j.envsoft.2011.09.009>
- McIntosh, B.S., Jeffrey, P., Lemon, M., Winder, N., 2005. On the design of computer-based models for integrated environmental science. *Environ. Manage.* 35, 741–752. <https://doi.org/10.1007/s00267-004-0172-0>
- McMahon, T.A., Adegoye, A.J., Zhou, S.-L., 2006. Understanding performance measures of reservoirs. *J. Hydrol.* 324, 359–382. <https://doi.org/10.1016/j.jhydrol.2005.09.030>
- McNie, E.C., 2007. Reconciling the supply of scientific information with user demands: an analysis of the problem and review of the literature. *Environ. Sci. Policy* 10, 17–38. <https://doi.org/10.1016/j.envsci.2006.10.004>
- Means, E., Laugier, M., Daw, J., Kaatz, L., Waage, M., 2010. Decision Support Planning Methods: Incorporating Climate Change Uncertainties into Water Planning (White Paper). Water Utility Climate Alliance.
- Meehl, G.A., Covey, C., Taylor, K.E., Delworth, T., Stouffer, R.J., Latif, M., McAvaney, B., Mitchell, J.F.B., 2007. THE WCRP CMIP3 Multimodel Dataset: A New Era in Climate Change Research. *Bull. Am. Meteorol. Soc.* 88, 1383–1394. <https://doi.org/10.1175/BAMS-88-9-1383>
- Melillo, J.M., Richmond, T.C., Yohe, G., 2014. Climate Change Impacts in the United States: The Third National Climate Assessment. U.S. Global Change Research program.
- Miller, K.A., Belton, V., 2014. Water resource management and climate change adaptation: a holistic and multiple criteria perspective. *Mitig. Adapt. Strateg. Glob. Change* 19, 289–308. <https://doi.org/10.1007/s11027-013-9537-0>
- Milly, P.C.D., Betancourt, J., Falkenmark, M., Hirsch, R., Kundzewicz, Z.W., Lettenmaier, D.P., Stouffer, R.J., 2008. Stationarity is Dead: Whither Water Management? *Science* 319, 573–574.
- Montgomery, H., 1983. Decision Rules and the Search for a Dominance Structure: Towards a Process Model of Decision Making**This study was financed by a grant from the Swedish Council for Research in the Humanities and Social Sciences. I am indebted to Hannes Eisler, Per-Håkan Ekberg, Eric Johnson, and Ola Svenson for their comments on earlier versions of the paper. *Adv. Psychol., Analysing and Aiding Decision Processes* 14, 343–369. [https://doi.org/10.1016/S0166-4115\(08\)62243-8](https://doi.org/10.1016/S0166-4115(08)62243-8)
- Morgan, D.L., 1993. Successful Focus Groups: Advancing the State of the Art. SAGE Publications.
- Mortazavi, M., Kuczera, G., Cui, L., 2012a. Multiobjective optimization of urban water resources: Moving toward more practical solutions. *Water Resour. Res.* 48. <https://doi.org/10.1029/2011WR010866>
- Mortazavi, M., Kuczera, G., Cui, L., 2012b. Multiobjective optimization of urban water resources: Moving toward more practical solutions. *Water Resour. Res.* 48. <https://doi.org/10.1029/2011WR010866>
- Mortazavi, M., Kuczera, G., Kiem, A., Henley, B., Berghout, B., Turner, E., 2013. Robust optimization of urban drought security for an uncertain climate. National Climate Change Adaptation Research Facility, Gold Coast.
- Moser, S., 2009. Making a difference on the ground: the challenge of demonstrating the effectiveness of decision support. *Clim. Change* 95, 11–21. <https://doi.org/10.1007/s10584-008-9539-1>
- Mostert, E., Craps, M., Pahl-Wostl, C., 2008. Social learning: the key to integrated water resources management? *Water Int.* 33, 293–304. <https://doi.org/10.1080/02508060802275757>

- Moy, W., Cohon, J.L., Revelle, C.S., 1986. A Programming Model for Analysis of the Reliability, Resilience, and Vulnerability of a Water Supply Reservoir. *Water Resour. Res.* 22, 489–498.
- Muleta, M., Nicklow, J., 2005. Decision Support for Watershed Management Using Evolutionary Algorithms. *J. Water Resour. Plan. Manag.* 131, 35–44. [https://doi.org/10.1061/\(ASCE\)0733-9496\(2005\)131:1\(35\)](https://doi.org/10.1061/(ASCE)0733-9496(2005)131:1(35))
- Murphy, L.J., Dandy, G.C., Simpson, A.R., 1994. Optimum design and operation of pumped water distribution systems, in: NATIONAL CONFERENCE PUBLICATION-INSTITUTION OF ENGINEERS AUSTRALIA NCP. Institution of Engineers, Australia, pp. 149–149.
- MWD, 2015. Integrated Water Resources Plan. Metropolitan Water District, Los Angeles, CA.
- Nasseri, M., Tavakol-Davani, H., Zahraie, B., 2013. Performance assessment of different data mining methods in statistical downscaling of daily precipitation. *J. Hydrol.* 492, 1–14. <https://doi.org/10.1016/j.jhydrol.2013.04.017>
- National Climatic Data Center, 2015. Average Statewide Precipitation For Western U.S. States. Western Regional Climate Center, Reno, Nevada.
- National Research Council, 2009. Informing Decisions in a Changing Climate. National Academies Press, Washington, D.C.
- National Research Council, 2009. Informing Decisions in a Changing Climate. National Academy Press.
- Newell, R., Pizer, W., 2001. Discounting the Benefits of Climate Change Mitigation: How Much do Uncertain Rates Increase Valuations? Pew Center on Global Climate Change, Arlington, Virginia.
- Newig, J., Gaube, V., Berkhoff, K., Kaldrack, K., Kastens, B., Lutz, J., Schlußmeier, B., Adensam, H., Haberl, H., 2008. The Role of Formalisation, Participation and Context in the Success of Public Involvement Mechanisms in Resource Management. *Syst. Pract. Action Res.* 21, 423–441. <https://doi.org/10.1007/s11213-008-9113-9>
- Nicklow, J., Reed, P., Savic, D., Dessalegne, T., Harrell, L., Chan-Hilton, A., Karamouz, M., Minsker, B., Ostfeld, A., Singh, A., Zechman, E., 2010. State of the Art for Genetic Algorithms and Beyond in Water Resources Planning and Management. *J. Water Resour. Plan. Manag.* 136, 412–432.
- NOAA Regional Integrated Sciences and Assessments Program (RISA), n.d.
- Northern Water, 2015. Northern Water Projects [WWW Document]. North. Water. URL http://www.northernwater.org/docs/Water_Projects/CBTandWgStats_2013.pdf (accessed 7.10.15).
- Nowak, K., Prairie, J., Rajagopalan, B., Lall, U., 2010. A nonparametric stochastic approach for multisite disaggregation of annual to daily streamflow. *Water Resour. Res.* 46. <https://doi.org/10.1029/2009WR008530>
- Obayashi, S., Jeong, S., Chiba, K., 2005. Multi-Objective Design Exploration for Aerodynamic Configurations, in: 35th AIAA Fluid Dynamics Conference and Exhibit. American Institute of Aeronautics and Astronautics. <https://doi.org/10.2514/6.2005-4666>
- Obayashi, S., Sasaki, D., 2003. Visualization and Data Mining of Pareto Solutions Using Self-Organizing Map, in: Evolutionary Multi-Criterion Optimization, Lecture Notes in Computer Science. Presented at the International Conference on Evolutionary Multi-Criterion Optimization, Springer, Berlin, Heidelberg, pp. 796–809. https://doi.org/10.1007/3-540-36970-8_56
- OECD, 1999. Household Water Pricing in OECD Countries. Organization for Economic Co-operation and Development, Paris.
- Oyama, A., Nonomura, T., Fujii, K., 2010. Data Mining of Pareto-Optimal Transonic Airfoil Shapes Using Proper Orthogonal Decomposition. *J. Aircr.* 47, 1756–1762. <https://doi.org/10.2514/1.C000264>
- P. O. Abbott, 1985. Description of Water-Systems Operations in the Arkansas River Basin, Colorado (No. Water-Resources Investigations Report 85-4092). Unites States Geological Survey, Lakewood, Colorado.
- Pahl-Wostl, C., Hare, M., 2004. Processes of social learning in integrated resources management. *J. Community Appl. Soc. Psychol.* 14, 193–206. <https://doi.org/10.1002/casp.774>

- Pareto, V., 1896. *Cours D'Economie Politique*. Rouge, Lausanne.
- Parsons, R., Bennet, R., 2006. Reservoir Operations Management Using a Water Resources Model, in: *Operating Reservoirs in Changing Conditions*. American Society of Civil Engineers, pp. 304–311.
- Paton, F.L., Dandy, G.C., Maier, H.R., 2014. Integrated framework for assessing urban water supply security of systems with non-traditional sources under climate change. *Environ. Model. Softw.* 60, 302–319. <https://doi.org/10.1016/j.envsoft.2014.06.018>
- Payne, J.W., Bettman, J.R., Johnson, E.J., 1992. Behavioral decision research: A constructive processing perspective. *Am. Rev. Psychol.* 43, 87–131.
- Pielke, R.A., Sr., Doesken, N., Bliss, O., Green, T., Chaffin, C., Salas, J.D., Woodhouse, C.A., Lukas, J.J., Wolter, K., 2005. Drought 2002 in Colorado: An Unprecedented Drought or a Routine Drought? *Pure Appl. Geophys.* 162, 1455–1479. <https://doi.org/10.1007/s00024-005-2679-6>
- Piscopo, A.N., Kasprzyk, J.R., Neupauer, R.M., 2014. An Iterative Approach to Multi-Objective Engineering Design: Optimization of Engineered Injection and Extraction for Enhanced Groundwater Remediation (In-Review). *Environ. Model. Softw.*
- Piscopo, A.N., Kasprzyk, J.R., Neupauer, R.M., Mays, D.C., 2013. Many-Objective Design of Engineered Injection and Extraction Sequences for In Situ Remediation of Contaminated Groundwater. ASCE.
- Prasad, A.M., Iverson, L.R., Liaw, A., 2006. Newer Classification and Regression Tree Techniques: Bagging and Random Forests for Ecological Prediction. *Ecosystems* 9, 181–199. <https://doi.org/10.1007/s10021-005-0054-1>
- Pretty, J.N., 1995. Participatory learning for sustainable agriculture. *World Dev.* 23, 1247–1263. [https://doi.org/10.1016/0305-750X\(95\)00046-F](https://doi.org/10.1016/0305-750X(95)00046-F)
- Quinn, J.D., Reed, P.M., Giuliani, M., Castelletti, A., 2017. Rival framings: A framework for discovering how problem formulation uncertainties shape risk management trade-offs in water resources systems. *Water Resour. Res.* 53, 7208–7233. <https://doi.org/10.1002/2017WR020524>
- Quinn, J.D., Reed, P.M., Keller, K., 2017. Direct policy search for robust multi-objective management of deeply uncertain socio-ecological tipping points. *Environ. Model. Softw.* 92, 125–141. <https://doi.org/10.1016/j.envsoft.2017.02.017>
- R Core Team, 2016. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.
- Rajagopalan, B., Nowak, K., Prairie, J., Hoerling, M., Harding, B., Barsugli, J., Ray, A., Udall, B., 2009. Water supply risk on the Colorado River: Can management mitigate? *Water Resour. Res.* 45. <https://doi.org/10.1029/2008WR007652>
- Rajagopalan, B., Salas, J., Lall, U., 2006. Hydrological Time Series Analysis, in: *Encyclopedia of Environmetrics*. John Wiley & Sons, Ltd.
- Rani, D., Moreira, M.M., 2010. Simulation–Optimization Modeling: A Survey and Potential Application in Reservoir Systems Operation. *Water Resour. Manag.* 24, 1107–1138. <https://doi.org/10.1007/s11269-009-9488-0>
- Ray, P.A., Brown, C.M., 2015. *Confronting Climate Uncertainty in Water Resources Planning and Project Design: The Decision Tree Framework*. The World Bank.
- 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. *Adv. Water Resour.* 51, 438–456.
- Reed, P.M., Kasprzyk, J., 2009. Water resources management: the myth, the wicked, and the future. *J. Water Resour. Plan. Manag.* 135, 411–413.
- Reed, P.M., Minsker, B.S., 2004. Striking the Balance: Long-Term Groundwater Monitoring Design for Conflicting Objectives. *J. Water Resour. Plan. Manag.* 130, 140–149.
- Ritzel, B.J., Eheart, J.W., Ranjithan, S.R., 1994. Using genetic algorithms to solve a multiple objective groundwater pollution contaminant problem. *Water Resour. Res.* 30, 1589–1603.

- Roberson, A., Aubuchon, C., 2013. Decreasing Climate-Induced Water Supply Risk Through Improved Municipal Water Demand Forecasting. American Water Works Association.
- Robles-Morua, A., Halvorsen, K.E., Mayer, A.S., Vivoni, E.R., 2014. Exploring the application of participatory modeling approaches in the Sonora River Basin, Mexico. *Environ. Model. Softw.* 52, 273–282. <https://doi.org/10.1016/j.envsoft.2013.10.006>
- Rogers, P.P., Fiering, M.B., 1986. Use of systems analysis in water management. *Water Resour Res* 22, 146S–158S. <https://doi.org/10.1029/wr022i09sp0146s>
- Rosenberg, D.E., 2015. Blended near-optimal alternative generation, visualization, and interaction for water resources decision making. *Water Resour. Res.* 51, 2047–2063. <https://doi.org/10.1002/2013WR014667>
- Rosenberg, D.E., Madani, K., 2014. Water Resources Systems Analysis: A Bright Past and a Challenging but Promising Future. *J. Water Resour. Plan. Manag.* 140, 407–409.
- Roy, B., 1999. Decision-aiding today: What should we expect?, in: *Multicriteria Decision Making*. Springer, pp. 1–35.
- Ruiz, A.G., Dobbie, M., Brown, R., 2015. Insights and future directions of transdisciplinary practice in the urban water sector. *J. Environ. Stud. Sci.* 1–13. <https://doi.org/10.1007/s13412-015-0351-8>
- Sahota, P.S., Jeffrey, P., 2005. Decision-support tools: moving beyond a technical orientation. *Proc. Inst. Civ. Eng. - Eng. Sustain.* 158, 127–134. <https://doi.org/10.1680/ensu.2005.158.3.127>
- Sarewitz, D., Pielke, R.A., 2007. The neglected heart of science policy: reconciling supply of and demand for science. *Environ. Sci. Policy* 10, 5–16. <https://doi.org/10.1016/j.envsci.2006.10.001>
- Seidl, R., 2015. A functional-dynamic reflection on participatory processes in modeling projects. *Ambio* 44, 750–765. <https://doi.org/10.1007/s13280-015-0670-8>
- Siegfried, T., Bleuler, S., Laumanns, M., Zitzler, E., Kinzelbach, W., 2009. Multiobjective Groundwater Management Using Evolutionary Algorithms. *IEEE Trans. Evol. Comput.* 13, 229–242. <https://doi.org/10.1109/TEVC.2008.923391>
- Siirtola, H., Rähkä, K.-J., 2006. Interacting with parallel coordinates. *Interact. Comput.* 18, 1278–1309. <https://doi.org/10.1016/j.intcom.2006.03.006>
- Singh, R., Reed, P., Keller, K., 2015. Many-objective robust decision making for managing an ecosystem with a deeply uncertain threshold response. *Ecol. Soc.* 20. <https://doi.org/10.5751/ES-07687-200312>
- Slovic, P., 1995. The construction of preference. *Am. Psychol.* 50, 364.
- Slovic, P., 1975. Choice between equally valued alternatives. *J. Exp. Psychol. Hum. Percept. Perform.* 1, 280–287.
- Smajgl, A., Ward, J., 2013. A framework to bridge science and policy in complex decision making arenas. *Futures* 52, 52–58. <https://doi.org/10.1016/j.futures.2013.07.002>
- Smith, R., Kasprzyk, J., Basdekas, L., In Review. Multiobjective optimization of long term planning portfolios on the Front Range of Colorado. *J. Water Resour. Plan. Manag.*
- Smith, R., Kasprzyk, J., Dilling, L., 2017. Participatory Framework for Assessment and Improvement of Tools (ParFAIT): Increasing the impact and relevance of water management decision support research. *Environ. Model. Softw.* 95, 432–446. <https://doi.org/10.1016/j.envsoft.2017.05.004>
- Smith, R., Kasprzyk, J., Dilling, L., In Review. A multiobjective tradeoff charrette to engage with Colorado water managers about long term planning. *Environ. Model. Softw.*
- Smith, R., Kasprzyk, J., Zagona, E., 2016. Many-Objective Analysis to Optimize Pumping and Releases in Multireservoir Water Supply Network. *J. Water Resour. Plan. Manag.* 142. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000576](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000576)
- Smith, R., Kasprzyk, J., Zagona, E., 2015. Many Objective Analysis to Optimize Pumping and Releases in Multi-Reservoir Supply Network. *J. Water Resour. Plan. Manag.*
- Smits, R., 2002. Innovation studies in the 21st century;: Questions from a user's perspective. *Technol. Forecast. Soc. Change, IPTS S.I.* 69, 861–883. [https://doi.org/10.1016/S0040-1625\(01\)00181-0](https://doi.org/10.1016/S0040-1625(01)00181-0)
- SPU, 2012. 2013 Water System Plan. Seattle Public Utilities, Seattle, WA.

- State of Colorado, 2017. Population Forecasts (2000 - 2050) [WWW Document]. Colo. Demogr. URL <https://demography.dola.colorado.gov/population/population-totals-colorado-substate/> (accessed 8.4.17).
- State of Colorado, 2015. Colorado's Water Plan. Denver, Colorado.
- Stave, K.A., 2002. Using system dynamics to improve public participation in environmental decisions. *Syst. Dyn. Rev.* 18, 139–167. <https://doi.org/10.1002/sdr.237>
- Stengel, A., 2009. Water Projects and Colorado's 1041 Regulations [WWW Document]. Colo. Riparian Assoc. URL <http://coloradoriparian.org/water-projects-and-colorados-1041-regulations/> (accessed 8.10.15).
- Sugimura, K., Obayashi, S., Jeong, S., 2010. Multi-objective optimization and design rule mining for an aerodynamically efficient and stable centrifugal impeller with a vaned diffuser. *Eng. Optim.* 42, 271–293. <https://doi.org/10.1080/03052150903171084>
- Taylor, A.C., 2009. Sustainable urban water management: understanding and fostering champions of change. *Water Sci. Technol.* 59, 883. <https://doi.org/10.2166/wst.2009.033>
- Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2011. An Overview of CMIP5 and the Experiment Design. *Bull. Am. Meteorol. Soc.* 93, 485–498. <https://doi.org/10.1175/BAMS-D-11-00094.1>
- Thomas, J.J., Cook, K.A., 2006. A visual analytics agenda. *IEEE Comput. Graph. Appl.* 26, 10–13.
- Thompson Klein, J., 2004. Prospects for transdisciplinarity. *Futures, Transdisciplinarity* 36, 515–526. <https://doi.org/10.1016/j.futures.2003.10.007>
- Tolchin, M., 1990. E.P.A. to Veto Huge Colorado Dam - NYTimes.com. *N. Y. Times*.
- Tsoukias, A., 2008. From decision theory to decision aiding methodology. *Eur. J. Oper. Res.* 187, 138–161.
- Tversky, A., 1972. Elimination by aspects: A theory of choice. *Psychol. Rev.* 79, 281–299.
- Udall, B., Overpeck, J., 2017. The twenty-first century Colorado River hot drought and implications for the future. *Water Resour. Res.* 53, 2404–2418. <https://doi.org/10.1002/2016WR019638>
- Ulrich, T., 2013. Pareto-Set Analysis: Biobjective Clustering in Decision and Objective Spaces. *J. Multi-Criteria Decis. Anal.* 20, 217–234. <https://doi.org/10.1002/mcda.1477>
- Ulrich, T., Brockhoff, D., Zitzler, E., 2008. Pattern Identification in Pareto-set Approximations, in: *Proceedings of the 10th Annual Conference on Genetic and Evolutionary Computation, GECCO '08*. ACM, New York, NY, USA, pp. 737–744. <https://doi.org/10.1145/1389095.1389236>
- U.S. Bureau of Reclamation, 2007. Colorado River Interim Guidelines for Lower Basin Shortages and the Coordinated Operations for Lake Powell and Lake Mead. U.S. Department of the Interior.
- US EPA, O., 2014. Public Participation Guide: Charrettes [WWW Document]. US EPA. URL <https://www.epa.gov/international-cooperation/public-participation-guide-charrettes> (accessed 11.18.17).
- van der Keur, P., Brugnach, M., Dewulf, A., Refsgaard, J.C., Zorilla, P., Poolman, M., Isendahl, N., Raadgever, G.T., Henriksen, H.J., Warmink, J.J., Lamers, M., Mysiak, J., 2010. Identifying Uncertainty Guidelines for Supporting Policy Making in Water Management Illustrated for Upper Guadiana and Rhine Basins. *Water Resour. Manag.* 24, 3901–3938. <https://doi.org/10.1007/s11269-010-9640-x>
- Velickov, S., Solomatine, D., 2000. Predictive Data Mining: Practical Examples. 2nd Jt. Workshop Appl. AI Civ. Eng.
- Verbyla, D.L., 1987. Classification trees: a new discrimination tool. *Can. J. For. Res.* 17, 1150–1152. <https://doi.org/10.1139/x87-177>
- Voinov, A., Bousquet, F., 2010. Modelling with stakeholders. *Environ. Model. Softw.*, Thematic Issue - Modelling with Stakeholders 25, 1268–1281. <https://doi.org/10.1016/j.envsoft.2010.03.007>
- Voinov, A., Kolagani, N., McCall, M.K., Glynn, P.D., Kragt, M.E., Ostermann, F.O., Pierce, S.A., Ramu, P., 2016. Modelling with stakeholders – Next generation. *Environ. Model. Softw.* 77, 196–220. <https://doi.org/10.1016/j.envsoft.2015.11.016>

- Voinov, A., Seppelt, R., Reis, S., Nabel, J.E.M.S., Shokravi, S., 2014. Values in socio-environmental modelling: Persuasion for action or excuse for inaction. *Environ. Model. Softw.* 53, 207–212. <https://doi.org/10.1016/j.envsoft.2013.12.005>
- Walski, T.M., 2001. The wrong paradigm—Why water distribution optimization doesn't work. *J. Water Resour. Plan. Manag.* 127, 203–205.
- Walski, T.M., E. Downey Brill, J., Gessler, J., Goulter, I.C., Jeppson, R.M., Lansey, K., Lee, H.-L., Liebman, J.C., Mays, L., Morgan, D.R., Ormsbee, L., 1987. Battle of the Network Models: Epilogue. *J. Water Resour. Plan. Manag.* 113, 191–203. [https://doi.org/10.1061/\(ASCE\)0733-9496\(1987\)113:2\(191\)](https://doi.org/10.1061/(ASCE)0733-9496(1987)113:2(191))
- Walters, G.A., Halhal, D., Savic, D., Ouazar, D., 1999a. Improved design of “Anytown” distribution network using structured messy genetic algorithms. *Urban Water* 1, 23–38. [https://doi.org/10.1016/s1462-0758\(99\)00005-9](https://doi.org/10.1016/s1462-0758(99)00005-9)
- Walters, G.A., Halhal, D., Savic, D., Ouazar, D., 1999b. Improved design of “Anytown” distribution network using structured messy genetic algorithms. *Urban Water* 1, 23–38. [https://doi.org/10.1016/S1462-0758\(99\)00005-9](https://doi.org/10.1016/S1462-0758(99)00005-9)
- Watkins, D.W., McKinney, D.C., 1997. Finding robust solutions to water resources problems. *J. Water Resour. Plan. Manag.* 123, 49–58.
- Watson, A.A., Kasprzyk, J.R., 2017a. Incorporating deeply uncertain factors into the many objective search process. *Environ. Model. Softw.* 89, 159–171. <https://doi.org/10.1016/j.envsoft.2016.12.001>
- Watson, A.A., Kasprzyk, J.R., 2017b. Incorporating deeply uncertain factors into the many objective search process. *Environ. Model. Softw.* 89, 159–171. <https://doi.org/10.1016/j.envsoft.2016.12.001>
- Wei, C.-C., Hsu, N.-S., 2008. Derived operating rules for a reservoir operation system: Comparison of decision trees, neural decision trees and fuzzy decision trees. *Water Resour. Res.* 44, W02428. <https://doi.org/10.1029/2006WR005792>
- Wei, W., Watkins, D.W., 2011. Data mining methods for hydroclimatic forecasting. *Adv. Water Resour.* 34, 1390–1400. <https://doi.org/10.1016/j.advwatres.2011.08.001>
- Wen, B., van der Zouwen, M., Horlings, E., van der Meulen, B., van Vierssen, W., 2015. Transitions in urban water management and patterns of international, interdisciplinary and intersectoral collaboration in urban water science. *Environ. Innov. Soc. Transit.* 15, 123–139. <https://doi.org/10.1016/j.eist.2014.03.002>
- Wheeler, K., Hall, J., Zagona, E., Abdo, G., Smith, R., Kasprzyk, J., In Review. Exploring Cooperative Transboundary River Management Strategies: A case study of the Eastern Nile Basin. *Water Resour. Res.*
- Wickson, F., Carew, A.L., Russell, A.W., 2006. Transdisciplinary research: characteristics, quandaries and quality. *Futures* 38, 1046–1059. <https://doi.org/10.1016/j.futures.2006.02.011>
- Woodbury, M., Baldo, M., Yates, D., Kaatz, L., 2012. Joint Front Range Climate Change Vulnerability Study. Water Research Foundation, Colorado.
- Woodruff, M.J., Reed, P.M., Simpson, T., 2013. Many Objective Visual Analytics: Rethinking the Design of Complex Engineered Systems. *Struct. Multidiscip. Optim.* 48, 201–219.
- Woods, M., 1994. The Holy Cross Wilderness Area and Homestake II: Case History, Conflict Analysis, and Intractability. Conflict Research Consortium.
- Wu, W., Dandy, G.C., Maier, H.R., Maheepala, S., Marchi, A., Mirza, F., 2017. Identification of Optimal Water Supply Portfolios for a Major City. *J. Water Resour. Plan. Manag.* 143, 05017007. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000811](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000811)
- Wu, W., Maier, H.R., Dandy, G.C., Leonard, R., Bellette, K., Cuddy, S., Maheepala, S., 2016a. Including stakeholder input in formulating and solving real-world optimisation problems: Generic framework and case study. *Environ. Model. Softw.* 79, 197–213. <https://doi.org/10.1016/j.envsoft.2016.02.012>

- Wu, W., Maier, H.R., Dandy, G.C., Leonard, R., Bellette, K., Cuddy, S., Maheepala, S., 2016b. Including stakeholder input in formulating and solving real-world optimisation problems: Generic framework and case study. *Environ. Model. Softw.* 79, 197–213. <https://doi.org/10.1016/j.envsoft.2016.02.012>
- WUCA, 2015. Embracing Uncertainty: A Case Study Examination of How Climate Change is Shifting Water Utility Planning. Water Utility Climate Alliance, Boulder, CO.
- Yang, T., Gao, X., Sorooshian, S., Li, X., 2016. Simulating California reservoir operation using the classification and regression-tree algorithm combined with a shuffled cross-validation scheme. *Water Resour. Res.* 52, 1626–1651. <https://doi.org/10.1002/2015WR017394>
- Zagona, E., Fulp, T.J., Shane, R., Magee, Y., Goranflo, H.M., 2001. RiverWare: A generalized tool for complex reservoir system modeling. *J. Am. Water Resour. Assoc.* 37, 913–929.
- 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. *Adv. Water Resour.* 92, 172–185. <https://doi.org/10.1016/j.advwatres.2016.04.006>
- Zechman Burgland, E., 2015. Using Agent-Based Modeling for Water Resources Planning and Management. *J. Water Resour. Plan. Manag.* 141. [https://doi.org/http://dx.doi.org/10.1061/\(ASCE\)WR.1943-5452.0000544#sthash.V9txSn8R.dpuf](https://doi.org/http://dx.doi.org/10.1061/(ASCE)WR.1943-5452.0000544#sthash.V9txSn8R.dpuf)
- Zechman, E., Ranjithan, R., 2007. Generating Alternatives Using Evolutionary Algorithms for Water Resources and Environmental Management Problems. *J. Water Resour. Plan. Manag.* 133, 156–165. [https://doi.org/10.1061/\(ASCE\)0733-9496\(2007\)133:2\(156\)](https://doi.org/10.1061/(ASCE)0733-9496(2007)133:2(156))
- Zeff, H.B., Herman, J.D., Reed, P.M., Characklis, G.W., 2016. Cooperative drought adaptation: Integrating infrastructure development, conservation, and water transfers into adaptive policy pathways. *Water Resour. Res.* 52, 7327–7346. <https://doi.org/10.1002/2016WR018771>
- Zeff, H.B., Kasprzyk, J.R., Herman, J.D., Reed, P.M., Characklis, G.W., 2014. Navigating financial and supply reliability tradeoffs in regional drought management portfolios. *Water Resour. Res.* 50. <https://doi.org/10.1002/2013WR015126>
- Zhu, T., Marques, G.F., Lund, J.R., 2015. Hydroeconomic optimization of integrated water management and transfers under stochastic surface water supply. *Water Resour. Res.* 51, 3568–3587. <https://doi.org/10.1002/2014WR016519>