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Incorporating deeply uncertain factors into the many objective search process

Abigail A. Watson, Joseph R. Kasprzyk*

Civil, Environmental, and Architectural Engineering Department, University of Colorado Boulder, UCB 428, Boulder, CO 80309, United States

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ABSTRACT

This paper proposes an approach for including deeply uncertain factors directly into a multi-objective search procedure, to aid in incorporating divergent quantitative scenarios within the model-based decision support process. Specifically, we extend Many Objective Robust Decision Making (MORDM), a framework for finding and evaluating planning solutions under multiple objectives, to include techniques from robust optimization. Traditional MORDM first optimized a problem under a baseline scenario, then evaluated candidate solutions under an ensemble of uncertain conditions, and finally discovered scenarios under which solutions are vulnerable. In this analysis, we perform multiple multi-objective search trials that directly incorporate these discovered scenarios within the search. Through the analysis, we have created multiple problem formulations to show how methodological choices of severe scenarios affect the resulting candidate planning solutions. We demonstrate the approach through a water planning portfolio example in the Lower Rio Grande Valley of Texas.

1. Introduction

Climate change, land use change, and other anthropogenic effects increase the variability of streamflow (Jain et al., 2005; Seager and Vecchi, 2010) and threaten water security (Gober, 2013; Vorosmarty et al., 2000). Population growth and urbanization can exacerbate potential water shortages (Feldman, 2009). Especially in river basins that straddle political boundaries, water shortages can strain political relationships between political actors (Wildman and Forde, 2012).

The hydrological and socioeconomic variables that define these phenomena can be considered deeply uncertain (Knight, 1921; Walker et al., 2013). Under deep uncertainty decision makers and stakeholders cannot agree on the full set of risks and consequences and the probability of their occurrence (Langlois and Cosgel, 1993). Scenario analysis (Arnell et al., 2004; Farber et al., 2008; Mahmoud et al., 2009) is one method for coping with this situation, where a group of experts define plausible storylines of the values of key uncertainties in a problem before the decision making process begins. However, specifying scenarios before performing modeling exercises lacks the ability to determine which scenarios are the most important ones for causing system vulnerabilities. To this end, a set of bottom-up decision making frameworks (as reviewed in Dittrich et al., 2016; Giuliani and Castelletti, 2016; Herman et al., 2015; Kwakkel et al., 2016) have focused on using simulation model runs to identify potentially severe scenarios based on the modeled performance metrics. The goal is to create and evaluate solutions that exhibit robustness. A robust solution is one in which the solutions' performance is insensitive to variations in the estimation of parameters that control the calculation of that performance (Herman et al., 2015; Matalas and Fiering, 1977). In other words, bottom-up frameworks test multiple assumptions about uncertain problem properties and subject planning alternatives to interesting combinations of various factors.

Herman et al. (2015) characterize bottom-up frameworks with four methodological choices: (i) how are alternatives identified or generated; (ii) how are different states of the world sampled; (iii) how are robustness measures calculated; and (iv) how are key uncertainties identified using sensitivity analysis or factor mapping (e.g., the Patient Rule Induction Method, PRIM (Friedman and Fisher, 1999)). This paper is focused on the first methodological choice of Herman et al.'s bottom-up taxonomy: how planning alternatives are generated. Mathematical conditions such as the nonseparability of decision alternatives and noise in the objective function can pose challenges to such generation techniques.

* Corresponding author.
E-mail addresses: abigail.watson@colorado.edu (A.A. Watson), joseph.kasprzyk@colorado.edu (J.R. Kasprzyk).

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Multiobjective Evolutionary Algorithms (MOEAs) are a search technique which has been increasingly employed to overcome these challenges (Maier et al., 2014; Reed et al., 2013). MOEA decision support uses a detailed simulation model of a system to characterize performance of solution alternatives, facilitating a realistic depiction of the solutions' performance. Beyond simply suggesting preferred alternatives, MOEAs can aid in analysts and stakeholders' understanding of a decision problem (Piscopo et al., 2015) by generating tradeoff sets that show compromises among the objectives. These tradeoff sets are defined by Pareto optimality. Solutions are Pareto optimal if their performance is not exceeded in any objective by another feasible solution (i.e., for a cost-reliability optimization problem, the optimal tradeoff is the set of least possible costs at every level of reliability). Although MOEAs are effective at generating alternatives, the proper usage of scenario information and uncertainty within MOEA search is still an open question.

A set of approaches broadly classified as robust optimization (RO) has sought to incorporate uncertainty information into optimization (Beyer and Sendhoff, 2007; Deb and Gupta, 2006; Hamarat et al., 2014; McInerney et al., 2012; Mortazavi-Naeini et al., 2015; Mulvey et al., 1995; Ray et al., 2014; Watkins Jr. and McKinney, 1997). Notably, Hamarat et al. (2014) uses an MOEA and incorporates uncertainty into the MOEA search process. In that study, a specific robustness objective function was created in order to optimize trigger points, which define when to enact changes to a base policy under changing future conditions. One potential limitation of such approaches is that it is difficult to combine robustness with respect to multiple objectives into a single objective function. Therefore, this paper will explore how to explore robustness across multiple objectives simultaneously, building on an existing framework termed Many Objective Robust Decision Making (MORDM, Kasprzyk et al., 2013).

MORDM is a bottom-up decision making framework that combines MOEAs with techniques from robust decision making (Lempert et al., 2006). The non-dominated set from MOEA search is subjected to ensembles of randomly generated values of uncertain factors (e.g., different scaling factors on hydrologic inflows or water demands). A set of calculations shows how the solutions' performance changes under this ensemble of uncertain conditions. Solutions that have low deviations in objective function performance in the ensemble are considered robust, and visualizations of robustness metrics are used to guide the choice of one or more candidate solutions. The final step uses statistical data mining techniques to discover the most important uncertain factors that cause the candidate solutions to perform poorly within the uncertainty ensemble.

In the previous applications of MORDM, authors performed the optimization using a single realization of input data termed the baseline scenario: default values of the input parameters and the input data exhibiting historical distributions. One potential limitation of this approach is that the set of decision variables comprising each solution are only "trained" to the historical data and may not be adaptable if the data fundamentally changes (Ignizio, 1998; Zeleny, 2005). Therefore, this paper incorporates multiple combinations of uncertain factors into the MOEA search process itself, with an approach inspired by RO literature.

Specifically, our approach chooses multiple discovered scenarios from the MORDM sensitivity analysis and then performs the optimization under each scenario. The goal is to develop more diverse sets of decision variables that have better objective function performance under extreme conditions. Our methodology seeks to generate a policy that will hold up to many uncertainties without future adjustments by re-evaluating the resulting solution sets under multiple scenarios, using visual analytic techniques (Woodruff et al., 2013) to explore the model results. Importantly, our approach replicates the runs with different assumptions about the properties of the included scenarios, which allows an analyst to interrogate the effect of these chosen scenarios on the optimized results. The ultimate goal is to develop policies that perform well under a wide range of plausible futures by exposing some of those futures directly within the optimization process. A case study of water planning within the Lower Rio Grande Valley (LRGV) of Texas is used to demonstrate the approach in order to best capitalize on previous MORDM work that has utilized this example.

2. Methods

2.1. Multi-objective evolutionary algorithms

MOEAs are heuristic search algorithms that mimic evolutionary processes to approximate the optimal tradeoff set of solutions to multi-objective optimization problems (Coello et al., 2007). Recall that a MOEA's tradeoff set is defined using the concept of Pareto optimality; a solution is Pareto-optimal if no other feasible solution exhibits improvement in an objective without sacrificing performance in another objective. For non-trivial problems, MOEAs can only approximate the true Pareto-optimal set, so the sets are often termed the non-dominated set or the Pareto-approximate set. By linking to a simulation model, the algorithms use realistic depictions of the modeled processes and can optimize based on meaningful objective functions. MOEAs are gaining prominence in the water resources community, both within real water planning activities within water utilities (Asefa, 2015; Basdekas, 2014) and in research applications, as reviewed in Nicklow et al. (2010) and Maier et al. (2014).

This study employs the Borg MOEA (Hadka and Reed, 2013) to generate alternatives. The Borg MOEA is a search framework that adapts its use of seven different variation operators (simulated binary crossover, differential evolution, parent-centric recombination, unimodal normal distribution crossover, simplex crossover, polynomial mutation, and uniform mutation) based on problem properties. The algorithm also features epsilon-dominance, which uses a user-defined epsilon grid to control the precision of each objective as well as maintains an epsilon-dominance archive of the best solutions in the search (Laumanns, 2002). Additionally, adaptive population sizing adapts the search population size to provide more diverse solutions to explore as the search continues. The Borg MOEA was chosen due to its favorable performance on the LRGV problem in diagnostic analyses (Kasprzyk et al., 2016; Reed et al., 2013), and the algorithm was also successfully applied to the LRGV problem using thousands of parallel processors (Reed and Hadka, 2014). Note that the methods presented in this study are not specific to the particular Borg MOEA, and researchers can use other modern MOEAs to explore similar concepts.

2.2. Many objective robust decision making

The many objective robust decision making framework (MORDM) is a planning framework for complex environmental systems that integrates MOEA optimization with the RDM framework to optimize and select planning strategies under conditions of deep uncertainty. MORDM has been applied to a multi-reservoir system with several different actors coordinating among each other (Herman et al., 2014), for water quality management (Singh et al., 2015), and to the LRGV (Kasprzyk et al., 2013), the example