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A multi-stakeholder portfolio optimization framework applied to stormwater best management practice (BMP) selection

Michael Di Matteo*, Graeme C. Dandy, Holger R. Maier

School of Civil, Environmental and Mining Engineering, University of Adelaide, Adelaide, 5005, Australia

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ABSTRACT

In this paper, an optimization framework for complex environmental management problems involving multiple stakeholders is developed and illustrated. In the framework, problems are represented as a series of smaller, interconnected optimization problems, reflecting individual stakeholders' interests. The framework uses interactive visual analytics to explore and analyse optimization results, and the concept of Best Alternatives to a Negotiated Agreement (BATNAs) and an approach to reframe visualizations to encourage stakeholder negotiation. To demonstrate the utility of the framework, it is applied to a realistic case study involving multiple stakeholder groups funding different stormwater best management practices (BMPs) for a catchment management plan for a region of a large city in Australia. The problem features a total of sixteen objectives for four stakeholders. The results indicate that the proposed framework enables the identification of solutions that provide optimal trade-offs between many objectives and provides an effective and efficient means of assisting stakeholders with identifying acceptable solutions.

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1. Introduction

Evolutionary algorithms (EAs) have been used successfully and extensively for solving water resources optimization problems in a number of areas, such as engineering design, the development of management strategies, and model calibration (Nicklow et al., 2010; Zecchin et al., 2012). Ultimately, EAs are intended to be used to support decision-making through application to complex real-world problems. However, for real-world problems, the identification of a good decision may be difficult, highly subjective, and dependent on stakeholder values and perceptions (Maier et al., 2014). These issues are compounded in problems that involve multiple stakeholders, each with their own understanding of the problem stemming from their values and priorities placed on outcomes, costs to be borne, and responsibilities once solutions are implemented.

Several schools of thought have evolved to approach the selection of optimal solutions to multi-objective problems involving multiple stakeholders. Multi-attribute utility theory (Keeney and Raiffa, 1993; Keeney and Wood, 1977) was developed as a normative means to identify solutions to resource-constrained problems that best satisfy a “utility function”, which is a quantity that explicitly captures a subset of the preferences of a decision-maker, usually ranging from 0 (no acceptance) to 1 (full acceptance). The utility function can be derived by combining objectives into an aggregate of stakeholder preferences, and has been used in collaborative optimization methods to develop objective functions that better represent stakeholder values (Mesmer et al., 2013). However, this approach does not permit full trade-offs between multiple objectives to be considered and explored simultaneously as it combines objectives, has difficulty representing varying stakeholder interests and value sets, and does not facilitate learning about important relationships between design variables and outcomes.

More recently, tradespace exploration (a term combining “trade-off” and “playspace” exploration) was developed (Ross and Hastings, 2005) as a means to communicate the impact of decision variables for complex engineering systems (where, perhaps, multiple models are used by different stakeholders to evaluate parts of a system). It is used to identify and learn about “deep” whole-system trade-offs, and to identify designs that feature desirable combinations of attributes, including technical attributes, cost, and utility (as determined by utility functions). In the approach, users search through a visual representation of the

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* Corresponding author.
E-mail addresses: michael.dimatteo@adelaide.edu.au (M. Di Matteo), graeme.dandy@adelaide.edu.au (G.C. Dandy), holger.maier@adelaide.edu.au (H.R. Maier).

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tradespace, which is the space of possible design options (i.e. the completely enumerated design variables). The tradespace exploration approach gives users freedom to rapidly determine design options that are Pareto optimal (i.e. where the utility function cannot be improved in value without increasing cost) for various utility functions. Furthermore, tradespace exploration has recently been adapted to facilitate negotiation between multiple stakeholders (Fitzgerald, 2016). However, generating the enumerated space of design variables can be computationally expensive for many complex problems.

In order to overcome this limitation, EAs can be used to identify solutions on or near the Pareto front, as they typically require fewer solution evaluations to identify a Pareto front compared with enumeration. EAs have already been used to approximate the trade-off fronts between individual objectives where the tradespace cannot practically be enumerated, such as for water resources management problems (Kasprzyk et al., 2016). However, such approaches have not yet been extended so that they can handle multiple stakeholder groups, with multiple objectives for each.

As pointed out by Maier et al., (2014) adapting optimization approaches to account for different stakeholder groups is difficult because: i) stakeholders have different value sets and interests, making it difficult to arrive at a consensus on one mathematical problem formulation that all stakeholders will accept, which may affect the likelihood that stakeholders will trust the optimization process and buy-into suggested solutions, ii) the exploration and analysis of optimization solutions requires stakeholder engagement and expert input, iii) the non-intuitive nature of multi-dimensional value analysis and unanticipated and emergent trends can further prevent decision-makers from understanding and trusting optimization results, and iv) the optimization framework is required to facilitate the identification of a final negotiated outcome and/or exploration of resource management alternatives to be considered further.

In the past, there has been little focus on these aspects of optimization, which largely featured studies on algorithm development, rather than optimization approaches for decision-making support in practice. However, there has been some progress in relation to this in recent years, including:

1. The use of iterative approaches, which has allowed for multiple formulations of the decision variables, objectives and constraints to be developed to progressively better define optimization problems and provide an opportunity for stakeholders to learn about the problem (Kollat and Reed, 2007; Woodruff et al., 2013; Piscopo et al., 2015; Wu et al., 2016).
2. The development of an optimization framework that provides opportunities for stakeholders to provide input into the various stages of optimization studies, including problem definition, the optimization process, and final decision-making (Wu et al., 2016).
3. The development of many-objective optimization approaches that identify solutions to complex problems that represent the optimal trade-off between numerous (>3) objectives to better capture stakeholder values (Kollat et al., 2011; Kasprzyk et al., 2012; Woodruff et al., 2013; Hadka et al., 2015; Matrosov et al., 2015; Borgomeo et al., 2016; Woodruff, 2016).
4. The use of visual analytics approaches to better communicate the outputs of optimization studies to stakeholders to help with exploration and analysis of the trade-offs between objectives, to identify the impact of decisions on performance, and ultimately select trusted solutions for further consideration (Kollat and Reed, 2007; Kollat et al., 2011; Woodruff et al., 2013; Hadka et al., 2015; Matrosov et al., 2015; Borgomeo et al., 2016; Woodruff, 2016).
5. The development of many-objective visual analytics (MOVA) approaches (Woodruff, 2016; Woodruff et al., 2013), combining multiple optimization formulations, iterative optimization approaches and visual analytics to overcome some of the limitations of utility theory approaches and tradespace exploration approaches.

These advances have made EAs more applicable to complex, real-world problems with multiple stakeholders and many objectives. However, in previous studies, the optimization problem to be solved has generally been represented by a single formulation, including all decision variable options, objectives and constraints that were considered to be relevant. This can result in the inclusion of a large number of objectives and decision variable options, making it difficult to identify solutions that represent the best trade-offs between objectives. This is because the number of solutions required to characterise the Pareto front increases exponentially as the number of objectives increases, thus making this process exceptionally computationally expensive and beyond the capability of the majority of current EAs. In addition, despite the recent advances in visual analytics approaches mentioned above, the inclusion of a large (e.g. >10) number of objectives makes the identification of solutions that provide acceptable trade-offs for different stakeholders extremely difficult, as this can be cognitively challenging for decision-makers, particularly when dealing with large solution sets.

In order to address the above difficulties, an innovative many-objective visual analytics framework for stakeholder-driven negotiated solutions is proposed in this paper for problems with distinct stakeholder groups with potentially competing sets of objectives. An example of this is the selection of stormwater best management practices (BMPs) for integrated management of a river system and its catchment, where the objectives of stakeholders managing separate sub-areas of the catchment are most likely different from each other, and different from those of stakeholders concerned with managing the catchment as a whole. As part of the framework, the overall optimization problem is represented as a series of smaller, interconnected optimization problems, reflecting individual stakeholders and their interests. The Pareto optimal solutions resulting from this analysis provide the input into a collaborative, multi-stakeholder negotiation process, as part of which visual analytics are used to identify trusted and accepted solutions.

The objectives of this paper are: (i) to present an optimization framework that is geared towards the identification of negotiated solutions for problems with multiple stakeholders with distinct sets of objectives; (ii) to demonstrate the usefulness of the framework by applying it to a case study based on the integrated management of a catchment in a major city in Australia; and iii) to use the case study to a) illustrate how the use of BATNAs can encourage the efficient identification of equitable solutions, and b) investigate how to identify solutions that distribute benefits and costs equitably across stakeholders.

The remainder of this paper is organized as follows. In the next section, the proposed framework is presented. This is followed by a description of the catchment management case study, analyses, discussion of results, and conclusions.

2. Proposed multi-stakeholder optimization framework

A conceptual outline of the proposed framework for addressing the limitations of existing optimization approaches outlined in the Introduction is shown in Fig. 1. As can be seen, the first step involves the solution of independent, multi-objective optimization problems for each stakeholder group in order to identify ‘best alternatives to negotiated agreement’ (BATNAs)’ for each of these groups,

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