Environmental Modelling & Software 68 (2015) 181–195

Contents lists available at ScienceDirect

Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft

Scenario driven optimal sequencing under deep uncertainty

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A R T I C L E I N F O

Article history:
Received 5 August 2014
Received in revised form
11 February 2015
Accepted 12 February 2015
Available online 12 March 2015

Keywords:
Optimal sequencing/scheduling
Multi-objective optimisation
Deep uncertainty
Robustness
Scenarios
Urban water supply augmentation

A B S T R A C T

The optimal sequencing/scheduling of activities is vital in many areas of environmental and water resources planning and management. In order to account for deep uncertainty surrounding future conditions, a new optimal scheduling approach is introduced in this paper, which consists of three stages. Firstly, a portfolio of diverse sequences that are optimal under a range of plausible future conditions is generated. Next, global sensitivity analysis is used to assess the robustness of these sequences and to determine the relative contribution of future uncertain variables to this robustness. Finally, an optimal sequence is selected for implementation. The approach is applied to the optimal sequencing of additional potential water supply sources, such as desalinated-, storm- and rain-water, for the southern Adelaide water supply system, over a 40 year planning horizon at 10-year intervals. The results indicate that the proposed approach is useful in identifying optimal sequences under deep uncertainty.

1. Introduction

The sequencing, staging or scheduling of activities (referred to as sequencing for the remainder of this paper) is important in many environmental and water resources application areas. Examples include the sequencing of urban water supply augmentation sources and infrastructure (Beh et al., 2014; Kang and Lansey, 2014; Mortazavi-Naeini et al., 2014; Ray et al., 2012), the scheduling of pumps and rehabilitation activities in water distribution systems (Kleiner et al., 1998; Dandy and Engelhardt, 2001, 2006; Savić et al., 2011; Zheng and Zecchin, 2014), the scheduling of wastewater discharges (Murillo et al., 2011), the scheduling of mining production activities (Badiozamani and Askari-Nasab, 2014), the scheduling of forest management activities (Sharples et al., 2009; Simon and Etienne, 2010; Zhang and Barten, 2009), the scheduling of irrigation water (Ge et al., 2013; Merot and Bergez, 2010), the scheduling of crop management activities (Lautenbach et al., 2013; Ripoche et al., 2011), the scheduling of environmental flows in rivers (Szemis et al., 2013, 2012) and determining the optimal schedule of investments of conservation funding (Bode et al., 2008; Wilson et al., 2006).

In order to make best use of available resources and to achieve the best possible outcomes, the use of formal optimisation techniques is highly desirable in order to identify these sequences. However, a potential problem with the use of formal optimisation methods is that solutions are only truly optimal if the assumptions under which the optimisation was performed hold. This is unlikely to be the case for real systems (Dessai et al., 2013; Gober, 2013), therefore necessitating the consideration of uncertainties as part of optimisation approaches (Maier et al., 2014). The uncertainties underpinning optimisation approaches generally fall into two categories: those resulting from a lack of information and those resulting from uncertainties about the future (which is referred to as deep uncertainty) (Walker et al., 2013). The latter type of uncertainty can also be thought of as global uncertainty, which results in significantly different trends in solutions, whereas the former type of uncertainty can be thought of as local uncertainty, which represents the imperfect knowledge surrounding a particular pathway resulting from global uncertainties (Mejia-Giraldo and McCalley, 2014).

Local uncertainty, or a lack of information, can generally be represented by probability distributions and there are well-established methods for dealing with this type of uncertainty within optimisation frameworks for optimal sequencing (e.g. Bode et al., 2008; Srinivasa Prasad et al., 2013; Wilson et al., 2006). In contrast, optimisation methods for dealing with optimal sequencing under global/deep uncertainty are much less developed. This is despite the fact that it has been recognised that most important strategic planning problems are characterised by deep uncertainty (Walker et al., 2013). In general, two of the most

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http://dx.doi.org/10.1016/j.envsoft.2015.02.006
1364-8152/

promising approaches to dealing with deep uncertainty include the development of robust solutions, which are designed to perform well under a wide range of future conditions, and the development of flexible solutions, which are designed to enable adaptation to changing future conditions (Walker et al., 2013). In the context of optimal sequencing, Woodward et al. (2014) and Basupi and Kapelan (2013) developed flexible approaches to the optimal sequencing of flood risk management and water distribution system design, respectively. However, in each case only a relatively limited range of reasonably well-known future conditions was considered (represented by probability distributions), rather than alternative scenarios, as is generally the case when dealing with deep uncertainty. As pointed out by Mahmoud et al. (2009), probabilistic predictions explicitly weight the likelihood of different outcomes, whereas scenarios are designed to represent a set of alternative plausible future states of the world. In addition, the approaches of Woodward et al. (2014) and Basupi and Kapelan (2013) were tailored to specific application areas.

Housh et al. (2013), Kang and Lansey (2014) and Ray et al. (2012) developed optimal sequencing approaches for water supply system management, water supply infrastructure and water sources, respectively, that consider performance under a wide range of future conditions with the aid of scenarios. However, all of these approaches are tailored to specific application areas. In addition, the methods proposed by Housh et al. (2013) and Ray et al. (2012) are based on traditional optimisation methods (i.e. stochastic and linear programming, respectively, in this case), which have a number of potential disadvantages compared with evolutionary optimisation approaches (see Maier et al., 2014). These include not being able to be linked with simulation models, thereby potentially ignoring important non-linear interactions and making the algorithms more difficult to apply, and not being truly multi-objective in the sense of being able to evolve fronts of Pareto-optimal solutions (Pareto, 1896) in a single optimisation run, which is becoming increasingly important when tackling real-life problems (Maier et al., 2014). Although Kang and Lansey (2014) use a genetic algorithm as their optimisation engine and indicate that their approach could be extended to include multiple objectives, this was not undertaken in their paper.

In order to address the shortcomings outlined above, the objectives of this paper are (i) to introduce an approach to the optimal sequencing of environmental and water resources activities that (a) is generic, (b) caters to a wide range of possible future conditions and (c) caters to multiple objectives; and (ii) to illustrate the approach on an optimal urban water resources augmentation case study, which is based on the southern water supply system of Adelaide, South Australia.

The remainder of this paper is organised as follows. In Section 2, the proposed optimal sequencing approach under deep uncertainty is introduced, while details of the case study and of the application of the proposed approach to the case study are given in Section 3. The results are presented in Section 4, before a summary and conclusions are given in Section 5.

2. Proposed approach

As illustrated in Fig. 1, the proposed approach to the optimal sequencing of environmental and water resources activities under deep uncertainty consists of three main steps, namely (i) the identification of a portfolio of diverse optimal sequences; (ii) the performance of global sensitivity analysis on each of the members of the portfolio of optimal sequences identified in (i); and (iii) the selection of the optimal sequence to be implemented. Details of each of these steps are given in the following subsections. It should be noted that the proposed approach assumes that the optimisation problem to be solved has already been formulated (e.g. identification of objectives, constraints and decision variables, planning horizon and interval etc.). As with all optimisation problems, problem formulation is vital and care needs to be taken to ensure the concerns of decision makers and other stakeholders are represented in the problem formulation (see Maier et al., 2014).

2.1. Determination of portfolio of diverse optimal sequences

In line with robust decision-making approaches (Lempert and Collins, 2007; Matrosov et al., 2013a), the purpose of the first step in the proposed approach is to identify a portfolio of diverse solutions that are likely to perform differently under various future conditions. This is also in keeping with the philosophy underpinning scenario analysis, in which scenarios “provide a dynamic view of the future by exploring various trajectories of change that lead to a broadening range of plausible alternative futures” (Mahmoud et al., 2009), enabling “… a creative and flexible approach to preparing for an uncertain future” (Mahmoud et al., 2009). As shown in Fig. 1, in order to achieve this, three steps are proposed in the context of developing optimal sequences under deep uncertainty. The first of these involves the identification of the uncertain variables (UV_1, UV_2, …, UV_x) that are likely to result in unknown futures of interest (Step 1.1, Fig. 1), as well as their plausible ranges over the selected planning horizon (e.g. $UV_{x,min}$,$UV_{x,max}$). For example, these variables could include population, land use, precipitation, temperature, evapotranspiration, water availability etc., depending on the environmental/water resources problem under consideration.

Next, a set of plausible future scenarios (S_1, S_2, …, S_y), which consist of different combinations of values of the selected uncertain variables, as well as their temporal variation over the selected planning horizon, should be selected (Step 1.2, Fig. 1). The purpose of the scenarios is not to predict the future, but to enable exploration of a relatively small number of different plausible futures that are generally not equally likely (Mahmoud et al., 2009). Most scenario development involves people from different disciplines and organisations (Mahmoud et al., 2009) and can be achieved using a range of formal (Leenhardt et al., 2012; Mahmoud et al., 2009) or informal approaches (e.g. Kasprzyk et al., 2012; Paton et al., 2013, 2014a, 2014b).

The final step involves the generation of Pareto-optimal sequences for each of the scenarios and the extraction of the portfolio of diverse solutions (P_1, P_2 to P_Z) (Step 1.3, Fig. 1), which is similar to the approach used by Kasprzyk et al. (2013) for problems that do not involve sequencing. The philosophy underpinning this step is to identify potential future pathways that are optimal with respect to the stated objectives under the conditions represented by the different scenarios (i.e. plausible futures). It should be noted that when dealing with multiple, competing objectives, there is no single optimal solution, but a collection of solutions that are all optimal, known as the Pareto front (Pareto, 1896). This is because for solutions on this front, improvements in one objective can only be achieved at the expense of degradation in at least one of the other objectives, requiring additional preference information to enable one of these solutions to be selected (Cohen and Marks, 1975). Consequently, the purpose of the proposed approach is not to identify a single optimal solution, but to sift through the large number of potential solutions in order to identify the solutions that provide the best possible trade-offs between objectives under a number of different future scenarios and therefore warrant further consideration by decision-makers.

Although a variety of approaches can be used to generate the front of (near) Pareto-optimal solutions, the use of multi-objective evolutionary algorithms (MOEAs), such as NSGAII (Deb et al.,