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Robust optimization of water infrastructure planning under deep uncertainty using metamodels

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ABSTRACT

Water resources planning and design problems, such as the sequencing of water supply infrastructure, are often complicated by deep uncertainty, including changes in population dynamics and the impact of climate change. To handle such uncertainties, robustness can be used to assess system performance, but its calculation typically involves many scenarios and hence is computationally expensive. Consequently, robustness has usually not been included as a formal optimization objective, but is considered post-optimization. To address this shortcoming, an approach is developed that uses metamodels (surrogates of computationally expensive simulation models) to calculate robustness and other objectives. This enables robustness to be considered explicitly as an objective within a multi-objective optimization framework. The approach is demonstrated for a water-supply sources sequencing problem in Adelaide, South Australia. The results indicate the approach can identify optimal trade-offs between robustness, cost and environmental objectives, which would otherwise not have been possible using commonly available computational resources.

1. Introduction

The sequencing of water resources infrastructure is commonly undertaken for a wide range of purposes, such as the augmentation of urban water supply sources (Beh et al., 2014), and the planning of urban water supply mains and other water supply infrastructure (Kang and Lansey, 2014; Creaco et al., 2014, 2015). This process is often carried out with the aid of optimization techniques, aiming to identify optimal sequences in order to make best use of available resources (Beh et al., 2015a). These optimal sequences have traditionally been obtained using deterministic optimization techniques such as linear programming (e.g. Ray et al., 2012; Beh et al., 2014), but in recent years, there has been a move towards the use of evolutionary algorithms (EAs) to identify optimal sequencing solutions (e.g. Kang and Lansey, 2014; Beh et al., 2015b). This is because EAs (i) are more effective in exploring the large and rugged search spaces associated with water resources problems when compared with deterministic optimization techniques (Nicklow et al., 2010); (ii) can be flexibly linked with simulation models of water resource systems (Maier et al., 2014), and (iii) can account for discrete or continuous decision variables, as well as multiple competing objectives (Kollat and Reed, 2007; Maier et al., 2015).

Given that the design life of water infrastructure is generally in the order of 30–100 years, long-term future conditions have to be taken into consideration when developing optimal sequence plans. Within a modelling context, the impact of future conditions on water infrastructure can be considered using three complementary paradigms (Maier et al., 2016). The first uses best available knowledge to identify a single set of "best guess" future conditions that would affect system performance (e.g. rainfall, Fu and Butler, 2014). The second paradigm considers future conditions as quantifiably uncertain, accounting for uncertainties through stochastic processes and statistical analysis of uncertain variables (e.g. Kapelan et al., 2005; Basupi and Kapelan, 2015). The third paradigm considers multiple plausible futures, generally arising from recognized ignorance or an unknown future, where it is no longer possible to place probabilities on particular future conditions, or even to rank them (e.g. Kwakkel, 2010). Consequently, the first paradigm does not consider future uncertainty explicitly, the second paradigm considers "local" uncertainty in the sense of

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considering the envelope of uncertainty surrounding a "best guess" future, and the third paradigm considers "global" or "deep" uncertainty in the sense of considering multiple plausible future trajectories that do not have an associated probability and cannot be ranked, which are generally represented via scenarios (Maier et al., 2016).

As many future changes that affect the satisfactory performance of water resource systems, such as changes in climate and population, are deeply uncertain, the consideration of deep uncertainty has received significant attention in the water resources optimization literature in recent years. The vast majority of these studies have only considered which options should be implemented, without consideration of their timing (Li et al., 2006; Jeuland and Whittington, 2014; Ray et al., 2014), although some studies have taken the optimal sequencing of options into account (Beh et al., 2015a).

When deep uncertainty is considered in water resources planning, the aim is to identify solutions for which systems perform satisfactorily in the face of changes in unknown future conditions. Such solutions are termed robust, as their ability to perform satisfactorily is insensitive to changes in uncertain future conditions. As discussed in Maier et al. (2016), robust solutions can be identified using two philosophically different approaches, including the use of a static approach, as part of which a single, fixed strategy is developed that can withstand a wide range of future conditions, and the use of an adaptive approach, as part of which multiple, flexible strategies are developed. Both approaches have been used extensively in water resources studies (Roach et al., 2016; Basupi and Kapelan, 2015) and have their strengths and weaknesses, although they can also be considered as complementary (Kwakkel et al., 2016a,b) and hybrid approaches that make use of elements of both have been developed (e.g. Beh et al., 2015b).

Given that water resource systems are considered to perform satisfactorily if supply is greater than or equal to demand, robust solutions are those that satisfy the above constraint under a range of plausible future conditions (i.e. under global/deep uncertainty). It should be noted that as a result of natural variability and other types of local uncertainty, the ability to satisfy demand is generally represented using a combination of probabilistic performance metrics, such as reliability, vulnerability and resilience (Hashimoto et al., 1982; Xu et al., 1998; Matrosov et al., 2013a, b; Beh et al., 2015a,b). Consequently, for water resource systems, robust solutions are those for which the system of interest can perform at satisfactory levels of a combination of reliability, vulnerability etc. under a range of plausible future conditions. It should also be noted that in cases where no minimum system performance levels exist, metrics such as reliability could be included as objectives, rather than constraints (e.g. Wu et al., 2013a), in which case the calculation of robustness would not be required, although this is generally not the case.

Although there are various definitions of robustness (see Hamarat et al., 2014; Herman et al., 2015) and different definitions can result in different outcomes (Giuliani and Castelletti, 2016; Kwakkel et al., 2016b), when developing robust long term water resources plans, robustness metrics based on satisficing criteria are most appropriate, as they align with the way the performance of water resources systems is generally assessed, as discussed above (i.e. whether a system performs adequately or not, such as ensuring constraints that supply is greater than demand). Of the different types of satisficing criteria (see Herman et al., 2015), ones that are based on the proportion of plausible future conditions under which the system performs adequately are preferable to those based on the deviation from an expected future state, as it is difficult to identify the latter under deep uncertainty (Maier et al., 2016). Consequently, the domain criterion (Schneller and Sphicas, 1983), which has already been used in a number of water resources planning studies (Paton et al., 2014a, b; Beh et al., 2015b), appears to be a suitable metric for assessing the performance of water resources systems under deep uncertainty.

In previous water resources planning optimization studies that considered robustness as a measure of system performance under deep uncertainty, regardless of whether sequencing was considered or not, robustness was not included as an objective in the optimization problem, but was considered post-optimization (Beh et al., 2015b; Kasprzyk et al., 2013; Paton et al., 2014a). As a result, it is unlikely that the most robust solutions were identified, as robustness was calculated for solutions that were optimized for other objectives, such as cost and greenhouse gas (GHG) emissions. It should be noted that while robustness has already been used as an objective in a small number of water resources optimization studies (Kapelan et al., 2005; Basupi and Kapelan, 2015; Zeff et al., 2016), these studies did not account for deep uncertainty, but only local uncertainty, therefore addressing a different problem from the work presented in this paper.

The most likely reason for the exclusion of robustness as an objective in water resources optimization studies considering deep uncertainty is that the calculation of robustness is often computationally expensive, as it requires satisfactory system performance to be calculated for a range of future conditions (Roach et al., 2016). This often makes the inclusion of robustness as an objective in optimization studies computationally intractable, particularly since the run-times of the simulation models needed to calculate satisfactory system performance are generally not insignificant. These computational issues are further exacerbated in water resources infrastructure sequencing problems, as the computationally expensive simulation model has to be run a large number of times to account for the natural variability in climatic variables affecting supply and demand (Mortazavi et al., 2012) for each of the plausible futures considered and for each stage of the planning process. In addition, if evolutionary algorithms (EAs) (Maier et al., 2014) are used as the optimization engine, as is often the case (e.g. Beh et al., 2015b; Kasprzyk et al., 2013; Paton et al., 2014a), the above model runs have to be repeated at each iteration of the optimization process, and the entire optimization process has to be repeated several times from different starting positions in solution space to account for the stochastic searching behaviour of EAs. While post-optimization consideration of robustness has successfully addressed these computational issues, it does not necessarily identify the most robust solutions, as robustness is not maximized explicitly during the optimization process (Beh et al., 2015b), as mentioned above.

In order to overcome the shortcomings outlined above, an approach is developed in the present study that uses metamodels (also called surrogate or emulation models) (Castelletti et al., 2012; Razavi et al., 2012), instead of computationally expensive simulation models, to calculate all objectives, including robustness, as part of a multi-objective evolutionary algorithm (MOEA) optimization framework. In other words, the objective is to develop models that emulate the function of the hi-fidelity simulation model of the water resource system of interest, but that are much more computationally efficient and can therefore be used in place of the simulation model during the optimization process in order to make the process computationally feasible.

While metamodels have already been used widely in water resources optimization frameworks in order to increase the computational efficiency of optimization processes (Razavi et al., 2012), their application in the context of uncertainty calculation has been limited, even though they offer significant potential for doing so (Maier et al., 2014; Mount et al., 2016). To our best knowledge, only Yan and Minsker (2011) and Broad et al. (2015) have developed