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A diagnostic assessment of evolutionary algorithms for multi-objective surface water reservoir control

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ABSTRACT

Globally, the pressures of expanding populations, climate change, and increased energy demands are motivating significant investments in re-operationalizing existing reservoirs or designing operating policies for new ones. These challenges require an understanding of the tradeoffs that emerge across the complex suite of multi-sector demands in river basin systems. This study benchmarks our current capabilities to use Evolutionary Multi-Objective Direct Policy Search (EMODPS), a decision analytic framework in which reservoirs' candidate operating policies are represented using parameterized global approximators (e.g., radial basis functions) then those parameterized functions are optimized using multi-objective evolutionary algorithms to discover the Pareto approximate operating policies. We contribute a comprehensive diagnostic assessment of modern MOEAs' abilities to support EMODPS using the Conowingo reservoir in the Lower Susquehanna River Basin, Pennsylvania, USA. Our diagnostic results highlight that EMODPS can be very challenging for some modern MOEAs and that epsilon dominance, time-continuation, and auto-adaptive search are helpful for attaining high levels of performance. The ϵ-MOEA, the auto-adaptive Borg MOEA, and ϵ-NSGAII all yielded superior results for the six-objective Lower Susquehanna benchmarking test case. The top algorithms show low sensitivity to different MOEA parameterization choices and high algorithmic reliability in attaining consistent results for different random MOEA trials. Overall, EMODPS poses a promising method for discovering key reservoir management tradeoffs; however algorithmic choice remains a key concern for problems of increasing complexity.

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1. Introduction

Operational water management within river basins worldwide is confronting a challenging combination of growing population pressures, evolving multi-sector demands, and climate change (Edenhofer et al., 2014). These challenges are pressing existing and planned hydropower operations to adopt integrated water resources management that takes into account a broad range of social, economic, and environmental issues (World Bank, 2009). Efficient multi-purpose reservoir management strategies are critical given the growing risks for flood and drought shocks as well as the need to meet evolving water allocation demands across a complex set of users (e.g., balancing the variability of renewables or flow maintenance for ecosystem services (Castelletti et al., 2011, 2014; Kern et al., 2015)). However; identifying efficient and balanced reservoir management strategies that meet energy needs while maintaining other key river basin services remains a severe challenge for actual operations.

Reservoir policies need to realistically consider the complex dynamics that typify river basin systems. Consequently, the optimization techniques used in their design need to avoid simplifications that widely discourage their application in real reservoir contexts Labadie (2004). Popular operational water management frameworks ranging from classical tools (e.g., dynamic programming (DP) or linear programming(LP) family of methods) to single-objective heuristics are limited in the breadth of multi-objective formulations that they can resolve (Castelletti et al., 2010, 2008; Giuliani et al., 2015a). Traditionally, these approaches were developed for single objective formulations and only recently have they extended to multi-objective formulations. Yet, they are still limited in their scalability and are not applied

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to many-objective formulations (with more than four objectives) (Fleming et al., 2005). The weighting schemes used in traditional multi-criterion implementations of single-objective methods are strongly sensitive to the convexity as well as the separability of the resulting aggregate management objectives (Castelletti et al., 2008, 2012). These issues pose important limits for formulations with heterogeneous objective functions. For instance, a minimax reliability objective and an expected cost objective may encounter difficulties when integrated into a single weighted function when using a DP framework. The classical approach for appropriately aggregating conflicting objectives requires an *a-priori*, well-specified set of weights (Efstratiadis et al., 2004). Using the terminology of Cohon and Marks (1975), DP-based solution strategies can also be used as generating methods, where a suite of optimization runs are executed as the weights for different objectives are varied to attain Pareto optimal solutions (Soncini-Sessa et al., 2007). The Pareto optimal set represents the suite of solutions whose performance in a single objective cannot be improved without degrading their performance in one or more other objectives. Plotting this Pareto optimal set of solutions in a problem's objective space yields the Pareto front, or the geometric representation of the optimal tradeoffs. This scalarization process requires one optimization run for each point that defines a trade-off curve, which is computationally very demanding and often results in poor representations of the Pareto frontier (Castelletti et al., 2013). These limitations make it important to understand the value of algorithms capable of approximating the Pareto front in a single run (e.g., (Castelletti et al., 2013; Reed et al., 2013; Vamplew et al., 2011)). Among these methods, Multi-objective Evolutionary Algorithms (MOEAs) have been demonstrated to be capable of discovering high quality representations of complex tradeoffs (Giuliani et al., 2014; Maier et al., 2014; Nicklow et al., 2010; Reed et al., 2013).

Evolutionary Multiobjective Direct Policy Search (EMODPS) provides a flexible framework for employing MOEAs in complex multi-purpose reservoir systems. Giuliani et al. (2015a) formalized this approach, which features reservoir policy identification, multi-objective evolutionary optimization and visual analytics to characterize the baseline operations and discover the key operational tradeoffs to provide operators with guidance on balancing a reservoir system's competing demands. Rosenstein and Barto (2001) first introduced direct policy search (DPS) in the general control theory literature. DPS is also known as parameterization-simulation-optimization in the water resources literature (Koutsoyiannis and Economou, 2003) with earlier water resources applications found in Guariso et al. (1986) and Oliveira and Loucks (1997). EMODPS provides users with flexibility in how to formulate and solve multi-objective reservoir control problems. EMODPS benefits from (1) the simultaneous consideration of heterogeneous forms of objective functions (e.g., minimax and expected value) (Giuliani and Castelletti, 2016), (2) the potential use of exogenous information to condition control decisions, (Giuliani et al., 2015b) and (3) simulation-based treatment of uncertainties in system dynamics or performance (Giuliani et al., 2014). EMODPS copes with high dimensionality reservoir's operational decisions by instead optimizing the parameters of a control policy. This is a parsimonious approach that broadens analysis of complex reservoir systems; the systems do not need to be simplified as the methodology can accommodate more objectives and uncertainties without increasing substantially a problem's difficulty.

Despite these practical advantages, the success of EMODPS is highly dependent on appropriately representing the space of possible operating policies as well as the MOEA's capability to optimize them. The flexibility and accuracy of global approximators to represent alternative operating policies has been assessed in Giuliani et al. (2015a). Although there are a growing number of studies exploring the EMODPS framework, at present no rigorous algorithmic assessments have been completed. The key contribution and focus of this study is to diagnose the difficulty of using MOEAs to support the EMODPS framework using the six-objective Lower Susquehanna test case, and analyze which MOEAs are more suitable for finding the best Pareto approximate set. The Lower Susquehanna test case is challenging due to its large number of conflicting multi-sector demands and the time resolution of the analysis, which is linked to the rapidly changing energy prices. Key system demands include hydropower production, urban water supply, recreation and environmental requirements.

2. Lower Susquehanna River Basin benchmark

The Susquehanna River is the largest river in the eastern United States, contributing 50% of the inflows to the Chesapeake Bay. The basin drains over a 71,000 km^2 watershed and provides public water supply for a population of 4.1 million people. In the Lower Susquehanna River Basin, the Conowingo dam plays a key role in balancing the multi-sector water demands within the region, representing one of the largest non-federal hydroelectric dams in the U.S. (see Fig. 1). The Conowingo Dam embodies a complex multi-objective system due to the competing demands between hydropower production, environmental flow requirements, cooling water for Peach Bottom Nuclear Power Plant, recreational use and water supply for Baltimore, MD and Chester, PA. (illustrated in Fig. 2). To address these issues, the Susquehanna River Basin Commission has historically led computer-aided adaptive management (Sheer and Dehoff, 2009) to mediate compromises across the system's multi-sector demands. More recently, Giuliani et al. (2014) have contributed a more explicit analysis of the tradeoffs confronting the Lower Susquehanna, highlighting important potential conflicts between hydropower revenue, nuclear power cooling water, and environmental flow requirements. The Lower Susquehanna test case is representative of the management challenges faced in reservoir systems worldwide. A key question explored in this study is how capable of MOEAs are at capturing their tradeoffs. Building off of the initial contributions of Giuliani et al. (2014), the Lower Susquehanna provides an excellent benchmarking test case to evaluate this question.

2.1. Susquehanna River Basin model

The Lower Susquehanna simulation model used in this study is based on the historical formulation in Giuliani et al. (2014), where a dynamic mass balance over a historical time series of inflows and evaporation rates as well as the Conowingo and Muddy Run Reservoirs' releases. Muddy Run Reservoir is a pumped hydropower operation which takes advantage of intra-daily cycles in energy prices. During off-peak hours, water is pumped uphill from Conowingo Reservoir into Muddy Run Reservoir; this water is released during peak hours to maximize hydropower profit for the combined system.

The power house, located in Conowingo, MD, exploits the reduced pricing associated with excess grid capacity during off peak hours to pump water from the Conowingo Reservoir uphill into Muddy Run, the water then relies on gravity-based return flows to Conowingo to take advantage of peak power demand periods.

Direct rainfall over the reservoir surface can be negligible in relation to flow contributions from upstream contributing areas. Evaporation, in the other hand, is considered since this test case focuses on prolonged summer droughts were the losses are not negligible. These relationships are described in Eq. (1):

$$
\begin{aligned}
s^{CO}_{t+1} &= s^{CO}_{t} + q^{CO}_{t+1} + q^{CO,L}_{t+1} - r^{CO}_{t+1} - E^{CO}_{t+1} - q^{p}_{t+1} + r^{MR}_{t+1} \\
s^{MR}_{t+1} &= s^{MR}_{t} + q^{MR}_{t+1} - r^{MR}_{t+1} - E^{MR}_{t+1} + q^{p}_{t+1}
\end{aligned}
\tag{1}
$$

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