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Many-objective reservoir policy identification and refinement to reduce policy inertia and myopia in water management

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Key Points:

- We capture the historical reservoir operation via implicit policy identification
- The current policy is refined via many-objective optimization under uncertainty
- Visual analytics helps DMs to overcome policy inertia and myopia

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Abstract This study contributes a decision analytic framework to overcome policy inertia and myopia in complex river basin management contexts. The framework combines reservoir policy identification, many-objective optimization under uncertainty, and visual analytics to characterize current operations and discover key trade-offs between alternative policies for balancing competing demands and system uncertainties. The approach is demonstrated on the Conowingo Dam, located within the Lower Susquehanna River, USA. The Lower Susquehanna River is an interstate water body that has been subject to intensive water management efforts due to competing demands from urban water supply, atomic power plant cooling, hydropower production, and federally regulated environmental flows. We have identified a baseline operating policy for the Conowingo Dam that closely reproduces the dynamics of current releases and flows for the Lower Susquehanna and thus can be used to represent the preferences structure guiding current operations. Starting from this baseline policy, our proposed decision analytic framework then combines evolutionary many-objective optimization with visual analytics to discover new operating policies that better balance the trade-offs within the Lower Susquehanna. Our results confirm that the baseline operating policy, which only considers deterministic historical inflows, significantly overestimates the system's reliability in meeting the reservoir's competing demands. Our proposed framework removes this bias by successfully identifying alternative reservoir policies that are more robust to hydroclimatic uncertainties while also better addressing the trade-offs across the Conowingo Dam's multisector services.

1. Introduction

River basin management has traditionally been challenged by multiple competing water demands, including domestic and irrigation supply, flood protection, and hydropower production. Additional challenges arise with environmental regulations for flows, water quality targets, recreational interests, and energy markets [e.g., *Brown and Carriquiry*, 2007; *Fernandez et al*., 2012], emphasizing the need to rethink the way freshwater resources are distributed, managed, and used [*Gleick*, 2002]. Concerning water storage systems, such a paradigm shift is not easily achievable: the possibility of redesigning water reservoir regulation is strongly limited by historical agreements and regulatory constraints [*Fernandez et al*., 2013]. The limited flexibility of water laws, for example, in the United States, creates policy inertia, where water institutions are highly unlikely to change their current practices in the absence of a dramatic failure or water conflict [*Sheer*, 2010]. Yet no guarantee exists that historical management policies will not fail in coming years, especially as water managers face growing water demands and increasingly uncertain hydrologic regimes [*Milly et al*., 2008]. There is a significant need to better understand the consequences of our current reservoir operations while discovering alternative policies that better balance competing objectives and performance uncertainties.

Prior studies in this area have often neglected the challenging realities of reservoir operations, assuming complete flexibility when designing optimal operation via optimization models [e.g., *Yeh*, 1985; *Labadie*, 2004; *Castelletti et al*., 2008, and references therein], and mostly focusing either on improving system-wide performance, by including hydroclimatic information to better condition the decisions [e.g., *Klemeš*, 1977; *Tejada-Guibert et al*., 1995; *Hejazi et al*., 2008], or on solving increasingly larger systems, by addressing the associated curse of dimensionality [e.g., *Cervellera et al*., 2006; *Castelletti et al*., 2010, and references therein]. Reservoir operators generally reject the validity of using optimization models to directly inform actual real-time operations, in particular when they include uncertainty explicitly [*Celeste and Billib*, 2009]. Consequently, these tools are rarely employed in real-operational contexts [*Teegavarapu and Simonovic*, 2001].

Instead, operators prefer simpler tools, such as rule curves [*Loucks and Sigvaldason*, 1982; *Loucks et al.*, 2005], even though these tools are not able to adapt release decisions when the system deviates from the "normal" hydroclimatic conditions assumed in the design of the rule [*Maass et al.*, 1962; *Howard*, 1999]. The more uncertain the hydrologic system, the more frequent the deviations from the assumed baseline flow conditions and, accordingly, the lower the effectiveness of rule-curve-based operations. This is particularly critical given that rule curves are rarely redesigned to account for changing hydroclimatic conditions. Closing the loop between operational decisions and evolving river conditions [e.g., *Soncini-Sessa et al.*, 2007] will be key to our ability to adapt to increasingly variable and extreme hydrologic conditions.

In addition to this inflexibility, traditional rule curves also suffer from policy myopia: they fail to explore the full set of trade-offs between evolving multisector objectives and preferences in river basins. Many examples [e.g., *Brill et al.*, 1990; *Balling et al.*, 1999; *Kasprzyk et al.*, 2009] show how preferences shift with the addition of new objectives due to the decision biases produced by cognitive myopia, where narrow or restrictive definitions of optimality strongly limit the discovery of decision relevant alternatives that could change stakeholder preferences [*Hogarth*, 1981], and cognitive hysteresis, where traditional strategies for addressing a problem restrict the generation of new hypotheses for innovative decisions or additional objectives [*Gettys and Fisher*, 1979]. Yet most major reservoirs have had their rule curves defined in prior decades, where planning methods required strong a priori assumptions on the preferences (or priorities) of a representative, idealized decision maker (DM) across a limited number of operating objectives [*U.S. Army Corps of Engineers*, 1977]. Just as a changing hydrological context poses a challenge, evolving objectives and preferences for reservoir operations can be another mode of failure for fixed rule curves. Following the classification of *Cohon and Marks* [1975], the legacy planning strategies that have predominately shaped modern operations are the results of a priori multicriteria decision analysis (MCDA) methods. As reviewed by *Chankong and Haimes* [1983], these methods first elicit (or assume) a priority ranking or weighting of objectives, which is then used to reduce the multiobjective operations problem into an aggregated single-objective optimization that sought one "compromise" solution. As reviewed by *Haimes and Hall* [1977], these approaches were recognized as making very strong assumptions (linearity, perfect foresight, limited if any uncertainty, convexity, well-defined understanding of planning alternatives and preferences, etc.) that could cause severe biases. Although these issues have long been recognized, only recently have new methods emerged to address them for complex engineered river basin systems.

Again following the classification of *Cohon and Marks* [1975], an alternative approach to a priori MCDA methods are a posteriori generating techniques, where the full set of Pareto-optimal (or approximate) solutions that comprise trade-off curves are generated prior to eliciting the DM's preferences. A solution is defined as Pareto-optimal (or nondominated) if no other solution gives a better value for one objective without degrading the performance in at least one other objective. The image in the objective space of the Pareto-optimal solutions is the Pareto front. The underlying benefit of the a posteriori approach is that DMs do not have to state what is preferred in absence of their understanding of what is attainable (assuming a well-formulated management problem). The core limitation in this approach is the computational cost of identifying the Pareto front. Classically, these approaches have required similar weighting based methods as used in MCDA a priori methods, with the distinguishing difference that the single-objective optimization is repeated for every Pareto-optimal point generated by adapting the weighting of the objectives. Although several sophisticated weighting schemes exist [*Chankong and Haimes*, 1983; *Soncini-Sessa et al.*, 2007; *Coello Coello et al.*, 2007], more recent strategies in water resources planning have transitioned to multiobjective evolutionary algorithms (MOEAs) to avoid the limitation of generating a single Pareto-optimal point per optimization run while also broadening the number and complexity of objectives that can be resolved [*Nicklow et al.*, 2010; *Reed et al.*, 2013]. A posteriori methods have been also limited by DMs' ability to explore the multidimensional Pareto front. The idea of searching and visualizing the Pareto front for two objectives was first introduced by *Gass and Saaty* [1955]. Then, *Louie et al.* [1984] and *Haimes et al.* [1990] proposed to use decision maps to show three-objectives trade-offs as collections of two-objective trade-off curves with different values of the third objective. Recent advances in visual analytics [e.g., *Thomas and Cook*, 2005; *Keim et al.*, 2006; *Kollat and Reed*, 2007; *Lotov and Miettinen*, 2008; *Woodruff et al.*, 2013] are capable of managing more than three objectives, thus allowing the exploration and understanding of complex, high-dimensional information through highly interactive visual tools.

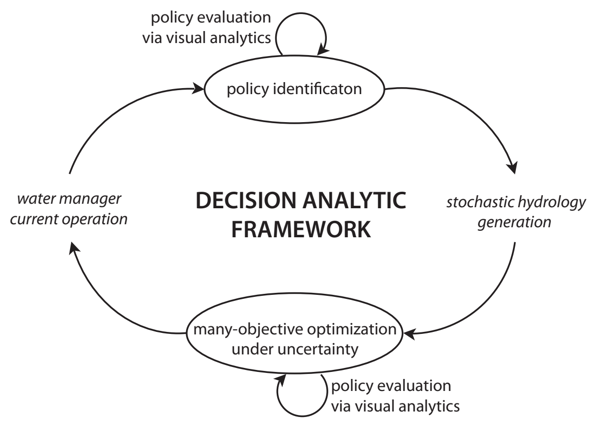

Figure 1. Illustration of the proposed decision analytic framework, which combines reservoir policy identification, policy refinement with many-objective optimization under uncertainty, and visual analytics.

In this work, we are proposing a decision analytic framework (Figure 1) that supports water managers in redesigning the operation of their systems using a combination of reservoir policy identification, policy refinement with many-objective optimization under uncertainty, and visual analytics to explore Pareto-optimal alternatives. This approach aims to overcome both policy inertia and myopia in water management in order to balance both competing objectives and performance uncertainties, which have often challenged the design of optimal water management strategies when experts neglect key decision relevant complexities of the real systems [*Shanteau*, 1992]. Moreover, in the long-term, the proposed framework might contribute to the shift from traditional reservoir operation based on rule curves, which require implicit, nonsequential, and nonrecoverable intuitive thinking, toward more explicit, sequential, and recoverable decisions [*Hammond et al*., 1987] relying on feedback operating policies. The framework is based on a two-step procedure: first, the current baseline operating policy is identified in the form of a mathematical relationship mapping relevant information into release decisions [*Corani et al*., 2009]. Subsequently, this policy is refined via many-objective optimization, and the associated trade-offs visually explored. According to *Fleming et al*. [2005], a problem is considered to take a *many-objective* nature when the number of objectives is equal or larger than four units. The performance of the alternative operating policies is evaluated for their robustness to future hydroclimatic uncertainty. Visual analytics plays a key role in the proposed framework, by allowing DMs to comparatively analyze their current policy in the context of the full trade-off surface as well as in the corresponding operating policy decision space.

Our discovery of optimal operating policies is based on the direct policy search (DPS) approach [*Schmidhuber*, 2001; *Rosenstein and Barto*, 2001], also known as parameterization-simulation-optimization in the water resources literature [*Guariso et al*., 1986; *Koutsoyiannis and Economou*, 2003], where the operating policy is first parameterized within a given family of functions (e.g., linear or piecewise linear) and then the parameters optimized with respect to the operating objectives [see also *Oliveira and Loucks*, 1997; *Momtahen and Dariane*, 2007; *Celeste and Billib*, 2009; *Pianosi et al*., 2011; *Ostadrahimi et al*., 2012; *Guo et al*., 2013]. Following *Nalbantis and Koutsoyiannis* [1997], DPS can be seen as an optimization-based generalization for multiobjective problems of well-known simulation-based, single-purpose heuristic operating rules [for a review, see *Lund and Guzman*, 1999]. Prior studies have adopted the DPS approach mainly to overcome the computational and dimensional limitations of dynamic programming family of methods [e.g., *Baglietto et al*., 2006; *Momtahen and Dariane*, 2009; *Castelletti et al*., 2013], without considering the realities of the current systems' operations and have thus rarely been adopted.

In the proposed framework, DPS is used to identify and refine the current operation in an enlarged many-objective space with the aim of providing more practical solutions, which maintain some features of the current operation, such as satisfaction of regulatory constraints or the operators' current preference structure, while better addressing the trade-offs between original and potentially new objectives given significant hydroclimatic uncertainties. The effectiveness of this approach depends on the flexibility of the selected class of functions used to define effective policies as well as the ability of the optimization algorithm to deal with a large number of objectives while identifying operational alternatives. We use Gaussian radial basis functions (RBFs) to parameterize the policies as they are capable of representing functions for a large class of problems [*Busoniu et al*., 2011]. We address the challenges posed by many-objective optimization under uncertainty by using the self-adaptive Borg MOEA [*Hadka and Reed*, 2013]. *Reed et al*. [2013]

Table 1. List of Abbreviations

DM	Decision maker
MCDA	Multicriteria decision analysis
MOEA	Multiobjective evolutionary algorithms
DPS	Direct policy search
RBF	Radial basis function
FERC	Federal Energy Regulatory Commissions
SRBC	Susquehanna River Basin Commission

performed a comprehensive diagnostic assessment of modern MOEAs where the Borg MOEA was demonstrated to increase the efficiency, effectiveness, and reliability by which complex many-objective water resources applications can be solved. Our framework provides DMs with an explicit representation of the trade-offs between their operating objectives, by which they can more fully understand the consequences of their chosen policy alternative(s) [see *Kollat et al*., 2011; *Kasprzyk et al*., 2012; *Woodruff et al*., 2013, and references therein].

The framework is demonstrated on the Conowingo reservoir, an interstate water body shared by Pennsylvania (PA) and Maryland (MD) in the Lower Susquehanna River, characterized by the presence of many conflicting stakeholders. Currently, the Conowingo dam provides water supply to Chester (PA) and Baltimore (MD), cooling water for the Peach Bottom atomic power plant, and minimum regulated flows as defined by the Federal Energy Regulatory Commission (FERC) to protect fishery resources. In low flow conditions, FERC requirements tend to drawdown storage levels, increasing the conflict between the other stakeholders' objectives and reducing the recreational value (e.g., boating and fishing activities) of the system. This Lower Susquehanna system is unique in that and it represents one of the few systems where adaptive management is actually in place. For example, in 2002, the Susquehanna River Basin Commission (SRBC) coordinated multistakeholder negotiations to modify FERC regulated releases while seeking to balance the stakeholders conflicting objectives [*Swartz*, 2006]. This study builds on the adaptive management efforts of the SRBC by comparing the alternatives they identified with the Pareto-optimal policies obtained with our framework. This study also contributes a set of candidate policies that could aid the dam operator in balancing its multisector demands and hydroclimatic uncertainty.

In summary, this paper contains three main contributions: (i) we propose an implicit optimization-based policy identification approach, which captures the historical operation of the Conowingo dam by assuming a rational behavior of the dam's operator aiming to guarantee the public water supply and to maximize the hydropower revenue and solving the associated policy design problem; (ii) we refine the current policy by adopting a many-objective DPS approach coupled with visual analytics in order to explore the entire space of the objectives and analyze the associated trade-offs over historical as well as stochastic hydroclimatic conditions; (iii) we demonstrate how the SRBC can overcome policy inertia and myopia by comparing the performance of the stochastic Pareto-optimal policies and the set of alternatives identified by SRBC.

The rest of the paper is organized as follows: the next section introduces the case study and section 3 describes the methodology. Results are reported in section 4 and final remarks, along with issues for further research, are presented in the last section. A list of abbreviations can be found in Table 1.

2. Case Study Description

2.1. The Lower Susquehanna System

The Susquehanna River (Figure 2a) is the longest river on the eastern United States, draining a catchment area of about 71,000 km^2 through New York, Pennsylvania, and Maryland, ultimately contributing 50% of the freshwater flowing into the Chesapeake Bay. The Conowingo reservoir is an interstate water body shared by Pennsylvania and Maryland in the Lower Susquehanna, about 16 km from the Susquehanna River mouth. The dam, which was completed in 1928 for hydropower generation purposes, is the largest nonfederal dam in the U.S. regulating a large share of the flow in the Lower Susquehanna with substantial impacts on multiple stakeholders. The Conowingo reservoir contributes to the water supply of Chester (PA) and Baltimore (MD). Conowingo releases are also critical for cooling the Peach Bottom atomic power plant and downstream releases are subject to minimum flow requirements defined by the Federal Energy Regulatory Commission (FERC) to protect fishery resources. Moreover, in 1968 the reservoir was connected to the Muddy Run Pumped Storage Hydroelectric Facility, which cycles water back and forth from Conowingo for additional power generation. Finally, the Conowingo reservoir provides valuable recreational and ecosystem services.

The FERC minimum flow requirements introduced in 1988 protect fishery resources threatened by the hydropower management of the dam. The Conowingo reservoir is unique as a high valued river basin

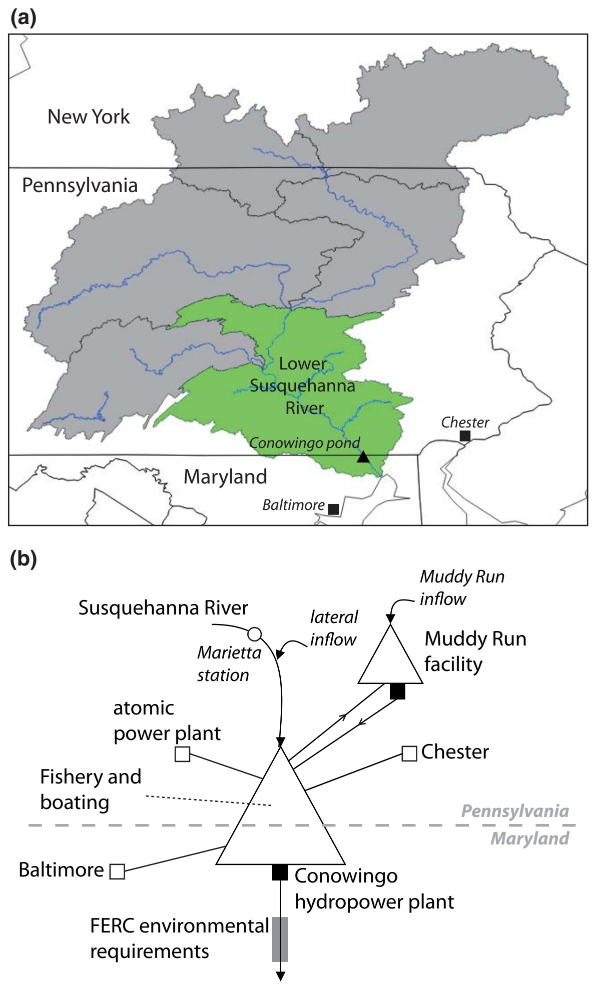

Figure 2. (a) Map of the Susquehanna River basin and (b) schematic representation of the main components described in the model.

system that is being adaptively managed by the SRBC in collaboration with its core service constituencies [*Federal Energy Regulatory Commission*, 1989]. In average flow conditions, water availability is generally sufficient to maintain hydroelectric operations, water supply, meet environmental flow requirements, and sustain recreational activities. Yet in low flow conditions challenging trade-offs emerge for Conowingo operations to supply water to Baltimore, Chester, and the Peach Bottom atomic power plant, while seeking to minimize negative impacts on the recreational and touristic interests. The normal level of the Conowingo reservoir along with the critical levels for water supply and the target level for recreation are reported in Table 2.

Although the SRBC actively coordinates conflicting water demands and water related interests between the basin's stakeholders, growing regional water demands and climate change are significant concerns. As a recent example, the SRBC coordinated a regional planning effort assessing a set of alternative modifications to the FERC requirements to mitigate the negative impacts of the low reservoir levels [*Swartz*, 2006]. The effort represents a substantial participatory negotiation process, with the SRBC promoting a direct involvement of the stakeholders to evaluate the different alternatives with the support of OASIS model simulations [*Randall et al*., 1997; *Sheer and Dehoff*, 2009], a general purpose water resources model that uses a linear program solver to allocate water to meet multisector demands. Given the results of the modeled alternatives, the possibility of including the 800 cfs leakages from the closed dam gates toward meeting the downstream minimum flow requirements has been selected as the most critical action in managing the Conowingo dam during drought periods. The result of this intensive planning effort is the identification of alternative management strategies for implementing the credit for leakages and specifying the hydrologic conditions under which this credit is warranted. According to *Swartz* [2006], the most promising alternatives are summarized below:

1. *Baseline*, representing the current situation where the Conowingo reservoir provides public water supply and the downstream releases are regulated by Exelon for hydropower production, subject to the downstream FERC minimum flow requirements (i.e., to release at least the maximum between the minimum environmental flow and the inflow registered at Marietta) without including the credit for the leakage.

2. *Automatic Credit*, which proposes to automatically include the credit allowance in meeting the FERC minimum flow requirements. Yet the credit is never available in April, May, or June, in order to protect fish migration.

Table 2. Reference Levels for the Conowingo Reservoir (ft)

Normal level	108.5
Touristic weekend recreational level	106.5
Critical level for Peach Bottom atomic power plant	103.5
Critical level for Chester water supply	100.5
Critical level for Baltimore water supply	91.5

3. *Critical Level*, which proposes to allow the 800 cfs credit only when the elevation of the Conowingo reservoir drops below a critical level equal to 104.5 ft. That stage was selected because it guarantees operations at Peach Bottom and Muddy Run facility. The credit is never available in April, May, or June.

4. *Minimum Flow*, which proposes to consider the FERC minimum flow requirements as absolute constraints independently from the flows at Marietta. The credit for the leakage is always counted in this scenario, but in April, May, or June.

All of these alternatives have been designed to manage credit for leakages and the minimum flow requirements only, according to the historical agreements and the regulatory constraints. However, there is currently a limited understanding of the potential benefits achievable by significant modifications of the current Conowingo reservoir operating policy as well as the impacts of uncertainties in the basin's hydrologic regimes.

2.2. Model Formulation

This work builds on the adaptive management efforts of the SRBC and contributes a set of candidate policies that could aid the dam operator in balancing its multisector demands and hydroclimatic uncertainty. We focus on the identification and refinement of the operating policy for the Conowingo dam, while we assume the fixed weekly rule reported in *Swartz* [2006] for the operation of Muddy Run. This rule defines an hydropeaking strategy, which turbines during the hours of high energy price and pumps overnight and in the weekends, when the energy price is low. The model of the system (Figure 2b) is mainly based on the representation of the dynamics of the two water reservoirs defined by the mass balance equations of the water volume s_t^i stored in each reservoir ($i =$ Conowingo, Muddy Run):

$$\begin{aligned} s_{t+1}^{CO} &= s_t^{CO} + q_{t+1}^{CO} + q_{t+1}^{CO,L} - r_{t+1}^{CO} - E_{t+1}^{CO} - q_{t+1}^{p} + r_{t+1}^{MR} \\ s_{t+1}^{MR} &= s_t^{MR} + q_{t+1}^{MR} - r_{t+1}^{MR} - E_{t+1}^{MR} + q_{t+1}^{p} \end{aligned} \tag{1}$$

where q_{t+1}^{CO} and $q_{t+1}^{CO,L}$ are the main (i.e., the flow measured at Marietta gauging station) and lateral inflow to the Conowingo reservoir in the interval $[t, t+1)$, respectively, and q_{t+1}^{MR} is the inflow to Muddy Run. The volume r_{t+1}^i released between t and $t+1$ is given by the release function $r_{t+1}^i = f(s_t^i, u_t^i, q_{t+1}^i, E_{t+1}^i)$, which depends on the storage s_t^i, the release decision u_t^i, the inflow q_{t+1}^i, and the loss for evaporation E_{t+1}^i. The function $f(\cdot)$ describes the nonlinear, stochastic relation between the decision u_t, and the actual release r_{t+1} [*Piccardi and Soncini-Sessa*, 1991]. The water pumped from Conowingo to Muddy Run is represented by q_{t+1}^p. The time subscript of each variable denotes the time instant at which it assumes a deterministic value. The reservoir storage is measured at time t and thus is denoted as s_t, while inflow in the interval $[t, t+1)$ is denoted as q_{t+1} because it can be known only at the end of the time interval. A 4 h decision time step is adopted to balance the need of following the hourly dynamics of the energy prices and the specification of a time step sufficiently long to not be impacted by the mechanics of turbines operation (e.g., cavitation, ramp up). Additional information about the modeled system are reported in Table 3.

2.3. Operating Objectives

The multistakeholder interests affected by the Conowingo dam operation are modeled using the following six objectives, computed over the simulation horizon (H):

1. *Hydropower Revenue*: The economic revenue from energy production at the Conowingo hydropower plant (to be maximized) defined in equation (2) as the product of the hourly energy production HP_t (MWh) and the hourly energy price ρ_t (US\$/MWh). The hydropower production is defined as $HP_t = (\eta g \gamma_w \bar{h}_t q_t^{Turb}) \cdot 10^{-6}$, where η is the turbine efficiency, $g = 9.81$ (m/s^2) the gravitational acceleration, $\gamma_w = 1000$ (kg/m^3) the water density, $\bar{h}_t$ (m) the net hydraulic head (i.e., reservoir level minus tailwater level), q_t^{Turb} (m^3/s) the turbined flow. According to *Exelon* [2010], the energy prices are defined by the 7 h moving average of the historical energy price trajectory in the Pennsylvania-New Jersey-Maryland energy market (i.e., the regional transmission organization that coordinates the movement of wholesale electricity in

Table 3. Lower Susquehanna River Characteristics

Conowingo reservoir capacity	310,000 acre-feet (0.38 km^3)
Muddy Run capacity	56,731 acre-feet (0.07 km^3)
Conowingo dam turbines capacity (13 turbines)	86,000 cfs
Conowingo dam installed capacity	573 MW
Muddy Run turbines capacity (eight turbines)	32,000 cfs
Muddy Run pumping capacity (eight pumps)	28,000 cfs
Muddy Run installed capacity	800 MW

Delaware, District of Columbia, Maryland, New Jersey, Ohio, Pennsylvania, Virginia, and West Virginia. Parts of Indiana, Illinois, Kentucky, Michigan, North Carolina, and Tennessee):

$$J^{hyd}=\sum_{t=1}^{H}(HP_t\cdot\rho_t) \tag{2}$$

2. *Water Supply to Baltimore, Chester, and the Atomic Power Plant*: The daily average volumetric reliability (to be maximized) defined as:

$$J^{VR,i}=\frac{1}{H}\sum_{t=1}^{H}\left(Y_t^i/D_t^i\right) \tag{3}$$

where $Y_t^i(\mathrm{m}^3)$ is the daily delivery, $D_t^i(\mathrm{m}^3)$ is the corresponding demand, and $i=$ (Baltimore, Chester, Atomic Power Plant).

3. *Recreation*: The storage reliability (to be maximized) in the weekends of the touristic season (i.e., from Memorial Day to Labor Day), defined as:

$$J^{SR}=1-\frac{n_F}{2N_{we}} \tag{4}$$

where n_F is the number of weekend days in the touristic season during which the reservoir level is below the target level of 106.5 ft (which guarantees boating and recreational activities) and N_{we} is the total number of weekends in the touristic season.

4. *Environment*: The daily average shortage index with respect to the FERC minimum flow requirements (to be minimized), defined as:

$$J^{SI}=\frac{1}{H}\sum_{t=1}^{H}\left(\frac{\max\left(Z_t-Y_t,0\right)}{Z_t}\right)^2 \tag{5}$$

where Y_t (m^3) is the daily release and Z_t (m^3) is the corresponding FERC flow requirement. The quadratic formulation aims to penalyze severe deficits in a single time step, while allowing for more frequent, small shortages [*Hashimoto et al.*, 1982].

The monthly water supply demands along with the FERC minimum flow requirements are represented in Figure 3. More details about the historical and stochastic problem formulations are defined in section 3.3.

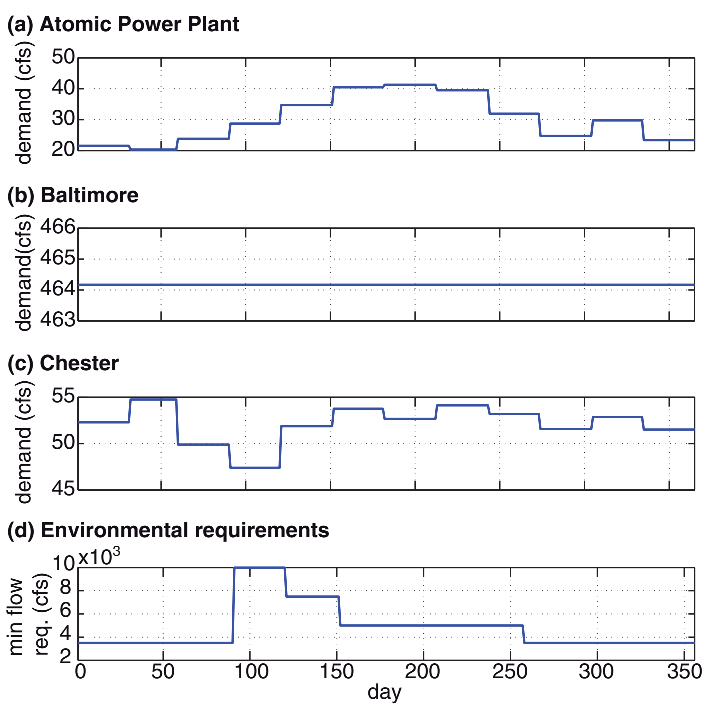

Figure 3. Public water supply demands for the (a) Peach Bottom atomic power plant, (b) Baltimore, and (c) Chester, and (d) the FERC minimum flow requirements.

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3. Methods and Tools

Sections 3.1.1–3.5 provide a detailed introduction to the primary components of our proposed decision analytic framework illustrated in Figure 1 as well as the specific details for demonstrating it using the Lower Susquehanna test case.

3.1. Policy Identification and Refinement

3.1.1 Identification

Although reservoir operators generally do not accept the validity of sophisticated decision tools, in making their decisions they necessarily look at the current or expected systems conditions (e.g., current level, forecasted inflow) when they close the loop between their operating decisions and the system's conditions [*Soncini-Sessa et al.*, 2007]. This is done either implicitly, while they are tracking the reservoir rule curve, or explicitly, when the operation relies on empirical operating rules (e.g., those reviewed by *Lund and Guzman* [1999]). In both cases, we can formalize the decision mechanism as an operating policy p defined as the sequence of operating rules, which provide the release decisions $\mathbf{u}_t = m_t(\mathbf{x}_t)$ at each time step t given the system conditions $\mathbf{x}_t$ (e.g., the Conowingo level). Modeling the behavior of the reservoir operator means identifying the policy p by assuming that the operating rules belong to a given class of functions, namely $\mathbf{u}_t = m(\mathbf{x}_t, \boldsymbol{\theta})$, where $\boldsymbol{\theta}$ is a vector of unknown time-varying parameters. The values of $\boldsymbol{\theta}$ can be determined by looking, when available, at the historical system operation, which in the simplest case is given by the time series of levels and associated releases. Hence, the historical policy can be derived via regression by estimating the parameters θ that minimize some distance metric between historical releases and modeled ones [*Guariso et al.*, 1986; *Corani et al.*, 2009]. This explicit policy identification approach can be adopted only when the historical time series are available. A more general procedure, which does not require historical data, is based on the assumption that the reservoirs' operators are rational agents acting to maximize their benefit, which can be expressed by a specific objective function. Optimizing the rule parameters with respect to this objective function yields to a policy that implicitly captures the actual decisions of the dam operator.

In the literature, a number of parameterizations of operating rules have been proposed, such as the New York City rule [*Clark*, 1950], the well known spill-minimizing "space rule" [*Clark*, 1956; *Johnson et al.*, 1991], or the Standard Operating Policy [*Draper and Lund*, 2004]. However, many rules in practice are based largely on empirical or experimental successes and they were designed, mostly via simulation, for single-purpose reservoirs [*Lund and Guzman*, 1999]. In complex many-objective problems, a priori knowledge can be counterproductive, since it might restrict the search for the optimal policy to a subspace of the decision space that does not include the optimal solution. The adoption of universal approximators such as artificial neural networks or basis functions [e.g., *Barron*, 1993; *Kurková and Sanguineti*, 2001; *Zoppoli et al.*, 2002] partially overcomes this limitation by providing flexibility to the shape of the operating rule. In this work, Gaussian radial basis functions are selected to model the operating rule as they are capable of representing functions for a large class of problems [*Tsitsiklis and Van Roy*, 1996; *Menache et al.*, 2005; *Busoniu et al.*, 2011]. With RBFs, the kth release decision in the vector $\mathbf{u}_t$ (with $k=1,\ldots,N_u$) is defined as:

$$u^k = \sum_{i=1}^{n} w_i^k \varphi_i \tag{6}$$

where n is the number of RBFs and w_i is the weight of the ith RBF (φ_i). The weights are formulated such that they sum to one (i.e., $\sum_{i=1}^{n} w_i = 1$) and are nonnegative (i.e., $w_i \geq 0 \quad \forall i$). The single RBF is defined as follows:

$$\varphi_i(\mathbf{x}) = \exp\left[-\sum_{j=1}^{m} \frac{(x_j - c_{j,i})^2}{b_{j,i}^2}\right] \tag{7}$$

where m is the number of input variables $\mathbf{x}$ (namely time and Conowingo level) and $\mathbf{c}_i, \mathbf{b}_i$ are the m-dimensional center and radius vectors of the ith RBF, respectively. The centers of the RBF must lie within the bounded input space and the radii must strictly be positive (i.e., using normalized variables, $\mathbf{c}_i \in [-1, 1]$ and

$\mathbf{b}_i \in (0,1]$). The parameter vector $\boldsymbol{\theta}$ is therefore defined as $\boldsymbol{\theta}=\left[c_{i,j}, b_{i,j}, w_i^k\right]$, with $i=1,\ldots,n$, $j=1,\ldots,m$, and $k=1,\ldots,N_u$.

3.1.2 Refinement

Once the historical operating policy has been identified, the same family of functions can be used to refine it in a multiobjective perspective, thus exploring the original operation for different trade-offs. Technically, the policy parameters ($\boldsymbol{\theta}$) are determined by solving the following multiobjective problem:

$$\boldsymbol{\theta}^* = \arg\min_{\boldsymbol{\theta}} \mathbf{J}(\boldsymbol{\theta}) \tag{8}$$

where the decision variables are the policy parameters $\boldsymbol{\theta} \in \Theta$, the objective functions are the reservoir operating objectives $\mathbf{J}$ defined in equations (2–5), which are obtained by simulating the system over the time horizon H under the policy $p=\{m(\mathbf{x}_t,\boldsymbol{\theta}); t=0,\ldots,H-1\}$ (see section 2.2, for the model formulation). To guarantee the correct verse of optimization, the performance in the objectives to be maximized is multiplied by -1 during the optimization process.

This approach goes under the name of direct policy search (DPS) [*Schmidhuber*, 2001; *Rosenstein and Barto*, 2001] and was introduced in the water resources literature first by *Guariso et al.* [1986] and subsequently formalized by *Koutsoyiannis and Economou* [2003]. DPS methods search for the optimal policy directly in the policy space, with the operating objectives that are optimized by moving the values of the policy parameters [e.g., *Rückstiess et al*., 2010; *Kormushev and Caldwell*, 2012], as opposed to dynamic programming family methods that evolve in the objective space.

Problem (8) can be solved by means of traditional mathematical programming techniques [e.g., *Orlovski et al*., 1984], evolutionary algorithms [e.g., *Chang et al*., 2005; *Momtahen and Dariane*, 2007; *Castelletti et al*., 2012] or ant colony optimization [e.g., *Jalali et al*., 2006]. DPS offers some advantages over dynamic programming family methods [e.g., *Powell*, 2007], as it does not require the system to be a discrete automaton, the objective function to be separable in time and the disturbances uncorrelated in time discretization. More practically, DPS helps to overcome (i) the curse of dimensionality [*Bellman*, 1957], namely the computational cost of dynamic programming grows exponentially with state, decision, and disturbance vectors and would be inapplicable with medium-to-high order dynamical models (e.g., water reservoir networks with more than two or three storage units); (ii) the curse of modeling [*Tsitsiklis and Van Roy*, 1996], meaning the use of in-line model-based computations that make impossible the direct, model-free use of exogenous information into the controller and the use of process-based simulation models (e.g., hydrodynamic and/or ecological). However, the DPS approach does not provide any theoretical guarantee on the optimality of the resulting operating policies, which are strongly dependent on the choice of the class of functions to which they belong and on the ability of the optimization algorithm to deal with nonlinear models and objectives functions, complex and highly constrained decision spaces, and many conflicting objectives (see section 3.4). In practice, identifying a baseline model for historical reservoir operations permits relativistic refinements of performance.

3.2. Stochastic Hydrology Generation

DPS requires that alternative policies be evaluated via simulation of the system over a wide range of hydroclimatic conditions. Consequently, the deterministic use of observed historical streamflow records to evaluate a reservoir's operating policies can strongly underestimate the impacts of hydrologic variability and extremes [*Cui and Kuczera*, 2005]. A large number of methods for synthetic hydroclimatic data generation have been proposed in the literature [e.g., *Box and Jenkins*, 1970; *Lall and Sharma*, 1996; *Yates et al*., 2003]. According to *Rajagopalan et al*. [2010], these methods can be classified as parametric approaches, which assume a standard functional form for the observed data, and nonparametric approaches, which instead define empirical distributions. In this work, we adopt the nonparametric *K*-Nearest Neighbor resampling method proposed by *Nowak et al*. [2010]. This data-driven method captures the observed statistics, is consistent with the lag correlation structures in the observed data, and ensures summability and continuity across the daily time scale.

To evaluate how hydroclimatic uncertainties impact the robustness of the reservoir policies explored in this study, we generate a stochastic ensemble of realizations for the hydroclimatic variables of the Lower

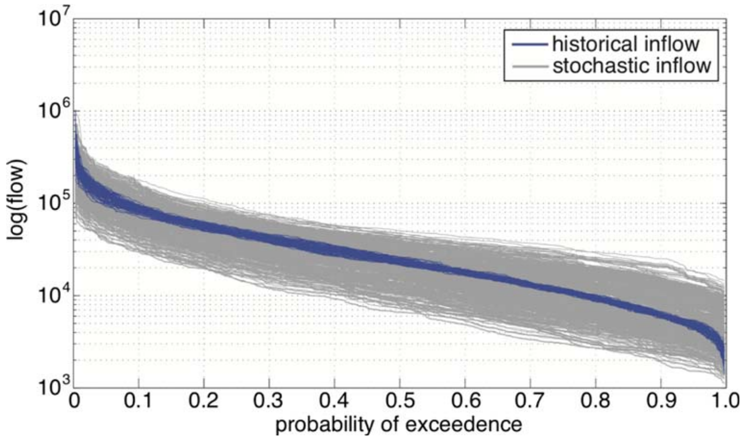

Figure 4. Annual flow duration curves of the flows at Marietta gauging station. The historical records (1930–2001) are in blue, the generated stochastic ensemble in gray.

Susquehanna system, namely inflows and evaporation rates at Conowingo and Muddy Run reservoirs. Figure 4 illustrates the annual flow duration curves for both the historical flows (1930–2001) as well as the stochastic ensemble at the Marietta gauging station. Although the stochastic ensemble directly models the autocorrelation and variability within historical record, the generated equally plausible water years clearly cover a far broader range of hydroclimatic conditions. This is especially true for the low flow conditions that have the most critical impact on the Conowingo dam's operations.

3.3. Problem Formulation

Given the historical records and the stochastic ensemble of hydroclimatic variables, in this study we consider two different formulations of the Lower Susquehanna management problem. The first formulation, which will be termed the historical formulation, is defined in equation (8), where the operating objectives (see equations (2–5)) are evaluated over the historical realization of the hydroclimatic variables, namely inflows and evaporation rates.

To assess the vulnerability of the solutions to hydroclimatic uncertainties, in the second formulation, which will be termed stochastic formulation, the same objectives are instead evaluated over an ensemble Ξ of stochastic inflows and evaporation rates realizations. The uncertainty is then filtered adopting a minimax approach formulated in equation (9), which minimizes the objectives in the worst-case realization. This approach identifies robust operating policies able to guarantee certain performance. The minimax operator has been independently applied for each objective, thus discounting the correlations among the objectives and providing an estimated lower-bound performance for each objective. This approach has been adopted in *Kasprzyk et al*. [2012], where it successfully improves the robustness of the identified solutions under conditions of deep uncertainty.

$$\boldsymbol{\theta}^* = \arg \min_{\boldsymbol{\theta}} \max_{\Xi} \mathbf{J}(\boldsymbol{\theta}) \tag{9}$$

The robustness of the operating policies is obtained by embedding multiple Monte Carlo simulations in the evolutionary search. Good solutions must indeed robustly perform for rapidly increasing numbers of Monte Carlo samples during the search process because new, independent samples are used to evaluate the objectives in successive iterations of the algorithm search. If a solution survives to the final generation, it has already been evaluated for a rapidly increasing number of realizations based on its ability to survive and propagate in the search population [*Miller and Goldberg*, 1996; *Smalley et al*., 2000; *Chan Hilton and Culver*, 2005].

3.4. Multiobjective Evolutionary Algorithms

Multiobjective evolutionary algorithms (MOEAs) are iterative search algorithms that evolve a Pareto-approximate set of solutions by mimicking the randomized mating, selection, and mutation operations that occur in nature [*Goldberg*, 1989; *Back et al*., 2000; *Coello Coello et al*., 2007]. These mechanisms allow MOEAs to deal with challenging multiobjective problems characterized by multimodality, nonlinearity, and discreteness [see *Nicklow et al*., 2010, for an extensive review of MOEA applications in water resources].

In this work, we use the self-adaptive Borg MOEA [*Hadka and Reed*, 2013], which employs multiple search operators that are adaptively selected during the optimization based on their demonstrated probability of generating quality solutions. The Borg MOEA has been shown to be highly robust across a diverse suite of challenging multiobjective problems, where it met or exceeded the performance of other state-of-the-art MOEAs [*Hadka and Reed*, 2012; *Reed et al*., 2013]. In addition to adaptive operator selection, the Borg MOEA assimilates several other recent advances in the field of MOEAs, including an ε-dominance archiving with internal algorithmic operators to detect search stagnation, and randomized restarts to escape local optima. The flexibility of the Borg MOEA to adapt to challenging, diverse problems makes it particularly useful for addressing DPS problems, where the shape of the operating rule and its parameter values are problem-specific and completely unknown a priori.

According to the DPS approach, the Borg MOEA starts with a population of N individuals, representing N randomly generated parameter vectors $\boldsymbol{\theta}$. The algorithm evaluates the fitness of each individual by simulating the system according to the operating policy defined by the corresponding value of $\boldsymbol{\theta}$ and evaluating the objective vector $\mathbf{J}(\boldsymbol{\theta})$. Then, a new population is generated by selection, crossover and mutation with respect to the best individuals (i.e., the ones obtaining the highest values of fitness) according to the Pareto dominance criterion. This process is then repeated for a given number of iterations until a good approximation of the Pareto front is obtained.

3.5. Computational Experiment

According to the policy identification and refinement procedure described in section 3.1, the Conowingo reservoir operation is modeled in terms of RBFs policies. The baseline policy is defined as a multiinput single-output function with $n = 4$ RBFs (determined by a vector $\boldsymbol{\theta}$ accounting for 20 parameters), which provides the downstream release decision as a function of time and reservoir level. Assuming the public water supplies are considered as primary objectives, the three water supply withdrawals are set equal to the corresponding demands. This hypothesis means that they are always satisfied if the level in the reservoir is sufficiently high to activate the corresponding outlets. The Pareto-optimal policies are instead defined as multiinput multioutput functions with $n = 4$ RBFs (determined by a vector $\boldsymbol{\theta}$ accounting for 32 parameters), which provide the four release decisions, corresponding to the downstream release as well as the ones for the public water supply, as a function of time and reservoir level.

The proposed many-objective policy identification and refinement method employs the Borg MOEA to optimize the operating policies via DPS (see section 3.1). The Borg MOEA has been demonstrated to be relatively insensitive to the choice of parameters, showing a high probability of attaining successful search if the algorithm is run for a sufficient number of iterations [*Hadka and Reed*, 2012; *Reed et al*., 2013]. We therefore use the default algorithm parametrization, with an initial population of $N = 100$ individuals [for further details see *Hadka and Reed*, 2013]. Epsilon dominance is used to set the resolution of the operating objectives. In this work, we set epsilon values equal to 0.5 for hydropower revenue, 0.05 for Baltimore, Chester, and Atomic Power Plant volumetric reliability, 0.05 for recreational storage reliability, 0.001 for the environmental shortage index.

The stochastic generation procedure presented in section 3.2 is applied to the hydroclimatic variables simulated in the Lower Susquehanna model (see section 2.2): inflow at Marietta, inflow to Muddy Run, lateral inflow between Marietta and Conowingo reservoir, evaporation rates at Conowingo and Muddy Run. For each variable, an AR(1) model is calibrated on the historical time series (1930–2001) to generate 1000 cumulated annual data. Then, 10 disaggregations of the same annual value are performed, yielding an ensemble of 10,000 independent stochastic realizations for each hydroclimatic variable.

To guarantee the design of robust operating policies with respect to the hydroclimatic uncertainty, we embedded multiple Monte Carlo simulations into the stochastic optimization (see section 3.3). For each objective functions evaluation, a set of 50 realizations of the hydroclimatic variables is randomly selected over the stochastic ensemble of 10,000 realizations. Then, the minimax operator (equation (9)) is applied to compute the worst-case performance. As the evolution process proceeds, new samples are used to evaluate the objectives in successive iterations of the Borg MOEA search. As an example, a solution in the present generation uses only 50 realizations to estimate its expected performance. In future generations, this solution and its child solutions all must survive additional draws. In net over a full run, solutions are tested with a very large combination of realizations.

The computational requirements for this study were dominated by the optimization under stochastic hydroclimatic conditions. In the stochastic optimization, each function evaluation performed by the Borg

MOEA comprises 50 Monte Carlo simulations over a 1 year horizon. The stochastic optimization was run for 1 million function evaluations. To improve solution diversity and avoid dependence on randomness, the solution set from each formulation is the result of 30 random optimization trials (i.e., 30 seeds with 50 million simulations each yields 1.5 billion simulations in total). The final Pareto-optimal policies are obtained as the set of nondominated solutions identified from the results of all the optimization trials.

The stochastic optimization was performed on the Texas Advanced Computing Center (TACC) Stampede Cluster (http://www.tacc.utexas.edu/stampede). The 6400 nodes of the TACC Stampede system each contain two Intel Xeon E5 processors and one Intel Xeon Phi Coprocessor, for a total of 102,400 processing cores. Each optimization run was parallelized to be run on 4096 processing cores simultaneously. In total, approximately 200,000 computing hours were required to complete the study, ensuring the best possible approximation to the Pareto-optimal solution set within the limits of computational tractability. It should be noted that our computational experiment is more rigorous than would be necessary in practice. We exploited parallel search to maximize our ability to explore the problem's decision space while minimizing the time required to attain our search results. Although we used 1,000,000 NFE per random trial of the Borg MOEA, we found that the algorithm reliably attained very high fidelity approximations of the Pareto approximate sets in approximately 100,000–200,000 NFE. In practice, it would be recommended to use emerging visual analytics frameworks [*Kollat and Reed*, 2007; *Reed and Kollat*, 2013] to monitor search dynamics and terminate search when users feel the results are acceptable and further search would yield diminishing returns.

4. Results

4.1. Identification of the Baseline Alternative

In order to discover operating policies that could improve the management of the Lower Susquehanna, it is pivotal to accurately model the dynamics and preferences currently guiding the operation of the Conowingo Dam. We exploit the implicit policy identification procedure described in section 3.1.1 using the only public information that is available for assessing the current Conowingo operations, namely the historical records of the flows at Marietta and downstream of the Conowingo Dam (Figure 2). To guarantee satisfaction of water supply and cooling demands, we specify constant withdrawals from the reservoir equal to the water demands of Baltimore, Chester, and the Peach Bottom atomic power plant when the level in the reservoir is sufficiently high to activate the corresponding outlets (see Table 2). Then, we define the regulation of the downstream releases by assuming that Exelon acts to maximize the hydropower revenues, subject to the FERC minimum environmental flow requirements. To validate this implicit policy identification approach, we run a deterministic simulation over historical hydroclimatic conditions (i.e., inflows and evaporation rates) and compare the resulting releases with respect to the flows measured at the USGS gauging station downstream of the Conowingo dam (USGS gauge 01578310).

The results of the policy identification are reported in Figure 5. Figure 5a shows the trajectory of the daily Conowingo reservoir level in 1999. Year 1999 was selected as it represents a highly challenging dry period, where operations in the system are actively managing the trade-offs for Conowingo in low flow conditions. The trajectory of reservoir levels varies between the minimum and maximum elevations of 101.2 and 110.2 ft. This range falls within the feasible limits imposed on Conowingo Dam. The simulated and observed trajectories of releases along with the cumulative releases are shown in Figures 5b and 5c, respectively. Both figures show that the implemented implicit modeling approach effectively captures the historical operation of the system. Note that the overestimation of the peaks (spills) in Figure 5b can be explained by the 4 h time step of the model which keeps the spillways open longer than in reality. Figure 5d shows the release decisions for different reservoir levels according to the estimated policy. The concave shape serves to maximize hydropower production, which depends on the turbined flow multiplied by the net hydraulic head (i.e., reservoir level minus tailwater level). The maximization of the hydropower revenue is then obtained by releasing more water in the hours with higher energy prices.

The baseline policy identified and illustrated in Figure 5 provides a highly flexible tool for contrasting how the Conowingo Dam's current operations perform relative to optimized alternative formulations of the Lower Susquehanna management problem. In this study, we contrast two formulations: the deterministic six-objective case formulated in equation (8) evaluated for the historical flows in 1999 and its stochastic

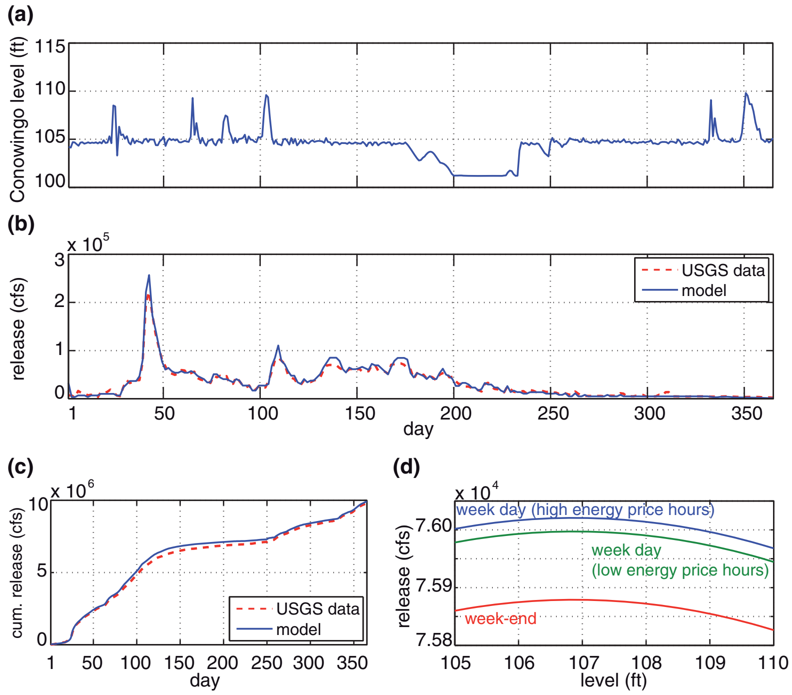

Figure 5. (a) Trajectories of Conowingo reservoir level in 1999 under the estimated baseline policy. Comparison of releases and cumulated releases in 1999 ((b and c), respectively) obtained via simulation of the estimated baseline policy with the ones measured downstream of Conowingo dam. (d) Representation of the estimated baseline policy.

ensemble extension defined in equation (9). Figure 6 compares the baseline performance with that achievable via many-objective optimization of RBF policies over the historical conditions. Figure 6a shows the six-objective Pareto front, where Recreation, Atomic Power Plant, and Environment are plotted on the primary axes, with the black arrows identifying the directions of increasing preference and the black circle, in the bottom-right corner of the figure, showing the ideal point with respect to the primary axes. The orientation of the cones represents the reliability of meeting Chester's water supply demands, with the best solutions represented by upward cones. The size of the cones is proportional to the reliability of meeting Baltimore's water supply demands, with the best solutions represented by the largest cones. Finally, the hydropower revenue is represented by the color of the cones where maximum revenues are red. So in the figure, the ideal solution of the six-objective problem is a large red cone, oriented upward, near the ideal point in the bottom-right corner of the figure. The baseline policy is identified by the boxed cone. This policy is very good in terms of hydropower production, with a revenue of 79 million US$, and water supply to Baltimore and Chester, with volumetric reliability equal to 1.0 in 1999. It also demonstrates good performance in terms of reliably meeting the Environment objective (i.e., the FERC minimum environmental flow constraint), while it struggles to reliably provide water for cooling the atomic power plant attaining a volumetric reliability of 0.85. The Peach Bottom atomic power plant has the highest intake (Table 2) and therefore suffers water shortages when the reservoir level decreases (see the trajectory in Figure 5a). Finally, the baseline policy has a very poor performance in terms of Recreation, with a storage reliability equal to 0.0. A unique contribution of our framework and the results shown in Figure 6a is that we can exploit publicly available historical streamflow observations to discover the implicit DM's preferences when evaluating alternative reservoir operation objectives. Our results show that hydropower revenue, water supply, and low flow environmental concerns are most strongly emphasized in the baseline operating policy for Conowingo. This can occur because either these concerns are easily satisfied or they are strongly shaping management preferences (or both).

Figure 6a also shows the optimized policies that compose the deterministic historical formulation's Pareto-optimal set. The objective calculations in these results are based on the historical realization of the hydroclimatic variables. The current operating policy performs very well in most objectives relative to the Pareto-optimal alternatives except for the Recreation and Atomic Power Plant objectives. Although recreation may

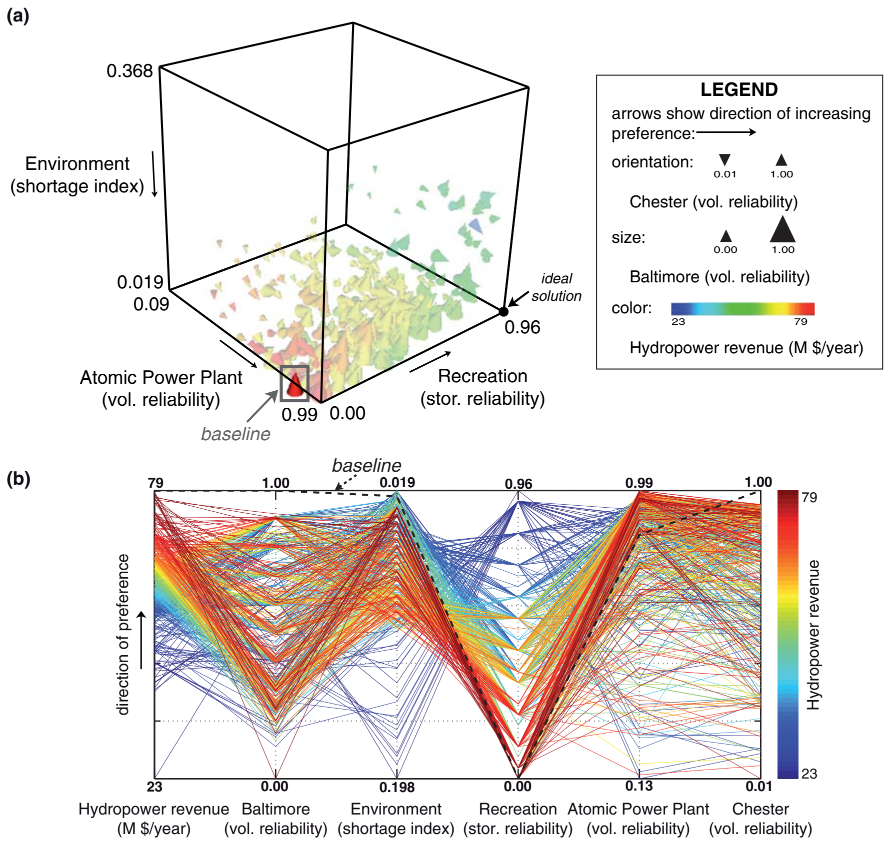

Figure 6. Comparison of the performances over historical hydroclimatic conditions of the baseline alternative and the historical Pareto-optimal policies. (a) The six-objective space, where Recreation, Atomic Power Plant, and Environment are plotted on the primary axes, the orientation of the cones represents Chester, the size of the cones Baltimore, and the colors the Hydropower revenue. (b) The same solutions in a parallel-coordinate plot, where the objective values are normalized between the minimum and maximum of each objective and the axes are oriented so that the direction of preference is always upward.

be viewed as a less critical concern, the reduced reliability of providing cooling water to the Peach Bottom atomic power plant is likely a far more critical concern. Our results highlight however that an increase in this meeting cooling water needs will negatively impact on the reliability of the water supply to Baltimore and Chester (i.e., a strong trade-off between these services/sectors). Figure 6b presents a parallel axes plot [*Inselberg*, 1997] to serve as another visual tool for understanding key interacting trade-offs for the Lower Susquehanna. This parallel-coordinate plot representation shows each solution as a line crossing the six axes, representing the six objectives, at the values of their corresponding performance. In the plot, the objective values are normalized between their minimum and maximum values and the axes are oriented so that the direction of preference is always upward. Consequently, the ideal solution would be a horizontal line running along the tops of all of the axes. The conflicts are designated as diagonal lines between two adjacent axes. Figure 6b shows clear trade-offs, especially when seeking to maximize the hydropower revenue represented by red solutions. Attaining high reliability for the atomic power plant cooling water supply strongly conflicts with contributing to Baltimore's water supply and maintaining sufficiently high reservoir levels for recreation. Baltimore's water supply contributions from Conowingo Dam also face a strong conflict with meeting the Environment objective (or FERC regulations), probably because Baltimore has the highest public water demand (see Figure 3).

Overall, when evaluated using solely the observed historical record for the Lower Susquehanna system, Conowingo Dam's current baseline policy effectively addresses several of the system's primary operating objectives and raises some concerns about reliably providing cooling to the Peach Bottom atomic power plant. However, these results are evaluated over a single realization of historical hydroclimatic conditions and are reflective of the current approach used to model and manage the basin. A key question still remains

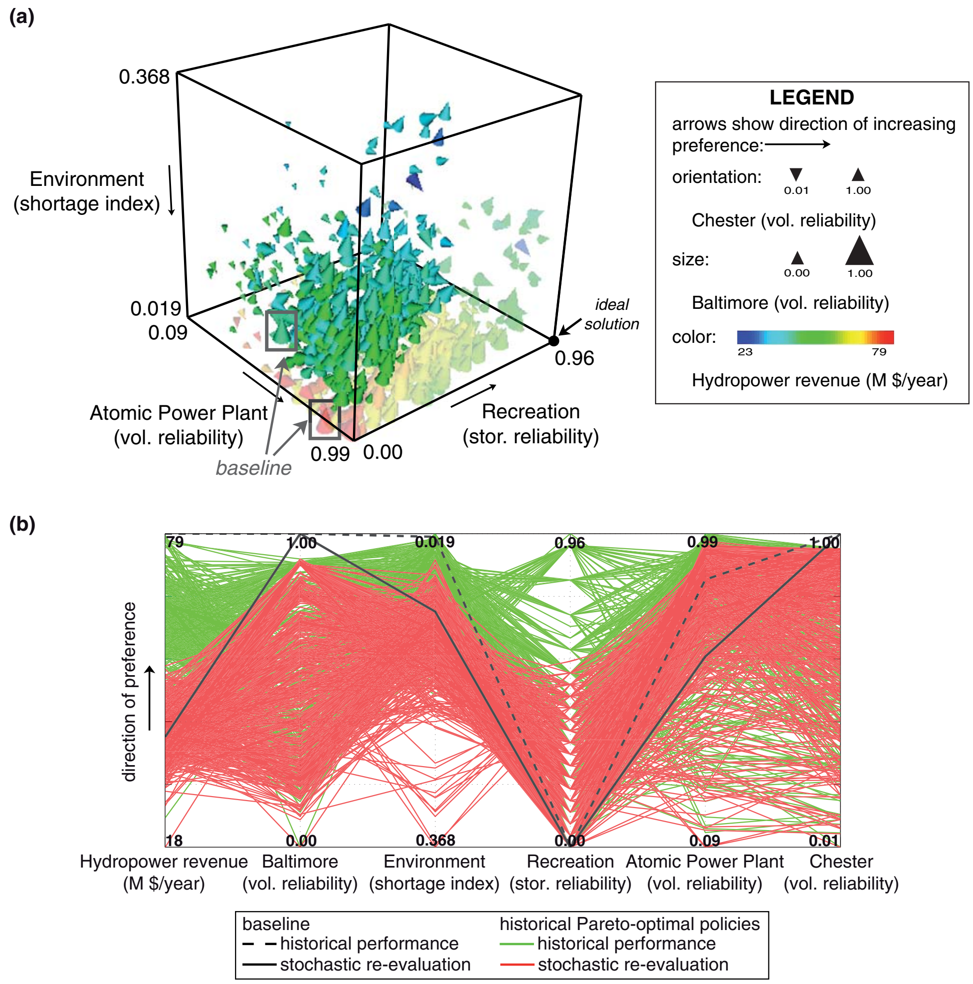

Figure 7. Comparison of the performances of the baseline policy and the historical Pareto-optimal policies simulated over historical hydroclimatic conditions and reevaluated over an ensemble of 50 stochastic realizations. The performances over history are represented by transparent cones in Figure 7a and by green lines in Figure 7b, while the reevaluation over stochastic conditions by opaque cones in Figure 7a and by red lines in Figure 7b.

unanswered by these results. Are the history-based reliabilities for the multisector services provided by Conowingo overconfident and biased by neglecting hydroclimatic uncertainties?

4.2. Policy Performance Over Stochastic Hydroclimatic Conditions

In order to reply to the above question, we reevaluated all of the alternatives illustrated in Figure 6 via simulation over an ensemble of 50 stochastic hydroclimatic scenarios, with the objective values computed according to the minimax approach (see section 3.3). The comparison between the performance differences between the historical and stochastic conditions is presented in Figure 7. Note that this performance evaluation is actually biased toward allowing the history-based to maintain high levels of performance given that our reevaluations use only 50 hydroclimatic scenarios versus the full 10,000 realizations illustrated in Figure 4. Consequently, degradations in performance are of significant concern. Figure 7 illustrates how the stochastic reevaluation degrades the prior results. The performance of the baseline solution is significantly worse under stochastic conditions, with substantial degradation in hydropower revenue (from 79 to 39 million US$), environmental shortage index (from 0.023 to 0.106), and reliability of the atomic power plant supply (from 0.85 to 0.63). On the other hand, it maintains high reliability for both Baltimore and Chester, while the Recreation reliability remains equal to zero. The performance of the historical Pareto-optimal policies also strongly degrades when moving to the stochastic simulation. This is clearly demonstrated in Figure 7a, where the opaque cones representing the stochastic reevaluation fall further from the ideal solution. Figure 7b provides a complementary perspective on the performance degradations caused by reevaluating the

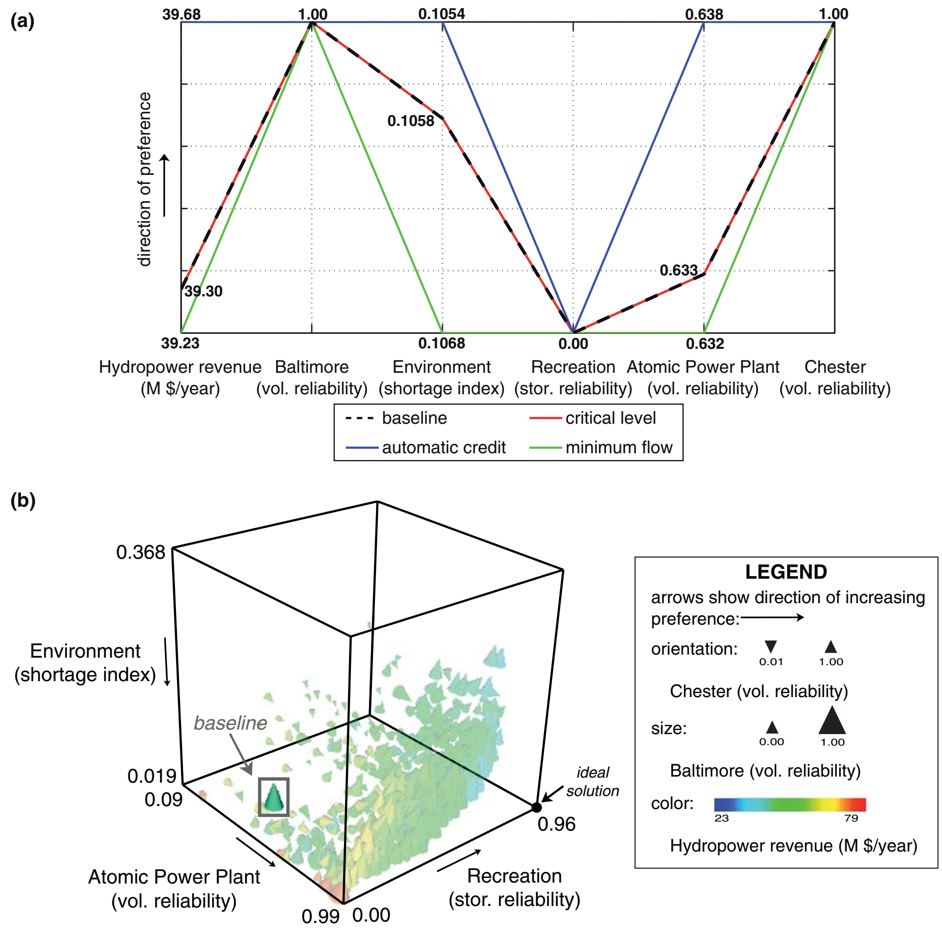

Figure 8. (a) Performances of the alternatives negotiated by the SRBC over an ensemble of 50 stochastic hydroclimatic realizations. (b) Comparison of these latter with the stochastic Pareto-optimal policies.

solutions with the small ensemble. The parallel axes visualization compares the historical evaluation (green) with the stochastic reevaluation (red). Significant reductions in performance occur for hydropower revenue (with the best solutions degrading from 79 to 53 million US$), environment (with the shortage index of the worst solutions increasing from 0.198 to 0.368), and recreation (with the highest reliability decreasing from 0.96 to 0.57). These results clearly show that the intrinsic uncertainties in the natural processes strongly impact the policies' performance, with some objectives more sensitive than others to hydroclimatic variability. The analysis over a single realization of historical hydroclimatic conditions is therefore weak, indicating that stochasticity must be explicitly considered in the design of effective water management strategies for the Lower Susquehanna.

4.3. Policy Analysis and Recommendations

Growing water demands and low flow conditions are significant concerns for the SRBC that shaped recent adaptive management efforts to identify a set of potential modifications to the current baseline operation seeking to better balance the multisector demands within the Lower Susquehanna. These alternatives differ from the baseline operating policy in the implementation of the credit for the leakages, as described in section 2.3. Figure 8a compares the relative performance of the baseline policy and these modified alternatives via simulation over the same 50 stochastic hydroclimatic scenarios discussed above. The proposed alternatives do offer different performance across the six objectives illustrated in the parallel axes plot. The critical level alternative (red) has the same performance in all objectives as the baseline solution (dashed black line). Interestingly, the minimum flow alternative (green) produces results that are counter to the goal of the negotiated agreements, obtaining lower performance than under the baseline operation in many objectives and demonstrating that the Conowingo reservoir is unable to meet the environmental requirements

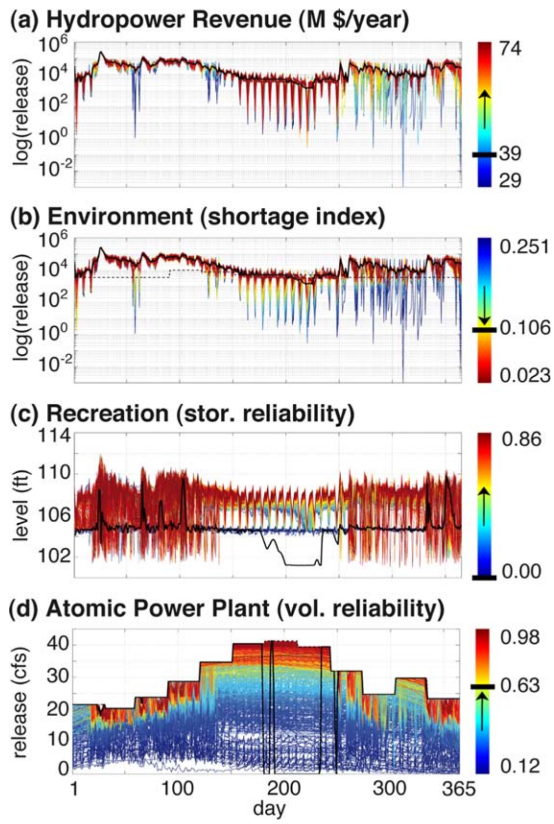

Figure 9. Comparison of the trajectories of the Conowingo downstream release, level, and water supply to the Peach Bottom atomic power plant for different policies over historical hydrology. The thick black line represents the baseline alternative, while the stochastic Pareto-optimal policies are colored with respect to the values of Hydropower revenue, Recreation, Environment, and Atomic Power Plant in Figures 8a–8d, respectively.

in drought conditions. Finally, the automatic credit alternative (blue) Pareto-dominates the baseline solution, making it the most promising alternative. Overall, the results of Figure 8a are consistent with those attained in the SRBC facilitated negotiation [*Swartz*, 2006].

However, this set of solutions has been identified by focusing solely on how to manage the credit for conveyance leakages. Figure 8b illustrates the effects of broadening the scope of the analysis to compare the performance of this set of alternatives with those achievable via policy refinement by using many-objective optimization under uncertainty. It shows the six-dimensional objective space, with the baseline and the three alternatives proposed by the SRBC shown opaque, while the stochastic Pareto-optimal policies are shown with transparency. The results in Figure 8b suggest that the alternatives proposed by the SRBC are essentially equivalent to the baseline policy. They are indeed represented by four cones which are almost overlapped in this broader scoped problem formulation. These results also illustrate how policy inertia (i.e., the resistance to changing operating policies) can induce policy myopia, with the alternatives negotiated by the SRBC which fail to explore the full set of objectives trade-offs. Moreover, Figure 8b shows the potential of the proposed decision analytic framework for providing a broader contextual understanding of system performance trade-offs and alternative reservoir policies. The analysis over stochastic hydroclimatic conditions clarifies the potential refinement of the baseline policy, especially in those objectives which are more sensitive to system uncertainties. The performance of the baseline solution can be significantly improved in terms of Hydropower, Atomic Power Plant, Environment, and Recreation at the cost of a small reduction in the reliability for Baltimore and Chester, which have the option to obtain water from other sources. Depending on the DM structure of preference, the hydropower revenue can be increased from 39 to 74 million US$, the reliability of the atomic power plant supply from 0.63 to 0.97, the storage reliability from 0 to 0.85, and the environmental shortage index can be reduced from 0.106 to 0.023. Our a posteriori decision analytic framework explicitly maps these potential gains across the high-dimensional tradeoffs that characterize the Lower Susquehanna.

To better understand how the stochastic Pareto-optimal policies impact on the system's dynamics to provide useful information for the SRBC, we analyze the dynamic behavior of the Lower Susquehanna system under these alternative reservoir regulations. Figure 9 shows the trajectories of downstream release, reservoir level, and atomic power plant supply in 1999 for different operating policies. The historical trajectory is shown as a thick black line and the stochastic Pareto-optimal solutions are colored for the respective Hydropower Revenue, Environment, Recreation, and Atomic Power Plant objectives in Figures 9a–9d, respectively. Figure 9a shows the downstream release trajectories (for illustration purposes in logarithmic scale). The

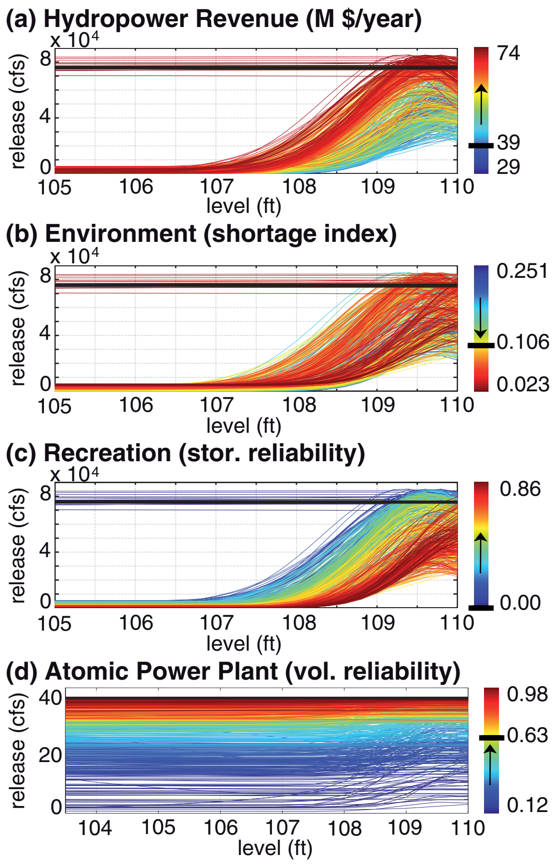

Figure 10. Comparison of the baseline alternative, represented by the thick black line, with the stochastic Pareto-optimal policies colored with respect to the values of Hydropower, Recreation, Environment, and Atomic Power Plant in Figures 10a–10d, respectively. The policy for (a) a week day, (b–d) a weekend in summer.

main difference between the current baseline operations for the Conowingo Dam and the high-revenue trajectories (red) is the latter's high releases during the summer, when the reservoir level is generally low and higher releases are needed to maximize energy production. The ability to sustain summer releases is also critical for maintaining high levels of performance for the Environment objective as shown by the red trajectories in Figure 9b. Here the red policies are able to provide higher releases in the summer by allowing small and short duration deficits with respect to the minimum flow requirements (dashed line) as induced by the quadratic formulation of the shortage index objective [*Hashimoto et al*., 1982]. These results highlight that FERC regulations may strongly reduces the sustainability of the basin's multisector services. We have purposefully avoided overly constraining our problem formulations to attain a broad scope of operating policies and their consequent trade-offs for the Conowingo Dam. Figure 9c shows the Conowingo reservoir level trajectories. A clear pattern is evident in summer (the recreation objective is formulated with respect to the tourist season only) with the red policies generating periodic peaks during the weekends. The baseline policy produces consistently draws down and consequently performs very poorly in terms of Recreation. Finally, Figure 9d represents the atomic power plant supply trajectories. The red trajectories, especially in summer, are slightly less than the water demand and this conservative strategy avoids the reservoir level drawdown obtained with the baseline regulation (see Figure 9c), thus ensuring the possibility of using the outlet located at 103.5 ft for a longer period.

To illustrate how our proposed decision analytic framework could be exploited to provide direct recommendations to the SRBC, we coupled the analysis of the trajectories shown in Figure 9 with the investigation of their corresponding reservoir policies as illustrated in Figure 10. In particular, since the policies are time-varying, we focus on the shape of the summer operating rules that define the release decisions as a function of the reservoir water levels for a fixed time instant. As shown in Figure 9, the summer is the most critical period of the year, when most of the challenging trade-offs emerges. Most of the stochastic Pareto-optimal policies representing the downstream releases (Figures 10a–10c) is more conservative and releases less water than the baseline alternative except for high water levels conditions, thus saving water to face droughts. Note the inversion of the colors between Figure 10a and Figure 10c, confirming the strong conflict existing between Hydropower and Recreation. The best policies for this latter (Figure 10c, red lines) do not release when the level is below 108 ft to maximize the storage reliability, but they strongly reduce the corresponding hydropower revenue (Figure 10a, blue lines). Conversely the best policies in Figure 10a are poorly performing in Figure 10c, with the baseline policies, which is similar to blue stochastic Pareto-optimal solutions, that attains a storage reliability equal to zero. The policies for the atomic power plant (Figure 10d) are more flat. Again, the best policies (dark red) are more conservative that the baseline and

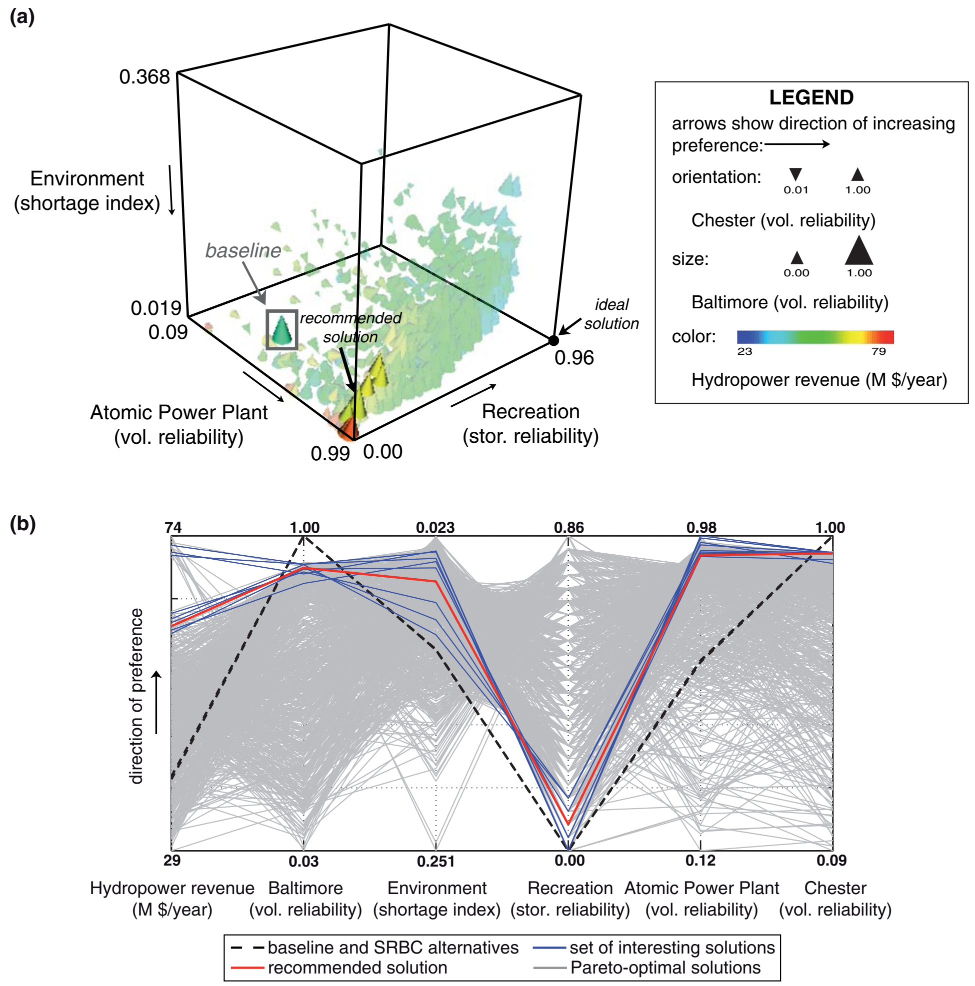

Figure 11. Identification of a set of potential candidate policies that might replace the baseline. The criteria adopted are the following: Hydropower revenue $\geq$60 million US$/yr, Atomic Power Plant reliability $\geq$0.90, Baltimore reliability $\geq$0.85, Chester reliability $\geq$0.90, environmental shortage index $\leq$ 0.10.

releases slightly less than the water demand. This strategy results to be particularly effective in uncertain conditions, and allows significantly improvements in the performance of the baseline policy marked on the colorbars. Moreover, Figure 10 shows the full range of options available to the SRBC to achieve a desired level of performance on the multiobjective trade-off surface. It is worth noting that 1261 stochastic Pareto-optimal policies (over the 1490 solutions) outperform the baseline alternative in terms of Hydropower Revenue, 1325 in terms of Atomic Power Plants, 1441 in terms of Recreation, and 1155 in terms of Environment.

To further illustrate how the SRBC could refine the current operation of Conowingo Dam, we demonstrate how performance goals or preferences can be used to eliminate (or "brush out") Pareto-optimal policies that fail to meet DMs requirements. The full stochastic Pareto-optimal set contains 1490 solutions (among which 841 overcome the baseline alternatives in Hydropower Revenue, Atomic Power Plant, Recreation, and Environment). Our prior results illustrate how this set of solutions provides a rich context for understanding complex management trade-offs and dynamics. Figure 11 further illustrates how to obtain a smaller subset of interesting candidates policies to improve upon the Conowingo Dam's current baseline operations. We apply the following criteria to select the policies shown in Figure 11: Hydropower revenue $\geq$60 million US$/yr, Atomic Power Plant reliability $\geq$0.90, Baltimore reliability $\geq$0.85, Chester reliability $\geq$0.90, and environmental shortage index $\leq$ 0.10. The underlying idea is to select solutions that outperform the baseline policy, as well as the other alternatives negotiated by the SRBC, at the cost of a small reduction in the reliability for Baltimore and Chester. All the selected alternatives represent potentially interesting compromise solutions which effectively balance the competing multisector demands in the Lower

Susquehanna system according to the preference structure associated to the baseline operation, which considers Recreation as a secondary objective. Among the set of policies selected in Figure 11, we also select one policy to be further analyzed.

Results show that adopting the recommended solution instead of maintaining the current reservoir regulation, the SRBC would potentially attain an increase in the hydropower revenue equal to 22 million US$/yr, 0.07 in recreational storage reliability, 0.29 in the Atomic Power Plant reliability, and a reduction of 0.05 in terms of environmental shortage index. These values correspond to a relative improvement of 56% in Hydropower, 47% in Environment, and 46% in Atomic Power Plant. The increase in Recreation is limited (i.e., from 0 to 0.07) as the current preference structure does not prioritize this objective. However, as shown in Figure 10c, there exists a large opportunity for obtaining higher storage reliability by adopting other policies with different balances of the objectives. In general, the recommended solution exhibits the potential to significantly outperform the baseline regulation with careful modification of summer releases, producing a policy that is more robust to hydroclimatic uncertainties and also better addresses the trade-offs across the Conowingo Dam's multisector services.

5. Conclusions

In this paper, we proposed a decision analytic framework to overcome policy inertia and myopia in complex river basin management contexts. The Conowingo reservoir in the Lower Susquehanna River, USA, is used as a case study. The framework combines reservoir policy identification, many-objective optimization under uncertainty, and visual analytics to characterize current operations and discover key trade-offs between alternative policies for balancing competing objectives and system uncertainties.

The implicit policy identification method captures the current operation of the dam and defines the historical policy by fitting radial basis functions to existing system dynamics. The analysis over stochastic hydroclimatic conditions shows the vulnerability of the baseline operating policy due to policy inertia: current history-based operations are indeed negatively biased to overestimate the reliability of the reservoir's multisector services. Moreover, the a posteriori analysis of the stochastic Pareto-optimal solutions and the set of alternatives negotiated by the Susquehanna River Basin Commission (SRBC), supported by visual analytics, shows the effects of policy myopia. The alternatives proposed by the SRBC are essentially equivalent to the historical policy and fail to explore the full set of objectives trade-offs. The proposed framework has successfully identified a subset of alternative reservoir policies that are robust to hydroclimatic uncertainties, while being capable of better addressing the trade-offs across the Conowingo Dam's multisector services. The comparison of the baseline alternative performance with the one that would be attained with the recommended policy provides an estimate of the regret that the SRBC would experience by maintaining the current policy. By adopting the recommended policies, the expected hydropower revenues increase by 22 million US$, with significant advantages also in Environment and Atomic Power Plant objectives.

Our results are obtained assuming stationary hydroclimatic conditions and only considering the uncertainty in the hydroclimatic variables. Broadly, there are many uncertain factors that can influence the system including shifting objectives, evolving demands, and climate change. Moreover, although the minimax approach used to filter the system uncertainties guarantee certain performance over different hydroclimatic conditions, other filtering criteria might be used depending on the risk aversion of the SRBC, such as the Laplace criterion [*Laplace*, 1951], which looks at the expected performance, the Hurwicz criterion [*Hurwicz*, 1951], which considers a weighted combination of the worst and best case, or the Savage criterion [*Savage*, 1951], which minimizes the regret of adopting a wrong decision. Depending on the adopted filtering criterion, the set of optimal solutions will vary.

Future efforts will concentrate on estimating the robustness of the policies under conditions of deep uncertainty [*Kasprzyk et al*., 2013], such as enlarging the variability of the hydroclimatic variables and considering uncertain water demands and energy prices. Furthermore, the introduction of hydroclimatic variables' ensembles characterized by nonstationarity due to climate change impacts will allow the estimate of the long-term robustness of the alternative reservoir operating policies. Finally, the possibility of designing policies which better reflect the actual decision making context to guarantee their practical value can be assessed. However, the proposed decision analytic framework provides a promising approach to bridge the gap between optimization techniques and current real-world water system operations, thus representing a critical step in designing water reservoir operating policies capable to face uncertain systems and multiple, conflicting objectives.

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