Case Study

Evolutionary Algorithm Optimization of a Multireservoir System with Long Lag Times

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Abstract: A scenario of particular importance in water resources management occurs when reservoir release decisions must be made well in advance of accurate hydrologic forecasts because of long travel times between reservoir releases and demand. This type of situation is evaluated using the Washington metropolitan area (WMA) water supply as a case study. Several classes of operating rules are evaluated using a state-of-the-art multiobjective evolutionary algorithm linked to a hydrologic simulation/decision model. Operating rules were evaluated using historical Potomac River streamflows (1929–2007) and synthetically generated time series. The proposed optimization framework is effective for a wide range of water resources vulnerability studies and was successful in improving the efficiency of the WMA system with respect to competing objectives ranging from reservoir storage to recreation and environmental flow requirements. **DOI:** 10.1061/(ASCE)HE.1943-5584.0000972. *© 2014 American Society of Civil Engineers.*

Author keywords: Water resources management; Multiobjective optimization; Evolutionary algorithms; Genetic algorithms; Reservoir; Drought.

Introduction

Optimization of water resources decision-making focuses on maximizing a system's benefit while considering competing objectives and the uncertainty inherent in natural systems. A scenario of particular importance for many water supply systems with long travel times occurs when release decisions must be made well in advance of the water's usage and subsequent benefit. This form of uncertainty is a unique water management challenge and must be handled carefully in optimization schemes to adequately simulate the effect of imperfect foresight. This case study demonstrates an optimization scheme using a state-of-the-art multiobjective evolutionary algorithm, capable of quantitatively and objectively determining the timing, magnitude and location of water supply releases in a system with long lag times.

The Potomac River (Fig. 1) is the primary source of water for the Washington, DC, metropolitan area (WMA). When it was implemented in 1982, the WMA water supply system was considered a model for combining optimization and simulation to improve water supply efficiency (Sheer and Flynn 1983), replacing plans for as many as 16 major reservoirs with a single, distant reservoir (Jennings Randolph Reservoir) and a small, nearby reservoir (Little Seneca Reservoir). Although this design allows the 38,000 km^2 Potomac watershed to remain largely uncontrolled, it increases the importance of effective water management decisions. The location of the Jennings Randolph Reservoir, 300 km upstream of the Washington, DC, water supply intakes, creates a 9-day to 10-day lag between reservoir releases and their subsequent capture. This delay remains beyond the forecast horizon of accurate weather predictions, requiring release decisions to be made amid significant uncertainty, with no ability to recapture release excess.

The field of water resources optimization has grown from relatively simple, conceptual system models to highly detailed and flexible that use modern optimization techniques and computing power to closely mimic the behavior of modern water supply systems (Loucks and Sigvaldason 1982; Yeh 1985; Lund and Guzman 1999; Labadie 2004). Within the range of available water resources optimization techniques, evolutionary, or genetic, algorithm solvers have proven successful because of their robustness and flexibility (Reed et al. 2013; Chen 2003; Momtahen and Dariane 2007; Oliveira and Loucks 1997; Wardlaw and Sharif 1999). Evolutionary algorithms are capable of searching large and complex decision spaces and evaluating nonlinear and nonconvex objective functions. Multiobjective evolutionary algorithm optimization solves for a set of compromise solutions, termed the Pareto optimal front, that represent optimal solutions which cannot be improved without affecting the other objectives (Reed et al. 2013). The Pareto front is therefore approached simultaneously across all objectives without the need to specify individual weights for each objective. Because of this, multiobjective evolutionary algorithms are considered a posteriori decision tools, producing a set of optimal solutions from which decision makers can weigh the relative importance of conflicting objectives after the optimization process. Evolutionary algorithms only approximate the Pareto front, and although these solvers have been shown to be successful at producing accurate approximations, true optimal results cannot be assured.

This case study evaluates five operating rule modifications to the WMA water supply system with respect to six objective functions, demonstrating the effectiveness of evolutionary algorithms for optimization of complex water supply systems with significant lag times. Capturing the imperfect foresight of daily water management decisions in a system with significant lags can be difficult to parameterize, particularly when using standard optimization techniques. Within the WMA system, operating rules are evaluated first using the historical Potomac River time series (1929–2007), which includes the drought of record (1930–1931), and then using long duration synthetic time series, which allow for a wider range of feasible hydrologic scenarios, each following the distribution

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Note. This manuscript was submitted on August 5, 2013; approved on January 22, 2014; published online on January 25, 2014. Discussion period open until November 20, 2014; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Hydrologic Engineering***, © ASCE, ISSN 1084-0699/05014011(10)/$25.00.

and temporal relationship of the historical record. Use of the evolutionary algorithm provides a flexible framework to permit complex objective function, whereas the use of synthetic time series tests the robustness of optimized rules and prevents overfitting to the relatively small set of historical drought events.

Study Area

This study uses the Potomac River Basin and the WMA as a case study to apply evolutionary algorithm optimization to a system with long lag times. The WMA is the country's seventh largest metropolitan area as of 2012 (U.S. Census Bureau 2013), houses approximately 5.6 million residents over its 14,500 km^2, and spans 15 counties and the District of Columbia (DC). The municipal water needs of the WMA are managed by three major suppliers:

1. Washington Suburban Sanitary Commission (WSSC), which serves the Maryland suburbs;
2. Fairfax Water, which serves Fairfax County, Virginia, and other northern Virginia suburbs; and
3. Washington Aqueduct, which provides water to the District of Columbia.

Additionally, the city of Rockville, Maryland, maintains a separate water supply system, drawing from the Potomac River. The Potomac River accounts for approximately 78% of the water treated by the WMA water suppliers in a typical year (Ahmed et al. 2010), with the remainder of demand met by reservoirs located outside the nontidal Potomac watershed on the Occoquan (Fairfax Water) and Patuxent (WSSC) Rivers (Fig. 1). For much of the year,

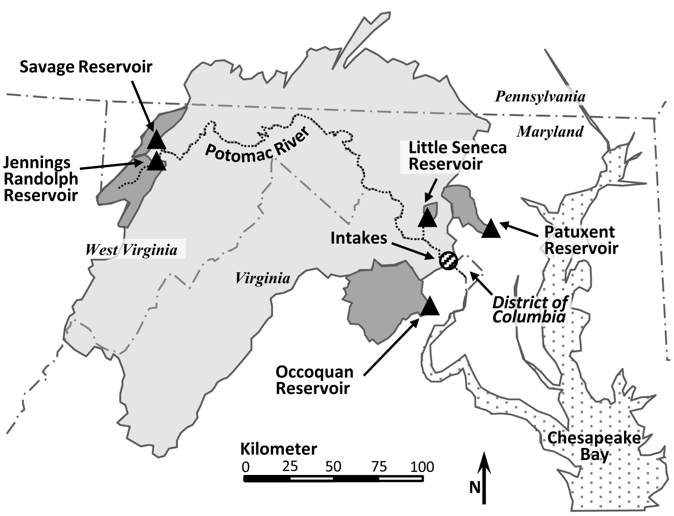

Fig. 1. Potomac watershed and Washington, DC, water supply; Potomac watershed shown in lighter shade, with reservoir watershed shown in a darker shade; reservoirs shown as triangles and intakes for the Washington, DC, metropolitan area shown as a hashed circle

withdrawals from the Potomac are a small fraction of the total flow, with average summer demands reaching 2×10^6 m^3/day and annual Potomac flows averaging 26×10^6 m^3/day (Ahmed et al. 2010). During periods of low flow, which typically occur in summer and early fall, the natural flow of the Potomac may be augmented with releases from the Jennings Randolph and Little Seneca reservoirs to satisfy withdrawal requirements. Reservoir characteristics are summarized in Table 1.

Of the two reservoirs that make releases to the Potomac, the Jennings Randolph Reservoir has significantly greater water supply storage capacity (51×10^6 m^3) than the Little Seneca (14×10^6 m^3) but is located approximately nine days of hydrologic travel time upstream of the WMA intakes. The Little Seneca is located only one day upstream of the WMA intakes. As such, the two reservoirs are operated in concert, with the Jennings Randolph making primary releases and the Little Seneca being used to fine tune flows upstream of the intakes.

The remaining capacity in the Jennings Randolph Reservoir is allocated for flood control (42×10^6 m^3, 28% of total storage) and water quality releases (58×10^6 m^3, 38%). The U.S. Army Corps of Engineers (USACE) manages these portions, leaving flood storage empty for emergencies and making water quality releases in conjunction with the Savage Reservoir to meet a low flow requirement in the North Branch of the Potomac measured at Luke, Maryland.

The Savage Reservoir, located eight kilometers downstream from the Jennings Randolph Reservoir, is owned by the Upper Potomac River Commission (UPRC) and operated with guidance from the USACE, Baltimore District to satisfy the North Branch low flow requirement and to supply water to the nearby town of Westernport, Maryland. Although it operates independently, during a drought event, water supply releases are made from the Savage Reservoir concurrently with releases from Jennings Randolph per a matching agreement.

In addition to the Potomac water supply system, three WMA reservoirs are located outside the Potomac watershed and used as off-line water supply storage. The Occoquan Reservoir, managed by Fairfax Water, is located on the Occoquan River on the border of Fairfax and Prince William counties in Virginia. The WSSC operates two reservoirs in series, the Triadelphia and T. H. Duckett Reservoirs, on the Patuxent River along the border of Montgomery and Howard counties in Maryland. Current operating rules specify that the WSSC and Fairfax Water rely more heavily on the Potomac River during winter and spring months to preserve storage in the off-line reservoirs for use during the summer low-flow season. In 2008, 31% of WSSC's production came from the Patuxent reservoirs and 42% of Fairfax Water's production came from the Occoquan Reservoir (Ahmed et al. 2010).

This system developed from the unique jurisdictional circumstances of Washington, DC, Following the drought of 1966, when Washington, DC, was forced to declare its first water emergency in more than a century (van Dyne 2007), studies predicted that demand would soon exceed the natural capacity of the Potomac

Table 1. WMA Operational Characteristics

Reservoir	Manager	Total storage (10^6 m^3)	Available storage (10^6 m^3)	Watershed area (km^2)	Upstream distance (km)	Travel time (days)
Jennings Randolph	CO-OP, USACE	109	51	681	320	9
Little Seneca	CO-OP	16	14	54	25	1
Savage	USACE	24	23	272	320	9
Patuxent	WSSC	51	39	342	—	—
Occoquan	Fairfax	31	30	1,533	—	—

River, prompting the identification of 16 potential dam sites on the river (USACE 1963). Because of public opposition, only one of these proposed reservoirs, the Jennings Randolph, was constructed. During construction, which lasted from 1975 to 1981, water allocation studies (Palmer et al. 1982, 1979; Sheer 1977) concluded that demand could be met through coordinated operation of the Jennings Randolph and the existing Patuxent and Occoquan Reservoirs, allowing flow in the Potomac to remain largely unimpeded. Additional protection was offered by constructing the smaller Little Seneca Reservoir in 1985 to act as a buffer against uncertainty in releases from the Jennings Randolph. The jurisdictional landscape, which involves the water suppliers, two state governments, and the federal government, is managed by several agreements designed to ensure equitable access to water during a drought event (MWCOG 1978) and to facilitate shared decision-making (USACE 1982). Since completion of the current WMA water supply system, water supply releases have been made on three occasions, in 1999, 2002, and 2010. Because of the 1999 drought event, when Maryland, Virginia, and Washington, DC, each imposed different water restrictions, the Metropolitan Washington Council of Governments (MWCOG) adopted a water supply and drought plan (MWCOG 2000) which contains specific triggers for water restrictions and requires restrictions be imposed equally across the region.

Methods

Systems Modeling

Hydraulic routing and reservoir operations were simulated using operation advisor and simulated intelligent system (*OASIS*) (Version 3.09.033), developed by Hydrologics (2009). *OASIS* is a water management simulation and decision model, which uses a node-arc architecture to model reservoirs, reaches, inputs, and withdrawals. Daily releases are controlled by prescribed operating rules and constraints, which in turn depend on the current state of the system and forecasts modeled on those used by the water suppliers. This model is designed to accurately mimic the imperfect foresight of daily operational decision-making within the WMA system.

The OASIS model was developed in conjunction with the Interstate Commission on the Potomac River Basin (ICPRB) and water suppliers to ensure that all data, operating rules, and assumptions were accurate. Reservoir details, including stage-storage curves, sedimentation rates, and existing operational rule curves, were provided by the ICPRB, along with Potomac channel routing and travel time estimates. Daily demand among the three major WMA water suppliers was simulated using a set of multivariate regression equations, incorporating an autoregressive-moving average (ARMA) error term, described in Ahmed et al. (2010).

Streamflow Time Series

Two streamflow time series were evaluated: the Potomac River historical time series (1929–2007) and a group of stochastically generated streamflow time series. The historical record was adjusted by the ICPRB to remove the effect of reservoir releases and upstream consumptive use by adding historical estimates of these withdrawals, creating a time series of historical streamflows unaffected by demand change and human interaction (Hagen and Steiner 1998, 1999; Hagen et al. 1998a, b).

Synthetic daily time series were generated using the stochastic method described in Stagge and Moglen (2013) and used to expand the set of feasible conditions beyond the historical time series. This method uses a coupled monthly Markov climate model and daily streamflow model to accurately reproduce the distribution (mean, variance, and skewness) and seasonality of the historical streamflow record at the annual, monthly, and daily time scales (Stagge and Moglen 2013). Flows were then spatially disaggregated based on the commonly used method of fragments (Porter and Pink 1991; Srikanthan and McMahon 2001) and bias corrected using quantile-quantile mapping (Panofsky and Brier 1968). An ensemble of 10 synthetic streamflow traces was used to simulate system performance; however, only a single trace with representative performance was used for optimization.

Optimization Scheme

The optimization scheme follows the parameterization-simulation-optimization (PSO) model (Koutsoyiannis and Economou 2003; Celeste and Billib 2009). The choice of a PSO approach was motivated by the desire to optimize the existing operating rules as they currently exist so that results could easily be understood and implemented by system operators. This required working with a relatively complex set of rules and constraints that have evolved over years of practice. Optimizing such a complex set of operating rules lends itself to the use of PSO.

Optimization of system operating rules was carried out using an S-metric evolutionary multiobjective algorithm (SMS-EMOA) (Beume et al. 2007; Emmerich et al. 2005; Mersmann 2012). Detailed performance data can be found in Beume et al. (2007) and Emmerich et al. (2005). SMS-EMOA is a steady state ($\mu + 1$) evolutionary algorithm, indicating that a constant population ($\mu = 35$) is maintained by the following steps:

1. SMS-EMOEA generates a set of new parameters.
2. These parameters define the operating rules for the WMA system.
3. Simulation is performed using the OASIS model and the historical/synthetic time series.
4. Six objectives are computed for the newest parameter set using the entire period.
5. SMS-EMOEA adds the new parameter set to the population ($\mu + 1$) and finds the combination of μ points with the highest fitness (i.e., hypervolume), removing the worst.
6. The process continues by generating a new parameter set.

The SMS-EMOA is designed to maximize the hypervolume (S-metric) dominated by a finite set of points. Use of hypervolume as a quality metric was originally proposed by Zitzler and Thiele (1998) and proven to converge to the Pareto set, given a finite search space and reference point (Fleischer 2003). Hypervolume measures are invariant to objective scaling and produce a well-distributed estimate of the Pareto front by assigning greater weight to regions with unique points or high curvature (Beume et al. 2007; Reed et al. 2013). A simulated binary crossover probability of 0.7 was used, with mutation probability set to produce one mutation per iteration, per recommendations in Wardlaw and Sharif (1999). Optimization was stopped when the S-metric decreased by no more than 1% within eight generations.

Rule Modifications

Five distinct rule modifications were considered: adjusting the buffer equation, load shifting, demand restrictions, and reservoir rule curves for the Jennings Randolph and Patuxent Reservoirs. Rule modifications were chosen carefully to minimize the number of free policy parameters, as too many parameters tends to cause overfitting and reduces computational efficiency (Momtahen and Dariane 2007). The buffer equation is designed to balance reservoir levels along the main stem of the Potomac River, whereas load shifting is designed to balance releases to the Potomac with load on the auxiliary reservoirs, the Occoquan and Patuxent. Demand restrictions control the set points for imposing mandatory water usage restrictions and reservoir rule curves manage the storage-based releases from a particular reservoir. The Jennings Randolph and Patuxent Reservoirs were selected for reservoir rule curve optimization because of the Patuxent Reservoir's high number of simulated storage failures and the Jennings Randolph's importance for water supply, recreation, and whitewater releases.

Objective Function and Constraints

Objectives were selected to cover the range of potential benefits within the Potomac River system in a quantifiable manner and were developed as updates to prior WMA optimization studies (Schwartz 2000) through close consultation with the water suppliers and the ICPRB. Target volumes and flows were often based on legal agreements, such as the low flow allocation agreement. Because the functional limit of current multiobjective evolutionary algorithms has been shown to be approximately ten objectives (Reed et al. 2013), this optimization scheme considers only six objectives, which include:

1. Shortage, which minimizes delivery shortages to the water suppliers (volume);
2. Storage, which minimizes low storage volumes in any of the reservoirs (volume);
3. Flowby, which minimizes days when flow in the Potomac River does not exceed low flow requirements (days of violation);
4. Recreation season, which minimizes days during the recreation season that Jennings Randolph Reservoir levels fall below recreation facilities (days of violation);
5. Whitewater, which minimizes days when whitewater releases cannot be made because of low storage volume (days of violation); and
6. Environmental flows, which minimizes days when flow in the Potomac River falls below recommended environmental levels for three consecutive days (days of violation).

These objectives are presented as a constrained multiobjective optimization problem:

$$\text{Minimize}\, Z = (Z_{\text{Short}}, Z_{\text{Stor}}, Z_{\text{Flowby}}, Z_{\text{RecSeason}}, Z_{\text{WW}}, Z_{\text{EnvFlows}}) \tag{1}$$

where each of the Z terms represents the individual objective functions described previously.

The first objective function, Z_{Short} [Eq. (2)], sums the percent water delivery shortage at all supply points, including WSSC, Fairfax Water, the USACE, the city of Westernport, Maryland, and the city of Rockville, Maryland. In Eq. (2), Dem_i refers to daily demand, Del_i refers to daily delivery, T represents the total number of days in the time series, and i represents the five water suppliers

$$Z_{\text{Short}} = \sum_i \sum_{t=0}^{T} \begin{cases} \frac{\text{Dem}_i(t)-\text{Del}_i(t)}{\text{Dem}_i(t)} & \text{if } \text{Dem}_i(t) > \text{Del}_i(t) \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

The second objective function, Z_{Stor} [Eq. (3)], calculates a penalty when reservoir usable storage falls below 40%, a level of concern identified by reservoir operators. In Eq. (4), S_j represents usable storage (%) in reservoir j, which corresponds to six reservoir storage accounts: (1) Jennings Randolph water quality, (2) Jennings Randolph water supply, (3) savage, (4) Patuxent, (5) Occoquan, and (6) littles. The storage penalty is a piecewise function [Fig. 2(a)], which applies increasingly larger penalties as reservoir usable storage approaches zero

$$Z_{\text{Stor}} = \sum_j \sum_{t=0}^{T} \begin{cases} 100 - 6 \times S_j(t) & \text{if } 0\% \le S_j(t) < 10\% \\ 60 - 2 \times S_j(t) & \text{if } 10\% \le S_j(t) < 20\% \\ 40 - S_j(t) & \text{if } 20\% \le S_j(t) < 40\% \\ 0 & \text{if } S_j(t) \ge 40\% \end{cases} \tag{3}$$

Eq. (4) describes the flowby penalty, Z_{Flowby}, which sums all days when the legally prescribed flowby, and Q_{Flowby} is not satisfied by flow, Q_k, at each of the k locations. The pertinent flowbys are $230 \times 10^3\ \text{m}^3/\text{d}$ at Luke, Maryland, $1{,}140 \times 10^3\ \text{m}^3/\text{d}$ at Great Falls, Maryland, and $380 \times 10^3\ \text{m}^3/\text{d}$ at Little Falls, Maryland

$$Z_{\text{Flowby}} = \sum_k \sum_{t=0}^{T} \left[\frac{Q_k(t) < Q_{\text{Flowby}}}{T} \right] \tag{4}$$

The fourth objective function, $Z_{\text{RecSeason}}$ [Eq. (5)], refers to the summer Recreation Season, which occurs each year between May 1 and August 31, represented in the function by $T_{\text{RecSeason}}$. During this period, water managers strive to maintain water levels in the Jennings Randolph Reservoir, represented as E_{JR}, above three recreation access points. These points, termed E_{Beach}, E_{WV}, and E_{MD}, are 443.5, 440.4, and 432.8 m above sea level, respectively. The penalty function increases as each access point becomes inaccessible [Fig. 2(b)]

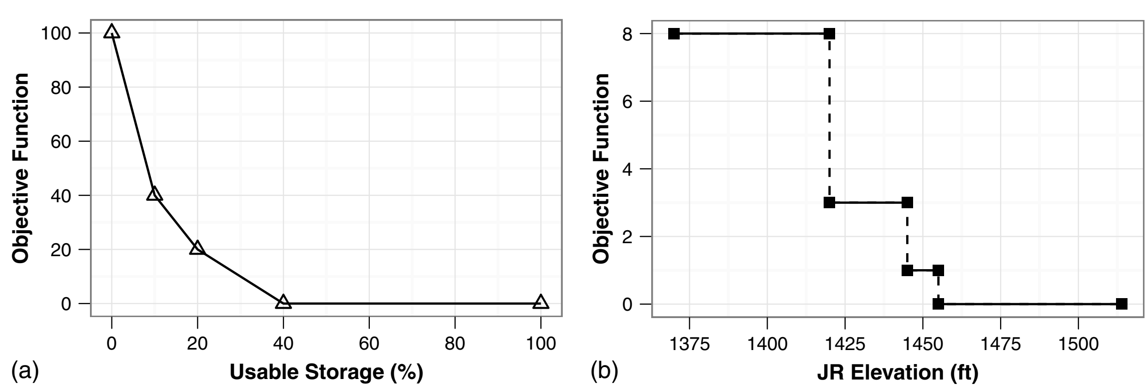

Fig. 2. Objective function penalty for percent: (a) usable storage (Z_{Stor}); (b) recreation season ($Z_{\text{RecSeason}}$)

$$Z_{\mathrm{RecSeason}} = \sum_{t=0}^{T_{\mathrm{RecSeason}}} \left\{ \left[\frac{E_{\mathrm{JR}}(t) < E_{\mathrm{Beach}}}{T_{\mathrm{RecSeason}}} \right] + 2 \times \left[\frac{E_{\mathrm{JR}}(t) < E_{\mathrm{WV}}}{T_{\mathrm{RecSeason}}} \right] + 5 \times \left[\frac{E_{\mathrm{JR}}(t) < E_{\mathrm{MD}}}{T_{\mathrm{RecSeason}}} \right] \right\} \tag{5}$$

Z_{WW} [Eq. (6)] is the ratio of days when whitewater releases cannot be made because of low storage volume. Whitewater releases are set to occur on the 15th and 30th of April and May, whose set is represented n_{WW} and whose total number is represented as T_{WW}. Whitewater releases are represented by Q_{WW}

$$Z_{\mathrm{WW}} = \sum_{t=0}^{n_{\mathrm{WW}}} \left[\frac{Q_{\mathrm{WW}}(t) = 0}{T_{\mathrm{WW}}} \right] \tag{6}$$

The final objective function, Z_{EnvFlows} [Eq. (7)], summarizes the effect of water supply activity on the ecological health of the Potomac River. Although the legal flowby requirement below Little Falls, Maryland, is set at $760 \times 10^3\ \mathrm{m^3/d}$, the Potomac Basin large river environmental flow needs study concluded that a continuous, multiday period of flows at or very close to $380 \times 10^3\ \mathrm{m^3/d}$ would be injurious to aquatic biota (Cummins et al. 2010). This function sums the number of occurrences over all days, n, when flow below Little Falls, Maryland, Q_{LF}, remains below $760 \times 10^3\ \mathrm{m^3/d}$ for three or more consecutive days

$$Z_{\mathrm{EnvFlows}} = \sum_{t=0}^{n} \left\{ \frac{[Q_{\mathrm{LF}}(t)\ \text{and}\ Q_{\mathrm{LF}}(t-1)\ \text{and}\ Q_{\mathrm{LF}}(t-2)] < 760 \times 10^3\ \mathrm{m^3/d}}{n} \right\} \tag{7}$$

Results

Performance of the system under existing reservoir release rules was compared with rules optimized using multiobjective evolutionary algorithms for both the historical time series and synthetic time series.

Potomac Water Supply Response

Simulation of the WMA water supply system response to historical and synthetic time series provides an insight into how the system reacts under drought conditions and can identify areas of particular vulnerability. Water supply response was simulated using the 79 year (1929–2007) historical record and ten synthetic streamflow time series of equal length. Stochastic streamflow time series closely match the daily, monthly, and annual distribution of historical streamflows, while maintaining autocorrelation structure (Stagge and Moglen 2013).

The WMA water supply system response to synthetic time series is similar to the simulated historical response with respect to the six objective functions. The synthetic streamflow realizations produce less severe storage and environmental flow failures than the historical record, yet produce more whitewater failures. The difference between historical and synthetic streamflow simulations is attributed solely to the drought of 1930–1932, which was related to the Dust Bowl and produced an extreme climatic anomaly that has not been duplicated (Cook et al. 2008; Schubert et al. 2004; Seager et al. 2008). Therefore, synthetic time series were considered typical low flow scenarios and the historical time series was used as the most extreme low flow scenario for system optimization

By comparing multiple synthetic realizations, patterns emerge among the objective functions. These patterns help to identify common failure types; however, similarities among objective functions are not an optimization concern as a posteriori multiobjective schemes do not preassign weights and the SMS-EMOA scheme is invariant to objective scaling. Storage, Z_{Stor}, and recreation objectives, $Z_{\mathrm{RecSeason}}$, are closely related as both are volumetric measures, albeit for different reservoirs and time frames. Operating rules that minimize these objectives can be classified as storage-conservative, favoring reservoir storage at the expense of downstream flows. The whitewater objective, Z_{WW}, is most closely related to recreation storage, although not strongly tied to Z_{Stor}. Whitewater releases and the recreation season objective both depend on maintaining adequate storage in the Jennings Randolph Reservoir during an overlapping season in the late spring (April 1–May 30). By comparison, Z_{Stor} tends to focus on extreme low flows, which occur in late summer, long after the whitewater season. Flowby, Z_{Flowby}, and environmental, Z_{EnvFlows}, objectives are closely related, as they favor larger and more frequent reservoir releases, prioritizing future downstream goals at the expense of current reservoir storage and may be termed flow-conservative.

No system shortage failures occur in simulations of current climate and demand because operating rules provided by the WMA water suppliers prioritize satisfying daily demand if at all possible. This is a reasonable model, as suppliers were reticent to allow service outage if demand could otherwise be met.

Operating Rule Optimization

An overview of optimization results is presented in Table 2, which shows the maximum percent improvement, relative to simulation using existing operating rules, for each rule modification. This table shows the maximum improvement for each objective. Maximum improvement, rather than the full Pareto set, is provided because the objectives tend to be weakly conflicting, with no catastrophic failures detected in the nondominated set. Operationally, detailed Pareto curves should be used to select a final compromise solution

Table 2. System Optimization Results

	Storage		Flowby		Recreation season		White water		Environmental flows	
Rule modification	Hist	Syn	Hist	Syn	Hist	Syn	Hist	Syn	Hist	Syn
Buffer equation	0.5	0.5	21.4	8.7	0.5	0	0	0	17.8	6.8
JR rule curve	0.01	0.3	10.7	30.4	0.5	4.2	66.7	90	18.9	27.3
Patux rule curve	8.6	8.4	0	0	0.3	0	0	0	1.1	0
Load shifting	2.4	0.2	7.1	8.7	0.1	0	0	0	4.4	0
Demand restriction	0.8	0	14.3	0	0.1	0	0	0	18.9	0

Note: All values represent the maximum percent (%) improvement over the existing operation rules compared for the historical time series (left) and synthetic time series (right).

and are provided in Stagge (2012). Each of the optimized rules tend to improve system performance, although no single modification is dominant across all objectives (Table 2). This is, in part, because each modification has a distinct purpose. For instance, the majority of storage failures in the historical record occur in the Patuxent Reservoir system. Because of this, the Patuxent rule curve is most effective at preventing this type of failure, followed by Load Shifting, which shifts demand to the Patuxent and Occoquan Reservoirs, with a preference for the reservoir with more usable storage capacity. Likewise, the objectives that deal with the main stem of the Potomac River, Z_{Flowby} and Z_{EnvFlows}, are most effectively minimized by the buffer equation and demand restrictions, which both control flows in the Potomac directly. Finally, the Jennings Randolph rule curve modification is most effective at minimizing $Z_{\mathrm{RecSeason}}$ and Z_{WW}, as these objectives deal directly with storage in the Jennings Randolph Reservoir and flow in the North Branch of the Potomac. The recreation season objective was most difficult to improve (Table 2) because recreation season releases are handled by a separate set of stepped rules not evaluated in this study.

The historical time series proved more challenging for the system, producing higher penalties, but also permitting greater improvements through modifications of the operational rules. Because the synthetic time series was less challenging for the WMA system, absolute improvements were less significant, although percent improvements were similar (Table 2).

Buffer Equation

Within the WMA water supply operating rules, the buffer equation is designed to balance storage levels along the main stem of the Potomac River, namely between the upstream Jennings Randolph and downstream Little Seneca Reservoirs. During regular operation, reservoir releases from the Jennings Randolph are calculated based on estimated demand using a nine-day look-ahead; however, when there is an imbalance in percent storage between the Jennings Randolph Water Supply volume and Little Seneca storage, the buffer equation adjusts releases to equalize the percent usable storage through the following equations:

$$Q_B = -568 \times 10^3 \, \frac{\mathrm{m}^3}{\mathrm{d}} (S_{\mathrm{LS}} - S_{\mathrm{JR,WQ}}) \tag{8}$$

$$Q_{\mathrm{JR,Target}} = Q_{9\ \mathrm{day}} + Q_{\mathrm{Flowby}} + Q_B + \Sigma\mathrm{Dem} \tag{9}$$

where Q_B = buffer flow, calculated by applying a constant to the difference in percent storage between Little Seneca, S_{LS}, and the Jennings Randolph Water Supply account, $S_{\mathrm{JR,WQ}}$. Daily estimated releases from the Jennings Randolph water supply account, $Q_{\mathrm{JR,Target}}$ are calculated by adding this buffer flow to the nine day flow forecast at Little Falls ($Q_{9\ \mathrm{day}}$), the minimum flowbye (Q_{Flowby}), and the estimated daily demand [$\Sigma\mathrm{Dem}_i(t)$]. This equation is shown visually as a solid line in Fig. 3.

An alternative formulation for the Buffer Equation is proposed, which deviates from existing policy by (1) allowing unique slopes for positive and negative storage imbalances, (2) adding a breakpoint to each equation permitting different slopes for high imbalances and low imbalances, and (3) handling storage imbalances in which reservoir storage remains nearly full (>90%) separately from all other cases. Each of these rule adjustments were designed to increase flexibility for specific instances, rather than applying a single rule for all circumstances. Results of multiobjective optimization show that a 21.4% (8.7%) improvement in Z_{Flowby} and a 17.8% (6.8%) improvement in Z_{EnvFlow} can be achieved for the historical (synthetic) time series by modifying the buffer equation (Table 2). Improvements in flowby, environmental flow, and storage are attributed to greatly increasing the slope of the Buffer Equation near zero, particularly for the positive buffer, which forces excess Jennings Randolph releases in the face of the nine-day forecast uncertainty [Fig. 3(a)]. This improvement comes at the expense of recreational season storage, because of the increased magnitude of Jennings Randolph releases and potential for excessive releases. Conversely, recreational season storage can be improved by maintaining the existing buffer equation [Fig. 3(b)] but greatly decreasing the buffer equation for situations when usable storage is greater than 90%. This additional rule prevents unnecessary attempts to balance storage between the Little Seneca and Jennings Randolph when storage is nearly full.

Load Shifting

Unlike the buffer equation, which controls the Potomac reservoirs, load shifting controls how daily demand is allocated to the offline reservoirs, the Patuxent and Occoquan. When predicted flow in the Potomac River is not sufficient to satisfy predicted demand, production at the Patuxent and Occoquan water treatment plants, P_{Pat} and P_{Occ}, is temporarily increased above standard production

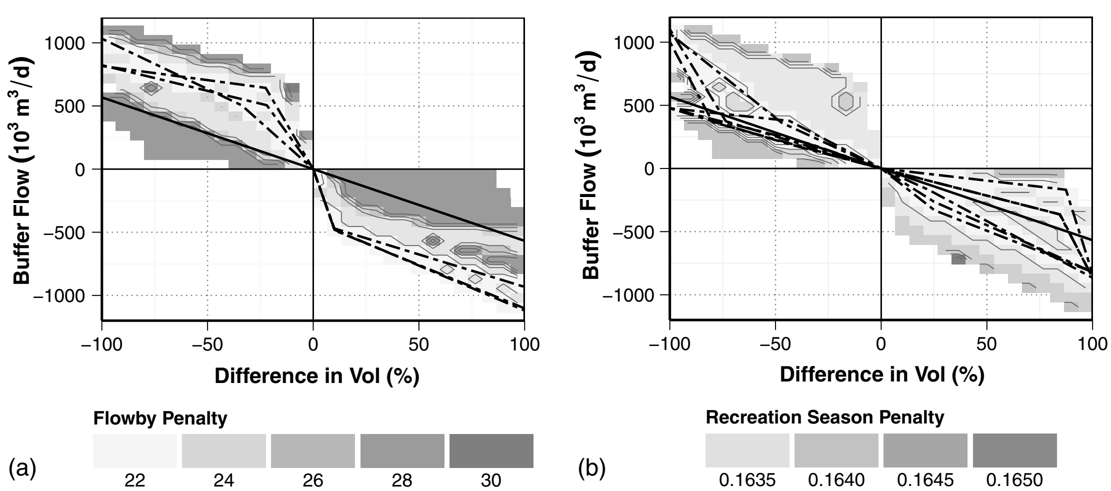

Fig. 3. Optimized buffer equation for the historical time series; current operating rules are shown by the solid diagonal line between 568×10^3 m^3/d and -568×10^3 m^3/d; the optimal buffer equations with respect to (a) flowby; (b) recreation season are shown by dashed lines; the set of Pareto-optimal solutions is shown by the filled regions, with darker areas corresponding to worse solutions (higher penalties)

levels, represented by P^0, thereby preventing releases from the Little Seneca or Jennings Randolph. The amount of load shifting, represented by LS, follows the rule

$$P_{\mathrm{Pat}} = P^0_{\mathrm{Pat}} + \mathrm{LS}_{\mathrm{Pat}} \tag{10}$$

$$\mathrm{LS}_{\mathrm{Pat}} = \min\begin{cases}\mathrm{LS}_{\mathrm{Ratio}}(\mathrm{Dem}-\mathrm{Del})\\ \mathrm{LS}_{\mathrm{Pat,Max}}\\ P_{\mathrm{Pat,Max}}\end{cases}, \quad \text{when } S_j > \mathrm{LS}_{\mathrm{Index},j}$$
$$\text{and} \quad \mathrm{Dem}-\mathrm{Del} < \mathrm{LS}_{\mathrm{Thresh}} \tag{11}$$

where $\mathrm{LS}_{\mathrm{Ratio}}$ controls the relative contribution of the Patuxent and Occoquan reservoirs, currently kept at an equal 0.5. Load Shift quantities are constrained by the maximum load shift, $\mathrm{LS}_{\mathrm{Pat,Max}}$, and maximum production at the reservoir, $P_{\mathrm{Pat,Max}}$. Load shifting occurs only when storage in the Jennings Randolph, Little Seneca, Occoquan and Patuxent remains above trigger points, called load shift storage indices and represented as $\mathrm{LS}_{\mathrm{Index}}$. Following a load shifting event, if flow in the Potomac exceeds demand by a certain threshold, represented by $\mathrm{LS}_{\mathrm{Thresh}}$, production at the offline reservoirs is curtailed an equivalent amount to replenish storage to preload shift levels. This load shift threshold is set to $1,136 \times 10^3\ \mathrm{m}^3/\mathrm{d}$ and operates as a buffer to prevent oscillating between load shifting and normal operations.

The modified load shift rules adjust the load shift storage indices, $\mathrm{LS}_{\mathrm{Index},j}$, and the allocation between the two offline reservoirs, $\mathrm{LS}_{\mathrm{Ratio}}$. Rather than maintain an equal apportionment between the two offline reservoirs ($\mathrm{LS}_{\mathrm{Ratio}}$) during a load shift event, the optimized rules allow $\mathrm{LS}_{\mathrm{Ratio}}$ to vary based on the percent available storage in the reservoirs. When usable storage is higher in the Patuxent Reservoir, a higher load is allocated to this reservoir, and vice versa. This load shift equation is therefore defined by three points and shown in Fig. 4, along with the current policy of $\mathrm{LS}_{\mathrm{Ratio}} = 0.5$. The final parameter evaluated in this scheme is the threshold ($\mathrm{LS}_{\mathrm{Thresh}}$) that determines when a load shift event ends and demand can be returned to the Potomac River.

Optimization of the load shifting policy produced two major findings: (1) that load shifting should be curtailed sooner, shifting a greater load to the underutilized Little Seneca Reservoir, and (2) that the Occoquan Reservoir is capable of handling more load than the Patuxent, in which the majority of storage failures occur in simulations. The first result is supported by improvement across all objectives when the load shift storage indices are increased for the Jennings Randolph ($1{,}000$–$1{,}500 \times 10^6\ \mathrm{m}^3$), the Patuxent ($700$–$1{,}000 \times 10^6\ \mathrm{m}^3$), and the Little Seneca (350–$800 \times 10^6\ \mathrm{m}^3$). An increase in these indices stop load shifting at a higher storage volume.

The robustness of the Occoquan Reservoir, because of its relative high watershed area, is supported by the negligible change in the Occoquan's load shift storage index (0–$200 \times 10^6\ \mathrm{m}^3$) and the benefits derived from decreasing the standard Patuxent load from 50 to 33% [Fig. 4(a)]. Decreasing the Patuxent's standard load and allowing for variable load shifts strikes an effective compromise between the competing storage and flow objectives, reducing Patuxent storage failures by 3.2%, Occoquan storage failures by 2.7%, causing no change in flowby failures, and improving environmental flows slightly. Even fewer flowby failures may be obtained by increasing the Patuxent load above 50%, but this greatly increases the number and severity of storage failures [Fig. 4(b)]. These optimal rules show the potential improvement if the system is managed optimally; however, this remains a jurisdictional challenge as current rules are designed to maintain equity between Maryland and Virginia.

Monthly Rule Curves

Jennings Randolph storage is managed by the USACE Baltimore District and uses three zone-based rule curves (high, medium, and low) to guide releases during the nonrecreation season months (September through April). Each zone has a specified daily release quantity. These releases are designed to approximate the natural contribution of the Potomac River's impounded North Branch, while refilling the reservoir prior to the summer recreation season. Multiobjective optimization was used to adjust the low and middle rule curves, ignoring the high rule curve, which is set near the USACE's upper storage limit to provide flood storage. Curves are adjusted by modifying the rule curve levels on the first of each

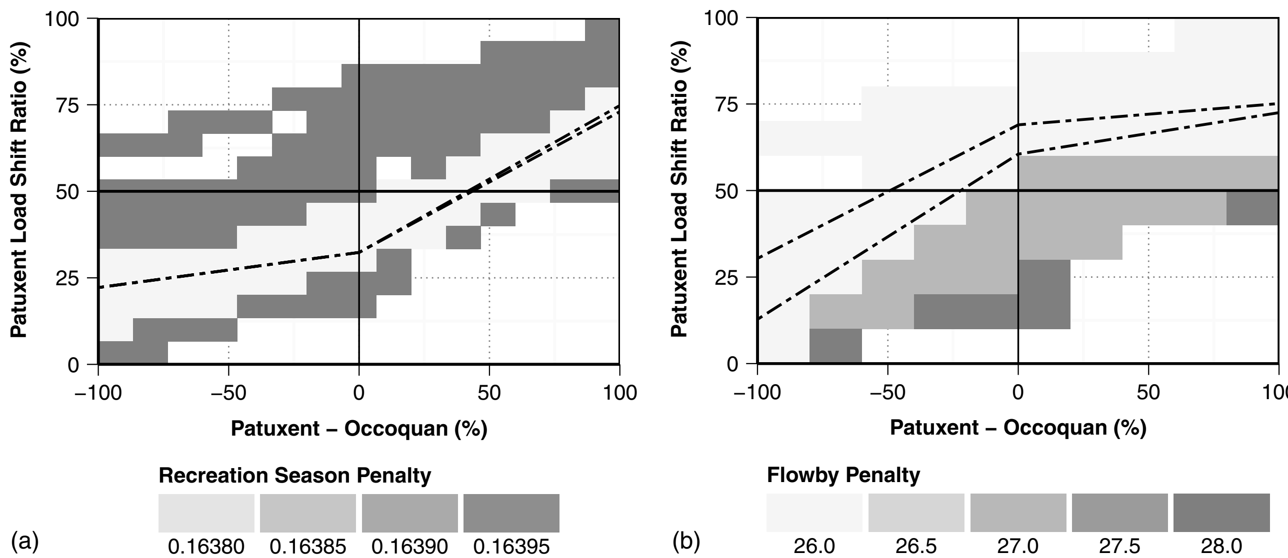

Fig. 4. Optimized load shift equation for the historical time series; current operating rules are shown by the solid horizontal line at 50%; the optimal load shift equations with respect to (a) recreation season; (b) flowby are shown by dashed lines; the set of Pareto-optimal solutions is shown by filled regions, with darker areas corresponding to worse solutions (higher penalties)

Table 3. Parameters of the Demand Restriction Rule

Rule modification	Jennings Randolph index (%)		Little Seneca index (%)		Demand restriction (%)			
					June-September		Remainder of year	
	MWCOG	Optimized	MWCOG	Optimized	MWCOG	Optimized	MWCOG	Optimized
Voluntary	60	75–84	60	74–85	5	1.2–4.7	3	4.1–7.3
Mandatory	25	25	25	25	9.2	—	5	—
Emergency	5	5	5	5	15	—	15	—

Note: Current MWCOG demand restriction policy is presented as a single value, labeled MWCOG, and optimized results, Optim, are presented as a range. Optimized values for mandatory and emergency restrictions are not presented, as these restrictions are not imposed.

month. Values within each month are interpolated based on these 12 points.

Adjustments to the Jennings Randolph rule curves produced the greatest effect on objectives directly related to Jennings Randolph storage, reducing $Z_{\mathrm{RecSeason}}$ by 0.5% and Z_{WW} by 66.7%. Z_{Stor} was not greatly affected by optimization because the majority of storage failures occur in other reservoirs. Consistent improvement was noted across all objectives by lowering Jennings Randolph rule curves during the fall (September through November) and increasing the middle rule curve in the spring months prior to the recreation season. In this way, the Jennings Randolph Reservoir operates less conservatively in the fall, making larger releases while droughts linger, and more conservatively during the spring recharge period, particularly if storage is low. This modification allows for an additional four whitewater releases over the course of the historical record, improves recreation season storage modestly (0.5%), and decreases the environmental flow penalty by 18.9%. Improvement in storage objectives, $Z_{\mathrm{RecSeason}}$ and Z_{WW}, is tied primarily to the more conservative spring modification, while flow objectives, Z_{Flowby} and Z_{EnvFlows}, are more closely linked to the less conservative operation during the fall.

Modification of the Patuxent rule curve follows the same pattern, adjusting the monthly endpoints of the storage rule curves, which in turn control the standard reservoir production based on daily storage levels. The Patuxent Reservoir operates based on two rule curves and an emergency storage trigger, which control daily water treatment withdrawals based on usable storage. Modification of the Patuxent rule curves is almost entirely designed to maintain storage in the highly stressed Patuxent Reservoir, thereby improving system storage, Z_{Stor}. The Patuxent Reservoir is typically the first reservoir in the WMA system to fall below 40% usable storage in any of the historical or simulated drought years and therefore, modification of the Patuxent rule curves is almost entirely designed to maintain storage in this high stressed reservoir, improving Z_{Stor}. Optimization of the upper and lower Patuxent rule curves produced an 8.6% improvement in system storage. This improvement is produced by raising the lower Patuxent curve consistently throughout the year and increasing the upper rule curve during the summer and early fall. Both of these increases force the Patuxent to operate more conservatively, reducing withdrawals earlier in the reservoir's drawdown. During the recharge period, beginning in December and continuing through May, the optimized upper rule curve remains nearly identical to current operations. The optimized rule curves greatly improve Z_{Stor} with little effect on other objectives, suggesting that the Patuxent Reservoir can be operated more conservatively without causing detriment to the remainder of the WMA system.

Demand Restrictions

Following inconsistent implementation of water restrictions during the drought of 1999, the Metropolitan Washington Council of Governments standardized the use of water demand restrictions by setting three trigger levels: voluntary, mandatory, and emergency (MWCOG 2000). As part of this agreement, regional governments agreed to declare water restrictions simultaneously based on the predetermined triggers. Voluntary restrictions are triggered when combined storage in the Jennings Randolph and Little Seneca Reservoirs falls below 60%. Trigger points for mandatory and emergency restrictions are set at 25 and 5% of either Jennings Randolph or Little Seneca storage, respectively, in the model. The model mandatory and emergency rules are close approximations of the actual MWCOG demand triggers, simplified to improve computational time.

Demand reduction values, shown in Table 3, are based on water use reductions during the drought of 1999 and other historical restrictions throughout the region. Reduction in water use is typically achieved by banning lawn watering, filling of swimming pools, operation of ornamental fountains, and other similar activities.

In both historical and synthetic streamflow simulations, voluntary restrictions (set at 60%) are never implemented because combined storage in the Little Seneca and Jennings Randolph water supply account remains greater than 75.8% at all times. Because this is not likely the intended goal of the MWCOG rules, demand triggers were allowed to increase in optimization runs. Results show that operations could be improved by increasing the trigger for voluntary demand restrictions to the range of 74–84% and considering the Jennings Randolph and Little Seneca reservoirs separately (Table 3). This modified rule triggers demand restrictions in only two to three years within the historical record (2.5–3.8%). Mandatory and Emergency restrictions are never imposed. This policy is more consistent with the MWCOG's expectation of requiring demand restrictions only during the most severe droughts. Because water use restrictions are called so infrequently, optimizing the percent demand reduction for each restriction level has little effect (Table 3). Increasing the demand restriction trigger primarily improves objectives at the downstream intakes (Z_{EnvFlows}, Z_{Flowby}, Z_{Stor}), while producing no effect on the upstream indices, $Z_{\mathrm{RecSeason}}$ and Z_{WW}. Demand restrictions are unnecessary in the synthetic streamflow time series and therefore, no improvements are noted (Table 2).

Conclusions

Efficient water management policies are critical in water supply systems with a significant lag between releases and their subsequent use. The Washington, DC, Metropolitan Area (WMA) water supply system, characterized by a nine-day lag between its primary water supply reservoir and its water supply intakes, was used as a case study to evaluate a rule optimization scheme, using a multiobjective evolutionary algorithm linked to a hydrologic/decision simulation model. Evolutionary algorithms are capable of searching large and complex decision spaces and are robust to nonlinear functions and constraints. In total, six objective functions were considered, which measured demand shortage, reservoir storage, minimum river flowby, recreation days, whitewater releases, and environmental benefit. Use of the evolutionary algorithm proved effective at improving system performance and identified several potential modifications to reduce the uncertainty caused by the physical layout of the system.

Although no single rule modification was dominant across all objectives, some modifications provided consistent improvements over the current policy, regardless of objective priorities. These findings include placing additional load on the Little Seneca Reservoir, which is underutilized, by reducing load shifting earlier in a drought event. Similarly, the Occoquan is slightly underutilized and can therefore manage a higher load shift than the Patuxent Reservoir, particularly if the load shift ratio is variable and related to the relative storage volume. Under historical (drought of record) and simulated time series, current water restrictions are never triggered, suggesting these restrictions are too conservative and could improve flowby and environmental flows by 14.3 and 18.9%, respectively, without negatively affecting storage.

Other modifications involve a tradeoff between objectives, which is a primary benefit of using a posteriori multiobjective optimization for water resources studies. Following optimization, decision makers can view the relative importance of the various objectives and determine the amount of improvement against the level of risk they are willing to accept. In this case study, modification of the buffer equation, which balances storage between the upstream Jennings Randolph Reservoir and the downstream Little Seneca Reservoir was able to improve both storage in the Jennings Randolph and downstream flow metrics. However, as Jennings Randolph storage was maximized through excessively conservative release policies, downstream flows were negatively affected.

The water resources optimization scheme proposed in this study has great potential for improving water resources management in complex water supply systems, particularly with long lag times. Evolutionary algorithm optimization provides a flexible framework that could be applied to nearly any water supply system with a well-defined physical model, system forcings (i.e., streamflow), system constraints, and objective functions that adequately quantify the goals of the watershed. Constraints and objective functions may be as simple or complex as desired. In the WMA example, the use of synthetic streamflow time series expands the set of feasible drought scenarios beyond the historical record, preventing overfitting and ensuring system robustness.

Acknowledgments

James Stagge is a Charles E. Via, Jr. Doctoral Fellow and gratefully acknowledges support from the Via program and the Institute for Critical Technology and Applied Science (ICTAS). The authors would also like to thank the Interstate Commission on the Potomac River Basin (ICPRB) and Hydrologics, Inc. for providing data access and research support. Finally, this manuscript benefitted greatly from the comments and feedback from four anonymous reviewers.

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