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Inferring efficient operating rules in multireservoir water resource systems: A review

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Abstract:

Coordinated and efficient operation of water resource systems becomes essential to deal with growing demands and uncertain resources in water-stressed regions. System analysis models and tools help address the complexities of multireservoir systems when defining operating rules. This paper reviews the state of the art in developing operating rules for multireservoir water resource systems, focusing on efficient system operation. This review focuses on how optimal operating rules can be derived and represented. Advantages and drawbacks of each approach are discussed. Major approaches to derive optimal operating rules include direct optimization of reservoir operation, embedding conditional operating rules in simulation-optimization frameworks, and inferring rules from optimization results. Suggestions on which approach to use depend on context. Parametrization–simulation–optimization or rule inference using heuristics are promising approaches. Increased forecasting capabilities will further benefit the use of model predictive control algorithms to improve system operation.

Introduction

Managing multireservoir systems can benefit from coordinating operation of facilities to better achieve objectives within system constraints (Labadie, 2004; Oliveira & Loucks, 1997). Coordination requires an integrated vision, accounting for interrelations and interdependencies among system components. However, integration increases the complexity of reservoir system operation and increases analysis complexity from the many variables, stakeholders, and often conflicting goals to consider, and uncertainty in the system's future (Loucks, 2017; Lund et al., 2017; Oliveira & Loucks, 1997; Rani & Moreira, 2010). System analysis tools, including simulation, optimization, and their combinations, can help address the complexities of operating multireservoir systems and deal with concerns such as stakeholder participation, water pollution, environmental awareness, sustainability, good governance, resiliency, and efficiency (Brown et al., 2015; Cai, Vogel, & Ranjithan, 2012; Lund et al., 2017). Achieving efficient water management is vital with increasing competition for water, growing demands, and uncertain water supplies. In response, the European Union considers increasing efficiency in water management and use as a main direction for water policy (European Commission, 2012a), establishing a hierarchy for policy-making in which additional water supply infrastructure should only be built when other options are impossible (European Commission, 2007, 2012b). Identifying and evaluating how efficiency in water management can be improved is a main objective of water resource systems models (Loucks, 2017). A wide range of system analysis models have been applied to improve efficient and integrated use of water resources with available infrastructure. They usually link system features (physical, hydrological, economic, institutional, etc.) with system management (target storages and releases, deliveries to the system's demands, hydropower scheduling, environmental protection, etc.) and performance (economic prosperity, public health, ecosystem support, equity, etc.) through a set of mathematical equations modeling system processes (hydrology, reservoir operation, conveyance, demand deliveries, etc.). These mathematical models can be divided into simulation and optimization. In simulation, operating rules are described and used as an input to assess system performance (positive approach), while in the second, system operation is prescribed (normative approach) to maximize defined system performance indicators. Simulation models have become routine and widespread for analyzing water policy impacts, assessing alternatives, and developing water plans (Brown et al., 2015).

Optimization models can be powerful tools to suggest efficient management strategies, but have drawbacks and limitations that hinder their use in practice (Jain & Singh, 2003; Labadie, 2004; Loucks, 2017; Maier et al., 2014; Rogers & Fiering, 1986), such as: approximate framing of optimization tools into wider management practices; problem simplifications commonly needed for optimization; the lack of decision-maker involvement in model development; and that many optimization models can only produce optimal time series of prescribed decisions for specified scenarios, rather than actual operation prescriptions. Furthermore, optimization requires substantial consensus on performance objectives or, ideally, a single objective (e.g., minimize net costs), as is common for water distribution, hydropower, and levee systems (Brown et al., 2015). Reservoirs usually operate using predefined rules that respond to regulatory frameworks rather than seeking an overall efficient operation of water resources (Labadie, 2004; Lund et al., 2017; Oliveira & Loucks, 1997). Simulation and optimization models have been combined in methodological frameworks to infer improved operating rules, employing the advantages of both methods. The ways in which efficient operating rules can be derived from optimization algorithms have increased recently with the rise in computer power and affordability and heuristic programming methods that more easily link simulation and optimization approaches (Maier et al., 2014; Rani & Moreira, 2010). Today, a wide range of methods can define operating rules based on mathematical algorithms. This paper reviews the use of mathematical models to infer operating rules in multireservoir water resource systems, focusing on inference for effective operations. Main novelty of this review is its focus on how to define and derive optimal operating rules, and the functional forms in which they can be represented. Alternatives to define reservoir operation policies from optimization algorithms are analyzed. These range from the traditional regressions on optimization results to recent applications of parametrization–simulation–optimization (PSO) frameworks and heuristic techniques such as artificial neural networks (ANNs) or machine learning. We make recommendations on how to infer efficient operating rules for problems with varying features and goals.

Deriving operation strategies using optimization models

Optimization models can provide time series of optimized decisions and, in some cases, optimal operating rules. System operators usually rely on conditional operating rules (Labadie, 2004), and decision-making is seen as a broader process in which operating rules help guide in achieving consensus on system management (Oliveira & Loucks, 1997). To identify promising optimal operating rules, system operators could use the following approaches (Figure 1): (a) direct optimization, by applying an optimization algorithm to directly suggest optimal operating decisions; (b) a priori functional forms, in which the mathematical formulation of the desired operating rules (rule form) is fixed, with parameter values to be optimized; and (c) inferring rules from optimization results, in which both the rule form and parameter values are inferred by manual or automated means. Optimization is required in all cases: in the first one, their application is the only process needed; while in other cases optimization is part of a broader framework to develop operating rules.

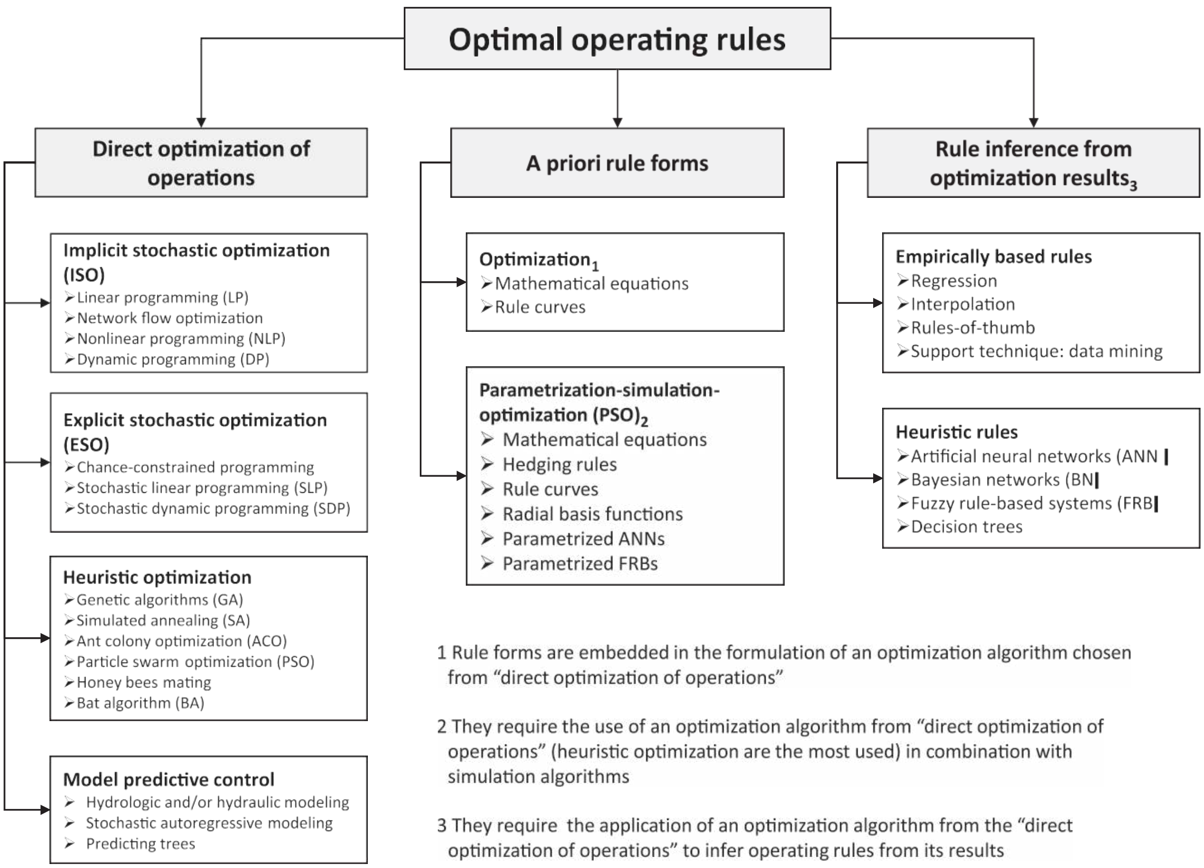

Figure 1. Approaches to develop optimal operating rules

Direct optimization of operations

Optimization models have been widely used to identify potential operation improvements for water resource systems. Some optimization methods, such as stochastic dynamic programming (SDP), provide optimal operating rules as output directly, while other methods provide time series of optimal decisions for specific inflow scenarios. If the rule form is in line with the user needs, or if just optimal decisions are desired directly, there is no need for postprocessing. Otherwise, optimization results need to be translated into operating rules using inference or with predefined rule forms. Many algorithms have been applied for optimizing the management of water resources systems, including deterministic (implicit stochastic) optimization, (explicit) stochastic optimization, heuristic optimization, and model predictive (optimal) control. Optimization algorithms have been commonly reviewed in the literature (Ahmad, El-Shafie, Razali, & Mohamad, 2014; Labadie, 2004; Rani & Moreira, 2010; Simonovic, 1992; Singh, 2012; Wurbs, 1993; Yeh, 1985).

Implicit stochastic optimization

Implicit stochastic optimization (ISO) uses deterministic programming procedures to optimize system operation for a large wide-ranging set of inflow time series that captures the stochastic nature of expected inflows. Its primary advantage is the reduced need to simplify system details compared to explicit stochastic programming. However, the optimal decisions obtained are unique to the employed time series and assume perfect foresight of future inflows, something unusual in real-life systems (Labadie, 2004). Common solution algorithms include (Table 1): linear programming, in which all the mathematical equations are linear; network flow optimization, in which the system is conceptualized as a network of nodes and links and solved using network algorithms; nonlinear programming which can cope with some nonlinearities; and dynamic programming, in which a multistage programming problem is decomposed into a set of sequentially solved single stages. The "curse of dimensionality" of dynamic programming is the exponential growing of the computational burden with the system size (Bellman, 1957; Bellman & Dreyfus, 1962; Giuliani, Castelletti, et al., 2016; Nandalal & Bogardi, 2007). Approaches reducing computational burden usually imply further simplifying the system, interpolating benefit values, and using alternative approaches (Goor, 2010).

Table 1. Implicit stochastic optimization solution algorithms and example applications

Algorithm	**Examples of application**
Linear Programming (LP)	Das et al. (2015); Jenkins et al. (2004); Satti et al. (2015)
Network flow optimization	Andreu et al. (1996); Andreu & Sahuquillo (1987); Haro-Monteagudo et al. (2017); Labadie et al. (2000); Lund & Ferreira (1996); Pulido-Velazquez et al. (2008)
Nonlinear Programming (NLP)	Cai et al, (2001); Satti et al. (2015); Theodossiou (2004); Vieira et al. (2011)
Dynamic Programming (DP)	Grüne and Semmler (2004); Hall & Buras (1961); Johnson et al. (1993); Liu et al. (2011); Nandalal & Bogardi (2007); Turner & Galelli (2015)

Explicit stochastic optimization

Explicit stochastic optimization (ESO) (stochastic programming) uses probabilistic descriptions of inflows in the formulation of the algorithm; thus, optimization is run with probabilistic (imperfect) knowledge of future inflows (Labadie, 2004; Rani & Moreira, 2010), the primary advantage of this approach. The primary disadvantages of ESO are the additional system simplification needed for computation and the limited types of correlation structures that can be represented. ESO models are more computationally challenging than their ISO equivalents as they need to embed the probabilistic description of inflows within its formulation (e.g., SDP). This approach is divided into (Table 2) chance-constrained programming, in which inflows are treated as simplified random variables and risk levels are assumed; stochastic linear programming, in which the problem is decomposed into two or three stages according to the uncertainty level; and SDP, which extends dynamic programming to include an explicit representation of inflow uncertainty.

Table 2. Explicit stochastic optimization algorithms and examples of application

Algorithm	Examples of applications
Chance-constrained programming	Eisel (1972); Houck (1979); Revelle et al. (1969); Sahinidis (2004); Sreekanth et al. (2012); Xu et al. (2017); Zeng et al, (2013)
Stochastic Linear Programming (SLP)	Loucks & van Beek (2005); Marques et al. (2005); Zhu et al. (2015)
Stochastic Dynamic Programming (SDP) and its derivatives	Nandalal & Bogardi (2007); Pereira-Cardenal et al. (2015); Pereira & Pinto (1991, 1985); Stedinger et al. (1984); Tejada-Guibert et al. (1993); Turner & Galelli (2015); Zhao et al. (2014); Haguma et al. (2018); Castelletti et al. (2013, 2010); Davidsen et al. (2014); Lee & Labadie (2007); Macian-Sorribes et al. (2017); Tilmant et al. (2008); Tilmant & Kelman (2007); Lei et al. (2018); Faber & Stedinger (2001); Kelman et al. (1990)

Subject to the curse of dimensionality, SDP provides optimal operating rules in policy tables (e.g., Karamouz & Houck, 1987; Nandalal & Bogardi, 2007). Some algorithms reduce SDP's curse of dimensionality, such as sampling SDP (Côté & Arsenault, 2019; Faber & Stedinger, 2001; Kelman et al., 1990); fuzzy SDP (Tilmant, Faouzi, & Vanclooster, 2002; Tilmant, Van Der Zaag, & Fortemps, 2007; Tilmant, Vanclooster, Duckstein, & Persoons, 2002); Bayesian SDP (Karamouz & Vasiliadis, 1992; Mujumdar & Nirmala, 2007); demand-driven SDP (Vasiliadis & Karamouz, 1994); reinforcement learning (Castelletti et al., 2010, 2013; Lee & Labadie, 2007); and stochastic dual dynamic programming (Macian-Sorribes et al., 2017; Pereira & Pinto, 1985, 1991; Rougé & Tilmant, 2016; Tilmant & Kelman, 2007).

Heuristic optimization

Heuristic optimization, also known as computational intelligence, evolutionary algorithms, or metaheuristics, addresses optimization by making analogies with natural selection based on the survival or success of better solutions (Labadie, 2004). Their main advantage is their efficiency in handling nonlinearities and discontinuous variables, their suitability to solve multiobjective (and even many-objective) problems and that they can be linked easily to simulation procedures (Maier et al., 2014; Rani & Moreira, 2010). For multiobjective and many-objective optimization, results can be shown as a Pareto front (Kasprzyk, Nataraj, Reed, & Lempert, 2013; Reed, Hadka, Herman, Kasprzyk, & Kollat, 2013).

A large range of algorithms have been developed to employ computational intelligence. Each algorithm has its own advantages, drawbacks and applicability range. The most popular are genetic algorithms (GA), based on evolutionary processes (Bozorg-Haddad, Azarnivand, Hosseini-Moghari, & Loáiciga, 2017; Chen, Leon, Fuentes, Gibson, & Qin, 2018; Giuliani, Castelletti, et al., 2016; Hu, Mao, Tian, Dai, & Rong, 2018; Maier et al., 2014; Oliveira & Loucks, 1997; Reed et al., 2013; Salazar, Reed, Herman, Giuliani, & Castelletti, 2016). The main advantages of GA are an ability to handle nonlinear and even discontinuous goal functions, its capacity to adapt to a wide variety of applications, and its ability to escape inferior local optima (Maier et al., 2014; Oliveira & Loucks, 1997). Multiobjective evolutionary algorithms (MOEAs) can efficiently handle problems with multiple operating goals expressed in different units to find Pareto-optimal alternatives (Reed et al., 2013).

Another heuristic technique is simulated annealing, which mimics the annealing process in glass making or metallurgy (e.g., Teegavarapu & Simonovic, 2002). Its main advantage is combining continuous and discrete variables. However, an adequate choice of annealing parameters and initial values for variables is crucial (Cunha & Antunes, 2012; Teegavarapu & Simonovic, 2002). Ant colony optimization is based on how ants find the shortest paths to food, being suited to deal efficiently with discrete variables, and with a low dependence between the problem size (variables and constraints) and the quality of optimal solution (e.g., Kumar & Reddy, 2006; Safavi & Enteshari, 2016). Particle swarm optimization is inspired by natural grouping behaviors (e.g., Kumar & Reddy, 2007; Ostadrahimi, Mariño, & Afshar, 2012; Spiliotis, Mediero, & Garrote, 2016; Taormina, Chau, & Sivakumar, 2015). It can handle nonlinearities and nonconvexities, although it can be trapped by local optima (Kumar & Reddy, 2007; Spiliotis et al., 2016). Honey bees mating reproduces honey bees behavior, and can solve highly nonlinear constrained and unconstrained optimization problems with discrete and/or continuous variables (e.g., Haddad, Afshar, & Mariño, 2006). Bat algorithms mimic the echolocalization system of bats when flying (e.g., Bozorg-Haddad, Karimirad, Seifollahi-Aghmiuni, & Loáiciga, 2014; Zarei, Mousavi, Eshaghi Gordji, & Karami, 2019). Recent heuristic algorithms and their application to water resource systems optimization include Tabu search (Marchand, Gendreau, Blais, & Emiel, 2019), spider monkey algorithm (Ehteram, Karami, & Farzin, 2018a) and kidney algorithm (Ehteram, Karami, & Farzin, 2018b).

Model predictive control

Optimal control with forecasting, or model predictive control (MPC) with forecasting (Castelletti, Pianosi, & Soncini-Sessa, 2008; Lin & Rutten, 2016), is based on a rolling horizon principle: the optimization problem is solved over a finite time horizon for which a forecast is available, but only the decision of the first-time step is implemented. Time step after time step, the problem is updated and resolved again (Bellman, 1957; Bellman & Dreyfus, 1962; Castelletti et al., 2008; Galelli, Goedbloed, Schwanenberg, & van Overloop, 2014; Lin & Rutten, 2016;

Yakowitz, 1982; Yeh, 1985). The main advantages of MPC are its flexibility and being more realistic (Jain & Singh, 2003). However, its applicability is restricted to situations in which forecasts with the adequate lead time are available and reliable enough to be employed.

The same optimization algorithms presented in ISO, ESO, and heuristic optimization can be used in a MPC approach once combined with forecasts, which is the main distinct feature of MPC. The direct use of optimization in real-time operation is mainly applicable to short-term (e.g., hourly or daily time steps and time spans of weeks or months), and in the operation of water resource systems with a clear and unique management objective, such as maximizing hydropower benefits or minimizing pumping cost (e.g., Castelletti et al., 2008; Ficchì et al., 2015; Galelli et al., 2014; Teegavarapu & Simonovic, 2000). The main options for inflow forecasting used in MPC are shown in Table 3, and the main applications are summarized in Table 4.

Table 3. Main options for inflow forecasting in Model Predictive Control

Inflow forecasting approach	**Examples of applications**
Hydrologic and/or hydraulic models forced with meteorological forecasts	Bianucci et al. (2015); Caseri et al. (2016); Côté & Leconte (2015); Faber & Stedinger (2001); Ficchì et al. (2015); Pianosi & Ravazzani (2010); Raso et al. (2014)
Stochastic autoregressive models	Mizyed et al. (1992); Pianosi and Ravazzani (2010); Pianosi and Soncini-Sessa (2009)
Prediction trees making forecasts based on present and past hydrometeorological information	Chazarra et al. (2016); Côté and Leconte (2015); Galelli et al. (2014); Raso et al. (2014, 2013)

Table 4. Main applications of Model Predictive Control

Application	**Examples**
Urban reservoir management	Galelli et al. (2014)
Irrigation and drainage control	Mizyed et al. (1992); Overloop et al. (2008)
Hydropower generation	Bianucci et al.(2015); Côté & Leconte (2015); Sordo-Ward et al. (2012); Teegavarapu & Simonovic (2000)
Flood protection	Caseri et al. (2016); Ficchì et al. (2015); Raso et al. (2014); (Vermuyten et al., 2018)

A priori rule forms

In this approach, the mathematical representation of the operating rule form is decided before running the optimization algorithm. The optimization essentially calibrates the parameters of the a priori rule form to achieve the best performance. This calibration can be optimized directly (optimization), or in combination with simulation (parametrization–simulation–optimization).

Optimization

Here the equations of the chosen rule form are directly introduced in the formulation of the optimization problem. The algorithm calibrates the rule parameters to optimize an indicator of system performance (e.g., economic efficiency). For example, Wan et al. (2016) used 2-stage optimization to find the parameters that define the optimal hedging rule for reservoir refill considering two conflicting economic objectives: reducing flood damage versus increasing water conservation benefits. Objective functions employed in the literature include minimizing the required reservoir capacity (Houck, 1979; Loucks, 1970; Luthra & Arora, 1976; Revelle et al., 1969); optimizing performance indicators (Bolouri-Yazdeli, Bozorg Haddad, Fallah-Mehdipour, & Mariño, 2014; Gundelach & ReVelle, 1975; ReVelle & Gundelach, 1975; Revelle & Kirby, 1970); and maximizing the economic benefits (Draper & Lund, 2004; Eisel, 1972; Houck, Cohon, & ReVelle, 1980; Wan et al., 2016).

These approaches yield optimal rules within the given form. Nevertheless, the rule form equations should be as simple as possible, or they might require simplifications for practical optimization algorithms. Optimization problem definition may require simplifications to deal with the additional equations and constraints of the given rule form, being subject to the drawbacks of the optimization algorithm employed. Main functional forms used when optimizing a priori operating are in Table 5.

Table 5. Main functional forms used when optimizing operating rules

Appliation	**Examples**
Mathematical equations (e.g. linear or piecewise linear functions)	Bolouri-Yazdeli et al. (2014); Eisel (1972); Gundelach and ReVelle (1975); Houck (1979); Houck et al. (1980); Loucks (1970); Luthra and Arora (1976); Revelle et al. (1969); ReVelle and Gundelach (1975); Revelle and Kirby (1970)
Rule curves	Draper & Lund (2004); Wan et al. (2016).

Parametrization–simulation–optimization

Parametrization-simulation-optimization (PSO), also known as direct policy search combines the detailed system representation allowed by simulation models with the efficiency levels attained by optimization. It uses an “intelligent search” of the best operating rules, able to obtain them without long trial-and-error processes (Celeste & Billib, 2009; Jacoby & Loucks, 1972; Johnson, Stedinger, & Staschus, 1991; Koutsoyiannis & Economou, 2003; Oliveira & Loucks, 1997). Its applications have risen considerably in the last decade due to faster heuristic optimization, which can combine simulation and optimization while considering complex performance criteria (Ashbolt, Maheepala, & Perera, 2016; Giuliani, Castelletti, et al., 2016; Kumar & Kasthurirengan, 2018; Lerma, Paredes-Arquiola, Andreu, & Solera, 2013; Lerma, Paredes-Arquiola, Andreu, Solera, & Sechi, 2015; Shourian, Mousavi, & Tahershamsi, 2008; Spiliotis et al., 2016; Yang & Ng, 2016).

PSO (Figure 2) requires establishing a rule form and its parameters. Their optimal values are obtained iteratively combining simulation and optimization (Celeste & Billib, 2009; Giuliani, Castelletti, et al., 2016; Koutsoyiannis & Economou, 2003; Nalbantis & Koutsoyiannis, 1997). For each iteration, a set of parameter values is chosen and used as input to the simulation algorithm, which obtains the system performance for the given operating rule (rule form plus parameter values) for different inflow scenarios. Their results are used by the optimization algorithm to update the parameter set, which is introduced into the simulation again. The process is repeated until the best performance is reached (Celeste & Billib, 2009). Its main advantage is its efficiency to obtain an optimal operating rule, achieving adequate performance levels regardless of the system's complexity and the rule's simplicity (Celeste & Billib, 2009; Koutsoyiannis & Economou, 2003; Nalbantis & Koutsoyiannis, 1997).

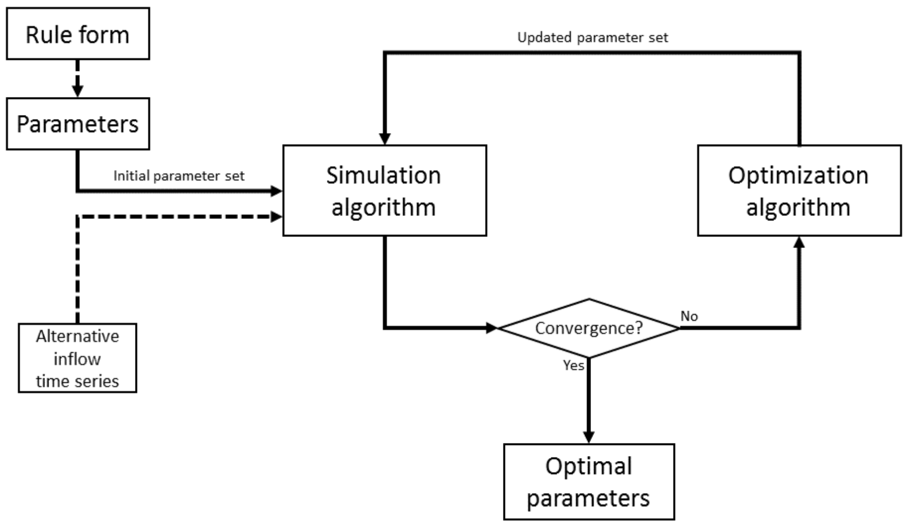

Figure 2. Parametrization–simulation– optimization flowchart

Main PSO methods, combining different rule forms and optimization algorithms, are shown in Table 6. Regarding rule form, main approaches are mathematical equations, hedging rules, rule curves, radial basis functions (RBF), ANNs, fuzzy rule-based (FRB) systems, and decision trees. Heuristic programming is the optimization method mostly adopted because it can handle nonlinear problems with local optima and discontinuities (Koutsoyiannis & Economou, 2003), commonly genetic and particle swarm algorithms. PSO approaches can benefit from using general-purpose decision support systems (DSS) as simulation models (Lerma et al., 2013, 2015; Shourian et al., 2008). The combination of MOEAs with PSO, known as evolutionary multiobjective direct policy search (EMODPS) can find Pareto-optimal operating rules for multipurpose water resource systems (Desreumaux et al., 2018; Giuliani et al., 2018; Giuliani, Castelletti, et al., 2016). Alternatively, optimization methods may be replaced by game theory approaches such as the Nash equilibrium (Wu, Li, Cheng, Miao, & Ying, 2019).

Table 6. Overview of main PSO methodologies and examples

Rule form	Optimization method	Examples
Mathematical equations	Genetic algorithms (GA)	Ahmadi et al. (2014); Dariane & Momtahen (2009); Fallah-Mehdipour et al. (2012); Guariso et al. (1986); Kim et al. (2008); Koutsoyiannis & Economou (2003); Oliveira & Loucks (1997)
Hedging rules	Genetic algorithms (GA)	Tan et al. (2017); Zeff et al. (2014); (Kumar & Kasthurirengan, 2018); Srinivasan & Kumar (2018); Azari et al. (2018)
	Particle swarm optimization (PSO)	Wan et al.,(2018)
	Pattern search	Celeste & Billib (2009); Xiaozhong, Chao, & Jijian(2018)
Rule curves	Genetic algorithms (GA)	Ahmadi Najl et al. (2016); Ashbolt et al. (2016); Borgomeo et al. (2016); Cui & Kuczera (2005); Lerma et al. (2015, 2013); Zhu et al. (2013); Ashbolt & Perera (2018); Rashid et al. (2018)
	Particle swarm optimization (PSO)	Guo et al. (2013); Shourian et al. (2008); Spiliotis et al. (2016); Wan et al. (2018)
	Pattern search	Celeste & Billib (2009)
Radial basis functions (RBF)	Genetic algorithms (GA)	Culley et al. (2016); Giuliani et al. (2018, 2016, 2014); Salazar et al. (2016); Desreumaux et al. (2018); Wild et al. (2019)
Artificial neural networks (ANN)	Genetic algorithms (GA)	Giuliani et al. (2015)
Fuzzy rule-based systems (FRB)	Genetic algorithms (GA)	Yang and Ng (2016)
Decision trees	Genetic algorithms (GA)	Herman & Giuliani (2018)

Rule inference from optimization results

This approach executes an optimization algorithm and analyses its results to infer optimal operating rules. Both implicit and explicit stochastic approaches can be used (e.g., Karamouz &

Houck, 1987; Labadie, 2004; Rani & Moreira, 2010). The fitting or learning required to transform time series of optimal decisions into operating rules depends on the selected rule form. The obtained operating rules should then be tested and refined using simulation models (Karamouz & Houck, 1987; Labadie, 2004). Most early applications employed regression (e.g., Loucks, 1970; Young, 1967) or interpolation from SDP-derived policy tables (Nandalal & Bogardi, 2007; Tejada-Guibert et al., 1993). New techniques include heuristic procedures, such as ANNs or FRB systems, taking advantage of the increased computer power and affordability.

Empirically based rules

This category includes regression, interpolation, rules-of-thumb, and data mining. They unambiguously obtain the operating decisions (target storages, releases, etc.) in response to the values of certain explanatory variables (storages, inflows, etc.) using classic mathematical formulations (e.g., linear equations, polynomial equations, logarithms, etc.). They are derived by mathematical procedures (fitting and interpolation), engineering principles, or even visual inspection (Lund, 1996; Lund et al., 2017; Lund & Ferreira, 1996).

Regression

Regression was the first wide-used method to represent optimal operating rules, often expressing reservoir releases at some time period as function of the current storage and inflow (Bhaskar & Whitlatch, 1980; Karamouz & Houck, 1982; Young, 1967). Advantages are that it is a well-known and simple method, with a wide range of application, scalability, and easiness to embed within optimization and simulation algorithms. The main drawback is that it may lead to poor correlation coefficients that invalidate the resulting rules (Labadie, 2004; Lund & Ferreira, 1996). Moreover, regression results depend on the functional form assumed. Table 7 shows the main regression types used in the literature.

Table 7. Examples of regression approaches applied to the development of reservoir operating rules

Regression procedure	**Examples**
Linear regression	Bhaskar & Whitlatch (1980); Dariane & Momtahen (2009); Karamouz et al. (1992); Karamouz & Houck (1987, 1982); Ostadrahimi et al. (2012); Young (1967)
Non-linear regression	Bhaskar & Whitlatch (1980); Celeste et al. (2009); Celeste & Billib (2009)
Piecewise linear regression	Huang et al. (2016); Lund (1996); Lund & Ferreira (1996); Pulido-Velazquez et al. (2004)
Fuzzy regression	Malekmohammadi et al. (2009); Mousavi et al. (2007)
Support vector regression	Aboutalebi et al. (2015); Ji et al. (2014)

Interpolation

Interpolation defines optimal operating rules by extending the values of optimal operation decisions available at some points (target storage and/or target release) to the whole state space of independent variables. It should be distinguished from interpolating benefit values, which is used in direct optimization of operations (see Section 3). The main advantage of interpolation is the conservation of the optimal values, as well as a better representation of the variability across the independent variables space (Celeste et al., 2009). However, the resulting equations can be complex. The most popular equations in interpolation are piecewise linear and piecewise cubic (a.k.a. cubic splines). Interpolation is often used with discrete dynamic programming or SDP. In these cases, interpolation reduces the need of finer discretizations of the state space, diminishing the computational and time requirements (Celeste et al., 2009; Davidsen, Liu, Mo, Rosbjerg, & Bauer Gottwein, 2016; Goor, 2010; Nandalal & Bogardi, 2007; Philbrick & Kitanidis, 1999; Tejada-Guibert et al., 1993).

Rules-of-thumb

These methods are based on conceptual or mathematical deductions, experience and engineering principles, or visible patterns in operation results (Lund, 1996; Lund et al., 2017; Lund & Guzman, 1999). Many rule forms have been developed such as the standard operating policy, hedging rules, rule curves, zone-based rules, space rules, and so on (Table 8, based on reviews by Jain & Singh, 2003; Lund, 1996; Lund et al., 2017; Lund & Guzman, 1999). Although each rule has advantages and drawbacks, all have in favor a conceptually simple definition and the confidence of system operators. Some are often used in regulatory frameworks. Since their purpose is to guide system operators, they are usually used in real-life in conjunction with expert judgment (Jain & Singh, 2003; Oliveira & Loucks, 1997). Often these rules or rule forms are derived by optimizing operating specific purposes.

Table 8. Examples of regression approaches applied to the development of reservoir operating

Rule name	**System types**	**Operating purposes**	**Examples**
Standard operating policy	Single reservoir	Water supply, flood control, navigation, environmental, recreation	Celeste and Billib (2009), Lund (1996), Vedula, Mujumdar, and Chandra Sekhar (2005)
Hedging rules	Single reservoir	Water supply, flood control, navigation, environmental, recreation	Celeste and Billib (2009), Draper and Lund (2004), You and Cai (2008), Wang, Cheng, Wu, Shen, and Cao (2019)
Pack rules	Single reservoir	Water supply, hydropower production	Lund (1996), Lund and Guzman (1999)
Rule curves	Single reservoir	Water supply, flood control, navigation, environmental, recreation	Andreu et al. (1996), Zhou and Guo et al. (2013)
Zone-based operation	Single reservoir	Multiple purposes	Andreu et al. (1996), Lund (1996), Lund and Guzman (1999)
Water storage rules	Reservoirs in series	Water supply, navigation, environmental, recreation	Lund (1996), Lund and Guzman (1999)

Rule name	System types	Operating purposes	Examples
Flood control rules	Reservoirs in series	Flood control	Lund et al. (2017), Lund and Guzman (1999)
Hydropower rules	Reservoirs in series	Hydropower production	Lund (1996), Lund et al. (2017), Zhang et al. (2019)
New York City space rule	Reservoirs in parallel	Water supply, navigation, environmental, recreation	Lund (1996), Lund and Guzman (1999)
Equal ratio space rule	Reservoirs in parallel	Water supply, navigation, environmental, recreation	Lund et al. (2017), Lund and Guzman (1999)
Flood control space rule	Reservoirs In parallel	Flood control	Hui, Lund, Zhao, and Zhao (2016), Lund (1996), Lund et al. (2017), Zhao, Zhao, Lund, et al. (2014)

Support technique: data mining

This technique efficiently analyses large data sets to reveal hidden patterns or trends (Bessler, Savic, & Walters, 2003), as well as which state variables are most important (Hejazi & Cai, 2009). Instead of using preset candidate variables, data mining identifies variables that best help define the operating rules by sorting the variables according to its relevance and redundancy with each other (Hejazi & Cai, 2011). Data mining can be used jointly with operating rule forms such as decision trees (Bessler et al., 2003; Wei & Hsu, 2008; Yang, Gao, Sorooshian, & Li, 2016) or as a preanalysis technique (Hejazi & Cai, 2009; Soleimani, Bozorg-Haddad, Saadatpour Loáiciga, 2016), to avoid an inadequate selection of state variables.

Heuristic operating rules

Operating rule definitions for water resource systems with multiple reservoirs and objectives using empirically based rules may be cumbersome. These systems would require complex fitting processes ending often with poor correlations (Labadie, 2004), or are beyond the applicability of rules-of-thumb (Lund et al., 2017). Heuristic operating rules are a suitable alternative in those cases (Rani & Moreira, 2010). Their use has grown favored by new heuristic methods and increasing computation power.

Artificial neural networks

ANNs link input to output variables based on a mathematical process inspired by the human brain, in which simple units (neurons) are massively aggregated and interlinked to reproduce complex relationships. Each neuron or node implements a single-input single-output function fed with a weighted sum of the inputs to the ANN (Labadie, 2004). Mathematical relationships can be modeled by establishing the number of nodes and the way they are connected (in different layers), as well as the functions and weights in each node. The advantages of the ANN are its ability to reproduce complex mathematical relationships and its computational efficiency compared with similar approaches (Cancelliere, Giuliano, Ancarani, & Rossi, 2002). Its main drawback is that they are perceived as “black boxes” whose behavior is difficult to understand by users and decision-makers (Russell & Campbell, 1996).

ANNs have been widely applied in assessing optimal operating rules since the 90s (Cancelliere et al., 2002; Chandramouli & Raman, 2001; Liu, Guo, Xiong, Li, & Zhang, 2006; Raman & Chandramouli, 1996). Its performance is often superior to regression (Chandramouli & Raman, 2001; Raman & Chandramouli, 1996), rules-of-thumb (Cancelliere et al., 2002; Chandramouli & Raman, 2001; Liu et al., 2006), and interpolation from SDP's results (Raman & Chandramouli, 1996). A derivative approach combining ANNs and FRB systems, named adaptive network-based fuzzy inference system, consisting in dynamically modifying the inputs of a FRB system using an ANN, has been applied to define optimal operating rules with good results (Celeste & Billib, 2009; Chang & Chang, 2001; Coerver, Rutten, & van de Giesen, 2018; Mousavi et al., 2007).

Bayesian networks

Despite being little used in reservoir optimal operating rules, Bayesian networks (BNs) have been widely applied in environmental modeling for decision-making under uncertainty (Castelletti & Soncini-Sessa, 2007a; Keshtkar, Salajegheh, Sadoddin, & Allan, 2013; Uusitalo, 2007). A BN has two components: a graphical representation of the logical relationships among variables, based on nodes and links, and a probabilistic model of conditional probabilities attached to each link (Castelletti & Soncini-Sessa, 2007b). Input values enter the network in the root nodes and follow the links between nodes until they find leaf nodes, whose values are the outputs. The distinctive features of BNs are that output values are given as probability distribution functions with inputs as single values (certain) or probability distributions (uncertain) (Castelletti & Soncini-Sessa, 2007b). Output probability functions can provide supporting information to decision-makers (Castelletti & Soncini-Sessa, 2007b), or single values and/or intervals can be picked from them using statistical moments or percentiles (e.g., Malekmohammadi et al., 2009 used the expected value).

BNs can be better understood by nonexperts on the method, using their explicit graphical representation. They are efficient in mapping complex relationships while taking into account uncertainty (Malekmohammadi et al., 2009). However, they cannot model multicomponent systems (like water resources systems) unless each component is expressed in a compatible way. Another important limitation is the difficulty to address dynamic processes, since nontransient treatments of the cause–effect relationships are assumed. Although dynamic BNs have been used for water resource system management (e.g., Molina, Pulido-Velázquez, García-Aróstegui, & Pulido-Velázquez, 2013; Ropero, Flores, Rumi, & Aguilera, 2017), they are mainly suitable for a nontransient treatment of cause and effect. BNs have been compared with regression procedures to reproduce optimal operating rules, showing better results (Malekmohammadi et al., 2009); as well to decision trees (Sherafatpour, Roozbahani, & Hasani, 2019).

Fuzzy rule-based systems

This procedure maps input to output variables using fuzzy set theory and fuzzy logic (Mamdani, 1974; Zadeh, 1965). A fuzzy rule-based system consists of a set of logical rules expressed using IF-THEN statements (fuzzy rules), using fuzzy numbers and fuzzy operators (Sen, 2010;

Shrestha, Duckstein, & Stakhiv, 1996). The mapping process is known as fuzzy inference procedure. Main advantages of fuzzy systems are its efficiency in input–output mapping and its ability to mathematically express linguistic concepts and thus to combine numerical data with expert judgment (Pedrycz, Ekel, & Parreiras, 2011; Sen, 2010; Simonovic, 2009). However, its concepts and quantifications may be perceived as "strange" in comparison with classical statistical approaches due to its different approach to uncertainty (Sen, 2010). Complex FRB systems may become cumbersome due to an excessive number of rules (Sen, 2010).

Fuzzy logic has been applied in combination with deterministic (Mousavi, Ponnambalam, & Karray, 2005; Senthil Kumar et al., 2013) and stochastic optimization algorithms (Macian-Sorribes, 2017; Panigrahi & Mujumdar, 2000; Russell & Campbell, 1996). Several studies have found fuzzy logic to be superior to interpolation (Moeini, Afshar, & Afshar, 2011; Russell & Campbell, 1996) and regression (Mousavi et al., 2005). It has also been compared with other heuristic procedures such as ANNs and decision trees showing better performance (Senthil Kumar et al., 2013).

Decision trees

Decision trees (e.g., Quinlan, 1986, 1993) develop operating rules by classifying input variables through "if-then" rules sequentially applied (Bessler et al., 2003). They adopt a graphical representation consisting of arcs and nodes. Nodes can be decision nodes with an "if-then" rule associated; or leaf nodes with an outcome (Bessler et al., 2003; Quinlan, 1986). To determine the operating decision to be made we start at the root node of the tree, evaluate its "if-then" rule, and move to the next node through the arc corresponding to the answer given. The process is repeated until a leaf node is reached. Decision trees can be built using data mining algorithms such as ID3 (Quinlan, 1986); C4.5 and its successor C5.0 (Quinlan, 1993); random forest (Breiman, 2001); and CART (Breiman, Friedman, Olshen, & Stone, 1984). Although the decision trees approach shares features with FRB systems (if-then rules) and BNs (graphical representation), the way information is treated and results are presented differs. Decision trees are combined with data mining to ensure an efficient choice of variables and tree structure.

Main advantages of decision trees are conceptual simplicity, large data sets handling and the possibility to complement them with expert knowledge (Bessler et al., 2003; Wei & Hsu, 2008). Main drawbacks are the possibility of overfitting, which would require to apply pruning methods to reduce the size of the tree (Bessler et al., 2003); and inefficiency in handling interdependencies among variables (Wei & Hsu, 2008). They are efficient approaches to infer optimal operating rules (Bessler et al., 2003; Senthil Kumar et al., 2013; Wei & Hsu, 2008; Yang et al., 2016). Their performance has been found to be superior to regression (Bessler et al., 2003); and similar to ANNs (Senthil Kumar et al., 2013) and BNs (Sherafatpour et al., 2019). They have also been used to forecast future inflows to be used by optimization algorithms (Castelletti et al., 2010; Chazarra et al., 2016; Côté & Leconte, 2015; Ficchì et al., 2015; Housh, Ostfeld, & Shamir, 2013).

Discussion

Each of the three families of methods described has its own advantages and limitations, depending on the context and the conditions of the applied problem. Direct optimization outperforms methods based on operating rules (Celeste & Billib, 2009; Dariane & Momtahen, 2009; Galelli et al., 2014; Lee & Labadie, 2007). However, this performance requires reliable forecasting for deriving optimal decisions (e.g., Ficchì et al., 2015; Raso et al., 2014). Direct optimization also assumes perfect cooperation in system operation, for which the results represent an upper bound of what could be achieved. Comparisons between a priori functional forms and rule inference from optimization results show no agreement on which one performs better. Celeste and Billib (2009) obtained better performance with the rule inference in the application to a single reservoir case. Dariane and Momtahen (2009) and Ostadrahimi et al. (2012) found the opposite for three-reservoir system case studies. The performance of the method to define the reservoir operating policy depends on issues like the system configuration, the operating goals, the system hydrology, and so forth.

The selection of the approach to define system operating rules should consider management goals and regulatory frameworks. Table 9 shows some suggestions on method depending on conditions. Direct optimization for real-time operation is preferable for well-defined problems with clear and measurable operating goals and performance indicators, in which an adequate forecast exists to support practical application, and in which real-time decisions depending on these results can be effectively made (e.g., Caseri et al., 2016; Ficchì et al., 2015; Galelli et al., 2014; Raso et al., 2014). In cases in which these premises hold, direct optimization of operations would be the best alternative, since its performance is superior to the others. However, most water systems do not fulfill all requirements to apply it. If realtime optimization-based operation is not suitable, a key question is what rule form is the best to choose. For that purpose, one should examine the existing regulatory framework, interact with stakeholders and operators, and examine available data records on operating decisions. If a rule form can be identified, an a priori functional form framework with this rule form is a promising alternative. If not, a desirable alternative is rule inference. Furthermore, a priori functional forms, in particular EMODPS, are promising alternatives if the operating goals are multiple and cannot be combined into a single objective. If expert knowledge is a key driver in decision-making it may be adequate to use rule inference from optimization results, more specifically heuristic rule forms able to include expert knowledge within its formulation (Bessler et al., 2003; Macian-Sorribes, 2017; Russell & Campbell, 1996; Wei & Hsu, 2008). For example, Macian-Sorribes et al. (2017) present development of optimal operating rules for the Jucar River basin (Eastern Spain) combining optimal results from stochastic programming with the expert knowledge of system operators from the Jucar River Basin Authority.

Table 9. Suggested approaches for optimal operating rule definition depending on system features

System condition			**Approach suggested for definition of optimal operating rule**	
Management goals	**Regulatory framework**	**Example cases**	**Method suggested**	**Examples of application**
Single and measurable goal, or aggregation of multiple goals into one	Flexible (no bounded rule form)	Single purpose water systems operated for economic profit (e.g., hydropower), or short-term operation for flood control	Direct optimization of operations (if adequate forecasts are available)	Galelli et al. (2014), Lee and Labadie (2007), Raso et al. (2014), Tilmant and Kelman (2007)
			Rule inference from optimization results (absent or unreliable forecasts)	Cancelliere et al. (2002), Celeste and Billib (2009), Lund and Ferreira (1996), Mousavi et al. (2005), Russell and Campbell (1996)
	Strong (rule form bounded by law or decisionmakers)	Multipurpose water systems with only commercial activities (e.g., agriculture and hydropower)	A priori functional form (with the selected rule form introduced)	Fallah-Mehdipour et al. (2012), Koutsoyiannis and Economou (2003), Lerma et al. (2013, 2015)
Multiple and measurable goals that cannot be aggregated	Flexible	Multipurpose systems combining commercial and nonprofit water uses (e.g., urban, agriculture and environment) with a centralized management	Direct optimization of operations (with heuristic optimization algorithms)	Bozorg-Haddad et al. (2014), Kumar and Reddy (2007), Maier et al. (2014), Reed et al. (2013), Teegavarapu and Simonovic (2002)
	Strong	Multipurpose systems combining commercial and nonprofit water uses (e.g., urban, agriculture and hydropower) with well-developed governance structures and precise operating rules	A priori functional form (with the selected rule form introduced)	Ahmadi et al. (2014), Giuliani et al. (2014), Giuliani, Castelletti et al. (2016), Kim et al. (2008), Oliveira and Loucks (1997), Salazar et al. (2016)

System condition			**Approach suggested for definition of optimal operating rule**	
Management goals	**Regulatory framework**	**Example cases**	**Method suggested**	**Examples of application**
Single or multiple nonmeasurable goals, or goals set by expert judgment	Flexible (but with complex governance)	Water systems without precise operating rules, in which decisions are made based on knowledge of operators and stakeholders	Water systems without precise operating rules, in which decisions are made based on knowledge of operators and stakeholders	Bessler et al. (2003), Macian-Sorribes et al. (2017), Panigrahi and Mujumdar (2000), Wei and Hsu (2008)

One critical issue in the management of water resource systems is how to deal with uncertainty. The degree of uncertainty associated with each case study may condition the choice of method (Dobson, Wagener, & Pianosi, 2019) and, conversely, each method implements and/or admits certain uncertainty analyses (e.g., BNs offer probabilistic outputs). A review of optimization algorithms with a focus on uncertainty was provided by Sahinidis (2004), dealing in particular with stochastic and fuzzy optimization algorithms. Dobson et al. (2019) present a classification of optimization methods based on how they handle uncertainty. The most likely influential source of uncertainty is hydrology. Sorted by growing uncertainty levels, in line with Dobson et al. (2019), the main approaches for integrating inflow uncertainty in the optimization algorithms are: (a) capturing the stochastic nature of inflows through a large set of inflow time series (ISO and derived operating rules); (b) characterizing inflows using probability distributions (ESO and operating rules derived); and (c) employing dynamically updated inflow forecasts (MPC). Alternative methods for dealing with inflow uncertainty include fuzzy set theory and logic (e.g., Mousavi, Karamouz, & Menhadj, 2004; Mousavi, Mahdizadeh, & Afshar, 2004; Nguyen & Novák, 2018; Sen, 2010), BNs (e.g., Kim & Palmer, 1997; Mujumdar & Nirmala, 2007), copula functions (Lei et al., 2018), and interval numbers (Luo, Maqsood, & Huang, 2007).

Besides hydrological uncertainty, there is uncertainty in the definition of demands (urban, agriculture, etc.), infrastructure features (reservoir capacity, dead storage, etc.), and even in the system configuration (future reservoirs, future demands, evolving legal frameworks, quality standards, etc.). The most widely used method to deal with those uncertainties consists in defining alternative scenarios for the uncertain variables and analyzing changes in system operation (Culley et al., 2016; Giuliani, Li, et al., 2016; Haguma & Leconte, 2018; Herman & Giuliani, 2018; Mateus & Tullos, 2016; Zhou & Guo, 2013). Alternative approaches expand the methods previously indicated to include additional uncertainty sources. These can be divided into: (a) using probability distributions to characterize uncertain variables (e.g., Biglarbeigi, Giuliani, & Castelletti, 2018; Kong et al., 2018; Qin & Boccelli, 2019; Sheibani, Alizadeh, & Shourian, 2019; Soleimani, Bozorg-Haddad, & Loáiciga, 2016); and (b) forecasting uncertain variables, for example water demands (e.g., Fazlali & Shourian, 2018; He et al., 2018; Li, Giuliani, & Castelletti, 2017; Zubaidi, Gharghan, Dooley, Alkhaddar, & Abdellatif, 2018). The impact of uncertainties in the operating rules can be analyzed using uncertainty and sensitivity analysis (Quinn, Reed, Giuliani, & Castelletti, 2019). In case of deep uncertainty, optimization algorithms could be replaced by uncertainty-driven procedures such as robust optimization (Ben-Tal, El Ghaoui, & Nemirovski, 2009; Fu, Li, Cui, Liu, & Lu, 2018; Hadka, Herman, Reed, & Keller, 2015; Kasprzyk et al., 2013; Kwakkel, Haasnoot, & Walker, 2016; Maier et al., 2016; Matrosov, Padula, & Harou, 2013; Roach, Kapelan, Ledbetter, & Ledbetter, 2016).

Another challenge in the definition of optimal operation strategies regards to adapting their time scales (from real-time to long-term) to operating needs. On a broader view, hydropower, flood protection, and urban uses would benefit from flexible operation at finer time scales (from real-time to daily time steps); agriculture would benefit from operative decisions made months in advance and maintained during the irrigation season (from weekly to monthly time steps); while river basin administrations need also to consider larger time periods (several years or decades) to foresee, design and develop programs of measures to adapt to climate and socioeconomic changes. Approaches relying on MPC are the most efficient to derive operation decisions at finer time scales (Galelli et al., 2014; Pianosi & Soncini-Sessa, 2009); while a priori approaches or rule inference provide stable conditional operating rules that better suit water systems with multiple competing users and complex decision-making processes (Labadie, 2004; Lund et al., 2017; Oliveira & Loucks, 1997). Methodological approaches to combine real-time (short-term) and long-term operation goals have been developed in the literature including: (a) prescribing final state boundary conditions and constraints to MPC (e.g., Becker & Yeh, 1974; Sreekanth et al., 2012); (b) using cost or benefit functions associated to the terminal system state of MPC, defined either by empirical experimentation or by optimization models working at larger time scales (e.g., Côté & Leconte, 2015; Faber & Stedinger, 2001; Ficchì et al., 2015; Kelman et al., 1990); and (c) employing variable time steps (e.g., Raso & Malaterre, 2017).

Most real-life applications of reservoir optimization are for hydropower systems, with a single and easily measurable goal (maximize economic profit), a fully coordinated operation and concerns on inflow uncertainty, features in line with the characteristics of optimization algorithms (Lund et al., 2017). Other real-life applications are challenged by the large number of variables, competing goals and alternatives existing in water resource systems operation. The gap between theory and practice has been distinctly narrowed with the use of DSS, stakeholder involvement, and combination between simulation and optimization algorithms (Loucks, 2017). Successful real-life applications of optimization algorithms require close communication between researchers and decision-makers, adequate framing of optimization algorithms and optimal operating rules into the wider concept of decision-making processes and advancing in developing decision support tools (Maier et al., 2014).

Conclusion

The most common challenge for optimal operation of water resource systems in multireservoir river basins regards governance and management complexity. Raising awareness and research on the nexus between water, energy, food, climate, and environment will keep adding stakeholders and conflicting objectives to water resource system operations. Moreover, nonstationarity of resources and demands due to population growth, increasing living standards, and climate change may require expanding operational integration to include surface and ground water, reuse, desalination, water transfers, rainwater harvesting, and demand management. The need to combine efficiently this increasing number of alternatives to satisfy growing demands will boost the necessity of optimal operating rules as well as improved governance to balance operation efficiency with equity, stakeholder preferences, and so forth. This will be particularly true in water systems with distinct impacts from climate and global change, which will offer the best opportunities to apply optimal operating rules. The need for improved governance structures to support the adoption of optimal operating rules will demand an active involvement of stakeholders and system operators in the codevelopment of optimal operating rules. The need to efficiently address a growing number of operational goals will favor the use of multiobjective optimization in which multiobjective heuristic algorithms, such as MOEAS, appear as a prominent area of future research. Promising methodological alternatives to build optimal operating rules in response to the highlighted challenges would be: (a) a priori PSO with heuristic multiobjective optimization (EMODPS) representing operating rules by RBF, ANNs, or FRB systems; and (b) rule inference from heuristic multiobjective optimization with heuristic rules. In both cases, stakeholder involvement will be needed to choose their preferred option considering trade-offs among objectives.

A key issue within this challenge is the nonstationarity of supply and demand, boosted by climate change and a quick global change in general (Cosgrove & Loucks, 2015), which will add distinct uncertainties to the definition of optimal operating rules. To adequately deal with this issue, operating rules should switch from being efficient against single/few future scenarios to be robust against a wide range of possible alternatives. This may be achieved by combining a priori or implicit approaches with robust optimization (e.g., Herman, Reed, Zeff, & Characklis, 2015; Kasprzyk et al., 2013; Lempert & Collins, 2007) or with decision scaling (e.g., Brown, Ghile, Laverty, & Li, 2012). Under this increasing uncertainty, each optimal operating rule would have an applicability range, which should be considered when choosing between alternatives. An alternative approach that would efficiently deal with nonstationarities while outperforming the use of operating rules would be to resort to MPC with forecasting. The continuous advance in forecasting systems, tools, and skill may improve the performance of MPC optimization models and expand its applicability. However, this will require distinct efforts to build trust in MPC and forecasting systems, as well as to achieve a fully coordinated operation. Furthermore, it will require forecasting systems skilful enough, as well as researchers adequately trained to acquire and integrate forecasting services with MPC models. Researchers should be ready to spot and exploit such opportunities of MPC implementation. Anyway, water resource system models relying on operating rules and/or MPC would need to constantly update their features to adapt to the dynamic evolution of water resource systems, including if necessary additional sources of information (e.g., climate change scenarios, population change, macro-economic indicators, farming decisions), and their performance would need to be constantly monitored with feedback from observations through a “learning by doing” process.

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The authors have declared no conflicts of interest for this article.

Author contributions

Hector Macian-Sorribes: Investigation; methodology; resources; supervision; writing-original draft; and writing-review and editing. Manuel Pulido-Velazquez: Investigation; methodology; resources; supervision; writing-original draft; and writing-review and editing.

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References

Aboutalebi, M., Bozorg-Haddad, O., & Loáiciga, H. A. (2015). Optimal monthly reservoir operation rules for hydropower generation derived with SVR-NSGAII. Journal of Water Resources Planning and Management, 141, 04015029. https://doi.org/10.1061/(ASCE)WR.1943-5452. 0000553

Ahmad, A., El-Shafie, A., Razali, S. F. M., & Mohamad, Z. S. (2014). Reservoir optimization in water resources: A review. Water Resources Management, 28, 3391–3405. https://doi.org/10.1007/s11269-014-0700-5

Ahmadi, M., Bozorg Haddad, O., & Mariño, M. A. (2014). Extraction of flexible multi-objective real-time reservoir operation rules. Water Resources Management, 28, 131–147. https://doi.org/10.1007/s11269-013-0476-z

Ahmadi Najl, A., Haghighi, A., & Vali Samani, H. (2016). Simultaneous optimization of operating rules and rule curves for multireservoir systems using a self-adaptive simulation-GA model. Journal of Water Resources Planning and Management, 4016041. https://doi.org/10. 1061/(ASCE)WR.1943-5452.0000688

Andreu, J., Capilla, J., & Sanchís, E. (1996). AQUATOOL, a generalized decision-support system for water-resources planning and operational management. Journal of Hydrology, 177, 269–291. https://doi.org/10.1016/0022-1694(95)02963-X

Andreu, J., & Sahuquillo, A. (1987). Efficient aquifer simulation in complex systems. Journal of Water Resources Planning and Management, 113, 110–129. https://doi.org/10.1061/(ASCE)0733-9496(1987)113:1(110)

Ashbolt, S., Maheepala, S., & Perera, B. (2016). Using multiobjective optimization to find optimal operating rules for short-term planning of water grids. Journal of Water Resources Planning and Management, 142, 4016033. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000675

Ashbolt, S. C., & Perera, B. J. C. (2018). Multiobjective optimization of seasonal operating rules for water grids using streamflow forecast information. Journal of Water Resources Planning and Management, 144, 5018003. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000902

Azari, A., Hamzeh, S., & Naderi, S. (2018). Multi-objective optimization of the reservoir system operation by using the hedging policy. Water Resources Management, 32, 2061–2078. https://doi.org/10.1007/s11269-018-1917-5

Becker, L., & Yeh, W. W.-G. (1974). Optimization of real time operation of a multiple-reservoir system. Water Resources Research, 10, 1107–1112. https://doi.org/10.1029/WR010i006p01107

Bellman, R. E. (1957). Dynamic programming (1st ed.). Princeton, NJ: Princeton University Press.

Bellman, R. E., & Dreyfus, S. E. (1962). Applied dynamic programming (1st ed.). Princeton, NJ: Princeton University Press. Ben-Tal, A., El Ghaoui, L., & Nemirovski, A. (2009). Robust optimization. Princeton, NJ: Princeton University Press.

Bessler, F., Savic, D., & Walters, G. (2003). Water reservoir control with data mining. Journal of Water Resources Planning and Management, 129, 26–34. https://doi.org/10.1061/(ASCE)0733-9496(2003)129:1(26)

Bhaskar, N. R., & Whitlatch, E. E. (1980). Derivation of monthly reservoir release policies. Water Resources Research, 16, 987–993. https://doi.org/10.1029/WR016i006p00987

Bianucci, P., Sordo-Ward, A, , Moralo, J., & Garrote, L. (2015). Probabilistic-multiobjective comparison of user-defined operating rules. Case study: Hydropower dam in Spain. Water, 7, 956–974. https://doi.org/10.3390/w7030956

Biglarbeigi, P., Giuliani, M., & Castelletti, A. (2018). Partitioning the impacts of streamflow and evaporation uncertainty on the operations of multipurpose reservoirs in arid regions. Journal of Water Resources Planning and Management, 144, 5018008. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000945

Bolouri-Yazdeli, Y., Bozorg Haddad, O., Fallah-Mehdipour, E., & Mariño, M. A. (2014). Evaluation of real-time operation rules in reservoir systems operation. Water Resources Management, 28, 715–729. https://doi.org/10.1007/s11269-013-0510-1

Borgomeo, E., Mortazavi-Naeini, M., Hall, J. W., O'Sullivan, M. J., & Watson, T. (2016). Trading-off tolerable risk with climate change adaptation costs in water supply systems. Water Resources Research, 52, 622–643. https://doi.org/10.1002/2015WR018164

Bozorg-Haddad, O., Azarnivand, A., Hosseini-Moghari, S.-M., & Loáiciga, H. A. (2017). WASPAS application and evolutionary algorithm benchmarking in optimal reservoir optimization problems. Journal of Water Resources Planning and Management, 143, 04016070. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000716

Bozorg-Haddad, O., Karimirad, I., Seifollahi-Aghmiuni, S., & Loáiciga, H. A. (2014). Development and application of the bat algorithm for optimizing the operation of reservoir systems. Journal of Water Resources Planning and Management, 141, 4014097. https://doi.org/10. 1061/(ASCE)WR.1943-5452.0000498

Breiman, L. (2001). Random forests. Machine Learning, 45, 5–32. https://doi.org/10.1023/A:1010933404324

Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (1984). Classification and regression trees. Belmont, CA: Wadsworth.

Brown, C., Ghile, Y., Laverty, M., & Li, K. (2012). Decision scaling: Linking bottom-up vulnerability analysis with climate projections in the water sector. Water Resources Research, 48. https://doi.org/10.1029/2011WR011212

Brown, C. M., Lund, J. R., Cai, X., Reed, P. M., Zagona, E. A., Ostfeld, A., … Brekke, L. (2015). The future of water resources systems analysis: Toward a scientific framework for sustainable water management. Water Resources Research, 51, 6110–6124. https://doi.org/10.1002/ 2015WR017114

Cai, X., McKinney, D. C., & Lasdon, L. S. (2001). Piece-by-piece approach to solving large nonlinear water resources management models. Journal of Water Resources Planning and Management, 127, 363–368. https://doi.org/10.1061/(ASCE)0733-9496(2001)127:6(363)

Cai, X., Vogel, R., & Ranjithan, R. (2012). Special issue on the role of systems analysis in watershed management. Journal of Water Resources Planning and Management, 139, 461–463. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000341

Cancelliere, A., Giuliano, G., Ancarani, A., & Rossi, G. (2002). A neural networks approach for deriving irrigation reservoir operating rules. Water Resources Management, 16, 71–88. https://doi.org/10.1023/A:1015563820136

Caseri, A., Javelle, P., Ramos, M. H., & Leblois, E. (2016). Generating precipitation ensembles for flood alert and risk management. Journal of Flood Risk Management, 9, 402–415. https://doi.org/10.1111/jfr3.12203

Castelletti, A., Galelli, S., Restelli, M., & Soncini-Sessa, R. (2010). Tree-based reinforcement learning for optimal water reservoir operation. Water Resources Research, 46. https://doi.org/10.1029/2009WR008898

Castelletti, A., Pianosi, F., & Restelli, M. (2013). A multiobjective reinforcement learning approach to water resources systems operation: Pareto frontier approximation in a single run. Water Resources Research, 49, 3476–3486. https://doi.org/10.1002/wrcr.20295

Castelletti, A., Pianosi, F., & Soncini-Sessa, R. (2008). Water reservoir control under economic, social and environmental constraints. Automatica, 44, 1595–1607. https://doi.org/10.1016/j.automatica.2008.03.003

Castelletti, A., & Soncini-Sessa, R. (2007a). Bayesian networks in water resource modelling and management. Environmental Modelling and Software, 22, 1073–1074. https://doi.org/10.1016/j.envsoft.2006.06.001

Castelletti, A., & Soncini-Sessa, R. (2007b). Bayesian networks and participatory modelling in water resource management. Environmental Modelling and Software, 22, 1075–1088. https://doi.org/10.1016/j.envsoft.2006.06.003

Celeste, A. B., & Billib, M. (2009). Evaluation of stochastic reservoir operation optimization models. Advances in Water Resources, 32, 1429–1443. https://doi.org/10.1016/j.advwatres.2009.06.008

Celeste, A. B., Curi, W. F., & Curi, R. C. (2009). Implicit stochastic optimization for deriving reservoir operating rules in semiarid Brazil. Pesquisa Operacional, 29, 223–234. https://doi.org/10.1590/S0101-74382009000100011

Chandramouli, V., & Raman, H. (2001). Multireservoir modeling with dynamic programming and neural networks. Journal of Water Resources Planning and Management, 127, 89–98. https://doi.org/10.1061/(ASCE)0733-9496(2001)127:2(89)

Chang, L. C., & Chang, F. J. (2001). Intelligent control for modelling or real-time reservoir operation. Hydrological Processes, 15, 1621–1634.https://doi.org/10.1002/hyp.226

Chazarra, M., Garcia-Gonzalez, J., Perez-Diaz, J. I., & Arteseros, M. (2016). Stochastic optimization model for the weekly scheduling of a hydropower system in day-ahead and secondary regulation reserve markets. Electric Power Systems Research, 130, 67–77. https://doi.org/10.1016/j.epsr.2015.08.014

Chen, D., Leon, A. S., Fuentes, C., Gibson, N. L., & Qin, H. (2018). Incorporating filters in random search algorithms for the hourly operation of a multireservoir system. Journal of Water Resources Planning and Management, 144, 4017088. https://doi.org/10.1061/(ASCE)WR. 1943-5452.0000876

Coerver, H. M., Rutten, M. M., & van de Giesen, N. C. (2018). Deduction of reservoir operating rules for application in global hydrological models. Hydrology and Earth System Sciences, 22, 831–851. https://doi.org/10.5194/hess-22-831-2018

Cosgrove, W. J., & Loucks, D. P. (2015). Water management: Current and future challenges and research directions. Water Resources Research, 51, 4823–4839. https://doi.org/10.1002/2014WR016869

Côté, P., & Arsenault, R. (2019). Efficient implementation of sampling stochastic dynamic programming algorithm for multireservoir management in the hydropower sector. Journal of Water Resources Planning and Management, 145, 5019005. https://doi.org/10.1061/(ASCE) WR.1943-5452.0001050

Côté, P., & Leconte, R. (2015). Comparison of stochastic optimization algorithms for hydropower reservoir operation with ensemble streamflow prediction. Journal of Water Resources Planning and Management, 142, 4015046. https://doi.org/10.1061/(ASCE)WR.19435452.0000575

Cui, L., & Kuczera, G. (2005). Optimizing water supply headworks operating rules under stochastic inputs: Assessment of genetic algorithm performance. Water Resources Research, 41. https://doi.org/10.1029/2004WR003517

Culley, S., Noble, S., Yates, A., Timbs, M., Westra, S., Maier, H. R., … Castelletti, A. (2016). A bottom-up approach to identifying the maximum operational adaptive capacity of water resource systems to a changing climate. Water Resources Research, 52, 6751–6768. https://doi.org/10.1002/2015WR018253

Cunha, M. C., & Antunes, A. (2012). Simulated annealing algorithms for water systems optimization. In K. L. Katsifarakis (Ed.), Hydrology, hydraulics and water resources management: A heuristic optimization approach (p. 160). Southampton, MA: WIT Press.

Dariane, A. B., & Momtahen, S. (2009). Optimization of multireservoir systems operation using modified direct search genetic algorithm. Journal of Water Resources Planning and Management, 135, 141–148. https://doi.org/10.1061/(ASCE)0733-9496(2009)135:3(141)

Das, B., Singh, A., Panda, S. N., & Yasuda, H. (2015). Optimal land and water resources allocation policies for sustainable irrigated agriculture. Land Use Policy, 42, 527–537. https://doi.org/10.1016/j.landusepol.2014.09.012

Davidsen, C., Liu, S., Mo, X., Rosbjerg, D., & Bauer Gottwein, P. (2016). The cost of ending groundwater overdraft on the North China Plain. Hydrology and Earth System Sciences, 20, 771–785. https://doi.org/10.5194/hess-20-771-2016

Davidsen, C., Pereira-cardenal, S. J., Liu, S., Mo, X., Rosbjerg, D., & Bauer-gottwein, P. (2014). Using stochastic dynamic programming to support water resources management in the Ziya River Basin, China. Journal of Water Resources Planning and Management, 141, 04014086. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000482

Desreumaux, Q., Côté, P., & Leconte, R. (2018). Comparing model-based and model-free streamflow simulation approaches to improve hydropower reservoir operations. Journal of Water Resources Planning and Management, 144, 5018002. https://doi.org/10.1061/(ASCE) WR.1943-5452.0000860

Dobson, B., Wagener, T., & Pianosi, F. (2019). An argument-driven classification and comparison of reservoir operation optimization methods. Advances in Water Resources, 128, 74–86. https://doi.org/10.1016/J.ADVWATRES.2019.04.012

Draper, A. J., & Lund, J. R. (2004). Optimal hedging and carryover storage value. Journal of Water Resources Planning and Management, 130, 83–87. https://doi.org/10.1061/(ASCE)0733-9496(2004)130:1(83)

Ehteram, M., Karami, H., & Farzin, S. (2018a). Reducing irrigation deficiencies based optimizing model for multi-reservoir systems utilizing spider monkey algorithm. Water Resources Management, 32, 2315–2334. https://doi.org/10.1007/s11269-018-1931-7

Ehteram, M., Karami, H., & Farzin, S. (2018b). Reservoir optimization for energy production using a new evolutionary algorithm based on multi-criteria decision-making models. Water Resources Management, 32, 2539–2560. https://doi.org/10.1007/s11269-018-1945-1

Eisel, L. M. (1972). Chance constrained reservoir model. Water Resources Research, 8, 339–347. https://doi.org/10.1029/WR008i002p00339

European Commission (2007). Communication from the Commission to the European Parliament and the Council: Addressing the challenge of water scarcity and droughts in the European Union, COM(2007) 414 final. Brussels, Belgium.

European Commission. (2012a). Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions: A Blueprint to Safeguard Europe's Water Resources, COM(2012) 673 final. Brussels, Belgium.

European Commission. (2012b). Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions: Report on the Review of the European Water Scarcity and Droughts Policy, COM(2012) 672 final. Brussels, Belgium.

Faber, B. A., & Stedinger, J. R. (2001). Reservoir optimization using sampling SDP with ensemble streamflow prediction (ESP) forecasts. Journal of Hydrology, 249, 113–133. https://doi.org/10.1016/S0022-1694(01)00419-X

Fallah-Mehdipour, E., Bozorg Haddad, O., & Mariño, M. A. (2012). Real-time operation of reservoir system by genetic programming. Water Resources Management, 26, 4091–4103. https://doi.org/10.1007/s11269-012-0132-z

Fazlali, A., & Shourian, M. (2018). A demand management based crop and irrigation planning using the simulation-optimization approach. Water Resources Management, 32, 67–81. https://doi.org/10.1007/s11269-017-1791-6

Ficchì, A., Raso, L., Dorchies, D., Pianosi, F., Malaterre, P., Van Overloop, P., & Jay-Allemand, M. (2015). Optimal operation of the multireservoir system in the Seine River basin using deterministic and ensemble forecasts. Journal of Water Resources Planning and Management, 142, 5015005. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000571

Fu, Q., Li, T., Cui, S., Liu, D., & Lu, X. (2018). Agricultural multi-water source allocation model based on interval two-stage stochastic robust programming under uncertainty. Water Resources Management, 32, 1261–1274. https://doi.org/10.1007/s11269-017-1868-2

Galelli, S., Goedbloed, A., Schwanenberg, D., & van Overloop, P.-J. (2014). Optimal real-time operation of multipurpose urban reservoirs: Case study in Singapore. Journal of Water Resources Planning and Management, 140, 511–523. https://doi.org/10.1061/(ASCE)WR.19435452.0000342

Giuliani, M., Castelletti, A., Pianosi, F., Mason, E., & Reed, P. M. (2016). Curses, tradeoffs, and scalable management: Advancing evolutionary multiobjective direct policy search to improve water reservoir operations. Journal of Water Resources Planning and Management, 142, 4015050. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000570

Giuliani, M., Herman, J. D., Castelletti, A., & Reed, P. M. (2014). Many-objective reservoir policy identification and refinement to reduce policy inertia and myopia in water management. Water Resources Research, 50, 3355–3377. https://doi.org/10.1002/2013WR014700

Giuliani, M., Li, Y., Castelletti, A., & Gandolfi, C. (2016). A coupled human-natural systems analysis of irrigated agriculture under changing climate. Water Resources Research, 52, 6928–6947. https://doi.org/10.1002/2016WR019363

Giuliani, M., Quinn, J. D., Herman, J. D., Castelletti, A., & Reed, P. M. (2018). Scalable multiobjective control for large-scale water resources systems under uncertainty. IEEE Transactions on Control Systems Technology, 26, 1492–1499. https://doi.org/10.1109/TCST.2017. 2705162

Goor, Q. (2010). Optimal operation of multiple reservoirs in hydropower-irrigation systems. Université Catholique de Louvain.

Grüne, L., & Semmler, W. (2004). Using dynamic programming with adaptive grid scheme for optimal control problems in economics. Journal of Economic Dynamics and Control, 28, 2427–2456. https://doi.org/10.1016/j.jedc.2003.11.002

Guariso, G., Rinaldi, S., & Soncini-Sessa, R. (1986). The Management of Lake Como: A multiobjective analysis. Water Resources Research, 22, 109–120. https://doi.org/10.1029/WR022i002p00109

Gundelach, J., & ReVelle, C. (1975). Linear decision rule in reservoir management and design: 5. A general algorithm. Water Resources Research, 11, 204–207. https://doi.org/10.1029/WR011i002p00204

Guo, X., Hu, T., Zeng, X., & Li, X. (2013). Extension of parametric rule with the hedging rule for managing multireservoir system during droughts. Journal of Water Resources Planning and Management, 139, 139–148. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000241

Haddad, O. B., Afshar, A., & Mariño, M. A. (2006). Honey-bees mating optimization (HBMO) algorithm: A new heuristic approach for water resources optimization. Water Resources Management, 20, 661–680. https://doi.org/10.1007/s11269-005-9001-3

Hadka, D., Herman, J., Reed, P., & Keller, K. (2015). An open source framework for many-objective robust decision making. Environmental Modelling and Software, 74, 114–129. https://doi.org/10.1016/j.envsoft.2015.07.014

Haguma, D., & Leconte, R. (2018). Long-term planning of water systems in the context of climate non-stationarity with deterministic and stochastic optimization. Water Resources Management, 32, 1725–1739. https://doi.org/10.1007/s11269-017-1900-6

Haguma, D., Leconte, R., & Côté, P. (2018). Evaluating transition probabilities for a stochastic dynamic programming model used in water system optimization. Journal of Water Resources Planning and Management, 144, 4017090. https://doi.org/10.1061/(ASCE)WR.19435452.0000883

Hall, W. A., & Buras, N. (1961). The dynamic programming approach to water-resources development. Journal of Geophysical Research, 66, 517. https://doi.org/10.1029/JZ066i002p00517

Haro-Monteagudo, D., Solera, A., & Andreu, J. (2017). Drought early warning based on optimal risk forecasts in regulated river systems: Application to the Jucar River Basin (Spain). Journal of Hydrology, 544, 36–45. https://doi.org/10.1016/j.jhydrol.2016.11.022

He, Y., Yang, J., Chen, X., Lin, K., Zheng, Y., & Wang, Z. (2018). A two-stage approach to basin-scale water demand prediction. Water Resources Management, 32, 401–416. https://doi.org/10.1007/s11269-017-1816-1

Hejazi, M. I., & Cai, X. (2009). Input variable selection for water resources systems using a modified minimum redundancy maximum relevance (mMRMR) algorithm. Advances in Water Resources, 32, 582–593. https://doi.org/10.1016/j.advwatres.2009.01.009

Hejazi, M. I., & Cai, X. (2011). Building more realistic reservoir optimization models using data mining – A case study of Shelbyville reservoir. Advances in Water Resources, 34, 701–717. https://doi.org/10.1016/j.advwatres.2011.03.001

Herman, J., Reed, P. M., Zeff, H. B., & Characklis, G. W. (2015). How should robustness be defined for water systems planning under change? Journal of Water Resources Planning and Management, 141, 4015012. https://doi.org/10.1061/(ASCE)WR.1943-5452. 0000509

Herman, J. D., & Giuliani, M. (2018). Policy tree optimization for threshold-based water resources management over multiple timescales. Environmental Modelling and Software, 99, 39–51. https://doi.org/10.1016/J.ENVSOFT.2017.09.016

Houck, M. H. (1979). A chance constrained optimization model for reservoir design and operation. Water Resources Research, 15, 1011–1016. https://doi.org/10.1029/WR015i005p01011

Houck, M. H., Cohon, J. L., & ReVelle, C. (1980). Linear decision rule in reservoir design and management: 6. Incorporation of economic efficiency benefits and hydroelectric energy generation. Water Resources Research, 16, 196–200. https://doi.org/10.1029/ WR016i001p00196

Housh, M., Ostfeld, A., & Shamir, U. (2013). Limited multi-stage stochastic programming for managing water supply systems. Environmental Modelling and Software, 41, 53–64. https://doi.org/10.1016/j.envsoft.2012.11.006

Hu, T., Mao, J., Tian, M., Dai, H., & Rong, G. (2018). New constraint-handling technique for evolutionary optimization of reservoir operation. Journal of Water Resources Planning and Management, 144, 4017097. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000891

Huang, C., Zhao, J., Wang, Z., & Shang, W. (2016). Optimal hedging rules for two-objective reservoir operation: Balancing water supply and environmental flow. Journal of Water Resources Planning and Management, 142, 4016053. https://doi.org/10.1061/(ASCE)WR.1943-5452. 0000699

Hui, R., Lund, J., Zhao, J., & Zhao, T. (2016). Optimal pre-storm flood hedging releases for a single reservoir. Water Resources Management, 30, 5113–5129. https://doi.org/10.1007/s11269-016-1472-x

Jacoby, H. D., & Loucks, D. P. (1972). Combined use of optimization and simulation models in river basin planning. Water Resources Research, 8, 1401–1414. https://doi.org/10.1029/WR008i006p01401

Jain, S. K., & Singh, V. P. (2003). Developments in water science. Amsterdam, The Netherlands: Elsevier Science B.V.

Jenkins, M. W., Lund, J. R., Howitt, R. E., Draper, A. J., Msangi, S. M., Tanaka, S. K., … Marques, G. F. (2004). Optimization of California's water supply system: Results and insights. Journal of Water Resources Planning and Management, 130, 271–280. https://doi.org/10.1061/(ASCE)0733-9496(2004)130:4(271)

Ji, C., Zhou, T., & Huang, H. (2014). Operating rules derivation of Jinsha reservoirs system with parameter calibrated support vector regression. Water Resources Management, 28, 2435–2451. https://doi.org/10.1007/s11269-014-0610-6

Johnson, S. A., Stedinger, J. R., Shoemaker, C. A., Li, Y., & Tejada-Guibert, J. A. (1993). Numerical solution of continuous-state dynamic programs using linear and spline interpolation. Operations Research, 41, 484–500. https://doi.org/10.1287/opre.41.3.484

Johnson, S. A., Stedinger, J. R., & Staschus, K. (1991). Heuristic operating policies for reservoir system simulation. Water Resources Research, 27, 673–685. https://doi.org/10.1029/91WR00320

Karamouz, M., & Houck, M. H. (1982). Annual and monthly reservoir operating rules generated by deterministic optimization. Water Resources Research, 18, 1337–1344. https://doi.org/10.1029/WR018i005p01337

Karamouz, M., & Houck, M. H. (1987). Comparison of stochastic and deterministic dynamic programming for reservoir operating rule generation. Journal of the American Water Resources Association, 23, 1–9. https://doi.org/10.1111/j.1752-1688.1987.tb00778.x

Karamouz, M., Houck, M. H., & Delleur, J. W. (1992). Optimization and simulation of multiple reservoir systems. Journal of Water Resources Planning and Management, 118, 71–81. https://doi.org/10.1061/(ASCE)0733-9496(1992)118:1(71)

Karamouz, M., & Vasiliadis, H. V. (1992). Bayesian stochastic optimization of reservoir operation using uncertain forecasts. Water Resources Research, 28, 1221–1232. https://doi.org/10.1029/92WR00103

Kasprzyk, J. R., Nataraj, S., Reed, P. M., & Lempert, R. J. (2013). Many objective robust decision making for complex environmental systems undergoing change. Environmental Modelling and Software, 42, 55–71. https://doi.org/10.1016/j.envsoft.2012.12.007

Kelman, J., Stedinger, J. R., Cooper, L. A., Hsu, E., & Yuan, S.-Q. (1990). Sampling stochastic dynamic programming applied to reservoir operation. Water Resources Research, 26, 447–454. https://doi.org/10.1029/WR026i003p00447

Keshtkar, A. R., Salajegheh, A., Sadoddin, A., & Allan, M. G. (2013). Application of Bayesian networks for sustainability assessment in catchment modeling and management (Case study: The Hablehrood river catchment). Ecological Modelling, 268, 48–54. https://doi.org/10. 1016/j.ecolmodel.2013.08.003

Kim, T., Heo, J.-H., Bae, D.-H., & Kim, J.-H. (2008). Single-reservoir operating rules for a year using multiobjective genetic algorithm. Journal of Hydroinformatics, 10, 163–179. https://doi.org/10.2166/hydro.2008.019

Kim, Y., & Palmer, R. (1997). Value of seasonal flow forecasts in Bayesian stochastic programming. Journal of Water Resources Planning and Management, 123, 327–335. https://doi.org/10.1061/(Asce)0733-9496(1997)123:6(327)

Kong, X. M., Huang, G. H., Li, Y. P., Fan, Y. R., Zeng, X. T., & Zhu, Y. (2018). Inexact copula-based stochastic programming method for water resources management under multiple uncertainties. Journal of Water Resources Planning and Management, 144, 4018069. https:// doi.org/10.1061/(ASCE)WR.1943-5452.0000987

Koutsoyiannis, D., & Economou, A. (2003). Evaluation of the parameterization–simulation–optimization approach for the control of reservoir systems. Water Resources Research, 39. https://doi.org/10.1029/2003WR002148

Kumar, D. N., & Reddy, M. J. (2006). Ant Colony optimization for multi-purpose reservoir operation. Water Resources Management, 20, 879–898. https://doi.org/10.1007/s11269-005-9012-0

Kumar, D. N., & Reddy, M. J. (2007). Multipurpose reservoir operation using particle swarm optimization. Journal of Water Resources Planning and Management, 133, 192–201. https://doi.org/10.1061/(ASCE)0733-9496(2007)133:3(192)

Kumar, K., & Kasthurirengan, S. (2018). Generalized linear two-point hedging rule for water supply reservoir operation. Journal of Water Resources Planning and Management, 144, 4018051. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000964

Kwakkel, J. H., Haasnoot, M., & Walker, W. E. (2016). Comparing robust decision-making and dynamic adaptive policy pathways for model-based decision support under deep uncertainty. Environmental Modelling and Software, 86, 168–183. https://doi.org/10.1016/J. ENVSOFT.2016.09.017

Labadie, J. W. (2004). Optimal operation of multireservoir systems: State-of-the-art review. Journal of Water Resources Planning and Management, 130, 93–111. https://doi.org/10.1061/(ASCE)0733-9496(2004)130:2(93)

Labadie, J. W., Baldo, M., & Larson, R. (2000). MODSIM: Decision support system for river basin management. Documentation and user manual.

Lee, J. H., & Labadie, J. W. (2007). Stochastic optimization of multireservoir systems via reinforcement learning. Water Resources Research, 43. https://doi.org/10.1029/2006WR005627

Lei, X., Tan, Q., Wang, X., Wang, H., Wen, X., Wang, C., & Zhang, J. (2018). Stochastic optimal operation of reservoirs based on copula functions. Journal of Hydrology, 557, 265–275. https://doi.org/10.1016/J.JHYDROL.2017.12.038

Lempert, R. J., & Collins, M. T. (2007). Managing the risk of uncertain threshold responses: Comparison of robust, optimum, and precautionary approaches. Risk Analysis, 27, 1009–1026. https://doi.org/10.1111/j.1539-6924.2007.00940.x

Lerma, N., Paredes-Arquiola, J., Andreu, J., & Solera, A. (2013). Development of operating rules for a complex multi-reservoir system by coupling genetic algorithms and network optimization. Hydrological Sciences Journal, 58, 797–812. https://doi.org/10.1080/02626667.2013. 779777

Lerma, N., Paredes-Arquiola, J., Andreu, J., Solera, A., & Sechi, G. M. (2015). Assessment of evolutionary algorithms for optimal operating rules design in real water resource systems. Environmental Modelling and Software, 69, 425–436. https://doi.org/10.1016/j.envsoft.2014.09.024

Li, Y., Giuliani, M., & Castelletti, A. (2017). A coupled human–natural system to assess the operational value of weather and climate services for agriculture. Hydrology and Earth System Sciences, 21, 4693–4709. https://doi.org/10.5194/hess-21-4693-2017

Lin, N. M., & Rutten, M. (2016). Optimal operation of a network of multi-purpose reservoir: A review. Procedia Engineering, 154, 1376–1384. https://doi.org/10.1016/j.proeng.2016.07.504

Liu, P., Cai, X., & Guo, S. (2011). Deriving multiple near-optimal solutions to deterministic reservoir operation problems. Water Resources Research, 47. https://doi.org/10.1029/2011WR010998

Liu, P., Guo, S., Xiong, L., Li, W., & Zhang, H. (2006). Deriving reservoir refill operating rules by using the proposed DPNS model. Water Resources Management, 20, 337–357. https://doi.org/10.1007/s11269-006-0322-7

Loucks, D. P. (1970). Some comments on linear decision rules and chance constraints. Water Resources Research, 6, 668–671. https://doi.org/10.1029/WR006i002p00668

Loucks, D. P. (2017). Managing water as a critical component of a changing world. Water Resources Management, 31, 2905–2916. https://doi. org/10.1007/s11269-017-1705-7

Loucks, D. P., & van Beek, E. (2005). Water resources systems planning and management: An introduction to methods, models and applications. Paris, France: UNESCO Publishing.

Lund, J. R. (1996). Developing seasonal and long-term reservoir system operation plans using HEC-PRM, Davis, CA.

Lund, J. R., & Ferreira, I. (1996). Operating rule optimization for Missouri River reservoir system. Journal of Water Resources Planning and Management, 122, 287–295. https://doi.org/10.1061/(ASCE)0733-9496(1996)122:4(287)

Lund, J. R., & Guzman, J. (1999). Derived operating rules for reservoirs in series or in parallel. Journal of Water Resources Planning and Management, 125, 143–153. https://doi.org/10.1061/(ASCE)0733-9496(1999)125:3(143)

Lund, J. R., Hui, R., Escriva-Bou, A., Porse, E. C., Adams, L., Connaughton, J., … Yi, S. (2017). Reservoir operation design. In A. Singh (Ed.), Handbook of applied hydrology (2nd ed., p. 1440). New York, NY: McGraw-Hill Education.

Luo, B., Maqsood, I., & Huang, G. H. (2007). Planning water resources systems with interval stochastic dynamic programming. Water Resources Management, 21, 997–1014. https://doi.org/10.1007/s11269-006-9069-4

Luthra, S. S., & Arora, S. R. (1976). Optimal design of single reservoir system using δ release policy. Water Resources Research, 12, 606–612.https://doi.org/10.1029/WR012i004p00606

Macian-Sorribes, H. (2017). Design of optimal reservoir operating rules in large water resources systems combining stochastic programming, fuzzy logic and expert criteria. Universitat Politècnica de València. https://doi.org/10.4995/THESIS/10251/82554.

Macian-Sorribes, H., Tilmant, A., & Pulido-Velazquez, M. (2017). Improving operating policies of large-scale surface-groundwater systems through stochastic programming. Water Resources Research, 53, 1407–1423. https://doi.org/10.1002/2016WR019573

Maier, H. R., Guillaume, J. H. A., van Delden, H., Riddell, G. A., Haasnoot, M., & Kwakkel, J. H. (2016). An uncertain future, deep uncertainty, scenarios, robustness and adaptation: How do they fit together? Environmental Modelling and Software, 81, 154–164. https://doi.org/10.1016/J.ENVSOFT.2016.03.014

Maier, H. R., Kapelan, Z., Kasprzyk, J., Kollat, J., Matott, L. S., Cunha, M. C., … Reed, P. M. (2014). Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions. Environmental Modelling and Software, 62, 271–299. https://doi.org/10.1016/j.envsoft.2014.09.013

Malekmohammadi, B., Kerachian, R., & Zahraie, B. (2009). Developing monthly operating rules for a cascade system of reservoirs: Application of Bayesian networks. Environmental Modelling and Software, 24, 1420–1432. https://doi.org/10.1016/j.envsoft.2009.06.008

Mamdani, E. H. (1974). Application of fuzzy algorithms for control of simple dynamic plant. Proceedings of the Institution of Electrical Engineers, 121, 1585–1588.

Marchand, A., Gendreau, M., Blais, M., & Emiel, G. (2019). Efficient Tabu search procedure for short-term planning of large-scale hydropower systems. Journal of Water Resources Planning and Management, 145, 4019025. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001064

Marques, G. F., Lund, J. R., & Howitt, R. E. (2005). Modeling irrigated agricultural production and water use decisions under water supply uncertainty. Water Resources Research, 41, 1–11. https://doi.org/10.1029/2005WR004048

Mateus, M., & Tullos, D. (2016). Reliability, sensitivity, and vulnerability of reservoir operations under climate change. Journal of Water Resources Planning and Management, 4016085, 04016085. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000742

Matrosov, E. S., Padula, S., & Harou, J. J. (2013). Selecting portfolios of water supply and demand management strategies under uncertainty—Contrasting economic optimisation and ‘robust decision making' approaches. Water Resources Management, 27, 1123–1148. https://doi.org/10.1007/s11269-012-0118-x

Mizyed, N. R., Loftis, J. C., & Fontane, D. G. (1992). Operation of large multireservoir systems using optimal-control theory. Journal of Water Resources Planning and Management, 118, 371–387. https://doi.org/10.1061/(ASCE)0733-9496(1992)118:4(371)

Moeini, R., Afshar, A., & Afshar, M. H. (2011). Fuzzy rule-based model for hydropower reservoirs operation. International Journal of Electrical Power & Energy Systems, 33, 171–178. https://doi.org/10.1016/j.ijepes.2010.08.012

Molina, J.-L., Pulido-Velázquez, D., García-Aróstegui, J. L., & Pulido-Velázquez, M. (2013). Dynamic Bayesian networks as a decision support tool for assessing climate change impacts on highly stressed groundwater systems. Journal of Hydrology, 479, 113–129. https://doi.org/10.1016/j.jhydrol.2012.11.038

Mousavi, S. J., Karamouz, M., & Menhadj, M. B. (2004). Fuzzy-state stochastic dynamic programming for reservoir operation. Journal of Water Resources Planning and Management, 130, 460–470. https://doi.org/10.1061/(ASCE)0733-9496(2004)130:6(460)

Mousavi, S. J., Mahdizadeh, K., & Afshar, A. (2004). A stochastic dynamic programming model with fuzzy storage states for reservoir operations. Advances in Water Resources, 27, 1105–1110. https://doi.org/10.1016/j.advwatres.2004.07.007

Mousavi, S. J., Ponnambalam, K., & Karray, F. (2005). Reservoir operation using a dynamic programming fuzzy rule-based approach. Water Resources Management, 19, 655–672. https://doi.org/10.1007/s11269-005-3275-3

Mousavi, S. J., Ponnambalam, K., & Karray, F. (2007). Inferring operating rules for reservoir operations using fuzzy regression and ANFIS. Fuzzy Sets and Systems, 158, 1064–1082. https://doi.org/10.1016/j.fss.2006.10.024

Mujumdar, P. P., & Nirmala, B. (2007). A Bayesian stochastic optimization model for a multi-reservoir hydropower system. Water Resources Management, 21, 1465–1485. https://doi.org/10.1007/s11269-006-9094-3

Nalbantis, I., & Koutsoyiannis, D. (1997). A parametric rule for planning and management of multiple-reservoir systems. Water Resources Research, 33, 2165–2177. https://doi.org/10.1029/97WR01034

Nandalal, K. W. D., & Bogardi, J. J. (2007). Dynamic programming based operation of reservoirs (Internatioal ed.). Cambridge, England: Cambridge University Press.

Nguyen, L., & Novák, V. (2018). Forecasting seasonal time series based on fuzzy techniques. Fuzzy Sets and Systems, 361, 114–129. https://doi.org/10.1016/J.FSS.2018.09.010

Oliveira, R., & Loucks, D. P. (1997). Operating rules for multireservoir systems. Water Resources Research, 33, 839–852. https://doi.org/10.1029/96WR03745

Ostadrahimi, L., Mariño, M. A., & Afshar, A. (2012). Multi-reservoir operation rules: Multi-swarm PSO-based optimization approach. Water Resources Management, 26, 407–427. https://doi.org/10.1007/s11269-011-9924-9

Panigrahi, D. P., & Mujumdar, P. P. (2000). Reservoir operation modelling with fuzzy logic. Water Resources Management, 14, 89–109.https://doi.org/10.1023/A:1008170632582

Pedrycz, W., Ekel, P., & Parreiras, R. (2011). Fuzzy multicriteria decision-making. Chichester, England: Wiley.

Pereira, M. V. F., & Pinto, L. M. V. G. (1985). Stochastic optimization of a multireservoir hydroelectric system: A decomposition approach. Water Resources Research, 21, 779–792. https://doi.org/10.1029/WR021i006p00779

Pereira, M. V. F., & Pinto, L. M. V. G. (1991). Multi-stage stochastic optimization applied to energy planning. Mathematical Programming, 52, 359–375. https://doi.org/10.1007/BF01582895

Pereira-Cardenal, S. J., Mo, B., Riegels, N., Arnbjerg-Nielsen, K., & Bauer-Gottwein, P. (2015). Optimization of multipurpose reservoir systems using power market models. Journal of Water Resources Planning and Management, 141, 04014100. https://doi.org/10.1061/(ASCE) WR.1943-5452.0000500

Philbrick, C. R., & Kitanidis, P. K. (1999). Limitations of deterministic optimization applied to reservoir operations. Journal of Water Resources Planning and Management, 125, 135–142. https://doi.org/10.1061/(ASCE)0733-9496(1999)125:3(135)

Pianosi, F., & Ravazzani, G. (2010). Assessing rainfall–runoff models for the management of Lake Verbano. Hydrological Processes, 24, 3195–3205. https://doi.org/10.1002/hyp.7745

Pianosi, F., & Soncini-Sessa, R. (2009). Real-time management of a multipurpose water reservoir with a heteroscedastic inflow model. Water Resources Research, 45, W10430. https://doi.org/10.1029/2008/WR007335

Pulido-Velazquez, M., Andreu, J., Sahuquillo, A., & Pulido-Velazquez, D. (2008). Hydro-economic river basin modelling: The application of a holistic surface–groundwater model to assess opportunity costs of water use in Spain. Ecological Economics, 66, 51–65. https://doi.org/10.1016/j.ecolecon.2007.12.016

Pulido-Velazquez, M., Jenkins, M. W., & Lund, J. R. (2004). Economic values for conjunctive use and water banking in southern California. Water Resources Research, 40. https://doi.org/10.1029/2003WR002626

Qin, T., & Boccelli, D. L. (2019). Estimating distribution system water demands using Markov chain Monte Carlo. Journal of Water Resources Planning and Management, 145, 4019023. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001077

Quinlan, J. R. (1986). Induction of decision trees. Machine Learning, 1, 81–106.

Quinlan, J. R. (1993). C4.5: Programs for machine learning. San Francisco, CA: Morgan Kaufmann Publishers Inc.

Quinn, J. D., Reed, P. M., Giuliani, M., & Castelletti, A. (2019). What is controlling our control rules? Opening the black box of multireservoir operating policies using time-varying sensitivity analysis. Water Resources Research, 55, 5962–5984. https://doi.org/10.1029/ 2018WR024177

Raman, H., & Chandramouli, V. (1996). Deriving a general operating policy for reservoirs using neural network. Journal of Water Resources Planning and Management, 122, 342–347. https://doi.org/10.1061/(ASCE)0733-9496(1996)122:5(342)

Rani, D., & Moreira, M. M. (2010). Simulation–optimization modeling: A survey and potential application in reservoir systems operation. Water Resources Management, 24, 1107–1138. https://doi.org/10.1007/s11269-009-9488-0

Rashid, M. U., Latif, A., & Azmat, M. (2018). Optimizing irrigation deficit of multipurpose Cascade reservoirs. Water Resources Management, 32, 1675–1687. https://doi.org/10.1007/s11269-017-1897-x

Raso, L., & Malaterre, O. (2017). Combining short-term and long-term reservoir operation using infinite horizon model predictive control. Journal of Irrigation and Drainage Engineering, 143, B4016002. https://doi.org/10.1061/(ASCE)IR.1943-4774.0001063

Raso, L., Schwanenberg, D., van de Giesen, N. C., & van Overloop, P. J. (2014). Short-term optimal operation of water systems using ensemble forecasts. Advances in Water Resources, 71, 200–208. https://doi.org/10.1016/j.advwatres.2014.06.009

Raso, L., van de Giesen, N., Stive, P., Schwanenberg, D., & van Overloop, P. J. (2013). Tree structure generation from ensemble forecasts for real time control. Hydrological Processes, 27, 75–82. https://doi.org/10.1002/hyp.9473

Reed, P. M., Hadka, D., Herman, J. D., Kasprzyk, J. R., & Kollat, J. B. (2013). Evolutionary multiobjective optimization in water resources: The past, present, and future. Advances in Water Resources, 51, 438–456. https://doi.org/10.1016/j.advwatres.2012.01.005

ReVelle, C., & Gundelach, J. (1975). Linear decision rule in reservoir management and design: 4. A rule that minimizes output variance. Water Resources Research, 11, 197–203. https://doi.org/10.1029/WR011i002p00197

Revelle, C., Joeres, E., & Kirby, W. (1969). The linear decision rule in reservoir management and design: 1. Development of the stochastic model. Water Resources Research, 5, 767–777. https://doi.org/10.1029/WR005i004p00767

Revelle, C., & Kirby, W. (1970). Linear decision rule in reservoir management and design: 2. Performance optimization. Water Resources Research, 6, 1033–1044. https://doi.org/10.1029/WR006i004p01033

Roach, T., Kapelan, Z., Ledbetter, R., & Ledbetter, M. (2016). Comparison of robust optimization and info-gap methods for water resource management under deep uncertainty. Journal of Water Resources Planning and Management, 4016028, 04016028. https://doi.org/10. 1061/(ASCE)WR.1943-5452.0000660

Rogers, P. P., & Fiering, M. B. (1986). Use of systems analysis in water management. Water Resources Research, 22, 146S–158S. https://doi.org/10.1029/WR022i09Sp0146S

Ropero, R. F., Flores, M. J., Rumi, R., & Aguilera, P. A. (2017). Applications of hybrid dynamic Bayesian networks to water reservoir management. Environmetrics, 28, e2432. https://doi.org/10.1002/env.2432

Rougé, C., & Tilmant, A. (2016). Using stochastic dual dynamic programming in problems with multiple near-optimal solutions. Water Resources Research, 52, 4151–4163. https://doi.org/10.1002/2016WR018608

Russell, S. O., & Campbell, P. F. (1996). Reservoir operating rules with fuzzy programming. Journal of Water Resources Planning and Management, 122, 165–170. https://doi.org/10.1061/(ASCE)0733-9496(1996)122:3(165

Safavi, H. R., & Enteshari, S. (2016). Conjunctive use of surface and ground water resources using the ant system optimization. Agricultural Water Management, 173, 23–34. https://doi.org/10.1016/j.agwat.2016.05.001

Sahinidis, N. V. (2004). Optimization under uncertainty: State-of-the-art and opportunities. Computers and Chemical Engineering, 28, 971–983. https://doi.org/10.1016/j.compchemeng.2003.09.017

Salazar, J. Z., Reed, P. M., Herman, J. D., Giuliani, M., & Castelletti, A. (2016). A diagnostic assessment of evolutionary algorithms for multiobjective surface water reservoir control. Advances in Water Resources, 92, 172–185. https://doi.org/10.1016/j.advwatres.2016.04.006

Satti, S., Zaitchik, B., & Siddiqui, S. (2015). The question of Sudan: A hydro-economic optimization model for the Sudanese Blue Nile. Hydrology and Earth System Sciences, 19, 2275–2293. https://doi.org/10.5194/hess-19-2275-2015 Sen, Z. (2010). Fuzzy logic and hydrological modeling. Boca Raton, FL: CRC Press.

Senthil Kumar, A. R., Goyal, M. K., Ojha, C. S. P., Singh, R. D., Swamee, P. K., & Nema, R. K. (2013). Application of ANN, fuzzy logic and decision tree algorithms for the development of reservoir operating rules. Water Resources Management, 27, 911–925. https://doi.org/10. 1007/s11269-012-0225-8

Sheibani, H., Alizadeh, H., & Shourian, M. (2019). Optimum design and operation of a reservoir and irrigation network considering uncertainty of hydrologic, agronomic and economic factors. Water Resources Management, 33, 863–879. https://doi.org/10.1007/s11269-0182148-5

Sherafatpour, Z., Roozbahani, A., & Hasani, Y. (2019). Agricultural water allocation by integration of hydro-economic modeling with Bayesian networks and random Forest approaches. Water Resources Management, 33, 2277–2299. https://doi.org/10.1007/s11269-019-02240-9

Shourian, M., Mousavi, S. J., & Tahershamsi, A. (2008). Basin-wide water resources planning by integrating PSO algorithm and MODSIM. Water Resources Management, 22, 1347–1366. https://doi.org/10.1007/s11269-007-9229-1

Shrestha, B. P., Duckstein, L., & Stakhiv, E. Z. (1996). Fuzzy rule-based modeling of reservoir operation. Journal of Water Resources Planning and Management, 122, 262–269. https://doi.org/10.1061/(ASCE)0733-9496(1996)122:4(262)

Simonovic, S. P. (1992). Reservoir systems analysis: Closing gap between theory and practice. Journal of Water Resources Planning and Management, 118, 262–280. https://doi.org/10.1061/(ASCE)0733-9496(1992)118:3(262)

Simonovic, S. P. (2009). Managing water resources: Methods and tools for a systems approach. Paris, France: UNESCO Publishing.

Singh, A. (2012). An overview of the optimization modelling applications. Journal of Hydrology, 466–467, 167–182. https://doi.org/10.1016/j. jhydrol.2012.08.004

Soleimani, S., Bozorg-Haddad, O., & Loáiciga, H. (2016). Reservoir operation rules with uncertainties in reservoir inflow and agricultural demand derived with stochastic dynamic programming. Journal of Irrigation and Drainage Engineering, 4016046, 04016046. https://doi. org/10.1061/(ASCE)IR.1943-4774.0001065

Soleimani, S., Bozorg-Haddad, O., Saadatpour, M., & Loáiciga, H. A. (2016). Optimal selective withdrawal rules using a coupled data mining model and genetic algorithm. Journal of Water Resources Planning and Management. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000717

Sordo-Ward, A., Garrote, L., Martín-Carrasco, F., & Dolores Bejarano, M. (2012). Extreme flood abatement in large dams with fixed-crest spillways. Journal of Hydrology, 466–467, 60–72. https://doi.org/10.1016/j.jhydrol.2012.08.009

Spiliotis, M., Mediero, L., & Garrote, L. (2016). Optimization of hedging rules for reservoir operation during droughts based on particle swarm optimization. Water Resources Management, 30, 5759–5778. https://doi.org/10.1007/s11269-016-1285-y

Sreekanth, J., Datta, B., & Mohapatra, P. K. (2012). Optimal short-term reservoir operation with integrated long-term goals. Water Resources Management, 26, 2833–2850. https://doi.org/10.1007/s11269-012-0051-z

Srinivasan, K., & Kumar, K. (2018). Multi-objective simulation-optimization model for long-term reservoir operation using piecewise linear hedging rule. Water Resources Management, 32, 1901–1911. https://doi.org/10.1007/s11269-018-1911-y

Stedinger, J. R., Sule, B. F., & Loucks, D. P. (1984). Stochastic dynamic programming models for reservoir operation optimization. Water Resources Research, 20, 1499–1505. https://doi.org/10.1029/WR020i011p01499

Sun, X., Ma, C., & Lian, J. (2018). Optimal operation of Danjiangkou reservoir using improved hedging model and considering the effects of historical decisions. Journal of Water Resources Planning and Management, 144, 4017080.

Tan, Q., Wang, X., Wang, H., Wang, C., Lei, X., Xiong, Y., & Zhang, W. (2017). Derivation of optimal joint operating rules for multi-purpose multi-reservoir water-supply system. Journal of Hydrology, 551, 253–264. https://doi.org/10.1016/j.jhydrol.2017.06.009

Taormina, R., Chau, K.-W., & Sivakumar, B. (2015). Neural network river forecasting through baseflow separation and binary-coded swarm optimization. Journal of Hydrology, 529, 1788–1797. https://doi.org/10.1016/j.jhydrol.2015.08.008

Teegavarapu, R. S. V., & Simonovic, S. P. (2000). Short-term operation model for coupled hydropower reservoirs. Journal of Water Resources Planning and Management, 126, 98–106. https://doi.org/10.1061/(ASCE)0733-9496(2000)126:2(98)

Teegavarapu, R. S. V., & Simonovic, S. P. (2002). Optimal operation of reservoir systems using simulated annealing. Water Resources Management, 16, 401–428. https://doi.org/10.1023/A:1021993222371

Tejada-Guibert, J. A., Johnson, S. A., & Stedinger, J. R. (1993). Comparison of two approaches for implementing multireservoir operating policies derived using stochastic dynamic programming. Water Resources Research, 29, 3969–3980. https://doi.org/10.1029/93WR02277

Theodossiou, N. P. (2004). Application of non-linear simulation and optimisation models in groundwater aquifer management. Water Resources Management, 18, 125–141.

Tilmant, A., Faouzi, E. H., & Vanclooster, M. (2002). Optimal operation of multipurpose reservoirs using flexible stochastic dynamic programming. Applied Soft Computing, 2, 61–74. https://doi.org/10.1016/S1568-4946(02)00029-7

Tilmant, A., & Kelman, R. (2007). A stochastic approach to analyze trade-offs and risks associated with large-scale water resources systems. Water Resources Research, 43. https://doi.org/10.1029/2006WR005094

Tilmant, A., Pinte, D., & Goor, Q. (2008). Assessing marginal water values in multipurpose multireservoir systems via stochastic programming. Water Resources Research, 44. https://doi.org/10.1029/2008WR007024

Tilmant, A., Van Der Zaag, P., & Fortemps, P. (2007). Modeling and analysis of collective management of water resources. Hydrology and Earth System Sciences, 11, 711–720. https://doi.org/10.5194/hessd-3-2707-2006

Tilmant, A., Vanclooster, M., Duckstein, L., & Persoons, E. (2002). Comparison of fuzzy and nonfuzzy optimal reservoir operating policies. Journal of Water Resources Planning and Management, 128, 390–398. https://doi.org/10.1061/(ASCE)0733-9496(2002)128:6(390)

Turner, S. W. D., & Galelli, S. (2015). Water supply sensitivity to climate change: An R package for implementing reservoir storage analysis in global and regional impact studies. Environmental Modelling and Software, 76, 13–19. https://doi.org/10.1016/j.envsoft.2015.11.007

Uusitalo, L. (2007). Advantages and challenges of Bayesian networks in environmental modelling. Ecological Modelling, 203, 312–318. https://doi.org/10.1016/j.ecolmodel.2006.11.033

van Overloop, P.-J., Weijs, S., & Dijkstra, S. (2008). Model predictive control on a drainage canal system. Control Engineering Practice, 16, 531–540.

Vasiliadis, H. V., & Karamouz, M. (1994). Demand-driven operation of reservoirs using uncertainty-based optimal operating policies. Journal of Water Resources Planning and Management, 120, 101–114. https://doi.org/10.1061/(ASCE)0733-9496(1994)120:1(101)

Vedula, S., Mujumdar, P. P., & Chandra Sekhar, G. (2005). Conjunctive use modeling for multicrop irrigation. Agricultural Water Management, 73, 193–221. https://doi.org/10.1016/j.agwat.2004.10.014

Vermuyten, E., Meert, P., Wolfs, V., & Willems, P. (2018). Combining model predictive control with a reduced genetic algorithm for real-time flood control. Journal of Water Resources Planning and Management, 144, 4017083. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000859

Vieira, J., Cunha, M. C., Nunes, L., Monteiro, J. P., Ribeiro, L., Stigter, T., … Lucas, H. (2011). Optimization of the operation of large-scale multisource water-supply systems. Journal of Water Resources Planning and Management, 137, 150–161. https://doi.org/10.1061/(ASCE) WR.1943-5452.0000102

Wan, W., Guo, X., Lei, X., Jiang, Y., & Wang, H. (2018). A novel optimization method for multi-reservoir operation policy derivation in complex Inter-Basin water transfer system. Water Resources Management, 32, 31–51. https://doi.org/10.1007/s11269-017-1735-1

Wan, W., Zhao, J., Lund, J., Zhao, T., Lei, X., & Wang, H. (2016). Optimal hedging rule for reservoir refill. Journal of Water Resources Planning and Management, 4016051, 04016051. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000692

Wang, J., Cheng, C., Wu, X., Shen, J., & Cao, R. (2019). Optimal hedging for hydropower operation and end-of-year carryover storage values. Journal of Water Resources Planning and Management, 145, 4019003. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001046

Wei, C.-C., & Hsu, N.-S. (2008). Derived operating rules for a reservoir operation system: Comparison of decision trees, neural decision trees and fuzzy decision trees. Water Resources Research, 44. https://doi.org/10.1029/2006WR005792

Wild, T. B., Reed, P. M., Loucks, D. P., Mallen-Cooper, M., & Jensen, E. D. (2019). Balancing hydropower development and ecological impacts in the Mekong: Tradeoffs for Sambor Mega dam. Journal of Water Resources Planning and Management, 145, 5018019. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001036

Wu, X., Li, S., Cheng, C., Miao, S., & Ying, Q. (2019). Simulation-optimization model to derive operation rules of multiple cascaded reservoirs for Nash equilibrium. Journal of Water Resources Planning and Management, 145, 4019013. https://doi.org/10.1061/(ASCE)WR.19435452.0001057

Wurbs, R. (1993). Reservoir system simulation and optimization models. Journal of Water Resources Planning and Management, 119, 455–472. https://doi.org/10.1061/(ASCE)0733-9496(1993)119:4(455)

Xu, B., Boyce, S. E., Zhang, Y., Liu, Q., Guo, L., & Zhong, P.-A. (2017). Stochastic programming with a joint chance constraint model for reservoir refill operation considering flood risk. Journal of Water Resources Planning and Management, 143, 04016067. https://doi.org/10. 1061/(ASCE)WR.1943-5452.0000715

Yakowitz, S. (1982). Dynamic programming applications in water resources. Water Resources Research, 18, 673–696. https://doi.org/10.1029/WR018i004p00673

Yang, P., & Ng, T. (2016). Fuzzy inference system for robust rule-based reservoir operation under nonstationary inflows. Journal of Water Resources Planning and Management, 143, 4016084. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000743

Yang, T., Gao, X., Sorooshian, S., & Li, X. (2016). Simulating California reservoir operation using the classification and regression-tree algorithm combined with a shuffled cross-validation scheme. Water Resources Research, 52, 1626–1651. https://doi.org/10.1002/2015WR017394

Yeh, W. W.-G. (1985). Reservoir management and operations models: A state-of-the-art review. Water Resources Research, 21, 1797–1818.https://doi.org/10.1029/WR021i012p01797

You, J.-Y., & Cai, X. (2008). Determining forecast and decision horizons for reservoir operations under hedging policies. Water Resources Research, 44. https://doi.org/10.1029/2008WR006978

Young, G. K. (1967). Finding reservoir operating rules. Journal of the Hydraulics, 93, 297–321.

Zadeh, L. A. (1965). Fuzzy sets. Information and Control, 8, 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X

Zarei, A., Mousavi, S.-F., Eshaghi Gordji, M., & Karami, H. (2019). Optimal reservoir operation using bat and particle swarm algorithm and game theory based on optimal water allocation among consumers. Water Resources Management, 33, 3071–3093. https://doi.org/10.1007/ s11269-019-02286-9

Zeff, H. B., Kasprzyk, J. R., Herman, J. D., Reed, P. M., & Characklis, G. W. (2014). Navigating financial and supply reliability tradeoffs in regional drought management portfolios. Water Resources Research, 50, 4906–4923. https://doi.org/10.1002/2013WR015126

Zeng, Y., Wu, X., Cheng, C., & Wang, Y. (2013). Chance-constrained optimal hedging rules for cascaded hydropower reservoirs. Journal of Water Resources Planning and Management, 140, 4014010. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000427

Zhang, X., Liu, P., Xu, C.-Y., Guo, S., Gong, Y., & Li, H. (2019). Derivation of hydropower rules for multireservoir systems and its application for optimal reservoir storage allocation. Journal of Water Resources Planning and Management, 145, 4019010. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001056

Zhao, T., Zhao, J., Lund, J. R., & Yang, D. (2014). Optimal hedging rules for reservoir flood operation from forecast uncertainties. Journal of Water Resources Planning and Management Preview, 140, 1–11. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000432

Zhao, T., Zhao, J., & Yang, D. (2014). Improved dynamic programming for hydropower reservoir operation. Journal of Water Resources Planning and Management, 140, 365–374. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000343

Zhou, Y., & Guo, S. (2013). Incorporating ecological requirement into multipurpose reservoir operating rule curves for adaptation to climate change. Journal of Hydrology, 498, 153–164. https://doi.org/10.1016/j.jhydrol.2013.06.028

Zhu, T., Marques, G. F., & Lund, J. R. (2015). Hydroeconomic optimization of integrated water management and transfers under stochastic surface water supply. Water Resources Research, 51, 3568–3587. https://doi.org/10.1002/2014WR016519

Zhu, X., Zhang, C., Yin, J., Zhou, H., & Jiang, Y. (2013). Optimization of water diversion based on reservoir operating rules: Analysis of the Biliu River reservoir, China. Journal of Hydrologic Engineering, 19, 411–421. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000805

Zubaidi, S. L., Gharghan, S. K., Dooley, J., Alkhaddar, R. M., & Abdellatif, M. (2018). Short-term urban water demand prediction considering weather factors. Water Resources Management, 32, 4527–4542. https://doi.org/10.1007/s11269-018-2061-y