Energy Reports 8 (2022) 8061–8078

Contents lists available at ScienceDirect

Energy Reports

journal homepage: www.elsevier.com/locate/egyr

Research Paper

Co-Optimization of Reservoir and Power Systems (COREGS) for seasonal planning and operation

Lucas Ford [a,*], Anderson de Queiroz [a,b], Joseph DeCarolis [a], A. Sankarasubramanian [a]

[a] Department of Civil, Construction, and Environmental Engineering, North Carolina State University, Raleigh, NC, United States of America
[b] Department of Decision Sciences, Economics and Finance, North Carolina Central University, Durham, NC, United States of America

ARTICLE INFO

Article history:
Received 1 April 2022
Received in revised form 2 June 2022
Accepted 15 June 2022
Available online xxxx

Dataset link: https://github.com/lcford2/coregs/releases/tag/v1.0.0, https://zenodo.org/record/6315941#.Yh5tKhtOlhE

Keywords:
Multireservoir optimization
Energy system optimization
Hydropower
Seasonal planning

ABSTRACT

Climate variability accounts for distinct seasonal differences in electricity demand and streamflow potential, which power systems rely on to assess available hydropower and to cool thermal power plants. Understanding the interactions between reservoir and power networks under varying climate conditions requires an integrated analysis of both systems. In this study, we develop Co-Optimization of Reservoir and Electricity Generation Systems (COREGS), a generalized, open-source, modeling framework that optimizes both systems with respect to reducing power generation costs using a multireservoir model (GRAPS) and an electricity system model (TEMOA). Three optimization schemes of varying degrees of model integration are applied to Tennessee Valley Authority's reservoir and electricity systems for the summer and winters from 2003 to 2015. We find that co-optimization of the systems results in more efficient water allocation decisions than separate optimization. Co-optimization solutions reduce reservoir spill and allocate water for hydropower only when and where it is beneficial to the power system as compared to stand-alone water system optimization. As the penetration of solar and wind power continues to increase, power systems will be more reliant on flexible reliable generating services such as reservoir systems and co-optimization of both systems will become more essential for efficient seasonal planning and operation.

1. Introduction

Despite the growth in solar and wind energy over the last decade, hydroelectric power still dominates the renewable energy landscape accounting 48% of installed capacity across the globe (International Renewable Energy Agency, 2021). In the United States, hydropower electricity production was the second largest renewable source in 2020 accounting 37% of renewable generation, surpassed only by wind power (US Energy Information Administration, 2021). While hydropower is an important link between power systems and water supply systems, reservoirs also provide large quantities of water for cooling to thermal power plants thus requiring effective operation of these two systems during drought conditions (IPCC, 2021). Seasonal climate variability further complicates this water–energy nexus as seasons with high electricity (i.e., winter/summer) demand may frequently overlap with recurrent drought patterns (IPCC, 2021; Helfer et al., 2012; Zerrahn and Schill, 2017). Efficient reservoir operation in wet years can result in reduced reservoir spillage and additional hydropower without increasing downstream flood risk (Zhou et al., 2018). In addition to seasonal climate variability, long-term climate change has impacted the operation of both reservoir and power systems (Bartos and Chester, 2015). Droughts also reduce the available water supply thus limiting the flexibility of reservoir operations and potentially decreasing the available capacity of thermal plants. In 2021, the International Panel on Climate Change reported with high confidence that the increase in the frequency of concurrent heatwaves and droughts since the 1950s has been driven, at least in some part, by anthropogenic influences (IPCC, 2021). Heatwaves cause increased power demand levels, which in turn increase cooling loads while simultaneously increasing evaporation from reservoirs, thereby further constraining the water supply (Helfer et al., 2012).

As electricity grids becomes more reliant on variable renewable energy (VRE) sources such as solar and wind, hydropower plays an important role in decarbonizing electricity generation by providing additional power system reliability. For instance, in addition to being a zero-carbon generation source, hydropower can provide large quantities of immediately dispatchable reliable energy storage to the electricity grid. Several studies have found that the penetration of VRE sources is limited without access to substantial amounts of energy storage (Zerrahn and Schill, 2017; de Sisternes et al., 2016; Denholm et al., 2011) and that the value of renewable energy is increased substantially when it is

* Corresponding author.
E-mail address: lcford2@ncsu.edu (L. Ford).

https://doi.org/10.1016/j.egyr.2022.06.017

Nomenclature

Indices

r	Reservoir index
t	Time index for GRAPS
t, s, d	Time period, season, and time of day index for Temoa
u	Index for upstream reservoirs
i	Iteration number for ICORPS solution method

Sets and subsets

R	Set of all reservoirs
T	Set of all time periods for GRAPS
U_r	Set of all reservoirs directly upstream of reservoir r

Variables

$S^i_{r,t}$	Storage for reservoir r at time t (for iteration i if included) [1000 ac-ft (SI: 1.233 million m^3)]
$D^i_{r,t}$	Hydropower discharge for reservoir r at time t (for iteration i if included) [1000 ac-ft/month]
$O^i_{r,t}$	Total outflow from reservoir r at time t in iteration i [1000 ac-ft/month]
$I^i_{r,t}$	Total inflow from reservoir r at time t in iteration i [1000 ac-ft/month]
$TW^i_{r,t}$	Tailwater for reservoir r at time t (for iteration i if included) [ft]
$HP^i_{r,t}$	Hydropower generation for reservoir r at time t (for iteration i if included) [MWh/month]
$UR^i_{r,t}$	Total release from reservoirs directly upstream of reservoir r at time t in iteration i [1000 ac-ft/month]
$F^i_{u,t}$	Contributing release fraction to $UR^i_{r,t}$ from reservoir u at time t in iteration i
$SP^i_{r,t}$	Spill for reservoir r at time t in iteration i [1000 ac-ft/month]
$DEF^i_{r,t}$	Deficit for reservoir r at time t in iteration i [1000 ac-ft/month]
$\pi^i_{r,t}$	Dual variable (shadow price) for maximum hydropower constraint in Temoa for reservoir r at time t in iteration i [$/MWh]
Obj_i	Objective function value at iteration i [$]
N	Total number of iterations
δ	Efficiency measure used to determine which method provided the most objective function improvement per unit of additional release

Parameters

$\beta_{r,1}, \beta_{r,2}, \beta_{r,3}$	Storage-elevation curve parameters for reservoir r
DEM_t	Electricity demand for time-period t [MWh]
$DSD_{(t),s,d}$	Demand specific distribution for time of day d in season s (in time-period t)
$dem_{t,s,d}$	Electricity demand for time of day d in season s in time-period t [MWh]
$LC_{r,t}$	Lower storage rule curve for reservoir r at time t [1000 ac-ft]
$UC_{r,t}$	Upper storage rule curve for reservoir r at time t [1000 ac-ft]
S^{max}_r	Maximum storage for reservoir r [1000 ac-ft]
S^{min}_r	Minimum storage for reservoir r [1000 ac-ft]
η_r	Generator efficiency for reservoir r
λ	Fractional value used to increase the release at a reservoir if the dual variable is non-zero and the original release is zero
α	Tuning parameter to control step size in ICORPS. The larger the value, the smaller the step size.
ε	Tolerance that determines how similar the objective function values must be between iterations to be considered equivalent
K	Minimum number of times the percent change in the objective function between iterations must be less than ε for ICORPS to converge

Constants

γ	Specific weight of water [62.4 lb/ft ^{3}, (SI: 9.81 kN/m^3)]

Functions

$\Gamma(i)$	Returns a 1 if the percent change in objective function values between iteration i and $i-1$ is less than ε, otherwise returns 0

deployed alongside energy storage capacity (Sodano et al., 2021). These interdependencies stress the importance of understanding the dynamics and uncertainties between reservoir and power systems to facilitate planning and operation at seasonal time scales.

Most studies have focused on the co-optimization of these two systems at hourly-to-daily time scales to address operational issues such as system reliability and outages (Mandal et al., 2008; Swain et al., 2011; Norouzi et al., 2014). Given that large reservoir systems typically guarantee the required power demand at hourly-to-weekly time scales, inflow variability during slowly evolving droughts could constrain the available storage for power generation at seasonal time scales (Oludhe et al., 2013). Further, given the increasing penetration of renewable energy and varying reservoir storage availability throughout the year, jointly operating water and power systems over sub-annual time periods (seasonal and beyond) may result in efficiency gains for both systems as well as reduced operational cost for the power system. Though there has been a recent push to study these systems for sub-annual time horizons, much of the existent literature (Oludhe et al., 2013; Li et al., 2015; Liu et al., 2015; Hunt et al., 2017; Mu et al., 2020; de Queiroz et al., 2019) focuses on modeling and optimization techniques of water and power systems independently rather than together.

The utility of seasonal streamflow forecasts for optimizing reservoir operations is demonstrated in Oludhe et al. (2013) and Hunt et al. (2017) explores the potential benefits of seasonal pumped storage systems with respect to the multi-reservoir system in Brazil. In Liu et al. (2015), the seasonally varying flood storage requirement for the Three Gorges Reservoir is optimized with respect to flood risk, hydropower generation and reliability, navigability, and end-of-horizon water levels. de Queiroz et al. (2019) modifies an energy systems optimization model for seasonal electricity planning and operations. Mu et al. (2020) explores the seasonal risk of the water–electricity nexus during dry periods but only by considering the water consumption for thermal electricity generation rather power and water system operations. Thus, a detailed modeling of water and power systems at seasonal time scales is not yet fully developed and analyzed showing the benefits of co-optimization of the two systems.

Studies that optimize both systems often simplify one system rather than fully resolving both. Turgeon (1980) and Pereira and Pinto (1985) use the equivalent reservoir method of Arvanitidis and Rosing (1970a) to simplify multireservoir systems while Zambon et al. (2012) models each individual reservoir but aggregates the power system into four regions. Baslis et al. (2009) models all reservoirs and thermal generators but simplify hydropower calculations by removing the dependence on reservoir head. The reliance on binary variables in Baslis et al. (2009) also make it poorly suited for seasonal analysis on larger water and power systems. The stochastic scheduling model in Yang et al. (2017) also resolves each reservoir and generator but ignores critical operational constraints such as ramping rates and minimum operating capacity of power plants. Stochastic Dual Dynamic Programming (SDDP) (Pereira, 1989) is often used when the stochasticity of state variables for water and power systems is of interest (Pereira and Pinto, 1991; Rougé and Tilmant, 2016; De Queiroz, 2016a); however, SDDP is not guaranteed to converge to a solution in practice and has limited ability to handle nonconvexity in problems (Shapiro, 2011; De Matos et al., 2015; Ávila et al., 2021).

While there have been efforts to model power and reservoir systems together, most have been limited by simplifications of one or both systems (Turgeon, 1980; Pereira and Pinto, 1985; Zambon et al., 2012; Baslis et al., 2009), narrow focus on a specific situation (Yang et al., 2017), short-term scheduling problems (Mandal et al., 2008; Swain et al., 2011; Norouzi et al., 2014), or applicability to only small-to-medium systems (Baslis et al., 2009). Further, there is a clear gap in co-optimization of water and power systems at seasonal to sub-annual time scales. This work presents an integrated optimization framework that can be used to analyze water and power systems together while fully resolving each reservoir and generator and by considering operational constraints such as varying reservoir storage rules, ramping and minimum operating rates of generators, and seasonally varying electricity demand profiles. In particular, to support season hydro-thermal operations and planning, we link an open-source generalized multireservoir model and an open-source energy system model to create a framework that dynamically shares information between the models, so decisions made in one system are accounted for in the other. The generalized nature of each model allows this framework to be applied for any system and, because their source code is openly available, they can be modified to suit the needs of a specific system or problem.

In Section 2, a short summary of existing optimization methods for water and power systems separately and together is presented. Section 3 discusses the water and power models used in this work any modifications from their original formulation. The way these models are integrated together and the methods for finding solutions are also presented in Section 3. The framework is applied to the Tennessee Valley Authority's reservoir and power system in Section 4. Following the study area description, the framework and its solution methods are evaluated based on reductions in cost to meet power demand, water use efficiency, reservoir spill, and reservoir deficit in Section 5. Additionally, the framework's operational capabilities are evaluated using a seasonal rolling horizon setup. Finally, the findings are summarized, and the benefits, limitations, potential uses, and future improvements are discussed in Section 6.

2. Background on water and power systems optimization

2.1. Reservoir system modeling

Reservoir and multireservoir optimization have been extensively researched over various spatial and temporal scales. While Labadie (2004) and Ahmad et al. (2014) provide comprehensive reviews of reservoir optimization techniques. Linear programming (Belaineh et al., 1999; Needham et al., 2000) and nonlinear methods such as sequential quadratic programming (Finardi et al., 2005) are among the most popular for single reservoir or small multireservoir systems. Various evolutionary algorithms, such as genetic algorithms (Sharif and Wardlaw, 2000), particle swarm optimization (PSO) (Al-Aqeeli and Mahmood Agha, 2020), and the Monarch Butterfly Algorithm (Ehteram et al., 2017) have been successfully used for multireservoir optimization for small and large systems over a variety of time horizons ranging from daily to yearly. Stochastic dynamic programming (SDP) is often employed to optimize multireservoir networks under inflow uncertainty (Alaya et al., 2003; Archibald et al., 2006; Li et al., 2014; Liu et al., 2018); however, SDP is typically limited to a single reservoir or small multireservoir systems due to the exponential growth in dimensionality in decision variables – reservoir releases – as more reservoirs are added.

One approach to manage the curse of dimensionality is to aggregate the reservoirs into an equivalent reservoir based on the potential energy of impounded water. This approach was initially developed by Arvanitidis and Rosing (1970a) and Arvanitidis and Rosing (1970b) and has since been used several times to reduce the dimensionality of multireservoir optimization (Brandão, 2010; Guo et al., 2013; Mukhopadhyay et al., 2021). Studies that compared equivalent reservoir models with the detailed cascade modeling approach found that the former perform poorly compared to the latter for reservoirs with smaller storage-to-demand ratio (Mukhopadhyay et al., 2021). Simulation–optimization methods have also been used to reduce the dimensionality of large multireservoir problems but have the benefit of maintaining the cascading structure (Koutsoyiannis and Economou, 2003; Sankarasubramanian et al., 2009). Xuan et al. (2020) present a simulation–optimization scheme that leverages the Feasible Sequential Quadratic Programming (FSQP) algorithm (Lawrence and Tits, 2001) and accounts for inflow uncertainty using streamflow ensembles while fully resolving each reservoir in a cascade. There is a wide array of optimization techniques for reservoir and multireservoir systems, each with benefits and drawbacks; however, very few of these techniques have been implemented alongside power system optimization models.

2.2. Power system modeling

For power systems, Ringkjøb et al. (2018) provide a comprehensive review of available models. As noted in Ringkjøb et al. (2018), the temporal resolution and horizon of interest for power system modeling can range from sub-second to decadal and beyond. Various mathematical programming techniques have been used to optimize power systems over the entire range of temporal resolutions and time horizons including linear, nonlinear, dynamic, and evolutionary programming methods. Most frequently, short term (sub-weekly) power system optimization is performed with unit commitment models (UCMs) that employ a mixed-integer linear programming formulation. Alternatively, long term (yearly to decadal) optimization focuses on planning and generation capacity expansion and is generally performed with energy system optimization models (ESOMs) that are pure linear formulations without unit commitment (de Queiroz et al., 2019; Ringkjøb et al., 2018; Hunter et al., 2013).

UCMs and ESOMs have dominated the power system modeling space for many years but they are generally not well equipped to handle seasonal time horizons (de Queiroz et al., 2019). To effectively capture seasonal power system dynamics, the temporal resolution needs to be high enough to account for operational complexities such as ramping rates and the formulation should be computationally efficient enough to allow for uncertainty quantification. As more variable renewable generation, such as wind and solar, is built, the need for seasonal power system planning models also increases [10,36 and references therein]. Though there are few power system models built specifically for seasonal analysis (Ringkjøb et al., 2018), there have been efforts to incorporate operational details within ESOMs (de Queiroz et al., 2019; Collins et al., 2017). In addition, linking UCMs and ESOMs together was explored by Deane et al. (2012) by feeding outputs from the TIMES energy system model into the PLEXOS power systems model to validate generation portfolios from ESOMs. de Queiroz et al. (2019) modified an open source ESOM, Temoa (Hunter et al., 2013), for applications related to seasonal planning and operations. These modifications include the addition of ramping constraints, altering the time indices to allow for an hourly temporal resolution, and disallowing capacity additions thus forcing demand to be met with current generation sources. An important attribute of this work is the lack of integer variables in the model formulation, allowing for solutions to be arrived at via pure linear programming methods. However, these power system models are not able to capture the dynamic interactions and dependencies between reservoir and power systems.

2.3. Combined reservoir and power system modeling

Though there are numerous studies on reservoir system or power system modeling, limited studies have focused on co-optimization of both systems together in an integrated framework at the seasonal time scale. For example, Turgeon (1980) presents an integrated reservoir-power system model that leverages the equivalent reservoir method of Arvanitidis and Rosing (1970a) and dynamic programming to find the optimal reservoir discharges to minimize the cost of meeting power demand. Pereira and Pinto (1985) apply the equivalent reservoir method to 37 reservoirs in the Brazilian system while also aggregating the regional thermal generating capacity into a single unit and using dynamic programming to find the optimal solution. It has been shown that these aggregation methods can result in similar solutions to methods that account for each reservoir individually (Brandão, 2010; Mukhopadhyay et al., 2021); however, equivalent reservoir models prevent reservoir specific constraints from being implemented, limits the ability to quantify water transfers and diversions, ignores travel time from one reservoir to another, and makes it difficult to incorporate forecasted inflow.

In studies where each reservoir in a cascade is fully resolved, it is common for the thermal power system to be aggregated. Zambon et al. (2012) develop an integrated reservoir-power system model for the Brazilian system that models each reservoir individually in the reservoir module, allowing for detailed, reservoir specific constraints to be implemented; however, the power system module aggregates all hydro and thermal load within four subregions to improve computational efficiency of their deterministic optimization model. However, as conventional thermal generators are replaced with variable renewable technologies such as wind and solar power, aggregated representations of power generation become less realistic as the resource quality is different in each region and the characteristics of the transmission system interconnecting these resources may play a bigger role in the decision-making process.

Baslis et al. (2009) propose a deterministic model for medium-term hydro-thermal scheduling that is applied to 29 thermal generators and 13 hydroelectric reservoirs in the Greek Power system. The authors model each individual reservoir and thermal plant; however, hydropower output is considered to be head independent and only a function of release in order to facilitate a linear model formulation. Additionally, the formulation in Baslis et al. (2009) is reliant on binary variables, which may limit the models applicability to very large systems due to extended solution times associated with mixed integer programming methods. Yang et al. (2017) develop a stochastic scheduling model for power systems that minimizes power generation costs while accounting for flood risk within a reservoir network. Though the authors account for individual reservoirs and thermal plants, their power system model does not consider important constraints such as ramping conditions and minimum operating requirements or variable renewable generators. Further, the focus on flood protection can limit the formulations applicability during drought conditions as there is little incentive to hold water, though that is when optimal hydrothermal scheduling may be most beneficial (O'Connell and Macknick, 2019).

Dynamic programming, specifically Stochastic Dynamic Programming (SDP) (Dias et al., 2010; Brandi et al., 2015) and Stochastic Dual Dynamic Programming (SDDP) (Pereira, 1989; Pereira and Pinto, 1991), is a frequently used method for solving hydrothermal scheduling problems (Rougé and Tilmant, 2016; De Queiroz, 2016b). These methods can reliably provide solutions while accounting for the stochasticity in future inflows, power demand, and fuel prices. SDP is plagued by the curse of dimensionality due to discretization of the state space, thus limiting the temporal and spatial extents of problems SDP can solve. Though SDDP avoids the discretization of state variables that lead to the curse of dimensionality in SDP, SDDP is poorly suited to non-convex problems and is not guaranteed to converge in a practical amount of time (De Matos et al., 2015; Ávila et al., 2021). Further, Rougé and Tilmant (2016) find that SDDP solutions can exhibit large variations for very small variations in input data. These variations are found to be especially prevalent when there are multiple near-optimal solutions, which is likely to occur in power and water system optimization due to large decision spaces.

3. COREGS methodology

To investigate the potential benefits of incorporating electric power system information in reservoir operation decisions, the Co-Optimization of Reservoir and Electricity Generation Systems (COREGS) modeling framework is developed. COREGS incorporates the Generalized Reservoir Analysis using Probabilistic Streamflow (GRAPS) model (Mukhopadhyay et al., 2021, and https://github.com/lcford2/GRAPS) to represent reservoir networks and the Tools for Energy Model Optimization and Analysis (Temoa) model (de Queiroz et al., 2019; Hunter et al., 2013) to optimize electric power systems operations. Both models are modified as below to facilitate co-optimization.

3.1. Reservoir system modeling–GRAPS

GRAPS is an open-source generalized multireservoir simulation–optimization model written in Fortran. It represents reservoir networks as directed graphs with reservoirs, users, watersheds, junctions, and sinks represented by nodes and water pathways as edges. With GRAPS, all mass balance and hydropower variables are resolved at a given time step for each reservoir. GRAPS also handles various constraints including operational rules and storage and release bounds for each reservoir. This allows for a detailed and realistic representation of the reservoir cascade. For the full modeling details of GRAPS, see (Mukhopadhyay et al., 2021, and https://github.com/lcford2/GRAPS).

To better represent seasonal reservoir operation patterns, the GRAPS formulation described in Xuan et al. (2020) is enhanced to allow for time varying operational rules for each reservoir. The new method for determining reservoir storage bounds is presented in Eq. (1).

$$\max\left(LC_{r,t}, S_r^{min}\right) \le S_{r,t} \le \min\left(UC_{r,t}, S_r^{max}\right) \quad (1)$$

Where $S_{r,t}$, $LC_{r,t}$, and $UC_{r,t}$ are the end-of-time-step storage, lower, and upper rule curves, respectively, for reservoir r and time step t. This ensures that the reservoir storages are always bound by the tighter constraint between the physical storage limits and the operational rules. In cases where the storage for a reservoir is greater than its upper bound, GRAPS increases the release to bring the storage down. If the reservoir is releasing the maximum allowable amount and the storage is still above the upper bound, the reservoir is forced to spill the difference between the simulated storage and the upper bound. When a reservoir's storage level is below the minimum allowable storage for a given month, GRAPS attempts to mitigate this deficit by reducing the release for that reservoir and month. If the reservoir is not releasing any water but still is violating the lower storage bound, the deficit at that reservoir will be the difference between the current storage and the lower storage bound. This is most likely to occur at reservoirs receiving only natural flow during drier periods. Depending on the optimization technique used for the reservoir network, the spill and deficit is handled slightly different with the overall goal of having zero spill and deficit across the network.

3.2. Power systems modeling–Temoa

Temoa is an open source generalized energy system optimization model (ESOM) written in Python. It was initially developed by Hunter et al. (2013) and modified for seasonal power generation planning in de Queiroz et al. (2019) by disabling capacity expansion, remapping time indices so the finest resolution is hourly, adding ramping up and down constraints, and incorporating startup costs. The seasonal planning model of de Queiroz et al. (2019) is modified here to facilitate its integration with GRAPS. Temoa minimizes the cost of meeting electricity demand by optimally dispatching generation units with respect to constraints such as thermal plant ramping and bounds on unit capacity and activity. The mathematical formulation of Temoa can be described as a directed network graph with energy commodities (fuel, electricity, water, and others) moving between and being transformed by processes (thermal power plants, hydropower plants, fuel refinement, and others).

Temoa traditionally represents time with three indices: time-periods (t), seasons (s), and times of day (d). Each time-period is subdivided into seasons and each season is subdivided into times of day. Electricity demand (DEM) is specified for each time-period and a Demand Specific Distribution (DSD) is used to determine the demand that must be met for each time of day within each season (dem) (Eq. (2)). The sum of the DSD must equal one to ensure all the specified demand is met.

$$dem_{t,s,d} = DEM_t \times DSD_{s,d} \quad (2)$$

One limitation of this approach is that the DSD is the same for all time-periods. This is not an issue if your time-periods represent long time intervals like a year, but for a seasonal operational planning model, the time-periods represent months. In this case, it is desirable to have different DSD's for different time-periods because electricity demand profiles change from month to month. To capture this monthly variation, the indexes of DSD are extended to include time-periods. Eq. (3) represents the use of DSD for each time-period.

$$dem_{t,s,d} = DEM_t \times DSD_{t,s,d} \quad (3)$$

The objective function of Temoa is explicitly defined by Eqs. (14)–(17) in Hunter et al. (2013); however, as this study focused on seasonal operation of the power system, only the variable costs are of interest and future costs are not discounted. Therefore, Temoa's objective function simplifies to the sum of generator variable costs times the amount generated for each generator and time slice.

Two of the co-optimization methods described rely on the availability of dual variables (shadow prices) for hydropower constraints in Temoa. Dual variables are a measure of the marginal effect of relaxing a constraint on the objective function and thus can be used to estimate the value of additional hydropower availability to a power system that has been optimized. Many linear programming solvers such as the GNU Linear Programming Kit (GLPK) (Makhorin, 2012), Gurobi (LLC Gurobi Optimization, 2020), and CPLEX (International Business Machines Corporation, 2019) provide dual variables for the optimal solution. For the purpose of this work we use Gurobi Optimizer (LLC Gurobi Optimization, 2020) to solve the Temoa optimization models; however, any mathematical optimization solver that calculates and provides dual variables for constraints can be used to solve the optimization models.

3.3. GRAPS and Temoa modeling framework

COREGS expects a specific configuration of GRAPS and Temoa to ensure that the exchange of information between them does not cause inaccuracies. The most important characteristic is that the lowest resolution time index in Temoa, time-periods (t), are the same temporal resolution as the time-steps in GRAPS and that each model have the same time horizon.

In this study, the reservoir network is modeled with a seasonal (three-month) time horizon with monthly time-steps; therefore, the time-periods in Temoa must be a set of three months. From there, time in Temoa is further subdivided into daily and hourly resolution where each month has thirty days, and each day has twenty-four hours. Thus, electricity generation in Temoa is allocated for every hour over a three-month window and is indexed for every hour of every day of every month for every generation technology.

With this configuration, total electricity demand must be specified at the monthly level. Temoa then disaggregates that monthly demand into an hourly demand time series using the Demand Specific Distribution (DSD). For each modeled hour, the generation activity (the sum of all the available generation) is required to equal the demand for that hour. Activity for each generator is bound at the hourly and monthly level to prevent unachievable peak power and unreasonable monthly utilization.

GRAPS only uses one time-index, as a result all variables, calculations, and constraints are with respect to a monthly time-step. Because the reservoir network is modeled at the monthly level, travel time for water released from one reservoir to reach another reservoir is neglected. As described in Xuan et al. (2020), if a finer time resolution is required, GRAPS provides the ability to account for travel time between reservoirs by lagging return flows.

3.4. Model formulations for the co-optimization of water and power systems

Three co-optimization methods are considered with differing levels of coupling between GRAPS and Temoa. In each method, hydropower generated from GRAPS for reservoir r and time-step t becomes the upper bound on hydropower activity in Temoa for reservoir r and time-period t where it can be optimally dispatched along with other generation units with a mathematical optimization solver. This creates a one-way path for sharing information from GRAPS with Temoa. Each co-optimization method optimizes the reservoir system and communicates with Temoa differently. These techniques are discussed below in order of increasing level of coupling between GRAPS and Temoa.

Briefly, the Maximize Hydropower method (MHP) maximizes the total amount of hydropower generation from the reservoir system using FSQP and then optimizes the energy system using that hydropower generation. Maximize Hydropower Benefits (MHB) takes this one step further by incorporating the spatio-temporal benefit of hydropower generation to the power system in the GRAPS objective function for optimizing the reservoir network using the FSQP. Iterative Co-Optimization of Reservoir and Power Systems (ICORPS) iterates between GRAPS and Temoa using heuristics to increase hydropower generation where it is most beneficial to the power system.

Maximize Hydropower (MHP)

Maximizing hydropower (MHP) attempts to reduce the cost to meet power demand by generating the most hydropower available within a season from the reservoir network. This is the baseline implementation that the other two methods will be compared against and optimizes the reservoirs system separately from the power system. MHP optimizes hydropower production in GRAPS with the Feasible Sequential Quadratic Programming (FSQP) solver (Lawrence and Tits, 2001) and then provides that hydropower to Temoa to use as upper bounds on monthly hydropower activity. As the objective function and all constraints are either linear or quadratic and mostly smooth, FSQP is a reasonable solver for this problem. The decision variables for FSQP are the discharge D for each reservoir r and time-step t. The reservoir network objective function is described by Eq. (4) where HP is hydropower in megawatt hours (MWh/month). Eq. (5) describes how hydropower is calculated where $_{\eta}$ is the generator/turbine efficiency, γ is the specific weight of water in pounds per cubic foot (lb/ft^3), $\beta_{r,1}$, $\beta_{r,2}$, and $\beta_{r,3}$ are the fitted stage-storage coefficients, $_{TW}$ is the tail water elevation in feet (ft), and D is the hydropower discharge in thousand acre feet per month (1000 ac-ft/month). The constant 0.0164 is included to resolve units between the left and right sides of Eq. (5).

$$\sum_{r\in R}\sum_{t\in T} HP_{r,t} \tag{4}$$

$$HP_{r,t} = (0.0164)\eta_r\gamma\left(\left(\beta_{r,1}S_{r,t}^2 + \beta_{r,2}S_{r,t} + \beta_{r,3}\right) - TW_{r,t}\right)D_{r,t} \tag{5}$$

All the physical constraints on the reservoir network are handled directly by GRAPS. The only constraints FSQP is responsible for meeting are minimum and maximum release bounds and ensuring that there is no spill or deficit across the cascade. Due to the spill and deficit constraints, there can be feasibility issues that do not let FSQP proceed with the optimization. For example, it could be impossible to eliminate a deficit for a reservoir if its initial storage is below the desired operational rule and there is very little inflow. These feasibility issues are addressed by relaxing the storage constraints that are causing the infeasibility just enough to achieve feasibility. Eq. (6) describes how the storage constraint is relaxed when FSQP cannot eliminate the spill at reservoir r during time-step t while Eq. (7) does the same for occurrences of unmitigable deficit.

$$S_{r,t} \le \min\left(UC_{r,t}, S_r^{max}\right) + SP_{r,t} + 1 \tag{6}$$

$$S_{r,t} \ge \max\left(LC_{r,t}, S_r^{min}\right) - DEF_{r,t} - 1 \tag{7}$$

This method assumes any additional hydropower from any reservoir at any point in time is worth the same amount and is a baseline comparison that provides the monthly maximum hydropower for Temoa to utilize as needed. Due to the low marginal cost of hydropower compared to thermal power generation, this assumption is reasonable for a baseline case. GRAPS still manages the complexities of the reservoir cascade, but the only constraints limiting hydropower are physical and operational constraints on the reservoir network (i.e., there is no information from the power system being used to inform water allocation decisions). Thus, in this case, GRAPS is run independently from Temoa once to maximize the monthly hydropower (Eq. (4)), which is then utilized by Temoa to minimize the cost of power generation considering all the generation units.

Maximize Hydropower Benefits (MHB)

Maximizing Hydropower Benefits (MHB) is similar to MHP but with a different objective function and with GRAPS and Temoa running twice instead of once. To setup MHB, GRAPS simulates the reservoir network given the initial releases provided by the user. The simulated hydropower is then passed to Temoa, which is then optimized. The dual variables (shadow prices) $_{(\pi_{r,t})}$ on the hydropower activity constraints are retrieved from Temoa and their absolute values become the benefits for hydropower generation in FSQP (Eq. (8)). The dual variable for each reservoir in a given month can be obtained after the TEMOA optimization model is solved as they represent the shadow prices associated with hydropower activity constraints (Bradley et al., 1977). Gurobi, the mathematical engine used in this work, provides the dual variables needed for COREGS.

$$max\sum_{r\in R}\sum_{t\in T}\left(\left|\pi_{r,t}\right| HP_{r,t}\right) \tag{8}$$

In this instance, dual variables on hydropower generation can be thought of as the value of water (Fernández-Blanco et al., 2017) as they represent the expected objective improvement that could be realized if a given reservoir is allowed to release more water (generate more power) in a given month. While the strict definition of a dual variable only allows for interpretation given a specific state of the decision variables, this method still provides information to FSQP on when and where water is the most valuable to the power system. Though this is a subtle improvement over MHP on the co-optimization between the two systems, it has potential to have a large impact on the solutions provided. The utility of this method is critical as it explicitly considers the temporal variability in power demand in maximizing hydropower generation. Since generation units are dispatched in order of increasing marginal cost, it is cost effective to hold water in low demand months to generate more hydropower in high demand months. Release and storage constraints on the reservoir network that limit this style of operation, but that is the utility of using a fully specified multireservoir model such as GRAPS to model the reservoir network. With the MHB method, the flow of information between GRAPS and Temoa is improved by using the initial optimal state of the electricity system to inform decisions in the reservoir system. However, the sharing of information is static and does not account for the dynamically changing value of hydropower to the power system as more hydropower is available.

Iterative Co-Optimization of Reservoir and Power Systems (ICORPS)

To address the issue of static hydropower benefits in the MHB method, the Iterative Co-Optimization of Reservoir and Power System (ICORPS) method is developed. ICORPS builds on the logic defined for the MHB method but iterates between GRAPS and Temoa until a solution is found while implementing heuristic rules for improving hydropower rather than relying on FSQP. The first iteration (iteration 0) in ICORPS begins the same as in MHB: GRAPS is simulated with an initial solution and then ICORPS obtains the release decisions and hydropower output. The

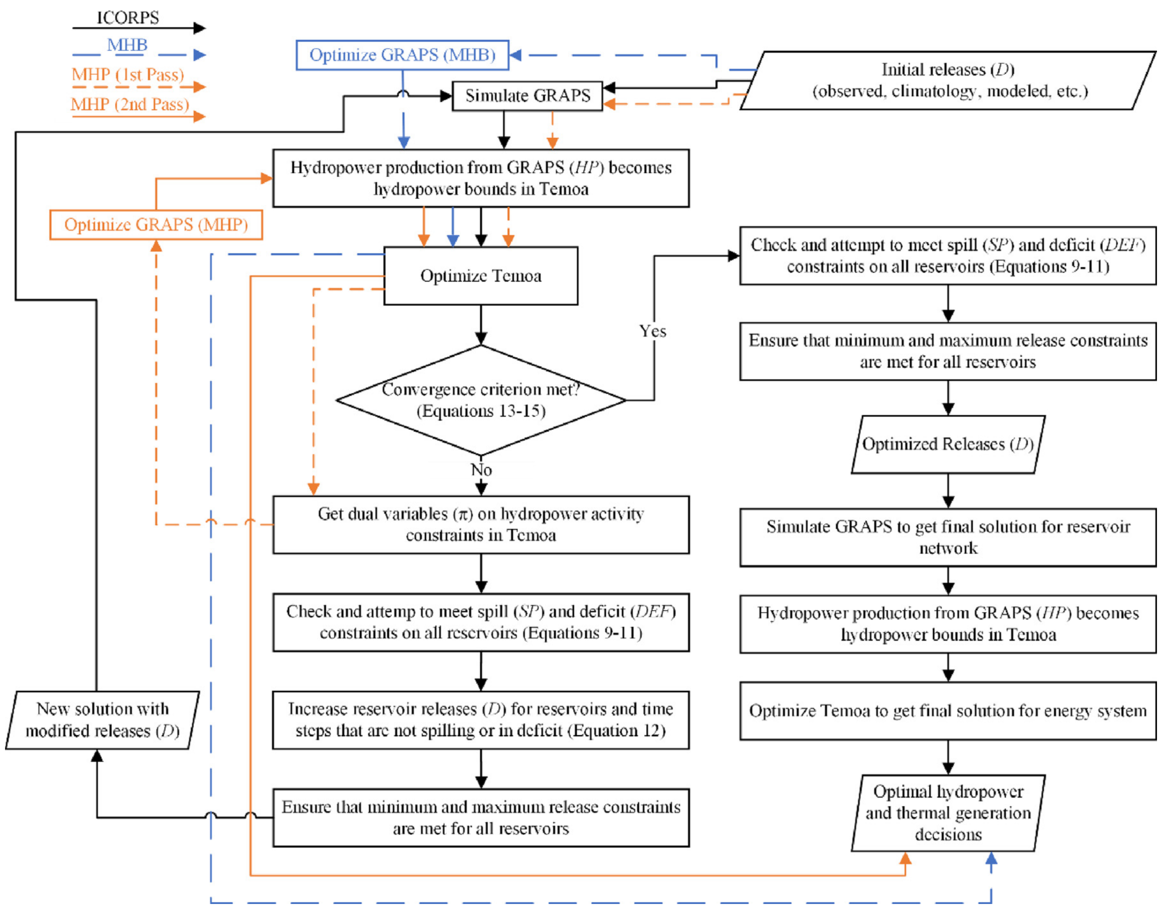

Fig. 1. High-level flowchart for Iterative Co-Optimization of Reservoir and Electric Power Systems (ICORPS) with each parallelogram, rectangle, and diamond representing data, model processes, and key decisions, respectively. Blue (orange) boxes indicate processes that only happen in the MHB (MHP) method. Solid orange lines are transitions between the two processes that occur twice for MHP. (For interpretation of the references to color in this figure legend, the reader is referred to the Iterative Co-Optimization of Reservior and Power Systems (ICORPS) section.)

hydropower is provided to Temoa, which is then optimized, then ICORPS obtains the dual variables associated with the maximum hydropower activity constraints. At this point ICORPS and MHB diverge as ICORPS now uses the releases from GRAPS and the dual variables from Temoa to increase release from the reservoirs where it is most beneficial. These new releases are passed back to GRAPS to simulate the reservoir network again and the process repeats. ICORPS continues to iterate between GRAPS and Temoa, constantly improving the releases based on changes in the value of hydropower to the power system. The iterative use of these dual variables is described via the release update procedure described below and in Fig. 1. Fig. 1 also depicts the MHB and MHP processes in blue and orange, respectively. Any box that is not outlined in black indicates a step that is only taken by the algorithm indicated by its color. Additionally, as the MHP method will repeat two steps (hydropower bound setting in Temoa and Temoa optimization), the transitions between those two steps are indicated in a solid orange line rather than a dashed line.

Before using the dual variables to update the release for hydropower, ICORPS checks and attempts to mitigate spill and deficit from the reservoir network. Contrary to the MHP and MHB methods, ICORPS does not use FSQP to eliminate spill and deficit from the network. As GRAPS ensures that spill or deficit only occurs if there is no flexibility in the mass-balance variables at a single reservoir (refer to Section 2.1), ICORPS alleviates the spill and deficit by modifying the release of upstream reservoirs. Spill and deficit mitigation begins by calculating the sum of the controlled release into the reservoir ($UR^i_{r,t}$) that is violating (Eq. (9)), where i is the iteration number and U_r is the set of all reservoirs directly upstream of reservoir r. This upstream inflow is used to determine modifying fractions ($F^i_{u,t}$) for each reservoir upstream of reservoir r using Eq. (10). These fractions are then directly used to decrease the release for reservoirs immediately upstream of a spilling reservoir r via Equation (11). For a spilling reservoir, the modifying fractions represent the amount of controlled inflow into reservoir r coming from reservoir u. This results in reducing release from reservoirs that contribute the most to a spilling reservoir.

$$UR^i_{r,t} = \sum\nolimits_{u \in U_r} D^i_{u,t} \tag{9}$$

$$F^i_{u,t} = \begin{cases} 1 & \text{if} \quad U_r = 1 \\ \frac{D^i_{u,t}}{UR^i_{r,t}} \; \forall\, u \in U_r & \text{if} \quad SP^i_{r,t} > 0 \\ \left(\frac{1}{|U_r|-1}\right) \frac{UR^i_{r,t} - D^i_{u,t}}{UR^i_{r,t}} \forall u \in U_r & \text{if} \quad DEF^i_{r,t} > 0 \end{cases} \tag{10}$$

$$D^i_{u,t} = \begin{cases} D^i_{u,t} - SP^i_{r,t} \times F^i_{u,t} & \text{if} \quad SP^i_{r,t} > 0 \\ D^i_{u,t} + DEF^i_{r,t} \times F^i_{u,t} & \text{if} \quad DEF^i_{r,t} > 0 \end{cases} \tag{11}$$

For a reservoir in deficit, release should be increased at reservoirs that are releasing the least. To accomplish this, discharge, $D^i_{u,t}$, from an upstream reservoir u is subtracted from the total controlled inflow, $UR^i_{r,t}$, into reservoir r, which is then divided by the total controlled inflow into reservoir r to get a fraction, $F^i_{u,t}$, that represents the amount of inflow into reservoir r if reservoir u released nothing. These intermediate fractions will increase as the amount of release from reservoir u decreases. Finally, to arrive at a set of modifying fractions whose sum is equal to 1, so all the deficit is mitigated, the intermediate fractions are divided by their sum. In Eq. (10), the sum of intermediate fractions has been algebraically simplified to the number of upstream reservoirs ($|U_r|$) minus 1.

One limiting case in distributing the spill and deficit based on Eqs. (9)–(11) is when a reservoir has no upstream reservoir (i.e. the only inflow it receives is natural). If there are no upstream reservoirs, spill or deficit cannot be eliminated unless the operational rules are modified. Rather than modifying the rules, ICORPS continues with the iteration with the understanding that there will be violations of the operational rules in the final solution. Using this method, nearly all spill and deficit is mitigated except for a few cases. It could be argued that this procedure should be recursive and move up the cascade until the violating reservoir is not spilling or in deficit; however, during testing, all but a single violation came from situations where there is little operation flexibility to mitigate spill and deficit therefore it was determined that recursion was not required.

If reservoir r is not spilling in time-step t, the release is increased using Eq. (12), which ensures that the reservoirs and time-steps that have the most benefit to the power system increase their water allocation for hydropower the most. The case when the current release is zero but there is some benefit for hydropower is handled by setting the release equal to a fraction (λ) of the maximum allowable release. The default value for λ is 5% but can be tuned to increase convergence speed (increasing) or find more exact solutions (decreasing). When $\pi^i_{r,t}$ is zero, indicating that hydropower reservoir r and time-step t is being constrained by something else in the power system, the release is not changed.

$$D^{i+1}_{r,t} = \begin{cases} D^i_{r,t} \times \left(1 + \frac{\pi^i_{r,t}}{\alpha \times \pi^i_{\max}}\right) & \text{if} \quad D^i_{r,t} > 0 \\ \lambda \times D_{r,\max} & \text{if} \quad D^i_{r,t} = 0 \text{ and } \left|\pi^i_{r,t}\right| > 0 \end{cases} \tag{12}$$

Eq. (12) also has a tuning parameter, α, that controls how large of an increase in release is allowed and π^i_{max} is the dual variable with the largest magnitude for iteration i. By default, $\alpha = 2$, limiting the maximum step to a 50% increase in release for the reservoir and time-step that has the maximum dual variable. Increasing α results in smaller steps, which could produce a better solution but would take longer to reach that solution. Reducing α decreases the solution time at the increased risk of overshooting the optimal decision variable values. The final step before passing the releases back to GRAPS is to ensure that the updated releases are not violating their release bounds by setting the releases equal to the bound they are violating. Finally, the updated release values are passed back to GRAPS for simulation and the process starts over again.

This process is repeated until ICORPS has converged to a solution. Convergence occurs when the percent change in Temoa's objective function between iterations lies between zero and a user specified tolerance (ε) a user specified number of times (K). This criterion is described in Eqs. (13) to (15) where N is the total number of iterations performed. The default values for K and ε are 5 and 0.01%, respectively. Similar to α, relaxing the values of these parameters can result in a shorter solution time and tightening them can result in a better solution. Requiring the percent change to be between zero and $_\varepsilon$ multiple times increases the confidence that the reported solution is near optimal.

$$\text{ICORPS converges when} \sum_{i=0}^{N} \gamma\,(i) = K \tag{13}$$

$$\Gamma\,(i) = \begin{cases} 1 & \text{if} \quad 0 < \%\Delta Obj_i < \varepsilon \\ 0 & \text{if} \quad \text{otherwise} \end{cases} \tag{14}$$

$$\%\Delta Obj_i = \frac{Obj_{i-1} - Obj_i}{Obj_{i-1}} \times 100\% \tag{15}$$

After the convergence criteria has been met, spill and deficit are checked similarly to the description above (Eqs. (13)–(15)). The difference is that when spill or deficit has been addressed at a reservoir, GRAPS is then ran again with the new releases rather than addressing spill at all reservoirs and then running GRAPS. This ensures that changes to the decision variables are accounted for when the next violating reservoir is addressed. This does not add significant time to the total run-time of ICORPS because GRAPS is just being simulated. After spill and deficit has been mitigated, and thereby GRAPS has been simulated with the optimal releases, Temoa is solved once more to provide the optimal solution for the electric power system generation scheduling.

ICORPS provides a solution to the static benefits that may hinder the MHB method, but it trades a proven mathematical solver like FSQP for a heuristic-based optimization-simulation approach over the reservoir network. It is technically feasible to adapt ICORPS to iteratively optimize Eq. (15) with FSQP or other solvers and then communicate with Temoa, effectively combining MHB and ICORPS; however, due to the long solution times required by FSQP this becomes impractical since it must be iteratively called. The MHB method and ICORPS are compared against the MHP method to analyze the potential benefits of incorporating power system benefits into reservoir releases for improving their operations during wetter and drier conditions. In addition to operational metrics such as hydropower generated, change in reservoir storage, and the cost to meet power demand, the ratio of the change in Temoa's objective function to the change in total system release between the optimal and initial solutions (Eq. (16)) is also considered. In Eq. (16), Obj_N and Obj_1 are the optimal value of Temoa's objective function for the final iteration and the initial iteration, respectively.

$$\delta = \frac{Obj_N - Obj_1}{\sum_{r\in R}\sum_{t\in T} D^N_{r,t} - \sum_{r\in R}\sum_{t\in T} D^1_{r,t}} \tag{16}$$

This δ is interpreted as the water allocation efficiency and provides insight into how each method generates optimal solutions. We consider this as an additional metric apart from the differences in the releases, spills from the reservoirs and operating costs from different optimal solutions.

4. COREGS Application to the Tennessee Valley Authority system

To evaluate the value of co-optimization of water and power systems, the COREGS framework is applied to the reservoir and power systems owned and operated by the Tennessee Valley Authority (TVA). TVA operates all the major dams on the Tennessee River while also supplying electricity to over nine million people (US Senate, 2015). COREGS is applied to winter (December, January, and February) and summer (July, August, and September) seasons starting in December of 2003 to September of 2015 as well as a rolling horizon analysis for 2004, 2007 and 2010. TVA's power and water systems are modeled as they were configured in 2008 (US Energy Information Administration, 2004, 2020a) (Fig. 2, Table 1).

4.1. TVA electricity system configuration

The configuration of the generation network is static through time, meaning that the decommissioning, construction, or modification of generation units is not considered in this study. TVA

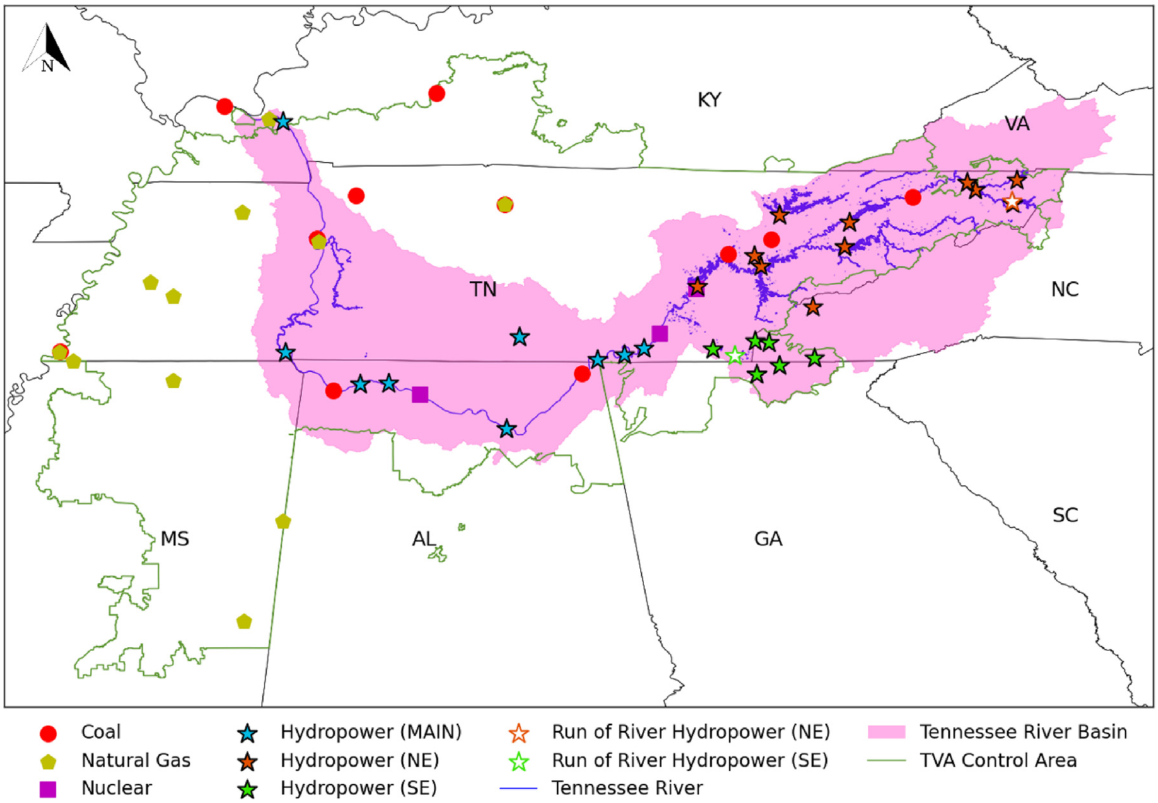

Fig. 2. Tennessee Valley Authority (TVA) generation units and control area (US Energy Information Administration, 2004; US Department of Homeland Security, 2017) with the Tennessee River Basin (US Geological Survey, 1994). Reservoirs have been grouped into three regions, North East (NE), South East (SE), and main stem (MAIN). NE reservoirs include Watts Bar and all reservoir upstream of it. SE reservoir include reservoirs Ocoee 1 and Apalachia and all reservoirs upstream of them. MAIN reservoirs include all reservoirs after the confluence of the NE and SE stems as well as Tims Ford.

Table 1
Tennessee Valley Authority (TVA) generation portfolio in 2008 (US Energy Information Administration, 2004).

Generator type	Number of plants	Nameplate capacity [MW]
Nuclear	3	7200
Natural gas combustion turbine	9	6295
Natural gas combined cycle	3	2605
Coal	11	17407
Conventional hydropower	27	3627
Pumped storage hydropower	1	1530

Note: Though this table shows aggregated capacity for different generation types, Temoa resolves generation for each individual plant.

delivers power to seven states: Alabama, Georgia, Kentucky, Mississippi, North Carolina, Tennessee, and Virginia. Electricity sales from Form EIA-861M (US Energy Information Administration, 2020a) and plant level net-generation from Schedules 3 A and 5 A of Form EIA-923 (US Energy Information Administration, 2020b) (formerly 906 and 920) for 2003 to 2015 are used to develop a monthly time series of demand for each state. Additionally, variable costs for thermal generators are developed using fuel receipts from Schedule 2 of Form EIA-923 (US Energy Information Administration, 2020b).

4.2. TVA reservoir system configuration

The reservoir network is configured based on information received directly from TVA (Tennessee Valley Authority, 2012). This information includes physical descriptions of each dam and reservoir such as storage and discharge bounds and information needed to fit storage-area curves. Daily time series of storage, headwater, tailwater, discharge through turbines, and total discharge were also provided by TVA. Net uncontrolled inflow for each reservoir is calculated by accounting for the controlled release of upstream reservoirs in the mass balance and solving for natural inflow and not explicitly calculating evaporation. This is described by Eq. (17), where I is the net uncontrolled inflow, O is the total outflow, S is the storage, and UR is the release from upstream reservoirs. This process is done for each reservoir r and data point t in the time series.

$$I_{r,t} = S_{r,t} + S_{r,t-1} - UR_{r,t} + O_{r,t} \tag{17}$$

The storage-area curves are not fit because the model is forced with net inflow, which accounts for evaporation. GRAPS can calculate evaporation volume given the coefficients for a storage-area curve and evaporation depths, but because the inflow time series is calculated from other mass balance variables, it does not need to be calculated here.

The upper and lower rule curves supplied to GRAPS are derived from the observed storage series provided by TVA. Though TVA provided operational rules for each reservoir, they only define guidelines for operation, not upper and lower bounds. Additionally, when those rules are compared with the observed data it is evident that it is common for the reservoirs to store water outside of those rules for flood control purposes. Rather than adhering strictly to the operational rules provided, quantiles on the monthly storage for each reservoir are used to define minimum and maximum storage bounds for simulation. The lower curve is defined as the 10th percentile of storage and the upper curve is defined as the 90th percentile of storage for each month. This results in operational storage bounds for every reservoir that is indexed by the month of the year but is constant throughout the years. Though there is storage data from as early as the 1940's

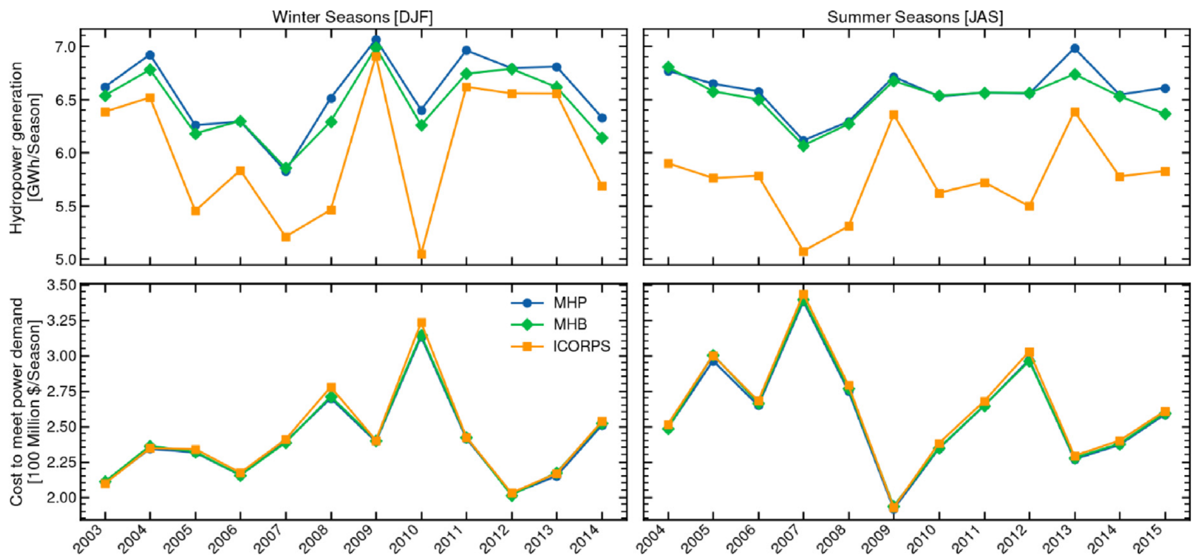

Fig. 3. Total seasonal hydropower generation and the cost to meet the seasonal power demand for each scenario modeled. Winter seasons start with December, January, February of 2003 and summer seasons start with July, August, September of 2004.

for some reservoirs, the period used to generate the rule curves is limited to 1975 to 2015. The operation of reservoirs changes over time as other reservoirs are built or new constraints are imposed and limiting the span of data used to define the operation ensures that the rules are representative of current operation.

4.3. Co-optimization scenario definitions

To evaluate the three co-optimization methods described above, 24 scenarios are developed that are defined by the season (winter or summer) and year in which they occur. Every winter and summer from December of 2003 to September of 2015 is modeled as separate scenarios with different power demand, natural inflow, and initial reservoir storage. Each three-month scenario is provided the observations for these three variables, and they vary for every month throughout the modeled period. The initial storage for every reservoir is defined as the storage at midnight of the last day of the preceding month (e.g., scenarios that start in December (winter scenarios) would start with the observed reservoir storage at midnight on November 30th). Additionally, the rule curves, demand specific distribution, and generator capacity vary between summer and winter scenarios but are constant from year to year.

5. Results

5.1. Performance comparison of co-optimizations methods

Each co-optimization method (MHP, MHB, and ICORPS) is applied to the scenarios defined in Section 4.3. We compare the performance of these methods for each scenario using two metrics: total hydropower generated from the system and the cost to meet the power demand. For a given scenario, each method begins with the same initial reservoir storages and is driven with the same monthly inflow and power demand; therefore, differences in hydropower generation and objective function values can be attributed to differences in the optimization method applied. Fig. 3 presents these values for each scenario in chronological order, separated for each season.

With respect to total hydropower generation, MHP provides the highest average seasonal generation compared to the other two methods in 16 of the 24 scenarios. MHB hydropower generation is similar to MHP for summer scenarios but generally trails behind in winter scenarios. Hydropower generation peaks in the winter for TVA as more water is released to maintain available flood storage. This seasonal pattern results in additional hydropower being worth less in the winter versus the summer, which MHB then accounts for while MHP cannot. For every scenario ICORPS generates less hydropower than each of the other two methods. As ICORPS is the only method that continuously exchanges information between GRAPS and Temoa this could indicate that generation from some reservoirs becomes less valuable as more hydropower is generated, leading to Temoa to stop requesting additional availability.

Further supporting this is the minimal differences in the cost to meet power demand across all scenarios. On average, MHP meets power demand at 249.8 million dollars per season where MHB and ICORPS average 250.7 million dollars per season and 252.7 million dollars per season, respectively. ICORPS solutions cost as much or more than MHP solutions in all scenarios and as much or more than MHB solutions in all but 5 winter scenarios and 2 summer scenarios. MHB meets power demand at less cost than MHP in 2 winter and 2 summer scenarios. Overall, though there are distinct differences in seasonal hydropower from each method, the objective function differences are minimal, indicating that MHB and MHP may be generating more hydropower than is necessary. This is primarily due to the ramping constraints and minimum operating requirements of other generation types that limit hydropower allocation to its fullest potential. We provide additional details regarding this by considering a wet season and dry season and analyze how ICORPS allocates power generation.

5.2. Evaluation of ICORPS solution pathway

Because ICORPS is a new heuristic algorithm, it is important to evaluate its performance and evolution. A series of evaluation scenarios (July, August, September of 2004 and 2007; December, January, February of 2004–05 and 2007–08) are chosen to test how the algorithm performs under different seasons with wet and dry inflow conditions. In 2004, a wet year, TVA reservoirs received approximately 60 million acre-feet of natural inflow (∼20% exceedance probability) while in 2007, a dry year, reservoirs only received approximately 20 million acre-feet (∼95% exceedance probability). To evaluate ICORPS for these scenarios, the relationships of hydropower (Fig. 4a) and storage (Fig. 4b)

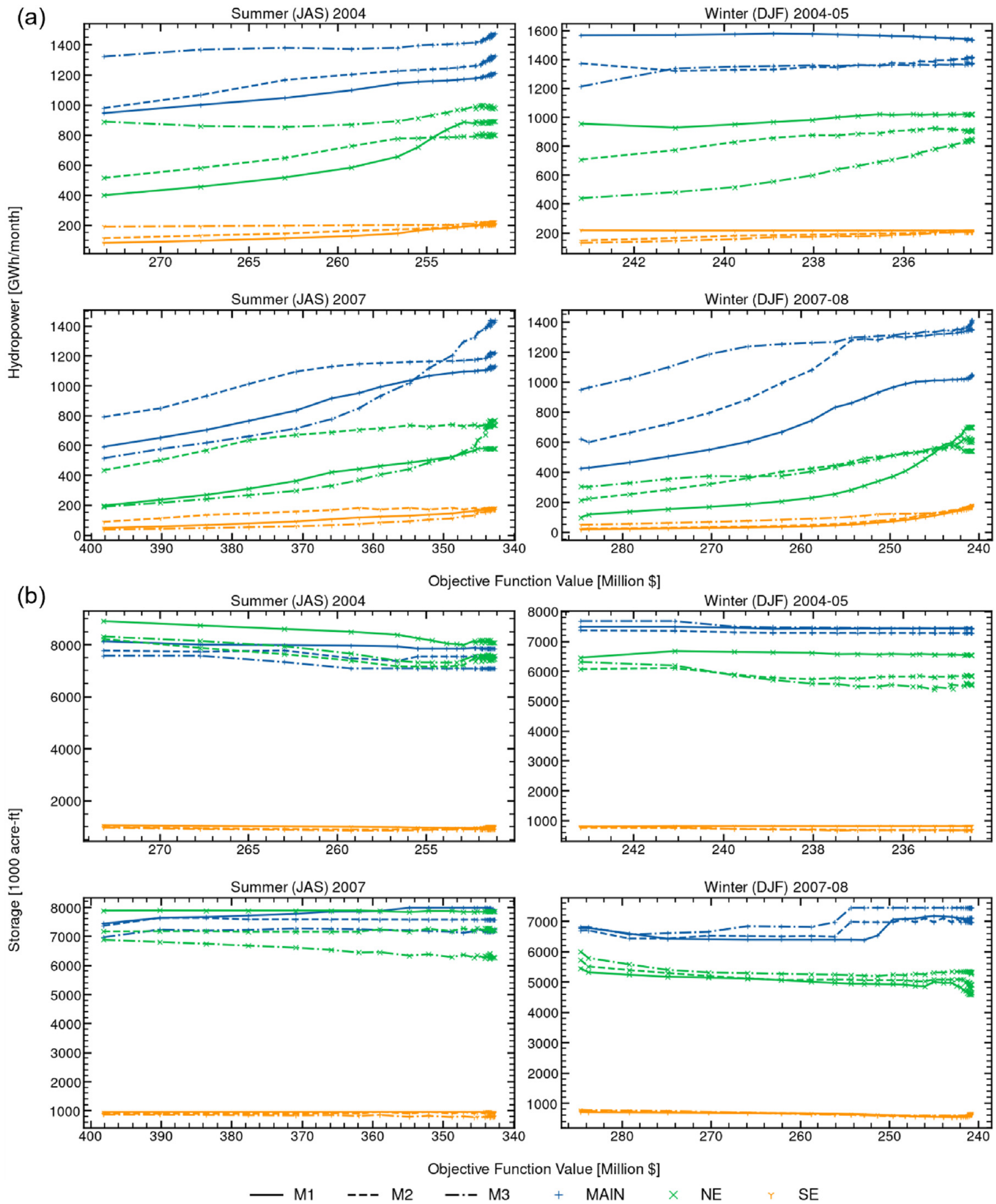

Fig. 4. Regional and monthly hydropower (a) and storage (b) as a function of the objective function for the winters of 2003–04 and 2007–08 and the summers of 2004 and 2007. M1, M2, and M3 refer to the first, second, and third month of the seasonal scenario, respectively, for each plot (e.g., M1 is July for and M2 is August for summer scenarios).

versus Temoa's objective function (the cost to meet power demand) are analyzed. Hydropower and storage are summed over all the reservoirs in each region. The *x*-axis for each of the plots is reversed so the objective function is decreasing from left to right. This provides a sense for the evolution of ICORPS because the objective function should decrease with each successive iteration.

Main stem reservoirs (MAIN) consistently generate more hydropower than the NE and SE reservoirs. In 2007, the change in objective function is much larger for both seasons than in 2004 indicating that there could possibly be more room for improvement in drier years than in wetter years. Additionally, the reduced inflow in 2007 is apparent in the reduced hydropower generation for NE and SE reservoirs. Due to additional controlled release from upstream reservoirs, main stem reservoir storages are less affected by the reduced inflow during dry years as evidenced by the lack of trend between main stem storages and the cost to meet power demand.

The relationships between monthly hydropower and the objective function provide insights into how the value of hydropower evolves. For example, hydropower from main stem reservoirs in the summer of 2007 initially seems to be equally valuable across all months as they increase at similar rates. As the objective

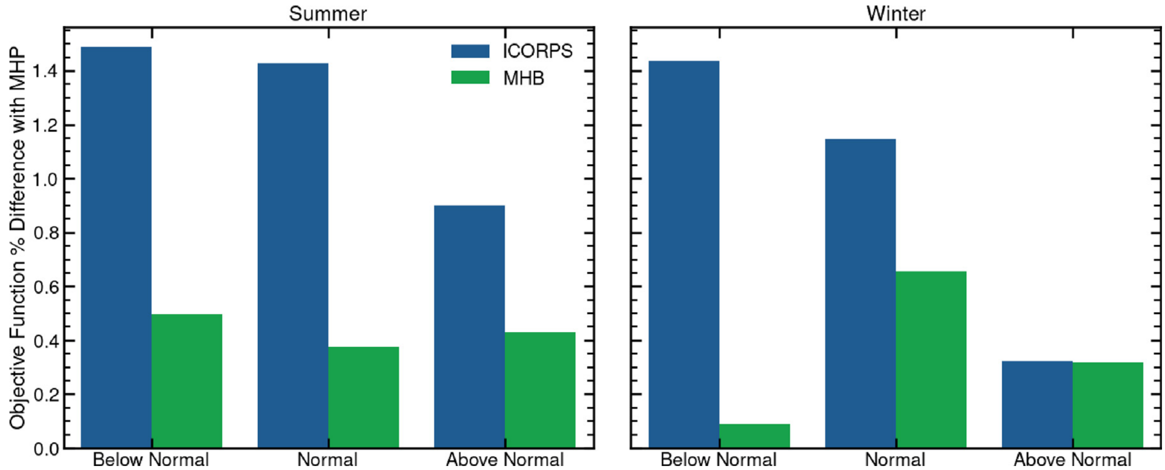

Fig. 5. ICORPS and MHB percent difference with MHP for below normal, normal, and above normal inflow scenarios for winter and summer seasons.

function nears the optimal value (the right most points on the plot), September hydropower seems to become more valuable as it increases dramatically faster than the other two months. This could be because additional hydropower for a specific month becomes less valuable (i.e., flattening of generation curve due to a combination of thermal/nuclear unit minimum loads, hydropower generator capacity, and reservoir operational rules) as more hydropower is generated.

The initial iterations produce large improvements in the objective function (3.7–7.3%), which is expected since the system should have the most flexibility initially as hydropower generation have very few binding constraints. As the systems evolve, the reductions in the objective function become smaller, even though more hydropower is generated. This suggests that for a more conservative operation, ICORPS could be stopped sooner than the default stopping criterion. Due to the specified operating rules, the storages across each region change marginally compared to hydropower production. This is primarily because the storage capacity of a reservoir is typically much larger than the maximum allowable release.

5.3. Benefits of incorporating power system information in reservoir decisions

As previously mentioned, one of the main research objectives of this study is elucidating the possible benefits of dynamic sharing of information between reservoir and power systems. This is done by treating MHP, where the only information shared is hydropower availability, as a baseline for comparison with MHB (static hydropower benefits) and ICORPS (dynamic hydropower benefits). Analyzing the solution space produced by each method requires consideration of several variables including the cost to meet power demand, total system release, spill, and deficit. Over 12 summer scenarios (July, August, September from 2004 to 2015), the average cost to meet power demand was 0.43% greater for MHB when compared to MHP. Similarly, ICORPS met power demand with an average cost that was 1.3% greater than MHP. For 12 winter scenarios (December, January, February from 2003 to 2014), MHB and ICORPS provided solutions that were 0.35% and 0.97% more expensive on average, respectively, than MHP. Fig. 5 breaks down the percent difference for ICORPS and MHB compared with MHP for the four below-normal inflow, four normal inflow, and four above-normal inflow scenarios in each season.

ICORPS and MHB meet power demand at a higher cost relative to MHP regardless of the inflow scenario, between the two, MHB meets power demand at the lower cost. As the scenarios receive more inflow, ICORPS solutions improve but there is no distinct trend for MHB solutions. TVA operates with less storage in the winter months for flood control purposes, leading to a winter peak in hydropower generation and observed operations. An example of this is the winter of 2004–05 (Fig. 4) where there is very little change in hydropower production over ICORPS evolution. This operational pattern may increase the benefit of power system information as water allocation decisions can be made more efficiently, even if the total generation for the season does not change significantly.

Table 2
Average objective function-release relationships (δ [$/1000 acre-ft/season]) for each season and optimization method.

Season	ICORPS	MHB	MHP
Summer	−925.9	−663.4	−658.4
Winter	−848.9	−596.5	−527.3

While providing the best objective function value is a crucial component in evaluating an optimization framework, it is also important to understand the operational changes that reduce the objective function. Though simply maximizing hydropower seems to result in slightly lower costs for the power system, it is likely that including power system information in reservoir operations will result in more efficient water usage. Considering the metric defined in Eq. (16), δ, the efficiency of water allocation can be compared across each method.

The term δ is calculated for each scenario and then averaged over each season and reported in Table 2. The more negative δ is, the more the cost is reduced per unit increase in release (i.e., a more efficient use of water). A δ value of -1 would indicate that the objective function is reduced by $1 for every 1000 acre-feet increase in release over a season. In the summer and winter there is a clear relationship between the level of integration between Temoa and GRAPS and δ. ICORPS allocates water more efficiently than MHB and MHB is more efficient than MHP in both seasons, suggesting that integrating power system information into water allocation decisions increases the water use efficiency. ICORPS is more than 35% more efficient than both other methods in the summer and more than 42% more efficient in the winter. While ICORPS and MHB tend to provide solutions that are more expensive than MHP, they both reduce the objective function more per unit water released indicating a more efficient water allocation.

While the δ values above provide a sense of the economic efficiency of the water allocation provided by each optimization

Table 3
Average seasonal spill and deficit [1000 acre-ft/season] and the number of spill occurrences for each season and solution method [spill (occurrences)]. A single reservoir spilling in a single month is considered an "occurrence".

	Season	ICORPS	MHB	MHP
Spill	Winter	156.0 (35)	7963 (303)	11970 (367)
	Summer	106.5 (35)	8709 (358)	12050 (346)
Deficit	Winter	1.92 (1)	156.3 (5)	348.2 (6)
	Summer	92.8 (4)	92.8 (4)	92.8 (4)

method, the operational efficiency of multireservoir networks can also be understood by examining the spill and deficit the system experiences. In COREGS, every method initially constrains spill and deficit to be zero for all reservoirs and time steps. However, cases can arise where spill and deficit cannot be mitigated, and these situations are summarized in Table 3. In the summer, all deficit occurs in the first modeled month and each method provides the exact same amount of deficit, indicating there is nothing that can be done short of changing the rule curves to eliminate that deficit. In the winter, deficit occurs 7 times in the first month and 5 times in the second month across all methods and scenarios. Only two reservoirs are in deficit more than once for any method: Fort Patrick is in deficit in for the first two months of the winter of 2014 in both MHB and MHP and Melton Hill is in deficit in December of 2005 and 2007 for MHB and MHP as well as January of 2008 (in the winter of 2007 scenario) for MHP. Four reservoirs (Douglas, Nottely, South Holston, and Tims Ford) experience deficit of the exact same amount across each method in the summer and Blue Ridge is the only reservoir that is the same across all methods in the winter. All these reservoirs receive all, or nearly all, natural inflow; therefore, if they are below the rule curve it may not be possible to decrease release enough to mitigate that deficit. Additionally, all deficit occurs during the driest 4 years modeled, further indicating that, short of modifying the reservoir rule curves, there is little operational capacity to bring the storage up enough to not have any deficit. With ICORPS, there is very little winter deficit in contrast to MHB and MHP, which have more winter deficit than summer deficit; therefore, MHB and MHP are leveraging deficit that could be mitigated to provide more hydropower.

ICORPS consistently produces solutions with much less spill than the other two methods (Table 3). As mentioned in Section 3.4, when FSQP cannot find a feasible solution to start the optimization process, the constraints that are causing infeasibility are relaxed just enough to provide a feasible solution and FSQP is ran again to achieve solutions that are comparable to ICORPS. For example, if a reservoir is spilling by 200,000 acre-ft/month, the upper bound on spill for that reservoir and time step becomes slightly greater than 200,000 acre-ft/month. This contrasts with ICORPS, which constantly tries to mitigate the spill but will not stop searching for a solution because there is spill in the system. Due to the different handling of infeasible solutions, ICORPS is technically more constrained than MHB or MHP for scenarios that have feasibility issues. Given that ICORPS solutions spill less than 2% of the spill from MHB or MHP and the cost to meet power demand is only around 1% greater, it seems both systems can be operated more efficiently when information is shared between them. Additionally, since MHB and MHP handle spill and deficit in the exact same manner, the reduction in spill from MHB compared to MHP is indicative of this increase in efficiency when power system information is integrated into reservoir system decisions.

5.4. Examining benefits of dynamic information sharing

In addition to studying the benefits of sharing information between reservoir and power systems, understanding the differences between static and dynamic hydropower benefits is also of interest. Comparing the total release (including spill) and objective function differences between ICORPS and MHB can provide insight into how the solutions from these two methods differ. Additionally, incorporating the amount of inflow the reservoirs receive into the analysis provides a sense of how each method performs given certain climatic conditions. Fig. 6 depicts these metrics in terms of percentage differences. The stream flow anomaly for each point is calculated based on the average natural stream flow into the reservoirs for the months in the respective seasons, allowing similar colors to represent similar streamflow conditions regardless of the season.

ICORPS always releases between 5% and 33% less water than MHB with the largest differences occurring during winter scenarios. Six of the seven ICORPS solutions that have a lower objective function value than MHB (those that are below the horizontal line at 0 in Fig. 6) receive above-normal inflow with an average streamflow anomaly of 3.0 million acre-ft per season, while most solutions where MHB outperforms ICORPS are below-normal inflow season with an average streamflow anomaly of −1.9 million acre-ft per season. This suggests that during periods of high inflow, up to date information regarding when and where hydropower should be generated could reduce operational costs of power systems. The large difference in total system release along with the smaller differences in optimal objective function values speak again to the more efficient use of water in ICORPS solutions compared to MHB solutions. The largest deviation in objective function and release differences occurs for the winter of 2010 where the solution from ICORPS is 2.7% more expensive and releases 32.9% less water than MHB. The winter of 2010 also receives 7.3 million acre-feet less inflow than an average winter. This higher cost from ICORPS suggest that FSQP may provide solutions with reduced power system operating costs, compared to ICORPS, during periods of extremely low inflow. However, ICORPS conserves much more water during a severe drought but provides a solution that is costlier than MHB. There are many circumstances where operators will emphasize water conservation and efficient use over reducing power system costs, and long-term droughts highlight these decisions. Under these conditions, our analysis shows relying on one metric is not the right approach, instead a comprehensive assessment on downstream ecological and water supply impacts during droughts also need to be considered.

5.5. Rolling horizon simulations

Though there can be significant operational improvements due to seasonal water and power system planning, optimizing over a seasonal window could lead to the over allocation of water and decrease the reliability and flexibility of the reservoir network in the following months. The lower rule curve constraints in GRAPS help ensure decisions made in one season are not substantially impacting subsequent seasons. For operational models, a common method for including future consequences for decisions made in the current time step is a rolling horizon analysis. To study how COREGS performs over an extended period, in this case a full calendar year, rolling horizon functionality is included in the modeling framework.

The rolling horizon in COREGS considers three-month windows where the decisions made in the first month of optimization are carried forward to the next three-month window. For example, for a rolling horizon analysis of 2004, the first scenario would

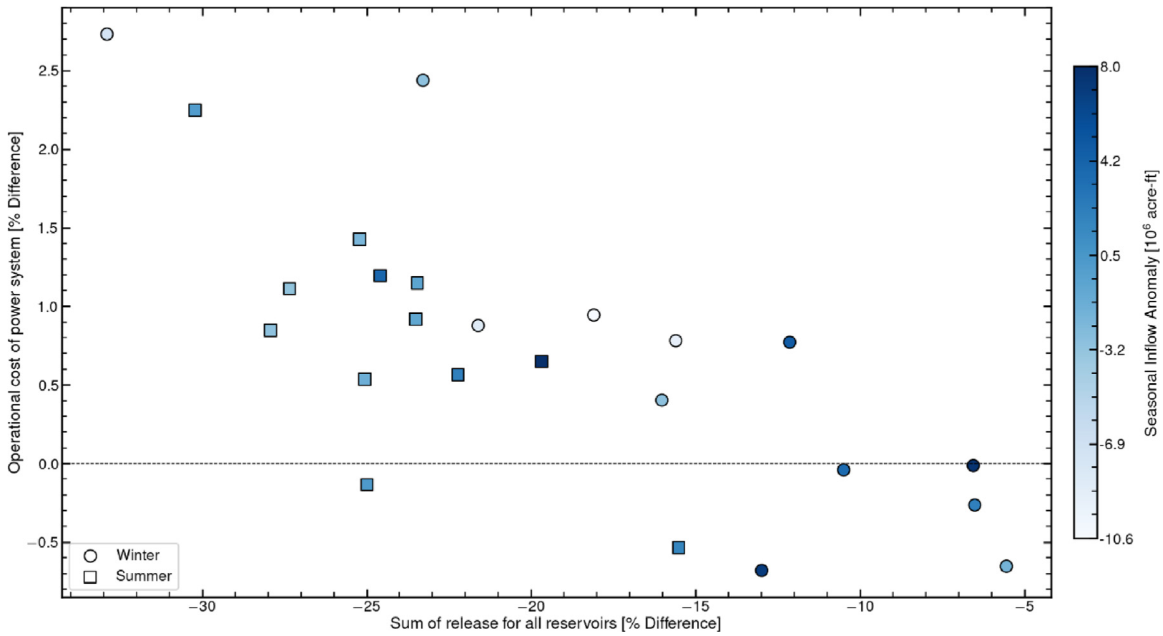

Fig. 6. Percentage difference between the operational cost of ICORPS and MHB and the corresponding percentage difference in system releases. Shading indicates seasonal streamflow variability expressed as anomalies compared to the 25-year seasonal means. Values from MHB solutions are subtracted from ICORPS solutions therefore negative percent differences along either axis indicate MHB values are greater than ICORPS values.

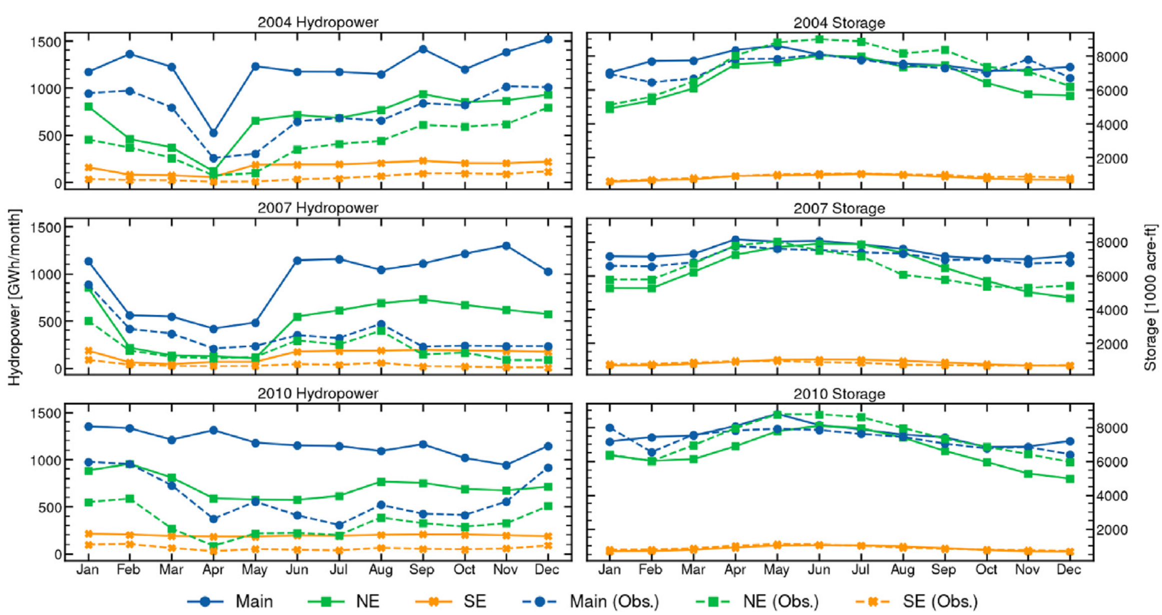

Fig. 7. Rolling horizon hydropower and storage results for 2004 (wet), 2007 (dry), and 2010 (normal). Dotted lines represent observed generation and storage levels. Hydropower and storage are summed over the three regions plotted here (Main, NE, and SE).

be January, February, and March of 2004. Water allocation and energy dispatch decisions made in January of that scenario are recorded and the storage at the end of January becomes the initial storage for the next scenario, which would be February, March, and April of 2004. This is repeated for every month of the year with the last scenario being December of 2004 and January and February of 2005. Thus, any success/error from ICORPS decisions (i.e., optimal solutions) in each month is carried forward to the subsequent three months. A rolling horizon approach such as this simulates how COREGS can be used for seasonal planning and operation of water and power systems.

We consider three representative years for the rolling horizon analysis with ICORPS: 2004 (above-normal streamflow), 2007 (below-normal streamflow), and 2010 (normal streamflow). The resulting hydropower and storage are shown in Fig. 7 along with the observed hydropower and storage. The rolling horizon analysis is not performed with MHB or MHP as the focus of this study is towards the benefits of continuous interaction between water and power systems. Hydropower generation is consistently greater than or equal to observed generation, indicating that decisions made by ICORPS do not reduce hydropower availability as compared to observed generation. An additional benefit of the rolling horizon approach can be seen in the hydropower generation for 2007. The year 2007 is a severe drought, one of the worst droughts over the Southeast US, which decreases the availability of hydropower over the entire year. The dip in

Table 4
Regional and monthly hydropower differences between the rolling analysis and the single season analysis for October, November, and December of 2004, 2007, and 2010. All values reported in gigawatt-hours.

Year	Main	NE	SE	Oct.	Nov.	Dec.	Total
2004	−436	−258.9	−13.8	−124.5	−279.9	−304.3	−708.8
2007	−813.7	19.4	38.7	89.7	−180.1	−665.3	−755.7
2010	−249.3	−284.5	48.2	−69.2	−161.0	−255.5	−485.6

hydropower generation from February to May suggests that the rolling horizon captures the effects of limited water availability and holds water for future months when the power demand, and thus the value of hydropower, is higher. This effect can also be seen for April of 2004 as April is typically a month of low power demand due to moderate temperatures in TVA's control area.

The storage plots indicate that there is very little storage tradeoff to achieve the increase in hydropower generation. It is common for storage in the Main stem reservoirs to be higher than the observations, though still not in the flood control pool. This is the impact that the increase in upstream release has on the downstream reservoirs. Northeast reservoirs tend to exhibit a decrease in total storage, which is expected because they have more reservoirs receiving only natural inflow. Southeast reservoirs operate near their observed storage levels. Because these reservoirs are smaller than other reservoirs in the system, they tend to have tighter rule curves and less flexibility, which results in the limited deviations from observations seen. Across these three years, the average final storage is 9.3% greater than observed for the Main stem and 12.9% and 8.0% less than observed for the NE and SE stem, respectively. The final total system storage from ICORPS is 0.1%, 2.9%, and 1.7% less than the observed storage for 2004, 2007, and 2010, respectively. The total system storage is not very different from observed for any of the years but where that storage is in the system can alter the risk associated with different climatic events. Main stem storage increases may be concerning because they seem to indicate an increase in flood risk, but the individual reservoirs do not store water in the flood control pool so the increase in flood risk is not substantial. Reductions in upstream storages could increase the risk of water shortages during droughts, though the reservoirs are still maintained within their normal operating limits.

Though Fig. 7 shows that optimal hydropower generation can meet or exceed observed generation given a rolling horizon, it is unclear if decisions made throughout the year reduce hydropower availability at the end of the year. This can be understood by comparing the optimal solutions from scenarios where the observed initial storage is provided (OBS) and where the initial storage is set as the final storage from a rolling horizon analysis (ROH). Performing this analysis on the last three months of the calendar year (October, November, and December) can help determine the impact of all the decisions made prior to October on the decisions that are made at the end of the year. For 2004, 2007, and 2010 the hydropower differences between ROH scenarios and OBS scenarios are reported in Table 4 in gigawatt-hours. The total column is representative of both sections of results and negative values indicate instances when the ROH scenario using ICORPS generated less hydropower than the corresponding OBS scenario.

All ROH scenarios considered generate less total hydropower than their corresponding scenario seeded with observed storages. 2007 exhibits the largest difference between ROH and OBS scenarios and this can be attributed to the below-normal inflow received during that year. For 2004 and 2010, most of the difference between ROH and OBS solutions is a result in differences in generation from NE reservoirs. This coincides with ICORPS reducing the storage in NE reservoirs more than other regions, thus limiting their ability to generate hydropower at the end of the year. This is further confirmed by the similar generation amounts from ROH and OBS in the NE reservoirs in 2007 as the initial storage in that region is nearly identical (Fig. 7).

Main stem reservoirs generating less in ROH scenarios than OBS scenarios, as occurs in every year, is unexpected as they should benefit from increased storages due to increased controlled flow from upstream reservoirs. This could be due to ROH scenarios considering the future impacts of releasing water whereas the OBS scenarios only consider the impacts within the current season. There is evidence that water allocations provided by ICORPS can compromise the ability to generate hydropower in the future with the largest difference, in 2007, being 11.3% less hydropower than in the ROH scenario than the OBS scenario. However, the hydropower discrepancies get larger from October to December, indicating that at least part of this reduction is due to the ROH scenarios considering the future worth of water.

6. Discussion

COREGS is evaluated for the reservoir and power systems owned and operated by the Tennessee Valley Authority over twelve summer and winters from 2003 to 2015. Additionally, three years (2004, 2007, and 2010) are modeled using a rolling horizon approach with seasonal windows to study the COREGS' effectiveness over multiple seasons given deterministic inflows and demand. Evaluation of COREGS is done with respect to the total cost to meet electricity demand in a season, reservoir spill and deficit, water allocation efficiency in terms of objective function improvement per increase in release, and relationships between total inflow into the system and allocation efficiency and objective function improvement.

Overall, there is limited reduction in power system operating cost by incorporating power system information in water allocation decisions. Neither of the methods that use power system information for reservoir allocations (ICORPS, MHB) produce objective function values that are consistently lower than MHP; however, all solutions from ICORPS and MHB are within 1.5% of MHP. This is partly because the share of hydropower in TVA's generation portfolio is only around 14%. Our analysis indicates that information on where and when additional hydropower is most beneficial can improve the water use efficiency of a reservoir system from the power system management perspective. ICORPS and MHB decreased the cost to meet power demand more per unit of additional release than MHP, which indicates ICORPS and MHB are more efficient in allocating hydropower spatio-temporally (which reservoir and what time) compared to bulk increase in release for hydropower. Between ICORPS and MHB, ICORPS provides the most efficient water use, indicating that dynamically sharing information and jointly operating the systems can provide solutions that use water much more efficiently while only being slightly more expensive. Further, ICORPS and MHB solutions have less spill and deficit than MHP solutions for winter and summer seasons. Though spill and deficit constraints are handled slightly differently between ICORPS and MHB, ICORPS violates these constraints much less frequently than MHB and at smaller overall values. Therefore, dynamically sharing information based on the dual prices of each reservoir from the power system can produce reservoir operation solutions (i.e., releases) that result in less total spill and deficit across the reservoir network, allocates water more efficiently in terms of power system costs, and provides operating costs that are, on average, 1.14% more expensive than MHP and 1% more expensive than MHB.

There are seven scenarios when ICORPS provides an objective function value less than MHB (five winters and two summers). On average, these seven scenarios receive more inflow than a normal winter or summer and the opposite is true for the remaining eighteen scenarios where MHB meets power demand cheaper than ICORPS. Additionally, the scenario with the largest inflow anomaly (the winter of 2007) coincides with the largest objective function and release deviations between ICORPS and MHB. Taken together, these results indicate that ICORPS provides better solutions under above-normal inflow conditions and MHB solutions are better during below average inflow. This is because excess water availability during above-normal inflow season can be used more effectively with the dynamically varying dual prices in ICORPS. However, both MHB and MHP are limited by the lack of information on varying dual prices on hydropower availability. Further, ICORPS conserves much more water than MHB (between 5 and 33% less water is released) regardless of the inflow scenario. During the winter of 2010, a season that received substantially less inflow than normal conditions, MHB released 32.9% more water than ICORPS for a 2.7% objective function improvement. During drought conditions there is likely to be a focus on water conservation and solutions that are less costly but conserve much more water are going to be favored over less efficient solutions.

The rolling horizon assessment demonstrates COREGS ability to improve hydropower production without increasing flood and drought risks in subsequent months. Main stem reservoirs have increased storage at the end of December than observed storage, while storage in NE and SE reservoirs is lesser than observed storage. The overall system storage decreases by approximately 3.5% on average but large portions of the storage is redistributed from upstream reservoirs to downstream reservoirs. This may increase the reservoir flood risk, though storage at all reservoirs is maintained below the flood control pool and lower storage in upstream reservoirs can provide an additional buffer for unexpectedly high inflows, thus increases in flood risk is not expected to be significant. During extended periods of drought, lower storage in upstream reservoirs may compromise the ability to meet demand from ecological, water supply, or thermal generation uses. Additionally, operational decisions made by ICORPS may limit the ability to generate hydropower in the future if downstream flow requirements are not considered in detail. Further, all the increased storage in main stem and reduced storage in upstream reservoirs are within the normal operating rule curves without storing water in the flood control space or below the conservation pool, thus any modification in the release scenarios suggested by ICORPS are within the realm of rebounding to increase/decrease storage as we roll forward which is indicated precisely by the rolling horizon analysis. Thus, the proposed ICORPS that shares dynamically varying information on hydropower value, expressed as dual prices from the power system model, with the reservoir system could provide efficient strategies for the co-optimization of water and power systems.

7. Concluding remarks

This work presents a new optimization framework, Co-Optimization of Reservoir and Electricity Generation Systems (COREGS) that can jointly operate linked reservoir and electricity systems. COREGS is built on two open-source, generalized models (GRAPS and Temoa) that allow water and power systems of any size to be modeled over any time horizon. Reservoirs and electric generators are resolved at the plant level which allows plant specific constraints – minimum operating levels and ramping rates – to be enforced, reservoir operating rules to vary across time and space, and potential transmission bottlenecks to be explicitly incorporated into COREGS to support seasonal water and power systems planning. COREGS provides solution methods that are built around the Feasible Sequential Quadratic Programming (FSQP) algorithm (Lawrence and Tits, 2001) as well as a new, purpose-built, heuristic optimization algorithm, Iterative Co-Optimization of Reservoir and Power Systems (ICORPS), that continuously shares relevant information between GRAPS and Temoa. Due to the open-source nature of the models used in COREGS and COREGS itself, the framework can be extended to problems with differing objectives, constraints, and research goals associated with co-optimization of water and power systems.

Though this work represents a step forward in the joint modeling of reservoir and power systems, it is not without limitations. Though GRAPS and Temoa provide the ability to handle stochastic streamflow and electricity demand, albeit in different ways, the current state of COREGS does not provide a mechanism for incorporating stochasticity while continuing to share information between the systems. Without including this uncertainty, the solutions provided by COREGS are deterministic in nature and do not provide uncertainty information for the outputs. The framework can still be evaluated with deterministic forecasts (mean/median) to quantify the forecasted/expected water and hydropower availability. Additionally, reservoirs in the Tennessee River Basin are primarily used for flood control, hydropower, and recreation; therefore, the results presented here may not translate to basins that have high levels of agriculture or water supply withdrawals. Including stochastic streamflow and power demand and testing COREGS for basins with more diverse water demands will help us to evaluate COREGS performance more rigorously.

Though Temoa can accurately model the electrical network constraints including capacities and transmission constraints, they are not rigorously explored in this work. As there is a lack of open data sets for modeling the intra-regional transmission network for the TVA area, we do not have detailed network and transmission data for the study region thus preventing their inclusion in the model. However, previous research by de Queiroz et al. (2019) shows that the network congestion and transmission details are not critical in seasonal power system planning and operation.

MHP and MHB rely on the FSQP optimization engine which has proven convergence properties for quadratic problems; however, the convergence properties of ICORPS have not been thoroughly evaluated. ICORPS convergence was achieved for all scenarios considered in this study, but the convergence properties should be explored further in future studies. Though there is room for improvement and further testing, the results presented here suggest reservoir systems with significant hydropower demand can be operated more efficiently using dynamic information that specify when and which hydroelectric plant will be most beneficial to a power system. Additionally, the COREGS framework provides a platform for the evaluation of integrated water and power systems with the ability to customize critically important aspects of both systems in order to support seasonal planning or specific research goals.

CRediT authorship contribution statement

Lucas Ford: Conceptualization, Methodology, Software, Investigation, Data curation, Writing, Visualization. **Anderson de Queiroz:** Conceptualization, Methodology, Software, Writing –

review & editing. **Joseph DeCarolis:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition. **A. Sankarasubramanian:** Conceptualization, Methodology, Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The COREGS source code is available at https://github.com/lcford2/coregs/releases/tag/v1.0.0. The input data and results for this work is available at https://zenodo.org/record/6315941#.Yh5tKhtOlhE.

Acknowledgments

This material is based upon work supported by the National Science Foundation, United States of America under Grants No. CyberSEES-1442909 and CBET-1805293.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.egyr.2022.06.017.

References

Ahmad, A., El-Shafie, A., Mohd Razali, S.F., Mohamad, Z.S., 2014. Reservoir optimization in water resources: A review. Water Resour. Manag. 28, 3391–3405. http://dx.doi.org/10.1007/s11269-014-0700-5.

Al-Aqeeli, Y.H., Mahmood Agha, O.M.A., 2020. Optimal operation of multi-reservoir system for hydropower production using particle swarm optimization algorithm. Water Resour. Manag. 34, 3099–3112. http://dx.doi.org/10.1007/s11269-020-02583-8.

Alaya, A., Souissi, A., Tarhouni, J., Ncib, K., 2003. Optimization of nebhana reservoir water allocation by stochastic dynamic programming. Water Resour. Manag. 17, 259–272. http://dx.doi.org/10.1023/A:1024721507339.

Archibald, T.W., McKinnon, K.I.M., Thomas, L.C., 2006. Modeling the operation of multireservoir systems using decomposition and stochastic dynamic programming. Nav. Res. Logist. 53, 217–225. http://dx.doi.org/10.1002/nav.20134.

Arvanitidis, N.V., Rosing, J., 1970a. Composite representation of a multireservoir hydroelectric power system. IEEE Trans. Power Appar. Syst. PAS- 89, 319–326.

Arvanitidis, N.V., Rosing, J., 1970b. Optimal operation of multireservoir systems using a composite representation. IEEE Trans. Power Appar. Syst. PAS 89, 327–335. http://dx.doi.org/10.1109/TPAS.1970.292596.

Ávila, D., Papavasiliou, A., Löhndorf, N., 2021. Parallel and distributed computing for stochastic dual dynamic programming. Comput. Manag. Sci. http://dx.doi.org/10.1007/s10287-021-00411-x.

Bartos, M.D., Chester, M.V., 2015. Impacts of climate change on electric power supply in the Western United States. Nat. Clim. Change 5, 748–752. http://dx.doi.org/10.1038/nclimate2648.

Baslis, C.G., Papadakis, S.E., Bakirtzis, A.G., 2009. Simulation of optimal medium-term hydro-thermal system operation by grid computing. IEEE Trans. Power Syst. 24, 1208–1217. http://dx.doi.org/10.1109/TPWRS.2009.2023261.

Belaineh, G., Peralta, R., Hughes, T., 1999. Simulation/optimization modeling for water resources management. Water Resour. Plan. Manag. 125, 154–161.

Bradley, S.P., Hax, A.C., Magnanti, T.L., 1977. Applied Mathematical Programming.

Brandão, J.L.B., 2010. Performance of the equivalent reservoir modelling technique for multi-reservoir hydropower systems. Water Resour. Manag. 24, 3101–3114. http://dx.doi.org/10.1007/s11269-010-9597-9.

Brandi, R.B.S., Ramos, T.P., Dias, B.H., Marcato, A.L.M., Da Silva Junior, I.C., 2015. Improving stochastic dynamic programming on hydrothermal systems through an iterative process. Electr. Power Syst. Res. 123, 147–153. http://dx.doi.org/10.1016/j.epsr.2015.02.011.

Collins, S., Deane, J.P., Poncelet, K., Panos, E., Pietzcker, R.C., Delarue, E., Gallachóir, B.P.Ó., 2017. Integrating short term variations of the power system into integrated energy system models: A methodological review. Renew. Sustain. Energy Rev. 76, 839–856. http://dx.doi.org/10.1016/j.rser.2017.03.090.

De Matos, V.L., Philpott, A.B., Finardi, E.C., 2015. Improving the performance of stochastic dual dynamic programming. J. Comput. Appl. Math. 290, 196–208. http://dx.doi.org/10.1016/j.cam.2015.04.048.

De Queiroz, A.R., 2016a. Stochastic hydro-thermal scheduling optimization: An overview. Renew. Sustain. Energy Rev. 62, 382–395. http://dx.doi.org/10.1016/j.rser.2016.04.065.

De Queiroz, A.R., 2016b. Stochastic hydro-thermal scheduling optimization: An overview. Renew. Sustain. Energy Rev. 62, 382–395. http://dx.doi.org/10.1016/j.rser.2016.04.065.

de Queiroz, A.R., Mulcahy, D., Sankarasubramanian, A., Deane, J.P., Mahinthakumar, G., Lu, N., DeCarolis, J.F., 2019. Repurposing an energy system optimization model for seasonal power generation planning. Energy 181, 1321–1330. http://dx.doi.org/10.1016/j.energy.2019.05.126.

de Sisternes, F.J., Jenkins, J.D., Botterud, A., 2016. The value of energy storage in decarbonizing the electricity sector. Appl. Energy. 175, 368–379. http://dx.doi.org/10.1016/j.apenergy.2016.05.014.

Deane, J.P., Chiodi, A., Gargiulo, M., Gallachóir, B.P.Ó., 2012. Soft-linking of a power systems model to an energy systems model. Energy 42, 303–312. http://dx.doi.org/10.1016/j.energy.2012.03.052.

Denholm, P., Ela, E., Kirby, B., Milligan, M., 2011. The role of energy storage with renewable electricity generation. Energy Storage Issues Appl. 1–58.

Dias, B.H., Marcato, A.L.M., Souza, R.C., Soares, M.P., Silva Junior, I.C., Oliveira, E.J.D., Brandi, R.B.S., Ramos, T.P., 2010. Stochastic dynamic programming applied to hydrothermal power systems operation planning based on the convex hull algorithm. Math. Probl. Eng. 2010, http://dx.doi.org/10.1155/2010/390940.

Ehteram, M., Karami, H., Mousavi, S.F., Farzin, S., Kisi, O., 2017. Optimization of energy management and conversion in the multi-reservoir systems based on evolutionary algorithms. J. Clean. Prod. 168, 1132–1142. http://dx.doi.org/10.1016/j.jclepro.2017.09.099.

Fernández-Blanco, R., Kavvadias, K., Hidalgo González, I., 2017. Quantifying the water-power linkage on hydrothermal power systems: A greek case study. Appl. Energy. 203, 240–253. http://dx.doi.org/10.1016/j.apenergy.2017.06.013.

Finardi, E.C., Da Silva, E.L., Sagastizábal, C., 2005. Solving the unit commitment problem of hydropower plants via lagrangian relaxation and sequential quadratic programming. J. Comput. Appl. Math. 24, 317–341. http://dx.doi.org/10.1590/S0101-82052005000300001.

Guo, X., Hu, T., Wu, C., Zhang, T., Lv, Y., 2013. Multi-objective optimization of the proposed multi-reservoir operating policy using improved NSPSO. Water Resour. Manag. 27, 2137–2153. http://dx.doi.org/10.1007/s11269-013-0280-9.

Helfer, F., Lemckert, C., Zhang, H., 2012. Impacts of climate change on temperature and evaporation from a large reservoir in Australia. J. Hydrol. 475, 365–378. http://dx.doi.org/10.1016/j.jhydrol.2012.10.008.

Hunt, J.D., de Freitas, M.A.V., Pereira Junior, A.O., 2017. A review of seasonal pumped-storage combined with dams in cascade in Brazil. Renew. Sustain. Energy Rev. 70, 385–398. http://dx.doi.org/10.1016/j.rser.2016.11.255.

Hunter, K., Sreepathi, S., DeCarolis, J.F., 2013. Modeling for insight using tools for energy model optimization and analysis (Temoa). Energy Econ. 40, 339–349. http://dx.doi.org/10.1016/j.eneco.2013.07.014.

International Business Machines Corporation, 2019. ILOG CPLEX optimizer.

International Renewable Energy Agency, 2021. Renewable energy statistics, 2021.

IPCC, 2021. Assessment report 6 climate change 2021: The physical science basis. https://www.ipcc.ch/report/ar6/wg1/.

Koutsoyiannis, D., Economou, A., 2003. Evaluation of the parameterization-simulation–optimization approach for the control of reservoir systems. Water Resour. Res. 39, 1170. http://dx.doi.org/10.1029/2003WR002148.

Labadie, J., 2004. Optimal operation of multireservoir systems: State-of-the-art review. Water Resour. Plan. Manag. 130, 93–111. http://dx.doi.org/10.1061/(ASCE)0733-9496(2004)130.

Lawrence, C.T., Tits, A.L., 2001. A computationally efficient feasible sequential quadratic programming algorithm. SIAM J. Optim. 11, 1092–1118. http://dx.doi.org/10.1137/S1052623498344562.

Li, F.F., Shoemaker, C.A., Qiu, J., Wei, J.H., 2015. Hierarchical multi-reservoir optimization modeling for real-world complexity with application to the three gorges system. Environ. Model. Softw. 69, 319–329. http://dx.doi.org/10.1016/j.envsoft.2014.11.030.

Li, X., Wei, J., Li, T., Wang, G., Yeh, W.W.G., 2014. A parallel dynamic programming algorithm for multi-reservoir system optimization. Adv. Water Resour. 67, 1–15. http://dx.doi.org/10.1016/j.advwatres.2014.01.002.

Liu, B., Cheng, C., Wang, S., Liao, S., Chau, K.W., Wu, X., Li, W., 2018. Parallel chance-constrained dynamic programming for cascade hydropower system operation. Energy 165, 752–767. http://dx.doi.org/10.1016/j.energy.2018.09.140.

Liu, P., Li, L., Guo, S., Xiong, L., Zhang, W., Zhang, J., Xu, C.Y., 2015. Optimal design of seasonal flood limited water levels and its application for the three gorges reservoir. J. Hydrol. 527, 1045–1053. http://dx.doi.org/10.1016/j.jhydrol.2015.05.055.

LLC Gurobi Optimization, 2020. Gurobi optimizer reference manual. http://www.gurobi.com.

Makhorin, A., 2012. GNU Linear programming kit (GLPK). https://www.gnu.org/software/glpk/.
Mandal, K.K., Basu, M., Chakraborty, N., 2008. Particle swarm optimization technique based short-term hydrothermal scheduling. Appl. Soft Comput. J. 8, 1392–1399. http://dx.doi.org/10.1016/j.asoc.2007.10.006.
Mu, M., Zhang, Z., Cai, X., Tang, Q., 2020. Seasonal risk assessment of water-electricity nexus systems under water consumption policy constraint. Environ. Sci. Technol. 54, 3793–3802. http://dx.doi.org/10.1021/acs.est.0c00171.
Mukhopadhyay, S., Sankarasubramanian, A., de Queiroz, A.R., 2021. Performance comparison of equivalent reservoir and multireservoir models in forecasting hydropower potential for linking water and power systems. J. Water Resour. Plan. Manag. 147, 04021005. http://dx.doi.org/10.1061/(asce)wr.1943-5452.0001343.
Needham, J.T., Watkins, Jr., D.W., Lund, J.R., Nanda, S.K., 2000. Linear programming for flood control in the iowa and des moines rivers. J. Water Resour. Plan. Manag. 126, 118–127.
Norouzi, M.R., Ahmadi, A., Sharaf, A.M., Esmaeel Nezhad, A., 2014. Short-term environmental/economic hydrothermal scheduling. Electr. Power Syst. Res. 116, 117–127. http://dx.doi.org/10.1016/j.epsr.2014.05.020.
O'Connell, N. Voisin, Macknick, Fu, 2019. Sensitivity of western U.S. power system dynamics to droughts compounded with fuel price variability. Appl. Energy 247, 745–754. http://dx.doi.org/10.1016/j.apenergy.2019.01.156.
Oludhe, C., Sankarasubramanian, A., Sinha, T., Devineni, N., Lall, U., 2013. The role of multimodel climate forecasts in improving water and energy management over the Tana river basin, Kenya. J. Appl. Meteorol. Climatol. 52, 2460–2475. http://dx.doi.org/10.1175/JAMC-D-12-0300.1.
Pereira, M.V.F., 1989. Optimal stochastic operations scheduling of large hydroelectric systems. Int. J. Electr. Power Energy Syst. 11, 161–169. http://dx.doi.org/10.1016/0142-0615(89)90025-2.
Pereira, M.V.F., Pinto, L.M.V.G., 1985. Stochastic optimization of a multireservoir hydroelectric system: A decomposition approach. Water Resour. Res. 21, 779–792. http://dx.doi.org/10.1029/WR021i006p00779.
Pereira, M.V.F., Pinto, L.M.V.G., 1991. Multi-stage stochastic optimization applied to energy planning. Math. Program. 52, 359–375. http://dx.doi.org/10.1007/BF01582895.
Ringkjøb, H.K., Haugan, P.M., Solbrekke, I.M., 2018. A review of modelling tools for energy and electricity systems with large shares of variable renewables. Renew. Sustain. Energy Rev. 96, 440–459. http://dx.doi.org/10.1016/j.rser.2018.08.002.
Rougé, C., Tilmant, A., 2016. Using stochastic dual dynamic programming in problems with multiple near-optimal solutions. Water Resour. Res. 52, 4151–4163. http://dx.doi.org/10.1002/2016WR018608.
Sankarasubramanian, A., Lall, U., Souza Filho, F.A., Sharma, A., 2009. Improved water allocation utilizing probabilistic climate forecasts: Short-term water contracts in a risk management framework. Water Resour. Res. 45, 1–18. http://dx.doi.org/10.1029/2009WR007821.
Shapiro, A., 2011. Analysis of stochastic dual dynamic programming method. European J. Oper. Res. 209, 63–72. http://dx.doi.org/10.1016/j.ejor.2010.08.007.
Sharif, M., Wardlaw, R., 2000. Multireservoir systems optimization using genetic algorithms: Case study. J. Comput. Civ. Eng. 14, 255–263.
Sodano, D., DeCarolis, J., Rodrigo de Queiroz, A., Johnson, J.X., 2021. The symbiotic relationship of solar power and energy storage in providing capacity value. Renew. Energy. 177, 823–832. http://dx.doi.org/10.1016/j.renene.2021.05.122.
Swain, R.K., Barisal, A.K., Hota, P.K., Chakrabarti, R., 2011. Short-term hydrothermal scheduling using clonal selection algorithm. Int. J. Electr. Power Energy Syst. 33, 647–656. http://dx.doi.org/10.1016/j.ijepes.2010.11.016.
Tennessee Valley Authority, 2012. TVA river operations & renewables data repository.
Turgeon, A., 1980. Optimal operation of multireservoir power systems with stochastic inflows. Water Resour. Res. 16, 275–283. http://dx.doi.org/10.1007/BF00941072.
US Department of Homeland Security, 2017. Homeland infrastructure foundation-level data (HIFLD). https://hifld-geoplatform.opendata.arcgis.com/datasets/control-areas.
US Energy Information Administration, 2004. Form EIA-860: Annual electric generator report. http://www.eia.gov/electricity/data/eia860/.
US Energy Information Administration, 2020a. Form EIA-861m: Monthly Electric Power Industry Report.
US Energy Information Administration, 2020b. Form EIA-923: Power Plant operations report. https://www.eia.gov/electricity/data/eia923/.
US Energy Information Administration, 2021. What is the U.S. electricity generation by energy source?. https://www.eia.gov/tools/faqs/faq.php?id=427&t=3.
US Geological Survey, 1994. 1:250, 000-scale hydrologic units of the United States. https://water.usgs.gov/GIS/metadata/usgswrd/XML/huc250k.xml.
US Senate, 2015. Tennessee valley authority: Full consideration of energy efficiency and better capital expenditures planning are needed. pp. 1–88, Tennessee Val. Auth. Priv. Resour. Plan. Financ. Issues..
Xuan, L., Ford, L., Mahinthakumar, G., Souza Filho, F.A., Lall, U., Arumugam, S., 2020. GRAPS: Generalized multi-reservoir analyses using probabilistic streamflow. Environ. Model. Softw. 133, 104802. http://dx.doi.org/10.1016/j.envsoft.2020.104802.
Yang, H., Zhang, L., Meng, K., Xu, J., Lai, M., Dong, Z.Y., 2017. Optimal scheduling of hydro-thermal power systems considering the flood risk of cascade reservoirs. Eng. Optim. 49, 1299–1316. http://dx.doi.org/10.1080/0305215X.2016.1245537.
Zambon, R.C.M, Barros, T.L., Lopes, J.E.G, Barbosa, P.S.F, Francato, A.L., Yeh, W.W.G, 2012. Optimization of large-scale hydrothermal system operation. Water Resour. Plan. Manag. 138, 135–143. http://dx.doi.org/10.1061/(ASCE)WR.1943-5452.0000149.
Zerrahn, A., Schill, W.P., 2017. Long-run power storage requirements for high shares of renewables: Review and a new model. Renew. Sustain. Energy Rev. 79, 1518–1534. http://dx.doi.org/10.1016/j.rser.2016.11.098.
Zhou, Y., Guo, S., Chang, F.J., Liu, P., Chen, A.B., 2018. Methodology that improves water utilization and hydropower generation without increasing flood risk in mega cascade reservoirs. Energy 143, 785–796. http://dx.doi.org/10.1016/j.energy.2017.11.035.