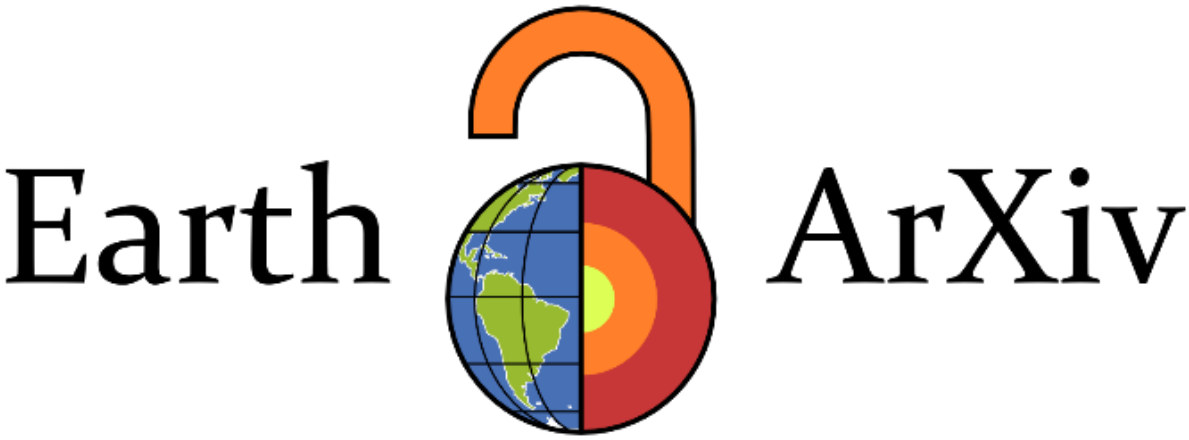

Adaptive Turbine Replacement Improves Hydropower Flexibility in a Changing Climate

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Key Points:

- HyTUNE identifies optimal turbine retrofit strategies that maximize performance and economic value under changing hydrologic conditions.
- Proactive, adaptive turbine replacements reduce efficiency losses from aging and variable operations, increasing firm power and peak capacity.
- The framework strengthens resilience to drought and hydrologic extremes by sustaining performance and economic returns at low reservoir levels.

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Abstract

Hydropower Plants (HP) will operate under new conditions as water regimes shift, reservoir operating rules evolve, and the grid requires flexible balancing of wind and solar. HP turbine systems are traditionally designed to operate at the highest efficiency within narrow ranges of flow and reservoir levels while deviations from design conditions can degrade HP efficiency and trigger failures, especially in aging infrastructure. Turbine replacements typically occur every 35 to 50 years, offering a rare opportunity to modernize turbine designs by adjusting turbine head and discharge capacity to fit new conditions, rather than replicating legacy designs. The central challenge is to determine when to replace instead of extending lifetime of existing fleet, which system signals indicate the need for redesign, and which configurations will deliver the most robust gains.

This study introduces HyTUNE (Hydropower Turbine Upgrade and Next-generation Planning), a dynamic decision-support tool that integrates basin hydrology, plant hydraulics, and adaptive optimization to guide turbine replacement timing and configuration. HyTUNE shifts planning from reactive, end-of-life replacement toward proactive, information-driven strategies. The framework learns from evolving system states, identifies threshold conditions where adjustments in head or capacity improve performance, and prescribes phased interventions that balance energy production, reliability, and cost under uncertainty. Application to the Hoover Hydropower Plant demonstrates that HyTUNE's adaptive policies consistently outperformed conventional reactive strategies across diverse hydrologic futures. HyTUNE is of considerable practical relevance as hydropower systems worldwide confront the dual challenge of modernization and adaptation to future uncertainty and demand growth.

1 Introduction

Hydropower is a key renewable energy source that provides large-scale, low-carbon electricity and supports the transition to decarbonized energy systems (Hertwich et al., 2016). Reservoir-based hydropower systems are expected to play an increasing role in the future grid, not only through reliable generation but also by acting as large-scale batteries that supply electricity on demand. This flexibility helps balance variable renewable sources such as wind and solar, maintaining grid stability as renewable penetration grows (H. Liu et al., 2019; Owolabi et al., 2022; Fälth et al., 2025).

Despite this central role, hydropower plant (HP) design has remained largely unchanged for decades. Designing a HP requires selecting an optimal turbine configuration, including the number of turbines, their discharge capacity, and head. This design is typically aimed at energy production efficiency within nominal hydrological "design" conditions, namely a narrow range of reservoir level and release (Kaunda et al., 2014; Singh & Singal, 2017; Kincic et al., 2022; Yildiz et al., 2024), while also aiming to simplify maintenance and operations (Witt et al., 2017; Amougou et al., 2022; Bisnett et al., 2022). The result is a uniform configuration of turbines at one plant, where identical turbines operate under the same head and capacity (e.g., M. M. Johnson, 2024; Quaranta & Hunt, 2022). While such systems yield very high efficiency within their design conditions (ESHA, 2004; USBR, 2011; X. Liu et al., 2015; Yildiz & Vrugt, 2019; Muntean et al., 2016; Mikhailov et al., 2021), efficiency declines sharply outside these conditions when reservoir levels fall below the design head, or releases become more variable. Energy production may have to stop altogether when reservoir head falls below the minimum design head. A loss in efficiency not only means that less energy is generated per unit of water released, but it also often leads to increased mechanical wear and operational challenges (Diaz et al., 2010; Dorji & Ghomashchi, 2014; Celebioglu et al., 2017; Quaranta et al., 2021).

Operating reservoir-based hydropower within its high-efficiency design range is becoming increasingly challenging. Shifts in water availability, energy demand, and operating constraints now push plants beyond the conditions for which they were designed. First, climate change is altering watershed hydrology, increasing variability in inflows and reservoir levels (Schaeffer et al., 2012; Van Vliet et al., 2016; Ramião et al., 2023). More frequent and severe droughts often lower reservoir water levels below design head, reducing efficiency or halting production. For example, California's Hyatt Hydropower Plant stopped generating in 2021 when record-low levels in Lake Oroville fell below the operational head (Kincic et al., 2022). Even less extreme conditions cause cumulative losses. Recent studies report a nationwide decline in hydropower capacity factors, largely driven by changing hydrologic regimes (Turner et al., 2024). The steepest reductions were recorded in the Pacific Northwest, California, and the Colorado River Basin. For example, climate variability explains more than 80 % of the observed decline in capacity factor of every major facility in the Colorado River Basin.

Second, the role of hydropower in the energy grid is evolving as the share of variable renewable energy increases. As countries pursue net-zero targets, wind and solar generation are growing rapidly due to falling costs, technological advances, and policy incentives (Carlino et al., 2023; Hassan et al., 2024). While essential for decarbonization, their production is inherently variable and non-dispatchable, increasing the risk of frequency instability (Gernaat et al., 2021; Smolarz et al., 2023; L. Liu et al., 2023; Sun et al., 2024). Hydropower is uniquely positioned to offer stabilizing services to the grid, offering rapid ramping capabilities that allow plants to adjust output quickly in response to fluctuations in demand or renewable supply (Egré & Milewski, 2002; Sternberg, 2010; Zhou et al., 2015; Emmanuel et al., 2020). In grids with high renewable shares, hydropower operations are increasingly constrained by the need to balance variable demand and supply patterns (De Silva et al., 2022; Datta et al., 2022; Arnold et al., 2024). These conditions often force plants to operate outside their optimal efficiency range (Turner et al., 2024). A recent study reported a 4 % decline in simulated generation due to efficiency losses when hydropower complemented wind and solar output (Q. Cheng et al., 2023).

Third, reservoir-based HP operations are evolving to meet shifting energy and water demands for agriculture, urban use, and ecosystem services, introducing new temporal and spatial challenges for water allocation (Huang et al., 2021; Mishra et al., 2021; Yildiz et al., 2022; M. Cheng et al., 2022). At the same time, stricter environmental flow requirements further constrain releases (Ramulifho et al., 2019; Cameron & Pracheil, 2022; Widén et al., 2024). These trends are driving a shift toward flexible reservoir management, where levels and releases vary to balance competing needs rather than staying within the narrow conditions that maximize turbine efficiency.

One promising strategy to expand operational flexibility is the use of heterogeneous turbine setups, where turbines operate at different heads and capacities (Sample et al., 2015; Mikhailov et al., 2021; Brown et al., 2024; Yildiz et al., 2025a). Such configurations broaden the range of efficient operation by matching turbine design to expected hydrologic and grid conditions. In reservoirs projected to experience declining water levels, lower-head turbines can sustain generation as storage decreases. In energy systems with high renewable penetration, larger-capacity turbines can improve the ability to provide peaking, ramping, and inertia services while maintaining overall efficiency. Although heterogeneous setups may slightly reduce maximum efficiency, they increase mean efficiency across a wider operating range, making them particularly valuable in systems un-

dergoing change. Real-world examples remain rare. During the recent drought in the Colorado River Basin, Hoover Dam replaced five of its seventeen turbines with lower-head models to maintain production under reduced reservoir levels (Farmer, 2020). Similarly, Conowingo Hydropower Plant in Maryland and Comerford in New Hampshire added smaller units to generate power from environmental flow releases (March & Jacobson, 2016). A nationwide assessment of more than 200 U.S. facilities estimated that installing environmental-flow turbines could add 730 MW of capacity and produce nearly 1.8 TWh of additional energy each year (Garrett et al., 2023).

Hydropower turbines typically require replacement every 35 to 50 years (International Energy Agency, 2021; Quaranta & Hunt, 2022). Each refurbishment is a multimillion-dollar intervention that shapes system reliability and generation capacity for decades. In the US, many facilities will reach refurbishment age within the next decade, creating a narrow window to reconsider turbine selection and plant configuration in light of shifting hydrologic regimes and operating constraints. Yet until now, most turbine replacements still replicate the existing design (e.g., M. M. Johnson, 2024; Quaranta & Hunt, 2022; Papillon & Freeman, 2013; Morgado et al., 2020). Upgrades often focus on newer turbine models that incorporate incremental mechanical improvements relative to the retired units (IRENA, 2012; Mikhailov et al., 2021) that yield slight efficiency gains (Muntean et al., 2016; Quaranta et al., 2021), but the overall system configuration typically remains unchanged.

We currently lack decision-support frameworks to determine the optimal timing and configuration of turbine retrofits under changing hydrology. Existing predictive maintenance tools, including the U.S. Bureau of Reclamation's HydroAMP system (Neijens & Hayes, 2017), focus on mechanical failure risk (Shanbhag et al., 2025) but do not consider climate uncertainty, evolving operational constraints, or long-term retrofit optimization.

A proactive framework should inform operators to determine two key decisions: when to replace or upgrade turbines (or, conversely, when to extend the lifetime of existing fleet), and which configurations best enhance system resilience to hydrologic and operational variability. We introduce HyTUNE (Hydropower Turbine Upgrade and Next-generation Planning), a dynamic decision-support tool that integrates basin-scale hydrology and plant hydraulics within a control framework. HyTUNE tracks variables such as reservoir level,

inflow, and turbine efficiency to identify when replacement is optimal. For each intervention, it specifies the number of turbines to replace and the ideal head and capacity for the new configuration. The framework also incorporates regulatory and institutional constraints; for example, upgrades that increase capacity by less than 15 % can avoid triggering re-licensing requirements in the United States (A. Levine et al., 2017; Sensiba & McCormick, 2021). The system is trained and tested across a broad ensemble of hydrologic scenarios to ensure robustness under uncertainty.

We apply this framework to the Hoover Hydropower Plant, a system that has recently experienced significant hydrologic variability and turbine retrofits in response to declining reservoir levels. Using HyTUNE, we explore how a proactive, data-driven approach to turbine replacement can guide future modernization under projected climate and operational uncertainty. The analysis benchmarks HyTUNE's optimized replacement policy against conventional reactive strategies to assess differences in energy production, economic performance, and system reliability. This application demonstrates how adaptive planning can inform long-term investment and operational decisions, enabling hydropower systems to sustain performance and resilience in an uncertain future.

Methodologically, HyTUNE advances hydropower adaptation by applying dynamic planning. Traditional robust planning seeks a single design that performs acceptably across many futures. In contrast, dynamic planning develops a policy that updates recursive decisions over time as new information emerges. This structure allows replacement pathways to diverge as hydroclimatic trajectories unfold, so that planning decisions under progressively wetter futures can differ from those under drier futures, reducing regret under deep uncertainty (Herman et al., 2020). Dynamic planning frameworks have been successfully applied to a variety of water-resource management problems. Examples include reservoir planning (S. Fletcher et al., 2019) and operation (Pei et al., 2024), urban water-supply infrastructure adaptation (S. M. Fletcher et al., 2017; Zaniolo et al., 2023), and flood-risk management (Kwakkel et al., 2016) and planning (Hui et al., 2018). These approaches show how adaptive policies can adjust infrastructure and operational decisions in response to observed changes. While dynamic planning has been widely explored in other water-management domains, it has not yet been applied to hydropower turbine planning and retrofitting.

The remainder of this study is organized as follows. Section 2 outlines the methodological framework, including the development of the hydraulic model, reservoir operation model, and retrofitting decision policy. Section 3 presents the case study, describing plant characteristics and operational policies. Section 4 presents the performance analysis of the proposed approach at the Hoover Hydropower Plant. Section 5 discusses the study's limitations and outlines directions for future work. Finally, Section 6 provides an overview of the U.S. hydropower fleet and summarizes the key findings and highlights the broader implications for hydropower modernization and climate adaptation.

2 Methodology

The proposed decision-support framework integrates a tightly coupled suite of models into a single modeling framework (Figure 1). The first component is a physics-based hydraulic simulator which computes power output at the Hydropower Plant (HP) as a function of reservoir release, level, and turbine configuration. The simulator considers variable turbine-efficiency curves and accounts for turbine specifications, frictional losses, minor losses, and dynamic tailwater elevations. The hydraulic simulator is nested within a reservoir operations model calibrated to historical records, which takes inflow and demand as inputs and produces time series of storage and releases. The final component is a dynamic planning optimization module that embeds the hydraulic and reservoir simulators. It uses hydrological conditions as inputs and outputs decisions such as turbine replacement schedules, head adjustments, and discharge modulation. In this framework, the hydraulic and hydrological models are calibrated to the case study, while the dynamic planning module is optimized to maximize net present value (NPV) under uncertainty.

2.1 Hydraulic model development

Hydraulic models are fundamental to accurately capture efficiency fluctuation in reservoir-based HP. Specifically, physics-based hydraulic models track the movement of water from reservoir intakes through penstocks to turbine runners, resolving time-varying frictional and minor head losses and capturing turbine efficiency as a function of reservoir head, release, and tailwater elevation. Modeling efficiency fluctuations in detail is necessary to enable the accurate calculation of dynamic HP power output.

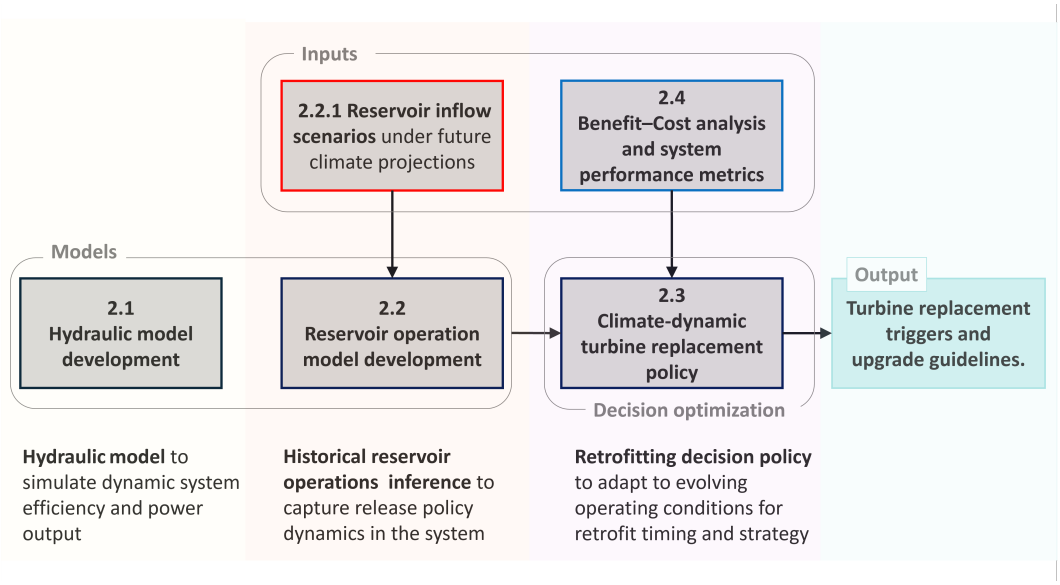

Figure 1: Methodological flowchart for our decision-support framework, with each step linked to the corresponding sections of the paper for detailed discussion.

The simulated daily HP generation, E_{sim}, (in kWh) for day t can be calculated as:

$$E_{\text{sim}}(t) = \rho\, g\, H(t)\, Q(t)\, \eta(t)\, 24 \tag{1}$$

where ρ denotes the volumetric mass density of water (kg/m^3), g is the gravitational acceleration constant (m/s^2), $H(t)$ is the net hydraulic head (m), $Q(t)$ is the volumetric water flow rate (m^3/s), and $\eta(t)$ is the turbine efficiency (dimensionless). Note that both H and η are time dependent and vary based on turbine inflow, penstock diameter and/or design flow, respectively. The simulated energy output, E_{sim}, also accounts for turbine outage probability as a function of age, as described in the Supplementary Information.

$H(t)$ is calculated as the dynamic difference between reservoir level and tailwater elevation (i.e., the level of the downstream river or water body that water is discharged into) adjusted for frictional and minor losses, namely:

$$H(t) = H_{\text{REL}}(t) - H_{\text{TEL}}(Q,t) - H_{\text{f}}(Q,t) - H_{\text{o}}(Q,t) \tag{2}$$

where H_{REL}(t) is the reservoir water level and H_{TEL}(Q, t) is the downstream water level at the tailrace, their difference is often referred to as the gross head. The friction losses in the penstock and tunnel (if present) are denoted as $H_{\text{f}}(Q,t)$, while $H_{\text{o}}(Q,t)$ accounts

for the total hydraulic (local) losses within the conveyance system. All heads and losses are expressed in meters.

Tailwater elevation $H_{\mathrm{TEL}}(Q,t)$ is a function of the reservoir release and is usually calculated based on historical measurements or HP design documents. Friction losses occur as water flows through penstocks or tunnels, increasing with flow velocity and pipe roughness. Minor (or local) hydraulic losses arise from turbulence at bends, valves, and transitions within the conveyance structure, and also scale with velocity and structural design. Equation 3 details these losses as a function of plant physical properties and flow. It consists of three key elements: the first term sums the friction losses in the Z series-connected pipes via the Darcy–Weisbach equation, the second term accounts for tunnel friction losses (if present) using the Manning formula; and the third term captures local (minor) losses in those same Z pipes.

$$
\begin{aligned}
H_{\mathrm{f}}(Q,t) &= \sum_{\chi=1}^{Z}\left[f_\chi(\epsilon,t)\frac{L_\chi}{D_\chi}\frac{V_\chi(t)^2}{2g}\right] + L_\tau\left(\frac{nV_\tau(t)^2}{R^{2/3}}\right)^2, \quad H_{\mathrm{o}}(Q,t) = \sum_{\chi=1}^{Z}\left[K_\chi\frac{V_\chi(t)^2}{2g}\right], \\
V_i(t) &= \frac{Q_i(t)}{A_i}, \quad i \in \{\chi,\tau\}.
\end{aligned}
\tag{3}
$$

where V_χ (m/s) represents the flow velocity in the χth pipe, f is a dimensionless friction factor (function of pipe roughness ϵ), L_χ (m) is the length of the χth pipe, D_χ (m) denotes the diameter of the χth pipe, g (m/s^2) signifies gravitational acceleration, n is the Manning roughness coefficient, K_χ $(-)$ accounts for aggregate resistance factors (intake trash racks, bends, transitions) in the χth pipe, V_τ (m/s) represents the flow velocity in the tunnel, L_τ (m) is the length of the tunnel, R (m) corresponds to the hydraulic radius, and A (m^2) is the cross-sectional area of the pipe or tunnel.

We note that in most water resources studies, H is usually approximated by reservoir level, but this approximation leads to overestimation of HP output especially when operating them outside of their design conditions. Similarly, the efficiency η in Eq. 1 is a function of turbine age, head (H), and discharge (Q). New turbines operating near their design head and discharge typically achieve efficiencies of about 90 %, but performance declines sharply outside these ranges. Many water-resources studies simplify by assuming a constant efficiency of 90 %, which systematically overestimates hydropower production outside of design ranges (Fälth et al., 2023). Research highlights measurable declines in turbine efficiency over time. Documented studies report age related reductions

that can be expressed as approximate annual rates (e.g., Goldberg & Lier, 2011; Quaranta et al., 2021), which supports modeling turbine efficiency as a linear function of age in this study:

$$\eta_j(t) = \eta_0(Q, H)\left[1 - \lambda\,\mu(t)\right], \quad \lambda = \frac{\omega}{L_s} \tag{4}$$

where $\eta_0(Q, H)$ denotes the baseline turbine efficiency as a function of discharge and head, $\mu(t)$ is the turbine's age in years (which resets to zero upon replacement), L_s represents the designed service life in years, and ω is the total percentage efficiency loss accumulated over L_s. The relationship among discharge, head, and efficiency is illustrated in the "hill" diagram in Figure **??** (SI). A typical Francis turbine (e.g. for moderate to large head facilities) maintains high efficiency between 75 % and 120 % of its design head (expressed as the ratio of actual head to design head) and remains efficient down to about 50 % of its design flow.

After establishing the physical equations that govern the calculation of H and η, and therefore the energy production in a HP system, we calibrate the parameters that appear in these equations based on historical observations of energy production, reservoir release, and reservoir level in our plant of interest.

We use a mixed literature-informed and data-driven approach. Literature allows us to identify plausible ranges of these parameters for a HP, and within these ranges we use a calibration approach to find the parameter combination that best explains the historical relationship between E_{sim}, Q and H in our plant of interest. Table **??**, in SI, outlines recommended sampling ranges for the key hydraulic calibration parameters: pipe roughness (ϵ), the Manning coefficient (n), and the aggregate resistance factor (K). Specifically, ϵ is varied between 0.03 mm and 2 mm, n between 0.011 and 0.018, and K between 0.5 and 5. These ranges reflect the broad variability introduced by factors such as the age and internal surface condition of conduits, the geometric attributes of bends and transition structures, and the flow distribution at elbows (Wahl & Cohen, 1999). We also account for turbine efficiency degradation (ω) over the service life. Industry assessments report efficiency losses of up to 8 % over 30 years (Quaranta & Hunt, 2022). Accordingly, we extend this range to 10–15 % to represent a service life of approximately 60 years. Using these parameter ranges, we run the hydraulic model hundreds of thousands of times with a search algorithm, iterating until the simulated energy production closely matches observed data. The fit is optimized by minimizing an objective function,

such as the mean absolute error, as described in Equation 5, ensuring accurate alignment with real-world conditions.

$$\min_{\epsilon,n,K,\omega} \; J = \frac{1}{N}\sum_{i=1}^{N}\left|E_{\text{actual},i} - E_{\text{sim},i}(\epsilon_\chi, n, K_\chi, \omega)\right| \tag{5}$$

where $E_{\text{actual},i}$ denotes the observed energy output for the ith observation, and $E_{\text{sim},i}(\epsilon_\chi, n, K_\chi, \omega)$ represents the simulated energy output based on the hydraulic loss parameters ϵ_χ, n, K_χ and ω. Here, N signifies the total number of observations. It is important to note that penstock's surface roughness, ϵ_χ, is related to the penstock friction factor, f_χ; therefore, optimizing ϵ_χ corresponds to adjusting the f_χ.

2.2 Reservoir operation model development

The hydraulic model described above is nested within a reservoir operation model that simulates reservoir level and releases based on inflow time series and an operating policy. The reservoir water balance is expressed as:

$$S(t+1) = S(t) + \big[I(t) - Ep(t) - R(t)\big]\Delta t \tag{6}$$

where $S(t)$ is the reservoir storage (m^3) at time t, $I(t)$ is the inflow (m^3/s), $R(t)$ is the outflow (m^3/s), $Ep(t)$ represents evaporation losses (m^3/s), and Δt is the model time step (s). The outflow of dam-regulated reservoirs is determined by reservoir operators, who release water according to a set of rules, known as the "operating policy", that determine how much water should be released based on inputs such as season, reservoir storage, water and power demand, and recent inflows (Loucks & Van Beek, 2017; X. Liu et al., 2011; Zhou & Guo, 2013). Accurately representing these policies is essential to simulate plant-specific reservoir dynamics and hydropower production over time.

The following two sections describe how we obtained simulations of reservoir inflows time series extending to 2100, and controlled outflows for Hoover HP to simulate reservoir dynamics. This provides the dynamic boundary conditions for simulating turbine discharge and head.

2.2.1 Reservoir inflow scenarios

Regulated reservoir inflow scenarios of Hoover Dam are leveraged from the Third Secure Water Act Assessment on the impact of Climate Change on Federal Hydropower (Broman & Voisin, 2025; Kao et al., 2022). This dataset presents a suite of high-resolution downscaled hydro-climate projections over the conterminous United States (CONUS), based on selected global climate models (GCMs) from the Coupled Model Intercomparison Project Phase 6 (CMIP6). The GCM outputs are downscaled using either statistical (DBCCA) or dynamical (RegCM) approaches, with bias correction based on two meteorological reference datasets (Daymet and Livneh) (Kao et al., 2022a).

The downscaled precipitation, temperature, and wind speed are used to drive two calibrated hydrologic models, VIC and PRMS, enabling the simulation of projected hydrologic responses across CONUS (Naz et al., 2016; Kao et al., 2022). This process produces an ensemble of 56 daily runoff projections spanning 1981–2099 under multiple emission scenarios. The runoff projections are then routed through the mosartwmpy water management and river routing framework (Voisin et al., 2013; Thurber et al., 2021), which simulates regulated streamflow, including reservoir operations based on historically derived policies (Turner et al., 2022; Broman et al., 2024) and accounting for sectoral water withdrawals (Voisin et al., 2017). The resulting dataset provides reservoir inflows that serve as inputs to our reservoir operation model, described in the next session.

2.2.2 Historical reservoir operations (HRO) inference

In dam-controlled reservoirs, releases are determined through an "operating policy" as a function of season, reservoir storage, water and power demand (Loucks & Van Beek, 2017; X. Liu et al., 2011; Zhou & Guo, 2013). Accurately representing these policies is essential to simulate plant-specific reservoir dynamics and hydropower production over time. In some cases, documented rule curves or operational guidelines are available in dam documentation or regulatory filings, but such information is not always accessible or up to date. In cases where formal operating rules are unavailable, release behavior can be inferred directly from historical inflow, storage, and outflow records using machine-learning techniques (Fakhfakh et al., 2017).

In recent years, deep learning methods such as long short-term memory (LSTM) networks have gained popularity in reservoir operation modeling, particularly for pre-

dicting water releases (Zhang et al., 2019; Wang et al., 2022). LSTMs effectively capture complex temporal patterns and nonlinear dynamics in hydrologic systems (Al-Hardanee & Demirel, 2024; Feng et al., 2023; Barzola-Monteses et al., 2022), allowing them to approximate the nuanced decision-making of experienced operators. In this study, we employ an LSTM network to model temporal dependencies in the reservoir operation time series. The full model setup, input structure, model parameter tuning, and training procedure are provided in the Supplementary Information.

2.3 Climate-dynamic turbine replacement policy

Water resource systems are undergoing unprecendented changes in water supply and demand that require planning strategies to adapt to evolving hydrologic conditions (Herman et al., 2020). We formulate the turbine replacement problem as a control problem that suggests turbine replacement timing and configuration as a function of the system state, such as observable reservoir levels averaged over different time windows and system efficiency.

As illustrated in Panel A of Figure 2, the model begins by comparing a feature of the system condition (e.g., Feature_1, reservoir levels) to a threshold. If the condition is met ("Yes"), the process proceeds to the next decision node (e.g., checking Feature_2, efficiency); otherwise, a default action (e.g., no replacement) is selected. Panel B of Figure 2 presents the optimized decision tree, which is detailed in the following sections.

The decision tree's structure, features, threshold values, and actions, are determined through an evolutionary simulation–optimization algorithm that iterates over hundreds of thousands of simulations for an ensemble of climate scenarios. The evolutionary algorithm applies operators such as mutation, crossover, and selection, to identify the tree configuration that maximizes net present revenue, calculated as the expected difference between energy revenue and turbine replacement costs. The optimized decision tree determines when to schedule turbine replacements and how to adjust their configuration (such as head and capacity) as a function of relevant system indicators such as reservoir head and turbine age. This approach was developed in (Cohen & Herman, 2021) and subsequently used in (Zaniolo et al., 2023) for a problem of urban water planning.

The following table summarizes the key decision actions and input features used in the model. Panel A of Table 1 organizes the 82 possible actions into four categories:

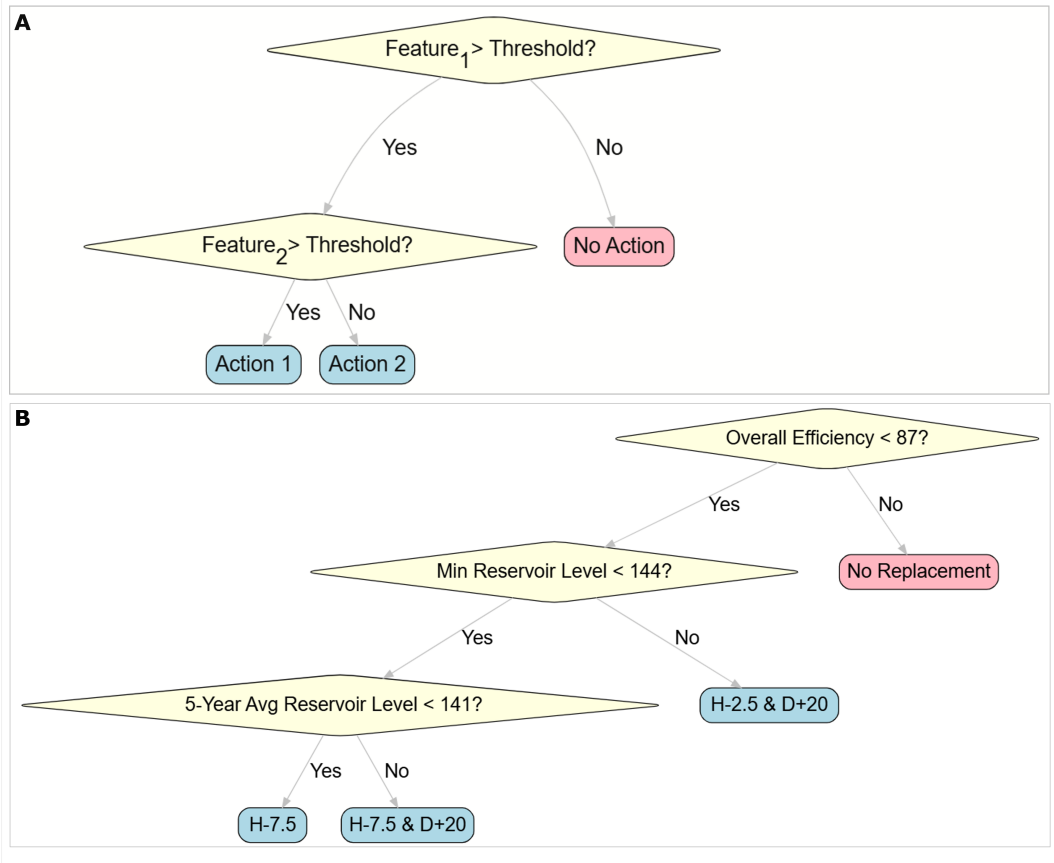

Figure 2: Panel A: Schematic of the decision tree model for hydropower planning. The model sequentially evaluates system features, beginning with a primary attribute (e.g., Feature_1) compared to a threshold. A "Yes" may branch to further nodes (e.g., Feature_2), while a "No" can terminate the path or trigger an action. Subsequent nodes similarly map system states to distinct operational actions. Panel B: Optimized decision tree showing the optimized structure.

no replacement, head adjustments, discharge adjustments, and combined adjustments. Panel B lists the 11 input features that describe the state of the hydropower system and inform the model's decision rules.

2.4 Benefit–Cost analysis and system performance metrics

Replacing hydropower turbines is a multimillion-dollar investment that shapes system reliability and energy generation capacity for decades into the future. Choosing what turbines to replace, when, and with what configuration (or conversely extending the life of existing units through repair) requires a careful weighing of capital costs against the benefits of higher conversion efficiency, greater operational flexibility, and improved re-

Table 1: Decision actions and model input features

A) Grouped decision actions	
Category	**Action options**
No/Replacement	No Replacement; Replace Existing
Head Adjustments	H+2.5, H+5, . . . , H-10
Discharge Adjustments	D+5, D+10, . . . , D-20
Combined H & D	All combinations (e.g. H+2.5 & D+5, . . .) (See Table **??** (in SI) for the complete list of 82 actions)
B) Input features	
Feature	**Explanation**
5-Year Avg Reservoir Level	5-year average net reservoir head
10-Year Avg Reservoir Level	10-year average net reservoir head
Max Reservoir Level	5-year maximum reservoir level
Min Reservoir Level	5-year minimum reservoir level
5-Year Avg Reservoir Release	5-year average reservoir release for power production
10-Year Avg Reservoir Release	10-year average reservoir release for power production
Upper Nominal Head	Design head of higher-head turbines
Lower Nominal Head	Design head of smaller-head turbines
Overall Efficiency	Overall system efficiency
Peak Efficiency	Peak efficiency of new turbines over a five-year period
Minimum Efficiency	Minimum efficiency of old turbines over a five-year period

liability. In the next three sections we report how we quantify the costs of replacement and benefits measured as the net present value of incremental hydropower revenue. We also present several other performance metrics used to further assess our turbine replacement policies such as firm energy production and capacity factors.

2.4.1 Benefits: hydropower revenue estimation

Benefits of hydropower plants are derived from the projected revenue generated over the project's operational lifetime, based on the expected energy production and the corresponding electricity market prices. Since electricity prices fluctuate throughout the day, energy output must be estimated across distinct time-of-use segments, namely, peak, mid-day, and off-peak periods. Although the exact timing of these segments varies by region and season (FERC, 2024; EIA, 2025), we adopt a simplified (generalized) approach, based on commonly observed U.S. wholesale electricity market dynamics (FERC, 2024; Millstein et al., 2025), dividing the day into three pricing blocks: 6 hours for peak, 12 hours for mid-day, and 6 hours for off-peak.

The annual revenue AR_y (in USD) for year y, over a period of Δt days, is obtained by summing the daily energy outputs in each tariff segment multiplied by their respective prices:

$$AR_y = \sum_{t=1}^{\Delta t} \sum_{j=1}^{K} E_{\mathrm{sim},j}(t)\, e_{p,j}, \quad K \in \{1,2,3\} \tag{7}$$

$K \in \{1,2,3\}$ indexes the three daily segments (peak, mid-day, and off-peak); $E_{\mathrm{sim},j}(t)$ (kWh) is the simulated energy in segment j on day t; and $e_{p,j}$ (USD/kWh) is the price for that segment.

Next, the lifetime expected net present revenues from hydropower production can be determined as follows:

$$\mathrm{R} = \sum_{y=1}^{L_s} \frac{AR_y}{\left(1+r_y\right)^y} \tag{8}$$

where L_s denotes the project's lifetime. The vectors $\mathbf{R} = \{R_1\ \ldots, R_{L_\mathrm{s}}\}$ and $\mathbf{r} = \{r_1, \ldots, r_{L_\mathrm{s}}\}$ represent the annual plant revenues (assuming average hydropower production throughout the year, in USD) and the annual interest (discount) rates in percentage, respectively, both over the project's lifetime.

HyTUNE is designed to adapt turbine replacement to nonstationary hydrology, but here we do not evaluate how long-term changes in electricity prices could alter replacement decisions. Credible projections of future prices require an explicit representation of power-system evolution and market dynamics, which is beyond the scope of this initial methodological contribution. We therefore represent intra-day price variability, but treat longer-term electricity price trajectories as exogenous and time-invariant.

2.4.2 Costs: hydropower turbine replacement

We use the Baseline Cost Model (BCM) for hydropower projects developed by Oak Ridge National Laboratory (Oladosu & Ma, 2025) to estimate retrofit costs. For projects with added capacity greater than 30 MW and hydraulic head exceeding 60 ft, the cost model is expressed as:

$$RC = \zeta\ \theta\ \exp\Big[\beta_0 + \beta_1 \ln(\mathrm{AddedCap}) + \beta_2 \ln(\mathrm{Head})\Big] \tag{9}$$

Turbine replacement costs (RCs) are estimated as a nonlinear function of installed capacity, design head, and categorical model terms. The full model expression, including all parameters used in this study, is provided in the Supplementary Information. A detailed description of the BCM and its components is available in O'Connor et al. (2015); Oladosu and Ma (2025).

The lifetime expected net present cost of turbine replacement is then computed as

$$C = \sum_{n=1}^{N} \frac{RC_n}{\left(1 + r_{T_n}\right)^{T_n}} \tag{10}$$

where N is the number of replacement events and T_n is the year in which the n^{th} replacement occurs.

2.4.3 Performance metrics: NPV and other reliability metrics

In this framework, design optimization relies on financial performance measures, emphasizing the lifetime net present value of benefits and costs. The primary objective is to maximize the net present value (NPV), which aggregates projected cash flows discounted to the present (Santolin et al., 2011). The NPV is defined as:

$$f_{\text{NPV}} = R - C \tag{11}$$

In this study, we use fixed energy prices of \$90/MWh (peak), \$50/MWh (mid-day), and \$30/MWh (off-peak) to represent western market dynamics and price variability. A 3 % discount rate was used, consistent with U.S. hydropower feasibility standards. Detailed assumptions and data sources are described in the Supplementary Information Section **??**.

While our policies are trained to maximize NPV, we also evaluate their performance across several additional indicators that capture broader aspects of hydropower operation. We benchmark the optimized HyTUNE policy (OPT) against two reactive approaches that reflect common industry practice. In the first approach (RA_1), all turbines are replaced with identical units after 55 years of operation. In the second approach (RA_2), identical replacements occur twice, after 40 and 80 years of operation. For the performance comparison, metrics with the subscript OPT refer to the HyTUNE strategy, and metrics with the subscript RA refer to the reactive approaches:

$$\Delta\text{AAE} = \text{AAE}_{OPT} - \text{AAE}_{RA}$$

$$\Delta\text{NPV} = \text{NPV}_{OPT} - \text{NPV}_{RA}$$

$$\text{FPG} = \text{E}_{\text{OPT},\,0.05} - \text{E}_{\text{RA},\,0.05} \tag{12}$$

$$\Delta\text{PP} = 365 \times \mathbb{E}[E_{\text{OPT,peak}} - E_{\text{RA,peak}}]$$

$$\text{EG}_{\text{IP}} = \left[\sum \text{E}_{\text{OPT}} / \sum \text{OPT}_{\text{cap}}\right] \div \left[\sum \text{E}_{\text{RA}} / \sum \text{RA}_{\text{cap}}\right]$$

Here, ΔAAE is the change in annual average energy generation (GWh), ΔNPV is the change in net present value (M $), FPG is the firm power gain, defined as the energy available 95 % of the time (MWh/day), ΔPP is the change in peak-period energy generation (GWh/year), representing the amount of energy produced during 6 daily peak hours, and EG_{IP}, analogous to a capacity factor, represents energy generated per installed capacity.

3 Case study and data

The Hoover Hydropower Plant, completed in 1936 on the Colorado River, operates seventeen Francis turbines, nine on the Arizona side and eight on the Nevada side, along with two 2.4 MW Pelton station-service units. Together they provide a total nameplate capacity of about 2,080 MW (USBR, 2018). Water enters the powerhouse through four 9.15 m penstocks that divide into 3.97 m pipes feeding the main turbines.

Figure 3 shows monthly reservoir elevation and discharge at Hoover HP from 1938 to 2023. After 2000, reservoir levels declined sharply as drought persisted and regional water demand increased. The drop in elevation reduced the gross head, defined as the difference between reservoir level and tailwater, and lowered power generation capacity (Hannoun & Tietjen, 2023; Huizar et al., 2024). Despite declining reservoir levels, the data show that discharges (blue line) remained relatively stable with seasonal variability.

Hoover's original HP design required a minimum power-pool elevation of 320 m. From 1986 to 1993, operators upgraded all Francis turbines to higher-capacity versions while maintaining the same design head (Rogers, 2010; M. Johnson et al., 2023). As Lake Mead levels continued to fall, these uprated units lost efficiency. Between 2012 and 2015,

operators replaced five turbines with low-head models optimized for reduced water levels (Farmer, 2020; M. Johnson et al., 2023). This is a rare example of a heterogeneous turbine configuration retrofit that had the effect of lowering the minimum power-pool to about 290 m thereby extending the plant's operating range during continued storage decline (Tweed, 2013; Jenkin et al., 2019).

Water management on the Colorado River requires balancing multiple and often competing objectives. State agencies, Native American tribes, irrigation districts, municipalities, and environmental groups depend on the river for municipal, agricultural, industrial, recreational, and ecological needs (Abboud et al., 2022). High hydrologic variability adds further complexity (McCoy et al., 2022; Smith et al., 2022). The "Law of the River," a collection of compacts, treaties, and statutes, governs allocations, release schedules, and storage priorities throughout the basin (Lukas & Payton, 2020; Wheeler et al., 2022; Fleck & Castle, 2022). All water releases for both downstream delivery and hydropower generation must follow these rules (see Table **??** in the Supplementary Information). As a result, operational decisions account not only on reservoir levels and turbine efficiency but also on legal allocations and environmental mandates.

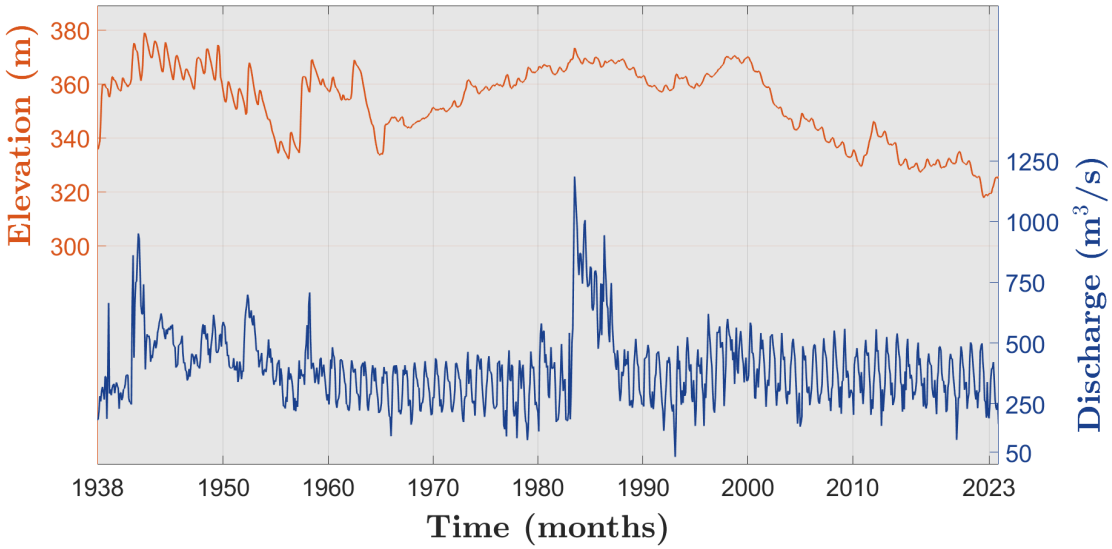

Figure 3: Temporal evolution of Hoover Dam reservoir elevation and discharge. The left y-axis (orange) indicates reservoir elevation (m), and the right y-axis shows discharge (m^3/s). The data represent monthly averages, with the x-axis denoting time in months.

4 Results

4.1 Hydraulic model calibration

We calibrated the hydraulic model using operational and hydrological data following the setup described in Section 2.1. Here, calibration means identifying the uncertain parameters in the physical loss and performance equations, such as penstock roughness and local loss coefficients, that allow simulated daily generation to match observed plant output under observed forcing. We used daily inflow and energy-generation records available from 1980 onward, and calibrated over 1980–2023. We compute tailwater elevation as a function of downstream conditions, using elevation observations at Davis Dam, located 108 km downstream and forming Lake Mohave. When the water level at Davis Dam exceeds 195 m (638 ft), tailwater at Hoover rises. We use this relationship to estimate tailwater elevation at the plant and compute gross head as the difference between reservoir elevation and tailwater level. Net head then follows from Eq. 2 after accounting for friction and local losses.

We performed calibration with a Monte Carlo search. We generated $M = 10{,}000$ parameter sets within the literature-informed ranges reported in SI Table **??**. The calibrated parameters include penstock roughness (ϵ), local loss coefficients (K_1, K_2), and turbine efficiency degradation (ω). For each parameter set, we simulated the full calibration period and computed the objective function J in Eq. 5, defined as the mean absolute error between simulated and observed daily generation. The best-fitting parameter set defines the calibrated model, which we then force with future inflow projections to translate hydrologic change into projections of hydropower generation.

Panel A of Figure 4 shows the Monte Carlo search space of (K_1, K_2, ϵ), where marker color indicates J and size represents ω. The optimal parameter set is $\epsilon = 0.636$ mm, $K_1 = 0.605$, $K_2 = 0.553$, and $\omega = 8.87$ %, yielding $J = 0.512$. Panel B presents a two-dimensional cross-section at $\epsilon = 0.636$ mm. When both K_1 and K_2 exceed 2, variations in ω produce only minor changes in J. This pattern shows that hydraulic headloss parameters dominate the calibration, while efficiency degradation plays a secondary role. Panel C compares observed and simulated power generation aggregated to monthly averages for clarity, with the daily comparison provided in the Supplementary Information (Figure **??**). The black line shows observed generation, and the gold line shows modeled output from the calibrated parameter set. The two curves align closely in both am-

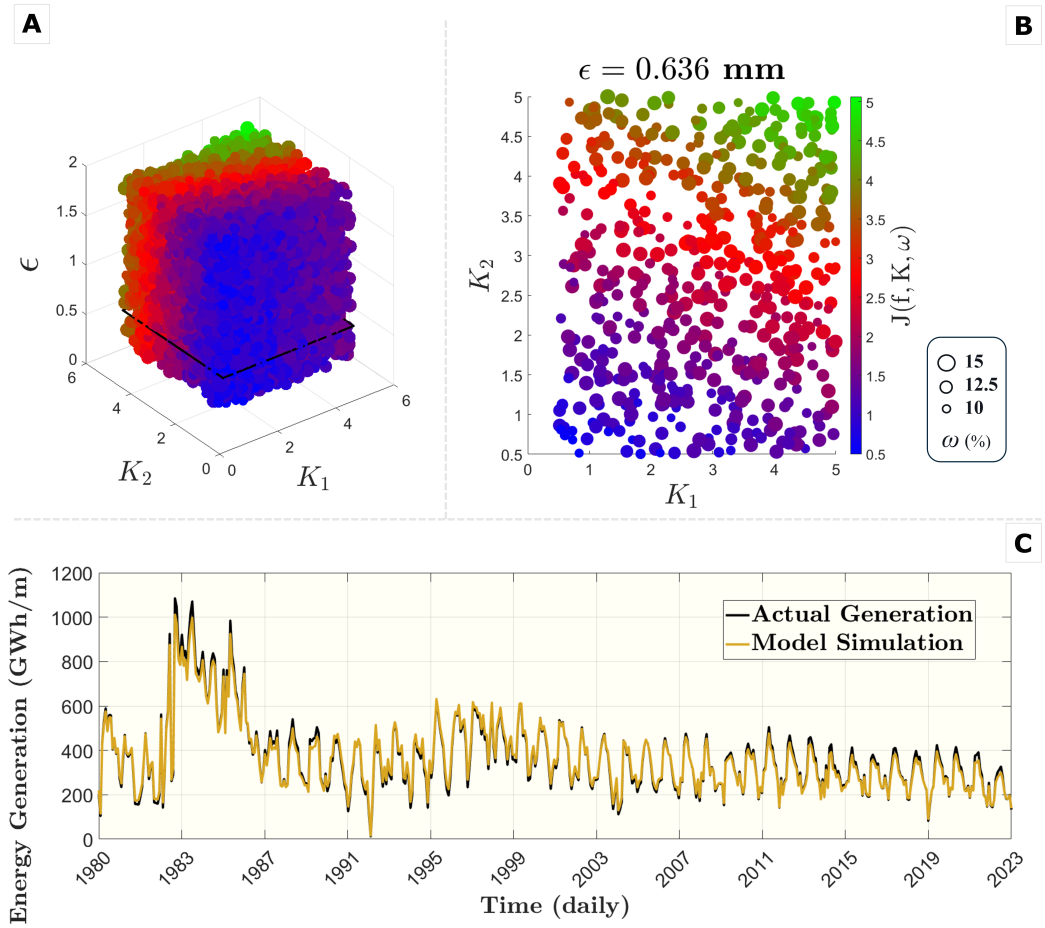

Figure 4: **Panel A:** 3D scatter plot of Monte Carlo–sampled parameter sets $(K_1, K_2, \epsilon, \omega)$, where marker color encodes the objective function J and marker size encodes turbine efficiency loss ω (legend at right: smallest circles = 10%, largest circles = 15% after 60 years of operation). **Panel B:** 2D cross-section at $\epsilon = 0.636$ mm, illustrating the sensitivity of J to variations in the minor-loss coefficients K_1 and K_2 and efficiency loss ω, using the same color and size mappings as in the left panel. **Panel C:** Monthly-aggregated power production (GW) at Hoover HP: observed genera-tion (black line) versus simulated output (golden line) from the calibrated hydraulic model using the optimized parameter set and historical inflow records. Daily data (1980–2023) were averaged to monthly resolution.

plitude and timing, reproducing seasonal and interannual variations with high fidelity. This agreement demonstrates that the calibrated model captures Hoover's operational behavior and provides a reliable basis for assessing future performance under climate-driven inflow scenarios.

4.2 Historical Reservoir Operation inference

After completing the model selection process described in Section 2.2.2, we apply the calibrated LSTM architecture to predict reservoir releases under a wide range of future climate scenarios.

Figure 5 summarizes the model trajectories linking projected inflows, model performance, and reservoir response under future climate scenarios. Panel A shows historical inflows (1938–2023; weekly data, 10-year moving average; gray) and bias-corrected CMIP6 inflow projections (purple). The darker purple line represents the multi-scenario mean. The historical record declines through the 1970s, then rises into the 1990s. The 10-year smoothing highlights long-term variability rather than short-term fluctuations. Projected inflows show a broader spread by mid and late century, reflecting increasing hydrologic uncertainty across the CMIP6 ensemble. Panel B evaluates the performance of the LSTM reservoir operation model. Observed discharge (solid gray) and model predictions (dashed red) align closely across the training and validation periods, with the shaded region marking the validation window. The model achieves $R^2 = 0.83$ during training and $R^2 = 0.67$ during validation, demonstrating its ability to capture nonlinear relationships among inflow, storage, and release. Panel C outlines the modeling workflow, where bias-corrected inflow projections drive the trained LSTM model to generate time-series estimates of discharge and reservoir elevation for each climate scenario. Panels D and E show the simulated reservoir releases and elevations, respectively. In Panel D, observed releases (gray) and modeled releases under future inflow scenarios (blue) share similar variability, with the darker blue line showing the ensemble mean. Panel E presents corresponding reservoir elevation trajectories (gold), with the darker line representing the mean across scenarios. Both panels show widening spreads after mid-century, indicating that inflow uncertainty propagates into increasingly variable operational outcomes. Some scenarios project persistently low reservoir levels, signaling risks to storage reliability and hydropower generation under drier futures. Overall, these results show that a data-driven reservoir model coupled with CMIP6 inflow projections can translate hydrologic uncertainty into plausible ranges of future discharge and storage.

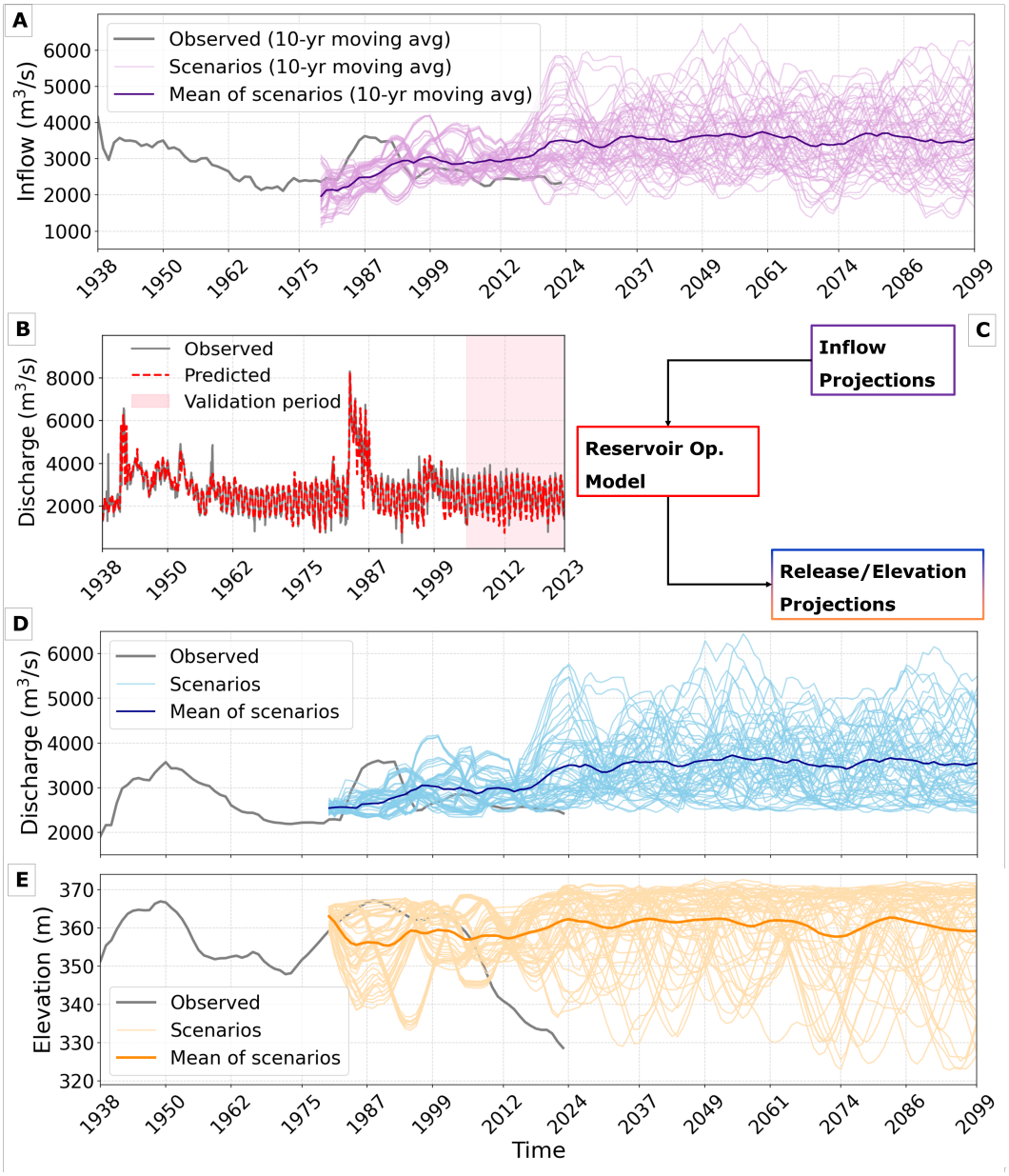

Figure 5: Observed and projected inflows, model performance, and scenario-based reservoir simulations. (A) Historical inflow (gray) and bias-corrected CMIP6 projections (purple). (B) Observed and LSTM-predicted discharge with R^2 of 0.84 and 0.67 for training and validation periods respectively. (C) Modeling workflow linking inflow projections to reservoir operation. (D–E) Simulated releases (blue) and elevations (gold) under future inflow scenarios, with darker lines denoting ensemble means. Results show divergent operational outcomes and potential low-storage futures under dry scenarios.

4.3 Climate dynamic turbine replacement policy

After simulating future releases and reservoir elevations, we performed a policy-search optimization to optimize the structure and elements of the decision tree that spec-

ifies the replacement policy, effectively identifying under what conditions changing turbine head or capacity improves system performance, and to what designs with the objective of maximizing NPV.

4.3.1 Optimized policy tree

HyTUNE uses policy search to develop a decision tree that defines optimal turbine replacement rules. The tree was trained on 80 % of randomly selected scenarios and tested on the remaining 20 %. The initial year of operation was set to 1985, the point at which climate scenario data become available and all turbines share the same design head. To evaluate performance, we benchmark the optimized HyTUNE policy (OPT) against two reactive approaches that follow fixed service life thresholds and do not account for system performance or changing conditions. In the first approach (RA_1), all turbines are replaced with identical units after 55 years. In the second approach (RA_2), identical replacements occur twice, after 40 and 80 years of operation.

The resulting OPT of HyTUNE is shown in Figure 2. We confirmed the stability of through multiple optimization runs. Each optimization involved 250,000 function evaluations and was repeated over 10 times (using 10 random seeds per run) to assess convergence consistency. Further details on the experimental setup are provided in the Supplementary Information. HyTUNE triggers a turbine replacement when the overall efficiency of turbines drops below 87 %. When efficiency is higher, no replacement occurs. When efficiency falls below this threshold, the policy evaluates recent hydrologic states. If the 5-year minimum reservoir level is above 144 m, the framework recommends lowering the design head by 2.5 % and increasing discharge capacity by 20 %. If the 5-year minimum level falls below 144 m, the model checks the 5-year average reservoir level. When this value is above 141 m, the framework increases discharge capacity by 20 % and decreases head by 7.5 % . Otherwise, it lowers the design head by 7.5 %. This policy tree defines adaptive retrofit rules that balance hydraulic efficiency, energy output, and operational flexibility across a range of future hydrologic conditions.

4.3.2 HyTUNE retrofitting adaptation to wet and dry futures

To explore how HyTUNE is able to observe and dynamically adapt to changing conditions in the system, we simulate the optimized decision tree for the scenario with the lowest median reservoir level (dry scenario) and the one with the highest median reser-

575 voir level (wet scenario). Figure 6 illustrates reservoir dynamics and turbine replacement outcomes under these contrasting futures. The top panel shows projected reservoir el-

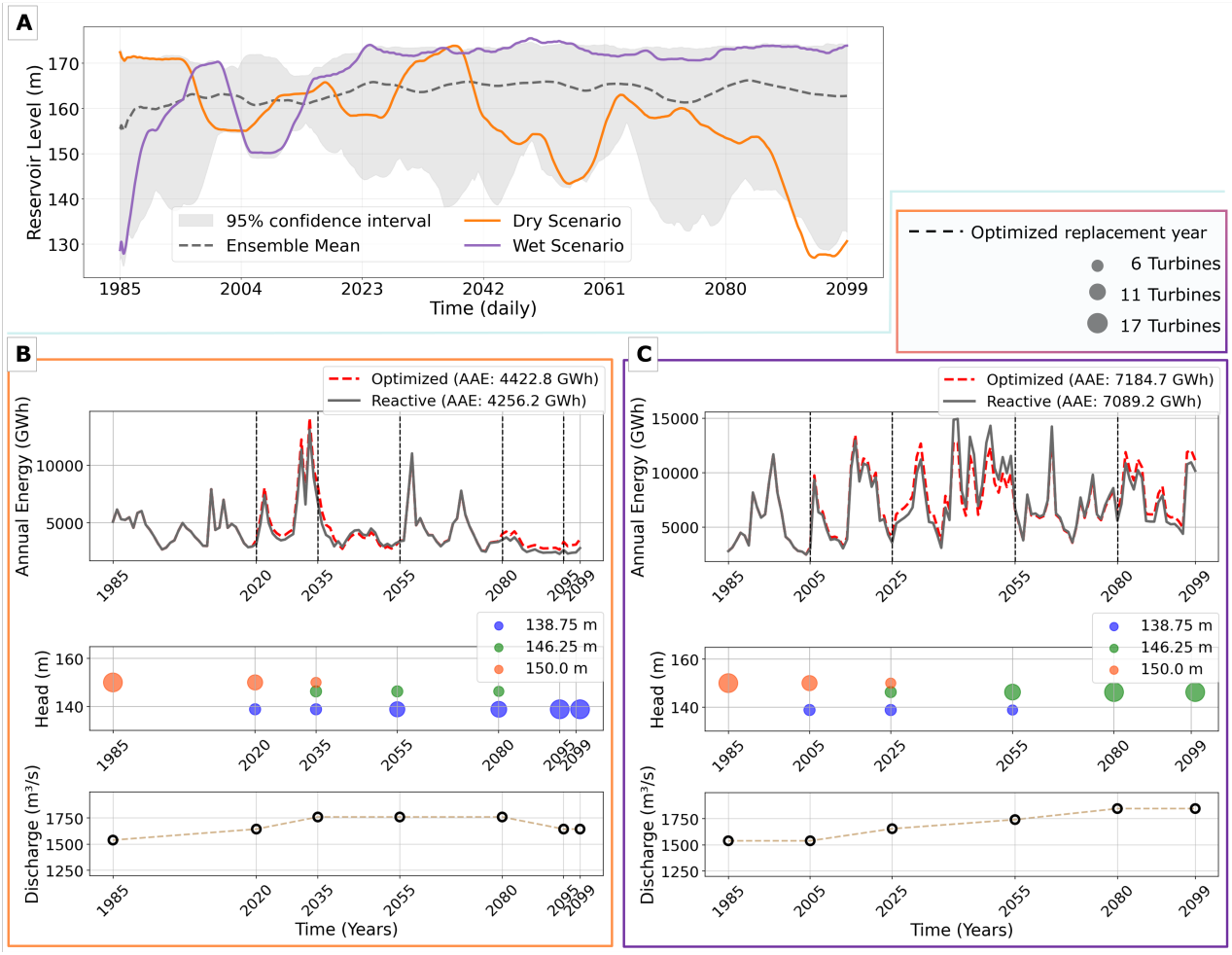

Figure 6: Reservoir dynamics and turbine replacement outcomes under diverse inflow scenarios. **Panel A:** Reservoir elevation trajectories for all projected inflow scenarios. The shaded gray region represents the 95 % confidence interval, and the dashed gray line shows the ensemble mean. The orange line marks the scenario with the lowest median reservoir level (dry scenario), while the purple line corresponds to the highest median reservoir level (wet scenario). **Panels B–C:** Effects of turbine replacement strategies on hydropower generation under the selected dry (left) and wet (right) scenarios. Each bottom panel includes three aligned plots: (*i*) annual energy generation (GWh) for the reactive one-time replacement strategy (solid gray) and the optimized replacement strategy (dashed red), with vertical dashed lines marking replacement years (black for optimized, blue for reactive); (*ii*) evolution of turbine design head over time, where circle size denotes the number of turbines operating at that head; and (*iii*) evolution of total design discharge over time. A separate legend in the top-right corner identifies the reactive and optimized replacement strategies for Panels B–C.

576

577 evations for all inflow scenarios. The shaded gray region marks the 95 % confidence in-

terval, and the dashed gray line indicates the ensemble mean, with the dry scenario shown in orange and the wet scenario in purple. The bottom panels show the performance and evolution of Hoover HP under these two representative scenarios using the optimized policy of HyTUNE. Each panel includes three time-aligned subplots. The top subplot presents annual energy generation in GWh for the reactive one-time replacement strategy (RA_1, solid gray) and the OPT (dashed red). The middle subplot shows the evolution of turbine design head, where symbol size represents the number of turbines operating at each head. The bottom subplot depicts the evolution of total design discharge. In both the dry and wet scenarios, the reactive approach replaces all 17 turbines simultaneously after 55 years of operation (blue dashed line).

Under the dry scenario (Panel B), the optimized policy (OPT) schedules five replacement phases involving a total of 29 turbines over several decades, resulting in higher average annual energy (AAE = 4422.8 GWh) compared with the reactive approach RA_1 (4256.2 GWh). Head variability reflects both hydrologic forcing and adaptive replacement decisions. OPT first reduces the design head by 7.5 % (from the original 150 m) and increases discharge by 20 % in 2020 by replacing six turbines. In 2035, it lowers the design head by 2.5 /% and again increases discharge by 20 % for another six turbines. A third phase occurs in 2055, when OPT reduces design head by 7.5 % and increases discharge by 20 % for the remaining five turbines, completing replacements across the 17-unit fleet. By 2080, the system undergoes another partial replacement as efficiency drops below the threshold, with six turbines replaced. This is followed by an additional six replacements in 2099, during which discharge is reduced to account for lower projected inflows. This phased strategy enables the plant to respond gradually to hydrologic change while preserving operational flexibility for future adaptation.

In the wet scenario, the optimized policy (OPT) still yields higher long-term benefits, with average annual energy (AAE = 7184.7 GWh) compared with 7089.2 GWh for RA_1. OPT follows a distinct pattern of phased replacements. In 2005, it reduces design head by 7.5 % for six turbines. In 2025, it lowers head by 2.5 % and increases discharge by 20 % for another six turbines. A third phase in 2055 applies the same 2.5 % head reduction and 20 % discharge increase to the remaining five turbines. By 2080, higher reservoir levels allow the framework to restore the first six low-head turbines to a head of 138.75 m (2.5 % below the original) while maintaining a 20 % increase in discharge capacity. Across both scenarios, the optimized policy consistently enhances lifetime energy gen-

eration, reduces efficiency losses, and adapts more effectively to changing hydrologic conditions. These results demonstrate that proactive, flow-informed turbine management enables smoother adaptation to evolving water regimes and provides sustained performance gains under future uncertainty.

The HyTUNE replacement strategy aligns closely with recent retrofitting efforts at the Hoover Hydropower Plant. After 2000, reservoir levels declined sharply as drought persisted and water demands increased. In response to lost capacity and reduced efficiency, operators replaced five turbines with low-head models optimized for reduced water levels, lowering the design head from 150 m to 138 m and increasing discharge capacity by 20 %. HyTUNE recommends a similar approach, increasing discharge capacity by 20 % while reducing the design head to 138.75 m in anticipation of projected inflow variability, illustrating how adaptive strategies can reconcile long-term hydrologic change with sustained generation performance. This agreement between model recommendations and actual retrofitting actions at Hoover indicates that the decisions taken there were technically well-founded and consistent with adaptive, performance-driven planning.

4.3.3 HyTUNE outperforms reactive approaches across all scenarios

Figure 7 shows a comprehensive analysis of HyTUNE against the two benchmark scenarios detailing how HyTUNE performance compares to the two benchmarks for different future climate characteristics and performance indicators. The top panels compare the RA_1 with the OPT from HyTUNE, while the bottom panels compare the RA_2 with the same OPT. The accompanying bar plots show the total number of turbines replaced under each strategy throughout the simulation period. Notably, OPT recommends different numbers of replacement phases (four or five) depending on system performance and prevailing hydrologic conditions. Each line in the parallel coordinate plot represents a single climate scenario, showing relationships among mean discharge (Q_{mean} in m^3/s), the 10th percentile and coefficient of variation of reservoir level (RL_{10} in m, RL_{CV}), drought frequency ($Fr_{drought}$) that measures the fraction of time reservoir discharge falls below 300 m^3/s. The color of each line in both panels corresponds to its ΔNPV value, where lighter tones indicate lower ΔNPV and darker tones indicate higher ΔNPV. While we optimize HyTUNE performance to maximize NPV, we also benchmark the produced strategies against other important performance metrics that are not directly used in calibra-

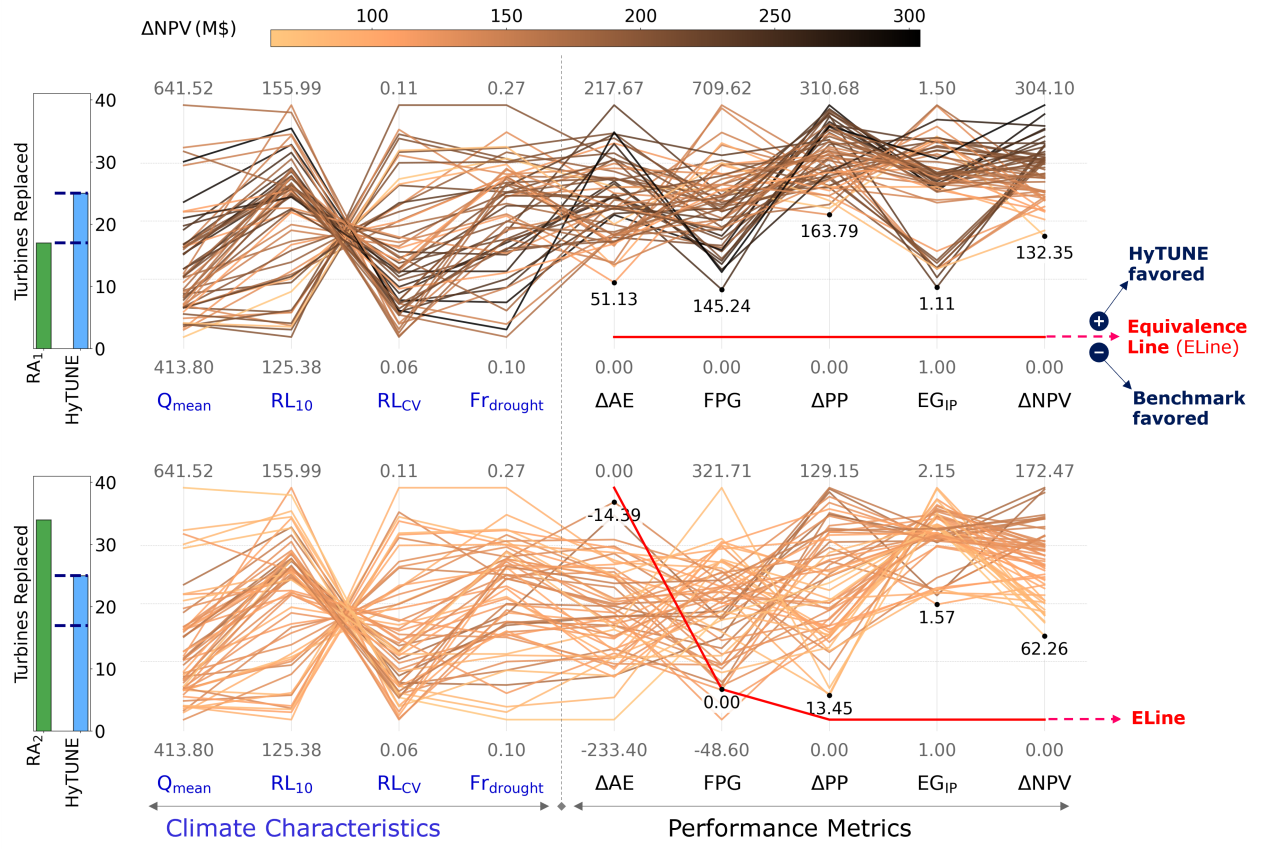

Figure 7: Parallel coordinate plots comparing scenario characteristics and retrofit strategies. The top panels contrast the one-time reactive replacement strategy (RA_1) with the optimized policy tree (OPT) from HyTUNE, and the bottom panels compare the two-time reactive replacement strategy (RA_2) with the same OPT. Each line represents an individual inflow scenario. Scenario characteristics (blue labels) include mean discharge (Q_{mean}), the 10th percentile and coefficient of variation of reservoir level (RL_{10}, RL_{CV}), and drought frequency ($Fr_{drought}$). Performance metrics (black labels) include the change in annual energy generation relative to the reactive cases (ΔAE), firm power gain (FPG), change in peak energy generation relative to the reactive cases (ΔPP), and energy generation per installed power (EG_{IP}). The final axis shows the change in net present value relative to the reactive cases (ΔNPV). Line colors represent ΔNPV, illustrating trade-offs among hydrologic and operational outcomes. Left-side bar plots compare the total number of turbines replaced under the reactive (green) and HyTUNE (blue) strategies. The red line on both panels marks performance equivalence; scenarios above the line indicate HyTUNE performs better, while those below indicate the benchmark performs better.

tion. These include the change in annual average energy generation (ΔAAE in GWh), firm power gain (FPG in MWh/day), change in peak-period energy generation (ΔPP in GWh/year), EG_{IP}, energy generated per installed capacity, and change in net present value (ΔNPV in M$). The red line denotes performance equivalence; scenarios above it

reflect higher HyTUNE performance, while those below reflect higher benchmark performance.

In the top-right bar plot, the reactive strategy (green) replaces all 17 turbines simultaneously at mid-life, whereas the optimized approach (blue) replaces 23 or 29 turbines selectively over time. Across all performance metrics, scenarios that fall above the equivalence line indicate higher HyTUNE performance compared with RA_1, even without considering specific climate characteristics. HyTUNE produces more energy, with annual gains ranging from 51 to 217 GWh and firm energy increases between 145 and 709 MWh/d. The mean peak-period energy generation gain (ΔPP) ranges from 163 to 310 GWh/y, demonstrating how the optimized policy enhances peak capacity and better meets peak grid demand. This targeted replacement schedule improves overall efficiency. Despite requiring additional replacements (six or twelve units), HyTUNE uses the total installed capacity more effectively, as indicated by the EG_{IP} ratio remaining near 1.1 for twelve additional units and 1.5 for six, along with higher ΔAE values.

These gains translate into greater economic feasibility and stronger returns. HyTUNE achieves a better NPV across all future climates, the benefits are largest for scenarios with higher discharges (Q_{mean}), reservoir elevations (RL_{10}) and fewer droughts ($Fr_{drought}$). In contrast, scenarios with lower Q_{mean} and RL_{10} and higher RL_{CV} exhibit greater FPG and EG_{IP} values, indicating that HyTUNE increases reliability by raising firm power and operating more efficiently under drier and more variable hydrologic conditions. In other words, the reactive approach (RA_1) performs worser under dry and highly variable hydrologic futures.

The bottom panels compare the two-time reactive replacement strategy (RA_2), which replaces all turbines twice after 40 and 80 years of operation, with the optimized policy (OPT) from HyTUNE. In this case, HyTUNE replaces 5 to 11 fewer turbines but does so gradually rather than through two bulk replacement cycles. Although RA_2 achieves higher total energy production due to its larger number of new turbines, the ΔAE values narrow under dry and highly variable futures, indicating that HyTUNE delivers comparable energy output despite fewer replacements. HyTUNE increases firm energy gain in more than 95 % of scenarios and outperforms RA_2 across nearly all other performance metrics. The mean peak-period energy generation gain (ΔPP) ranges from 13 to 129 GWh/y, demonstrating enhanced peak capacity and improved alignment with grid demand. The

minimum EGIP ratio exceeding 1.5 further confirms that the optimized policy achieves superior operational efficiency compared with RA_2. ΔNPV for HyTUNE increases by 62–172 M $, underscoring the economic advantage of adaptive planning. These results show that adaptive scheduling sustains reliable generation more efficiently than repetitive, full-fleet replacements. scheduling sustains reliable generation more efficiently than repetitive, full-fleet replacements. Similar to the RA_1 comparison, scenarios with lower Q_{mean} and RL_{10} and higher RL_{CV} show higher FPG values, indicating that HyTUNE increases reliability under such conditions.

5 Limitations and Future work

This study has several limitations that also point to directions for future work. Although HyTUNE is broadly applicable to hydropower retrofitting, it was demonstrated through a single case study. Future research will test HyTUNE's potential across diverse climatic, socio-economic, and regulatory conditions. A key extension is to couple HyTUNE with basin-scale water resources models so it can represent the coordinated operation of hydropower plants within larger water systems. This expansion will increase computational demands, because a replacement decision at one facility can alter flows, constraints, and dispatch opportunities at others. At the same time, such expansion would create opportunities to coordinate operations, reduce exposure to future variability, and sustain efficient performance across entire river basins.

Similarly, Hydropower will play an important role in future low carbon systems. As power systems incorporate more renewable generation such as wind and solar, hydropower will shift from prioritizing energy production to providing flexibility and balancing variable renewable generation. Extending HyTUNE to account for ancillary services will allow the framework to capture these emerging operational roles. This capability can be achieved by coupling HyTUNE with power system models, which would link water system optimization with grid dynamics and market evolution. Such integration would create a unified planning tool that aligns plant level modernization with power system needs while retaining HyTUNE's core functionality for turbine evaluation. It will also allow HyTUNE to produce turbine replacement policies that are responsive to changing electricity prices, in addition to changing hydrology.

The Hoover Hydropower Plant, selected as a case study, is a key facility for U.S. power production and highlights the risks that changing hydrology poses to hydropower infrastructure. It also introduces unique modeling challenges. Hoover's release policies are revised frequently and depend primarily on demand rather than reservoir storage, which adds uncertainty when extrapolating historical behavior into future conditions. In contrast, most reservoirs follow rule curves that remain more consistent over time and are therefore easier to project. Inflow scenarios introduce an additional limitation. The mean flow of the projected scenarios does not match historical conditions after 2004 when compared with observations. This mismatch reflects constraints in the calibration period. Representing inflow to Hoover is therefore challenging, yet the conceptual approach and resulting performance insights remain robust.

Relicensing introduces an additional consideration for hydropower plants, including those in the United States. Major retrofits often coincide with relicensing cycles, and many owners evaluate turbine replacement and/or capacity upgrades as part of this process (A. L. Levine et al., 2017; IHA, 2022). These regulatory milestones can accelerate or delay modernization actions independent of hydrologic or economic drivers. HyTUNE does not currently represent relicensing constraints, so future work should incorporate regulatory timing and compliance requirements to improve alignment with real decision processes. Future applications should also prioritize plants approaching relicensing, as nearly 30 percent of U.S. hydropower projects will enter relicensing within the next decade (Russo, 2021), and modernization decisions are most likely to occur during these periods.

The current version of HyTUNE generates strategies that maximize net present value while improving firm power, peak capacity, and operational efficiency. These results demonstrate strong potential to enhance economic and technical performance under uncertainty. Future extensions could expand the framework to explore alternative operating objectives, including maximizing hydropeaking capacity or capacity factor, which helps identify designs that remain efficient under emerging flow variability and shifting system requirements. Additional extensions could improve efficiency at low flows or support ecological releases during periods of reduced water availability. These enhancements would broaden the relevance of HyTUNE across diverse hydrologic and operational contexts while retaining its core strength as a decision tool for turbine modernization.

Overall, HyTUNE has strong potential for extension. The framework provides a flexible and modular structure that can support new case studies, additional turbine types such as Kaplan and Pelton, emerging technologies including fish friendly and variable speed designs, and repair oriented cost models. These extensions are valuable because (i) different turbine types and technologies can outperform existing configurations under specific hydrologic or operational conditions, and (ii) component level repair costs or partial rehabilitation options can be incorporated into the policy tree to evaluate their economic and operational value alongside full replacement. New replacement policies can be generated for any site by substituting local data on hydrology, reservoir operations, or turbine characteristics. New actions, thresholds, and triggers can also be added as project priorities evolve, allowing HyTUNE to align with diverse site specific objectives.

6 Discussion and conclusions

The results of this study highlight both the scale of the hydropower modernization challenge and the opportunities for adaptive planning. Turbine retrofitting remains understudied in the water resources literature, where they are often treated as stable components that perform consistently regardless of changing conditions. Climate variability and evolving grid demands now place increasing pressure on their efficiency and flexibility. These trends underscore the need for models that link long term investment decisions with hydrologic and operational change. We therefore frame the discussion in two parts. First, we assess national patterns in turbine aging to quantify the modernization gap. Second, we argument how HyTUNE supports resilient turbine planning through adaptive optimization and flexible integration with hydrologic information.

6.1 In the US, turbine aging significantly outpaces replacement

Across the U.S., 2252 hydropower plants with approximately 5100 turbines have an installed capacity of 80.58 GW (Uría-Martínez & Johnson, 2023). In 2022, these facilities generated 28.7 % of the nation's renewable electricity and 6.2 % of its total electricity, making HP a key component of the US energy mix.

In this section, we present an overview of the condition of the national hydropower fleet by combining turbine-level data from the Existing Hydropower Assets (EHA) database (M. Johnson et al., 2023) with system-level replacement statistics from the U.S. Hydropower

771 Market Report (HMR) (Uría-Martínez et al., 2022). Merging these datasets allowed us
772 to reconstruct the evolution of average turbine age from 1990 to 2024 with its associated
773 uncertainty arising from incomplete replacement records (Figure 8).

774 To analyze turbine aging patterns, we extracted the commissioning year of each
775 unit from the EHA database. These data were used to produce the "no replacement" curve
776 in Figure 8, which shows how the national fleet would age if no replacements occurred.
777 The blue curve ("with recorded replacements") resets turbine age at each documented
778 replacement event, yielding a more realistic estimate of the fleet's age distribution. To
779 account for replacements, we used unit-level replacement years from the EHA database
780 and integrated aggregate statistics from the HMR, which report the total number of tur-
781 bines replaced between 2007 and 2022 but do not specify which units or plants were in-
782 volved. Because the two datasets differ in the number of reported replacements and the
783 HMR lacks unit-level attribution, we assumed a replacement age of 55 years and assigned
784 each inferred replacement to units that would have reached that age during the reported
785 period (i.e., commissioning year = 2020 − 55). This combined dataset provides a com-
786 prehensive reconstruction of the historical evolution of the U.S. turbine fleet, capturing
both recorded and inferred replacement activity.

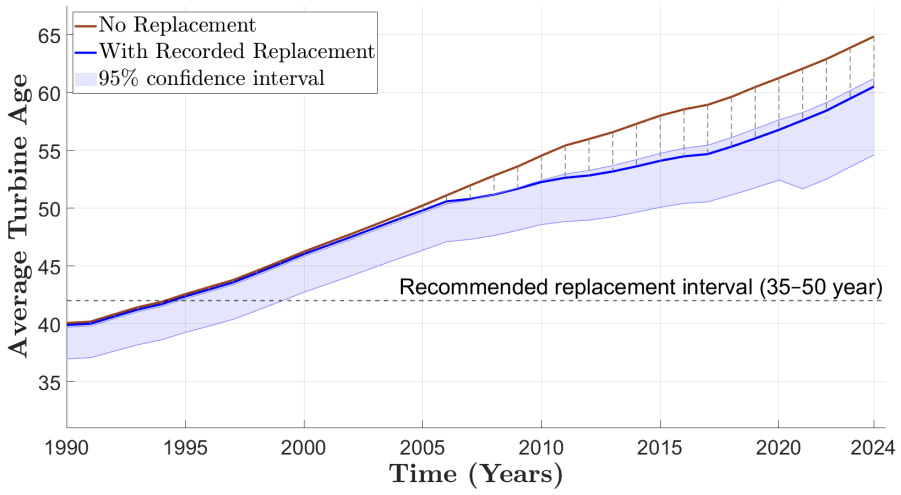

Figure 8: Average turbine age in the U.S. hydropower fleet (1990–2024). The brown line shows the average operational age, while the blue line accounts for recorded turbine replacements. The blue shaded band denotes the 95 % Monte Carlo interval derived from 2000 replacement scenarios. The dashed horizontal line indicates the manufacturer-recommended replacement range of 35–50 years.

787

Unit-level analysis of hydropower facilities in the Columbia and Colorado River basins indicates that up to 10 % of turbine replacement records are missing or inconsistently reported. To account for this data uncertainty, we developed a Monte Carlo framework that perturbs missing or inconsistent records. For turbines commissioned before 1990, the algorithm randomly replaces between 0% and 15% of units in each realization, assigning replacement ages uniformly distributed between 30 and 70 years. The same lifetime range randomizes the 2007–2022 aggregate adjustments, producing 5000 independent realizations. The 2.5^t and 97.5^t percentiles of the ensemble define the 95 % confidence interval (blue shaded region).

The small separation between the deterministic blue curve and its uncertainty band indicates that, although replacement data errors exist at the unit level, the fleet-average trend is robust. This figure reveals a concerning trend: the average turbine age is rising steadily, indicating that replacements are not keeping pace with aging. The horizontal dashed line marks the manufacturer-recommended replacement window (35–50 years), serving as a benchmark for assessing modernization needs. By 2010, roughly half of U.S. turbines had exceeded the manufacturer-recommended replacement range of 35–50 years (Quaranta & Hunt, 2022), and the national mean has now surpassed 55 years. This growing imbalance suggests that many turbines operate well beyond their intended lifespan, increasing risks of mechanical failure and efficiency loss. This persistent imbalance between aging and replacement underscores the urgent need for proactive modernization strategies that safeguard reliability and sustain the long-term performance of the U.S. hydropower fleet.

6.2 Adaptive optimization for turbine modernization and operational resilience: The role of HyTUNE

Modernizing hydropower plants has become essential as aging infrastructure, climate variability, and changing grid demands reduce efficiency and operational flexibility. Historically, expanding hydropower capacity relied on the construction of new dams and large civil works, but this hard-path approach is no longer viable given its environmental consequences. Modernization of existing plants now focuses on maintenance and life-extension programs (Mikhailov et al., 2021; Quaranta & Hunt, 2022). Although extending turbine lifetimes can be beneficial, outdated designs often perform poorly under evolving hydrologic and grid conditions. Maintenance and rehabilitation should there-

fore include systematic assessments to determine when and how turbine replacement can improve efficiency and long-term value. Delayed or poorly informed modernization decisions risk decades of reduced generation efficiency, lost revenue, and declining reliability.

We introduce HyTUNE, a dynamic decision-support tool that integrates basin hydrology, plant hydraulics, and adaptive optimization to guide turbine replacement timing and configuration. HyTUNE applies dynamic planning to hydropower adaptation, formulating the retrofitting problem as a control problem with a flexible policy structure. Retrofitting policies are represented as decision trees, where system indicators such as reservoir level or turbine efficiency trigger actions that include replacing turbines with new head and/or discharge models or deferring upgrades. This approach enables operational decisions to evolve in response to observed hydrologic and performance changes, improving resilience under uncertainty.

Applied to the Hoover Hydropower Plant, HyTUNE generated adaptive operational policies that consistently outperformed conventional reactive strategies across a wide ensemble of hydrologic futures. Relative to two benchmark scenarios, the optimized approach dynamically adapted turbine configurations (turbine design head and discharge capacity), as well as the number and timing of replacements, applying more frequent interventions in drier futures to manage rising variability in reservoir and inflow conditions. This strategy increased net present value, firm power, peak-period generation, and operational efficiency, even though one benchmark scenario replaced more than 30 % more turbines. The framework maintained strong performance without explicit conditioning on specific climate scenarios. Climate variability still influenced outcomes; economic gains were greatest under wetter conditions with higher outflows and fewer droughts, whereas improvements in firm power were most pronounced under drier conditions.

HyTUNE and its optimization framework provide a flexible foundation for turbine planning under evolving hydrologic and operational conditions. The framework is generalizable. It can use inflow projections developed at grid scale, such as recent continental datasets (Broman et al., 2024), or plant level inflow estimates and high resolution reservoir operation models. It also accommodates data driven representations of operating behavior, including the LSTM model employed here. This flexibility allows the framework to support large scale power system planning, which requires reliable insight into

852 future hydropower generation and capacity. It also enables site specific assessments that
853 capture the detailed behavior of individual plants. Together, these elements help bridge
854 the gap between long term power system studies and the operational realities that shape
855 hydropower performance.

856 Although proprietary retrofit models exist within the hydropower industry, their
857 structure and capabilities are not publicly documented. HyTUNE provides an open and
858 transparent platform that supports systematic exploration of turbine retrofitting. This
859 capability enables resource adequacy studies to revisit the common assumption of fixed
860 hydropower performance over 10 to 20 year horizons and allows reliability studies to eval-
861 uate how changes in turbine technologies influence system flexibility and resilience. New
862 turbine designs, modernization strategies, and operational pathways can therefore be as-
863 sessed consistently across water and energy domains.

864 Together, these features position HyTUNE as a practical tool for hydropower mod-
865 ernization in a changing world. Its adaptive structure supports continuous decision mak-
866 ing as hydrologic, economic, and policy conditions evolve. By enabling direct coupling
867 with future inflow projections, evaluating multiple turbine configurations, and interfac-
868 ing with power system models, HyTUNE bridges plant scale modernization with system
869 scale planning and helps align long lived investment decisions with the operational re-
870 alities that shape hydropower performance over time.

871 7 Data Availability Statement

872 The HyTUNE model and data used in this study are openly available through the
873 Zenodo repository (Yildiz et al., 2025b) at `https://doi.org/10.5281/zenodo.18058173`.
874 The repository includes the complete HyTUNE implementation, all input datasets, and
875 two Jupyter notebooks: one for decision-tree optimization and one for scenario-based sim-
876 ulation and post-processing. Together, these resources enable full reproduction of the
877 HyTUNE simulations and figures presented in this paper.

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References

Abboud, H., Baker, E., Baiotto, T., Weigand, C., & Quinn, J. (2022). Optimizing for water equity in the colorado river basin. In *2022 systems and information engineering design symposium (sieds)* (pp. 190–195).

Al-Hardanee, O. F., & Demirel, H. (2024). Hydropower station status prediction using rnn and lstm algorithms for fault detection. *Energies*, *17*(22), 5599.

Amougou, C. B., Tsuanyo, D., Fioriti, D., Kenfack, J., Aziz, A., & Elé Abiama, P. (2022). Lcoe-based optimization for the design of small run-of-river hydropower plants. *Energies*, *15*(20), 7507.

Arnold, W., Giuliani, M., & Castelletti, A. (2024). Floating photovoltaics may reduce the risk of hydro-dominated energy development in africa. *Nature Energy*, 1–10.

Barzola-Monteses, J., Gomez-Romero, J., Espinoza-Andaluz, M., & Fajardo, W. (2022). Hydropower production prediction using artificial neural networks: an ecuadorian application case. *Neural Computing and Applications*, *34*(16), 13253–13266.

Bisnett, R., Grossmann, N., Andrews, T., Milanowicz, D., & Maas, H. (2022). Red rock hydroelectric project–new hydro development at an existing flood control dam. In *E3s web of conferences* (Vol. 346, p. 04006).

Broman, D., & Voisin, N. (2025, June). *Cmip6-based mosartwmpy simulations (inflow, storage, release) for conus multi-use reservoirs.* Zenodo. Retrieved from `https://doi.org/10.5281/zenodo.15611029` doi: 10.5281/zenodo.15611029

Broman, D., Voisin, N., Kao, S.-C., Fernandez, A., & Ghimire, G. R. (2024). Multi-scale impacts of climate change on hydropower for long-term water-energy planning in the contiguous united states. *Environmental Research Letters*, *19*(9), 094057.

Brown, S., Yildiz, V., & Rougé, C. (2024, April). Modernising RoR Hydropower: A Study on Retrofitting Aged Turbines for Optimal Performance. In *Egu general assembly conference abstracts* (p. 9612). doi: 10.5194/egusphere-egu24-9612

Cameron, A., & Pracheil, B. (2022). *Environmental flow requirements from ferc licenses across the us* (Tech. Rep.). Oak Ridge National Lab.(ORNL), Oak Ridge, TN (United States). Retrieved from `https://hydrosource.ornl.gov/`

data/datasets/ornl-environmental-flow-requirements/

Carlino, A., Wildemeersch, M., Chawanda, C. J., Giuliani, M., Sterl, S., Thiery, W., ... Castelletti, A. (2023). Declining cost of renewables and climate change curb the need for african hydropower expansion. *Science*, *381*(6658), eadf5848.

Celebioglu, K., Altintas, B., Aradag, S., & Tascioglu, Y. (2017). Numerical research of cavitation on francis turbine runners. *International Journal of Hydrogen Energy*, *42*(28), 17771–17781.

Cheng, M., McCarl, B., & Fei, C. (2022). Climate change and livestock production: a literature review. *Atmosphere*, *13*(1), 140.

Cheng, Q., Liu, P., Feng, M., Cheng, L., Ming, B., Luo, X., ... Xia, J. (2023). Complementary operation with wind and photovoltaic power induces the decrease in hydropower efficiency. *Applied Energy*, *339*, 121006.

Cohen, J. S., & Herman, J. D. (2021). Dynamic adaptation of water resources systems under uncertainty by learning policy structure and indicators. *Water Resources Research*, *57*(11), e2021WR030433.

Datta, S., Somani, A., Alam, M. J. E., Sun, X., Fotedar, V., & Banicki, A. (2022). Changes in hydropower resource operations following participation in the caiso energy imbalance market-a case study. In *2022 ieee power & energy society general meeting (pesgm)* (pp. 1–5).

De Silva, T., Jorgenson, J., Macknick, J., Keohan, N., Miara, A., Jager, H., & Pracheil, B. (2022). Hydropower operation in future power grid with various renewable power integration. *Renewable Energy Focus*, *43*, 329–339.

Diaz, F. J., Contreras, J., Muñoz, J. I., & Pozo, D. (2010). Optimal scheduling of a price-taker cascaded reservoir system in a pool-based electricity market. *IEEE Transactions on Power Systems*, *26*(2), 604–615.

Dorji, U., & Ghomashchi, R. (2014). Hydro turbine failure mechanisms: An overview. *Engineering Failure Analysis*, *44*, 136–147.

Egré, D., & Milewski, J. C. (2002). The diversity of hydropower projects. *Energy Policy*, *30*(14), 1225–1230.

EIA. (2025, March). *Electricity monthly update: Wholesale electricity markets.* Retrieved from https://www.eia.gov/electricity/monthly/update/wholesale-markets.php (Accessed May 4, 2025)

Emmanuel, M., Doubleday, K., Cakir, B., Marković, M., & Hodge, B.-M. (2020). A review of power system planning and operational models for flexibility assessment in high solar energy penetration scenarios. *Solar Energy*, *210*, 169–180.

ESHA. (2004). Guide on how to develop a small hydropower plant [Computer software manual].

Fakhfakh, R., Ammar, A. B., & Amar, C. B. (2017). Deep learning-based recommendation: Current issues and challenges. *International Journal of Advanced Computer Science and Applications*, *8*(112).

Fälth, H. E., Hedenus, F., Reichenberg, L., & Mattsson, N. (2025). Through energy droughts: hydropower's ability to sustain a high output. *Renewable and Sustainable Energy Reviews*, *214*, 115519.

Fälth, H. E., Mattsson, N., Reichenberg, L., & Hedenus, F. (2023). Trade-offs between aggregated and turbine-level representations of hydropower in optimization models. *Renewable and Sustainable Energy Reviews*, *183*, 113406.

Farmer, M. (2020, August 7). The past, present, and future of maintenance at the hoover dam. *Power Technology*. Retrieved from `https://www.power-technology.com/features/hoover-dam-maintenance-covid-19-hydro-generation-lake-mead-climate-change-post-apocalypse/`

Feng, Z.-k., Luo, T., Niu, W.-j., Yang, T., & Wang, W.-c. (2023). A lstm-based approximate dynamic programming method for hydropower reservoir operation optimization. *Journal of Hydrology*, *625*, 130018.

FERC. (2024, March). *2023 state of the markets report* (Tech. Rep.). Federal Energy Regulatory Commission. Retrieved from `https://www.ferc.gov/sites/default/files/2024-03/24_State-of-the-market_0320_1715.pdf` (FERC Staff Report, Office of Energy Policy and Innovation)

Fleck, J., & Castle, A. (2022). Green light for adaptive policies on the colorado river. *Water*, *14*(1). Retrieved from `https://www.mdpi.com/2073-4441/14/1/2` doi: 10.3390/w14010002

Fletcher, S., Lickley, M., & Strzepek, K. (2019). Learning about climate change uncertainty enables flexible water infrastructure planning. *Nature communications*, *10*(1), 1782.

Fletcher, S. M., Miotti, M., Swaminathan, J., Klemun, M. M., Strzepek, K., & Siddiqi, A. (2017). Water supply infrastructure planning: Decision-making frame-

work to classify multiple uncertainties and evaluate flexible design. *Journal of Water Resources Planning and Management*, *143*(10), 04017061.

Garrett, K. P., McManamay, R. A., & Witt, A. (2023). Harnessing the power of environmental flows: Sustaining river ecosystem integrity while increasing energy potential at hydropower dams. *Renewable and sustainable energy reviews*, *173*, 113049.

Gernaat, D. E., de Boer, H. S., Daioglou, V., Yalew, S. G., Müller, C., & van Vuuren, D. P. (2021). Climate change impacts on renewable energy supply. *Nature climate change*, *11*(2), 119–125.

Goldberg, J., & Lier, O. E. (2011). *Rehabilitation of hydropower: an introduction to economic and technical issues*. World Bank, Washington, DC.

Hannoun, D., & Tietjen, T. (2023). Lake management under severe drought: lake mead, nevada/arizona. *JAWRA Journal of the American Water Resources Association*, *59*(2), 416–428.

Hassan, Q., Viktor, P., Al-Musawi, T. J., Ali, B. M., Algburi, S., Alzoubi, H. M., ... Jaszczur, M. (2024). The renewable energy role in the global energy transformations. *Renewable Energy Focus*, *48*, 100545.

Herman, J. D., Quinn, J. D., Steinschneider, S., Giuliani, M., & Fletcher, S. (2020). Climate adaptation as a control problem: Review and perspectives on dynamic water resources planning under uncertainty. *Water Resources Research*, *56*(2), e24389.

Hertwich, E., de Larderel, J. A., Arvesen, A., Bayer, P., Bergesen, J., Bouman, E., ... Suh, S. (2016). *Green energy choices: The benefits, risks, and trade-offs of low-carbon technologies for electricity production*. Report of the International Resource Panel, United Nations Environment Program (UNEP).

Huang, Z., Yuan, X., & Liu, X. (2021). The key drivers for the changes in global water scarcity: Water withdrawal versus water availability. *Journal of Hydrology*, *601*, 126658.

Hui, R., Herman, J., Lund, J., & Madani, K. (2018). Adaptive water infrastructure planning for nonstationary hydrology. *Advances in Water Resources*, *118*, 83–94.

Huizar, L., Díaz, S., Lansey, K., & Arnold, R. (2024). Economic impacts of the 2019 drought contingency plan in the lower colorado river basin: Water, energy, and

recreation. *Journal of Environmental Engineering*, *150*(4), 04024004.

IHA, I. H. A. (2022). *Modernisation of hydropower.* IHA Factsheet. Retrieved from https://www.hydropower.org/factsheets/modernisation (Accessed: 2025-12-07)

International Energy Agency. (2021). *Hydropower special market report: Analysis and forecast to 2030.* Paris: International Energy Agency. Retrieved from https://www.iea.org/reports/hydropower-special-market-report (Licence: CC BY 4.0)

IRENA. (2012, June). *Renewable energy cost analysis: Hydropower* (Tech. Rep. Nos. Volume 1: Power Sector, Issue 3/5). Bonn, Germany: International Renewable Energy Agency (IRENA). Retrieved from https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2012/RE_Technologies_Cost_Analysis-HYDROPOWER.pdf (Prepared by the IRENA Secretariat; internal review and external contributions acknowledged)

Jenkin, T. J., Feldman, D. J., Kwan, A., & Walker, B. J. (2019). *Estimating the impact of residual value for electricity generation plants on capital recovery, levelized cost of energy, and cost to consumers* (Tech. Rep.). Golden, CO (United States): National Renewable Energy Lab.(NREL).

Johnson, M., Kao, S.-C., & Uria-Martinez, R. (2023). *Existing hydropower assets unit dataset fy23* (Tech. Rep.). Oak Ridge National Lab.(ORNL), Oak Ridge, TN (United States). Retrieved from https://doi.org/10.21951/EHA_FY2024/2344935

Johnson, M. M. (2024). *Existing hydropower assets (eha) capacity factor plant database, 2005–2023* (Tech. Rep.). Oak Ridge, Tennessee, USA: Oak Ridge National Laboratory. Retrieved from https://hydrosource.ornl.gov/data/datasets/existing-hydropower-assets-eha-capacity-factor-plant-database-2005-2023/ (HydroSource) doi: 10.21951/EHA_CapacityFactor_FY2024/2406172

Kao, S.-C., Ashfaq, M., Rastogi, D., & Gangrade, S. (2022a). Cmip6-based multi-model hydroclimate projection over the conterminous us. *HydroSource. Oak Ridge National Laboratory, Oak Ridge, Tennessee, USA. DOI: https://doi.org/10.21951/SWA9505V3/1887469*.

Kao, S.-C., Ashfaq, M., Rastogi, D., Gangrade, S., Uria Martinez, R., Fernan-

dez, A., ... others (2022, 09). *The third assessment of the effects of climate change on federal hydropower* (Tech. Rep.). Oak Ridge National Laboratory (ORNL), Oak Ridge, TN (United States). Retrieved from https://www.osti.gov/biblio/1887712 doi: 10.2172/1887712

Kaunda, C. S., Kimambo, C. Z., & Nielsen, T. K. (2014). A technical discussion on microhydropower technology and its turbines. *Renewable and Sustainable Energy Reviews*, *35*, 445–459.

Kincic, S., Samaan, N., Datta, S., Somani, A., Yuan, H., Tan, J., ... Mosier, T. M. (2022). *Hydropower modeling gaps in planning and operational studies* (Tech. Rep.). WA (United States ...: Pacific Northwest National Laboratory (PNNL), Richland.

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

Levine, A., Curtis, T., & Kazerooni, B. (2017, October). *Regulatory approaches for adding capacity to existing hydropower facilities* (Technical Report No. NREL/TP-6A20-70121). National Renewable Energy Laboratory. Retrieved from https://docs.nrel.gov/docs/fy18osti/70121.pdf doi: 10.2172/1391100

Levine, A. L., Curtis, T. L., & Kazerooni, B. (2017). *Regulatory approaches for adding capacity to existing hydropower facilities* (Tech. Rep.). Golden, CO, USA: National Renewable Energy Laboratory.

Liu, H., Brown, T., Andresen, G. B., Schlachtberger, D. P., & Greiner, M. (2019). The role of hydro power, storage and transmission in the decarbonization of the chinese power system. *Applied Energy*, *239*, 1308–1321.

Liu, L., He, G., Wu, M., Liu, G., Zhang, H., Chen, Y., ... Li, S. (2023). Climate change impacts on planned supply–demand match in global wind and solar energy systems. *Nature Energy*, *8*(8), 870–880.

Liu, X., Guo, S., Liu, P., Chen, L., & Li, X. (2011). Deriving optimal refill rules for multi-purpose reservoir operation. *Water Resources Management*, *25*, 431–448.

Liu, X., Luo, Y., Karney, B. W., & Wang, W. (2015). A selected literature review of

efficiency improvements in hydraulic turbines. *Renewable and Sustainable Energy Reviews*, *51*, 18–28.

Loucks, D. P., & Van Beek, E. (2017). *Water resource systems planning and management: An introduction to methods, models, and applications*. Springer.

Lukas, J., & Payton, E. (2020). *Colorado river basin climate and hydrology: State of the science* (Technical Report). Boulder, CO: Western Water Assessment, Cooperative Institute for Research in Environmental Sciences. doi: 10.25810/3hcv-w477

March, P., & Jacobson, P. (2016, 07). Industry experience with power generation options for environmental flows..

McCoy, A. L., Jacobs, K. L., Vano, J. A., Wilson, J. K., Martin, S., Pendergrass, A. G., & Cifelli, R. (2022). The press and pulse of climate change: extreme events in the colorado river basin. *JAWRA Journal of the American Water Resources Association*, *58*(6), 1076–1097.

Mikhailov, V., Ivanchenko, I., & Prokopenko, A. (2021). Modern state of hydropower and construction of hydro turbines in russia and abroad. *Thermal Engineering*, *68*, 83–93.

Millstein, D., O'Shaughnessy, E., & Wiser, R. (2025). *Renewables and wholesale electricity prices (rewep) tool.* Retrieved from `https://emp.lbl.gov/renewables-and-wholesale-electricity-prices-rewep` (Interactive visualization tool exploring trends in nodal wholesale energy pricing and their relationship to wind and solar generation)

Mishra, B. K., Kumar, P., Saraswat, C., Chakraborty, S., & Gautam, A. (2021). Water security in a changing environment: Concept, challenges and solutions. *Water*, *13*(4), 490.

Morgado, D., Troja, N., Kadyrzhanova, A., & Samuel, D. (2020). Hydropower modernization needs in asia. *no*, *1*, 1–22.

Muntean, S., Susan-Resiga, R., Göde, E., Baya, A., Terzi, R., & Tîrşi, C. (2016). Scenarios for refurbishment of a hydropower plant equipped with francis turbines. *Renewable Energy and Environmental Sustainability*, *1*, 30.

Naz, B. S., Kao, S.-C., Ashfaq, M., Rastogi, D., Mei, R., & Bowling, L. C. (2016). Regional hydrologic response to climate change in the conterminous united states using high-resolution hydroclimate simulations. *Global and Planetary*

Change, *143*, 100–117.

Neijens, B., & Hayes, C. (2017). Asset management partnership goes from strength to strength after 15 years. *International Journal on Hydropower and Dams*, *Issue Four*, 59–62. Retrieved from https://go.copperleaf.com/rs/727-PJA-841/images/Hydropower%26Dams_IssueFour_2017_Asset_Management_Partnership.PDF

O'Connor, P. W., DeNeale, S. T., Chalise, D. R., Centurion, E., & Maloof, A. (2015, September). *Hydropower baseline cost modeling, version 2* (Tech. Rep. No. ORNL/TM-2015/471). Oak Ridge, TN: Oak Ridge National Laboratory. Retrieved from https://info.ornl.gov/sites/publications/files/Pub58666.pdf

Oladosu, G. A., & Ma, Y. (2025). *Baseline cost model for hydropower: Documentation (2025)* (Tech. Rep. No. ORNL/TM-2025/3733). Oak Ridge, TN (United States): Oak Ridge National Laboratory (ORNL).

Owolabi, O. O., Lawson, K., Sengupta, S., Huang, Y., Wang, L., Shen, C., ... Sunter, D. A. (2022). A robust statistical analysis of the role of hydropower on the system electricity price and price volatility. *Environmental Research Communications*, *4*(7), 075003.

Papillon, B., & Freeman, T. (2013). Rehabilitating the francis units at chief joseph. *Hydr o Rev*, *32*(8).

Pei, Z., Rojas-Arevalo, A. M., de Haan, F. J., Lipovetzky, N., & Moallemi, E. A. (2024). Reinforcement learning for decision-making under deep uncertainty. *Journal of Environmental Management*, *359*, 120968.

Quaranta, E., Aggidis, G., Boes, R. M., Comoglio, C., De Michele, C., Patro, E. R., ... others (2021). Assessing the energy potential of modernizing the european hydropower fleet. *Energy Conversion and Management*, *246*, 114655.

Quaranta, E., & Hunt, J. (2022). Retrofitting and refurbishment of hydropower plants: Case studies and novel technologies. In *Renewable energy production and distribution* (pp. 301–322). Elsevier.

Ramião, J. P., Carvalho-Santos, C., Pinto, R., & Pascoal, C. (2023). Hydropower contribution to the renewable energy transition under climate change. *Water Resources Management*, *37*(1), 175–191.

Ramulifho, P., Ndou, E., Thifhulufhelwi, R., & Dalu, T. (2019). Challenges to imple-

menting an environmental flow regime in the luvuvhu river catchment, south africa. *International Journal of Environmental Research and Public Health*, *16*(19). Retrieved from https://www.mdpi.com/1660-4601/16/19/3694 doi: 10.3390/ijerph16193694

Rogers, J. D. (2010). Hoover dam: Operational milestones, lessons learned, and strategic import. In *Hoover dam: 75th anniversary history symposium* (pp. 189–215).

Russo, T. N. (2021). Rethinking low impact hydropower and renewable energy certificates. *Climate and Energy*, *37*(9), 26–32.

Sample, J. E., Duncan, N., Ferguson, M., & Cooksley, S. (2015). Scotland's hydropower: Current capacity, future potential and the possible impacts of climate change. *Renewable and Sustainable Energy Reviews*, *52*, 111–122.

Santolin, A., Cavazzini, G., Pavesi, G., Ardizzon, G., & Rossetti, A. (2011). Techno-economical method for the capacity sizing of a small hydropower plant. *Energy Conversion and Management*, *52*(7), 2533–2541.

Schaeffer, R., Szklo, A. S., de Lucena, A. F. P., Borba, B. S. M. C., Nogueira, L. P. P., Fleming, F. P., ... Boulahya, M. S. (2012). Energy sector vulnerability to climate change: a review. *Energy*, *38*(1), 1–12.

Sensiba, C., & McCormick, E. (2021). Ferc regulatory considerations for project modifications. *Hydro Leader Magazine*. Retrieved from https://hydroleadermagazine.com/ferc-regulatory-considerations-for-project-modifications/ (Accessed: May 11, 2026)

Shanbhag, V. V., Kandukuri, S. T., Olimstad, G., & Schlanbusch, R. (2025). Predictive maintenance of critical components in hydroelectric turbines: A review. *IEEE Sensors Journal*.

Singh, V. K., & Singal, S. K. (2017). Operation of hydro power plants-a review. *Renewable and Sustainable Energy Reviews*, *69*, 610–619.

Smith, R., Zagona, E., Kasprzyk, J., Bonham, N., Alexander, E., Butler, A., ... Jerla, C. (2022). Decision science can help address the challenges of long-term planning in the colorado river basin. *JAWRA Journal of the American Water Resources Association*, *58*(5), 735–745.

Smolarz, A., Lezhniuk, P., Kudrya, S., Komar, V., Lysiak, V., Hunko, I., ... Orazbekov, Z. (2023). Increasing technical efficiency of renewable energy

sources in power systems. *Energies*, *16*(6), 2828.

Sternberg, R. (2010). Hydropower's future, the environment, and global electricity systems. *Renewable and Sustainable Energy Reviews*, *14*(2), 713–723.

Sun, J., Wang, Y., He, Y., Cui, W., Chao, Q., Shan, B., ... Yang, X. (2024). The energy security risk assessment of inefficient wind and solar resources under carbon neutrality in china. *Applied Energy*, *360*, 122889.

Thurber, T., Vernon, C., Sun, N., Turner, S., Yoon, J., & Voisin, N. (2021). mosartwmpy: A python implementation of the mosart-wm coupled hydrologic routing and water management model. *Journal of Open Source Software*, *6*(PNNL-SA-161232).

Turner, S. W., Ghimire, G. R., Hansen, C., Singh, D., & Kao, S.-C. (2024). Hydropower capacity factors trending down in the united states. *Nature Communications*, *15*(1), 5445.

Turner, S. W., Voisin, N., & Nelson, K. (2022). Revised monthly energy generation estimates for 1,500 hydroelectric power plants in the united states. *Scientific data*, *9*(1), 675.

Tweed, K. (2013). Colorado river hydropower faces a dry future [news]. *IEEE Spectrum*, *50*(10), 14–15.

Uría-Martínez, R., & Johnson, M. M. (2023). Us hydropower market report (2023 edition). *ORNL/SPR-2023/3076, Oak Ridge National Laboratory*.

Uría-Martínez, R., White, D., Oladosu, G. A., DeSomber, K., & Johnson, M. M. (2022). *Hydropower: Supply chain deep dive assessment* (Tech. Rep.). Oak Ridge National Laboratory (ORNL), Oak Ridge, TN (United States). Retrieved from `https://www.energy.gov/sites/default/files/2024-12/Hydropower%2520Supply%2520Chain%2520Report%2520-%2520Final%5B1%5D.pdf`

USBR. (2011, March). *Hydropower resource assessment at existing reclamation facilities* (Tech. Rep.). U.S. Bureau of Reclamation. Retrieved from `https://large.stanford.edu/courses/2016/ph240/lewis1/docs/USBRHydro.pdf`

USBR. (2018). *Hydroelectric power – hoover dam.* Retrieved from `https://www.usbr.gov/lc/hooverdam/faqs/powerfaq.html` (Accessed: 2025-04-18)

Van Vliet, M. T., Sheffield, J., Wiberg, D., & Wood, E. F. (2016). Impacts of recent drought and warm years on water resources and electricity supply worldwide.

Environmental Research Letters, *11*(12), 124021.

Voisin, N., Hejazi, M. I., Leung, L. R., Liu, L., Huang, M., Li, H.-Y., & Tesfa, T. (2017). Effects of spatially distributed sectoral water management on the redistribution of water resources in an integrated water model. *Water Resources Research*, *53*(5), 4253–4270.

Voisin, N., Li, H., Ward, D., Huang, M., Wigmosta, M., & Leung, L. (2013). On an improved sub-regional water resources management representation for integration into earth system models. *Hydrology and Earth System Sciences*, *17*(9), 3605–3622.

Wahl, T. L., & Cohen, E. A. (1999). Determination of controlled-release capacity from trinity dam. In *1999 international water resources engineering conference.*

Wang, Y., Xiao, Z., Liu, D., Chen, J., Liu, D., & Hu, X. (2022). Degradation trend prediction of hydropower units based on a comprehensive deterioration index and lstm. *Energies*, *15*(17), 6273.

Wheeler, K. G., Udall, B., Wang, J., Kuhn, E., Salehabadi, H., & Schmidt, J. C. (2022). What will it take to stabilize the colorado river? *Science*, *377*(6604), 373–375.

Widén, Å., Renöfält, B. M., & Jansson, R. (2024). Environmental flows in a future climate: Balancing hydropower production and ecosystem rehabilitation in the ume river system, sweden. *Science of the Total Environment*, *955*, 176622.

Witt, A. M., Fernandez, A., Mobley, M. H., DeNeale, S., Bevelhimer, M., & Smith, B. T. (2017). *How standard modular hydropower can enhance the environmental, economic, and social benefits of new small hydropower development* (Tech. Rep.). Oak Ridge, TN (United States): Oak Ridge National Laboratory (ORNL).

Yildiz, V., Brown, S., & Rougé, C. (2024). Importance of variable turbine efficiency in run-of-river hydropower design under deep uncertainty. *Water Resources Research*, *60*(6), e2023WR035713.

Yildiz, V., Brown, S., & Rougé, C. (2025a). Robust and computationally efficient design for run-of-river hydropower. *Environmental Modelling & Software*, *183*, 106220. Retrieved from `https://www.sciencedirect.com/science/article/pii/S1364815224002810` doi: https://doi.org/10.1016/j.envsoft.2024.106220

Yildiz, V., Hatipoglu, M. A., & Kumcu, S. Y. (2022). Climate change impacts on water resources. In *Water and wastewater management: global problems and measures* (pp. 17–25). Springer.

Yildiz, V., & Vrugt, J. A. (2019). A toolbox for the optimal design of run-of-river hydropower plants. *Environmental modelling & software*, *111*, 134–152. Retrieved from `https://doi.org/10.1016/j.envsoft.2018.08.018`

Yildiz, V., Zaniolo, M., & Voisin, N. (2025b, December). *HyTUNE: Hytune v1.0.1.* Zenodo [code]. Retrieved from `https://doi.org/10.5281/zenodo.18058173` doi: 10.5281/zenodo.18058173

Zaniolo, M., Fletcher, S., & Mauter, M. S. (2023). Multi-scale planning model for robust urban drought response. *Environmental Research Letters*, *18*(5), 054014.

Zhang, D., Peng, Q., Lin, J., Wang, D., Liu, X., & Zhuang, J. (2019). Simulating reservoir operation using a recurrent neural network algorithm. *Water*, *11*(4), 865.

Zhou, Y., & Guo, S. (2013). Incorporating ecological requirement into multipurpose reservoir operating rule curves for adaptation to climate change. *Journal of Hydrology*, *498*, 153–164.

Zhou, Y., Hejazi, M., Smith, S., Edmonds, J., Li, H., Clarke, L., ... Thomson, A. (2015). A comprehensive view of global potential for hydro-generated electricity. *Energy & Environmental Science*, *8*(9), 2622–2633.