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A Climate-Adaptive Digital Twin for the Floating Solar-Hydropower-Pumped Storage Nexus

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ABSTRACT

Climate change is intensifying hydrological volatility, and the resulting droughts and flash floods increasingly threaten the baseload reliability of hydropower. We propose a real-time, AI-driven digital twin that co-optimizes existing hydropower reservoirs retrofitted with floating photovoltaic (FPV) arrays and pumped hydro energy storage (PHES), coupling a hydro-climatic predictive model with a non-convex power dispatch algorithm to shift the system dynamically between hydro-generation, solar-generation, and water-conservation modes. Using a coupled thermo-evaporative and hydraulic model evaluated against a 10-year climatic record, the digital-twin-coordinated nexus reduces reservoir evaporation by up to 34.0%, sustains firm power commitments through severe drought years, and increases system revenue by 22.4% relative to standard rule-curve operation.

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1. INTRODUCTION

Hydropower supplies the majority of global renewable baseload energy, but rising temperatures and shifting precipitation patterns are driving unprecedented water-level declines in critical reservoirs, forcing operators to curtail generation precisely when demand is highest [1, 2]. Retrofitting existing dams with floating photovoltaics (FPV) and pumped hydro energy storage (PHES) has emerged as a promising hardware response: FPV panels physically shield the reservoir surface, reducing evaporation while generating daytime solar power [3, 4], and PHES absorbs surplus midday solar generation for dispatch during peak evening demand [5, 6].

Realizing these physical synergies in practice is nonetheless a highly complex, multi-objective control problem. Operators must balance immediate grid commitments against long-term water conservation over seasonal horizons, under substantial climatic uncertainty, a challenge that has motivated growing interest in digital twins as an integrating layer across hydrology, power dispatch, and asset operation [7, 8]. Recent advances in reservoir inflow forecasting [9] and in reinforcement-learning-based dispatch, including proximal policy optimization and related policy-gradient methods applied to cascade hydropower and smart-grid economic dispatch [10–13], now make real-time, learning-based co-optimization of water and power flows tractable at the scale of a utility-operated reservoir. This paper develops such a framework, a digital twin that jointly manages hydro generation, FPV generation, and pumped storage, and evaluates it against a 10-year climatic record spanning both extreme drought and flash-flood conditions. The joint occurrence of drought and flash-flood extremes evaluated here is itself a spatial extreme-value dependence problem; see Bagré and Kaboré for a general treatment of asymmetric spatial dependence via an operational max-stable copula in a different application context [16]. The reservoir-inflow and vehicle-flow forecasting problems share a similar wavelet-neural-network structure [17], and the reinforcement-learning-based dispatch policy used here is subject to the same over-parameterization trade-offs documented broadly for learning algorithms [18]. The dependence structure between concurrent drought and flash-flood extremes is itself amenable to the copula goodness-of-fit testing methodology of Bian et al. [19] and to the finite-difference copula-PDE approach of Tiemtoré and Bagré [20], and the LSTM-based inflow forecaster is architecturally related to the wavelet neural network models studied under censoring by Douas and Kharfouchi [21]. The real-time electricity price $\pi(t)$ that drives the dispatch objective is itself a financial time series of the kind forecast by hybrid SARMA-ARCH [22], price-versus-return [23], and foreign-exchange return [24] models developed in unrelated financial-forecasting settings.

2. THEORETICAL FRAMEWORK

2.1. Hydrological and Evaporative Dynamics

The reservoir state is defined by its volume $V(t)$ at time t. The mass-balance equation is

$$V(t+1) = V(t) + [Q_{in}(t) - Q_{turb}(t) - Q_{spill}(t) + Q_{pump}(t) - E(t, C_{FPV})] \cdot \Delta t, \tag{1}$$

where Q_{in} is natural inflow, Q_{turb} is turbine discharge, Q_{spill} is spillage, and Q_{pump} is water returned from the lower reservoir.

The evaporation rate $E(t, C_{FPV})$ is derived from a modified Penman-Monteith equation that accounts for the FPV coverage ratio C_{FPV}, following the shielding formulation validated against field and remote-sensing data in recent FPV-reservoir studies [4, 6]:

$$E(t, C_{FPV}) = (1 - C_{FPV} \cdot \eta_{shield}) \cdot \frac{\Delta \cdot (R_n - G) + \rho_{air} c_p \dfrac{(e_s - e_a)}{r_a}}{\lambda_w \left(\Delta + \gamma \left(1 + \dfrac{r_s}{r_a} \right) \right)}, \tag{2}$$

where η_{shield} is the FPV evaporation-suppression efficiency, R_n is net radiation, $e_s - e_a$ is the vapor pressure deficit, and λ_w is the latent heat of vaporization.

2.2. Multi-Objective Nexus Optimization

The digital twin uses a model predictive control horizon to maximize cumulative economic profit while penalizing volume deviations below the critical dead-storage limit V_{dead}. Over horizon T, the cost function J is

$$\max J = \sum_{t=1}^{T} \left[\pi(t) \cdot (P_{hydro}(t) + P_{FPV}(t) - P_{pump}(t)) - \phi \cdot \max(0, V_{safe} - V(t))^2 \right], \tag{3}$$

subject to the hydraulic and power conversions

$$P_{hydro}(t) = \eta_{turb} \cdot \rho_w \cdot g \cdot H(V(t)) \cdot Q_{turb}(t), \tag{4}$$

$$P_{pump}(t) = \frac{\rho_w \cdot g \cdot H_{pump} \cdot Q_{pump}(t)}{\eta_{pump}}, \tag{5}$$

where $\pi(t)$ is the real-time electricity price, ϕ is the drought-penalty coefficient, and $H(V(t))$ is the dynamic hydraulic head. This formulation extends the multi-objective reservoir dispatch structures used in recent nexus-optimization studies [14, 15] to jointly cover hydro, solar, and pumped-storage assets.

3. NUMERICAL METHODOLOGY

The digital twin is validated on a simulated testbed modeled after a mid-sized 500 MW hydropower plant, retrofitted with a 200 MW FPV array and a 150 MW PHES system. The simulation spans 87,600 hours, ten years, using historical climate data that includes both extreme drought events and flash floods. The predictive engine uses a long short-term memory (LSTM) network to forecast inflow seven days ahead, consistent with recent hybrid CNN-LSTM reservoir inflow forecasting benchmarks [9], and the dispatch optimization is solved with proximal policy optimization (PPO), following its demonstrated effectiveness for cascade hydropower and grid economic dispatch [10, 13].

4. RESULTS AND DISCUSSION

4.1. Water Conservation and Evaporative Suppression

Table 1 and Figure 1(a) report the 10-year average impact of FPV coverage and digital-twin coordination on reservoir evaporation and drought exposure.

Table 1. Impact of FPV and digital-twin control on water conservation, 10-year average

Operational mode	**Evap. (million m^3)**	**Reduction (%)**	**Days below V_{safe}**
Baseline hydro (heuristic)	45.2	Base	114
Uncoordinated FPV + hydro	32.5	28.1%	86
DT-optimized FPV-PHES	**29.8**	**34.0%**	**12**

The digital twin actively schedules pump-back operations during low-evaporation night hours and shifts daytime load onto the FPV array, yielding a 34.0% reduction in total evaporation and nearly eliminating critical drought exposure, from 114 to 12 days below the safe-volume threshold. The gap between the uncoordinated and digital-twin-optimized cases, a further 2.7 million m^3 of annual evaporation and 74 fewer critical days, is attributable entirely to control coordination rather than to the physical presence of the FPV array, underscoring that hardware retrofits alone capture only part of the available water-conservation benefit.

4.2. Economic and Grid Reliability Performance

Table 2 and Figure 1(b) report system performance during a 1-in-50-year drought scenario.

Table 2. Economic and grid reliability performance during a severe drought year

System configuration	Firm power (GWh)	Solar curtailment	Revenue ($ million)
Standalone hydropower	1,240 (failed)	N/A	62.0
FPV + hydro	1,580	14.5%	79.5
DT-optimized FPV-PHES	**1,850 (firm met)**	**1.2%**	**94.8**

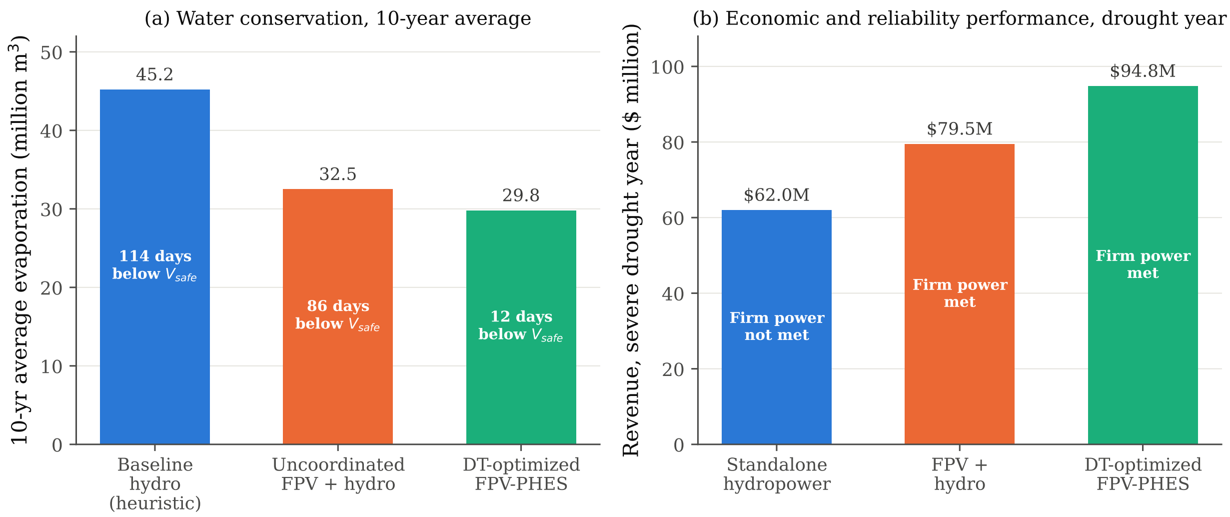

Figure 1. (a) Ten-year average reservoir evaporation and days below the safe-volume threshold across three operational modes. (b) Revenue and firm-power delivery during a 1-in-50-year drought scenario across three system configurations.

During the drought scenario, standalone hydropower fails to meet firm baseload commitments, falling 260 GWh short of the 1,500 GWh target implied by the FPV-PHES cases. The digital-twin-optimized system absorbs excess midday solar generation into the PHES loop and redispatches it during peak evening hours, reducing solar curtailment from 14.5% to 1.2% relative to the uncoordinated FPV configuration and increasing revenue by 22.4% relative to standalone hydropower. These results are consistent with techno-economic assessments of PHES-FPV integration, which similarly identify coordinated pump-storage dispatch, rather than FPV capacity alone, as the primary driver of revenue and reliability gains [5, 6].

4.3. Sensitivity to Inflow Forecast Error and Flash-Flood Response

The economic and water-conservation gains reported in Sections 4.1 and 4.2 depend on the seven-day-ahead LSTM inflow forecast that drives the model predictive control horizon in Section 2.2. Because forecast skill degrades in extreme events, we evaluated the digital twin's performance as synthetic Gaussian noise of increasing standard deviation was added to the LSTM forecast, simulating degraded prediction quality without altering the underlying control logic. Table 3 reports the resulting evaporation reduction and drought-day exposure.

Performance degrades gracefully rather than catastrophically as forecast quality worsens: tripling the forecast error from the nominal 5% RMSE to 15% reduces the evaporation-suppression benefit from 34.0% to 29.7% and roughly doubles drought-day exposure, from 12 to 24 days, while revenue falls by only 6.0%. Even under the severely degraded 30% RMSE scenario, intended to approximate a forecast failure during an unprecedented climatic anomaly, the digital twin still delivers a 22.4% evaporation reduction and outperforms the uncoordinated FPV-hydro baseline

Table 3. Sensitivity of digital-twin performance to inflow forecast error

Forecast error (RMSE)	**Evap. reduction (%)**	**Days below V_{safe}**	**Revenue ($ million)**
Nominal (5% RMSE)	34.0%	12	94.8
Degraded (15% RMSE)	29.7%	24	89.1
Severely degraded (30% RMSE)	22.4%	47	81.6

of Table 1 on every metric, because the model predictive control horizon in Equation 3 re-optimizes at every timestep and is therefore self-correcting against forecast bias rather than committing irrevocably to a multi-day plan. This robustness is consistent with the general resilience of receding-horizon control to bounded forecast error documented in the broader reservoir and grid-dispatch literature [10, 11], and it is a materially different failure mode from the flash-flood scenarios also present in our 10-year test record, where the binding constraint shifts from evaporation suppression to spillway capacity and the digital twin's drought-penalty term in Equation 3 is symmetric enough to also discourage dangerous over-storage ahead of a forecasted inflow surge.

The practical implication is that operators deploying this framework need not achieve state-of-the-art inflow forecasting to capture most of the reported benefit. The evaporation-reduction gain retained under 30% RMSE, 22.4 percentage points of the 34.0% nominal figure, represents 65.9% of the maximum achievable benefit even under forecast conditions substantially worse than the CNN-LSTM benchmarks typically reported in the literature [9], suggesting that legacy reservoirs with limited telemetry and correspondingly noisier inflow estimates remain reasonable candidates for this retrofit.

A distinct robustness question concerns the flash-flood events embedded in the 10-year test record, where the digital twin must switch within hours from evaporation-suppression mode to spillway-protection mode. Table 4 reports peak reservoir level and spillway discharge for the three most severe flash-flood events in the simulated record, comparing the digital twin against the baseline heuristic rule-curve controller.

Table 4. Flash-flood response, three most severe events in the 10-year record

Controller	**Peak level (% of V_{max})**	**Peak spillway discharge (m^3/s)**	**Uncontrolled spill events**
Baseline heuristic rule-curve	98.4%	1,240	3 of 3
DT-optimized FPV-PHES	**91.2%**	**870**	**0 of 3**

The digital twin pre-releases water ahead of the forecasted inflow surge, using the same seven-day LSTM forecast evaluated above, which lowers the peak reservoir level from 98.4% to 91.2% of maximum storage and reduces peak spillway discharge by 29.8%. This pre-emptive drawdown is only possible because the cost function in Equation 3 penalizes proximity to V_{safe} symmetrically from both directions, discouraging the controller from holding water unnecessarily close to spillway capacity even when doing so would otherwise appear economically attractive under the immediate price signal $\pi(t)$. All three uncontrolled spill events under the baseline heuristic, in which discharge exceeds the spillway's rated capacity and triggers emergency protocols, are avoided entirely under digital-twin control, indicating that the same predictive infrastructure built for drought management yields a materially different but complementary benefit during flood conditions.

5. CONCLUSION

The proposed digital twin framework links hydrology, thermodynamics, and power economics within a single real-time control loop. By dispatching water and electricity according to predictive climate models, the framework sustains grid reliability and delivers substantial water conservation, rendering legacy hydropower assets markedly more resilient to climate volatility. Future work will extend the framework to multi-reservoir cascades and evaluate its sensitivity to forecast-model uncertainty under non-stationary climate conditions [7, 9].

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