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Khojiakbar Khasanov

kh.khasanov@tiiame.uz

“TIIAME” National Research University

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Joint water-supply and hydropower management in a capacity-depleted multipurpose reservoir: the two-input AD-2I-WE model for Akhangaran

Khojiakbar Khasanov^{1*}

^{1*} “TIIAME” National Research University, Tashkent, Uzbekistan.

Corresponding author(s). E-mail(s): kh.khasanov@tiiame.uz;

Abstract

Reservoir sedimentation alters not only geometric storage but also seasonal carryover capacity, the physical meaning of legacy rule curves, and hydropower operating conditions. This study integrates repeated elevation–area–volume surveys (1972–2022), a 2,192-day operational record (2020–2025), a quality-controlled 1988–2023 inflow–outflow archive, measured downstream-tributary volumes, and daily hydropower records for the Akhangaran Reservoir, Uzbekistan, within a single adaptive decision framework (AD-2I-WE) driven by two open inputs: current storage and the annual irrigation order. Storage at the normal pool level declined from 197.7 to 169.4 million m³ between 1972 and 2022, a loss of 28.3 million m³ (14.3%). Three water-management benchmarks were compared: an observed-operation stress test (W0), a fixed-terminal-storage optimization (W1), and the adaptive AD-2I model with a 15 million m³ intra-annual safety floor (W2). Under W0, mean volumetric reliability was 69.72% and the mean deficit was 240.08 million m³/year, with 68.3% of the deficit concentrated in July–September. Under its base 313.5 million m³ irrigation order, W2 raised volumetric reliability to 76.05% and cut the deficit by 20.9% relative to W0 while maintaining the safety floor in every year. Lexicographic re-timing of hydropower releases (AD-2I-WE) increased energy from 41.18 to 55.16 GWh/year (+33.9%) without degrading the water-security solution, although modeled energy remained 22.0% below observed 2022–2024 generation. A 63.08 million m³ forced spill in the wet year 2022 revealed a structural constraint imposed by reduced storage and turbine conveyance capacity. The results demonstrate that adaptive, two-input operation can jointly improve water security and hydropower value in a capacity-depleted multipurpose reservoir.

Keywords: Akhangaran Reservoir, sedimentation, adaptive reservoir operation, hydropower, water–energy nexus, reliability

1 Introduction

Multipurpose reservoirs simultaneously reconcile seasonal flow regulation, irrigation and municipal-industrial supply, hydropower, environmental flow, and flood safety — functions that all depend on actual storage capacity and the temporal distribution of water. When useful storage declines through sedimentation, the design rule curve may stay nominally unchanged even though the same water level now corresponds to a smaller volume. Sedimentation is therefore not merely a bathymetric change but also a matter of operational reliability and a water–energy trade-off (Chang et al. 2003; Olsson et al. 2011; Rakhmatullaev et al. 2012; Yin et al. 2014).

The performance of water-supply systems is commonly evaluated through time-based reliability, volumetric reliability, resilience, and vulnerability (Hashimoto et al. 1982; Wu et al. 2021; Simeone et al. 2024). Reservoir operation has widely used linear and dynamic programming, hedging rules, rule-curve optimization, model predictive control, and rolling-horizon approaches (Shih and ReVelle 1994; Tu et al. 2003; Draper and Lund 2004; You and Cai 2008). However, an optimization not grounded in institutional meaning can achieve a high “reliability” figure simply by reducing demand. Where an irrigation order already exists, driving the deficit to zero by driving demand to zero is not an operational solution; the plan, the limit, actual delivery, and undelivered volume must remain distinct.

This problem is especially acute in Central Asia, where mountainous basins generate most flow during snow and glacier melt while irrigation demand peaks in late summer (Allen et al. 1998; Pereira et al. 2009; Rakhmatullaev et al. 2010, 2012). Even when annual availability appears adequate, transferring spring water into the summer–autumn period requires active storage and appropriate operating rules, and reduced capacity directly curtails this transfer function. The annual inflow-to-demand ratio alone therefore does not describe water security; decadal or monthly time alignment is required.

Hydropower adds a second dimension: generation depends not only on turbine flow volume but also on head at release, so the same volume yields more energy at higher storage (Lund 2000; Zhao et al. 2014; Mousavi et al. 2021). A release schedule optimal for water supply may therefore not be optimal for energy, and maximizing energy can compromise summer demand or the safety margin. Water–energy nexus research has revealed such trade-offs through multi-objective optimization (Dai et al. 2018; Yang et al. 2019; Yan et al. 2020; Saadatpour et al. 2020), yet studies integrating sedimentation-updated morphometry with local irrigation demand and turbine constraints remain scarce.

The current operating rules for the Akhangaran Reservoir are based on 2006 morphometry (Botiometrik Markaz 2006), while the 2022 bathymetric survey shows storage at $H^*=1070.5$ m declined from 188.4 to 169.4 million m^3 . The total annual demand specified in the operating rules is 792.9 million m^3 — 479.4 million m^3 non-irrigation and 313.5 million m^3 irrigation. The relevant question is therefore not “how should demand be reduced” but “which volume should be planned under diminished

capacity, which portion made conditional, which reserve protected, and how should release timing reconcile water-supply and energy objectives.”

This study develops and retrospectively evaluates an AD-2I-WE adaptive decision model for the Akhangaran Reservoir, driven by two open inputs — current storage and the annual irrigation order — integrating repeated elevation–area–volume (H–A–V) data, the 2020–2025 operational record, and hydropower plant data. Four research questions are addressed: (RQ1) how closely does the observed regime match the normative demand and dispatch zones; (RQ2) does a hard terminal storage target resolve the deficit and intra-annual safety problem; (RQ3) how does a 15 million m³ safety buffer combined with a 280–350 million m³ irrigation corridor affect water supply; and (RQ4) how much energy can be gained by optimizing release timing without degrading the water solution, and when do turbine and storage constraints bind?

2 Study Area and Data

2.1 The Akhangaran Reservoir and its morphometric change

The Akhangaran Reservoir is a multipurpose facility that seasonally regulates flow on the Akhangaran River in Tashkent Province. The normal pool level is 1070.5 m and the dead-storage level 1010.0 m; per the 2022 H–V curve, storage at normal pool level is 169.4 million m³ and dead storage 5.8 million m³. To compare operational data across years in a single coordinate system, the 2020–2025 water-level record was converted to volume using the 2022 H–V curve — a unified morphometric basis that does not imply the 2020–2021 bed configuration was identical to 2022’s.

Table 1 summarizes the repeated bathymetric surveys and the resulting rate of capacity loss.

Table 1 Repeated bathymetric surveys and the rate of capacity loss

Year	Volume at H*=1070.5 m, million m ³	Loss from previous period, million m ³	Rate, million m ³ /year
1972	197.7	—	—
2002	190.0	7.7	0.257
2006	188.4	1.6	0.400
2022	169.4	19.0	1.188

Between 1972 and 2022, total capacity loss reached 28.3 million m³, or 14.3%. The 2006–2022 interval alone accounted for a loss of 19.0 million m³, a markedly higher rate than in the preceding intervals. From an operational standpoint, this figure reflects a shrinking of the buffer available for carrying spring inflow through to summer demand.

2.2 Operational and hydrological data

The primary water-balance dataset spans 2,192 days, from 1 January 2020 to 31 December 2025, with daily records of water level, volume recomputed via the 2022 H–V curve, reservoir inflow, and reservoir release. Data were screened for date continuity, duplicate entries, out-of-range values, and abrupt jumps; unambiguous entry errors were fixed, and remaining questionable cases retained in the QC log. Flow-to-volume conversion used $1 \text{ m}^3/\text{s} = 0.0864 \text{ million m}^3/\text{day}$.

The daily record was aggregated into calendar ten-day periods (decades): days 1–10, 11–20, and 21 through month-end. Because the third decade can span 8–11 days, demand and tributary volumes were apportioned by actual day count. Each year was initialized from the first observed storage, without carrying modeled end-of-year storage into the next year — so the computations constitute six independent retrospective annual trials rather than a continuous multi-year simulation.

Table 2 reports the annual water exchange and the results of stress-testing the observed regime against normative demand.

Table 2 Annual water exchange and stress-testing of the observed regime, million m^3

Year	Reservoir inflow	Reservoir release	Downstream tributaries	W0 deficit	First observed storage	Last observed storage
2020	545.6	534.8	463	249.2	34.0	24.4
2021	473.9	455.7	446	282.2	24.4	25.1
2022	727.9	689.6	545	213.6	25.1	45.6
2023	570.4	587.4	512	245.7	45.3	26.2
2024	731.4	627.1	552	170.6	26.5	32.8
2025	426.5	411.2	387	279.2	32.2	37.7

The beginning- and end-of-year storages in Table 2 are independent first/last observations. The 0.3–0.6 million m^3 discrepancy at certain year boundaries was not artificially reconciled between consecutive values, because the timestamp of the source record and the level-to-volume recomputation process were preserved as distinct observations. The model’s initial condition was taken directly from the first valid observation of the corresponding year.

For long-term context, an additional archival series of ten-day mean reservoir inflow and outflow was examined for 1988–2024. The 2024 outflow record contained one physically inconsistent value (1037.741 m^3/s) and was excluded from the long-term diagnostic rather than corrected by assumption. The quality-controlled 1988–2023 series was used only to characterize the historical inflow–release coupling, not as independent evidence that future inflow is known in advance.

Figure 1 shows the annual water exchange in 2020–2025 together with volumetric reliability relative to the normative demand.

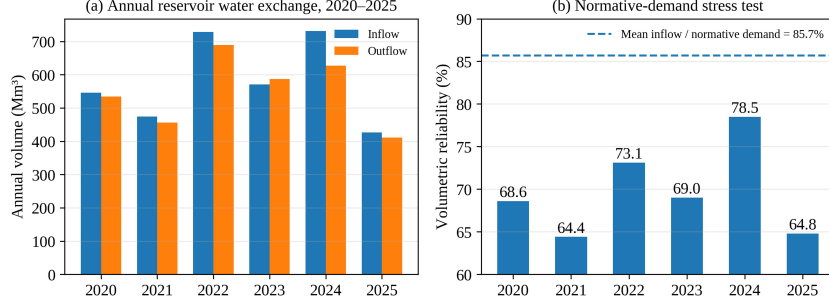


Fig. 1 Annual water exchange in 2020–2025 and volumetric reliability relative to the normative demand

2.3 Demand and downstream tributaries

The total annual demand specified in the operating rules is 792.9 million m³: 479.4 million m³ non-irrigation and 313.5 million m³ irrigation. Because the rounded monthly values in the source document sum to 792.8 million m³, a 0.1 million m³ discrepancy exists relative to the normative annual figure; in the adaptive scenarios the components were proportionally normalized to the target annual volume to preserve exact mass balance. The irrigation order was represented at three planning levels: 280 million m³, the first-priority protected minimum; 313.5 million m³, the base order; and 350 million m³, a conditional upper limit released only under a favorable water balance.

Annual downstream-tributary volumes for 2020–2025 were measured, but no monthly record exists. Accordingly, the annual tributary volume for each year was proxy-distributed according to the monthly shares of that year’s reservoir inflow:

$$Q_{y,m}^{trib} = Q_{y,annual}^{trib} \times \frac{Q_{y,m}^{in}}{\sum_m Q_{y,m}^{in}} \quad (1)$$

This formula preserves the monthly proxy sum exactly equal to the measured annual tributary volume; however, because this proxy is constructed from reservoir inflow, Q^{trib} and Q^{in} are not mutually statistically independent. Correlation with the downstream tributary was therefore not used as independent causal evidence, only as a physical water-balance component and seasonal descriptor, to be revalidated once monthly or decadal tributary observations become available.

Table 3 lists the demand components and the adaptive irrigation-management corridor.

2.4 Hydropower plant data and quality control

The Akhangaran hydropower plant (HPP) was commissioned in 2010 with two hydro-generating units. Technical sources report a total design capacity of 26.2 MW and an actual installed capacity of 21.0 MW; given normal daily maxima and generator nameplate data, the primary calculations adopted the 21 MW electrical limit, retaining 26.2 MW as a design alternative pending verification against the equipment passport. The design total turbine flow is 42.0 m³/s, with a head range of 27–70 m.

Table 3 Demand components and the adaptive irrigation-management corridor

Component	Annual value, million m ³	Role in the model
Non-irrigation demand	479.4	Fixed priority demand
Irrigation — planning minimum	280.0	First-priority protected block
Irrigation — base order	313.5	Primary plan under normal conditions
Irrigation — conditional maximum	350.0	Additional block released only when water is available
Total demand range	759.4–829.4	Depends on the irrigation level
Downstream tributaries	463; 446; 545; 512; 552; 387	Measured annual volumes, 2020–2025

The HPP dataset spans 1,979 records from 2020-01-01 to 2025-05-31. Quality control identified 1,946 unique dates, 66 duplicate rows, an erroneous attachment of the May 2021 file to May 2020, a gap in May 2021, and a physically inconsistent 87.738 MW record on 2024-08-08; the more complete, internally consistent 2022–2024 period was therefore selected for direct comparison with observed energy output, while 2020, 2021, and 2025 informed model construction and diagnostics without serving as a reliable multi-year benchmark.

3 Methodology

3.1 Data harmonization and the decadal time step

The methodological chain has five stages: (i) reconciling level–volume data to the 2022 H–V curve; (ii) aggregating daily inflow, release, and storage into ten-day periods; (iii) disaggregating normative demand and measured annual downstream-tributary volumes into decadal mass; (iv) solving the water balance under the W0–W2 benchmarks and the AD-2I algorithm; and (v) optimizing HPP release timing through AD-2I–WE while preserving the water-balance solution — linking morphometry, demand, hydrology, and energy into one reproducible framework.

3.2 Decadal water balance and demand coverage

The decadal reservoir water balance was calculated using the following continuity equation:

$$V_{t+1} = V_t + I_t - R_t - SP_t \quad (2)$$

Here, V_t is reservoir storage at the start of the decade; I_t is net input from daily observations; R_t is controlled release; and SP_t is forced spill from storage or conveyance constraints. Because net input is reconstructed from the observed change in storage and actual release, it implicitly absorbs evaporation, seepage, measurement residuals,

and other minor unaccounted losses as an internal residual term — so a separate loss term L_t is not reintroduced, avoiding double counting.

$$S_t = R_t + Q_t^{trib}; \quad Def_t = \max(0, D_t - S_t) \quad (3)$$

Downstream tributaries were treated not as inflow into the reservoir but as an external supply serving consumers located below the dam. They were therefore excluded from the reservoir mass balance but added to R_t in the demand-coverage equation. D_t is the total decadal demand. This separation eliminates the risk of double-counting the tributary volume.

3.3 Performance indicators

Water-supply performance was evaluated using reliability and vulnerability indicators:

$$Rel_t = \frac{N(Def_t \leq \varepsilon)}{N}; \quad Rel_v = 1 - \frac{\sum Def_t}{\sum D_t} \quad (4)$$

$$Vul_{mean} = \frac{\sum Def_t}{N_{fail}}; \quad Vul_{max} = \max(Def_t) \quad (5)$$

Time-based reliability (Rel_t) reflects the share of decades in which demand was essentially fully met, while volumetric reliability (Rel_v) reflects the share of total demand mass delivered; $\varepsilon=10^{-7}$ million m³ was used for numerical zero. Vulnerability was expressed as the mean and maximum deficit during failure decades, and minimum storage, end-of-year storage, decades at dead storage, spill, and HPP indicators were evaluated jointly — no single “best” scenario was declared on any one indicator.

3.4 Retrospective audit of the dispatch (rule) curve

The upper and lower guaranteed-supply lines of the current dispatch curve, together with the $K=0.80$ and $K=0.75$ thresholds, were digitized across 36 decades and the actual end-of-decade levels mapped onto these zones. Digitization uncertainty was estimated at ± 0.2 – 0.3 m, and classification stability was tested by shifting thresholds ± 0.3 m. This audit is not a finding of regulatory non-compliance but a retrospective diagnostic of the correspondence between the actual level trajectory and the existing operating rules.

Figure 2 shows actual water levels relative to the current dispatch trajectory and their deviation from the central line.

3.5 Water benchmarks: W0, W1, and W2

In earlier versions, the reuse of the labels S1/S2/S3 for subsequent energy scenarios produced a nomenclature collision. In the final version, the water benchmarks were assigned a separate W prefix, so that water and energy results no longer overlap.

Table 4 defines the final, collision-free nomenclature of the water benchmarks used throughout this article.

W0 is not an optimization: the actual release and downstream-tributary proxy are compared against normative demand. W1 minimizes the total deficit over 36 decades

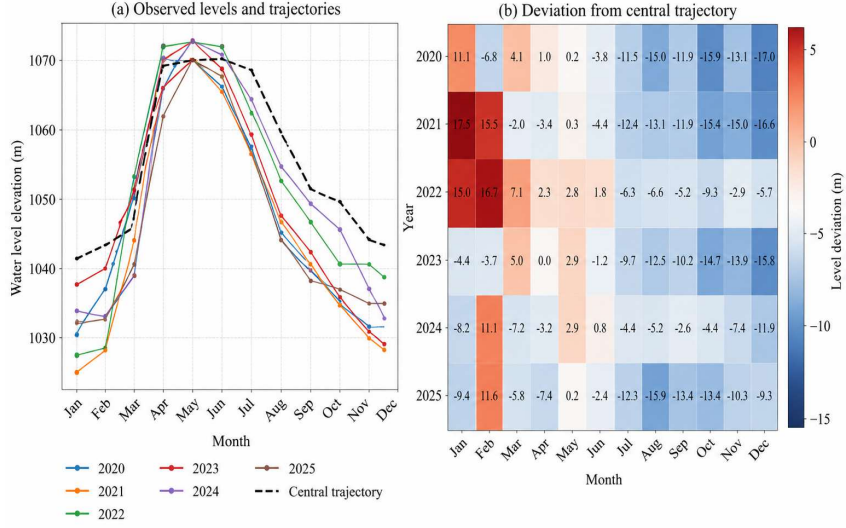


Fig. 2 Actual water levels relative to the current dispatch trajectory and their deviation from the central line

Table 4 Final, collision-free nomenclature of the water benchmarks

Code	Definition	Demand policy	Storage policy	Scientific role
W0	Observed-stress benchmark	792.9 million m ³ normative demand	Actual storage	Water-supply capability of the observed regime relative to normative demand
W1	Fixed-terminal benchmark	Demand unchanged	$V_{36} \geq 59.74$ million m ³ ; $V_{\min}=5.8$	Theoretical effect of a hard terminal storage target
W2	AD-2I water-secure model	479.4 + irrigation 280–350	$V_t \geq 15$; $V_{36} \rightarrow 59.74$ target	Adaptive management of the demand corridor and intra-annual safety

and strictly enforces 59.74 million m³ at year-end, constraining intra-annual storage only by the 5.8 million m³ dead-storage floor — an optimistic benchmark for the terminal-storage approach, not an operational recommendation. W2, by contrast, introduces a hard intra-annual buffer of 15 million m³, converting the 59.74 million m³ terminal target from a hard constraint into a secondary objective.

3.6 W2 lexicographic optimization and the safety storage margin

W2 was optimized sequentially using a two-stage lexicographic objective:

$$\text{Stage 1: } \min \sum Def_t \quad (6)$$

$$\text{Stage 2: } \max V_{36} \quad \text{subject to: } \sum Def_t \leq Def^* + \varepsilon, \quad V_{36} \leq 59.74 \quad (7)$$

In the lexicographic sequence, the water deficit is first minimized as the absolute priority objective; then, among solutions that do not degrade this optimum, terminal storage is maximized. This differs from a weighted-sum objective function, where the trade-off coefficient between deficit and storage reserve would be fixed by a subjective weight. For W2, the 15 million m³ safety margin is not a normative value but was tested as a conservative buffer above the 5.8 million m³ dead storage.

Table 5 presents the sensitivity results for the W2 safety storage margin.

Table 5 Sensitivity results for the W2 safety storage margin

Vsafe, million m ³	Rel _v , %	Rel _t , %	Deficit, million m ³ /year	Terminal storage, million m ³	Dead storage, decades/year
5.8	77.64	61.57	177.27	7.55	21.00
10	76.94	60.65	182.87	11.75	0.00
15	76.05	59.72	189.88	16.75	0.00
20	75.06	56.48	197.72	21.75	0.00
25	73.96	55.09	206.47	26.75	0.00

With Vsafe=5.8 million m³, Rel_v is higher and the deficit lower, but the reservoir falls to dead storage in an average of 21 decades per year. With Vsafe=10 million m³ this drops to zero, while the deficit rises to 5.60 million m³/year; at 15 million m³, safety is preserved at the cost of an additional 7.01 million m³/year of deficit. At 20–25 million m³, safety improves further but reliability declines faster. 15 million m³ was therefore adopted not as a “formal optimum” but as a practical operating point within the trade-off.

3.7 The two-input AD-2I algorithm and the WCR coefficient

The AD-2I operator interface has two open inputs: $x_1=V_t$, current reservoir storage, and $x_2=D_y^{irr}$, the annual irrigation order, constrained to 280–350 million m³/year. Other factors — inflow forecast, downstream-tributary contribution, remaining non-irrigation demand, decade index, Vsafe, and Vmax — are retrieved automatically from the database. “Two-input” thus does not mean only two variables enter the mass balance, but that two explicit signals are placed under direct operator control.

$$W_{safe} = [V_t - V_{safe}]^+ + \sum (\hat{Q}^{in} + \hat{Q}^{trib}) - D_{rem}^{nonirr} - \sum \hat{L} - V_{terminal} \quad (8)$$

$$WCR = \frac{W_{safe}}{D_{rem}^{irr}} \quad (9)$$

WCR expresses the degree to which the remaining irrigation demand is covered by the forecast safe water supply. The initial operating classes represent an engineering hypothesis rather than a universal norm. They must be calibrated against historical hindcasts, forecast error, and a sector-specific damage function.

Table 6 defines the AD-2I operating regimes.

Table 6 AD-2I operating regimes

Regime	WCR	Meaning	Decision priority
R1	<0.60	Emergency deficit	Non-irrigation obligation and safety
R2	0.60–0.80	Sharply constrained	Minimizing damage to the guaranteed block
R3	0.80–1.00	Protecting the minimum	280 million m ³ plan block
R4	1.00–1.15	Base supply	Order near 313.5 million m ³
R5	≥1.15	Conditional surplus	Additional block up to 350 million m ³

In the computational database, cases with $WCR \geq 1.15$ had previously been mislabeled “R1: surplus,” and certain values in the 1.00–1.15 range had been labeled “R2.” This was purely a textual classification error that did not affect the underlying water-balance results. In the final database and in this article, the classification has been strictly aligned with Table 6.

Figure 3 illustrates the two-input AD-2I decision architecture, showing user inputs, automatic drivers, safe water, and adaptive outputs.

3.8 The head–storage relationship and the energy model

Based on head–storage pairs corresponding to the physical range in the HPP database, an empirical linear regression was fitted:

$$H_t = clip(0.25670 \bar{V}_t + 18.589; 27; 70), \quad R^2 = 0.976 \quad (10)$$

This equation does not separately resolve tailwater level and hydraulic losses; it is a working regression bounded within the 27–70 m nameplate range, where $H=27$ m corresponds to $V \approx 32.8$ million m³. In the W2 base water trajectory, 154 of 216 decades (71.3%) fell below this storage threshold, so during low-storage periods the 27 m clip materially affects the energy computation. Energy results — particularly for

Two-Input Adaptive Reservoir–Demand Algorithm

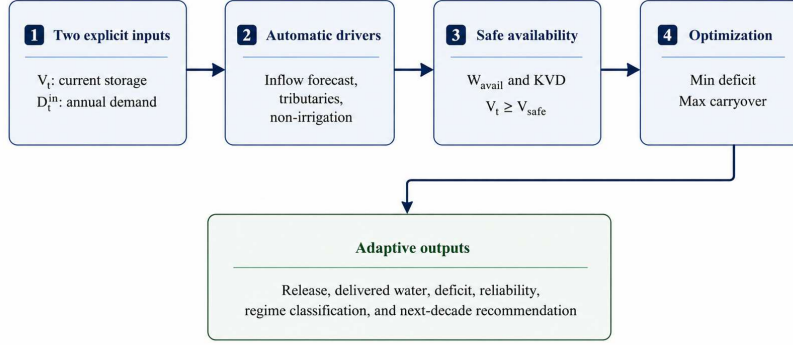


Fig. 3 Two-input AD-2I decision architecture: user inputs, automatic drivers, safe water, and adaptive outputs

the low-storage July–autumn period — should therefore be revisited once nameplate Q – H – η surfaces become available.

As a morphometric diagnostic, the regression was applied to historical maximum storage values: 1972’s 197.7 million m^3 corresponds to $H \approx 69.34$ m, 2006’s 188.4 million m^3 to $H \approx 66.95$ m, and 2022’s 169.4 million m^3 to $H \approx 62.07$ m — an empirical head roughly 7.27 m (10.5%) lower than the head implied by the 1972 capacity. This illustrates sedimentation’s effect on physical energy potential, but because the HPP was commissioned only in 2010 and the $H(V)$ regression derives from contemporary data, it is not equivalent to a historical claim that “energy generation declined by 10.5% between 1972 and 2022.”

$$Q_t^T = \frac{R_t^T}{0.0864 n_t}, \quad 0 \leq Q_t^T \leq 42.0 \text{ m}^3/\text{s} \quad (11)$$

$$P_t = \min \left[21; \frac{\rho g \eta Q_t^T H_t}{10^6} \right], \quad E_t = \frac{P_t \cdot 24 n_t}{1000} \quad (12)$$

The calculation adopted $\rho=1000 \text{ kg/m}^3$, $g=9.81 \text{ m/s}^2$, and $\eta=0.85$. When generator output exceeded 21 MW, the power cap and the physically admissible upper flow bound were updated iteratively as $Q \leq P_{\max} \cdot 10^6 / (\rho g \eta H)$ — introducing the 21 MW limit not as a post-processing “cutoff” but as a constraint binding the release decision itself. Iteration began from $H=45$ m and was deemed convergent once the maximum head difference between successive iterations fell below 0.01 m, with a maximum of eight iterations allowed.

3.9 The AD-2I–WE lexicographic objective hierarchy

Blending the water and energy objectives into a single weighted function risks implicitly trading safety for energy. For this reason, the integrated problem was solved through a three-stage lexicographic ordering:

$$1) \min \sum Def_t \quad (13)$$

$$2) \max V_{36} \quad | \quad \sum Def_t \leq Def^* + \varepsilon \quad (14)$$

$$3) \max \sum E_t \quad | \quad \sum Def_t \leq Def^* + \varepsilon, \quad V_{36} \geq V_{36}^* - \varepsilon \quad (15)$$

The first stage minimizes the water deficit. The second stage, while preserving this minimum, maximizes the terminal storage. The third stage maximizes energy without altering the water-deficit and terminal-storage optima beyond a numerical tolerance. In this way, the energy gain achieved under AD-2I-WE is not obtained at the cost of additional water consumption or a hidden reduction in safety.

3.10 Final experimental design and nomenclature

The energy section previously used labels S0–S6, which collided with the water-side labels S1–S3. Here, only computation-supported experiments are separately named: E0, the observed 2022–2024 energy benchmark; E1, post-processing energy of the W2 base water-priority schedule; E2, the energy-optimized AD-2I-WE solution under the base 313.5 million m³ order; E3, energy sensitivity across the 280–350 million m³ demand corridor; and E4, the structural spill test for wet 2022. The Pareto tolerance $Def \leq (1+\alpha)Def^*$, $\alpha=0;0.02;0.05;0.10$, is retained as a methodological extension, but since a sector-specific damage function and environmental-flow requirements are not fully available, $\alpha>0$ points are not interpreted as final recommendations — avoiding presenting uncomputed Pareto points as “results.”

3.11 Verification, uncertainty, and reproducibility

Numerical results were verified at three levels. First, the annual and six-year sums of the water scenarios were re-aggregated from the underlying decadal database results. Second, energy results were checked arithmetically: $55.78+48.53+63.33+61.32+56.74+45.25$ GWh over six years gives $55.158 \approx 55.16$ GWh/year; $CF=55,160$ MWh/(21 MW $\times$ 8,760 h)= $29.98 \approx 30.0\%$; the E1→E2 gain is 13.98 GWh/year (33.95%); the 2022–2024 observed and modeled averages are 77.51 and 60.46 GWh/year (22.0% difference). Third, the safety storage margin was sensitivity-tested over the 5.8–25 million m³ range.

Correlation diagnostics were not used as a causal test. Although N=72 monthly aggregates exist, strong seasonality, temporal autocorrelation, and the fact that the tributary proxy is constructed from inflow all violate the classical independence assumption; reported r-values were therefore treated only as descriptive signals, with no inferential p-value claimed as “independent proof.” Genuine operational validation would require a rolling-origin hindcast withholding future observations, together with an ensemble inflow forecast.

3.12 Statistical robustness and uncertainty testing

Because the six-year retrospective period is relatively short, two complementary methods tested whether the mean indicators depend on a single extreme year. First, a

nonparametric year-block bootstrap with 10,000 resamples was applied to the W2 base scenario’s annual volumetric reliability (Rel_v), deficit, and E2 energy output (Kunsch 1989; Efron and Tibshirani 1993): the six annual 2020–2025 outcomes were resampled with replacement as six blocks, and the 2.5th–97.5th percentiles taken as the 95% empirical confidence interval. This treats decadal observations as non-independent, avoiding an artificial inflation of sample size to $N=216$ through seasonal autocorrelation.

Second, a leave-one-year-out (LOYO) robustness test was performed: at each step one year was excluded and mean Rel_v , deficit, and energy recomputed over the remaining five years. A narrow LOYO range indicates the conclusion does not depend on any single year, a wide range substantial interannual variability. These tests are not causal inference or a forecast, but an assessment of the sample-level stability of the 2020–2025 retrospective results.

The constant efficiency $\eta=0.85$ used in the energy module remains a source of parametric uncertainty; the range $\eta=0.80\text{--}0.90$ is designated as the recommended sensitivity range. However, because of the 21 MW power cap and the Q–H relationship, energy does not always scale proportionally with η , so a full η -sensitivity analysis is treated as inferential only once the decadal turbine flow has been re-solved — η results not re-optimized were not padded with speculative figures.

4 Results

4.1 Capacity loss and the narrowing of seasonal management capability

At $H^*=1070.5$ m, storage declined from 197.7 million m^3 in 1972 to 169.4 million m^3 in 2022 — a total loss of 28.3 million m^3 (14.3%), with the largest interval loss occurring during 2006–2022 (19.0 million m^3). This volume equals 11.2% of the current maximum storage and narrows the reserve window for transferring spring inflow into summer demand, so even where the legacy rule curve is preserved in terms of level, its volumetric meaning has changed.

4.2 W0: a normative-demand stress test of the observed regime

Over 2020–2025, mean volumetric reliability under W0 was 69.72%, mean time-based reliability 36.11%, and mean deficit 240.08 million m^3 /year. Annual Rel_v ranged from 64.40% (2021) to 78.49% (2024). In 2022, despite a reservoir inflow of 727.9 million m^3 , Rel_v remained at only 73.05%, indicating annual inflow alone is insufficient to explain demand fulfillment.

Over the six years, the total diagnosed deficit reached 1,440.47 million m^3 . The July–September deficit accounted for 984.39 million m^3 , or 68.3% of the total deficit; the June–September share was 71.9%. The previously reported figures of 69.4% and 72.7% could not be confirmed upon re-aggregation and were corrected to 68.3% and 71.9%, respectively.

Figure 4 shows the seasonal distribution of decadal deficit under the W0 stress test, 2020–2025.

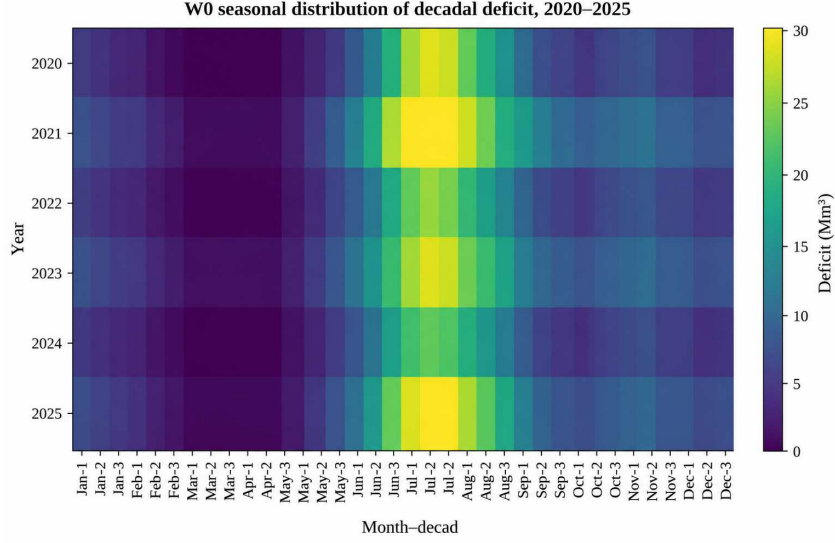


Fig. 4 Seasonal distribution of decadal deficit under the W0 stress test, 2020–2025

4.3 The physical and operational mechanism of the deficit

The deficit was not random but exhibited a stable seasonal structure. 63.0% of the irrigation order fell within July–September, a period during which only 5.1% of the downstream-tributary proxy was available. In spring, by contrast, both inflow and the tributary contribution are high while irrigation demand remains lower. The phase of water availability and demand is thus essentially inverted: most of the water arrives before the demand peak.

Reservoir storage approaches its maximum in spring and declines rapidly through summer: mean storage fell from about 175.3 million m³ at end-May to 159.2 in late June, 117.0 in July, 76.7 in August, and 59.8 million m³ in September — highlighting the need to reconcile release timing with forecasts given sedimentation-reduced carryover storage. The correlation between demand and monthly deficit ($r \approx 0.70$) and between deficit and net input ($r \approx -0.51$) is consistent with this mechanism as a descriptive diagnostic, but because of seasonal autocorrelation these are not independent causal tests.

4.4 Audit of dispatch zones

Of the 216 decadal states, 73 (33.8%) fell within the guaranteed-supply zone and 39 (18.1%) within the high-supply or spill zone; 104 (48.1%) fell below the lower guaranteed-supply line, and 47 (21.8%) below the $K=0.75$ threshold. End-of-month levels fell below the central trajectory in 58 of 72 cases. Shifting thresholds ± 0.3 m changed below-guarantee cases within 104–106, indicating the principal conclusion is robust to digitization uncertainty.

4.5 Comparison of the W0–W2 benchmarks

Table 7 presents the six-year mean results for the W0–W2 water benchmarks.

Table 7 Six-year mean results for the W0–W2 water benchmarks

Benchmark	Rel_t , %	Rel_v , %	Deficit, million m^3 /year	Deficit decades/year	Min. storage, million m^3	Dead storage, decades/year
W0	36.1	69.7	240.1	23.0	20.9	0.0
W1	59.3	71.1	229.4	14.7	5.8	9.7
W2 (313.5)	59.7	76.1	189.9	14.5	15.0	0.0

W1 sharply increased time-based reliability but caused the reservoir to fall to dead storage for an average of 9.7 decades per year. The hard 59.74 million m^3 terminal constraint limited current-year supply in certain years; in 2021, the W1 deficit exceeded the W0 deficit by 2.76 million m^3 . This demonstrates that strictly enforcing a terminal target does not automatically guarantee intra-annual safety.

Under the base 313.5 million m^3 order, W2 increased Rel_v relative to W0 by 6.33 percentage points and reduced the deficit by 50.20 million m^3 /year (20.9%); relative to W1, the deficit fell by 39.49 million m^3 /year (17.2%) and dead-storage occurrence was eliminated entirely. W2’s principal benefit lies less in reducing the number of deficit decades than in reducing deficit magnitude during failure periods while staying within the safety threshold.

4.6 W2 base annual results and the terminal target

Table 8 reports the annual results under the W2 base 313.5 million m^3 order.

Table 8 Annual results under the W2 base 313.5 million m^3 order, million m^3

Year	Irrigation plan	Total demand	Rel_v , %	Deficit	Min. storage	Terminal storage
2020	313.5	792.9	74.9	199.4	15.0	15.0
2021	313.5	792.9	68.5	249.5	15.0	15.0
2022	313.5	792.9	78.5	170.8	15.0	15.0
2023	313.5	792.9	75.5	194.3	15.0	15.0
2024	313.5	792.9	87.1	102.1	15.0	25.5
2025	313.5	792.9	71.8	223.2	15.0	15.0

W2 maintained the 15 million m^3 intra-annual safety margin every year. In the most favorable year, 2024, the deficit was 102.12 million m^3 with terminal storage

reaching 25.53 million m³; in the most challenging year, 2021, the deficit was 249.50 million m³. The 59.74 million m³ terminal target was not fully met in any year — significant, since converting it into a hard obligation would substantially degrade water supply, while removing it entirely would heighten the risk of low storage. W2 separates these two objectives hierarchically.

4.7 The irrigation-order corridor

Table 9 summarizes the six-year mean results for the W2 irrigation-order corridor.

Table 9 Six-year mean results for the W2 irrigation-order corridor, million m³

Irrigation regime	Irrigation	Total demand	Rel_v , %	Rel_t , %	Deficit	Terminal storage
Planning minimum	280.0	759.4	78.61	60.19	162.43	17.13
Base order	313.5	792.9	76.05	59.72	189.88	16.75
Conditional maximum	350.0	829.4	73.46	57.41	220.08	16.35

As the order rose from 280 to 313.5 million m³, the deficit increased by 27.45 million m³/year; from 313.5 to 350 million m³, by a further 30.20 million m³/year. Total delivered water, however, rose only from 596.97 to 609.32 million m³/year — just 12.35 million m³. Most of the additional 70 million m³ order thus translates not into extra delivery but into undelivered commitment, so 350 million m³ should be treated not as a firm norm but as a conditional block renewed over the growing season.

Figure 5 shows the 280–350 million m³ irrigation-order corridor under W2 and the resulting annual deficit.

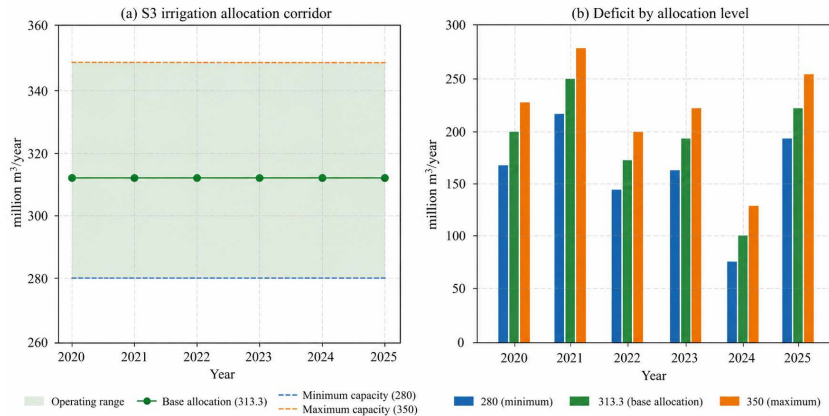


Fig. 5 The 280–350 million m³ irrigation-order corridor under W2 and the resulting annual deficit

4.8 The response characteristics of the two-input algorithm

In the perfect-information hindcast, the irrigation input was tested at 280, 300, 313.5, 330, and 350 million m^3 . As demand increased, Rel_v declined from 78.61% to 73.46% while the deficit rose from 162.43 to 220.08 million m^3/year , and delivered water rose only from 596.97 to 609.32 million m^3/year . This response surface shows the two inputs' direction clearly: higher initial storage increases the safe-release buffer, while higher irrigation demand enlarges undelivered commitment under the same hydrology.

Figure 6 shows the response of delivered water, deficit, and volumetric reliability to the irrigation order.

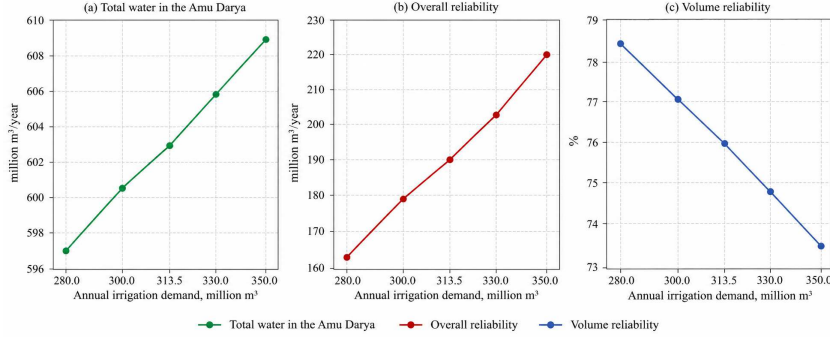


Fig. 6 Response of delivered water, deficit, and volumetric reliability to the irrigation order

Figure 7 shows the AD-2I climatological response surface as a function of initial storage and irrigation demand.

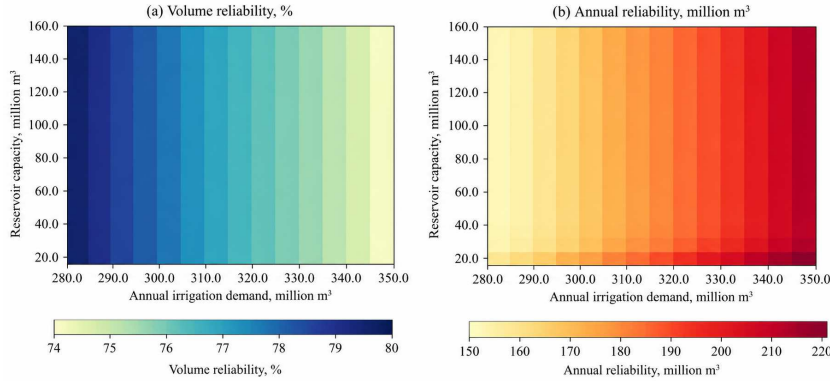


Fig. 7 AD-2I climatological response surface as a function of initial storage and irrigation demand

4.9 Head–capacity diagnostics: the energy implications of sedimentation

Per the empirical $H(V)$ regression, the 2022 maximum storage of 169.4 million m^3 corresponds to $H \approx 62.07$ m, versus $H \approx 69.34$ m for the 1972 storage of 197.7 million m^3 — a 7.27 m difference. Since power output is proportional to head under identical turbine flow and efficiency, this morphometric change may reduce theoretical hydraulic energy density at maximum storage by roughly 10.5%. This figure, however, is a diagnostic from extrapolating a contemporary regression to a historical capacity; given tailwater conditions, turbine efficiency, and the HPP’s commissioning date, it is not a direct measure of historical power-generation loss.

Another important result is that the $H=27$ m lower bound activates at $V \approx 32.8$ million m^3 , and 71.3% of decades in the W2 water trajectory fell below this storage level — meaning that precisely during the low-storage season when deficit tends to be highest, the energy model relies more on the 27 m physical/nameplate limit than on the empirical regression. This identifies acquiring nameplate $Q-H-\eta$ characteristics as a priority for future refinement.

4.10 E2: base AD-2I–WE energy results

Table 10 presents the E2 base results under the 313.5 million m^3 AD-2I–WE order.

Table 10 E2 base results under the 313.5 million m^3 AD-2I–WE order

Year	Energy, GWh	HPP Spill, million m^3 water, mil- lion m^3	Deficit, million m^3	Rel_v , %	Operating days
2020	55.78	556.30.00	199.36	74.86	306
2021	48.53	461.50.00	249.50	68.53	293
2022	63.33	658.50.08	170.77	78.46	345
2023	61.32	600.90.00	194.32	75.49	335
2024	56.74	634.00.00	102.12	87.12	356
2025	45.25	435.50.00	223.22	71.85	294

The six-year mean energy output was 55.16 GWh/year, with 557.83 million m^3 /year passed through the HPP over 321.5 operating days/year ($CF=30.0\%$). Computed only as post-processing on the W2 water-priority release schedule, energy was $E1=41.18$ GWh/year; under E2, with the same minimum deficit (189.88 million m^3 /year) and terminal solution preserved within tolerance, energy rose to 55.16 GWh/year — a gain of 13.98 GWh/year (33.9%) that reflects not “consuming more water” but re-timing releases toward periods of higher head.

Figure 8 compares the E2 AD-2I–WE energy output against the observed 2022–2024 generation benchmark.

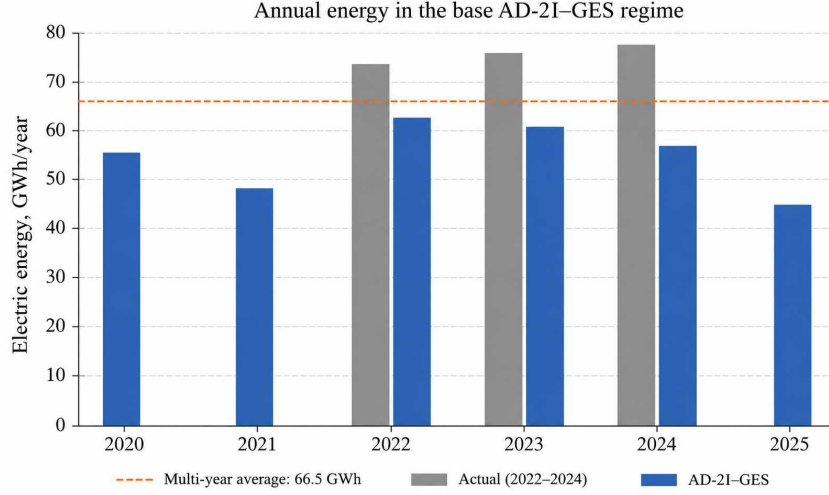


Fig. 8 E2 AD-2I-WE energy output versus the observed 2022–2024 generation benchmark

4.11 E3: the demand–energy–deficit trade-off

Table 11 presents the water–energy results across the irrigation corridor.

Table 11 Water–energy results across the irrigation corridor

Irrigation demand	Energy, GWh	Deficit, Rel_v , %	Terminal storage	Operating days
		mil- lion m^3 /year		
280.0	55.29	162.43 78.61	17.13	325.0
300.0	55.21	178.82 77.06	16.90	321.7
313.5	55.16	189.88 76.05	16.75	321.5
330.0	55.10	203.44 74.86	16.57	319.3
350.0	55.13	220.08 73.46	16.35	314.3

As demand rose from 280 to 350 million m^3 /year, energy changed only marginally, from 55.29 to 55.13 GWh/year (0.16 GWh, 0.3%), while the deficit rose by 57.65 million m^3 /year (35.5%). The slight dip to 55.10 GWh at 330 million m^3 followed by partial recovery to 55.13 GWh at 350 is not a computational error: in the lexicographic model, the decade in which storage, the 21 MW power cap, or the 42 m^3 /s flow limit binds shifts with demand level. This 0.03 GWh/year (0.05%) difference is negligible; the principal conclusion is that energy stays nearly flat across the demand corridor while the deficit rises sharply.

Figure 9 contrasts the response of energy and deficit to increasing irrigation demand.

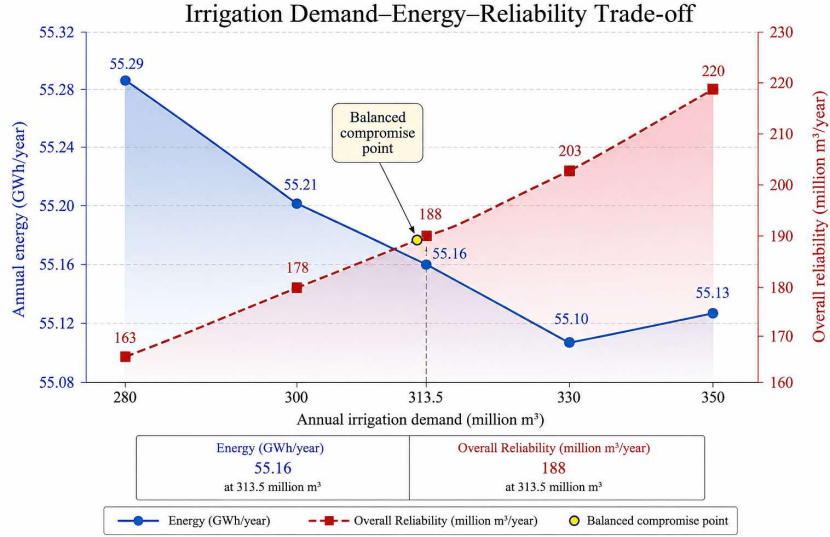


Fig. 9 Contrasting response of energy and deficit to increasing irrigation demand

4.12 E4: turbine constraint and structural spill

In 2020, 2021, and 2023–2025, the model redistributed releases over time to reduce forced spill to zero. In 2022, however, high net input, the 169.4 million m³ storage capacity, and the 42 m³/s turbine-flow limit became simultaneously binding, leaving a 63.08 million m³ spill — one that persisted even under perfect information, indicating a structural component rather than a consequence of forecast error.

The decadal trajectories showed that the HPP operating on many days does not imply operating at full capacity at all times. Low storage reduces head, while at high storage the 21 MW generator cap may become binding. Energy therefore cannot be evaluated solely from annual release volume; the joint trajectory of storage, head, and release is required.

Figure 10 shows the decadal trajectory of power output and storage under AD-2I–WE for selected years.

4.13 Comparison with observed energy

Because of QC constraints, comparison with observed data was limited to 2022–2024: observed energy was 74.14, 78.60, and 79.79 GWh, versus E2’s 63.33, 61.32, and 56.74 GWh, giving three-year means of 77.51 vs 60.46 GWh/year — a difference of –17.05 GWh/year (–22.0%). Relative to the 66.5 GWh long-term norm reported in the source documentation, the six-year E2 mean is 11.34 GWh/year (17.1%) lower. E2 should therefore not be read as an “energy maximum” but as a solution maximizing energy within the freedom remaining after first protecting against water deficit and intra-annual security.

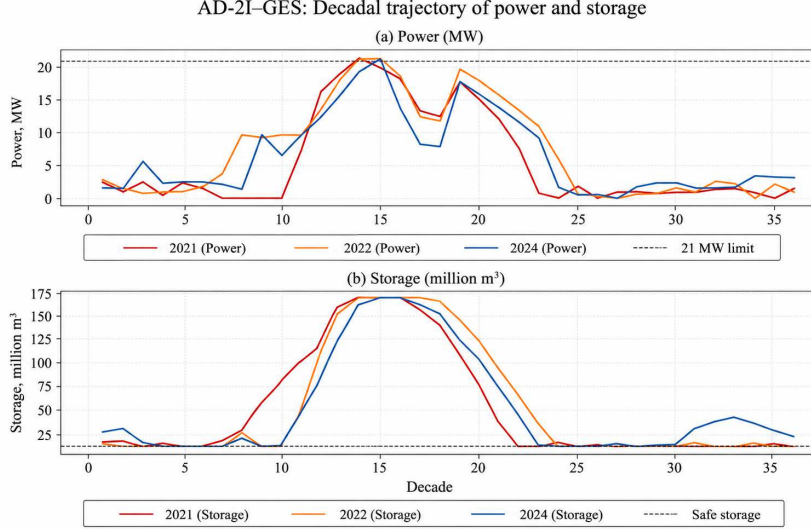


Fig. 10 Decadal trajectory of power output and storage under AD-2I-WE (selected years)

4.14 Bootstrap and leave-one-year-out robustness results

For the W2 base 313.5 million m³ scenario, the six-year mean Rel_v was 76.05%, with a year-block bootstrap (10,000 resamples) 95% empirical interval of 71.80–81.09%. The same method gave the mean deficit of 189.88 million m³/year an interval of 149.95–223.59 million m³/year, and E2 energy of 55.16 GWh/year an interval of 49.85–60.14 GWh/year. These relatively wide intervals mainly reflect genuine hydrological contrast across 2020–2025 and the limited number of annual blocks (six), rather than model error.

The LOYO test demonstrated that the principal conclusion does not depend on any single year: with one year excluded at a time, Rel_v ranged from 73.84% to 77.56%, deficit from 177.96 to 207.43 million m³/year, and energy from 53.52 to 57.14 GWh/year. The largest Rel_v decline occurred excluding 2024 — the base record’s highest-reliability year (73.84%) — while excluding 2021 raised Rel_v to 77.56%. Point estimates are thus sensitive to interannual hydrology, but W2’s overall performance pattern is not generated by any single year.

Table 12 summarizes the statistical robustness of the base W2/E2 results.

Table 12 Statistical robustness of the base W2/E2 results

Indicator	6-year mean	Bootstrap 95% interval	LOYO range
Rel_v , %	76.05	71.80–81.09	73.84–77.56
Deficit, million m ³ /year	189.88	149.95–223.59	177.96–207.43
E2 energy, GWh/year	55.16	49.85–60.14	53.52–57.14

4.15 Long-term inflow–outflow consistency (1988–2023)

The longer archival record shows that annual reservoir release closely tracked annual inflow across 1988–2023. The Pearson correlation was $r=0.992$ ($R^2=0.983$), and the least-squares relationship was $Q_{out}=0.990 \cdot Q_{in}+5.77$ million m^3 /year. The near-unity slope indicates that, at the annual scale, most interannual variation in release was governed by the amount of water entering the reservoir rather than by an independent long-term release trend.

This strong historical coupling is operationally useful but must not be confused with perfect foresight: it demonstrates persistence of the reservoir’s annual water-balance response and supports using historical hydrological regimes as priors or scenario classes for rolling-horizon operation, without establishing that next year’s inflow magnitude can be known exactly. The long record thus strengthens the empirical basis for forecast-conditioned AD-2I–WE operation while leaving rolling-origin forecast validation necessary.

Figure 11 shows the long-term annual inflow and outflow of the Akhangaran Reservoir, 1988–2023.

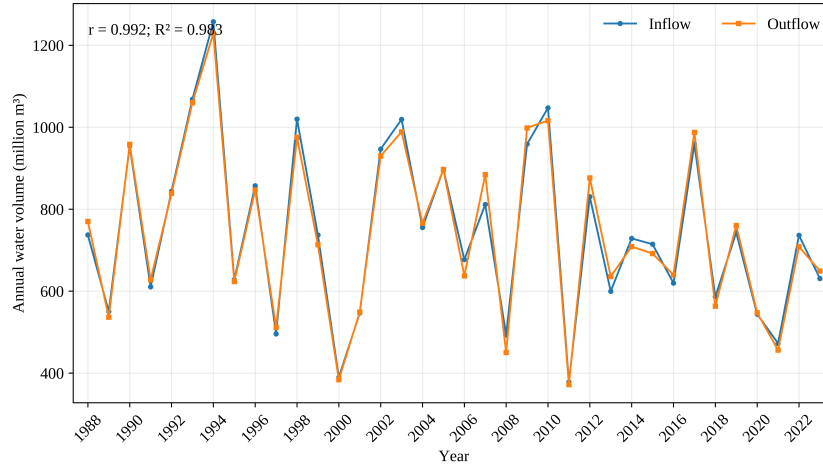


Fig. 11 Long-term annual inflow and outflow of the Akhangaran Reservoir, 1988–2023. The 2024 outflow record was excluded from this diagnostic because the source series contains a physically inconsistent value

5 Discussion

5.1 The mechanism by which sedimentation becomes an operational problem

The central conclusion is that capacity loss from sedimentation is not merely a morphometric indicator: the 28.3 million m^3 loss has narrowed the physical buffer for transferring spring inflow into July–September demand. [Morris \(2020\)](#), [Perera et al.](#)

(2023), and [Rahmani et al. \(2018\)](#) identify declining reservoir capacity through sedimentation as a long-term water-security concern; the Akhangaran results extend this to the operational level — as capacity declines, an unchanged level-based rule curve represents less volume than before at the same level, so preserving rules solely in terms of level is no longer sufficient.

[Khasanov \(2025\)](#), [Khasanov and Bakiev \(2025, 2026\)](#), and regional assessments for Central Asia ([Rakhmatullaev et al. 2010, 2012](#)) demonstrate the regional significance of sedimentation. This study’s distinguishing contribution is integrating repeated bathymetry with the daily operational record, the irrigation order, and physical HPP constraints within a single model — shifting the question from “how much capacity has been lost?” to “which purpose is harmed in which season, and what can operations do about it?”

5.2 AD-2I versus classical hedging and rule-curve approaches

Hedging theory deliberately curtails current supply to reduce the risk of a larger future deficit or low storage ([Shih and ReVelle 1994](#); [Tu et al. 2003](#); [Draper and Lund 2004](#); [You and Cai 2008](#)). The Akhangaran W2 approach is conceptually close but differs institutionally: demand is not eliminated. The 280 million m³ figure remains a first-priority protected block, 313.5 million m³ the base order, and 350 million m³ a conditional block; any undelivered volume is explicitly reported as a deficit — avoiding conflation of “adapting demand” with “removing demand from the statistical denominator.”

The optimal rule-curve literature demonstrates the effectiveness of optimizing storage and release rules ([Zhao et al. 2011](#); [Huang et al. 2016](#); [Xu et al. 2017](#); [Kangrang et al. 2017](#)). The W1–W2 contrast at Akhangaran adds a further point: protecting terminal storage alone is not sufficient. W1 restores 59.74 million m³ at year-end, yet the reservoir still falls to dead storage for an average of 9.7 decades per year, whereas W2’s intra-annual 15 million m³ buffer also reduces the deficit. A terminal carryover target and an intra-annual safety floor are therefore not equivalent constraints.

5.3 The trade-off between the safety margin and reliability

The Vsafe sensitivity analysis rejects the simplistic notion that “more storage margin is always better.” The 5.8 million m³ variant increases reliability but leaves the reservoir at dead storage for extended periods; the 25 million m³ variant strengthens safety but raises the deficit to 206.47 million m³/year. 15 million m³ is therefore not an arbitrary choice but an initial working point within the observed water–safety trade-off; a formal value should be established through technical review incorporating the water-intake structure’s minimum operating level, environmental flow, emergency reserves, and sediment deposition patterns.

The reliability–resilience–vulnerability framework developed by [Hashimoto et al. \(1982\)](#) emphasizes that a single high reliability value does not fully capture system safety. Akhangaran’s W1 is a direct illustration: its time-based reliability substantially exceeds that of W0, yet it carries a dead-storage risk. This article therefore interprets Rel_t and Rel_v jointly with minimum storage, deficit mass, and dead-storage duration.

5.4 The water–energy nexus: the “free” benefit of re-timing and the real trade-off

The 33.9% energy increase from E1 to E2, without any change in water deficit or terminal storage, demonstrates that water and energy objectives are not always zero-sum: shifting the same water volume toward periods of higher head creates an operational synergy, consistent with the storage–release complementarity documented by Zhao et al. (2014) and the energy drawdown value described by Lund (2000). At Akhangaran, this principle holds even under sedimentation-reduced capacity and an existing irrigation commitment.

That E2 remains 22.0% below observed 2022–2024 generation is an important counterpoint: AD-2I–WE does not improve all objectives simultaneously, but first protects water security and safety, then maximizes energy within the remaining freedom. Dai et al. (2018) showed certain multi-node systems can improve both water deficit and hydropower benefit simultaneously; at Akhangaran, however, a single smaller reservoir, a 42 m³/s turbine constraint, and a 14.3% capacity loss narrow this freedom, so the synergy found in other basins does not automatically transfer here.

Yang et al. (2019) show that the priority among water, power, and environmental objectives shifts over time. The WCR regimes in AD-2I translate this into an operational signal: safety and priority supply dominate under water-scarce conditions, the base order governs under normal conditions, and the conditional block and energy freedom expand under water-abundant conditions. Distinctively, this study employs a lexicographic hierarchy rather than dynamic weights, so water security is never implicitly traded away for energy.

5.5 Relationship to Pareto-based approaches

Yan et al. (2020), Saadatpour et al. (2020), and Wang et al. (2022) show the need for a set of nondominated solutions rather than a single optimum in multi-objective reservoir management. For Akhangaran, the protocol $\text{Def} \leq (1+\alpha)\text{Def}^*$, $\alpha=0;0.02;0.05;0.10$, provides a means of constructing such a front, but points with $\alpha>0$ are not declared a final “best scenario” because the economic damage of deficit by sector, the value of minimum ecological flow, and the temporal profile of energy prices remain unavailable. Uncomputed or economically unquantified Pareto points are therefore deliberately not presented as practical recommendations.

5.6 Structural spill and infrastructure limits

The 63.08 million m³ spill in 2022 is among the model’s most practically significant findings: that it persisted even under perfect information rules out a simple operator-error explanation. Mousavi et al. (2021) use a water/energy pinch approach to identify system-wide conservation opportunities; at Akhangaran, the spill remaining after optimal re-timing is interpreted as a “structural” volume, providing a direct entry point for a techno-economic assessment of turbine modernization, an additional generating unit, pre-emptive release, or an alternative outlet.

5.7 Joint interpretation of sedimentation and hydropower head

The $H(V)$ diagnostic sharpens the water–energy linkage: at the current maximum storage of 169.4 million m^3 , the empirical head is about 62.1 m, versus about 69.3 m at the historical storage of 197.7 million m^3 — indicating that sedimentation narrows not only storage capacity but also the head attainable at high storage. This is interpreted cautiously, however, since tailwater geometry, hydraulic losses, and the turbine efficiency curve were not modeled separately; the 7.27 m difference should be read as an “energy-potential diagnostic” rather than a directly measured historical generation loss.

5.8 Rolling-horizon implementation and decision support

These computations constitute a perfect-information retrospective benchmark: the full historical year’s net input is assumed known in advance. In real operation, AD-2I–WE should run in rolling-horizon mode (Alemu et al. 2011; Wang et al. 2014; Kangrang et al. 2017; Li et al. 2018): at each decade’s start, storage is updated from the observed level, a 3–6 decade inflow ensemble is obtained, remaining demand and the tributary forecast are recomputed, only that decade’s release is confirmed, and the problem is re-solved next decade — so forecast error is never “frozen” into a single annual decision.

The 1988–2023 archive provides an additional empirical basis for this transition: annual inflow and release were very strongly coupled ($r=0.992$; $R^2=0.983$), showing the operating system has historically responded consistently to interannual water availability. This relationship can define hydrological analogues and prior scenario classes in a rolling-horizon forecast; however, because release is itself an operational response to inflow, the correlation is not a forecast-skill metric and does not remove the need to withhold future observations during hindcast validation.

In practical deployment, the model should function not as an automatic command system but as a decision-support tool for the dispatcher; when an operator deviates from its recommendation for reasons of safety, maintenance, hydraulic-structure condition, or an external directive, a reason code should be logged, so that later recalibration can examine the discrepancy between recommendation, decision, and actual outcome. This does not shift institutional responsibility onto the model but improves the consistency and transparency of decision-making.

5.9 Transferability of the model

The AD-2I–WE architecture transfers to other reservoirs, but the numerical parameter values do not: for each facility, the H – V curve, inflow forecast, downstream supply, mandatory demand, V_{safe} , turbine Q_{max} , P_{max} , and head–efficiency characteristic must be determined locally, and the R1–R5 WCR thresholds are not a universal standard. The model’s transferable component is its architecture: data $\rightarrow$ safe water $\rightarrow$ lexicographic allocation $\rightarrow$ energy optimization $\rightarrow$ decision signal.

5.10 Limitations and future research

The first limitation is the absence of actual sector-level consumer orders and delivery records; demand was derived from the normative operating rules. The second is that only annual downstream-tributary volumes were measured, with monthly distribution proxy-derived from reservoir inflow, so the tributary–inflow correlation cannot serve as an independent statistical test. The third is that net input combines evaporation, seepage, and measurement residuals, which should be modeled separately in future work.

The fourth limitation is that the 15 million m^3 safety margin is not a formal operational norm. The fifth is that the energy module uses a constant $\eta=0.85$, and the $H(V)$ regression does not separately represent tailwater level and hydraulic losses; the 27 m clip is frequently active at $V<32.8$ million m^3 . The sixth is that duplicate records and the May 2021 gap in the HPP dataset restricted observed-data validation to 2022–2024. The seventh is that minimum ecological flow, unit commitment, minimum turbine flow, ramping, and maintenance constraints are not fully incorporated, though frameworks embedding ecological-release constraints exist (Wang et al. 2015; Sunil et al. 2024) and could be integrated in future work.

The eighth limitation is that years were optimized independently; the carryover effect of a sequential multi-year drought was not separately simulated. The ninth is that the perfect-information benchmark does not evaluate real forecast error — the strong 1988–2023 annual inflow–release coupling is a water-balance/operational relationship, not independent forecast skill. Future work should include a rolling-origin hindcast, ensemble forecasting, uncertainty in η and H , multi-year simulation, and a Pareto analysis incorporating a sector-specific damage function.

5.11 Robustness of the results and strength of evidence

The bootstrap and LOYO results distinguish two sources of uncertainty. The first is interannual hydrological variability: excluding a favorable year such as 2024 lowers Rel_v , while excluding a stress year such as 2021 raises it. The second is sample length: bootstrapping six annual blocks naturally widens the interval. Nevertheless, in the LOYO test all five-year means of Rel_v remained above 73.84%, and energy remained within 53.52–57.14 GWh/year, so the central conclusion — that the adaptive W2/E2 policy jointly improves water security and energy timing — does not rest on any single extreme year. This should not, however, be read as a guarantee for climatic conditions outside the 2020–2025 hydrological ensemble.

An important methodological distinction is that this bootstrap does not resample the 216 decadal points as independent observations; entire years are resampled as blocks. This preserves seasonal and within-year dependence and reduces the risk of obtaining an artificially narrow confidence interval. The resulting interval is accordingly interpreted as a retrospective robustness interval rather than as classical i.i.d. inference.

5.12 Map of model limitations and their effect on conclusions

Table 13 maps the AD-2I-WE model’s limitations and their potential effect on the conclusions.

Table 13 Map of AD-2I-WE model limitations

Limitation / uncertainty	Potential effect on results	Control applied in this study	Future resolution
6-year operational period	Mean indicators sensitive to interannual hydrology	Year-block bootstrap + LOYO	Longer record and climate ensembles
Monthly tributary proxy	Simplifies the shape of decadal lateral inflow	Not used as an independent statistical predictor	Decadal / measured lateral flow
Perfect-information hindcast	Does not account for real forecast error	Result interpreted as an upper-bound benchmark	Rolling-horizon hindcast + real forecast
Linear $H(V)$ regression and 27 m clip	Increases energy uncertainty at low storage	Clip activation reported openly (154/216 decades)	Physical head model with tailwater and head losses
Constant $\eta=0.85$	Affects point estimates of energy	Reported openly as a limitation	$\eta(Q,H)$ efficiency hill-chart
$Q_{\max}=42 \text{ m}^3/\text{s}$	May cause structural spill in wet years	Identified via the 2022 E4 experiment	Technical sensitivity analysis and modernization feasibility study for 42–50 m^3/s
No sector damage functions	Limits economic interpretation of the Pareto front	Lexicographic water-first objective adopted	Multi-objective model with sector values and ecological flow

This map is provided not to obscure the model’s weaknesses but to distinguish which conclusions rest on which level of evidence. The water balance and the W0–W2 benchmarks are directly supported by available data; energy results depend more heavily on $H(V)$, η , and the turbine constraints; and rolling-horizon and modernization scenarios remain subjects for future testing.

6 Conclusions and Practical Recommendations

1. Storage at $H^*=1070.5 \text{ m}$ in the Akhangaran Reservoir declined from 197.7 to 169.4 million m^3 between 1972 and 2022, a loss of 28.3 million m^3 , or 14.3%. This loss changes the volumetric meaning of the legacy dispatch levels and narrows the seasonal water-transfer capability.
2. Under the W0 observed-regime stress test, $Rel_v=69.72\%$, $Rel_t=36.11\%$, and the deficit was 240.08 million m^3/year . 68.3% of the total deficit occurred in

July–September, indicating that the problem lies not only in annual water quantity but in the temporal mismatch between demand and inflow.

3. W1, with a hard 59.74 million m³ terminal storage target, reduced the deficit to 229.37 million m³/year but caused the reservoir to fall to dead storage for an average of 9.67 decades per year. A terminal carryover target cannot substitute for an intra-annual safety floor.
4. W2, under the base 313.5 million m³ irrigation order, maintained the 15 million m³ safety margin while raising Rel_v to 76.05% and reducing the deficit relative to W0 by 50.20 million m³/year, or 20.9%.
5. Under irrigation orders of 280, 313.5, and 350 million m³, the deficit was 162.43, 189.88, and 220.08 million m³/year, respectively. 350 million m³ should not be treated as a pre-committed firm norm but rather as a conditional block released incrementally as actual storage and updated forecasts allow.
6. The H(V) regression gives an empirical head of approximately 62.1 m at the current 169.4 million m³ maximum storage, versus approximately 69.3 m at the 1972 storage of 197.7 million m³. This illustrates the morphometric effect of sedimentation on energy potential but should not be interpreted as a historical generation loss.
7. AD-2I-WE increased energy from 41.18 to 55.16 GWh/year (+33.9%) without degrading the water deficit or terminal storage, demonstrating that when the available water is released matters as much as how much is released.
8. As irrigation demand increased from 280 to 350 million m³/year, energy changed by only 0.3%, while the deficit rose by 35.5%. A higher water order therefore cannot be justified on energy grounds.
9. The 63.08 million m³ spill in 2022 persisted even under perfect information, revealing a structural constraint imposed by the 169.4 million m³ storage capacity and the 42 m³/s turbine conveyance limit. This signals the need for a dedicated techno-economic assessment of modernization options.
10. AD-2I-WE produced 22.0% less energy than observed in 2022–2024. The model’s purpose is therefore not to dominate every indicator simultaneously but to make the best use of the available energy freedom once water security has been given first priority.
11. The year-block bootstrap yielded a 95% empirical interval of 71.80–81.09% for W2’s Rel_v =76.05%; the LOYO test kept Rel_v within 73.84–77.56%, the deficit within 177.96–207.43 million m³/year, and energy within 53.52–57.14 GWh/year. This indicates that the main conclusions are not driven by any single year, while the six-year record means that residual uncertainty should be kept explicit.
12. The quality-controlled 1988–2023 archive showed a very strong annual inflow–outflow coupling (r =0.992; R^2 =0.983). This supports the use of historical hydrological analogues in rolling-horizon operation, but it should not be interpreted as evidence that future inflow is known exactly; out-of-sample forecast validation remains necessary.
13. Before practical implementation, it is recommended to formalize the 2022 H–A–V curve for operational use, establish at least monthly or decadal monitoring of downstream tributaries, subject the 15 million m³ safety buffer to technical review,

incorporate nameplate HPP $Q-H-\eta$ surfaces, and conduct a rolling-origin hindcast using a 3–6 decade ensemble forecast.

Declarations

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Competing Interests

The author declares that there are no competing financial or non-financial interests that could have influenced the work reported in this manuscript.

Ethics Approval

Not applicable. This study was based exclusively on hydrological, reservoir-operation, bathymetric, and hydropower datasets and did not involve human participants, human-derived data, animals, or biological materials.

Consent to Participate

Not applicable. The study did not involve human participants.

Consent for Publication

Not applicable. The manuscript does not contain identifiable personal information or other material requiring consent for publication.

Data Availability

The data supporting the findings of this study include historical bathymetric height–area–volume (H–A–V) relationships, reservoir operational records for 2020–2025, digitized dispatcher-rule information, and hydropower plant operational data. Some of the primary operational and hydropower datasets were obtained from the relevant operating organizations and are therefore subject to institutional data-sharing restrictions. These data may be made available by the corresponding author upon reasonable request and with permission from the respective data-owning organizations.

The processed computational database used to implement the AD-2I–WE framework, including quality-control records, reconstructed demand series, digitized dispatcher trajectories, scenario definitions, intermediate calculations, and aggregated model outputs, can be made available as supplementary material where permitted. To ensure consistency and reproducibility, the source computational database was subjected to additional quality control during manuscript preparation, including correction of a textual misclassification in the Water Coverage Ratio (WCR) regime labels. This correction affected the regime labels only and did not alter the underlying water-balance calculations or the reported quantitative results.

Author Contributions

Khojiakbar Khasanov: Conceptualization, methodology, data curation, data verification, formal analysis, software, model development and implementation, validation, visualization, investigation, interpretation of results, writing—original draft, and writing—review and editing.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this manuscript, generative AI-assisted tools were used to support language editing, improvement of scientific clarity and structure, and assistance with computational coding and visualization. All scientific concepts, methodological decisions, input data, model assumptions, calculations, interpretations, and conclusions were critically reviewed and verified by the author. The author takes full responsibility for the accuracy, integrity, and content of the final manuscript.

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