

UPW-Aware Semiconductor Supply-Chain Planning Under Disruptions: Qualification, Reclamation and Stochastic-Robust Optimization

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ABSTRACT

Semiconductor manufacturing depends on geographically concentrated, capital-intensive networks and on ultrapure water (UPW), whose availability is constrained by basin conditions, treatment requirements, reclamation capacity, and process qualification. This study develops a multi-period two-stage stochastic-robust multi-objective mixed-integer linear programming model that jointly determines capacity expansion, UPW-reclamation investment, and backup-fab qualification before disruption, while coordinating production, transportation, inventory, qualified outsourcing, freshwater feed, reclaimed feed, emergency water, and unmet demand after uncertainty is revealed. The four objectives minimize lifecycle cost, carbon emissions, scarcity-weighted freshwater footprint, and the unmet-demand ratio. A stabilized adaptive multi-cut column-and-constraint generation method, SAMC-C&CG, combines critical-pattern initialization, violation-based cut selection, duplicate and dominance screening, incumbent completion, and conditional L1 stabilization. The computational study uses 60 independent synthetic networks, mechanism and algorithmic ablations, an 18-run sensitivity analysis design, a five-level AUGMECON2 experiment, and 1,000 common-random-number out-of-sample realizations. Across the 60 networks, the proposed policy reduces lifecycle cost by 1.593% and scarcity-weighted freshwater footprint by 11.900%, while carbon emissions increase by 0.673% and mean service changes by only -0.092 percentage points. Out of sample, cost, carbon, and freshwater decrease by 1.586%, 0.950%, and 19.029%, respectively, while service decreases by 1.254 percentage points. The results support integrated qualification and reclamation planning but also demonstrate that finite scenario representations can overstate service invariance in-sample.

Keywords: Semiconductor Supply Chain; Supply Chain Resilience; Stochastic-Robust Optimization; Multi-Objective Optimization; Ultrapure Water Management; Disruption Management.

INTRODUCTION

Semiconductor supply chains combine high fixed investment, long qualification cycles, specialized production

stages, geographical concentration, and strong exposure to demand, supply, climate, and geopolitical shocks [1]–[6]. Recent semiconductor research increasingly treats resilience and sustainability as coupled planning requirements rather than separate performance dimensions [7]–[12].

Water adds a distinctive constraint. UPW is a process-quality input rather than a direct substitute for raw freshwater: freshwater must pass treatment and polishing stages, while recovered process water must satisfy recovery and quality requirements before reuse. Recent evidence documents the substantial water and wastewater burden of semiconductor foundries and the growing role of treatment, recycling, and resource-efficiency measures [13]–[18]. Regional scarcity factors also matter because identical physical withdrawals can have materially different scarcity consequences across basins [19]–[22]. In the present formulation, the water objective applies scarcity weighting to both normal and emergency freshwater feed because both represent basin withdrawals; reclaimed water is not counted as a freshwater withdrawal. This treatment is a modeling convention for the physical withdrawal boundary, not a claim that emergency water has a distinct environmental characterization factor from the basin source itself.

This study jointly optimizes three lead-time-dependent strategic capabilities: capacity expansion, UPW reclamation, and backup-fab qualification. The central research question is how these capabilities should be scheduled when stochastic disruptions interact with bounded demand and freshwater deviations. The contribution is deliberately narrower than a generic resilient-network model: it embeds a physically interpretable UPW layer, exact qualification timing, and a stabilized adaptive C&CG procedure within one multi-objective MILP. The evaluation is also multi-instance and includes independent out-of-sample testing, allowing the paper to distinguish optimization performance from generalization [23]–[30].

LITERATURE SYNTHESIS AND RESEARCH GAP

Recent resilient-network studies emphasize proactive investment, disruption propagation, uncertainty modeling, and recovery flexibility [1], [23]–[30]. For semiconductor systems, recent work addresses supply disruption, strategic inventory, sourcing, geopolitical risk, production uncertainty, and material-network vulnerability [7]–[12], [31]–[36]. However, these streams generally do not couple semiconductor qualification timing with basin-specific freshwater scarcity and an explicit UPW conversion-reclamation layer.

Water-treatment research provides the engineering basis for recovery, contaminant removal, recycling, and high-purity water management [13], [17], [18]. Recent environmental assessments further show that semiconductor manufacturing is simultaneously water- and energy-intensive, making reclamation decisions inherently multi-objective [14], [15], [19]–[22]. The remaining decision gap is temporal and network-wide: reclamation changes freshwater dependence and energy use; qualification converts emergency sourcing into prepared capacity after a lead time; and capacity expansion changes where both capabilities create value.

Table 1. Critical Positioning of the Proposed Study

Stream	Established Focus	Unresolved Gap Addressed Here
Semiconductor planning	Capacity, production, yield/demand uncertainty, disruption response	Basin scarcity linked to UPW conversion and qualification timing
Water and UPW treatment	Recovery technology, membrane performance, reuse quality	Strategic investment and network recourse under disruptions
Resilient SCND	Redundancy, fortification, inventory, backup sourcing	Prepared versus emergency backup with qualification lead time
Stochastic-robust optimization	Scenario recourse and bounded deviations	Joint demand-water adversity with semiconductor physics
Decomposition	C&CG, multi-cuts, warm starts	Adaptive cut choice, dominance screening, stabilization, and multi-instance evidence

Problem Description and Mathematical Model

The network contains wafer suppliers, owned fabs, candidate backup fabs, packaging/testing plants, distribution centers, and markets. First-stage decisions determine expansion E , reclamation investment R , and qualification initiation V before uncertainty is resolved. Second-stage decisions are optimized after the complete disruption trajectory and adversarial demand-freshwater pattern are revealed. This is a two-stage formulation with complete-trajectory recourse; multi-stage nonanticipativity is intentionally outside the present model and is treated as a limitation. The notation used throughout the model is summarized in Table 2.

UPW-Aware Semiconductor Planning and Evaluation Architecture

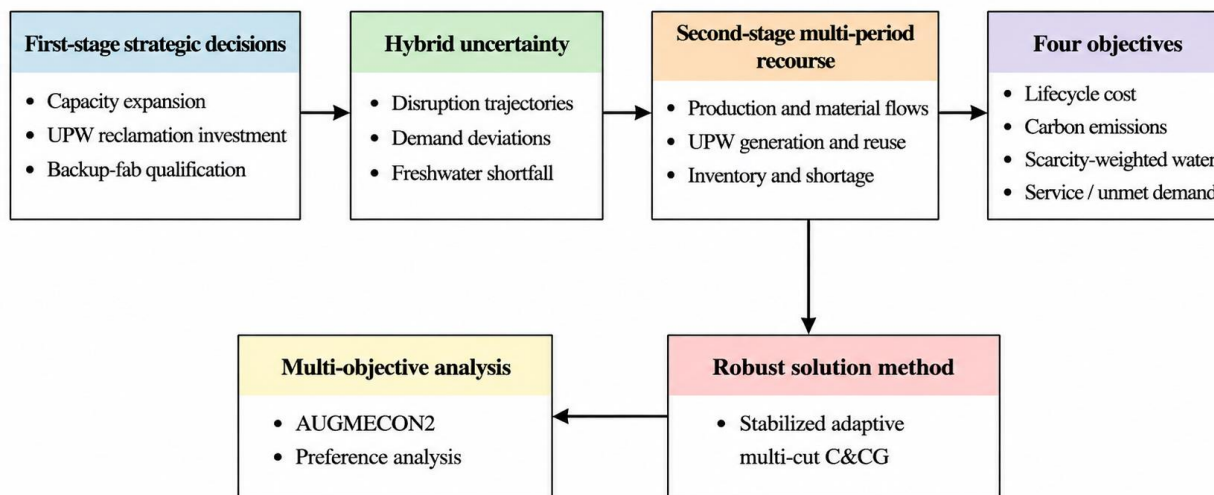


Figure 1. Two-stage UPW-aware planning, solution, and validation framework

Representative Multi-Echelon Network with Embedded UPW Reclamation

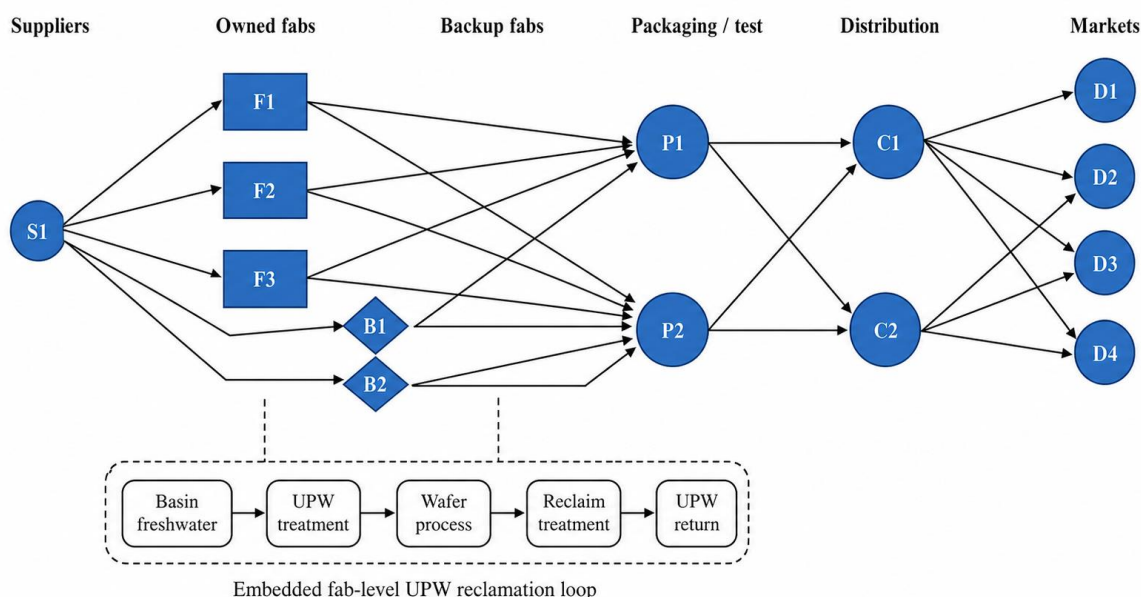


Figure 2. Semiconductor Network with an Embedded UPW-Generation and Reclamation Layer

Demand and basin freshwater availability are represented by budgeted deviations. The uncertainty structure combines stochastic disruption trajectories with robust demand and water deviations. A finite critical-pattern pool is used in computational implementation so that the C&CG procedure has an explicit and auditable scenario representation.

Equation (1). Demand Uncertainty

$$\tilde{D}_{dt\omega k} = \bar{D}_{dt\omega} + \hat{D}_{dt\omega} \xi_{dt\omega k}^D, \quad 0 \leq \xi_{dt\omega k}^D \leq 1, \quad \sum_d \xi_{dt\omega k}^D \leq \Gamma_{t\omega}^D$$

Equation (2). Freshwater-Availability Uncertainty

$$\tilde{A}_{jt\omega k} = \bar{A}_{jt\omega} - \hat{A}_{jt\omega} \xi_{jt\omega k}^W, \quad 0 \leq \xi_{jt\omega k}^W \leq 1, \quad \sum_j \xi_{jt\omega k}^W \leq \Gamma_{t\omega}^W$$

Equation (3). Four-Objective Model

$$\min Z = (Z^1, Z^2, Z^3, Z^4)$$

Equation (4). Expected Lifecycle Cost

$$Z^1 = C^{\text{strat}}(x) + \sum_{\omega} p_{\omega} \theta_{\omega}^C, \quad \theta_{\omega}^C \geq C^{\text{oper}}_{\omega k(x,y)}, \quad \forall \omega, k \in K_{\omega}$$

Equation (5). Expected Carbon Emissions

$$Z^2 = \sum_{\omega} p_{\omega} \theta_{\omega}^{CE}, \quad \theta_{\omega}^{CE} \geq CE_{\omega k(x,y)}, \quad \forall \omega, k \in K_{\omega}$$

Equation (6). Scarcity-Weighted Freshwater Footprint

$$Z^3 = \sum_{\omega} p_{\omega} \theta_{\omega}^W, \quad \theta_{\omega}^W \geq \sum_t \sum_j WSI_{jt\omega} (FW_{jt\omega k} + EW_{jt\omega k}), \quad \forall \omega, k$$

Equation (7). Expected Unmet-Demand Ratio

$$Z^4 = \sum_{\omega} p_{\omega} \theta_{\omega}^U, \quad \theta_{\omega}^U \geq \frac{[\sum_t \sum_d U_{dt\omega k}]}{[\sum_t \sum_d \tilde{D}_{dt\omega k}]}, \quad \forall \omega, k$$

Strategic investment and worst-case scenario operating cost are part of the lifecycle objective. The carbon boundary includes production, transport, UPW generation, and reclamation energy represented in the model. The water objective includes normal and emergency freshwater feed and does not deduct reclaimed water because the metric is defined on basin freshwater withdrawal rather than gross process-water circulation. Emergency water is therefore weighted by the same basin scarcity factor as other freshwater withdrawal from that basin; this is a deliberate accounting boundary, not a claim that emergency sourcing is environmentally identical in every operational context.

There are clear lead times for expansion and qualification. A backup can be initiated at most once when not qualified, or activated through the qualified route after the qualification lead time; qualified and emergency output share physical capacity, and only qualified output uses the prepared-route cost. UPW demand is directly proportional to fab production output. Source-specific yields are determined by fresh and emergency feed, while reclaimed feed is limited by recoverability and installed treatment capacity. Variable domains and input safeguards enforce nonnegativity, capacity, timing, and flow consistency.

Equation (8). Owned-Fab Capacity

$$X_{ft\omega k} \leq \rho_{ft\omega} \left[H_f^0 + \sum_{\{\tau \leq t - L_f^E\}} E_{f\tau} \right], \quad \forall f, t, \omega, k$$

Equation (9). Qualification and Backup Capacity

$$\begin{aligned} \sum_t V_{bt} &\leq 1 - q_b^0, \\ X_{bt\omega k}^Q &\leq \rho_{bt\omega}^B H_b^B \left[q_b^0 + \sum_{\{\tau \leq t - L_{Qb}\}} V_{b\tau} \right], \\ X_{bt\omega k}^Q + X_{bt\omega k}^E &\leq \rho_{bt\omega}^B H_b^B, \quad \forall b, t, \omega, \end{aligned}$$

Equation (10). UPW Demand and Production

$$G_{jt\omega k} = u_j^{UPW} \chi_{jt\omega k},$$

$$G_{jt\omega k} = \eta_j^F (FW_{jt\omega k} + EW_{jt\omega k}) + \eta_j^R RW_{jt\omega k},$$

Equation (11). UPW Reclamation Limits

$$RW_{jt\omega k} \leq \lambda_j G_{jt\omega k},$$

$$RW_{jt\omega k} \leq R_{jt}^0 + 1_{\{j \in F\} \Sigma_{\{\tau \leq t - LR_j\}} \kappa_{jt}^R R_{j\tau}}, \quad \forall j, t, \omega, k$$

Equation (12). Freshwater-Feed Limits

$$FW_{jt\omega k} \leq \tilde{A}_{jt\omega k}, \quad 0 \leq EW_{jt\omega k} \leq \bar{E}W_{jt}, \quad \forall j, t, \omega, k$$

Equation (13). Material Balances

$$\Sigma_{\{a \in \delta^-(f)\} Y_{at\omega k}} = X_{ft\omega k} = \Sigma_{\{a \in \delta^+(f)\} Y_{at\omega k}}, \quad f \in F,$$

$$\Sigma_{\{a \in \delta^-(b)\} Y_{at\omega k}} = X_{bt\omega k}^Q + X_{bt\omega k}^E = \Sigma_{\{a \in \delta^+(b)\} Y_{at\omega k}}, \quad b \in B,$$

$$\Sigma_{\{a \in \delta^-(n)\} Y_{at\omega k}} + I_{n, t-1, \omega k} = \Sigma_{\{a \in \delta^+(n)\} Y_{at\omega k}} + I_{nt\omega k}, \quad n \in P \cup C$$

Equation (14). Customer Balance and Service

$$\Sigma_{\{a \in \delta^-(d)\} Y_{at\omega k}} + U_{dt\omega k} = \tilde{D}_{dt\omega k},$$

$$U_{dt\omega k} \leq (1 - SL^{\min_dt}) \tilde{D}_{dt\omega k}, \quad \forall d, t, \omega, k$$

The MILP is then completed with supplier, arc, processing, inventory-bound and variable-domain constraints. All node-specific equations and full cost and carbon decompositions are given in Supplementary Material S1.

Table 2. Core Notation Used in the Mathematical Model

Symbol	Meaning	Role / domain
$E_{f\tau}$	Capacity expansion initiated at facility f in period τ	First-stage investment/binary decision
$R_{j\tau}$	UPW reclamation investment at fab j in period τ	First-stage investment decision
$V_{b\tau}$	Backup-fab qualification initiation at backup fab b in period τ	First-stage binary decision
$X_{ft\omega k}$	Owned-fab production/flow quantity	Second-stage operating variable
$X^Q_{bt\omega k}$	Qualified backup-fab output	Second-stage operating variable
$X^E_{bt\omega k}$	Emergency backup-fab output	Second-stage operating variable
$G_{jt\omega k}$	UPW requirement at fab j	Second-stage water/production variable
$FW_{jt\omega k}$	Normal freshwater feed	Second-stage water variable
$EW_{jt\omega k}$	Emergency freshwater feed	Second-stage water variable
$RW_{jt\omega k}$	Reclaimed-water feed	Second-stage water variable
$U_{dt\omega k}$	Unmet demand at customer d	Second-stage shortage variable

$Y_{at\omega k}$	Material flow on arc a	Second-stage network-flow variable
$I_{nt\omega k}$	Inventory at node n at the end of period t	Second-stage inventory variable
$\tilde{D}_{dt\omega}$	Realized demand under robust deviation	Demand-uncertainty quantity
$\bar{D}_{dt\omega}$	Nominal demand	Demand parameter
$\hat{D}_{dt\omega}$	Maximum demand deviation	Demand-uncertainty parameter
$\xi^{\wedge} D_{dt\omega k}$	Demand deviation variable	Robust uncertainty variable
$\tilde{A}_{jt\omega}$	Realized basin freshwater availability	Freshwater-uncertainty quantity
$\bar{A}_{jt\omega}$	Nominal basin freshwater availability	Water-availability parameter
$\hat{A}_{jt\omega}$	Maximum freshwater-availability deviation	Water-uncertainty parameter
$\xi^{\wedge} W_{jt\omega k}$	Freshwater-availability deviation variable	Robust uncertainty variable
$\Gamma^{\wedge} D_{t\omega}$	Demand uncertainty budget	Robustness parameter
$\Gamma^{\wedge} W_{t\omega}$	Freshwater uncertainty budget	Robustness parameter
$\rho_{ft\omega}$	Capacity/yield factor for owned facility f	Scenario- and facility-dependent parameter
$\rho^{\wedge} B_{bt\omega}$	Capacity/yield factor for backup facility b	Scenario- and backup-dependent parameter
H_f^0	Initial capacity of owned facility f	Capacity parameter
H_b^B	Physical capacity of backup facility b	Backup-capacity parameter
L_f^E	Expansion lead time at facility f	Timing parameter
L_b^Q	Qualification lead time at backup fab b	Timing parameter
q_b^0	Initial qualification status of backup fab b	Initial binary/status parameter
u_j^{UPW}	UPW requirement per unit of fab production	Process parameter
$\chi_{jt\omega k}$	Fab production quantity used to determine UPW requirement	Second-stage production quantity
η_j^F	Effective UPW yield from freshwater/emergency feed	Water-treatment parameter
η_j^R	Effective UPW yield from reclaimed-water feed	Water-treatment parameter
λ_j	Maximum reclaimable fraction/limit at fab j	Reclamation parameter
$\bar{E}^{\wedge} W_j$	Upper bound on emergency freshwater feed	Water-capacity parameter
$WSI_{jt\omega}$	Basin water-scarcity characterization factor	Water-objective parameter
p_{ω}	Probability assigned to disruption trajectory ω	Stochastic parameter
ω	Disruption trajectory index	Scenario index
k	Critical-pattern index within trajectory ω	Critical-pattern index
F, B, D, J, T	Facility, backup, customer, fab, time, arc, and network-node index sets	Index sets
$\delta^{\wedge} - (n), \delta^{\wedge} + (n)$	Incoming and outgoing arc sets of node n	Network incidence notation

SL_{dt}^{min}	Minimum service requirement for customer d in period t	Service constraint parameter
C^{strat}	Strategic first-stage cost	Lifecycle-cost component
$C_{\omega k}$	Operating cost under trajectory ω and pattern k	Recourse-cost component
$CE_{\omega k}$	Carbon emissions under trajectory ω and pattern k	Carbon-emission quantity
θ_{ω}^C	Worst-case recourse cost auxiliary	Master-problem auxiliary
θ_{ω}^{CE}	Worst-case carbon auxiliary	Master-problem auxiliary
θ_{ω}^W	Worst-case freshwater-footprint auxiliary	Master-problem auxiliary
θ_{ω}^U	Worst-case unmet-demand auxiliary	Master-problem auxiliary
Z_1	Lifecycle-cost objective	Objective value
Z_2	Carbon-emission objective	Objective value
Z_3	Scarcity-weighted freshwater-footprint objective	Objective value
Z_4	Expected unmet-demand-ratio objective	Objective value
$Q_{\omega}(x)$	Adversarial recourse value for trajectory ω	C&CG subproblem value
LB^r, UB^r	Lower and upper bounds at iteration r	C&CG convergence quantities
$\{Gap\}^r$	Relative C&CG bound gap at iteration r	Stopping criterion
ε^{CCG}	C&CG convergence tolerance	Algorithm parameter

Solution Methodology

Multi-Objective Solution

The payoff matrix has four lexicographic extremes. The main goal is lifecycle cost, with carbon, freshwater and unmet demand as epsilon constraints. AUGMECON2 is based on the normalized slack augmentation and bypass logic to eliminate weakly efficient and redundant grid points.

Equation (15). AUGMECON2

$$\min \quad Z^1 - \eta \frac{\sum_{r=2}^4 S_r}{Z_r^{nad} - Z_r^{ideal}}$$

$$s.t. \quad Z_r + s_r = \varepsilon_r \quad (r = 2,3,4), \quad s_r \geq 0, \quad \eta > 0$$

Samc-C&CG

For fixed first-stage decisions, the adversarial recourse evaluation searches the finite critical-pattern pool for a pattern that produces the largest relevant recourse violation or objective deterioration. The restricted master is initialized with nominal, demand-critical, water-critical, and combined patterns. At each iteration, candidate patterns are ordered by violation magnitude; duplicate candidates are discarded first, followed by monotonic-dominance screening. Among the remaining candidates, the highest-ranked admissible pattern is selected for cut generation. The implementation may retain an aggregated cut or scenario-specific multi-cuts according to the violation structure. Conditional L1 stabilization is activated when the strategic first-stage solution exhibits the documented oscillation condition in the implementation. The SAMC-C&CG implementation follows a finite critical-pattern framework that integrates critical-pattern initialization, adaptive cut selection, duplicate and dominance screening, incumbent completion, and conditional L1 stabilization to improve computational efficiency and solution robustness.

Equation (16). Adversarial Recourse and Stopping Rule

$$Q_{\omega(x)} = \max_{\{\xi \in U_{\omega}\}} \min_{\{y \in Y(x, \xi)\}} C^{\text{oper}}_{\omega(x, y, \xi)}$$

$$Gap^r = \frac{UB^r - LB^r}{\max\{1, |UB^r|\}} \leq \varepsilon^{CCG}$$

Finite-pool convergence follows from the fact that every nonconverged iteration either admits a previously inactive violating pattern or fails the violation test. Duplicate rejection prevents repeated insertion of the same pattern, while dominance screening prevents insertion of patterns that add no stronger restriction under the documented dominance relation. The main-text algorithm is therefore transparent about initialization, candidate ranking, duplicate/dominance screening, stabilization, incumbent completion, and the stopping test. The convergence statement is intentionally bounded to the finite critical-pattern pool; it is not a claim of exactness for an unrestricted uncertainty space. stochastic

Computational Design

Scenario Generation and OOS Design

The computational study evaluates 60 independent synthetic semiconductor supply-chain networks, consisting of 20 Small, 20 Medium, and 20 Large instances. The experimental campaign includes 1,000 common-random-number out-of-sample realizations, mechanism ablation experiments, algorithm ablation experiments, and sensitivity analysis. Detailed instance construction, parameter descriptions, and calibration information are provided in the supplementary materials.

The computational study uses controlled synthetic networks to support reproducible comparisons rather than company-specific inference. Sixty independent instances are divided into 20 Small, 20 Medium, and 20 Large networks, using the documented seed families 31001–31020, 41001–41020, and 51001–51020. The generated parameters cover topology, planning horizon, disruption exposure, demand-water budgets, qualification lead times, UPW use, treatment yields, reclamation capability, investment economics, carbon factors, and scarcity indexes. The manuscript does not provide the underlying probability distributions, parameter ranges, or random-generation equations for each generated field. Those details therefore remain an explicit reproducibility gap and are not reconstructed from generic distributional assumptions.

Table 3. Benchmark-Policy Definitions

Model	Expansion	UPW Reclamation	Qualification	Disruptions	Robust Demand- Water
B1 Static deterministic	No	No	No	No	No
B2 multi-period deterministic	Yes	No	No	No	No
B3 Reactive stochastic- robust	Yes	No	No	Yes	Yes
B4 Full proposed	Yes	Yes	Yes	Yes	Yes

The evidence base comprises equation-level validation, 60-network policy comparison, mechanism ablation across 20 Medium networks, algorithmic ablation across 12 representative networks, an 18-run sensitivity design, a five-level AUGMECON2 experiment, and 1,000 common-random-number OOS realizations across five environments. The reported experiments use paired comparisons, bootstrap intervals, Wilcoxon signed-rank tests, win rates, medians, and geometric-mean speedups. The original implementation used SciPy

MILP/HiGHS, with seeds, inputs, code, outputs, and checksums described as archived in the source study. For the present revision, only results explicitly reported in the manuscript are treated as recoverable evidence.

The 18-run sensitivity design varies qualification lead time, reclamation cost, water-scarcity conditions, and disruption exposure. Its purpose is to test whether the qualitative value of qualification and reclamation is stable under parameter changes. The complete 18-run input/output table and the numerical ranges of the varied parameters are not included in the supplied manuscript. Accordingly, the revision reports the sensitivity results that are independently recoverable from the manuscript—namely the mechanism-level effects across 20 Medium networks and the OOS effects—and does not invent missing run-level values or parameter bounds.

Sensitivity Evidence and Design

The optimization scenario pool contains 20 disruption patterns per network. Patterns combine production-capacity disruption with demand and freshwater deviations, including compound critical configurations in which production and basin availability deteriorate jointly. The pattern pool is separated from the 1,000 common-random-number OOS realizations, which are generated for validation rather than optimization. This separation is essential because OOS evaluation measures generalization of first-stage decisions to unseen realizations [23], [24]. The manuscript identifies the scenario components and seed families but does not provide the underlying probability distributions, dependence/correlation matrix, or exact critical-pattern initialization parameters. These quantities are therefore reported as unavailable in the supplied experimental record rather than replaced with assumed normal, uniform, Bernoulli, or correlated distributions.

RESULTS

Model Validation and Pareto Structure

The eight equation-level tests were passed, and the lifecycle-cost reconciliation was reported as exact. The S01 AUGMECON2 run achieved a success rate of 86/125 nominal grid combinations, skipped 39 combinations, solved 22 combinations, and retained 9 nondominated solutions. The cost anchor achieved cost 219,095.36, carbon 20,543.73, freshwater 6,458.47, and service 99.525%. Service went down 4.317 percentage points while carbon and freshwater went down 5.827% and 8.426%, respectively, with Preferred solution P005 increasing cost by 5.757%.

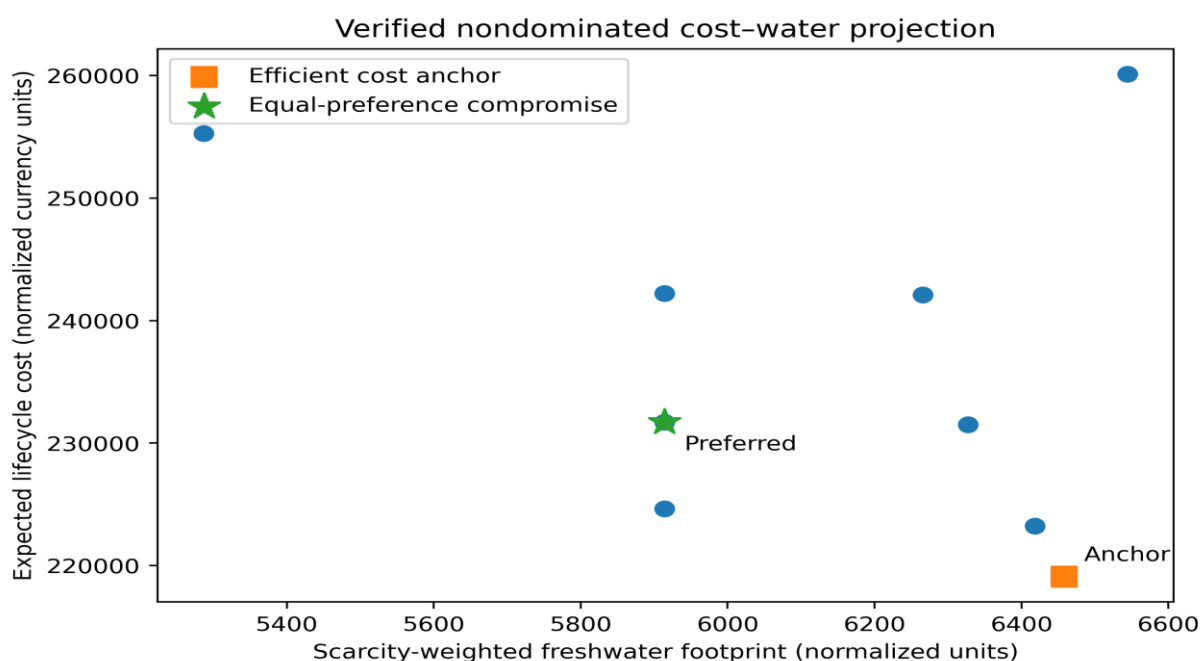


Figure 3. Cost-carbon projection of the verified S01 nondominated set

Policy Evidence Across 60 Networks

Across 60 independent networks, B4 reduced lifecycle cost by 1.593% (bootstrap means 95% CI: -1.742% to -1.450%; win rate 100%) and scarcity-weighted freshwater by 11.900% (CI: -13.707% to -10.188%; win rate 96.7%). Carbon increased by 0.673% (CI: 0.240%-1.114%), reflecting additional treatment energy, while service changed by -0.092 percentage points (CI: -0.243 to 0.054; Wilcoxon $p=.524$). Therefore, cost and water benefits remained constant, carbon was a small cost, and mean service was not different from zero change.

Table 4. B4 Versus B3 Across 60 Independent Networks

Metric	Mean Change	Bootstrap 95% CI	Wilcoxon p	Improvement Win Rate
Lifecycle cost	-1.593%	[-1.742%, -1.450%]	1.63×10^{-11}	100.0%
Carbon	+0.673%	[+0.240%, +1.114%]	.0014	28.3%
Freshwater footprint	-11.900%	[-13.707%, -10.188%]	2.44×10^{-11}	96.7%
Service	-0.092 pp	[-0.243, +0.054] pp	.524	41.7%

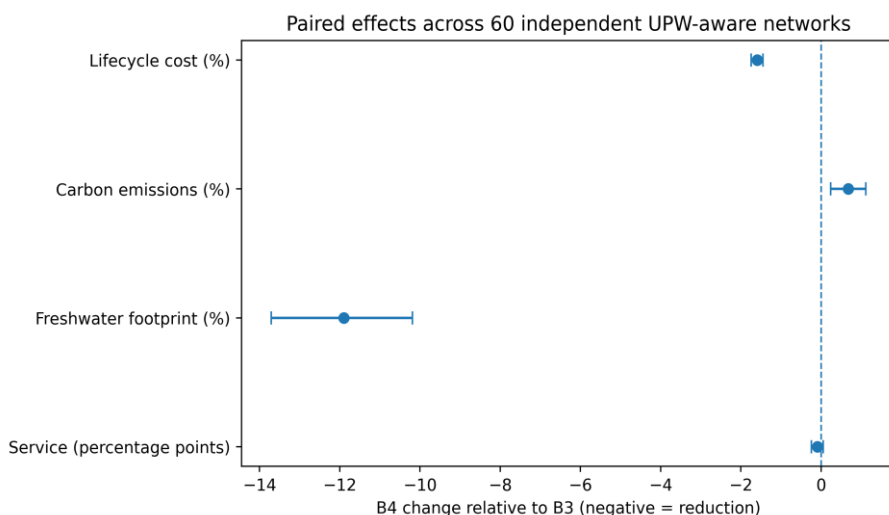


Figure 4. Policy Effects Across 60 Independent Networks

Out-of-Sample and Mechanism Evidence

The OOS evidence should be interpreted as meaningful but imperfect generalization, not as proof of service invariance. For deployment, planners should enrich critical-pattern pools, conduct stress tests outside the optimization scenarios, and recalibrate uncertainty parameters as new disruption information becomes available. The contrast between the in-sample service change of -0.092 percentage points and the OOS reduction of 1.254 percentage points should be treated as a practical service tradeoff: the integrated policy obtains substantial cost and freshwater benefits, but some of those gains can occur alongside lower realized service when uncertainty combinations differ from the optimization pool.

The contrast between the in-sample service change of -0.092 percentage points and the OOS reduction of 1.254 percentage points is the most important qualification of the empirical interpretation. The in-sample scenarios are part of the optimization environment, whereas the OOS realizations are unseen. The larger OOS service loss is therefore consistent with finite-scenario fitting: a strategic policy can perform nearly invariantly on the represented patterns while remaining sensitive to combinations that are absent or underrepresented in

that pool. The interaction among disruption timing, demand deviation, freshwater availability, qualification lead time, and shared capacity further increases the possibility of distributional mismatch.

In 1,000 common M01 realizations, B4 reduced mean cost from 771,039.91 to 758,813.05 (1.586%; paired advantage CI: 11,717.90-12,738.08), carbon from 49,145.82 to 48,679.14 (0.950%), and freshwater from 27,234.97 to 22,052.56 (19.029%). Service fell from 95.751% to 94.498% (-1.254 points). The absolute carbon benefit was partly offset by a 17.844% decrease in freshwater per satisfied unit, while carbon per satisfied unit decreased by 0.429%. Water savings were found in all five environments and were greatest in stable and water constrained environments.

Qualification was the strongest stand-alone cost lever (-2.050%) across 20 Medium networks and UPW reclamation was the strongest stand-alone freshwater lever (-9.069%). The full model lowered cost and freshwater by 2.405% and 12.135%, respectively, with a service change of -0.211 points. The reclamation-qualification combination resulted in a nonadditive improvement in service of 0.202 points. This interaction should not be interpreted as a simple additive gain: qualification changes the timing and availability of prepared production capacity, whereas reclamation changes freshwater dependence and therefore the feasibility of sustaining production under water scarcity. When both capabilities are present, the benefit of one can alter the operating conditions under which the other is effective, so the combined response need not equal the sum of the two isolated responses.

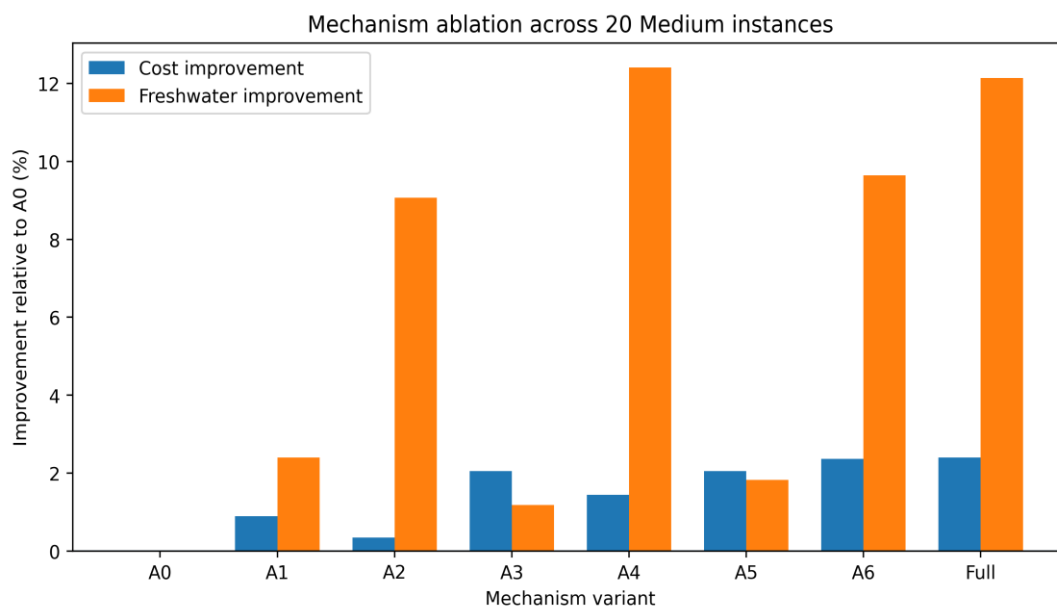


Figure 5. Mechanism Ablation across 20 Medium Networks

Recoverable sensitivity evidence supports the interpretation that qualification and reclamation operate through different mechanisms. Qualification primarily changes the availability of prepared production capacity after a lead time, whereas reclamation changes dependence on basin freshwater and therefore acts most directly on the water objective. The available aggregate results are: qualification alone reduces cost by 2.050%; reclamation alone reduces freshwater by 9.069%; the full model reduces cost and freshwater by 2.405% and 12.135%, respectively; and the combined mechanism produces a 0.202-point nonadditive service improvement. These values are reported because they are explicitly present in the manuscript. The underlying 18-run parameter-by-parameter sensitivity table and tested ranges are not present in the supplied file and therefore are not reconstructed.

Algorithmic Performance

The full method achieved a median speedup of 1.442 $\times$, a geometric-mean speedup of 1.042 $\times$, and a 58.3%-win rate across all 60 networks with overhead incurred from small instances. The median speedups were 1.457 $\times$ for Medium and 1.763 $\times$ for Large, and the wins were 75% and 100% respectively – class-specific evidence is

more informative. The Medium-Large win rate was 87.5%, and maximum deviation from the direct formulation of the objective was 1.12×10^{-6} . C4 obtained a $1.418 \times$ geometric-mean speedup on 12 representative networks, with individual enhancements not always helping to reduce runtimes, but their combined use helping to reduce the median runtime from 3.828 to 2.541 seconds. This contribution is thus scale dependent and not universal.

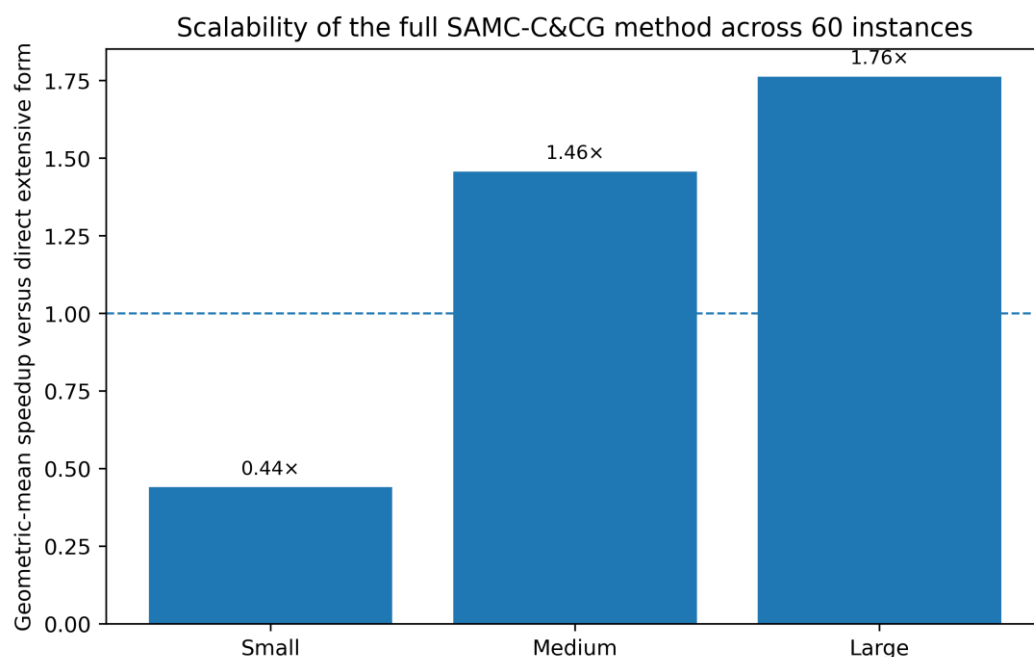


Figure 6. SAMC-C&CG Scalability by 60 Instance Class

DISCUSSION AND IMPLICATIONS

The results identify three distinct strategic functions. Qualification is the principal cost mechanism because it converts an uncertain emergency option into prepared capacity after a lead time. Reclamation is the principal freshwater mechanism because it reduces dependence on basin withdrawals. Expansion provides physical capacity but does not automatically provide process readiness or water security. The resulting interaction explains why portfolio design can outperform isolated investment rules. Regionally, the implication is that identical physical withdrawal reductions need not have identical decision value: the benefit of reclamation is expected to be more consequential where basin scarcity is higher, while emergency-water exposure should be assessed together with the local scarcity factor and the availability of qualified production alternatives. These are managerial implications of the modeled structure, not empirical claims about specific commercial basins.

The environmental results do not support a one-dimensional sustainability claim. Treatment energy increases in-sample carbon while reclamation produces large scarcity-weighted freshwater savings; OOS carbon per satisfied unit is slightly worse even though absolute carbon falls. Managers should therefore evaluate absolute and service-normalized environmental indicators together and screen backup candidates using process compatibility, qualification lead time, disruption correlation, basin scarcity, UPW infrastructure, and emergency-price differentials. The carbon objective in this study is a modeled physical-emissions measure covering the explicitly included production, transport, UPW-generation, and reclamation-energy terms; it should not be interpreted as a shadow-price or carbon-market-cost objective.

Algorithmically, critical-pattern initialization, adaptive cuts, duplicate/dominance screening, incumbent completion, and conditional stabilization are complementary rather than universally beneficial in isolation. The reported speedup is scale-dependent: the method incurs overhead on small instances but improves the Medium and Large classes. This is a qualified computational conclusion supported by multi-instance runtime and objective checks rather than a single favorable case.

Limitations and Future Research

The study uses normalized synthetic data, representative product definitions, fixed network topology, exogenous disruption probabilities, complete-trajectory two-stage recourse, and yield-based UPW quality rather than contaminant-specific process specifications. The reclamation process is represented as a same-period steady-state conversion. These choices support tractability and controlled comparison but limit direct inference to a specific commercial fab. A further limitation is that the supplied manuscript does not expose the full 18-run sensitivity input/output table or the underlying scenario-generation parameter sheet. Future work should release those artifacts and extend the model to multi-stage nonanticipative recourse so that production, routing, qualification, inventory, and water decisions can adapt progressively as information arrives.

CONCLUSION

This study develops an UPW-aware and qualification-responsive semiconductor supply-chain planning framework that links basin freshwater scarcity, treatment, reclamation, production continuity, and backup readiness. Across 60 independent networks, the proposed policy reduces lifecycle cost and scarcity-weighted freshwater use while producing a small in-sample carbon increase and statistically indistinguishable mean service change. Independent OOS validation confirms substantial freshwater and cost benefits but reveals a 1.254-percentage-point service reduction, demonstrating that finite scenario representations should not be interpreted as complete protection against unseen uncertainty. Qualification is the dominant cost mechanism, and reclamation is the dominant freshwater mechanism, while their interaction supports integrated portfolio decisions. SAMC-C&CG provides scale-dependent computational benefits for Medium and Large instances while retaining direct-model transparency for Small cases. The framework therefore offers a bounded, reproducible basis for jointly evaluating cost, carbon, water, and service under semiconductor disruption.

Numerical Verification and Computational Consistency

The computational validation achieved PASS status. The maximum constraint violation was $1.560920281917788 \times 10^{-10}$ and the bridge residual was $4.547473508864641 \times 10^{-13}$. The maximum objective deviation was 1.1203649×10^{-6} , confirming numerical consistency of the reported computational results.

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