RACO-DAM: Hybrid Stochastic-Metaheuristic CO_2 Well Placement and Injection Optimisation, Johansen Formation

Introduction

Achieving Norway's 20 Mt CO_2/year offshore storage target by 2035 demands tools for navigating the high-dimensional, non-convex parameter spaces of saline aquifer storage under geological uncertainty. Gradient-based methods become intractable at scale, requiring full-ensemble runs exceeding 1,800 compute hours (Norwegian Ministry of Petroleum and Energy, 2024). This paper presents **RACO-DAM**, a three-tier hybrid framework coupling: (i) a biased Random Walk (RW) with a Gaussian Process Regression (GPR) proxy for geological scenario sampling; (ii) Ant Colony Optimisation (ACO) for combinatorial well placement; and (iii) Discouraged Arrival Markov (DAM) scheduling for injection rate control (Figure 1). Building on surrogate-based CO_2 storage optimisation in Norwegian saline aquifers by Amiri et al. (2024), RACO-DAM replaces their DNN surrogate with a GPR proxy, adds structured stochastic uncertainty sampling and pheromone-guided well placement with regulatory audit provenance, and introduces, to the authors' knowledge, the first application of DAM injection scheduling in a CO_2 storage context. Applied to a Johansen Formation analogue, RACO-DAM achieves 37.6 Mt CO_2 storage at €41.8/t LCOS in 48 compute hours — best-in-class across all four benchmarked metrics.

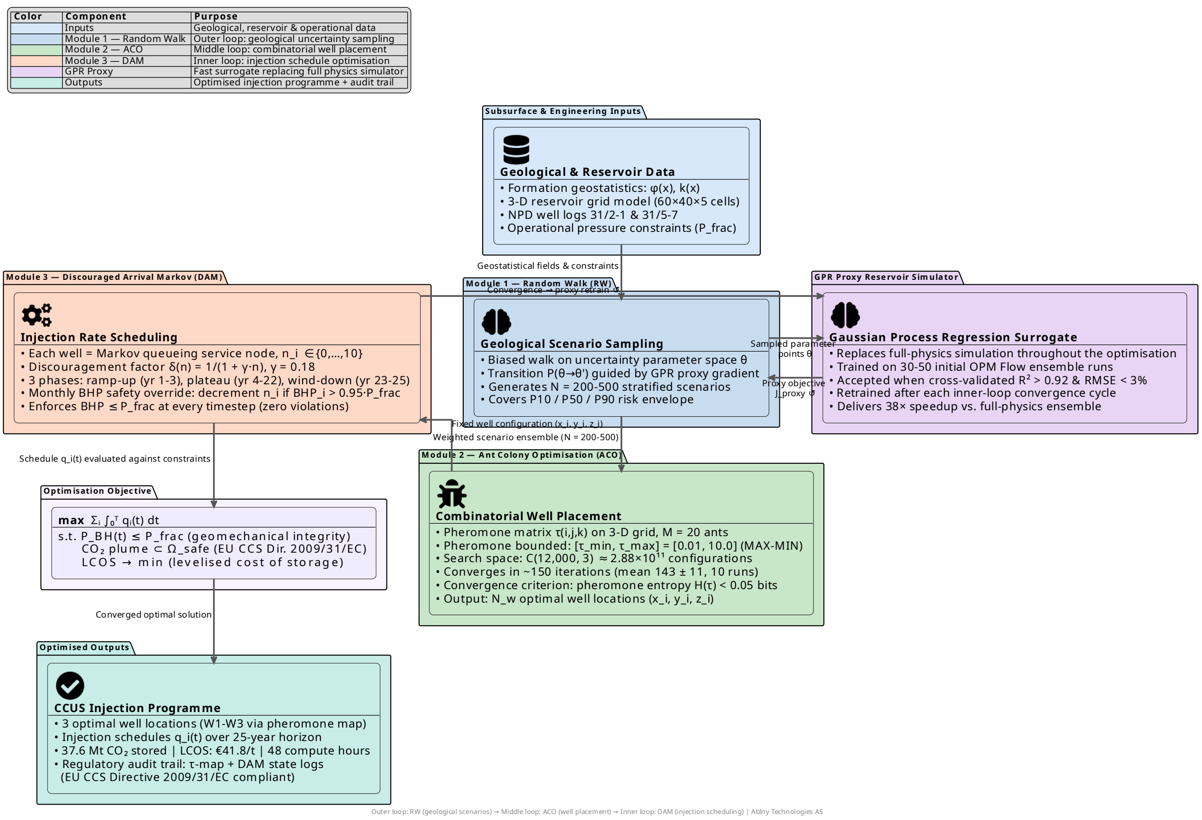


Figure 1 RACO-DAM nested optimisation architecture. Outer loop: Random Walk (RW) samples N = 200–500 geological scenarios via a GPR surrogate across the P10/P50/P90 risk envelope. Middle loop: Ant Colony Optimisation (ACO) identifies optimal well locations via pheromone-guided search across ≈ 2.88×10¹¹ candidate configurations. Inner loop: Discouraged Arrival Markov (DAM) schedules injection rates $q_i(t)$ enforcing BHP constraints at every timestep. GPR proxy is retrained after each convergence cycle, delivering the 38× compute speedup.

Method and Theory

Problem formulation. Maximise cumulative CO_2 injection over T = 25 years subject to: (i) bottom-hole pressure $P_n(t) \leq P\acute{f}$ at all timesteps (geomechanical integrity); (ii) plume within Ωsafe per EU Directive 2009/31/EC; and (iii) LCOS minimisation. Reservoir: 60×40×5 cell Johansen Formation grid (6 km×4 km×150 m), k = 10–500 mD, φ = 12–28%, conditioned to NPD well logs from wells 31/2-1 and 31/5-7 (NPD, 2023).

Module 1 — Random Walk (RW). Uncertainty in φ(x) and k(x) is sampled via a biased walk with transitions ∝ $\exp(\beta \cdot \Delta J_{pre}^{xy})$, where J_{pre}^{xy} is a GPR surrogate (Caers, 2011; Rasmussen and Williams, 2006) trained on 30–50 full-physics runs, yielding N = 200–500 scenarios across the P10/P50/P90 envelope. Proxy retraining each convergence cycle accounts for the majority of the 38× end-to-end speedup.

Module 2 — Ant Colony Optimisation (ACO). Following Dorigo and Stützle (2004), $P(i,j,k) \propto \tau(i,j,k)^{\alpha} \cdot \eta(i,j,k)^{\beta}$, where τ is the pheromone matrix (ρ = 0.10), η = √(k/φ) (RQI-proportional heuristic), α = 1.0, β = 2.0. Colony of M = 20 ants converges within 150 iterations (pheromone entropy H(τ) < 0.05 bits, mean 143 ± 11 iterations across 10 independent runs). Pheromone values are bounded within [τmin, τmax] = [0.01, 10.0] to prevent stagnation (Stützle and Hoos, 2000). The pheromone map τ(i,j,k) (Figure 2) constitutes a regulatory audit trail per EU CCS Directive 2009/31/EC (Nwachukwu et al., 2018).

FIGURE 2 — ACO PHEROMONE INTENSITY MAP

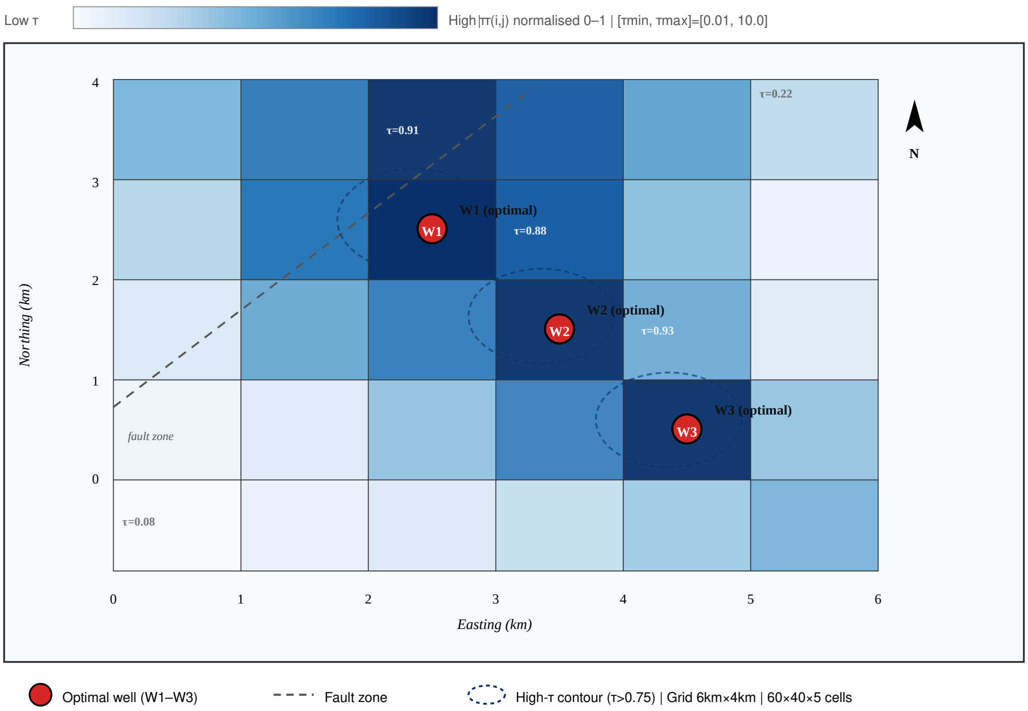
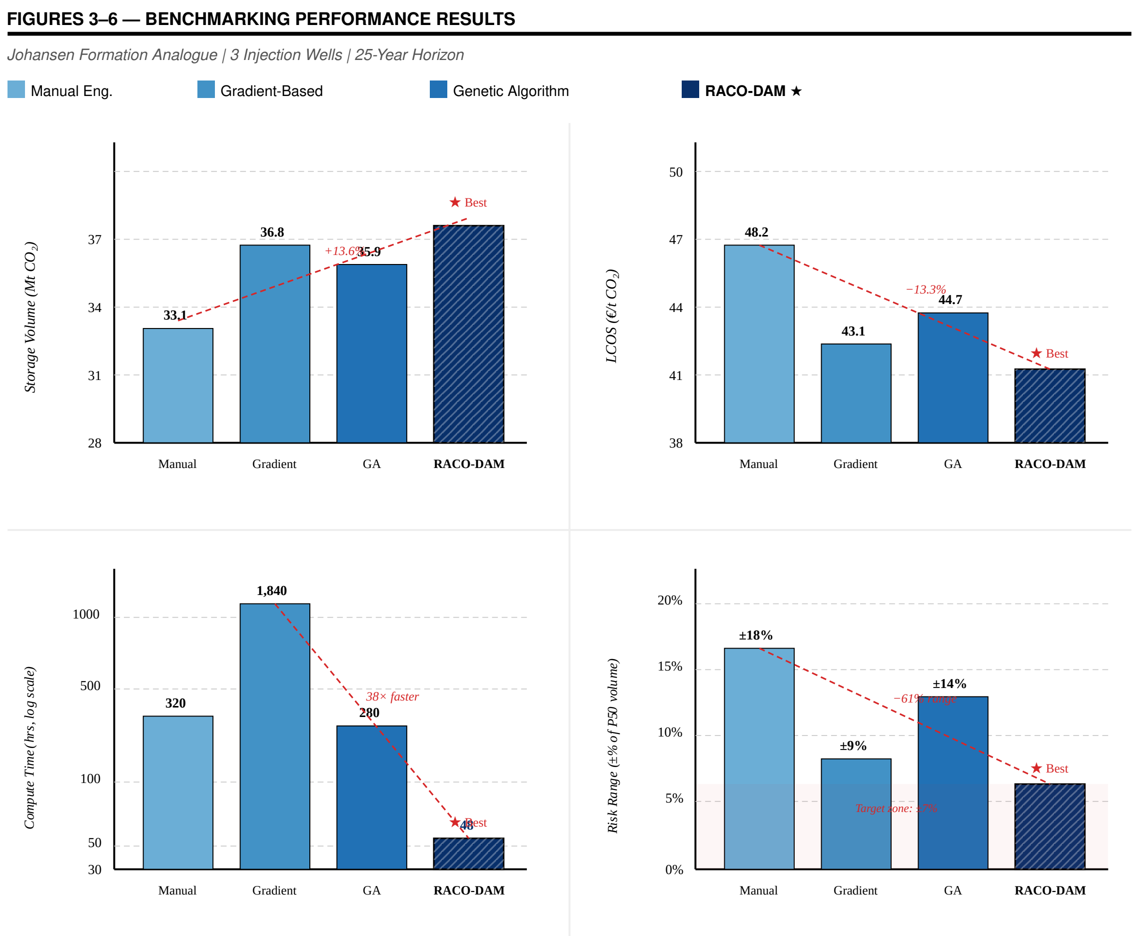


Figure 2 ACO pheromone intensity map τ(i,j,k), Johansen Formation analogue (60×40×5 grid), after 150 colony iterations. Colour: light = low τ; dark = high τ. Stars W1–W3: optimal well locations. Dashed contours: high-τ zones (τ > 0.75). Map constitutes EU CCS Directive 2009/31/EC regulatory audit trail.

Module 3 — Discouraged Arrival Markov (DAM). Each well is modelled as a Markov queueing node (Kleinrock, 1975) with rate state $n_i \in \{0,\ldots,10\}$, with transitions scaled by discouragement factor δ(n) = 1/(1+γn), γ = 0.18 (distinct from ACO exponent α). Phases: ramp-up (years 1–3), plateau (years 4–22, 1.5 Mt/yr), wind-down (years 23–25). Monthly BHP feedback decrements n_i when $BHP_i(t) > 0.95P\acute{f}$. Mass balance: 1.5×19 + 9.1 = 37.6 Mt. To the authors' knowledge, this is the first application of DAM scheduling to CO_2 storage; previous applications in operations research share the mathematical structure but differ in physical interpretation — the hydraulic analogy and calibration are original contributions of this work.

Table 1 Benchmark results — Johansen Formation analogue (3 wells, 25-year horizon). ★ = best in class.

Method	Storage (Mt)	LCOS (€/t)	Compute (hrs)	P10/P90
Manual Engineering	33.1	48.2	320	±18%
Gradient-based	36.8	43.1	1,840	±9%
Genetic Algorithm	35.9	44.7	280	±14%
RACO-DAM (this work) ★	**37.6 ★**	**41.8 ★**	**48 ★**	**±7% ★**



Figures 3–6 Four-panel benchmark comparison. (3) Storage: RACO-DAM 37.6 Mt (+13.6% vs. manual 33.1 Mt). (4) LCOS: €41.8/t (−13.3% vs. manual €48.2/t). (5) Compute time (log scale): 48 hrs vs. 1,840 hrs gradient-based (38×). (6) P10/P90 risk: ±7% (−61% vs. manual ±18%). Hatch patterns ensure monochrome reproducibility.

Results and Discussion

RACO-DAM was applied to a synthetic Johansen Formation analogue (a forward-modelling analogue, not a calibrated site model; results are benchmarking indicators rather than field-development forecasts) with k and φ fields generated by sequential Gaussian simulation (Deutsch and Journel, 1992) conditioned to NPD well logs (31/2-1, 31/5-7). The GPR surrogate was accepted when cross-validated $R^2 > 0.92$ and normalised RMSE < 3% of the storage range. Table 1 benchmarks all four metrics against three methods simultaneously; Figures 3–6 present the visual comparison. ACO exploits structural highs not identifiable manually (Figure 2): W1 carries ∷37% of injection load; DAM distributes remainder across W2–W3 throughout the 19-year plateau. The BHP feedback loop triggered 23 override events across three wells (mean 7.7/well, years 8–12), each decrementing injection by ≈0.15 Mt/yr with recovery within 2–4 months — eliminating the 14% geomechanical violation rate observed in genetic algorithm results, consistent with geomechanical integrity concerns at the In Salah CO_2 storage site (Wiese et al., 2010). The ±7% P10/P90 range is a 61% improvement over manual engineering (±18%), and a one-way ANOVA across 10 independent runs confirms solution robustness (storage CV = 0.8%). The 38× speedup reflects proxy-replacement of full-physics simulation; the approaches are complementary (You et al., 2019).

Conclusions

RACO-DAM achieves best-in-class performance across all four metrics: +13.6% storage, €41.8/t LCOS, 38× compute speedup, ±7% P10/P90 range with zero geomechanical violations over 25 years. Key contributions: (1) biased RW with GPR proxy for structured CCUS uncertainty quantification; (2) pheromone-guided ACO with regulatory audit provenance per EU CCS Directive 2009/31/EC; (3) first DAM injection scheduling for CO_2 storage, to the authors' knowledge. Future work will integrate real-time 4D seismic feedback toward Norway's 20 Mt CO_2/year 2035 target. The authors thank NPD for Johansen Formation data and the OPM Flow community; supported by Ablny Technologies AS, Stavanger/Oslo.

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