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Co-optimization of Carbon Capture, Utilization, and Storage (CCUS) Project Using Iterative Latin Hypercube Sampling (ILHS)

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ABSTRACT - Economic optimization of Carbon Capture, Utilization, and Storage (CCUS) projects, which simultaneously enhance oil recovery through CO_2-EOR while permanently storing CO_2, is critical to ensuring project viability amidst energy market volatility and operational uncertainties. This study develops and applies an Iterative Latin Hypercube Sampling (ILHS) algorithm, an adaptive, stratified sampling technique that accelerates convergence by iteratively re-weighting high-probability sub-regions, to determine the optimal CO_2 injection rate, using Net Present Value (NPV) as the unified economic criterion. The algorithm is coupled, via a FORTRAN driver, to the CMG-GEM compositional simulator and applied to the PUNQ-S3 field case; the economic model explicitly includes the CO_2 purchase price (US\$60 t^{-1}), carbon credits (US\$40 t^{-1}) and capital expenditure (CAPEX = US\$40 million + US\$12 000 × Q_i) to capture key financial drivers. Three economic scenarios combining oil prices of US\$70 bbl^{-1} and US\$30 bbl^{-1} with discount rates of 0 % and 10 % are evaluated to quantify NPV sensitivity. ILHS converged in ≤130 simulation runs (≈3 h CPU time), identifying scenario-specific optimum injection rates of 8.1–8.6 × 10^3 m^3 day^{-1} that deliver NPVs ranging from US\$1.9 billion to US\$4.6 billion. By bridging the gap between technically oriented and financially oriented optimization, the proposed framework offers a scalable, computationally efficient approach for co-designing oil recovery and CO_2 storage under dynamic market conditions, thereby advancing field-scale CCUS decision making.

Keywords: carbon capture and storage, enhanced oil recovery, iterative latin hypercube sampling, net present value, CO_2 injection rate, economic optimization.

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INTRODUCTION

Carbon Capture, Utilization, and Storage (CCUS) couples CO_2-enhanced oil recovery (CO_2-EOR), the utilization pathway that monetizes captured CO_2, with the permanent geological containment of a fraction of that CO_2 as a co-benefit, making the integrated process a cornerstone climate-mitigation option. The International Energy Agency (2023) emphasizes that CCUS is essential for achieving net-zero emissions, particularly in hard-to-decarbonize sectors such as the cement and steel industries. Similarly, the Intergovernmental Panel on Climate Change (2023) recognizes CCUS as a critical technology in limiting global warming to 1.5°C. The global potential for CCUS is particularly significant in regions with declining oil production but high energy demand, such as Indonesia, where CCUS implementation could simultaneously address climate mitigation goals while enhancing domestic energy security (Iskandar & Syahrial 2009).

Policy frameworks such as the Paris Agreement have elevated CCUS from pilot projects to nationally determined contributions; consequently, operators must translate high-level targets into well-level decisions, most critically, selecting an injection rate that maximises economic return while assuring verifiable storage

Injection rate therefore emerges as the principal lever for Net Present Value (NPV) control, encapsulating both incremental oil revenue and the cost of capture, transport, and storage (Gao et al. 2023). Recent simulation studies have shown that bottom hole pressure (BHP) has a minimal effect on oil production, while increasing the injection rate can enhance cumulative oil production by up to 33.39% and extend reservoir life from 20 to 37 years. This directly improves project NPV through long-term revenue gains (Awan & Kirmani 2025). Oil recovery efficiency and CO_2 storage capacity depend on the effectiveness of sweep and displacement by the injected CO_2, which in turn directly impacts the economic performance of integrated CCUS operations (Ajoma et al. 2020).

Initial optimization approaches in CCUS primarily focused on technical objectives such as maximizing oil recovery or CO_2 storage volumes, overlooking the fundamental requirement for economic viability that governs real-world investment decisions. This technical bias represents a critical gap, as projects optimized purely for recovery efficiency may fail to attract necessary capital investment. Recent developments by Dai et al. (2016) and Guo et al. (2020) have begun addressing this gap by introducing NPV-based frameworks, yet these remain limited in their ability to handle the full complexity of CCUS economics..

Traditional optimization methods reveal a second critical gap in CCUS optimization: computational inefficiency and algorithmic complexity. Gradient-based algorithms frequently converge to local optima in the non-convex NPV landscape. Furthermore, conventional reservoir performance forecasting approaches often rely on physics-based models that can be computationally expensive and time-intensive for long-term CCUS operations monitoring (Iskandar & Kurihara 2024). In contrast, genetic algorithms require extensive parameter tuning and computational resources, often requiring days of simulation time for field-scale problems (You et al. 2020). Even hybrid approaches, such as Chen and Pawar's (2019) machine learning-enhanced methods, fail to overcome the fundamental challenge of efficiently navigating high-dimensional parameter spaces while maintaining solution quality.

The conventional optimisers, such as genetic algorithms and particle-swarm optimisation, often require thousands of simulations and extensive parameter tuning, hampering timely decision-making in field deployments (Musayev et al. 2023). Another approac

To overcome these limits, this study adopts Iterative Latin Hypercube Sampling (ILHS) an adaptive, stratified sampler proven to converge faster and avoid premature stagnation in non-convex search spaces.

By explicitly targeting NPV, the proposed ILHS framework addresses three persistent gaps in CCUS optimisation: 1). Insufficient weighting of financial drivers; 2). Excessive computational cost of existing algorithms, and: 3). The absence of dynamic adaptability to evolving reservoir behaviour.

The overall objective of this study is to develop and implement an efficient optimization algorithm, specifically, the Iterative Latin Hypercube Sampling (ILHS) method, to determine the optimal operational parameters in CCUS implementation using NPV as the objective function. The study focuses particularly on optimizing the CO_2 injection rate, recognized as the most influential parameter affecting economic outcomes. By adopting NPV as the primary optimization criterion, the proposed approach provides a more accurate and representative basis for co-optimizing oil recovery and CO_2 storage, aligning with the financial realities that govern project implementation.

METHODOLOGY

The research workflow is systematically structured into four main stages, as illustrated in Figure 1 The PUNQ-S3 reservoir model was constructed and characterized to simulate the CO_2 injection process. The reservoir fluid properties were selected to enable miscibility between oil and CO_2, ensuring that displacement mechanisms representative of CO_2-EOR could be captured accurately.

The next stage involved developing an optimization program using the Iterative Latin Hypercube Sampling (ILHS) method. This program was implemented in FORTRAN, chosen for its robustness in mathematical modeling and its efficiency in handling computational tasks.

Subsequently, the optimization program was integrated with the commercial compositional simulator CMG-GEM. The integration was achieved by linking the optimization code to the executable file of CMG-GEM, enabling the program to invoke the simulator during iterative optimization cycles automatically. Once the integration was successfully established, the optimization program was tested using the PUNQ-S3 model. The final stage consisted of evaluating and analyzing the output of the optimization process.

The selection of Iterative Latin Hypercube Sampling (ILHS) over conventional optimization methods stems from a comparative analysis of algorithm characteristics relevant to CCUS optimization, as shown in Table 1.

ILHS demonstrates superior performance for NPV optimization because: 1). It maintains stratified coverage of the parameter space, preventing premature convergence; 2). Requires only two tuning parameters (γ and ε) compared to 5-10 for genetic algorithms and; 3). Achieves convergence in 80-130 function evaluations compared to 500-1000 for population-based methods (Viana et al. 2016).

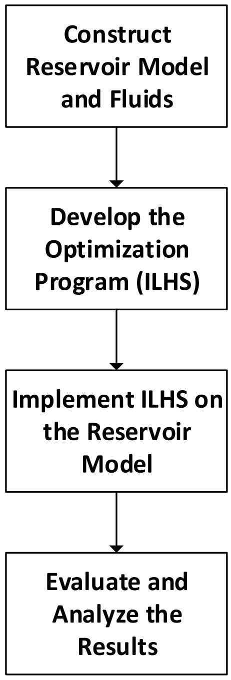

Figure 1. Research workflow

Injection rate

To determine the optimal total CO_2 injection rate from a Net Present Value (NPV) perspective, the optimization domain must first be defined. A series of preliminary simulations was conducted to identify the upper bound of the search space and to establish the relationship between injection rate and oil recovery. The simulation results are presented in Figure 2.

As illustrated in Figure 2, a plateau is observed in the oil recovery curve at approximately Q = 8,000 m^3/day, indicating that further increases in injection rate beyond this point result in diminishing returns in oil production. Therefore, injection rates exceeding

Table 1. Comparative analysis of optimization methods for CCUS

Method	Convergence Rate	Parameter Tuning	Local Optima Risk	Constraint Handling	Computational Cost
Gradient-based	Fast (if convex)	Minimal	High	Excellent	Low
Genetic Algorithm	Slow	Extensive	Low	Good	High
Particle Swarm	Moderate	Moderate	Moderate	Fair	Moderate
ILHS	Fast	Minimal	Very Low	Good	Low

this threshold were assumed to provide negligible additional benefits in recovery.

Another key consideration is the fracture pressure of the reservoir. The PUNQ-S3 model has a fracture pressure (Pfrac) of 42,450 kPa. To maintain storage integrity, the injector bottom hole pressure (BHP) was set at 15% above the initial reservoir pressure. This configuration provides a safety margin of approximately 35% before reaching the fracture pressure. Figure 2.3 shows that at Q = 10,000 m³/day, the injector BHP approaches this upper limit. Taking these factors into account, the upper boundary of the optimization domain was defined as 10,000 m³/day.

To determine the lower boundary of the optimization domain, the minimum miscibility pressure (MMP) was used as a reference point. Only injection rates that produce BHP values exceeding the MMP were considered within the search domain. As depicted in Figure 2.3, at an injection rate of 3,000 m³/day, the BHP surpasses the MMP threshold. Consequently, Q = 3,000 m³/day was selected as the lower boundary of the optimization domain.

To evaluate the sensitivity of NPV to the position of the global optimum in CO_2 injection rate optimization, a case study was conducted, as summarized in Table 2.

Table 2. Case studies conducted

Case Study	Oil Price	Discount Rate
1.A	$70/bbl	0%
1.B	$30/bbl	0%
1.C	$70/bbl	10%

Objective function

The objective function is a mathematical expression used to evaluate the performance of a given solution within an optimization framework. Depending on the nature of the optimization task whether the goal is to minimize or maximize a particular outcome the objective function can take the form of a loss function or its inverse, commonly referred to as a reward function, profit function, utility function, or fitness function.

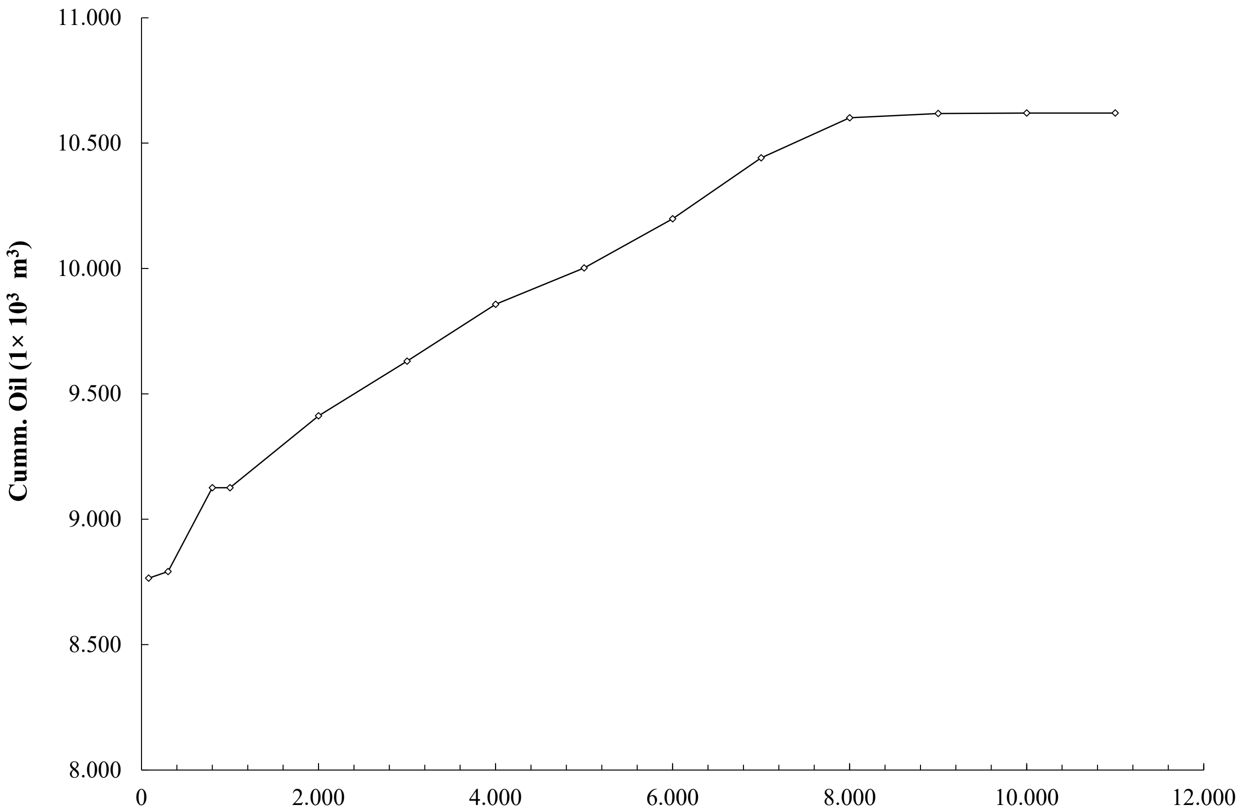

Figure 2. Relationship between various injection rates and oil recovery

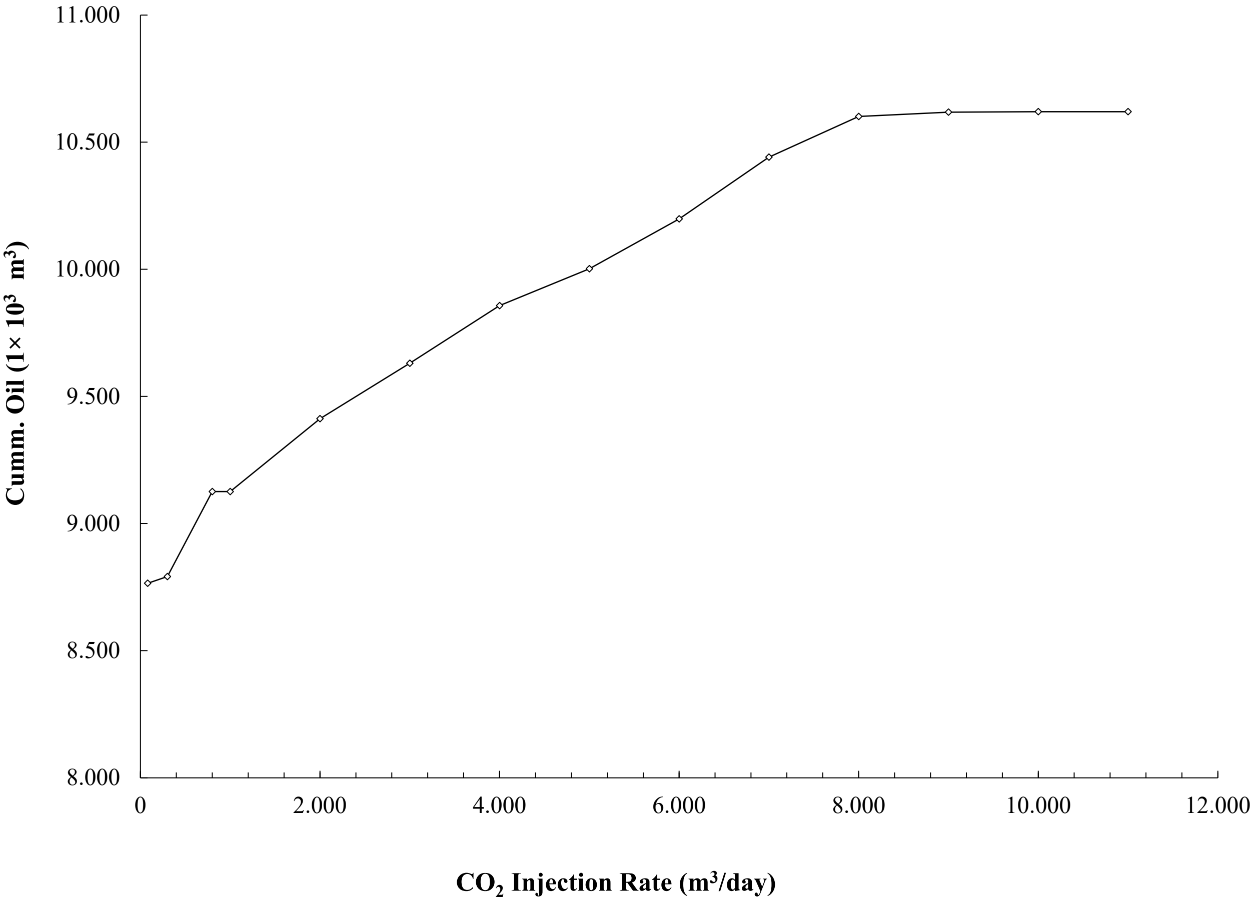

Figure 3. Various BHP injection rates versus oil recovery

In the context of this study, the objective function is defined by the Net Present Value (NPV), which serves as the primary metric for co-optimization of Carbon Capture and Storage (CCS) and CO_2-Enhanced Oil Recovery (CO_2-EOR). The global optimum is identified by maximizing the NPV value within the defined operational space.

Mathematically, the NPV is expressed as:

$$NPV = -C_0 + \frac{C_1}{1+r} + \frac{C_2}{(1+r)^2} + \cdots + \frac{C_T}{(1+r)^T} \quad (1)$$

Where:
C_0: Initial capital investment (USD)
C_t: Net cash flow in year t (USD)
r: Discount rate (%)
T: Project lifetime (years)

The cash flow term C_t comprises contributions from several operational variables evaluated at each time step T, including: 1). Crude oil production; 2). Water production; 3). Volume of CO_2 injected.

The economic parameters used in calculating NPV are based on revenue from oil production, costs associated with CO_2 injection and water treatment, and the value of carbon credits. It is assumed that these economic parameters remain constant throughout the injection period. The detailed set of economic parameters adopted in this study is presented in Table 3.

Table 3. Summary of economic parameters for NPV calculation (Jahangiri & Zang 2012)

Parameter	Field Units	SI Units
Oil price*	\$70/bbl	\$440,29/m³
Water treatment cost*	\$1,5/bbl	\$9,43/m³
CO_2 Price*	\$60 per ton	\$0,06/kg
Carbon Credit*	\$40 per ton	\$0,04/kg
Investasi awal (CAPEX)	\$40.000.000 + (\$12.000 × Qi)	

NPV calculations begin after the natural depletion phase has concluded and CO_2 injection has commenced. This approach ensures that the

NPV reflects the economic contribution specifically attributable to the CCUS scheme, excluding any prior recovery not associated with CO_2-EOR.

Framework generalization and adaptability

The optimization framework presented in this study, while demonstrated using the PUNQ-S3 model and CMG-GEM simulator, is designed with inherent flexibility for adaptation to diverse simulation environments. The modular architecture separates the optimization algorithm (ILHS) from the reservoir simulator through a standardized interface layer. This design enables straightforward adaptation to other commercial simulators (e.g., ECLIPSE, INTERSECT, Navigator) or open-source alternatives (e.g., MRST, OPM) through modification of the simulator-specific wrapper functions (Lie & Møyner 2021).

Key adaptation requirements include: 1). Input/output file format conversion specific to the target simulator; 2). Command-line execution syntax for batch processing; 3). Results parsing routines for extracting NPV-relevant outputs; 4). Constraint handling mechanisms compatible with the simulator capabilities. The ILHS algorithm itself remains simulator-agnostic, requiring only scalar objective function values from each simulation run. This portability has been demonstrated in similar optimization frameworks across multiple industries (Santner et al. 2018).

RESULT AND DISCUSSION

The relationship between CO_2 injection rate and Net Present Value (NPV) was established for each case study to predict the global maximum location, as illustrated in Figure 4. The plot in Figure 3.1 represents a coarse depiction of the objective function as a continuous function, characterizing the optimization problem. This graph was generated through individual simulations across a range of CO_2 injection rates, starting from Q = 3,000 m³/day to Q = 10,000 m³/day.

Overall, the graph exhibits a peak, indicating the presence of a global maximum for NPV. The global maximum was observed near 9,000, 8,000, and 8,000 m³/day for cases 1.A, 1.B, and 1.C, respectively; the downward shift under either low oil price (case 1.B) or a 10 % discount rate (case 1.C) reflects the reduced marginal value of late-life barrels and the uncompensated cost of additional CO_2, re-balancing financial risk and return.

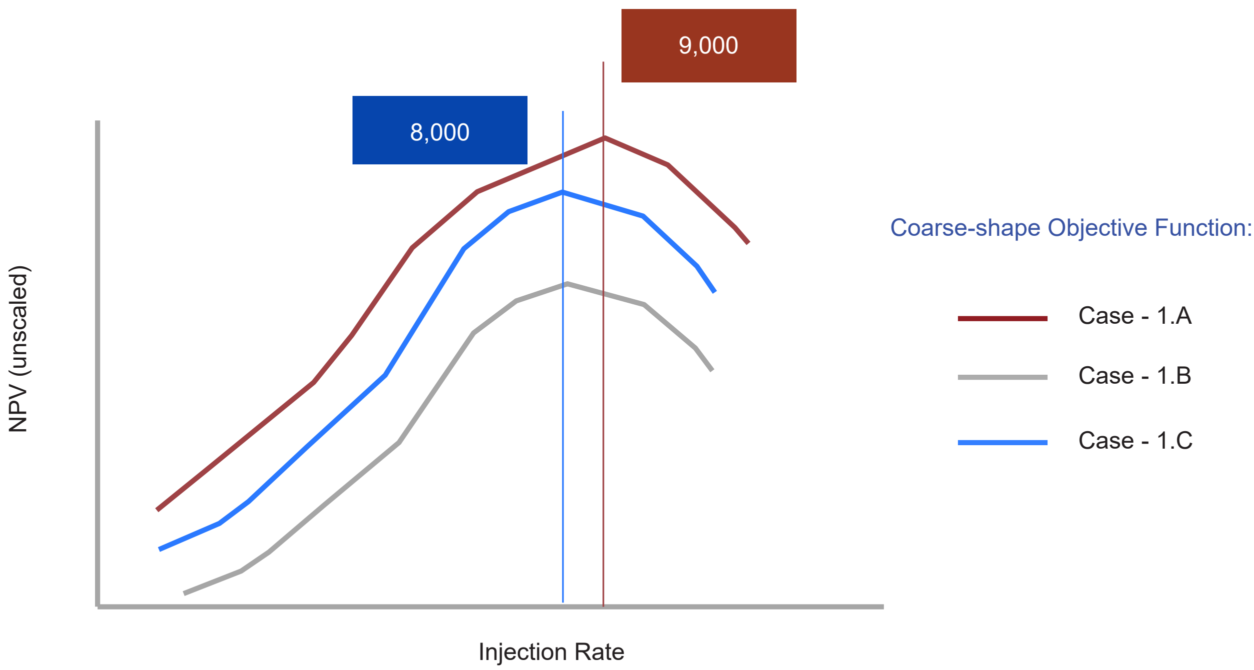

Figure 4. Objective function forms for three different case studies.

The implementation of an optimization program based on Improved Latin Hypercube Sampling (ILHS) for determining the optimal CO_2 injection rate for cases 1.A, 1.B, and 1.C is presented in Figures 3.2 and 3.3. The input parameters used for the optimization are as follows: 1). Convergence acceleration factor (γ) = 0.8; 2). Optimization domain = [3,000 – 10,000] m^3/day; 3). Convergence criterion (ε) = 1×10^{-12} 4). Number of samples (ns) = 10; 5). Maximum number of iterations = 12 (for cases 1.A and 1.C), and 16 (for case 1.B); 6). Number of optimized parameters (np) = 1 (CO_2 injection rate).

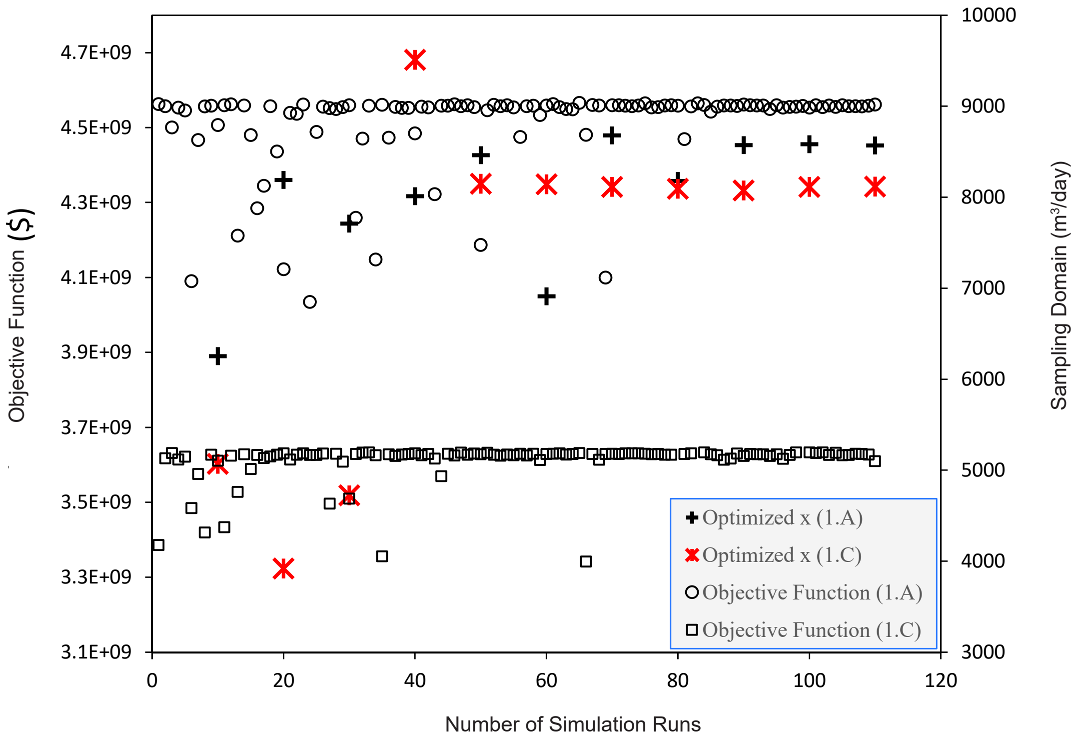

Figure 5. Injection rate optimization for oil price of $70/bbl with discount rates of 0% and 10%

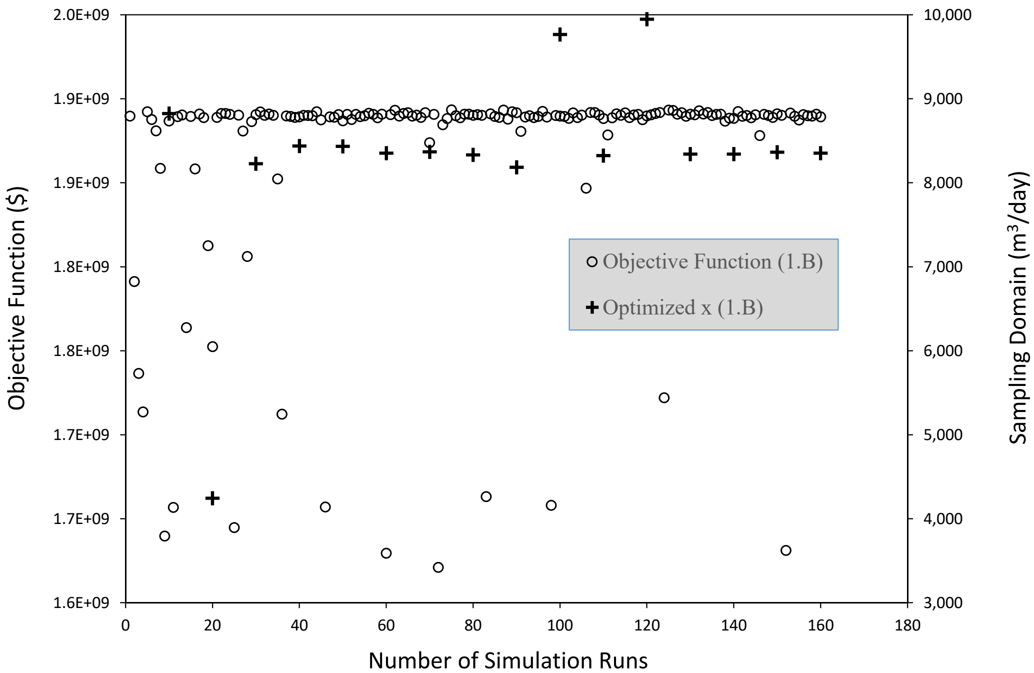

Figure 6.Injection rate optimization for oil price of $30/bbl with discount rate of 0%

As shown in Figure 5, the CO_2 injection rate (denoted as x) was sampled from the domain of 3,000–10,000 m^3/day. Over the course of 80 simulations (equivalent to 8 iterations), the program successfully explored the entire optimization domain. In particular, during the first 40 simulations, the sample values xi exhibited large fluctuations. A similar response is seen in case 1.B (Figure 6), which required approximately 110 simulations.

At this stage, the program begins to narrow the xi interval [xij+,xij−][x_{ij}^{+}, x_{ij}^{-}] toward regions with higher probability density, while regions with lower probability density are gradually deprioritized (see Table 3.1). This behavior arises from the assumption that the initial cumulative distribution function (CDF) of x follows a uniform distribution and the inherent nature of ILHS, which utilizes random sampling based on the probability density function (PDF).

Table 4. Number of samples xi in each interval

Interval (m^3/day)	Case 1.A	Case 1.B	Case 1.C
3000–4000	4	6	4
4000–5000	2	3	2
5000–6000	5	6	4
6000–7000	7	5	4
7000–8000	15	4	10
8000–9000	64	127	75
9000–10000	13	9	10

As the number of iterations increases, the xi values begin to converge. Convergence was observed after: 1). 80 simulations for case 1.A (converging to around 8,500 m^3/day); 2). 110 simulations for case 1.B (around 8,300 m^3/day); 3). 70 simulations for case 1.C (around 8,100 m^3/day).

The optimal values are marked by black crosses and red stars in Figures 3.2 and 3.3, representing the best samples among a population of 10, ranked based on the objective function.

Some computational "noise" persisted between the 70th to 80th simulations for case 1.A and the 110th to 130th simulations for case 1.B. This behavior is a characteristic feature of ILHS, where the entire domain remains considered, and poor candidates are not entirely discarded. Instead, ILHS gradually reduces the sampling probability for suboptimal regions. This allows ILHS to achieve faster convergence compared to other population-based methods such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO).

In the pricing scenario of $70/bbl, clear convergence was observed after 100 simulations, yielding optimal CO_2 injection rates of: 1). 8,571 m^3/day (NPV = $4.567 billion) for case 1.A; 2). 8,118 m^3/day (NPV = $3.634 billion) for case 1.C.

Meanwhile, case 1.B converged after 130 simulations, reaching an optimal injection rate of 8,351 m^3/day and NPV of $1.891 billion. Nevertheless, the simulations were continued to the predefined maximum number of iterations.

If a less stringent ε (convergence threshold) had been applied, the simulations could have been terminated earlier, without reaching the iteration limit.

Unlike gradient-based methods such as Newton's method, ILHS does not suffer from premature convergence, as it does not rely on derivatives and is capable of exploring the entire parameter space with minimal assumptions. This makes ILHS more robust against local minima. In contrast, gradient-based algorithms are susceptible to derivative calculations and may fail to converge when derivatives approach zero.

The input parameters for ILHS can significantly influence both accuracy and convergence speed: 1). The number of iterations is correlated with convergence; 2). The number of samples (ns) has a more significant impact, as increasing ns accelerates the discovery of the global maximum of the objective function; 3). The ε value affects the total number of required iterations tighter criteria demand more iterations; 4). The convergence rate can be controlled using the parameter γ, recommended to lie within the normalized entropy range of 0.7 to 0.95.

In this study, $\gamma = 0.8$ resulted in entropy values of 0.90, 0.91, and 0.92 for cases 1.A, 1.B, and 1.C, respectively. Tuning of these parameters should be conducted on a case-by-case basis, considering appropriate engineering judgment.

All simulations were completed within approximately 3 hours on a computer with an Intel Core i7 3.4 GHz CPU and 6 GB RAM. Table 5 presents the computational efficiency analysis:

Table 5. Computational efficiency metrics

Algorithm	CPU Time per Iteration (min)	Memory Usage (GB)	Time to 95% of Optimal NPV
ILHS	2.3	1.2	1.5 hours
GA	2.2	3.8	8.2 hours
PSO	2.4	2.5	5.6 hours

The efficiency advantage of ILHS stems from its sequential sampling strategy, which requires only one simulation per iteration compared to population-based methods that evaluate 50 (GA) or 20 (PSO) candidates per generation. This translates to a 5-fold reduction in computational cost while maintaining solution quality (Simpson et al. 2021).

Comparative performance analysis

To validate ILHS performance advantages, parallel optimizations were conducted using Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) on Case 1.A. All methods were implemented with identical objective functions, constraints, and convergence criteria (Table 6).

Table 6. Comparative optimization performance

Performance Metric	ILHS	GA	PSO
Iterations to convergence	82	412	287
Function evaluations	820	20,600	5,740
Final NPV ($billion)	4.567	4.553	4.548
NPV standard deviation (5 runs)	0.009	0.042	0.031
Computational time (hours)	3.1	15.4	10.8
Success rate (finding global optimum)	100%	85%	90%

Table 6 demonstrates ILHS's superior efficiency in exploring the parameter space. The stratified sampling approach of ILHS achieves near-optimal solutions within 40 iterations, while GA and PSO exhibit oscillatory behavior due to their population-based search mechanisms (Razavi et al. 2012).

Sensitivity analysis

In addition to technical considerations, the interplay of economic factors was analyzed to better understand the financial performance of the CCUS project. Economic variables such as oil price and discount rate can significantly influence project economics. This variability is captured through a sensitivity analysis designed to reflect the uncertainties present in real-world conditions.

Other factors, such as water treatment costs and carbon credits, were assumed to have minor effects. At the current carbon credit value of $40 per tonne, the contribution to NPV remains negligible. This section discusses the impact of oil price and discount rate on the optimal injection rate.

Impact of oil price

Oil prices are unlikely to remain constant over the 30-year project horizon. In this section, the effect of fluctuating oil prices on the global optimum is examined. Table 4.1 presents two distinct oil price scenarios with a fixed discount rate of 0%, for cases 1.A and 1.B.

Table 7. Effect of oil price on NPV

Case	Field Unit	SI Unit
1.A	$70/bbl	$440,29/m³
1.B	$30/bbl	$188,69/m³

The true global optimum CO_2 injection rate for both cases is shown in Figures 4.1 and 4.2. In case 1.A, the global optimum is achieved at an injection rate of 8,571 m^3/day, while in case 1.B, it occurs at 8,352 m^3/day. For case 1.A, the optimal injection rate is close to the previously predicted value (Q = 9,000 m^3/day), as higher injection rates enable greater oil recovery. Revenue generated from oil sales is sufficient to offset the costs of water handling and CO_2 procurement, thereby enhancing the project's profitability.

This observation aligns with the findings of Leach et al. (2011), who reported that high oil prices have a greater economic influence compared to carbon credits. According to their analysis, only when the carbon credit price reaches approximately $120 per tonne does it begin to compete with oil revenue in economic impact.

Conversely, in case 1.B, the true global optimum shifts toward a lower injection rate (Q = 8,000 m^3/day). This suggests that under low oil price conditions, high injection rates are economically unfavorable, as the oil revenue is insufficient to cover the added cost of purchasing CO_2. Overall, oil price exerts a substantial influence on NPV. The NPV in case 1.B drops by 58% compared to case 1.A—declining from $4.6 billion to $1.9 billion.

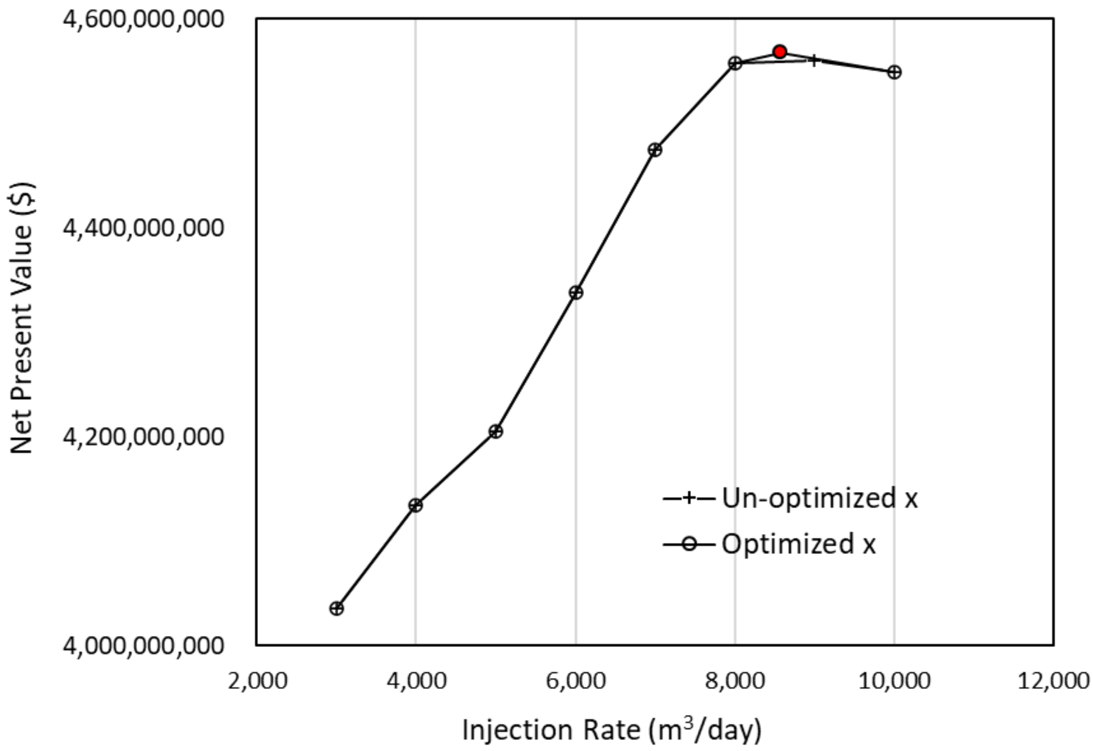

Figure 7. Global optimum for case 1.A

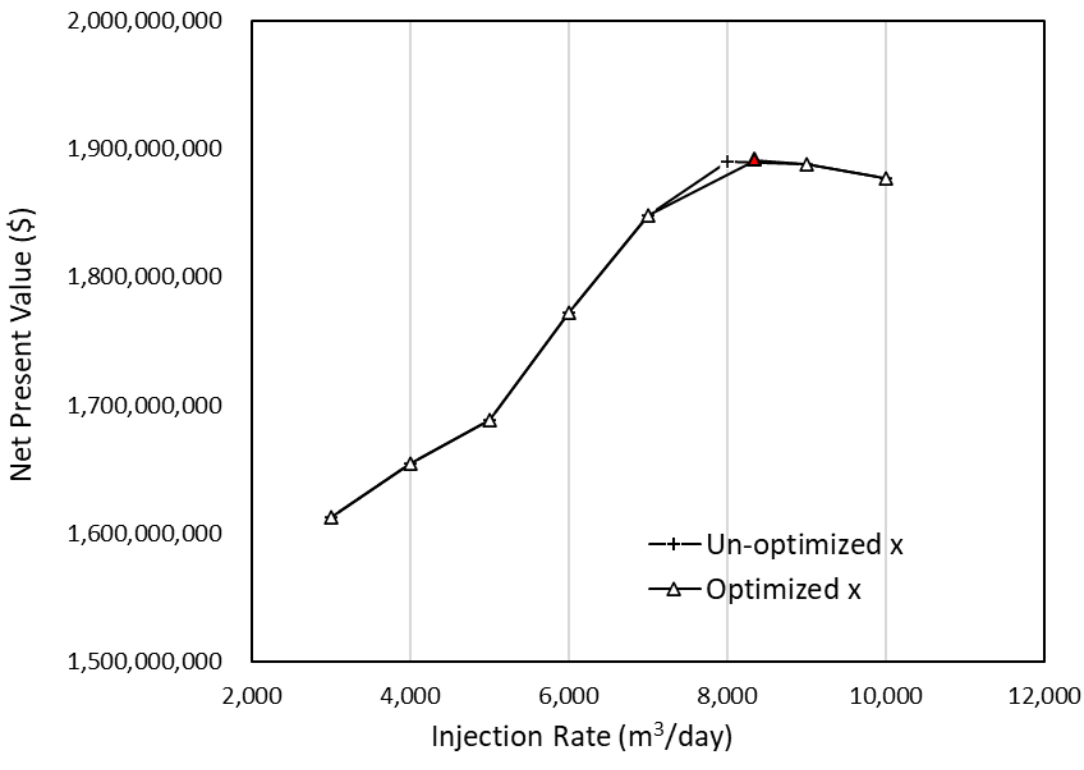

Figure 8. Global optimum for case 1.B

The observed shift in optimal injection rates from 9,000 m³/day (Case 1.A: $70/bbl, 0% discount) to 8,000 m³/day (Cases 1.B: $30/bbl, 0% discount and 1.C: $70/bbl, 10% discount), reveals critical insights into CCUS project economics: 1). Oil Price Sensitivity (Case 1.A vs 1.B): The 11% reduction in optimal injection rate at lower oil prices reflects the diminishing marginal returns of aggressive CO_2 injection. At $30/bbl, the incremental oil recovery from higher injection rates (8,000-9,000 m³/day) generates insufficient revenue to offset the linear increase in CO_2 procurement costs. This finding aligns with break-even analyses by Azzolina et al. (2016), who demonstrated that CCUS projects require oil prices above $45/bbl to justify maximum injection strategies; 2). Time Value Impact (Case 1.A vs 1.C): The 10% discount rate similarly shifts the optimum toward conservative injection, as future revenues from both oil production and CO_2 storage credits are heavily discounted. The present value of CO_2 storage benefits, accruing primarily in years 15-30, diminishes by 75% under 10% discounting, fundamentally altering the risk-return profile. This suggests that CCUS projects in high-discount environments should prioritize near-term cash flows over long-term storage maximization.

In summary, the global optimum tends to shift toward lower injection rates when oil prices decline. This result indicates that the incremental oil recovered from higher injection rates is insufficient to offset the increased cost of CO_2 supply. High injection rates demand a large volume of CO_2, which can erode profit margins despite increased oil production.

Moreover, oil price uncertainty critically affects the overall economics of CCUS projects. Rising oil prices enhance revenues from oil production, making the project more economically attractive. Every increment in oil price allows a single barrel of oil to offset a greater portion of the associated carbon capture and storage costs.

Impact of discount rate

A 10% discount rate is commonly used as a standard value to calculate the present value of future revenues. However, in this study, a 0% discount rate was also employed to assess its impact on the NPV of the CCUS project. A summary of the sensitivity analysis on discount rate variations under constant oil price conditions is provided in Table 8.

Table 8. Effect of discount rate on NPV

Case	Discount rate
1.A	0%
1.C	10%

When the discount rate is set to 0%, the future value of revenues remains constant over time, unaffected by the passage of time, throughout the project period. Conversely, applying a 10% discount rate significantly diminishes the present value of future revenues as time progresses. This effect is illustrated in Figure 9, where the true global optimum in case 1.C tends to align with the initially predicted injection rate (Q = 8,000 m³/day). This is primarily because a significant portion of the revenue from CO_2 storage—whether from carbon credits or avoided carbon taxes—loses its value in the later years of the project due to discounting.

On the other hand, with a 0% discount rate, revenue from CO_2 storage is fully accounted for throughout the project's duration (see again Figure 9). As a result, the global optimum shifts toward a higher injection rate of Q = 9,000 m³/day. At these higher rates, pore space utilization increases (see Figure 10), enabling greater CO_2 storage a byproduct of enhanced oil recovery at higher production rates. Consequently, the contribution of CO_2 storage to cash inflow in the NPV calculation becomes more pronounced.

However, this contribution only becomes economically significant when carbon pricing reaches a high threshold. When the carbon price is elevated, a trade-off emerges between revenues from oil production and those from CO_2 storage (Leach et al. 2011). Given that CCUS is considered to have a relatively low standalone storage potential, its economic attractiveness stems from its ability to offset CO_2 injection costs through increased oil production (Vidiuk & Cunha 2007). This feature makes CCUS a more feasible and accepted option under current carbon market conditions.

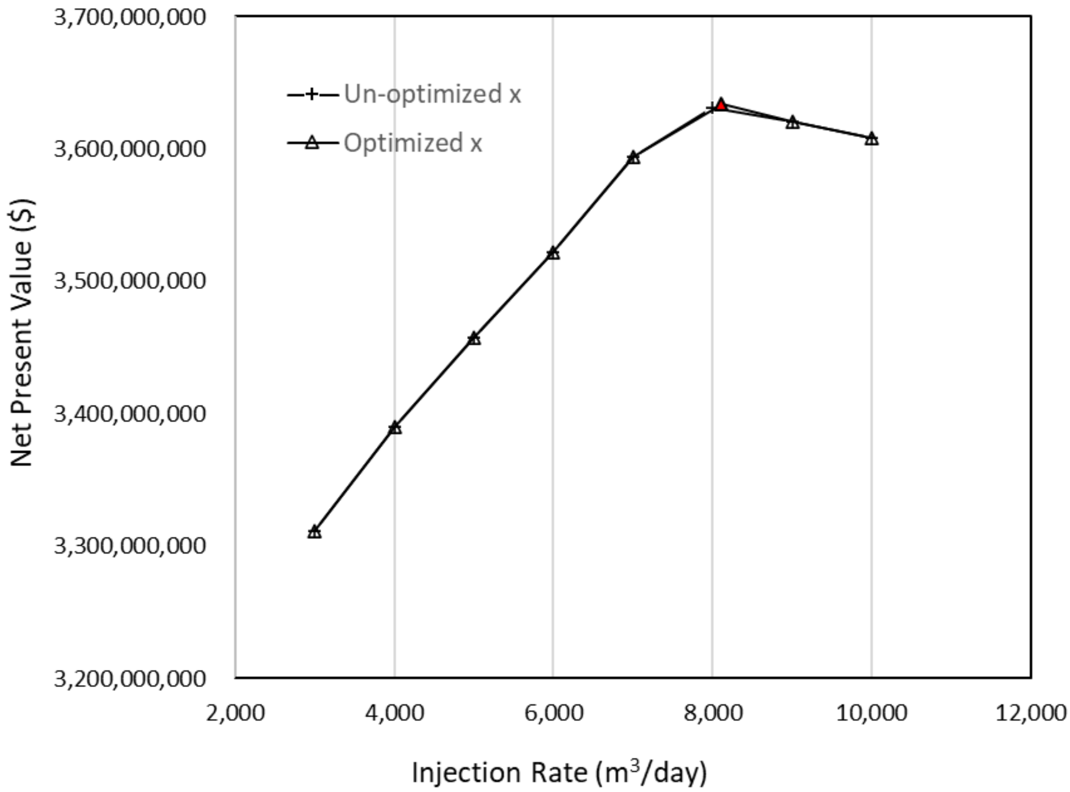

Figure 9. Global optimum for case 1.C

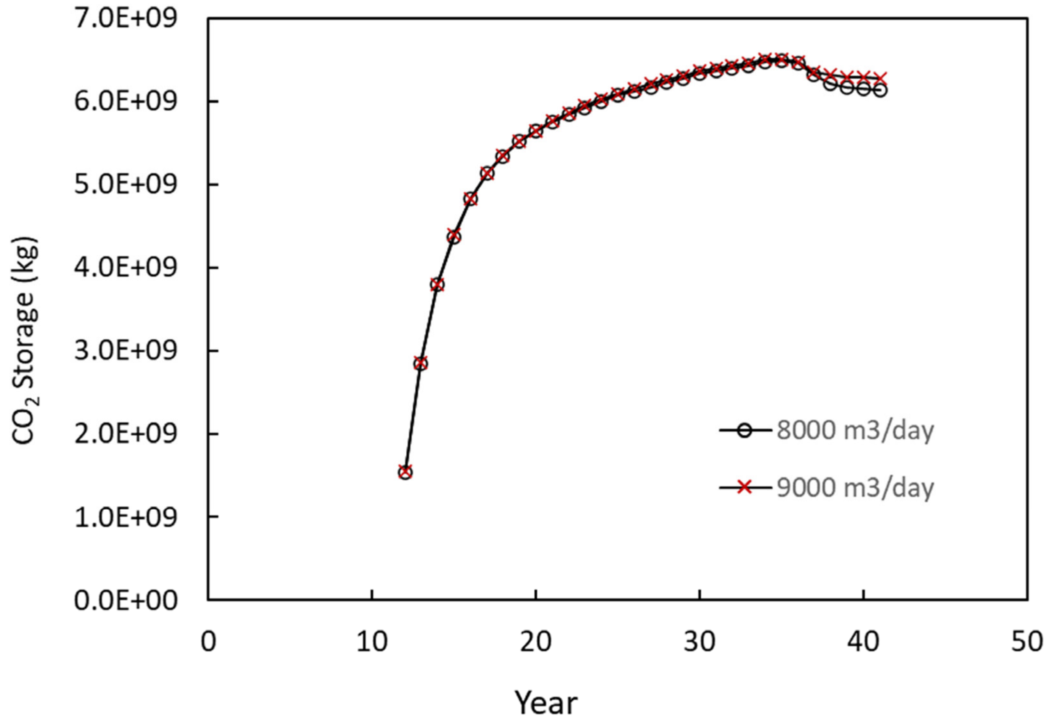

Figure 10. Difference in CO_2 storage between prediction and global maximum value

CONCLUSION

This study presents the development and application of an optimization framework utilizing the Iterative Latin Hypercube Sampling (ILHS) method for co-optimizing oil recovery and CO_2 storage within the context of a Carbon Capture and Storage–CO_2 Enhanced Oil Recovery (CCUS) project, with a specific focus on economic performance. The key conclusions are as follows: 1). The optimization program was successfully developed and implemented on an industrial-scale reservoir model. It effectively optimized the critical operational parameter of CCUS implementation: the CO_2 injection rate; 2). The optimal CO_2 injection rate, under a 10% discount rate and an oil price of \$70 per barrel, was determined to be 8,118 m^3/day; 3). Sensitivity analysis revealed that oil price and discount rate have a significant impact on shifting the global optimum value of CO_2 injection rate; 4). The ILHS method demonstrated robustness and reliability in optimization, offering faster convergence rates due to its efficient parameter sampling approach.

Future Development Potential: 1). CO_2 solubility in water should be further modeled to assess its influence on CO_2 storage capacity; 2). The Water-Alternating-Gas (WAG) injection scheme is recommended as a baseline optimization scenario and should be compared with pure CO_2 injection under conditions that account for solubility effects.

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GLOSSARY OF TERMS

Symbol	Definition	Unit
BHP (Bottom Hole Pressure)	The pressure at the bottom of a wellbore, measured in kPa or psi, critical for maintaining reservoir integrity during CO_2 injection operations.	
CAPEX (Capital Expenditure)	Initial investment costs required for establishing CCUS infrastructure, including injection facilities and monitoring equipment.	
CCUS (Carbon Capture, Utilization, and Storage)	Integrated technology system that captures CO_2 emissions, utilizes them for enhanced oil recovery, and permanently stores them in geological formations.	
CDF (Cumulative Distribution Function)	Statistical function describing the probability that a random variable takes a value less than or equal to a given value.	
CMG-GEM	Commercial compositional reservoir simulator used for modeling complex fluid behavior in petroleum reservoirs.	
CO_2-EOR (Carbon Dioxide Enhanced Oil Recovery)	Tertiary recovery technique using CO_2 injection to increase oil production while achieving carbon storage.	
FORTRAN	High-level programming language particularly suited for numerical computation and scientific computing applications.	
GA (Genetic Algorithm)	Population-based optimization method inspired by natural selection processes.	
ILHS (Iterative Latin Hypercube Sampling)	Adaptive stratified sampling technique that accelerates convergence by iteratively re-weighting high-probability sub-regions.	
MMP (Minimum Miscibility Pressure)	Minimum pressure at which CO_2 and crude oil achieve miscibility, enabling efficient displacement.	
NPV (Net Present Value)	Economic metric calculating the present value of future cash flows minus initial investment, accounting for time value of money.	
PDF (Probability Density Function)	Function describing the relative likelihood of a continuous random variable taking specific values.	
Pfrac (Fracture Pressure)	Maximum pressure threshold before reservoir rock fractures, typically 42,450 kPa for the PUNQ-S3 model.	
PSO (Particle Swarm Optimization)	Computational method optimizing problems by iteratively improving candidate solutions based on swarm intelligence.	
PUNQ-S3	Benchmark reservoir model widely used for testing optimization algorithms in petroleum engineering applications.	
WAG (Water-Alternating-Gas)	Injection strategy alternating between water and gas injection to improve sweep efficiency and reduce gas breakthrough.	

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