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Optimizing fluid(s) circulation in a CO_2-based geothermal system for cost-effective electricity generation

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ABSTRACT

Carbon Capture and permanent geologic Storage (CCS) can be utilized (U) to generate electrical power from low- to medium-enthalpy geothermal systems in so-called CO_2-Plume Geothermal (CPG) power plants. The process of electrical power generation entails a closed circulation of the captured CO_2 between the deep underground geological formation (where the CO_2 is naturally geothermally heated) and the surface power plant (where the CO_2 is expanded in a turbine to generate electricity, cooled, compressed, and then combined with the CO_2 stream, from a CO_2 emitter, before it is reinjected into the subsurface reservoir).

In this research, initially a comprehensive techno-economic method (Adams et al., 2021), which coupled the surface power plant and the subsurface reservoirs, supplies the curves for CO_2-based geothermal power potential and its Levelized Cost of Electricity (LCOE) as a function of the mass flowrate. This way, the optimal mass flowrate can be determined, which depends on the wellbore configuration and reservoir properties. However, the method does not account for the possibility of unwanted water accumulation in the production wells (liquid loading). In order to account for this in the optimization process, a wellbore-reservoir coupling is necessary.

In this research, flow of fluids from the geological formation into the production wellbores has been analysed by optimizing the reservoir modelling. The optimization method has been extended to a set of representative geological realizations (500+). The optimal CO_2 mass flowrate provided using genGEO, which maximizes net-electrical power output while minimizing LCOE, can now be related to the risk of liquid loading occurring. Additionally, the resultant reservoir model can forecast the CO_2-plume migration, the reservoir pressure streamlines among the wellbores, and the CO_2 saturation around the production wellbore(s).

1. INTRODUCTION

Stabilizing the Earth's temperature over the next millennia will need not just a near-total decarbonization of the global energy supply, but also capturing currently existent CO_2 from the atmosphere and storing it permanently underground, a process known as Carbon Capture and Storage (CCS). Instead of merely storing CO_2 in geologic reservoirs at depths greater than 0.8 km during CCS, the CO_2-Plume Geothermal (CPG) system circulates CO_2 that has been injected into deep (>2 km) reservoirs, and thereby geothermally heated, back to the surface, where it is expanded in a turbine to enable more efficient geothermal power generation with less need for auxiliary power (e.g., Randolph and Saar, 2011; Adams et al., 2015; Fleming et al., 2020; Hefny et al., 2020; Ezekiel et al., 2022; and references therein). Thereafter, the CO_2 is cooled, water is removed, and the dry CO_2 is reinjected into the geological reservoir, together with the CO_2 stream coming from the capture facility (Figure 1), so that 100% of the initially injected CO_2 is ultimately permanently stored underground.

It has been shown that the power output of a CPG system is controlled by the heat extraction rate from the reservoir, which is determined by the CO_2 mass flowrate (e.g., Randolph and Saar, 2011; Adams et al., 2015). However, as the CO_2 mass flowrate from the well head to a direct CPG turbomachinery increase, the system pressure losses increase as well, resulting in the production of CO_2 below the ambient temperature, making power generation unfeasible (Adams et al., 2015). This work presents the development of a robust optimization approach and a quantification of the role of various subsurface parameters (including the CO_2 mass flowrate) on the rated of electrical power generation using CPG systems. In our paper, we (1) simulate fluid circulating through the surface facility and underground through the reservoir for two inverted 5-spot well pattern-based reservoir models, (2) optimize the fluid circulation (for the same well-pattern-based models), and (3) conduct uncertainty analyses.

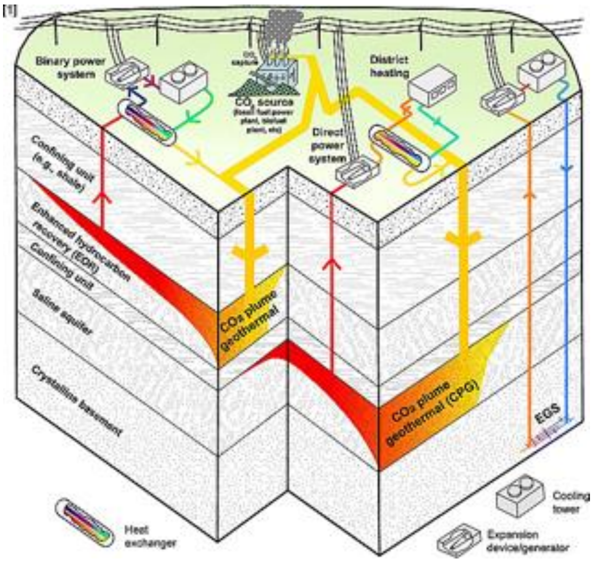

Figure 1: A CPG system illustration, showing a cross-section of the reservoir, wellbores, and the surface power plant (After Randolph and Saar, 2011)**.**

2. METHODOLOGY

Two multi-objective optimization algorithms, including subsurface reservoir and surface power plant, were used to obtain the optimal solutions for the economical CPG operation schemes with the associated uncertainty analysis. Two objectives were considered: maximizing the electrical power generation and minimizing Levelized Cost of Electricity (LCOE).

2.1 Surface power plant optimization

A simplified techno-economics assessment of the surface power plant, using an in-house developed algorithm, genGEO (Adams et al., 2021), is employed to investigate the scenarios. The levelized cost of the electricity (LCOE) and the electrical power generation from a CPG system were estimated for optimal values of CO_2 mass flowrates at the wellhead. For this estimation, we used the optimization to maximize the electrical power generated, per unit of produced geofluid (CO_2), because such optimization does not require any knowledge or assumption of the cost analysis. Realization of the maximum power is achieved by reducing all heat exchanger temperature differences to the smallest value possible to extract the maximum heat from the produced CO_2 (Adams et al., 2021). The **Appendix** contains all simulated parameters.

2.2 Subsurface reservoir optimization

In the subsurface optimization, the reservoir simulation covers the 11-years of the CPG operation (for example from January 1st, 2020, to December 1st, 2030). The optimization workflow is explained as follows: reservoir modelling/simulation ➔ optimization ➔ uncertainty analysis. We employed an initial (base) reservoir model, which is a conceptual model of an inverted 5-spot well pattern, to reduce the computing time and cost of each optimization run. An inverted 5-spot well pattern, where four production wells are located at the corners of a square and the injector well sits in the centre, and its parameterizations are listed in the **Appendix**.

The Nubian sandstone reservoir, as depicted in Figure 1 Hefny et al., (2021), is a highly compartmentalized clastic reservoir with around 72 identified faults. Some fault blocks have hydraulically isolated lateral borders, where pressure can build up quickly during CO_2 injection, posing a substantial risk of reactivation of the bounding faults. Other fault blocks have open lateral boundaries (i.e., are fluid-supported from the far-field). As a result, we create two inverted 5-spot well pattern models: (1) a closed-boundaries pattern model (10 layers with 1 km^2 footprint), representing the hydraulically disconnecting fault blocks, and (2) an open-boundaries-pattern model to represent the other fault blocks. The reservoir model is a sandstone that is 100% saturated with only pore water present at initial condition.

Both models are only simplifications of a real system. The purpose of these numerical models is to learn about the behaviour of actual systems. We use the thermal simulator (STARS, CMG©) to build the base reservoir model and to simulate the CO_2 injection/production strategies. Utilizing artificial intelligence (AI) and machine learning techniques, included in CMG CMOST, we define a Design of Experiments (DoE) workflow to perform optimizations, sensitivity analyses, and uncertainty assessments to identify the most uncertain parameters, impacting the subsurface CO_2 plume migration and associated mass flowrate behaviour.

In the reservoir optimization, we used the Particle Swarm Optimization (PSO) method, which was proposed by Eberhart and Kennedy (1995) and Kennedy and Eberhart (1995) and inspired by social behaviour of bird flocking and fish schooling. PSO is a population-based stochastic computing approach for optimizing random (particle) solutions to a problem. It seeks optima by iteratively seeking to evaluate particle solutions in terms of a particular quality measure and remembering the position of their best success, making this information available to their neighbours. Movements in the search space are controlled by the best-known position of each particle (Equation 1), which is additionally updated by better positions found by other particles in each iteration (Equation 2). The iteration is stopped once the pre-set stop criteria are met. Once all the particles' locations are updated, the objective function values are evaluated by conducting reservoir simulations. For a detailed explanation of the PSO optimizer, see Raquel and Naval's (2005) paper.

$$v_i^{t+1} = wv_i^t + c_1 r_1 (p_i^t - x_i^t) + c_2 r_2 (g^t - x_i^t) \quad [1]$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad [2]$$

where, v is particle velocity, x particle position, p stands for personal best solution of particle, g Global best solution of swarm, ω is the inertial weight, c_1 is the cognitive weight, c_2 the social weight, r_1 is a random number between 0 and 1, r_2 is a random number between 0 and 1, i is the patricle, and finally t is the time step.

Because the CO_2 mass flowrate can have a significant impact on a CPG project's economic viability, the subsurface optimization tries to determine the ideal subsurface conditions that replicate the forecasted CO_2 mass flowrate at the wellhead by the genGEO's optimizer, while minimizing liquid co-production. In this study, we considered, therefore, many non-lineally correlated subsurface parameters to make the optimal solution typical for a heterogeneous reservoir. In the reservoir optimization, the surface mass flowrate (or slug size of injection), the size of wellbore inner tubing (as a function of the inner and outer tubing case and radius insulation), the maximum bottomhole pressure (BHP), the perforation length of the production wells, and surface temperature and pressure are selected as the optimization parameters.

For the uncertainty analysis, we employ Monte Carlo (MC) simulations to capture the uncertainty propagation from variables we can measure to the output variable(s) of interest, which must be estimated. We used the Latin Hypercube Sampling (LHS) method (McKay and Conover, 1979) for the best sampling of the probability distribution for all input variables. Based on LHS, we performed a total of 625 numerical simulations.

3. RESULTS AND DISCUSSIONS

3.1 Base model simulation

In the base model simulation, we set a limit of 500 meters between injector and producer for the well interval. The injection well is perforated throughout the reservoir thickness, whereas production wells are simply perforated in the top half (i.e., 1-5 layers of the model). The injector borehole's fluid composition is 100% pure CO_2, and the injection process starts in 2020 and is planned to end in the year 2030.

Fluid injection into (and migrating through) the storage reservoir can potentially trigger shallow micro-seismic events that can be monitored from the ground surface. Therefore, the maximum CO_2 injection rate is fixed at $1{\times}10^6$ m^3/day, while the permitted injection pressure is maintained at a safe level of avoiding caprock integrity. Considering that the initial reservoir pressure is 25 MPa at a depth of 2 km, we set the maximum BHP of the injector to 29 MPa. Consequently, the maximum BHP control of the injector borehole was given an additional constraint to prevent the reservoir pressure from exceeding the threshold pressure when the seal integrity is lost, or fault reactivation occurs. Additionally, co-production of the resident formation brine is controlled to keep the reservoir pressure at 26 ±3 MPa. The CO_2 injection and production rates, water production rate, and BHP of the injector and producer boreholes of each model are presented in Figure 2. A substantial proportion of brine production occurs during the first two years of injections, after which it begins to stabilize when the subsurface CO_2-plume is well-established and CO_2 production begins.

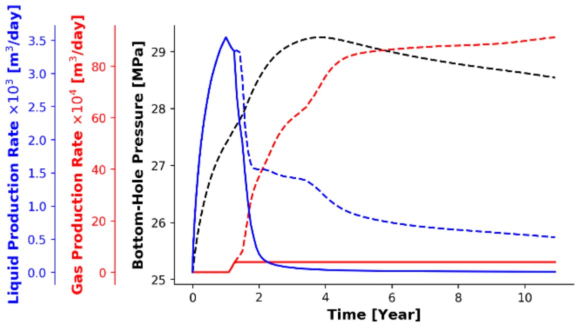

Figure 2: CO_2 injection simulation using the Base model. The solid lines depict the closed-pattern model, whereas the dashed lines depict the open-pattern model. BHP for the closed-pattern model is set to 24 MPa during the whole simulation period. The CO_2 injection rate was fixed to $1{\times}10^6$ m^3/day for both cases.

3.2 Optimization

3.2.1 Techno-Economic analysis

By employing the generalizable GEOthermal techno-economic simulator (genGEO) for the base-case model, we solve for the optimal solution of the mass flowrate that maximizes the net electrical power, while maintaining LCOE to a minimum. As shown in Figure 3, a CO_2 mass flowrate of 83±9 kg/s (a volumetric [m^3/day] equivalent will depend on wellhead temperature and pressure using the simulation conditions) is an optimal mass flowrate to generate 0.73±0.06 MWe of net electrical power at an LCOE [$/MWh] of 400±100 for one well-doublet. A quick summary of the simulated parameters is provided in Section 2 and in the Appendix.

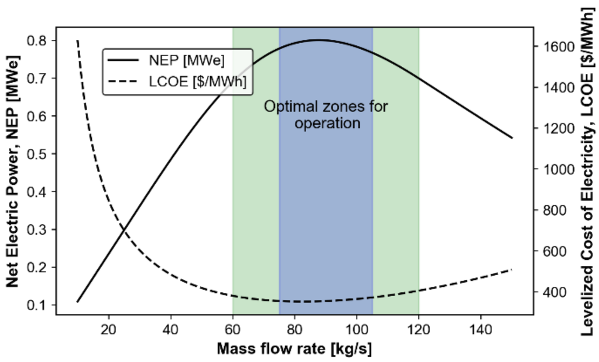

Figure 3: The electricity generated and Levelized Cost of Electricity (LCOE) as a function of production well mass flowrate for a well doublet of a CPG system using genGEO. For the simulation parameters, one can refer to section 2.

3.2.2 Minimization of brine production optimization

Using the PSO method, our primary goal is to find the optimal combination of the subsurface parameters that replicate the quantity of CO_2 mass flowrate predicted by genGEO at the wellheads while minimizing the amount and timing of the liquid produced. The PSO algorithm's termination condition, when employing the employed the base-case reservoir model (see Section 2), is set to a maximum of 1,814 runs. Minimizing brine co-production (i.e., end of liquid production) is achieved at an experiment ID optimization case of 1,696 (Figure 4) following an exponential reduction production rate (Figure 5). The optimization findings suggest that the following variables are critical to achieve the goal of minimizing brine co-production:

- Injection rate/slug size
- Perforation Length: 60%
- Tubing Size

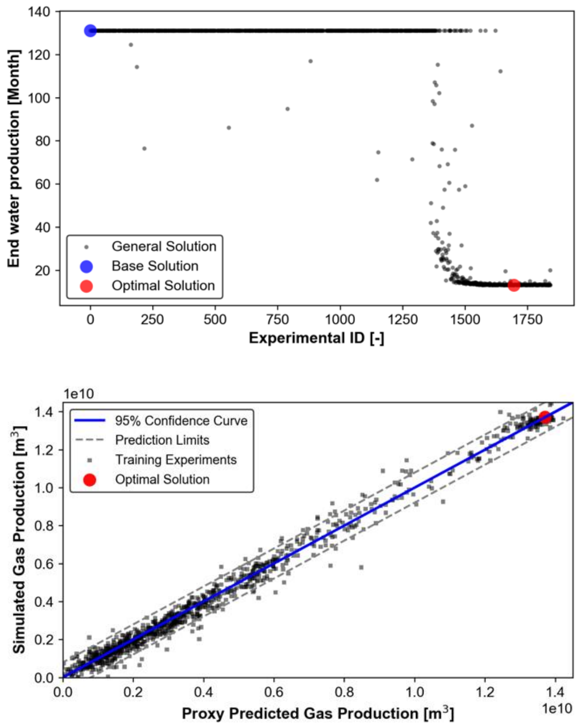

Figure 4: top: Experimental run progress of end brine production optimization with PSO algorithm. Bottom: Polynomial proxy verification for CO_2 production.

The optimization findings, as illustrated in Figure 5 are listed in the Appendix, indicate that:

- **For a closed-pattern reservoir model:**

CO_2 can be injected at a constant rate of 28×10^3 m^3/day for the full duration of the simulation. The production wells established an extensive rise in CO_2 production rate of around 21×10^3 m^3/day until the end of the first year. The production rate was continued with a little increase while attaining a comparable rate with the CO_2 injection (Figure 5).

- **For an open-pattern reservoir model:**

CO_2 can be injected at a maximum rate of 260×10^3 m^3/day for the first month from the injection start. Thereafter, the rate decreases to about 121×10^3 m^3/day, keeping the rate with a slight increase (127×10^3 m^3/day) until the year 2030.

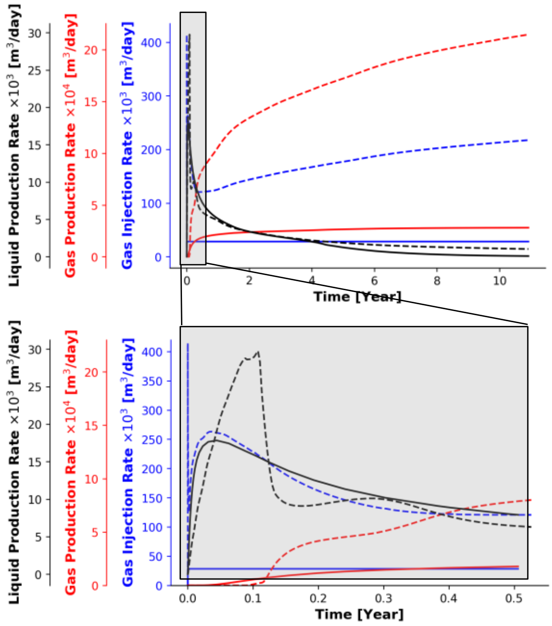

Figure 5: PSO optimization for minimizing the water co-production using the closed-pattern model (solid lines) and open-patten model (dash lines). The top figure depicts the whole simulation period, while the bottom figure illustrates a zoom-in plot for the first five months of the simulation.

It is apparent from Figure 5 that both models experience a high-water co-production rate in the first six months following the start of CO_2 injection. This is followed by a sharp fall in the water production rate (m^3/day) of 1000 and 130, near the end of the simulation period for the open-pattern model and the closed-pattern model, respectively. In these optimal cases, the production wells are effectively controlling the reservoir pressure. However, one of the CPG system's concepts is that less water production is preferable.

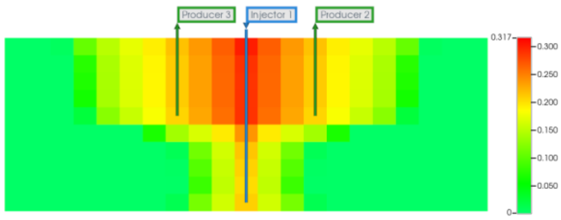

Figure 6: Two-dimensional slice shows the spatial distribution of the CO_2 saturation at the end of simulation (December 30, 2030) in a reservoir of an open-pattern model. The injection wellbore is located in the center.

As a result, depending on a variety of characteristics such as salinity, reservoir depth, public acceptance, and governmental regulations, one alternate option to dealing with co-produced water (or brine) is re-injection into a shallower and/or deeper reservoirs. To analyse the techno-economic viability of subsurface brine disposal, it is necessary to estimate the Net

Present Value (NPV). As shown in Equation **3**, NPV is the difference between the present value of cash inflows and the present value of cash outflows over a period of time.

$$\boldsymbol{NPV = -C_{well} + \sum_{t=1}^{n} \frac{P_{CO2} \times \kappa_{CO2}^{inj}(t) - C_{waterT} \times \kappa_{waterT}^{prod}(t)}{(1+DR)^t}} \qquad \textbf{[3]}$$

where, P_{CO2} is the profit from CO_2 injected, $\kappa_{CO2}^{inj}(t)$ is CO_2 injection rate per year t, $\kappa_{CO2}^{inj}(t)$ is water production rate per year, C_{well} stands cost of drilling/completion of a well, C_{waterT} stands water treatment cost, and DR is the discount rate (assumed to be a constant value of 0.04/year, See appendix).

Given the cost assumptions of water treatment = 1.82\$/m^3, CO_2 profit[1] = 0.028 \$/m^3, and an average well cost = \$1.2 million, the CCS net present value (NPV) was estimated to be \$$2.06\times10^6$ for the brine disposal wellbore (Figure 7). The characteristics of the wellbore configuration in a real heterogeneous geological system, such as depth, location, deviation, completion, and radius, can all contribute to maximizing the NPV (Equation **3**). Therefore, a new PSO optimization approach must be developed that include the maximization of NPV using the above-mentioned PSO as a single optimization system.

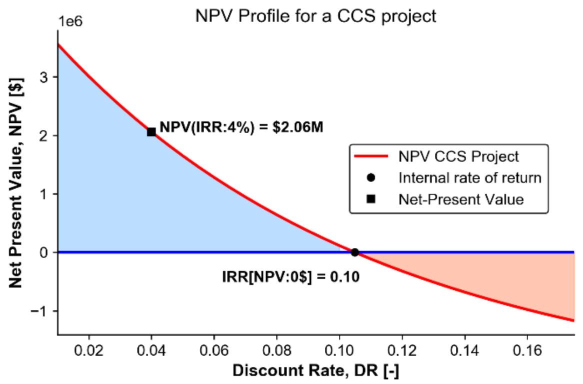

Figure 7: Figure 7: NPV profile for a brine disposal wellbore during CO2 injection. At a discount rate of 10% (where the internal rate of return is) or less, the brine disposal is likely to turn a profit (the blue area). Given all other parameters being identical, the profitability of brine disposal at a discount rate above 11% is unlikely (red area).

Figure 8 demonstrate that using the PSO's optimization outputs, particularly the volumetric CO_2 production rate of the geothermally heated CO_2 as a heat extraction fluid can potentially produce an electrical output of 1.96 to 1.6 MWe at a corresponding cost of 194 to 224 \$/MWh, using a well doublet. The economics estimate is calculated for the year 2019. Other optimization outputs include the estimation of the wellhead pressure and temperature, so that the mass flowrate can be quantified. Additionally, Figure 8 shows a slight increase in the LCOE over the simulated period.

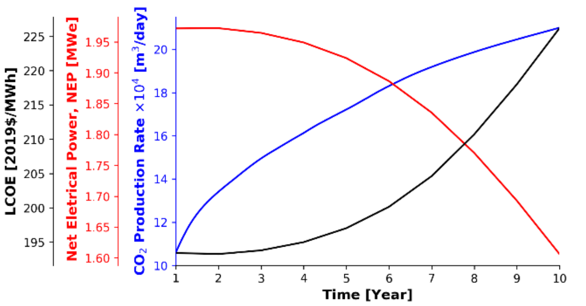

Figure 8: Brownfield CPG systems' potential net electrical power generation and techno-economic assessment for a 10-year timeframe.

3.3 Uncertainty analysis

In the uncertainty analysis, a polynomial proxy model was built using 600 training experiments and verified using 14 blind test cases. The proxies generated were accurate enough to be used in Monte Carlo (MC) simulations (Figure 4 bottom), with all R^2 values above 0.85. Each MC simulation uses 65,000 samples to minimize the number of gaps in the sampling space. As shown in Figure 9, the most likely value for the CO_2 production rate at the end of the simulation periods (i.e., 11 years) is 3.45×10^7 m^3/day (i.e., P50) with a possible range running from 1.62×10^7 m^3/day (i.e., P10) to 4.58×10^7 m^3/day (i.e., P90).

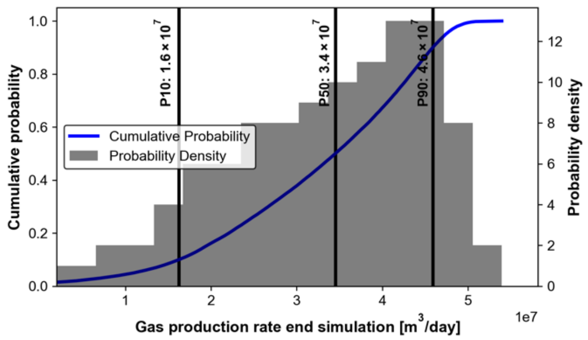

Figure 9: Results from MC simulations, showing the CO_2 gas production rates. Shown is a cumulative probability distribution (blue line) and the probability distribution function (bars).

4. CONCLUSIONS AND OUTLOOK

Rather than considering CO_2 as a waste to be disposed of, new technologies, such as CO_2 Plume Geothermal (CPG), use the geothermally heated CO_2 to be circulated to the land surface to generate geothermal power. At the end of its life cycle, CPG is expected to permanently sequester 100 percent of the injected CO_2 in the geological reservoir. Some parameters of the CPG concept can be optimized, in contrast to the mostly unchangeable intrinsic properties of the reservoirs, in an effort to maximize CO_2 circulation, while keeping

[1] The profit from CO_2 injection is calculated by subtracting the capture and storage costs of 35 \$/tonCO_2 from the benefit from avoiding CO_2 tax of 50 \$/tonCO_2.

the liquid co-production rate to a minimum. An optimization method has been employed to understand the most impactful variables for our study and to find the optimal CO_2 production rate and the minimum brine production rate. The main conclusions are as follows:

- The Particle Swarm Optimization (PSO) algorithm was found to be particularly useful to find the optimal solutions in a homogeneous reservoir, and it can be extended to account for highly heterogeneous reservoirs, resulting in various implications that are rarely considered when working with a complicated geological system.
- During the first operation phase (i.e., the first 6-12 months), the CPG system exhibits strong dynamic behaviours regarding fluid flow rates and reservoir pressures. As a result, it will be critical to conduct in-depth monitoring of the reservoir until the subsurface CO_2 plume is well-established.
- Water/brine disposal into shallower/deeper aquifers can be an efficient way for treating co-produced fluids. This strategy, however, appears to be highly expensive. As a result, considering the maximizing NPV optimization as part of the entire CPG PSO optimization algorithm will be a future study to incorporate the unpredictability of economic factors on the overall CPG system.
- From the Monte Carlo simulations performed, the most likely value for CO_2 production rate at the end of the simulation periods is generally high, with P50 values above 80%

The proposed optimization technique will next be applied to an up-scaled and full-field model of the Nubian Sandstone reservoir (Gulf of Suez, Egypt), where the static reservoir model was built using accessible subsurface data (Hefny et al., 2021). Production data, such as subsurface fluid model, real-time production rates, dynamic reservoir pressure and temperature, etc., must be used to constrain and validate the developed model as soon as it becomes available.

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APPENDIX

The reservoir geometry is an inverted 5-spot well pattern with the reservoir properties listed in the table below. We assume that the reservoir is initially 100% brine-saturated at first.

Parameters	Value	Units
1. Subsurface properties		
Depth	2500	m
Porosity	0.25	-
Permeability	3.0×10^{-13}	m^2
Pressure gradient	11.2	MPa/km
Temperature gradient	0.038	°C/m
Rock density, Compressibility, Thermal conductivity, Volumetric heat capacity	2650, 4.5×10^{-7}, 2.1, 2.347×10^{6},	kg/m^3, 1/Pa, W/m C, $J/(m^3$ C)
Transmissivity	300.0×10^{-13}	m^3
Well radius	0.08	m
Well spacing	707	m
Friction factor	55	μm
2. genGEO simulation parameters [*]		
Optimization Mode	Minimize LCOE Brownfield	-
Lifetime	11	year
ORC Fluid	R245fa	-
Cooling Tower Technology	Wet	-
Well-Field Type	Doublet	-
Discount Rate	0.04	-
Capacity Factor	0.95	-
Cost Year	2019	-
Success Rate well	0.95	-
CPG Turbine efficiency	0.78	-
CPG Pumping efficiency	0.9	-
ORC Heat Exchanger Overall Heat Transfer Coefficient	500	W/m^2-C
Cooling Tower Approach Temperature	7	°C
ORC Heat Exchanger Pinch Minimum Temperature	5	°C
ORC Cycle Type	Subcritical, single pressure	-
ORC turbine efficiency	0.8	-
ORC pump efficiency	0.9	-
Pump Depth	500	m
Max. Pump dP	10	MPa
Water Downhole Pump efficiency	0.75	-
Fraction of Operation/maintenance	0.045	-

[*] genGEO simulations

- do account for reservoir temperature depletion, wellbore heat loss, and surface gathering system,
- do not account for reservoir pressure transient, and silica precipitation

Below is the list of parameterizations for the PSO optimization

Parameter	**Base**	**Lower Limit**	**Upper Limit**	**Prior probability function**
PSO optimization:				
Injection rate [m^3/day]	-	10^7	10^8	Uniform
Perforation Length [%]	-	50	100	Uniform
Production tubing Size [m]	-	0.0603	0.1143	-
Uncertainty analysis:				
Reservoir thickness [m]	50	10	100	Uniform
Porosity [-]	0.25	0.1	0.33	Normal
Horizontal Permeability [m^2]	3.0 $\times10^{-13}$	1.0 $\times10^{-13}$	10.0 $\times10^{-13}$	Normal
Vertical Permeability [m^2]	1.0 $\times10^{-13}$	1.0 $\times10^{-15}$	1.0 $\times10^{-13}$	Normal
Injection pressure [MPa]	20.684	20.0	100.0	Uniform
Reservoir top depth [m]	2000	1500	6000	Uniform
Maximum Bottom-hole pressure [MPa]	48.579	As a function of formula [a]		
Production tubing Size [m]	0.15	0.0603	0.1143	Uniform
Geothermal gradient [°C/kg]	35	25	35	Uniform

[a] Bottom-Hole Pressure = 0.7 × reservoir depth × 3.334× 6.8948

Sobol sensitivity analysis of the influence of 10 parameters on the CO_2 production rate.