Original Paper

Coupled optimization framework of CO_2-WAG injection for enhanced oil recovery and storage: Integrating MLP with evolutionary and metaheuristic algorithms

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A B S T R A C T

This study introduces a machine-learning-driven workflow to optimize CO_2-WAG by considering both oil production and CO_2

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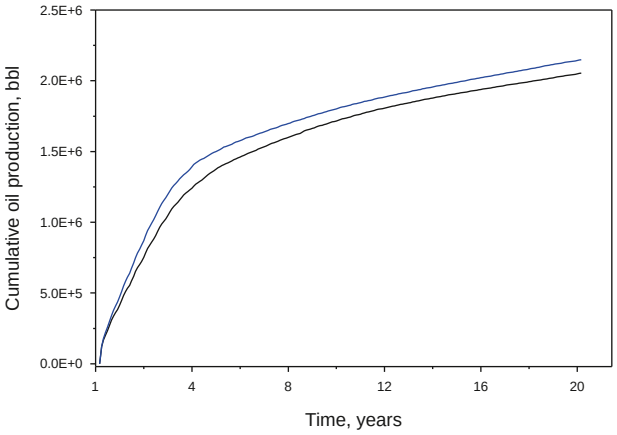
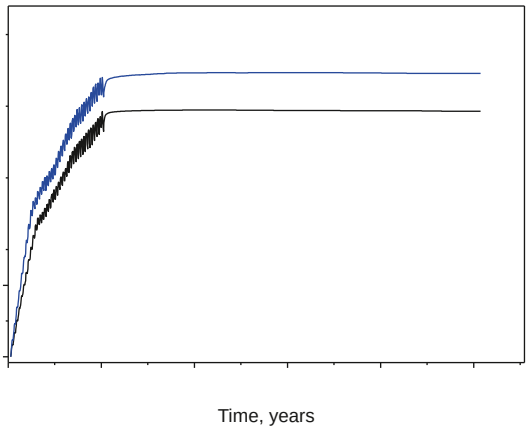




Time, years

Time, years

PSO optimal model oil production, storage, and injection rates plots. Cumulative oil production, CO_2 storage, water injection rate, and CO_2 injection rate.

RSA model loss vs. epochs plots. Cumulative oil production Proxy 1, CO_2 storage Proxy 2.

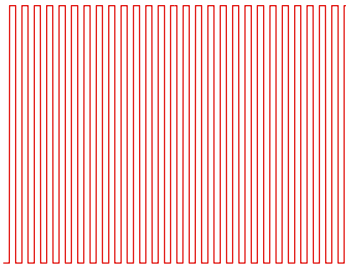
increase in injection rate led to improved oil recovery, greater CO_2 storage, and maintenance of the reservoir pressure above the MMP, as shown in Fig. S10.

4.5. Comparative analysis

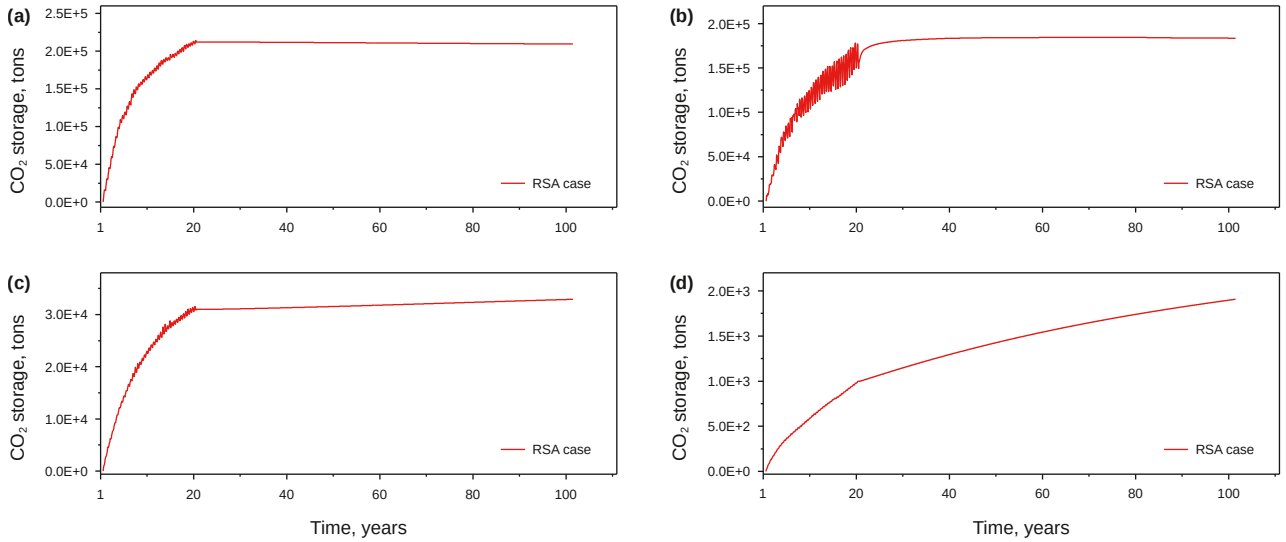
This study utilizes a novel technique that employs GA, PSO, and RSA to determine the best input parameters to optimize the desired objective function. All three algorithms use different approaches to search for the optimal objective function value.

4.5.1. Objective function optimization

A comparative assessment of the three machine learning models, MLP-GA, MLP-PSO, and MLP-RSA, is presented in Table 5, focusing on their ability to predict cumulative oil production and CO_2 storage. All models utilized the same objective function. The analysis revealed that MLP-RSA achieved better predictions compared to MLP-PSO and MLP-GA, as shown in Fig. 20(a and b). This advantage can be attributed to the higher objective function value obtained by RSA 1.088, where PSO and GA resulted in objective values of 1.007 and 0.91, respectively, as illustrated in



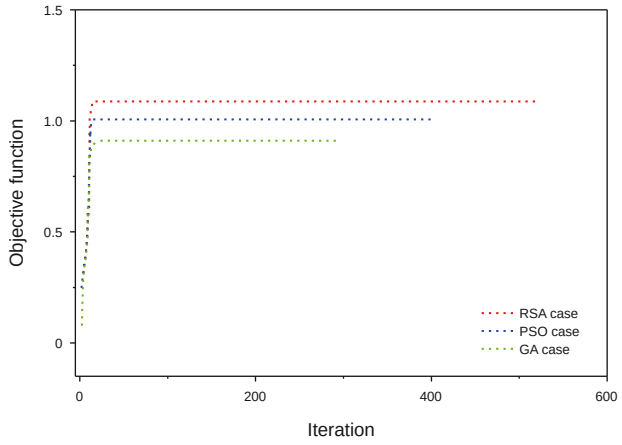
" RSA optimal model oil production, storage, and injection rates plots. Cumulative oil production, CO_2 storage, water injection rate, and CO_2 injection rate.



Optimum model (RSA) based CO_2 trapping by all mechanisms. Stratigraphic trapping, residual trapping, solubility trapping, and mineralization trapping.

principles, depends on social and cognitive factors, along with inertial weights, to direct particles toward ideal solutions (Hassan et al., 2005; Huang et al., 2023). GA, an evolution-based algorithm, utilizes genetic mechanisms, such as selection, crossover, and mutation, to progressively improve solutions (Hassan et al., 2005). The selection of these parameters significantly influences the convergence patterns and the ultimate results of each algorithm (Naga and Prakash, 2020; Shanthi and Chethan, 2022). Despite their methodological distinctions, all three algorithms exhibited outstanding optimization capabilities.

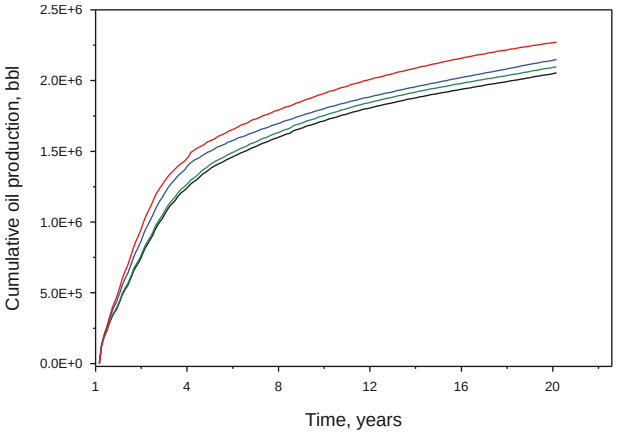
After careful structural examination of the algorithms, the mean absolute relative error between the actual and predicted



$ Proposed workflow performance indicator, objective function vs. iteration plot.

Base case and optimal case results and comparison.

Results	Base case	Optimal case	Difference
Water injection rate, 10^3 bbl/day	1.7	2.7	1
Gas injection rate, 10^2 tons/day	1.1	1.8	0.7
Cumulative oil production, 10^6 bbl	2.05	2.27	10.65%
Cumulative CO_2 storage, 10^5 tons	3.43	4.28	24.72%
Oil revenue, million USD bbl oil price	143.76	159.07	15.31
Objective function (w ˆ 0.5)	0.88	1.088	0.208
Slug size, PV	0.98	1.58	0.6
Pressure profile (average), MPa	14.15	15.65	1.47



Time, years

Time, years

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% Base GA, PSO, and RSA optimal models oil production, storage, and injection rates plots. Cumulative oil production, CO_2 storage, water injection rate, and CO_2 injection rate.

values falls between 0 and 1, 0 1.2, and 0 1.2 for RSA, PSO, and GA, respectively. The loss vs. epoch plots showed that the proxy models trained by these algorithms converged effectively without overfitting. Additionally, the R^2 values of all the models fall in the range of 0.99 and 0.97 for Proxy 1 and Proxy 2. Based on the above evaluation and optimization, the RSA algorithm outperformed both the PSO and GA algorithms by suggesting higher operational parameters, resulting in high cumulative oil production and CO_2 storage. Compared with the base case, all three algorithms outperformed the base case. The optimal values suggested by these algorithms indicate the robustness and effectiveness of the proposed model. Furthermore, these optimization techniques

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This study introduced a machine-learning-driven workflow for the coupled optimization of cumulative oil production and CO_2 storage for CO_2-WAG EOR project. A dataset of 700 samples was generated by utilizing CMG-GEM, consisting of 9 input and two output parameters, that served as an input for training MLP proxy models for predictions. The proxy models were then coupled with evolutionary and metaheuristic optimization algorithms such as GA, PSO, and RSA to predict optimal operating strategies. The proposed workflow gives an alternate approach to conventional optimization techniques by reducing computational time while maintaining accuracy.

The conclusions drawn are as follows:

1) Machine learning-driven MLP proxy models developed for CO_2-WAG projects exhibited precise and fast predictions of cumulative oil production and CO_2 storage, providing engineers with a better understanding of fluid dynamics, carbon-trapping mechanisms, and reservoir behavior.
2) The newly developed MLP-GA, MLP-PSO, and MLP-RSA workflows demonstrated its capability to optimize cumulative oil production and CO_2 storage for CO_2-WAG projects in various operational settings. This process exhibits excellent efficiency, stability, and speed. Using these models allows engineers to make wise operational decisions without resorting to extensive numerical simulation.
3) In terms of performance, all three optimization models outperformed the base model, particularly MLP-RSA. Optimizing both cumulative oil production and CO_2 storage by 10.65% and 24.72% respectively, and increasing the oil revenue, followed by MLP-PSO and MLP-GA.
4) By comparing the three algorithms, RSA optimization outperformed both PSO and GA algorithms, resulting in 5.74% and 8.10% higher cumulative oil production and 9.33% and 19.10% greater CO_2 storage. MLP-RSA, MLP-PSO, and MLP-GA demonstrated exceptional computing efficiency compared with traditional reservoir simulators, requiring minutes for optimization, thereby accelerating the optimization process.

Furthermore, the proposed methodology can also be employed in other EOR techniques (chemical flooding), and fields encounter similar optimization problems due to its flexibility. Therefore, the development of this optimization workflow will provide additional insights into the resolution of multi-objective optimization problems in various fields.

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+ , - . Writing original draft, Validation, Software, Conceptualization. / . Supervision, Methodology, Conceptualization. 0/ 1 . Writing review & editing, Conceptualization. - 0- 2 . Writing review & editing. 3 04 / . Writing review & editing. 5 4 . Writing review & editing.

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Data will be made available upon request.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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