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Performance of Water Injection and CO_2 Injection into Oil Reservoirs based on Field Data: Using ANNs to Predict in the Selected Scenario

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Abstract

As carbon dioxide emissions rise worldwide, the world is still experiencing many consequences of these emissions. This challenge can be addressed using carbon capture, utilization, and storage (CCUS). Energy transfer generally requires a good program in which CCUS plays a crucial role. CO_2-EOR, which allows for storing carbon dioxide (CO_2), is a suitable option in this area. It provides economic returns from oil that could not be recovered before without this method and has environmental benefits, which shows its importance compared to other EOR methods. In this study, an oil reservoir is simulated using field data to compare this method with the water injection method and natural depletion method of the reservoir. Water and CO_2 injection increased oil recovery by 8.4% and 12.7%, compared to natural depletion. The surrogate reservoir model was built using the machine learning (ML) technique by choosing the scenario of CO_2 injection to reduce the computational load and the possibility of using it in optimization tasks. Therefore, using the data-driven model, we can reproduce the data related to the CO_2-EOR process in a much shorter period of time, thereby allowing us to select the most efficient parameters and their ranges for different processes. The numerical simulator was run 250 times to extract the necessary data. The ANN is applied to the data and trained after the database is built and the hyper-parameters have been optimized. ANN consists of two hidden layers with 81 and 51 neurons, respectively, and a 0.05 learning rate after optimization. The trained two-objective ANN was a MAPE of less than 2.5% in the test data for both objectives, i.e., oil recovery and carbon dioxide storage. To further validate and ensure the accuracy of the trained ANN, the numerical simulator was run randomly ten times and compared with the values predicted by the ANN. MAPE for both objectives was less than 2.6%. Therefore, the ANN that makes predictions in a fraction of a second has a suitable accuracy that can be used as a surrogate reservoir model.

Keywords: Enhanced Oil Recovery, CO_2-EOR; Simulation, Oil Reservoirs, Artificial Neural Networks (ANNs), Water Injection.

Introduction

The global economy and central elements of modern society already depend on fossil fuels for their energy, and any sudden change in the composition of these fuels could have serious consequences. The issue of climate change, however, has become one of the most pressing challenges in the world, and various studies are being conducted across many fields concerning it. Climate change is not only a problem of the future but a problem of the present. The issue of global warming is critical because increased CO_2 and other greenhouse gases have caused rising sea levels and climate change [1-4]. In 2019, greenhouse gas emissions were 59 $GtCO_2eq$, an increase in twelve percent over 2010 and fifty-four percent over 1990 [5]. CO_2 gas is the most significant greenhouse gas. According to a new International Energy Agency (IEA) analysis, energy-related carbon dioxide emissions increased by 6%, reaching 36.3 billion tons in 2021. It is the highest level ever because the global economy has recovered strongly since the Covid-19 crisis and has relied heavily on coal to fuel this growth [6]. One option to address this challenge is CCUS, which enhances oil recovery by injecting carbon dioxide gas (also known as CO_2-EOR), one of the best options for storing CO_2 [7]. Energy transfer generally requires a good program in which CCUS plays a crucial role. CCUS is the only technology of sufficient scale to reduce greenhouse gas emissions from coal- and gas-fired power generation and the only technology through which industries like steel, cement, and petrochemicals can become carbon-free [8].

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Therefore, storing CO_2 gas in underground formations plays a significant role. Many techniques are used for enhanced oil recovery (EOR), including gas injection, chemical injection, microbial injection, or thermal recovery [9,10]. As a result of the frontal-advance theory, researchers explained how chemicals move during oil displacement during chemical injection EOR. Based on the results, continuous injection of chemicals (for example, polymers, surfactants, or miscible solvents) is not an economically feasible option due to its high cost [10]. The use of captured CO_2 for EOR dates back to the origins of the EOR industry in the early 1970s with captured CO_2 from natural gas production [11]. EOR can store large amounts of CO_2 geologically; however, many have evaluated its ability to reduce greenhouse gas emissions [11-13].

From successful CO_2-EOR and geological storage projects worldwide, it has been confirmed that CO_2-EOR is suitable for a wide range of reservoirs. Apart from providing an economic return on oil that previously couldn't be produced, it can also be used to store the gas that causes climate change. As a result of CO_2-EOR, some CO_2 remains in the reservoir, which is classified as CO2 storage. Combined with CO_2 gas, oil in a CO_2-EOR project has high mobility, which means CO_2 injection into oil reservoirs has the potential to increase oil production significantly [14]. The CO_2-EOR process is considered the largest EOR process in the world after the thermal EOR process used in heavy oil fields [15]. Gas injection into oil reservoirs can be done in two ways: miscible and non-miscible injection, which can be distinguished by the minimum miscibility pressure (MMP) [16]. When CO_2 is injected into oil, it can swell the oil, reduce its viscosity, reduce interfacial tension, and usually have a higher recovery [17,18]. Even though CO_2 injection is primarily used in EOR, it also has the advantage of storing CO_2, which reduces global warming. Therefore, in addition to the injection of CO_2 during CO_2-EOR, much attention is given to investigating the long-term use of CO_2-EOR as a storage application for anthropogenic CO_2. One of the major projects launched is the Weyburn CO_2-EOR project using anthropogenic CO_2 in Canada, successfully using the CO_2-EOR technique to store large amounts of anthropogenic CO_2 safely. The project began CO_2 injection in October 2000 and it has been continued to produce oil from the Weyburn and Midale fields at a rate of 14,000 barrels of oil per day [19, 20].

One of the main advantages of CO_2 in comparison with other types of gases that are used to increase oil recoveries, such as methane and nitrogen, is the significantly low MMP.

Consequently, CO_2 can be used to improve miscible oil recovery in various oil reservoirs [21]. According to the studies, it was found that the highest oil recovery in the miscible gas injection is achieved by optimizing the gas composition with the lowest MMP and the lowest density [22].

The researchers explained the CO_2 mixing process using the transition zone between the injection and production wells. Their theory states that mass transfer between oil and CO_2 creates a completely miscible zone without any interfaces, followed by a transition zone, which is miscible with oil at the front and CO_2 at the back [23]. However, some problems occur during the process with miscible flooding. One of them is the asphaltene deposit, which, even in small amounts, may block fluid flow and significantly reduce movement [24]. The effect of CO_2-water-rock interaction on the change of rock permeability and final oil recovery was evaluated experimentally during the injection of CO_2 into carbonate rock. The results showed that the damage severity is directly related to the injection rate. Still, the change in the displacement type from miscible to immiscible reduces the intensity of chemical reactions in the porous medium [25]. Researchers have developed precise relationships for CO_2 solubility in oil and the corresponding oil swelling and viscosity using genetic algorithm techniques. Their results have been validated using published experimental data [26,27]. Understanding the underlying processes behind CO_2-EOR is crucial for successful field applications. In addition to maintaining or increasing reservoir pressure, which provides an artificial drive for oil production, CO_2 injection is the reason for other effects that increase oil recovery. Oil viscosity reduction, oil swelling, oil and water density reduction, and oil vaporization and extraction are the four main CO_2-EOR processes [15, 28]. CO_2 is highly soluble in oil hydrocarbons, so it causes the oil to swell and reduce its density and viscosity. Furthermore, since there is some water in the oil reservoir, the injection of CO_2 also reduces its density, making water and oil density similar and, therefore, reducing the gravity segregation effect [29]. There has been extensive development of machine learning models to proxy numerical models with high accuracy by using regression [30, 31], artificial neural networks (ANNs) [32, 33], and support vector machines [34].

To predict asphaltene precipitation in reservoirs under certain conditions, an ANN has been generated with a coefficient of determination (R2) larger than 0.996 [35]. Also, an ANN-based proxy model was developed to evaluate the performance of the CO_2-EOR project and CO_2 storage capacity. The objectives of this study were oil recovery, CO_2 storage, and net present value. The ANN model shows high adaptability to CO_2-WAG projects' complex data structures. Furthermore, an ANN model was utilized in the proposed workflow to aid in optimization [36]. To analyze the uncertainty of the CO_2 storage project, a surrogate reservoir model was created using artificial intelligence. A surrogate reservoir model was utilized to predict the pressure and distribution of CO_2 throughout the reservoir with reasonable accuracy in seconds [37]. Surrogate models run in a fraction of a second, while numerical models run in minutes to hours, depending on their size. Therefore, using ML algorithms can reduce simulator load and computational time.

This article presents a study of the CO_2-EOR process and numerical modeling with field data and different scenarios. As a result, a commercial simulator is used to model natural depletion, water injection, and CO_2-EOR scenarios to determine which scenario leads to the highest oil recovery. Additionally, CO_2 gas injection could be used to take advantage of the environmental benefits. In fact, by choosing the desired scenario, the maximum production of oil in the existing conditions and the maximum amount of CO_2 that can be stored is provided, which can play a significant role in climate change. By choosing the type of scenario with more oil recovery and using the data-driven model, the data related to the CO_2-EOR process is reproduced in a much shorter period of time, which helps us choose the best parameters involved in the CO_2-EOR process. In this study, two-objective ANN is used. Several objectives are defined for training the ANN, including oil recovery and carbon dioxide storage, which can reduce the computational load on the numerical simulation model by using the trained ANN to reproduce these objectives. Therefore, it can be beneficial during optimal studies and becomes increasingly important. Eventually, the ANN is evaluated on its ability to predict the percentage of oil recovery and carbon dioxide gas storage. Field data were used in this study to assess the surrogate model's performance under these conditions. Comparing the scenarios allows first selecting the desired scenario and then building a surrogate model for prediction in less time than the numerical model using the framework presented in this article. It can be used and generalized, and other models with more complex scenarios can be implemented.

Materials and Methods

In the first step, the reservoir containing oil for EOR is simulated based on field data used in this study. By setting the same constraints for all the scenarios considered, the numerical simulator is run for 15 years. This study investigated three scenarios of natural depletion, water injection, and carbon dioxide gas injection. The scenario more suitable for oil recovery (CO_2 injection also brings environmental benefits) is selected. A surrogate reservoir model is built using ML techniques by selecting the desired scenario. First, data extraction and database creation are required to construct an accurate surrogate reservoir model. For this purpose, 250 simulations are run, and data are extracted. ANNs inputs include CO_2 gas injection rate, oil production rate, production bottom-hole pressure limitation, and injection bottom-hole pressure limitation, and ANNs outputs include oil recovery and CO_2 storage. The hyperparameters of the two-objective ANN are optimized using the tuner package in the Python environment, and finally, the ANN is applied to the database. After training the ANN, we evaluated it using test data. To ensure its performance, the numerical simulator ran randomly ten times and re-evaluated the trained ANN using that data. Then, the error values provide the possibility to ensure the correctness of the prediction capability of the ANN. Figure 1 briefly depicts the workflow chart of the research work.

Reservoir Model

Using a commercial simulator, we can determine how much oil will be produced and how much CO_2 will be stored. To build a reservoir model in a commercial simulator, field data (fluid properties and rock properties) were used in studies to simulate the CO_2-EOR process [38-40]. The oil reservoir simulation model has dimensions of 81*58*20 with a total number of 93960 cells. The overall dimensions of the reservoir are also 8*5.7*0.16 km. The existing reservoir is located at a depth of 2800 to 3300 meters with an average pressure of 324 bar, and the reservoir temperature is equal to 140 degrees Celsius. The reservoir model has heterogeneous porosity and permeability. Figure 2 shows the porosity distribution, and Figure 3 shows the reservoir permeability distribution and the location of the wells. The petrophysical properties of the reservoir model are given in Table 1. In addition, the MMP which was performed in the compositional simulator is equal to 145 bar, and the volume of oil in place of the reservoir is 138.4 million Sm^3. Table 2 shows the properties related to components in compositional simulation. The values attributed to the C_{7+} fraction represent the average weight for components larger than C_7.

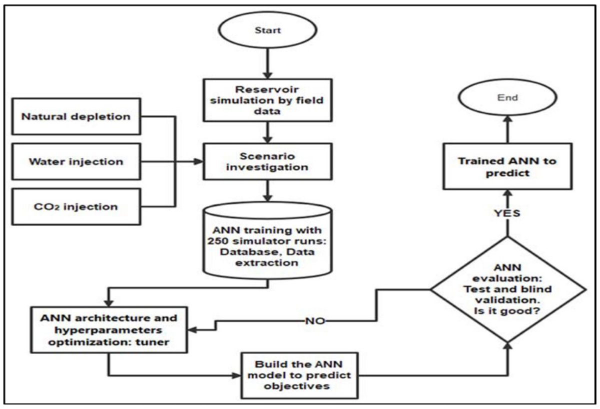

Fig. 1 The main workflow of this study.

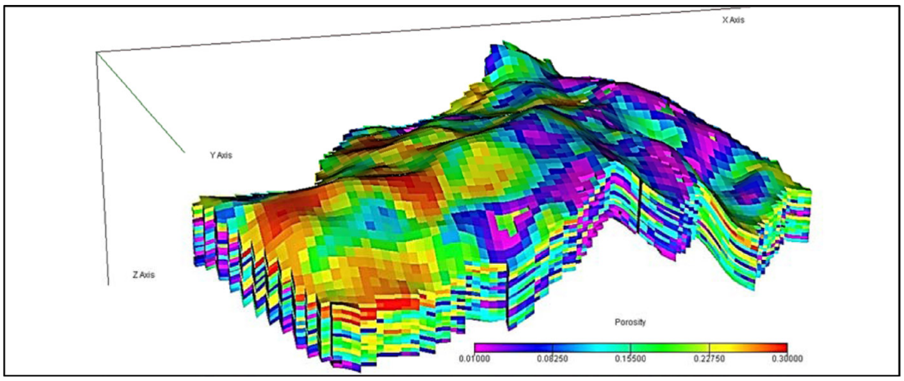

Fig. 2 Porosity distribution.

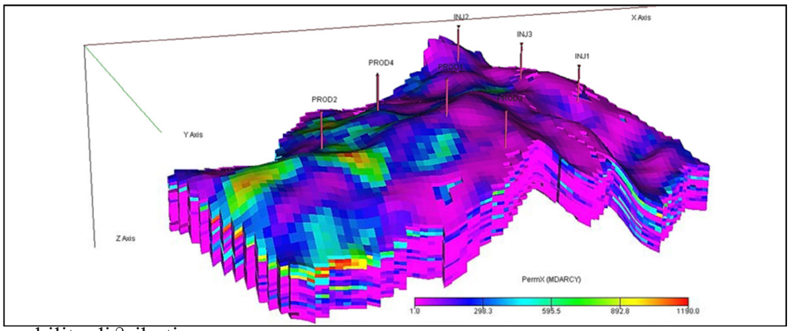

Fig. 3 Well placement and Permeability distribution.

Table 1 Summary of petrophysical properties of the reservoir model

Petrophysical Properties	
Parameter	Value (Unit)
Average porosity	13.6 (fraction)
Average permeability	132.5 (md)
Rock Compressibility	5.4E-5 (1/bar)
NTG	0.76

In this model, four oil production wells (PROD1 to PROD4) and three CO_2 gas injection wells (INJ1 to INJ3) are considered, and their locations are also shown in Figure 4. Well locations will remain unchanged in all reservoir model scenarios. The minimum oil production rate and maximum water cut in the production wells are 100 Sm^3/day and 35%, respectively. Also, the other considered limitations are shown in Table 3, which will be true for all the examined scenarios. This study examines how the reservoir performs in three scenarios: natural depletion, water injection, and production with continuous carbon dioxide gas injection. In all scenarios, the maximum oil production rate from four oil production wells equals 9000 Sm^3/day.

Table 2 Molar percentages and critical properties of the components.

Component	Molar %	Mol. weight	Critical pressure(bar)	Critical temperature (°C)
CO_2	9.9	44	119.1	-22.2
C_1	26.6	16	74.2	-116.2
C_2	6.5	30	78.4	-24
C_3	5.2	44	68.8	31.3
$C_{4\text{-}6}$	6.7	70.2	56.8	107.4
C_{7+}	54.1	218	27.5	340.2

Table 3 Operating constraints oil reservoir simulation.

Operating Constraints	
Parameters	Values (Unit)
Max Injector BHP	450 (bar)
Min Producer BHP	82.7 (bar)
Producer Oil Target Rate (minimum)	100 (Sm^3/day)
Max Water cut	35 (%)
End of Simulation	15th (years)

Results and Discussion

Natural Depletion

At first, the natural depletion scenario of the reservoir was investigated in the reservoir model for 15 years. As a result, the bottom-hole pressure of the production wells is set lower than the average reservoir pressure, which leads to oil production naturally until reaching the existing limits. The performance results of this scenario are shown in Figure 4. The daily oil production rate of the reservoir, in natural depletion, was initially 9000 Sm^3/day, but it reached 2227 Sm3/day after 15 years of simulation, which goes beyond the economic limits. At the end of the simulation period, the pressure level reached 152.4 bar, and the pressure drop in the reservoir was 171.6 bar in these 15 years. This pressure drop in the reservoir can lead to the waste of a large amount of oil inside the reservoir. In this scenario, the cumulative oil production was 27.7 million Sm^3, and the oil recovery factor was calculated as 17.8%. Figure 4 also shows the status of oil and gas production rates.

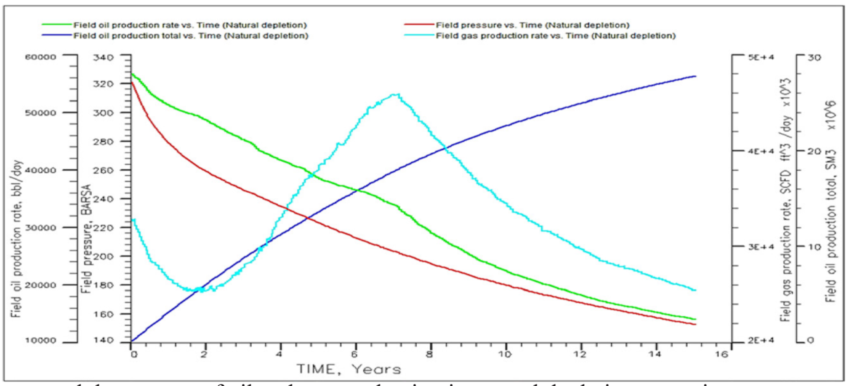

Fig. 4 Reservoir performance and the amount of oil and gas production in natural depletion scenario.

As mentioned, the initial reservoir pressure is 324 bar, so oil production is able to reach the desired oil rate, and it is maintained for less than 1 year. Gas production also decreases a bit due to reaching the limits of the well bottom pressure of a production well. Then, with more oil production, gas production increases and peaks in the first 7 years. As more oil and gas are produced, reservoir pressure begins to decrease. Production will drop drastically when the reservoir pressure gets closer to the minimum bottom-hole pressure. Subsequently, oil and gas production will decrease and even stop because the reservoir will not have enough pressure support to produce more oil under natural depletion.

Water Injection

In this case, all the conditions of the previous scenario are established. Furthermore, water injection takes place in three injection wells, with injection rates of 2000, 3000, and 3500 Sm^3/day during 15 years of simulation, so its results can be evaluated. Table 4 shows the performance results of the reservoir in this scenario.

Table 4 The performance results of the water injection scenario.

Index	Field injection rate (ksm^3/day)	Cumulative oil production (million Sm^3)	Oil recovery (%)	Field pressure at the end of injection (bar)
1	2	36.8	24.7	228
2	3	38	26.2	255.9
3	3.5	38	26.24	255.7

As a result of injecting water in this scenario, the pressure drop is compensated and works better than in the natural depletion scenario. However, increasing the injection rate by more than 3 million sm3/day and due to the injection well pressure limitation, injections are not possible over this rate. Therefore, oil recovery will not increase significantly by increasing the injection rate. Thus, the amount of oil recovery is 26.2% in this scenario.

Continuous CO_2 Injection

Due to the problem of high-pressure drop in the field and low recovery, CO_2 is injected into the reservoir to take advantage of its environmental benefits in addition to maintaining the pressure of the reservoir and producing more oil. To investigate the effect of injection rates on the reservoir behavior in the continuous injection scenario, CO_2 gas is injected into the reservoir at different rates. According to Table 5, the reservoir performance with different injection rates was investigated and reported in this scenario.

Table 5 The performance results of the CO_2 injection scenario.

Index	Field injection rate (million Sm^3/day)	Cumulative oil production (million Sm^3)	Oil recovery (%)	CO_2 storage (million KG-M)	Field pressure at the end of injection (bar)
1	1.7	37.1	25.4	340.8	239.7
2	2.5	39.8	28.2	512.7	282.7
3	3.4	42.1	30.4	680.1	323
4	4.3	42.6	30.5	775	349

According to the table above, the best scenario is related to the injection of CO_2 at a rate of 4.3 million Sm^3/day. Figure 5 shows the results of the reservoir performance in this scenario. Based on the simulation results related to the scenario with an injection rate of 4.3 million Sm3/day, the cumulative oil production at the end of the simulation period was 42.6 million Sm^3 with a recovery factor equal to 30.5%. Also, the amount of CO_2 storage in this scenario equals 775 million KG-M. By injecting CO_2 gas in this scenario, the pressure drop is compensated and works much better than natural depletion. However, by increasing the injection rate to more than 4.3 million Sm^3/day and considering the injection well pressure limitation, the amount of injection will not be able to be increased. Thus, oil recovery by increasing the injection rate more than this amount will not increase significantly. Most CO_2-EOR projects, at different project stages, are conducted in the USA and China, followed by Canada, Brazil, Saudi Arabia, and the United Arab Emirates [41]. As a result of CO_2 injection in the Ivanic field between 2014 and 2019, recovery has increased by 35% [42], and in some other projects by 22% and more [43]. Continuous CO_2 injection can substantially increase oil production and CO_2 storage [44].

Machine Learning Implementation

As shown in Figure 6, CO_2 injection has a higher percentage of oil recovery than natural depletion and water injection. Therefore, considering the environmental benefits of CO_2 injection and the higher oil recovery amount in this scenario, the CO_2 injection method is used in the ML model, which in addition to higher oil recovery, provides us with the possibility of CO_2 storage. In fact, by using the existing data, the model can be built with higher accuracy and speed. After the numerical simulation, the data needed to build the database is extracted from the numerical simulator. The percentage of oil recovery and the amount of CO_2 storage are the two objectives of this section, and ML model and ANN algorithm are used to predict these values. According to the values and their ranges in Table 6, the numerical simulator is produced and injected in 8 years to extract the necessary data for ANN training. The numerical simulator is run 250 times to extract the required data. According to the objectives, the database will be built based on the extracted data. 85% of the data is used for training, and 15% is used to evaluate the performance of the ANN. Data extraction parameters and their non-linear relationship are demonstrated in a heat map (as seen in Figure 7). A heat map displays the independence of the input parameters, which it ensures that parameters with the same information will not interfere.

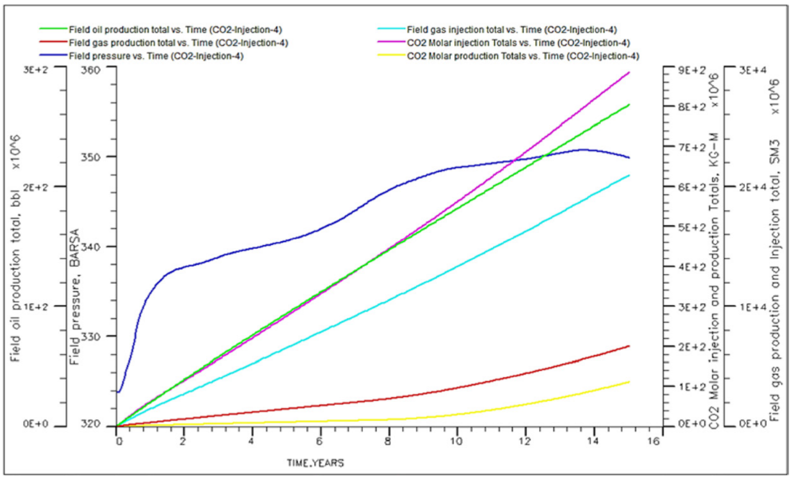

Fig. 5 The performance results of the reservoir with an injection rate of 4.3 million Sm^3/day.

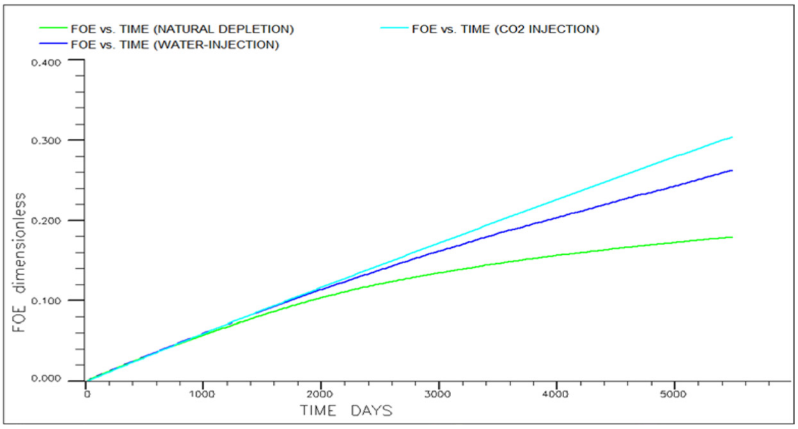

Fig. 6 Comparison of field oil efficiency of existing scenarios.

Table 6 ANN input parameters and their operational ranges to build the model.

Parameters	Unit	Range
Gas injection rate	million Sm^3/day	[1-5]
Oil production rate	Sm3/day	[9000-12000]
Production BHP limitation	Barsa	[55-110]
Injection BHP limitation	Barsa	[350-550]

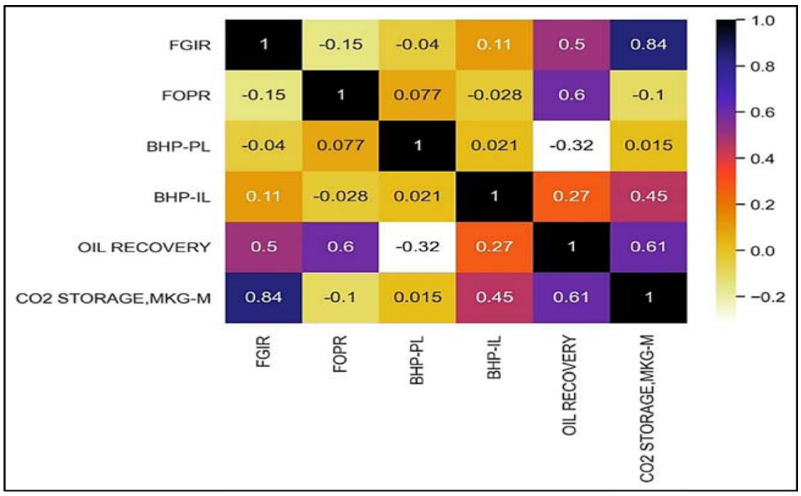

Fig. 7 Input parameter heat map diagram (BHP-IL: bottom-hole pressure of injection well limitation, BHP-PL: bottom-hole pressure of production well limitation, FGIR: field gas injection rate, FOPR: field oil production rate).

In Figure 8, in addition to the ANN architecture, the inputs of the ANN include the CO_2 injection rate, oil production rate, production bottom-hole pressure limitation, and injection bottom-hole pressure limitation, as well as its output, including the percentage of oil recovery and the amount of carbon dioxide gas storage.

ANN architecture describes the pattern of connections between neurons. This study has three parts in the ANN: an input layer, an output layer, and hidden layers. The consideration interval in the tuner package in the Python environment to optimize the hyper-parameters in this study is shown in Table 7. After evaluating the hyper-parameters, two hidden layers are selected, and the number of neurons in the first and second hidden layers is 81 and 51, respectively. Also, the learning rate was determined to be 0.05.

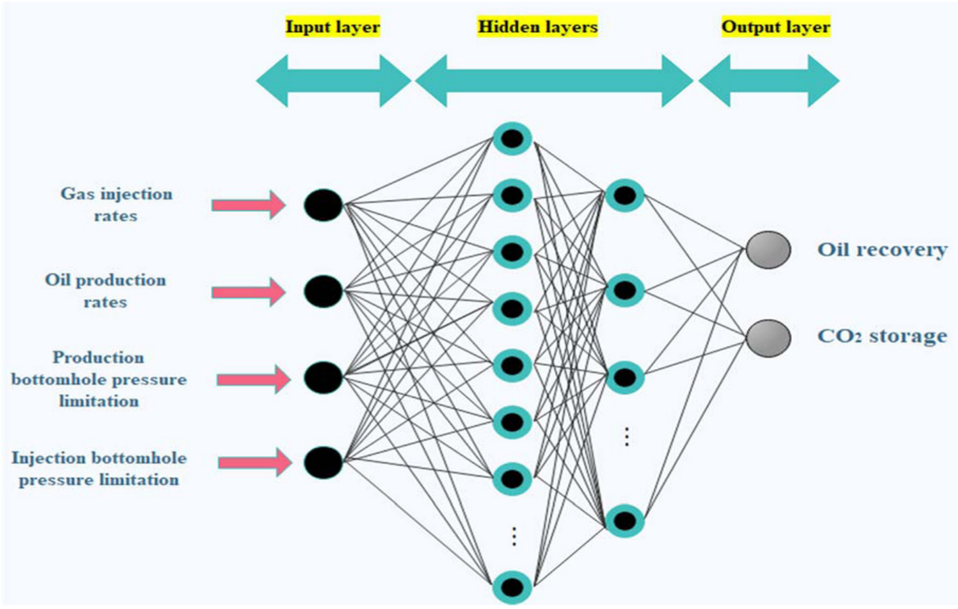

Fig. 8 Architecture of the proposed ANN model and ANN inputs and outputs.

Table 7 Hyperparameters space used for ANN training.

Hyperparameters	Range
Number of hidden layers	[1-3]
Numbers of neurons	[1-100]
Learning rate	[0.01-0.08]

As a next step, the ANN is trained using the data extracted from the database, which is used to ensure the proper training of the ANN from the mean square error (MSE) of the data during training. The ANN is trained, and the MSE of the data during training is shown in Figure 9. It can be seen that the MSE decreased with the increase in the number of epochs and became close to zero, which it indicates the proper training of the ANN.

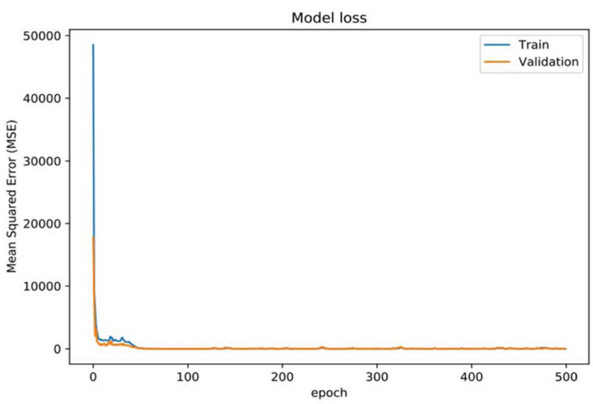

Fig. 9 Mean square error during training and validation of the ANN.

By training the ANN, the trained model is applied to the test data to validate the ANN. According to the test data, in Figure 10 (blue dots) and Figure 11 (blue dots) the values predicted by the ANN for the existing purposes, i.e., carbon dioxide storage and oil recovery, are shown respectively. The predicted values are close to their actual values, confirmed by the R2 values . To verify the trained model's accuracy, the values of root mean square error (RMSE) and mean absolute percentage error (MAPE) in the test data set are also checked, as shown in Table 8.

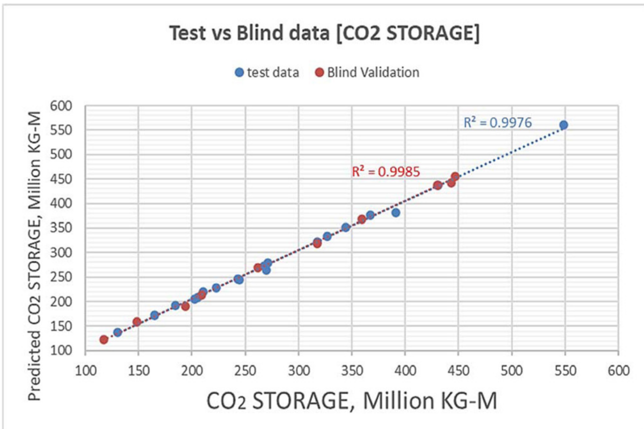

Fig. 10 Predicted Values by ANN versus actual values of CO_2 storage (million KG-M). blue dots: test data and red dots: blind data.

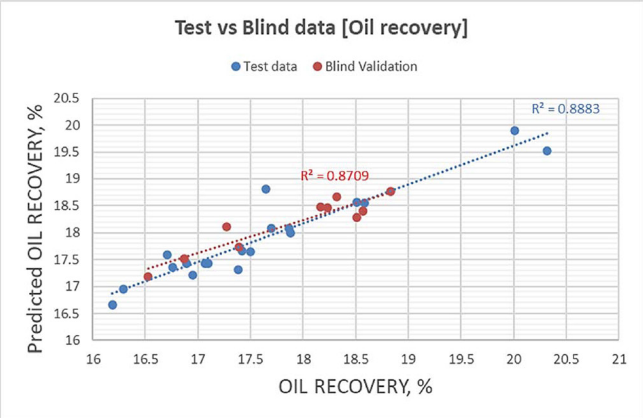

Fig. 11 Predicted Values by ANN versus actual values of oil recovery (%). blue dots: test data and red dots: blind data.

Table 8 Evaluation of RMSE, MAPE and R^2 in the two-objective ANN testing data.

Evaluation	Oil Recovery (%)	CO_2 Storage (Million KG-M)
MAPE	2.37	2.43
RMSE	0.55	6.85
R^2	0.88	0.99

To ensure the predictive capability of the trained ANN, 10 times simulations were run with random values. Then the values predicted by the trained ANN were compared with the actual values obtained from the numerical simulator, and the performance results of the trained ANN on these blind data (The data on which the trained ANN has not been previously observed or applied.) are shown in Figure 10 (red dots) and Figure 11 (red dots). The trained ANN in the test data is able to predict the target values with less than 2.5% error and in the blind data with less than 2.6% error, which a summary of the evaluation criteria of trained two-objective ANN is shown in Figure 12. In this way, ANN can predict target values in a shorter period and with sufficient accuracy in the CO_2-EOR scenario and reduces the computation load involved in predicting target values. Field data were used to investigate the possibility of building an ANN model in an oil reservoir, and the objectives of the study, namely, oil recovery and carbon dioxide storage, are important in the oil industry, and they can be used for optimization studies. In addition to reproducing the desired data in a fraction of a second, the trained ANN model can also be integrated and coupled for other purposes, such as optimization. Therefore, with the high-speed capability of ML technique, oil recovery, and carbon dioxide storage can be calculated with reasonable accuracy and high speed.

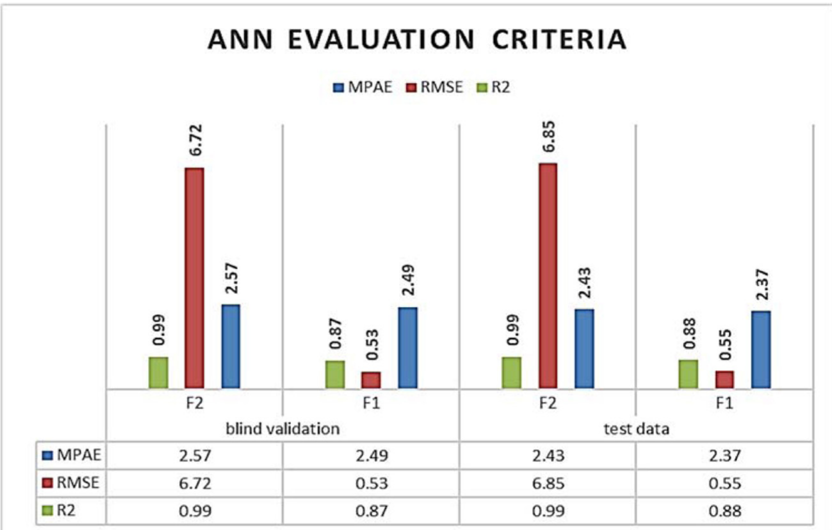

Fig. 12 Evaluation of trained ANN on two existing targets. F1: percentage of oil recovery and F2: CO_2 storage.

Conclusions

In this study, different scenarios for oil production were compared and then a scenario was selected that allowed us to take advantage of the environmental effects while producing more oil. The following results were obtained from this study.

- The oil reservoir simulation was done with field data to investigate various scenarios and extract data for ANN training. Three scenarios of natural depletion, water injection, and continuous CO_2 injection were investigated, and oil recovery was 8.4% higher in water injection and 12.7% higher in CO_2 injection than in natural depletion. As well as providing better oil recovery, CO_2 injection can also benefit the environment by storing CO_2 gas, making the use of this method even more appealing.
- The surrogate reservoir model was built using ML technique by choosing the scenario of CO2 injection to reduce the computational load and the possibility of using it in optimization tasks.
- To train ANN, the numerical simulator was run 250 times to extract the necessary data. As a result, the trained two-objective ANN was a MAPE of less than 2.5% in the test data for both objectives, i.e., oil recovery and carbon dioxide storage.
- To further validate and ensure the accuracy of the performance of the two-objective ANN, the numerical simulator was run randomly 10 times and compared with the values predicted by the ANN. According to the results, MAPE for both existing objectives was less than 2.6%. Therefore, the ANN that makes predictions in a fraction of a second has a suitable accuracy that can be used as a surrogate reservoir model.

References

1. Ranathunga A S, Perera M S A, Ranjith P G (2014) Deep coal seams as a greener energy source: a review, Journal of Geophysics and Engineering, 11, 6: 063001, https://doi.org/10.1088/1742-2132/11/6/063001.
2. Perera M S A, Ranjith P G (2012) Carbon dioxide sequestration effects on coal's hydro-mechanical properties: a review, International Journal of Energy Research, 36, 10: 1015-1031, https://doi.org/10.1002/er.2921.
3. Perera M S A, Ranjith P G, Choi S K, Bouazza A, Kodikara J, Airey D (2011) A review of coal properties pertinent to carbon dioxide sequestration in coal seams: with special reference to Victorian brown coals, Environmental Earth Sciences, 64: 223-235, doi.org/10.1007/s12665-010-0841-7.
4. Schrag D P (2007) Preparing to capture carbon, Science, 315, 5813: 812-813 812-813, DOI: 10.1126/science.1137632.
5. Change I C (2007) Mitigation of climate change—summary for policymakers. working group iii contributions to the intergovernmental panel on climate change, Bangkok, Thailand.
6. Agency I E (2021) Global energy review: CO_2 emissions in 2021 Global emissions rebound sharply to highest ever level, International Energy Agency, https://iea.blob.core.windows.net/assets/c3086240-732b-4f6a-89d7-db01be018f5e.
7. Ettehadtavakkol A, Lake L W, Bryant S L (2014) CO_2-EOR and storage design optimization, International Journal of Greenhouse Gas Control, 25: 79-92, doi.org/10.1016/j.ijggc.2014.04.006.
8. Bui M, Adjiman C S, Bardow A, Anthony E J, Boston A, Brown S, Fennell P S, Fuss S, Galindo A, Hackett L A (2018) Carbon capture and storage (CCS): the way forward, Energy and Environmental Science, 11, 5: 1062-1176. 11, 1062–1176. https://doi.org/10.1039/C7EE02342A.
9. Lake L, Johns R T, Rossen W R, Pope G A (2014) Fundamentals of enhanced oil recovery, Society of Petroleum Engineer, https://doi.org/10.2118/9781613993286.
10. Green D W, Willhite G P (2018) Enhanced oil recovery, Society of Petroleum Engineers, https://doi.org/https://doi.org/10.2118/9781613994948.
11. Marston P M (2017) Incidentally speaking: a systematic assessment and comparison of incidental storage of CO_2 during EOR with other near-term storage options, Energy Procedia, 114: 7422-7430, https://doi.org/https://doi.org/10.1016/j.egypro.2017.03.1872.
12. Cooney G, Littlefield J, Marriott J, Skone T J (2015) Evaluating the climate benefits of CO_2-enhanced oil recovery using life cycle analysis, Environmental science and technology, 49, 12: 7491-7500, https://doi.org/https://doi.org/10.1021/acs.est.5b00700.
13. Jaramillo P, Griffin W M, McCoy S T (2009) Life cycle inventory of CO_2 in an enhanced oil recovery system, 8027-8032,https://doi.org/https://doi.org/10.1021/es902006h.
14. Holm, L. W. (1986) Miscibility and miscible displacement. Journal of Petroleum Technology, 38, 08: 817-818, https://doi.org/10.2118/15794-PA.
15. Kulkarni M M (2003) Immiscible and miscible gas-oil displacements in porous media, Louisiana State University and Agricultural and Mechanical College, https://doi.org/10.31390/gradschool_theses, 259.
16. Martin D F, Taber J J (1992) Carbon dioxide flooding, Journal of Petroleum Technology, 44, 04: 396-400, https://doi.org/10.2118/23564-PA.
17. Liya Z, Jin P, Shishi T (2012) CO_2-Rich Associated gas re-injection miscible flooding mechanism research, In 2012 Fourth International Conference on Computational and Information Sciences, 1297-1299, IEEE, doi: 10.1109/ICCIS.2012.101.
18. Dong J, Wu S, Xing G, Fan T, Li H, Wang B (2019) Factors affecting water alternating hydrocarbon gas miscible flooding in a low permeability reservoir, In International Petroleum Technology Conference, OnePetro, https://doi.org/10.2523/IPTC-19063-MS.
19. Weyburn-Midale Fact Sheet: Carbon Dioxide Capture and Storage Project, https://sequestration.mit.edu/tools/projects/weyburn.html.
20. Jensen G (2022) Assessing the Potential for CO_2 EOR and CO_2 Storage in Depleted Oil Pools in Southeastern Saskatchewan, Canada, http://dx.doi.org/10.2139/ssrn.4298632.
21. Farouq Ali S M, Thomas S (1994) A realistic look at enhanced oil recovery. Scientia Iranica, 1: 3.
22. Hashemi S M H, Sedaee B (2022) Mechanistic simulation of fracture effects on miscible CO_2 injection, Petroleum Research, 7, 4: 437-447, https://doi.org/10.1016/j.ptlrs.2022.01.006.
23. Jarrell P M, Fox C E, Stein M H, Webb S L (2002) Practical aspects of CO_2 flooding, 22: 13-35, Richardson, TX: Society of Petroleum Engineers, doi.org/10.2118/9781555630966.
24. Alian S S, Alta'ee A F, Omar A A, Hani I (2011) Study of asphaltene precipitation during CO_2 injection for Malaysian light oil reservoirs, In 2011 National Postgraduate Conference, 1-5, IEEE, doi: 10.1109/NatPC.2011.6136535.
25. Okhovat M R, Hassani K, Rostami B, Khosravi M (2020) Experimental studies of CO_2-brine-rock interaction effects on permeability alteration during CO_2-EOR, Journal of Petroleum Exploration and Production Technology, 10: 2293-2301, https://doi.org/10.1007/s13202-020-00883-8.
26. Emera M K, Sarma H K (2007) Prediction of CO_2 solubility in oil and the effects on the oil physical properties. Energy Sources, Part A, 29, 13: 1233-1242, https://doi.org/10.1080/00908310500434481.
27. Al-Jarba M, Al-Anazi B D (2009) A comparison study of the of the CO_2-oil physical properties literature correlations accuracy using visual basic modelling technique, Nafta, 60, 5: 292-295.
28. Rojas G, Ali S F (1986) Scaled model studies of carbon dioxide/brine injection strategies for heavy oil recovery from thin formations, Journal of Canadian Petroleum Technology, 25, 01: https://doi.org/10.2118/86-01-07.
29. Tunio S Q, Tunio A H, Ghirano N A, El Adawy Z M (2011) Comparison of different enhanced oil recovery techniques for better oil productivity, International Jour-

nal of Applied Science and Technology, 1: 5.

30. Ampomah W, Balch R S, Cather M, Will R, Gunda D, Dai Z, Soltanian M R (2017) Optimum design of CO_2 storage and oil recovery under geological uncertainty, Applied Energy, 195: 80-92, https://doi.org/10.1016/j.apenergy.2017.03.017.
31. He J, Xie J, Wen X H, Chen W (2015) Improved proxy for history matching using proxy-for-data approach and reduced order modeling, In SPE Western Regional Meeting, OnePetro, https://doi.org/10.2118/174055-MS.
32. Haghshenas Y, Niri M E, Amini S, Kolajoobi R A (2021) A physically-supported data-driven proxy modeling based on machine learning classification methods: Application to water front movement prediction, Journal of Petroleum Science and Engineering, 196: 107828, https://doi.org/10.1016/j.petrol.2020.107828.
33. Kim M, Shin H (2020) Machine learning-based prediction of the shale barrier size and spatial location using key features of SAGD production curves, Journal of Petroleum Science and Engineering, 191: 107205, 916-928, DOI: 10.1016/j.apenergy.2016.10.012.
34. El-Sebakhy E A (2009) Forecasting PVT properties of crude oil systems based on support vector machines modeling scheme, Journal of Petroleum Science and Engineering, 64, 1-4: 25-34, https://doi.org/10.1016/j.petrol.2008.12.006.
35. Ahmadi M A (2012) Neural network based unified particle swarm optimization for prediction of asphaltene precipitation, Fluid Phase Equilibria, 314: 46-51, https://doi.org/10.1016/j.fluid.2011.10.016.
36. You J, Ampomah W, Sun Q (2020) Development and application of a machine learning based multi-objective optimization workflow for CO_2-EOR projects, Fuel, 264: 116758, https://doi.org/10.1016/j.fuel.2019.116758.
37. Amini S, Mohaghegh S, Gaskari R, Bromhal G (2012) Uncertainty analysis of a CO_2 sequestration project using surrogate reservoir modeling technique, In SPE Western Regional Meeting, OnePetro, https://doi.org/10.2118/153843-MS
38. Gaspar A T, Santos A, Maschio C, Avansi G, Schiozer D (2015) UNISIM-IM: study case for management variables optimization of reservoir exploitation strategy, International Journal of Modeling and Simulation for the Petroleum Industry, 9: 1-7.
39. John F O (2015) Optimization of a water alternating gas injection compositional fluid flow simulation with water alternating gas injection optimization on the upscaled synthetic reservoir CERENA-I, Master of Science Thesis, Instituto Superior Técnico, Universidade de Lisboa.
40. Yeap W J (2018) Study of EOR-CO_2 miscible flooding performance using compositional reservoir simulation with local grid refinement, Master's Thesis, Texas A and M University, https://hdl.handle.net/1969.1/173312
41. Novak Mavar K, Gaurina-Međimurec N, Hrnčević L (2021) Significance of enhanced oil recovery in carbon dioxide emission reduction. Sustainability, 13, 4: 1800, https://doi.org/10.3390/su13041800.
42. Gaurina-Međimurec N, Mavar K N (2019) Carbon capture and storage (CCS): geological sequestration of CO_2, CO_2 Sequestration, 1-21.
43. Lake L W, Lotfollahi M, Bryant S L (2019) CO_2 enhanced oil recovery experience and its messages for CO_2 storage, In Science of Carbon Storage in Deep Saline Formations 15-31, Elsevier, https://doi.org/10.1016/B978-0-12-812752-0.00002-2.
44. Ren D, Wang X, Kou Z, Wang S, Wang H, Wang X, Zhang R (2023) Feasibility evaluation of CO_2 EOR and storage in tight oil reservoirs: a demonstration project in the Ordos Basin, Fuel, 331: 125652, https://doi.org/10.1016/j.fuel.2022.125652.