Introduction

ADNOC is aligned with the commitment of the UAE to be net zero CO_2 emissions by 2050. To that end, ADNOC is currently progressing two major CCS projects. For both projects the acerage in the area of interest is extremely large (over 150 thousand acres each). This presents a challenge to assure that the minimum number of wells and their locations have been selected. The locations of the CO_2 injectors can be selected using a semi-automated process based on predefined candidate locations, drilling queues and subsequent clustering. This will result in the minimal set of injectors and a reduced surface layout for the set of candidate locations considered. However, it is likely that better locations and sequences are possible. To increase efficiency of the full cycle process and provide assurance that the most suitable well clustering for CCS development is identified, we propose a hybrid methodology that integrates machine learning (ML), reduced-physics models and conventional simulation.

Method

The conventional process used by ADNOC has been presented previously (Aikman et al, CCUS-4185989, 2025). The storage and seal zones for both storage sites are well known in the region and are extensive, underlying most (if not all) of the country. One of the storage sites, including the area of interest (red polygon), is shown in Figure 1. Extensive 3D seismic was available to map the subsurface horizons and faulting. Regional wells are available to estimate and set formation properties such as lithology, porosity and permeability as well as pressure and water salinity. The site has been selected in accordance with procedures found in ISO-27914. The site is characterized by two thick stacked carbonate formations which initially contain only high salinity water. The topmost seal consists of a carbonate formation in which there are many laterally extensive, thick anhydrite layers. A thick, extensive ultralow permeability shale separates the two carbonate storage formations. The base seal is a tight carbonate zone. The development strategy is evaluated and optimized using a commercial reservoir simulator that allows advanced scripting and control.

For the process set up, around 35 potential gas injection candidates were positioned in the model and set to be “undrilled” at the beginning of the run (Figure 2). An advanced drilling queue system was used to ensure that sufficient wells were drilled to meet field injection targets. If additional injection was required, an additional well would be activated.

The candidate wells can be activated either by the total injection potential of both zones at a given location or by defining a specific drilling order. The first pass was to allow wells to be activated by potential, and then to examine the CO2 plume migration and how the best locations can be clustered together, then defining the drilling sequence according to this order. The plots of the active wells are shown in Figure 2. It is found that for the targeted injection requirement, around 10 wells were required for the case where the development is clustered by defining a specific order for well activation. In contrast, if the wells are activated by the injection potential, only 8 wells are required. However, this savings in drilling cost will be more than offset by an increase facility and pipeline costs.

In this approach, we integrate reduced physics models (Fast-Marching Model), and reservoir simulations under ML algorithms to create a proxy model. ML model is trained with simulation outputs as target to learn the complex relationships between well trajectory, reservoir characteristics and corresponding well performance. Fast-Marching Model (FMM) which determines pressure propagation within the reservoir and identifies dynamically connected volumes is further integrated with ML model to significantly improve prediction capabilities. Finally, coupling the trained ML model with global optimization algorithms, we efficiently determine optimal well locations and trajectories that maximize CO2 sequestration.

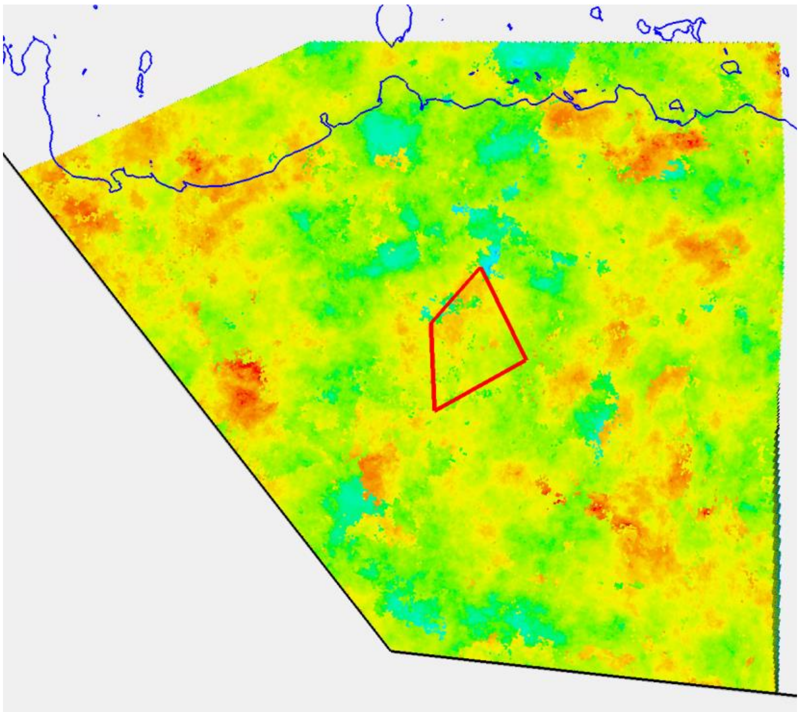

***Figure 1**: geologic model which shows the Volume of interest (VOI) for the CCS project (red diamond). The VOI has an area of approximately 140 thousand acres.*

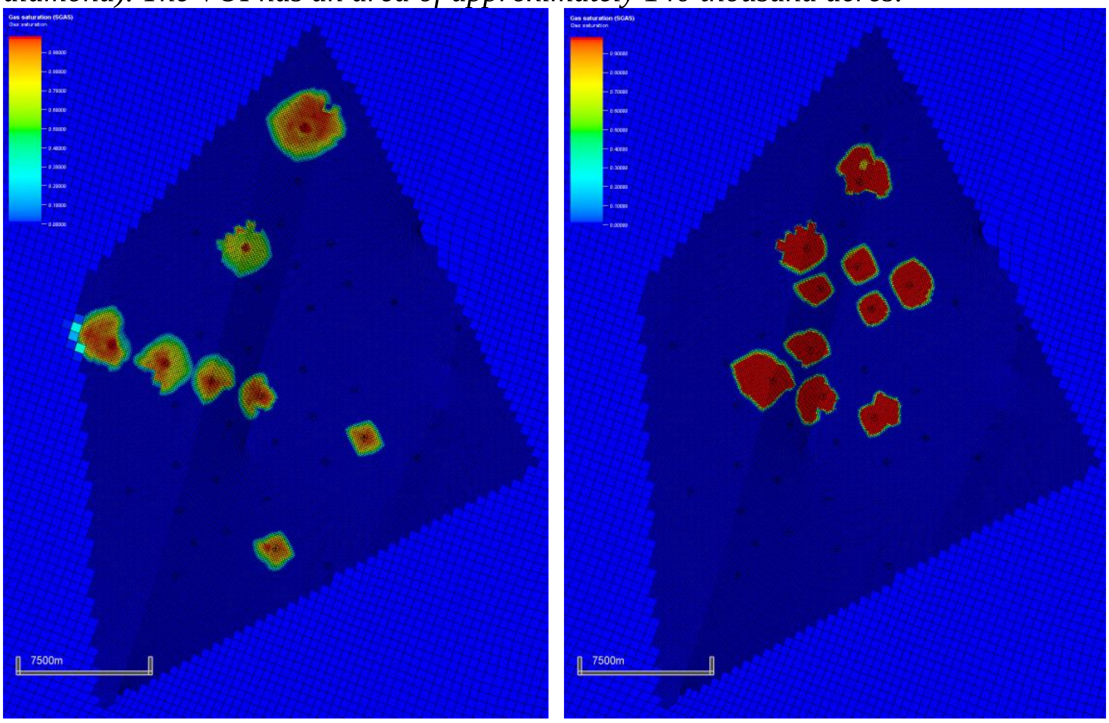

***Figure 2**: Location of wells for Drill-By-Potential (left) vs Drill-By-Order (right)*

Examples

Successful application of hybrid ML workflow to a real multilayer reservoir is presented. Results indicate that for a specified CO_2 injection function, the hybrid ML model can provide the optimal well configuration in a reduced amount of time and with high assurance. This improves confidence in the well count, well sequence and well placement from the trained hybrid ML model that is required to meet a specified CO_2 injection target (both rate and total amount sequestered). The well strategy can be directly input into a commercial reservoir simulation for the final design phase of the project. This paper demonstrates that the optimization process utilizing machine learning algorithms will reduce the overall design time and can be quickly adapted and updated as new information is obtained or additional geostatistical distributions are used in the static model.

Conclusions

This study highlights the potential of combining machine learning with reduced-physics modeling to optimize well placement in CO_2 sequestration projects. By introducing a process at the front end to augment the workflow which heavily relies on conventional reservoir simulation methods, the proposed methodology offers an improved and efficient approach to define the well drilling program for CO_2 storage projects.

Acknowledgements

ADNOC management for permission to publish this technology implementation project with Resermine.

References

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