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Perspective

A real-time autonomous adjusting process for fluid-fluid displacement in CO_2 geological sequestration

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Abstract:
To achieve net-zero carbon emission, securely and permanently sequestrating CO_2 into deep underground is internationally assured as a robust solution, although a few technical challenges on complex in-situ storage process are yet to be overcome. Despite researchers are increasingly familiar with laboratory-scale CO_2-brine displacement and how to characterize and improve the process, field implementation is not that simple and of great challenge. In this article, an opportunity on an approach that utilizes fluid-fluid displacement fundamentals is discussed to predict CO_2 sequestration using artificial intelligence. A concept of machine learning is introduced, where computer programs can learn and improve automatically via previous experiences. With machine learning model, fluid displacement behaviors that are spontaneously monitored are emphasized to predict the displacement result, which is readily adjusted if needed while training the model from real-time CO_2 injection response. Such an approach is a real-time autonomous adjusting process, consisting of three main stages: Selection of first appraisal fluid for trial injection, real-time machine learning from in-situ injection response, and fluid adjustment if needed or continuation on the same injection until achieving a maximum CO_2 storage. This approach could play a vital role in the carbon capture and storage industry to develop CO_2 storage effectively with adequate resources, and yet has a potential to substitute a conventional design or fluid screening approach for subsurface fluid injection, including underground hydrogen storage and hydrocarbon recovery.

Carbon dioxide (CO_2) geological sequestration (CGS) is a crucial downstream part of CO_2 capture and storage (CCS) that was highlighted in the recent United Nations Climate Change Conference to be implemented globally as a robust solution to tackle climate change by this mid-century. CGS is an inverse approach to hydrocarbon recovery, aiming to inject fluid (CO_2) into subsurface formation to be stored securely and permanently (Thanasaksukthawee et al., 2022; Zhang et al., 2022a). Storing CO_2 into subsurface rock formation is a complex and challenging process per se, requiring the holistic knowledge of geophysics, petrophysics, and petroleum engineering (Zhang et al., 2022a). One interesting question to ask is not just which subsurface reservoirs are suitable for CGS (Mohamed and Nasr-El-Din, 2012; Jin et al., 2016; Zhang et al., 2022b, 2022c), but more importantly how can we store CO_2 at a maximum with no damage to storing formation?

Storing CO_2 is performed by injecting compressed or supercritical CO_2 into deep structural formation (1$\sim$3 km) where its pore spaces are pre-saturated with formation brine. With some additional energy, invading CO_2 could displace such saturated brine and reside "partially" in the pore spaces (Ringrose, 2020). To overcome defending energy of pre-saturated brine in porous rock, researchers have elucidated a number of interfacial phenomena (e.g., change in fluid-fluid interfacial tension, rock-fluid-fluid wettability alteration, and manipulating capillary-gravitational driving forces) that affect such fluid-fluid displacement, and hence been able to engineer the process by either facilitating displacing energy increment

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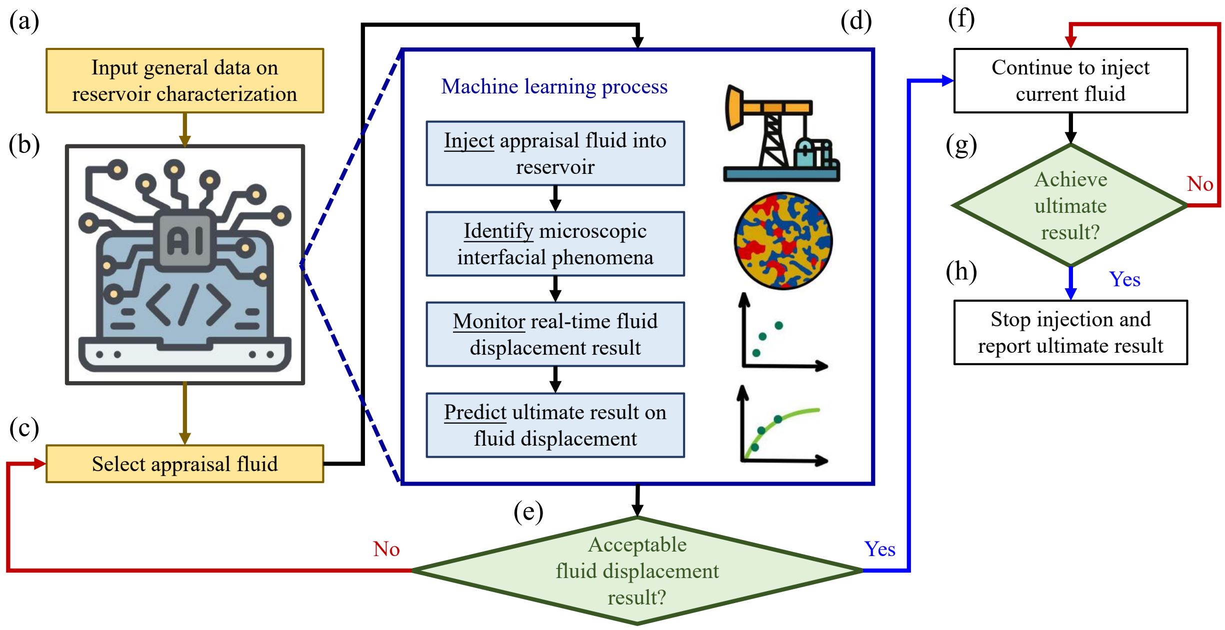

Fig. 1. Schematic diagram illustrates a RAAP for fluid displacement in CO_2 geological sequestration, separated into three main stages: selection of first appraisal fluid (a)-(c), real-time training of a machine learning model from in-situ injection response (d)-(e), and fluid adjustment if needed or continuation on the same injection until achieving the maximum CO_2 storage (f)-(h).

or weakening defending energy (Celia et al., 2015). It is noted that excess defending energy could fracture reservoir rock and therefore risking CO_2 leakage. During CO_2 injecting, chemicals are added or injection techniques are amended cautiously to optimize such CO_2-brine displacement. For example, continuous gas injection, water alternating gas, or water curtain injection (Núñez-López et al., 2019). In addition, owing to variety (i.e., clastic and carbonate sediments) and heterogeneity (i.e., great distribution of different reservoir porosity and permeability (Reynolds et al., 2018)) of storing formations, selecting chemical additives or designing injection techniques are not instantaneously simple and of great challenge.

As such, "full-chain" examination on a targeted storing formation is usually conducted to ensure a maximum and secured CGS. A full study on fluid displacement, which is timely and costly, is inevitably performed with focuses on both length-scale and time-scale (Bartels et al., 2019). A complete study package consists of ex-situ, in-situ, and in-silico studies, including microscopic interfacial phenomena, two-dimensional micromodel displacement, three-dimensional coreflooding, reservoir modeling and upscaling, reservoir simulation, and even a field trial (Bachu, 2015; Ajayi et al., 2019; Rajabi and Chen, 2022). This circumstance brings us to an idea on developing a more effective approach that bridges well-established fundamentals to uncertain reservoir characteristics of prospective formation for CGS. With the help of artificial intelligence (AI), such a full-chain examination can be eased, and a fluid displacement prediction model could be performed spontaneously based on dataset from available research, and hence readily adjusted if needed while training the model from real-time CO_2 injection response in-situ.

This work herein emphasizes an importance of a systematic process to design a CO_2-brine displacement scheme with any necessary adjustments followed autonomously, aiming to obtain the best fluid displacement, i.e., maximizing CO_2 storage safely and securely. Such a process applies an AI technique with instantaneous machine learning (ML) while injecting CO_2 in-situ in a targeted reservoir, without any physical pre-examinations needed as mentioned above. As a branch of an AI, ML enables us to train a model by learning from datasets, such as previous data logs or experiences. Machines with ML models can predict or make a decision by itself without pre-programmed explicitly. This approach is a real-time autonomous adjusting process (henceforth referred to as real-time autonomous adjusting process (RAAP)) and its workflow is illustrated in Fig. 1. RAAP can be separated into three main stages: selection of first appraisal fluid, real-time ML from in-situ injection response, and fluid adjustment if needed or continuation on the same injection until achieving a maximum CO_2 storage.

In the first stage, reservoir characteristics of a targeted storage formation is provided to the model, which then autonomously selects the appraisal injecting fluid that is most suitable for CO_2-brine displacement for this storing reservoir (Figs. 1(a)-1(c)). Such a selection is based on the available research or guidelines taken from published research, such as effects of water chemistry and interfacial phenomena on CO_2 geochemical reactions and mineralization (Jun et al., 2017; Liang et al., 2017; Noiriel and Daval, 2017). Prior to incorporating ML techniques, the significant characteristics (i.e., features) have to be extracted from a targeted reservoir. Some examples of ML algorithms include, but not limited to, artificial neural network, support vector machine, and extreme gradient boosting, etc.

Selected appraisal injecting fluid is then physically injected into the storing formation in the second stage of the real-time ML process (Figs. 1(d) and 1(e)). While the appraisal fluid is being injected into the reservoir, with the extracted features from the first stage as input data, the ML model constantly analyzes and predicts the behaviors of fluid displacement by concurrently identifying microscopic interfacial phenomena and monitoring the displacement result. With such a process, the model is thereafter able to predict an ultimate result that would be likely yielded from such appraisal fluid in the current injection. The predicted ultimate displacement is then assessed against a constraint of acceptable displacement performance, which is pre-defined by developer (e.g., reservoir engineer or production engineer).

In the third stage (Figs. 1(f)-1(h)), if the predicted ultimate displacement result satisfies the constraint, the ML model continues to inject the current fluid until an actual ultimate displacement is achieved, and hence the displacement result will be reported once the injection is ceased, otherwise an alternative appraisal fluid is re-selected and another consequent trial (i.e., the second stage) is performed consecutively until the constraint is satisfied.

Although a full-chain RAAP is to be implemented, some subsurface fields have recently begun to use some of ML algorithms as part of RAAP in developing stage. For example, the hydrocarbon development in Southwestern Pennsylvania have begun to implement an ML approach using a historical data (e.g., reservoir characteristics and production history) to model hydrocarbon production which results in an acceptable accuracy (Esmaili and Mohaghegh, 2016), and this approach could be potentially used in CGS. Similar to the subsurface reservoir in the Middle East (Anifowose et al., 2019), AI integrated with big data was used to improve a decision making process for reservoir characterization, although the work did not further predict or adjust the production process on the fly which our current perspective presents.

Toward a real-world implementation, the RAAP has a potential to outperform and even substitute a conventional design or a fluid screening approach for subsurface fluid injection, including underground hydrogen storage and hydrocarbon recovery. With the promising real-time learning process and autonomous response, this custom-made fluid displacement model is suitable for any formations that anticipate a better ultimate storage result. However, technologies for monitoring and identifying fluid displacement behaviors in-situ can be challenging and have yet to be achieved with classical backgrounds from petroleum engineering, e.g., X-ray imaging and computed tomography scanning (Alqahtani et al., 2020). More endeavors should be exerted to scale up the specific microscopic phenomena to be effectively linked or forecast a thorough field-scale storage.

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Conflict of interest

The authors declare no competing interest.

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