Contribution ID: **64** Type: **Oral Presentation**

Predicting ultimate hydrogen production and residual volume during cyclic underground hydrogen storage in porous media using machine learning

Monday, 13 May 2024 17:15 (15 minutes)

In the context of climate change mitigation, underground/subsurface hydrogen storage (UHS) is regarded as a solution that could help tackle the imbalance in renewable energy supply. Excess energy can be stored as molecular hydrogen (H2) and re-used when it is needed. To enable large-scale storage in underground geologic formations, reservoir simulation of cyclic loading scenarios will be used to optimize the storage operations. Hydrogen storage in geological reservoirs involves many physical phenomena related to reservoir dynamics, trapping mechanisms, and potential reactions with minerals and bacteria. Simulating different scenarios of fast H2 injection and production while considering those physical constraints and optimized economic and operational parameters generates loads of data and therefore requires high computational power. The nature of UHS operations and the underlying storage reservoir physics make variations in the generated data sets extensive. Predictive tools like machine learning (ML) that are data dependent can to some extent fill the knowledge gap while simultaneously making the operations more viable. It is therefore interesting to develop tools that can predict parameters associated with fast cyclic operations while minimizing the computational cost. Such methods could help optimize storage operations and reduce operational costs.
The work summarized in this abstract attempt to showcase how machine-learned models trained with data generated from simulated UHS systems in porous media can be used to predict ultimate hydrogen production. The same approach is applied to predict H2 amounts that remain trapped in the reservoir due to physics-related parameters. The OPM flow reservoir simulator is used to build models encompassing physical and dynamic parameters to generate cyclic field data which are then used to train time series neural network (NN) models. In the presented work, the reliability and accuracy of the model are ensured through hyper-parameter tuning and cross-validation analysis on a windowed time-series NN. The results obtained in the study show the relevance of machine learning (ML) methods in predicting ultimate H2 production and residual H2 amount in geological reservoirs. The trained models captured the data trends with mean squared error (MSE) and mean absolute error (MAE), commonly termed as loss functions, from training and validation steps used as accuracy metrics. In one of the reservoir-scale cases, the machine-learned training and predictions in a physics-oriented approach reduced the computational time by about 6773% in comparison with simulation runs by OPM flow on a 4-layer reservoir model. The accuracy metrics and predictions are even much better on simulation data obtained with a one-layer model having a horizontal well along its top and based on a complex cyclic schedule. By showing how machine-learned models can capture some of the complex physical uncertainties associated with underground/subsurface hydrogen storage, our research aims to bring a technical contribution to the development of this technology. Field-scale simulated production and injection data are used to train the models. The paper therefore presents the methodology followed, results from the machine learning methods, and the outlook for future tasks.

Acceptance of the Terms & Conditions

Click here to agree

Student Awards

I would like to submit this presentation into both awards

Country

Norway

Porous Media & Biology Focused Abstracts

References

Sarah Eileen Gasda

Primary author: MUSHABE, Raymond (University of Bergen)

Co-authors: Mr TOR, Sandve (Norwegian research center (NORCE)); Mr BIRANE, Kane (Norwegian research center (NORCE)); Mr WENDPANGA, Donald (University of Stavanger); Mr MARBAN, David (Norwegian research center (NORCE))

Presenter: MUSHABE, Raymond (University of Bergen)

Session Classification: MS15

Track Classification: (MS15) Machine Learning and Big Data in Porous Media