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Data-driven based investigation of pressure dynamics in underground hydrocarbon reservoirs

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Abstract

The process of storing natural gas in geological formations involves applying pressure to force the gas into and out of the porous and permeable reservoir. In response to gas extraction/withdrawal and storage/injection, the reservoir compresses and expands as a major consequences of fluid pore pressure variations. The major challenge associated with this type of energy systems is learning the pore pressure variations within the grid as fluid is being injected and/or withdrawn. As such, it is essential to identify a realistic model that accounts for the pore pressure variations at any point in time. In this paper, we present a data-driven technique called Dynamic Mode Decomposition (DMD) to investigate the pressure dynamics of an underground hydrocarbon reservoir model in relation to natural gas injection/storage. For demonstration purpose, we first implement a hydrocarbon reservoir model using a benchmark data of the first Society of Petroleum Engineers (SPE1) Comparative Solution Project. Applying DMD to a pressure field data of the simulated reservoir model, we show that DMD is capable of approximating the average reservoir pressure change and pore pressure variations within the reservoir grid over time with up to 99% accuracy. Given that depleted reservoirs are already developed hydrocarbon reservoirs, we conclude that DMD could serve as a reliable tool for fast evaluation of pressure dynamics of underground natural gas storage given its low complexity and insignificant loss of prediction accuracy.

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Keywords: Data-driven modelling; Depleted reservoirs; Dynamic mode decomposition; Reservoir pressure dynamics; Underground natural gas storage

1. Introduction

Underground natural gas storage (UNGS) plays a crucial role in ensuring that any excess gas delivered during the hot season (summer months) is available to meet the raised demand of the cold season (winter months). According

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to Teatini et al. [1], two major reasons that necessitate natural gas storage are: first, meeting seasonal consumption requirements and second, as a security against unanticipated supply interruptions. Among the major types of UNGS facilities, depleted hydrocarbon reservoirs are considered economical due to their known geological characteristics compared to aquifers and salt caverns [2]. Storage of natural gas in depleted hydrocarbon reservoirs has been considered a strategic practice to meet the increasing seasonal demand of natural gas in different parts of the world. In 1915, the first successful underground storage of natural gas in a depleted hydrocarbon reservoir occurred in Ontario, Canada. Since then, several of such facilities have been built in North America, Canada, Europe, Asia–Oceanic, Middle East, Argentina, and other parts of the world [3]. Underground natural gas storage may be regarded as a long-term confinement of natural gas within geological formations. Hence, two of the most fundamental static parameters of an underground storage facility are porosity (its ability to keep natural gas for future use) and permeability (its ability to transmit gas into and out of the formation). According to Plaat [4], the process of storing natural gas in geological formations involves applying pressure to force the gas into and out of the porous and permeable reservoir. As natural gas is being injected into the geological formation, pressure is being built up within the formation, thereby making the geological formation becoming a type of pressurized natural gas container. As described in Verga [3], the proportion of natural gas that can be stored and withdrawn during a normal cycle of a depleted reservoir is referred to as working gas while the proportion of the natural gas that must remain in the reservoir to maintain pressure within the reservoir is called base gas (also known as cushion gas).

As described in Evans [5], during the normal operation of the depleted storage reservoir, base gas remains permanent within the reservoir to maintain pressure required to drive the natural gas into the well. Working gas which is referred to as the volume of natural gas available for withdrawal during the normal functioning of the storage reservoir, is injected during storage and this process causes the pressure in the reservoir to increase. This makes the pressure within the storage reservoir becomes high. Converting a depleted hydrocarbon (oil or natural gas) reservoir from production facility to storage facility takes advantage of using an already developed reservoir with existing wells, pipeline connections, as well as extraction and distribution equipments that were leftover when the reservoir was productive [6]. Having these equipments in place cuts down the cost of converting depleted oil or natural gas reservoirs into storage facilities and thereby making depleted reservoirs, on average, the easiest and cheapest to develop, operate and maintain compared to other types of UNGS facilities such as caverns and aquifers [7].

Recently, application of machine learning and data-driven techniques to track and predict dynamic parameters have been receiving attentions in the energy sector [8–13]. In recent years, a large body of research called Dynamic Mode Decomposition (DMD) has emerged around modal decomposition and machine learning methods. Developed by Schmid in 2010, DMD originated as a new promising tool in the fluid dynamics community to discover spatiotemporal meaningful structures from high-dimensional fluids data [14]. The evolving success of DMD arises from the fact that it is a data-driven and equation-free technique that is capable of discovering spatiotemporal meaningful patterns that may be used for diagnosis, control, state estimation and future-state prediction of complex dynamical systems [15].

Given that the UNGS industry borrowed much of its knowledge from oil and gas reservoir engineering [3], the present article focuses on applying DMD to investigate the pressure dynamics in an underground hydrocarbon reservoir model that operates under natural gas injection that mimics the process of storing/injecting working gas in depleted storage reservoirs.

The remaining sections of this article is organized as follows: section two presents materials and methods with focus on a brief description of the reservoir model used as a reference to the proposed DMD method. The section also describes the DMD algorithm utilized in this study. Section three presents computational results of both the reference model and the data-driven model. We end the paper with some conclusions and next steps towards future work.

2. Materials and methods

2.1. Numerical reservoir simulation: The reference model

The first step towards achieving the aim of this study is the development of a numerical reservoir simulation model to simulate the process of storing natural gas (working gas) in a depleted reservoir. The reservoir model which serves as a reference model in this paper is developed using the available dynamic and static data of the first SPE Comparative Solution Project [16]. The first SPE Comparative Solution Project was organized by [16] and is a description of a depletion problem with natural gas injection into a 10 × 10 × 3 reservoir model with an injector and a producer in diagonally opposite corners. The natural gas injection well was completed in layer 1 and is located at grid point (1, 1) while the producing well was completed in layer 3 and is located at grid point (10, 10). The reservoir has a porosity of 0.3 and is uniformly distributed within the grid blocks, whereas the permeability is heterogeneous with values 500, 50, and 200 mD in layers 1, 2, and 3, respectively with thickness 20, 30, and 50 ft. Initially, the reservoir is undersaturated with a constant pressure field in each layer, a homogeneous mixture of water ($S_w = 0.12$) and oil ($S_o = 0.88$), and zero free gas ($S_g = 0.0$) throughout the reservoir model. Detailed data that describe the petrophysical and PVT properties as well as the relative permeabilities of the reservoir model can be found in [16]. As mentioned earlier, the geological structure of the reservoir model is a three-dimensional formation that consists of 10 × 10 grid blocks in the x–y dimension and 3 layers in the z dimension. Thus, the numerical reservoir simulation model consists of 10 × 10 × 3 = 300 grid blocks (cells). In this study, the reservoir was simulated for 1200 days in 120 time-steps. This resulted to a 300 × 120 matrix that contains 36,000 grid cells in the spatiotemporal database. Each grid cell in the spatiotemporal database contains some dynamics of the reservoir's parameters in a given run and given time step. For the purpose of this study, the pressure field data of the gas injection reservoir model was retrieved and utilized by the proposed data-driven technique. For the sake of simplicity, the simulation process neglects the effect of interface pressure, and as for inlet boundary condition, a bottom-hole pressure is assigned to the injection well. Details of the numerical simulation process is available in [17].

2.2. Dynamic mode decomposition (DMD)

The propose method utilizes the capability of DMD as a data-driven modal reduction technique to provide accurate reconstruction of reservoir pressure field and approximation of average pressure change from the numerical simulation data. From the DMD perspective, the pressure field data collected from the numerical simulation of the reservoir model were arranged in two snapshot matrices as follows:

$$\boldsymbol{Y} = \begin{bmatrix} | & | & | \\ \boldsymbol{y}_1 & \dots & \boldsymbol{y}_{m-1} \\ | & | & | \end{bmatrix}, \tag{1a}$$

$$\boldsymbol{Y}' = \begin{bmatrix} | & | & | \\ \boldsymbol{y}_2 & \dots & \boldsymbol{y}_{m} \\ | & | & | \end{bmatrix}. \tag{1b}$$

These two matrices have large number of rows than columns, that is, $n \gg m$ and consist of the states of the system and their columns were captured in equal-spaced time, with a time step Δt. Each $\boldsymbol{Y}_i = \boldsymbol{Y}(i\Delta t)$ is a vector with gridlock components c, as such, $\boldsymbol{Y}, \boldsymbol{Y}' \in \mathbb{R}^{c\times(m-1)}$. Using data from the numerical simulations, DMD attempts to construct a linear dynamical system

$$\boldsymbol{Y}_{t+1} \approx \boldsymbol{A}\boldsymbol{Y}_t \tag{2}$$

and thus

$$\boldsymbol{Y}' \approx \boldsymbol{A}\boldsymbol{Y}. \tag{3}$$

It is interesting to realize that the least-squares solution of (3) leads to

$$\boldsymbol{A} = \boldsymbol{Y}'\boldsymbol{Y}^{\dagger} \tag{4}$$

here, $\boldsymbol{Y}^{\dagger}$ stands for the Moore–Penrose pseudo-inverse of $\boldsymbol{Y}$. To get an estimate of matrix $\boldsymbol{A}$, Singular Value Decomposition (SVD) has to be computed on the snapshot matrix $\boldsymbol{Y}$ as follows

$$\boldsymbol{Y} = \boldsymbol{U}\boldsymbol{S}\boldsymbol{V}^* \tag{5}$$

where $\boldsymbol{U} \in \mathbb{R}^{n\times r}$, $\boldsymbol{S} \in \mathbb{R}^{r\times r}$, $\boldsymbol{V} \in \mathbb{R}^{m\times r}$ and $r \le m$ stands for the rank of the data matrix $\boldsymbol{Y}$. the columns of $\boldsymbol{U}$ are referred to as POD modes, and they satisfy $\boldsymbol{U}^* \cdot \boldsymbol{U} = \boldsymbol{I}$. In the same manner, columns of $\boldsymbol{V}$ are orthonormal, and satisfy $\boldsymbol{V}^* \cdot \boldsymbol{V} = \boldsymbol{I}$. The diagonal of $\boldsymbol{S}$ contains the singular values of matrix $\boldsymbol{Y}$. The full matrix $\boldsymbol{A}$ can be acquired by solving the pseudo-inverse of $\boldsymbol{Y}$ as follows

$$\boldsymbol{A} = \boldsymbol{Y}'\boldsymbol{V}\boldsymbol{S}^{-1}\boldsymbol{U}^*. \tag{6}$$

In DMD, the interest is in the leading eigenvalues r and eigenvectors of $\boldsymbol{A}$, for this reason, one can therefore project A onto the POD modes in U as follows

$$\tilde{\boldsymbol{A}} = \boldsymbol{U}^*\boldsymbol{A}\boldsymbol{U} = \boldsymbol{U}^*\boldsymbol{Y}'\mathbf{V}\boldsymbol{S}^{-1}. \tag{7}$$

The point here is, instead of working on the high-dimensional matrix $\boldsymbol{A}$, one can directly compute the reduced $\tilde{\boldsymbol{A}}$ in such a way that the full matrix $\boldsymbol{A}$ and the reduced matrix $\tilde{\boldsymbol{A}}$ have the same nonzero eigenvalues. Thus, the spectral decomposition of $\tilde{\boldsymbol{A}}$ can be computed as

$$\tilde{\boldsymbol{A}}\boldsymbol{W} = \boldsymbol{W}\boldsymbol{\Lambda}. \tag{8}$$

Here, the DMD eigenvalues are the elements of the diagonal matrix Λ and the eigenvectors of $\tilde{\boldsymbol{A}}$ are represented by the columns of $\boldsymbol{W}$. The high-dimensional DMD modes ϕ can then be reconstructed by using $\boldsymbol{W}$ of the reduced system and the snapshot matrix $\boldsymbol{Y}'$ as follows

$$\phi = \boldsymbol{Y}'\mathbf{V}\boldsymbol{S}^{-1}\boldsymbol{W}. \tag{9}$$

It is worth noting here that the eigenvectors of the high-dimensional matrix $\boldsymbol{A}$ are these DMD modes which correspond to the eigenvalues in Λ. Finally, average reservoir pressure at each time step can be approximated from the reconstructed pressure field by taking the average of all pressures in all grid cells at a particular time step.

3. Computational results and discussion

3.1. Numerical simulation of natural gas injection/storage

As described in Section 2, the reservoir model was first simulated for a period of 1200 days of injecting/storing natural gas into the formation while the production well remained closed. Results for the reservoir's pressure field that form the spatiotemporal database were compiled and saved. Plots of the reservoir model depicting the injection well (I), production well (P), porosity, and permeability distributions within the reservoir are shown in Figs. 1 and 2, respectively.

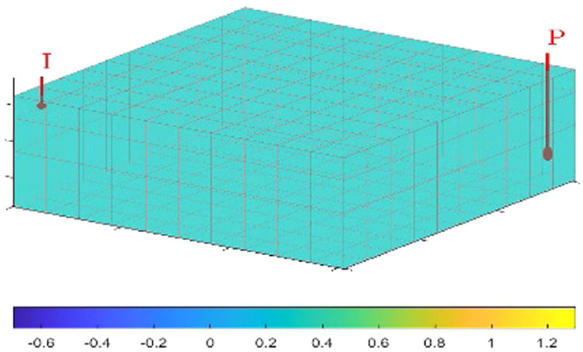

Fig. 1. Porosity distribution within reservoir model.

To gain an insight of how the pressure evolves within the reservoir grid cells as natural gas is being injected, the plot of the reservoir's average pressure change over time is shown in Fig. 3 and the reservoir's pore pressure evolution for some selected days from the time that storage starts is shown in Fig. 4. As it can be seen from Figs. 3 and 4, as natural gas is being injected/stored into the reservoir model, the formation pressure keeps raising and thereby making the reservoir a sort of pressurized gas storage as it expands to accommodate the injected natural gas. This depicts the real behaviour of an UGNS in depleted reservoir.

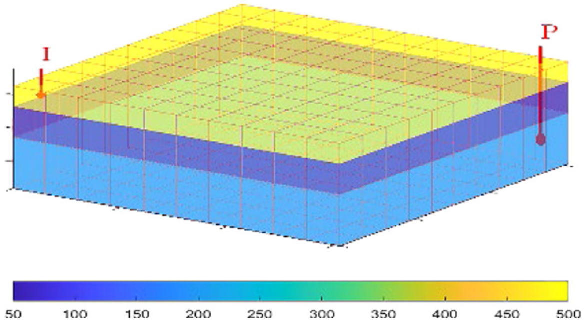

Fig. 2. Permeability distribution within reservoir model.

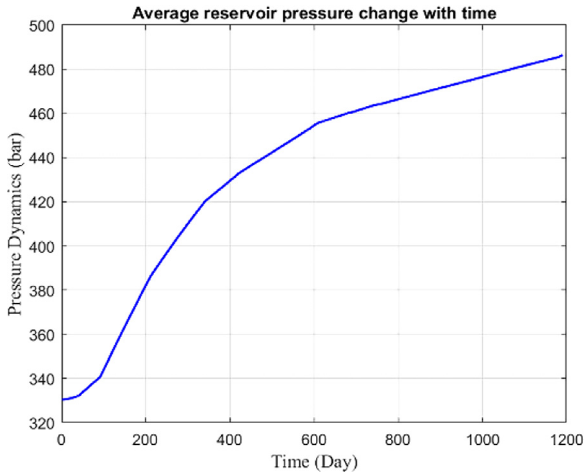

Fig. 3. Reservoir pressure evolution with time.

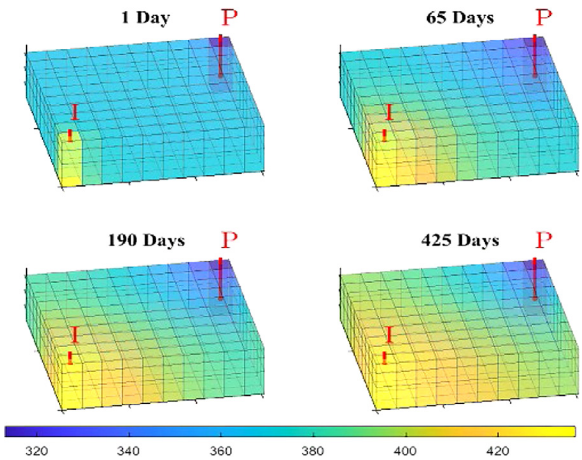

Fig. 4. Reservoir pore pressure variations for some selected days of natural gas storage.

3.2. DMD prediction of pressure dynamics

Next step involves applying DMD on the spatiotemporal pressure field database to predict the pressure dynamics over time and to visualize the pore pressure variations. By setting the value of $r = 15$, DMD was able to reduce

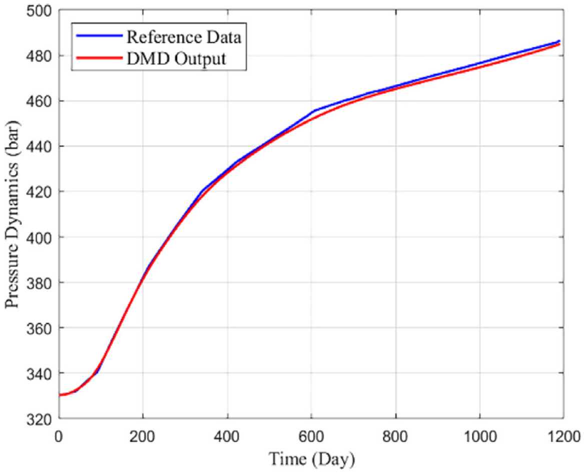

Fig. 5. Reference data versus DMD prediction of pressure dynamics with time.

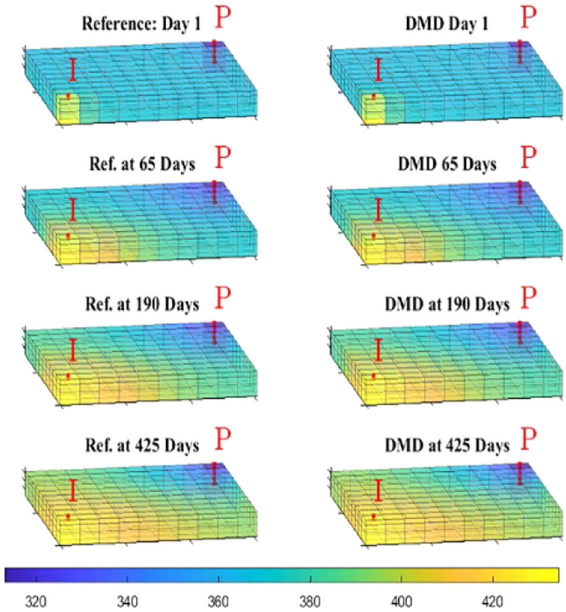

Fig. 6. Comparisons of reservoir pore pressure variations versus DMD output for the selected days shown in Fig. 4.

the pressure field matrix into a low-dimensional space and reconstruct the original pressure field data using 15 eigenvalues with insignificant error. To illustrate the ability of DMD to capture the reservoir's pressure dynamics, comparison of the reservoir's average pressure dynamics versus DMD prediction is shown in Fig. 5, and comparison of the reservoir's pore pressure variations versus DMD outputs are shown in Fig. 6. It can be seen from Figs. 5 and 6 that DMD is able to predict the reservoir's pressure dynamics and capture the pressure evolution within the reservoir grid cells with very high accuracy.

4. Conclusion and future work

In this paper, a data-driven method that decomposes and reconstructs a pressure field of a depleted reservoir model that mimics the behaviour of an underground natural gas storage is proposed. The reservoir model was first simulated numerically as natural gas is being injected into the formation and spatiotemporal data that represent the reservoir's pressure field were compiled. Results of applying DMD on the pressure field data show that the proposed technique is capable of approximating the average reservoir pressure change and pore pressure evolution over time with mean square error (MSE) and coefficient of determination (R^2) of 2.1944 and 0.9996, respectively. Considering that storing natural gas in depleted reservoirs is more economical, the proposed technique can be used as a reliable tool for monitoring the pressure dynamics of underground natural gas storage in depleted reservoirs. As part of our future work, steps have been taken to incorporate the production of the stored/injected natural gas from the storage reservoir in the simulation process and to apply the proposed data-driven technique to the pressure dynamics.

Declaration of competing interest

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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References

[1] Teatini P, Castelletto N, Ferronato M, Gambolati G, Janna C, Cairo E, Marzorati D, Colombo D, Ferretti A, Bagliani A, Bottazzi F. Geomechanical response to seasonal gas storage in depleted reservoirs: A case study in the po river basin, Italy. J Geophys Res 2011;116:1–21. http://dx.doi.org/10.1029/2010JF001793.
[2] Healey M. Underground gas storage in cheshire – The costain experience. White Paper 2008;1–9.
[3] Verga F. What's conventional and what's special in a reservoir study for underground gas storage. Energies 2018;11(5). http://dx.doi.org/10.3390/en11051245.
[4] Plaat H. Underground gas storage: Why and how. Geol Soc Spec Publ 2009;313:25–37. http://dx.doi.org/10.1144/SP313.4.
[5] Evans DJ. An appraisal of Underground Gas Storage technologies and incidents for the development of risk assessment methodology. British Geological Survey Open Report OR/07/023, 2007, p. 10–20. http://dx.doi.org/10.1016/j.jfca.2010.03.028.
[6] Mgbaja UM, Enwere N. Reservoir characterization, simulation & estimation of storage capacity of depleted reservoirs in Niger delta for underground natural gas storage. In: Society of petroleum engineers - Nigeria annual international conference and exhibition; 2017. p. 1373–87.
[7] Azin R, Nasiri A, Entezari AJ. Ungerdorund gas storage in a partially depleted gas reservoir. Oil Gas Sci Technol 2008;63(6):9–19. http://dx.doi.org/10.2516/ogst.
[8] Ali A, Guo L. Neuro-adaptive learning approach for predicting production performance and pressure dynamics of gas condensation reservoir. IFAC-PapersOnLine 2019;52(29):122–7. http://dx.doi.org/10.1016/j.ifacol.2019.12.632.
[9] Hasan M, Goharshenasan P. A new hybrid method based on Fuzzy Logic for maximum power point tracking of Photovoltaic Systems. Energy Rep 2020;6:1619–32. http://dx.doi.org/10.1016/j.egyr.2020.06.010.
[10] Zeng B, Zhou M, Liu X, Zhang Z. Application of a new grey prediction model and grey average weakening buffer operator to forecast China' s shale gas output. Energy Rep 2020;6:1608–18. http://dx.doi.org/10.1016/j.egyr.2020.05.021.
[11] Ali A, Guo L. Adaptive neuro-fuzzy approach for prediction of dewpoint pressure for gas condensate reservoirs. Petroleum Sci Technol 2020;38(9):673–81. http://dx.doi.org/10.1080/10916466.2020.1769655.
[12] Aliyuda K, Howell J, Hartley A, Ali A. Stratigraphic controls on hydrocarbon recovery in clastic reservoirs of the Norwegian Continental Shelf. Petroleum Geosci 2020;9(4):330–49. http://dx.doi.org/10.1144/petgeo2019-133.
[13] Ali A. Ensemble learning model for prediction of natural gas spot price based on least squares boosting algorithm. In: 2020 international conference on data analytics for business and industry: Way towards a sustainable economy. Bahrain: Sakheer; 2020, p. 1–6. http://dx.doi.org/10.1109/ICDABI51230.2020.9325615.
[14] Schmid PJ. Dynamic mode decomposition of numerical and experimental data. J Fluid Mech 2010;656:5–28. http://dx.doi.org/10.1017/S0022112010001217.
[15] Tu JH, Rowley CW, Luchtenburg DM, Brunton SL, Kutz JN. On dynamic mode decomposition: Theory and applications. J Comput Dyn 2014;1(2):391–421. http://dx.doi.org/10.3934/jcd.2014.1.391.
[16] Odeh A, Corp D. Comparison of solutions to a reservoir simulation problem. SPE; 1981, p. 1–14.
[17] Lie K-A. An introduction to reservoir simulation using Matlab/Gnu Octave: User guide for the MATLAB reservoir simulation toolbox (MRST). Cambridge: Cambridge University Press; 2019, p. 355–99.