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Geomechanical reservoir modelling with Thermodynamics-based Artificial Neural Networks (TANNs)

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Geological subsurface storage is a promising strategy for large-scale, cost-efficient energy storage systems. Stress sensitivity has notably influence on the long-term stability and serviceability of subsurface reservoirs set for energy storage use. The evolution of the field stress of stress-sensitive reservoirs and the associated structural deformation, often a consequence of fluid production and injection, can cause significant changes to the reservoir stress-dependent properties [1]. These properties include pore and void compressibility, and porosity. For fractured and faulted reservoirs, field stress variation may also impact fracture conductivity, alter pre-existing fractures, and reactivate faults [4].

Current geomechanical reservoir simulators incorporate the evolution of the reservoir mechanical state by means of material constitutive modelling, typically within a Finite Element Modelling (FEM) framework. In efforts to honour the heterogeneity and multi-scale nature of subsurface reservoirs, multi-scale solution methods are commonly adopted. For a reservoir multi-scale simulation, the micro-scale problem must be iteratively solved for different input parameters, rendering the solution method computationally exhaustive, particularly for two-way coupled problems.

The combination of machine learning-based solution methods and FEM frameworks can address the computational inefficiency of conventional multi-scale reservoir modelling schemes. In principle, a machine learning algorithm trained to learn the constitutive behaviour of a material can replace in-built material constitutive models in a FEM framework. We resort to Thermodynamics-based Artificial Neural Networks (TANNs), a physics-based data-driven machine learning algorithm introduced in [5] for material constitutive modelling. TANNs have been shown to guarantee the thermodynamic consistency of learnt material constitutive models. The first and second laws of thermodynamics are directly encoded in the architecture of TANNs through the definition of two scalar functions, an energy potential and a dissipation function, and the computation of their differentials [3].

TANNs can be incorporated in FEM tools, in what is referred to as TANNxFEM in [6]. We present the application of the TANNxFEM framework to geomechanical reservoir modelling. This work aims to introduce a computationally efficient reservoir modelling framework, for which uncertainty quantification is possible. The proposed framework can maximise the use of information inherently contained in high-dimensional data, and significantly reduce computation demands necessary for accurate statistical evaluation, while warranting physical and geological realism.

TANNs are first trained on analytical material data, computed by numerical integration of an incremental, thermodynamically consistent material model presented in [2]. The trained TANNs are then imported into a user material subroutine for the finite element package Abaqus. Through an input file, the parameters of the trained neural network are read as a set of material properties. The material subroutine then evaluates the incorporated trained neural network to construct the stress and elasticity tensors necessary for large-scale finite element reservoir simulation. The above proposed framework is validated against a large-scale finite element simulation with a user material subroutine implementing the constitutive model

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used to first generate the training data for TANNs. The free-energy, dissipation, and the stress-strain response of the two finite element simulations are compared for model verification.

Contributor statement

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References

[1] Chen, S., & Li, H. (2008). A New Technique for Production Prediction in Stress-Sensitive Reservoirs. Journal of Canadian Petroleum Technology, 47(03). https://doi.org/10.2118/08-03-49

[2] Einav. "The unification of hypo-plastic and elasto-plastic theories." International Journal of Solids and Structures 49.11-12 (2012): 1305-1315

[3] Houlsby, G. T., & Puzrin, A. M. (2007). Principles of Hyperplasticity: An Approach to Plasticity Theory Based on Thermodynamic Principles. Springer Publishing.

[4] Lima, R. O., Do Nascimento Guimarães, L. J., & Pereira, L. C. (2021). Evaluating geomechanical effects related to the production of a Brazilian reservoir. Journal of Petroleum Exploration and Production Technology, 11(6), 2661–2678. https://doi.org/10.1007/s13202-021-01190-6

[5] Masi, F., Stefanou, I., Vannucci, P., & Maffi-Berthier, V. (2021). Thermodynamics-based Artificial Neural Networks for constitutive modeling. *Journal of the Mechanics and Physics of Solids*, *147*, 104277. https://doi.org/10.1016/j.jmps.2020.104277

[6] Masi, F., & Stefanou, I. (2022). Multiscale modeling of inelastic materials with Thermodynamics-based Artificial Neural Networks (TANN). *Computer Methods in Applied Mechanics and Engineering*, *398*, 115190. https://doi.org/10.1016/j.cma.2022.115190