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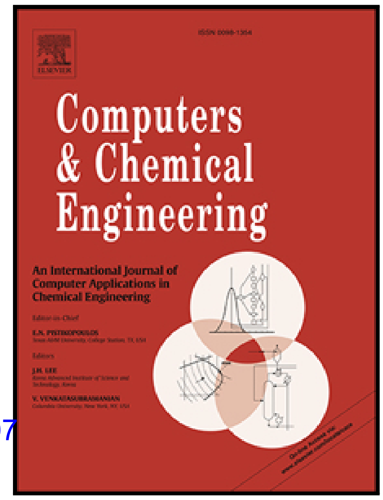

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Highlights

- A survey of applying ML and coupled ML-metaheuristic paradigm in intelligent proxy modeling of NRS is provided.
- Discussion about relevant previous works is outlined.
- General methodology of developing models using ML is expounded.
- Application of ML and coupled ML-metaheuristic paradigm in different domains of reservoir simulation is discussed.

Paper Draft

A Survey on the Application of Machine Learning and Metaheuristic Algorithms for Intelligent Proxy Modeling in Reservoir Simulation

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Abstract

Machine Learning (ML) has demonstrated its immense contribution to reservoir engineering, particularly reservoir simulation. The coupling of ML and metaheuristic algorithms illustrates huge potential for application in reservoir simulation, specifically in developing proxy models for fast reservoir simulation and optimization studies. This is conveniently termed the coupled ML-metaheuristic paradigm. Generally, proxy modeling has been extensively researched due to the expensive computational effort needed by traditional Numerical Reservoir Simulation (NRS). ML and the abovementioned coupled paradigm are effective in establishing proxy models. We conduct a survey on the employment of ML and the coupled paradigm in proxy modeling of NRS. We present the respective successful applications as reported in the literature. The benefits and limitations of these methods in intelligent proxy modeling are briefly explained. We opine that some study areas, including sampling techniques and dimensionality reduction methods, are worth investigating as part of the future research development of this technology.

Keywords

Machine Learning; Metaheuristic Algorithms; Data-Driven Modeling; Intelligent Proxies; Reservoir Engineering; Numerical Reservoir Simulation

1. INTRODUCTION

As global technology advances, the energy demand continues to evolve exponentially (Tillerson, 2008). This noticeable demand has made fossil fuels the dominant link in the energy subject area despite the continuous efforts made by the industrial sector to promote the vision and importance of renewable energies (British Petroleum, 2021). This source of energy, i.e., fossil fuels mainly from oil and gas reservoirs, goes through a step-by-step process to achieve the most desirable recovery factors. As a result, exploitation and development methods have been distinguished and classified into three categories, namely primary, secondary and tertiary recovery techniques (Ahmed, 2018). Fundamentally, these two latter techniques are designed to ensure the continuous production of hydrocarbons given the inefficacy of primary recovery. During primary recovery, the driving mechanism of hydrocarbon production originates from the natural source of energy associated with the rock and fluids in the reservoir. The mechanisms include expansion of liquids and reservoir rock, natural energy from aquifers and gas caps, expansion of dissolved gas, and gravity drainage. Secondary recovery processes are often implemented by injecting water into the aquifer or injecting gas into the gas cap, to maintain the reservoir pressure. Recovery factors after primary drainage mechanisms and the implementation of secondary recovery techniques are generally moderate (Enick et al., 2012), hence there is a need for tertiary recovery techniques (Enhanced Oil Recovery, EOR) (Ahmadi et al., 2018). The latter aim to improve the recovery by acting on fluids and reservoir rock. Some of the most successful tertiary recovery techniques include water alternating gas injection, miscible CO_2 injection, polymer and surfactant injection, etc. (Afzali et al., 2018; Ahmadi et al., 2016; Dai et al., 2014; Ghriga et al., 2019; Vahdanikia et al., 2020; Xu, 1998). In addition to these three famous recovery stages of hydrocarbon reservoirs, other intervention strategies can be considered during the lifecycle of oil and gas reservoirs, mainly by infill drilling as well as the conversion of wells (e.g. producers into injectors, or vertical into horizontal) (Ding et al., 2020; Jesmani et al., 2020; Redouane et al., 2019).

The optimization of the recovery processes during the different recovery stages is crucial to optimize the techno-economic parameters such as Net Present Value (NPV) while taking into account the different constraints linked to production systems (pressure types such as Minimum Miscibility Pressure (MMP) and Bottom Hole Pressure (BHP) in miscible gas injection, as well as other production parameters such as water cut and Gas Oil Ratio (GOR), etc.) and the cost of the operation (cost of water injection, gas injection, well intervention operations, etc.) (Dai et al., 2014; Nait Amar et al., 2020c; Nait Amar and Zeraibi, 2019; You et al., 2020a, 2020b). Given the non-linearity of differential equations and thermodynamic models describing the different recovery processes, as well as the irregularity and heterogeneity of geometry (computational domain), the description and prediction of the evolution of key design parameters are commonly done numerically by using very powerful computing tools (Nait Amar et al., 2018a; Shahkarami et al., 2014a, 2014b). In this context, several commercial software such as Eclipse™ and CMG™ have been developed in the petroleum industry to allow a rigid optimization of the different tasks related to development strategies of reservoirs and production, while integrating advanced computing paradigms such as black oil, compositional, and streamline approaches. However, the optimization of a process described by a highly non-linear model with non-linear constraints and dependent on a significant number of parameters is very complex even using these advanced simulation tools (Panjalizadeh et al., 2015). Carrying out a direct simulation scenario with the latter for cases close to reality takes time and very efficient computing means (multiprocessors, parallel computing, etc.).

All the aforementioned technical constraints have led a great part of the petroleum community to investigate new alternatives which enable the same problems to be solved with considerable precision but with means that are not binding in terms of calculation time (Ertekin and Sun, 2019; Mohammadi and Ameli, 2019). Among these alternatives, Data-Driven Modeling (DDM) has gained increasing interest in the field of reservoir simulation. Approaches to DDM are generally statistics-based (or mathematics-based), e.g., the surface response method, and Machine Learning (ML) based. DDM may alternatively be known as proxy modeling while proxy model development englobes other approaches such as reduced-order modeling which mainly involve simplification of problems and are not purely data-driven.

The word proxy means to act on behalf of another. This definition has a projection on the technical or numerical sense of proxy models (also known as surrogate models). These are models built from data exploited from numerical simulations, capable of reproducing the simulator's responses with very high precision at a speed of execution that is in the order of a few seconds (Zubarev, 2009). These models have had vast use since the beginning of the 21st century in various areas. The use of proxy models has quickly been proposed in the field of reservoir engineering where there is a wide application of proxy models as substitutions for commercial software in various vital tasks such as well placement optimization (Hassani and Sarkheil, 2011; Sayyafzadeh, 2015a; Zarei et al., 2008), history matching (Sayyafzadeh, 2015b; Shahkarami et al., 2014b), and uncertainty studies (Mohaghegh et al., 2012a, 2006).

As proxy modeling can be regarded as a kind of pattern recognition and functionality identification, the model construction can be done with interpolation methods and Artificial Intelligence (AI) and ML methods. In this aspect, AI can be perceived as technology or tools that simulate the human brain and logic to perform analysis or any assigned task whereas ML denotes the application of computer algorithms to enable learning through data (Mohaghegh, 2018, 2017a, 2017b). Thus, ML is the subset of AI. The effectiveness of a proxy is very dependent on the robustness of the technique used for its elaboration (Na-udom and Rungrattanaubol, 2015; Zubarev, 2009). The robustness of an ML technique can touch upon various aspects, specifically the training procedure including the evolved relevant model parameters to improve the training and the considered mathematical operators (e.g., backpropagation process) in the calculation process. Artificial Neural Networks (ANNs), Support Vector Machines (SVM), kriging, and Response Surface Models (RSM) are among the widely applied techniques for building proxy models in the oil industry. In general, the first two approaches are ML-based whereas the last two are statistics-based. In this paper, our focus is on the ML-based proxy, also known as an intelligent or smart proxy[1]. It is worth mentioning that before proceeding to the building stage of the proxy, a primordial step consisting of generating a set of points or a database should be done properly. The judicious choice for sampling of the points will bring precision and generalization to the built model because the chosen sampling method tries to capture a wide variety of information about the inputs/responses of the simulators (Yeten et al., 2005). Design of Experiments (DoE) is the statistics branch assembled with proxy models through its methods (Crombecq, 2011; Forrester et al., 2008; Zubarev, 2009). Several works comparing different DoE methods have been published (Crombecq, 2011; Viana, 2016; Yeten et al., 2005). The main conclusion that can be retrieved from applying DoE in the building phase of proxy models is that space-filling techniques, such as Latin Hypercube Design (LHD), are one of the most efficient methods for building rigorous proxy paradigms. The details of the paradigm of intelligent proxy will be delineated later.

The optimization of different complex processes in the oil industry, such as EOR techniques, is a crucial step in reservoir management that significantly affects the efficiency and production strategy (Yazdanpanah and Hashemi, 2012). Several time-dependent parameters and the management procedure should be optimized in such projects (Yazdanpanah and Hashemi, 2012). Thus, traditionally the optimization methods evaluate hundreds or even thousands of potential scenarios to search for the optimal solution, using time-consuming numerical simulations. To deal with this issue which includes the significant calculation time and the considerable number of simulation runs, coupling metaheuristic algorithms with a powerful clustering-based proxy model is generally considered a better alternative for non-linear and multidimensional problems

[1] To avoid confusion, “intelligent proxy” (or intelligent model) and “smart proxy” models share the same definition in this paper.

(Onwunalu et al., 2008). Metaheuristic algorithms are population-based optimization techniques that consider a predefined criterion (fitness function) to distinguish between the performance of the individuals mimicking the scenarios of the problem. The gain of this kind of coupling is ensured by the exploitation of the advantages of the two approaches, namely the reduced calculation time of the proxy models, and the oriented and targeted runs to perform based on the fitness function of the metaheuristic algorithms. As discussed in (Onwunalu et al., 2008), a proxy model is employed to approximate the objective function values of different scenarios. When the estimated values exceed a certain threshold, the respective scenario will be chosen for simulation and optimization. Besides, it is worth mentioning that a smart proxy that is built using a significant number of numerical simulations can be used for dealing with uncertainties as the generated information is generally widespread and it involves an extensive number of interactions between the main parameters of the model for covering this kind of tasks.

Metaheuristic algorithms are the optimization algorithms we would like to emphasize in this work. Metaheuristics algorithms can be defined as mathematical frameworks with advanced searching mechanisms in the solution space (Gogna and Tayal, 2013; Wong and Ming, 2019; Yang et al., 2014). The advanced searching mechanisms of metaheuristic algorithms consist of the exploration and exploitation steps which involve specific operators that help the orientation of the optimization process towards regions of interest within the search space (Hemmati-Sarapardeh et al., 2020b). Exploration refers to inspecting the unexplored parts of the search space, while exploitation corresponds to the search of the neighborhood of the promising area (Tilahun, 2019). In general, these algorithms are derivative-free and nature-inspired. Examples of these algorithms include Genetic Algorithm (GA), Differential Evolution (DE), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), Firefly Algorithm (FA), Imperialist Competitive Algorithm (ICA), Simulated Annealing (SA), Gray Wolf Optimization (GWO), Cuckoo Optimization Algorithm (COA), etc. These algorithms have demonstrated their robustness in many areas of application, including prediction of stocks, image processing, bioinformatics, etc. (Gogna and Tayal, 2013).

In terms of reservoir simulation, metaheuristic algorithms have been extensively and successfully employed not only to train different types of proxies but also to solve optimization problems (coupled with either numerical models or proxies). For clearer perusal, implementation of metaheuristic algorithms in the establishment of ML-based proxies and resolution of optimization problem is conveniently termed the coupled ML-metaheuristic paradigm. Based on our studies (Nait Amar et al., 2021, 2020c; Ng et al., 2021a), the paradigm illustrated excellent results of implementation in developing ML-based proxy models where the metaheuristic algorithms were used for training. Additionally, optimization problems can be handled efficiently by applying the coupled ML-metaheuristic paradigm where this paradigm achieves optimum results within reasonable calculation time. Therefore, it is important to have a survey of how useful ML methods are to establish intelligent proxies when being solely employed or coupled with metaheuristic algorithms. Moreover, we opine that there is a necessity to provide this survey since there is not much available discussing these domains together.

This survey paper covers a wide range of research studies related to the application of ML techniques and the coupled ML-metaheuristic paradigm in intelligent proxy modeling. This work will contribute to the research and development related to various reservoir simulation applications mainly by shedding light on the smart schemes and intelligent methods based on ML and metaheuristic algorithms that were implemented for reducing the calculability efforts associated.

The rest of the paper is formulated as follows: Section 2 provides a brief discussion regarding some of the previous literature and reviews on the relevant topics. Section 3 demonstrates the general framework that can be employed to develop an intelligent model. Thereafter, Section 4 briefs several examples of the application of intelligent proxies and the coupled ML-metaheuristic paradigm in the context of reservoir simulation. Section 5 outlines the benefits and limitations of these paradigms as well as the associated challenges in the research domain before ending this survey paper with concluding remarks.

2. PREVIOUS WORKS

As briefly mentioned, Data-Driven Modeling (DDM) is considered another modeling approach aside from traditional physics-based modeling. The availability of a large database in petroleum engineering (Mohammadpoor and Torabi, 2020) has, to a certain extent, contributed to the prevalence of data-driven models as data is one of the main building blocks for the use of ML (Mohaghegh, 2022). Explicitly speaking, these data are applied to develop a model that can provide useful insights to petroleum engineers to do some engineering judgments. In the domain of reservoir engineering, DDM has provided a fast and efficient alternative for reservoir simulation (Mohaghegh, 2017a). More intriguingly, the coupling of the metaheuristic algorithms with ML-based data-driven models is another topic that is worth a discussion. To have a better outlook on the development of ML and metaheuristic algorithms[2] in the oil and gas industry, we will briefly discuss some relevant previous works and review papers.

2.1. Proxy Modeling

DDM is considered proxy modeling in the aspect of reservoir simulation. Using the proxy model as the substitute for Numerical Reservoir Simulation (NRS) has been applauded due to its quick computation and satisfactory accuracy of results (Mohaghegh, 2022; Nait Amar et al., 2021; Ng et al., 2022a). A simple illustration is displayed in Fig 1 to outline the relationship between proxy modeling and other terminologies that would be expounded on in the following subsections. The terminologies, such as Subsurface Data Analytics, Top-Down Modeling (TDM), and Smart Proxy Modeling (SPM), will be explained in detail in Section 2.3. ML is one of the approaches to proxy modeling. Zubarev (2009) provided a comparative analysis regarding the effectiveness of four different techniques of proxy modeling as the substitute for complete reservoir simulations. These methods included polynomial regression, multivariate kriging, thin-plate splines, and ANNs. He inferred that in history matching, the proxy models could perform reasonably well in a deterministic case but not in a probabilistic fashion. In the optimization of infill-drilling, the proxy models also illustrated reasonable performance, but the solutions were not optimal. Nevertheless, these models demonstrated excellent performance in terms of prediction of initial hydrocarbons in-place and oil recovery. In general, he stated that kriging models outperformed the others but induced the highest computational footprint. There was another constructive comment that the proxy modeling methods heavily relied upon the sophistication of the model, size of the design space, and quality of input data. This gives us a very well-established cognizance of the limitations or constraints that proxy modeling methods are subject to (Zubarev, 2009). He also opined that the option of proxy modeling methods was problem-dependent and quantifying the errors induced by proxy modeling techniques was needed for quality assurance.

[2] Based upon our survey of the literature, there are not many papers that solely discuss the coupling of metaheuristic algorithms with ML in the petroleum industry. Thus, in this survey paper, apart from explaining the use of ML, one of our discussions is intended to focus on how metaheuristic algorithms can be effectively implemented along with ML mostly in the context of reservoir simulation.

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