Emission Reduction in Oil & Gas Subsurface Characterization Workflow with AI/ML Enabler

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Abstract

According to (McKinsey & Company, 2020), drilling and extraction operations are responsible for 10% of approximately 4 billion tons of CO_2 emitted yearly by Oil and Gas sector. To lower carbon emissions, companies used different strategies including electrifying equipment, changing power sources, rebalancing portfolios, and expanding carbon-capture-utilization-storage (CCUS). Technology evolution with digital transformation strategy is essential for reinventing and optimizing existing workflow, reducing lengthy processes and driving efficiency for sustainable operations.

Details subsurface studies take up-to 6–12 months, including seismic & static analysis, reserve estimation and simulation to support drilling and extraction operations. Manual and repetitive processes, aging infrastructure with limited computing-engine are factors for long computation hours. To address subsurface complexity, hundred-thousand scenarios are simulated that lead to tremendous power consumption. Excluding additional simulation hours, each workstation uses 24k kWh/month for regular 40 hours/month and produces 6.1kg CO_2.

Machine Learning (ML) become crucial in digital transformation, not only saving time but supporting wiser decision-making. An 80%-time-reduction with ML Seismic and Static modeling deployed in a reservoir study. Significant time reduction from days-to-hours-to-minutes with cloud-computing deployed to simulate hundreds-thousands of scenarios. These time savings help to reduce CO_2-emissions resulting in a more sustainable subsurface workflow to support the 2050 goal.

Keywords: *CO_2 emission, net zero carbon, machine learning, CCUS, digital transformation, emission reduction, digital subsurface workflow*

Introduction

Sustainability and emissions reduction have attracted attention in the oil and gas industry to optimize recovery and increase efficiency. According to (McKinsey & Company, 2020), oil and gas drilling and extraction operations are responsible for 10% of approximately 4 billion tons of CO_2 emitted yearly to the atmosphere. This has made an enormous impact in the oil and gas industry and on analyzing carbon footprint reduction opportunities.

A report by the International Energy Agency estimates that the use of Artificial Intelligence and Machine-Learning (AI/ML) could reduce global greenhouse gas emissions by up to 4% by 2030, which is equivalent to nearly 2.4 gigatons of carbon dioxide. The use of AI/ML enables workflows, i.e., Subsurface Reservoir Characterization and Field Development Planning enabler workflows, and has the potential to play a significant role in reducing carbon emissions and mitigating the impacts of climate change.

In this paper, we will present an overview of AI/ML Subsurface Characterization Workflows for optimizing performance in reservoir management and operations while reducing their emissions footprint. We will outline via AI/ML subsurface workflows to showcase the areas of improvement over data insights and domain sciences to manage and reduce reservoir uncertainty.

Conventional Subsurface Reservoir Characterization and Key Challenges

The Subsurface Reservoir Characterization is an integral part of sequences geoscience processing and interpretation workflows. A prolonged data-gathering process may require due to inadequate data management and governance in obtaining necessary workable datasets to proceed with the study. The interpretation scopes also required significant turnaround time due to the multiple iterations of Quality Check (QC) and review processes, silos domain data processing and interpretation, and complex domain workflow for complex reservoir environment. Moreover, most conventional reservoir characterization employs core data measurements and local correlations as input for reservoir properties modeling, whereby a strong correlation between core-log is not always available. Therefore, higher reservoir uncertainties may also require multiple screening and simulation runs to better quantify and address the reservoir uncertainties. Infrastructure limitation has always been a major challenge to most of the Oil and Gas Operators where the complicated procedure is involved whenever storage or RAM needs to be upgraded. Infrastructure ownership and maintenance further contribute to a higher cost where upfront CAPEX allocation is required. The subsurface domain workflow gaps and work inefficiency with the on-premises solution also serve as another concern, in addition to poor data management which ultimately leads to poor business investment decisions due to data unreliability.

Digital Transformation

To resolve those complex challenges of the subsurface environment and optimize its processing and interpretation

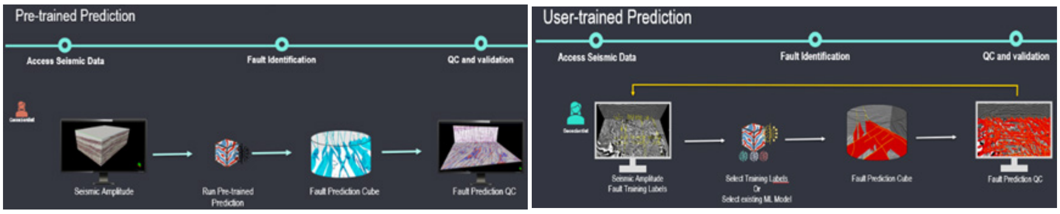

Fig. 1. Two model types of ML Fault Prediction

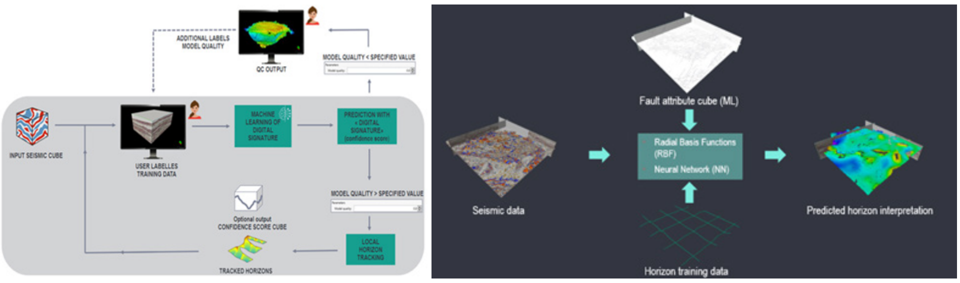

Fig. 2. ML Horizon Prediction Workflow

workflows, the majority of Oil & Gas Operators have to keep upgrading their IT infrastructure every few years to accommodate the evolution of technology and fast-changing applications. Each new user laptop or workstation has a carbon footprint of 331 kg CO_2 which 75–80% is from manufacturing processes (Circular Computing, n.d.). If multiplying these numbers by hundreds or thousands, it will contribute to the increase in CO_2 emission. Hence, migrating operators' IT architecture and workflows to digital cloud solutions will enable them to build up a more sustainable workflow that supports the achievement of CO_2 emission reduction.

Firstly, ability accessing to High Cloud Computing (HPC) simulation power will ease the need of purchasing a new laptop or workstation as well as speed up the simulation running time.

Secondly, Oil and Gas Operators will be able to build an efficient collaborative working environment, enabling access to intelligent insights from the data with cloud technology. In addition, it allows the embedded of Artificial Intelligence/Machine Learning (AI/ML) application into the traditional reservoir characterization study to have a more data-driven insights for accurate outputs. More importantly, a much shorten turn-around time from days-to weeks which traditionally could takes months-to-years to complete. (Woodside Energy, n.d.) (OMV, n.d.) (ADNOC, n.d.)

Last but not least, digitalizing the current subsurface characterisation workflow will allow the testing of different scenarios for uncertainty analysis and provide an in-depth understanding of the geological settings of Areas of Interest (AOI) before any decision-making required.

AI/ML Enablers Subsurface Reservoir Characterization Workflows

Many of the worldwide Oil and Gas Giant Operators invested tremendously in the development of AI/ML cloud-based subsurface workflows or applications. An example, BP Ventures invested five million pounds in the "Sandy" platform that is capable of linking information to identify new connections and workflows and creating a robust knowledge graph of BP's subsurface assets. This project is expected to reduce project life cycles by reducing the time necessary for data collection, interpretation, and simulation.

In a similar feat, Shell International Petroleum Company has partnered with Microsoft Corporation in different projects to improve its processes. From the use of the Microsoft DevOps platform to improve teamwork and standardize operations to partnering to reduce carbon emissions.

In the following sessions, we would like to share several AI/ML workflows that have the potential to improve exploration accuracy and reduce repetitive routine processing workflows and interpretation uncertainty. This body of information can serve as a guideline for adopting AI/ML in subsurface reservoir characterization – a trend of more effective and efficient industry-tailored intelligence solutions.

(A) Automated Wellbore and Log Interpretation

Oftentimes, the Petrophysicist are expected to evaluate the potential of reservoir properties and volumetric in-places in time-constraint situations while maintaining the consistency and accuracy of parameters and interpretations. Nevertheless, more challenges may arise when working with older wells and vintage data where data maybe appears to be incomplete and inadequate. Traditionally, weeks-to-months needed for a Petrophysicist to complete the scopes for data screening and review, key well formation evaluation, establish of core-log correlations, multiwell evaluations, poro-perm, rock-typing and saturation modeling.

The Automated Machine Learning Wellbore and Log Interpretation include automated Log Data Quality Checks (LogQC) and Composite Log Preparations, followed by Formation Evaluation for volumetric calculations to reduce the repetitive scopes for a Petrophysicist to hours-to-days.

Automating the log data QC and conditioning processes could significantly reduce repetitive human manual efforts thus increasing the process cycle efficiency in the reservoir characterization process. Taking advantage of a high-computing engine of machine learning, automation, and new technologies to speed up this manually intensive task will ultimately make more quality ranked data available for the interpretation workflows in a smaller fraction of the time.

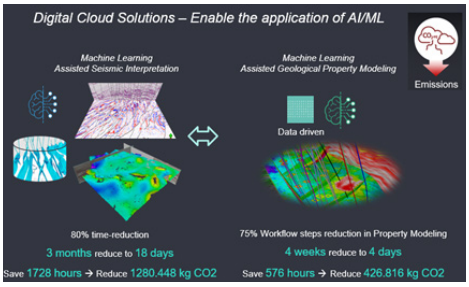

Fig. 3. CO_2 emission reduction using AI/ML workflow

The scope of work for the automated wellbore and log interpretation could include a series of data quality checks from 'Family and Unit check & correct', 'First & Last Reading detection', 'Depth-shift check', 'Resampling & Splicing', 'Bad-hole Flagging', 'Outlier Detection', 'Log Normalization', 'Log Prediction', etc. The automated log interpretation could automatically compute lithology and QC the conditioned log data using hierarchical Element Analysis (ELAN). The outputs of auto-petrophysical interpretation could be used as inputs to subsequent Rock-Typing and Saturation Height Modeling workflow. Lastly, a statistical method that looks at the variability of the input data and the changes made by the algorithms to establish a traffic light validation for accessing the uncertainties and assurance.

(B) Machine-Learning-Assisted-Seismic-Interpretation (ML-ASI)

Although the Seismic Interpretation has long been a crucial part of subsurface characterization workscope, there is still an enormous operational obstacle when it comes to interpretation and extracting the most value out of such information. A time-consuming process that frequently yields inconsistent results is caused by the combination of large amounts of data and a series of repetitive, time-consuming, and subjective workflow and interpretation approaches.

The Machine-Learning Assisted Seismic Interpretation (ML-ASI) has defined a new style of working that has resulted in enabling higher productivity and efficiency in delivering the seismic interpretation. The Seismic Interpreter now has the opportunity to test and run multiple scenarios with much lesser turnaround time to enable faster decision-making. The Elastic Cloud-Computing and Domain-Driven ML-ASI have the ability to significantly improve seismic interpretation efficiency and reveal an immense amount of information from expensive and unwieldy seismic datasets.

In this paper, using the Petrel platform in a cloud environment as an example, we will explain how ML-ASI can accelerate the existing seismic interpretation process in the modern subsurface workflow.

Two innovative Machine-Learning (ML) methods were developed, starting with Fault Interpretation, based on the fundamental design of Deep Convolution Neural Networks (CNN) U-Net Architecture. These methods were then modified for use in the seismic interpretation.

Utilizing a range of seismic data sets, the first method required to have a pre-trained model to be developed. Observed fault locations were designated as positive training examples. To further enhance our understanding of the possible structure in the data, the pre-trained fault prediction offers an accurate estimation of where the faults will be located. The main benefit of this method is that the acquisition of this information without the need for tedious data preparation, parameterization, manual picking, or training labels tailored to particular sets of data.

As for the second method, the user must input their fault labels from the particular dataset of interest, which employs a user-supervised model. Since it was only trained on the relevant dataset, this could increase the prediction's quality. In comparison to the first pre-trained approach, this supervised method relies on minimum interpreter labeling however could produces a more accurate fault prediction. To perform better than humans, the traditional Deep-Neural-Network-Based categorization schema typically needs a lot of training data. One of the key difficulties was that the workflow's principal goal was to execute tasks with the least amount of human intervention possible. The machine can usually be trained with just a handful of lines.

During the exploration stage whereby time is essential and information is limited, the pre-train model can provide preliminary ideas about the area's fault structure system. Then, combined with geological understanding and minimum interpretation guidelines, the user-trained model will deliver the completed fault model within days or weeks, instead of weeks or months previously.

In the development stage, especially when planning for infilled wells, re-interpreting the existing data is always considered. However, human bias will eventually lead to the same output, or low data quality of interpretation. Leveraging ML to get the data-driven output will provide better outcomes and a different perspective for interpreters. In addition, if there are limited resources available for this re-interpreting study, ML will help to reduce time significantly.

Currently, the majority of workflows for autonomous fault identification and extraction include these four steps:

- Seismic conditioning or filtering to improve signal-to-noise (SNR) ratio.
- Edge detection based on one or combined (multi-scale) seismic attributes.
- Edge enhancement.
- Fault patches/surfaces extraction.

The quality of the seismic data typically affects the first two phases. The faults may be selected directly from the edge attribute set if they are well-imaged on the seismic volume. However, preconditioning the seismic and adjusting the resulting edge attributes to the needs of the interpretation will be more difficult with a low-quality seismic image. A common trade-off is between gaining detail and decreasing SNR. To help shorten the time needed for this stage, the Petrel ML method often does not require any preconditioning.

Moving to Machine-Learning Assisted Horizon Interpretation, the idea behind this approach is a semi-automated method. Users can submit single points, or a continuous horizon reflection pick of the training data as labelled seismic reflection events. The prediction from the ML model is used to detect high confidence, and the ML model is generated using labels. Users can produce a confidence cube based on how closely it resembles QC.

An overview of the Horizon prediction workflow is provided below to illustrate the concept. However, depending on the model quality value, the procedure may go through numerous rounds to meet the value. When it's done, the algorithm can continue with ML-Based Horizon Prediction by lowering the model quality value or by adding more labels to the same horizon interpretation.

In further detail, the algorithm learns the pattern while tracking and makes use of Radial Basis Functions (RBF). It utilizes pattern recognition in the same trace that labels are used. By analyzing neighboring values in a vertical direction and determining the confidence score values for additional expansion, it broadens a horizon.

The Neural Network is executed once the label has accumulated sufficient training data to create a more reliable model. In contrast to Radial Basis Functions, which learn patterns, Neural Net weights store class information. For training and later for prediction, the algorithm feeds the selected training data into one of the models. The iterative procedure comes to an end when it reaches the model quality value that reduces the chance of tracing the incorrect event. When tracking needs to be stopped or continued, it might be utilized as a signal.

The production of anticipated horizon interpretation can be supported by the fault attribute cube produced by the preceding ML stage. A horizon interpretation and confidence score cubes are this method's outputs.

Only one waveform may be tracked at a time by conventional waveform trackers, which rely on cross-correlation. Additionally, the settings may be overly convoluted when a horizon prediction method based on ML can track numerous waveforms simultaneously. It is more effective at extracting the particular waveform that is present around a reflector. In contrast to conventional trackers, it prevents cycle skipping. Even with the bare minimum parameters, it can produce reliable results.

Lastly, the output from both automated fault extraction and horizon using ML will be directly consumed in the structural model process without any further modification. Whether the stage of subsurface study is exploration or development, leveraging the application of ML seismic interpretation definitely helps to shorten the turnaround time, remove unnecessary manual steps and focus on the analysis of complex geological structures and validate its uncertainty.

The structure of AOI or the types of studies that the Oil and Gas industry is conducting nowadays are becoming increasingly complex and demanding a significant amount of time and resources to finish. Hundreds-to-thousands of simulation hours run continuously every day, six-to-nine months or a year of study have contributed to the release of CO_2 emission. Therefore, the assistance of Machine-Learning with significant time saving not only supports the reduction of CO_2 but also provides a more accurate structural model and allows various scenarios analysis to be performed. Several studies such as (INPEX, n.d.) have shown 80% time-reduction after applying ML for Seismic Interpretation.

(C) Machine-Learning Assisted Geological Property Modeling (EMBER)

Perhaps the most often utilized method in reservoir description to date is the classification of geological features like faults using seismic data. Another interesting field is the use of Generative Adversarial Networks (GANs) for property modeling, which are based on large analogue training data sets. However, there hasn't been as much work made towards integrating geostatistical techniques with ML algorithms for property modeling. These techniques can be used to estimate and virtually realize reservoir properties like porosity and permeability. Despite being highly useful and becoming the standard for modeling reservoir features, they do require a few workarounds in real-world circumstances.

The Embedded Model Estimator (EMBER) approach uses a combination of ML and conventional geostatistical estimation and simulation methods to quickly and accurately estimate reservoir parameters. This machine learning-based method aims to generate reservoir characteristics from input well data as well as additional information such as seismic attributes/features.

EMBER produces modeling results with a significant reduction in effort compared to traditional petrophysical modelling algorithms, which rely on labor-intensive manual data analysis, including stationarity determination and factoring, trend removal, and variogram analysis per zone, region, and direction. Such cutting-edge hybrid modeling techniques can perform noticeably better than any traditional technique. Little setup time and exposure to complicated geostatistical contexts are required for the approach. It enables reservoir model construction to move along much more quickly and consistently, which has an adverse impact on field development planning.

Without running dozens of repetitive processes for each zone and/or facies as well as performing different scenarios set up to populate reservoir properties distribution, which can take many hours or days; EMBER enables 70–75% workflow steps reduction in those property modeling process, stated by many operators such as (Pertamina Hulu Mahakam, n.d.). Additionally, a 15–20% improved accuracy of reservoir properties prediction was reported. Generally, EMBER supported the acceleration of the geological property modeling process and improvement of output.

Emissions Reduction

The U.S. Department of Energy claims that buildings account for over 76% of electricity use and only about 20% of electricity comes from renewable sources. It tends to be an obvious starting point when calculating greenhouse gas emissions and carbon footprint because electricity is relatively easy to measure – and just about everyone uses it.

As the emission factor for electricity is 0.256kg of CO_{2e} per kWh, each laptop uses an average of 24k kWh per month for the standard 40 hours per month, excluding additional simulation hours, producing 6.1kg of CO_{2e}. (PlanetMark, n.d.)

In Oil & Gas subsurface reservoir characterization workflow, the simulation of hundreds and thousands of scenarios to increase the accuracy of outputs will require machines running continuously for days, weeks, and months. Hence, contributing to the release of CO_2 emissions significantly.

Moving to a digital platform, not only helps Oil & Gas operators minimise the purchase of new laptops as longer lifecycle usage but also enables the application of AI/ML to shorten the subsurface study duration and simulation time.

According to (Sustainable Energy Development Authority Malaysia, n.d.), each hour saving equals to 0.741kg CO_2 reduction. As stated earlier, many studies have shown Machine Learning Assisted Seismic Interpretation workflow has reduced 80% processing time from 3 months to 18 days, saving up to 1728 hours and reducing 1280.448kg CO_2. (INPEX, n.d.).

Studies also reported Machine-Learning Assisted Geological Property Modeling helped to reduce 75% of workflow steps and make the process simpler and faster from 4 weeks to 4 days, saving 576 hours and reducing 426.816 kg CO_2. (Pertamina Hulu Mahakam, n.d.)

Conclusions

The Machine-Learning workflows presented in this paper have allowed us to resolve most of the common or known processing and interpretation challenges that a conventional subsurface characterization study would require tremendous effort to handle. An advantage of machine-learning methods is that they can be implemented to produce results without the need to have a complete and established reservoir model. The principal challenge of machine learning lies in attaining enough training information, which is essential in obtaining an adequate model that allows for a prediction with a high level of accuracy.

A significant time reduction from months-weeks to days-hours potentially shortens the overall subsurface evaluation timeframe with Machine-Learning applications and reduces the carbon emissions and footprint.

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