An Integrated Deep Learning Solution for Petrophysics, Pore Pressure and Geomechanics Property Prediction

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Abstract

Pore pressure prediction plays a critical role in the ability to predict areas of high overpressure and fracture behavior for the exploitation of unconventional plays, which are both correlated with production. Shales in these plays have variable clay content and complex multi-mineral fractions that require a detailed petrophysical assessment reinforced with rock physics modelling as needed. For example, changes in total organic content have a similar elastic response to changes in porosity. Therefore, any pressure-stress property model for unconventional plays must be supported by petrophysically conditioned elastic logs and accurate multi-mineral volume sets calibrated to core data.

A supervised deep neural network approach is introduced as an alternative innovative tool for petrophysical, pore pressure and geomechanics analysis enabling the use of all the previously collected and interpreted data to devise solutions which simultaneously integrate wide ranging well bore and wireline logs. We implement three neural networks, all with similar structure, as each of these networks had a different objective and the outputs from one were the inputs for the other.

The first network was trained to predict petrophysical volume logs (shale, sand, dolomite, calcite, kerogen and also porosity) simultaneously from compressional velocity (Vp), Gamma ray, density (rho), resistivity and Neutron logs. The second neural network, cascaded from the first, was then designed to match the manually predicted pore pressure. The inputs were Vp and shear velocity (Vs), Rho, resistivity, Neutron logs as well as the results of the first network. The third network focused on predicting various properties of interest, in this case pore pressure, minimum horizontal stress (Shmin), maximum horizontal stress (SHmax), and volume of kerogen, based on only Vp, Vs, and Rho logs which is an example building a neural network capable of predicting key rock properties directly from seismic inversion results to produce meaningful 3D interpretations.

The volumetric pore pressure model was also positively correlated to cumulative production values from blind long horizontal wells. The results show a promising outlook for the application of deep learning in integrated studies such as those shown in this paper.
**Introduction**

For the exploitation of unconventional plays, pore pressure prediction plays a critical role in the safe planning and execution of the well and ability to predict areas of higher productivity, assuming a direct relationship to overpressure and stress magnitudes. Shales in these plays have variable clay content and complex multi-mineral fractions that require a detailed petrophysical assessment reinforced with rock physics and geomechanical modelling. For example, changes in total organic content have a similar elastic response to changes in porosity. Therefore, any pressure-stress property model for unconventional plays must be supported by petrophysically conditioned elastic logs and accurate multi-mineral volume sets calibrated to core data.

In unconventional plays, given the comparatively short drilling times and the likelihood that operators have multiple active rigs, wells are drilled and data are acquired at an unprecedented rate. In the Permian Basin, a typical well takes approximately 3-4 weeks to complete from rig up to release, and given that major operators can have upwards of 25 rigs running concurrently means, on average, a new well is completed every 1-2 days at a cost of $6-9M per well.

Therefore, performing manual, consecutive workflows for petrophysics, pore pressure and geomechanics prediction can be impractical due to turnaround considerations and the multiple personnel required. This, together with technical challenges of complex stratigraphy, multiple facies, variable rock properties, and the interaction of pore pressure and geomechanics, calls for more consistent, sophisticated, and faster analytical tools. Importantly, given that pressure and stress are critical to safe drilling and, along with relevant mineral volumes, are key drivers to identify areas of high production, i.e., sweet-spot detection, it is of obvious importance for the industry to develop safe and innovative methods to keep pace with the drilling activity and to harness all existing and newly acquired data effectively. This paper shows that a machine learning approach, allied to new methods in 3D quantitative seismic interpretation, can offer such a solution and presents a case study from the Permian Basin, one of the most significant unconventional plays currently being explored.

**Methods**

Machine learning can play an important role in making sub-surface interpretation workflows faster, more efficient and more consistent, leading to more confident results and improved decision making. There are two categories of machine learning workflows applicable to the challenges of predicting rock properties in the sub-surface.

The first workflow utilizes 1D data, i.e., well data, in which a model is calibrated to data from a relatively small number of wells in the relevant basin or sub-basin. In the application phase, the calibrated model is applied to all other wells in the same region of interest. This workflow is primarily about efficiency, for example, train a supervised model to predict, e.g., porosity, on 10 wells with manual interpretation, and apply to the other 90 wells. Application of this type of machine learning workflow allows personnel to focus on adding value to the interpretation process by fine-tuning the training data by feeding back information from the blind test wells, rather spending a significant amount of time repeating standard workflows on a large number of wells which may still need to be modified once the results are generated.

The second workflow utilizes 1D data, i.e., well data, in which a model is calibrated to the data from all wells, or a representative sub-set of the wells, in and around a 3D seismic volume. In the application phase, the calibrated model is applied in 3D to seismic attributes and/or seismic inversion results (e.g., elastic properties), potentially simultaneously. This workflow is mostly about improving accuracy and confidence. To date, upscaling the well-based models into 3D has been performed using Rock Physics Models (calibrated to well data) to transform elastic properties into rock properties such as porosity or
pore pressure. Machine learning improves on this by incorporating more information than using only the elastic properties; such as well coordinates (so that lateral trends are captured), depth below datum (to incorporate compaction trends), and temperature information.

However, it should be stressed that using machine learning to predict absolute quantities (e.g. porosity, pore pressure etc.) directly from seismic, a relative measure, is unrealistic. Low frequencies must somehow be inserted, a process known as (model-based) seismic inversion. A facies-based seismic inversion (Zabihi Naeini and Exley, 2017) is optimal for this purpose, which means the outputs from this process are not only elastic properties but also a discrete facies distribution.

**Results: Delaware (Permian) Basin, New Mexico**

The Permian Basin, which is a mature hydrocarbon ‘super-basin’ located primarily in west Texas and extending into south-eastern New Mexico, has produced more than 39 billion barrels (cumulative) of oil since it first began production in the 1920s. The conventional production peak in 1973 of 790 million barrels was surpassed in 2017 with 815 million barrels of oil (IHS, 2018) due to unconventional production. The most astonishing fact of all is that as many as 1 million additional wells might be drilled in the foreseeable future (Nunn et al., 2018). This, together with the Permian Basin’s technical challenges in terms of complex stratigraphy, near surface complications that affect velocity modeling, multiple play types, variable rock properties and various elements of pore pressure, geomechanics, fracturing and diagenesis, calls for more sophisticated, faster, consistent, and wider ranging analytical tools. Given the scale of the work, i.e. the number of wells, performing classical workflows is impractical (if not impossible) due to turnaround considerations and also may not use the previous regional studies efficiently.

The generalized workflow undertaken within this study to generate the manual interpretations can be summarized as follows;

1. Petrophysical processing of wireline data to create multi-mineral volume and porosity logs,
2. Construct a 1D pore pressure prediction model and blind test against additional wells,
3. Construct a 1D geomechanical model and blind test against additional wells. The results of Step 1 are a critical input into deriving the geomechanical model and there is an intrinsic feedback loop between the two models,
4. Derive a geologically-realistic 3D property model for compressional velocity (Vp), shear velocity (Vs), density (Rho), and lithofacies using facies-based seismic inversion,
5. Integrate the 1D pore pressure and geomechanics models with the 3D inversion (elastic properties and facies) and generate a calibrated 3D model of pressure and stress.

The pore pressure model was constructed using direct measurements of pore pressure, taken from either Dynamic Fracture Initiation Tests (DFIT), Drill-Stem Tests (DST), or by an influx as interpreted from the drilling history. The pressure data, expressed as Vertical Effective Stress (VES; Vertical Stress minus Pore Pressure) were cross-plotted against the compressional velocity (Vp) normalized to 5000 ft/s following Bowers (1994). Each of the data were then assigned a quality flag based on lithology and confidence in the wireline data at that depth. The primary concern was the role of cement producing fast velocities which produced incorrect Vp-VES models. Secondary concerns were Total Organic Carbon (TOC) and in-situ gas neither of these are a concern within the sand-rich intervals (but remain a source of uncertainty within the shale-rich units).

The geomechanical analysis commenced with an interpretation of the image logs. A 1D analytical geomechanical model was then constructed using the poro-elastic equations (Thiercelin & Plumb, 1994)
and the elastic properties calculated from the well logs, using core data to constrain the dynamic to static conversion. The regional strain parameters were calibrated to the minimum horizontal stress by solving the circumferential (hoop) stress around a vertical borehole and matching the predicted shear failure to the occurrence (and non-occurrence) of drilling induced tensile fractures observed in the image logs.

The seismic inversion used a facies-based Bayesian pre-stack approach (Kemper and Gunning, 2014). There were two key advantages to applying this approach: firstly, the inclusion of facies in the inversion process removed the requirement for a conventional low frequency model. This ensured that the distribution of laterally discontinuous undrilled heterogeneities are defined only by the seismic reflectivity and not biased by any well derived interpolation assumptions. Secondly, the inversion approach was calibrated using a set of facies-dependent elastic property trends, rather than a single set of trends for the whole inversion window (Payne & Meyer, 2017).

A supervised deep neural network approach is introduced as an innovative tool for petrophysical, pore pressure and geomechanics analysis enabling the use of all the previously collected and interpreted data to devise solutions which simultaneously integrate wide ranging well bore and wireline logs. We implement three neural networks, all with similar structure, as each of these networks had a different objective and two of the networks were connected such that the outputs from one were the inputs for the other (Figure 1).

Figure 1. A schematic display of the neural network implemented in this study. Each neuron is characterized by its weights, bias and Rectified Linear Unit (ReLU) activation function.

The first network was trained to predict volumes of shale, sand, dolomite, calcite, kerogen and also porosity simultaneously from compressional velocity, Gamma ray, density, resistivity and Neutron logs. Petrophysical interpretation of wells incorporates a holistic use of well data in which almost every aspect
of the borehole/well data ought to be captured. The data should be processed consistently and rigorously across the study region. With this labor intensive task complete, the question then is how to use this knowledge most effectively. That has two aspects: 1) the regional knowledge is not effectively used for new wells unless done by an experienced interpreter and nonetheless it would still require manual interpretation, and 2) when the experienced practitioners leave, the knowledge could be lost from the organization. This is where the implementation of the first machine learning workflow above could potentially address these challenges. Once an appropriate machine learning algorithm is trained then the applications to new wells can be extremely fast (i.e. in the order of seconds as opposed to a day or two for manual interpretation). Also once the algorithm is trained then all the knowledge is effectively stored so the model can always be called on demand for a quick petrophysical interpretation. This is shown on a well from the Delaware Basin in Figure 2. Interestingly, machine learning algorithms can be further improved by means of “transfer learning” if and when new data are available.

The second cascaded neural network was then designed to match the manually predicted pore pressure (Figure 2). The inputs were Vp and Vs, Rho, resistivity, neutron as well as the results of the first network. Both of these networks are of the first type outlined above, i.e., generating efficiency and consistency of petrophysical log interpretation in a fraction of the time when compared to a manual workflow. Furthermore, use of a machine-learning algorithm to generate the input data to the cascaded neural network ensures that all wells have a complete dataset from which to predict pore pressure minimizing the influence of missing wireline data due to tool problems while logging.

![Figure 2. Example of a blind test well located approximately 50 km from the training data, there is an excellent match between the well-based (black) and machine-learning-based (red) results at most depths. There is a mismatch in the upper section (e.g. 10000 ft) where the machine learning algorithm predicts higher lime/lower sand content relative to the well curves. This could be either a difference in interpretation from human vs. machine or the lack of enough training data for that particular interval as nothing obvious can be observed from the log responses.](image-url)
The third network focused on predicting various properties of interest, in this case pore pressure, Shmin, SHmax, and volume of kerogen, based on only Vp, Vs, and Rho logs which is an example of the second type of machine learning implementation described previously. The deep neural networks can work in a cascaded manner such that the outputs from one forms the inputs to the other. That means the outputs from a neural network trained to predict multi-mineral volumes and porosity simultaneously subsequently be used in a subsequent neural network to predict pore pressure. A neural network can also be designed in such a manner that certain properties, e.g. pore pressure, are derived from elastic logs solely (so that this neural net, once properly trained, can be used in the second workflow described above).

Designing a network in such manner allows one to not only predict these properties at wells with limited available logs but also be able to predict based on inverted elastic properties from seismic amplitudes. Once a suite of geologically-realistic 3D properties have been generated from the model(s) then those properties can be used to provide key feedback into the drilling process, not only advising on physical drilling parameters but also informing on optimal well locations and geosteering through sweet-spot detection. As an example Figure 3 shows such a possibility but performing a simple cutoff on the outcomes of deep neural network in 3D (e.g. select those areas with high pressure and high volume of Kerogen). Furthermore, the 3D pore pressure model from this study can be shown to correlate with cumulative production values from blind horizontal wells such that areas of high pressure relate to higher producing wells (Rauch-Davies et al., 2018), thereby informing on business critical decisions as well as providing the property volumes required to aid operational decisions in the safe, efficient drilling of future wells.

Figure 3. 3D geobody based on conditional cut-offs of pressure, stress and kerogen predicted using a deep neural network highlighting many wells are not optimally positioned with respect to sweet-spots.
Conclusions

A supervised deep neural network approach is presented as an innovative tool for solving the complex inter-relationships between petrophysical, pore pressure, and geomechanics analysis enabling the use of all existing, newly acquired, and interpreted data to devise solutions which simultaneously integrate myriad data types. Furthermore, an algorithm was developed to predict a certain number of attributes solely from a facies-based seismic inversion, namely Vp, Vs, and Rho. The application of these algorithms on various blind wells from a Permian Basin case study, both within and outside the seismic survey, shows a reasonable accuracy when compared to manually interpreted counterparts but were obtained in a fraction of the time. The underlying rock physics behavior in the case study is an ideal scenario with a relatively predictable regional pressure/stress system and only a single mineralogical property; however, the results show a promising outlook for the application of deep learning to save valuable turnaround time in integrated studies such as those shown in this paper.

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References


