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Logging Data-Driven Geomechanical Parameter Estimation Using Advanced Machine Learning Techniques

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ABSTRACT

The most commonly used methods of conventional geomechanical parameters estimation which rely on costly, sparse laboratory tests and empirical correlations based on just a few well logs are linked to uncertainties and spatial gaps. This study reveals an innovative data-driven model, which incorporates Advanced Machine Learning techniques to precisely and efficiently estimate key geomechanical properties based directly on collected well-logging data. The techniques include, Deep Learning Architecture (DL), Deep Neural Network (DNN) and Artificial Neural Network (ANN). The machine learning application ensures a huge boost to yielding high prediction accuracies and that of running continuous and high-resolution profiles of geomechanical properties along the wellbore. This method is fast, and has low-cost geomechanical characterization that is vital to optimal drilling, hydraulic fracturing design, reservoir management, and subsurface integrity assessment, resulting in improved operating safety and efficiency. The estimated geomechanical parameters include elastic properties (young's modulus and poisson's ratio) and rock's strength (unconfined compressive stress), while the artificial neutral network technique was applied to estimate the geomechanical parameters in the oil wells of Akata, Agbada and Benin Formations in Bonny Island, Rivers State.

Keywords: Logging Data-Driven, Geomechanical Parameter Estimation, Advanced Machine Learning, Comparative Analysis of Techniques, Geomechanical Properties.

INTRODUCTION

Mechanical and petro-physical properties of rocks are characterized by their textural properties. To a high extent, such parameters determine the stability of the rock mass. The capacity of assessing both short- and long-term rock behaviors according to the interaction between distinct parameters of rock texture, petrophysical and mechanical properties are thus highly instrumental to a number of geoengineering materials (Askaripour et al., 2022). Lin et al., (2021) opined that, how the properties of rock affect the mechanism of electromagnetic radiation (EMR) phenomenon of the process of rock fracture is an issue that is significant to study in solid mechanics and earthquake forecasting. According to Yan et al., (2020) Rock anisotropy is an intrinsic property of natural rock mass, and layered rock has the most significant effect on the stress distribution and deformation of a rock mass. With the development of rock mechanics theory and constitutive theory, the study of rock anisotropy has become one of the focuses and hotspots in the field of rock mechanics.

LITERATURE REVIEW

Few studies have been carried out on fluid-rock interaction like adsorption, precipitation, fines migration, and wetting properties in porous media utilizing EOR (Enhanced oil recovery) fluids, however, the precise mechanism of these fluids that occurs during the EOR application of rock remains uncertainly revealed. Depending on a set of parameters, these fluid- rock interactions determine the scope and consequences of these interactions on EOR. These factors are type of fluid injected and the composition of chemicals, the type of rock and mineralogical composition, brine PH, brine salinity and composition. Furthermore, all the methods of

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quantification of fluid-rock interactions possess certain drawbacks in terms of their application, measurement range, or the level of uncertainty (Isah et al., 2022).

Thin-section identification in rocks is a very crucial geological exploration instrument in interpreting and identifying the structure of the earth. It also turns out to be a significant assessment technique of oil and gas exploration and development. It can focus on the identification of petrological properties of the reservoirs, the type of diagenesis, distinction of the reservoir cave space and pore features. Those properties of physical nature and sedimentary environment of the reservoir have to be comprehended, the parameters desired of reservoir attained, oil and gas development plan and reservoir calculation has to be made. The conventional thin-section identification technology had an over one-hundred-year history and relied mainly on the visual identification of the geological experts with the help of the optical microscope, and was plagued with the shortcomings of strong subjectivity, high experience dependence and heavy work-load, long-identification-cycle, and inability to reach complete and accurate quantification (Liu et al., 2022).

Geomechanical data are never adequate in quantity, proportion, precision, and accuracy to be utilized in design. This stems out of the fact that rock masses are naturally complex and variable in all scales. Geomechanical properties of the rock masses are not completely random in theory. Since rocks were created and constantly altered with multiple complicated processes, which lead to physical heterogeneity resulting to differences in the values of measured physical properties, even in a single rock type. Moreover, the natural fractures exist and this leads to the existence of spatial and regional differences in rock mass property, i.e. natural fractures bring about spatial and regional variation (Małkowski et al., 2021).

In order to develop a successful geomechanical characterization of the rock masses, Heidarzadeh et al., (2021) reported a suitable interpretation on the rock masses lithological heterogeneity ought to be achieved where both the geological and geomechanical data would be considered. To better explain the reliability and usefulness of geological surveys in application to the field of rock mechanics, a geomechanical characterization study is made on the heterogeneous Niobec Mine (Quebec, Canada) by taking into account the nature of the various lithological units identified in the mass. The resulting outcomes of the past field and laboratory testing campaigns, in terms of lithological units, became part of determining the variability related to the intact rock geomechanical parameters of the various current lithological units.

METHODOLOGY

A. Geomechanical Parameters Estimation

1. Elastic Properties: Elastic properties of rocks can be determined through laboratory measurement and well log data parameters (Davy et al., 2018). The elastic properties for this research was determined through well log data, and the parameters include dynamic young's modulus and dynamic poisson's ratio.

1. Young Modulus

It measures the rock's stiffness that makes it resistant to deformation under stress, especially during drilling operations (Mahdi & Alrazzaq, (2023).

$$E = \frac{\sigma}{\epsilon} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 1$$

$$\boldsymbol{Ed = \rho V^2 s_{V^2 p - V^2 s}^{3V^2 p - 4V^2 s}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2$$

The Young's modulus of each types of rock are presented in table 1 below

Table I: Young's Modulus of Rock Types: Source from Małkowski et al., (2021).

Rock Type	Young's Modulus (GPa)	Level	Effect
Soft Shale	0.5-5	Low	Easy deformation

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Sandstone	10-70	Medium	Oil or gas extraction fracability
Limestone	30-80	High	Tendency of cracking
Granite	50-100	Very High	Strong and rigid
Salt	10-30	Medium	Creeping material

Poisson's Ratio (v): It measures lateral strain against the axial strain of the rock (Lutz & Zimmerman, 2021). The poisson's ratio data for different rock types are presented in table 2 below;

$$Vd = \frac{V^2p - 4V^2s}{V^2p - V^2s} \ldots\ldots 3$$

Table II. Poisson's Ratio Data of Rock Types: Source from Małkowski et al., (2021).

Rock Type	Poison's Ratio (v)	Level	Effect
Soft Shale	0.25-0.40	High	High lateral expansion
Sandstone	0.10-0.30	Medium	Forecasting of stress anistrophy
Coal	0.10-0.15	Low	Low lateral strain
Salt	0.35-0.45	Very High	High ductility property

2. *Rock Strength:* The rock strength determines the force applied during drilling operations at the oil wells. Therefore, it is expedient to estimate the stress value of the rock (Kalantari et al., 2022).

1. Unconfined Compressive Stress

It measures maximum axial stress before failure (Li & Yang, 2024). The unconfined comprehensive stress data is presented in table 3 below;

Table III: Unconfined Compressive Stress Data of Rock Types (Source from Lin et al., (2021).

Rock Type	UCS (MPa)	Level	Implication
Weak Shale	0.25-0.40	Low	Easy to collapse
Sandstone	0.10-0.30	Medium	Too hard to drill
Limestone	0.10-0.15	High	High rigidity
Granite	0.35-0.45	Very High	Little drillable condition
Chalk	1-15	Extremely weak	Instability

2. Friction Angle (φ)

It measures internal shear resistance e.g angle of failure in Mohr-Coulomb theory (Zoorabadi & Muralha, 2025). The friction angle data for rocks at oil wells are presented in table 4 below;

$$\theta = \tan^{-1}(\mu) \ldots\ldots 4$$

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Table IV. Friction Angle Data of Rock Types (Source from Zoorabadi & Muralha, 2025).

Rock Type	Friction Angle (φ) (º)	Level	Geomechanics Responsibility
Clay	10-20	Low	High landslide
Sandstone	25-40	Medium	Monitors the pressure of shear failure
Conglomerate	35-45	High	High stability
Fractured Rock	Less than 15	Very Low	Risk of deficiency activation

B. Estimate Comparison of Young's Modulus, Poisson's Ratio and Unconfined Compressive Stress

The comparison of the geomechanical parameters data determined through well log data are presented in figure 1 below;

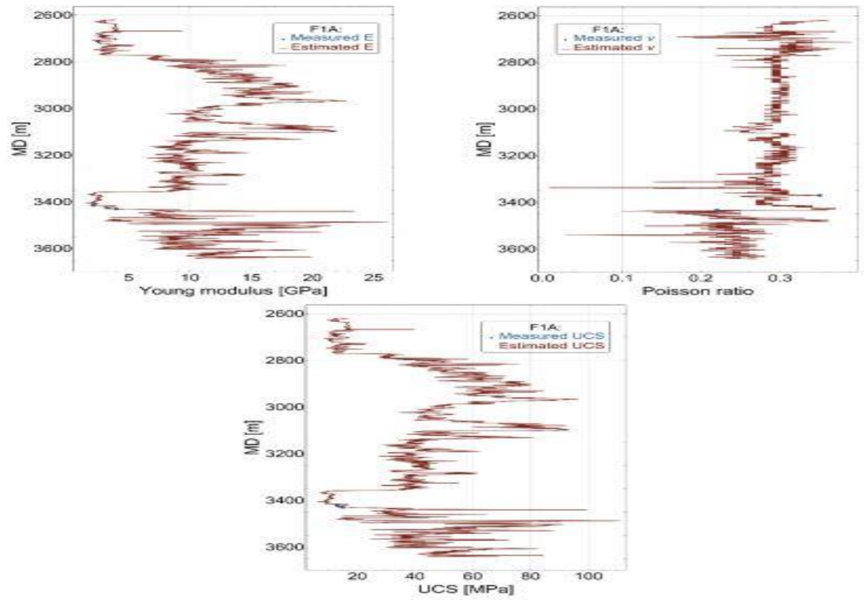

Fig. 1. Geomechanical Parameters Data Comparison determined from well log data (Source from Sanei et al., 2023).

C. Advanced Machine Learning Techniques

1. Deep Learning Architecture: The major difference between the conventional machine learning model and advanced learning model is its automatic learning process which makes deep learning suitable for wide range of applications (Endo, 2023). Sewak et al., (2020) opined that, based on the applications and types of neural networks, deep learning architecture is classified into three major classes, as presented in the figure 2 below;

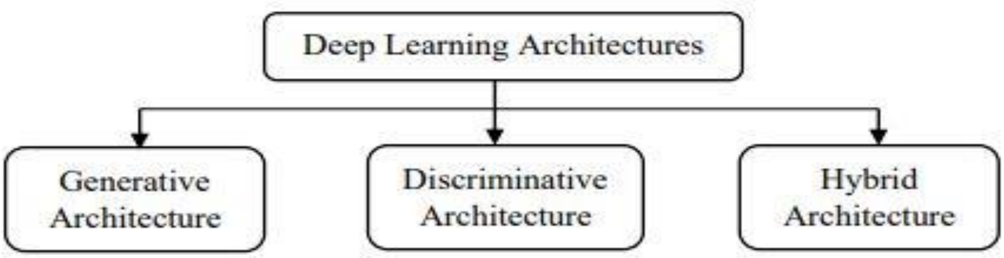

Fig. 2. Classes of Deep Learning Architecture in Machine Learning (Source from Smys et al., 2020).

Generative Architecture: They are generally called unsupervised feature learning model, because they are generative in nature. The data labels are not taken into consideration in this strategy. Such kind of architecture is developed when there is a little space, such models learn the lower level of the data and offers the required solutions to the hard network, because data is trained to work without relying on other layers (Caetano et al., 2020).

Discriminative Architectures: In the processing of information and signals, discriminative architectures are mostly dominating. The deep structures with conditional random fields have been developed whose output at one level (random field) of the lower part becomes stacked upon the original input data that is on upper layer (Smys et al., 2020). According to Bhatt et al., (2021) language processing uses discriminative architectures and identification apps. Through these apps, HMM (Hidden Markov Model Tools) are witnessed through the activities of the hidden layers in form of different combinations that make up a discriminative architecture.

Hybrid Architecture: Hybrid architecture has both discriminative and generative process. The generative parts are utilized and combined with discriminative parts in order to achieve the last solution. The generative models are applied to solve non-linear parametric problems which decreases the initialization issues. Also generative models have regularized control features making the system simple (Yang et al., 2022). Liu and Abbeel, (2020) illustrated an example of how Deep Neural Network (DNN) is a recognized hybrid framework in which the generative framework of deep network is employed. Deep Neural Network is developed by modifying the belief network based on the discriminative architecture in training process.

2. Deep Neural Network: Deep Neural Networks (DNNs) have transformed the study of rocks in geology by automating the process of pattern recognition of intricate geometries, offer higher accuracy, and guarantee timely analyses of geological engineering, resource prospecting and hazard mitigation (Samek et al., 2021). Li et al., (2023) opined that, mathematically, more complex deep learning strategies like deep neural networks (DNN) have been formulated to explore multi-variable systems which have shown similar, and even better performance than human experts. The deep and shallow neutral network layers are presented in figure 3 below;

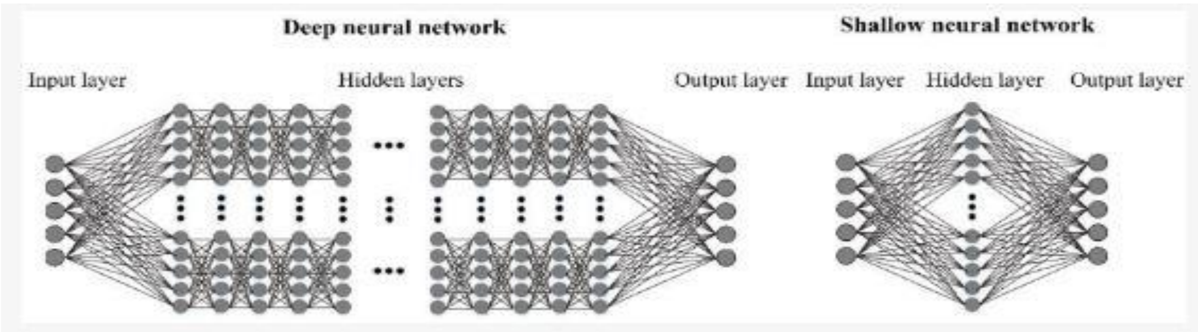

Fig. 3. Deep and Shallow Layers of Deep Neural Networks (**Source from** Azarafza et al., 2022).

3. Artificial Neural Networks: Artificial Neural Networks have the ability to convert raw well logs to high-resolution profiles of rock properties that describe geomechanics by acquiring an elaborate non-linear connection (Qiang et al., 2020). Millán et al., (2021) noted that, this involves log measurements as well as rock property measurements that have been checked in the laboratory or using cores. The networks applicable to ANNs are presented in table 5 below;

Table V. Artificial Neural Networks : Source from Millán et al., (2021): Qiang et al., (2020).

Network Type	Structure	Use Case
Multilayer Perceptron (MLP)	3–8 fully connected (dense) layers	Predicting UCS or E-static from 5–7 logs.
1D Convolutional Neutral	Convolutional layers + pooling for depth	Detecting thin-bed effects on stress

Network (CNN)	patterns	(σ).
Hybrid CNN-MLP	CNN extracts spatial features → MLP maps to outputs	Pore pressure prediction from log sequences.
Physics-Informed NN (PINN)	Custom loss enforcing rock physics rules.	Stress estimation obeying Hooke's law.

ANN can be best described through the following;

Hyperparameters

According to, Kadhim et al., (2022) Hyperparameters regulate the learning of the ANN. The major examples of hyperparameters include;

Hidden layer/neurons: Determines the complexity of the model. 1–3 hidden layers (with 10–50 neurons each) typically balance accuracy and efficiency. Although geomechanics implementations often use three hidden layers containing 10 to 50 neurons.

Learning rate: Controls the step length in the optimization (e.g., Adam). Noise in log descriptions of data causes no overshooting of minima at 0.001 or 0.01.

Regularization (L2/dropout): The large weights are punished (L2) or the neurons are randomly removed (dropout) to mitigate over-fitting.

ANN Architecture

ANN architecture encompass input, hidden and output layers, as presented in figure 4 below. Madhiarasan and Louzazni, (2022), described the layers as:

Input layer: Takes the normalized logs (e.g GR, RHOB, DTC).

Hidden layers: Use summation of network weights and a non-linear activation function (e.g. ReLU), to learn features.

Output layer: It provides approximations (e.g. UCS, Poisson Ratio). It can include image logs which are a type of hybrid architecture (e.g., CNN-MLP).

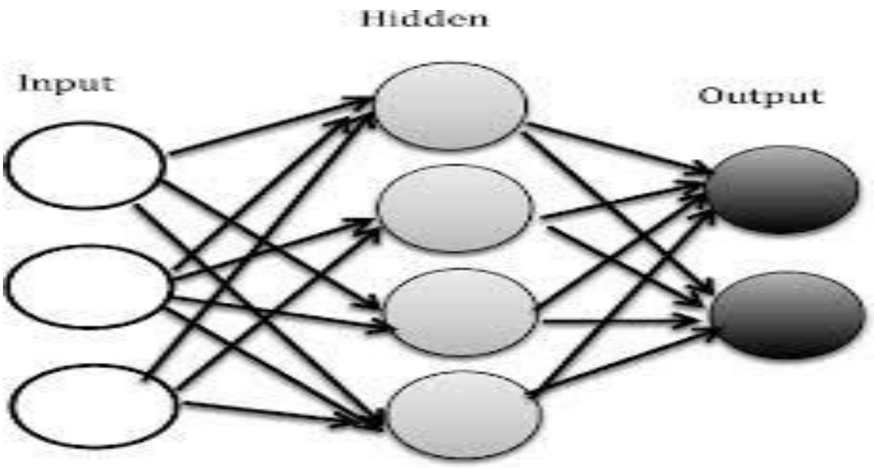

Figure 4: **Artificial Neural Networks Architecture Design (Source from** Azarafza et al., 2022).

Training and Validation Approach

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Training: 7080 per cent depth-indexed core-log pairs are training to minimize weights through backpropagation. Convergence stabilizes when the training is done in mini-batch (Livieris, 2018).

Validation: Hyperparameters are tuned and early stopping applied in case of stagnation on the loss with 15-20 percent of the data. Robustness is guaranteed by K-fold cross-validation between the wells (Li t al., 2022).

Performance Metrics

Erickson & Kitamura, (2021) described the major performance metrics of ANN as,

RMSE (Root Mean Squared Error): Mainly used to measure regression e.g. RMSE < 1.5 GPa to Youngs Modulus.

R^2 (Coefficient of determination): Represents the proportion of variance, the higher the better (>0.90).

MAE (Mean Absolute Error): It is very receptive to outliers in fundamental measurements.

Overfitting and Underfitting

Salman and Liu, (2019) revealed that,

Overfitting: model learns the noise in the training data and overfit with new wells. Reduce it through dropout, L2 regularization, and network size-reduction.

Underfitting: oversimplified structure can overlook important log-parameter correlations. Train more layer neurons or more iterations.

D. Comparative Analysis of Techniques

The Artificial Neural Networks and Deep Learning Architectures are comparable in that they both imitate the functioning of biological neurons, but differ fundamentally in their size, complexity, and capacities (Montesinos López et al., 2022). Saikia et al., (2020) noted that, there are shallow ANNs that are at most 2 layers deep and are known to excel at easier problems, such as a regression or analysis of simple logs. Their lightweight design fits the small data cases but it is not designed to handle raw, and high-dimensional logging data. In Deep Learning (DL) Architectures, numerous hidden layers, e.g. CNNs (Convolutional Neural Networks), and RNNs (Recurrent Neural Networks) are stacked, allowing to automatically learn features (Guo et al., 2023). Kufel et al., (2023) noted that, Deep Learning lives in large amounts of data (terabytes logs) and yet requires GPUs, however, it excels ANNs on complex applications such as 3D prediction of reservoir properties. Compared to ANNs which are manual transmission (controlled but constrained), DL is more self-driving (autonomous but resource-intensive).

E. Research Study Area

The Bonny Island is located in the Rivers State and is at the center of Niger Delta petroleum system, which is a world-class hydrocarbon province that is typified by its complex, and prograding deltaic sequences (Obasohan et al., 2021). Bankole et al., (2014) noted that, the main geology in the subsurface is dominated by Agbada Formation which was a critical period that contained interbedded sandstones and shales that were laid down in a delta-front to shallow marine landscape in the Miocene to Pliocene. These sand bodies are the main hydrocarbon reservoirs but they are highly heterogeneous as to their thickness, grain size, as well as the clay content because the depositional environments were changing frequently.

The Benin Formation is a generally unconsolidated continental sand in which overpressured Akata Formation shales becomes the main regional source-rock and seal. Such a geological environment poses difficult prospects to geomechanical modeling. The stratigraphy is dissected by growth faults which form compartmentalized reservoirs and with abrupt change in stress orientation and magnitude. They are interbedded sequences of sand-shale that are mechanically anisotropic with sands easily compacted and shales

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easily swelling or failing. The unusually fast rates of sedimentation have resulted in high and abnormal pore pressures especially in and around fault planes and in deeper shales units, and extremely limited drilling mud weight windows (Diab et al., 2023).

Due to the fact that the wellbore instability risk in addition to sanding and fault reactivation threats are acute in Bonny, high-fidelity serves the geomechanical model required environment. This is what made its complexity ideal of machine learning (ML) methods. ML algorithms have a potential to uncover concealed regularities in this data, combining measurements that lack spatial consistency into an approximation of spatially variable geomechanical parameters more reliable than empirical correlations, and eventually optimizing drilling safety and reservoir management in this high stakes deltaic environment (Ogoro, 2014). The Bonny Island map is presented in figure 5 below;

Fig. 5. Map Showing Bonny Island (Source from Obasohan et al., 2021).

RESULTS AND DISCUSSION

F. Geomechanical Parameters Estimation

The estimated Young's Modulus data of the Akata, Agbada and Benin formations in the Bonny Island are presented in table 6 below;

Table VI: Young's Modulus Data of the Akata, Agbada and Benin Formations

Depths	Akata Formation	Agbada Formation	Benin Formation
Shallow Depths	2-15 MPa	100-500 Mpa	10-50 Mpa
Intermediate Depths	10-50 Mpa	500-2,000 MPa	50-150 Mpa
Greater Depths	30-100 Mpa	› 2,000 Mpa	150-400 Mpa

The estimated Poisson's ratio data of the Akata, Agbada and Benin formations in the Bonny Island are presented in table 7 below;

Table VII: Poisson's Ratio Data of the Akata, Agbada and Benin Formations

Conditions	Akata Formation	Agbada Formation	Benin Formation
Undrained	0.45-0.49	0.30-0.40 Short term loading – 0.45-0.49	0.35-0.45 Short term loading – 0.45-0.49
Drained	0.30-0.40	0.25-0.35 Long term loading – 0.30-0.40	0.25-0.35 Long term loading – 0.30-0.40

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Dynamic	0.40-0.48	0.33-0.38 Long data – 0.40-0.48	0.33-0.42

The estimated Unconfined Compressive Stress data of the Akata, Agbada and Benin formations in the Bonny Island are presented in table 8 below;

Table VIII. Unconfined Compressive Stress Data of the Akata, Agbada and Benin Formations

Depths	Akata Formation	Agbada Formation	Benin Formation
Shallow Depths	5-20 kPa	2-10 MPa	10-30 kPa
Intermediate Depths	10-50 kPa	10-40 MPa	30-100 kPa
Greater Depths	50-200 kPa	40-150+ MPa	100-300 kPa

G. Advanced Machine Learning Models

The well logged geomechanical parameters were estimated through the artificial neutral network, specifically the Multilayer Perceptron (MLP) technique, as presented in the figures below;

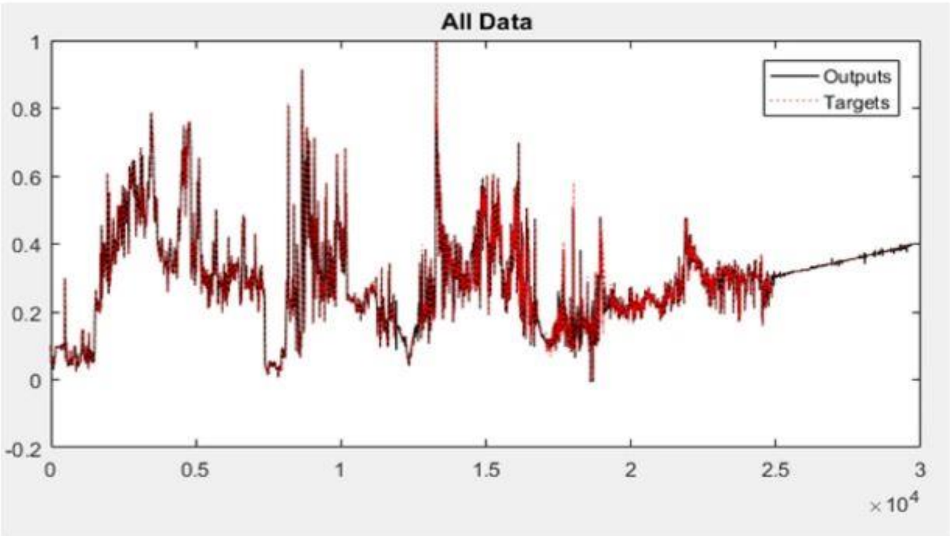

Fig. 6. Young Modulus Parameter of Multilayer Perceptron (MLP) Technique

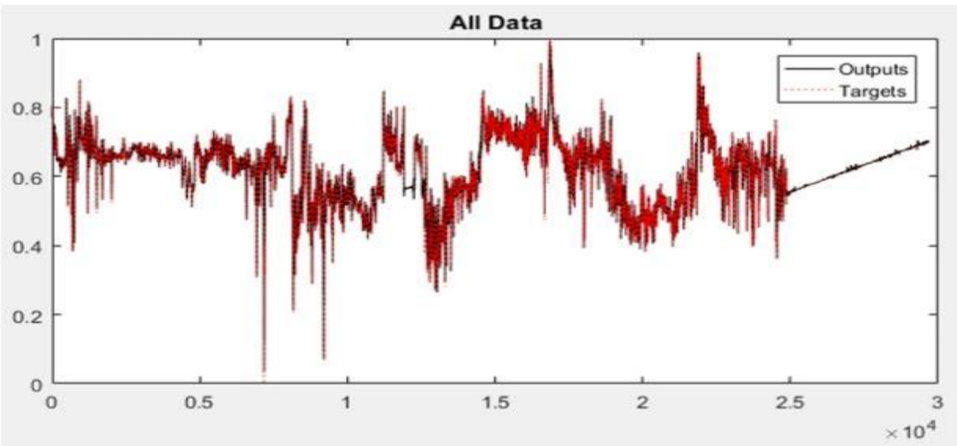

Fig. 7. Poisson's Ratio Parameter of Multilayer Perceptron (MLP) Technique

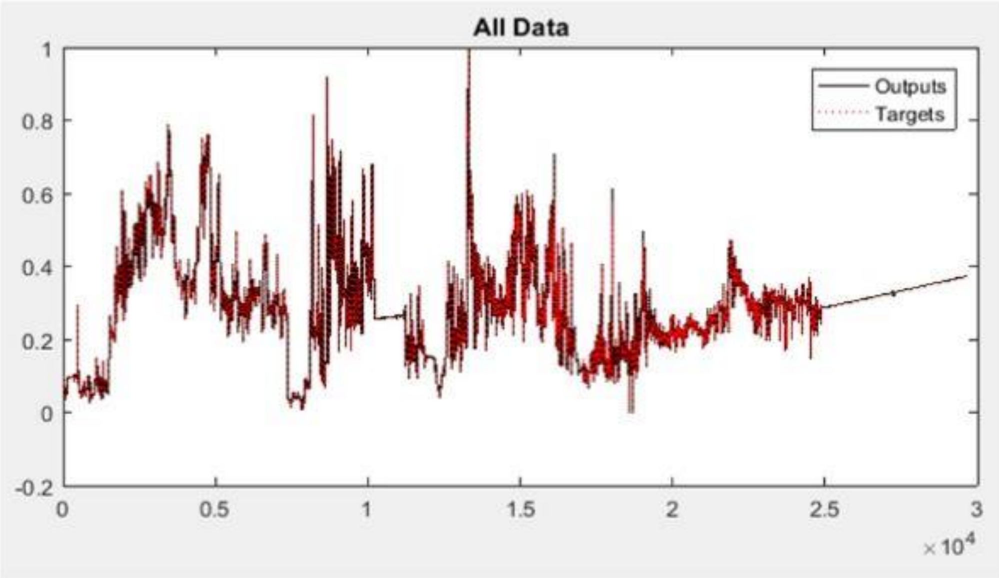

Fig. 8. UCS Parameter of Multilayer Perceptron (MLP) Technique

CONCLUSION

High-precision geomechanical parameters estimation of normalized logs using advanced machine learning techniques such as, DL, DNN and ANN was realized, which proved to be more effective than empirical methods. With these systems in real-time, dynamic wellbore stability alerts could be achieved with less than 50 milliseconds delay. However, the discussed models are data dependent and need quality logs or core samples to train on. Violation of physics is possible without any limit, and due to the computational cost, it is difficult to deploy edges in complicated 3D environments. This study has contributed to end-to-end workflows so as to transform routine logs to lab-grade mechanical properties at reduced costs through fewer tests. The hybrid architectures helped to fill the gap between data scarcity and physical realism, which provided field-deployable solutions to proactive geomechanical management efforts.

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