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Machine Learning Implications for Sand Management and Geomechanical Characterization: A Case Study in the Nahr Umr Formation, Southern Iraq

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Abstract

Sand production is one of the major challenges in the oil and gas industry, so comprehensive geomechanical analysis is necessary to mitigate sand production in mature fields. The absence of crucial well logs is an essential challenge in the oil and gas industry, necessitating geologists and engineers to rely on empirical equations to predict the absence of log intervals.

A comprehensive study was carried out on geomechanical modeling using data logs from two wells located in the Nahr Umr formation in Southern Iraq. Furthermore, the geomechanical parameters used by the predictive model were verified through caliper measurements. A machine learning technique was employed to predict the absence of acoustic log in Well-5 instead of using empirical equations. Additionally, two sand management models were developed and compared - one using the empirical Gardner equation and the other employing machine learning techniques.

The sand management model based on the Gardner equation predicted the production of sand from the beginning. However, it did not match the actual production data observed in real life. On the other hand, the machine learning-based model indicated no probability of sand generation, which aligned with the observed production data. The findings of this study demonstrate the advantages of using machine learning over traditional empirical equations for geomechanical studies in the particular area under study. Also, these findings suggest that machine-learning techniques might be applied to more basins in southern Iraq. The current research improves our understanding of the impact of machine learning on sand management as well as geomechanical characterization. This study has the potential to enhance procedures for making decisions in the petroleum and natural gas industries and contribute valuable knowledge to improved ways of handling sand production problems.

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Keywords: Sand production, CDDP, Sand Management Model, Machine Learning, Wellbore Stability.

تطبيق استخدام التعلم الآلي على إدارة الرمال والخصائص الجيوميكانيكية: دراسة حالة في تكوين نهر عمر، جنوب العراق

الخلاصة:

يشكل إنتاج الرمال تحديات كبيرة في صناعة النفط والغاز الطبيعي، مما يتطلب تحليلًا جيوميكانيكيًا شاملاً لتقليل تأثيره في الحقول القائمة. يمثل غياب سجلات الآبار الحاسمة تحديًا أساسيًا في صناعة النفط والغاز، مما يستلزم من الجيولوجيين والمهندسين الاعتماد على المعادلات التجريبية للتنبؤ بغياب تسجيلات الابر.

لقد أجرينا تحليلاً شاملاً للنمذجة الجيوميكانيكية باستخدام جميع السجلات التي تم الحصول عليها من بئرين يقعان في تكوين نهر عمر في جنوب العراق. كان هدفنا تحديد الخصائص الجيوميكانيكية والتنبؤ بحدوث إنتاج الرمال. بالإضافة إلى ذلك، قمنا بالتحقق من صحة المعلمات الجيوميكانيكية المستخدمة في نموذجنا التنبؤي من خلال قياسات caliper. استخدمنا تقنية التعلم الآلي للتنبؤ بغياب السجل الصوتي في Well-5 كبديل للمعادلات التجريبية. علاوة على ذلك، قمنا بإنشاء ومقارنة نموذجين لإدارة الرمال - أحدهما يستخدم معادلة Gardner التجريبية والآخر يطبق تقنيات التعلم الآلي (ML). نموذج إدارة الرمال المبني على معادلة Gardner تنبأ بإنتاج الرمال منذ البداية. ومع ذلك، فإنها لم تتطابق مع بيانات الإنتاج الفعلية التي تمت ملاحظتها في الحياة الواقعية. ومن ناحية أخرى، أشار النموذج القائم على التعلم الآلي إلى عدم وجود احتمال لتوليد الرمال، وهو ما يتماشى مع بيانات الإنتاج المرصودة.

توضح نتائج هذه الدراسة مزايا استخدام التعلم الآلي على المعادلات التجريبية التقليدية للدراسات الجيوميكانيكية في المنطقة المحددة قيد الدراسة. وتشير هذه النتائج أيضًا إلى إمكانية تطبيق تقنيات التعلم الآلي على المزيد من الأحواض في جنوب العراق. يعمل البحث الحالي على تحسين فهمنا لتأثير التعلم الآلي على إدارة الرمال وكذلك التوصيف الجيوميكانيكي. تتمتع هذه الدراسة بالقدرة على تعزيز إجراءات اتخاذ القرارات في صناعات النفط والغاز الطبيعي والمساهمة بمعارف قيمة في تحسين طرق التعامل مع مشاكل إنتاج الرمال.

1. Introduction

Geomechanics has become a crucial and vital part of all field development strategies [1]. This approach is applied to all stages of the petroleum extraction procedure, starting from the initial exploration phase and extending through production and even beyond field abandonment. Geomechanics has various applications in the oil and gas field, including forecasting in situ stresses, estimating the pressure in the pores, determining the properties of the formations, evaluating the performance of drilling and production, optimizing the stability and trajectory of the wellbore, and predicting and controlling the production of sand [2, 3]. Understanding the geomechanical properties of reservoirs is crucial for maintaining the stability of wellbores, determining the direction of perforations, and devising effective strategies for stimulation and completion. All of these factors have a significant impact on reservoir production [1, 4]. Insufficient prediction of geomechanical behavior before production operations can lead to sand production issues [5]. Therefore, it is vital to develop a mathematical model or conduct empirical studies to estimate geomechanical parameters to ensure efficient and successful production operations in oil and gas fields.

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Controlling sand during the production phase is a major challenge for oil companies. Many wells face sand-related issues that affect production planning and result in higher maintenance costs. Sand production can happen when loose grains in the formation are released or when rocks break due to activities like drilling, perforation, or hydrocarbon production [6, 7]. The oil and gas industry is greatly concerned about sand production as unconsolidated sediments and high production rates can cause sand to be produced, leading to well blockages. This can result in decreased productivity, damage to equipment, both downhole equipment and surface facilities, the potential of the formation collapsing, and the potential of pipelines becoming plugged. Therefore, it is a critical problem that requires careful consideration and management [8, 9].

Accurate and reliable data on the stress state, mechanical properties of rocks, and measurements of reservoir and rock are crucial for conducting geomechanical studies on sand production. Well logs are commonly used to evaluate the in-situ conditions in a reservoir, but it is important to note that their data may not always be entirely accurate. Such variations can affect the accuracy of calculated geomechanical parameters and lead to incorrect interpretations [1, 10]. Many geomechanical studies employ empirical equations to calculate the mechanical characteristics of rocks. Geomechanical research globally depends on empirical equations to determine geomechanical parameters, which may be successful in specific fields but not everywhere [11].

Applying machine learning (ML) or artificial intelligence (AI) techniques for problem-solving has shown cost-effectiveness, time efficiency, and success [12-16]. Sand production represents another challenge to well completion engineers who work on the development of sandstone reservoirs [17-19]. Petroleum engineers and earth scientists have employed machine learning algorithms to analyze well logs and other characteristics, leading to an enhanced knowledge of geomechanics [20-23].

This study aims to conduct a thorough analysis of the geomechanical properties and sand management of the Nahr Umr formation in southern Iraq. Two wells have been utilized in the present study. The first one provides all the necessary information, but the other, namely Well-5, is missing the sonic log, a crucial characteristic. The offset well data for well-4 was implemented to estimate the sonic log for well-4, and a sanding model analysis was conducted using machine learning and empirical equations. Two methodologies will be utilized, and the outcomes will be analyzed to evaluate their impact on the final sand model. The application of

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machine learning will be used to improve control over reservoir sand production in the studied formation.

2. Material and Methods

2.1. Databases

During the purpose of this study, two wells were used. They were drilling in the Nahr Umr formation of southern Iraq and were given the names Well-4 and Well-5. As can be seen in Figure (1), Well 4 comes with a comprehensive collection of wireline logs, which include sonic (us/ft), gamma ray (API), density (g/cm3), neutron porosity (v/v), and caliper (in). For the purpose of calculating the entire geomechanical parameters, which include the rock parameters for strength and the mechanical earth model, the full well logs set is applied. The Nahr Umr was divided into four zones based on the interpretation of the wells, as well as the core sample.

2.2. In-situ stresses (Far Field Stresses)

Far-field stresses in the Earth are characterized by three principal stresses that are mutually perpendicular to each other. One of the principal stresses, known as the overburden stress (Sv), acts perpendicular to the Earth's surface and is exerted by the overlying rocks. The other two principal stresses are horizontally applied. The horizontal stresses are referred to as the maximum horizontal stress (SHmax) and the minimum horizontal stress (Shmin) as displayed in [24, 25]. We utilised the calliper data from well-4 to determine the direction of horizontal strains.

Vertical stress (Sv) may be determined by vertically integrating the bulk density of rock derived from wirline logging data. The upper interval is usually not logged in oil wells since the reservoir portion is the main focus. The densities of the shallowest depths must thus be linearly extrapolated to the surface to determine the density values at shallow depths:

$$\rho_{EXT} = \rho_{MGL} + A_0(TVD - AG - WD)^n \quad (1)$$

$$Sv = \int_0^D \rho_D g d_D \quad (2)$$

Where: Sv represents vertical stress in psi, D is the real vertical depth in feet, $\rho_{(D)}$ is the bulk density at depth D in gm/cc, g is the gravitational constant, and ρ_{EXT} is the estimated density for shallower depths using linear extrapolation in gm/cc. ρ_{MGL} represents the density at the sea bottom in grammes per cubic centimeter. TVD stands for true vertical depth and is measured in meters. AG and WD represent the distance in meters between the earth's surface and the air gap and water levels, respectively. A_o and n are the parameters used for fitting.

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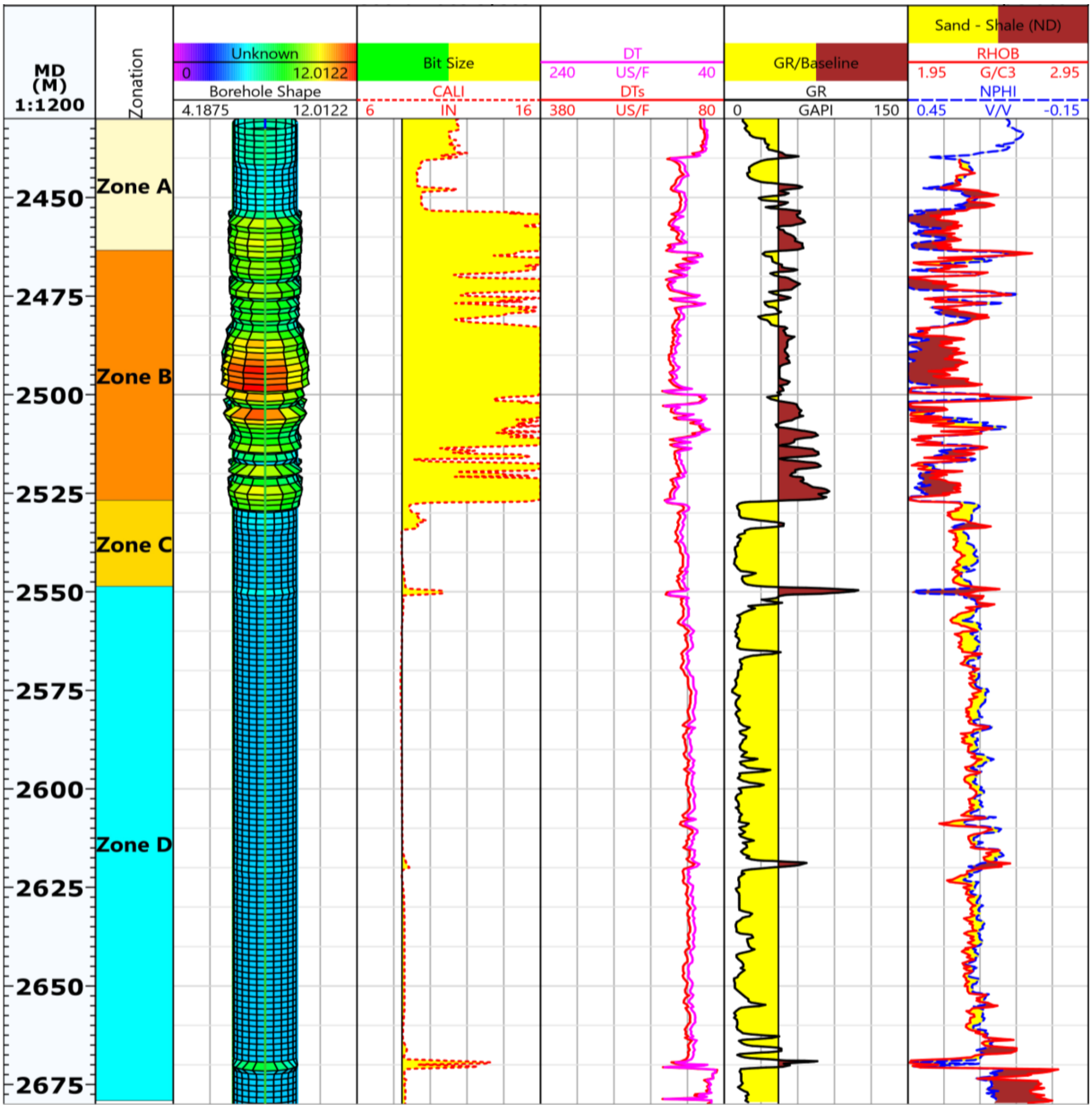

Fig. (1): Wireline logs of Well-4.

The maximum and lowest horizontal stress in the Nahr Umr formation may be determined by taking into account the tectonic stress [26, 27]:

$$S_{hmin} = \frac{PR_{sta}}{1-PR_{sta}} S_v + \frac{1-2PR_{sta}}{1-PR_{sta}} \alpha P_P + \frac{E_{sta}}{1-PR_{sta}^2} E_{max} + \frac{E_{sta} PR_{sta}}{1-PR_{sta}^2} E_{min} \quad (3)$$

$$S_{Hmax} = \frac{PR_{sta}}{1-PR_{sta}} S_v + \frac{1-2PR_{sta}}{1-PR_{sta}} \alpha P_P + \frac{E_{sta}}{1-PR_{sta}^2} E_{min} + \frac{E_{sta} PR_{sta}}{1-PR_{sta}^2} E_{max} \quad (4)$$

The variables are defined as follows: "S_{hmin}" and "S_{Hmax}" denote the lowest and highest horizontal stresses, "*PR*" represents the static Poisson's ratio, "S_V" stands for the overburden stress, "α" indicates the Biot's coefficient, "*Esta*" denotes the static Young's modulus, & "*Pp*"

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refers to the pore pressure. "*Emin*" and "*Emax*" represent the lowest and highest primary horizontal strains.

2.3. Formation Pore Pressure

Pore pressure is the pressure exerted on the walls of pores by fluids in the formation [28]. The normal pressure is often calculated linearly utilizing the pressure at sea floor (Pp_0), and a constant gradient (k) at the total vertical depth (TVD) [29]:

$$P_{pn}=P_{p0}+k\,TVD \tag{5}$$

Abnormal pore pressure (Pp) of shale intervals is calculated by using slowness Eaton equation as showing respectively [29-31].

$$Pp = Sv - (Sv - P_{norm})^{(\frac{DTC_n}{DTC})^X} \tag{6}$$

Where: DT_C stands for compressional transit time (us/ft) in shale at P_{pn}, whereas DT_{Cn} represents the compressional transient time (us/ft) in shale obtained from the log. X is defined by the trend line for standard compaction, which becomes known at 3.

2.4. Mechanical properties and sand production model inputs.

In this study, 1D MEM characterization developed by Schlumberger Tech-log Software was used to estimate, predict, and quantify wellbore instability and sand production model of the Nahr Umr formation. To construct the mechanical earth model (MEM) many parameters are needed, such as Biot coefficient, Young's modulus, UCS, and Poisson's ratio. We utilized the methodologies proposed by (Chang et al., 2006, Zhang, 2019, Radwan and Sen, 2021) [5, 29, 32] to determine the critical geomechanical parameters as follows:

$$E_{sta} = 0.032 * E_{dyn}^{1.632} \tag{7}$$

$$PR_{sta} = PR_{dyn} * P_R\ multiplier \tag{8}$$

$$T_0 = K * UCS \tag{9}$$

$$UCS = 4.242 * E_{sta} \tag{10}$$

Where: E_{sta}, PR_{sta}, and PR_{dyn} are the static Young's modulus in Mpsi, static Poisson ratio, and dynamic Poisson ratio (unitless) respectively. UCS output in units of psi. To units according to UCS units. K in Eq. (9) is a lithology factor had default value = 0.1.

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Perforation data from the wells under study was input into the sand management model. With a maximum perforation diameter of 0.3 inch and a 60-degree phasing orientation, the perforations are able to be observed in all directions. Based on the data collected from logs and the caliper, we can see that the Maximum Horizontal Stress is 45 degrees. We used a sand particle size of 160 micrometers and a stress change ratio of 0.5.

2.5. Neural network

A neural network works on the assumption of a nonlinear relationship among logarithmic characteristics. The definition is determined by the number of layers, connection weights, and neurons in each layer. ML techniques are widely applied to solve numerous problems in geoscience and subsurface engineering [21, 33]. The study used Schlumberger's K.mod (probabilistic neural network pattern recognition) to forecast, understand, and simulate reservoir parameters, especially the sonic log, which impact sand management and overall geomechanical properties. The primary goal of using K.mod is to develop a network model that can forecast the values of a specified logging curve based on various types of input log data. K.mod is a Multilayer Perceptron (MLP) neural network. The system is composed a layer for input, hidden pattern layer, accumulation layer, output layer, and linking loops as seen in Figure (2) very node represents an attribute, and each connection indicates the conditional relationship (probability) among a certain attribute and training datasets. The Nahr Umr formation's compressional slowness was predicted using gamma-ray, density, and neutron porosity as input parameters.

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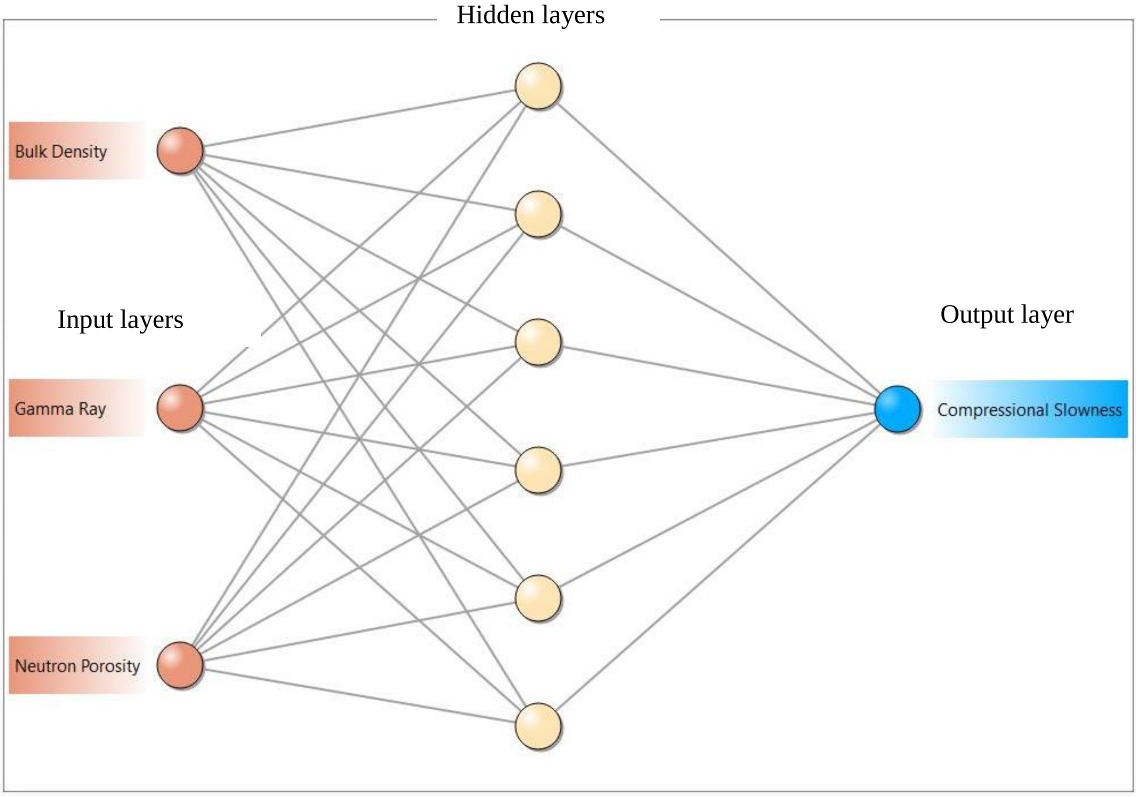

Fig. (2): Displays the log data utilized for machine learning to predict sonic log.

3. Results and Discussion

3.1. Wellbore stability model for Nahr Umr

We verified the reliability of our rock strength, poro-elastic, and earth models for Well-4 by conducting a comprehensive wellbore stability study on the reservoir section. The poro-elastic horizontal strain approach is used to determine the lowest and highest horizontal stress values by applying tectonic strain component values that are 0.0014 and 0.00175, respectively. The failure criterion was chosen for this research by using Modified Lade failure criteria, as it gave a complete match to the caliper log as illustrated in Figure (3). Therefore, this criterion is appropriate and gives consistency that the equations used to calculate the rock properties were correct.

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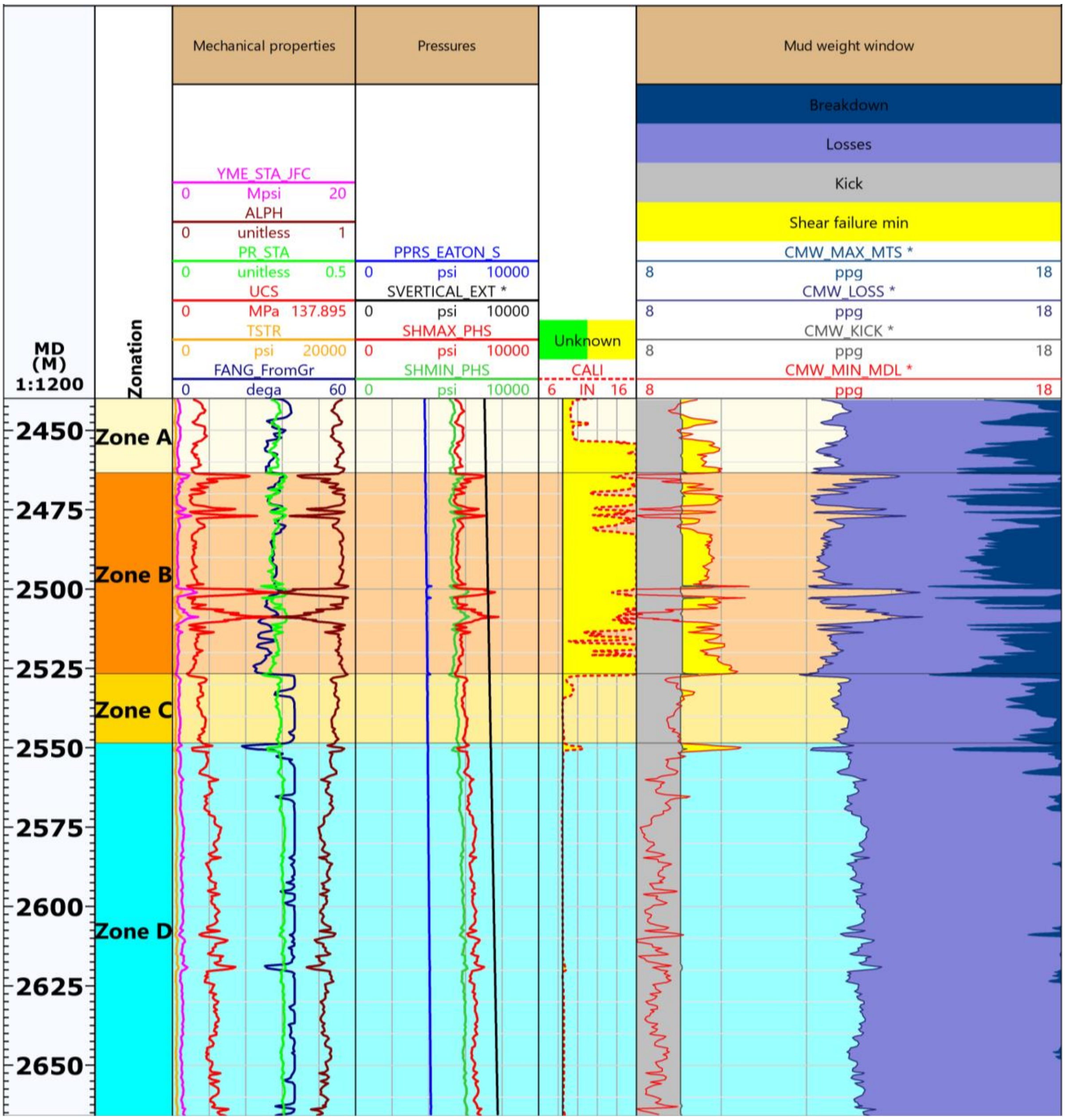

Fig. (3): Displays the wellbore stability results for well-4.

3.2. Sand management of the Well-4

The sand production of the Nahr Umr formation was constructed for Well-4 by using the outputs of the Mechanical Earth Model and using them as inputs in the sanding model. The sand management research results for well-4 indicated no expected sand failure over the whole formation section. Various CDDP (critical drawdown pressures) were utilized, including 0%, 15%, 25%, 35%, and 45%, which were graphed in Figure (4). Perforations were done in this well from depth 2529 to 2545, which is within zone C. Through the results of the sand model, it became clear we can produce with bottom hole following pressure reaching zero without

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producing sand. The sand management assessment for the Nahr Umr well indicated that sand generation is not possible based on the present parameters, as shown by the green flag up to zero pore pressure in the single depth analysis (Figure 5).

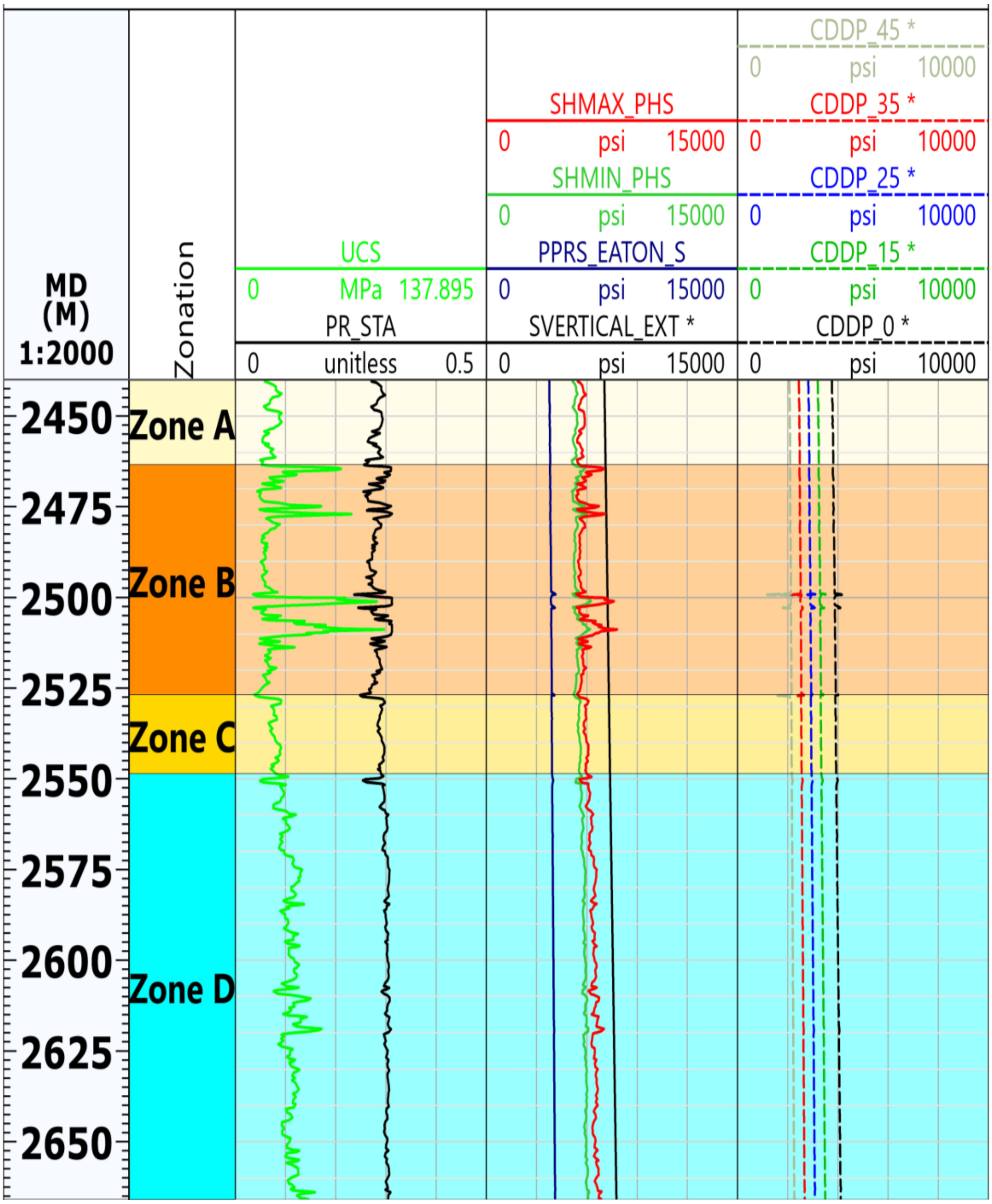

Fig. (4): Reservoir Pressure Depletion Impact on CDPP along the Depth Profile for well-4 in the Nahr Umr Formation at Depletion Rates of 0%, 15%, 25%, 35% and 45%.

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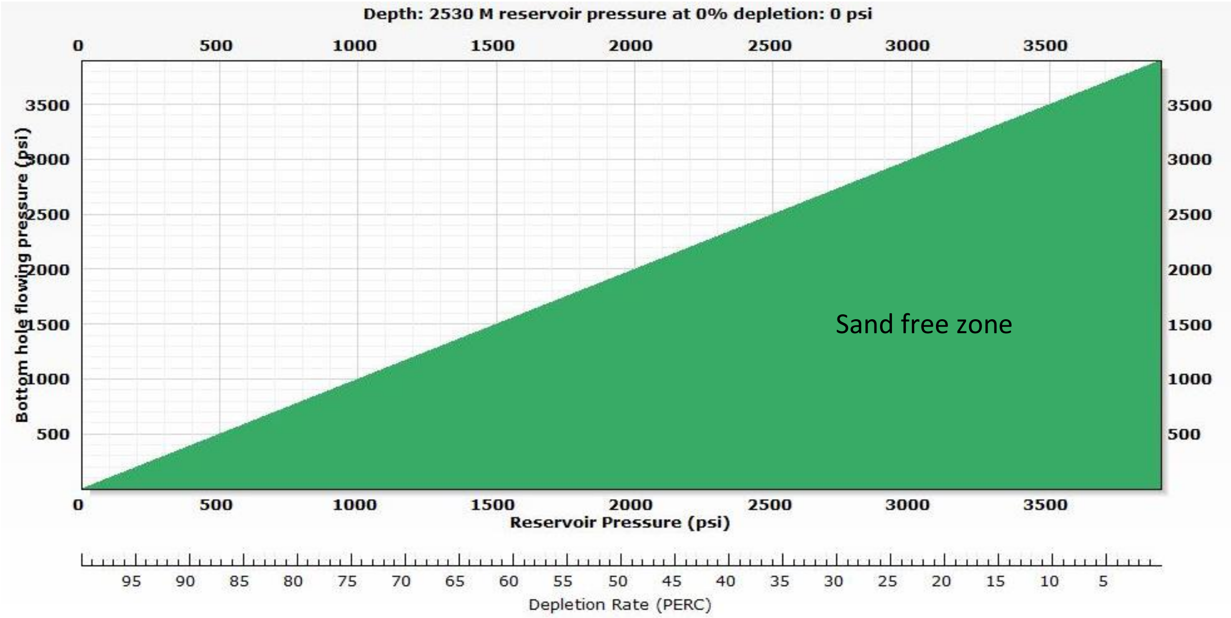

Fig. (5): Single depth sand management results for well-4.

3.3. Neural network application

To clarify the importance of using ML in the sand model, where well-5 was used to be compared with well-4. One significant challenge the researcher faced while investigating well-5 was not having an acoustic log (sonic log). The sonic log is utilized for the complete mechanical earth model (MEM) and for determining rock strength. A neural network technique was used to forecast the sonic log by studying data from adjacent wells to decrease uncertainty and manage risk. Three different kinds of logs neutron porosity, density, and gamma ray are used for building a model and forecasting the missing log in the well, shown in Figure (6).

The Gardner equation is often used for predicting the compressional slowness of a log based on density data, although it has many limitations.

$$V_p = 0.11 * \rho_{bulk}^{4.1} \qquad (11)$$

Where: Bulk density is measured in grams per cubic centimeter and Vp refers to the velocity of the P- waves in feet per second.

We applied the Gardner method and machine learning in the Well-5 to establish a correlation between their outputs. This was done to demonstrate the impact on the final sand model. Additionally, we applied the K.mod technique in the context of ML and neural networks.

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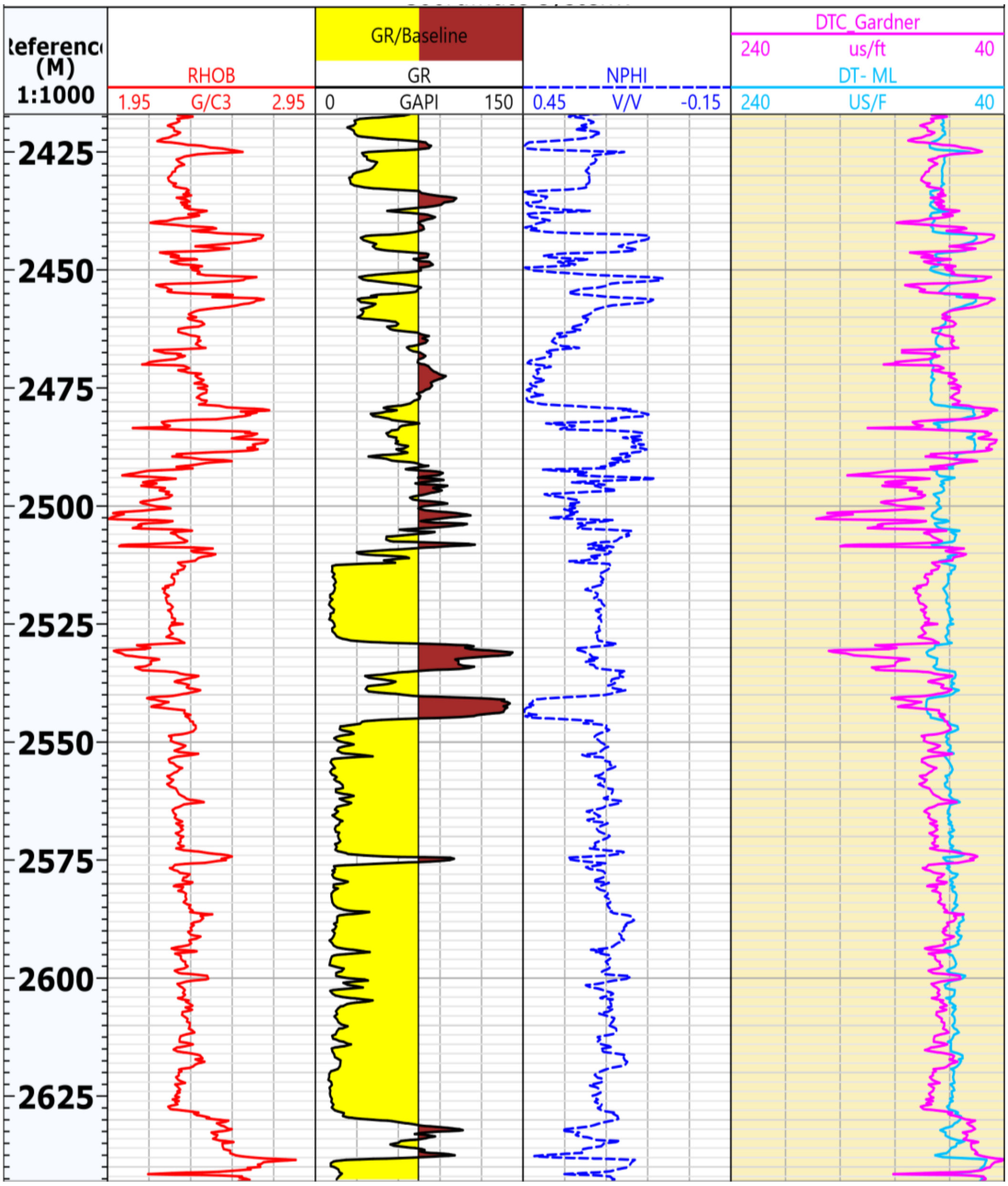

Fig. (6): Comparison of DTc values between the Gardner empirical equation and ML.

3.4. Machine Learning Implications on Geomechanical Modelling

The comparison of the two models showed significant variations in the predicted compressional slowness values. The model created using machine learning showed reduced slowness values in sand areas and increased slowness values in shale sections, as seen in Figure (7). Consequently, a significant disparity in the parameters of the two models occurred when using compressional slowness inputs for mechanical earth modeling and rock strength computations. The machine learning outputs displayed higher values for unconfined

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compressive strength as well as static Young's modulus, with similar values for Poisson's ratio (PR_STA_ML) compared to other models, as seen in Figure (7).

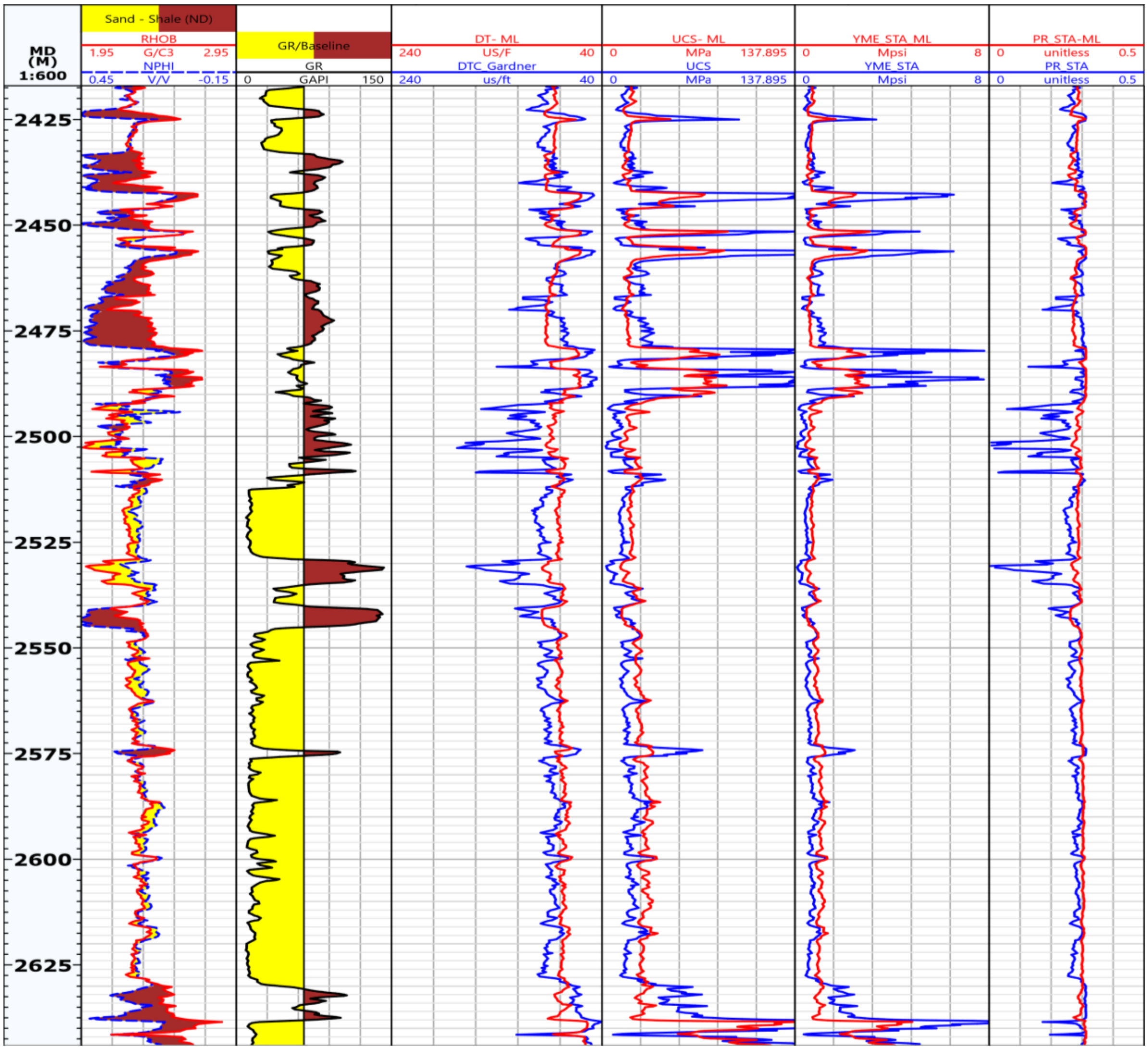

Fig. (7): Correlation between the mechanical earth model values in the two models.

Two sand management studies have been conducted using various techniques to compare neural network outputs against empirical equation results. The research used the results of the empirical equation, especially the Gardner equation, to examine the Nahr Umr formation. The results showed that sand failure happened in different parts of the formation. The failed intervals displayed the smallest unconfined compressive strength (UCS) values and the greatest Poisson's ratio values, as illustrated in Figure (8).

The research specifically concentrated on controlling sand production at a specific depth (2531 m) in the Nahr Umr formation. Figure (9) shows that sand failure happened in the initial stages of production, emphasizing the difficulties related to sand management at this specific time.

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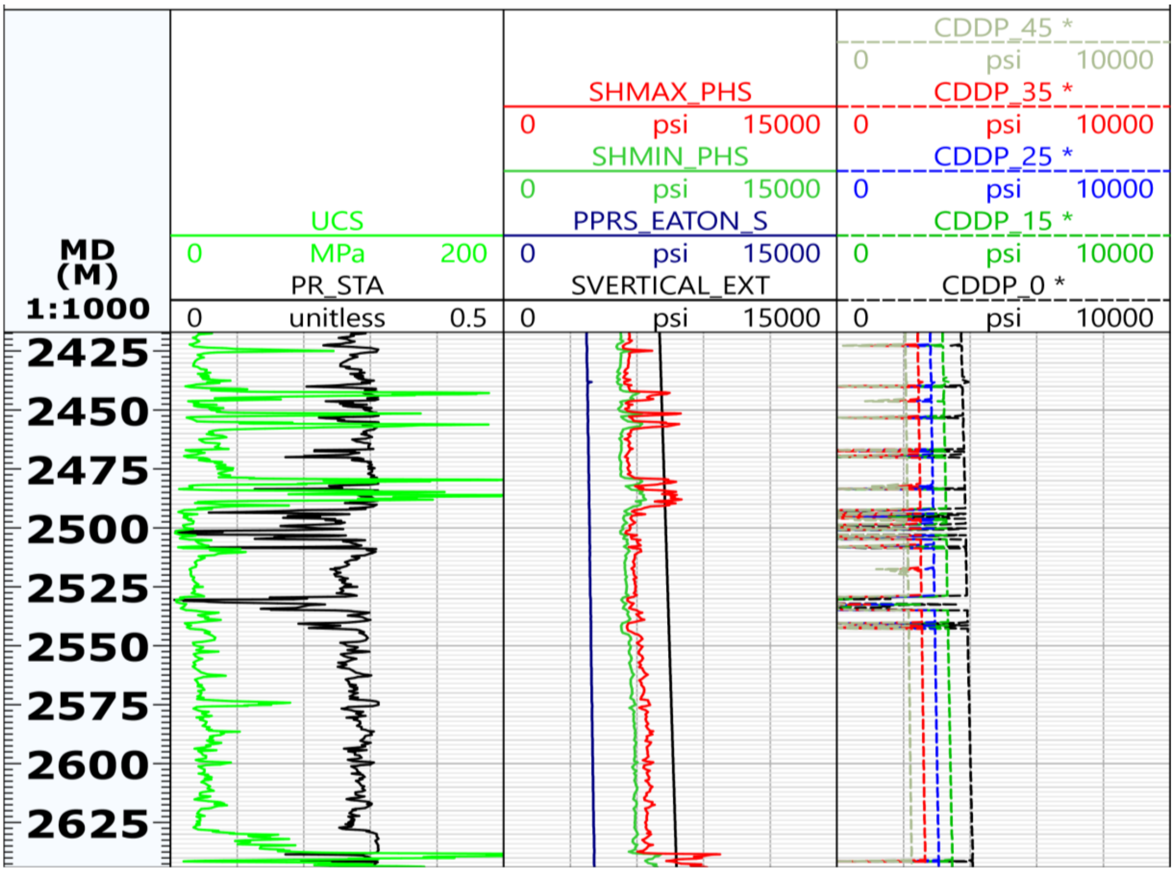

Fig. (8): Sand model using empirical equation technique for well-5.

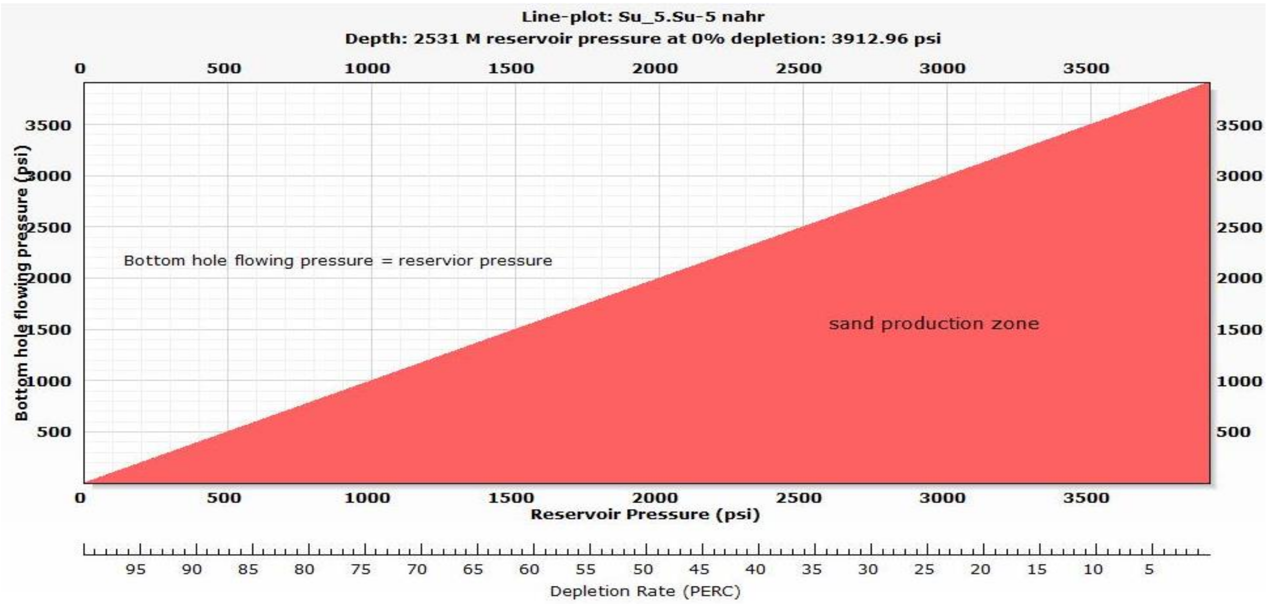

Fig. (9): Sand management at a single depth for a weakly failing zone in Nahr Umr formation.

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Surprisingly, the findings demonstrated that there had been no occurrence of sand failure across the whole Nahr Umr formation, as seen in Figure (10). This indicates that the model developed using machine learning successfully and accurately detected and predicted the absence of sand production in this specific formation.

Furthermore, a sand management study performed at an exact depth in the Nahr Umr formation showed favorable results. Figure (11) shows that the analysis result in a "green flag" status, suggesting that the occurrence of sand production in this well is unlikely based on the current parameters. The results closely matched to the observations from Well-4, emphasizing the accuracy and efficacy of the machine learning model in estimating the compressional slowness parameter and its influence on sand production. The findings indicate that using the empirical equation in the sand management model without key well logs, such as the sonic log, can lead to mistakes in calculation. This is evident from the production data of the Nahr Umr formation, which indicates that zone C is not producing sand. The Gardner equation-based model reliably predicts sand production from the first moment. On the other hand, the machine learning technique produces more reliable results that match with the actual production data, indicating that there is no sand production in Well-5 from Zone C. In the current scenario, the machine learning technique performs better than the empirical equations. By incorporating key well log, this method improves prediction accuracy and eliminates errors, leading to a more accurate sand management model.

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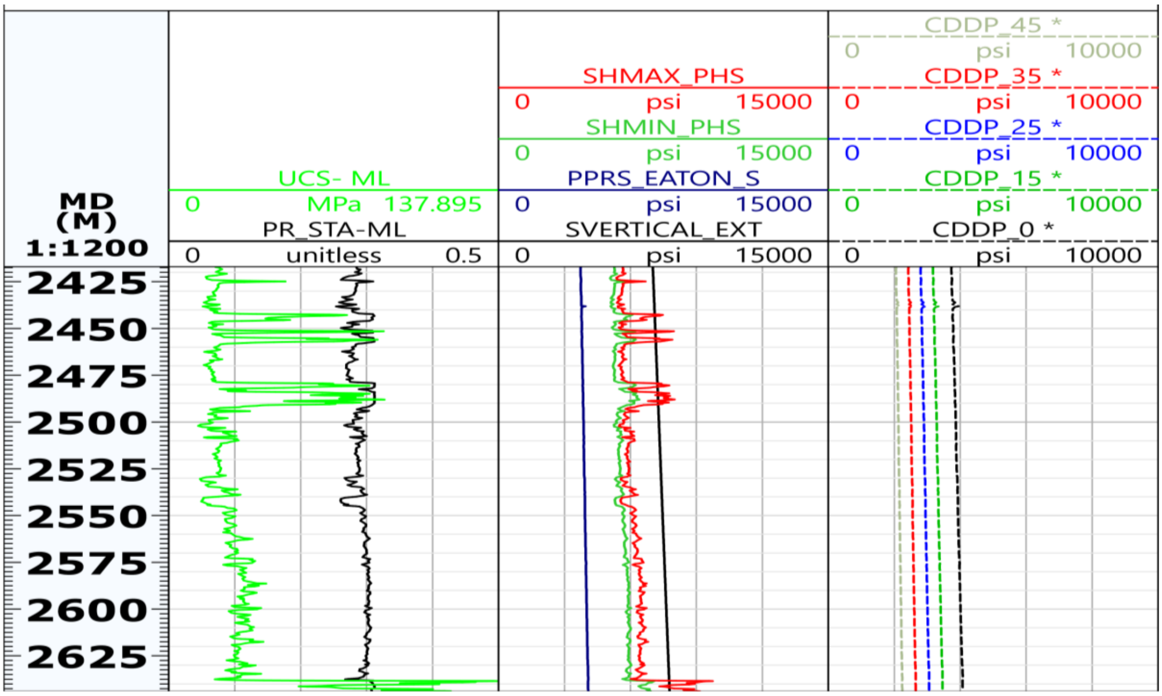

Fig. (10): Displays the outcomes of a sand management investigation for well-5 based on machine learning parameters.

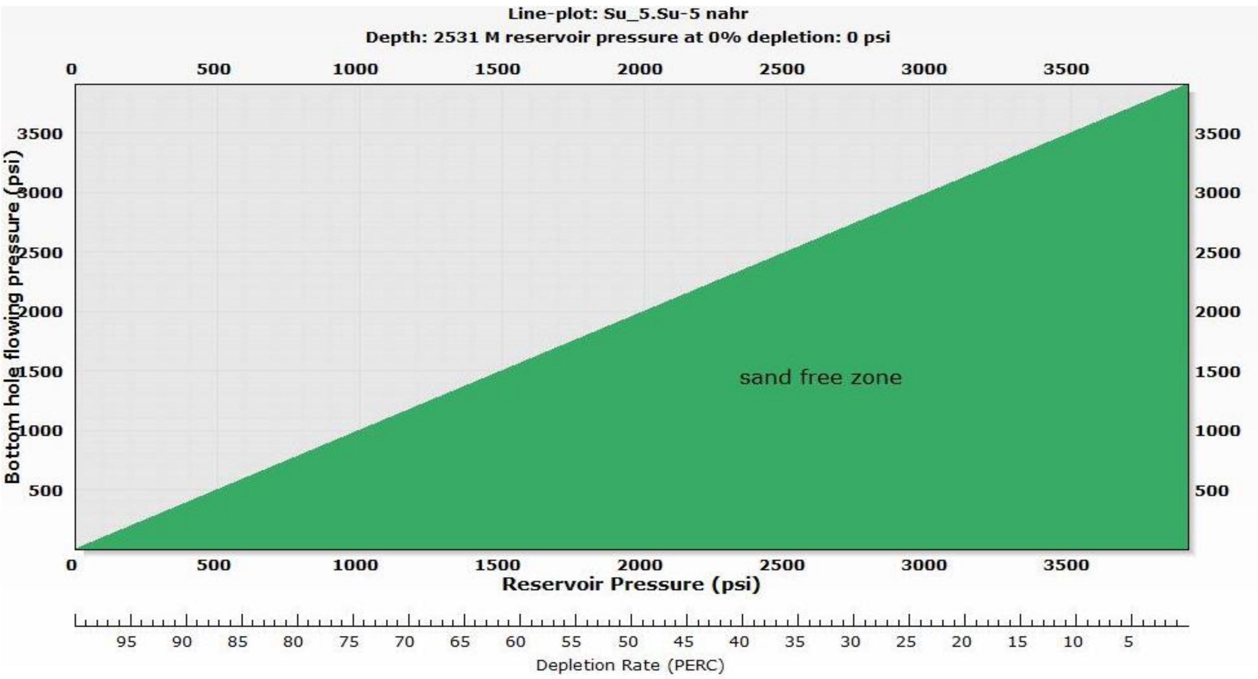

Fig. (11): Displays the sand management outcomes for well-5 in the Nahr Umr Formation at a single depth.

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4. Conclusions

Ultimately, the empirical equation method often leads to inaccurate estimations of rock strength in different intervals, overestimating it in shale intervals and underestimating it in sand intervals. Similarly, the model driven by the Gardner equation incorrectly predicts sand production right from the beginning, contradicting the actual production data. On the other hand, the machine learning model demonstrates better alignment with the production data, providing a more accurate representation of the sand production behavior. The validation of the machine learning output models with the well production profile further confirms their realistic and reliable performance. In the case of the Well-5, the machine learning model accurately indicates no occurrence of sand failure. The suggested approach offers guidance on how to use machine learning techniques to improve precision and produce the best results for geomechanical parameter prediction. Furthermore, machine learning parameters derived from well-integrated log data serve as optimal inputs for sand management studies. Therefore, it is recommended to apply machine learning techniques in geomechanical studies when key logs are missing, as they can replace empirical equations and provide more reliable results.

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