



Implications of machine learning on geomechanical characterization and sand management: a case study from Hilal field, Gulf of Suez, Egypt

Wael K. Abdelghany¹ · M. S. Hammed² · Ahmed E. Radwan³ · Nassar T.²

Received: 14 April 2022 / Accepted: 13 July 2022 / Published online: 6 August 2022
© The Author(s) 2022

Abstract

Sand production is one of the major challenges in the oil and gas industry, so a comprehensive geomechanical analysis is necessary to mitigate sand production in mature fields. As the pore pressure drastically decline in depleted reservoirs, the sand production risk becomes more critical and needs to be studied. However, the absence of key logs in many wells is a big challenge in the petroleum industry, and most geologists and engineers use empirical equations to predict missed log intervals. We conducted a comprehensive geomechanical modeling study on a full set of logs from two wells from the Hilal field, Gulf of Suez, Egypt, to infer the geomechanical elements and predict sand production. We have used the multi-arm calipers to calculate the actual depth of damage ratio to validate the geomechanical parameters in the prognosis model and confirm the stress orientations. We used machine learning approach to infer key sonic log in X-10 well to replace the empirical equations. The multi-arm calipers analysis showed an observed anisotropy in the hole diameter size with more enlargement in the ENE direction and fits with the minimum horizontal stress direction in the direction of N 60°E. The later also deduced the maximum horizontal stress direction in N150 ° based on the induced fractures from borehole image data in a nearby field. We developed and compared two sand management models: one using empirical equation and the other using machine learning. The model driven by the Gardner equation suggests sand production from day one, which is not matched with the production data, while the model driven by machine learning suggests no sand production risk, which is matched with the actual production data. Our results demonstrate the advantage of using machine learning technique in geomechanical studies on the classical empirical equations in the area of study that can be applied in other basins. The findings of this study can help with a better understanding of the implications of machine learning on geomechanical characterization and sand management.

Keywords Sand production · Geomechanical characterization, machine learning, UCS · Sonic log · Gulf of Suez

Introduction

Reservoir geomechanical characterization is crucial in achieving stable wellbore, perforation direction, stimulation and completion schemes, which greatly impacts reservoir production (Blanton and Olson 1999; Zoback 2007; Sen et al. 2019; Taghipour et al. 2019; Baouche et al. 2022; Radwan and Sen 2021a, b). The sedimentary basins for petroleum accumulations are subjected to in situ stresses which are mainly related to their geological tectonic setting. The in situ stress changes under the influence of local factors, making its distribution complicated (Yang et al. 2013; Radwan et al. 2021b). Several drilling and production problems, including blowouts, borehole fills, drilling stuck, mud losses and sand production, occur if the geomechanical

✉ M. S. Hammed
salehhammed@cu.edu.eg; salehhammed@gmail.com

✉ Ahmed E. Radwan
radwanae@yahoo.com; ahmed.radwan@uj.edu.pl

¹ Exploration Department, Gulf of Suez Petroleum Company, Cairo, Egypt

² Geology department, Faculty of Sciences, Cairo University, Giza, Egypt

³ Faculty of Geography and Geology, Institute of Geological Sciences, Jagiellonian University, Gronostajowa 3a, 30-387, Krakow, Poland

studies are not correctly predicted prior to drilling and production operations (Radwan et al. 2019, 2020a; Radwan 2021b). Therefore, having a mathematical model or empirical equations to predict the geomechanical parameters is necessary for economically vital and successful drilling and production operations in oil and gas fields. The resultant depletion conditions of mature fields are globally promote reservoir geomechanical studies as a critical topic for the later stages of field development. The primary challenges are faced due to reservoir depletion, necessary repressurization by water injection and mitigating sand production to maintain production targets as well as cap rock integrity (Addis 1997a,b; Rahmati et al. 2013; Ranjith et al. 2014; Radwan et al. 2021a).

Sand control during production is one of the geomechanical challenges in the oil industry, where some wells suffer from sand production problems that affect the production strategy and additional repair cost. In addition, sand production alongside the formation fluids due to the unconsolidated nature of the formation and production rate is a critical industry problem which can plug wells, leading to loss of production, erode equipment and settle in surface vessels (Suman et al. 1983; Rahmati et al. 2013; Ranjith et al. 2014; Javani et al. 2017; Subbiah et al. 2021). To perform geomechanical studies related to sand production, it is necessary to have the most accurate parameters of the stress state and rock mechanical properties accompanied by reservoir and rock measurements. Well logs are commonly used to derive the in situ stress state at the reservoir level; however, they do not provide the most accurate parameters, which affect the results of the estimated geomechanical elements and may lead to incorrect interpretation (Zoback 2010; Radwan et al. 2021). Geomechanical studies in many areas worldwide are dependent on empirical equations for geomechanical parameter estimation, which may work in some places but not always (Sarkar et al. 2012; Suorineni 2014a, b; Najibi et al. 2015; Iramina 2018). Machine learning techniques have been widely used in the oil and gas industry as a powerful tool for prediction of several vital parameters in the energy industry (e.g., Vo Thanh et al. 2020; Ashraf et al. 2020, 2021; Rajabi et al. 2021; Thanh and Lee 2022; Thanh et al. 2022; Mustafa et al. 2022; Safaei-Farouji et al. 2022; Radwan et al. 2022). Geoscientists and petroleum engineers have applied machine learning application on well logs and other parameters to infer the most critical geomechanics parameters (e.g., Miah 2020; Mohamadian et al. 2021; Kor et al. 2021; Radwan et al. 2022). Machine learning techniques have been applied to sand production prediction by many authors using reservoir parameters (Khamehchi et al. 2014; Gharagheizi et al. 2017; Olatunji and Micheal 2017; Appalov et al. 2020; Zamani and Knez 2021; Ngwashi et al. 2021). To the best of our knowledge, machine learning has not been applied to the input parameters of the sand

management study, especially in light of the lack of key well logs prior to this work. In this work, we have applied the neural network to better estimate the input parameters of the sand management study and to better control the sand management of the Miocene sandstone reservoirs in the Hilal field, Gulf of Suez, Egypt.

The purpose of this study is to perform a comprehensive geomechanical characteristics and sand management study of the Middle Miocene sandstones of Kareem Formation. The sonic logs, which are essential parameters, do not exist in one of the wells (X-10 well), so we have used the offset well data (X-5 well) to predict the sonic log of the X-10 well and perform a sand management study using equations and machine learning. We apply the two approaches and compare the two results to see the difference and how much it affects the modeling. In addition, test the application of machine learning and its implications for better reservoir sand production control in the studied reservoir. First, the geological background is explained. Following that, the methods used and geomechanical modeling were described by the pore pressure and reservoir condition and the orientation and magnitude of the horizontal stress components. Later, the wellbore stability model was discussed, followed by the two developed sand management models. Finally, the implications of machine learning on the geomechanical modeling study were discussed.

Geological setting

The Gulf of Suez occupies the northern end of the Red Sea rift. The development of this NW–SE-oriented fault-forming basin has provided good sites for hydrocarbon generation and maturation (Robson 1971; EGPC 1996; Patton et al. 1994; Radwan et al. 2021a; Dolson et al. 2001). The basin is bounded to the east by the Sinai basement hills and to the west by the Eastern Desert basement complex (Fig. 1). The basin has witnessed extension phases in the Late Oligocene–Early Miocene times (Robson 1971). The basin is characterized by normal faults in the NW–SE (Clysmic) and SW–NE directions (Patton et al. 1994). Long-lived normal faults have been reactivated multiple times during the basin's geological evolution through the rotation of fault blocks in the basin areas during the rift phases (Patton et al. 1994). The basin hosts a cumulative thickness up to 8000 m of sedimentary succession (EGPC 1996). Most of the oil and gas accumulations in the Gulf of Suez Basin are located in the central and southern parts of the basin (Alsharhan, 2003; Radwan et al. 2020a, b, c; Radwan 2021a, b, c, 2022). A regional lithostratigraphic section is provided in Fig. 1. The primary hydrocarbon reservoirs of the Gulf of Suez Basin are sandstones dating from the Early Cretaceous to the Middle Miocene (EGPC 1996).

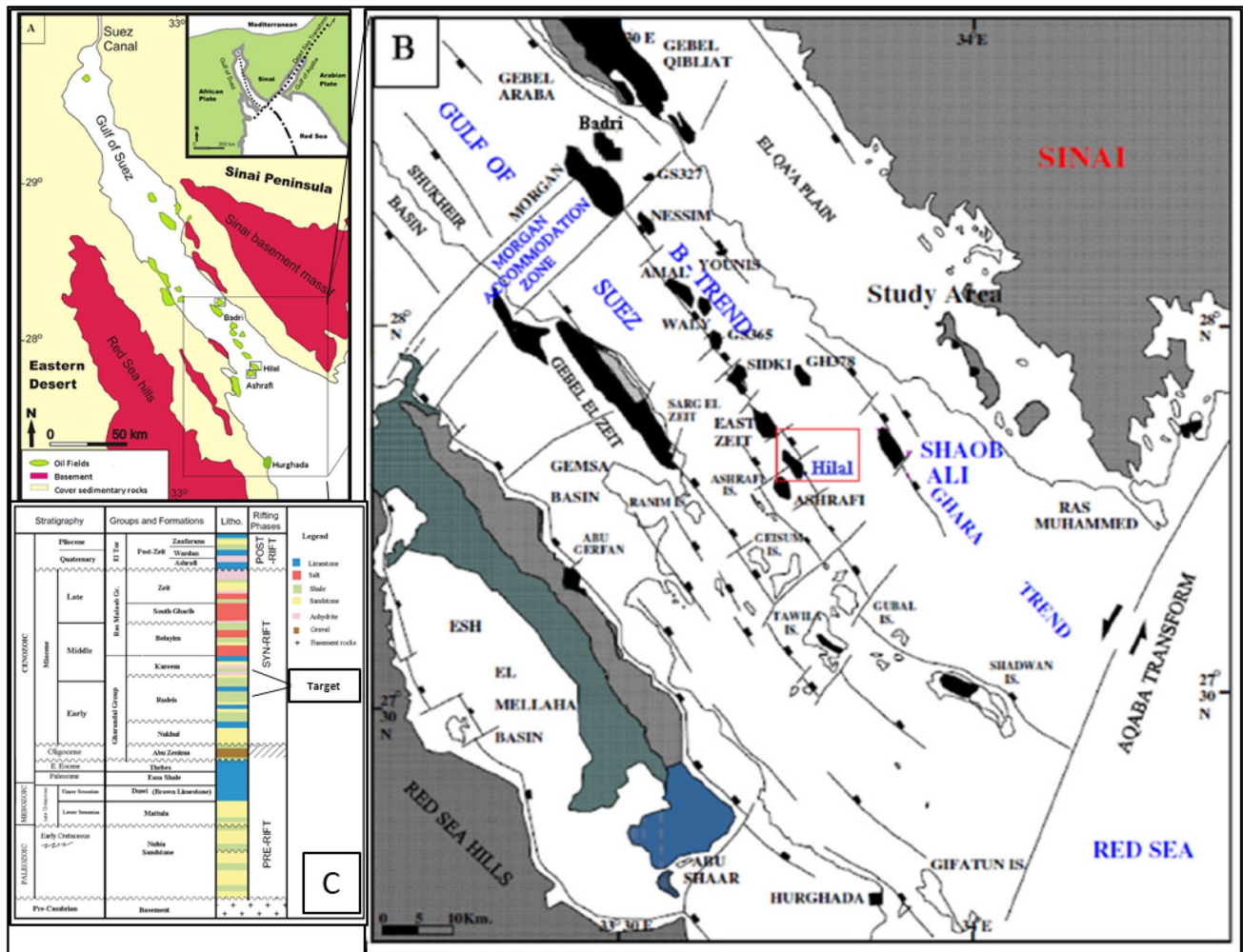


Fig. 1 a Location map of the studied field (modified after Braathen et al. 2018), b map focus on the main fields and structural features of the southern Gulf of Suez sub-basin (modified after Omran and El Sharawy, 2014), c stratigraphic units and dominant lithologies in Hilal field

Hilal oil field is the area of study and covers an area of about five km², located in the southern area of the basin. The field structure is a southwest dipping NW- trending horst of a complex, where the Nubia, Nukhul, Upper Rudeis and Kareem reservoirs are the main reservoirs in Hilal field (Fig. 1) (Helmy 1990). The established source rocks, with high total organic carbon content (6%), are the Campanian–Maastrichtian and Eocene Carbonates (EGPC 1996). The Miocene evaporites formed the regional seal for the petroleum system. The target formations in this study are Kareem Formation, which are dominated by sandstone intercalated with shale and anhydrite streaks (Fig. 1). The dominant lithology in Hilal field is illustrated in Fig. 1c.

Databases and methods

We have used two drilled wells in two different pressure regimes and trajectories, namely X-5 and X-10 wells, from the Hilal Field. The X-5 well had a full set of wireline logs including gamma ray (api), resistivity (ohm), sonic (us/ft), density (gm/cc), neutron (v/v) and multi-arm calipers (inch) (Fig. 2). The X-5 well was drilled during the early age of the Hilal field, and the other well, namely X-10, was recently drilled. The well logs full set is used to calculate the full geomechanical parameters, including the mechanical earth model and the rock strength parameters.

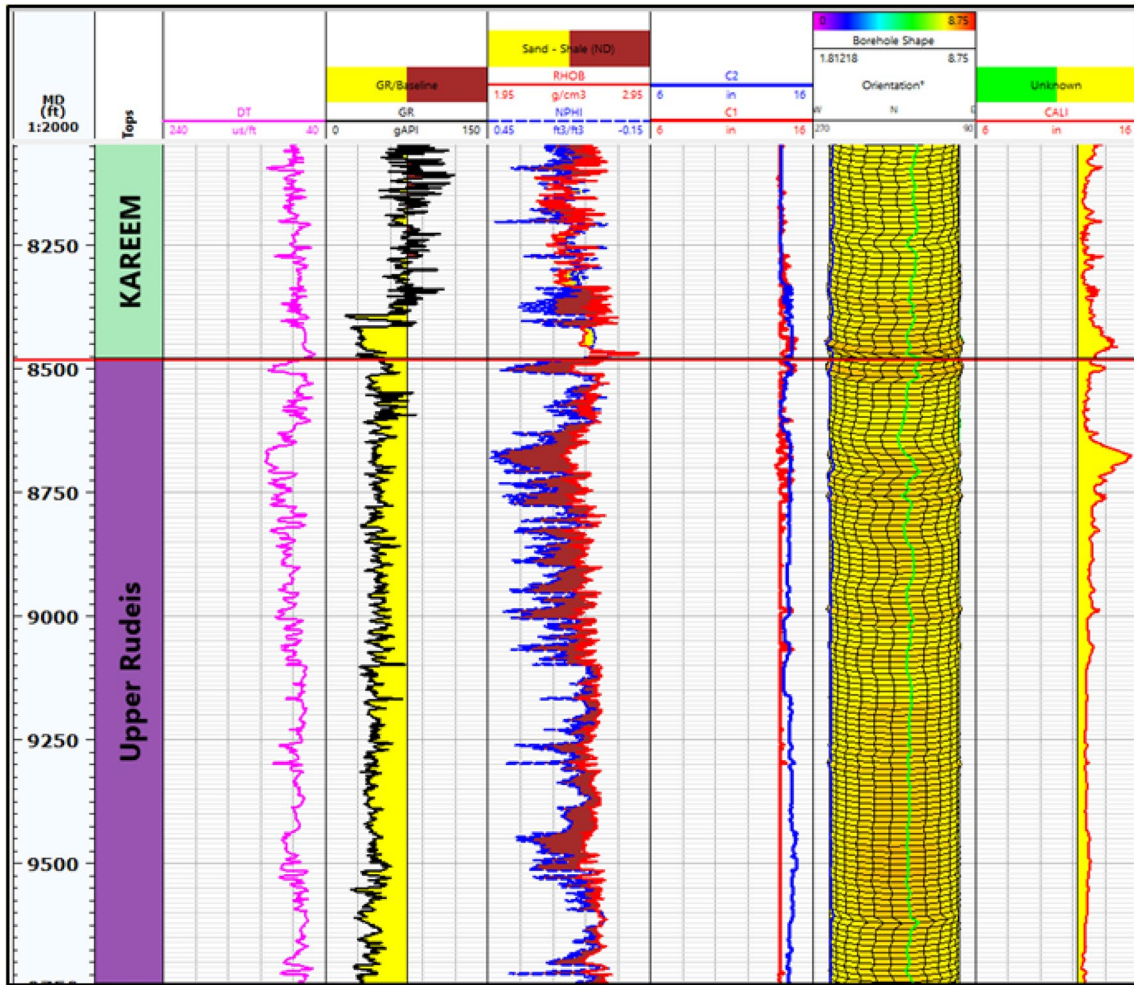


Fig. 2 Wireline logs of X-5 Well

In situ stress estimation

One of the key steps in a geomechanical model is to determine the direction of in situ stress. There are several ways which are widely used to estimate the three principal stresses and rely on field measurements and well log data, including the Fullbore Formation MicroImager (FMI) to define the magnitude and directions of in situ stress. For example, the fast shear slowness direction is the direction of maximum horizontal stress, and the azimuth of wellbore breakout in the FMI figure indicates the direction of minimum horizontal stress (Zoback 2007, 2010; Radwan et al. 2021b).

The vertical stress (S_v) can be calculated with the integration of rock bulk density vertically, and the rock bulk density (RHOB) is obtained from the well logging data (Plumb et al. 1991):

$$S_v = \int_0^H \text{RHOB}(H) * g \, dH \tag{1}$$

With consideration of the tectonic stress, the maximum and minimum horizontal stress of the sedimentary section in Hilal field can be calculated as follows (Blanton and Olson 1999):

$$S_{h\min} = \frac{v_s}{1 - v_s} (S_v - \alpha PP) + \alpha PP + \frac{E_s}{1 - v_s^2} (\epsilon_x + v_s \epsilon_y) \tag{2}$$

$$S_{H\max} = \frac{v_s}{1 - v_s} (S_v - \alpha PP) + \alpha PP + \frac{E_s}{1 - v_s^2} (v_s \epsilon_x + \epsilon_y) \tag{3}$$

where the subscripts $S_{H\max}$, $S_{h\min}$ and S_v represents maximum horizontal stress, minimum horizontal stress and

vertical stress, respectively. α is Biot’s coefficient ($\alpha = P_p$ is the pore pressure in MPa, E is Young’s modulus, ν is Poisson’s ratio, and ϵ_x and ϵ_y are tectonic strain).

For the horizontal stresses orientation, we have used the available full arm caliper data from the well X-5. We compared the results of the caliper with previous results from image logs interpretation of Radwan et al. (2021) in the southern Gulf of Suez.

Pore pressure

In Eqs. (2) and (3), pore pressure (PP) is another key factor for estimating the in situ stress. In the absence of well logs and measurements, traditional methods such as Eaton’s and Bowers methods are used for pore pressure estimation. Traditional Eaton’s pore pressure estimation method cannot reflect this property in some cases or at least delivers overestimated or underestimated values. Bowers (1995) proposed an exponential equation based on the effective stress theory, and both the loading and unloading mechanisms can be reflected. In Hilal field, the direct pressure measurements of the Upper Rudeis and Kareem reservoirs are available, so they have been used in this work.

Estimation of mechanical properties and sand production model inputs.

Building the mechanical earth model (MEM) and further well-bore stability requires several parameters, including Young’s modulus (E), Biot coefficient and Poisson’s ratio (ν), UCS. We have applied the approaches of (Chang et al. 2006; Zhang 2013; Radwan and Sen 2021a,b; Radwan et al. 2021) to calculate the most important geomechanical parameters as follows:

$$vd = \frac{Vp^2 - 2Vs^2}{2(Vp^2 - Vs^2)} \tag{4}$$

$$Ed = \text{RHOB} * Vs^2 \left[\frac{3Vp^2 - 4Vs^2}{Vp^2 - Vs^2} \right] \tag{5}$$

$$\text{UCS} = 1277e^{-0.036\Delta t} \tag{6}$$

$$\phi = \text{Sin}^{-1} \left(\frac{Vp - 1000}{Vp + 1000} \right) \tag{7}$$

$$\text{TSTR} = K * \text{UCS} \tag{8}$$

$$Es = y1 \text{Ed}^{y2} \tag{9}$$

$$vs = vd * \text{PRmultiplier} \tag{10}$$

In the sand management model, we have used the field data for the perforation in the studied wells, where the maximum perforation diameter was 0.3 inch and the perforation orientation was in all directions with 60 deg phasing. The field regional direction is 150 deg as inferred from image logs and caliper data from this research. We have used the stress change ratio value of 0.5 and sand grain diameter of 160 μm (Table. 1).

Neural network

A neural network assumes a nonlinear relationship between log attributes and is completely defined by the number of layers, the neurons in each layer and the connection weights (Al-Bulushi et al. 2012; Ashraf et al. 2021). In the present research, the probabilistic neural network pattern recognition (K.mod) of Schlumberger (2020) was used for inferring, predicting and modeling reservoir properties specifically the sonic log that influence the sand management and the whole geomechanical characteristics. K.mod module can predict nonrecorded parameters; in other words, it reconstruct missing or poor quality data in order to compensate for bad log response coming from bad hole conditions. It comprises of the input layer, hidden pattern layer, summation layer, an output layer and connection loops (Fig. 3).

Each node represents an attribute, and each connection represents a conditional relationship (likelihood) between an individual attribute and training data sets. A supervised training algorithm was employed for the sonic prediction in which the neural network was structured based on the already computed well log attribute combinations from the multiregression analysis. The input parameters in this study were the gamma ray, density and resistivity to predict the compressional slowness of

Table 1 Sand management input parameters

Completion type	Perforation	Maximum perforation diameter 0.3 inch
Maximum horizontal stress direction	Field regional direction	150 deg
Stress change ratio	Default ratio	0.5
Perforation orientation	All directions with 60 deg phasing	N/A
Sand grain diameter	Fit with well site description	160 μm

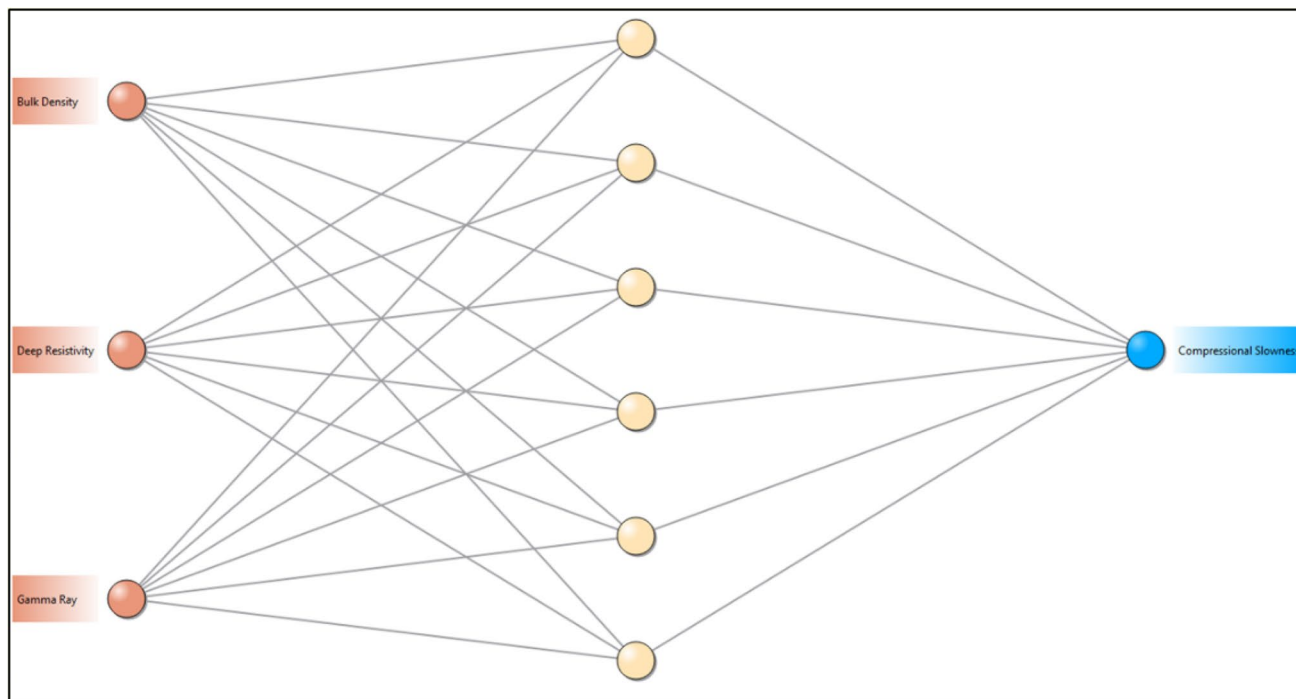


Fig. 3 log data used for machine learning

the Upper Rudeis and Kareem formations. The data are modeled directly from log data via an interactive learning process.

Results and discussions

Reservoir pore pressure and condition

The reservoir section is a depletion drive and suffered from severe pressure depletion as it started with a recorded pressure equivalent to 10.8 ppg. According to the latest pressure measurements, direct downhole measurements by the MDT tool indicate PP equivalent to 3.3 ppg against the reservoir. Two different wells were included in the study: One was drilled during the early age of the field and the other well, namely X-10, was recently drilled in two different pressure regimes and in different directions. At the first well X-5 drilled in 1985, the pore pressure in the Miocene section, including the Kareem and upper Rudeis formations, was characterized by high virgin pressure, reaching 10.8 ppg, which is the normal trend in the Miocene reservoirs charged by oil in the Southern Gulf of Suez.

Orientation and magnitude of the horizontal stress components

Analyzing image logs is crucial to obtain meaningful information about borehole failures, within which breakouts emerge as two parallel furrows (failure zones) having a

180° angle from each other and parallel to Sh_{\min} azimuth (Barton and Moos 2010). When the borehole image logs are not available in all wells, the full arm caliper data can be used to infer or verify the direction of horizontal stresses. In our case, the unavailable borehole image logs were substituted with the caliper log to recognize the directions of the penetrated horizontal stresses by X-5 well in Hilal field. Then, the deduced horizontal stresses of X-5 well by caliper log was compared to the previous results of (Radwan et al. 2021b; Abdelghany et al. 2021) from different wells in the same field. A detailed multi-arm calipers analysis showed hole washout along the whole reservoir section corrected by the used bit size of 12.25'' (Fig. 4). The analysis showed an observed anisotropy in the hole diameter size with more enlargement in the ENE direction (Fig. 4) and fits with the minimum horizontal stress direction in the direction of N 60°E of Radwan et al. (2021b). The later also deduced the maximum horizontal stress direction in N150° based on the induced fractures from borehole image data in a nearby Ashrafi field. The various geomechanical parameters in the studied wells are listed in Table 2.

Wellbore stability model of the Miocene reservoirs

We have performed full wellbore stability model for the reservoir section of the X-5 well in order to validate our mechanical earth model, rock strength parameters and the proelastic horizontal strain model parameters. The

Fig. 4 **A** image logs from nearby wells in the field after Radwan et al. (2021b), **b** well X-5 multi-arm calipers section view shows enlargement direction

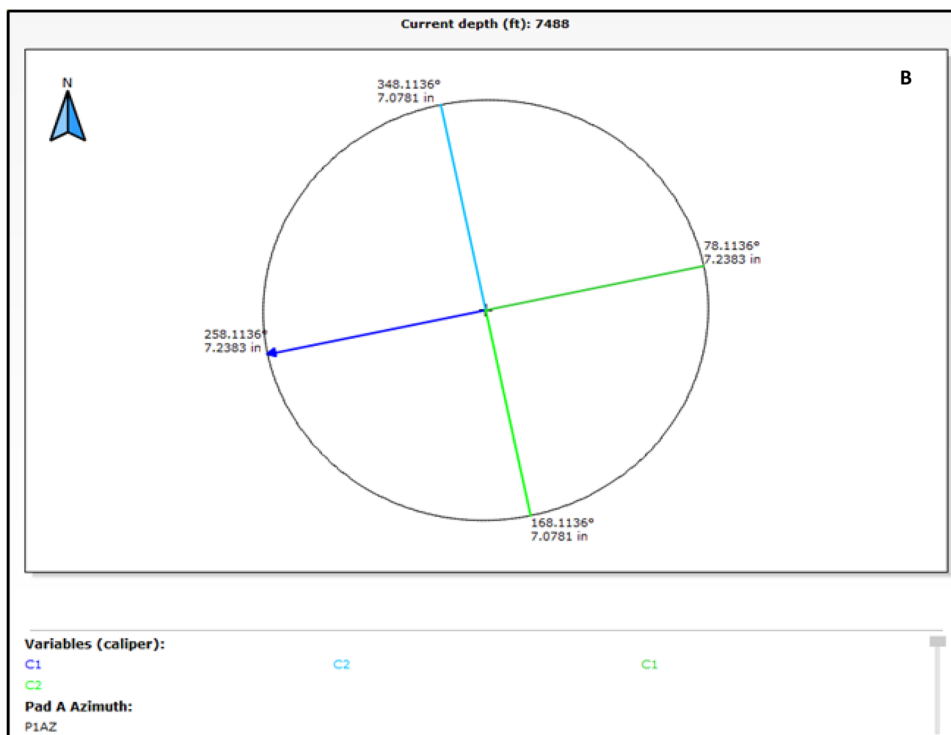
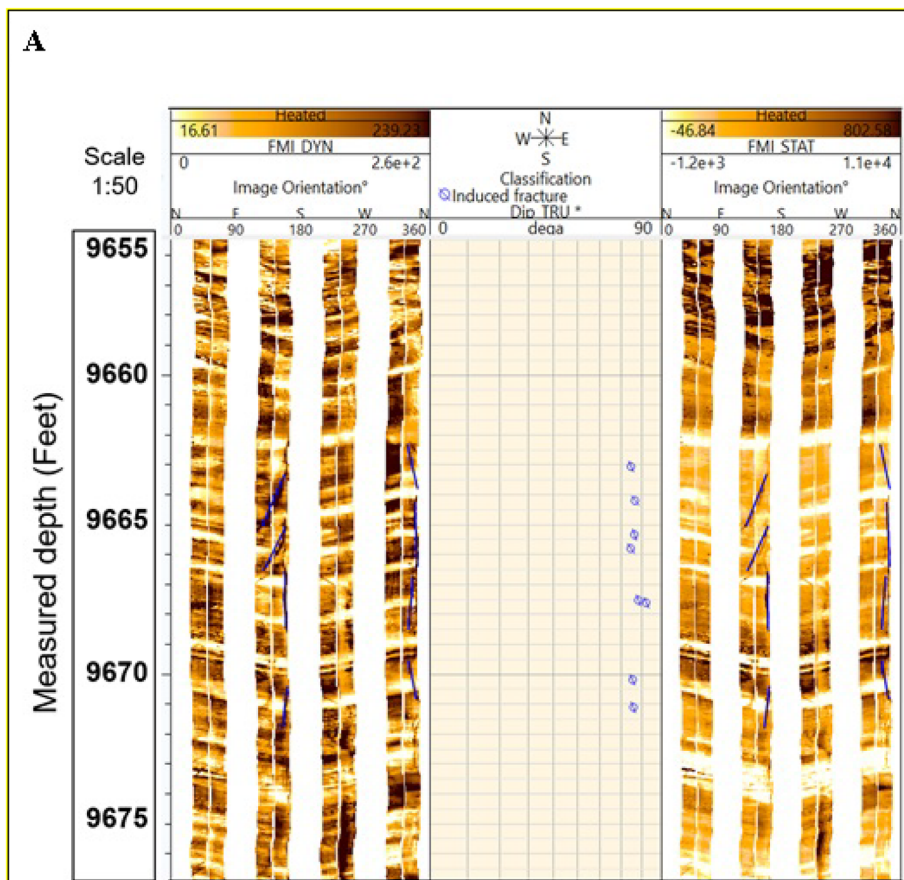


Table 2 Geomechanical characteristics (range values) in X-5 well and X-10 using the gardener and machine learning outputs

Well	Compressional slowness	UCS	Poisson ratio	Azimuth	Deviation	Pore pressure	Shmin	SHmax
	Us/ft	psi	unitless	deg	deg	ppg	ppg	ppg
X-5	64–110	2900–13,000	0.2–0.33	350	15–20	10.8	14.2–15.1	14.5–15.2
X-10 Gardner outputs	57–120	2300–15,000	0.16–0.34	224–267	20–21	3.3	9.2–12.2	10–12.3
X-10 Machine Learning outputs	65–110	2700–11,000	0.21–0.36	224–267	20–21	3.3	9.3–12.2	9.8–12.3

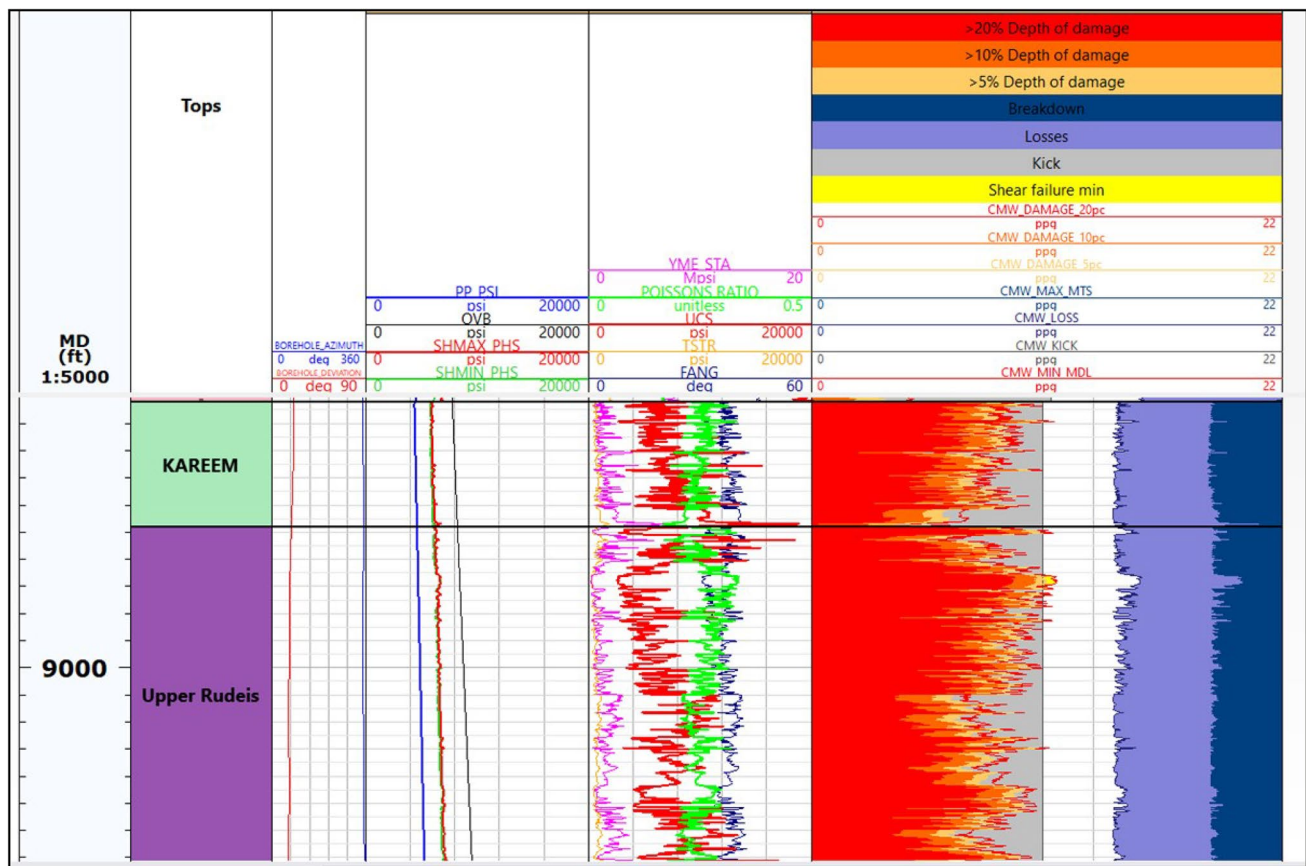


Fig. 5 Wellbore stability results for the well X-5

model results showed the different mud weights to control the wellbore hole versus the shale breakout in 4 outputs: shear failure mud weight, 5% dod, 10% dod and 20% dod (Fig. 5). Based on the parameters used in the model, the used mud weight while drilling the well was in the range between 5 and 10% dod, which fits with the calculated dod from the calipers versus the bit size (Table 2).

Sand management control of the X-5 well

The poroelastic horizontal strain method is used to calculate the minimum and maximum horizontal stresses magnitudes using tectonic strain component values of 0.005 and 0.007, respectively, as published for the Hilal field (Abdelghany et al. 2021; Radwan et al. 2021b). Although the borehole

showed an anisotropic hole, the difference between the two caliper readings (Fig. 3) is low, which is reflected in the difference between the two tectonic stress components and, consequently, the deduced maximum and minimum horizontal stress values. Moreover, these values were validated using the resultant depth of damage versus the actual break-out ratio from calipers.

To investigate the sand production risk under the virgin pressure and through the well X-5 profile, a full sand management study was conducted using the same MEM that was validated in the previous wellbore stability analysis (Fig. 5). The McNally equation is used to calculate the UCS values in the sandstone, which is totally different than the equation used for shale calculations.

Sand management study results for well X-5 (virgin pressure case) showed no estimated sand failure along the whole reservoir section and used different critical drawdown pressures, which were plotted as 0%, 15%, 25%, 35%, 50% and 90% critical drawdown pressure (Fig. 6). The single depth sand management study for the Kareem section showed a green flag till zero pore pressure as an indication of the impossibility of sand production along this well using the current parameters (Fig. 7).

Sand management study results for well X-5 (virgin pressure case) showed no estimated sand failure along the whole reservoir section and used different critical drawdown pressures, which were plotted as 0%, 15%, 25%, 35%, 50% and

90% critical drawdown pressure (Fig. 6). The single depth sand management study for the Kareem section showed a green flag till zero pore pressure as an indication of the impossibility of sand production along this well using the current parameters (Fig. 7).

Sand management control of the X-10 well and Neural network application

On the other hand, the X-10 well was drilled recently in 2015 with a recorded depleted pressure of 3.3 ppg, which increases the sand production risk, which badly needed to be studied, especially with production. One of the major uncertainties while studying the well was the absence of the sonic log, which is used in the entire MEM and the rock strength calculations.

To overcome this risk and to minimize the uncertainty, a machine learning model was used to predict the sonic log using the offset wells data. Three different types of logs, including gamma ray, density and resistivity, are used to build the model and to estimate the missed log in the well (Fig. 8). The Gardner equation (Eq. 11) is mainly used to predict the compressional slowness of logs using density data with some limitations (Gardner et al. 1997).

$$\rho = 0.23Vp^{0.25} \tag{11}$$

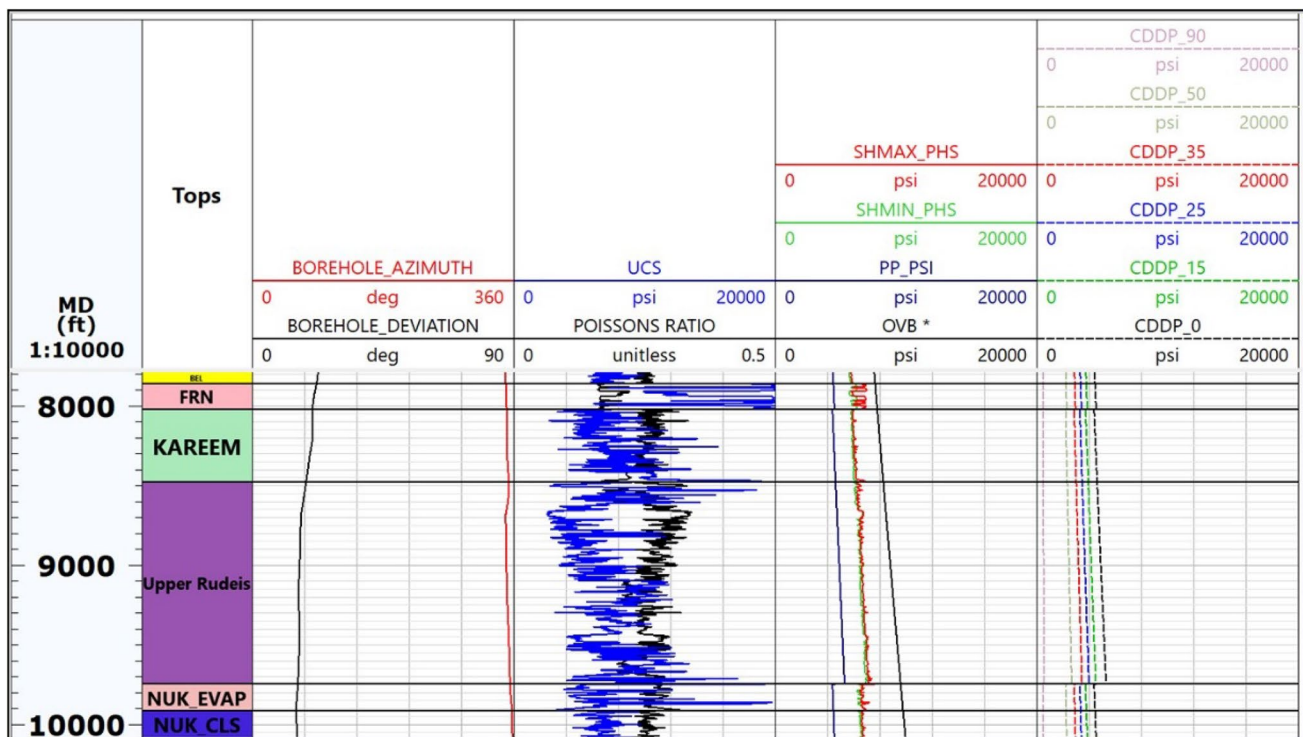


Fig. 6 Sand management study results for well X-5 using virgin pressure

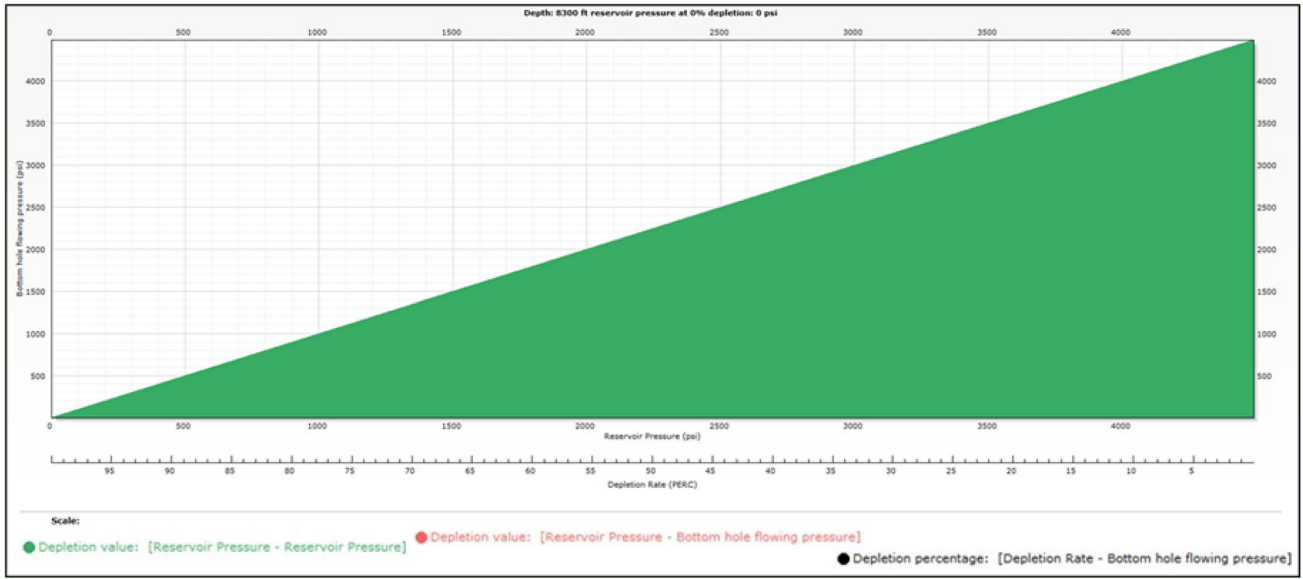


Fig. 7 Single depth sand management results for well X-5 in Kareem formation

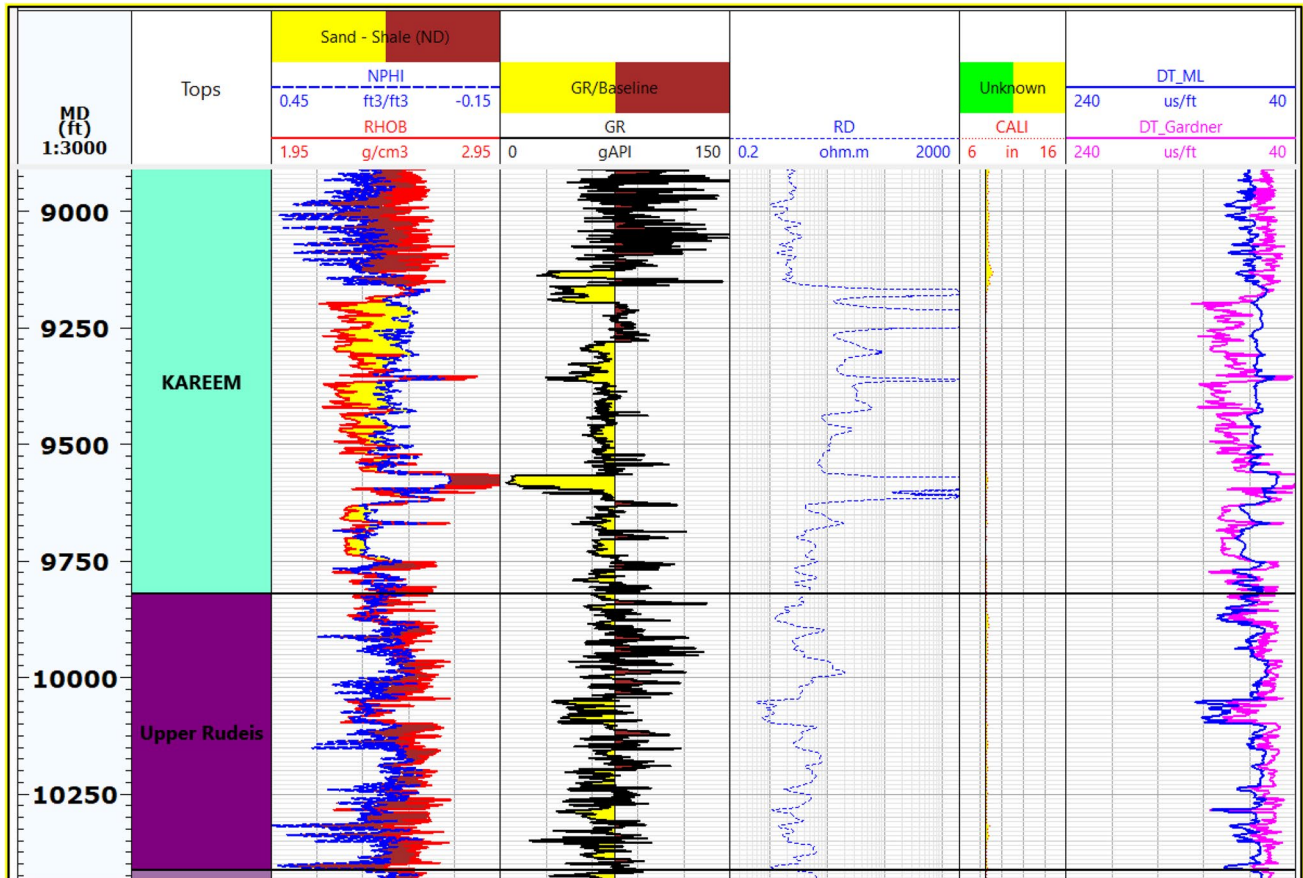


Fig. 8 DT values comparison between machine learning (DT_ML) and the Gardner empirical equation (DT_Gardner)

where ρ is bulk density in g/cc and V_p is P -wave velocity in ft/s.

In this work, we have applied both the Gardner method in the X-10 well and the machine learning technique to make a correlation between its outputs and the machine learning outputs to display how much it would affect the final model, while in terms of neural networks and machine learning, we have applied the K.mod technique.

Implications of machine learning on the geomechanical modeling study

A comparison between the two models showed extremely different values estimated for compressional slowness. Machine learning results showed lower slowness values in sandy intervals and showed higher slowness values in shale intervals (Fig. 9). As a result of using the compressional slowness inputs for mechanical earth modeling and rock strength calculations, the resulted parameters showed a tremendous difference between the two models. Machine learning outputs showed higher unconfined compressive strength (UCS_{ML}), static Young’s modulus (YME_{STA}_{ML}) and

lower Poisson ratio (PR_{STA}_{ML}) than the other models (Fig. 10).

In order to highlight the impact of the machine learning outputs and their difference with empirical equation outputs, two sand management studies were conducted using two different approaches.

The study built using the empirical equation outputs (Gardner equation) showed sand failure along different sections in the Kareem formation using the depleted pressure that was recorded during the well drilling process. The failed intervals have the lowest UCS and the highest Poisson ratio (Fig. 10). Single depth sand management through one of the weak intervals in the Kareem formation shows sand failure from day one production as shown in Fig. 11.

The study built using the machine learning outputs showed no sand failure along the whole reservoir sand section using the depleted pressure that was recorded during the well drilling process (Fig. 12). A single depth sand management study for the Kareem section revealed a green flag until zero pore pressure, indicating that sand production along this well is impossible with the current parameters, as shown in (Fig. 13).

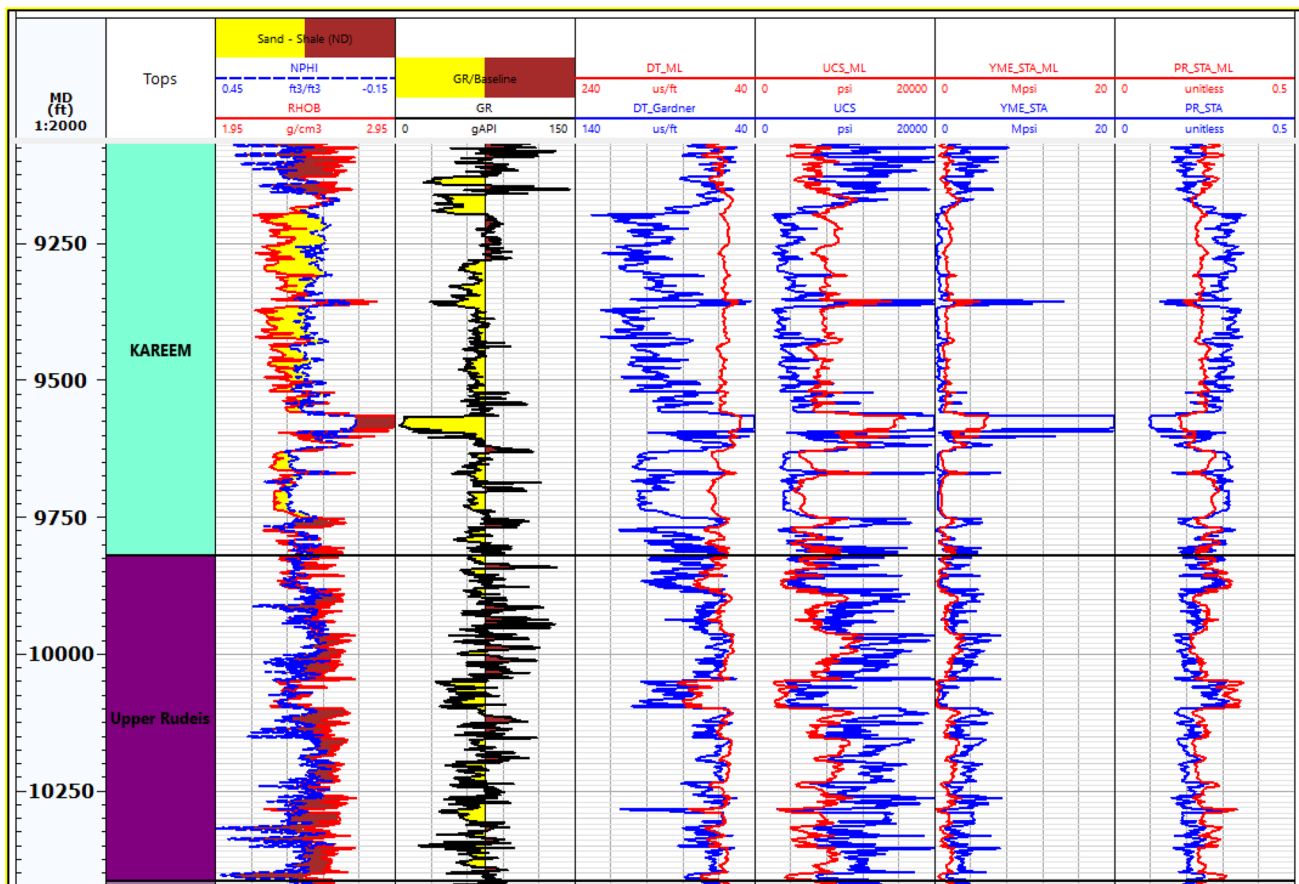


Fig. 9 MEM and UCS values correlation between the two models

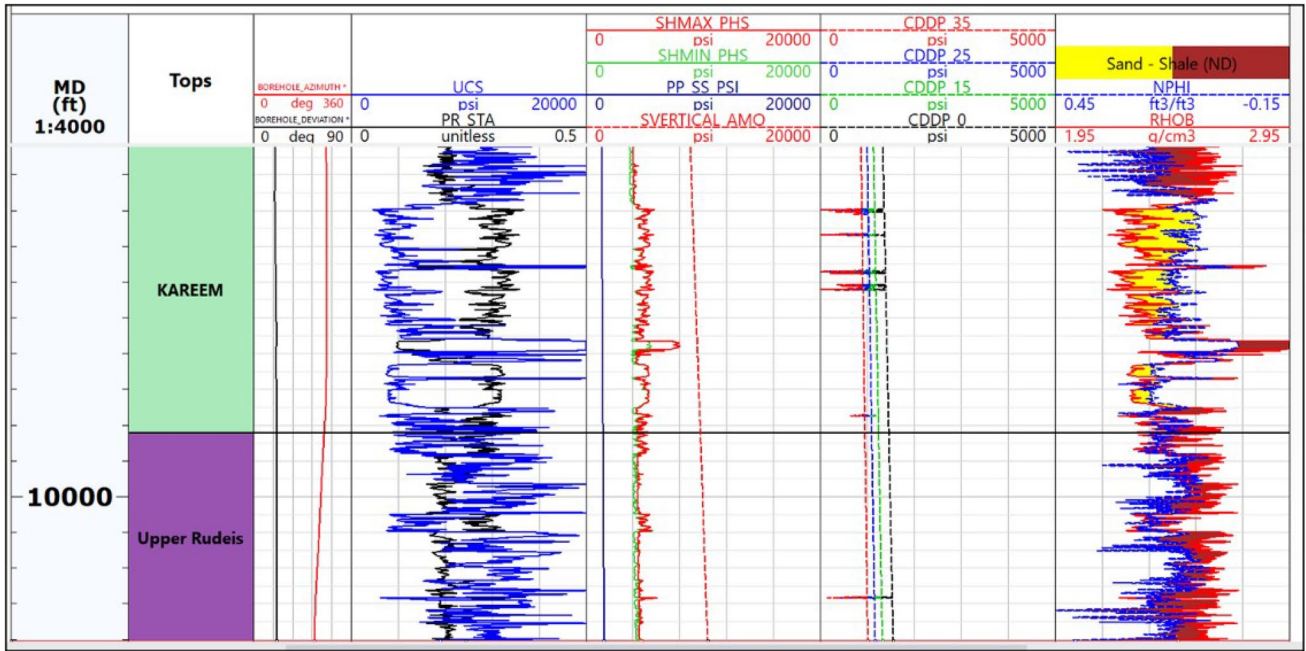


Fig. 10 Sand management study results for well X-10 using empirical equation method

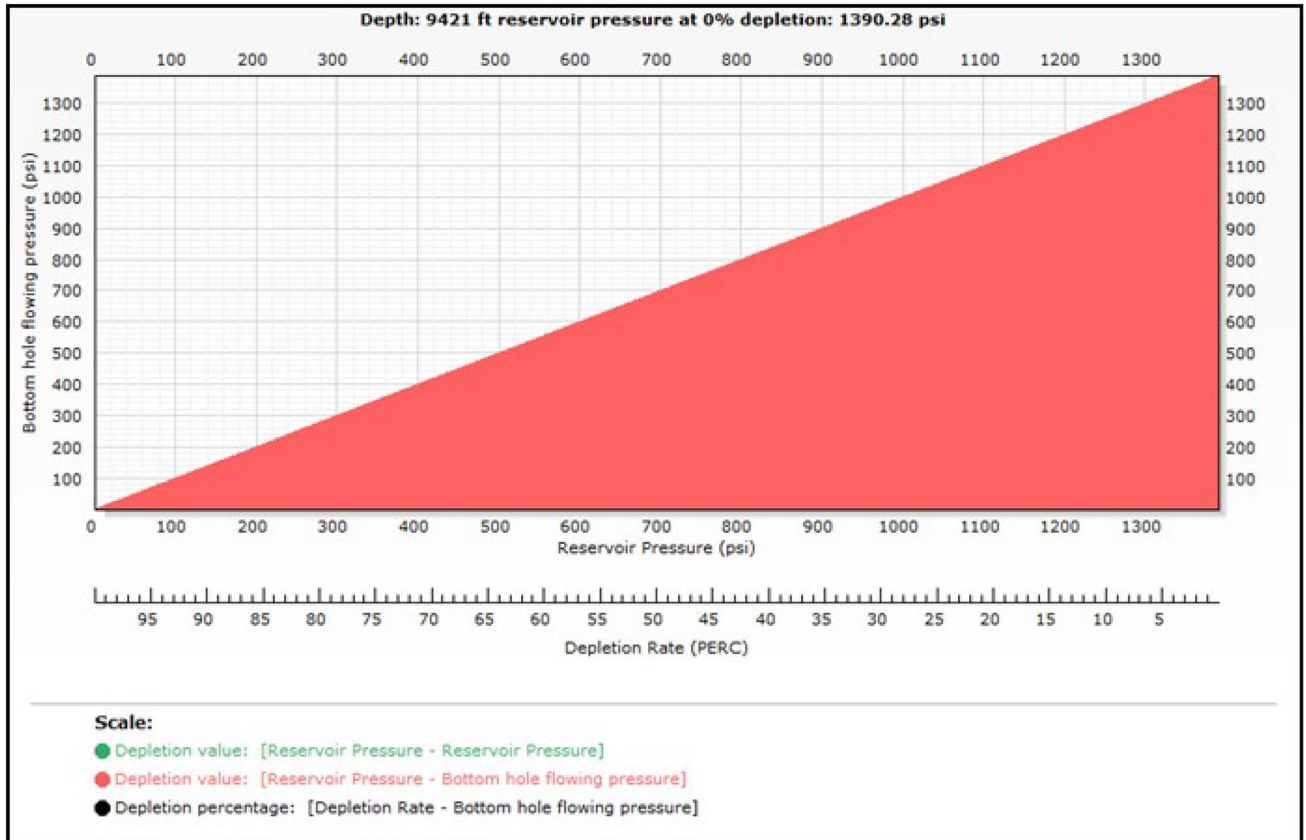


Fig. 11 Single depth sand management for a weak failed zone in Kareem Formation

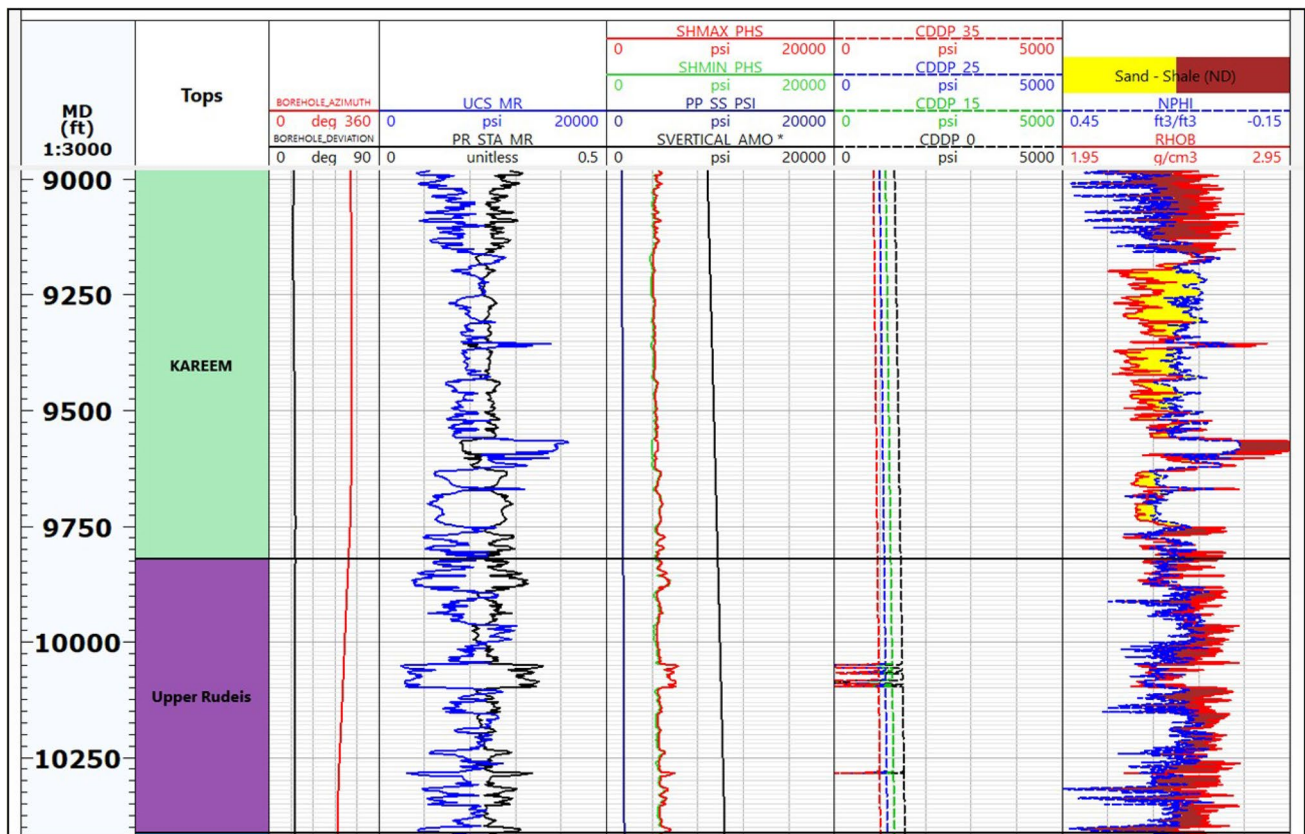


Fig. 12 Sand management study results for well X-10 using machine learning parameters

We can infer that applying the empirical equation in the absence of key well logs such as the sonic can lead to errors in the sand management model. According to the production data from the Hilal field, it is demonstrated that there is no sand production in the field. The model driven by the Gardner equation suggests sand production from day one. The machine learning approach is more realistic and provides results that match with the production data, where the model expects no sand production in the X-10 well. Compared to the empirical equations, the machine learning technique shows better performance.

Conclusions

- The X-10 well sand management study proceeded on to demonstrate the variation in horizontal stress values along the well caused by different well deviation and azimuth.
- Using the empirical equation method results provides an overestimation of the rock strength in shale intervals while underestimating the rock strength in sand intervals.
- The model driven by the Gardner equation suggests sand production from day one, which is not matched with the production data, while the model driven by machine learning is matched with the production data.
- Machine learning output models represent a more realistic approach after validation with the well production profile, which indicates no sand failure in the X-10 well.
- Machine learning parameters act as the optimum inputs for the sand management study, in which they are derived from well integrated log data.
- We recommend the application of machine learning in the absence of key logs in geomechanical studies to replace empirical equations.

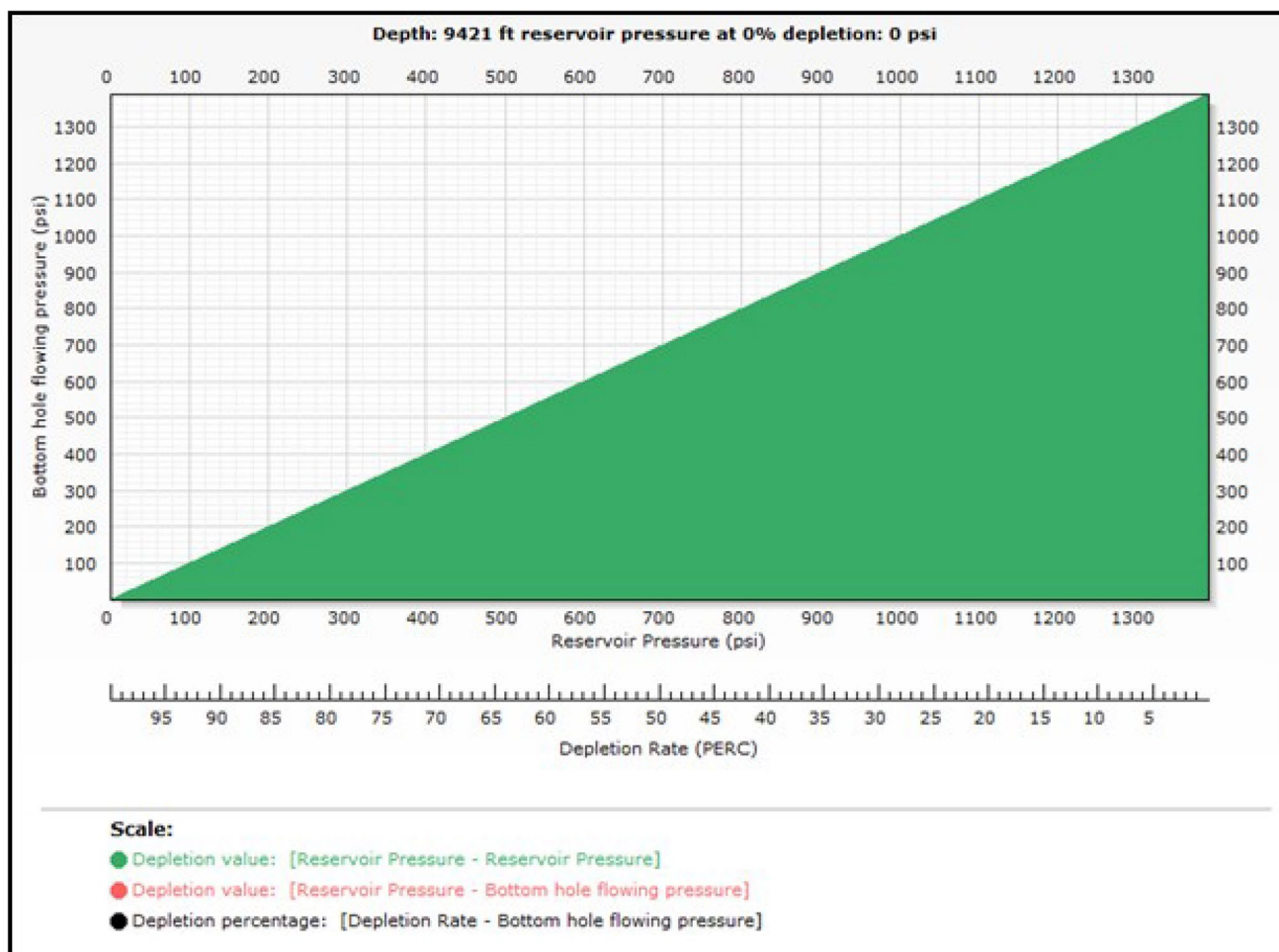


Fig. 13 Single depth sand management results for well X-10 in Kareem Formation

Acknowledgements We thank the Gulf of Suez Petroleum Company (GUPCO) and Egyptian Petroleum Corporation (EGPC) are sincerely acknowledged which supported this work with data and required permissions. The author Ahmed E. Radwan thankful to the support by the Priority Research Area Anthropocene under the program “Excellence Initiative—Research University” at the Jagiellonian University in Kraków.

Funding Open access funding provided by The Science, Technology & Innovation Funding Authority (STDF) in cooperation with The Egyptian Knowledge Bank (EKB). The author Ahmed E. Radwan is thankful to the support by the Priority Research Area Anthropocene under the program “Excellence Initiative—Research University” at the Jagiellonian University in Kraków.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in

the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

- Abdelghany WK, Radwan AE, Elkhawaga MA, Wood D, Sen S, Kassem AA (2021) Geomechanical modeling using the depth-of-damage approach to achieve successful underbalanced drilling in the Gulf of Suez rift basin, *J Petrol Sci Eng* 202:108311. <https://doi.org/10.1016/j.petrol.2020.108311>
- Addis MA (1997a) Reservoir depletion and its effect on wellbore stability evaluation, *Int J Rock Mech Min Sci* 34(3):4.e1-4.e17. [https://doi.org/10.1016/S1365-1609\(97\)00238-4](https://doi.org/10.1016/S1365-1609(97)00238-4)
- Addis MA (1997b) The stress-depletion response of reservoirs. In: SPE annual technical conference and exhibition, San Antonio, Texa, p 5–8
- Al-Bulushi NI, King PR, Blunt MJ, Kraaijeveld M (2012) Artificial neural networks workflow and its application in the petroleum industry, *Neural Comput Appl* 21(3):409–421

- Alsharhan AS (2003) Petroleum geology and potential hydrocarbon plays in the Gulf of Suez rift basin, Egypt. *AAPG Bull* 87(1):143–180
- Appalonov A, Maslennikova Y, Khasanov A (2020) Advanced data recognition technique for real-time sand monitoring systems. In: *International conference on analysis of images, social networks and texts*, Springer, Cham, p 319–330
- Ashraf U, Zhang H, Anees A, Nasir Mangi H, Ali M, Ullah Z, Zhang X (2020) Application of unconventional seismic attributes and unsupervised machine learning for the identification of fault and fracture network. *Appl Sci* 10(11):3864
- Ashraf U, Zhang H, Anees A, Mangi HN, Ali M, Zhang X, Tan S (2021) A core logging, machine learning and geostatistical modeling interactive approach for subsurface imaging of lenticular geobodies in a clastic depositional system. *SE Pakistan Nat Resour Res* 30(3):2807–2830
- Baouche R, Sen S, Ferial HA, Radwan AE (2022) Estimation of horizontal stresses from wellbore failures in strike-slip tectonic regime: a case study from the Ordovician reservoir of the Tinzaouatine field Illizi Basin Algeria. *Interpretation* 10(3):SF47–SF54. <https://doi.org/10.1190/INT-2021-0254.1>
- Blanton TL, Olson JE (1999) Stress magnitudes from logs-effects of tectonic strains and temperature. *SPE Reservoir Eval Eng* 2(1):62–68. <https://doi.org/10.2118/54653-PA>
- Dolson JC, Shann MV, Matbouly SI, Hammouda H, Rashed RM (2001) Egypt in the twenty-first century: petroleum potential in offshore trends. *GeoArabia* 6(2):211–230. <https://doi.org/10.2113/geoarabia0602211>
- EGPC (Egyptian General Petroleum Corporation) (1996) Gulf of Suez oil fields (A comprehensive overview)
- Gharagheizi F, Mohammadi AH, Arabloo M, Shokrollahi A (2017) Prediction of sand production onset in petroleum reservoirs using a reliable classification approach. *Petroleum* 3(2):280–285
- Helmy HM (1990) Southern Gulf of Suez, Egypt: structural geology of the B-trend oil fields. *Geol Soc London, Special Publ* 50(1):353–363
- Iramina WS, Sansone EC, Wichers M, Wahyudi S, Eston SMD, Shimada H, Sasaoka T (2018) Comparing blast-induced ground vibration models using ANN and empirical geomechanical relationships. *REM-Int Eng J* 71:89–95
- Javani D, Aadnoy B, Rastegarnia M, Nadimi S, Aghighi MA, Maleki B (2017) Failure criterion effect on solid production and selection of completion solution. *J Rock Mech Geotech Eng* 9:1123–1130. <https://doi.org/10.1016/j.jrmge.2017.07.004>
- Khamehchi E, Kivi IR, Akbari M (2014) A novel approach to sand production prediction using artificial intelligence. *J Petrol Sci Eng* 123:147–154
- Kor K, Ertekin S, Yamanlar S, Altun G (2021) Penetration rate prediction in heterogeneous formations: a geomechanical approach through machine learning. *J Petrol Sci Eng* 207:109138
- McNally GH (1987) Estimation of coal measures rock strength using sonic and neutron logs. *Geoexploration* 24(4–5):381–395
- Miah MI (2020) Predictive models and feature ranking in reservoir geomechanics: a critical review and research guidelines. *J Nat Gas Sci Eng* 82:103493
- Mohaghegh S, Arefi R, Ameri S, Aminiand K, Nutter R (1996) Petroleum reservoir characterization with the aid of artificial neural networks. *J Petrol Sci Eng* 16(4):263–274
- Mohamadian N, Ghorbani H, Wood DA, Mehrad M, Davoodi S, Rashidi S, Shahvand AK (2021) A geomechanical approach to casing collapse prediction in oil and gas wells aided by machine learning. *J Petrol Sci Eng* 196:107811
- Mustafa A, Tariq Z, Mahmoud M, Radwan AE, Abdulraheem A, Abouelresh MO (2022) Data-driven machine learning approach to predict mineralogy of organic-rich shales: an example from Qusaiba Shale, Rub'al Khali Basin. *Saudi Arabia Marine Petrol Geol* 137:105495. <https://doi.org/10.1016/j.marpetgeo.2021.105495>
- Najibi AR, Ghafoori M, Lashkaripour GR, Asef MR (2015) Empirical relations between strength and static and dynamic elastic properties of Asmari and Sarvak limestones, two main oil reservoirs in Iran. *J Petrol Sci Eng* 126:78–82
- Ngwashi AR, Ogbe DO, Udebhulu DO (2021) Evaluation of machine-learning tools for predicting sand production. In: *SPE Nigeria annual international conference and exhibition, OnePetro*
- Olatunji OO, Micheal O (2017) Prediction of sand production from oil and gas reservoirs in the Niger Delta using support vector machines SVMs: a binary classification approach. In: *SPE Nigeria annual international conference and exhibition, OnePetro*
- Patton TL, Moustafa AR, Nelson RA, Abdine SA (1994) Tectonic evolution and structural setting of the Suez Rift: Chapter 1: Part I. Gulf of Suez, Type Basin
- Plumb RA, Evans KF, Engelder T (1991) Geophysical log responses and their correlation with bed-to-bed stress contrasts in Paleozoic rocks Appalachian Plateau New York. *J Geophys Res Solid Earth* 96(B9):14509–14528. <https://doi.org/10.1029/91JB00896>
- Radwan AE (2021a) Modeling the depositional environment of the sandstone reservoir in the middle miocene sidri member, badri field, Gulf of Suez Basin, Egypt: integration of gamma-ray log patterns and petrographic characteristics of lithology. *Nat Resour Res* 30:431–449. <https://doi.org/10.1007/s11053-020-09757-6>
- Radwan AE (2021b) Modeling pore pressure and fracture pressure using integrated well logging, drilling based interpretations and reservoir data in the Giant El Morgan Oil Field, Gulf of Suez, Egypt. *J African Earth Sci*. <https://doi.org/10.1016/j.jafrearsci.2021.104165>
- Radwan AE (2021c) Integrated reservoir, geology, and production data for reservoir damage analysis: a case study of the Miocene sandstone reservoir, Gulf of Suez, Egypt. *Interpret* 9(4):1–46. <https://doi.org/10.1190/int-2021-0039.1>
- Radwan A, Sen S (2021a) Stress path analysis for characterization of in situ stress state and effect of reservoir depletion on present-day stress magnitudes: reservoir geomechanical modeling in the Gulf of Suez rift basin, Egypt. *Nat Resour Res* 30(1):463–478. <https://doi.org/10.1007/s11053-020-09731-2>
- Radwan AE, Sen S (2021b) Characterization of in-situ stresses and its implications for production and reservoir stability in the depleted El Morgan hydrocarbon field, Gulf of Suez Rift Basin, Egypt. *J Struct Geol*. <https://doi.org/10.1016/j.jsg.2021.104355>
- Radwan AE, Abudeif AM, Attia MM, Mohammed MA (2019) Pore and fracture pressure modeling using direct and indirect methods in Badri Field, Gulf of Suez, Egypt. *J African Earth Sci* 156:133–143. <https://doi.org/10.1016/j.jafrearsci.2019.04.015>
- Radwan AE, Abudeif AM, Attia MM, Elkhawaga MA, Abdelghany WK, Kasem AA (2020a) Geopressure evaluation using integrated basin modelling, well-logging and reservoir data analysis in the northern part of the Badri oil field, Gulf of Suez, Egypt. *J African Earth Sci* 162:103743. <https://doi.org/10.1016/j.jafrearsci.2019.103743>
- Radwan AE, Kassem AA, Kassem A (2020b) Radwany formation: a new formation name for the early-middle eocene carbonate sediments of the offshore October oil field, Gulf of Suez: contribution to the eocene sediments in Egypt. *Mar Pet Geol* 116:104304. <https://doi.org/10.1016/j.marpetgeo.2020.104304>
- Radwan AE, Abudeif AM, Attia MM (2020c) Investigative petrophysical fingerprint technique using conventional and synthetic logs in siliclastic reservoirs: a case study. Gulf of Suez basin, Egypt. *J African Earth Sci* 167:103868. <https://doi.org/10.1016/j.jafrearsci.2020.103868>
- Radwan AE, Nabawy BS, Kassem AA, Hussein WS (2021a) Implementation of rock typing on waterflooding process during

- secondary recovery in oil reservoirs: a case study, El Morgan Oil Field, Gulf of Suez, Egypt. *Nat Resour Res* 30(2):1667–1696
- Radwan AE, Abdelghany WK, Elkhawaga MA (2021b) Present-day in-situ stresses in Southern Gulf of Suez, Egypt: insights for stress rotation in an extensional rift basin. *J Struct Geol* 147:104334. <https://doi.org/10.1016/j.jsg.2021.104334>
- Radwan AE (2022) Provenance depositional facies and diagenesis controls on reservoir characteristics of the middle Miocene Tidal sandstones Gulf of Suez Rift Basin: Integration of petrographic analysis and gamma-ray log patterns. *Environ Earth Sci* 81(15):382. <https://doi.org/10.1007/s12665-022-10502-w>
- Radwan AE, Wood DA, Radwan AA (2022) Machine learning and data-driven prediction of pore pressure from geophysical logs: a case study for the Mangahewa gas field, New Zealand. *J Rock Mech Geotech Eng*. <https://doi.org/10.1016/j.jrmge.2022.01.012>
- Rahmati H, Jafarpour M, Azadbakht S, Nouri A, Vaziri H, Chan D, Xiao Y (2013) Review of sand production prediction models. *J Petrol Eng* 2013:1–16. <https://doi.org/10.1155/2013/864981>
- Rajabi M, Beheshtian S, Davoodi S, Ghorbani H, Mohamadian N, Radwan AE, Alvar MA (2021) Novel hybrid machine learning optimizer algorithms to prediction of fracture density by petrophysical data. *J Petrol Explor Prod Technol*. <https://doi.org/10.1007/s13202-021-01321-z>
- Ranjith PG, Perera MSA, Perera WKG, Choi SK, Yasar E (2014) Sand production during the extrusion of hydrocarbons from geological formations: a review. *J Petrol Sci Eng* 124:72–82
- Robson DA (1971) The structure of the Gulf of Suez (Clysmic) rift with special reference to the eastern side. *J Geol Soc* 127(3):247–271. <https://doi.org/10.1144/gsjgs.127.3.0247>
- Safaei-Farouji M, Thanh HV, Dashtgoli DS, Yasin Q, Radwan AE, Ashraf U, Lee KK (2022) Application of robust intelligent schemes for accurate modelling interfacial tension of CO2 brine systems: Implications for structural CO2 trapping. *Fuel* 319:123821. <https://doi.org/10.1016/j.fuel.2022.123821>
- Sarkar K, Vishal V, Singh TN (2012) An empirical correlation of index geomechanical parameters with the compressional wave velocity. *Geotech Geol Eng* 30(2):469–479
- Sen S, Kundan A, Kalpande V, Kumar M (2019) The present-day state of tectonic stress in the offshore Kutch-Saurashtra Basin, India. *Mar Pet Geol* 102:751–758. <https://doi.org/10.1016/j.marpetgeo.2019.01.018>
- Subbiah SK, Samsuri A, Mohamad-Hussein A, Jaafar MZ, Chen YR, Kumar RR (2021) Root cause of sand production and methodologies for prediction. *Petroleum* 7(3):263–271
- Suman GO, Ellis RC, Snyder RE (1983) Sand control handbook: prevent production losses and avoid well damage with these latest field-proven techniques, Gulf Publishing Company, Book Division
- Suorinen FT (2014a) Reflections on empirical methods in geomechanics—the unmentionables and hidden risks. In: *Proceedings AusRock*
- Suorinen FT (2014b) Empirical methods in mining geomechanics—reflections on current state-of-the-art. In: *Proceedings of 1st international conference on applied empirical design*
- Taghipour M, Ghafoori M, Lashkaripour GR, Moghaddas NH, Mola-ghab A (2019) Estimation of the current stress field and fault reactivation analysis in the Asmari reservoir, SW Iran. *Pet Sci* 16(3):513–526. <https://doi.org/10.1007/s12182-019-0331-9>
- Thanh HV, Lee KK (2022) Application of machine learning to predict CO2 trapping performance in deep saline aquifers. *Energy* 239:122457. <https://doi.org/10.1016/j.energy.2021.122457>
- Thanh HV, Yasin Q, Al-Mudhafar WJ, Lee KK (2022) Knowledge-based machine learning techniques for accurate prediction of CO2 storage performance in underground saline aquifers. *Appl Energy* 314:118985. <https://doi.org/10.1016/j.apenergy.2022.118985>
- Vo Thanh H, Sugai Y, Sasaki K (2020) Application of artificial neural network for predicting the performance of CO2 enhanced oil recovery and storage in residual oil zones. *Sci Rep* 10(1):1–16. <https://doi.org/10.1038/s41598-020-73931-2>
- Vo-Thanh H, Amar MN, Lee KK (2022) Robust machine learning models of carbon dioxide trapping indexes at geological storage sites. *Fuel* 316:123391. <https://doi.org/10.1016/j.fuel.2022.123391>
- Wescott WA, Atta M, Dolson JC (2016) PS A brief history of the exploration history of the Gulf of Suez, Egypt
- Yang Y, Zoback M, Simon M, Dohmen T (2013) An integrated geomechanical and microseismic study of multi-well hydraulic fracture stimulation in the Bakken formation. In: *SPE/AAPG/SEG unconventional resources technology conference, OnePetro*
- Zamani MAM, Knez D (2021) A new mechanical-hydrodynamic safety factor index for sand production prediction. *Energies* 14(11):3130
- Zhang J (2013) Borehole stability analysis accounting for anisotropies in drilling to weak bedding planes. *Int J Rock Mech Min Sci* 60:160–170. <https://doi.org/10.1016/j.ijrmms.2012.12.025>
- Zoback MD (2007) *Reservoir geomechanics*. Stanford University, California
- Zoback MD (2010) *Reservoir geomechanics*. Cambridge University Press

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.