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Machine learning application to predict in-situ stresses from logging data

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Determination of in-situ stresses is essential for subsurface planning and modeling, such as horizontal well planning and hydraulic fracture design. In-situ stresses consist of overburden stress (σ_v), minimum (σ_h), and maximum (σ_H) horizontal stresses. The σ_h and σ_H are difficult to determine, whereas the overburden stress can be determined directly from the density logs. The σ_h and σ_H can be estimated either from borehole injection tests or theoretical finite elements methods. However, these methods are complex, expensive, or need unavailable tectonic stress data. This study aims to apply different machine learning (ML) techniques, specifically, random forest (RF), functional network (FN), and adaptive neuro-fuzzy inference system (ANFIS), to predict the σ_h and σ_H using well-log data. The logging data includes gamma-ray (GR) log, formation bulk density (RHOB) log, compressional (DTC), and shear (DTS) wave transit-time log. A dataset of 2307 points from two wells (Well-1 and Well-2) was used to build the different ML models. The Well-1 data was used in training and testing the models, and the Well-2 data was used to validate the developed models. The obtained results show the capability of the three ML models to predict accurately the σ_h and σ_H using the well-log data. Comparing the results of RF, ANFIS, and FN models for minimum horizontal stress prediction showed that ANFIS outperforms the other two models with a correlation coefficient (R) for the validation dataset of 0.96 compared to 0.91 and 0.88 for RF, and FN, respectively. The three models showed similar results for predicting maximum horizontal stress with R values higher than 0.98 and an average absolute percentage error (AAPE) less than 0.3%. a^{20} index for the actual versus the predicted data showed that the three ML techniques were able to predict the horizontal stresses with a deviation less than 20% from the actual data. For the validation dataset, the RF, ANFIS, and FN models were able to capture all changes in the σ_h and σ_H trends with depth and accurately predict the σ_h and σ_H values. The outcomes of this study confirm the robust capability of ML to predict σ_h and σ_H from readily available logging data with no need for additional costs or site investigation.

List of symbols

AAPE	Average absolute percentage error
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural network
DFIT	Diagnostic fracture injection test
DTC	Compressional waves transit time, $\mu\text{s}/\text{ft}$
DTS	Shear waves transit time, $\mu\text{s}/\text{ft}$
FN	Functional network
FNFSM	Functional network forward-selection method
FNESM	Functional network exhaustive-search method
FNBEEM	Functional network backward-elimination method
FNFBM	Functional network forward-backward method
FNBFM	Functional network backward-forward method
GR	Gamma-ray, API
LOT	Leak-off test
N	The number of data points
ML	Machine learning

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R	Correlation coefficient
RF	Random forest
RHOB	Formation bulk density, g/cm ³
x_i	The independent parameter
XLOT	Extended leak-off test
y_i	The dependent parameters
σ_V	Overburden stress, psi/ft
σ_h	Minimum horizontal stress, psi/ft
σ_H	Maximum horizontal stress, psi/ft
σ_x and σ_y	The standard deviation for the independent and dependent parameters
μ_x and μ_y	Mean for the independent and dependent parameters

In-situ stresses are presented in overburden stress (σ_V), and horizontal stresses, named minimum (σ_h) and maximum (σ_H) horizontal stresses. The stress state of the earth's subterranean formations is considered one of the essential information that has a great interest in petroleum engineering and geoscience fields. Therefore, fully understanding the stress state is crucial for well orientation and hydraulic fracture design that may significantly affect oil and gas production. For example, a horizontal gas well drilled in the direction of the σ_h direction of Marcellus shale has a 40–50% increase in productivity compared to a 45° off-azimuth well. Moreover, σ_h is essential for geomechanical evaluation, such as wellbore stability¹. Furthermore, different seismic studies in the Permian basin showed the importance of σ_h in controlling hydraulic fracture propagation. Hence, horizontal stresses should be estimated accurately to optimize drilling and completion operations and improve the hydraulic fracturing process. The challenging task in the in-situ stress analyses is the estimation of the σ_h and σ_H , because the σ_V can be directly computed by integrating the rock density with depth using the density logs².

The stress distribution around the borehole directly impacts the drilling operation and the associated wellbore instability, affecting the wellbore integrity and causes many drilling-related issues such as lost circulation, pack-off, stuck bottom-hole-assembly (BHA) or casing^{3,4}. Thus, a comprehensive geomechanical model of downhole formations helps address many issues through different stages of reservoir life. An example of these issues are maintaining borehole stability in drilling operations, formation instability within the production operations and sand production, and the applicable wellbore completion design selection^{5–10}.

The σ_h can be estimated through different injection tests. These tests include Minifrac, Leak-off Test (LOT), eXtended Leak-off Test (XLOT), or Diagnostic Fracture Injection Test (DFIT)^{10–13}. The σ_H cannot be directly measured using these methods¹⁴, and theoretical and empirical correlations are required to estimate the σ_H depending on the values of σ_V and σ_h ^{15,16}. The main challenges for the direct measurements are time-consuming and high cost. Besides, it would not provide a continuous profile of the least principal stresses because such tests are typically performed at specific depths.

Numerical modeling depends on the finite different and finite element systems that can be used to model the in-situ stresses. Other physics-based theoretical models, such as uniaxial strain theory, poroelastic strain models, were developed to determine the in-situ stresses of the downhole formations^{10,17–19}. These models depend on having measurements of some in-situ geomechanical parameters, static elastic modulus, static Poisson's ratio, and elastic strains. The most accurate method for obtaining such measurements is retrieving core samples from the downhole formations and conducting triaxial tests to estimate these parameters¹⁹. The measured parameters would be correlated to the conventional logging data to develop a continuous profile before applying the aforementioned models. Besides, at least one direct field test, i.e., leak-off test, should be conducted to calibrate these profiles and include the effect of the tectonic stresses so that they would effectively represent the in-situ stress state of the downhole formations^{20–22}. However, the main limitation of this technique is that retrieving such core samples is an expensive and laborious process that makes such measurements not usually available for all drilled wells.

Applications of machine learning in geomechanics

Machine learning (ML) models can be built to predict specific parameters as a function of available logging data without adding more cost or well intervention. Different ML techniques such as RF, ANFIS, FN, ANN, and support vector machine (SVM), have been applied in the petroleum industry^{23–26}. Acar and Kaya applied SVM to estimate the elastic modulus for weak rocks. They found that the SVM model was more effective than the multiple regression process²³. Similarly, Gowida et al. used different ML techniques including ANN, ANFIS, and SVM to calculate the unconfined compressive strength (UCS) from the drilling data. They found that using ML techniques to predict UCS was superior compared to the available empirical correlations²⁴. Moreover, ML were used to calculate the oil production rate as a function of the choke parameters²⁶. ANFIS and FN models outperform the available empirical correlation to forecast oil production, especially in complex systems with high gas-oil ratios and high water cut.

Bayesian Network (BN) and random forest (RF) models were used to estimate the ground vibration result from the quarry blasting²⁷. RF model showed higher accuracy results compared to the BN model, where the accuracy level was 90% for the RF model comparing to 87% for the BN model for the testing dataset. Zhou et al. used different ML to forecast the shear strength of rockfill materials²⁸. The results revealed that RF models were capable to produce accurate results for the shear strength comparing to the ANN model and multiple regression analysis, and the R-value was 0.98 from the RF model comparing to 0.96 for the ANN model. Similarly, ANFIS and ANN models predicted UCS and Young's modulus²⁹. ANFIS model showed a superior behavior comparing to the ANN model and multiple regression process. R² for the ANFIS model was 0.99 comparing to 0.91, and 0.6 for the ANN model and the multiple regression analysis, respectively²⁹. Another ANFIS model was

	GR (API)	DTC (μs/ft)	DTS (μs/ft)	RHOB (g/cm ³)	NPHI	PRd	Ed (psi)	σ _h (psi)	σ _H (psi)	σ _h (psi/ft)	σ _H (psi/ft)
Mean	29	49	90	2.8	0.30	0.30	84,534	11,851	13,724	0.88	1.02
Standard deviation	14	3	7	0.1	0.01	0.01	11,203	300	485	0.00	0.02
Minimum	3	45	81	2.3	0.28	0.28	33,367	11,240	12,308	0.87	0.94
Quartile 25%	17	47	86	2.8	0.29	0.29	77,235	11,616	13,395	0.88	1.01
Quartile 50%	28	47	88	2.8	0.29	0.29	87,839	11,864	13,803	0.88	1.02
Quartile 75%	37	50	94	2.9	0.30	0.30	92,950	12,082	14,044	0.88	1.03
Maximum	90	66	132	3.0	0.32	0.33	101,968	12,361	14,599	0.89	1.05
Skewness	0.68	2.43	2.43	- 0.87	0.95	1.36	- 1.37	- 0.14	- 0.41	0.11	- 1.09

Table 1. Statistical analysis for the collected dataset for the two wells.

developed to calculate the bearing capacity of the cohesive soft soils³⁰. The ANFIS model revealed an R value of 0.99, and 0.96 between the actual and the estimated data for the training, and testing datasets, respectively. Based on this analysis, random forest and ANFIS machine learning revealed a superior performance to predict the geomechanical parameters.

In-situ stress determination is crucial for well planning and hydraulic fracture designing. Borehole injection tests or theoretical methods can be used to estimate the in-situ stresses. However, these methods are complex, expensive, need unavailable tectonic stress data, and only can be conducted at a specific depth. Therefore, this study aims to apply different machine learning tools to predict the σ_h and σ_H and provide a continuous profile of in-situ stress using the conventional well-log data with no additional cost or well intervention. The logging data consist of gamma-ray (GR) log, formation bulk density (RHOB) log, compressional (DTC), and shear (DTS) wave transit-time log. Two wells with 2307 data were used to build and validate the RF, ANFIS, and FN models.

Methodology

Data description. Well-logs data from two wells were collected from the Middle East region representing a complex carbonate formation. A dataset of 2307 points included GR, DTC, DTS, RHOB, neutron porosity (NPHI) log, dynamic elastic modulus (Ed), dynamic Poisson's ratio (PRd), and the corresponding σ_h and σ_H. Table 1 summarizes the statistical analysis of the dataset from both wells, including mean, symmetry coefficients (skewness), and the quartiles of each parameter. Most of the parameters have a positive skewness factor, except σ_H has a negative skewness factor, with most of the data concentrated to the upper end of the σ_H range. The σ_h and σ_H gradients are recorded in psi/ft to account for the change of stresses with depth.

Since large numbers of input features may cause poor performance for ML models, the redundant and irrelevant features were removed, considering not incurring much loss of information. A dimensionality reduction process was applied to simplify the developed models. The correlation coefficient (R value) was calculated between the inputs to evaluate the dependency of each input on each other, and the following equation was used to calculate the R value.

$$R = \frac{\left[\frac{\sum (x_i - \mu_x)(y_i - \mu_y)}{N-1} \right]}{\sigma_x \sigma_y} \quad (1)$$

where R is the Pearson's correlation coefficient between the dependent parameters y_i and independent parameters, x_i. The μ_x and μ_y are the mean values of the independent and dependent parameters, respectively. The σ_x and σ_y are the standard deviation of the independent and dependent parameters, respectively.

Figure 1 shows a heat map for the absolute value for the correlation coefficient between the input parameters with each other. A high absolute R-value between two parameters indicates a high dependency on each other, hence, only one of them would be considered, and the others would be excluded. Therefore, only GR, RHOB, DTS, and DTC were selected to feed the proposed models, while the other input features were excluded since they depend on the selected ones. Moreover, Sensitivity analysis for the input parameters in the model performance was conducted to judge the model performance with the selected input features as will be discussed in detail in "Result" section.

Figure 2 shows a scatter matrix plot for the data features and how two properties vary and give insights into whether there is a direct correlation between the properties. The diagonal charts show the distribution of each parameter. Most of the parameters showed a slightly positive skewness, where the mass of the distribution is concentrated on the left (lower values). The σ_h gradient is normally distributed, whereas the σ_H gradient showed negative skewness with a long tail due to the left side of the graph. Figure 2 shows that the validation set, in green, is located within the training and testing sets in the different parameters.

Pearson's correlation coefficient was used to explore the importance of each of the input parameters in the prediction of minimum and maximum horizontal stress. Equation 1 was used to calculate the R values, where y_i was the σ_h and σ_H, and x_i is the input parameters (GR, RHOB, DTS, and DTC). Figure 3 presents the correlation coefficient for σ_h and σ_H with the input parameters. GR and RHOB showed a positive relationship with the stresses (psi). RHOB reflects the overburden stress, which is directly related to the minimum and maximum horizontal stress. GR reflects the clay and shale concentrations that increase the formation stresses. DTS and DTC reflect the formation compaction. With high formation stresses, the formation grains' compaction increases.

Figure 1. A heat map for the absolute value for the correlation coefficient between the input parameters with each other.

Hence, the DTC, and DTS decreases, which was indicated by a negative correlation coefficient between the DTC and DTS, and σ_h and σ_H .

Models development. The dataset from Well-1 (1614 points) was used to develop models with training to testing data ratio of 75/25. The unseen dataset from Well-2 (693 points) was used to validate the developed model for each technique. The quality of the model was measured using different performance indicators. The goodness of fit between the actual and the predicted stresses values were evaluated using the R value and coefficient of determination (R^2). The error between the actual and the predicted values of σ_h and σ_H was calculated using the absolute average error (AAPE), root mean squared error (RMSE), variance account for (VAF), and the a^{20} index. The correlation coefficient (R) was calculated using Eq. (1), where x_i and y_i are the actual and the predicted σ_h and σ_H gradient values, respectively.

AAPE, RMSE, VAF, a^{20} index and R^2 were calculated using the following equations, respectively.

$$AAPE = \frac{\sum_{i=1}^N \text{abs}(\frac{y_{i\text{actual}} - y_{i\text{predicted}}}{y_{i\text{actual}}} \times 100\%)}{N} \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (y_{i\text{actual}} - y_{i\text{predicted}})^2}{N}} \quad (3)$$

$$VAF = \left(1 - \frac{\text{var}((y_{i\text{actual}} - y_{i\text{predicted}}))}{\text{var}(y_{i\text{actual}})}\right) \times 100 \quad (4)$$

$$a^{20}\text{index} = \frac{n^{20}}{N} \quad (5)$$

Figure 2. Scatter matrix plot of data features. Blue dots for the training dataset, orange dots for the testing dataset, and green dots for the validation dataset. The diagonal charts show the distribution of each parameter.

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_{i\text{actual}} - y_{i\text{predicted}})^2}{\sum_{i=1}^N \left(y_{i\text{actual}} - \frac{\sum_{i=1}^N y_{i\text{actual}}}{N} \right)^2} \quad (6)$$

where, $y_{i\text{actual}}$ and $y_{i\text{predicted}}$ are the actual and the predicted output value (σ_h and σ_H) respectively, and N is the total number of data in the dataset. $\text{var}(y_{i\text{actual}} - y_{i\text{predicted}})$ is the variance of the difference between the actual and the estimated stress values, while $\text{var}(y_{i\text{actual}})$ is the variance of the actual data. In the a^{20} index, the n^{20} is the number of points with the ratio of $(y_{i\text{actual}}/y_{i\text{predicted}})$ is between 0.8 and 1.2. It defines the number of data that estimated the outputs values with a divergence of $\pm 20\%$ from the actual values.

Three different machine learning techniques were applied to the well-log data to predict σ_h and σ_H . For each technique, two models were built, one to predict the σ_h gradient and the other model to predict the σ_H gradient. Figure 4 presents a flowchart for the different model development processes. The data from the first well were randomly split into training and testing datasets. Different splitting ratios were tested varied from 60/40 to 85/15 for the training/testing data points ratio. The model hyperparameters were then optimized to improve

Figure 3. Correlation coefficient between the conventional logging parameters and the minimum and maximum (σ_h and σ_H) horizontal stresses.

the model results. After the model development, the model was verified with unseen data from the dataset from the second well.

RF model comprises many decision trees that accomplish great functioning in a low-dimension dataset. RF overcome the high variance and the overfitting problem by using the single decision tree technique. RF consists of thousands of decision trees, that were built in different bootstrapped data to lower the variance and enhance the power ability of the RF machine. Additionally, during the tree building procedure, a limited number of features are randomly chosen utilizing the cross-validation process, which assists in de-correlate the input trees and consequently improves the model precision^{31,32}. Different patterns of RF hyperparameters were applied, including the maximum depth of the tree, the maximum features to be counted when splitting the node in every single tree, and the number of trees that were used to build the forest (N of estimators). The N estimators varied from 3 to 150; the maximum depth had values varied from [3, 4, 5, ..., 30]. The maximum feature varied between different three features ["auto", "sqrt", "log2"]. These parameters were optimized to improve the model results and achieve the best indicators (AAPE and R).

The FN technique was provided as an alternative ML tool for ANN. Compared to ANN, FN keeps changing throughout the learning process by adapting to the data³³. FN does not require weights to be assigned to the neurons because the effect of the weights already exists within the neuron functions from which the outputs obtained are converted to an equivalent output forcefully^{33–36}. The neural functions in FN can take various forms chosen from one or more basic families (polynomial and trigonometric, etc.). In the FN, different methods and types can be used to optimize the model parameters for high prediction accuracy. Such methods as functional network forward-backward (FNFBM), functional network backward-forward (FNBFM), and others, while linear and non-linear types can be used in combinations with the FN methods. Similar to RF development, the FN methods and types were optimized to improve the model performance.

ANFIS combines both neural networks and fuzzy logic concepts by depending on a Takagi–Sugeno inference system for data processing applying Boolean logic. After the inputs and outputs are identified, fuzzy if-then rules are used for fitting non-linear regression. ANFIS is optimized through the number of fuzzy rules and epoch size to achieve accurate predictions without overfitting^{27–29}. The fuzzy network, cluster radius, and epoch size were optimized for the model performance^{37–39}.

Results and discussion

The three machine learning techniques were used to build six different models, three for σ_h prediction and three for σ_H .

Minimum horizontal stress prediction. The Well-1 dataset was used to train and test the different ML models. Figure 5 display a cross plot for the actual versus the predicted minimum horizontal stress gradient for RF, ANFIS, and FN.

The RF parameters were optimized to improve the model behavior, as described in Fig. 4. The optimum parameters were N of the estimator is 100, the maximum depth is 25, and the maximum feature is log2. RF cross plot shows that the RF model was capable of estimating accurately σ_h from the conventional well-log data. Most of the estimated points were aligned to the 45° line for the training dataset. While the model accuracy marginally reduced for the testing dataset with an R of 0.90. The RF model has R of 0.99 and 0.90 for training, and testing datasets, respectively. AAPE for the RF model was found to be 0.10 and 0.13% for training and testing datasets. GR, DTC, DTS, and RHOB were input to the model. R-value in the case of the testing dataset was found to be 0.88.

Figure 4. Flowchart for building the different RF, FN, and ANFIS models.

To explore the effect of all collected input data on the estimation of the horizontal stresses. Various models with different dataset combinations were developed as shown in Table 2. Excluding NPHI, Ed, and PRd from the input dataset, did not affect the model performance, and GR, DTC, DTS, and RHOB can be used to estimate the horizontal stress.

Similarly, the ANFIS technique was applied to the dataset from Well-1 to train and test the model. ANFIS parameters were optimized. The optimal input and the output membership function are gaussmf and linear, respectively. The optimal cluster radius and epoch size are 0.1 and 10, respectively. The ANFIS cross plot in both training and testing datasets shows the capability of the ANFIS model to predict σ_h from the conventional well-log data with a good alignment with the 45° line. ANFIS model slightly outperforms RF model with less overfitting effect. Both training and testing datasets have AAPE of 0.10 with R values of 0.94 and 0.93 in the cases of training and testing datasets.

The FN was then implemented on the dataset from Well-1. Different combinations of FN methods and types were used to optimize the developed model performance. Table 3 summarizes FN methods and types and the corresponding R values and AAPE from the testing dataset. The different combinations showed that the FN model was less performed compared to RF and ANFIS models with optimum R values of 0.83 and 0.85 for the

Figure 5. Cross plots of the actual versus the predicted σ_h for the training and the testing datasets from RF, FN, and ANFIS models.

No	Inputs	The validation set using RF Model			
		R	R ²	AAPE, %	RMSE
1	GR, DTC, DTS, RHOB, NPHI, Ed, PRd	0.9	0.81	0.17	1.9E-3
2	GR, DTC, DTS, RHOB, NPHI, Ed	0.9	0.81	0.15	1.9E-3
3	GR, DTC, DTS, RHOB, NPHI	0.91	0.82	0.13	1.6E-3
4	GR, DTC, DTS, RHOB	0.91	0.83	0.13	1.6E-3
5	GR, DTS, RHOB	0.91	0.82	0.13	1.6E-3

Table 2. Performance of different sets of inputs.

Method	'FNBFBM'	'FNBFBM'	'FNBFBM'	'FNBFBM'
Type	'Non-Linear(2)'	'Non-Linear(2)'	'Non-Linear(2)'	'Non-Linear(1)'
AAPE %	0.19	0.193	0.23	0.24
R	0.85	0.85	0.79	0.78

Table 3. Different FN methods and types to optimize the developed model performance with AAPE and R-values for the testing dataset.

training and testing datasets, respectively. Most of the data aligned to the 45° line, with some points deviated from it. AAPE was estimated to be 0.19% in both training and testing datasets.

The dataset from Well-2 was used to validate the different ML models for σ_h prediction. Figure 6 shows the actual versus the predicted σ_h gradient for the validation dataset. In both RF and ANFIS models, the graph shows that the actual and estimated values are almost identical, which proves the ability of RF and ANFIS models to predict accurately σ_h gradient from well-log data. FN model was capable of describing the general trend of the σ_h gradient with marginal deviation from the actual values at some locations, particularly at the spikes.

Table 4 summarizes the quality indicator for RF, ANFIS, and FN models for the different datasets. It shows that the ANFIS model has the best performance with R and AAPE values are almost the same for training, testing, and validation datasets. RF displays overfitting behavior slightly where the training R value was 0.99 that decreased to 0.90 with the testing dataset and 0.91 in the validation dataset. FN had the lowest accuracy with an R factor of 0.85 and 0.88 for the testing and validation datasets. The calculated a^{20} index for the three ML techniques showed 100%, which indicates that all the predicted stresses were within 20% deviation from the actual σ_h gradient.

Maximum horizontal stress prediction. The Well-1 logging data, including GR, DTC, DTS, and RHOB as inputs and the σ_H gradient as output were used to train and test the RF, ANFIS, and FN models. Figure 7 presents the actual versus the estimated σ_H cross plots for the training and testing datasets for the RF, ANFIS, and FN models.

The RF parameters were optimized to improve the model performance. The optimum N of the estimator, maximum depth, and maximum feature were 100, 20, and log2. Similarly, the optimal parameters for the ANFIS input and the output membership functions were found to be gaussmf and linear, whereas the cluster radius was 0.1, and the epoch size was 15. The best combination of the FN method and type was found to be the FNBFBM and non-linear (2).

Figure 7 shows plots of the actual versus the estimated σ_H gradient of the RF, FN, and ANFIS models for both training and testing datasets. The three model presents a very accurate prediction of σ_H from the conventional well logs with all the data lined up with the 45° line. The R values for the three models' training and testing dataset were higher than 0.98, with AAPE less than 0.3%.

The Well-2 dataset was used to validate the RF, ANFIS, and FN developed models that predict σ_H gradient. Figure 8 shows the actual versus the predicted σ_H gradient for the validation dataset. In the RF, ANFIS, and FN models, the actual and predicted σ_H gradient curves are identical, which confirms the three models' prediction accuracy.

Table 5 summarizes the quality indicator for RF, ANFIS, and FN models for the training, testing, and validation datasets. It shows the three models' optimal robust performance where the R and AAPE values are almost the same for the different datasets. R-value for the different models was higher than 0.97 in all datasets with AAPE of 0.3% and RMSE of 3.9E-6. The a^{20} index was found to be 100% for the different datasets with the different models.

The established ML models were able to estimate the σ_h and σ_H gradients from the logging data; GR, DTC, DTS, and RHOB. Hence, a continuous profile for the σ_h and σ_H with depth can be obtained. Having continuous profiles of the least principal stresses for the drilled wells provides practical solutions to several wellbore instability issues, which assist well integrity and better hydraulic fracturing design.

It should be emphasized that the application of the developed models is limited to carbonate formations because other formations may have different log responses to the geomechanical properties that control the horizontal stresses values. Moreover, similar to any developed model, it should be applied to input data within the model's inputs ranges in Table 1 to guarantee trustworthy results. For future work, a similar analysis will be

Figure 6. Actual versus the predicted σ_h for the validation dataset from (a) RF model, (b) ANFIS model, and (c) FN model.

	RF			ANFIS			FN		
	Train	Test	Val	Train	Test	Val	Train	Test	Val
R	0.99	0.90	0.91	0.94	0.93	0.96	0.83	0.85	0.88
R ²	0.97	0.82	0.83	0.88	0.86	0.86	0.7	0.72	0.77
AAPE%	0.10	0.13	0.13	0.10	0.10	0.10	0.19	0.19	0.18
RMSE	6E−4	1.5E−3	1.6E−3	1.3E−3	1.2E−3	1.4E−3	2E−3	2E−3	1.5E−3
VAF%	97	81.6	82	88	86.6	86.1	69.1	72	77.4
A20%	100	100	100	100	100	100	100	100	100

Table 4. Performance indicators summary for the training, testing, and validation datasets from the RF, ANFIS, and FN models to predict σ_h from well-logs.

conducted on a dataset for a sandstone formation to evaluate the application of ML techniques to predict the σ_h and σ_H in sandstone formations.

Conclusions

This study presents the application of RF, ANFIS, FN techniques to predict the minimum and maximum horizontal stress gradients from the convention well-logs, including GR, DTC, DTS, and RHOB. Following are the main conclusions;

Figure 7. Cross plots of the actual versus the predicted σ_H for the training and the testing datasets from RF, FN, and ANFIS models.

- The GR, DTC, DTS, and RHOB logs showed a strong correlation with σ_h and σ_H .
- RF and ANFIS models were able to predict accurately σ_h and σ_H gradients from the conventional well-logs with AAPE less than 0.3%.

Figure 8. Actual versus the predicted σ_h gradient for the validation dataset from (a) RF model, (b) ANFIS model, and (c) FN model.

	RF			ANFIS			FN		
	Train	Test	Val	Train	Test	Val	Train	Test	Val
R	0.99	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.97
R ²	0.98	0.97	0.96	0.94	0.98	0.96	0.92	0.98	0.95
AAPE%	0.19	0.3	0.29	0.3	0.3	0.30	0.3	0.3	0.32
RMSE	2.6E-3	3.2E-3	3.6E-3	3.7E-3	3.8E-3	3.8E-3	4.2E-3	3.9E-3	3.9E-3
VAf%	98	97.3	95.7	93.8	98.4	95.6	91.9	98.2	95.4
A20%	100	100	100	100	100	100	100	100	100

Table 5. Performance indicators summary for the training, testing, and validation datasets from the RF, ANFIS, and FN models to predict σ_H from well-logs.

- FN model accurately predicted σ_H gradient from the well-logs but did not provide the same accuracy in predicting σ_h gradient.

This study showed the capabilities and robustness of machine learning techniques to predict the minimum and maximum horizontal stress gradients from the conventional well-logs with about $\pm 0.3\%$ accuracy error and goodness of fit (R) of 0.90–0.98.

Received: 3 August 2021; Accepted: 2 November 2021

Published online: 06 December 2021

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Author contributions

S.E. A.A. conceived the idea and collected the required data and participated in the methodology design. A.I., A.G., conducted the data analysis, designed the methodology, run the algorithms and performed the sensitivity and the optimization of the results. S.E., A.A. also participated in methodology design and results validation supervising. The original manuscript was written by A, I., and all authors participated in the manuscript revision and editing.

Competing interests

The authors declare no competing interests.

Additional information

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