New Models for Predicting Pore Pressure and Fracture Pressure while Drilling in Mixed Lithologies Using Artificial Neural Networks

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ABSTRACT: Precise prediction of pore pressure and fracture pressure is a crucial aspect of petroleum engineering. The awareness of both fracture pressure and pore pressure is essential to control the well. It helps in the elimination of the problems related to drilling, waterflooding project, and hydraulic fracturing job such as fluid loss, kick, differential sticking, and blowout. Avoiding these problems enhances the performance and reduces the cost of operation. Several researchers proposed many models for predicting pore and fracture pressures using well log information, rock strength properties, or drilling data. However, some of these models are limited to one type of lithology such as clean and compacted shale formation, applicable only for the pressure generated by under compaction, and some of them cannot be used in unloading formations. Recently, artificial intelligence techniques showed a great performance in petroleum engineering applications. Hence, in this paper, two artificial neural network models are developed to estimate both pore pressure and fracture pressure through the use of 2820 data sets obtained from drilling data in mixed lithologies of sandstone, carbonate, and shale. The proposed artificial neural network (ANN) models achieved accurate estimation of pore and fracture pressures, where the coefficients of determination \( R^2 \) for pore and fracture pressures are 0.974 and 0.998, respectively. Another data set from the Middle East was used to validate the developed models. The models estimated the pore and fracture pressures with high \( R^2 \) values of 0.90 and 0.99, respectively. This work demonstrates the validity and reliability of the developed models to calculate pore and fracture pressures from real-time surface drilling parameters by considering the formation type to overcome the limitation of previous models.

1. INTRODUCTION

For the purpose of drilling wells safely, economically, and efficiently, it is vital to estimate the pore and fracture pressures with high accuracy; thus, the mud density can be enhanced to achieve adequate overbalance.1 Drilling and production operations can be successful throughout the lifecycle of a hydrocarbon field if appropriate prediction models of pore and fracture pressures are used.2

Pore pressure is referred to as the pressure exerted by formation fluids within porous media. Generally, the pore pressure can be easily predicted by assuming a normal formation fluid pressure gradient ranging from 0.433 psi/ft in the case of freshwater to 0.465 psi/ft in the case of saltwater. In practice, during drilling operations, some formations encountered either subnormal or abnormal pressure due to different mechanisms.3 The most important mechanisms that are responsible for generating abnormal or Geo-pressured pore pressure are compaction, diagenesis, density difference, and fluid migration, while subnormal pore pressure occurs less frequently than abnormal pore pressure and is commonly found in depleted zones. Well control problems occurring in the case of pore pressure are not accurately determined, which may result in the loss of circulation problems in depleted zones or kick and blowout problems in pressurized formations. Therefore, understanding pore pressure is a critical part of the well design to select the casing setting depth, design the casing program, and maintain well control during drilling and completion operations.4 Pore pressure can be measured directly or indirectly at the wellbore. The most common direct methods for measuring pore pressure are repeat formation tests (RFTs) and drill stem tests. These methods are time-consuming and expensive.5 In addition, these methods provide discrete data of pore pressure measurements at specific depths, but only after the formation has been drilled.

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Hottmann and Johnson, Jorden and Shirley, Matthews and Kelly, Pennebaker, Rehm and McClendon, Zamora, and Eaton can be utilized to detect and predict the pore pressure based on seismic velocity and Petrophysical calculations before the drilling and/or while drilling by monitoring the drilling surface parameters.\(^6\)\(^{−}\)\(^{14}\)

The fracture pressure, on the other hand, is the pressure that causes the rock formation to fracture when it exceeds the critical pressure value. Determination of fracture pressure is a critical part of drilling, waterflooding, and hydraulic fracturing operations. In the case of drilling and waterflooding projects, the accurate determination of the fracture pressure value controls the well and prevents the loss of circulation problems. Moreover, for a successful hydraulic fracturing job, the formation should be pressurized higher than fracture pressure. Besides, fracture pressure determination impacts several aspects of a well plan, including mud weight, cement preparation, casing design, and wellbore instability.\(^15\)\)

The fracture pressure can be measured either in the field using the leak-off test (LOT) or using several developed correlations such as Hubbert and Willis, Matthews and Kelly, Pennebaker, Eaton, Christman, and Anderson et al.\(^{26}\)\(^{−}\)\(^{31}\).

In an effort to minimize the lost circulation risk during drilling, enhancing the estimation accuracy of fracture and pore pressures is an effective method, and it can assist drilling engineers in improving the drilling fluids and measures to prevent lost circulation. Therefore, several researchers had developed models by artificial intelligence to improve the estimation accuracy of fracture and pore pressures. Hu et al.\(^{20}\) presented a new ANN model for predicting pore pressure that consists of three layers: two hidden layers and one output layer. The first hidden layer’s input data includes γ-ray and formation density, while the second hidden layer’s input data includes depth, formation density, and interval transit time. They verified the accuracy and feasibility of the ANN model using actual normal and overpressurized field data. Rashidi and Asadi\(^{24}\) proposed an ANN model for predicting pore pressure in sandstone formations using drilling parameters such as mechanical specific energy and drilling efficiency. Hutomo et al.\(^{28}\) used three layers and 20 neurons in each layer to build an ANN model to estimate pore pressure in terms of seismic attributes such as acoustic impedance, shear impedance, seismic frequency, and seismic amplitude as input data for the neural network model. Abdeelal et al.\(^{23}\) developed different models using support vector machines (SVMs) and functional networks (FNs) for predicting pore pressure while drilling based on different parameters of hydraulic and mechanical drilling. Sadiq and Nashawi\(^{29}\) developed an ANN model using actual field data as input parameters such as depth, overburden stress gradient, and Poisson’s ratio to estimate the fracture pressure gradients. They found that the ANN model using generalized regression neural networks yielded an appropriate approximation of the fracture gradient. Malallah and Nashawi\(^{35}\) used the pore pressure, rock density, and depth as inputs to develop an ANN model to estimate the fracture gradient for reservoirs of the Middle East. They collected the data from 16 wells and found that the developed ANN model yielded a more accurate prediction of fracture pressure gradients than existing correlations. Keshavarzi et al.\(^{26}\) developed an ANN model that could be utilized for estimating the fracture gradient in oil and gas wells accurately when the formation density, pore pressure, and depth are available. Kiss et al.\(^{37}\) collected hydraulic fracturing data from 55 wells to establish an ANN model for fracturing pressure gradient prediction. They observed that the ANN model reduced the uncertainties in fracture pressure prediction by less than 10% in all types of reservoir rocks. Ahmed et al.\(^{28}\) used drilling parameters such as rate of penetration, pore pressure, revolution per minute, weight on bit, and mud weight to build an ANN model for fracture pressure gradient estimation. They found that the ANN model with 13 neurons with a tan sigmoid transfer function estimated the fracture pressure gradient with high accuracy ($R^2$) greater than 0.99. Ahmed et al.\(^{29}\) built five AI models based on available surface drilling parameters to predict the fracture pressure gradients. They compared the results of AI models with empirical correlations such as Matthews and Kelly, Eaton, and Pennebaker models. They found that the ANN model predicted the fracture pressure with high accuracy and a high coefficient of determination ($R^2$) rather than other empirical models. In this paper, two neural network models are established for estimating the fracture and pore pressures in mixed lithologies (sandstone, carbonate, and shale). These models are based on readily available data during the drilling process as weight on bit, mud weight, flow rate, RPM, and pump pressure.

2. METHODOLOGY

2.1. Artificial Neural Network. The artificial neural network (ANN) is a prominent computational technique for solving complex problems involving nonlinear relationships in a variety of applications, making it superior to traditional regression techniques. Also, the ANN can be able to approximate the nonlinear relationship between several variables.\(^{30}\) The neural network consists of artificial neurons, an appropriate number of hidden layers, the optimum transfer function for the selected data learning function of the first data sets, and the optimum training function.\(^{31}\) Neurons are components that have a specific input/output and are connected to build a network of nodes that make up organic neural networks.\(^{32}\) A typical artificial neural network (ANN) involves an input layer (first layer) and hidden layers (middle layers), and the last layer is the output layer. The data are received by the input layer, and then the hidden layers create a connection between the parameters, and the results are produced in the output layer.\(^{33}\) Each neuron in one layer is connected to each neuron in the next layer. Each connection has an assigned weight. The input parameters are handled by biases and weights to find relationships among the source and neurons.\(^{34}\) As a result, the network’s performance is determined by the biases and weights chosen. Furthermore, the ANN performance is evaluated using sensitivity analysis on the number of neurons, the number of middle hidden layers, and training and transfer functions.\(^{35}\) The sensitivity analysis on both neurons and middle layer numbers is evaluated using trial and error. This process is required to prevent overfitting by choosing many neurons or underfitting by choosing a fewer number of neurons.\(^{36}\) Increasing the model’s size by adding more hidden layers and neurons leads to increase computing time, which results in a decrease in training error, while the error increases during testing the validation data, which is known as an overfitting issue. To avoid overfitting in neural networks, it is suggested that the early stopping criteria can be used with a portion of the data allocated for validation purposes. According to Niculescu,\(^{37}\) the first stage in building the ANN is to normalize the inputs and outputs values in the range of $−1$ to $1$. In general, collected data are categorized into
three subsets on a regular basis. The training set is employed to calculate the gradient and to fine-tune both network parameters (weights and biases). The validation set is the second subset. Furthermore, the error of the validation data set is carried out during the training stage. During the initial stage of the training of the data, both training data set error and validation data error decrease. At this stage, as the error of the validation data set increases, this is considered an overfit issue. Also, the training phase is terminated when the error of the validation data set increases for a predetermined number of

### Table 1. Statistical Details of the Obtained Data (2820 Data Points)

| statistical parameter | unit | true vertical depth | weight on bit | pore pressure | mud weight | flow rate | bit rotational speed | pump pressure | fracture pressure |
|-----------------------|------|---------------------|---------------|--------------|------------|-----------|---------------------|---------------|------------------|
|                       |      | (M)                 | (10^3 lb)     | (Pa)         | (PCF)      | (Gpm)     | (RPM)               | (Pa)          | (Pa)             |
| mean                  |      | 2822.37             | 21.02         | 5382.41      | 94.99      | 550.9     | 138.36              | 1939.51       | 7876.22          |
| median                |      | 2924.25             | 20            | 4456.21      | 79         | 530       | 147.7               | 2230.53       | 8714.18          |
| mode                  |      | 3595                | 22.5          | 2625.98      | 140        | 950       | 180                 | 2505.56       | 8876.27          |
| kurtosis              |      | 0.18                | -1.14         | -1.38        | -1.36      | -0.73     | -0.49               | -0.89         | -0.32            |
| skewness              |      | -0.47               | 1.05          | 0.37         | 0.51       | 0.19      | -0.6                | -0.89         | -0.32            |
| range                 |      | 5645                | 69            | 9253.13      | 130        | 920       | 155.28              | 2657.17       | 11639.8          |
| minimum               |      | 17                  | 1             | 1254.78      | 30.5       | 80        | 42.83               | 297           | 1970.56          |
| maximum               |      | 5662                | 70            | 10507.91     | 160.5      | 1000      | 198.11              | 2954.17       | 13610.36         |
| count                 |      | 2820                | 2820          | 2820         | 2820       | 2820      | 2820                | 2820          | 2820             |

**Figure 1.** Correlating the input parameters with pore pressure.

**Figure 2.** Correlating the input parameters with fracture pressure.
In drilling engineering applications, ANN helps in calculating the nonlinear multiple regression (NLMR) and ANN model. Several researchers utilized artificial neural networks in different petroleum engineering applications. In reservoir work, an ANN model is developed to estimate the pore pressure as a function of true vertical depth, formation type, weight on bit, mud weight, flow rate, and pump pressure. The model is built based on three layers. The first layer is the input layer, which has six neurons for inputs. There are 10 neurons that contribute to the hidden layer, which is the second layer. The output layer, which has one neuron to predict the output parameter, pore pressure, is the third layer. To reach the optimum ANN model, we first examined the Levenberg–Marquardt approach as a training algorithm at different numbers of neurons (6, 7, 8, 9, and 10), as shown in Table 2. We found that with 10 neurons, the model would be more accurate with a coefficient of determination (R²) of 0.974 and an absolute mean relative error of 6.83%. Then, after several trials on the data using different training algorithms, it is discovered that the optimal training algorithm is the Levenberg–Marquardt approach, as presented in Table 3. To achieve this fact, a tan sigmoid function was selected as a transfer function for the middle hidden layer, and pure linear function was examined to be the output function. The characteristics of the proposed model are introduced in Table 4.

3. RESULTS AND DISCUSSION

3.1. Neural Network Model for Pore Pressure. In this work, an ANN model is developed to estimate the pore pressure as a function of true vertical depth, formation type, weight on bit, mud weight, flow rate, and pump pressure. The data are normalized between −1 and 1 to build the ANN models.

Table 2. Pore Pressure Model Accuracy at Various Numbers of Neurons in the Hidden Layer

| no. of neuron | 6   | 7   | 8   | 9   | 10  |
|---------------|-----|-----|-----|-----|-----|
| R²            | 0.959834 | 0.957698 | 0.968537 | 0.973057 | 0.974209 |
| SD            | 11.9194 | 12.59648 | 10.77635 | 10.56451 | 10.19303 |
| AE            | 8.193236 | 8.238022 | 7.336244 | 6.991868 | 6.82669  |

Table 3. Pore Pressure Model Optimization

| training algorithms                              | parameters | no. of neurons | R²  | SD   | AE   |
|-------------------------------------------------|------------|----------------|-----|------|------|
| quasi-Newton method                             |            | 10             | 0.829518 | 20.62054 | 14.10447 |
| Bayesian regularization                         |            | 10             | 0.973244 | 10.38439 | 6.908809 |
| conjugate gradient backpropagation with Powell–Beale restarts | 10     | 0.869605 | 18.64701 | 12.63703 |
| conjugate gradient backpropagation with Fletcher–Reeves updates | 10     | 0.865919 | 18.28273 | 11.85177 |
| conjugate gradient backpropagation with Polak–Ribière updates | 10     | 0.871454 | 19.98383 | 13.11599 |
| gradient descent                                |            | 10             | 0.746621 | 25.63 | 17.55691 |
| Levenberg–Marquardt optimization                |            | 10             | 0.974209 | 10.19303 | 6.82669  |

2.2. Data Description and Analysis. In this paper, 2820 data sets of fracture pressure, pore pressure, true vertical depth, weight on bit, mud weight, flow rate, bit rotational speed, and pump pressure are collected from 305 wells with mixed lithologies of sandstone, carbonate, and shale in the Marun oil field to develop two ANN models for predicting the fracture and pore pressures. The collected data are statistically described in Table 1.

In the building of any mathematical model on the basis of ANN, data preparation and analysis are critical steps. Besides, the quality and number of data points in the developed model determine its performance. Before developing the model, it is also very important to check the effect of each parameter on the required output. Figure 1 shows that the pore pressure is directly proportional to four parameters (mud weight, TVD, formation type, and pump pressure) and inversely proportional to the flow rate and weight on bit. Figure 2 illustrates that the fracture pressure is directly proportional to four parameters (pore pressure, TVD, mud weight, and formation type) and inversely proportional to another four parameters (flow rate, weight on bit, RPM, and pump pressure).

2.3. Data Splitting. Before building ANN models to predict the pore and fracture pressures, the collected data sets are divided into three sets. The first set is employed for the process of model training, which represents 1974 data sets out of 2820 (70%), while 423 data sets (15%) are used for the purpose of validation, and the remaining 423 data sets (15%) are used to test the performance of the models. Besides, all of the data are normalized between −1 and 1 to build the ANN models.
3.2. Neural Network Model for Fracture Pressure. In this work, a neural network model for fracture pressure is built in terms of pore pressure, formation type, flow rate, weight on bit, bit rotational speed, and pump pressure. As shown in Table 9, many trials have been carried out to achieve the optimum fracture pressure model architecture that is made up of three layers (an input layer, one hidden layer, and an output layer). The input layer has eight neurons, one hidden layer has 10 neurons, and the output layer has one neuron to predict the fracture pressure. To reach the optimum ANN model, we first examined different numbers of hidden neurons (5, 6, 7, 8, 9, and 10) using the Levenberg–Marquardt approach, as presented in Table 7. We found that the optimum number of hidden neurons is 10, where the coefficient of determination ($R^2$) is 0.998 and the absolute mean relative error is 1.07%. As shown in Table 8, the Levenberg–Marquardt approach showed superior performance over the other training algorithms. In addition, tan sigmoid and pure linear functions are the more suitable transfer functions between the input layer and the hidden layer, and between the hidden layer and the output layer, respectively (Table 9).

The developed model for fracture pressure using the ANN can be expressed as follows:

First, the input parameters are normalized using eqs 1–6 and 9–10:

$$\text{pore pressure}_n = 0.000216 \times \text{pore pressure} - 1.2712$$

$$\text{bit rotational speed}_n = 0.01288 \times \text{bit rotational speed} - 1.5516$$

The hidden inputs are calculated using eq 7 for $i = 1$ to neuron number and for $j = 1$ to input number:

$$S_{ij} = \sum_{j=1}^{N} (w_{ij}p_j) + b_i$$

(7)

where $p_j$ represents the normalized input parameters.

The following function in eq 8 can be used to estimate the pore pressure:

$$\text{pore pressure} = 4626.565 \left[ b_{ho} + \sum_{i=1}^{n} w_{iho} \left( \frac{2}{1 + \exp(-2S_i)} - 1 \right) \right] + 5881.345$$

(8)

The proposed pore pressure model's coefficients are listed in Tables 5 and 6.

Regression plots for the pore pressure model, as indicated in Figure 3, present the relation between network outputs and targets for training, validation, testing, and all data points. The fit is good for all of the sets of data in this work, and the $R$-squared values are higher than 0.974.

### Table 5. Pore Pressure ANN Model's Weights and Biases between Both Input and Middle Layers

| neuron # | $w_{ij} = 1$ | $w_{ij} = 2$ | $w_{ij} = 3$ | $w_{ij} = 4$ | $w_{ij} = 5$ | $w_{ij} = 6$ | $b_i$ |
|----------|----------------|----------------|----------------|----------------|----------------|----------------|----------|
| 1        | 9.6497         | -1.348         | 0.3481         | 2.5739         | 0.4746         | 1.923          | 2.6811    |
| 2        | -0.3027        | 3.5919         | 0.3604         | -1.105         | 0.2562         | 0.4659         | 0.8272    |
| 3        | -0.4159        | 3.457          | 0.3705         | -0.848         | 0.3948         | 0.3184         | 0.8055    |
| 4        | 2.5997         | 3.5953         | 0.033          | 0.9389         | 0.4317         | -1.44          | -2.166    |
| 5        | 2.0827         | 3.1662         | 0.0841         | 0.6651         | 0.181          | -1.294         | -2.009    |
| 6        | 0.4062         | -20.25         | 0.6306         | 1.863          | 0.1061         | 1.6308         | 3.0477    |
| 7        | -4.1664        | -15.54         | 1.7787         | 4.9956         | 8.2936         | 13.537         | -13.02    |
| 8        | 0.4958         | 10.495         | -0.045         | 0.1314         | 0.0131         | 0.0411         | 8.3527    |
| 9        | -8.6798        | 7.3081         | 2.0131         | 8.2407         | 0.2335         | 7.052          | 0.4109    |
| 10       | 0.8955         | 3.6642         | 1.1215         | -5.383         | -0.016         | -2.086         | 2.1503    |

### Table 6. Pore Pressure ANN Model's Weights and Biases between the Hidden and Output Layers

| neuron # | $w_{ho}$ | $b_{ho}$ |
|----------|----------|----------|
| 1        | 0.0895   | -0.274   |
| 2        | 3.3274   | 0.0418   |
| 3        | -3.567   | 0.0941   |
| 4        | -1.416   | 0.0808   |
| 5        | 1.8164   | 0.0996   |
| 6        | 0.4929   | 0.1166   |
| 7        | 0.808    | 0.0941   |
| 8        | 0.0941   | 0.1166   |
| 9        | 0.0808   | 0.1166   |
| 10       | 0.0996   | 0.1166   |
fit is good for all of the sets of data in this work, and the R-squared values are higher than 0.998.

3.3. Model Performance Evaluation. The performance of the developed two models for estimating the pore and fracture pressures was validated using 25 data points from a well located in the Middle East. A comparison between the actual pressures versus the calculated pressures from the models was established. Two ANN models achieved outstanding performance for predicting pore and fracture pressures with high coefficients of determination ($R^2$) values of 0.90 and 0.99, respectively. Figure 5 demonstrates the crossplots between the observed and calculated pore and fracture pressures. As displayed in Figure 5, the fit is good and shows the high accuracy of pore pressure and fracture pressure prediction.

4. CONCLUSIONS

The following conclusions can be drawn from the results of this work:
Two Artificial neural network (ANN) models are developed to estimate both pore and fracture pressures using more than 2820 field data points.

An artificial neural network (ANN) model for estimating the pore pressure is developed in terms of real drilling surface available parameters (WOB, TVD, MW, flow rate, pump pressure, and formation type). The developed model shows outstanding performance with a high coefficient of determination of 0.974 and an absolute mean relative error of 6.83%.

An artificial neural network (ANN) model for estimating the fracture pressure is developed based on real drilling surface available parameters (pore pressure, WOB, TVD, MW, flow rate, pump pressure, RPM, and formation type). The developed model achieves superior accuracy with a high coefficient of determination of 0.998 and an absolute mean relative error of 1.07%.

The developed models achieved high accuracy in predicting the pore and fracture pressures for the validation stage with coefficients of determination of 0.90 and 0.99, respectively.

These developed ANN models have the advantage of real-time prediction of both pore and fracture pressures using real-time surface drilling data.

Table 10. Fracture Pressure ANN Model’s Weights and Biases between the Input and Hidden Layers

| neuron # | $w_{ij} = 1$ | $w_{ij} = 2$ | $w_{ij} = 3$ | $w_{ij} = 4$ | $w_{ij} = 5$ | $w_{ij} = 6$ | $w_{ij} = 7$ | $w_{ij} = 8$ | $b_i$ |
|----------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|-------|
| 1        | 0.3241        | −1.151        | −0.051        | −1.501        | −0.587        | −0.258        | −0.347        | −0.119        | 1.1758 |
| 2        | 0.1026        | −0.044        | 0.0638        | 0.6821        | 0.2901        | −0.057        | −0.394        | 0.3779        | −0.641 |
| 3        | 0.1102        | −2.464        | −0.064        | −2.569        | −0.045        | −0.052        | −0.971        | −0.189        | 1.4431 |
| 4        | −1.0031       | −1.644        | 0.1305        | 3.3006        | 0.8315        | 0.4596        | 0.4791        | 0.2237        | 0.682  |
| 5        | 0.8207        | 0.1819        | −0.06         | 0.0877        | −1.535        | −0.209        | 0.3499        | −0.346        | −0.578 |
| 6        | 0.7997        | 1.3559        | −0.105        | −3.443        | −0.631        | −0.369        | −0.478        | −0.316        | −1.071 |
| 7        | −0.5945       | −0.112        | 0.0829        | −0.254        | 1.1137        | 0.1322        | −0.243        | 0.5406        | 0.3886 |
| 8        | −0.2573       | −1.125        | −0.019        | −3.359        | 0.6707        | 0.2162        | −0.042        | −0.369        | −2.776 |
| 9        | −1.0237       | 0.7814        | 0.0217        | 1.1339        | 0.1426        | −0.11         | −1.033        | 0.1404        | −0.541 |
| 10       | −1.1454       | 0.8031        | 0.007         | 2.0968        | 0.9148        | 0.4497        | 0.3113        | −0.136        | −1.662 |

Table 11. Fracture Pressure ANN Model’s Weights and Biases between the Hidden and Output Layers

| neuron # | $w_{hoi}$ | $b_{ho}$ |
|----------|-----------|----------|
| 1        | 0.825     | 0.1801   |
| 2        | 0.8292    |          |
| 3        | −0.314    |          |
| 4        | −0.495    |          |
| 5        | −0.889    |          |
| 6        | −0.657    |          |
| 7        | −1.226    |          |
| 8        | −0.266    |          |
| 9        | −0.166    |          |
| 10       | 0.5124    |          |

Figure 4. Crossplots of the ANN model of fracture pressure (after this work).
The formation type is taken into consideration in both developed ANN models, which overcomes the limitation of previous empirical models and shows the novelty of these outstanding ANN models in the estimation of both pore and fracture pressures.

### APPENDIX

**Correlation coefficient equation**

\[
    r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2}(y_i - \bar{y})^2}
\]

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**Notes**

The authors declare no competing financial interest.

### ABBREVIATIONS

ANN: artificial neural network

FT: formation type

MW: mud weight

Q: flow rate

PP: pump pressure

WOB: weight on bit

TVD: true vertical depth

RPM: revolution per minute

GPM: gallon per minute

PCF: pound per cubic feet

R²: coefficient of determination

Figure 5. Crossplots between the observed and calculated pore and fracture pressures.
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**NOTE ADDED AFTER ASAP PUBLICATION**

This paper was published ASAP on August 24, 2022 with errors in eqs 1–6 and 9–11. These errors were corrected and the paper reposted on August 25, 2022. The paper published on August 25 included a production error in eq 3. This error was corrected and the paper reposted on August 26, 2022.