An Artificial Intelligence-Based Model for Performance Prediction of Acid Fracturing in Naturally Fractured Reservoirs

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ABSTRACT: Acid fracturing is one of the most effective techniques for improving the productivity of naturally fractured carbonate reservoirs. Natural fractures (NFs) significantly affect the design and performance of acid fracturing treatments. However, few models have considered the impact of NFs on acid fracturing treatments. This study presents a simple and computationally efficient model for evaluating acid fracturing efficiency in naturally fractured reservoirs using artificial intelligence-based techniques. In this work, the productivity enhancement due to acid fracturing is determined by considering the complex interactions between natural and hydraulic fractures. Several artificial intelligence (AI) techniques were examined to develop a reliable predictive model. An artificial neural network (ANN), a fuzzy logic (FL) system, and a support vector machine (SVM) were used. The developed model predicts the productivity improvement based on reservoir permeability and geomechanical properties (e.g., Young’s modulus and closure stress), natural fracture properties, and design conditions (i.e., acid injection rate, acid concentration, treatment volume, and acid types). Also, several evaluation indices were used to evaluate the model reliability including the correlation coefficient, average absolute percentage error, and average absolute deviation. The AI model was trained and tested using more than 3100 scenarios for different reservoir and treatment conditions. The developed ANN model can predict the productivity improvement with a 3.13% average absolute error and a 0.98 correlation coefficient, for the testing (unseen) data sets. Moreover, an empirical equation was extracted from the optimized ANN model to provide a direct estimation for productivity improvement based on the reservoir and treatment design parameters. The extracted equation was evaluated using validation data where a 4.54% average absolute error and a 0.99 correlation coefficient were achieved. The obtained results and degree of accuracy show the high reliability of the proposed model. Compared to the conventional simulators, the developed model reduces the time required for predicting the productivity improvement by more than 60-fold; therefore, it can be used on the fly to select the best design scenarios for naturally fractured formations.

INTRODUCTION

Hydraulic fracturing is applied to improve the productivity of tight hydrocarbon-bearing formations. The fracturing fluids either contain a proppant or acid to keep the fracture open against formation closure stresses.1,2 Propped fracturing can be applied to all lithology types, while acid fracturing can be applied only in carbonate reservoirs.3 Acid fracturing applicability stems from its ability to generate rough fracture surfaces that could remain open. Acid fracturing does not suffer from the screen-out issues that its sister operation does. Hence, it is especially favorable in fractured carbonate reservoirs where proppant slurry injection is a challenge due to the high fluid loss. Acid is usually injected in stages separated by nonreactive (i.e., pad) fluid injection. These nonreactive stages could also contain diverters to reduce fluid loss and plug natural fractures.4,5 Performance prediction of acid fracturing operations is necessary to optimize the design.2 Conventionally, computational models were developed to estimate the acid penetration distance and fracture conductivity. These two parameters are used to estimate the fractured well performance.6,7 The acid penetration distance represents the location within the fracture that the acid may reach before it is consumed. The conductivity is the ability of the fracture to deliver reservoir fluids to the wellbore. The fracture conductivity depends on the dissolved voids, roughness, and channels created by the acid and maintained after fracture closure.8

Estimation of the fracture dissolved width, to predict conductivity, and acid penetration distance is achieved through acid transport reactive modeling. An accurate model should integrate fracture propagation with reactive transport and heat transfer. Early, analytical models were implemented to predict the acid penetration distance and dissolution profile.9,10 Many limiting assumptions were imposed to obtain analytical solutions such as infinite reactivity, constant temperature, and...
fracture size, Newtonian fluids, etc. Numerical models were developed to simulate acid fracturing more realistically by overcoming the limiting assumptions. These models could be one-dimensional (1D), two-dimensional (2D), or three-dimensional (3D). Few studies also coupled acid fracture modeling with reservoir simulation for design optimization. Recently, a lab-scale model was developed to reproduce the roughness on the fracture surface created by acid to simulate the complex interactions in the large-scale block experiment.

Carbonate reservoirs are usually abundant in natural fractures. However, they are seldom considered in acid fracturing modeling. Dong et al. created a small-scale model for acidizing naturally fractured carbonate rocks. However, the model could only be applied for matrix acidizing. One major challenge of acid fracture in naturally fractured formation is the high fluid loss rate. Estimating the fluid loss from such a system was discussed by Mou et al. It was noticed that most of the acid loss takes place in the natural fractures intersecting the hydraulic fracture. Ugursal et al. considered the impact of natural fractures on acid fracture modeling and on productivity estimation. It was concluded that natural fractures could enhance or reduce the productivity of an acid-fractured well as compared to a no natural fracture case. Chen et al. considered the impact of complex networks of natural fractures on acid fracture propagation and productivity enhancement. It was observed that higher injection pressures resulted in better productivity. The aforementioned models assumed a pre-existing hydraulic fracture intersecting natural fractures. This is a significant limitation as hydraulic fracture length is greatly influenced by the intensity of natural fractures (i.e., number, length, and width). Aljawad et al. created a dynamic model where the hydraulic fracture propagates and activates the interesting natural fractures. It was observed that the intensity of natural fractures significantly reduced the hydraulic fracture length. Also, natural fractures tend to reduce the productivity of an acid-fractured well. The study suggested that maximum productivity could be achieved by targeting the maximum injection rate.

Acid fracture conductivity is usually estimated from correlations that consider the fracture dissolved width. These correlations could be divided, based on their techniques, into empirical, analytical, and numerical. Recently, empirical correlations of acid fracture conductivity based on artificial intelligence (AI) methods were proposed. The general agreement between these models is that the closure stress negatively impacts the fracture conductivity while the rock strength and dissolved width have positive effects.

In addition, AI methods have been applied to the area of acid fracturing in terms of conductivity prediction. Akbari et al. proposed a robust intelligent model to determine the fracture conductivity based on the rock strength. More than 100 data points were used to train and test the developed model. Also, genetic algorithms were utilized to provide a mathematical correlation based on the optimized model. The proposed correlation showed better accuracy compared to the popular correlations for predicting the acid fracture conductivity. However, the proposed correlation is very complicated and cannot be used for initial or fast estimations for fracture conductivity. Hence, they recommended that the proposed correlation should be modified to reduce its complexity.

Eliebid et al. developed predictive models to estimate the conductivity of acid fracturing treatments in carbonate formations. Two types of artificial intelligence techniques were used, which are a fuzzy logic system and an artificial neural network. More than 100 data points were used to develop the AI models. Seventy percent of the data was used to train the AI models, while the rest of the data (30%) was used to validate the developed models. An average percentage error of 1.36% and a correlation of determination of 0.99 were reported. Also, the proposed models showed higher accuracy compared to Eliebid et al.’s model. However, no mathematical correlations were provided, which will make the developed models as black boxes and limit their future applications.

Desouky et al. developed new acid fracture conductivity correlations utilizing artificial intelligence techniques. Around 560 data sets that cover different etching patterns and rock types were used to develop the new correlations. Several AI methods were examined including multivariate regression and an artificial neural network. The fracture conductivity was estimated for dolomite, limestone, and chalk rocks. Also, the reliability of the developed models was evaluated using different techniques such as precision metrics and cross validation. A prediction accuracy of 93% and a correlation coefficient of higher than 0.87 were achieved. However, the impact of natural fractures on the treatment performance was not studied. Reservoir parameters such as natural fracture width, half-length, and fracture spacing were not included in the models’ development. Therefore, in this work, the impact of natural fractures on the conductivity of hydraulic fractures will be included.

Artificial intelligence techniques showed very promising performance in predicting the effectiveness of fracturing treatments. The common AI techniques are the artificial neural network (ANN), fuzzy logic system (FLS), and support vector machine (SVM). These techniques showed higher prediction performance compared to other AI methods examined in previous studies in this field. Hence, ANN, FLS, and SVM methods will be used in this study. Also, mathematical correlations can be developed from the optimized models, especially ANN models. The mathematical correlations will allow easy and direct applications for the developed models. Moreover, AI models can be utilized to improve the computational efficiency of complex fractures’ models. Artificial intelligence models can reduce the time required to estimate the fracture performance by several orders of magnitude. Therefore, and because of the above-mentioned advantages of artificial intelligence techniques, we employed several AI tools in this work to provide quick and reliable estimations for the fracture conductivity.

Moore et al. developed a new model to predict the fracture growth in brittle materials containing pre-existing fractures. The developed model was trained utilizing simulation data that were generated using the finite–discrete element method (FDEM). Good prediction performance was reported, and the model’s accuracy was higher than 85%. Also, the developed model showed a significant reduction in computational cost. The simulation time was reduced by multiple orders of magnitude compared to the finite–discrete approach. Srinivasan et al. simulated the flow behavior within a fractured network using artificial intelligence techniques. A new model was developed by utilizing simulation data. A discrete fracture network (DFN) approach was used to generate sufficient data sets that were utilized to train and test the AI model. The developed model showed considerable improvement in the prediction performance and computational time. The simulation time was reduced
simulation results. They concluded that AI techniques can randomly forest (RF), and support vector machine (SVM). methods were used including the neural network (NN), produced from unconventional tight reservoirs. Several AI to predict the productivity of hydraulically fractured wells performance.16

However, most of the AI-developed models ignore important geological and reservoir properties such as formation permeability or the presence of natural fractures within the treated formations. Wang and Chen16 applied di

permeability or the presence of natural fractures within the geological and reservoir properties such as formation permeability or the presence of natural fractures within the treated formations. Wang and Chen16 applied different AI tools to predict the productivity of hydraulically fractured wells produced from unconventional tight reservoirs. Several AI methods were used including the neural network (NN), random forest (RF), and support vector machine (SVM). Good agreement was observed between the actual data and the simulation results. They concluded that AI techniques can significantly improve the design of hydraulic fracture treatments by providing fast and accurate estimations for the treatment performance.16

Wang et al.22 utilized deep neural networks to predict the productivity of multistage hydraulically fractured wells. Cross validation was utilized to assess the predictive ability of the developed model. Sensitivity analysis was conducted to improve the model’s accuracy. The number of hidden layers and neurons in each layer was changed to optimize the model’s performance. Their proposed model consisted of 3 hidden layers and 200 neurons in each layer. The trained model resulted in a small root-mean-square error (RMSE) when predicting the productivity for 6 and 18 months of production. Also, the developed model was utilized to optimize the treatment efficiency. They found out that the amount of the proppant placed in each stage is the most important parameter in controlling the fracture productivity. Finally, they mentioned that the developed model can be directly integrated into the existing hydraulic fracturing design routines to achieve better stimulation performance.

Complex numerical modeling is usually associated with high computational costs. Predicting the productivity of a complex system of hydraulic and natural fractures could be challenging, and optimizing the design is prohibitively expensive. In this study, a complex model of acid fracture in naturally fractured formation that is coupled with a reservoir simulator is utilized. We trained the model using AI-based techniques such as the artificial neural network (ANN), fuzzy logic system (FLS), and support vector machine (SVM). More than 3100 scenarios were tested to investigate the impact of different parameters on productivity improvement. The used data were generated by utilizing an integrated acid fracture model, described in the methodology section. The ranges for each parameter used in generating the studied scenarios were precisely selected to ensure a wide and practical range for each parameter; hence, a good level of reliability for the developed models will be achieved. Also, several evaluation indices were used to evaluate the model reliability including the following. The correlation coefficient (CC), average absolute percentage error (AAPE), and average absolute deviation (AAD) were utilized. The developed model predicts the productivity improvement based on reservoir properties, geomechanical parameters, natural fracture properties, and design conditions. The model inputs are the reservoir permeability, natural fracture (NF) spacing, NF width, half-length, acid injection rate, acid concentration, treatment volume, acid types (represented by the diffusion coefficient and fluid loss), Young’s modulus, and closure stress. The model can be used on the fly to select the best design scenarios in naturally fractured formations.

**METHODOLOGY**

The approach used in this study consists of utilizing an in-house developed fully integrated model to generate productivity enhancement data due to acid fracturing of the naturally fractured formation. Then, AI-based algorithms were used to analyze the data and build a reliable correlation. The simulations were based on a specific reservoir volume. Hence, the developed correlation should be used for better design selection (i.e., the one that optimizes productivity) rather than accurate production rate estimation. It could be also used to investigate the impact of NFs on productivity enhancement. This section describes the integrated acid fracture model and the artificial intelligence approach.

**Integrated Acid Fracture Model.** Figure 1 shows the flow diagram of the integrated acid fracture and reservoir productivity model. It consists of fracture propagation, reactive transport, heat transfer, and reservoir productivity models. After reading the input data, the fracture propagation model is run to estimate the hydraulic fracture (HF) size. It assumes that once the HF intersects natural fractures (NFs), they get activated through dilation. For simplification, NFs are assumed to be orthogonal to the HF. Then, the acid concentration profiles in both HF and NFs are estimated by solving the mass balance equation. This is coupled with the heat transfer model as both concentration and temperature are dependent on each other. This is done at each time step until reaching the final treatment...
time. Then, the final dissolution profiles along both HF and NFs are converted to conductivity distribution through the Deng et al.’s correlation. These along with the fracture dimensions are imported to the built-in reservoir model. The model simulates the productivity and compares it to the initial productivity without stimulation. The mathematical approach is described briefly in this study; nevertheless, the reader should refer to the original work by Aljawad et al. for detailed discussions. The color-coded boxes in the diagram are the fundamental models.

Fracture Propagation Model. The contribution of the developed model over the aforementioned ones is the ability of the fracture to propagate and activate NFs. As the HF propagates, new grids are generated to account for the increase in HF size and the activation of NFs. The interaction between HF and NFs could be complex as many intersection modes could occur such as branching, jogging, arresting, and crossing. It is assumed in this study that crossing and dilation are the mode that HF activates NFs as shown in Figure 2. This is possible only if the fracture pressure is larger than the normal stress acting to close the NF. Also, the pressure has to exceed the re-initiation pressure for the HF to propagate in the same direction. The HF length is obtained by solving the material balance equation considering the fluid loss impact of natural fractures.

Reactive Transport Model. The fluid velocity distribution along HF and NFs was solved according to the Berman approach for fluid flow in leaky channels. This enables solving both the mass and heat transfer models during the acid injection. The acid-reactive model is based on the HCl acid component mass balance, written as

\[ \frac{\partial C_A}{\partial t} + \nabla \cdot (u C_A) = \nabla \cdot (D_A \nabla C_A) \]  

where \( C_A \) is the concentration of HCl acid, \( u \) is the fluid velocity, and \( D_A \) is the effective acid diffusion coefficient. The effective acid diffusion coefficient is well-documented in the literature for various acid systems. The process is transient, and hence, the first term is the accumulation term. The second term represents acid transport due to advection, while the last term represents the transport of acid due to diffusion. Figure 3 shows the schematic of HF intersecting an NF with an illustration of the boundary conditions. Notice that the inlet acid concentration, \( C_0 \), is shown in the west part of the figure. The reaction of the acid with the carbonate minerals appears as a boundary condition as shown in the bottom left corner of Figure 3. It states that the diffusion rate of acid to the walls of the fracture is equal to the reaction rate. The acid/rock dissolution profile is then estimated based on the HCl acid concentration profile.

Heat Transfer Model. The acid reaction rate is strongly related to the temperature magnitude. This is because the diffusion coefficient and the reaction rate constant both depend exponentially on temperature according to the Arrhenius model. The heat transfer model within the fracture, which is based on the energy balance equation, can be written as

\[ \rho_i C_{f} \frac{dT_f}{dt} + \nabla \cdot (u T_f) = \nabla \cdot (k_f \nabla T_f) \]  

where \( T_f \) is the fracture fluid temperature, \( \rho_i \) is the fluid density, \( C_{f} \) is the fluid specific heat capacity, and \( k_f \) is the thermal conductivity. The first term represents the heat accumulation within the fracture. The second term is the heat advection, and the last term is the conduction of heat within the fluid system. The released heat of reaction due to the exothermic reaction is shown in the upper right corner of Figure 3. It states that the increase in the fracture fluid temperature is due to heat flux from the reservoir, \( q_r \), and heat of reaction, \( \Delta H_r \).

Reservoir Productivity Model. The acid fracture model is used to generate the dissolution profiles within both the HF and NFs. They are converted to permeability distribution based on the Deng et al.’s correlation. The permeability of the fracture network is imported into the reservoir model to estimate

![Figure 2. Schematic showing the HF crossing and dilating an NF.](https://doi.org/10.1021/acsomega.1c00809)

![Figure 3. Schematic showing the boundary conditions for a representative section of the HF and NF.](https://doi.org/10.1021/acsomega.1c00809)
productivity. This was done first by solving the diffusivity equation, which is presented as
\[
\nabla \cdot (k \nabla p) = \phi \mu c \frac{\partial p}{\partial t}
\]
where \( p \) is the reservoir pressure, \( \phi \) is the formation porosity, \( k \) is the permeability tensor, \( c \) is total compressibility, and \( \mu \) is the reservoir fluid viscosity. The productivity index, \( J \), represents the production rate from a given reservoir for a certain pressure drop. Better hydraulic fracture design should result in a better productivity index. It can be written mathematically as
\[
J = \frac{q}{\Delta p}
\]
where \( q \) is the production rate and \( \Delta p \) is the pressure drawdown. Finding the best design scenarios can be done by comparing the fold on the increase in productivity, \( J/J_o \). It represents the ratio of the stimulated well productivity to that of the original reservoir, \( J_o \).

**Artificial Intelligence Approach.** In this work, several artificial intelligence (AI) tools were used to develop a new model to estimate the productivity improvement (\( J/J_o \)). The AI techniques used in this study are the artificial neural network (ANN), fuzzy logic system (FLS), and support vector machine (SVM). Among all AI methods, these techniques were selected because they showed very effective prediction performance. Also, mathematical correlations can be extracted from these models. An artificial neural network is one of the most efficient artificial intelligence techniques. The ANN has been widely implemented for prediction, optimization, and classification purposes. ANN model consists of several hidden layers and a number of neurons in each layer. Usually, the ANN model is trained based on training data sets in order to capture the relationship between the target parameter and the model inputs. Then, testing data that are unseen during the training stage are used to assess the model’s reliability. The correlation coefficient (CC), average absolute percentage error (AAPE), and average absolute deviation (AAD) were used. Also, the model parameters (such as the number of neurons, the number of hidden layers, and training functions) were fine-tuned to optimize the model performance. Hyperparameter tuning was performed in two stages: selection of input types and optimization of AI model structures. MATLAB codes of the ANN, SVM, and FLS were used to perform the modeling work. First, the number and the type of input parameter were examined to select the optimum inputs that can maximize the prediction performance of the developed AI models. The input variables were determined based on the statistical analysis and the importance of each parameter. Then, the structure of each AI model was optimized to reduce the estimation error for the testing data set. Single and multiple hidden layers were examined, and a wide range of model neurons and training functions were investigated till the best prediction performance was achieved. Hidden layers between 1 and 3 were examined, neuron numbers between 1 and 50 were used, and training functions such as Levenberg-Marquardt (\texttt{trainlm}), BFGS quasi-Newton (\texttt{trainbfg}), and resilient backpropagation (\texttt{trainrp}) were studied. The best prediction models will be defined in terms of training functions, the number of hidden layers, and the number of neurons per layer. The best predictive model was defined with the smallest AAPE and AAD and the highest CC value. Equations 5–7 were used to calculate the

| Table 1. Statistical Analysis for the Fold Increase in Productivity and Design Parameters |
|---------------------------------------------------------------|
| **parameters** | \( J/J_o \) | \( q \) (bpm) | diffusion coefficient (cm\(^2\)/s) | fluid loss (ft/sqrt(min)) | conc. (wt %) | treatment vol. (bbl) |
| Minimum | 1.38 | 3.00 | \( 1.00 \times 10^{-06} \) | 0.001 | 5.00 | 100.00 |
| Maximum | 8.15 | 80.00 | \( 1.00 \times 10^{-04} \) | 0.004 | 25.00 | 2500.00 |
| Arithmetic mean | 3.46 | 31.54 | \( 1.36 \times 10^{-05} \) | 0.004 | 19.23 | 1426.06 |
| Geometric mean | 3.33 | 22.48 | \( 1.03 \times 10^{-05} \) | 0.004 | 18.72 | 1279.29 |
| Harmonic mean | 3.20 | 14.01 | \( 7.96 \times 10^{-06} \) | 0.004 | 17.74 | 893.97 |
| Mode | 3.34 | 30.00 | \( 1.00 \times 10^{-05} \) | 0.004 | 20.00 | 1500.00 |
| Range | 6.76 | 77.00 | \( 9.90 \times 10^{-05} \) | 0.003 | 20.00 | 2400.00 |
| Mid-range | 4.77 | 41.50 | \( 5.05 \times 10^{-05} \) | 0.003 | 15.00 | 1300.00 |
| Variation | 0.97 | 501.31 | \( 2.89 \times 10^{-05} \) | 0.00 | 10.96 | 177593.58 |
| IQR | 1.17 | 33.00 | \( 0.00 \times 10^{-05} \) | 0.00 | 0.00 | 0.00 |
| Standard deviation | 0.98 | 22.39 | \( 1.70 \times 10^{-05} \) | 0.00 | 3.31 | 421.42 |
| Skewness | 0.80 | 0.63 | \( 4.32 \times 10^{-05} \) | \( -10.20 \) | \( -3.00 \) | \( -1.45 \) |
| Kurtosis | 3.69 | 2.40 | \( 2.12 \times 10^{-05} \) | 105.14 | 12.75 | 7.36 |
| Coefficient of variation | 28.43 | 70.99 | \( 1.25 \times 10^{-02} \) | 7.26 | 17.22 | 29.55 |
correlation coefficient, average absolute percentage error, and average absolute difference, respectively.

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

(5)

\[
AAPE (\%) = \frac{100}{N} \sum_{i=1}^{N} \left( \frac{|Y_p - Y_i|}{Y_p} \right)
\]

(6)

\[
AAD = \left| \frac{Y_p - Y_i}{Y_i} \right|
\]

(7)

where \( x_i \) represents the input parameter, \( \bar{x} \) is the mean value for each input, \( y_i \) represents the target parameter (productivity ratio), \( \bar{y} \) is the mean value for the target parameter, \( N \) is the total number of samples, and \( Y_p \) and \( Y_i \) indicate the predicted and actual values of the target parameter, respectively.

Statistical analysis was also conducted to determine statistical parameters such as minimum, maximum, standard deviation, and skewness. The statistical analysis can help in determining the applicability limits of the developed AI models. Moreover, Pearson parametric correlation analysis was performed in order to assess the strength of the association between multiple parameters and productivity improvement. Equation 5 was used to determine the correlation coefficient for the reservoir properties and the treatment design parameters. The correlation coefficient analysis would help in selecting the input parameters for predicting the productivity ratio.

**RESULTS AND DISCUSSION**

**Statistical Analysis.** Table 1 lists the results of statistical analysis for the fold of increase in productivity and design parameters. The fold of increase in productivity (\( J/J_a \)) varies between 1.39 and 8.15, the injection rate changes from 3 to 80 bpm, and the chemical concentrations vary between 5 and 25 wt \%.

| parameters | K (mD) | spacing (ft) | half-length (ft) | NF width (in.) | Young’s modulus (psi) | closure stress (psi) |
|------------|--------|--------------|-----------------|----------------|----------------------|---------------------|
| minimum    | 0.001  | 5.00         | 5.00            | 0.005          | 1.00 × 10^60        | 2.00 × 10^60        |
| maximum    | 10.00  | 60.00        | 50.00           | 0.50           | 6.00 × 10^60        | 1.20 × 10^60        |
| arithmetic mean | 4.80  | 30.016       | 20.04           | 0.017          | 5.63 × 10^60        | 5.53 × 10^60        |
| geometric mean | 0.29  | 24.82        | 19.82           | 0.006          | 5.39 × 10^60        | 5.35 × 10^60        |
| harmonic mean | 0.016 | 19.81        | 19.47           | 0.005          | 4.85 × 10^60        | 5.15 × 10^60        |
| mode       | 0.010  | 30.00        | 20.00           | 0.005          | 6.00 × 10^60        | 5.50 × 10^60        |
| range      | 9.99   | 55.00        | 45.00           | 0.49           | 5.00 × 10^60        | 1.00 × 10^60        |
| mid-range  | 5.00   | 32.50        | 27.50           | 0.25           | 3.50 × 10^60        | 7.00 × 10^60        |
| variation  | 24.77  | 263.16       | 8.86            | 0.004          | 1.28 × 10^12        | 2.14 × 10^10        |
| IQR        | 9.99   | 40.00        | 0.00            | 0.00           | 0.00 × 10^30        | 0.00 × 10^30        |
| standard deviation | 4.97 | 16.22        | 2.97            | 0.063          | 1.13 × 10^60        | 1.46 × 10^60        |
| skewness   | 0.80   | 0.05         | 5.01            | 6.51           | −3.19 × 10^30       | 2.18 × 10^60        |
| kurtosis   | 1.01   | 1.55         | 65.35           | 47.23          | 1.20 × 10^61        | 1.34 × 10^61        |
| coefficient of variation | 103.70 | 54.05 | 14.86 | 375.62 | 2.01 |

Pearson parametric analysis was utilized to determine the relative importance of the reservoir properties and design parameters on productivity enhancement. Figure 4 shows the relative importance of design parameters in relation to the productivity improvement. Some of the treatment parameters show positive CC values such as the injection rate (\( q \)), chemical concentration, and treatment volume, indicating that increasing any of these parameters will increase the productivity ratio. Meanwhile, the diffusion coefficient and fluid loss show negative CC values revealing that increasing any of these parameters will reduce the productivity ratio. Importantly, the results of statistical analysis are aligned with the general practices of the acid fracturing treatment. For example, it is desirable to have a retarded acid system with a small fluid loss coefficient. Hence, the fluid loss harms the formation productivity, and higher fluid loss can lead to lower productivity improvement, as indicated by the statistical analysis. The relative importance of reservoir properties and productivity improvement (see Figure 5) indicates that the reservoir permeability and NF spacing significantly impact the productivity ratio. The negative correlation with permeability demonstrates that increasing productivity is more challenging in high permeability formations versus tight ones. Overall, the results of correlation coefficient analysis indicate that the reservoir properties (such permeability), NFs’ properties (such as NF spacing), and design parameters (such as the injection rate and injected volumes) have a significant impact on the performance of the acid fracturing treatment (i.e., productivity improvement).
Parametric Investigations. The statistical analysis revealed that the most critical design parameters are the acid treatment volume and the acid injection rate, while the most critical reservoir properties are the number of natural fractures (i.e., spacing) and reservoir permeability. This section investigates these parameters meticulously to provide the reasoning behind their importance.

It is evident that increasing the treatment volume enhances the stimulated area around the wellbore. Larger stimulated areas are correlated positively with productivity enhancement. Figure 6 shows two scenarios where in the first, 300 bbl of acid was injected while the second assumes 1500 bbl of acid. All other designs and reservoir parameters are assumed to be constant. The NF half-length was 20 ft, the width was 0.005 inch, and the spacing was 20 ft while the injection rate was 30 bpm. These parameters were used in all the simulations in this subsection. It can be observed that larger HF was created, and more NFs were activated at the higher treatment volume. Notice that only a quarter of the reservoir was simulated due to the symmetry assumption.

The impact of the treatment volume on productivity enhancement at different reservoir permeability values is shown in Figure 7. It is observed that higher treatment volumes are always desirable in terms of productivity improvement, no matter the reservoir permeability range. Nevertheless, the rate of increase in productivity decreases at larger treatment volumes. There could be a treatment volume at which the cost increase is higher than the productivity gain. It could be observed that the fold of increase in productivity is higher at low permeability reservoirs. Introducing fractures to tight (i.e., low productivity) formations is likely to increase the productivity multiple folds.

Figure 8 shows the impact of the injection rate on the stimulated area around the wellbore. A higher injection rate is associated with higher efficiency where an acid can travel longer distances within the fractures. Hence, a higher injection rate results in longer HF and more activated NFs, as the figure indicates.

Figure 9 shows the impact of the injection rate on productivity improvement at different reservoir permeabilities. The injection at a high rate results in better productivity, especially for tight formations. Nevertheless, lowering the injection rate is desirable at relatively high permeability as conductivity becomes more important than the stimulated

![Figure 5](https://pubs.acs.org/acsomega/18022Z09)

**Figure 5.** Relative importance of reservoir properties in relation to the productivity improvement.

![Figure 6](https://pubs.acs.org/acsomega/18022Z10)

**Figure 6.** Impact of the acid treatment volumes (a) 300 bbl and (b) 1500 bbl on the stimulated reservoir volume.

![Figure 7](https://pubs.acs.org/acsomega/18022Z11)

**Figure 7.** Acid treatment volume impact on productivity improvement at different reservoir permeabilities.

![Figure 8](https://pubs.acs.org/acsomega/18022Z12)

**Figure 8.** Impact of the injection rate on the stimulated area around the wellbore.
volume around the wellbore. A lower injection rate creates more dissolution and hence enhances the fracture conductivity.

The impact of NF spacing on the stimulated reservoir volume is shown in Figure 10. The lower the intensity of the NFs, the longer the HF length is, which results in a larger drainage area. The impact of NFs on productivity improvement is shown in Figure 11. In general, the lower the intensity of NFs, the higher the productivity is as long as HF can be created. The 20 and 40 ft spacings showed an opposite behavior, but the difference in productivity improvement is marginal. Larger NF spacing usually results in a larger drainage volume and hence higher productivity. However, in few cases, that relation does not hold, and hence, an opposite behavior is observed.

**Artificial Intelligence Techniques.** In this work, several artificial intelligence techniques were used, including the artificial neural network (ANN), fuzzy logic system (FLS), and support vector machine (SVM) techniques. This section discusses the performance of different AI models in estimating the productivity enhancement ($\frac{J}{J_0}$) utilizing the reservoir

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**Figure 8.** Impact of the injection rates (a) 10 bbl/min and (b) 90 bbl/min on the stimulated reservoir volume.

**Figure 9.** Injection rate impact on productivity improvement at different reservoir permeabilities.

**Figure 10.** Impact of NF spacings (a) 10 ft and (b) 50 ft on the stimulated reservoir volume.
properties and design parameters as model inputs. The structure of all AI models was optimized in order to minimize the prediction errors. The number of neurons, hidden layers, and training functions were adjusted to improve the model's performance. The hyperparameter tuning of AI models was conducted using MATLAB codes developed in-house. The best model was selected based on the smallest prediction errors and the highest correlation coefficient values. Equations 5–7 were used to calculate the evaluation indices (CC, AAPE, and AAD).

**Artificial Neural Network.** The artificial neural network (ANN) technique was used to develop a new ANN model to estimate the productivity ratio \((J/J_o)\) based on the reservoir properties and treatment parameters. The data were randomly divided into two sets: training and testing sets. Seventy percent of the data was used for training the ANN model, while the rest of the data (30%), which was unseen during the training stage, was used to evaluate the model performance. Also, the impact of model inputs on the prediction performance was studied. Different model inputs were used to estimate the productivity improvement, and three cases were investigated. The selection of input parameters was made based on the correlation coefficient analysis. All parameters were ordered based on the CC values (provided in Figures 4 and 5). Then, the parameters of higher CC values were chosen as inputs, and the number of model inputs was increased sequentially from 4 to 11 inputs.

**Table 3. Predicting the Productivity Ratio Using Different Inputs**

| case no. | number of inputs | inputs                                                                 | CC  | AAPE (%) | AAD |
|---------|------------------|------------------------------------------------------------------------|-----|----------|-----|
| 1       | 4                | \(q, K, NF\) spacing, and treatment vol.                               | 0.90 | 12.27    | 0.42|
| 2       | 7                | \(q, K, NF\) spacing, treatment vol., \(NF\) width, conc., diffusion coeff. | 0.93 | 9.68     | 0.31|
| 3       | 11               | \(q, K, NF\) spacing, treatment vol., \(NF\) width, conc., diffusion coeff, fluid loss, half-length, Young's modulus, and closure stress | 0.98 | 3.58     | 0.11|

The prediction errors during the testing stage are 0.99, 3.13%, and 0.09 for CC, AAPE, and AAD, respectively. In comparison, the prediction errors during the training stage are 0.99, 3.13%, and 0.09 for CC, AAPE, and AAD, respectively.

Based on the results presented in Table 3, reservoir and treatment parameters will be used to predict the productivity ratio \((J/J_o)\). Figure 12 shows the performance of the developed ANN model during the training and validation stages. These profiles indicate that no model memorization has occurred since the validation errors are always higher than the training errors. Also, the best validation performance can be obtained at 26 epochs, where the minimum error was obtained for the testing data set. Also, it should be noted that multiple scenarios were examined; hidden layers between 1 and 3 were investigated, and model neurons of 1 to 50 were used to obtain the best validation performance that has the minimum estimation errors (AAPE and AAD). In this work, the optimized ANN model consists of one hidden layer and 8 neurons per layer, and the training and transfer functions are Levenberg–Marquardt (trainlm) and hyperbolic tangent sigmoid (tansig) functions, respectively. Additionally, a learning rate of 0.12 and a maximum number of iterations of 1000 were used. Figures 13 and 14 show the predicted against the actual productivity ratio \((J/J_o)\) for training and testing data, respectively. During the training stage, the ANN model predicts the productivity ratio with a CC value of 0.99, an AAPE of 2.89%, and an AAD of 0.09. In comparison, the prediction errors during the testing stage are 0.99, 3.13%, and 0.09 for CC, AAPE, and AAD, respectively.

Figure 15 shows the error distribution for the developed ANN model. More than 95% of the examined cases showed reasonable estimation errors, less than 10%. In contrast, around 20 cases out of 3100 cases showed high estimation errors, more than 20%. Importantly, the cases that showed relatively high error (more than 20) represent only around 0.6% of the studied cases. Moreover, the impacts of the injection rate and reservoir permeability on the estimation errors were examined. Figure 16a shows the error profile against the injection rate, and average values were used to indicate the general trend for each parameter. The prediction error is less than 5% for all examined values of the injection rates (3–80 bpm). Figure 16b shows the estimation error against the reservoir permeability. The average estimation error is around 4%, for all permeability ranges. Also, the estimation error was determined against the NF spacing and treatment volume, as shown in Figure 16c,d. Most of the examined values showed an average estimation error of around 4.5%. Overall, the developed ANN model showed a very acceptable performance in predicting the productivity improvement for acid fracturing treatment. The developed model can provide an average estimation error of around 3.5% for a wide range of reservoir and treatment parameters. It should be noted that the ANN model outperforms other AI tools, and direct correlation can be extracted from the ANN model; hence, more details and analysis are provided for the ANN model, as will be discussed in the following sections.

**Fuzzy Logic System.** A new predictive model was developed to predict the productivity ratio \((J/J_o)\) using the fuzzy logic
(FL) system. Similar to the ANN approach, the data were classified into training and testing groups. Seventy percent of the data was used to train the fuzzy logic system, and 30% was used to test the developed model. The best FL model consists of 5 membership functions, and the types of input and output membership functions are Gaussian (gauumf) and linear.
functions, respectively. Also, a cluster radius of 0.8 and a maximum number of iterations of 500 were used. Figures 17 and 18 show the actual against the predicted productivity ratio ($J/J_o$) for the training and testing data, respectively. During the training stage, the FL model predicted the $J/J_o$ with a correlation coefficient of 0.94, an average absolute percentage error of 8.34%, and an average absolute difference of 0.26. Meanwhile, for the testing data, the developed model gave a CC value of 0.93, an AAPE of 8.81%, and an AAD of 0.27. The error profile for the developed FL model was also determined, as shown in Figure 19. More than 80% of the studied cases showed reasonable estimation errors (less than 10%), while around 20% of the studied cases showed relatively high prediction errors (more than 20%). Moreover, the impacts of the injection rate and reservoir permeability on the estimation errors using the FL system were examined. The obtained results are almost similar to the profiles obtained from the ANN model, as shown in Figure 16. Overall, the fuzzy logic model showed lower prediction performance compared to the ANN model, and estimation errors of 3.13 and 8.81% were obtained using the ANN and FL system, respectively, for the testing data set.

Support Vector Machine. The productive improvement ($J/J_o$) was predicted using the support vector machine (SVM) technique. The reservoir properties and treatment conditions were used to estimate the productivity enhancement. In this work, the best SVM model uses kernel functions of the Gaussian type, and the values of conditioning parameters epsilon and lambda are 0.5 and 0.00001, respectively. Also, the bound for

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**Figure 15.** Error distribution profiles for the developed ANN model.

**Figure 16.** Estimation errors using the ANN model for (a) injection rate, (b) reservoir permeability, (c) NF spacing, and (d) treatment volume.
Lagrangian multipliers is 3000. All model parameters were determined based on a trial and error approach till the minimum estimation errors for the testing data set were achieved. Figure 20 shows the actual $J/J_o$ against the predicted using the SVM model. A relatively high estimation error was observed compared to the previous AI models. The SVM model predicts the productivity improvement with an AAPE of 10.28% for the training data. Figure 21 shows the actual $J/J_o$ against predicted using the developed SVM model, for the testing data set. Compared to other AI models, the SVM showed the highest estimation error during both training and testing stages. Figure 22 shows the error profiles for the developed SVM model.

Figure 17. Actual against predicted productivity ratios using the developed FL model, for training data sets.

Figure 18. Actual against predicted productivity ratios using the developed FL model, for testing data sets.

Figure 19. Error distribution profiles for the developed FL model.
some cases, the estimation error is more than 90%, confirming that the SVM model has poorer performance compared to the studied AI models. Furthermore, the estimation error profiles using the SVM were studied for different model parameters, and trends similar to Figure 16 were achieved. Overall, the SVM model showed the weakest performance compared to other AI models studied in this work, as will be described in the coming section of the paper.

**Comparison.** Figure 23 shows the actual $J/J_o$ against the predicted using the developed ANN, FL, and SVM models, all
for the testing (unseen) data. ANN and FL models showed very good performance. The predicted and actual $J/J_o$ are aligned around the 45° line; however, the $J/J_o$ predicted using the SVM model showed some deviation from the 45° line. It should be noted that all AI models (ANN, FL, and SVM) were validated using the same data sets; hence, the best prediction performance will depend mostly on the training approach for each AI model. Table 4 lists the estimation errors for predicting the productivity ratio ($J/J_o$) using ANN, FL, and SVM models.

Among all AI techniques, the ANN model showed the highest correlation coefficient value (around 0.99), while the SVM provided the lowest CC value (0.89). Also, the ANN model predicted the productivity improvement with an average estimation error of 3.13%; however, the SVM showed a higher estimation error, more than 11%. Also, some of the SVM estimations showed considerable deviations from the actual data, and these results are located away from the 45° line. Such deviations were confirmed by the error distribution profiles for the developed SVM model, as shown in Figure 22. Overall, the best model for predicting productivity improvement is the ANN followed by FL and SVM models. Therefore, the ANN model will be used to develop a new correlation to estimate the productivity enhancement ($J/J_o$), as will be discussed in the following sections.

**ANN-Based Correlation.** The optimized ANN model was used to develop a new empirical correlation that can provide a reliable and quick estimation for the productivity ratio. The proposed correlation can be used to determine the improvement in the productivity index due to acid fracturing treatment ($J/J_o$), using reservoir and treatment conditions. Weights and biases were extracted from the best ANN model. In this work, the optimized ANN model consists of one hidden layer and 8 neurons. Figure 24 shows a schematic of the ANN model developed in this study. The following equation gives the new correlation for estimating productivity improvement due to acid fracturing treatment ($J/J_o$)

$$J/J_o = \frac{2}{1 + e^{-2(w_1X_0 + b_1)}} + b_2$$

where $J/J_o$ is the productivity improvement, $N$ is the total number of neurons, $w_1$ and $w_2$ are the weights of the input and output layers respectively, $X_0$ represents the normalized model inputs (reservoir and treatment parameters, listed in Tables 1 and 2), and $b_1$ and $b_2$ are the biases for the input and output layers, respectively. The values of the weights and biases needed

Table 4. Estimation Errors Using ANN, FL, and SVM Models

| AI model | CC   | AAPE (%) | AAD   |
|----------|------|----------|-------|
| ANN      | 0.99 | 3.13     | 0.09  |
| FL       | 0.93 | 8.81     | 0.27  |
| SVM      | 0.89 | 11.01    | 0.35  |

![Figure 23. Actual $J/J_o$ against predicted using the developed ANN, FL, and SVM models, for testing data sets.](https://pubs.acs.org/doi/10.1021/acsomega.1c00809)

![Figure 24. Schematic of the proposed ANN model that can be used to predict the productivity improvement due to acid fracturing treatment.](https://pubs.acs.org/doi/10.1021/acsomega.1c00809)
same conditions, the conventional simulators may take up to 90 min to compute the enhancement in reservoir productivity, while the proposed equation needs very small time (milli- or microsecond) to estimate the productivity improvement, using personal computers. Hence, the ANN-based equation can provide a quick and reliable estimation for the productivity improvement \((J/J_o)\) due to acid fracturing treatment.

**CONCLUSIONS**

This work presents a simple and computationally efficient model for evaluating the performance of acid fracturing treatment in naturally fractured reservoirs using artificial intelligence techniques. Several artificial intelligence (AI) tools were examined, such as the artificial neural network (ANN), fuzzy logic system (FLS), and support vector machine (SVM). Based on this work, the following conclusions can be drawn:

- The developed AI model can be used on the fly to select the best design scenarios for acid fracturing treatment in naturally fractured formations.
- The developed model predicts productivity improvement \((J/J_o)\) based on the reservoir permeability and geological properties, natural fractures properties, and design conditions.
- The statistical analysis and parametric investigations showed that the treatment volume and the injection rate are the most important design parameters, while reservoir permeability and NF spacings are the most influential reservoir properties.

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Table 5. The Values of the Weights and Biases Needed for Predicting the Productivity Ratio

| number of neurons | input layer weights \((w_i)\) | biases \((b_i)\) | output layer weights \((w_o)\) | bias \((b_o)\) |
|-------------------|-------------------------------|-----------------|----------------------|--------------|
| 1                 | \(X_1\) = \(-2.93\) \(X_2\) = \(-0.34\) \(X_3\) = \(-0.51\) \(X_4\) = \(-0.146\) \(X_5\) = \(-0.113\) \(X_6\) = \(-0.08\) \(X_7\) = \(-0.05\) \(X_8\) = \(-0.43\) \(X_9\) = \(-0.02\) \(X_{10}\) = \(-0.44\) \(X_{11}\) = \(-1.00\) | \(b_1\) = \(0.02\) | \(w_1\) = \(-0.11\) |
| 2                 | \(X_1\) = \(-4.08\) \(X_2\) = \(0.62\) \(X_3\) = \(0.51\) \(X_4\) = \(0.51\) \(X_5\) = \(0.423\) \(X_6\) = \(1.77\) \(X_7\) = \(-0.84\) \(X_8\) = \(-1.54\) \(X_9\) = \(-5.03\) \(X_{10}\) = \(-0.41\) \(X_{11}\) = \(-1.27\) | \(b_1\) = \(1.12\) | \(w_1\) = \(1.00\) |
| 3                 | \(X_1\) = \(-0.44\) \(X_2\) = \(0.91\) \(X_3\) = \(-1.76\) \(X_4\) = \(0.95\) \(X_5\) = \(-0.32\) \(X_6\) = \(-0.60\) \(X_7\) = \(-0.10\) \(X_8\) = \(-0.75\) \(X_9\) = \(-0.08\) \(X_{10}\) = \(-0.14\) \(X_{11}\) = \(-0.23\) | \(b_1\) = \(0.40\) | \(w_1\) = \(0.14\) |
| 4                 | \(X_1\) = \(-2.52\) \(X_2\) = \(-1.39\) \(X_3\) = \(0.14\) \(X_4\) = \(-0.15\) \(X_5\) = \(-0.27\) \(X_6\) = \(0.08\) \(X_7\) = \(-0.03\) \(X_8\) = \(0.28\) \(X_9\) = \(0.07\) \(X_{10}\) = \(-0.03\) \(X_{11}\) = \(-0.38\) | \(b_1\) = \(-0.076\) | \(w_1\) = \(-0.03\) |
| 5                 | \(X_1\) = \(3.09\) \(X_2\) = \(0.27\) \(X_3\) = \(1.53\) \(X_4\) = \(-0.03\) \(X_5\) = \(1.75\) \(X_6\) = \(4.09\) \(X_7\) = \(0.15\) \(X_8\) = \(-0.02\) \(X_9\) = \(-2.40\) \(X_{10}\) = \(0.01\) \(X_{11}\) = \(0.84\) | \(b_1\) = \(-1.76\) | \(w_1\) = \(0.03\) |
| 6                 | \(X_1\) = \(-0.12\) \(X_2\) = \(0.99\) \(X_3\) = \(-0.24\) \(X_4\) = \(-1.49\) \(X_5\) = \(-0.86\) \(X_6\) = \(-1.48\) \(X_7\) = \(-0.64\) \(X_8\) = \(4.03\) \(X_9\) = \(-0.55\) \(X_{10}\) = \(1.11\) \(X_{11}\) = \(0.07\) \(X_{12}\) = \(0.09\) | \(b_1\) = \(1.17\) | \(w_1\) = \(0.03\) |
| 7                 | \(X_1\) = \(-1.61\) \(X_2\) = \(0.21\) \(X_3\) = \(0.24\) \(X_4\) = \(0.66\) \(X_5\) = \(-4.63\) \(X_6\) = \(1.47\) \(X_7\) = \(0.04\) \(X_8\) = \(-0.65\) \(X_9\) = \(-0.01\) \(X_{10}\) = \(-0.18\) \(X_{11}\) = \(-0.45\) \(X_{12}\) = \(0.08\) | \(b_1\) = \(-0.72\) | \(w_1\) = \(-0.03\) |
| 8                 | \(X_1\) = \(2.31\) \(X_2\) = \(0.81\) \(X_3\) = \(-0.26\) \(X_4\) = \(-0.69\) \(X_5\) = \(-0.91\) \(X_6\) = \(-0.29\) \(X_7\) = \(0.53\) \(X_8\) = \(-3.10\) \(X_9\) = \(1.16\) \(X_{10}\) = \(0.95\) \(X_{11}\) = \(0.05\) \(X_{12}\) = \(0.42\) | \(b_1\) = \(-0.61\) | \(w_1\) = \(-0.03\) |

**Model Validation.** The new ANN-based equation was evaluated using validation data. Seventy-one scenarios that cover a wide range of model inputs and \(J/J_o\) values were used to validate the ANN model. The validation sets were not used for developing the model and were kept unseen by the model during the training stage and used only to measure the reliability of the proposed correlation. Figure 25 shows the actual \(J/J_o\) against the predicted using the ANN-based equation developed in this work. The productivity improvement \((J/J_o)\) was predicted with a correlation coefficient of 0.99, an average absolute error of 4.54%, and an average absolute difference of 0.12. The obtained results indicate that the developed equation has high reliability in estimating the productivity enhancement. The developed equation can also reduce the time required for predicting productivity improvement by more than 60-fold compared to the conventional simulators, on average. At the same conditions, the conventional simulators may take up to 90 min to compute the enhancement in reservoir productivity, while the proposed equation needs very small time (milli- or microsecond) to estimate the productivity improvement, using personal computers. Hence, the ANN-based equation can provide a quick and reliable estimation for the productivity improvement \((J/J_o)\) due to acid fracturing treatment.

Figure 25. Validation of the ANN-based equation developed in this work.

\[
X_{jn} = 2 \times \left( \frac{X_i - X_{i\text{min}}}{X_{i\text{max}} - X_{i\text{min}}} \right) - 1
\]  

(9)
The comparison study indicated that the best model for predicting productivity improvement is ANN followed by FL and SVM models.

Among all studied AI techniques, the ANN model showed the highest correlation coefficient value (around 0.99), while the FL and SVM provided CC values of 0.93 and 0.89, respectively.

The developed ANN model showed the best predictive performance and can predict the productivity improvement with an average absolute error of 3.13% and a correlation coefficient of 0.99, for the testing (unseen) data sets.

A new ANN-based equation is proposed that can provide a direct estimation for the productivity improvement based on the reservoir and treatment design parameters.

The new equation can predict the productivity ratio with an average absolute percentage error of 4.54% and a correlation coefficient of around 0.99.

The developed equation reduces the time required for predicting the productivity improvement by more than 60-fold compared to the conventional simulators.

Overall, the new equation will help in improving the design of acid fracturing treatment by providing quick and reliable estimations.

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**Author Contributions**

The manuscript was written through contributions of all authors.

**Notes**

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**NOMENCLATURE**

- $c_p$: fluid specific heat capacity
- $C_A$: acid concentration
- $D_A$: acid effective diffusion coefficient vector
- $T_f$: fracture fluid temperature
- $k_l$: total compressibility
- $k_t$: fracture fluid thermal conductivity
- $r$: reaction rate constant
- $n$: reaction rate exponent
- $w$: etched width
- $r$: reservoir fluid viscosity
- AAD average absolute deviation
- AAPE average absolute percentage error
- AI: artificial intelligence
- ANN: artificial neural network
- $b_i$: biases of the input layer
- $b_o$: biases of the output layer
- CC: correlation coefficient
- conc.: concentration
- SVM: support vector machine
- $w_i$: weights of the input layer
- $w_o$: weights of the output layer
- $x$: input parameter
- $y$: target parameter
- $Y$: actual value of the target parameter
- $Y_p$: predicted value of the target parameter
- $v$: volumetric dissolving power
- $f$: productivity index
- $f/J_s$: fold of increase in productivity
- $p$: pressure
- $k$: permeability tensor
- $u$: velocity vector
- $\phi$: formation porosity
- $\rho$: fluid density

**REFERENCES**

1. Li, Y.; Sullivan, R.B.; de Rozieres, J.; Gaz, G.L.; Hinkel, J.J. An overview of current acid fracturing technology with recent implications for emulsified acids. *Proceedings of the SPE Annual Technical Conference and Exhibition*, Houston, Texas, 3–6 Oct 1993.

2. Aljawad, M. S.; Aljulaih, H.; Mahmoud, M.; Desouky, M. Integration of field, laboratory, and modeling aspects of acid fracturing: A comprehensive review. *J. Pet. Sci. Eng.* 2019, 181, 106158.

3. Kalfayan, L. Production Enhancement with Acid Stimulation; Pennwell Books: 2008.

4. Gomaa, A. M.; Nino-Penaloza, A.; McCartney, E.; Mayor, J. Engineering Solid Particulate Diverter to Control Fracture Complexity: Experimental Study. In *the SPE Hydraulic Fracturing Technology Conference*. The Woodlands: Texas, USA, 9–11 Feb 2016.

5. McCartney, E.; Al-Othman, M.; Alam, A.; Nino-Penaloza, A.; Pirogov, A., Nagarkoti, M., Mendez, A. Enhanced Acid Fracturing with Improved Fluid Loss Control and Near Wellbore Diversion Increases Production in Kuwait. In *SPE Annual Technical Conference and Exhibition*. Society of Petroleum Engineers: San Antonio, Texas, USA, 9–11 Oct. 2017.

6. Aljawad, M. S.; Schwalbert, M. P.; Mahmoud, M.; Sultan, A. Impacts of natural fractures on acid fracture design: A modeling study. *Energy Rep.* 2020, 6, 1073–1082.

7. Aljawad, M. S.; Schwalbert, M. P.; Zhu, D.; Hill, A. D. Improving acid fracture design in dolomite formations utilizing a fully integrated acid fracturing model. *J. Pet. Sci. Eng.* 2020, 184, 106481.

8. Schechter, R. S. Oil Well Stimulation; Englewood Cliffs, New Jersey: Prentice-Hall, Inc. 1992.

9. Deng, J.; Mou, J.; Hill, A. D.; Zhu, D. A new correlation of acid-fracture conductivity subject to closure stress. *SPE Prod. Oper.* 2012, 27, 158–169.

10. Nierode, D. E.; Kruk, K. F. An Evaluation of Acid Fluid Loss Additives Retarded Acids, and Acidized Fracture Conductivity. In *Fall Meeting of the Society of Petroleum Engineers of AIME*. 1–4 Jan 1973.

11. Nasr-El-Din, H. A.; Al-Driweesh, S. M.; Chesson, J. B.; Metcalf, A. S. Fracture acidizing: what role does formation softening play in production response. In *The SPE Annual Technical Conference and Exhibition*; San Antonio, Texas, USA, 24–27 Sep. 2006.
(12) Walsh, J. B. Effect of pore pressure and confining pressure on fracture permeability. *International Journal of Rock Mechanics and Mining Sciences & Geomechanics Abstracts*; 1981, 18 (5), 429−435.
(13) Akbari, M.; Ameri, M. J.; Kazrati, S.; Motamed, Y.; Pournik, M. New Correlations to Predict Fracture Conductivity Based on the Rock Strength. *J. Pet. Sci. Eng.* 2017, 152, 416−426.
(14) Eliebid, M.; Hassan, A. M.; Mahmoud, M.; Abdulaheem, A.; Elkatatny, S. Intelligent Prediction of Acid-Fracturing Performance in Carbonates Reservoirs. In *the SPE Kingdom of Saudi Arabia Annual Technical Symposium and Exhibition*; Dammam, Saudi Arabia, 23−26 April 2018.
(15) Desouky, M.; Tariq, Z.; Aljawad, M. S.; Alhoori, H.; Mahmoud, M.; AlShedr, D. Data-Driven Acid Fracture Conductivity Correlations Honoring Different Mineralogy and Etching Patterns. *ACS Omega* 2020, 5, 16919−16931.
(16) Wang, S.; Chen, S. Insights to fracture stimulation design in unconventional reservoirs based on machine learning modeling. *J. Pet. Sci. Eng.* 2019, 174, 682−695.
(17) Hassan, A.; Elkatatny, S.; Abdulaheem, A. Application of Artificial Intelligence Techniques to Predict the Well Productivity of Fishbone Wells. *Sustainability* 2019, 11, 6083.
(18) Moore, B. A.; Rougier, E.; O’Malley, D.; Srinivasan, G.; Hunter, A.; Viswanathan, H. Predictive modeling of dynamic fracture growth in brittle materials with machine learning. *Comput. Mater. Sci.* 2018, 148, 46−53.
(19) Srinivasan, G.; Hyman, J. D.; Othuso, D. A.; Moore, B. A.; O’Malley, D.; Karra, S.; Rougier, E.; Hagberg, A. A.; Hunter, A.; Viswanathan, H. S. Quantifying topological uncertainty in fractured systems using graph theory and machine learning. *Sci. Rep.* 2018, 8, 1−11.
(20) Awoleke, O.; Lane, R. Analysis of data from the Barnett shale using conventional statistical and virtual intelligence techniques. *SPE Res. Eval. 2011, 14, 544−556.
(21) Lafortune, R.; Holcomb, W. D.; Aragon, J. Impact of completion system, staging, and hydraulic fracturing trends in the Bakken Formation of the Eastern Williston Basin. In *the SPE Hydraulic Fracturing Technology Conference*, 5−8 Jan 2012.
(22) Wang, S.; Chen, Z.; Chen, S. Applicability of deep neural networks on production forecasting in Bakken shale reservoirs. *J. Pet. Sci. Eng.* 2019, 179, 112−125.
(23) Roberts, L. D.; Guin, J. A. A New Method for Predicting Acid Penetration Distance. *SPE J.* 1975, 15, 277−286.
(24) Lo, K. K.; Dean, R. H. Modeling of Acid Fracturing. *SPE Prod. Facil.* 2001, 16, 122−130.
(25) Mou, J.; Li, C.; Zhang, S.; Li, D. Research on acid leakoff reduction by injecting large volume of slick water in acid fracturing of naturally fractured oil reservoirs. *Oxid. Commun.* 2016, 39, 2566−2579.
(26) Oth, C. V.; Hill, A. D.; Zhu, D. Acid Fracture Treatment Design with Three-Dimensional Simulation. In *the SPE Hydraulic Fracturing Technology Conference*; The Woodlands: Texas, USA, 4−6 Feb 2014.
(27) Li, X.; He, Y.; Yang, Z.; Zhu, J.; Li, F.; Song, B. Fully coupled model for calculating the effective acid penetration distance during acid fracturing. *J. Nat. Gas Sci. Eng.* 2020, 77, 103267.
(28) Al-Thunayan, K.; Ali, M. T.; Nasr-El-Din, H. A. Modeling Wormhole Propagation During Closed-Fracture-Acidizing Stimulation in Tight-Carbonate Formations. *SPE Journal* 2020, 25, 2373−2400.
(29) Luo, Z.; Zhang, N.; Zhao, L.; Li, N.; Ren, D.; Liu, F. An extended finite element method for the prediction of acid-etched fracture propagation behavior in fractured-vuggy carbonate reservoirs. *J. Pet. Sci. Eng.* 2020, 107170.
(30) Dong, C.; Zhu, D.; Hill, A. D. Modeling of the acidizing process in naturally fractured carbonates. *SPE Journal* 2002, 7, 400−408.
(31) Ugursal, A.; Schwalbert, M. P.; Zhu, D.; Hill, A. D. Acid Fracturing Productivity Model for Naturally Fractured Carbonate Reservoirs. In *the SPE International Hydraulic Fracturing Technology Conference and Exhibition*; Muscat, Oman, 16−18 Oct. 2018.
(32) Chen, Y.; Wang, H.; Wang, Y.; Ma, G. Numerical evaluation of a fracture acidizing treatment in a three-dimensional fractured carbonate reservoir. *J. Nat. Gas Sci. Eng.* 2020, 81, 103440.
(33) Agrawal, S.; Shrivastava, K.; Sharma, M. M. Effect of shear slippage on the interaction of hydraulic fractures with natural fractures. In *the SPE Hydraulic Fracturing Technology Conference and Exhibition*; The Woodlands: Texas, USA, 5−7 Jan 2019.
(34) Potluri, N. K.; Zhu, D.; Hill, A.D. The effect of natural fractures on hydraulic fracture propagation. In *The SPE European formation damage conference*. Sheveningen, The Netherlands, 25−27 May 2005.
(35) Berman, A. S. Laminar flow in channels with porous walls. *J. Appl. Phys.* 1953, 24, 1232−1235.
(36) Sargolzahi, J.; Saghatoleslami, N.; Mosavi, S. M.; Khoshnoodi, M. Comparative Study of Artificial Neural Networks (ANN) and statistical methods for predicting the performance of Ultrafiltration Process in the Milk Industry. *Iran. J. Chem. Eng.* 2006, 25, 67−76.
(37) Lippmann, R. An introduction to computing with neural nets. *IEEE ASSP Mag.* 1987, 4, 4−22.
(38) Berman, A. S. Laminar flow in channels with porous walls. *J. Appl. Phys.* 1953, 24, 1232−1235.
(39) Berman, A. S. Laminar flow in channels with porous walls. *J. Appl. Phys.* 1953, 24, 1232−1235.