

Acid Fracture Design Optimization in Naturally Fractured Carbonate Reservoirs

BY

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A Thesis Presented to the
DEANSHIP OF GRADUATE STUDIES

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

In

PETROLEUM ENGINEERING

May 2022

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN- 31261, SAUDI ARABIA

DEANSHIP OF GRADUATE STUDIES

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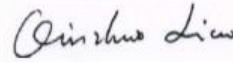


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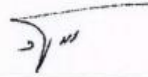
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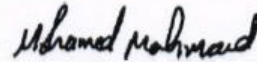
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"All that I am or ever hope to be, I owe to my angel mother."

Abraham Lincoln

ACKNOWLEDGMENT

We have a famous Arabic saying: those who do not thank people; do not thank god. Therefore, I sincerely thank Dr. Murtada AlJawad for his patience and endless support. I was provided with open-door help. Also, I would like to thank Dr. Amjed Hassan for his great help in resolving issues using artificial intelligence techniques. Moreover, I would like to thank my dear father, who kept pushing me to complete my master's degree.

Finally, I would like to thank Saudi Aramco for sponsoring me and King Fahad University for Petroleum and Minerals for providing the facility and the needed software.

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LIST OF ABBREVIATIONS

AI	:	Artificial intelligence
CC	:	Correlation Coefficient
FLS	:	Fuzzy Logic System
SVM	:	Support Vector Machine
ANN	:	Artificial Neural Network
AAPE	:	Average Absolute Percent Error
AAD	:	Average Absolute Deviation
HF	:	Hydraulic Fracture
NF	:	Natural Fracture
PI	:	Productivity Index

ABSTRACT

Full Name : Monther Mohammed AlSulaiman

Thesis Title : Acid Fracture Design Optimization in Naturally Fractured Carbonate
Reservoirs

Major Field : Petroleum Engineering

Date of Degree : May 2022

Carbonate formations, candidates for acid fracturing, are usually naturally fractured. Therefore, the existence of fracture networks has an important impact on fracture design outcomes. This work develops a model to explain acid distribution in hydraulic and intersecting natural fractures. This model is then used to optimize acid fracture design parameters based on the goal of maximizing productivity.

This research utilizes an in-house developed model that captures the complex interaction between hydraulic and natural fractures to calculate the conductivity outcomes of an acid fracturing design job at different reservoirs' natural fracture density. Furthermore, this model is integrated with an in-house productivity model to calculate productivity enhancement. As a result, it helps run a way higher number of sensitivities for various acid fracturing designs.

A parametric study has been done to determine the impact of natural fractures on acid placement in the reservoir and compare productivity folds in cases with natural fractures with those without

natural fractures. Also, to find the optimum design conditions (e.g., injection rate and volume) based on the natural fractures' characteristics and reservoir properties.

Artificial intelligence (AI) to deliver a fast and dependable predictive model for fracture productivity enhancement. Three methods of AI were examined: support vector machine (SVM), fuzzy logic system (FLS), and Artificial neural network (ANN). The developed mathematical correlations from the selected artificial intelligence methods, notably the ANN, allowed easy and fast performance prediction. Additionally, AI models give reliable predictions of the productivity folds. For example, the artificial neural network model has a prediction error of 3.3%. In addition, an empirical equation has been obtained from the ANN model.

The model developed here explains the complex interactions of acid fractures in naturally fractured carbonate formations. As a result, the effects of natural fractures on acid placement and optimum design conditions can now be estimated. Such information is imperative for better stimulation design in this type of formation, which has rarely been considered.

ملخص الرسالة

الاسم الكامل: منذر محمد السليمان

عنوان الرسالة: تحسين توصيلية التكسير بالحمض في المكامن الكربونية الغنية بالكسور طبيعيًا

التخصص: هندسة البترول

تاريخ الدرجة العلمية: مايو 2022

عادة ما تكون مكامن الصخور الكربونية، المرشحة للتكسير الحمضي، مكسورة بشكل طبيعي. لذلك، فإن وجود شبكات الكسر له تأثير مهم على نتائج تصميم الكسر الحمضي. يطور هذا العمل نموذجًا لشرح التوزيع الحمضي في الكسور الهيدروليكية المتقاطعة مع الكسور الطبيعية. ثم يتم استخدام هذا النموذج لتحسين معلمات تصميم الكسر الحمضي بناءً على هدف زيادة الإنتاجية. يستخدم هذا البحث نموذجًا مطورًا داخليًا يلتقط التفاعل المعقد بين الكسور الهيدروليكية والكسور الطبيعية الموجودة لحساب نتائج التوصيل لوظيفة تصميم التكسير الحمضي عند كثافة التصدع الطبيعية لمكامن مختلفة. علاوة على ذلك، تم دمج هذا النموذج مع نموذج إنتاجية داخلي لحساب تحسين الإنتاجية. نتيجة لذلك، يساعد في اختبار سيناريوهات لتصاميم التكسير الحمضي المختلفة.

تم إجراء دراسة للمتغيرات لتحديد تأثير الكسور الطبيعية على عملية التكسير الحمضي في المكامن ومقارنة الإنتاجية في حالات الكسور الطبيعية مع تلك التي لا توجد بها كسور طبيعية. أيضًا، للعثور على ظروف التصميم المثلى (على سبيل المثال، معدل الحقن وكمية الحمض) بناءً على خصائص الكسور الطبيعية وخصائص المكامن. الذكاء الاصطناعي (AI) لتقديم نموذج تنبؤي سريع ويمكن الاعتماد عليه لحساب إنتاجية التكسير الحمضي. تم فحص ثلاث طرق للذكاء الاصطناعي: آلة ناقلات الدعم (SVM)، ونظام المنطق الضبابي (FLS)، والشبكة العصبية الاصطناعية (ANN). سمحت الارتباطات الرياضية المطورة من أساليب الذكاء الاصطناعي المختارة، ولا سيما ANN، بالتنبؤ السهل والسريع بإنتاجية البئر. بالإضافة إلى ذلك، تقدم نماذج الذكاء الاصطناعي تنبؤات

موثوقة عن طيات الإنتاجية. على سبيل المثال، يحتوي نموذج الشبكة العصبية الاصطناعية على خطأ تنبؤ بنسبة

3.3%. بالإضافة إلى ذلك، تم الحصول على معادلة تجريبية من نموذج ANN.

يشرح النموذج الذي تم تطويره هنا التفاعلات المعقدة للكسور الحمضية في تكوينات الكربونات المكسورة بشكل

طبيعي. نتيجة لذلك، يمكن الآن تقدير تأثيرات الكسور الطبيعية على وضع التكسير الحمض وظروف التصميم

المثلى. هذه المعلومات ضرورية لتصميم تحفيز أفضل في هذا النوع من المكامن، والذي نادرًا ما تم النظر فيه.

CHAPTER 1

INTRODUCTION

1.1 Stimulation Methods and Resulted Conductivity

One of the most widely used stimulation treatments for enhancing well productivity (and hence, total hydrocarbon recovery) is hydraulic fracturing. The two well-known hydraulic fracturing treatments are proppant and acid fracturing. In proppant fracturing, after a hydraulic fracture is created by viscous fluid injection at high pressure, small sand particles are injected to maintain an open path for the reservoir fluids to flow to the wellbore. This option is favorable because the created conductivity withstands high closure stress and is easy to predict. Acid fracturing is another option that is especially favorable in heterogeneous and naturally fractured carbonate reservoirs. It consists of three main stages of injection. The first is pre-flush, where viscous fluid initiates the fracture. The second consists of acid injection to grow the length of the fracture and width by etching its walls. The last is over-flush to drive the acid to the tail of the fracture, improving acid penetration. The dissolution of the fracture walls occurs in a non-uniform manner, creating variable channels and rough surfaces. These channels and rough surfaces prevent the fracture from full closure and work as pathways for fluid flow from the matrix to the wellbore. Improving acid fracture design requires an integrated model that predicts the resultant productivity. Such an integrated model should include both acid fracture and reservoir productivity models.

Some scholars have attempted acid fracture modeling. In 1972, Williams and Nierode utilized Terrill's (1965) analytical solution to estimate acid penetration length and the correlating fracture conductivity. Later, numerical methods introduced the ability to solve the acid profile in acid fracturing. In 1989, Ben-Naceur and Economides established guidelines for acid fracture design based on their model, suggesting that acid fracturing should minimize fracture height growth, maintain adequate fracture width, and control the leak-off flow rate. Settari et al. (2001) developed a 2D acid transport model that solved equations across the fracture width. The model was more comprehensive than previous ones. Romero et al. (2001) created an acid fracture model that solved velocity and acid concentration in three dimensions. Aljawad et al. (2016) studied the impacts of various fluid systems on acid fracturing outcomes based on a completely numerical 3D model.

After modeling the acid fracturing, estimating the resultant well productivity is essential. In past decades, many approaches have been developed to evaluate improvements in well productivity. In 1960, McGuire and Sikora invented a graphical approach, approximating the ratios of fracture conductivity to reservoir permeability and fracture length to drainage radius to determine productivity enhancement after fracturing. The assumptions were uniform vertical fracture conductivity and a pseudo-steady flow. In 1967, Binder created a formula for calculating productivity that considered variable vertical fracture conductivity with a radial steady-state flow (both were productivity models). However, the numerical reservoir simulator is the most reliable method for estimating a fractured well's productivity.

Few models consider the natural fractures' influence on fractured well's performance. Dong et al. (2002) established a model for simulating the acidization of naturally fractured carbonate reservoirs. When the natural fracture width was more extensive than 0.01 cm, the results were similar to acidizing hydraulic fractures where the fracture surface was etched and wormhole

creation was minimized. When the natural fracture width was less than 0.002 cm, the author found that wormholes were created, and the process looked like matrix acidization. This model depicted the acidization of naturally fractured core samples.

Ugursal et al. (2018a) established a model that described acid fracturing when natural fractures intersect a hydraulic fracture. The concentration for natural fractures was based on Terrill's analytical solution; the acid in the hydraulic fracture was numerically solved. It was assumed that the acid only leaked through the natural fracture. The leak-off in natural fractures was calculated based on its size. The conductivity of the primary fracture was inversely related to the number and size of any natural fractures. Ugursal et al. (2018b) extended the study by including the leak-off and fractured well productivity calculation by simulating the flow from the fracture system into the reservoir. The main finding is that natural fractures enhance or decrease well productivity based on intensity. A significant drawback of their model was that hydraulic fracture size was assumed to be constant, as the work did not consider fracture propagation.

In the present study, the acid model considers the natural fractures' influence on the propagation of hydraulic fractures. When more natural fractures intersected the hydraulic fracture, its penetration distance was reduced. The coupled mass and heat transfer model was solved numerically for hydraulic and natural fractures. Moreover, conductivity enhancement was seen across the intersecting natural fractures due to their reaction to the acid.

1.2 Problem Description

The existing natural fractures network tremendously impacts the productivity from acid fractured well in naturally fractured dolomite reservoir as they either could enhance or reduce it. Most of the existing acid fracturing models assume the acid reaction happens only in the main hydraulic

fracture, neglecting the effect of natural fractures on fracture propagation and the total conductivity. The presence of natural fracture could enhance or deteriorate the final conductivity and productivity.

Moreover, there is a lack of prediction models that can predict productivity enhancement of acid fracturing in the naturally fractured reservoir.

1.3 Research Objectives

This study aims to demonstrate the impact of natural fractures intersecting a hydraulic fracture in the dolomite reservoirs. The study is focused on the performance of the well (PI) and comparing it to the case where no natural fractures intersect the hydraulic fracture. Also, to understand the impact of different natural fracture intensity (spacing) in multiple scenarios of reservoir permeability at different temperatures. In addition, evaluate the change in some parameters of the acid fracturing job to obtain the optimum well productivity (e.g., injection rate, injection temperature, acid type, and treatment volume). Finally, develop a productivity enhancement prediction model to save computational time utilizing AI.

CHAPTER 2

LITERATURE REVIEW

A reliable model that estimates the acid penetration length and conductivity distribution for a given reservoir is required to design an acid fracturing job successfully. Then, a productivity model is needed to predict the fractured well productivity accurately. The literature includes several models developed to predict the conductivity of acid fracturing jobs. These models are empirical, semi-empirical, analytical, and numerical approaches.

2.1 Acid Fracturing Modeling

Over the last 60 years, many scholars attempted acid fracture modeling. In 1972, Nierode and Williams utilized Terrill's (1964) analytical solution to estimate acid penetration length and the correlating fracture conductivity. The approach has a workflow of steps to predict the stimulation ratio. First, the Peclet number is calculated. Then, the dimensionless acid penetration distance is found from the chart in Figure 1 and at a specific acid concentration value. A more detailed example is presented in the paper by Nierode and Williams (1972). The limitation with these charts is that they are upscaled laboratory results from a few limited cores representing field fractures with hundreds of feet in length.

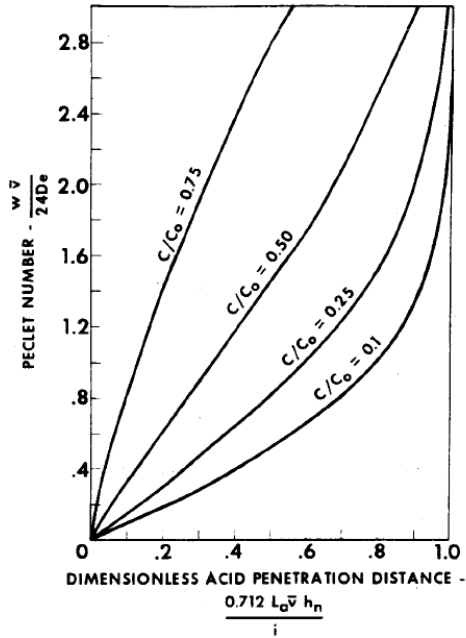


Figure 1: Acid penetration distance as a function of Peclet number and acid concentration (Williams and Nierode, 1972).

In 1974, Roberts and Guin provided a model correlating the effective diffusion of HCl acid to Reynolds number and temperature. The acid mass balance was solved numerically with the finite difference method. A finite reaction rate was assumed at the boundary condition. Different experiments were conducted to find a correlation for the effective diffusion at the boundary condition to replace the ionic diffusion. The author has introduced parameters that affected the effective diffusion and then focused on Reynolds number and temperature in his paper. He numerically provided a solution for dimensionless acid concentration in fracture length and width. Based on this solution, multiple charts of acid concentration were generated as a function of reaction parameters and Peclet number. The weakness of this model is that it did not include the fracture geometry propagation effect in the solution.

Later, numerical methods enable solving the acid profile in acid fracturing. In 1989, Ben-Naceur and Economides established guidelines for acid fracture design based on their model, suggesting that acid fracturing should minimize fracture height growth, maintain adequate fracture width, and control the leakoff flow rate. In the same year, Dean and Lo introduced an acid transport model based on a 2D continuity equation and acid mass balance equation, and an infinite reaction rate is assumed. They provided an acid fracturing model utilizing a 2D PKN model to handle two fluids injection and find each fluid's position as a function of time. Also, the acid model is derived based on averaging the 2D continuity and mass balance to a 1D acid equation along fracture length. The model showed good approximations of the corresponding equations. However, the model did not address the accumulation effect in the acid material balance equation and the temperature variation from the wellbore to the fracture tips. In 1992, Schechter presented an approach to design an acid-fracturing theoretically. Schechter used the Berman solution for the velocity profiles in the x and y directions, satisfying the Navier-Stokes equations and the continuity equation. These 2D analytical solutions are presented in Eqs. 2.1-2.3:

$$u(x, y) = \left[u_{in} - \frac{2v_L x}{\bar{w}} \right] f(\eta) \quad (2.1)$$

Where u is the x-direction velocity

$$v(y) = v_L \frac{\left(y - \frac{\bar{w}}{2} \right)}{\frac{\bar{w}}{2}} = v_L \eta \quad (2.2)$$

Where v is y-direction velocity, v_L is the leakoff velocity during fracture closure and η is a dimensionless value of the acid position in the direction of the fracture width.

Then, the acid mass balance equation is solved to calculate the acid concentration in the x-direction, while

the y-direction concentration values are averaged. The acid mass balance equation and the analytical solutions are shown in Eq. 2.4-Eq. 2.6:

$$\frac{\bar{C}}{C_i} = \sum_{n=0}^{\infty} G_n \left(1 - \frac{x}{x_f}\right)^{2\lambda_n^2/3N_{Pe}} \quad (2.4)$$

eigenvalues are the acid concentration, $\bar{C}$ is the average acid concentration, C_i is the initial acid concentration, and L is the acid penetration distance.

$$N_{Pe} = \frac{\bar{v}_L \bar{W}}{2D_A} \quad (2.5)$$

$$u(x, y) \frac{\partial C_A}{\partial x} + v(x, y) \frac{\partial C_A}{\partial y} = D_A \frac{\partial^2 C_A}{\partial y^2} \quad (2.6)$$

From Figure 2, when $N_{Pe} > 1$, the acid leaked off before it completely reacted. When the N_{Pe} is < 1 , the acid is entirely consumed before reaching the end of the fracture. The limitation of this approach is that the secondary flow and wall roughness effects are neglected because of the laminar flow and infinite reaction assumptions for the solution. As a result, the length (L) could be shorter or longer than the actual fracture half-length to satisfy the volume balance (volume injected = volume loss), making L equivalent to the acid-penetration length.

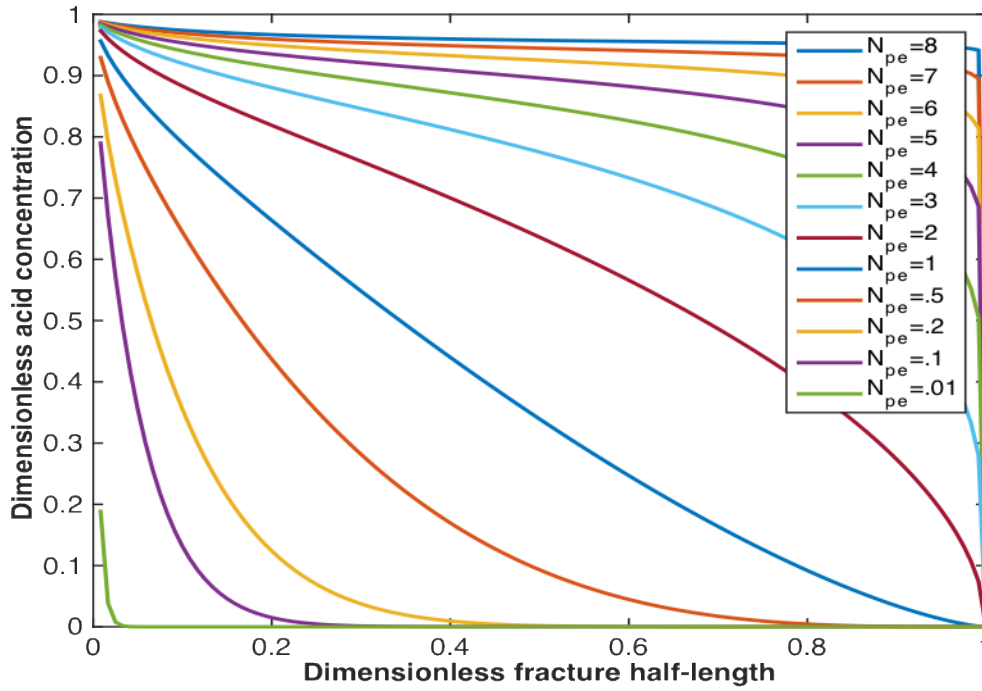


Figure 2: Acid invasion distance as a function of Peclet number & concentration (Schechter, 1992).

In 1993, Settari established a model that handles fluids with different rheology, worm holing effect in leakoff calculations, reaction heat, fracture geometry coupling, mass transfer, and rate of limited reaction cases. Settari, in his acid model, introduced new essential features for acid model designing. The first feature can handle fluids rheology (acid, gels, and foams) and acid/gel sequences. The second feature controls the acidizing process by both mass transfer and reaction rate. Third, a new way of calculating leakoff caused by matrix acidizing and wormhole effects at the fracture wall. Fourth, the acid model was coupled with heat transfer coming from the reaction. Fifth, the acid model was coupled with the forecasting reservoir model for job optimization. Settari et al. (2001) developed a 2D acid transport model that solved equations across the fracture width. It was more comprehensive than previous models. Romero et al. (2001) created an acid fracture model that solved velocity and acid concentration in three dimensions. In 2012, Deng established

a new correlation to calculate the acidic-etched fracture conductivity. It included the impact attributed to the mineralogy, permeability and rock elastic properties on the total conductivity. Aljawad et al. (2016) studied the impacts of various fluid systems on acid fracturing outcomes based on a completely numerical 3D model.

Few models consider the natural fractures' influence on the fractured well performance. Dong et al. (2002) established a model for simulating the acidization of naturally fractured reservoirs. When the natural fracture width was more extensive than 0.01 cm, the results were similar to acidizing hydraulic fractures where the fracture surface was etched and wormhole creation minimized. When the natural fracture width was less than 0.002 cm, the authors found that wormholes were created, and the process looked like matrix acidization. Between 0.01 cm and 0.002 cm, a channel was created that was broad near the inlet and narrow near the outlet. Their model depicted the acidization of naturally fractured core samples.

Ugursal et al. (2018a) established a model that described acid fracturing when natural fractures intersect a hydraulic fracture. The concentration for natural fractures was based on Terrill's analytical solution; the acid in the hydraulic fracture was numerically solved. It was assumed that acid only leaked through the natural fracture. The leakoff in natural fractures was calculated based on size. The conductivity of the main fracture was found inversely related to the number and size of any natural fractures. Ugursal et al. (2018b) extended the study by including the leakoff and fractured well productivity calculation by simulating the flow from the fracture system into the reservoir. The natural fractures could improve or lower well productivity based on natural fracture intensity and reservoir permeability. A significant drawback of their model was that hydraulic fracture size was constant, as the work did not consider fracture propagation.

2.2 Acid Fracturing Conductivity Prediction

Many researchers studied the resulting acid fracture conductivity and its factors to find a reliable model or correlation to predict it.

In 1973, Nierode and Kruk developed one of the first correlations for acid fracturing conductivity calculation. Utilizing 25 laboratory experiments, they determined that the conductivity is a function of rock embedment strength, the amount of dissolved rock, and formation closure pressure.

The Nierode and Kruk conductivity correlation is shown in Eqs. 2.6-2.8:

$$wk_f = C_1 \exp(-C_2 \sigma_c) \quad (2.6)$$

Where wk_f is the Fracture conductivity, C_1, C_2 are the Nierode-Kruk correlation's constants, and σ_c is the formation closure stress.

$$C_1 = 0.265 (DREC)^{0.822} \quad (2.7)$$

Where DREC is the amount of dissolved rock.

$$C_2 * 10^3 = \begin{cases} 19.9 - 1.3 \ln(RES) & 0 < RES < 20,000 \text{ psi} \\ 3.8 - 0.28 \ln(RES) & 20000 \leq RES \leq 500,000 \text{ psi} \end{cases} \quad (2.8)$$

Where RES is the rock embedment strength

This correlation is widely used in commercial software because of the ease of obtaining the parameters from core analysis or field data. However, it fails to capture formation heterogeneity impact on the conductivity of the fracture.

Gangi (1978) provided a theoretical model where he included the surface asperities distribution (C_3) as a parameter in calculating the conductivity as below:

$$(k_f w)^{1/3} = C_1 - C_2 (\sigma_c)^{C_3} \quad (2.9)$$

Walsh (1981) gave another theoretical model as shown:

$$(k_f w)^{1/3} = C_1 - C_2 \ln(\sigma_c) \quad (2.10)$$

The previous theoretical models predict the change in conductivity under different closure stresses with suitable C_1 and C_2 values. However, Pournik (2008) found that they are less accurate than Neirode and Kruk's correlation.

Anderson and Fredrickson (1989) stated that conductivity is primarily influenced by the amount of rock removed and the pattern. While the quantity of rock dissolved is affected by kinetic parameters like acid type concentration, temperature, contact time, and flow regime, the rock mineralogical composition governs the etching pattern.

Gong (1997) developed a theoretical model presented in equation 2.11 that predicts conductivity values closer to experimental results when compared with the Neirode-Kruk empirical one. However, this model needs more complex parameters, e.g., a measurement of the surface roughness distributions after acidizing. The fracture deformation model considers surface roughness and mechanical rock properties. First, the fracture closure under stress is modeled as plastic deformation of asperities. Then, the fracture conductivity can be estimated by the following cubic law:

$$k_f w_i = (k_f w_i)_0 \left[1 - \left(\frac{\gamma}{1+\gamma} \right) \left(\frac{2\sigma_c}{c\sigma_y} \right)^{1/\gamma} \right]^6 \quad (2.11)$$

where $(k_f w_i)_0$ is the fracture conductivity at zero stress (mD*ft), σ_y is the rock yield stress (psi), γ is a parameter for the shape of the distribution function curve of the asperities, and c is the stress correction factor.

Nasr-Eldin (2008) separated the original Neirode-Kruk correlation based on lithology into two correlations for limestone and dolomite and used the experimental data to find new C_1 and C_2 values. For the same acid system, contact time may influence the etching pattern. The resulting conductivity increases as the contact ratio between the fracture's two faces increases.

Chen et al. tried to evaluate the effect of a complex natural fracture system on the penetration distance of the main hydraulic fracture and how the productivity is changing. He observed that as the injection pressure increased, productivity improved.

Aljawad et al. (2020) developed a dynamic model that captures the effect of natural fractures as the main hydraulic fracture intersects them. This model concludes that its propagation length gets shorter as the main hydraulic fracture intersects with more natural fractures. Hence, the natural fracture existence generally tends to reduce productivity improvement compared to a reservoir without natural fractures. Also, an optimum injection rate should be selected based on reservoir permeability to maximize productivity. A high injection rate is preferred in the low permeability reservoirs as it extends the fracture half-length, enabling more flow from the reservoir to the wellbore. While in a high permeability reservoir, a moderate injection rate is preferred.

2.3 Artificial Intelligence

The empirical correlations which depend on experimental studies are conveniently applied, and their parameters can be found easily. The analytical correlations based on theoretical derivations

are complicated and require a lot of sophisticated parameters. Some parameters require experimental results to tune them through regression analysis. The artificial intelligence models require accurate and consistent data. The accuracy of these models improves with increasing the data set size.

AI methods have been used for the conductivity prediction of acid fracturing. Akbari et al. (2017) Developed an intelligent model to estimate the formation conductivity after performing acid fracturing treatment, utilizing the rock properties as inputs and using a genetic algorithm. The developed model outperformed other approaches. However, it cannot be used for quick estimations because of the model complexity.

Eliebid et al. (2018) Utilized fuzzy logic systems and artificial neural networks to estimate conductivity after conducting acid fracturing stimulation. A relative error was 1.4%, and a correlation coefficient was 0.99. Although it was less complex than Akbari et al.'s model, no direct equations were reported, limiting future applications of such models.

Desouky et al.(2020) Proposed an artificial intelligence-based model to estimate acid fracturing conductivity. Over 560 datasets covering different rock types and etching patterns were used to develop the new correlations Artificial neural networks, and multivariate regression techniques were utilized. In addition, cross-validation and precision metrics approaches were used to assess the model reliability. The estimation error was 7%, and the correlation coefficient was around 0.896. However, their model did not consider important characteristics such as width, half-length, and spacing of the fractures, leading to reduced model applicability.

Hassan et al. (2021) developed an ANN-based equation that predicts reservoir productivity after performing acid fracturing treatments utilizing artificial intelligence techniques. It accounts for the reservoir properties, the acid design parameters, and the reservoir geomechanical parameters. A

new correlation allows a fast and direct application with a 4.5% error and a correlation coefficient of 0.98.

CHAPTER 3

METHODOLOGY

The fracture conductivity enhances the productivity of the well. However, it is subject to the created fracture width and the created channel that remains open under the reservoir closure stress (penetration distance). Therefore, estimating the fracture width and the acid penetration distance is required to predict fracture conductivity. It can be achieved by utilizing an integrated fracture propagation model with acid reaction transport along the fracture and heat transfer. In the old days, analytical models were used to predict acid fracturing outcomes of the dissolution profile and the penetration distance. However, the downside of analytical models is the multiple limiting assumptions such as constant temperature, infinite reactivity, fracture size, and Newtonian fluid. Nowadays, we have numerical models that overcome these limitations, which can be three-dimensional, two-dimensional, or one-dimensional.

3.1 Acid Model

In this part, using an in-house developed fully integrated model, a numerical simulator is integrated with a model for generating the productivity folds. The model considers the temperature impact, especially when injecting weak acid or acid fracturing dolomite formation. It provides reliable acid penetration distance and etched width profile for the fracture.

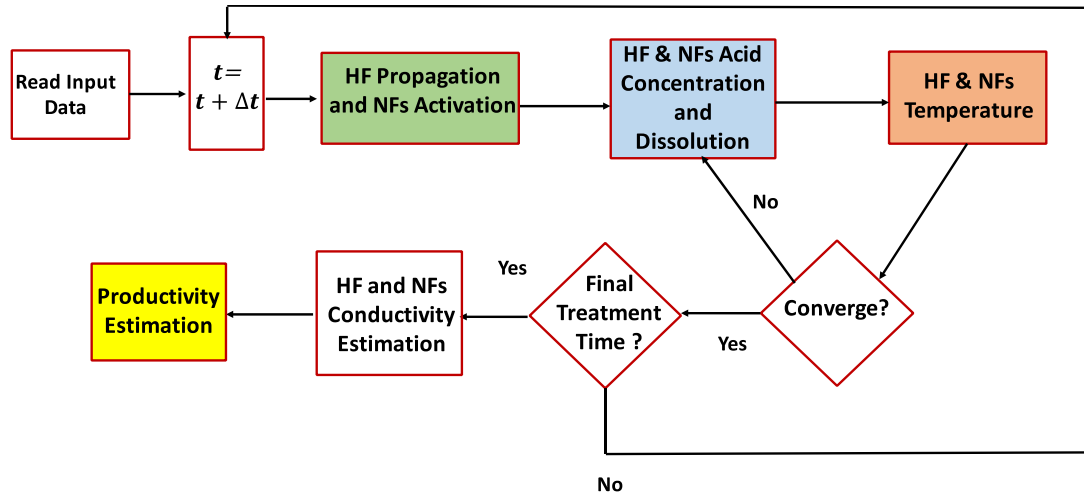


Figure 3: Productivity estimation workflow

Figure 3 shows the fundamental models: fracture propagation model, concentration transport model, temperature heat transfer model, and reservoir productivity model. Figure 3 shows the workflow. It starts with reading the input data. Then it goes through the fracture propagation model for estimating the hydraulic fracture length (HF). The first assumption is that once the natural fractures (NFs) intersect by the hydraulic fracture, they get stimulated and activated through dilation. This ability to activate natural fractures as the hydraulic fracture propagates makes the model unique compared to the other models. The intersection between the natural and main hydraulic fractures could have different angles and develop various forms such as jogging, branching, arresting, and crossing. So, the second assumption in this model to simplify things is that the natural fractures are orthogonal to the hydraulic fracture. The interaction between the hydraulic and the natural fractures is crossing and dilation, as shown in Figure 4. This interaction between the hydraulic and natural fractures happens when the fracture pressure exceeds the normal stress, which keeps the natural fractures closed. Then the material balance equation is solved to find the hydraulic fracture length considering the fluid loss due to the activated NFs.

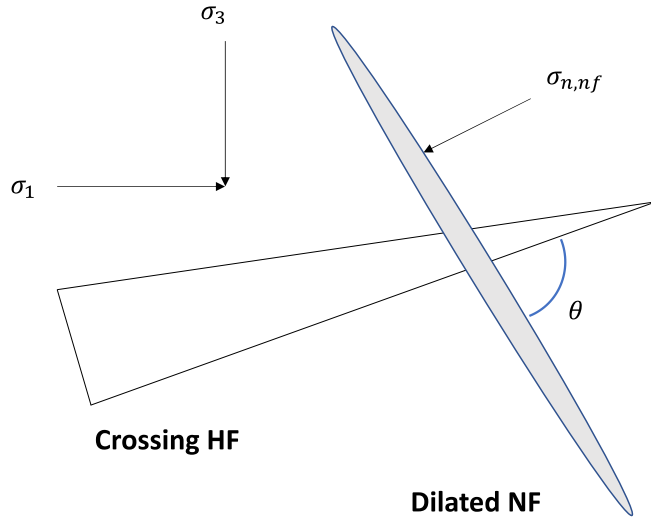


Figure 4: Schematic the HF crossing an NF

Equation 3.1 is Carter's equation (Carter, 1957), which was used for fluid loss calculation:

$$q_L = \frac{2C_L h_f}{\sqrt{t-\tau(x)}} \quad (3.1)$$

Where C_L is the leakoff coefficient and $\tau(x)$ is the time when the fracture reached position x . This equation was employed to calculate the fluid loss from the hydraulic and natural fractures.

The acid concentration profile was calculated based on solving the acid mass balance Equation 3.2:

$$\frac{\partial C_A}{\partial t} + \nabla \cdot (\mathbf{u} C_A) = \nabla \cdot (D_A \nabla C_A) \quad (3.2)$$

Where D_A is the effective mixing acid diffusion coefficient, C_A is the acid concentration, and u is the velocity in the x direction. The acid model incorporated the temperature impact into the reaction and diffusion rates. The acid temperature increased due to the heat from the acid reaction and the reservoir temperature. The temperature rise affected the reaction rate, which impacted the etching profile and distance of acid penetration. The equation used to calculate the temperature distribution in Equation 3.3:

$$\rho c_p \left(\frac{\partial T}{\partial t} + \nabla \cdot (uT) \right) = \nabla \cdot (k \nabla T) \quad (3.3)$$

Where T is the temperature, k is the thermal conductivity ρ is the fluid density c_p is fluid heat capacity.

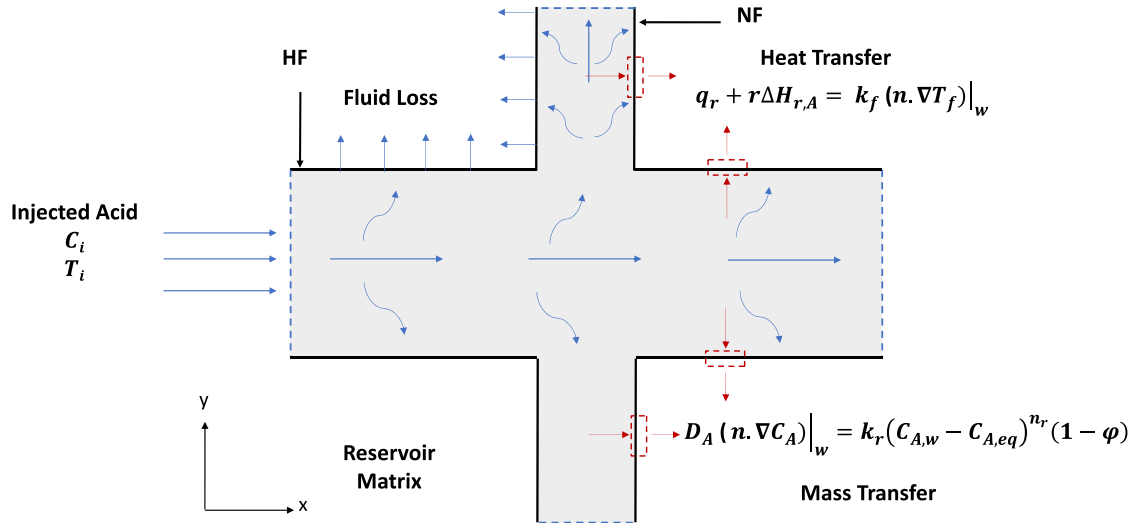


Figure 5: Schematic of the hydraulic and natural fracture crossing at boundary conditions.

Figure 5 shows the representation of the hydraulic fracture intersecting a natural fracture with the inclusion of the boundary conditions. It demonstrates that the acid diffusion rate to the fracture walls and the reaction rate are the same. Therefore, the energy balance equation for the heat transfer model:

$$\rho_f \widehat{c_{pf}} \left[\frac{\partial T_f}{\partial t} + \nabla \cdot (\mathbf{u} T_f) \right] = \nabla \cdot (k_f \nabla T_f) \quad (3.4)$$

Where $\widehat{c_{pf}}$ is the specific fluid heat capacity, and k_f is the fluid thermal conductivity and T_f is the fracture temperature. The left side of Equation 3.4 is the heat storage and the heat convection due to fluid flow. The right side of the equation is the heat conduction. The reaction heat and the reservoir heat flow are considered at the domain boundary described as:

$$q_r + r \Delta H_{r,A} = k_f (n \cdot \nabla T_f) \big|_w \quad (3.5)$$

The diffusion coefficient and The reaction rate constants are strongly temperature-dependent according to the Arrhenius formula:

$$D = D_o \exp \left(- \frac{\Delta E_D}{RT} \right) \quad (3.6)$$

Where R is the universal gas constant, T is the absolute temperature and ΔE_D is the activation energy for the diffusion. Similarly, the reaction rate is a function of the temperature, according to the Arrhenius formula:

$$k_r = k_r^0 \exp\left(-\frac{\Delta E}{RT}\right) \quad (3.7)$$

Where k_r^0 is the pre-exponential factor and ΔE is the activation energy. The boundary states that the heat conducted towards the fracture wall equals the heat of reaction and heat flux from the formation. Therefore, the heat flux from the reservoir can be described as:

$$q_r = \overline{k_e}(n \cdot \nabla T_r)|_w \quad (3.8)$$

Where T_r is the reservoir temperature and $\overline{k_e}$ is the effective (rock & fluids) thermal conductivity and. The heat transfer in the reservoir is solved To obtain the heat flux from the reservoir to the fracture. The heat convection and conduction equation can calculate it:

$$\overline{\rho \hat{c}_p} \frac{\partial T_r}{\partial t} + \rho_f \hat{c}_{pf} \mathbf{u} \cdot \nabla T_r = \nabla \cdot (\overline{k_e} \nabla T_r) \quad (3.9)$$

where $\overline{\rho \hat{c}_p}$ is the average fluid and rock properties. The heat accumulation plus the heat convection within the reservoir equals to the heat conduction.

Then, the etched-width profiles of the hydraulic and natural fractures can be found as follow:

$$\frac{\partial w_e}{\partial t} = \frac{\mathcal{X}}{1 - \varphi} \left(f_a u_L C_{A,w} - D_A \frac{\partial C_A}{\partial y} \Big|_w \right) \quad (3.10)$$

Where w_e is the etched width by acid, χ is the volumetric dissolving power and f_a is the acid lost fraction that reacts at the fracture surfaces. Then, the etched width is used to estimate the fracture conductivity, wk_f , profile based on the Nierode and Kruk correlation (1972) and presented as:

$$wk_f = \alpha e^{-\beta \sigma_c} \quad (3.11)$$

Where σ_c is the closure stress acting normal to the fracture surface, and β and α are constants.

The generated conductivities of the hydraulic and natural fractures go to the productivity model. It is an in-house reservoir simulator that mimics fluid flow in a fractured domain to calculate the productivity by solving the diffusivity equation, shown as:

$$\nabla \cdot (\mathbf{k} \cdot \nabla p) = \phi \mu_r c_t \frac{\partial p}{\partial t} \quad (3.12)$$

Where p is the pressure, ϕ is the rock porosity, μ_r is the reservoir fluid viscosity, and c_t is total compressibility and $\mathbf{k}$ is the permeability tensor. The condition at well boundary can be described as a constant flow rate as in equation 3.13 for solving the diffusivity Equation 3.12:

$$\left(\frac{\partial p}{\partial x} \right)_{wellbore} = - \frac{qB\mu_r}{(wk_f)_o 2h_{fo}} \quad \text{at the wellbore} \quad (3.13)$$

where q is production rate, $(wk_f)_o$ is wellbore-fracture contact conductivity, B is the oil formation volume factor and h_{fo} is the fracture height at the wellbore entrance.

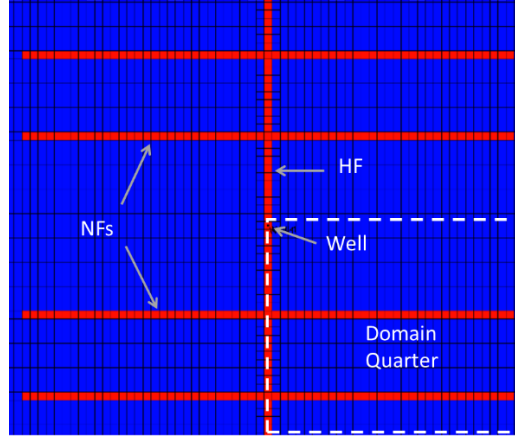


Figure 6: Schematic of the hydraulic and natural fractures simulation domain.

Figure 6 shows the distribution of the hydraulic fracture intersecting multiple natural fractures. The hydraulic fracture is growing in the north-south direction from the center where the well is located. The natural fractures intersect the main hydraulic fracture at 90° angle and extend in the west-east direction. The simulation is done on a quarter of the domain only due to the symmetry of the reservoir. The refinement is done along the hydraulic fraction and the natural fractures. Except at the wellbore, the no-flow boundary condition is applied everywhere within the reservoir quarter:

$$\mathbf{n} \cdot \nabla p = 0 \quad (3.14)$$

The productivity of the fractured well is estimated for a specific acid fracturing design by running simulation of the reservoir flow. The productivity index is calculated using following equation:

$$J = \frac{q}{\Delta p} \quad (3.15)$$

Where Δp is the drawdown pressure and q is the production rate.

3.2 Artificial Intelligence

Three artificial intelligence methods are selected and used to analyze the connection between model inputs and outputs of all performed scenarios to build a model that can be used for productivity enhancement prediction. In addition, an equation was obtained from the artificial neural network developed model. The equation is a quick and reliable predictive tool for enhancement fold.

CHAPTER 4

RESULTS AND DISCUSSION

Compared with calcite, the dolomite reactivity with acid is significantly sensitive to the temperature. As the acid moves into the reservoir, it gets heated by the heat flux from the reservoir. As a result, the reactivity of dolomite with acid sharply increases, creating a bell-shaped conductivity profile. Therefore, using one average conductivity value for the dolomite fracture will predict false reservoir performance.

4.1 Acid Model Cases

Table 1 lists the reservoir properties, and Table 2 lists acid design parameters used to generate the productivity folds.

Table 1: Reservoir properties inputs

Reservoir Properties				
Permeability (md)	Reservoir Tr (°C)	Temp.	Closure Stress (psi)	Natural Fractures Spacing (ft)
0.001	50		5500	10
0.01	100		6000	40
0.1	150		7000	60
1	200		8000	No Natural Fractures
10				

Table 2: Acid design inputs

Acid Design Parameters						
Treatment Vol (bbl)	Acid Conc. (%)	Injection Temp. Ti (°C)	Diffusion Coefficient Di	n	K	Injection Rate qi (bpm)
1500	10	30	0.0001	1	2.0E-05	10
3000	20	40	0.000008	0.55	0.0082	20
4000	30	60				30
4500		80				40
5000						50

4.2 Parametric Study

More than 4,900 Scenarios, including reservoir cases without natural fractures, were performed to evaluate the impact of natural fractures on productivity enhancement by acid fracturing. This part thoroughly studies reservoir properties and acid design parameters of all run cases.

4.2.1 Conductivity Profile

Figures 7 and 8 show the different permeability profiles in calcite mineralogy versus dolomite mineralogy. Figure 7 represents the case of acid fracturing calcite formation with no natural fractures, a 30 bpm injection rate, 1500 bbl of acid treatment volume, and straight acid. The permeability profile is declining as going away from the wellbore.

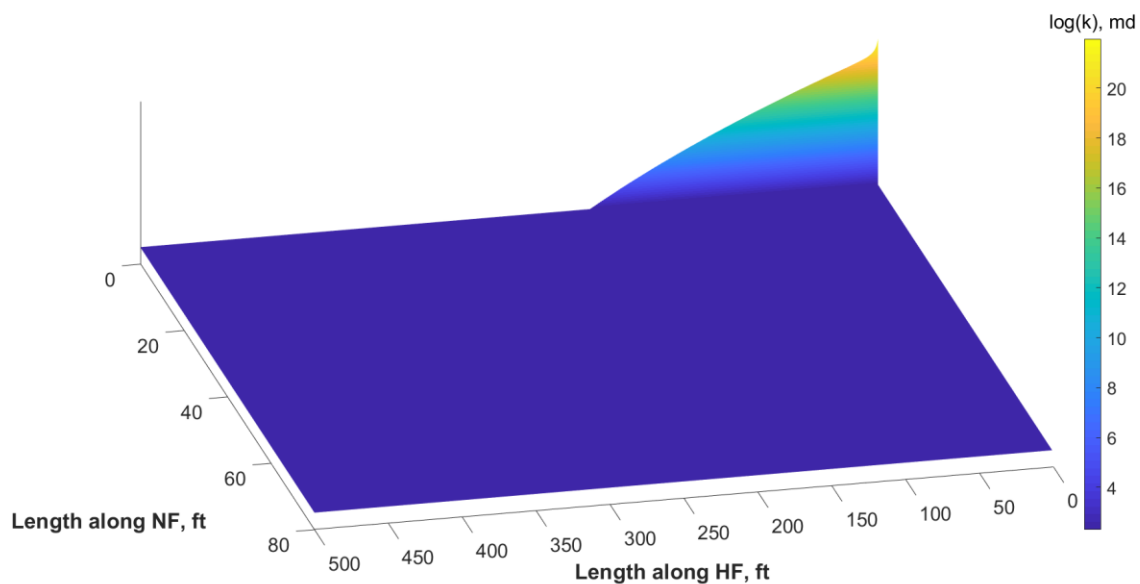


Figure 7: Permeability profile for calcite with straight acid treatment volume 1500 bbl

Figure 8 represents the case of acid fracturing dolomite formation with no natural fractures with a 30 bpm injection rate, 1500 bbl of acid treatment volume, and straight acid. The only difference between Figures 8 and 7 is the mineralogy. The permeability profile in dolomite is bell-shaped.

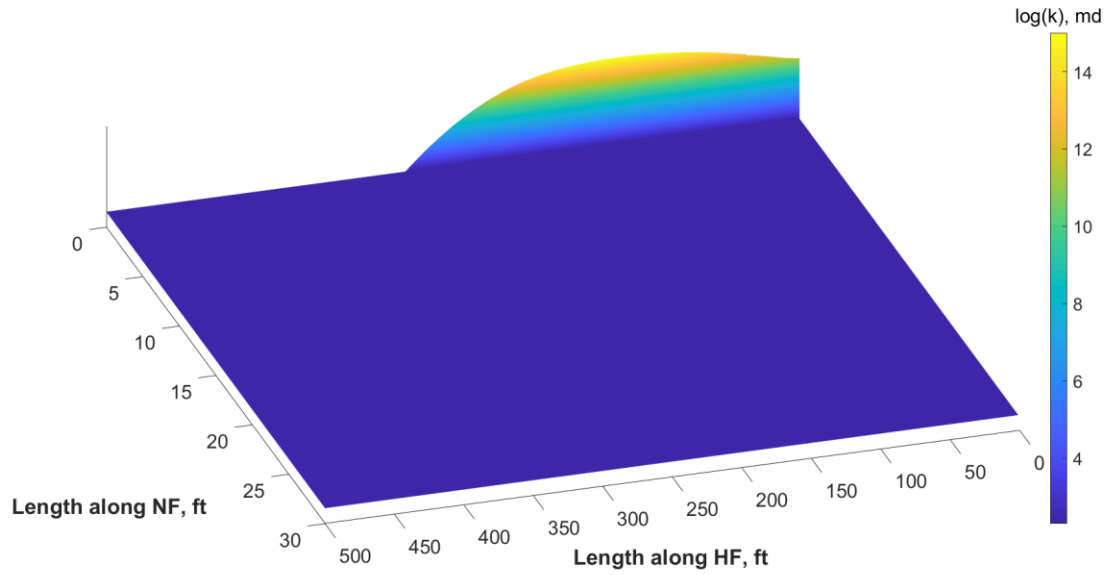


Figure 8: Permeability profile for dolomite with straight, acid treatment volume 1500 bbl.

The etched width in Figure 9 and Figure 10 is for the case of acid fracturing calcite formation with natural fractures intersecting every 10 ft with a 30-bpm injection rate and 1,500 bbls of the straight acid treatment volume. Also, the permeability profile is shown in Figure 11.

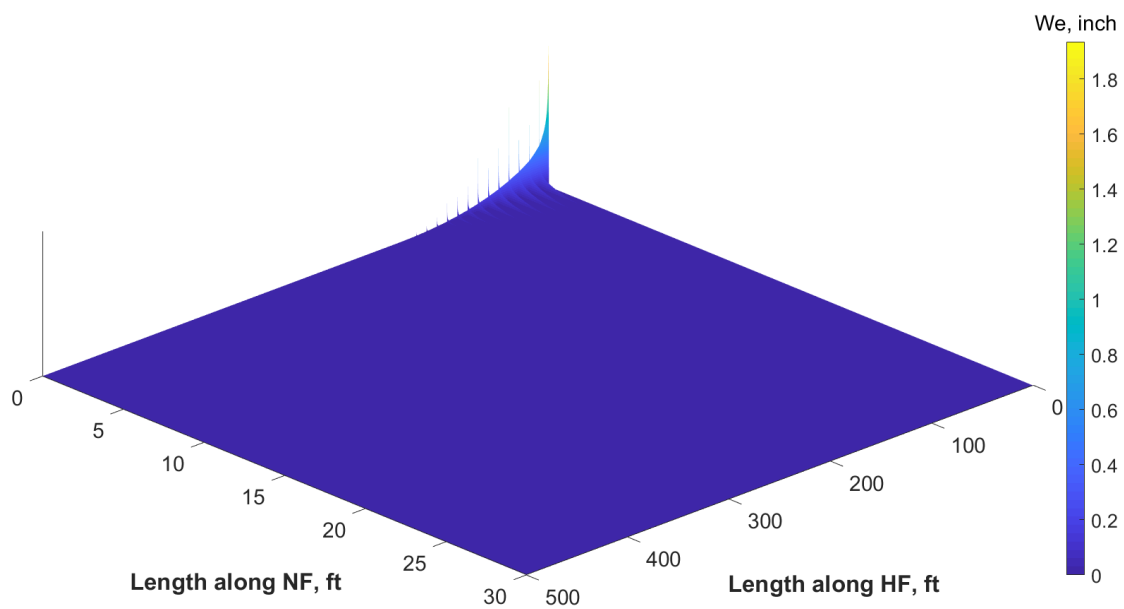


Figure 9: 3D Etched width for limestone with 10' NF spacing

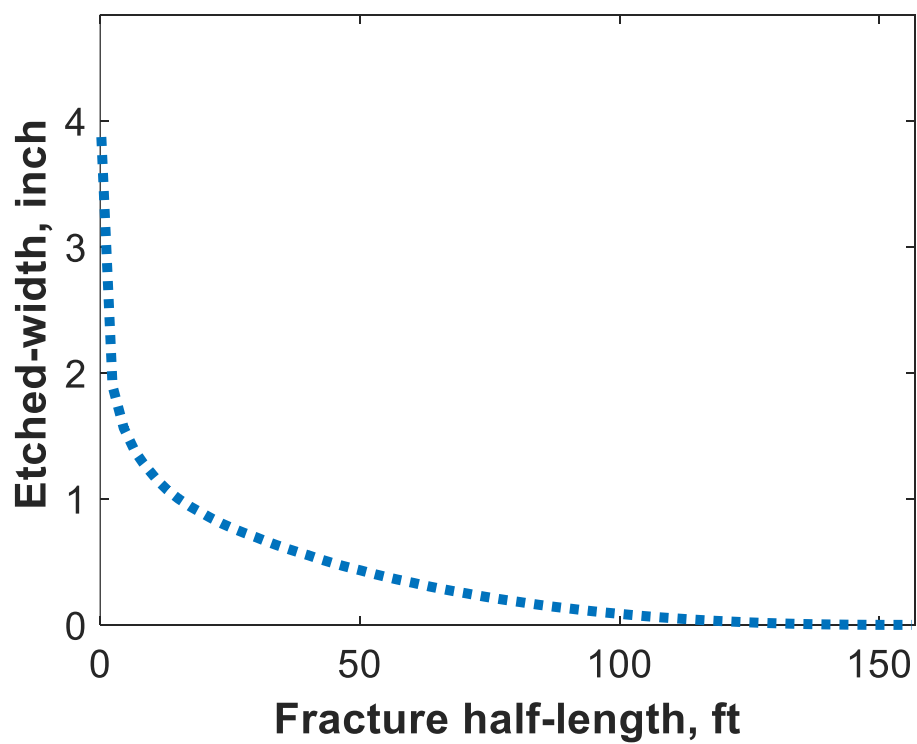


Figure 10: 2D Etched width for limestone with 10' NF spacing

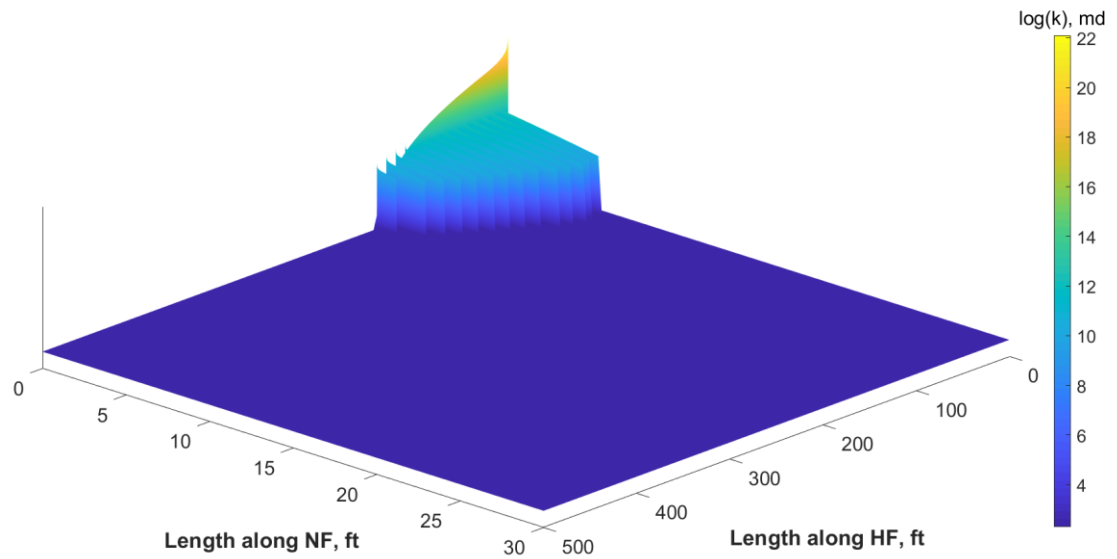


Figure 11: 3D permeability profile for limestone with 10' NF spacing

The etched width in Figures 12 and 13 is for the case of acid fracturing dolomite formation with natural fractures intersecting every 10 ft with a 30-bpm injection rate and 1,500 bbls of the straight acid treatment volume. Also, the permeability profile is shown in Figure 14.

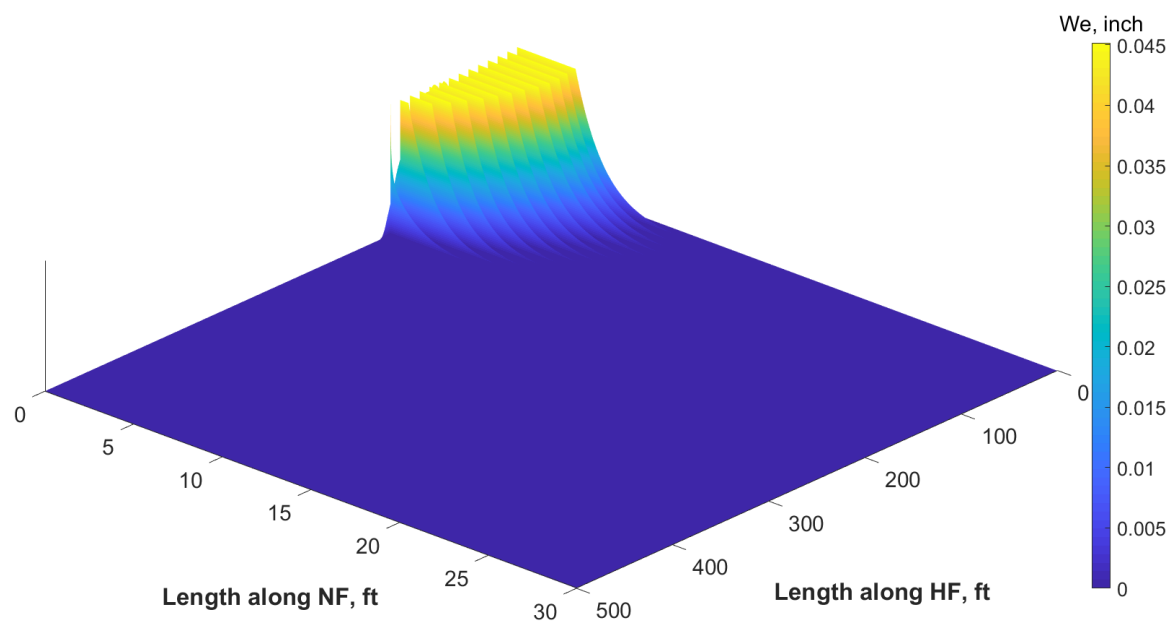


Figure 12: 3D Etched width for dolomite with 10' NF spacing

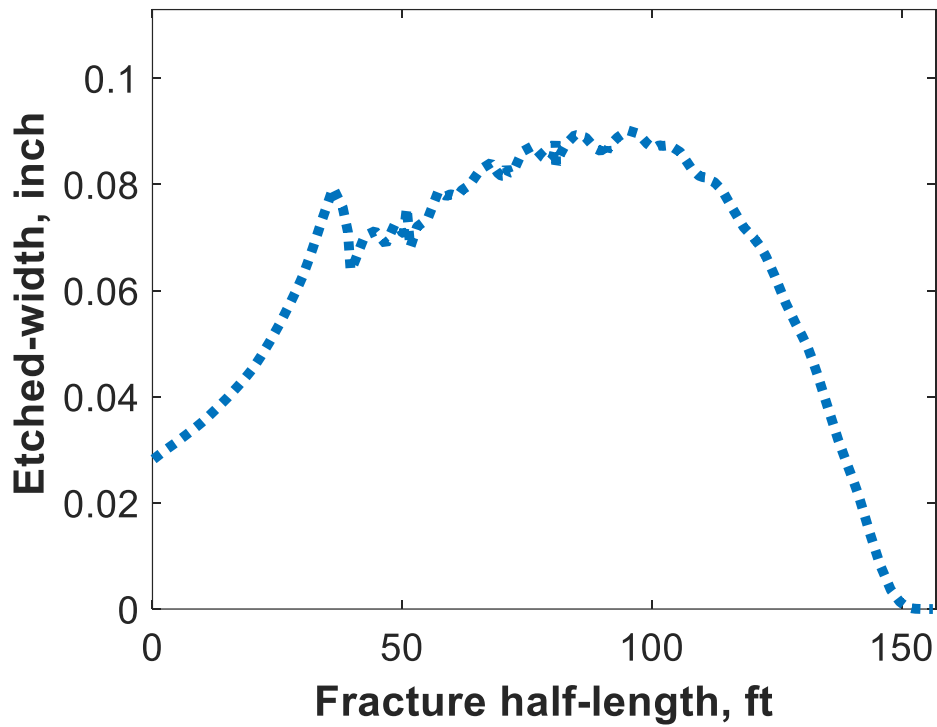


Figure 13: 2D Etched width for dolomite with 10' NF spacing

Figure 14 represents the case of acid fracturing dolomite formation with natural fractures intersecting every 10 ft with a 30-bpm injection rate, 1500 bbls of acid treatment volume, and straight acid. The only difference between Figures 14 and 8 is the existence of the natural fractures. The hydraulic fracture length is significantly reduced because of the natural fractures. As a result, the drainage region gets limited within the wellbore. Hence the well productivity will be less.

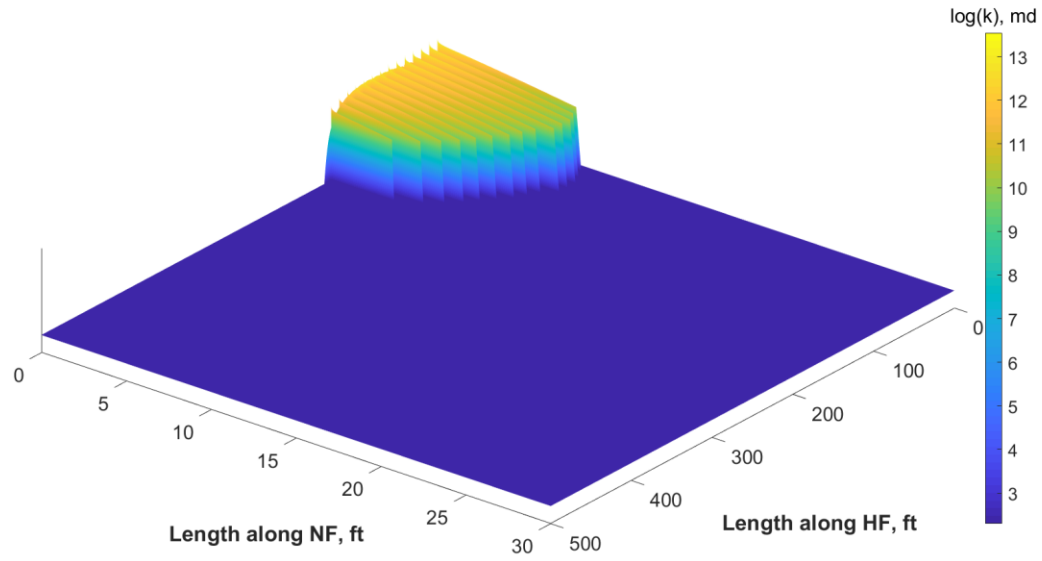


Figure 14: Permeability profile for dolomite with straight acid treatment volume 1,500 bbl & 10 NF

Figure 15 shows the conductivity profile for the same acid fracturing job at two different reservoir's mineralogy. The blue curve is for calcite, and the red curve is for dolomite.

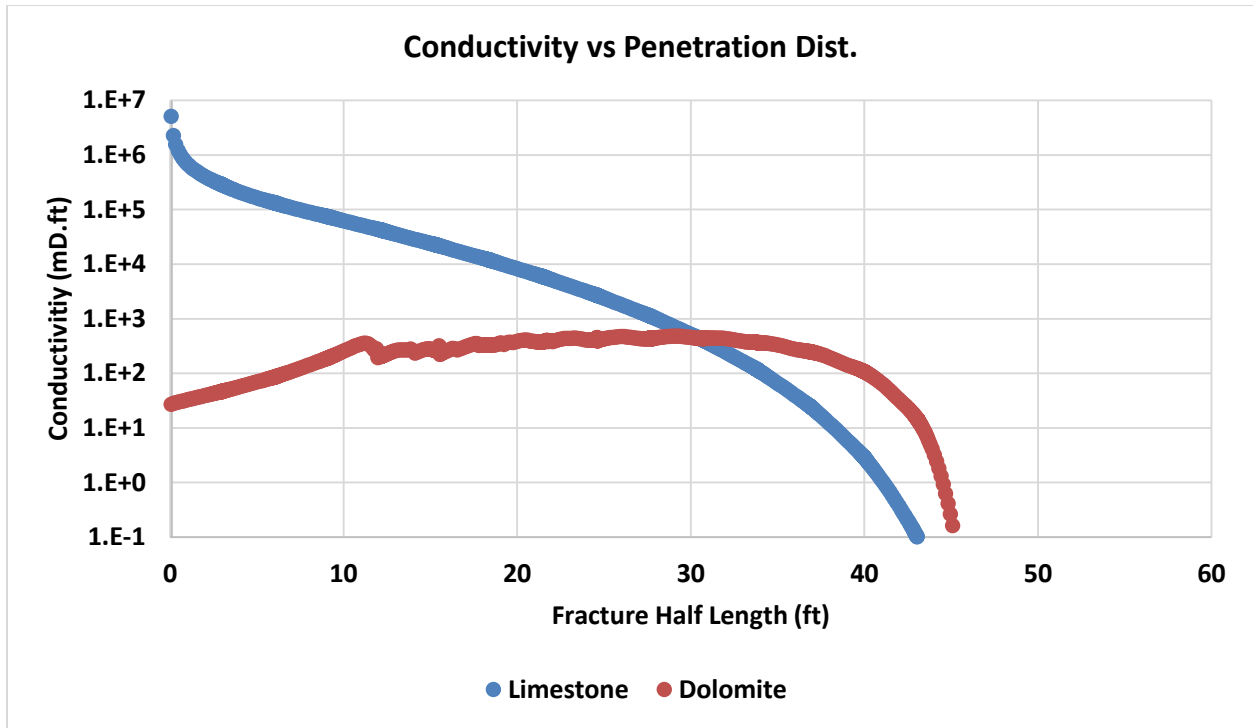


Figure 15: Conductivity profile along the hydraulic fracture for limestone vs. dolomite

The enhancement in the well productivity is impacted by the reservoir mineralogy type, as summarized in table 3. The difference between Limestone and Dolomite gets significant as reservoir permeability increases.

Table 3: Productivity improvement for limestone versus dolomite

PI Folds		
Permeability, mD	Limestone	Dolomite
0.001	3.062	3.119
0.01	3.028	3.095
0.1	2.963	2.964
1	2.863	2.299
10	2.704	1.363

Figure 16 represents the conductivity profile for the case of acid fracturing dolomite formation with natural fractures intersecting every 10 ft with a 30-bpm injection rate, 3,000 bbls of acid treatment volume, and straight acid. The only difference between Figure 16 and Figure 8 is the doubling of the treatment volume. The HF is much longer, the NFs have a better conductivity profile, and the stimulated area is more significant than the smaller volume. Hence the well productivity will be higher.

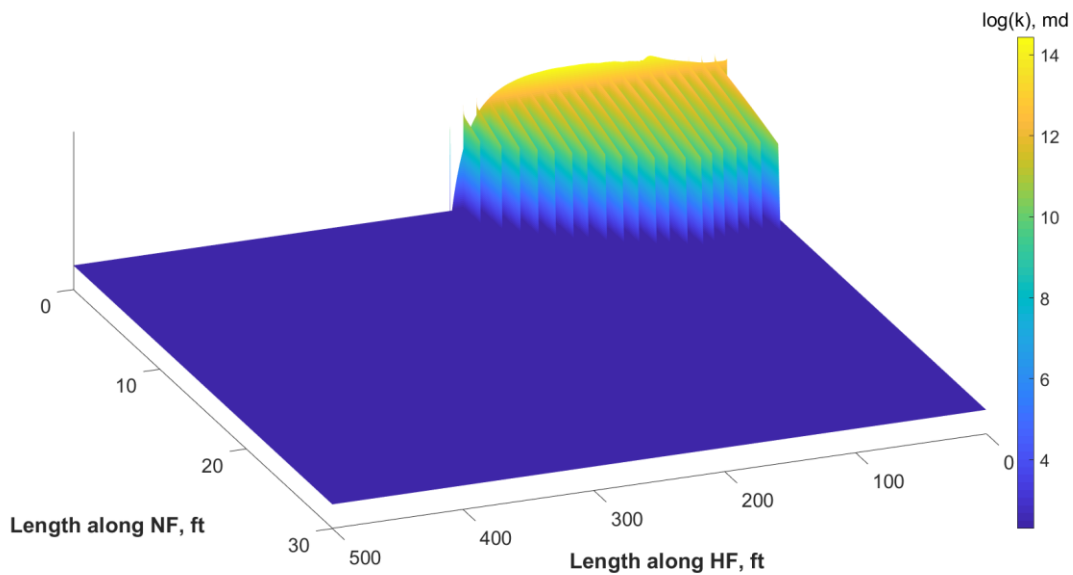


Figure 16: Permeability profile for dolomite with straight acid treatment volume 3000 bbl & 10 NF

Figure 17 represents the conductivity profile for the case of acid fracturing dolomite formation with natural fractures intersecting every 10 ft with a 30-bpm injection rate, 1,500 bbls of acid treatment volume, and straight acid. The only difference between Figure 17 and Figure 8 is the changing acid type to gel acid. The NFs have a better conductivity profile. Hence the well productivity will be higher

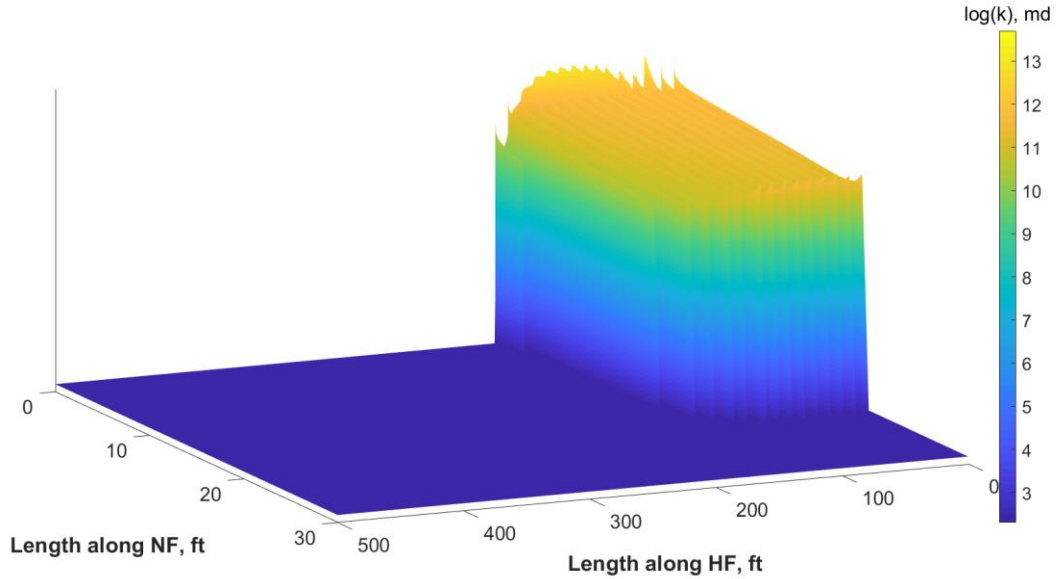


Figure 17: Conductivity profile for dolomite with gel acid treatment volume 1500 bbl & 10 NF

4.2.2 Sensitivity Analysis

A sensitivity analysis is conducted to determine the impact of NF density on acid fractured wells' productivity. The smaller natural fracture spacing means more number NFs. With more natural fractures intersecting the hydraulic fracture, the length of the hydraulic fracture gets shorter because of the additional fluid loss into natural fractures. Figure 18 shows the impact of NF spacing on productivity fold at different reservoir permeabilities. It can be seen that the productivity is getting less for the same permeability at a smaller number of NF. The impact is utmost at the reservoirs with low permeabilities. In a low permeability reservoir, a more extended hydraulic fracture is better; the HF-only case showed way higher productivity.

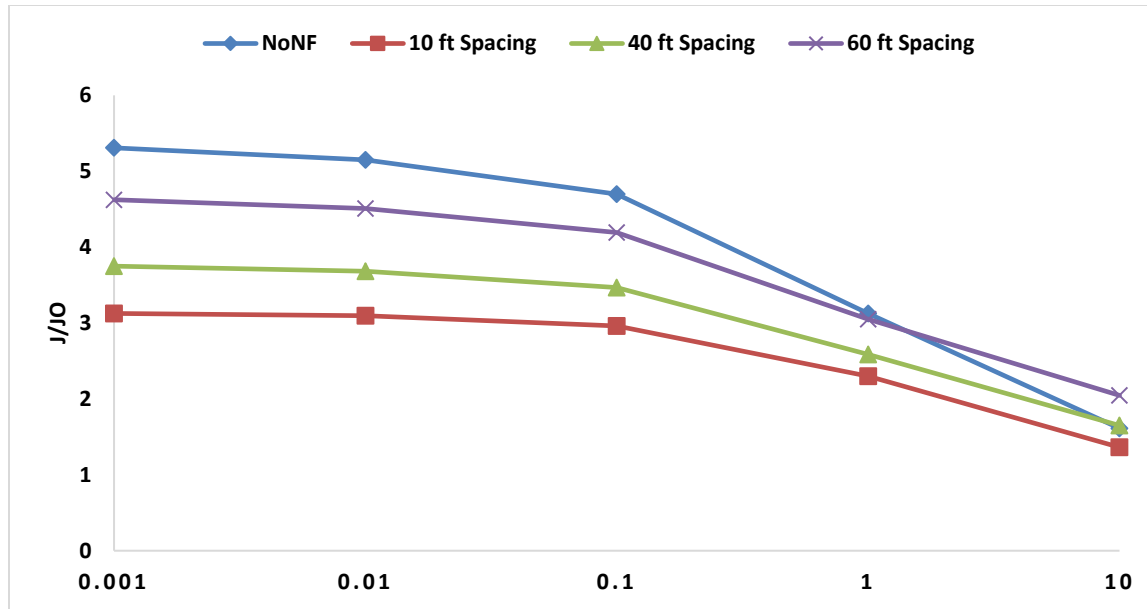


Figure 18: Impact of natural fracture density on productivity folds at different permeabilities.

4.3 Statistical Analysis

This study aimed for the naturally fractured dolomite reservoirs, so the cases with no natural fractures were excluded from the statistical analysis. The statistical analysis results for the productivity folds and acid fracturing design parameters are listed in Table 4.

Table 4: Statistical Analysis of Acid Design Parameters.

Parameters	J/J_o	Treatment Vol. (bbl.)	Conc (wt.%)	T_i (°C)	Diffusion Coefficient (cm ² /s)	n	K	q_i bpm
Minimum	1.1311	1500.00	10.00	30.00	8.00E-06	0.55	2.0E-05	10
Maximum	9.5145	5000.00	30.00	80.00	0.0001	1	0.0082	50
Arithmetic Mean	3.5356	2139.19	20.53	38.92	5.97E-05	0.8031	0.00359	29.149
Geometric Mean	3.3639	1935.82	20.03	36.51	3.31E-05	0.7698	0.00028	25.310
Harmonic Mean	3.1932	1799.64	19.45	34.86	1.66E-05	0.7364	3.55E-5	21.348

Mode	1.6159	1500.00	20.00	30.00	0.0001	1	2.0E-05	20
Range	8.3834	3500.00	20.00	50.00	9.20E-05	0.45	0.00818	40
Mid-Range	5.3228	3250.00	20.00	55.00	5.40E-05	0.775	0.00411	30
Variation	1.2900	1189461.36	18.78	261.1	2.08E-09	0.0499	1.65E-5	193.08
IQR	1.2791	1500.00	0.00	10.00	9.20E-05	0.45	0.00818	20
Standard Deviation	1.1358	1090.62	4.33	16.16	4.56E-05	0.2233	0.00406	13.896
Skewness	1.0436	1.42	0.28	1.73	-0.251699	-0.2517	0.2517	0.0707
Kurtosis	5.2685	3.58	5.18	4.54	1.0633527	1.0634	1.06335	1.7464
Covariance	1.2900	1189461.36	18.78	261.1	2.08E-09	0.0498	1.65E-5	193.08
Coefficient of variation	32.12448	50.98	21.11	41.52	76.40319843	27.8011	112.759	47.6711
CC	1	0.3666	0.0464	-0.045	-0.2179	-0.2179	0.2179	0.1904

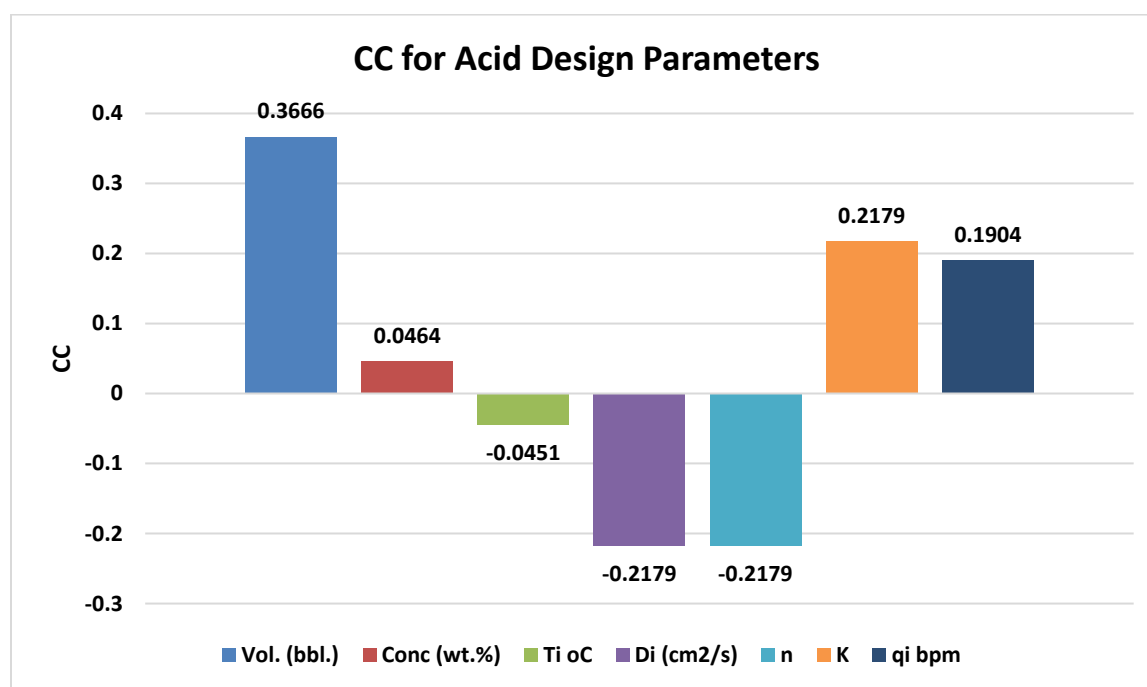


Figure 19: Acid design parameters' relative importance to the productivity folds.

Each acid fracturing design parameter impacts the productivity fold increment by either enhancing or declining. The relative importance of each one was calculated using parametric analysis. Figure 19 shows that the treatment volume, acid concentration, K, and injection rate have positive CC values. Positive CC indicates that increasing these parameter values increases the reservoir productivity fold. The treatment volume has the most significant positive CC value.

On the other hand, the diffusion coefficient, the injection temperature, and n have negative CC values. Negative CC indicates that decreasing these parameters improves the reservoir's productivity fold. These statistical analyses align with some of the general acid fracturing practices. For instance, increasing acid treatment volume generally leads to higher productivity. However, as dolomite reservoirs are reaction-limited, a higher diffusion coefficient lowers the productivity fold. As a result, gelled acid generally gives higher productivity than straight acid.

Furthermore, Table 5 summarizes the reservoir properties' statistical analysis. The examined reservoirs have a wide range of permeability values from very tight reservoir 0.001 to very permeable reservoir 10 mD, a multiple reservoir temperature to evaluate the impact of temperature in dolomite reservoirs, and variation of natural fracture intensity. In addition, the impact of mechanical rock properties such as closure stress between 5,500 and 8,000 psi was tested.

Table 5: Statistical Analysis for the Reservoir Properties.

Parameters	<i>Perm md</i>	<i>Tr °C</i>	<i>Closure Stress (psi)</i>	<i>NF Spacing (ft)</i>
Minimum	0.001	50	5500	10
Maximum	10	200	8000	60
Arithmetic Mean	2.1911624	143.0945946	5591.216216	36.67567568
Geometric Mean	0.0982545	134.8418638	5578.92103	28.8583508

Harmonic Mean	0.0044888	125.1762052	5568.871785	21.18826056
Mode	0.01	150	5500	40
Range	9.999	150	2500	50
Mid-Range	5.0005	125	6750	35
Variation	15.086547	2035.973747	169090.1668	422.0359045
IQR	0.99	100	0	50
Standard Deviation	3.8841404	45.12176578	411.2057475	20.54351247
Skewness	1.491103	-0.186572132	4.901267997	-0.239975909
Kurtosis	3.275646	2.024257751	26.6969395	1.501383082
Covariance	15.086547	2035.973747	169090.1668	422.0359045
Coefficient of variation	177.26392	31.53282338	7.354495545	56.01399862
CC	-0.4731	0.0503	-0.1154	0.4539

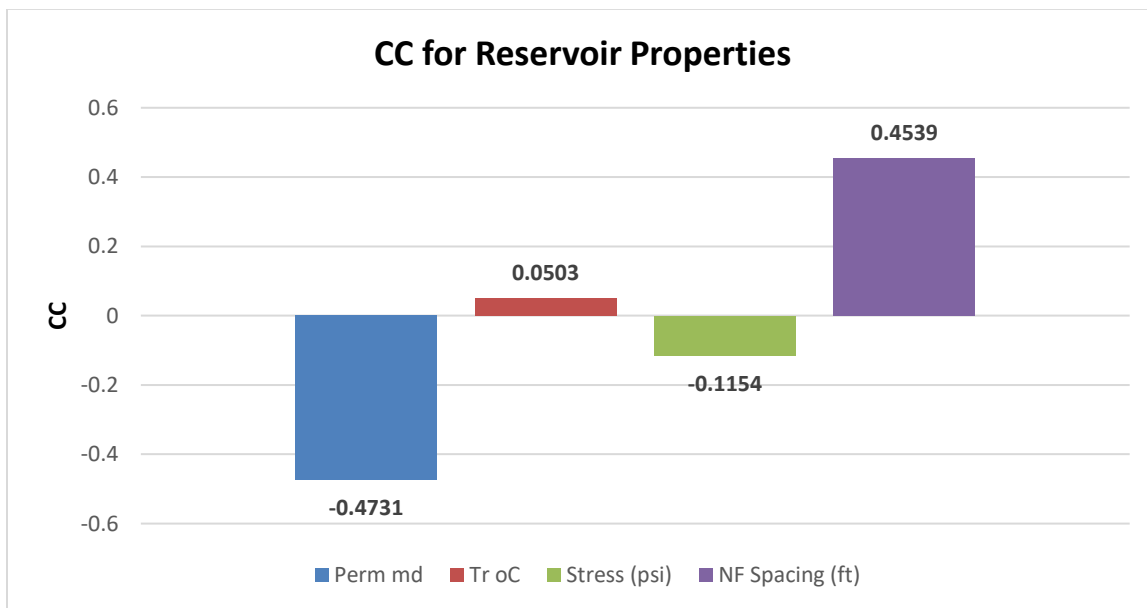


Figure 20: The reservoir properties' relative importance to productivity folds.

Each reservoir parameter impacts the productivity fold, either enhancing or declining. The relative importance of each one was founded using parametric analysis. Figure 20 shows the reservoir properties' relative importance to the productivity fold. From this Figure, the reservoir permeability and closure stress have a negative correlation coefficient. Lowering any of these parameter values will improve the productivity fold of the reservoir. The reservoir permeability has the highest positive CC value among all reservoir properties and acid design parameters. The reservoir permeability significantly impacts the productivity ratio, implying it is much easier to increase in tight reservoirs than in a permeable reservoir.

On the other hand, the reservoir temperature and the natural fracture spacing show positive CC values. Therefore, increasing any of these parameters improves the reservoir productivity fold. However, the natural fracture's spacing significantly impacts the productivity ratio, indicating it is more challenging to increase the productivity ratio in the high density of natural fracture reservoirs.

The reservoir statistical analysis reveals that the most significant impact on productivity is reservoir permeability and the natural fracture intensity. At the same time, the acid design statistical analysis shows that the most critical parameters are the pumping rate, the treatment volume, and the acid type.

The relative importance has been broken down by reservoir permeability to understand how acid design parameters impact well productivity at each permeability. Table 6 lists the relative importance of acid design parameters at different reservoir permeability.

Table 6: Relative importance breakdown by permeability.

Reservoir Properties			Acid Desing Parameters				
Perm	NF	Tr	Vol	Conc.	Ti	Di	qi
(md)	Spacing (ft)	(°C)	(bbl)	(%)	(°C)	(cm ² /s)	(bpm)
0.001	0.585	0.002	0.391	0.021	-0.153	-0.248	0.423
0.01	0.591	-0.007	0.408	0.006	-0.15	-0.27	0.427
0.1	0.567	0.056	0.46	0.059	-0.116	-0.304	0.345
1	0.48	0.2	0.548	0.15	0.042	-0.306	0.018
10	0.403	0.162	0.401	0.071	0.256	-0.156	-0.354

Figure 21 shows the relative importance of acid design parameters to the productivity folds for 0.001 mD permeability. Also, figure 22 shows the relative importance of acid design parameters to the productivity folds for 10 mD permeability. By comparing the two plots, the relative importance values of all parameters are different, especially the injection temperature, which switches from a negative impact in a tight reservoir to a positive impact in a high permeability reservoir. On the contrary, the injection rate switches from being a positive impact in a tight reservoir to a negative impact in a high permeability reservoir

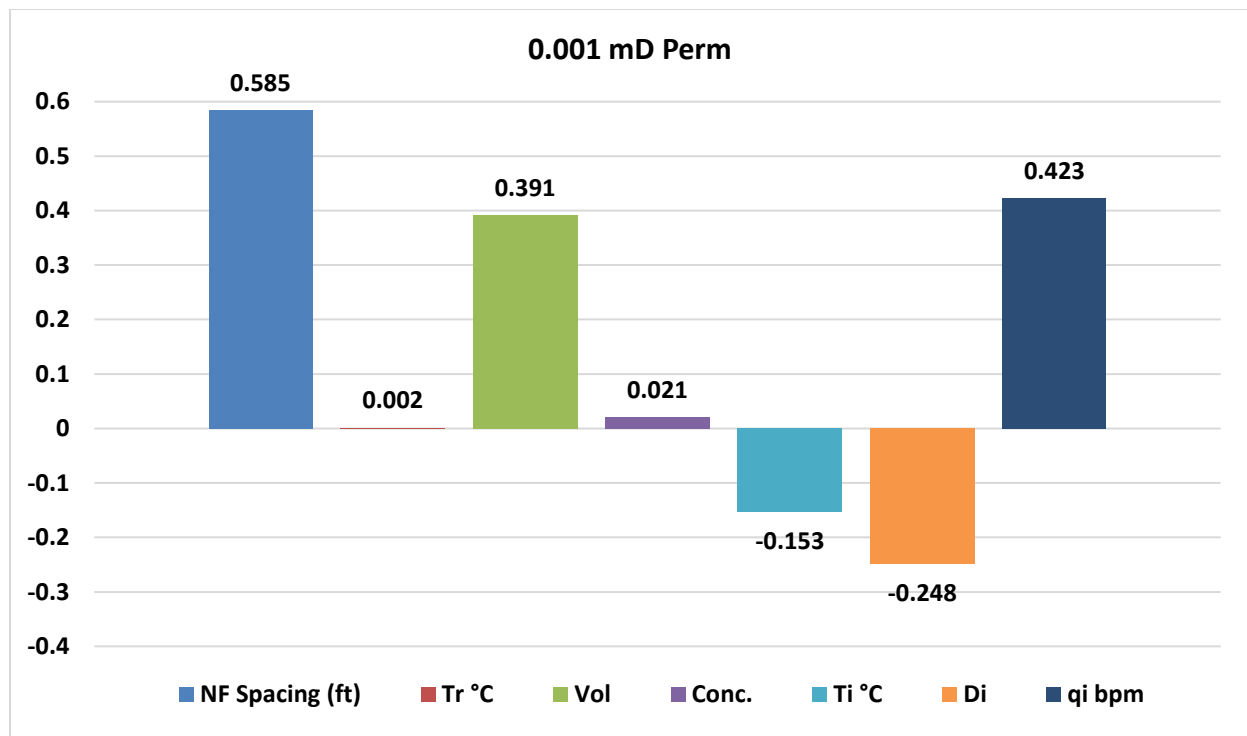


Figure 21: The relative importance of acid design parameters to the productivity folds for 0.001 mD permeability.

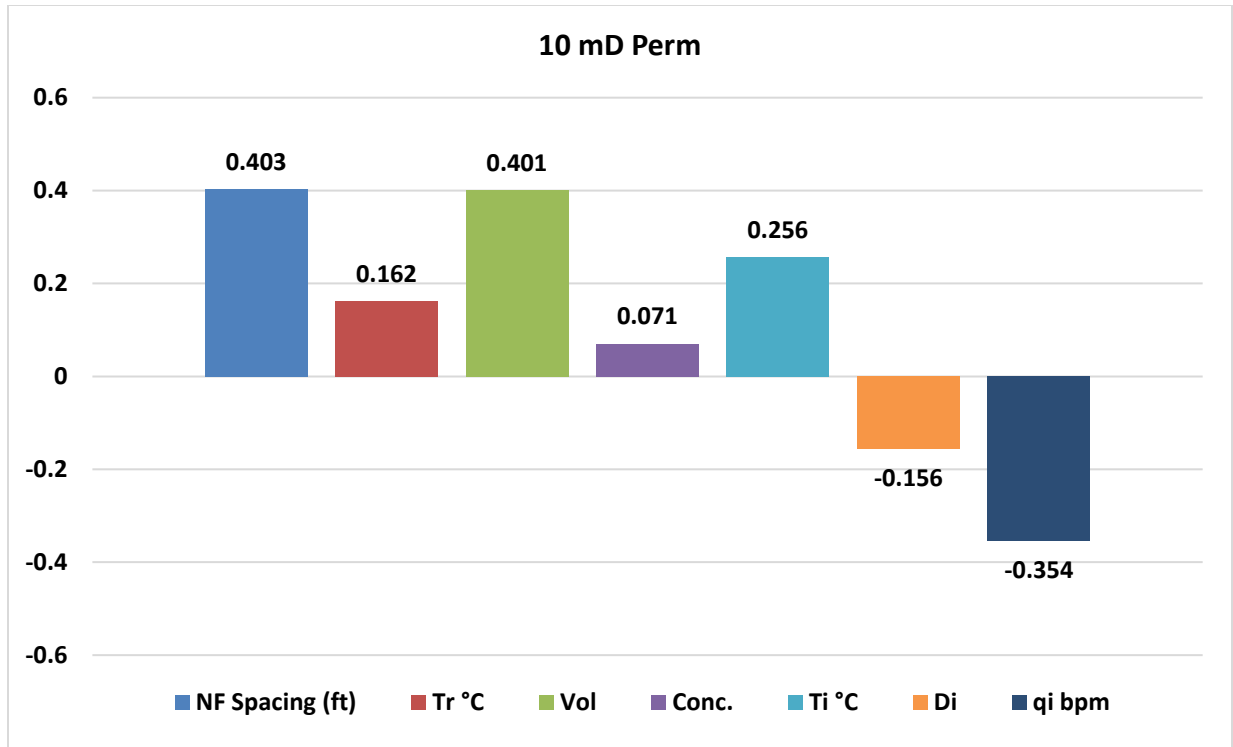


Figure 22: The relative importance of acid design parameters to the productivity folds for 10 mD permeability.

4.4 Acid Optimization

The performed cases with natural fractures have 60 unique reservoirs considering five different permeabilities, three different natural fracture spacing, and four different temperatures (5x3x4). The maximum productivity fold and its acid design parameters for each reservoir are listed in Table 7 for 1,500 bbls acid treatment volume and Table 8 for 3,000 bbls acid treatment volume. It is always favorable if the acid volume increases until a specific volume where the productivity gain does not justify the cost; that is why two treatment volumes are analyzed.

Table 7: Maximum Productivity fold for the different reservoirs at 1500 bbls treatment volume

Rsvr No.	Perm md	NF Spacing (ft)	Tr °C	Max PI	Vol (bbl)	Conc.(%)	Ti °C	qi bpm	Acid Type
1	0.001	10	50	3.478449	1500	20	40	50	Straight
2			100	3.570194		30	30	50	Gel
3			150	4.02176		30	30	10	Straight
4			200	5.792712		30	30	10	Straight
5		40	50	4.449749		20	40	50	Straight
6			100	4.553743		30	30	50	Gel
7			150	4.538751		20	30	50	Gel
8			200	4.531778		30	30	50	Gel
9		60	50	5.714643		20	40	50	Straight
10			100	5.965459		30	30	50	Gel
11			150	5.943006		20	30	50	Gel
12			200	5.939224		30	30	50	Gel
13	0.01	10	50	3.426945	1500	20	40	50	Straight
14			100	3.535947		20	60	50	Gel
15			150	3.534422		20	60	50	Gel
16			200	3.536018		30	30	50	Gel
17		40	50	4.305758		20	40	50	Straight
18			100	4.474141		20	60	50	Gel
19			150	4.468841		20	60	50	Gel
20			200	4.478879		30	30	50	Gel
21		60	50	5.451054		20	40	50	Straight
22			100	5.812166		20	60	50	Gel
23			150	5.802128		20	60	50	Gel
24			200	5.82798		30	30	50	Gel
25	0.1	10	50	3.230058	1500	20	40	50	Straight
26			100	3.483231		20	60	50	Gel
27			150	3.482207		20	60	50	Gel
28			200	3.476091		20	60	50	Gel
29		40	50	3.773923		20	40	40	Straight
30			100	4.31171		20	80	50	Gel
31			150	4.308228		20	80	50	Gel
32			200	4.297655		20	60	50	Gel
33		60	50	4.574507		20	40	40	Straight
34			100	5.489524		20	80	50	Gel
35			150	5.483706		20	80	50	Gel
36			200	5.484727		30	30	50	Gel
37	1	10	50	2.741596	1500	20	40	30	Straight
38			100	3.354599		20	80	50	Gel
39			150	3.354512		20	80	50	Gel

40		40	200	3.347442		20	80	50	Gel
41			50	3.056132		20	40	20	Straight
42			100	3.864062		20	80	50	Gel
43			150	3.873234		20	80	50	Gel
44			200	3.865521		20	80	50	Gel
45		60	50	3.60473		20	40	20	Straight
46			100	4.687201		20	80	50	Gel
47			150	4.705226		20	80	50	Gel
48			200	4.695449		20	80	50	Gel
49	10	10	50	2.377813	1500	20	40	10	Straight
50			100	3.005709		20	80	50	Gel
51			150	3.01303		20	80	50	Gel
52			200	3.009757		20	80	50	Gel
53		40	50	2.565736		20	40	10	Straight
54			100	3.364224		10	30	40	Gel
55			150	3.097238		20	80	30	Gel
56			200	3.093759		20	80	30	Gel
57		60	50	2.947075		20	40	10	Straight
58			100	4.049321		20	30	50	Gel
59			150	3.778869		10	30	50	Straight
60			200	3.542631		20	80	30	Gel

Table 8: Maximum Productivity fold for the different reservoirs at 3000 bbls treatment volume.

Rsvr No.	Perm md	NF Spacing (ft)	Tr °C	Max PI	Vol (bbl)	Conc. (%)	Ti °C	qi bpm	Acid Type
1	0.001	10	50	4.102115	3000	20	30	50	Straight
2			100	4.217105		20	30	50	Gel
3			150	4.19517		20	30	50	Gel
4			200	5.732994		20	30	20	Straight
5		40	50	5.525781		20	30	50	Straight
6			100	5.707911		20	30	50	Gel
7			150	5.6939		20	30	50	Gel
8			200	5.66657		20	30	50	Gel
9		60	50	7.742364		20	30	50	Straight
10			100	8.023739		20	30	50	Gel
11			150	8.009356		20	30	50	Gel
12			200	7.980718		20	30	50	Gel
13	0.01	10	50	4.022525	3000	20	30	50	Straight
14			100	4.163013		20	30	50	Gel
15			150	4.171846		20	30	50	Gel
16			200	4.169256		20	30	50	Gel

17		40	50	5.295109		20	30	50	Straight
18			100	5.568334		20	30	50	Gel
19			150	5.585856		20	30	50	Gel
20			200	5.581343		20	30	50	Gel
21		60	50	7.259854		20	30	50	Straight
22			100	7.768787		20	30	50	Gel
23			150	7.800516		20	30	50	Gel
24			200	7.782024		20	30	50	Gel
25	0.1	10	50	3.599516	3000	20	30	40	Straight
26			100	3.874294		20	30	50	Gel
27			150	3.969564		20	30	50	Gel
28			200	4.002417		20	30	50	Gel
29		40	50	4.392331		20	30	40	Straight
30			100	4.939892		20	30	50	Gel
31			150	5.184043		20	30	50	Gel
32			200	5.266395		20	30	50	Gel
33		60	50	5.624572		20	30	40	Straight
34			100	6.573516		20	30	50	Gel
35			150	7.006601		20	30	50	Gel
36			200	7.145339		20	30	50	Gel
37	1	10	50	3.0329	3000	20	30	20	Straight
38			100	3.264996		20	30	20	Gel
39			150	3.345112		20	30	30	Gel
40			200	3.40527		20	30	30	Gel
41		40	50	3.526014		20	30	20	Straight
42			100	3.981563		20	30	20	Gel
43			150	4.128354		20	30	30	Gel
44			200	4.26245		20	30	30	Gel
45		60	50	4.204162		20	30	20	Straight
46			100	4.946118		20	30	20	Gel
47			150	5.191602		20	30	30	Gel
48			200	5.390722		20	30	30	Gel
49	10	10	50	2.60329	3000	20	30	10	Straight
50			100	2.806297		20	30	10	Gel
51			150	2.844738		20	30	10	Gel
52			200	2.863344		20	30	10	Gel
53		40	50	2.850115		20	30	10	Straight
54			100	3.209515		20	30	10	Gel
55			150	3.292036		20	30	10	Gel
56			200	3.321908		20	30	10	Gel
57		60	50	3.328112		20	30	10	Straight
58			100	3.818071		20	30	10	Gel
59			150	3.927413		20	30	10	Gel

60			200	3.960194		20	30	10	Gel
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Reservoir permeability has the most significant impact on productivity. In order to have an overall picture, the 60 reservoirs are summed up into five reservoirs based on permeability. Within each permeability segment, there are 12 reservoirs with different reservoir temperatures and natural fracture spacing. Table 9 lists average acid design parameters using 1,500 bbls of the acid treatment volume, while Table 10 lists average acid design parameters using 3,000 bbls of the acid treatment volume

Table 9: Average acid design parameters based on Table 4.5 at different permeabilities.

Perm (mD)	Conc. (%)	Ti °C	qi bpm	Vol (bbl)
0.001	26	33	43	1500
0.01	23	48	50	1500
0.1	21	59	48	1500
1	20	70	43	1500
10	18	58	34	1500

Table 10: Average acid design parameters based on Table 4.5 at different permeabilities.

Perm (mD)	Conc. (%)	Ti °C	qi bpm	Vol (bbl)
0.001	20	30	47.5	3000
0.01	20	30	50	3000
0.1	20	30	47.5	3000
1	20	30	25	3000
10	20	30	10	3000

CHAPTER 5

PRODUCTIVITY FOLD PREDICTION USING MACHINE-LEARNING TECHNIQUES (MODELLING RESULTS)

5.1 Artificial Intelligence Approach

For predicting productivity folds (J/J_0), three methods of AI are used. These methods are support vector machine (SVM), fuzzy logic system (FLS), and the artificial neural network (ANN). These methods are selected for their effectiveness in building correlation for performance prediction.

Figure 23 summarizes the workflow to select the best AI model.

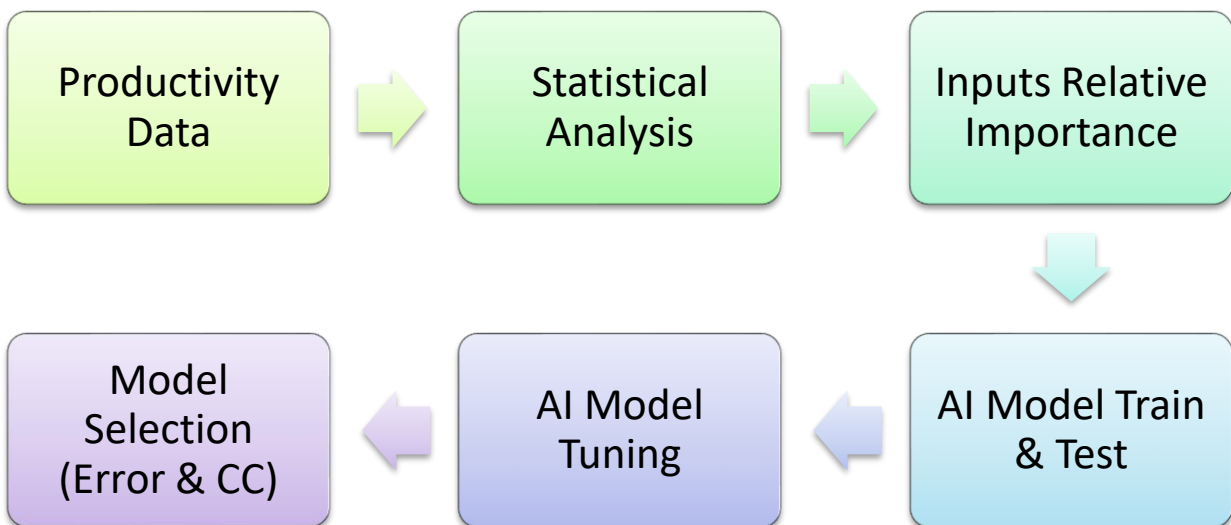


Figure 23: Workflow of AI modeling

Preparing Data

More than 4,900 scenarios were performed utilizing the previously described acid model. These data were randomly split into two groups: the training group, 70% of the data, and the remaining 30%, the testing group. The training group is used for the AI model training to find the relationship between the input (reservoir and acid fracture design parameters) and the output (the productivity folds). In addition, because the testing data group was unseen during the training phase, they can assess the model reliability.

AI Model Assessment and Tuning

The average absolute percentage error, Correlation coefficient, and average absolute deviation are used to assess and rank the AI models. These indices can be calculated using Equations 5.1 – 5.3 correspondingly. The selection criteria for the best AI model is the highest correlation coefficient (CC) with the lowest error. Improving the AI model indices requires tweaking the model parameters to lessen the estimated error of the testing data set and increase the correlation coefficient value. There are no unique numbers. For example, in the ANN, the number of neurons can be tested at different values. A higher number of neurons does not certainly give the best results.

$$AAPE (\%) = \frac{100}{N} \sum_{i=1}^N \left| \frac{(Y_p)_i - (Y_a)_i}{(Y_a)_i} \right| \quad (5.1)$$

$$CC = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \quad (5.2)$$

$$AAD = |(Y_p)_i - (Y_a)_i| \quad (5.3)$$

Where Y_p is the predicted productivity ratio and Y_a is the actual productivity ratio.

This section talks about the performance of the three AI models in estimating the productivity folds. Each AI model parameter was adjusted to minimize prediction errors. The AI models were run using in-house MATLAB codes.

5.2 Support Vector Machine.

The first method is the support vector machine (SVM). It requires a relatively lower computational load than other AI methods and can be used for prediction and categorization. It uses the kernel function in the training phase.

SVM models use the kernel function of Gaussian type. After a series of trial-and-error to minimize the estimation errors, the optimum SVM model was selected. The values of conditioning parameters are 0.1 for lambda and 0.001 for epsilon, and 3000 for the bound for lagrangian multipliers.

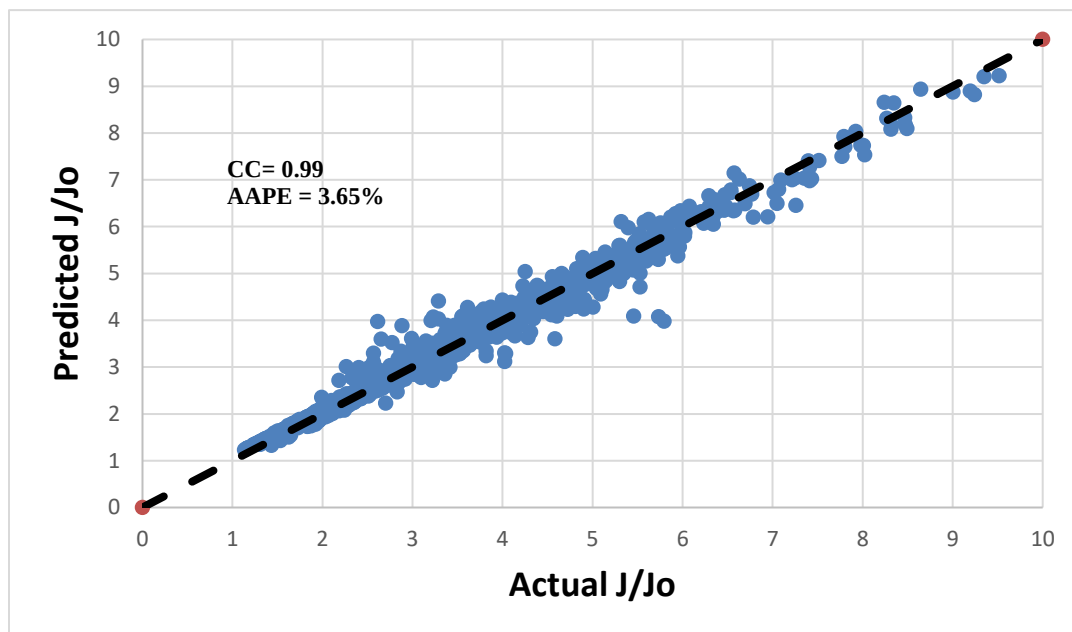


Figure 24: Predicted productivity folds versus Actual ones (SVM model, for training)

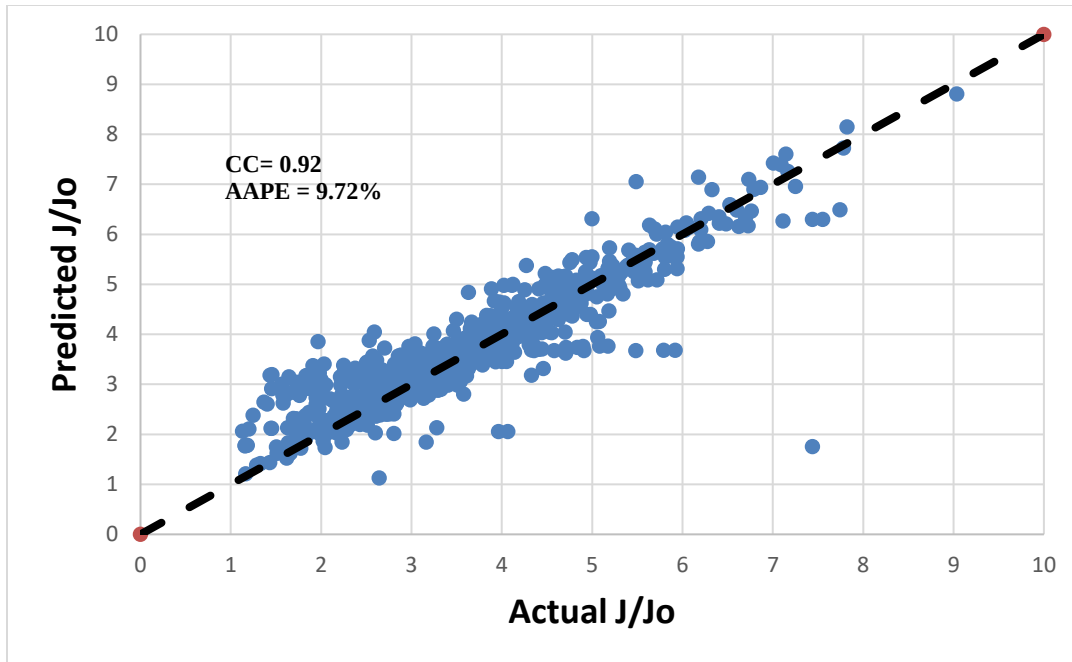


Figure 25: Predicted productivity folds versus Actual ones (SVM model, for testing)

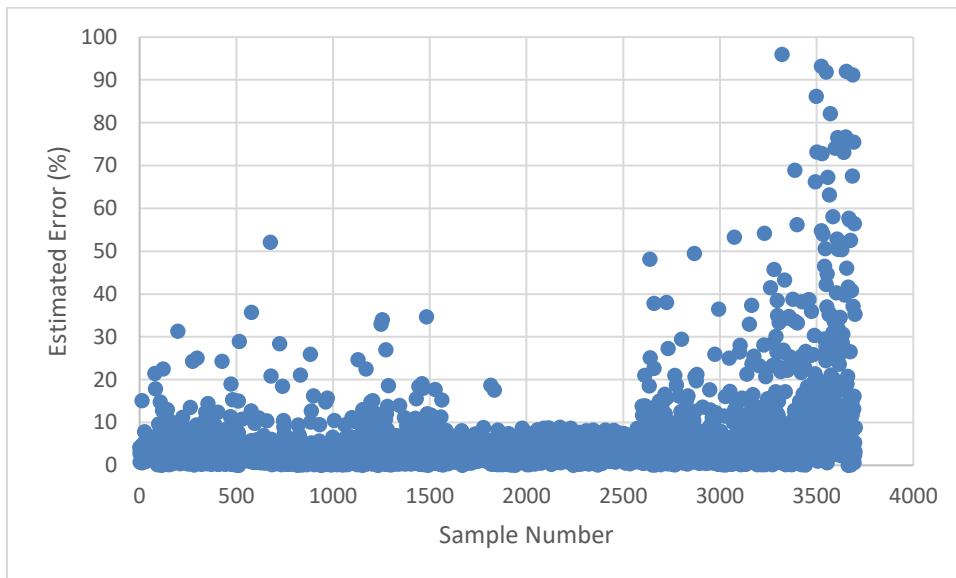


Figure 26: Error distribution (SVM model).

Figure 26 displays all prediction errors for all cases. Overall, it is showing poor performance as some of them exceed 90%

5.3 Fuzzy logic Model

The second method is the fuzzy logic system used effectively in several petroleum applications such as permeability prediction and drilling optimization. It is an integral of fuzzy logic with neural network technique. It works by allocating a partial truth or relevance from zero to one for the training data.

The selected model has five membership functions, Gaussian input, and linear output membership functions, a cluster radius of 0.5, and a maximum number of iterations of 200. In addition, the fuzzy logic model performs prediction better than the SVM model as it has a lower error and higher correlation coefficient.

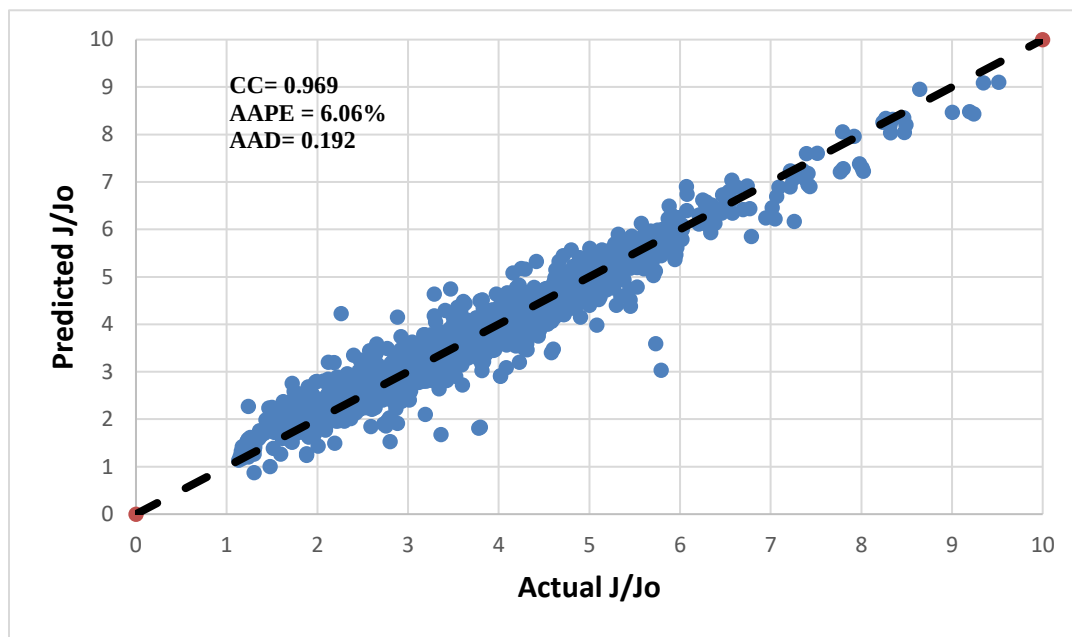


Figure 27: Predicted productivity folds versus Actual ones (FL model, for training)

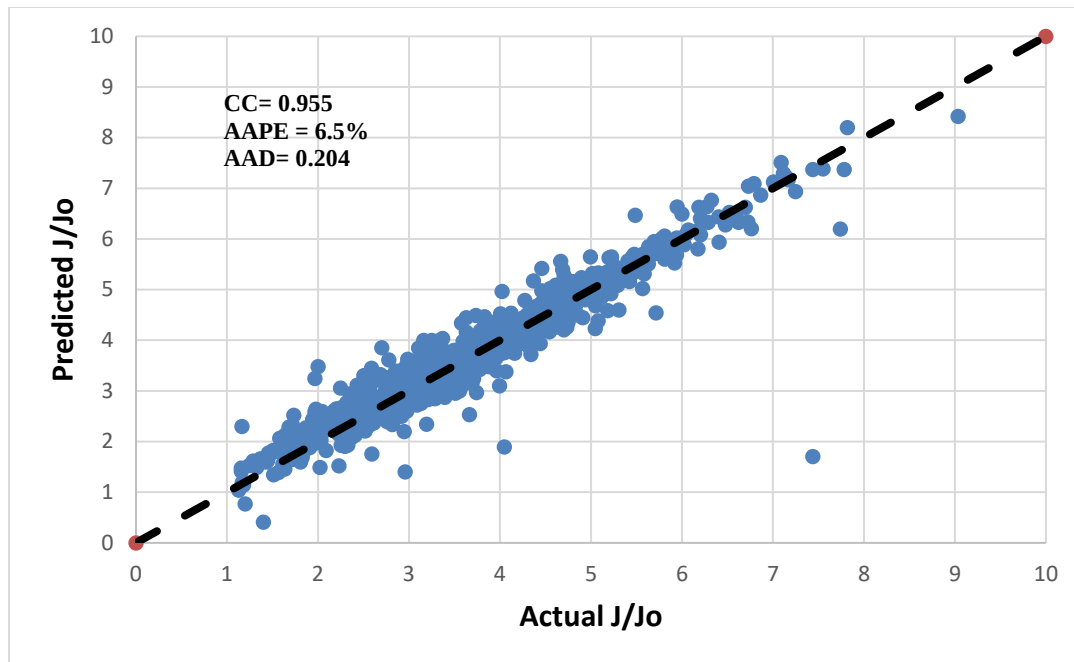


Figure 28: Predicted productivity folds versus Actual ones (FL model, for testing)

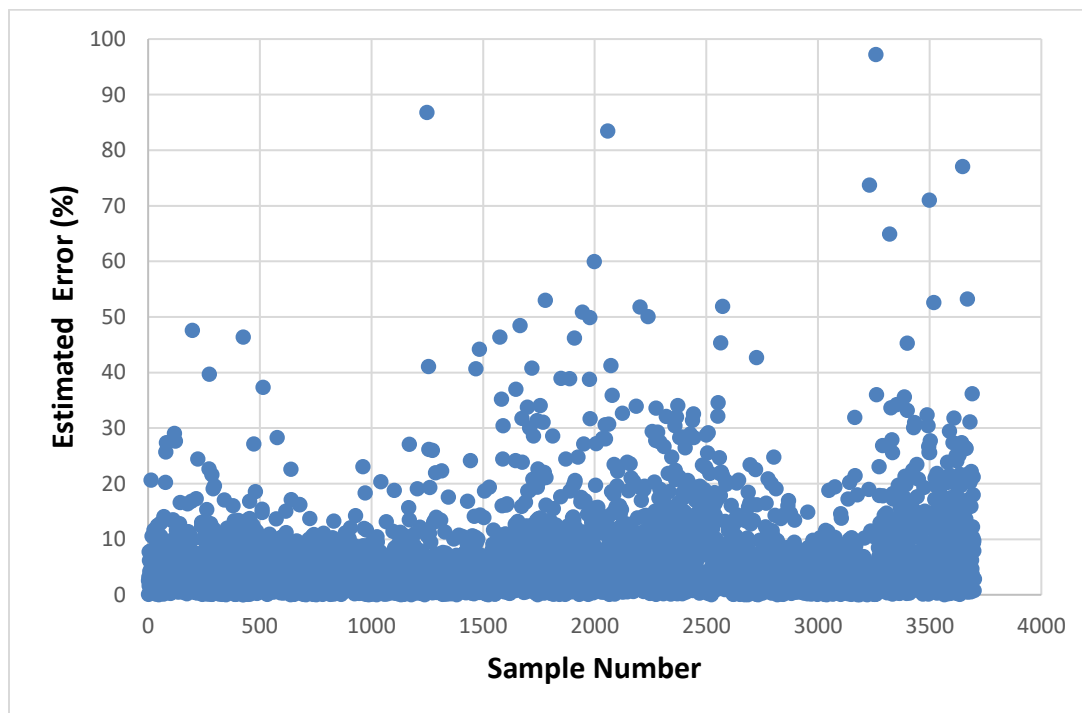


Figure 29: Error distribution (FL model).

5.4 Artificial Neural Network

The third method is an artificial neural network (ANN), which is very common in prediction or classification studies. First, the training is done on a data set segment to determine the relationship between input data and the target output. After that, the remaining data unseen in training is used to evaluate the model's reliability. It can be one or multiple hidden layers with an assigned number of neurons for each layer.

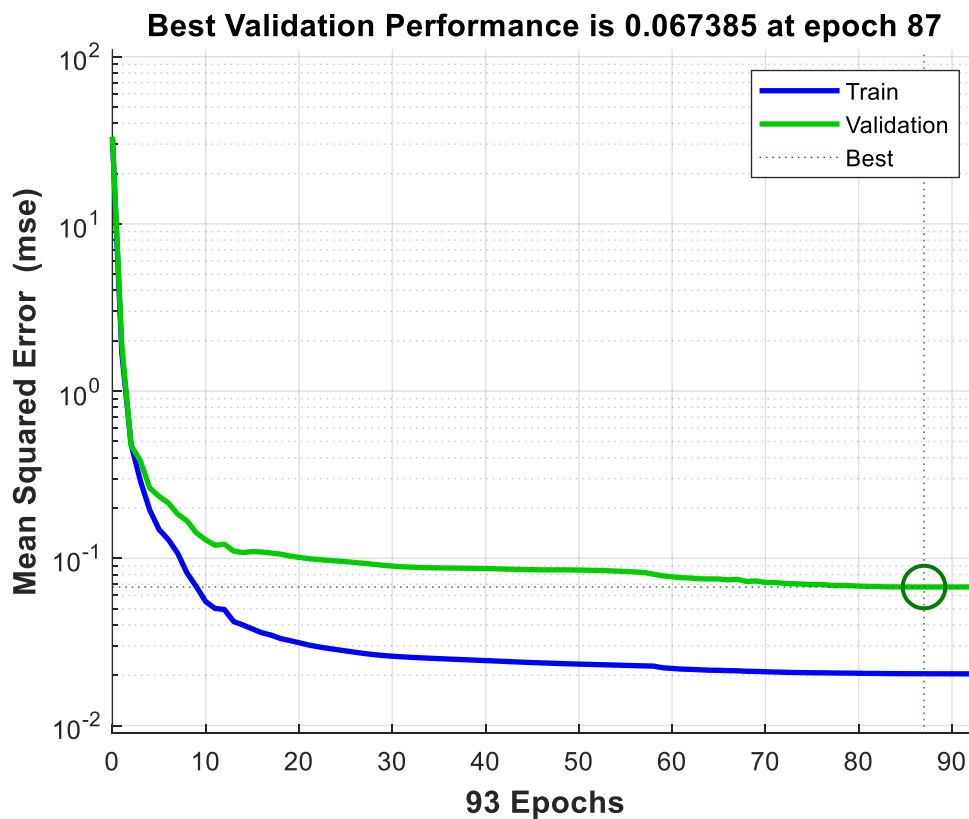


Figure 30: Performance of ANN model during the training and validation stages

Figure 30 displays the ANN model performance during the training and validation phases. It is observed that the validation error is always higher than the training error. Therefore there is no model memorization.

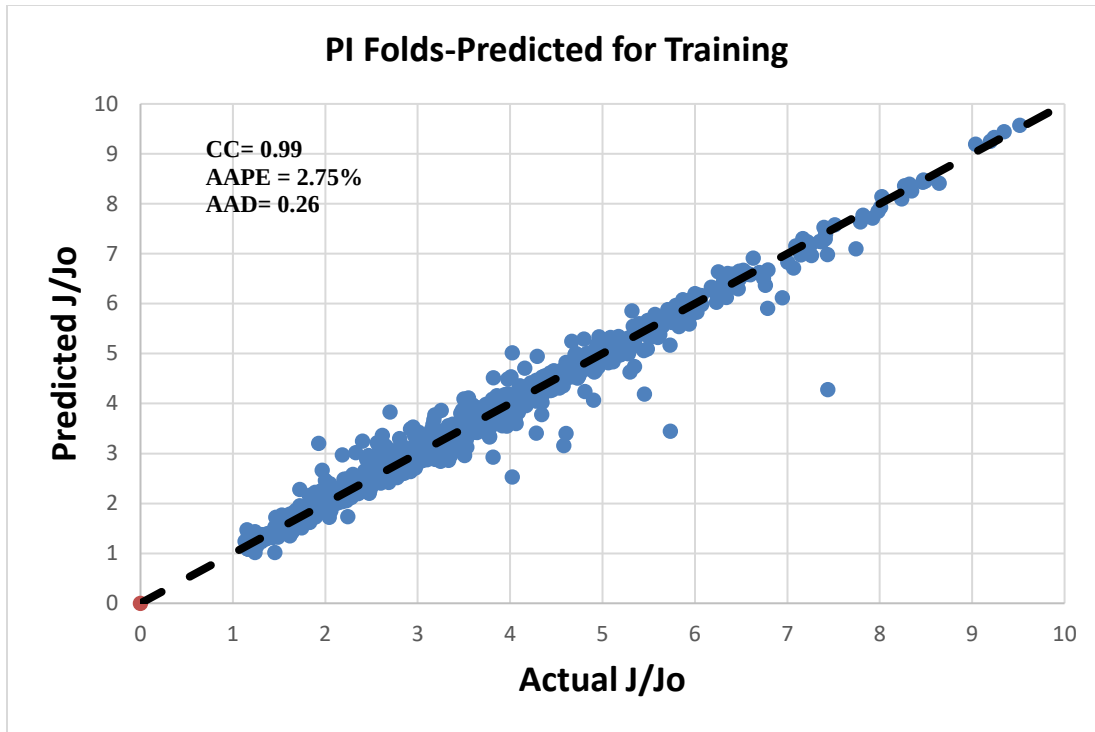


Figure 31: Predicted productivity folds versus actual ones using (ANN model, training data set)

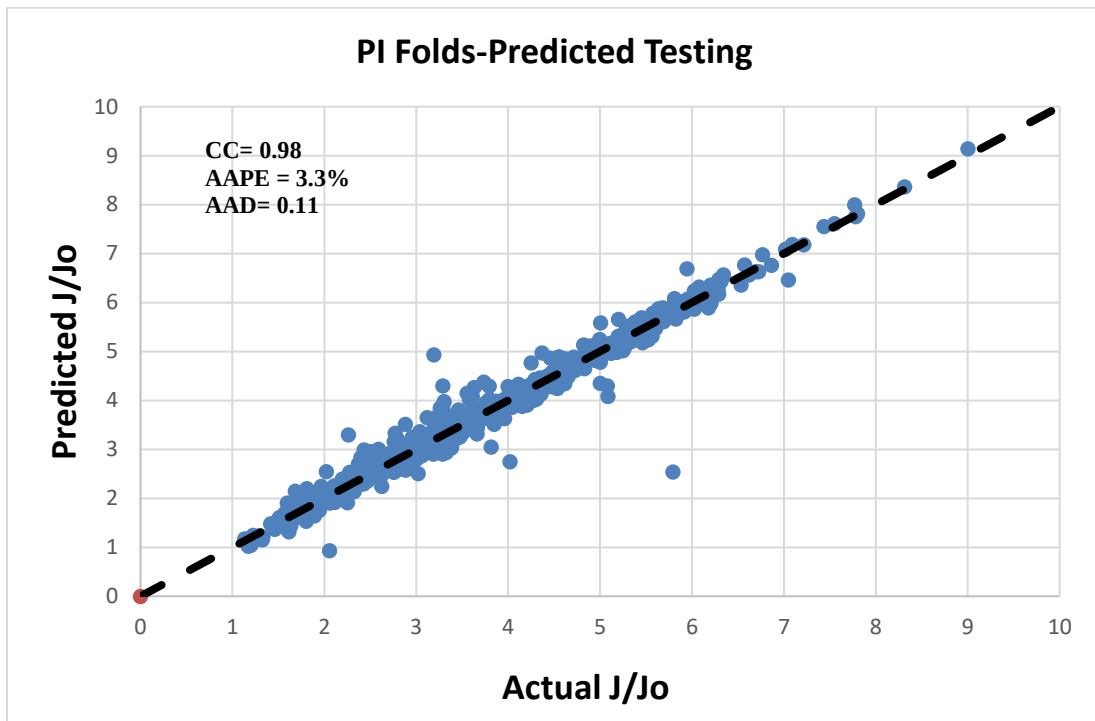


Figure 32: Predicted productivity folds versus actual ones using (ANN model, testing data set)

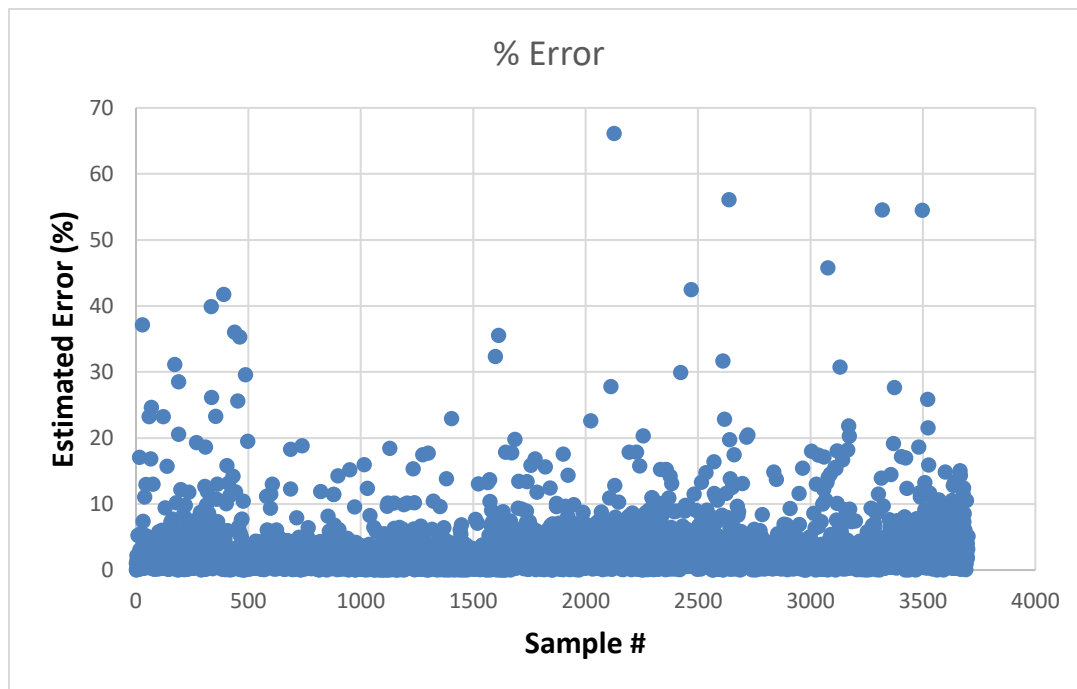


Figure 33: Error distribution (ANN model).

The overall estimated error has been broken down as per injection rate as in Figure 34. The lowest error is between 20-30 bpm. The error increases as the injection rate get lower or higher than this range.

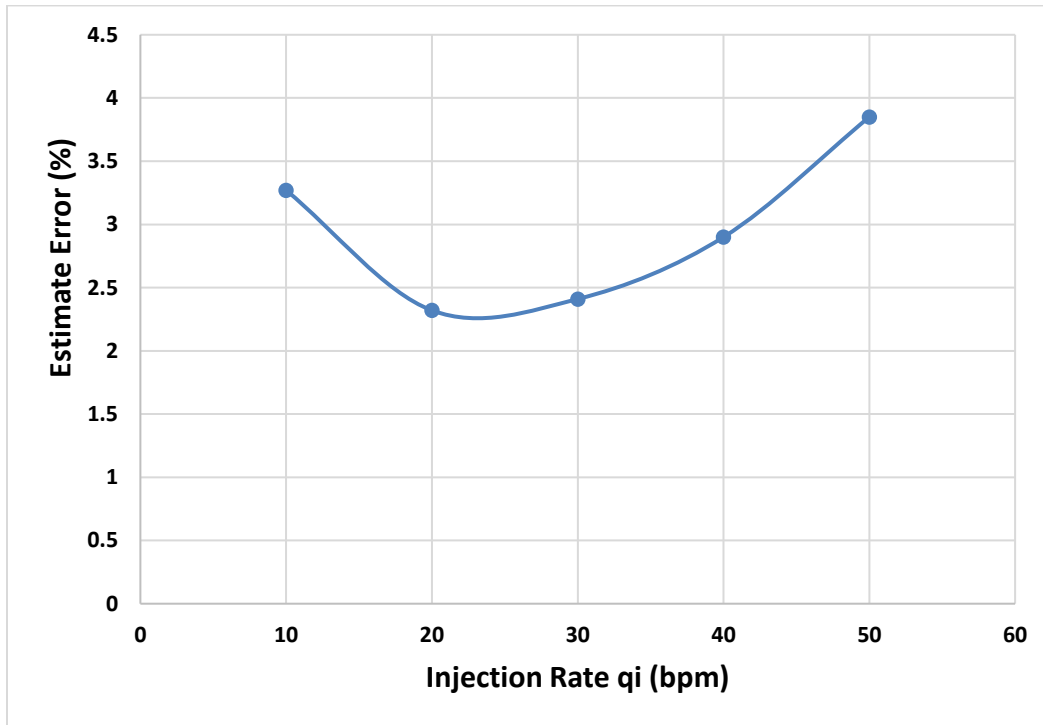


Figure 34: Estimation error as per injection rate.

Also, the overall estimated error has been broken down as per natural fracture spacing as in Figure 35. The lowest error is at 40 ft NF spacing. The error increases as NF spacing gets lower or higher than 40 ft.

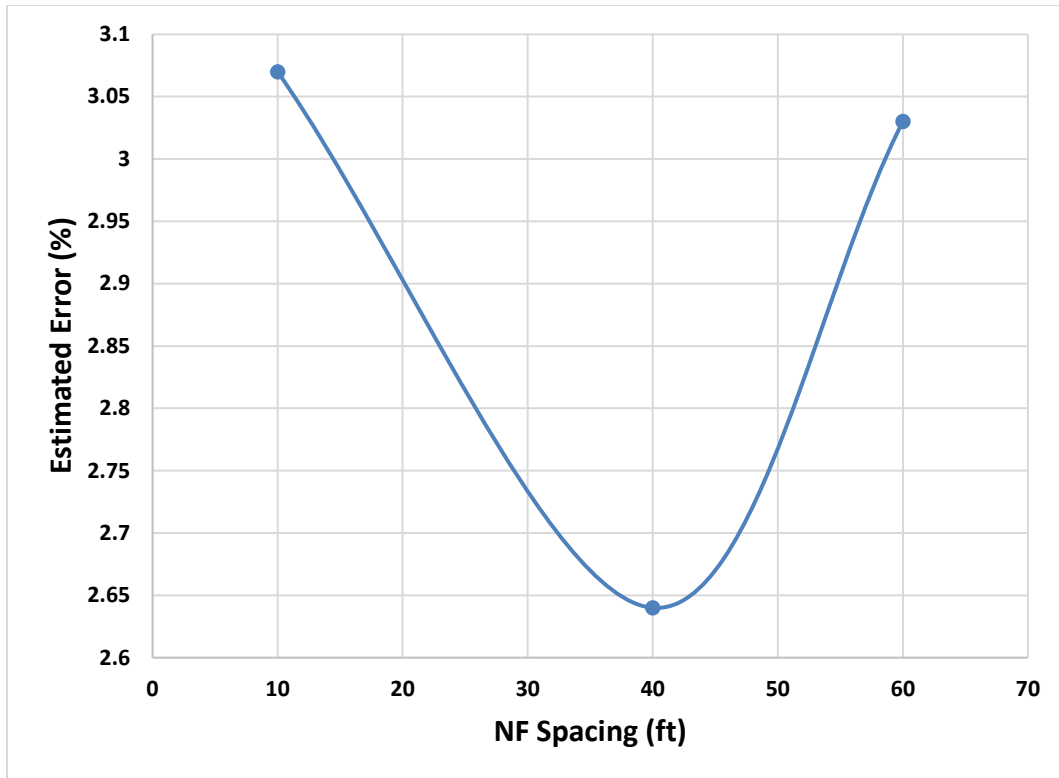


Figure 35: Estimation error as per natural fracture spacing.

Finally, the estimated error has been broken down per reservoir permeability as in Figure 36. The lowest error is at 0.01 mD. Then going lower or higher than this 0.01 mD causes the error to go higher.

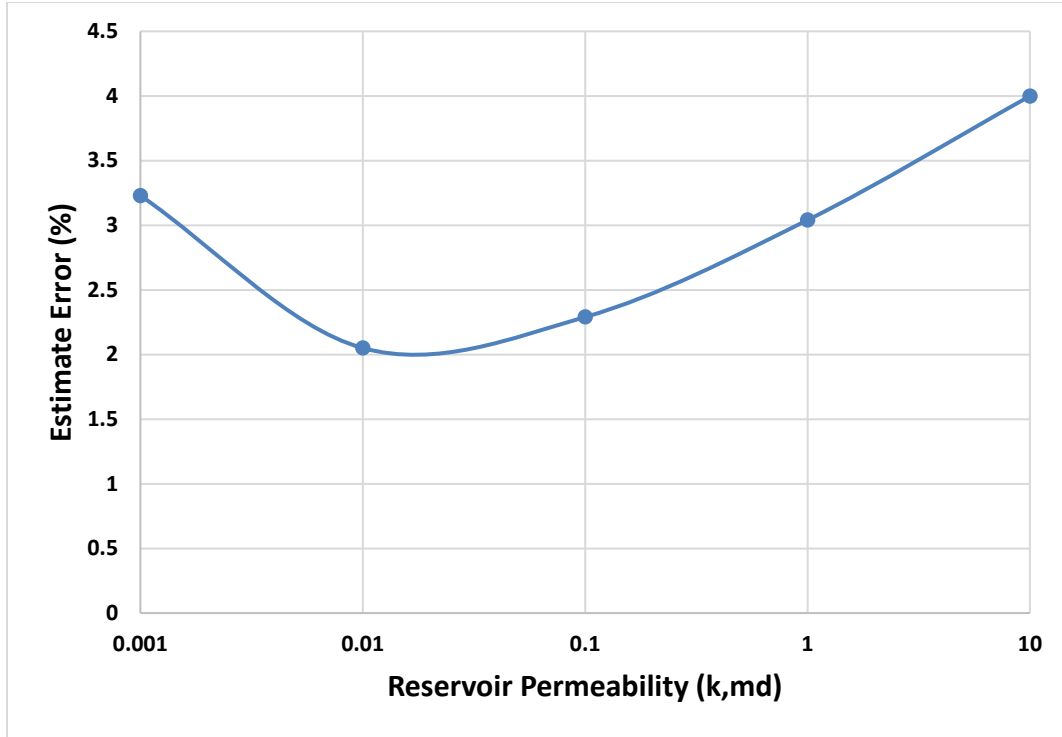


Figure 36: Estimation errors as per reservoir permeability.

5.4.1 ANN-Based Equation

An equation was obtained from the selected ANN model. Weights and biases were extracted from the best ANN model. The optimized ANN model consists of one hidden layer and 20 neurons in this work. Figure 37 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).

$$J/J_o = \left[\sum_{i=1}^N w_{2i} \left(\frac{2}{1 + e^{-2(w_{1i,1}x_{j_n} + b_{1i})}} \right) \right] + b_2 \quad (5.4)$$

where (J/J_o) is the productivity fold, w_1 is inputs' weights, w_2 is the outputs' weights, N is the number of neurons, X_{j_n} is the normalized model inputs, b_1 is the input biases for the input and b_2 output biases. Table 11 lists the weights and biases based on the selected ANN model. X_{j_n} is calculated as per the following equation:

$$X_{j_n} = 2 \times \left(\frac{X_j - X_{j_{min}}}{X_{j_{max}} - X_{j_{min}}} \right) - 1 \quad (5.6)$$

Where X_j is input value, $X_{j_{min}}$ and $X_{j_{max}}$ values are available in Table 3 s for each input.

Table 11: The values of the weights and biases needed for predicting the productivity ratio.

Number of Neurons	Input layer												Output Layer	
	Weights (w1)											Biases (b ₁)	Weights	Bias
	X ₁	X ₂	X ₃	X ₄	X ₅	X ₆	X ₇	X ₈	X ₉	X ₁₀	X ₁₁	(b ₁)	(w ₂)	(b ₂)
1	0.31	-0.46	-0.38	-1.89	-0.51	0.28	-0.04	0.02	0.11	0.51	0.27	-2.98	-1.16	6.25
2	-0.45	-0.52	0.35	0.87	-0.01	-0.12	-0.41	-0.76	1.62	-0.39	0.12	2.4	-0.36	
3	0.62	-0.31	-0.09	-0.44	-0.16	0.19	-0.30	0.28	0.41	-0.21	-0.15	0.23	-0.43	
4	0.24	-0.05	0.02	-0.51	-0.04	-0.58	0.57	-0.36	0.25	-0.16	-0.65	0.49	-2.2	
5	-0.28	-0.18	-0.08	0.66	0.06	0.74	0.37	-0.39	-0.16	0.20	0.73	-0.74	-1.32	
6	0.50	-0.44	-0.17	-0.58	-0.10	0.64	-1.34	-0.46	1.84	-0.16	-0.55	-2.59	0.55	
7	-1.35	0.30	-0.54	-2.04	2.25	-0.90	-0.82	-1.52	1.52	-1.00	0.62	1.17	0.02	
8	0.32	-0.18	-0.03	-0.45	-0.11	-0.28	0.19	0.33	-0.23	0.19	-0.20	-0.15	1.42	
9	0.77	-0.51	-0.35	-1.91	-0.53	0.19	0.72	-0.38	0.31	0.49	0.19	-4.49	4.1	
10	-0.46	0.36	0.12	1.02	0.61	-0.22	-0.06	1.14	-1.28	-0.45	0.03	-1.98	-0.45	
11	13.33	-0.15	0.22	0.24	0.19	-0.06	-0.95	0.76	-0.28	-0.48	-0.34	15.43	-3.17	
12	0.02	-0.49	0.15	2.22	0.10	-0.33	-0.14	-0.92	0.02	-0.04	-0.36	1.5	-0.43	
13	0.48	0.61	-0.11	-0.05	-0.27	-0.03	0.26	0.73	-0.43	0.55	0.26	0.17	-0.33	
14	1.12	-0.26	0.13	0.08	-0.05	0.27	-2.01	-1.25	1.94	0.89	-0.44	-1.67	0.77	
15	-0.43	0.29	0.23	0.57	0.23	-0.29	-0.02	-0.36	-0.31	-0.77	0.03	0.41	0.38	
16	-0.03	0.07	-0.02	-0.52	-0.04	0.08	0.00	0.45	0.78	0.00	-0.15	-0.86	-2.9	
17	-4.16	-0.95	-0.55	-3.57	-1.03	0.29	0.16	0.03	0.18	0.87	0.19	-9.02	0.27	
18	0.20	0.02	-0.16	-0.14	-0.33	0.12	-0.16	-1.53	0.40	0.83	0.59	1.04	-0.26	
19	0.21	-0.23	0.03	0.56	0.04	-0.49	0.07	0.06	-1.03	0.03	0.07	1.11	-1.98	
20	0.03	-0.28	-0.16	-1.09	-0.08	-0.14	-0.96	-0.79	0.81	0.09	0.49	1.62	-0.53	

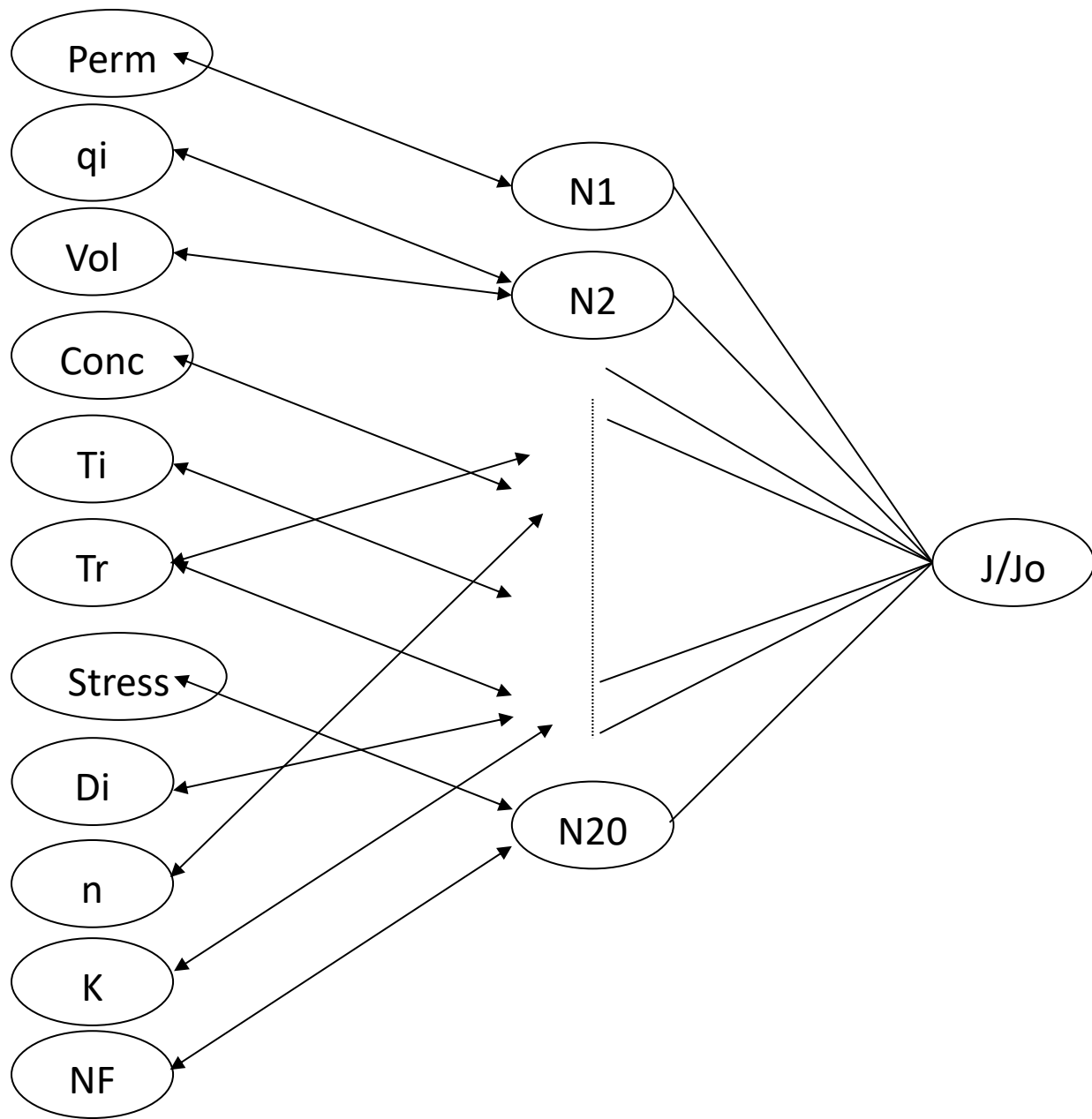


Figure 37: A simplified schematic of the selected ANN model.

The new ANN-based equation was validated using a group of unseen data by the model. A total of 111 scenarios were selected, which cover a wide range of inputs and outputs values. Figure 38 shows the predicted productivity folds by the ANN-based equation versus the actual ones from the acid model. The average prediction accuracy is 96.65%, and the correlation coefficient is 0.97. These numbers indicate the high reliability of the developed equation based on ANN. Also, the time required to predict productivity folds (J/J_o) can be lessened significantly compared to conventional simulators.

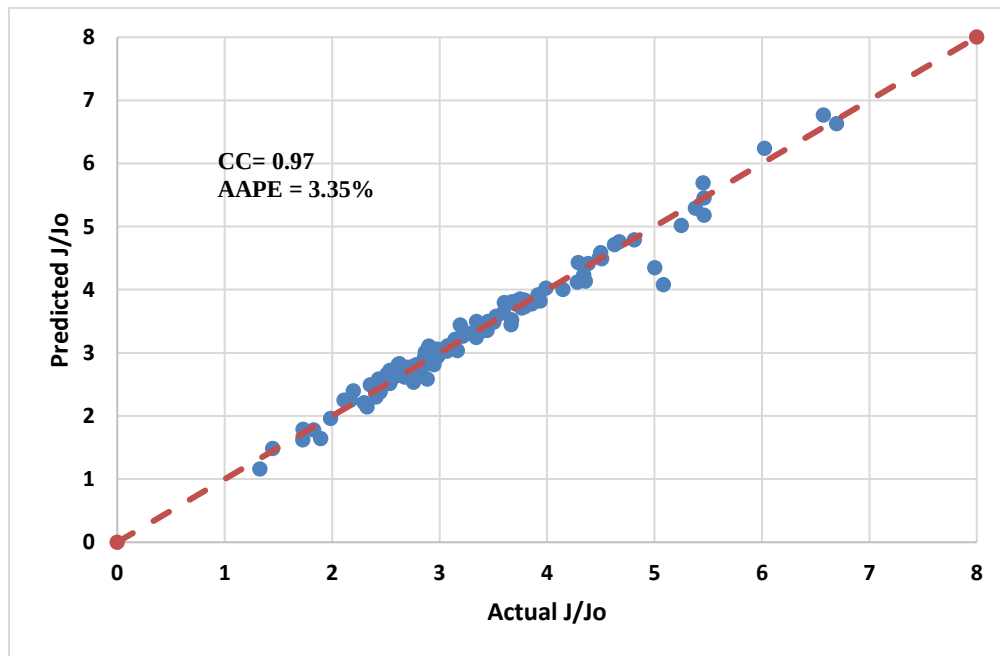


Figure 38: Predicted productivity folds versus the actual ones (ANN-based equation Validation).

After selecting the best ANN model, this model was tested with a smaller number of inputs to check if the same accuracy could be achieved with a smaller number of inputs. It is found that the best accuracy is achieved with all the 11 inputs, as summarized in Table 9.

Table 12: Predicting the productivity ratio using a different number of inputs.

Case #	Number of inputs	Inputs	CC	AAPE (%)	AAD
1	4	Perm, qi, NFs spacing, and Treatment Vol.	0.90	12.0	0.38
2	6	Conc., Perm, qi, NFs spacing, Treatment Vol, and Diffusion Coeff.	0.95	7.6	0.23
3	11	Conc., Perm, qi, NFs spacing, Treatment Vol, and Diffusion Coeff., Tr, Ti, n, K and Closure Stress	0.98	3.3	0.11

5.5 The Three AI Models Comparison

Table 10 summarizes the correlation coefficient and the average absolute percent error for the three AI models. Again, the ANN comes first as the best model for predicting productivity fold, having the lowest error and the highest correlation coefficient.

Table 13: Correlation Coefficient and Estimation errors for AI models.

AI model	CC	AAPE (%)
ANN	0.98	3.3
FL	0.96	6.5
SVM	0.92	9.72

Figure 39 is a combined plot of the predicted productivity fold versus the actual ones for the three discussed AI techniques. Again, it is evident in the plot that the ANN has the maximum number of points around the 45° line.

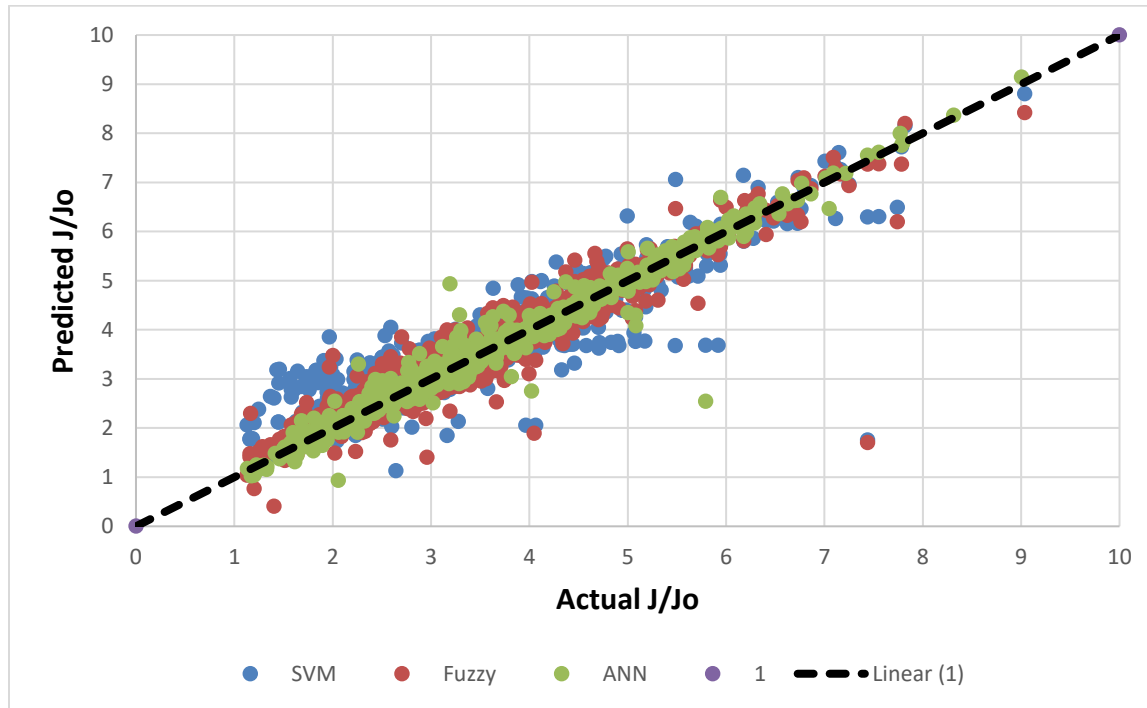


Figure 39: Predicted folds versus actual ones (ANN, FL, & SVM). for testing data

CHAPTER 6

CONCLUSION AND RECOMMENDATIONS

The acid model demonstrates that more natural fractures intersect a hydraulic fracture, causing a shorter half-length fracture and lowering the well's PI.

Based on the different scenarios' results at different permeabilities, wells in reservoirs without natural fractures usually have the highest PI except for the high permeability reservoirs. However, all spacing scenarios showed similar PI values in the high permeability reservoirs.

This study shows that natural fractures in the carbonate reservoir tend to reduce the performance of acid fractured well because the natural fractures increase leakoff, which causes the main hydraulic fracture to be shorter. Furthermore, the impact of natural fractures was highest in low permeability reservoirs.

Regarding the acid fracturing operation design, it was observed that a high acid injection rate is recommended to obtain the best well productivity in a low permeability naturally fractured reservoir. On the other hand, the acid injection rate should be moderate for a high permeability reservoir.

Three artificial intelligence (AI) tools were utilized in this study: artificial neural network (ANN), fuzzy logic system (FLS), and support vector machine (SVM).

The developed AI models can predict productivity improvement (J/J_o).

The statistical analysis and parametric investigations showed that the most critical design parameters are the treatment volume and injection rate. At the same time, reservoir permeability and NFs spacings are the most influential reservoir properties.

The ANN model has the most excellent prediction of productivity enhancement among the three AI models, with an average absolute error of 3.3% and a correlation coefficient of 0.98.

A new ANN-based equation was developed, directly estimating the productivity folds based on the acid job parameters and reservoir characteristics.

Productivity enhancement can be calculated using the ANN equation with an average absolute percentage error of 3.35% and a correlation coefficient of 0.97.

For a specific acid fracturing design, the equation from the ANN model can give a reliable and quick approximation for the productivity folds.

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APPENDIX

Nomenclature

C_A	Acid concentration
C_L	Leakoff coefficient
C_1, C_2	Nierode-Kruk correlation's constants
c_p	Heat capacity
D_A	Effective mixing acid diffusion coefficient
J	Wellbore productivity
K	Flow consistency index
L_x	Reservoir length
L_y	Reservoir width
Nt	Number of time steps
NX	Number of x-direction grids
NY	Number of y-direction grids
P_r	Reservoir pressure
P_{ref}	Reference pressure
q_i	Fluid injection rate
q_L	Leakoff rate per unit length

R	Universal gas constant
r_w	Wellbore radius
T	Temperature
t	Time
u	Velocity in the x direction
v	Velocity in the y direction
wk_f	Fracture conductivity
$w_{\max,0}$	Maximum fracture width at entrance
x_f	Fracture half-length
$\tau(x)$	Time when the fracture reached position x
$\hat{c}p_f$	Fluid specific heat capacity
C_A	Acid concentration
D_A	Acid effective diffusion coefficient vector
T_f	Fracture fluids temperature
c_t	Total compressibility
k_f	Fracture fluid thermal conductivity
k_r	Reaction rate constant
n_r	Reaction rate exponent
w_e	Etched width
μ_r	Reservoir fluid viscosity

AAD	Average absolute deviation
AAPE	Average absolute percentage error
AI	Artificial intelligence
ANN	Artificial neural network
b_1	Biases of the input layer
b_2	Biases of the output layer
CC	Correlation coefficient
Conc	Chemical concentration
FLS	Fuzzy logic system
N	Total number of samples
q	Injection rate
SVM	Support vector machine
w_1	Weights of the input layer
w_2	Weights of the output layer
x_j	Represents the input parameter
y	Represents the target parameter
Y_a	The actual value of the target parameter
Y_p	The predicted value of the target parameter
χ	Volumetric dissolving power
J	Productivity index
J/J_o	Fold of increase in productivity
p	Pressure
k	Permeability tensor
u	Velocity vector
ρ_f	Fluid density

φ

Formation porosity

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