Predicting Hydraulic Fracture Direction of Propagation When Intersect With Natural Fracture by Using Artificial Neural Network (ANN)

by

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14359

Dissertation submitted in partial fulfilment of
the requirement for the
Bachelor of Engineering (Hons)
(Petroleum)

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CERTIFICATION OF APPROVAL

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Approved by,

……………………
(Dr Masoud Rashidi)

UNIVERSITI TEKNOLOGI PETRONAS
TRONOH, PERAK
September 2014

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

…………………………………………………….

NURUL SHAHIZATUL FAZILA BT ABD RANI

ABSTRACT

Successfulness of the hydraulic fracture treatment in unconventional reservoir especially in shale gas reservoir was depends on the communication between hydraulic fracture and natural fracture. Hydraulic fractures propagate across the reservoir during the treatment and intersect with discontinuities present in the reservoir, in this case is pre-existing natural fracture. At this point, several events might occur during intersection. Firstly, hydraulic fracture propagation might step over the pre-existing natural fracture. Secondly, hydraulic fracture is caught up by natural fracture and stop the propagation. Thirdly, hydraulic fracture tip turn into the natural fracture, dilating and opening the natural fracture as the fracture fluid infiltrate the natural fracture. In a very low permeability reservoir, effective treatment should step over the pre-existing natural fracture, extending the network deep into the reservoir, connecting all the natural fracture to increase fracture conductivity and optimizing production of natural resources especially in unconventional shale reservoir. Therefore, parameters that characterized under which condition hydraulic fracture will step over and arrested into natural fracture at the intersection point need to be study and fully understand for designing the best hydraulic fracture treatment.

Parameters that affecting the course of fracture propagation, rock properties and fluid properties, was determined and a set of input data was prepared by collecting the data from the previous related research paper. Matlab software was used to develop the artificial neural network (ANN) model that give prediction on the course of hydraulic fracture propagation direction when intersecting with natural fracture by mapping a set of input data to a set of output. The ANN model has been trained, validated and tested by using 46 set of collected data and produced predicted output with good accuracy. Mean squares error (MSE) and regression analysis was used to calculate the output error to show the difference between predicted output and observed output from the experiment. By using the same model, sensitivity analysis was also conducted to see which parameter give the most effect and the least effect on the fracture propagation during intersection.

ACKNOWLEDGEMENT

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ABBREVIATIONS AND NOMENCLATURES

ANN	Artificial Neural Network
K_f	Coefficient of friction
K_I	Stress intensity I
K_{II}	Stress intensity II
$P_{closure}$	Closure pressure
P_{fluid}	Pressure of fracture fluid
P_{net}	Net pressure
P_{pore}	Pore pressure
S_t	Natural fracture tensile strength
Smax	Maximum horizontal stress
Smin	Minimum horizontal stress
T_o	Rock tensile strength
σ_{max}	Maximum horizontal stress
σ_{min}	Minimum horizontal stress
σ_n	Normal stress
σ_v	Vertical overburden stress
τ	Shear stress

CHAPTER 1

INTRODUCTION

1. INTRODUCTION

This chapter is dedicated for introduction and background study of hydraulic fracturing treatment in naturally fractured unconventional reservoir and working function of artificial neural network (ANN) model. The aim of the research work are justified and mentioned in this section.

1.1 Background of Study

Extensive demand for natural gas causes a serious exploitation and development in unconventional reservoir such as shale, tight gas sand and coal bed methane to ensure continuous supply for the future. Over a decade, hydraulic fracturing became a major approach in optimizing the hydrocarbon and natural gas production because of its effectiveness, safe and efficient practice. Hydraulic fracturing believed to help increase the well-reservoir contact enormously hence improving well productivity and maximizing the underground resources after the treatment. Beside, hydraulic fracture treatment also can prolong the life of older and mature field and recovered the natural resources in a place that that once believed by the geologist as impractical to produce.

Unconventional reservoir has large volume of natural gas and oil that exist in tight fissures. These sedimentary rocks usually have good porosity to store the natural gas but extremely poor permeability that eventually blocks the movement or restrict flow of natural gas from the reservoir to the producing well. Well-testing analysis revealed that large numbers of micro cracks or natural fractures present in tight sand and shale gas reservoir (Sondergeld, Newsham et al.). While, studies from the outcrop show that the natural fractures were sealed with the precipitated cement which poorly bonded with weak mineralization and adhesion (Keshavarzi and Mohammadi , Gale, Reed et al. 2007). Sealed natural fracture may be reactivated but it will provide a weak path for the fracture propagation.

Hydraulic fracturing is a process of pumping or injecting fracture fluid usually waters containing sands or other proppants at sufficient pressure to create the fractures in the rock. Proppant will keep the fracture open creating fracture conducting that allow the natural gas flow from the reservoir that usually impractical to be produced into the producing well. Mechanism behind the hydraulic fracturing is the generation of the tensile stress at the tips of pressurized fractures that induced the opening of natural fracture.

In common practices, short fractures are needed for economic production. However, for unconventional gas reservoir that has very low permeability, long effective penetrating fractures are required. In order for hydraulic fracturing treatment to be effective, it should cross and connect the system of natural fracture. However, induce fracture might also propagate to different paths depending on the type of interaction between hydraulic fracturing and pre-existing natural fracture. Interactions are patterned by arresting, opening and dilating and crossing.

Artificial neural network (ANN) is a computer information processing system that mimic human's brain processing structure that has been used in many areas of sciences and engineering. It recognised as promising method because of their simplicity toward modelling, prediction and simulation. ANN model provide good predictive solution to the problem by using the interconnected artificial neuron inside the network. Similar to brain function that solve the new problem by considering a lesson learn from previous experience, ANN model will also learn from the previous solved pattern and correctly predicted a new pattern.

1.2 Problem Statement

Fracture propagation has been studied theoretically, numerically and experimentally to further investigates and explains the factor that controlling the interaction between hydraulic fracture and natural fracture. Assumptions were made and dominant parameters involved were test and analysed for comprehensive understanding. In-situ differential rock stresses (maximum and minimum horizontal stress), natural fractures properties, rock tensile strength and brittleness and fracture fluid properties are example of the parameters studied for prediction of hydraulic fracture and natural fracture interaction. Even though, these parameters has been testing, researcher still find blindness in determining and analysing how each parameter influence the behaviour of hydraulic fracture interaction with natural fracture in details.

Existing models of hydraulic propagation crossing natural fractures have been created by many researchers. However rarely fracking fluid properties such as viscosity and injection rate of fracture fluid are put into account. Usually, these parameters were held constant. Therefore, the artificial neural network (ANN) model will help to understand better the effect of these parameters toward the propagation of hydraulic fracturing by predicting the propagation behaviour and eventually help in removing blindness in fracturing design of unconventional shale reservoir.

1.3 Objectives

There are three main objectives need to be achieved;

i. To develop a model that can predict the course of direction of hydraulic fracture propagation during intersection with natural fracture.
ii. To investigate the effect of the viscosity and injection rate of fracture fluid in generation of hydraulic fracture advancement and interaction with natural fracture
iii. To identify the parameters that significant affecting the hydraulic fracture propagation when intersecting with natural fracture by performing sensitivity analysis

1.4 Scope of Study

The study will focus on develop a model that can demonstrate and predict the course of propagation for hydraulic fracturing during intersection with natural fracture at the intersection point. Hydraulic fracture is propagating from the vertical wellbore into the very-low permeability reservoir containing geologic discontinuities, pre-existing natural fracture. In the model, hydraulic fracture is assume to be ideal; simple, straight, bi-wing, vertical single planar fracture in the region of normal faulting stress region. Normal faulting stress region meaning that vertical stress (overburden stress) is the maximum stress (vertical stress>maximum horizontal stress>minimum horizontal stress).

Model exhibit three possibilities that can happen during intersection between two fracture which is crossing or opening and dilating or arresting. Effectiveness of hydraulic fracturing treatment on the very low-permeability formation is observed from the interaction between natural fracture and hydraulic fracture during intersecting. Effective interaction given by the hydraulic fracture steps over the natural fracture and continue advancement into the next natural fracturing creating a longer network of fractures deep into reservoir.

However, the data is limited since the author did not perform any experiment to obtain the real data. The input data for training, validating and testing the model was collected from the research papers that related to the subject of study. The author of the research papers has conducted the experiment to study the interaction between hydraulic fracture and natural fracture and produce the observed result from the experiment.

CHAPTER 2

LITERATURE REVIEW

2. LITERATURE REVIEW

2.1 Hydraulic Fracturing

Hydraulic fracture is a process of transmitting pressure into by fluid or gas to initiate crack or open the existing fracture in oil and gas bearing formation. Main purpose of hydraulic fracturing is to create the paths that enable oil and gas to flow easily from the reservoir into producing well. Fluid flow into the open fracture depends on the state stress of the rock mass which are vertical overburden stress and maximum and minimum horizontal stress (Pyrak-Nolte, Myer et al. 1987). Rock formations stress system can be differentiated into three orthogonal stresses which name as rock in-situ principle stress: σ_v is orthogonal stress in vertical direction, σ_H is orthogonal horizontal stress with maximum value and σ_h is orthogonal horizontal stress with minimum value (Hossain, Rahman et al. 2000). Injecting highly pressurized fluid that is more than geological in-situ principle stress will initiate network of crack that allow gas to flow into the wellbore but more power is needed to extend the crack growth far into the reservoir. This extra power is supply by the injection rate at which the fluid is pumped.

When intact rock breaks, the individual failure surfaces are called fractures. When a fracture is stressed, the void space deforms. Rocks break in either tension, resulting in tensile fractures, or compression, resulting in shear fractures. In the fracturing of materials, there are three main modes of failure. Mode I fractures or opening mode fractures occur when fracture opens against the least principal stress acting on the material, meaning the tensile stress in the fracture must exceed the least principle stress. Mode II and III fractures both result from relative movement in shear but differ in the direction of fracture propagation, or growth, relative to the applied stress. In Mode II, also called sliding mode, the fracture propagates parallel to the maximum stress. In Mode III, also called tearing mode, the fracture propagates perpendicular to the maximum stress (Chang, Lee et al. 2002). In hydraulic fracturing, opening mode 1 is the most commonly occurred.

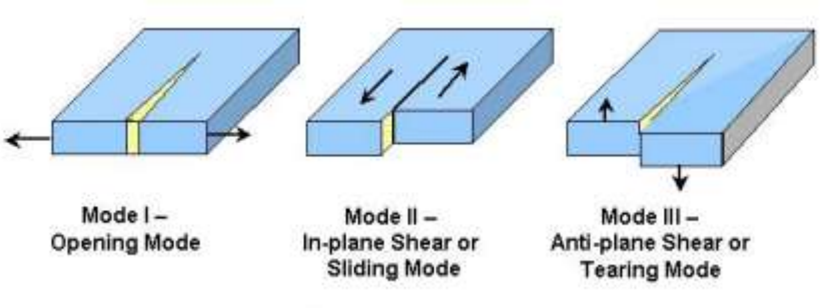


Figure 1: Fracture displacement mode

2.2 Hydraulic Fracturing In Naturally Fractured Reservoir

During hydraulic fracturing stimulation, combination of different viscosity fluids and proppant is pumped into the formation through the wellbore. Unconventional reservoir required hydraulic fracturing stimulation because of its very low permeability (micro- to nano-Darcy permeability) compared to conventional reservoir (mili-Darcy permeability) (Ozkan, Brown et al.).

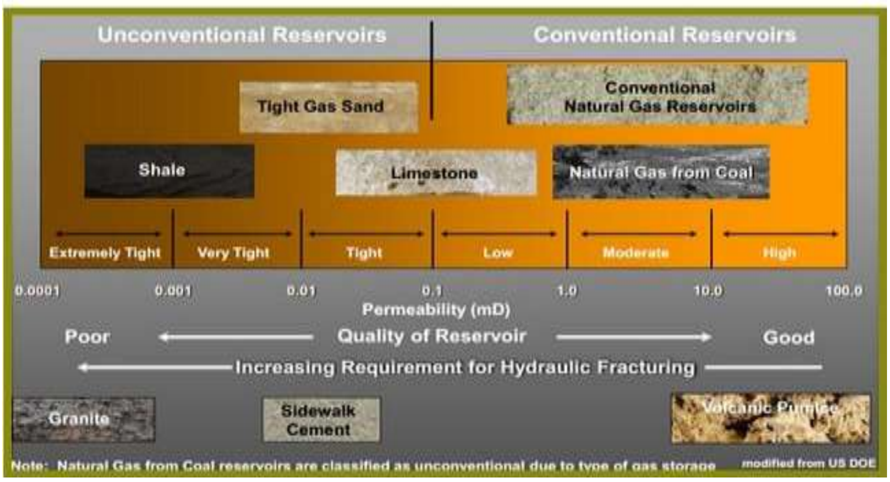


Figure 2: The link between hydraulic fracturing and permeability

Tight gas reservoir contain pre-existing natural fracture. According to Pitman et al, multiple fracture types occur on a macroscopic and microscopic scale in the Bakken Formation and majority of these fractures are open (nonmineralized), discontinuous features oriented subparallel to bedding with aperture widths commonly exceeding 30 μm (Pitman, Price et al. 2001). Present of natural fractures help in optimizing economic production from the unconventional reservoir. However, Montgomery et al. stated that natural fractures is not desirable for production and might reduce well performance (Montgomery, Jarvie et al. 2005). Conversely, Gale et al concur with the finding and demonstrated that in natural, regionally developed, opening-mode fractures in the Barnett Shale can reactivate during hydraulic fracture treatments, providing a larger rock volume in contact with the wellbore (Gale, Reed et al. 2007).

According to Aguilera, natural fracture created because of local deformation happened when stress concentration surpass the rock cohesion strength (Aguilera 2008). As reservoir depleted, natural fracture will still remain opened with the condition it position is perpendicular to the minimum horizontal stress. Whereas, if the position of natural fracture is parallel to the minimum horizontal stress, natural fracture is more likely to be secured. Nevertheless, secondary mineralization adding exception for the theory when they acting as natural proppant agent. Gale at el (Gale, Reed et al. 2007) in his experiment found large assembly of fracture-lining minerals in the layer of Barnett shale. Mineralization that forms a cemented seal in natural fracture can be calcite, quartz, albite, phyrite, barite and dolomite. These natural proppant uphold the opening of natural fracture as reservoir depleted. However, natural fracture that contain micro-filling will act as barrier and form a weak path for the hydraulic fracture advancement.

2.3 Hydraulic Fracture Extension and Propagation

Warspinski et al studies show that fracture opening width and propagation are largely controlled by the magnitude of in-situ stress and the fluid injection rate. In-situ stress predominantly affect hydraulic fracture propagation by not only dictate the orientation but also the gradient and discontinuity of the stress can act as barrier to the fracture growth (Warpinski, Schmidt et al. 1982). Studies indicate that there are at least three parameters that can control vertical fracture growth in layered rock

i. differences in the mechanical properties of the formations on either side of the interface
ii. changes in the horizontal stress state across the interface
iii. shear strength of the interface

According to Shakib, hydraulic fracture can follow different paths once intersecting with the natural fracture. Most likely, hydraulic fracture will advance and follow the path that has highest energy release rate (Taheri Shakib and Jalalifar 2013). Wu et al (2014) mentioned that hydraulic fracture propagation are more likely to follow in the direction parallel to the maximum horizontal stress and perpendicular to the direction of minimum horizontal stress (WU, CHENG et al. 2014).

Interaction between hydraulic fracture and natural fracture can form a complex fracture pattern. Warpinski et al. envisioned four major categories of fracture manifested in tight gas reservoir which is (Warpinski, Mayerhofer et al. 2009):

a) single plane biwing fracture
b) multiplex fracture
c) multiplex fracture with dilating natural fracture
d) multiplex fracture that form interconnected network.

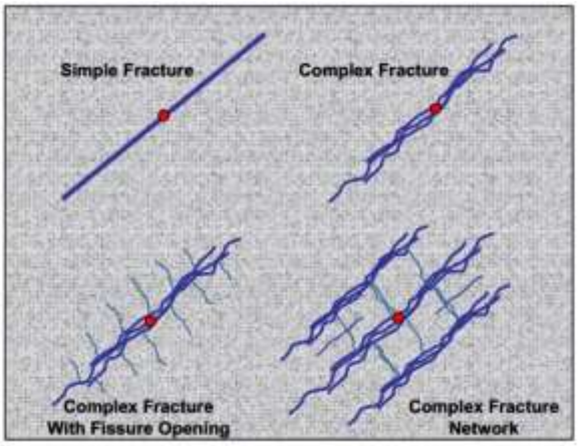


Figure 3: Classification of fracture from simple fracture to complex fracture complex fracture

Blanton conducted an experiment on the naturally fracture Devonian shale conclude that hydraulic fracture behaviour when intersect with natural fracture can be referred to as opening, arresting or crossing (Blanton 1982). Whereas, Daneshy argued that at intersection point, hydraulic fracture appear to get caught up by natural fracture when the natural fractures were open and step over the natural fracture when the natural fractures were secured (Daneshy 1974).

Three possible paths cause by the hydraulic fracture and natural fracture interaction was described in details by Shakib. Firstly, hydraulic fracture may propagate parallel to the direction of highest horizontal stress. Natural fracture may not have any influence here because of high cement strength or unpropitious natural fracture orientation or low fracking fluid pressure to surmount the normal stress that perpendicular to the pre-existing natural fracture. Secondly, when the hydraulic fracture intersects the natural fracture, hydraulic fluid is arrested and fracking fluid filled in the natural fracture. Once growing shear stresses can surmount the friction between fracture surfaces or high energy of hydraulic fracture can start debond the cement, natural fracture will open. Debonding of cemented natural fracture occur due to high energy of hydraulic fracture cause high tensile stress to be exerted at the head of hydraulic fracture tip. Thirdly, pre-existing natural fracture interacts and cross over hydraulic fracture in complex manner (Taheri Shakib 2013).

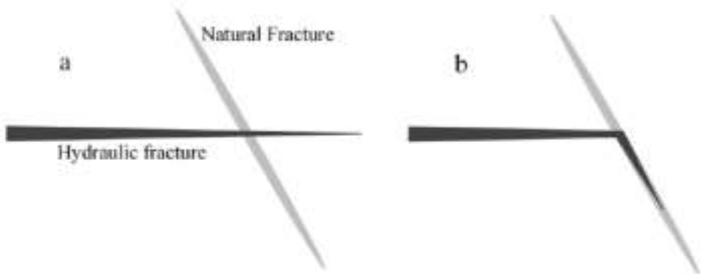


Figure 4: Illustration of pre-existing natural fracture and hydraulic fracture interaction: (a) hydraulic fracture step over the natural fracture (b) hydraulic fracture caught up in natural fracture and dilate it

When hydraulic fracture encounter pre-existing natural fracture in the unconventional reservoir, hydraulic fracture will get arrested into natural fracture, dilating and opening natural fracture when the energy inside hydraulic fracture was high enough to overcome normal stress acting on the interface and interfaces friction of coefficient and cohesions. Natural fracture will use up the energy inside hydraulic fracture to reactivate and dilating the interface (WU, CHENG et al. 2014).

Kresse at el in his unconventional fracture modelling (UFM) apply cross-linked gel and slick water to demonstrate the outcome of using different viscosity on the advancement of hydraulic fracture when meeting natural fracture. When fluid viscosity is increase, pattern differences were considerably observed. Viscous fluids tend to intersect and cross all the natural fractures resulting in bi-wing shape while less viscous fluid tend to infiltrate into natural fracture and dilating it more easily without crossing (Kresse, Weng et al. 2013). In the other hand, Beugelsdijk et al study on how flow rate, Q and fracturing fluid viscosity, μ affect advancement of hydraulic fracture propagation by applying and testing of different product of Qμ. Experiment show low Qμ tend to leak into natural fracture forming complex fracture pattern and single fracture that cross natural fracture form by using high Qμ (Beugelsdijk, De Pater et al. 2000).

However, according to Ren at al, low fluid viscosity is preferable for generation of complex fracture network due to easier pressure conduction and smaller fluid pressure drop along natural fracture. Hence, fluid pressure at natural fracture tips is easier to reach the pressure threshold that initiate and propagate hydraulic fracture(Ren, Zhao et al. 2014). Cipolla et al support the statement by calculating and contrasting the simulated reservoir volume (SRV) for two different fracturing fluid of different viscosity. Less viscous fluid exhibit much larger SRV compare to more viscous fluid which indicated that low viscosity fluid easily form complex fracture network (Cipolla, Lolon et al. 2009).

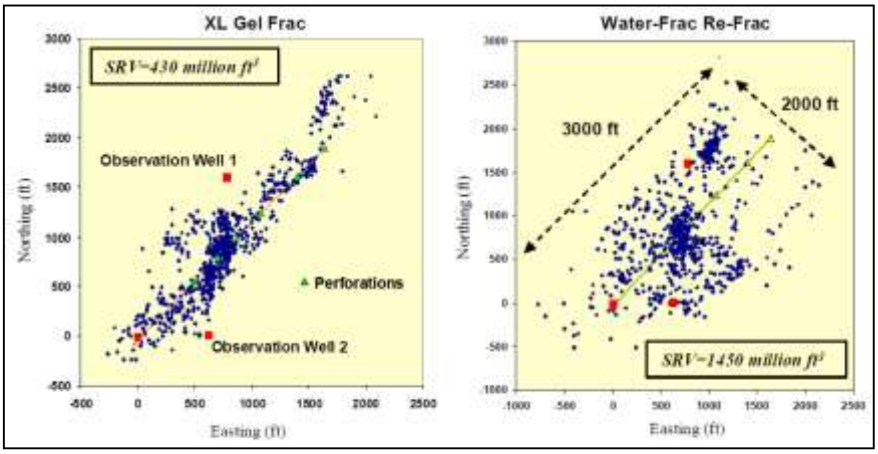


Figure 5: SRV comparison of using gel fracturing fluid and slick water fracturing fluid.

2.3.1 Criterion of Hydraulic Fracture Propagation

Hydraulic fracture criterion has been extensively described by Blanton (1986), Warpinski and Teufel (1987) and Renshaw (1995). Blanton criterion are focusing on fracture approaching angle and far-field stress differential. According to Blanton (1986), crossing and opening of natural fracture depends on the pressure concentration at the blunted tips of hydraulic fracture. Pressure at the intersection that exceed the normal stress acting perpendicular to the interface cause the hydraulic fracture to turn into natural fracture. Whereas when the pressure at the tips of hydraulic fracture that is less than normal stress, crossing can happened when it satisfied the condition of pressure at the point of intersection must be greater than rock tensile stress and stress acting corresponding to the length of natural fracture (Blanton 1982).

Warpinski and Teufel applied concept of Mohr-Coulomb failure criterion to describe shear slippage that arrested hydraulic fracture propagation or shear dilation that open natural fracture once fluid leak off into natural fracture. Shear slippage happened when

$$(\sigma_{max} - \sigma_{min}) > \frac{2\tau_o - 2P_{net}K_f}{\sin 2\theta + K_f \cos 2\theta - K_f}$$

and shear dilation

$$P_{net} > \frac{(\sigma_{max} - \sigma_{min})(1 - \cos 2\theta)}{2}$$

Similarly with Blanton (1987) analysis, pressure at the intersection point that exceed normal stress acting perpendicularly to the interface of natural fracture will be immediately dilating natural fracture. However, he mentioned that the condition still be influenced by on the degree of the horizontal differential stress, angle of approach and net pressure and the effect of fluid leak off into the natural fracture is deliberated. (Warpinski 1991). Net pressure can be obtained from;

$$\begin{aligned} P_{net} &= P_{fluid} - P_{closure} \\ &= P_{fluid} - (\sigma_{min} + P_{pore}) \end{aligned}$$

Renshaw's criterion (Renshaw and Pollard 1995) simply describe the crossing behaviour by using horizontal minimum and maximum stress, rock tensile strength and interface coefficient of friction. His observation show that crossing will only occur when stress acting perpendicular to the interface is adequately sufficient to not allowing slip to happen at the interface of natural fracture and stress can be induced to the opposite side of natural fracture. However, weakness of Renshaw's criterion is that he only restricted the mathematically crossing criterion to the interaction between hydraulic fractures to natural fracture in orthogonal angle.

$$\frac{-\sigma_{min}}{T_o - \sigma_{max}} > \frac{0.35 + \frac{0.35}{K_f}}{1.06}$$

Wu at el (WU, CHENG et al. 2014) further explain Renshaw criterion in the mathematic language. Dilation occurred when the following requirements are fail to be accomplished.

1) $|\tau| < So - K_f(\sigma_n)$
2) $\sigma_n < S_t$

3) $\sigma_{max} = T_o$

Criterion described by these three individual group show that the rock properties is the main component in determining the crossing and dilating behaviour of hydraulic fracture propagation. Therefore, these parameter such as angle of approach, maximum and minimum horizontal stress, natural fracture interface coefficient of friction and cohesion should be included in the study.

2.4 Black Box Model

The 'Black Box' model is defined as the portion of the system that contains formulas and calculations, but the user does not see nor need to know to use the system. It only know the relationship between input (causes) and output (effect) without having any knowledge of the interior workings of the application nor physical insight is available, but the chosen model structure belongs to families that are known to have good flexibility and have been successful in the past (Ljung, 2001).

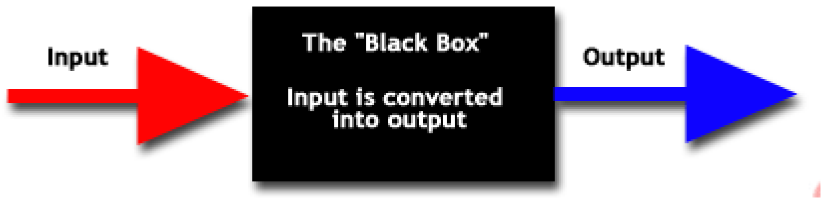


Figure 6: Black box testing tool

It is useful when your primary interest is in fitting the data regardless of a particular mathematical structure of the model. Black-box modeling is usually a trial-and-error process, where you estimate the parameters of various structures and compare the results. Most black-box testing tools employ either coordinate based interaction with the applications graphical user interface (GUI) or image recognition. Two types of black-box is linear black-box model and non-linear black-box model.

Table 1: Example of black-box model

Linear Black-box model	Non-linear black-box model
• The Linear State-Space Assumed Model • The Innovations Model • The ARMAX Assumed Model	• Input-Output Modeling • State-Space Modeling • Determistic State-Space Models • Stochastic State-Space Models

Compare to other black-box model, neural network is very general and captured a variety of pattern accurately. It provide a method to fit the parameters of a particular function to a given set of data. When using neural network black-box model, the author do not need to assume an underlying input data distribution when programming a neural network and neural network able to detect all possible, complex nonlinear relationships between input and outputs.

2.4.1 Artificial Neural Network (ANN)

Artificial network is an electric model of a computer based on real-life nerve cell of the human biological brain. Human brain was filled with 140 million number of neuron with billions of connection between each other. These neuron keep transmitting electrical signals to solve problem, make decision, perform computation, translate language and others.

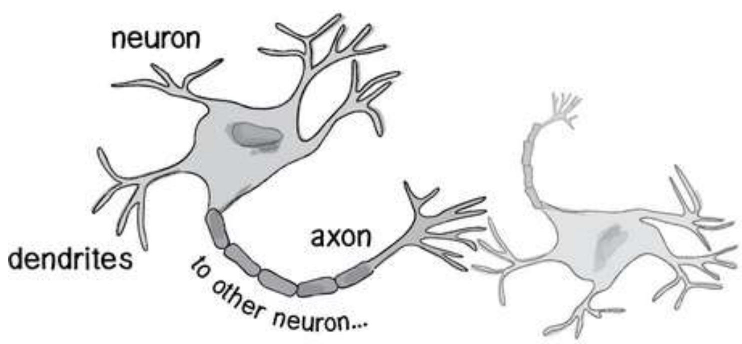


Figure 7: Human brain neuron

This neuron can communicate with each other faster than the speed of light. The structure of neuron itself is relatively simple but it carries a complex task within its part. The neuron consist of 4 major parts which is the dendrites that control and accept inputs, soma which has the nucleus and responsible for the input processing, axon which convert the inputs into outputs and synapses that create contacts with other neuron or the receptor for which the final outcome is produced. Human brain adapt learning process by modifying this the neuron’s strength of connection.

Through the advancement of computing technology coupled with recent biological advancement, scientist has been able to relate this way of learning to produce a significant leap in computer and information field. True purpose of artificial neural network is not to reproduce brain function but to imitate neuron capabilities into solving problems that traditional computing method cannot handle (Wasserman 1993).

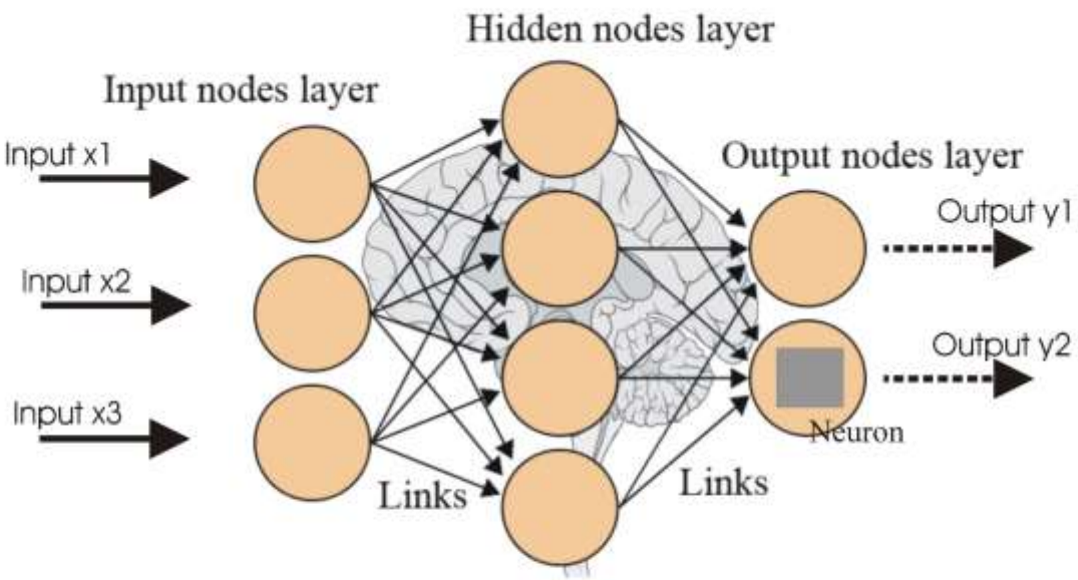


Figure 8: Artificial neural network structure

System in ANN consist of input layer, hidden layer and output layer. Each layer has number of neuron that responsible to send the signal to the next interconnected neuron just like synapse in the human brain. Each neuron has their own weighting system and bias that evaluate the output decision.

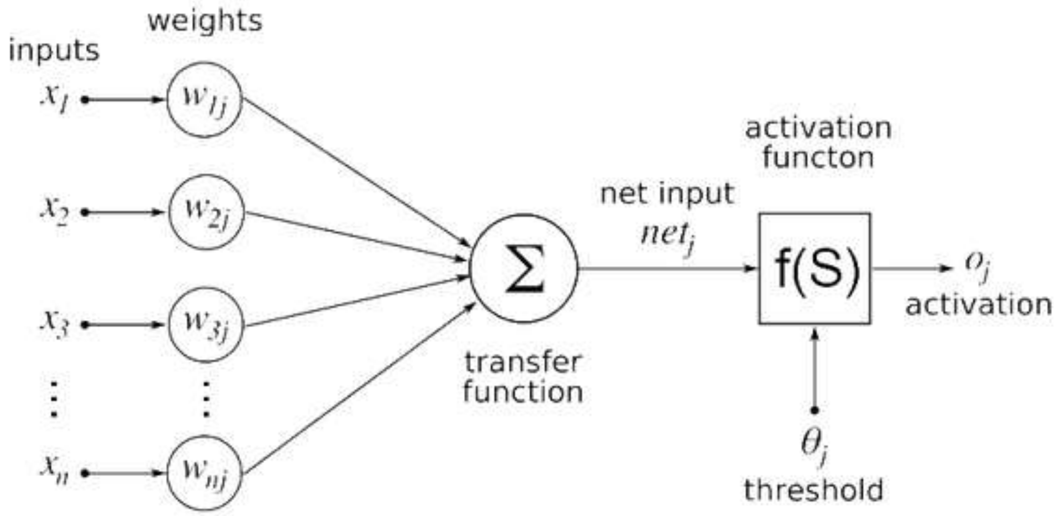


Figure 9: Network of ANN model

Figure show that each input will be send to the each neuron which each neuron has their own weight. This weight system is a number that control the strength between interconnected neuron. Best weighting system will generate the output with good accuracy and no adjustment or iteration need to be repeated. Conversely, when ANN model produce an output with poor accuracy with an error, iteration is repeated continuously to improve subsequent results, adapting the system to a new altered weight. For a single input neuron, neuron output is calculated as;

$$a = f(w\,x + b),$$
$$a = f(n)$$

For multiple input neuron, each of input are weight individually by the corresponding weight matrix, W.

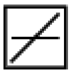
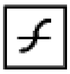
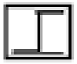
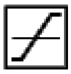
$$n = w_{1,1}x_1 + w_{1,2}x_2 + \ \dots\dots\dots\dots.. + w_{1,R}x_R + b$$

Where n is the net input, w is the weight, x is the input, b is the bias, and R is the number of neuron in previous layer.

Actual output is depend on chosen activation transfer function to generate the output based on the problem requirement (Hagan, Demuth et al. 1996). Transfer function can be linear or nonlinear function of net input (n). Common problem solving by using

ANN model will use purelin and tansig transfer function to solve and predict the output.

Table 2: ANN common transfer function

Name	Input/Output relation	Icon	Matlab function
Linear	$a = n$		Purelin
Hyperbolic tangent sigmoid	$a = \frac{e^{n} - e^{-n}}{e^{n} + e^{-n}}$		Tansig
Hard limit	$a = 0, n < 0$ $a = 1, n \geq 0$		Hardlim
Log-sigmoid	$a = \frac{1}{1 + e^{-n}}$		Logsig
Symmetrical saturating linear	$a = -1,\ n < -1$ $a = n, -1 \leq n \leq 1$ $a = 1, n > 1$		Satlins

CHAPTER 3

METHODOLOGY

3. METHODOLOGY

3.1 Research Methodology

In order to study the hydraulic fracture propagation behaviour in naturally fractured reservoir, the fundamental parameters that affect the direction of propagation is determined and studied comprehensively. Parameters used in the study can be divided into two categories which is rock properties and fluid properties. But additional important parameter such as angle of approach is also included to observed and predict the course of hydraulic fracture propagation when intersecting with natural fracture.

Table 3: Parameters used in the study

Rock properties	Fluid properties	Addition parameter
Maximum horizontal stress (psi)	Viscosity (cp)	Angle of approach (°)
Minimum horizontal stress (psi)	Injection rate (m3/s)	
Interface coefficient of friction, K (dimensionless)		
Natural fracture cohesion (psi)		

A model was develop to further understand the effect of each parameter to the hydraulic fracture propagation at the point of intersection with natural fracture. Artificial neural network (ANN) in MATLAB software was used to develop the model that has the ability to accurately predict whether hydraulic fracture will cross or open and dilating natural fracture. Since the model need to learn from the previous experience, it need the experimental input data and observed target in order to train, validating and testing the model to produce the best weighting network system. These input and observed target data was collected from the related research paper that has conduct the experiment to observe the interaction between hydraulic fracture and natural fracture. Four research papers has been used as references to obtain 46 number of data.

After the model has been trained, validated and tested, the best weighting network is used to predict the output. The predicted output was classified to a numerical number for ANN to recognize the pattern. These predicted output acquire from ANN model was compared to the observed target from experiment to look for the model accuracy in predicting the output.

For a second time, the best weighting network was used to conduct sensitivity analysis on each of parameter to see the significant of each parameter in affecting the hydraulic fracture propagation course. Each of the parameter will be increase and decrease by 5%. The result obtain will be interpreted and discuss in the chapter of result and discussion and conclusion will be made at the end of the project report.

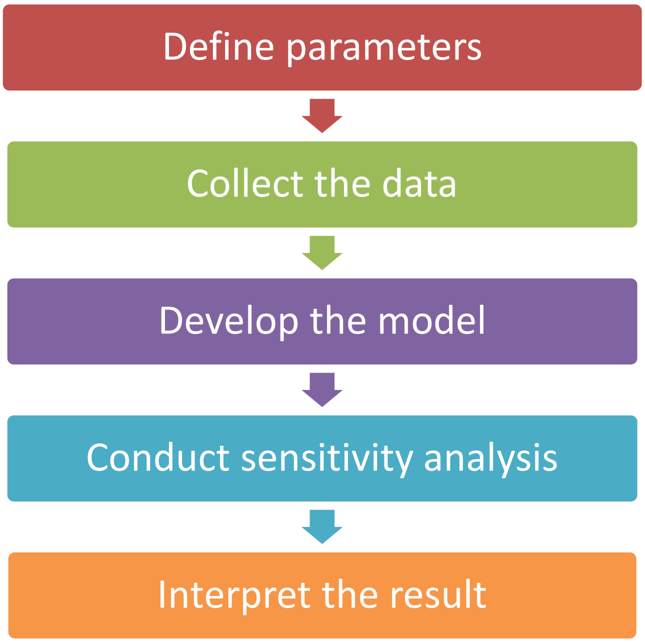


Figure 10: Research methodology

3.2 Designing Artificial Neural Network (ANN) Model

Figure 11: Systematic procedure of constructing an ANN model

Data collection consisted of 46 dataset with 7 input parameter and 1 observed target. As outline in table 3, this are the parameters that will be inserted into the model for the next pre-processing data to train the data competently.

Table 4: Range of input parameter

Input parameters	Minimum	Maximum
Angle of approach (°)	0	90
Maximum horizontal stress (psi)	1000	2900
Minimum horizontal stress (psi)	725	1000
Friction coefficient, K (dimensionless)	0.6	1.21
Interface cohesion (psi)	0	464
Viscosity (cp)	1	1000cp
Injection rate (m3/s)	4.20E-09	8.194E-07

Number of hidden layers, neuron in each layer, and type of transfer function in each layer are specified in building the network. In the next step, the network will be train and tested by using the inserted dataset from the data collection. During this training and testing, the model randomly pick at what number of dataset will be used at the training section and testing section. The weighting network was adjusted iteratively by the model network to make the predicted ANN output as close as possible to observed target. The best weighting network will then use to conduct the sensitivity analysis for each of the parameter.

3.2.1 Programming the Artificial Neural Network (ANN) Model

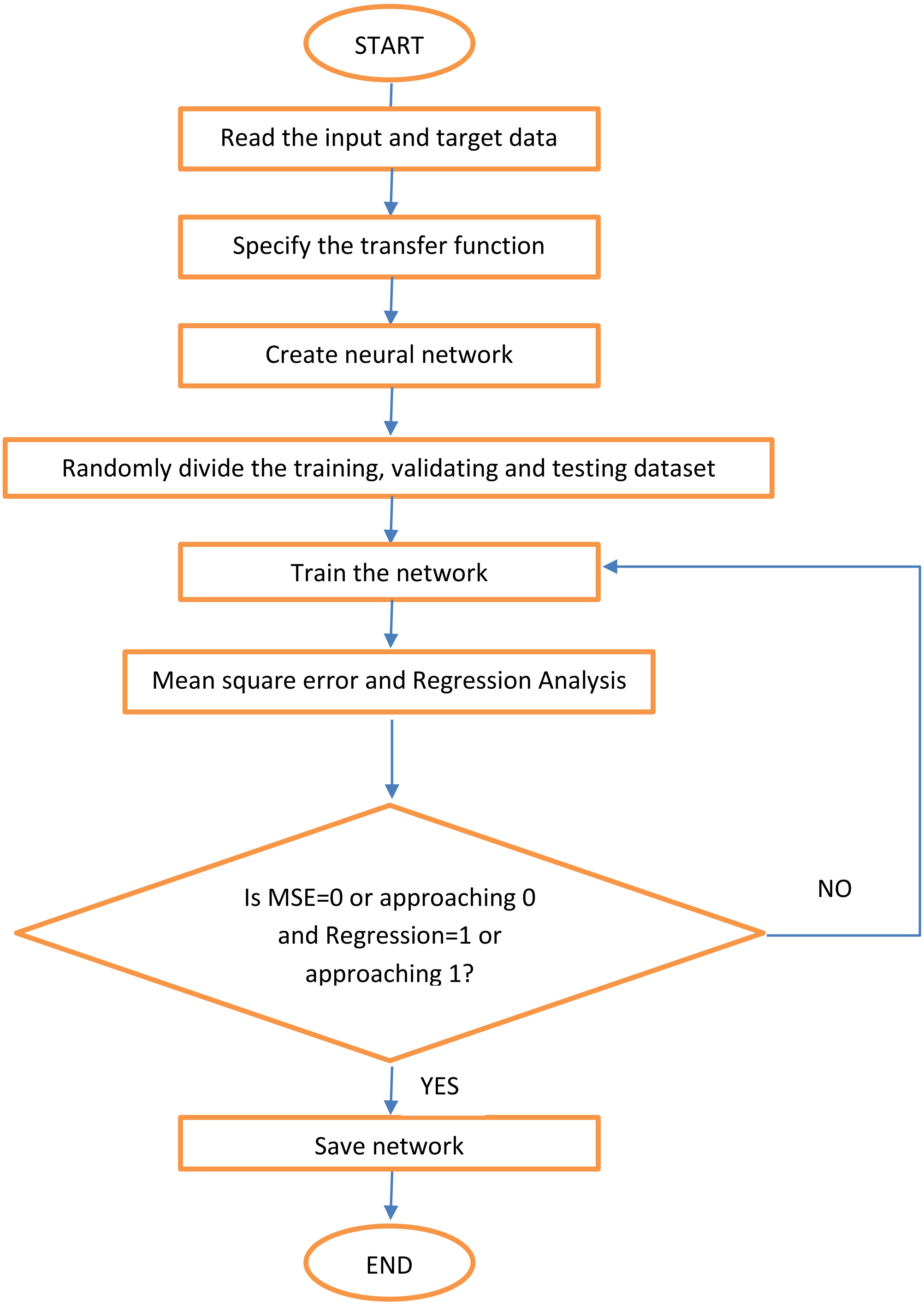


Figure 12: Flowchart of constructing ANN model

3.3 Artificial Neural Network (ANN) Model Construction

The interaction between hydraulic fracture and natural fracture can be categories into crossing or opening and dilating. A build model from Artificial Neuron Network (ANN) will classify the input data into a categories. In this study, ANN will recognise the pattern of crossing or opening and dilating of the interaction. The model recognised output 0 as opening and dilating whereas output 1 as crossing behaviour of interaction.

Table 5: Pattern categories

ANN Output	Pattern
0	Arrested
1	Opening and Dilating
2	Crossing

3.3.1 Artificial Neural Network (ANN) Architecture

The build model of ANN implemented the feed forward network in order to predict the specific output pattern for every given set of input data. 7 input parameters with each having 46 set of data were considered to be inserted into the model. The model has two layers of network with 5 number of hidden neuron in the first layer and 1 hidden neuron in the output layer. In the first layer of the feed-forward network, hyperbolic tangent sigmoid (tansig) transfer function was used and in the output layer, linear (purelin) transfer function was used. The build model was trained using the backpropagation algorithm to initialize the network weight and bias iteratively to reduce the network error.

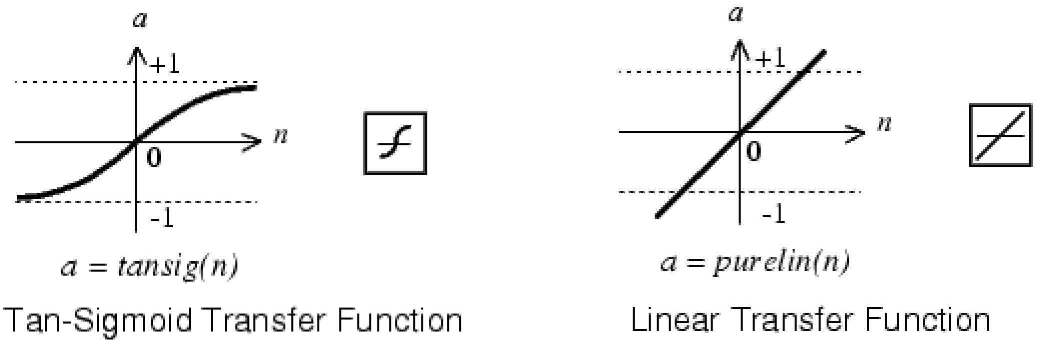


Figure 13: Tan-sigmoid transfer function (left) and Purelin transfer function (right)

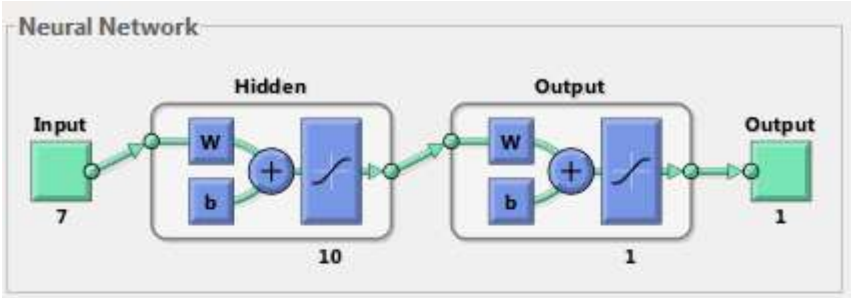


Figure 14: Artificial Neural Network (ANN) architecture

3.3.2 Training, Validating and Testing

The model has been trained, validated and tested by using the 7×46 matrices set of input data with 1×46 matrices set of observed target. The input data has been randomly pick up by the model for the purpose of training, validating and testing of the model according to the percentages ratio that has been set at the beginning of the model setup.

Table 6: Percentage division for training, validating and testing the model

Process	Number of sample	Percentage of sample (%)
Training	32	70
Validating	7	15
Testing	7	15

3.3.3 Weighting Network

Table 7: Weighting network in hidden layer 1

	Neuron 1	Neuron 2	Neuron 3	Neuron 4	Neuron 5
Parameter 1	-3.8461818	-3.591566	14.293429	1.9766574	-0.325506
Parameter 2	7.0922069	1.7097224	17.290451	5.3688063	0.137671
Parameter 3	-6.4081326	-3.09026	-1.300432	-3.039921	0.5111512
Parameter 4	0.5026538	-1.749781	-4.355953	1.4125316	-1.980319
Parameter 5	5.102008	2.4770809	-7.152801	0.4991922	-0.265442
Parameter 6	-5.7267748	1.1410637	-12.24925	-1.17406	-0.114511
Parameter 7	2.877985	-0.020367	0.0508651	1.140045	0.3627602

Table 8: Bias in hidden layer 1 and output layer

No of neuron	Bias hidden layer 1	Bias output layer
Neuron 1	1.39016769	0.82287863
Neuron 2	-1.671686024	
Neuron 3	1.146970557	
Neuron 4	0.446955402	
Neuron 5	-0.272190092	

3.4 Data Gathering

No	Angle (°)	Smax (psi)	Smin (psi)	Viscosity (cp)	Injection Rate (m3/s)	Friction Coefficient, K (dimensionless)	Cohesion (psi)	observed output
1	60	1740	1450	1	8.194E-07	0.75	218	1
2	30	2755	1450	1	8.194E-07	0.75	218	1
3	60	2900	1450	1	8.194E-07	0.75	218	2
4	30	2900	725	1	8.194E-07	0.75	218	0
5	45	2900	725	1	8.194E-07	0.75	218	0
6	45	2610	725	1	8.194E-07	0.75	218	0
7	45	2320	725	1	8.194E-07	0.75	218	0
8	45	2030	725	1	8.194E-07	0.75	218	0
9	90	2030	725	1	8.194E-07	0.75	218	2
10	60	2030	725	1	8.194E-07	0.75	218	0
11	45	1450	725	1	8.194E-07	0.75	218	1
12	90	1450	725	135	4.20E-09	0.38	464	2
13	90	1450	435	135	4.20E-09	0.38	464	2
14	60	1450	435	135	4.20E-09	0.38	464	2
15	60	1885	435	135	4.20E-09	0.38	464	2
16	60	1160	725	135	4.20E-09	0.38	464	1
17	30	1450	725	135	4.20E-09	0.38	464	1
18	30	1160	725	135	4.20E-09	0.38	464	1
19	30	1885	435	135	4.20E-09	0.38	464	0
20	90	1160	435	135	4.20E-09	0.89	464	1
21	90	1885	435	135	4.20E-09	0.89	464	2
22	60	1885	435	135	4.20E-09	0.89	464	1

No	Angle (°)	Smax (psi)	Smin (psi)	Viscosity (cp)	Injection Rate (m3/s)	Friction Coefficient, K (dimensionless)	Cohesion (psi)	observed output
23	60	1450	435	135	4.20E-09	0.89	464	1
24	30	1885	435	135	4.20E-09	0.89	464	1
25	30	1160	435	135	4.20E-09	0.89	464	1
26	90	1740	870	135	4.20E-09	1.21	464	1
27	90	1740	870	135	4.20E-09	1.21	464	1
28	60	1740	870	135	4.20E-09	1.21	464	1
29	60	1740	870	135	4.20E-09	1.21	464	1
30	30	1740	870	135	4.20E-09	1.21	464	1
31	30	1740	870	135	4.20E-09	1.21	464	1
32	30	1000	500	320	1.00E-07	0.6	15	1
33	30	1500	500	320	1.00E-07	0.6	15	1
34	30	2000	500	320	1.00E-07	0.6	15	1
35	60	1000	500	320	1.00E-07	0.6	15	1
36	60	1500	500	320	1.00E-07	0.6	15	1
37	60	2000	500	320	1.00E-07	0.6	15	2
38	90	1000	500	320	1.00E-07	0.6	15	1
39	90	1500	500	320	1.00E-07	0.6	15	2
40	90	2000	500	320	1.00E-07	0.6	15	2
41	90	2000	1000	1000	5.00E-07	0.615	0	2
42	90	1100	1000	1000	5.00E-07	0.615	0	1
43	75	2500	1000	1000	5.00E-07	0.615	0	2
44	75	1200	1000	1000	5.00E-07	0.615	0	1
45	45	2500	1000	1000	5.00E-07	0.615	0	1
46	45	1200	1000	1000	5.00E-07	0.615	0	1

3.5 Gantt Chart

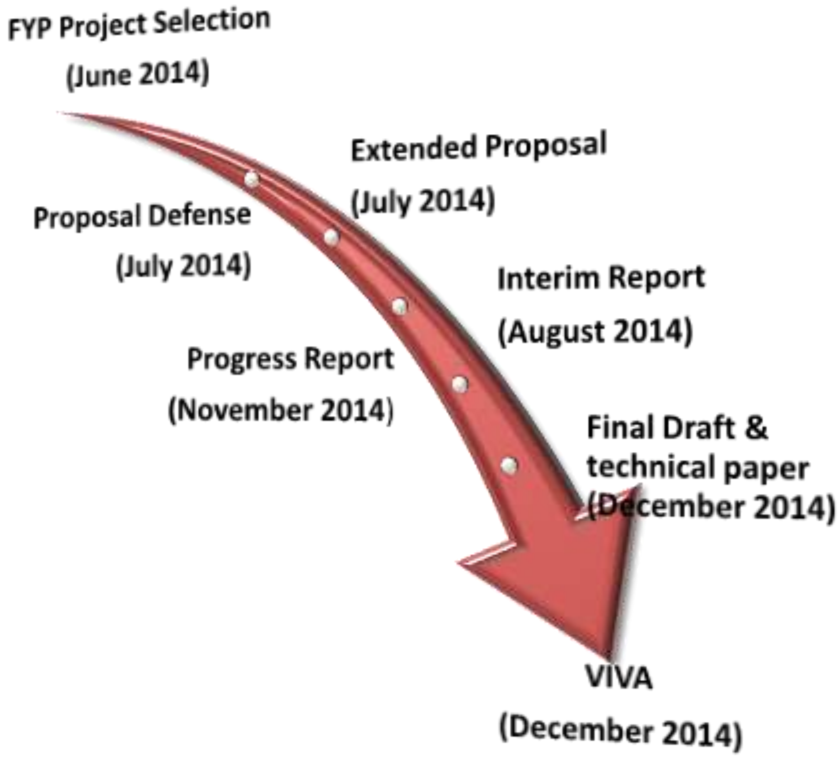
Gantt chart FYP I:

No	Details/Week	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Selection of FYP topic														
2	Research work finding														
3	Extended proposal submission														
4	Proposal Defence														
5	Continue with the project work														
6	Interim draft report submission														
7	Interim report of submission														

Gantt chart FYP II:

No	Details/Week	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Student/SV update progress																
2	Project commencement																
3	Progress report submission																
4	Pre-SEDEX																
5	Continue with the project work																
6	Final Draft & Technical paper submission																
7	SEDEX 33																
8	Final oral presentation/ VIVA																
9	Submission of hard copy																

3.6 Key Milestone Final Year Project (FYP I & FYP II)



CHAPTER 4

RESULTS AND DISCUSSION

4. RESULT AND DISCUSSION

This chapter describes the result of interaction between natural fracture and hydraulic fracture predicted by the model using the Artificial Neural Network (ANN). It is composed of two main sections. The first section explains the result of training, validation and testing of the model based on the inserted input data. The model has been interpreted by using mean square error (MSE) and regression analysis and the model performance was discussed. Next section of the chapter discussed on the sensitivity analysis for different parameters such as angle of approach, maximum and minimum horizontal stress, viscosity and injection rate of the fracture fluid, cohesion of the natural fracture and friction coefficient of the interface.

4.1 Artificial Neural Network (ANN) Model Performance

The model has been train and retrain repeatedly until it can produce the best weighting and bias for the model to perform at highest accuracy. Mean squared error and regression was used to analyse the output different between the observed output and targeted output by ANN model.

$$Mean\ square\ error, MSE = \left(\frac{1}{N}\right) * \sum (Ypredicted - yactual)^2$$

$$standard\ error\ of\ estimate, \sigma^{est} = \sqrt{\frac{\sum (Yactual - Ypredicted)^2}{N}}$$

Table 9: Network process error

Process	Dataset number	Regression	Performance
Training	3, 4, 6, 8, 9, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 24, 25, 27, 28, 29, 30, 32, 33, 34, 35, 36, 37, 40, 41, 42, 45	0.956664764	0.034591989
Validation	5, 22, 23, 24, 31, 38, 39	0.983042687	0.00089917
Testing	1, 2, 7, 10, 15, 26, 43	0.969291584	0.060524683

Regression, R measure the correlation between ANN output and observed target. Regression that approaching to 1 mean the ANN output has very closed relationship to the observed target. From the table 8, the model was said to have high accuracy as the build model has the regression, R of approaching to 1 for every training, validating and testing. Additionally, the model also has perform excellently for every training, validating and testing network process as all the performance was approaching to 0.

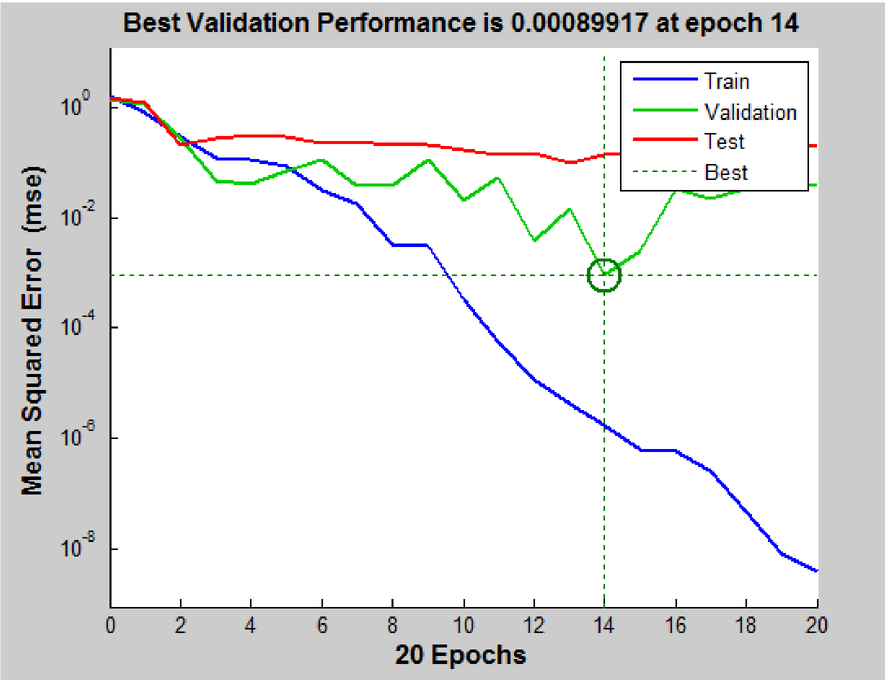


Figure 15: Performance of the ANN model

The training that undergo iteration to estimate the best weighting network has stopped at epoch of 20 which mean the network has undergo backpropagation training algorithm iteration for 20 times. Further validation stop the iteration with the best validation performance of 0.00089917at epochs of 14. The validation performance was almost approaching to 0 indicated that the model was performing well.

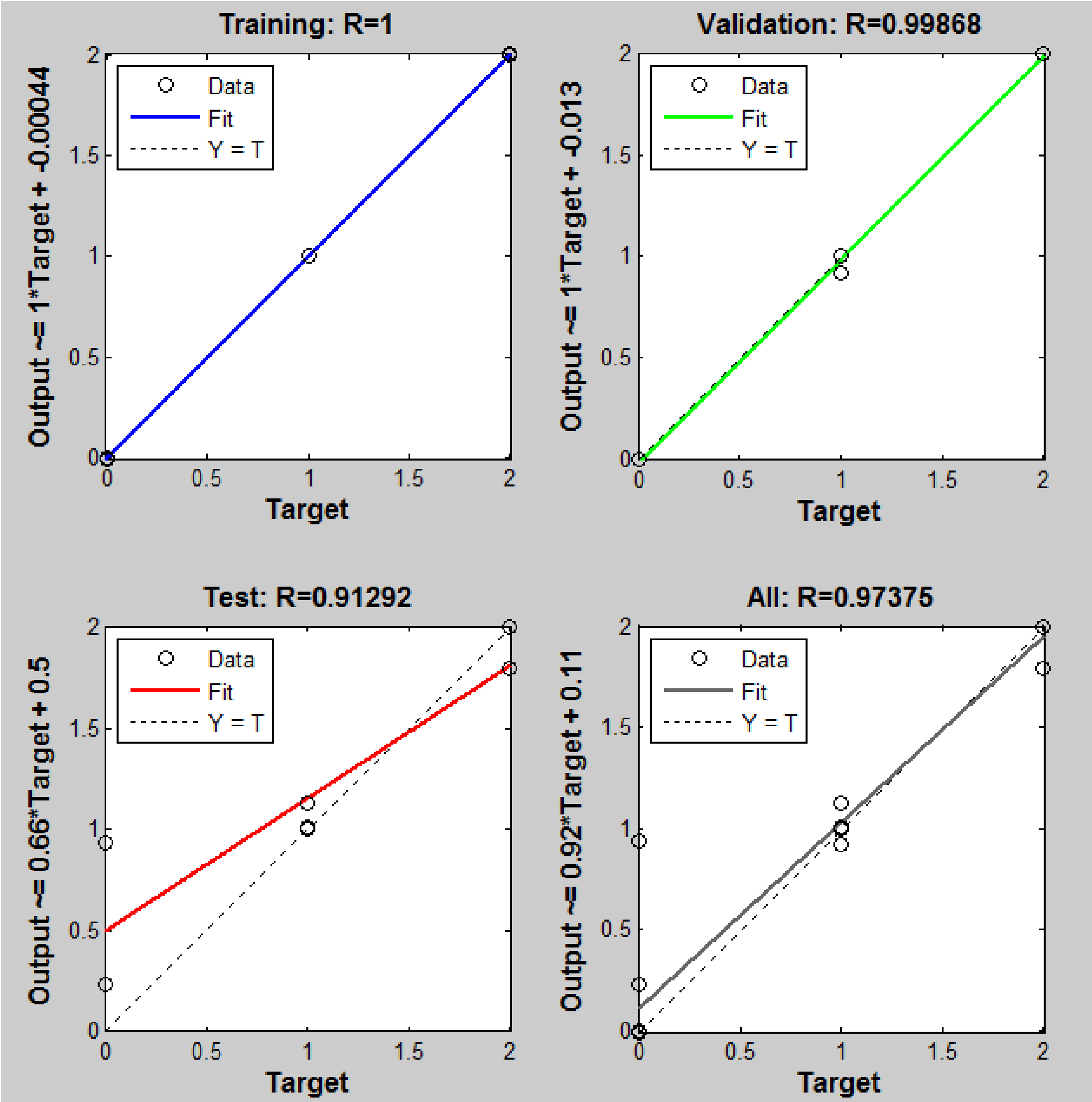


Figure 16: Regression plot

From the figure, regression plot for the training and validating show that both ANN output and observed target was accurately matched with regression of 1 and 0.99898 respectively. Whereas in the regression plot testing has the regression of 0.91292, approaching to 1.However, for the overall training, validating and testing produce a good regression plot with R=0.97375. The model is in good accuracy when regression for all is more than 0.95, R>0.95.

4.2 ANN Prediction and Experimental Result

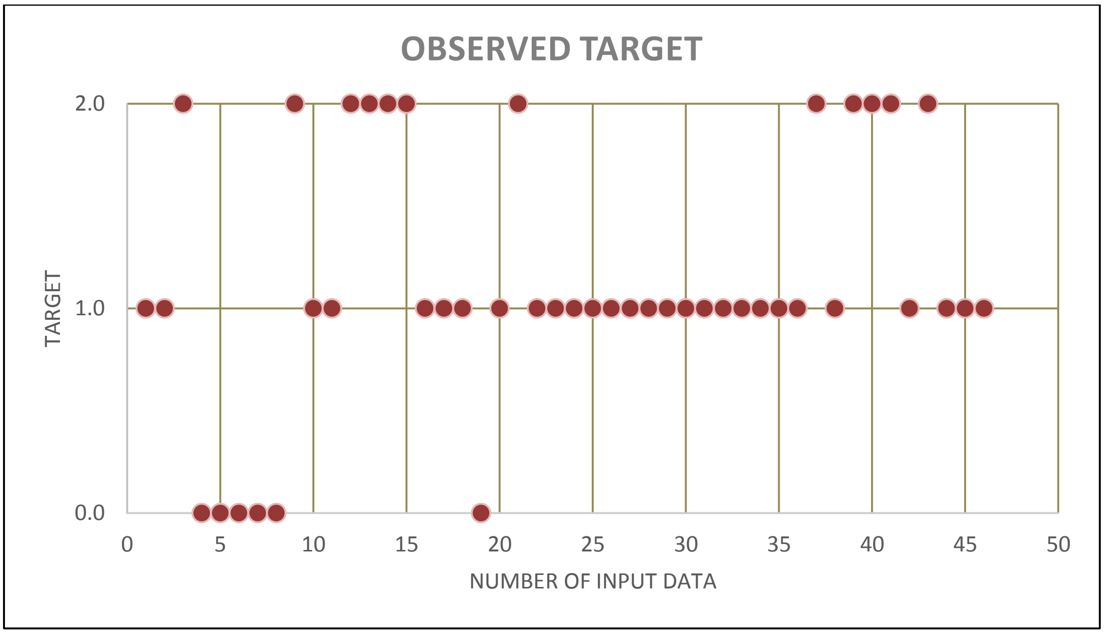


Figure 17: Experimental output for each data set

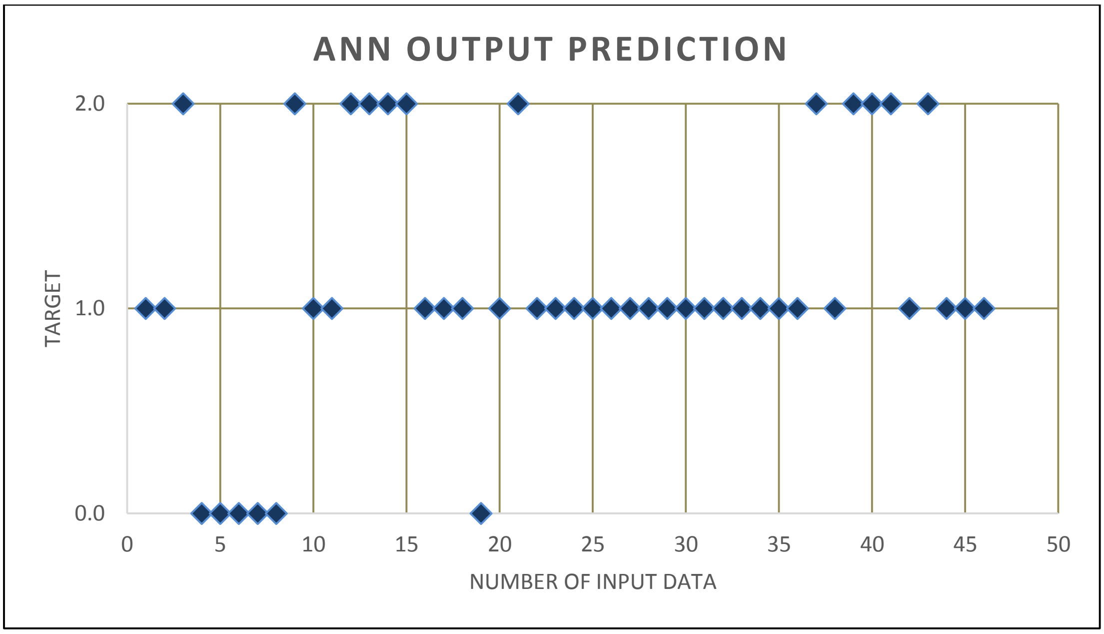


Figure 18: ANN model output prediction

ANN model has predicted that three propagation behaviour was observed during the hydraulic fracture interaction with natural fracture which is arresting, opening and dilating and crossing. The output show that at high horizontal differential stress and high angle of approach ($\theta>70°$), hydraulic fracture will cross natural fracture. Conversely, if the horizontal differential stress is high but the angle of approach is low ($\theta<45°$) or horizontal differential stress is low and the angle of approach is high, hydraulic fracture will not continue propagation instead turn into natural fracture or get arrested. Hydraulic fracture will open natural fracture at intermediate angle of approach and arrested at the intersection when the angle of intersection lower than 45° primarily because the fluid pressure in the hydraulic fracture was sufficient to open and divert fluid along the pre-fracture.

Table 10: Effect of horizontal stress and angle of approach

Angle (°)	Smax (psi)	Smin (psi)	Stress difference (psi)	Viscosity (cp)	Injection Rate (m3/s)	Friction Coefficient (demensionless)	Cohesion (psi)	Result
75	2500	1000	1500	1000	5.00E-07	0.615	0	Cross
75	1200	1000	200	1000	5.00E-07	0.615	0	Open
90	2000	1000	1000	1000	5.00E-07	0.615	0	Cross
90	1100	1000	100	1000	5.00E-07	0.615	0	Open

Whereas, result from ANN also predict that at low interface friction of coefficient and cohesion, more crossing occurred. Natural fracture parameters depend on the state of stress and diagenesis. Value of interface friction of coeficient is mainly decided by filled condition of pre-fracture, such as the degree of filled, filled material, aperture and roughness. The angle of internal friction is led by the condition of pre-fracture and it decides shear strength of pre-fracture. Mohr-Coulomb strength envelopes show high coefficient of friction has higher shear strength compared to low coefficient of friction. These observation agreed well with Zhou et al, by increasing shear strength of these pre-fractures, the possibility of arrested behavior also increased (Zhou, Chen et al. 2008).

Table 11: Effect of interface friction of coefficient and cohesion

Angle (°)	Smax (psi)	Smin (psi)	Stress difference (psi)	Viscosity (cp)	Injection Rate (m3/s)	Friction Coefficient (dimensionless)	Cohesion (psi)	Result
90	1740	870	870.2262	135	4.20E-09	1.21	464	Open
90	1500	500	1000	320	1.00E-07	0.6	15	Cross

Increasing injection rate and viscosity show crossing to occur more often compare to using low rate and low viscosity. Nagel, Neal Borden et al mentioned that high injection rate and viscosity increase the generation of tensile failure compare to shear strengh, meaning more crossing can happen. On the other hand, lower injection rate and viscosity of fracture fluid show increase of shear failure generation cause the hydraulic fracture to turn into natural fracture without crossing hydraulic fracture (Nagel, Gil et al. 2011).

Table 12: Effect of Viscosity and injection rate of fracture fluid

Angle (°)	Smax (psi)	Smin (psi)	Stress difference (psi)	Viscosity (cp)	Injection Rate (m3/s)	Friction Coefficient (dimensionless)	Cohesion (psi)	Result
45	2320	725	1595	1	8.194E-07	0.75	218	Arrest
90	1740	870	870.2262	135	4.20E-09	1.21	464	Open
30	2000	500	1500	320	1.00E-07	0.6	15	Open
90	2000	1000	1000	1000	5.00E-07	0.615	0	Cross
75	2500	1000	1500	1000	5.00E-07	0.615	0	Cross

Injection rate and viscosity also has mere significant on the opening of the fracture width after dilation. From the equation, the fracture opening was dependent on injection rate, Q and fluid viscosity,μ.

$$\bar{w} = 2.53\left[\frac{Q\mu L^2}{E'H}\right]^{1/4}$$

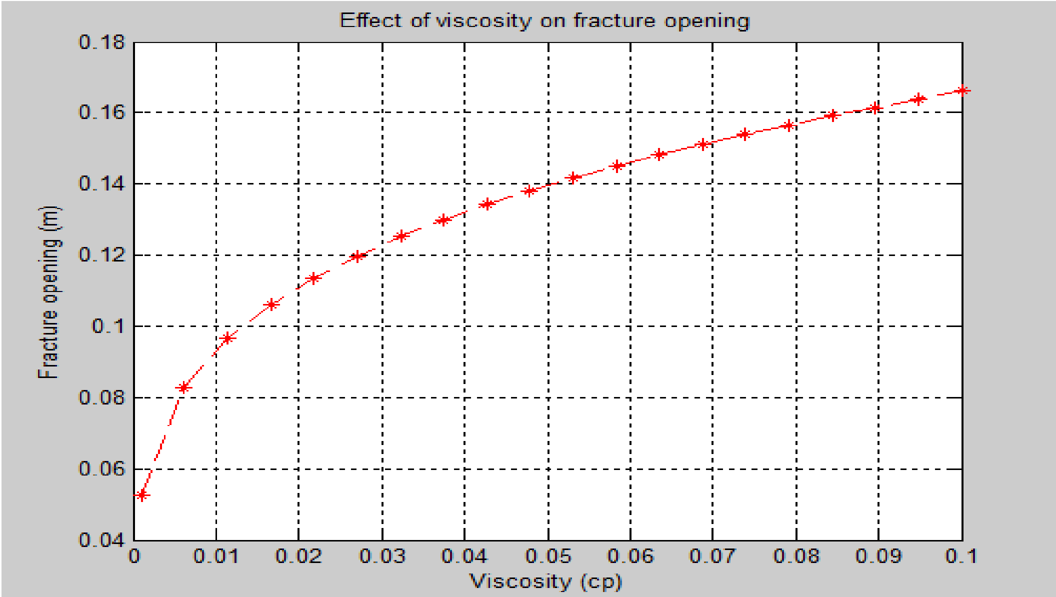


Figure 19: Effect of viscosity on natural fracture opening

From the figure 18, it show that viscosity of fracture fluid is directly proportional to the opening fracture. The opening size increasing with the increase of fracture fluid viscosity. When, hydraulic fracture arrested into the natural fracture, high viscosity of fracture fluid allowed natural fracture to dilate larger in size. When the fracture opening width is large, the turning rate to create new initiated fracture from the tips of natural fracture will be slower hence make it difficult for hydraulic fracture to create the secondary fracture turning into natural fracture.

4.2.1 ANN Model Vs Observed Data

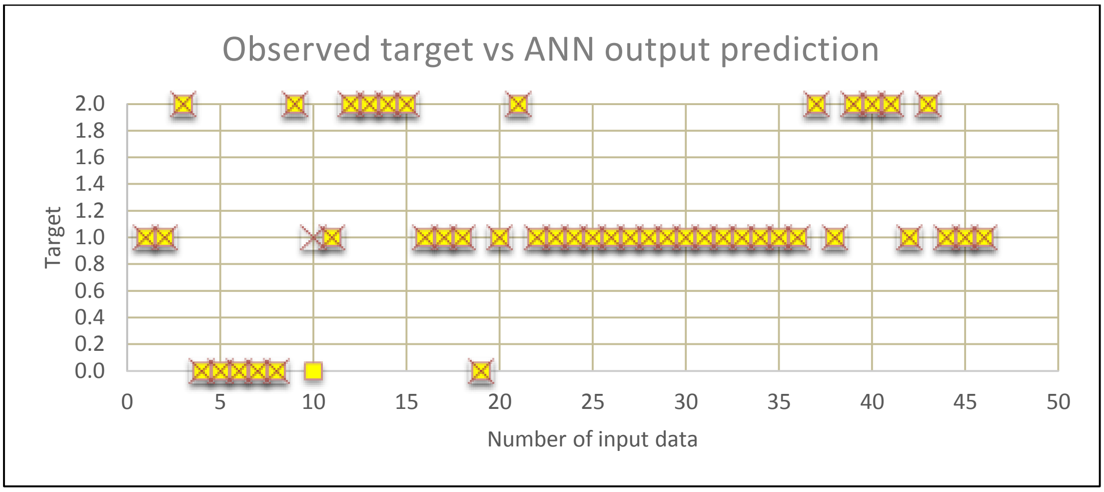


Figure 20: Comparison between ANN model outputs with Experimental output

ANN output prediction and observed target from the experiment was plotted and compared. As shown in the figure 19, the ANN model has produce a promising result as it able to predict the output that match with the observed target with an overall accuracy of 96.49%. ANN model prediction agree very well with the observed target for almost all data point indicated that artificial neural network approach is efficient in forecasting the hydraulic fracture propagation when intersecting with natural fracture. The result of comparison between ANN model and actual case was presented in the table 9. At the data point of 10, the ANN has predicted the output as 1 which mean hydraulic fracture is open and dilating natural fracture after interaction. Whereas, conducted experiment show hydraulic fracture to be arrested by natural fracture at the intersection.

Table 13: Comparison between ANN model outputs with Experimental output

No	Observed target	Pattern	ANN output	Pattern
1	1	Open	1.0	Open
2	1	Open	0.9	Open
3	2	Cross	2.0	Cross
4	0	Arrest	0.0	Arrest
5	0	Arrest	0.0	Arrest
6	0	Arrest	0.0	Arrest
7	0	Arrest	0.0	Arrest
8	0	Arrest	0.2	Arrest
9	2	Cross	2.0	Cross
10	0	Arrest	0.9	Open*
11	1	Open	1.0	Open
12	2	Cross	2.0	Cross
13	2	Cross	2.0	Cross
14	2	Cross	2.0	Cross
15	2	Cross	1.8	Cross
16	1	Open	1.0	Open
17	1	Open	1.0	Open
18	1	Open	1.0	Open
19	0	Arrest	0.0	Arrest
20	1	Open	1.0	Open
21	2	Cross	2.0	Cross
22	1	Open	1.0	Open
23	1	Open	1.0	Open

No	Observed target	Pattern	ANN output	Pattern
24	1	Open	1.0	Open
25	1	Open	1.0	Open
26	1	Open	1.0	Open
27	1	Open	1.0	Open
28	1	Open	1.0	Open
29	1	Open	1.0	Open
30	1	Open	1.0	Open
31	1	Open	1.0	Open
32	1	Open	1.0	Open
33	1	Open	1.0	Open
34	1	Open	1.0	Open
35	1	Open	1.0	Open
36	1	Open	1.0	Open
37	2	Cross	2.0	Cross
38	1	Open	1.1	Open
39	2	Cross	2.0	Cross
40	2	Cross	2.0	Cross
41	2	Cross	2.0	Cross
42	1	Open	1.0	Open
43	2	Cross	2.0	Cross
44	1	Open	1.0	Open
45	1	Open	1.0	Open
46	1	Open	1.0	Open

4.2.2 Percentage Of Model Accuracy

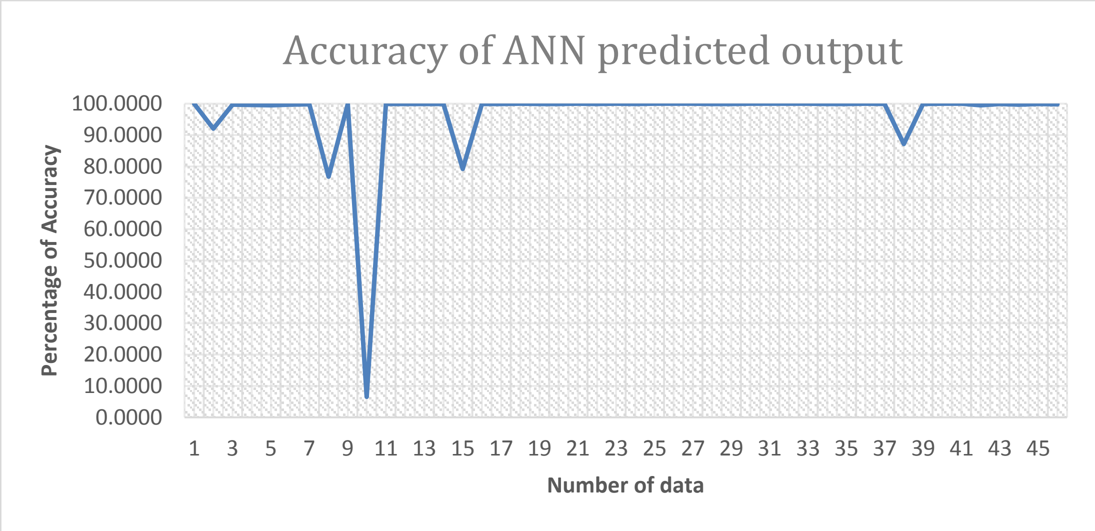


Figure 21: Output accuracy of each data point

The figure above show that only at data point number 10, the ANN prediction is different from the observed target cause the accuracy to greatly decrease at this data point. However, ANN model has been train, validated and tested previously which make it a superior model for prediction. Overall, the ANN model has generated an accuracy of 96.5% which make it a promising model with high efficiency.

4.2.3 Error Analysis

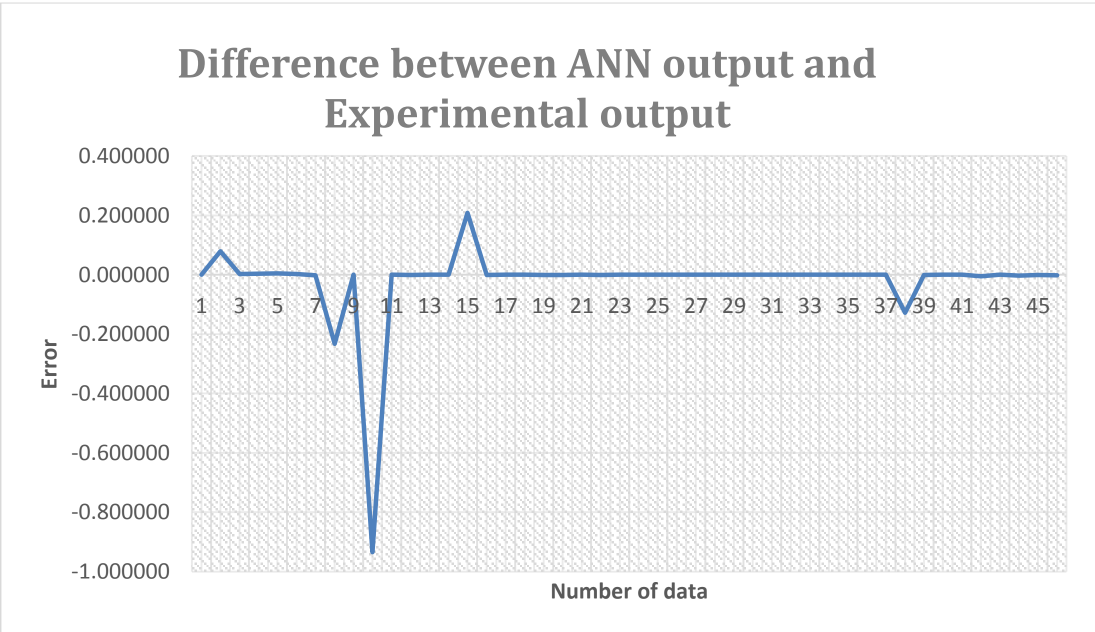


Figure 22: Difference between ANN output and observed target

The figure show that at data point number 10, the difference between ANN output and observed target is high. ANN has predicted that the propagation to be opening and dilating the natural fracture whereas the observed target is hydralic fracture to be arrested. However, at the rest of the data point, the result match well between both ANN model prediction and observd target.

4.3 Sensitivity Analysis

The best weighting network from the training, validation and testing process was used to conduct the sensitivity analysis for each of the parameter. From the sensitivity analysis performed with the ANN model, we can know which parameter that give more significant effect on the interaction between hydraulic fracture and natural fracture and which parameter give the least effect.

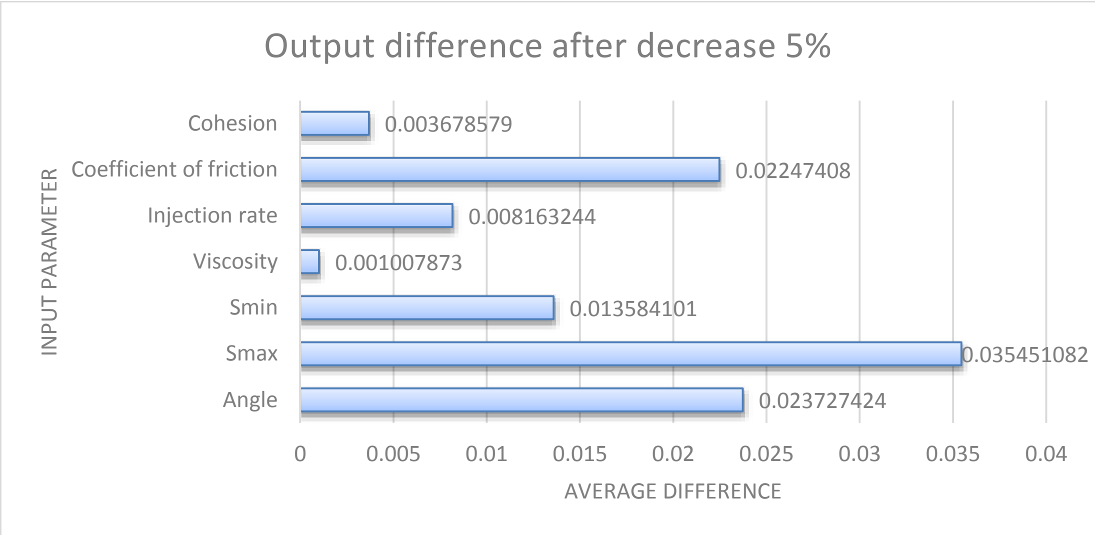


Figure 23: Sensitivity analysis of every parameter when decrease by 5%.

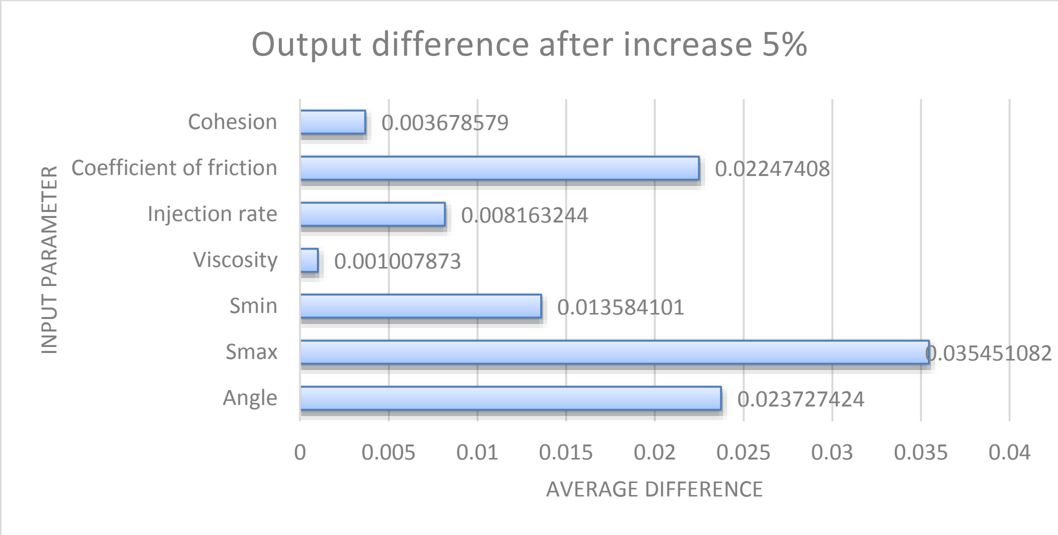


Figure 24: Sensitivity analysis of every parameter when increase by 5%.

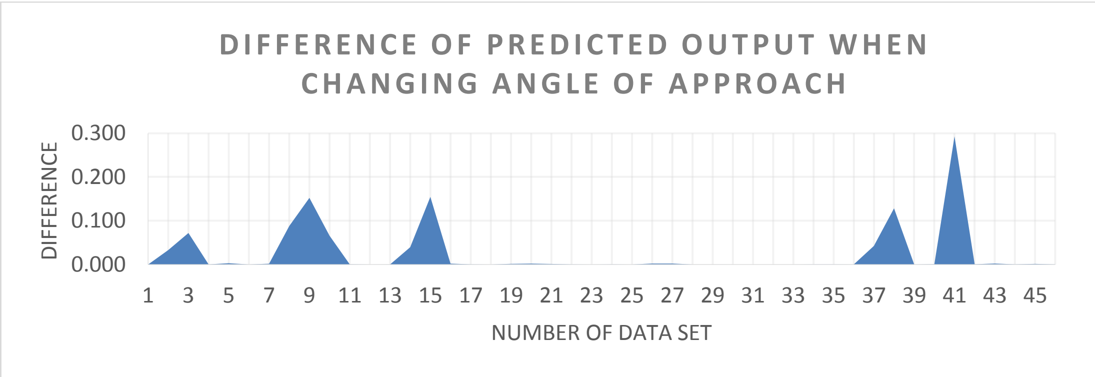


Figure 25: Difference of predicted output when changing angle of approach

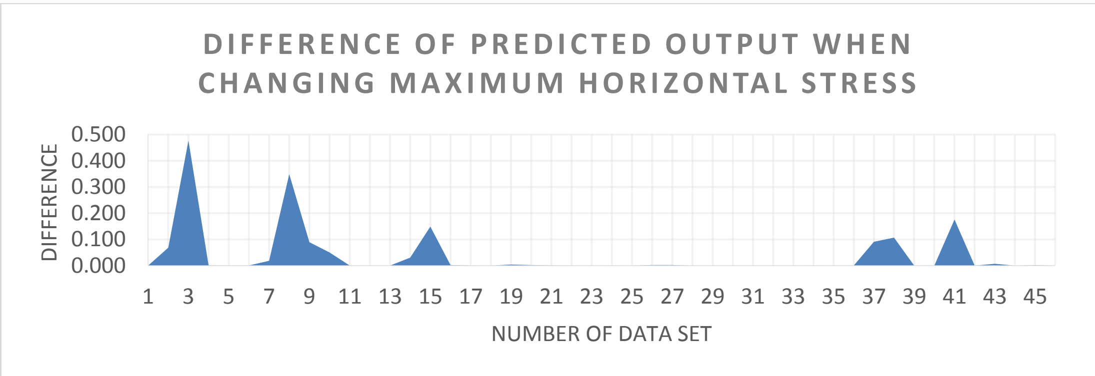


Figure 26: Difference of predicted output when changing maximum horizontal stress

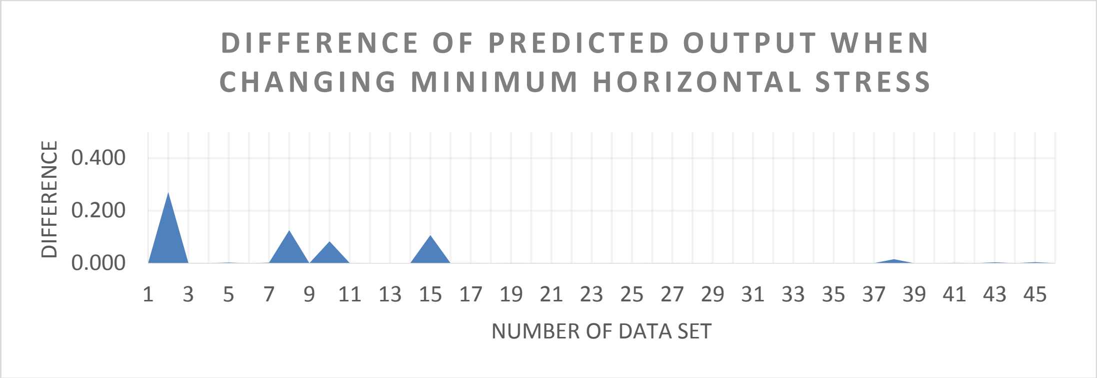


Figure 27: Difference of predicted output when changing minimum horizontal stress

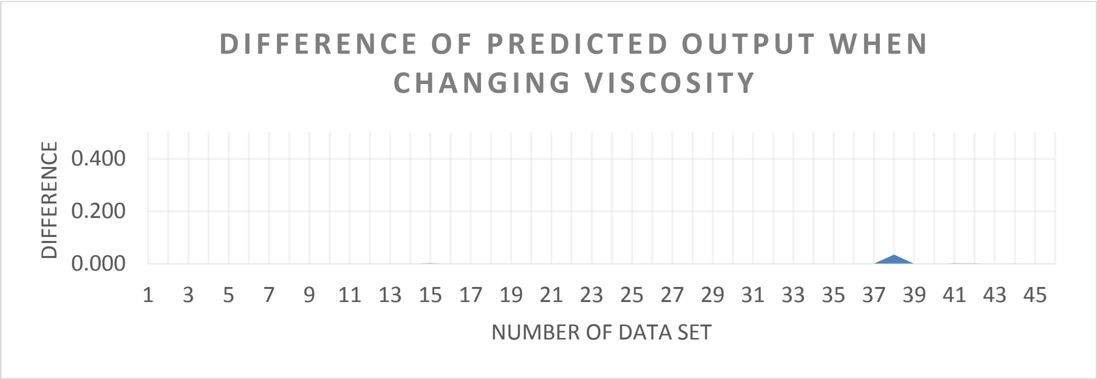


Figure 28: Difference of predicted output when changing viscosity

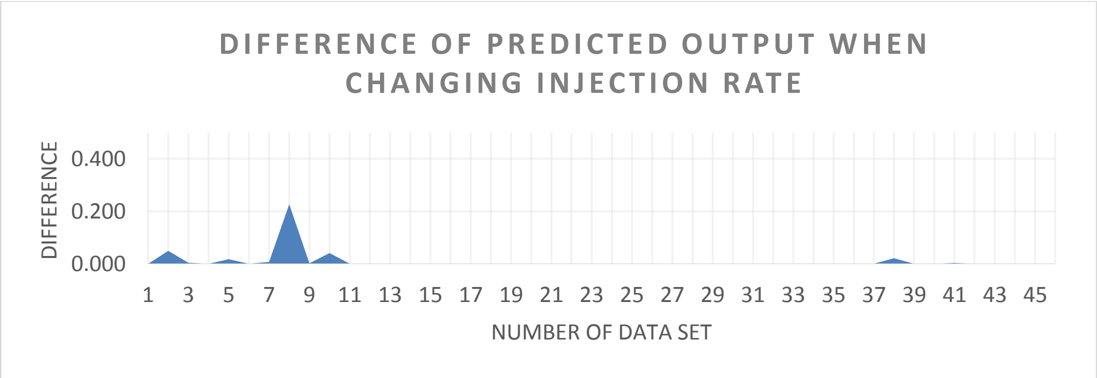


Figure 29: Difference of predicted output when changing injection rate

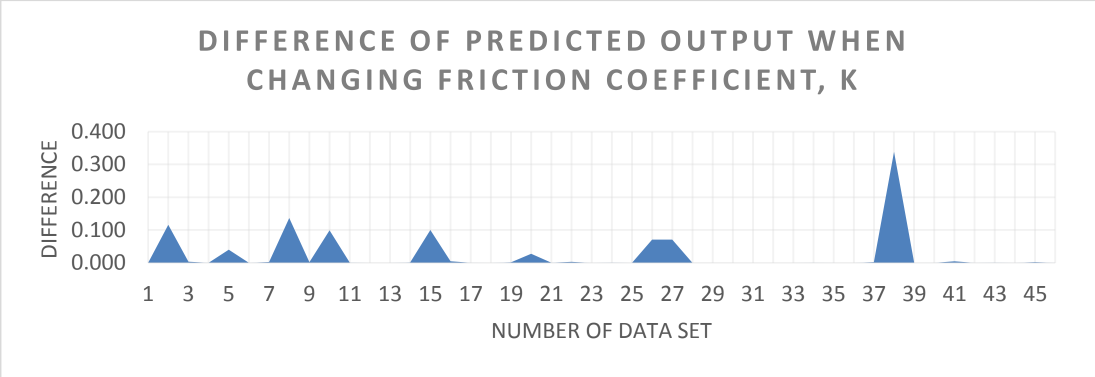


Figure 30: Difference of predicted output when changing friction of coefficient

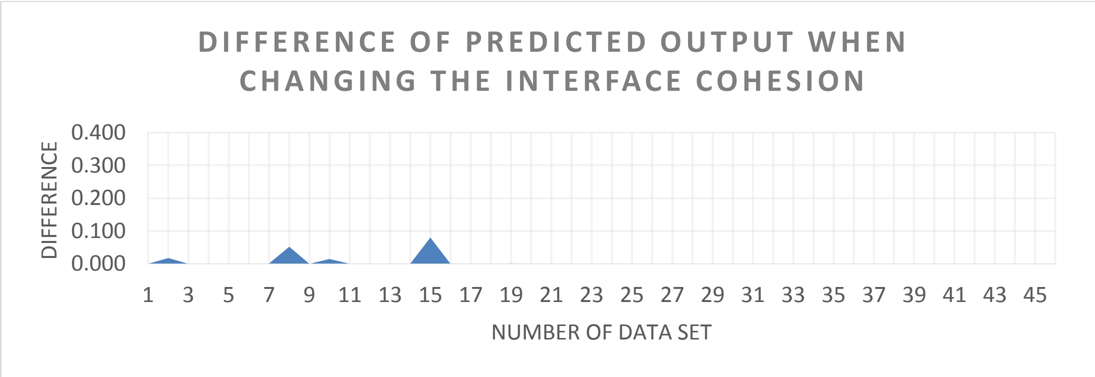


Figure 31: Difference of predicted output when changing interface cohesion

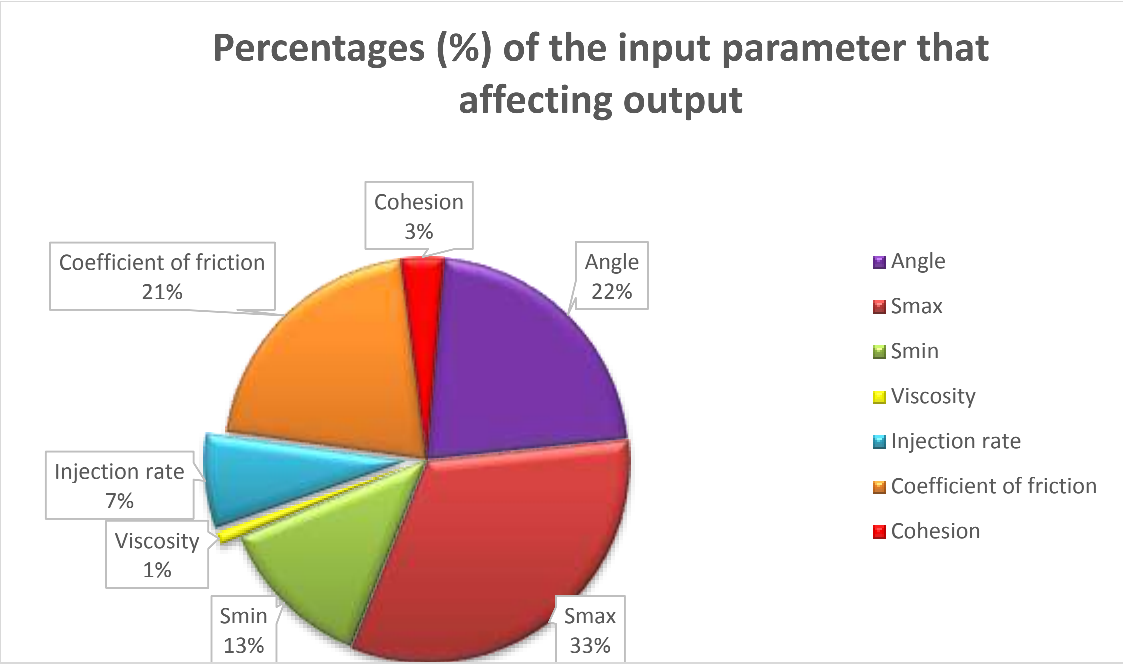


Figure 32: Percentage of input parameter that affecting output

From the pie chart in figure, it is clearly show the percentage of every input parameter that affecting the direction of hydraulic fracture propagation when intersecting with natural fracture in naturally fracture reservoir. Observation from the output predicted by ANN model show that maximum horizontal stress has the most significant effect with 33% effect followed by the angle of approach with 22%. Whereas, injection rate have only 7% chance to affect the hydraulic fracture propagation pattern and viscosity has the least effect with only 1%. Changing the viscosity and injection rate give an effect on the propagation but it is not as significant as maximum horizontal stress.

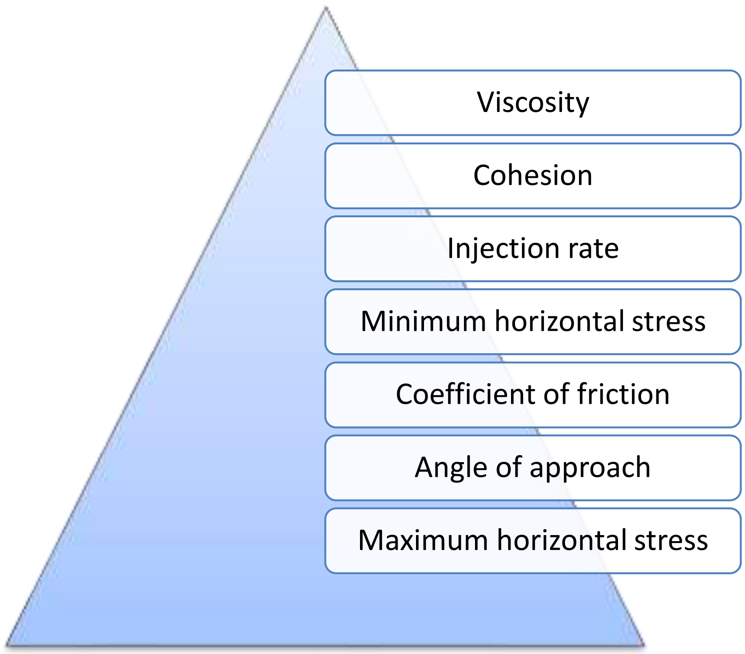


Figure 33: Parameter's affecting hydraulic fracture propagation at the intersection of natural fracture

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

Feasible model was develop by using artificial neural network (ANN) based on angle of approach, maximum horizontal stress, minimum horizontal stress, viscosity of fracture fluid, injection rate of fracture fluid, interface friction of coefficient and interface cohesion. The model has been train, validated and tested with the set of input data. ANN model yield promising prediction on the direction of hydraulic fracture propagation when intersecting with natural fracture with an accuracy of 96.5%.

Fluid properties affect the propagation of the hydraulic fracture but not very significantly. Turn out that fluid properties has more effect on widen the natural fracture once hydraulic fracture were arrested and dilating natural fracture. Sensitivity analysis conducted on each of the parameter found that in-situ stress has more important role in determining the direction of hydraulic fracture propagation whereas viscosity has the least effect.

5.2 Recommendations

Based on what we achieved by this study we recommend that:

1. The model should also predict whether the new fracture might initiated from the natural fracture tips or at any length of natural fracture after hydraulic fracture turning into natural fracture, dilating and reactivate natural fracture.
2. Experiment is conducted by the researcher to further develop the model to fully study and understand the direction behaviour of hydraulic fracture in naturally fractured reservoir.

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APPENDICES

Appendix I

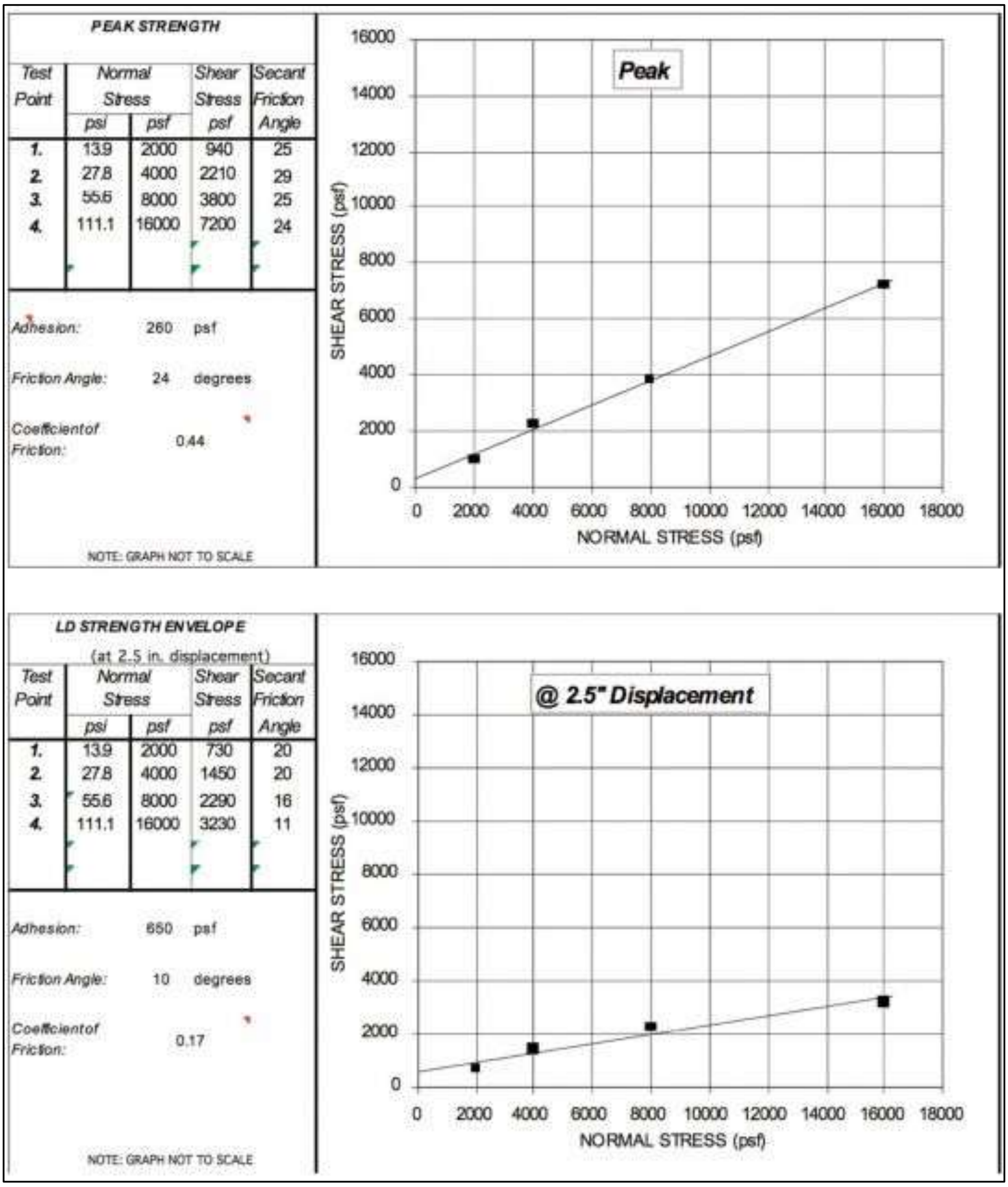

Figure 34: Peak and large-displacement strengths plotted as a function of normal stress.

Appendix II

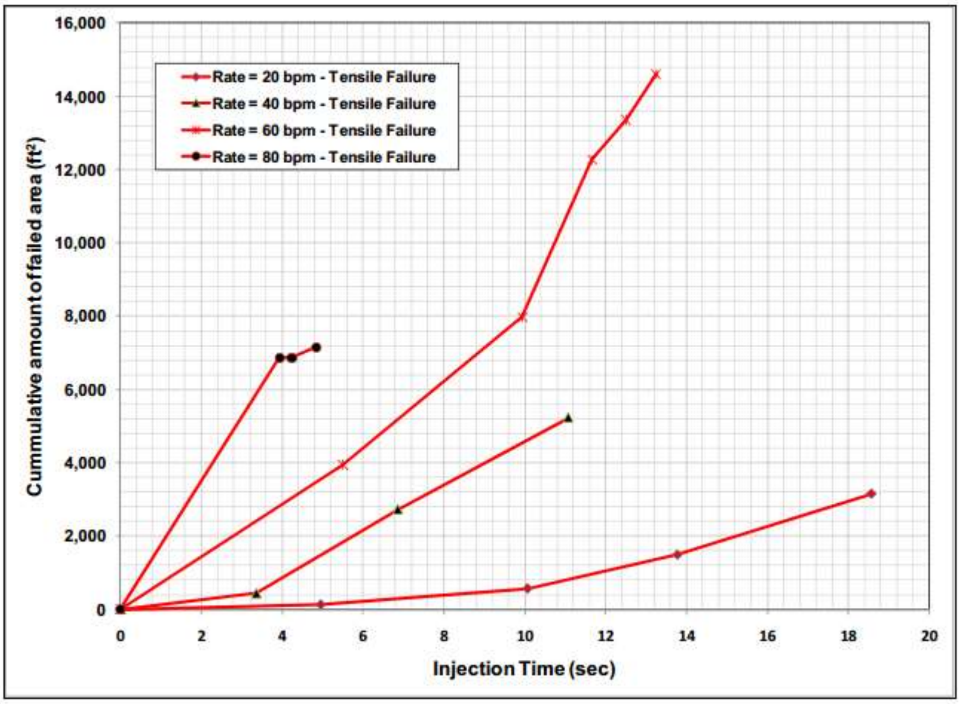

Figure 35: Effect of fluid injection rate on tensile failure generation

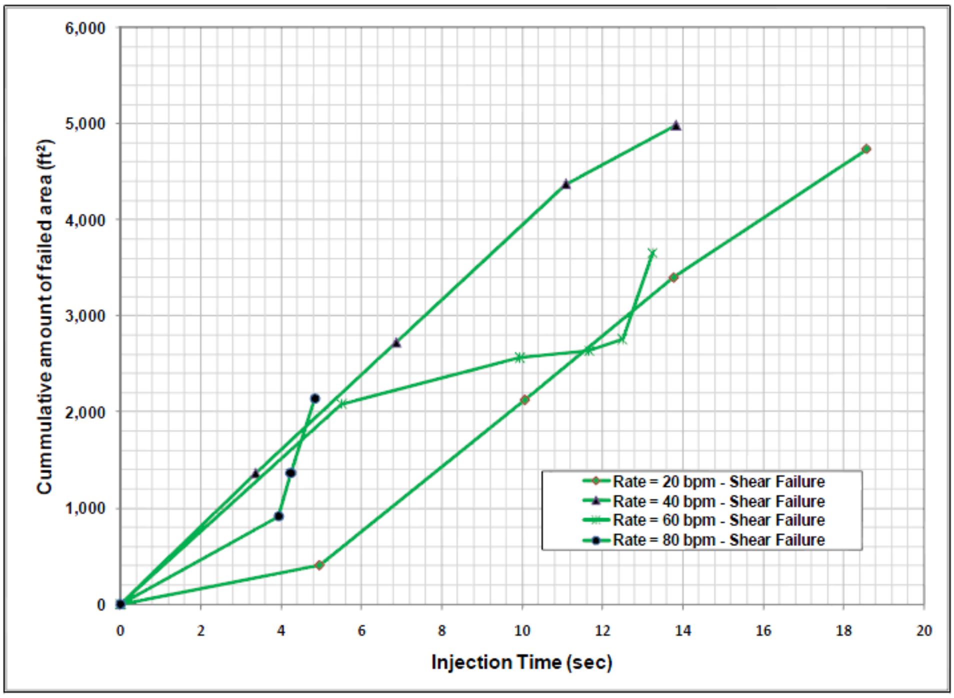

Figure 36: Effect of injection rate on shear failure generation

Appendix III

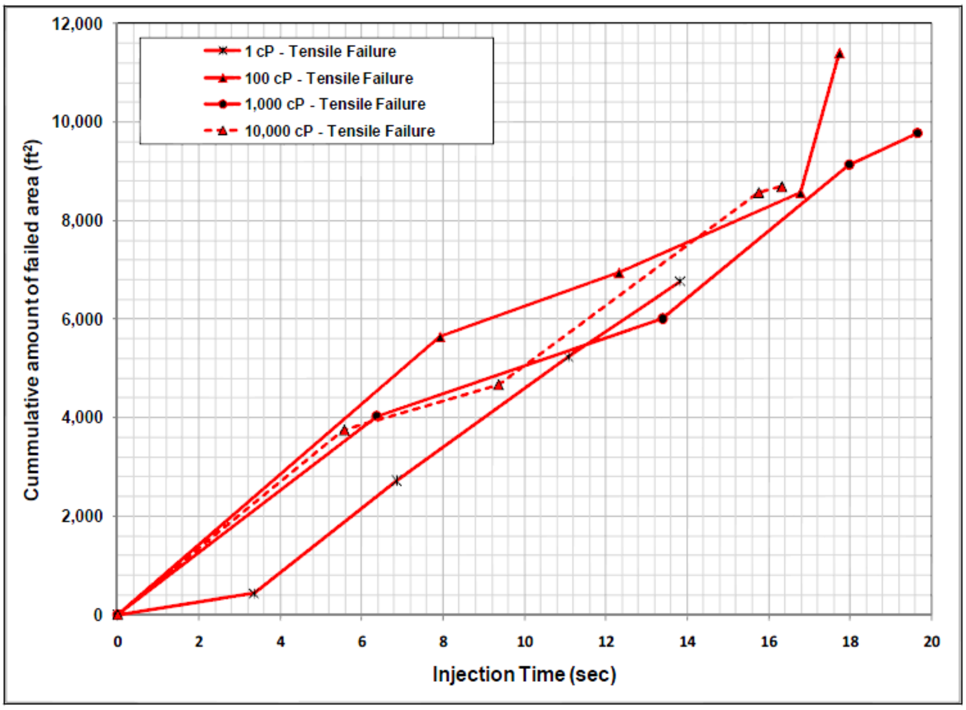

Figure 37: Effect of injection fluid viscosity on tensile failure generation

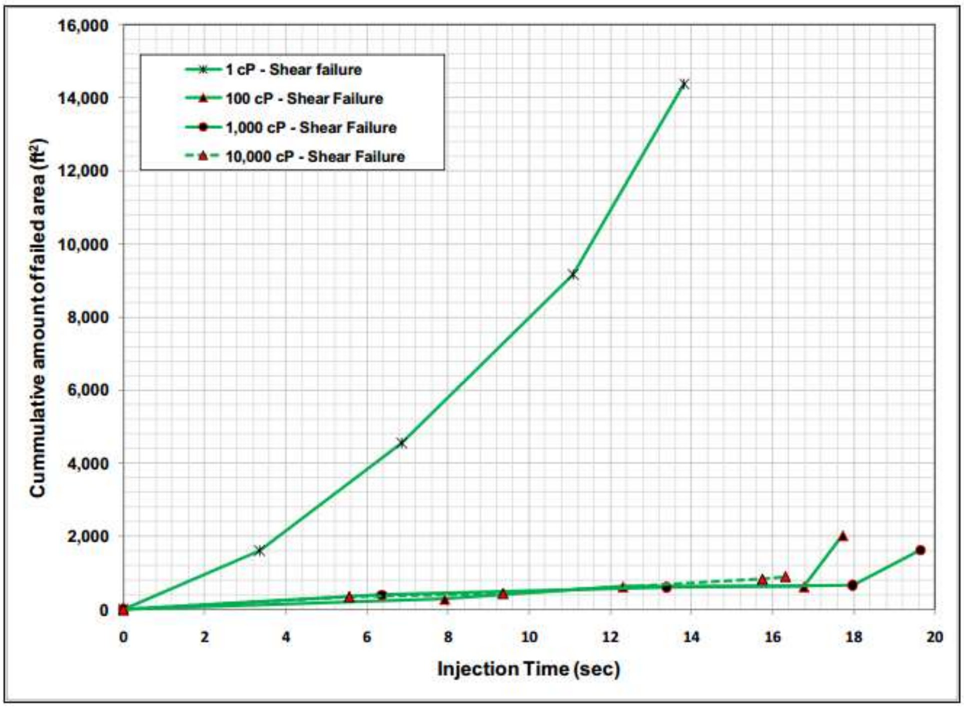

Figure 38: Effect of injection fluid viscosity on shear failure generation

Appendix IV

```
% Solve an Input-Output Fitting problem with a Neural Network

inputs = inputdata';
targets = observeddata';
hiddenLayerSize = 8;

net = fitnet(hiddenLayerSize);
net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};
net.outputs{2}.processFcns = {'removeconstantrows','mapminmax'};

net.divideFcn = 'dividerand';
net.divideMode = 'sample';
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
net.trainFcn = 'trainlm';
net.performFcn = 'mse';
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...

'plotregression', 'plotfit'};
[net,tr] = train(net,inputs,targets);

outputs = net(inputs);
errors = gsubtract(targets,outputs);
performance = perform(net,targets,outputs)
trainTargets = targets .* tr.trainMask{1};
valTargets = targets .* tr.valMask{1};
testTargets = targets .* tr.testMask{1};

trainPerformance = perform(net,trainTargets,outputs)
valPerformance = perform(net,valTargets,outputs)
testPerformance = perform(net,testTargets,outputs)
view(net)

figure, plotperform(tr)
figure, plottrainstate(tr)
figure, plotfit(net,inputs,targets)
figure, plotregression(targets,outputs)
figure, ploterrhist(errors)
```