Pressure Drop in Vertical Multiphase Flow using Neuro Fuzzy Technique; A Comparative Approach

by

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CERTIFICATION OF APPROVAL

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Approved by,

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(Dr. Mohammed Abdalla Ayoub)

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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.

Mohamed AlaaElDin Mohamed

Abstract

The sole objective of this study is to develop a model for estimating the pressure drop in vertical multiphase flow using one of the artificial intelligence techniques which is Neuro Fuzzy Systems with a good and acceptable accuracy that can work for a wide range of well flowing conditions that can replace the rigorous empirical and mechanistic correlations.

In this study a number of 206 data sets collected from some fields in the Middle East were used to develop the Neuro Fuzzy Model.

Many attempts have been done to estimate the pressure drop in vertical multiphase flow starting from the homogeneous models, the empirical models and the mechanistic models. But yet, none of the traditional correlations works well for the variety of well conditions that are found in the oil industry. Thus, the accuracy of the old pressure drop correlations cannot be raised to a generally accepted level. For this purpose, one of the artificial intelligence techniques (Neuro Fuzzy System) is used to have a significant reduction in the error involved with estimating the pressure drop.

The Neuro Fuzzy Model was developed through 3 stages; Training, Validation, Testing.

The developed Neuro Fuzzy Model has successfully achieved the lowest Average Absolute Percentage Error (AAPE%) of 2.92% that could overcome all the empirical and mechanistic correlations when tested against the same set of data. It can be concluded that Neuro Fuzzy system has overcame the performance of the models currently used in the industry.

Acknowledgment

All praises be to God, The One, The Almighty for his countless bounties on me.

I would like to thank Dr. Mohammed Abdalla Ayoub for supervising my graduation thesis and would like to express all the respect to him for the information he has taught me and for his guidance to complete this project.

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Table of Contents

List of Figures

List of Tables

Abbreviations and Nomenclature

AAPE: Average Absolute Percentage Error

AI: Artificial Intelligence

ANFIS: Adaptive Neuro Fuzzy Inference System

ANN: Artificial Neural Network

MaxAE: Maximum Average Error

MinAE: Minimum Average Error

RMSE: Root Mean Squared Error

STD: Standard Deviation

Chapter 1

Introduction

1.1 Project Background

Vertical multiphase flow might happen in the well during the production phase. It involves having natural gas, hydrocarbon oil and water being produced out of the well. The multiphase flow is governed by the bubble point, whenever the pressure drops below the bubble point, gas will come out of the solution and will start flow until it reaches the surface.

Multiphase flow is normally characterized by different flow regimes. The flow regimes can be defined as a description of the distribution of the phases flowing in the well. Many studies have shown that for multiphase flow where the tubing has gas, oil and water flowing simultaneously, certain important properties of the flow such as the in-situ fractions of the phases present and the pressure drop behavior as well with the liquid hold up depend strongly on the flow regime.

Many researchers have tried to describe the flow patterns that exist in vertical multiphase flow. The four flow patterns that are agreed upon are bubble, slug, churn and annular flow

The flow experiences different patterns depending on the gas rate that exist in flow. The various flow patterns that can happen in vertical multiphase flow are shown in figure 1.1.

- Bubble (Dispersed Bubble):

  It has the form of small bubbles of gas dispersed in a continuous liquid phase. Because of the gas having density less than oil, the gas bubbles travel faster that the liquid phase.

- Slug Flow:

  As the gas rate increases in the stream due to the amount of gas that comes out of solution, the bubbles coalesce into larger bubbles that will eventually fill the entire pipe cross section. In between the large gas bubbles are slugs of liquid that contain smaller gas bubbles entrained in the liquid.

- Churn (Forth) Flow:

  With further increase in the gas rate larger bubbles would become unstable and collapse resulting in a churn flow which experiences a highly turbulent flow pattern with both phases dispersed. The liquid phase experiences up and down motion.

- Annular Flow:

  At higher flow rates, gas become the continuous phase with liquid flowing in an annulus coating the surface of the pipe and liquid droplets entrained in the gas phase.

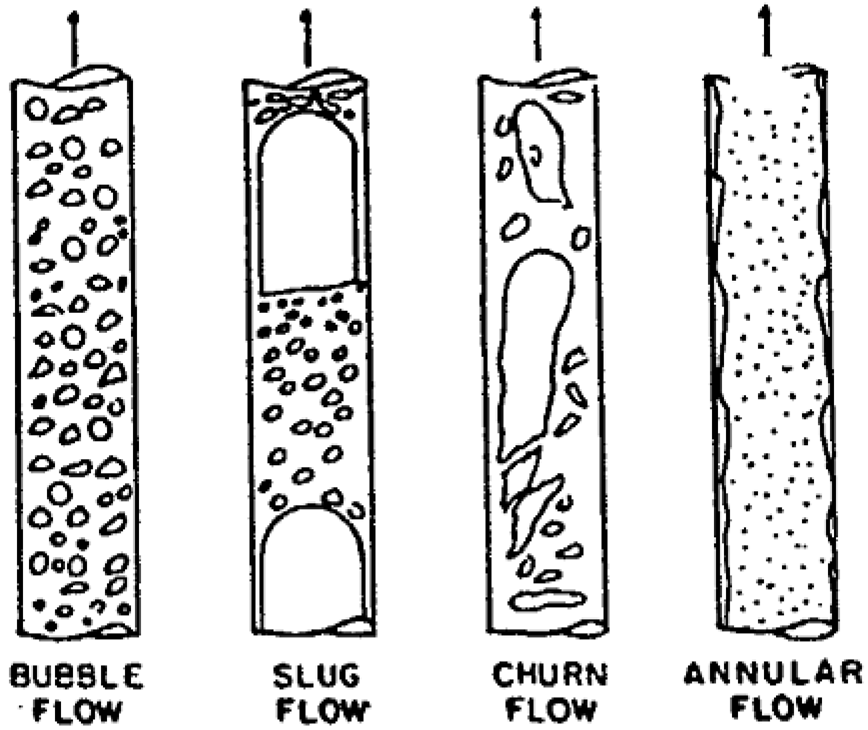


Figure 1.1: Flow regimes in vertical multiphase flow

According to (Kabir & Hasan, 1986), the hydrostatic head contributes to the most of the pressure drop (90 % +) when the flow is restricted to bubble and slug flow. While in the case of annular flow, the friction head is the main contributor to the pressure drop.

1.2 Parameters Governing Pressure drop in vertical multiphase flow:

According to (Abdul-Majeed, 1993), the parameters that strongly affect the pressure drop in vertical multiphase flow are:

- Liquid Flow rate
- Water Cut
- Gas- Liquid ratio
- Tubing Diameter
- Oil API gravity
- Wellhead pressure
- Bottom hole temperature
- Average temperature
- Well depth

1.3 Importance of Estimating pressure drop:

Estimating the pressure drop in vertical multiphase flow is essentially used for a number of design calculations such as:

- Tubing size and operating well head pressure in a flowing well
- Well completion or re-completion scheme
- Artificial lift during either gas lift or pump operation in a low energy reservoir
- Liquid unloading in gas wells
- Direct input for surface flow line and equipment design calculations

However, estimating the pressure drop in vertical multiphase flow is not that easy due to the various limitations that it has. The difficulties that feature the multiphase flow in the petroleum industry are very wide such as and not limited to:

- The multi component mixture which is having a very complex phase behavior.
- The range of pressure in the well that can vary from 15000 psia to atmospheric pressure.
- The range of temperature that can be as high as $200^{o}c$ to below the freezing temperature in the permafrost in arctic locations.

1.4 Artificial Intelligence

Soft computing and Artificial Intelligence has become popular among researchers because of the non-requirement of a mathematical model. It can be defined as "the development of algorithms that supports machines to perform certain tasks that requires learning abilities and awareness when performed by human" (BURAGOHAIN, 2008).

The main purpose of Artificial Intelligence (AI) is to model an imprecisely defined real world system so it can forecast future values.

Artificial Intelligence can be classified into:

- Artificial Neural Network (ANN)
- Fuzzy Logic
- Genetic Algorithm

In this study the author focuses on the use of ANN alongside with Fuzzy logic which when combined together form Neuro Fuzzy Logic in order to estimate the pressure drop in vertical multiphase flow.

1.4.1 Artificial Neural Network:

The ANN was developed as a result of the attempt of researchers to model the human brain as the human brain can process highly complex incomplete information obtained by perception at a very rapid rate. The ANN is supposed to work on the same way thus, it consists of neurons or progressing units which are interconnected by weights and are expected to mimic the human brain so it also has the ability of learning and adaptation by adjusting the interconnection between layers.

The neurons are arranged in layers and each layer has a certain task to perform. The ANN consists of 3 layers; an input layer that has a number of neurons that should be equivalent to the number of input parameters, an output layer and a number of hidden layers that intervene between the external input and the network output.

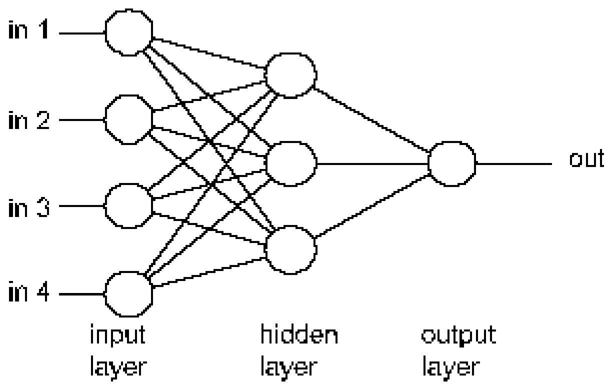


Figure 1.2: Artificial Neural Network Strucutre

The main important characteristics of the Artificial Neural Network are:

- The presence of a large number of simple units
- The presence of a large number of highly parallel units
- The presence of strongly connected units
- Robustness in relation to disturbance
- Generalization capacity

1.5 Fuzzy Logic

Fuzzy logic was introduced by (Zadeh, 1965) which is considered as an extension to the conventional Boolean Logic (0 and 1). It was developed to deal with the concept of partial truth values that exist between strictly true and strictly false. The word fuzzy refers to uncertainty, ambiguity and imprecise not well defined data. As the name implies, fuzzy logic is normally used to represent uncertainty which is caused by inaccurate data or lack of parameters that have strong impact on the results.

Unlike the crisp logic that describes things as black and white, true and false, 0 and1. As an example, let's consider two values of porosity, 22% and 10%. The crisp logic can describe those values as strictly high for 22% and strictly low for 10% and there is no in between description. It can be considered that the boundary between high and low porous intervals is at 15% porosity. According to the crisp logic, the porosity 14.99 is low and 15.01 is high. If the crisp logic is used with the previous definition in the rest of the oil industry, it is going to create ambiguities. Thus, the fuzzy logic can be used instead for better description of imprecise data (Mohaghegh, 2000).

Applying the fuzzy logic in the previous example, it can describe the porosity 15.01 as high but 20 is better and 25 even better.

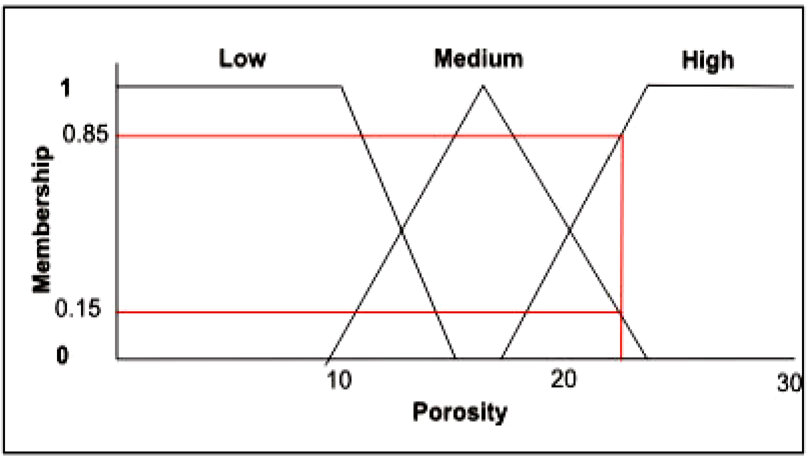


Figure 1.3: Fuzzy logic concept for different porosity sets

Thus as defined by (Zadeh, 1965), fuzzy logic is a mathematical way to represent linguistic vagueness. In other words, it is a methodology for computing using words.

The basic structure of a fuzzy inference system consists of main three parameters as shown below:

- A rule base comprising of the selected fuzzy rules
- A database that defines the membership functions of the fuzzy rules
- A reasoning mechanism which performs a fuzzy reasoning inference with respect to the rules to reach a reasonable output or conclusion

Although fuzzy logic has many advantages, it also has some limitations that can be summarized in the following points:

- The fuzzy logic is incapable to generalize. In other words, it only answers to what is written in its rule base
- It is not robust in relation the topological changes of the system, such changes would require alterations in the rule base
- It depends on the existence of an expert to determine the inference logical rules

To overcome the disadvantages of the fuzzy logic, researchers have combined the use of Neural Networks with fuzzy logic. The neural network has a learning capacity, generalization capacity and robustness in relation to disturbance so it can make up for the individual illness of the fuzzy logic (BURAGOHAIN, 2008).

The combination of Neural Network with the fuzzy logic has resulted in the development of Neuro Fuzzy systems. The Neuro Fuzzy systems have three methods:

- Cooperative Neuro Fuzzy System
- Concurrent Neuro Fuzzy System
- Hybrid Neuro Fuzzy System

In this study, the author is going to use the hybrid Neuro Fuzzy System for modeling the pressure drop in vertical multiphase flow. Most of the researchers refer to the hybrid fuzzy system as just neuro fuzzy system.

1.5.1 Hybrid Neuro Fuzzy System

In this system, the neural network is exploited to learn some parameters of the fuzzy system such as:

- The parameters of the fuzzy sets
- Fuzzy rules
- Weights of the rules

The combination of the Neural Networks with the fuzzy logic in a hybrid system has the advantage of learning through patterns and the easy interpretation of its functionality. In addition to that it has the ability to visualize the flow of data through the system. Thus, the neuro fuzzy system has many architectures.

This study is going to use the Adaptive Network based Fuzzy Inference System (ANFIS) for dealing with the data.

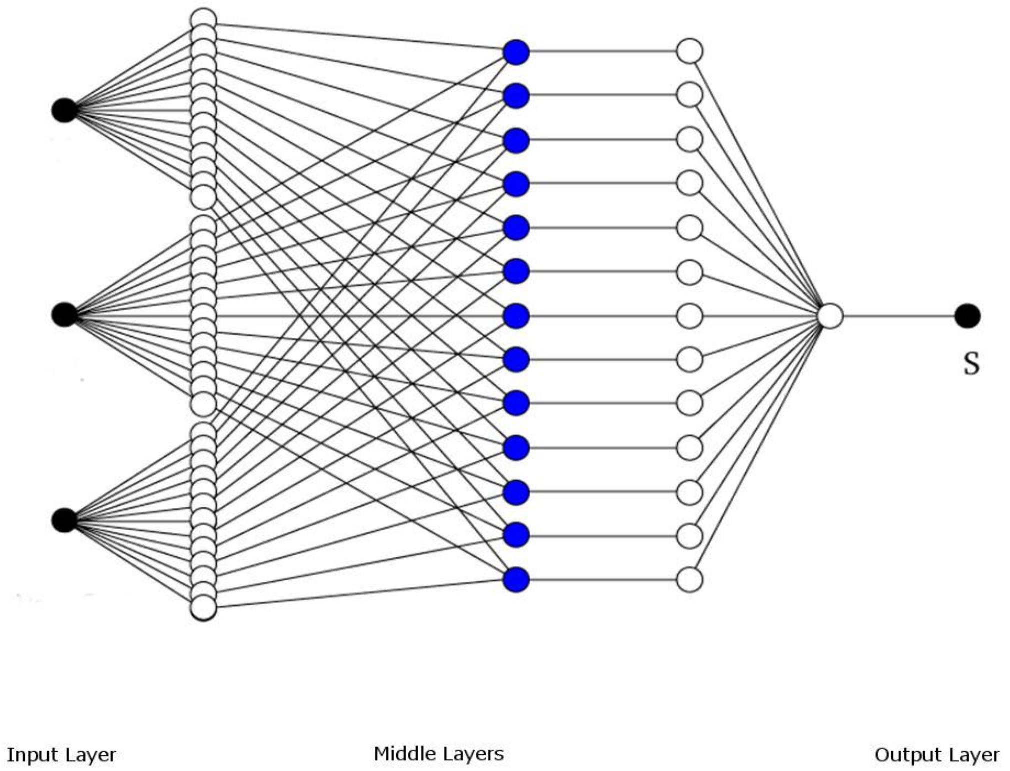


Figure 1.4: ANFIS Architecture

1.6 Problem Statement

Estimating the pressure drop in vertical multiphase flow is essential for selecting tubing size, wellhead pressure, completion scheme, cost management for production phases and other design objectives. However, measuring the pressure drop in vertical sections of the well is not practical as it involves high cost.

The main difficulties that are faced in predicting pressure drop in vertical multiphase flow is attributed to the variety of flow regimes that cannot be described by a single correlation scheme, the large number and type of the independent dimensionless variables that can affect the pressure drop. As an example, the friction factor for a single phase flow in pipe depends on a single dimensionless group which is Reynolds number. However, in the case of two phase flow, the pressure drop is a function of at least six variables. In such a situation, the friction factor will be a function of a Froude number, Weber number, Reynolds number, density ratio (Kabir & Hasan, 1986).

The complex relationships between the parameters that are used in the prediction of pressure drop such as: the multiphase nature and the number of flow patterns and transition boundaries that exist, the change of pressure and temperature along the wellbore, the amount of gas phase in the flow (GOR), gas slippage, the fluid properties and the flow rate of each phase.

Due to the stated reasons, an accurate analytical solution for analyzing these problems is difficult to be achieved.

Many attempts have been done to estimate the pressure drop in vertical multiphase flow starting from the homogeneous models, the empirical models and the mechanistic models. But yet, non of the traditional correlations works well for the variety of well conditions that are found in the oil industry especially for such conditions that exhibits the existence of emulsions, non-Newtonian flow behavior, excessive scale or wax deposition on the tubing wall. Thus, the accuracy of the current pressure drop correlations cannot be raised to a generally accepted level.

1.7 Objectives and Scope of Study

The sole objective of this study is to develop a model for estimating the pressure drop in vertical multiphase flow using Neuro Fuzzy Systems with a good and acceptable accuracy that can work for a wide range of well flowing conditions and to compare its performance with the currently used methods.

1. Defining the parameters and factors that affect the pressure drop.

2. Construct a Neuro Fuzzy model for predicting the pressure drop in vertical multiphase flow.

3. Testing the constructed Neuro fuzzy model against the actual field data.

4. Validating the model by conducting trend and statistical analysis.

5. Comparing the developed model with the most accurate empirical and mechanistic models.

1.8 Feasibility of the study

In order for this study to be accomplished, it requires a modeling software. The Matlab software and its ANFIS tool box are going to be used for that purpose along with an open source code software for modeling the pressure drop using the empirical and mechanistic correlations. All the softwares are available in the facilities at UTP. Hence, the study is considered as feasible to be implemented.

Chapter 2

Literature review

2.1 Overview

The early efforts to predict the pressure loss in an oil well can be dated back to 1952 starting by the predictive scheme of Poetmann and Carpenter. Since that time, many attempts were made to predict the fluid behavior for complex situations. But yet, the main limitation is that no single correlation is able to predict the pressure drop under the wide range of operating conditions faced in various well situations as shown in a study carried by (Kabir & Hasan, 1986).

Estimating the pressure drop in vertical multiphase flow have gone through many development stages starting by the early homogeneous correlations by (Poettman & Carpenter, 1952), (Baxendell & Thomas, 1961) and (Fancher & Brown, 1962).However, There was a need to develop new models as the complexity of the flow increased due to the drop in flow rate and decrease in pressure in the producing wells.

Many Models have been developed to estimate the pressure drop in a vertical well by using empirical correlations such as Hagedorn & Brown (1965), Duns & Ros (1963) and Orkiszewski (1967). Then as the complexity and uncertainty increases, the mechanistic models were developed such as: Ansari (1994) and Aziz et al (1972).

Recently, the researchers started to use the artificial intelligence techniques to address the problems faced in the oil industry. Thus some artificial models using artificial neural networks (ANN) were proposed such as Ayoub (2004) and Mohammadpoor (2010)

This chapter is going to address the each of the correlation models.

2.2 Early Homogeneous Models

Due to the fact that most of the hydrocarbons that were discovered in the early times were being producing at very high flow rates that could eliminate the phases between the different fluids so that the multiphase fluids could exist as a homogeneous mixture. In other words, gases and liquids could almost travel at the same velocity. Some of the correlations that were developed with this model are (Poettman & Carpenter, 1952), (Baxendell & Thomas, 1961) and (Fancher & Brown, 1962).

For such homogeneous cases, a first attempt was done to use a single phase flow equation by replacing flow and physical property variables with mixture variables.

$$\frac{dp}{dl} = \frac{\rho_m \, g \, sin\theta}{g_c} - \frac{f_m \rho_m v_m^2}{2d g_c} - \frac{\rho_m v_m dv_m}{g_c \, dl}$$

Where:

$$l: pipe\ length$$

$$\rho_m: density\ of\ two\ phase\ mixture$$

$$g: acceleration\ of\ gravity\ {}^{ft}/_{sec^2}$$

$\theta: pipe\ inclination\ angle\ from\ horizontal$

$f_m: friction\ factor\ of\ two\ phase\ mixture$

$v_m: velocity\ of\ two\ phase\ mixture$

$d: internal\ pipe\ diameter$

Any error that was encountered while using this equation was accounted for a single empirical mixture friction factor.

The homogeneous correlations are less accurate and it is normally corrected with local operating conditions in field applications.

Poetmann & Carpenter (1952):

Poetman and Carpenter tried to correlate the irreversible energy loss of 49 well tests by using a fanning type friction term. This correlation did not take the liquid hold up into account instead of that an average density of the produced fluids corrected for down hole conditions. This correlation showed an average deviation of 1.8 % and a standard deviation of 8.3 % (Lawson & Brill, 1974).

The assumptions of Poetmann and Carpenter are very limiting in addition to that the effects of gas liquid ratio, total well flow rate, liquid viscosity and tubing diameter are not properly handled in this model

Although this equation had an excellent performance but it could not be applied for wide ranges of flow variables that are encountered in oil production problems.

Baxendell & Thomas (1961):

Baxendell and Thomas expanded the correlations of Poetman and Carpenter to work for higher flow rates and recorded $\pm$ 5 to $\pm$ 10 % accuracy.

Fancher & Brown (1962):

This correlation applied the Poetmann and Carpenter to 94 tests from experimental wells. It introduced Gas Liquid Ratio (GLR) as a new parameter in the friction correlation. Fancher and Brown correlation yielded an accuracy of predicting pressure losses with in $\pm$ 10 %.

One of the strong limitations of the homogeneous models is that it did not consider the various flow regimes so the accuracy of the results was not pleasant.

2.3 Empirical correlations

This type of correlation is built on developing simplified models that have certain parameters which should be evaluated based on experimental data. The empirical correlations acquired data from laboratory tests. Data such as: volumetric flow rate for gas and liquid, physical properties for each of the flowing phase as well with the pipe diameter, inclination angle and inlet and outlet pressures were considered in the correlation.

The empirical correlations deal with the fluids as a homogeneous mixture so the flow patterns are not considered, however, it allowed the liquid and gas to travel at different velocities (Brill & Arirachakaran, 1992). And the gas slippage was also taken into account with in the empirical liquid hold up correlations.

Later, many problems were raised with using the empirical correlations. The reason is that the empirical correlations assume that the flow pattern transitions depend only on the flow rate, however, it was discovered that other parameters could also affect the flow patterns especially the inclination angle. Moreover, the empirical correlations did not describe why or how things happen (Brill & Arirachakaran, 1992) .

Duns & Ros correlation (1963):

This correlation was developed based on extensive laboratory experiments that covered around 4000 two phase flow tests conducted in a 33 ft vertical transparent flow loop. The pipe diameter varied from 1.26 to 5.6 in and the experiments included 2 annulus configuration. The experiments were conducted at conditions near to the atmospheric conditions. The liquid phase is represented by liquid hydrocarbon or water. The gas phase is represented by air phase.

Duns & Ros correlation considered the first dimensionless analysis of multiphase flow. It could define 12 variables that were found to be important for the prediction of pressure drop resulting in 9 independent dimensionless groups that were supposed to be important for the prediction of multiphase flow behavior.

It was concluded that 4 of these groups were important for predicting the flow pattern and the degree of slippage at any location in the vertical pipe.

Hagedorn & Brown (1965):

Hagedorn and Brown correlation is one of the most common correlations used in the industry. It can be considered as the first attempt to obtain large quantity of high quality data in vertical pipes. It was developed based on 475 tests in a 1500 ft experimental with 3 different pipe diameters. The experiments used 5 different fluid types in the experiment which is water and four types of oil.

At the beginning, Hagedorn & Brown did not recognize the importance of considering liquid hold up in their correlations. Later, the liquid hold up was calculated from the total measured pressure loss and the calculated values for friction and acceleration losses. Due to the fact that the liquid hold up was not measured directly, the predicted hold up values can yield unrealistic results that predict liquid to flow faster than gas (Lawson & Brill, 1974) and (Brill J. P., 1987).

This correlation involves only dimensionless groups of variables and it can be applied over a much wider range of conditions compared to other correlations.

Orkiszewski Correlation (1967):

Orkiszewski had tested several existing pressure drop correlations against field data and the conclusion that was made is that none of the correlations could yield sufficient accuracy for all flow patterns. Then, Orkiszewski chose the most accurate of these correlations to be combined with his newly proposed correlation for slug flow. The slug flow correlation was developed based on a parameter called “Liquid Distribution Coefficient”.

For the bubbly to slug flow transition, Griffith and Wallis correlation was used. Dons & Ros correlation was used for the transition from slug to churn and churn to annular flow (Piwoda, 2003). The correlation was tested against the measured pressure drop from 148 well tests and it could predict the measured pressure losses with a 10.8 percent standard deviation from the average error (Lawson & Brill, 1974). However, the correlation was not evaluated against certain well conditions such as flow in the casing annulus.

Beggs & Brill Correlation (1973):

This correlation was developed for the purpose of predicting pressure drop and liquid hold up in horizontal, inclined and vertical flow. It was delivered based on a small test facility of 1 in – 1.5 in, 90 ft long acrylic pipe and 584 well tests were conducted with air and water as the flowing fluids. Gas flow rate, liquid flow rate, pipe diameter, inclination angle, liquid hold up, pressure gradient were used as the parameters for evaluating the pressure drop.

The ranges of the parameters were:

Table 2.1: Flow Parameters for Beggs & Brill Correlation

Parameter	Range
Gas Flow Rate	0 - 300 MSCF/D
Liquid Flow Rate	0 - 30 gal/min
Average System Pressure	35 - 95 Psia
Pipe Diameter	1 - 1.5 in
Liquid Hold up	0 - 0.87
Pressure Gradient	0 – 0.8
Inclination Angle	-90^{o} to $+ 90^{o}$

However, a recent study done by (Yuan & Zhou, 2008) shows that Beggs & Brill correlation always over-predicted the pressure drop values.

Gray Correlation (1978):

Gray has performed his experiments on 108 gas wells that are producing some liquids (wet gas wells). Although this correlation was developed for wet gas vertical flow, it can also be used in multiphase vertical and inclined flow.

The parameters that were considered in this correlation are having the following range values:

Table 2.2: Flow parameters for Gray Correlation

Flow Paramter	Range
Gas Rate	0.12 – 24.2 MMSCF/D
Gas Gravity	0.58 – 0.887
Condensate Ratio	1 – 79 bbl/MMSCF
Free Water Ratio	0 - 292 bbl/MMSCF
Bottom Hole Pressure	144 – 2878 Psia
Depth	6180 - 12000

Mukherjee & Brill Correlation (1985):

Mukherjee & Brill proposed a correlation for pressure loss, holdup and flow map. This correlation was developed based on extensive experiments done on a 1.5 inch pipe using kerosene – air and light lube oil – air systems. Their correlation was developed following a study of pressure drop behavior in two-phase horizontal, uphill, vertical and downhill flow (Arya & Gould, 1981). The pressure drop values obtained out of the experiments have been verified with Prudhoe Bay and North Sea data.

2.4 Mechanistic Models

The development of the mechanistic correlations came as a result of the failure of the empirical correlations to address the complex physical phenomena encountered in multiphase flow. According to (Brill J. P., 1987), when the empirical correlations were tested against a broad range of data the error involved with the pressure prediction can be up to ± 20 %.It was developed based on mathematical modeling approach.

The mechanistic models could recognize and determine the flow regimes, temperature profile and develop separate models for the prediction of vertical pressure drop and liquid hold up (Yahaya & Al Gahtani, 2010). Moreover, the model is assisted with laboratory and field data. Thus, the pressure predicted from the mechanistic models can yield significant enhancement over the one obtained from the empirical. The first objective of these models is to predict the flow pattern then the pressure drop and liquid hold up can be identified.

Aziz et al. Model (1972):

Aziz, Govier and Fogarasi have developed a correlation for estimating pressure loss, liquid hold up and flow regimes. A new equation for predicting pressure drop in slug and bubble flow was developed where Duns & Ros model was used for estimating pressure gradient in mist and forth flow. The study was done on a number of 102 wells producing gas and condensate. The GLR ranged from 3900 to 1170000 SCF/bbl (Ruiz, Brito, & Marquez, 2014). The correlation developed a flow pattern map that identifies 4 flow regimes namely, bubble, slug, mist and transition zone.

The model has presented 44 value of predicted pressure drop with an absolute error almost equal to the Orkiszewski correlation. However, the uncertainties and lack of some filed data made it difficult to develop a fully mechanistically, reliable based computation method.

Ansari et al. Model (1994):

Ansari et al. developed a model for describing pressure drop in upward two phase fluid flow in wellbores. The model recognizes four flow patterns: bubble flow, slug flow, churn flow and annular flow. Ansari et al. correlation was found to yield better results in high angle wells, that is, wells with angles between 47^o to 57^o. The model was tested against a vast range of data from the Tulsa University Fluid Flow Projects (TUFFP) which contains 1775 well cases (Yahaya & Al Gahtani, 2010).

Ansari claimed that his model was superior to all other models except Hagedorn & Brown empirical model. However, a further investigation was done by (Pucknell, Mason, & Vervest, 1993) concluded that there is an increase error resulted from Ansari's correlation when the GOR is increased. Moreover, the correlation shows large errors in predicting pressure drop when liquid and gas velocities are in low to moderate range.

2.5 Artificial Neural Networks (ANN)

An artificial neural network (ANN) is a computing system built on a large number of parallel layers. It is considered as an attempt to mimic the human brain in its ability of processing imprecisely defined data structure (network) composed of a number of interconnected units (artificial neurons). It consists of multilayers that are divided into input layer, output layer and a layer in between called hidden layer. The processing units exist in the hidden layer and they are called as nodes. The number of nodes in the hidden layer depends on the complexity of input and the available amount of training data (Attia, Mahmoud, Abdulraheem, & Al-Neaim, 2013). Recently, the ANN has gained popularity to be used in industry. Now, it is widely used in banking systems, credit cards and high tech companies.

The use of Artificial Neural Networks (ANNs) have been used in several area of oil and gas industry such as; permeability prediction, well testing, enhanced oil recovery, PVT properties prediction, improvement of gas well production, prediction & optimization of well performance, integrated reservoir characterization and portfolio management (Ayoub, 2004).

Experience showed that empirical correlations and mechanistic models failed to provide a satisfactory and reliable tool for estimating pressure drop in multiphase flowing wells. Large errors are usually associated with these models and correlations (Takacs, 2001). Artificial neural networks gained wide popularity in solving difficult and complex problems, especially in petroleum engineering (Mohaghegh and Ameri, 1995).

Ayoub Model (2004):

Ayoub has presented one of the first Artificial Neural Networks (ANNs) models for prediction of the bottom-hole flowing pressure and the pressure drop in vertical multiphase flow. The model was tested against 206 field data from some wells in the Middle East which cover a wide range of variables. Trend analysis of this model not only shows that it predicted the pressure drop correctly but also it outperforms all the existing models and it provides results with higher accuracy. However, Ayoub warned that caution should be taken when using this model with data beyond the range of input variables. Ayoub (2004) model demonstrates the power of artificial neural networks model in solving complicated engineering problems.

Chapter 3

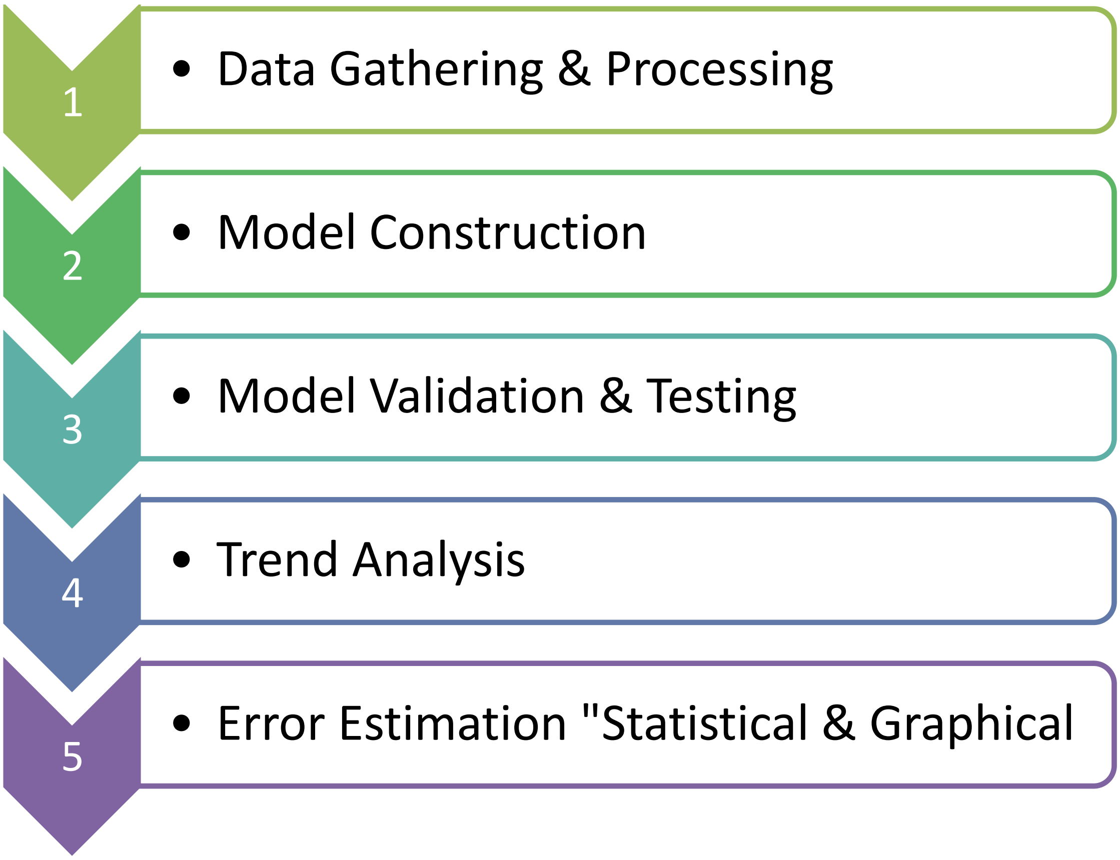
Research Methodology

3.1 Overview

This chapter is going to discuss the procedures that are going to be followed in order to obtain a reliable Neuro Fuzzy model that can predict the pressure drop in multiphase vertical flow.

The Neuro Fuzzy logic is considered as a modeling approach that can be used to solve engineering problems. Hence, this study aims at using the Neuro Fuzzy models for acquiring the pressure drop at a good accuracy over a wide range of well conditions that can replace the rigorous empirical and mechanistic correlations.

The methodology contains the following structure



3.2 Data Gathering & Processing

The data set contains data collected from 206 wells. Many Parameters and variables are contributing to the estimation of pressure drop in vertical multiphase flow. However, not all the parameters are having the same weight and effect on the pressure drop. Moreover, some of these parameters might not be collected from the well due to some technical limitations. Therefore, some of these parameters were removed from the final data sets. The input variables have been selected based on the most common and available variables used in the empirical and mechanistic correlations such as:

- Well Head Pressure
- Oil Rate
- Gas Rate

- Water Rate
- Tubing Diameter
- Length of Tubing
- API
- Surface Temperature
- Bottomhole Temperature

Table 3.1: Flow parameters for the Neuro Fuzzy Model

Flow Parameter	Min	Max	Average
Wellhead Pressure, psia	80	960	321.0777
Oil Rate, bbl/d	280	19618	6321.515
Water Rate, bbl/d	0	11000	2700
Gas Rate, Mscf/d	33.6	13562.2	3416.071
Depth, ft	4550	7100	6359.869
Tubing Diameter, inch	1.995	4	3.83
Surface Temperature, ^{o}F	76	160	117.73
Bottomhole Temperature, ^{o}F	157	215	203.64
Oil Gravity, API	30	37	33.77

3.3 Model Construction

The main software to be used for establishing the Neuro Fuzzy model is the Matlab software with its Artificial Network and Fuzzy Logic tool boxes. Along with Matlab, an open source software is used for calculating the pressure drop using empirical and mechanistic correlations.

3.4 Model Validation and Testing

The term partitioning represents dividing the data into three data sets:

- Training Set
- Validation Set
- Testing Set

The function of the training set is to develop and adjust the weights of the network. The validation set is used to ensure the generalization of the development network during the training phase. The testing set which is not seen by the network during the training phase is used to assess the final performance of the model.

Many partitioning ratios can be tested such as (**2:1:1, 3:1:1**, **4:1:1**) depending on the ability to yield better training and testing results, the partitioning ratios will be chosen.

3.5 Trend Analysis

A trend analysis will be carried out to check whether the model is physically possible. Synthetic sets will be prepared so that in each cell one input parameter only will be changed while other parameters will be kept constant. The significant input parameters that affect the pressure drop such as: oil flow rate, water flow rate, gas flow rate, oil gravity (API), depth will be changed while other parameters will be kept constant to check the validity of the Neuro Fuzzy model as well with the empirical and mechanistic models.

3.6 Statistical Analysis

A statistical analysis will be done to check the accuracy of the constructed Neuro Fuzzy model and to check the accuracy of the empirical and mechanistic correlations as well. The statistical parameters used are:

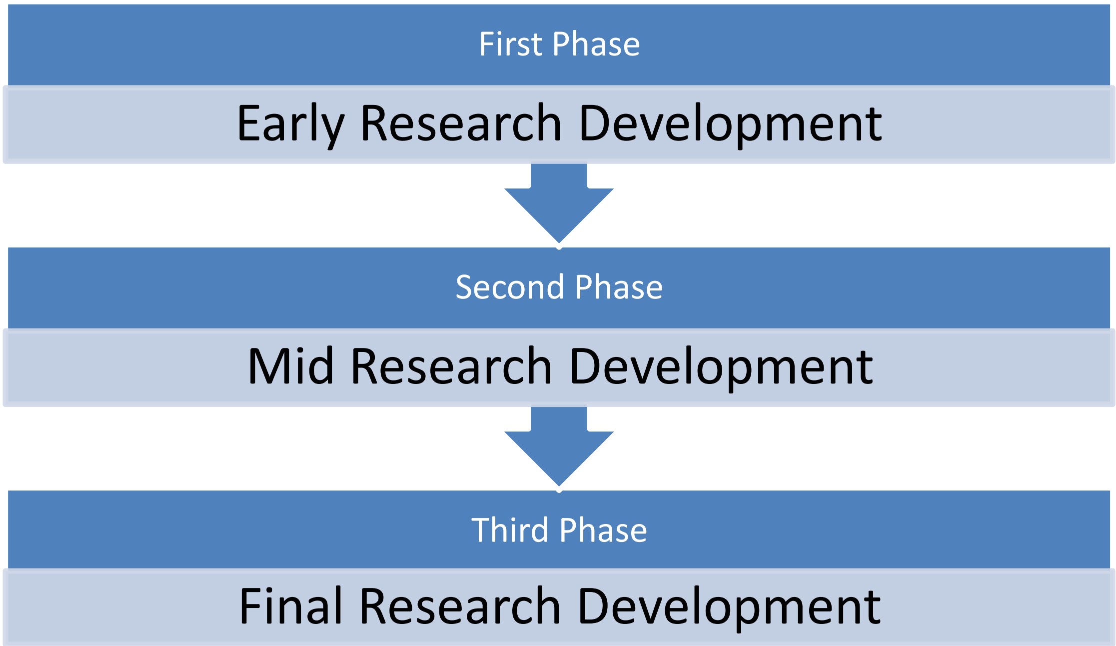
- Average Absolute Percentage Relative Error (AAPE)
- Average Percentage Relative Error (APE)
- Maximum Absolute Percentage Error
- Minimum Absolute Percentage Error
- Root Mean Square Error
- Coefficient of determination
- Standard Deviation

3.7 Error Estimation

Cross plots and Error distribution will be used for comparing the accuracy of the constructed model against the empirical and mechanistic correlations and for constructing error sharing histograms for the Neuro Fuzzy model (for the training, testing and Validating data sets).

3. 8 Project Work

The project activities are divided into three stages:



1- Early research development

In this stage, the author focuses on the background study of the following:

- An overview of the Multiphase flow
- An overview of the Neuro Fuzzy Logic

1- Mid research development:

In this stage, a focus is given on:

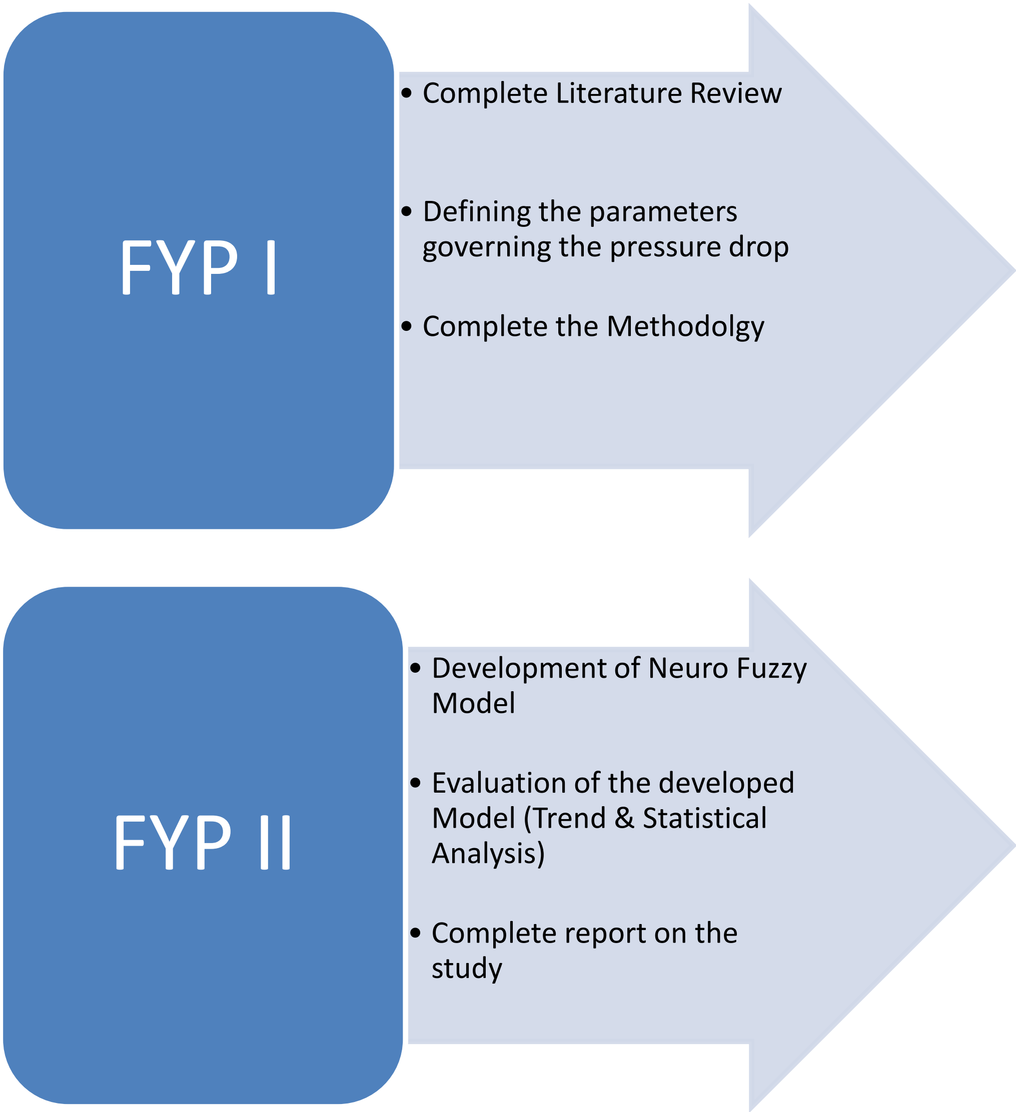
- The development of empirical and mechanistic correlations
- The parameters that affect the pressure drop
- Evaluation of the accuracy and limitations of the existing correlations
- The applications of fuzzy logic in the petroleum industry

2- Final research development:

This stage involves:

- Generating Neuro Fuzzy model
- Assessing the accuracy of the generated model
- Testing the generated model against the existing correlations

3.9 Key Milestone:



Chapter 4

Results and Discussion

4.1 Development of the Neuro Fuzzy Model

A number of 206 data sets collected from some fields in the Middle East were used. The first step in developing the Neuro Fuzzy Model is dividing the data into 3 sets; Training, Validation and Testing. A partitioning ration of (3:1:1) was used. Nine parameters that affect the pressure drop were used as an input to the software. The nine parameters are: Well Head Pressure, Oil flow rate, Gas Flow Rate, Water Flow Rate, Tubing Diameter, Tubing Length, API, Surface Temperature and Bottomhole Temperature.

To develop a Neuro Fuzzy Model with a good accuracy, some of the training options need to be modified to optimize the training. Those training options are:

- Clustering Radius: is used to arrange data into clusters with various degrees of membership.

  In this study, various clustering radii were tried in order to choose the optimum radius for these data such as: 0.145, 0.3, 0.35, 0.6, 0.65, and 1.42

- Learning step size: the learning step size should be kept large while keeping learning stable

- Decreasing Rate: if the error involved in estimating the pressure drop is increased, the learning step size is decreased by multiplying by the decrease rate

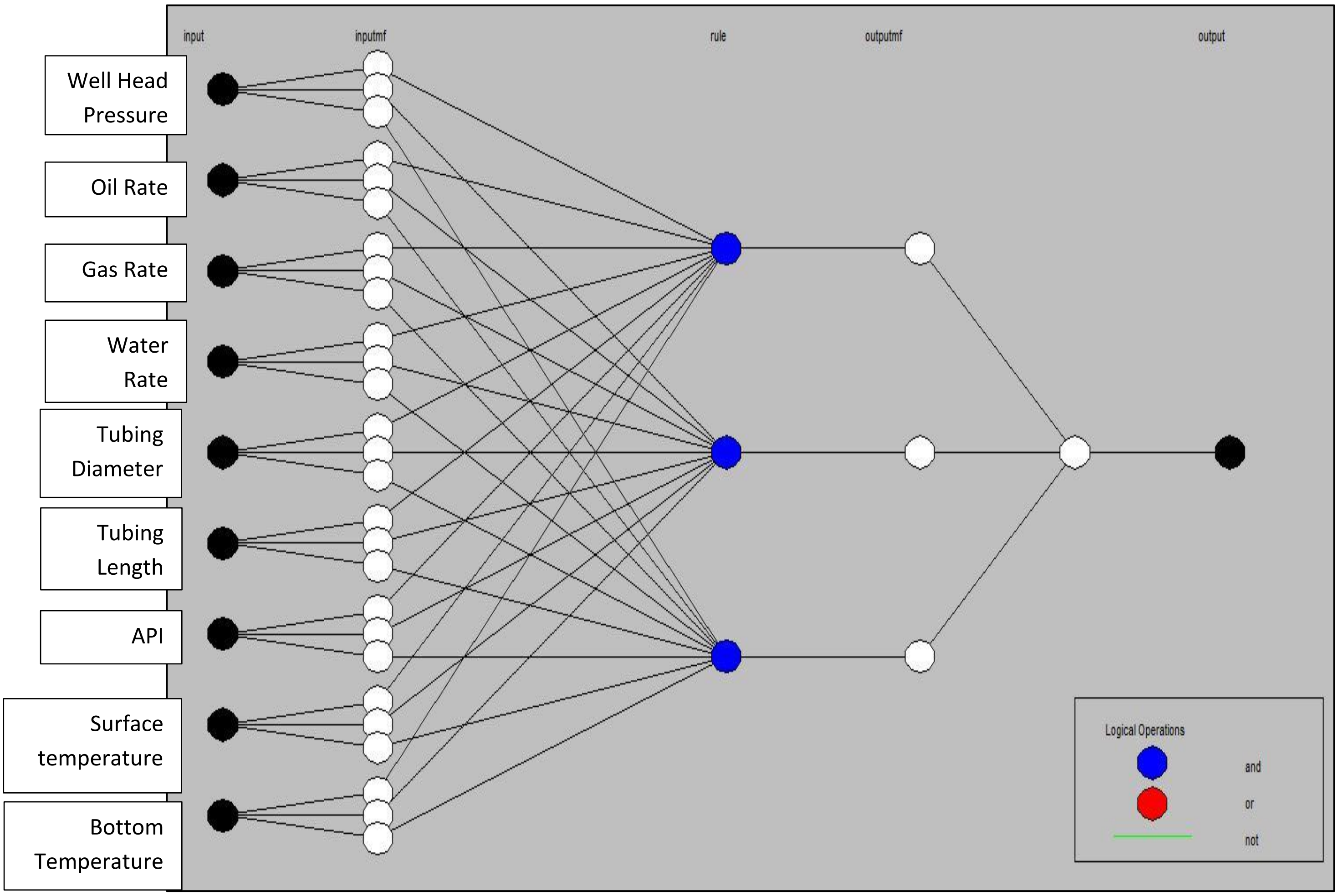


Figure 4.1 : Schematic of the Developed Model

- Increasing Rate: if the new error is less than the old error, the learning step size is increased by multiplying by the increasing rate

4.2 Trend Analysis for the Proposed Neuro Fuzzy Model

A trend analysis was carried out to check whether the developed model is physically sound or not. For that purpose, the effect of variation in Water rate, Oil rate, Gas Rate and tubing diameter was assessed.

The trend analysis shows that the Neuro Fuzzy Model could match the normal pressure trends. An increase in the Water rate, Oil rate and gas rate will cause increase in pressure drop. While an increase in the tubing diameter will result in a reduction in pressure drop.

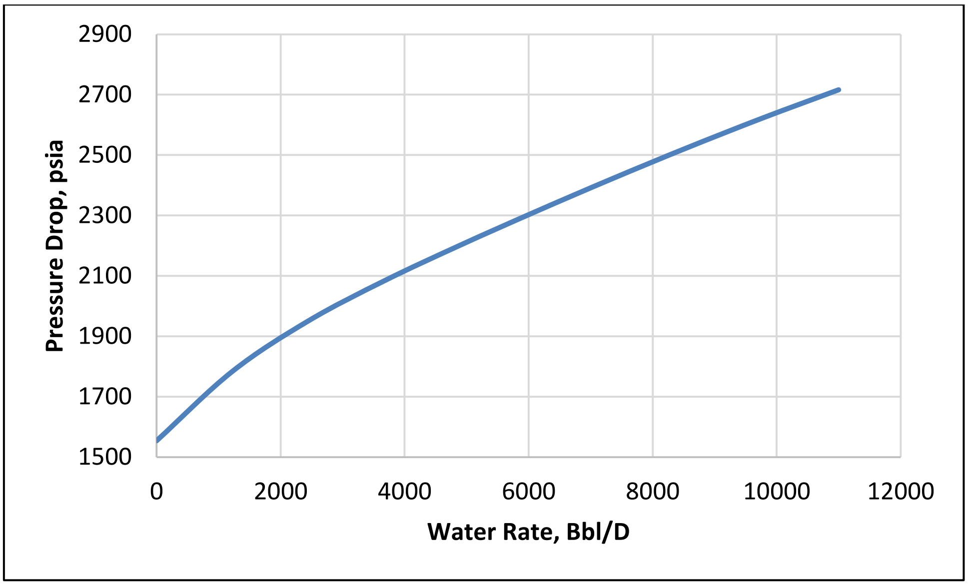


Figure 4.2: Effect of Water Rate on Pressure Drop

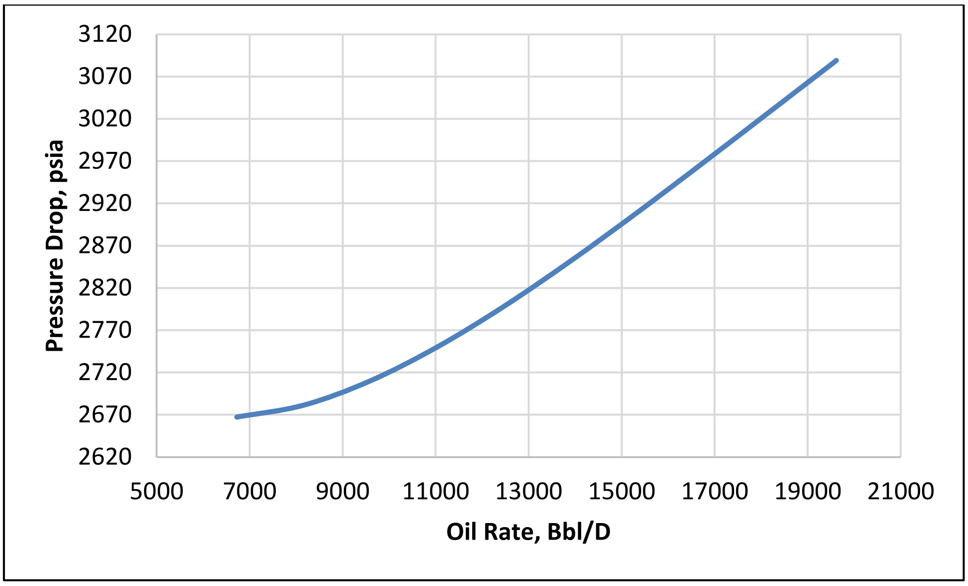


Figure 4.3: Effect of Oil Rate on Pressure Drop

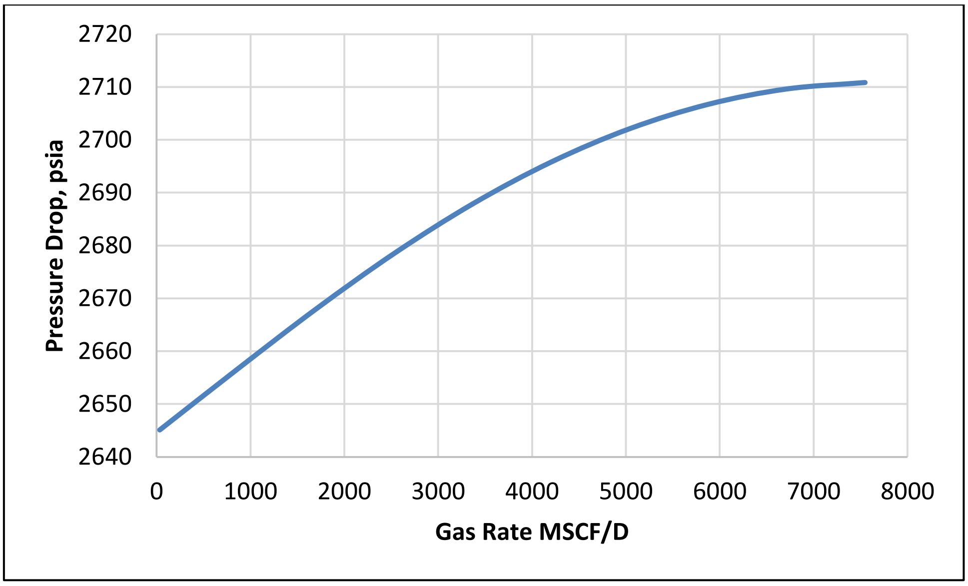


Figure 4.4: Effect of Gas Rate on Pressure Drop

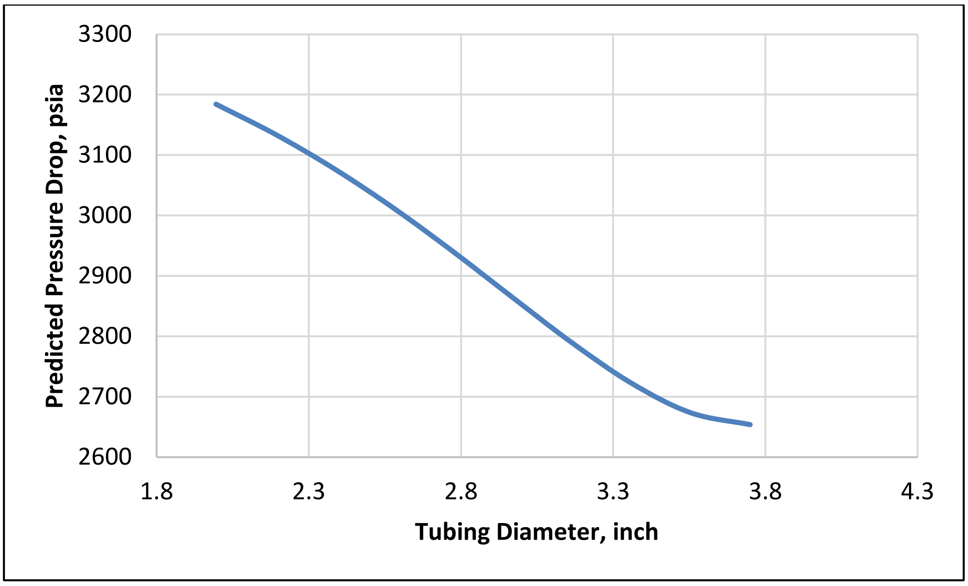


Figure 4.5: Effect of changing tubing diameter on Pressure Drop

4.3 Statistical Error Analysis for the Neuro Fuzzy Model against other investigated Models

The statistical parameters that are used to assess the model are:

- Average Absolute Percentage Error (AAPE)
- Maximum Absolute Percentage Error (MaxAE)
- Minimum Absolute Percentage Error (MinAE)
- Root Mean Square Error (RMSE)
- Standard Deviation (STD)
- Coefficient of Determination (R^2)

The statistical parameters of the training and testing data sets are presented in Table 4.1.

Table 4.2 shows the Neuro Fuzzy Model and the previous empirical and mechanistic models assessed against the above mentioned parameters which show the significance of the Neuro Fuzzy model over the old Models.

The Neuro fuzzy Model could achieve the lowest Average Absolute Percentage Error (AAPE) of 2.929% and the lowest Root Mean Square Error (RMSE) of 1.9638% and the highest coefficient of determination (R^2) of 0.9645 and the lowest Standard Deviation (STD) of 1.9102.

The above Statistical Analysis shows the significance of the Neuro Fuzzy Model over the old models

Table 4.1: Statistical Analysis Result of the Proposed Neuro Fuzzy Model

	Training Set	Testing Set	Validation Set
AAPE	1.8123	2.929	2.9109
MaxAE	5.9743	8.3431	5.355
MinAE	5.9743	0.2359	0.0556
RMSE	2.2148	1.963	0.6124
R^2	0.9832	0.9645	0.8662
STD	1.3630	1.9101	1.9275

Table 4.2: Statistical Analysis of Neuro Fuzzy Model and old Investigated Models

	AAPE	MaxAE	MinAE	RMSE	R2	STD
Govier, Aziz	**12.0968**	**46.6863**	**0.1688**	**15.8240**	**0.5158**	**14.6847**
Hagedron & Brown	**11.9864**	**31.3833**	**0.2806**	**13.7535**	**0.8065**	**9.0999**
Gray	**11.8941**	**50.6174**	**0.4964**	**14.3411**	**0.7875**	**10.3591**
Orkzwiski	**11.0000**	**26.7816**	**0.0611**	**13.0893**	**0.7692**	**9.7455**
Mukhrejee & Brill	**9.1695**	**39.3635**	**0.0004**	**11.4425**	**0.7981**	**10.6956**
Ansari	**7.6344**	**24.2722**	**0.0475**	**9.5011**	**0.8442**	**8.1114**
Duns & Ros	**7.5593**	**30.0916**	**0.0851**	**9.3525**	**0.8537**	**8.6421**
Beggs & Brill	**6.4278**	**24.9539**	**0.0851**	**8.2240**	**0.8667**	**7.9252**
Ayoub	**4.8010**	**20.1594**	**0.0150**	**6.6274**	**0.9095**	**6.4987**
ANFIS	**2.9290**	**8.3432**	**0.2359**	**1.9638**	**0.9645**	**1.9102**

4.3.1 Cross Plots of Neuro Fuzzy Model against investigated Models

Figures (4.6) and (4.7) show the cross plots of Estimated pressure Drop versus Actual pressure Drop for the training set and testing set respectively. The coefficient of determination for the training set is 0.9668 and for the testing set is 0.9645.

Figure (4.8) through figure (4.16) show the cross plots of the estimated pressure drop versus the actual pressure drop for the other investigated models including the coefficient of determination of each model.

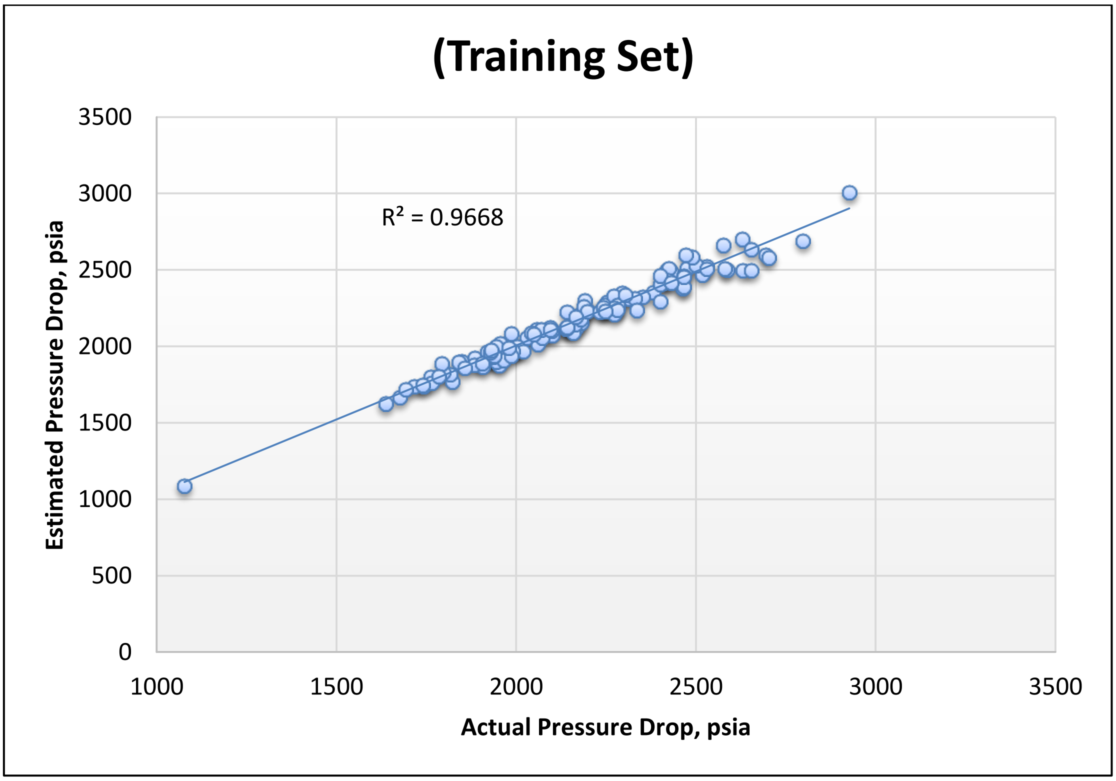


Figure 4.6: Cross plot of pressure drop (Training Set)

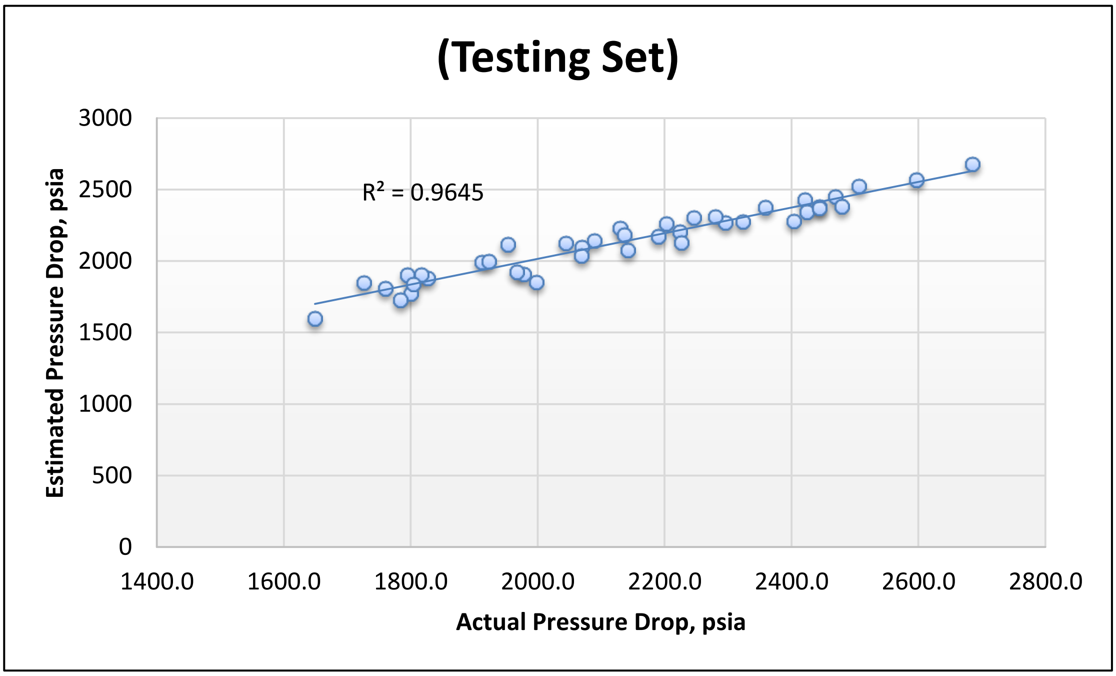


Figure 4.7: Cross plot of pressure drop (Testing Set)

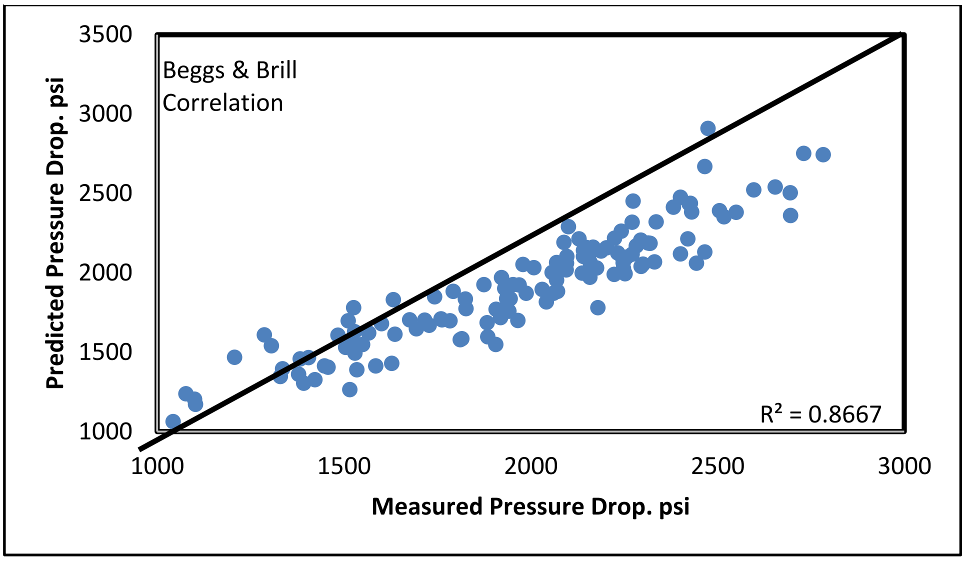


Figure 4.8: Cross plot of pressure drop for Beggs & Brill Correlation

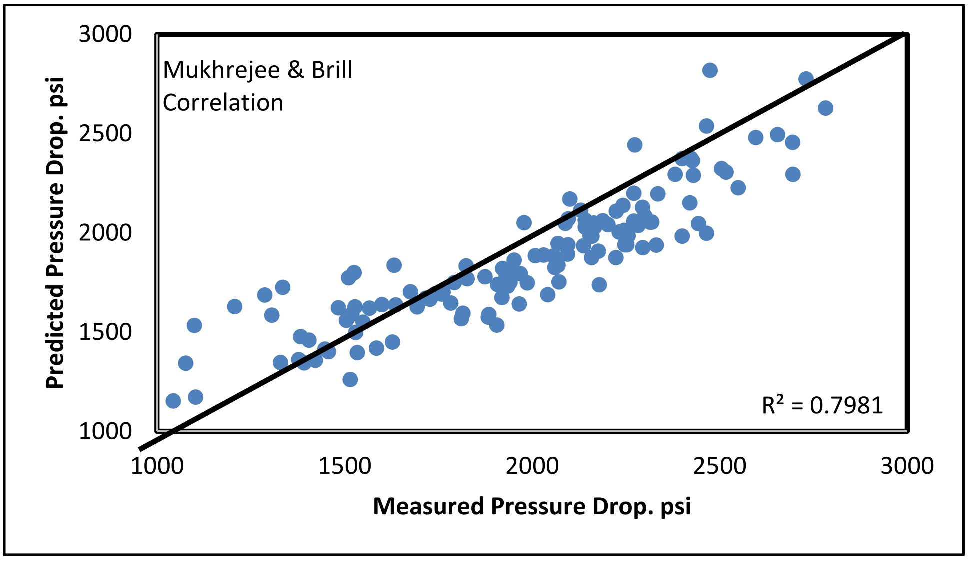


Figure 4.9: Cross plot of pressure drop for Mukhrejee & Brill Correlation

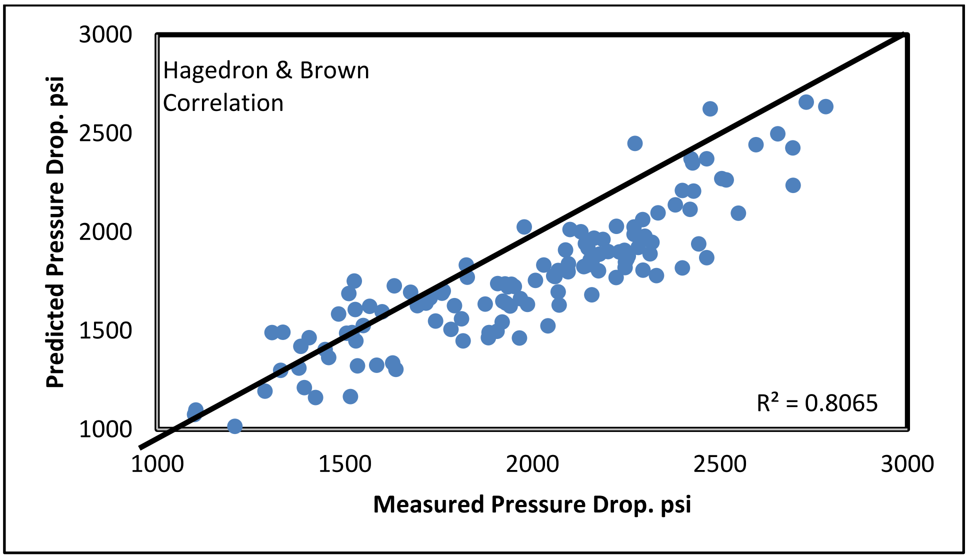


Figure 4.10: Cross plot of pressure drop for Hagedron & Brown Correlation

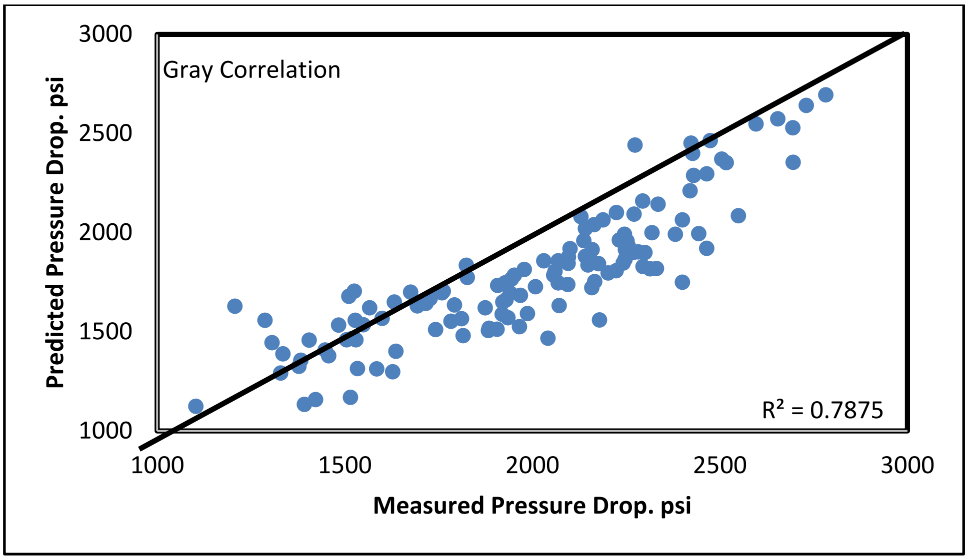


Figure 4.11: Cross plot of pressure drop for Gray Correlation

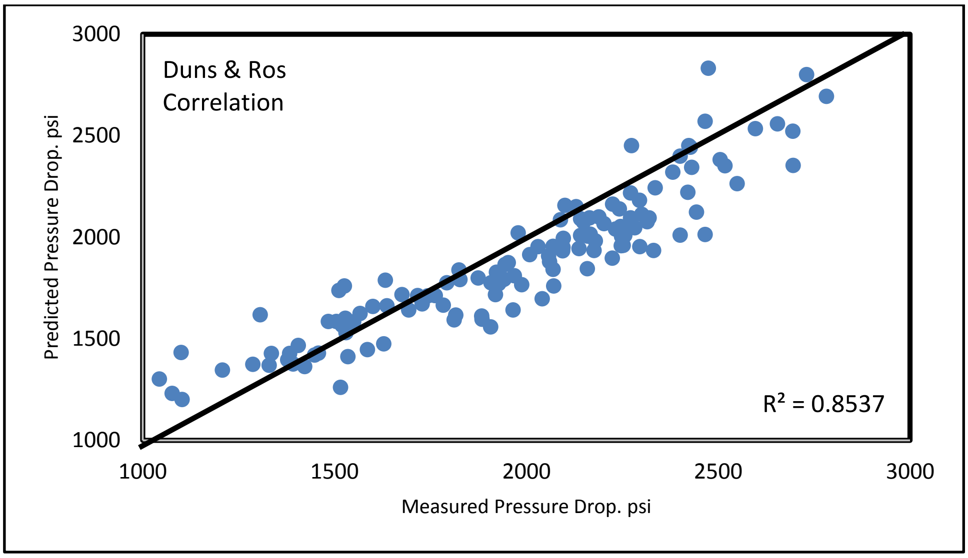


Figure 4.12: Cross plot of pressure drop for Duns & Ros Correlation

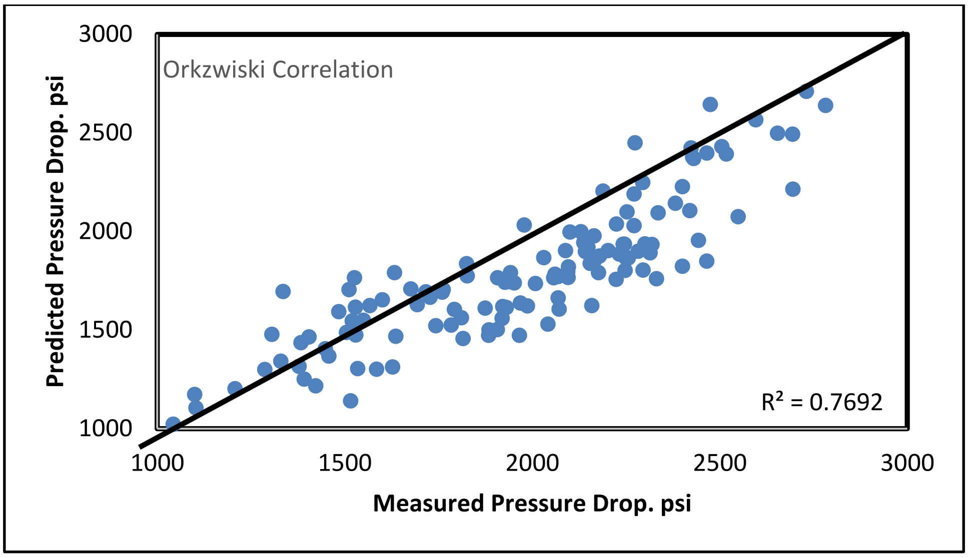


Figure 4.13: Cross plot of pressure drop for Orkzwiski Correlation

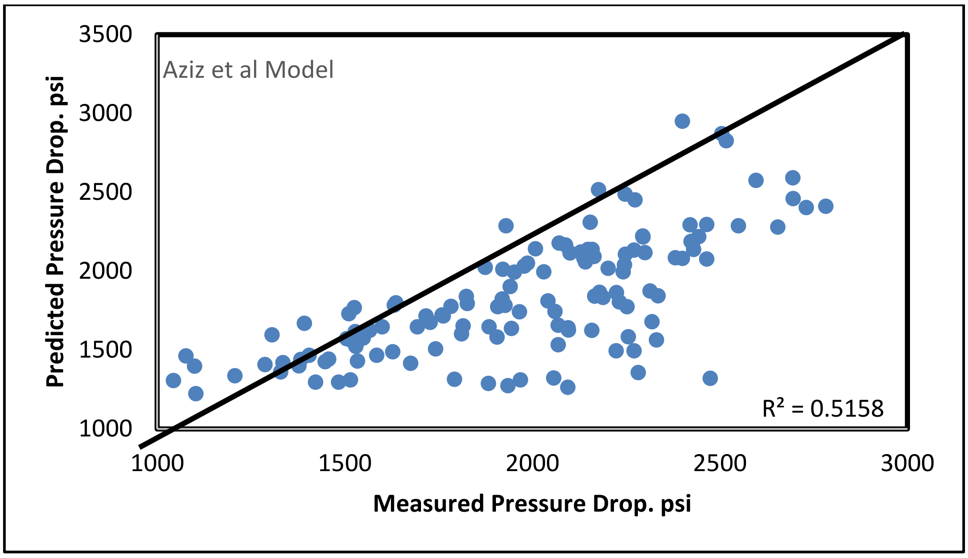


Figure 4.14: Cross plot of pressure drop for Aziz et al Model

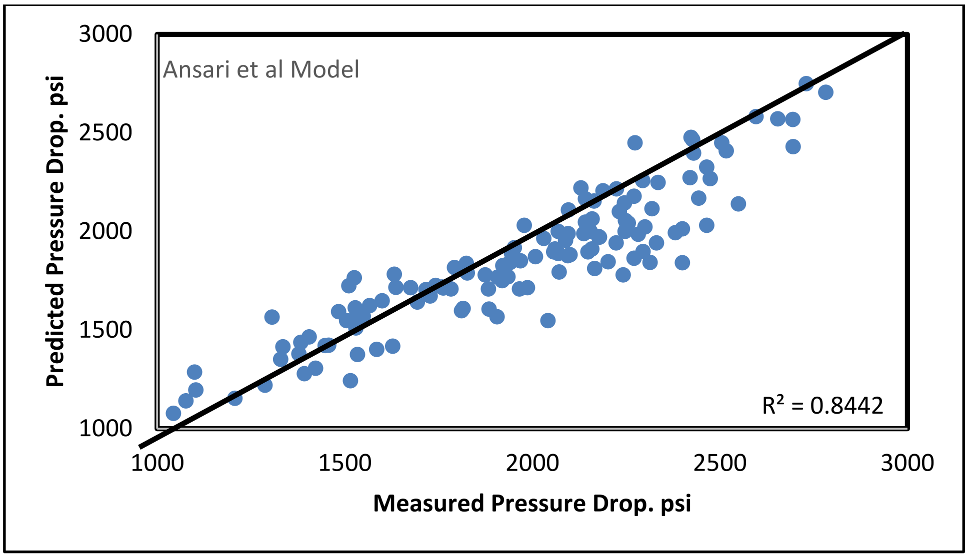


Figure 4.15: Cross plot of pressure drop for Ansari et al Model

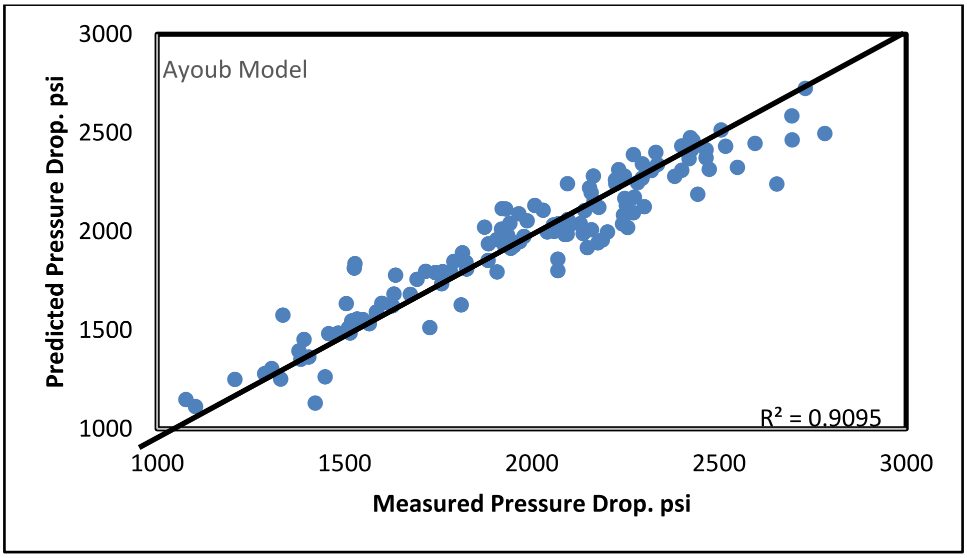


Figure 4.16: Cross plot of pressure drop for Ayoub Model

4.4 Error Distribution of the Neuro Fuzzy Model

Figures (4.19) and (4.20) show the error distribution histograms for the Training and Testing sets.

By analyzing the histogram of the training set, it shows a light shift to the left that means the pressure drop value was overestimated. The histogram of the testing set also shows a light shift to the left that indicates an overestimation in the pressure drop values.

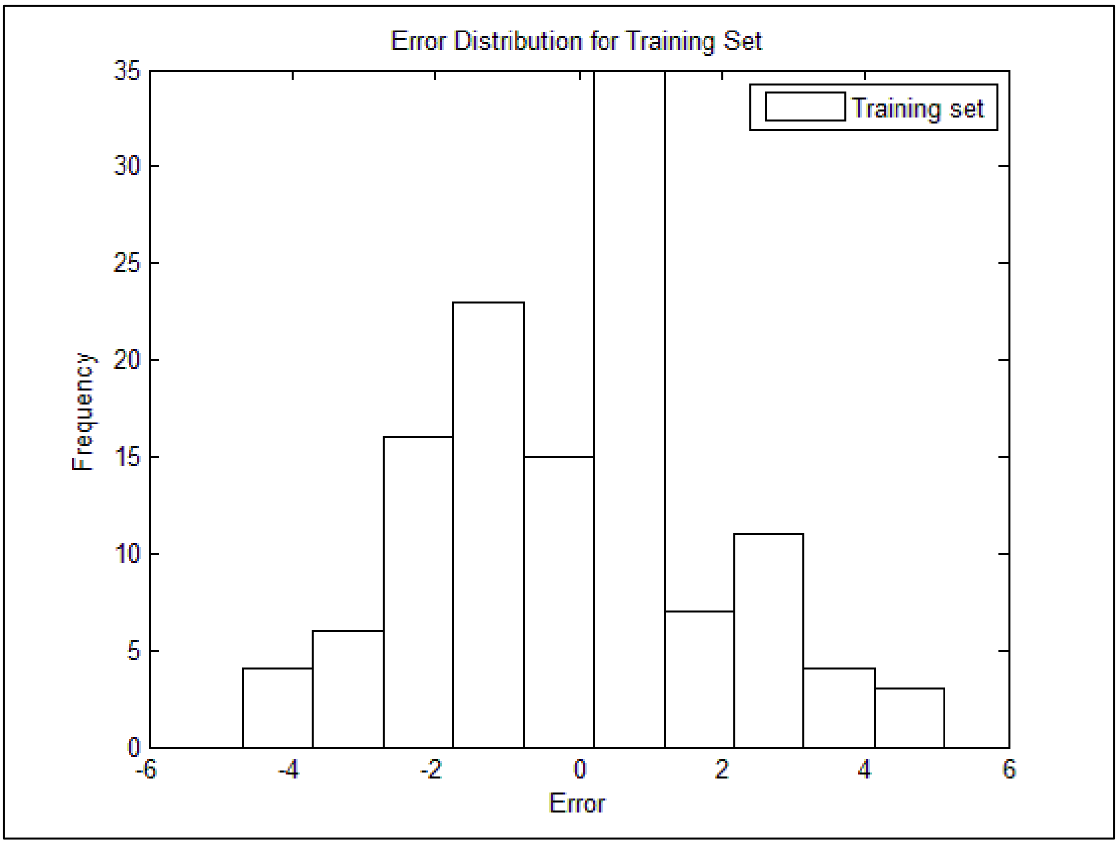


Figure 4.17: Error Distribution for Training Set

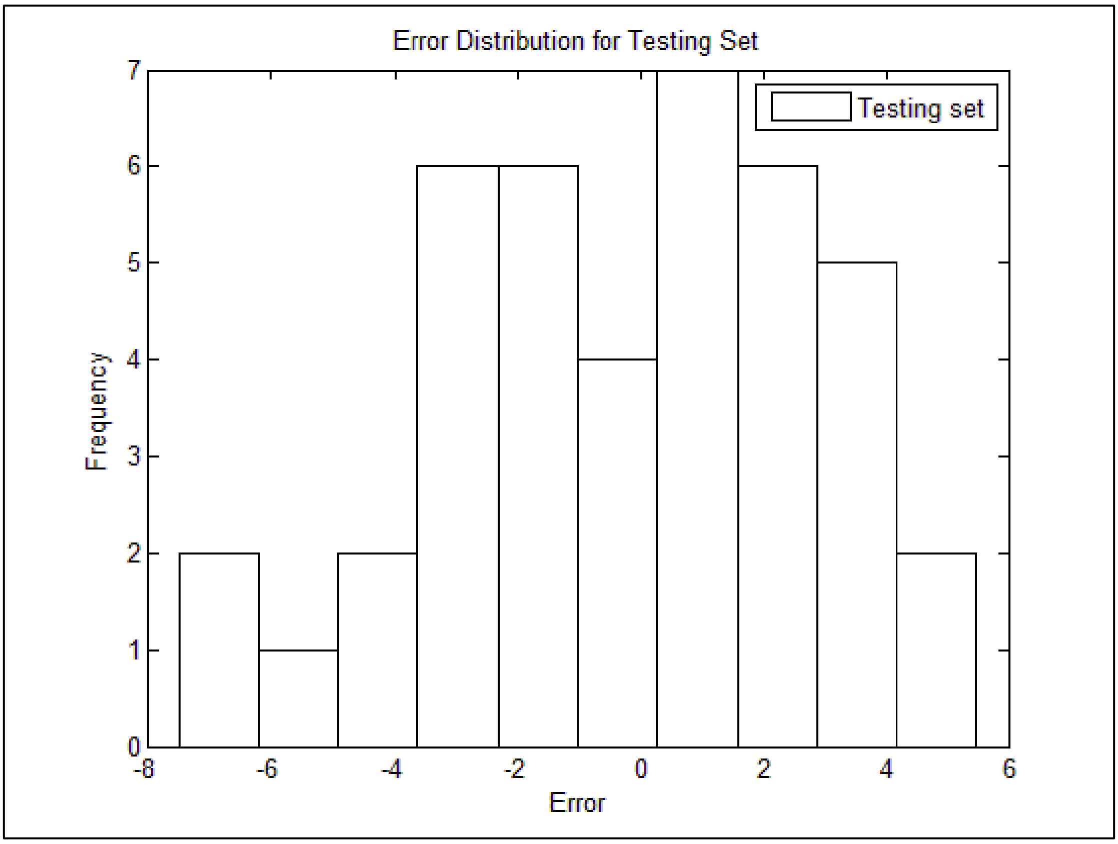


Figure 4.18: Error Distribution for Testing Set

4.5 Discussion of the results

A statistical comparison between the Neuro Fuzzy Model and the other investigated models has been presented earlier in table 4.2. The following figures from figure (4.21) to figure (4.24) show the performance of all the investigated Models. As expected, the Neuro Fuzzy Model (ANFIS) has the best performance over all the investigated Models where Govier, Aziz Model has the worst AAPE, RMSE and Coefficient of Determination.

A more descriptive view is obtained when the Root Mean Square Error (RMSE) is plotted against the Standard Deviation (STD) in figure(4.24) where the best performance will fall in the bottom left corner of the plot where it has a low value of RMSE and low value of STD.

In figure (4.25), the coefficient of Determination (R^2) is plotted against the Average Absolute Percentage Error (AAPE) where the best model should achieve high value for R^2 and low value for AAPE which is the top right corner of the plot

In both figures, the Neuro Fuzzy Model (ANFIS) has fallen in the best regions of the plot. This shows the high performance and reliability of the ANFIS Model over the other investigated models.

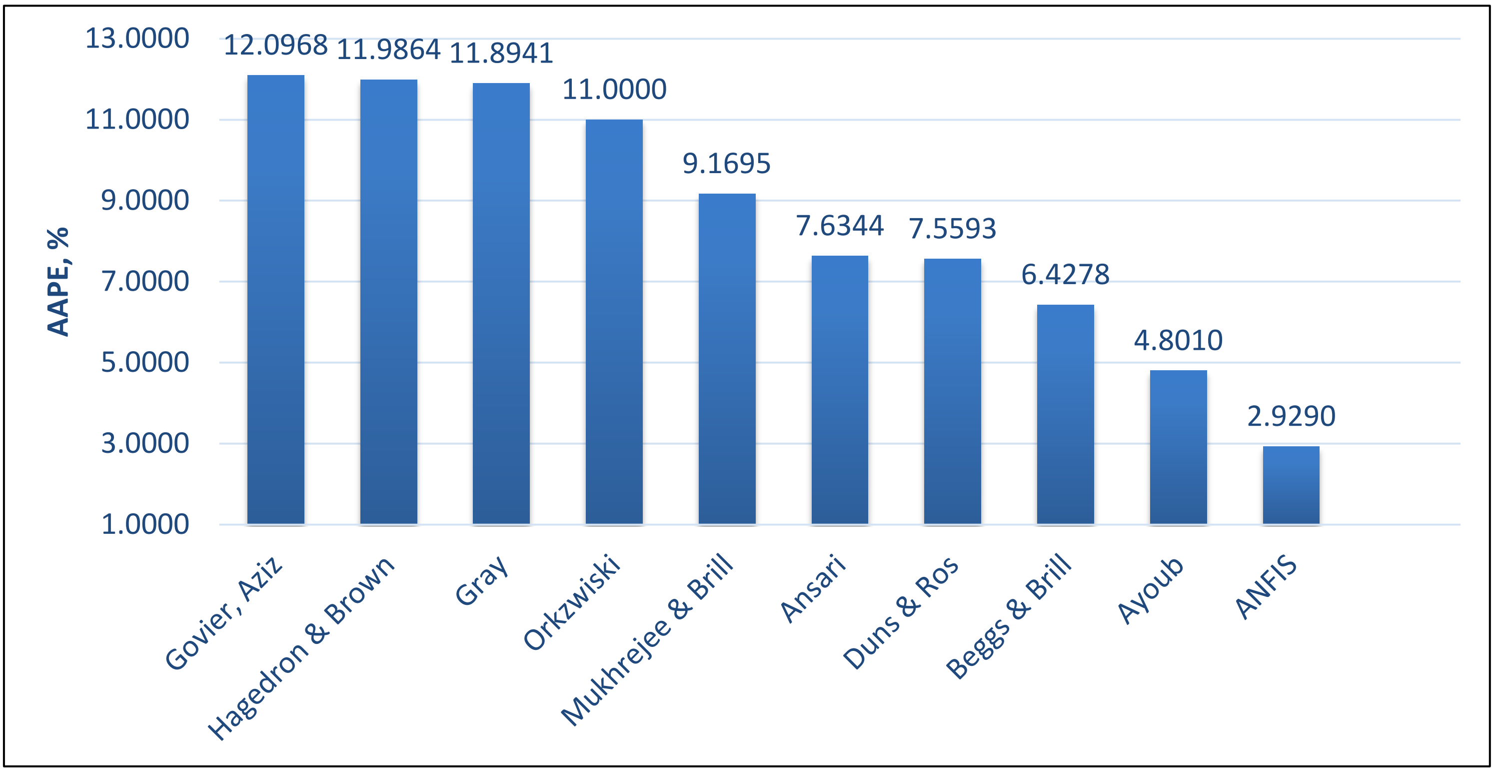


Figure 4.21: Average Absolute Percentage Error for all the Models

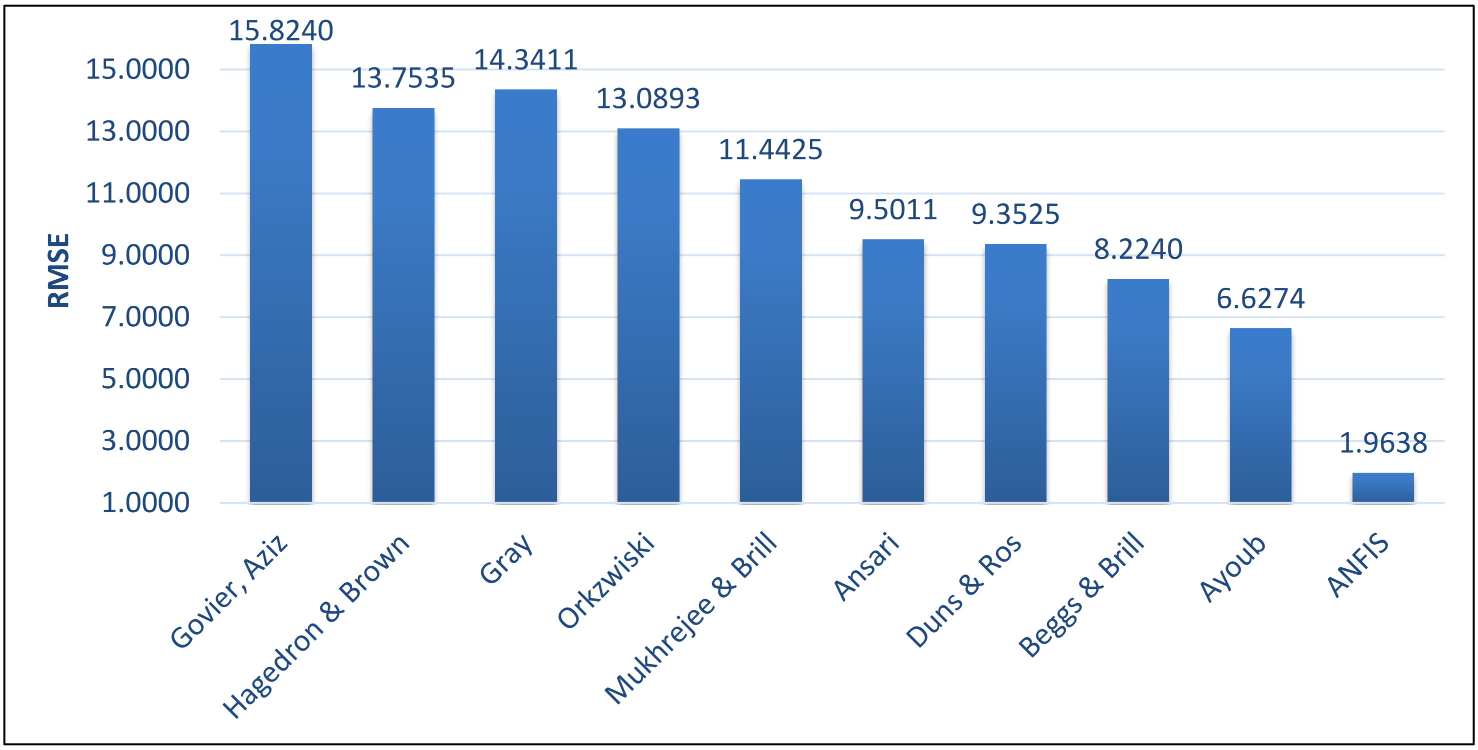


Figure 4.22: Root Mean Squared Error for all the Models

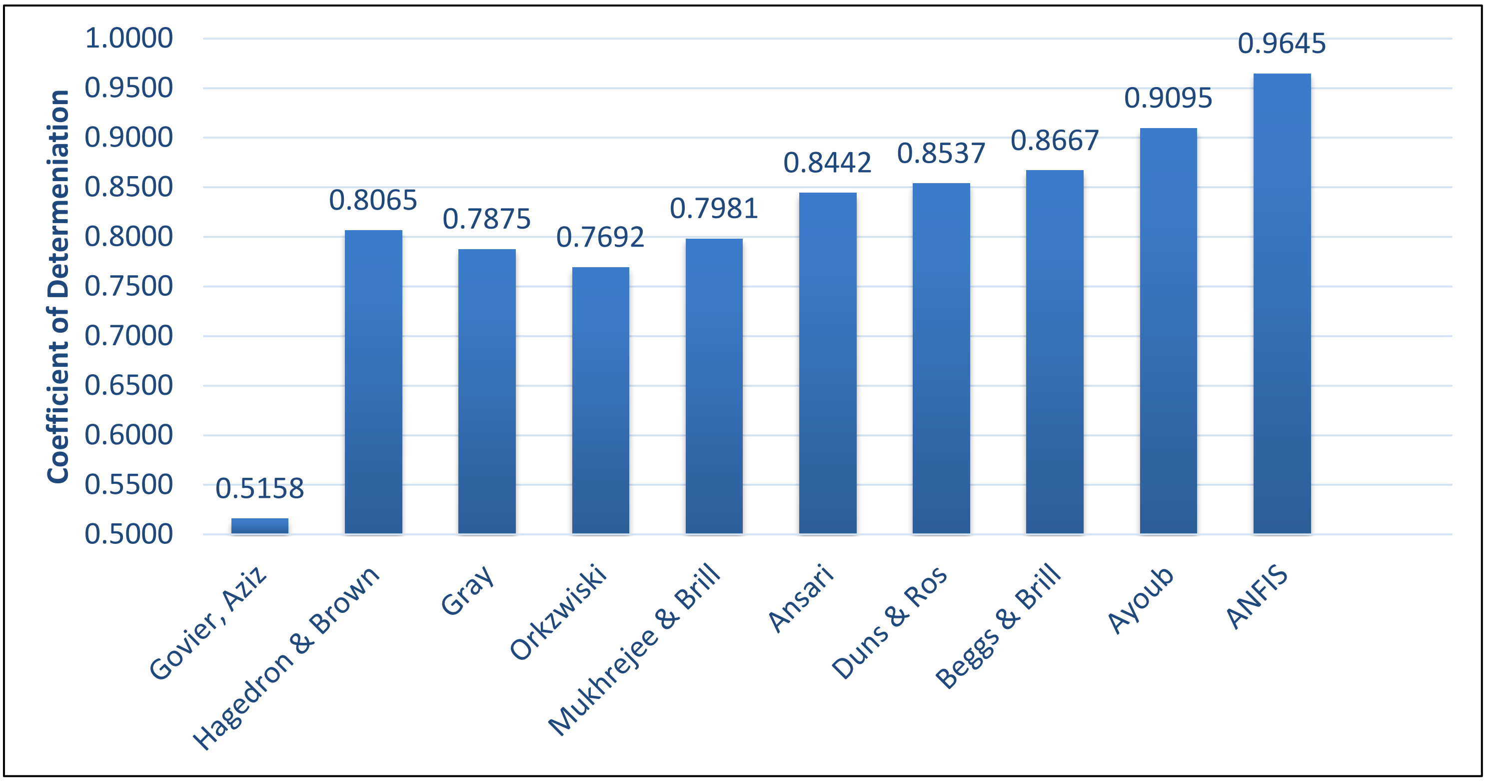


Figure 4.23: Coefficient of Determination for all the Models

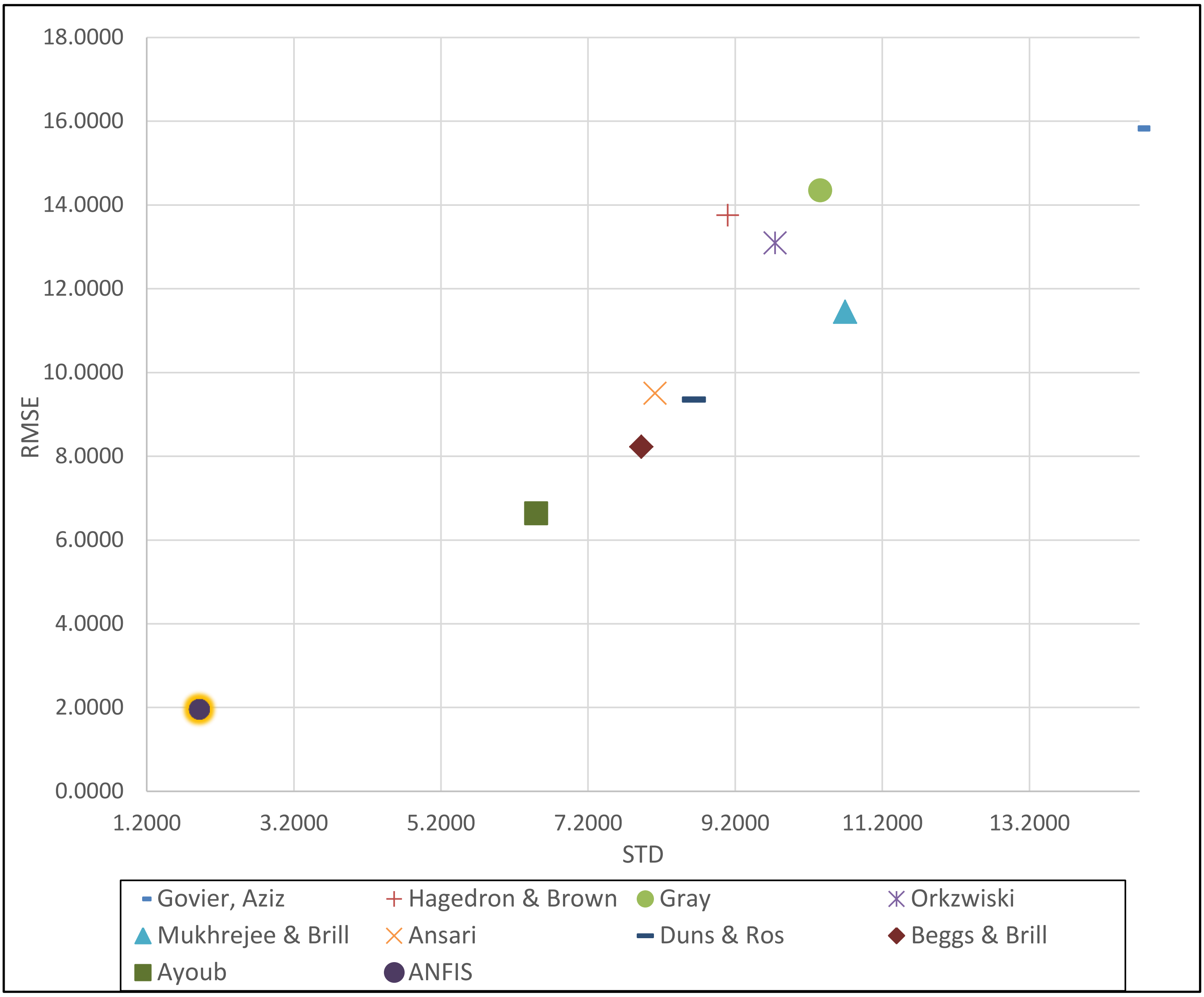


Figure 4.24: Standard Deviation vs. Root Mean Squared Error

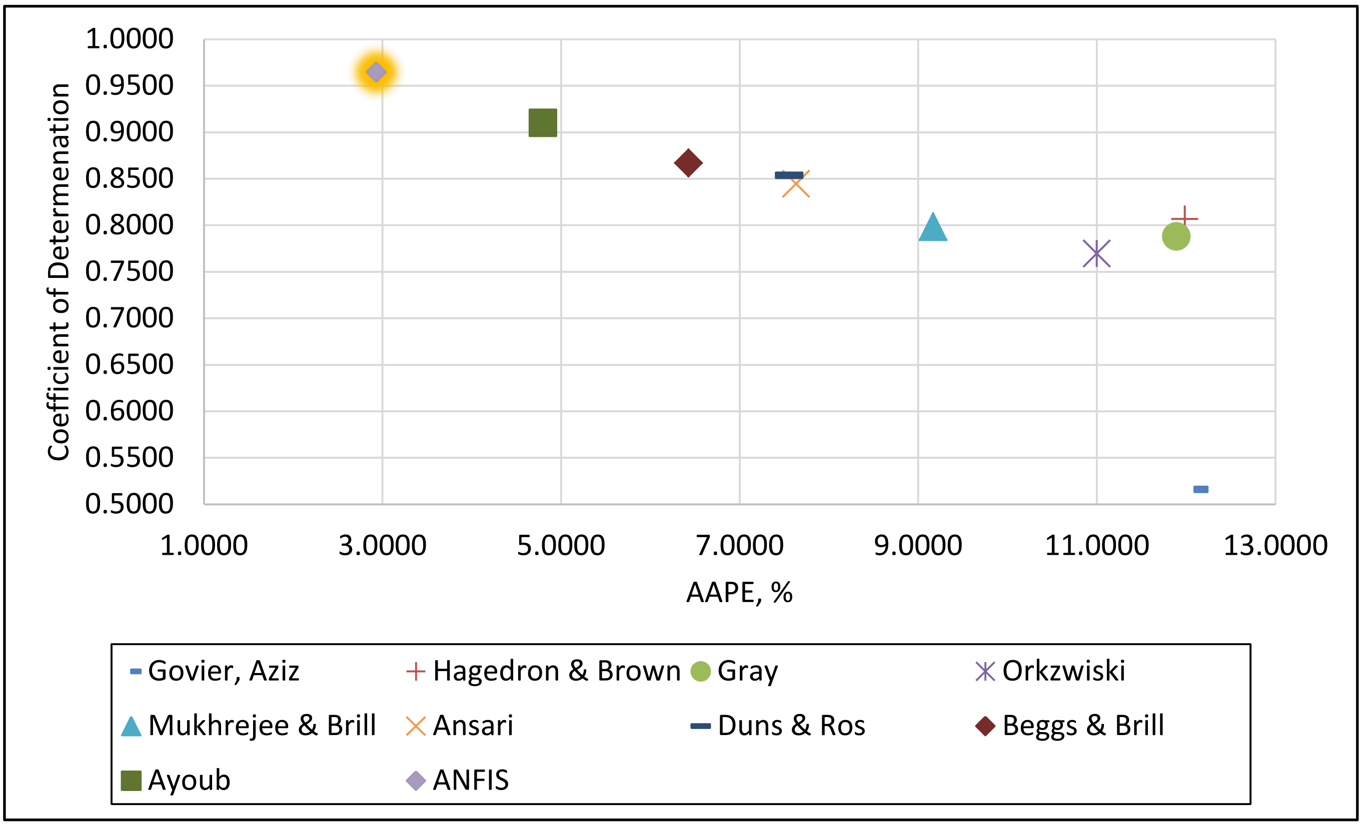


Figure 4.25: Average Absolute Percentage Error vs. Coefficient of Determination for all the Models

Chapter 5

Conclusion and Recommendation

5.1 Conclusion

This study aimed at developing a Neuro Fuzzy Model that can be utilized in estimating the pressure drop in vertical multiphase flow.

The Neuro Fuzzy Model has been successfully developed and shows high performance when compared with the commonly used models in the industry.

The statistical comparison presented in chapter 4 between the Neuro Fuzzy Model and the other investigated models shows the superiority of the new model which has the lowest AAPE of 2.92%, the lowest RMSE of 1.9638% and the highest coefficient of determination (R^2) of 0.9645

The Neuro Fuzzy Model has successfully met the objectives of this study.

5.2 Recommendations:

The author advises that:

- This Neuro Fuzzy Model should be used within the same range of data used. Otherwise, unexpected results might come out.

- Expanding the range of data used in this study will enhance the reliability of the Neuro Fuzzy Model to be used over a wider range of input parameters.

- Some commercial softwares such as PROSPER and Pipesim can be used to obtain fast results for the empirical and mechanistic models.

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APPENDIX A - Statistical Error Equation

a) Average Absolut Percent Relative Error:

$$E_a = \frac{1}{n}\sum_{i=1}^{n}|E_i|$$

b) Average Percent Relative Error:

$$E_r = \frac{1}{n}\sum_{i=1}^{n}E_i$$

c) Maximum Absolute Relative Error:

$$E_{max} = {}_{i+1}^{n}\max|E_i|$$

d) Minimum Absolute Relative Error:

$$E_{max} = {}_{i+1}^{n}\min|E_i|$$

e) Root Mean Square Error:

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}{E_i}^2\right]^{0.5}$$

f) Coefficient of determination:

$$R^2 = \sqrt{1 - \frac{\sum_{i=1}^{n}[(\Delta P)_m - (\Delta P)_c]}{\sum_{i=1}^{n}[(\Delta P)_m - \overline{\Delta\Delta P}]}}$$

g) Standard Deviation:

$$STD = \sqrt{\left[\left(\frac{1}{m-n-1}\right)\right]\left[\sum_{i=1}^{n}\left\{\frac{[(\Delta P)_m - (\Delta P)_c]}{(\Delta P)_m}\right\} * 100\right]^2}$$

Where, E_i is the relative deviation of a calculated value from the measured value;

$$\boldsymbol{E_i} = \left[\frac{(\Delta P)_m - (\Delta P)_c}{\Delta P_m}\right] * \mathbf{100\%}, \qquad \boldsymbol{i} = \mathbf{1, 2, 3}, \ldots\ldots\ldots, \boldsymbol{n}$$

Where:

$(\Delta P)_m = Measured\ value\ pressure\ drop$

$(\Delta P)_c = calculated\ valuepressure\ drop$

$$\overline{\Delta\Delta P} = \frac{1}{n}\sum_{i=1}^{n}[(\Delta P_m)]_i$$

APPENDIX B: Neuro Fuzzy Model Code

```
clc
clear all

%%%%%%% recieving training and test  data
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
trndatain=xlsread('Data.xlsx',4,'B2:J130');
[trndatainn,ps1] = mapminmax(trndatain');
trndataout=xlsread('Data.xlsx',4,'K2:K130');
[trndataoutn,pst1] = mapminmax(trndataout');
testdatain=xlsread('Data.xlsx',4,'B179:J215');
testdatainn= mapminmax('apply',testdatain',ps1);
testdataout=xlsread('Data.xlsx',4,'K179:K215');
testdataoutn = mapminmax('apply',testdataout',pst1);
trnData=[trndatainn' trndataoutn'];


testRMSE=90 %initial Condition
testRMSE2=90 %initial Condition
% Function Approximation/Fuzzy Inference System Phase to get the
FIS%%%%%%%
t1=tic;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%search for best
clustering%%%%%%%%%%%%%%%%%%
radii=1.4261   %Training Option
% %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%  membership
function%%%%%%%%%%%%%%%
mfType='gaussmf';  %Training Option
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%
fismat=genfis2(trndatainn',trndataoutn',radii);
[Inputt,numInp]=size(fismat.input);
[Rulet,numRule]=size(fismat.rule);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%
            z=1;
            Epoch=0;
            while z<36
                Epoch=Epoch+1
                    t2=tic;
                    MU=0.01             %Training Option learning
rate
                    dec_rate=0.8;       %Training Option
                    inc_rate=5;        %Training Option
      [fismat1,trnError,ss]=anfis(trnData,fismat,[Epoch 0 MU
dec_rate inc_rate],1);
      fuzout_n=evalfis(trndatainn',fismat1);
      trnRMSE_n=norm(trndataoutn'-fuzout_n)/sqrt(length(fuzout_n));
      trnMSE_n=mse(trndataoutn'-fuzout_n);
      fuzout=mapminmax('reverse',fuzout_n,pst1);
      trnRMSE=norm(trndataout-fuzout)/sqrt(length(fuzout))
      trnMSE=mse(trndataout-fuzout);
      error_percent_train=((trndataout-fuzout)./(trndataout))*100;

trnrmse_4=sqrt((1/length(error_percent_train))*sum(error_percent_tra
in.^2))
      max_error_percent_train=max(abs(error_percent_train))
```

```
        fuzout2_n=evalfis(testdatainn',fismat1);
        testRMSE_n=norm(testdataoutn'-
fuzout2_n)/sqrt(length(fuzout2_n));
        testMSE_n=mse(testdataoutn'-fuzout2_n);
        fuzout2=mapminmax('reverse',fuzout2_n,pst1);
        testRMSE1=norm(testdataout-fuzout2)/sqrt(length(fuzout2))
        testMSE=mse(testdataout-fuzout2);
        error_percent_test=((testdataout-fuzout2)./(testdataout))*100;
        testrmse_4=
sqrt((1/length(error_percent_test))*sum(error_percent_test.^2))
        max_error_percent_test=max(abs(error_percent_test))
                              tElapsed2=toc(t2);
                              tElapsed_2=toc(t2);

                              if     testRMSE1<testRMSE
                                            save 'result';
                                     end;
                                             if testRMSE1<testRMSE
                                             testRMSE=testRMSE1;
                                             end;
                      if testRMSE<testRMSE2
                      testRMSE2=testRMSE;
                      z=1;
                      elseif z<36
                      z=z+1;
                      end

              end;% for while z
tElapsed_1=toc(t1);
```