Bit Selection Using Drilling Data By Artificial Neural Networks

By

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CERTIFICATION OF APPROVAL

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A project dissertation submitted to the

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(PETROLEUM ENGINEERING)

Approved by,

____

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MAY 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.

(PRETHIPKUMAR A/L WATALINGAM)

ABSTRACT

Bit selection is an important task in drilling optimization process. To select a bit is considered as an important issue in planning and designing a well. This is simply because the cost of drilling bit in total cost is quite high. Thus, to perform this task, a back propagation ANN model will be developed. This is done by training the model using drilling bit records from offset wells. In this project, two models will be developed by the usage of the ANN. One is to find predicted IADC bit code and one is to find Predicted ROP. Stage 1 was to find the IADC bit code by using all the given filed data. This data includes Size(in), Flow area (in^2), Depth out (m MD), Bit meter (m), Rotation hours (hrs), ROP(m/hr), Minimum Rotation (rpm), Maximum Rotation (rpm), Total bit revolution, Minimum Weight (kN), Maximum Weight (kN), Minimum Flow (l/min), Maximum Flow (l/min), Minimum Pump Pressure (bar), and Maximum Pump Pressure (bar). The output is the Targeted IADC bit code. Stage 2 was to find the Predicted ROP values using the gained IADC bit code in Stage 1. This time, the data used as input in the ANN modeling process includes Targeted IADC bit code, Size(in), Flow area (in^2), Depth out (m MD), Bit meter (m), Rotation hours (hrs), Minimum Rotation (rpm), Maximum Rotation (rpm), Total bit revolution, Minimum Weight (kN), Maximum Weight (kN), Minimum Flow (l/min), Maximum Flow (l/min), Minimum Pump Pressure (bar), and Maximum Pump Pressure (bar). The output is the Predicted ROP. Next is Stage 3 where the Predicted ROP value is used back again in the data set to gain Predicted IADC bit code value. The input parameters was Size(in), Flow area (in^2), Depth out (m MD), Bit meter (m), Rotation hours (hrs), Predicted ROP(m/hr), Minimum Rotation (rpm), Maximum Rotation (rpm), Total bit revolution, Minimum Weight (kN), Maximum Weight (kN), Minimum Flow (l/min), Maximum Flow (l/min), Minimum Pump Pressure (bar), and Maximum Pump Pressure (bar). The output is the Predicted IADC bit code. Thus, at the end there will be two models that give the Predicted ROP values and Predicted IADC bit code values. Results showed that the final Regression value obtained overall was more than 95% accurate for Predicted IADC bit code and Predicted ROP values.

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LIST OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

NOMENCLATURE

SHORT FORM	MEANING
ANN	Artificial neural networks
Ar_{abr}	Relative abrasiveness
BP	Back-propagation
CB	Bit cost($)
CR	Rig cost($/hr)
GA	Genetic algorithm
HPHT	High-Pressure/High-Temperature
IADC	International Association of Drilling Contractor's
LM	Levenberg-Marquardt
MLP	Multi-layer perceptrons
MSE	Mean Square Error
MW	Mud weight(PPG)
NSRB	Non-Sealed Roller Bearings
PDC	Polycrystalline Diamond Compact
R	Regression Value
ROP	Rate of penetration(ft/hr)
RPM	Rotation per minute (rad/min)
SLJB	Sealed and Lubricated Journal Bearings
SLRB	Sealed and Lubricated Roller Bearings
TFA	Total flow area (ft^2)
TRAINLM	Training program for Levenberg-Marquardt
TR	Rotating time(hr)

TT	Trip time(hr)
UCS	Unconfined compressive strength of formation
WOB	Weight on bit(lb)
Y	Footage drilled(ft)
$/ft	Cost per foot

CHAPTER 1
INTRODUCTION

1.1. BACKGROUND

The basic form of bit selection is normally done based on cost per foot. This method is simply choosing the bit that will provide the lowest cost per foot over the upcoming interval. In addition to that, other factors are taken into consideration as well such as offset, journal angle, and other design aspects. This differentiates one bit to another according to the specific environments. Therefore, understanding bit types is a vital step before moving on to bit design as well as bit selection.

1.2. BIT TYPES

Rotary drilling bits can be generally classified as either drag bit or rolling cutter bits according to the design features. Drag bits have fixed cutter blades in common. These blades are integrated within the body of the bit. The rotation takes place with the drill string as one unit. On the other hand, the rolling cutter bits normally have 2 or more cones which have basic cutting elements. These cutters rotate about the axis of the cone during the bottomhole rotation (Fasheloum, 1997).

1.2.1. DRAG BITS

Drag bits are bits that physically machine the cuttings during drilling. The drag bits include bits with steel cutters, diamond bits as well as PDC bit. The drag bit does not have rolling parts like how a rolling cutter bit does. It drills as a single unit. It is basically made of one solid piece of steel. This further brings down the chance of bit breakage that normally being one of the main factors of having junk at the bottomhole which can be time and money consuming (Azar & Knowlton, 1991; Fasheloum, 1997).

1.2.2.1. POLYCRYSTALLINE DIAMOND COMPACT, (PDC) BITS

The PDC bits are the latest generation of drag bits. It was made of a thin layer of synthetic diamond which was bonded and cemented to a tungsten carbide substrate via a HPHT process. Today, the cutters are present in numerous sizes and shapes which completely depends on bit design and application (Winters & Warren, 1986). The tungsten carbide is noted to be a good erosion and abrasion resistant which allows the bit to have a high fluid velocity across the face. On contrary, there exists an economical disadvantage whereby the tungsten carbide body is an expansive raw material as compared to ordinary steel (Warren & Armagost, 1988)

1.2.2. ROLLING CUTTER BITS

One of the most common types of bit currently in use in the rotary drilling operation is none other than the Tricone bit. This type of bit comes in a large variety in terms of tooth design and bearing types. It is built in such a way to suit a wide variety of formation characteristics. Basically, the drilling action of a rolling cutter bit depends up to a certain extend on the offset set in the cone. Normally, offsetting will cause the cone to stop rotating for a period of time during bit turning whereby at this point of time the teeth of the bit scrape the bottom of the hole more like a drag bit. Thus, this action improves drilling speed in most formation types (Harrell, 1994). The drilling action of a rolling cutter bit is affected by the bit teeth based on its shape and size. Normally, soft formation will be using long and widely spaced teeth while hard formation will be depending on shorter teeth in order to avoid breakage (Warren, 1984). The drilling action of this drilling bit utilizing zero cone offset is found to be a crushing action. The two primary types used are:

- Milled Tooth Cutters
- Tungsten Carbide Insert Cutters

1.3 BIT DESIGN

1.3.1 BIT DESIGN FOR ROLLING CUTTER ROCK BITS

This section of the report describes the components of a rolling cutter rock bits. Basically, there are 3 basic types of bearings which will be discussed below:

- The Non-Sealed Roller Bearings (NSRB)
- The Sealed and Lubricated Roller Bearings (SLRB)
- The Sealed and Lubricated Journal Bearings (SLJB)

The wellbore environment and the cost per foot value will be taken into consideration in the choosing of a bearing. The first type of bearing is there NSRB whereby it is the cheapest and the least advanced type of ball bearing. It comes with an anti friction roller bearing within the cone and part of the leg. The roller and friction bearing function to grip the load on the cone whenever the weight is provided to the bit. It keeps the cone in place (Bovenkerk, 1978; Fasheloum, 1997).

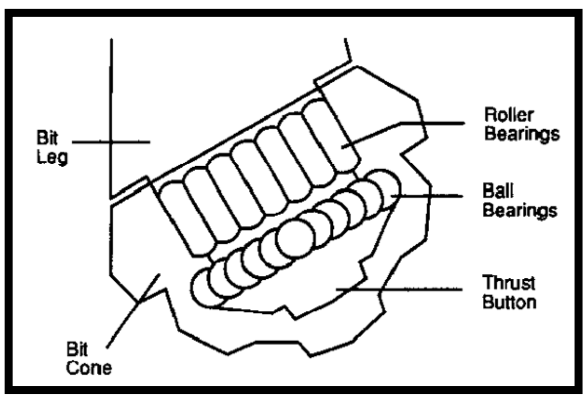


Figure 1: Typical Roller Bearing Construction (Fasheloum, 1997)

The bearing assembly configuration is neither sealed nor grease lubricated. This is one of the reasons in why drilling fluid flows easily towards the bearing. The solid particles found within the mud will scrape the metal of the rollers. This will result in uneven distribution of the loads as the cones loosen up. Pushing the bearing with further rotation might cause severe metal loss at all contact points. In simple words, NSRB is recommended for large diameter milled steel tooth bits. This is because the bearing surface will be larger and the weight on drilling will be smaller making it to last longer. On the other hand, SLRB utilizes roller and ball bearing to seize the drilling load. SLRB has a seam that aids in avoiding mud invasion into bearings. This bearing will be greased and sealed off in a compact manner (Cawthorne, McDonough, Portwood, & Siracki, 1994). The SLRB holds a grease reservoir which is coated by a rubber diaphragm that balances the hydrostatic pressure of the wellbore during pullout session of the bit. This is an advantage of SLRB over the NSRB. However, the usage of SLRB remains for milled tooth cutters (Cawthorne, Portwood, & Siracki, 1994). Sealed roller bearing is noted to hold on up to 5000lbs per inch of bit diameter when it comes to maximum bit weight. On the other hand, SLJB tends to distribute the radial load over a larger surface area. Loads are held with minor metal deformation. The SLJB utilizes 2 bearing surfaces in contact with each other with minimized tolerance. Ball bearings also come in handy to support longitudinal loads. The journal bearing produces quite a number of internal heats through friction. However, the tight clearance within the bearings allows this heat to dissipate. Thus, SLJB must not be spun too fast (Oteri, 2000).

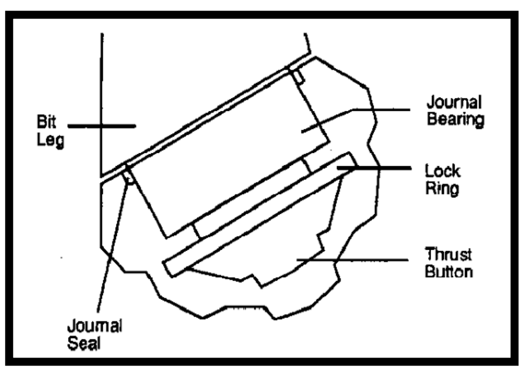


Figure 2: Typical Sealed Journal Bearing Construction (Fasheloum, 1997)

1.3.2 BIT DESIGN FOR PDC BITS

The PDC bit is known to be a solid one piece tool holding polycrystalline diamond cutters. The synthetic diamonds are molded into a thin layer to be attached to a tungsten carbide disc. This is done via a HPHT process. The shock load propagates through entire cutting via the random orientation of the cleavage planes that indirectly allows reduction in breakage. PDC bits are known to shear the rock which helps save energy. Thus, optimized drilling can be gained with the usage of less WOB. Given a favorable formation, PDC bits are acknowledged to perform longer and harder. The effectiveness is about 3 times than conventional rolling cutter bit (Nygaard & Hareland, 2007). Having all this plus point, PDC bits are quite expansive and can be destroyed by gumbo type formations. Therefore, a proper geologic analysis together with PDC bit compatibility must be done before drilling. The detailed field analysis for PDC bit has not been completed and this report is based on the data limitations (Oteri, 2010). Now that the bit types and bit design features have been explained, the report will now move to bit selection method.

1.4 IADC BIT CLASSIFICATION SYSTEM

1.4.1 ROLLING CUTTER BIT CLASSIFICATION

The International Association of Drilling Contractors, IADC bit code classification system was first introduced in 1940 globally. IADC bit code classification for rolling cutter bit was established back in 1987 and was further improved in 1992 by including more features to it. The following is an example of standard roller cone nomenclature:

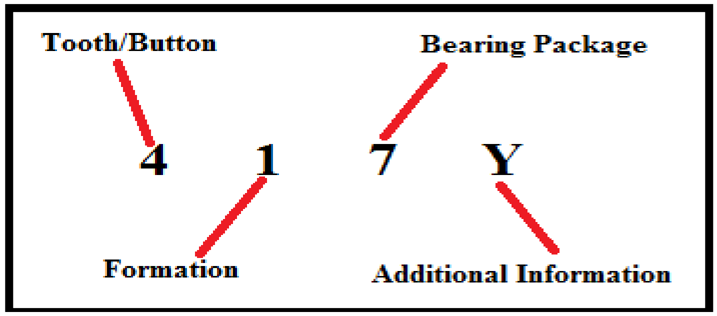


Figure 3: Standard Roller Cone Nomenclature (McGehee et al., 1992)

Table I: Standard Rolling Cutter Bit Nomenclature (McGehee et al., 1992)

DIGIT 1			DIGIT 2		DIGIT 3		ALPHABET	
No	Type	Tooth/ Button	No	Formation	No	Bearing	A	Air Application
1	Soft	Tooth	1	Soft	1	NSRB	B	Special Bearing
2	Medium		2	Medium	2		C	Center Jetted
3	Hard		3	Hard	3		D	Deviation Control
4	Soft	TCI	4	Hardest	4	SLRB	E	Extended Jets
5	Medium				5		G	Extra Gauge
6	Medium Hard				6	SLJB	H	Horizontal Application
7	Hard				7		J	Jet Deflection
8	Hardest						L	Lug Pads
							M	Motor Application
							S	Standard Steel Tooth
							T	Two Cone
							X	Enhanced Cutting Structure
							X	Chisel Inserts
							Y	Conical Inserts
							Z	Other Inserts

1.4.2 PDC DRILL BITS CLASSIFICATION

The nomenclature of PDC drill bits can be seen as to be one letter and three numbers. The letter indicates body type e.g. M=Matrix, S=Steel, or D=Diamond. Meanwhile, the first digit shows the type of formation that will be drilled. Digit number two will be representing cutting structure and digit number three will represent the bit profile. The specification of each one of these digits can be seen in the table below.

Table II: Classification of Geological Formation Type to Be Drilled (Brandon et al., 1992)

No	Type	Description	PDC Cutting Structure
1	Soft and soft sticky	Highly drillable formations (clay, marble, gumbo, unconsolidated sands)	Normal size
2			
3	Soft-medium	Low compressive strength sands, shale and anhydrites with hard layers intermixed.	
4	Medium	Moderate compressive strength sand, chalk, anhydrite and shale.	
5			
6	Medium hard	Higher compressive strength with non or semi-sharp sand, shale, lime and anhydrite.	19mm cutters
7	Hard	High compressive strength with sharp layers of sand or siltstone	13mm cutters
8	Extremely hard	Dense and sharp formations such as quartzite and volcanic rock.	8mm cutters

Table III: Cutting Structure and Bit Profile (Brandon et al., 1992)

CUTTING STRUCTURE		BIT PROFILE	
1	Natural Diamond	1	Short Fishtail
2	TSP (Thermally Stable Polycrystalline)	2	Short Profile
3	Combination	3	Medium Profile
4	Impregnated Diamond	4	Long Profile

1.5 BIT SELECTION METHODS

A bit cost might be relatively small in a well's budget which is approximately 5%, but the impact of bit performance on overall well cost might end up being considerably large. (Lummus, 1971; Mostafavi & Jamshidi, 2013; Yılmaz, Demircioglu, & Akin, 2002). Bit selection is basically classified into three categories namely:

- Cost Analysis
- Offset Well Log Analysis
- Bit Performance Modeling Using ANN and Genetic Algorithm

1.5.1 COST ANALYSIS

Cost analysis method is normally done when analyzing historical data from offset wells. It is also used during bit run monitoring. The performance level of the bit will be viewed in an economical manner. However, this method consumes precious time (Rabia, Farrelly, & Barr, 1986). The formula below highlights the bit cost estimation:

$$\$/ft = \frac{C_B + C_R \times T_R + C_R \times T_T}{Y} \qquad \text{(Eq.1)}$$

The method mentioned above is not considered as a good measure when it comes to bit selection as it does not take into consideration of drilling parameters. Thus, other methods will be looked upon (Bataee, Edalatkhah, & Ashena, 2010).

1.5.2 OFFSET WELL LOG ANALYSIS

(W. J. Hightower, 1964) used the help of gamma ray and spontaneous potential log data in order to develop a sophisticated graphical representation of the formation being studied. This method considers the comparison of different types of drilling bits, drilling conditions as well as lithology using sonic log and other lithology log data to be utilized in the selection of proper bit and it is based on the rock compressive strength (Onyia, 1988). However, current drilling data is still not being considered and bit selection relied completely on previous offset bit records only.

1.5.3 BIT PERFORMANCE MODELING, USING ANN AND GENETIC ALGORITHM

Artificial Neural Network, ANN is a systematic modeling tool which is generally used for complex systems. Basically, the ANN is made up of computational units which will be called as neurons being connected in a parallel structure. Drilling bit selection can be very systematic and complex at the same time as it consists of numerous parameters. Thus, ANN aids in recognizing complex relationship among all the variables which is needed for a particular situation. The ANN model was first brought into the oil and gas industry in the year 2000. It was a systematic neural network generated mathematical model (Bilgesu, Al-Rashidi, Aminian, & Ameri, 2000). The neural network used field data in order to establish bit code with finest ROP. Mounting number of data fed to the neural network reduces percentage of error.

1.6 PROBLEM STATEMENT

Problem 1:

There are two different models that which have been used previously to predict IADC code through ANN. The first model used a three digit number as a targeted output for the IADC code (e.g. 115). At the same time, ANN will predict the three digit number (e.g.115.2 or 114.9). Therefore, the targeted output cannot be concluded from the predicted output. Whereas, the second model used a three digit comma delimited numbers (e.g. 2, 3, 2). The ANN predicts the three digit comma delimited numbers as (e.g. 2.2, 2.8, 1.8). Therefore, the values of the targeted output cannot be concluded.

Problem 2:

The researchers in order to predict the IADC codes by implementing ANN model have used information from an offset well where either PDC bit or rolling cutter bit was used to drill the entire drilling interval section. Based on what has been done so far, no prediction was performed by using a mixture of PDC bit and rolling cutter bit.

1.7 OBJECTIVE AND SCOPE OF STUDY

Objective 1:

To predict IADC bit codes by using drilling data given. This can be done by using the ANN simulation process with drilling data as inputs and setting targeted IADC bit code as output. The ANN will then train a model to produce predicted IADC bit code values.

Objective 2:

To predict ROP by using drilling data given. This can be done by using the ANN simulation process with drilling data and targeted IADC as inputs and setting ROP as output. The ANN will then train a model to produce predicted ROP values.

Objective 3:

To determine the most accurate number of hidden neuron layer. This can be done by ANN simulation process for a range of 1 until 23 to gain the best regression value for test data.

The scope of this research will be 2 sets of Anaran oil field drilling data, a well located in the west of Iran. Meanwhile the reconfirmation model used the Shadegan Oil Field drilling data.

CHAPTER 2
LITERATURE REVIEW

Determining the optimum bit to be used has always been an important task. Latest technology was put into account in selecting rotary drilling bits. Bit types to be used is selected based on a three layer feed forward neural network system (Bilgesu, Al-Rashidi, Aminian & Ameri, 2000). The complicated relationship between formation, bit properties, and operating parameters was determined using various neural network models. The data sets utilized in this study were gained from Middle East fields. It was checked to remove reaming and coring operations. The first data set was labeled (K-1) and it had about 2000 sets of recorded field information. It also had 277 different bit types from a region. The first neural network design was given an input of bit size, total nozzle area of the bit, depth the bit was pulled, drilled interval length, ROP, WOB, RPM, and mud circulation rate. These input parameters were used to predict bit type for the upcoming drilling interval. Next, the second data set (K-2) was introduced using different regions from Middle East. It had 489 different bit types. Other variables were similar to K-1. Third data set (K-3) had more than 2000 records with similar variables too. The neural network which was developed has successfully chosen the bits for the preferred drilling sections. It was used to improvise planning process for new wells. Thus, it was concluded that a correlation coefficient of 0.857 and 0.975 was achieved for neural network predicted bit types and bit types used respectively.

Unconventional method was also used in choosing drilling bits. This was carried out by the usage of a three layer feed forward neural network system (Bilgesu, Al-Rashidi, Aminian & Ameri, 2000). 2 different neural network systems were designed in a way where one determines the bit type and another for cost per foot value. A same sort of approach was used to relate formation characteristics and bit properties utilizing the neural network system. The drilling operation data from the Middle East region was used for this purpose. The first set contains 1500 sets of recorded parameters. In this case study, 520 different bits ranging from the sizes of 4 ½ inches up to 28 inches was used. Input used were pretty much the same as the one mentioned previously. The next set used approximately 3200 recorded parameters. The information gathered from this study is that the identification of bit in relation to their codes can be done. However, the relationship between the bit types was not stated clearly. In this study, the correlation coefficient was between 0.831 and 0.995 for the data sets used.

Another literature showed that (M. Bataee & S. Mohseni, 2011) utilized intelligent systems in ROP optimization. During this modeling process, proper parameters were chosen based on the targeted ROP. Inputs for the ANN were bit diameter, depth, WOB, RPM, and MW and the output was ROP. Development of a 2 layered network was done. This was followed by the development of a 3 layered network and followed by a 4 layered network. Among all 3 types, it was noted that the 3 layered networks resulted in the least amount of error prediction. Thus, many tests were run for the 3-layered network and finest correlation coefficient was selected among the tested models. During the training, the Back-Propagation algorithm with Levenberg-Marquardt training function was utilized. Data sets from fifteen different offset wells were taken into account in the training and testing process of the network. From this data, 60% was used for training purposes. The remaining 20% is applied in validation process and another 20% was used for testing purpose. This training program used up about 1810 data point. From this detail, it was noted that an improvement in WOB or rotary speed does not necessarily improve ROP. This is observed through the results when the driller used high WOB and RPM in certain parts. The ROP value decreased due to cleaning problem and bit floundering. Thus, results proved that using less MW leads to higher ROP value. Besides that, a wide range of RPM and WOB was used and the observation indicated that the best value was neither the maximum nor the minimum value. Therefore, a suitable ROP from the list was chosen from the previous one that was targeted but by the utilization of a modeled function. Necessary drilling parameters were used.

(Mostafavi & Jamshidi, 2013) A proper bit was chose to gain the targeted ROP by utilizing the pre modeled IADC bit code and using the given drilling parameters. A GA was modified to optimize the modeled ROP function which was gained through ANN. Besides that, different hole sections were drilled and during this process, parameters such as optimum Rate Of Penetration, Total Flow Area, Mud Circulation Flow Rate, Rotation Per Minute, Weight On Bit, and pressure was noted down. The result with the highest expected ROP was taken as a result and was recommended out of the available bits. The R-values was noted to be over 0.95 in the first model and over 0.93 in the second model respectively. To focus on a reasonable results using ANN model, training was stopped when the validation error begin to increase.

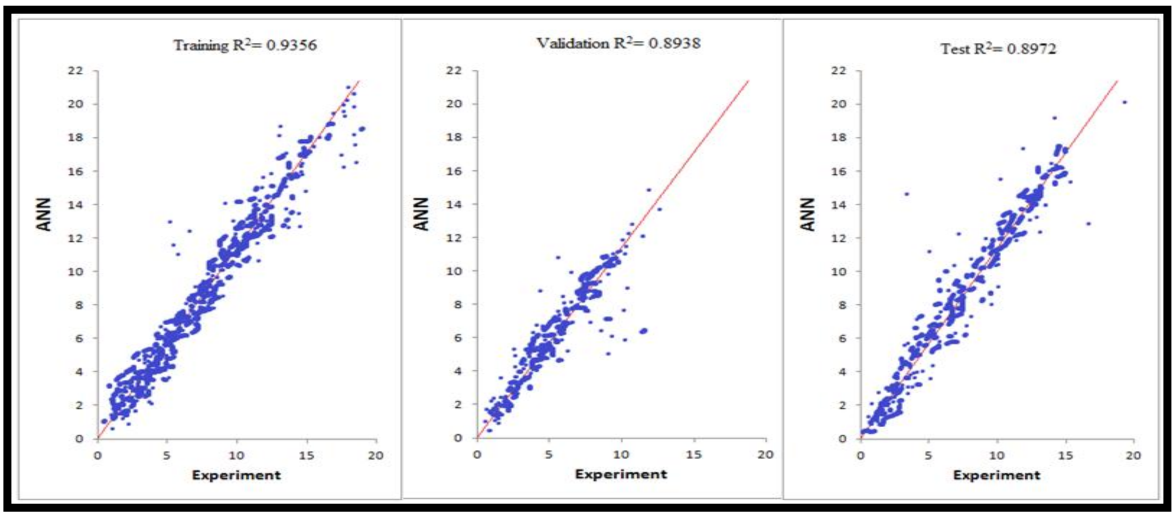


Figure 4: ANN Results for Bit IADC Function (Mostafavi & Jamshidi, 2013)

From all the bits available, the bit with maximum predicted ROP was then recommended. In this literature, it was not mentioned as to how the networks were optimized. The methods to optimize the drilling process for a new well were also not mentioned. Furthermore, the IADC code that was used was a three digit number which might not be a fairly good idea.

CHAPTER 3

RESEARCH METHODOLOGY

ANN is a computational technique used to solve complex problems. MLP network is one of the most popular neural network architectures for modeling process (Feng, Li, Cen, & Huang, 2003). It consists of input layer of source nodes, hidden layer of computation nodes (neurons), and output layer. The number of nodes that is being used in the input as well as the output layer is completely dependent on the number of input and output variables being used respectively (Pinar et al., 2010). The figure shown is a schematic of MLP network. Further theoretical details about MLP networks is presented by (Haykin, 1994). In this project the MLP network will be trained by the usage of LM technique. One of the advantages of using the LM technique is that it produces efficient and faster second order convergence rate and is capable to maintain the stability at the same time (Cigizoglu & Kisi, 2005; Hagan & Menhaj, 1994). Based on the research papers, it is clearly stated that the single layer is good enough to approximate a complex function (Wilamowski, Iplikci, & Efe, 2001).Therefore, in this study, a three layered Feed-Forward Network will be developed namely input, hidden, and output layers. Among the available data sets which are gathered from different offset wells, 70% will be used for training, 15% will be applied for validation process and the remaining 15% will be used to test gained results from the bit being modeled as well as the ROP functions. Stage 1 was to find the Targeted IADC bit code by using all the given filed data. This data includes Size(in), Flow area (in^2), Depth out (m MD), Bit meter (m), Rotation hours (hrs), ROP(m/hr), Minimum Rotation (rpm), Maximum Rotation (rpm), Total bit revolution, Minimum Weight (kN), Maximum Weight (kN), Minimum Flow (l/min), Maximum Flow (l/min), Minimum Pump Pressure (bar), and

Maximum Pump Pressure (bar). The output is the Targeted IADC bit code. Stage 2 was to find the Predicted ROP values using the gained Targeted IADC bit code in Stage 1. This time, the data used as input in the ANN modeling process includes Targeted IADC bit code, Size(in), Flow area (in^2), Depth out (m MD), Bit meter (m), Rotation hours (hrs), Minimum Rotation (rpm), Maximum Rotation (rpm), Total bit revolution, Minimum Weight (kN), Maximum Weight (kN), Minimum Flow (l/min), Maximum Flow (l/min), Minimum Pump Pressure (bar), and Maximum Pump Pressure (bar). The output is the Predicted ROP. Next is Stage 3 where the Predicted ROP value is used back again in the data set to gain Predicted IADC bit code value. The input parameters was Size(in), Flow area (in^2), Depth out (m MD), Bit meter (m), Rotation hours (hrs), Predicted ROP(m/hr), Minimum Rotation (rpm), Maximum Rotation (rpm), Total bit revolution, Minimum Weight (kN), Maximum Weight (kN), Minimum Flow (l/min), Maximum Flow (l/min), Minimum Pump Pressure (bar), and Maximum Pump Pressure (bar). The output is the Predicted IADC bit code.

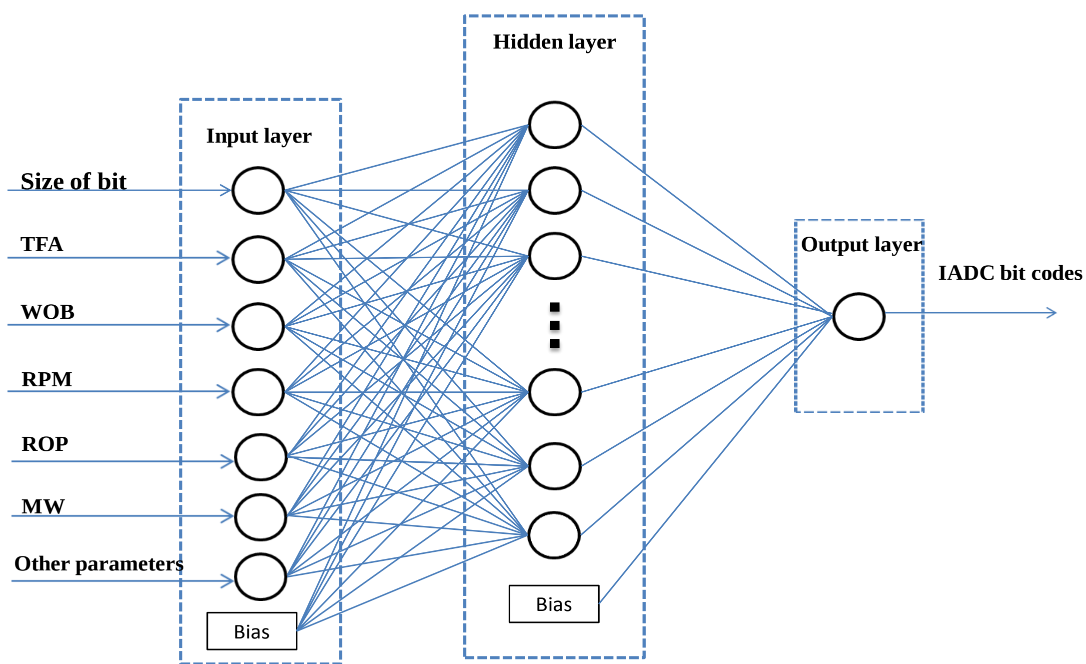


Figure 5: Schematic Structure of MLP Network Structure (Haykin, 1994)

Table IV: Method in Obtaining ANN Results

Model	Data Being Used	Output	Example	Description
ANN	Drilling Data	IADC Bit Code	10,20,30	10= 512X 20=434X 30=532M Ex: ANN predicts the numbers as perhaps 11.5 (10), 23.4 (20), and 32.7 (30)

The results of the three methods discussed above will be considered for ROP prediction and improve predicted IADC bit code value. The general path of the study is sketched in the Figure 6.

3.1. KEY MILESTONE AND SCHEDULE GANTT CHART

To ensure the time for completing this project, a key milestone is presented in Table IV and a schedule in the form of a Gantt chart is prepared at Table V that will be used to track the progress of the research study and implementation.

Table V: Key Milestone for the Project

Time	Activity
Feb,2014	Initial research
April,2014	Completion on background studies
May,2014	Simulation of IADC Bit code Simulation for Optimized ROP
June,2014	Simulation for Optimized IADC Bit code
July,2014	Compilation of progress report
Aug,2014	Presentation and modification in the results if necessary

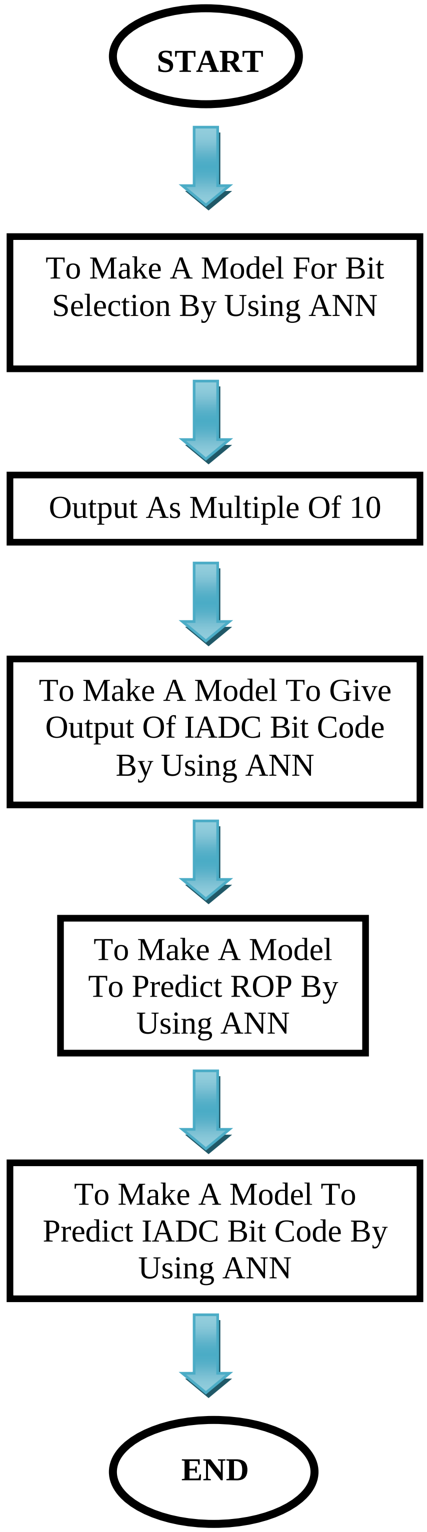
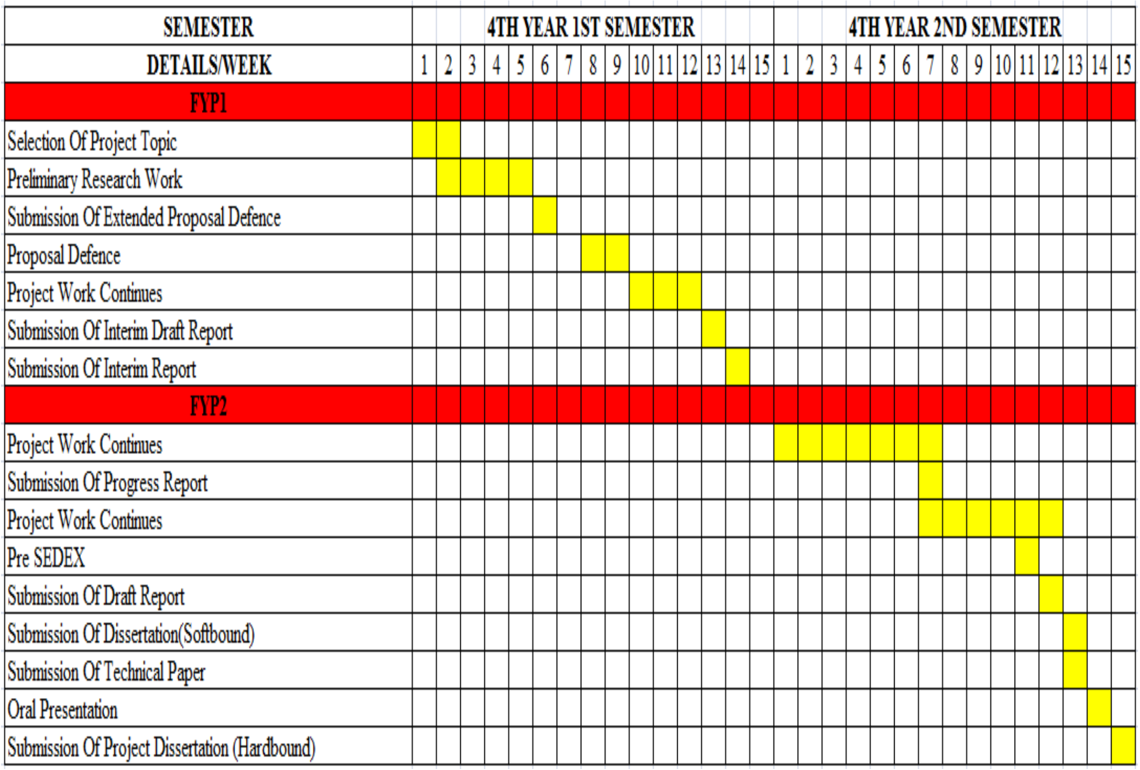


Figure 6: Overall Flow Chart of the Study

Table VI: Gantt Chart For The Project



CHAPTER 4

RESULTS AND DISCUSSION

4.1. DATA GATHERING AND ANALYSIS

For the ANN simulation process, the Matlab software was used. The Neural Network tool which was prebuild in this Matlab software was used to gain all the results and generate all the graphs needed.

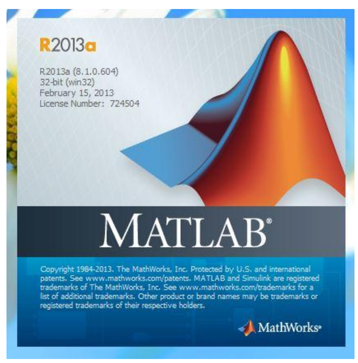


Figure 7: Matlab Software

Diagram below shows some of the steps of the simulation process done to gain the following results. Figure below shows the drilling data being used as an input to gain an output of IADC bit code. The output was set to be targeted IADC bit code.

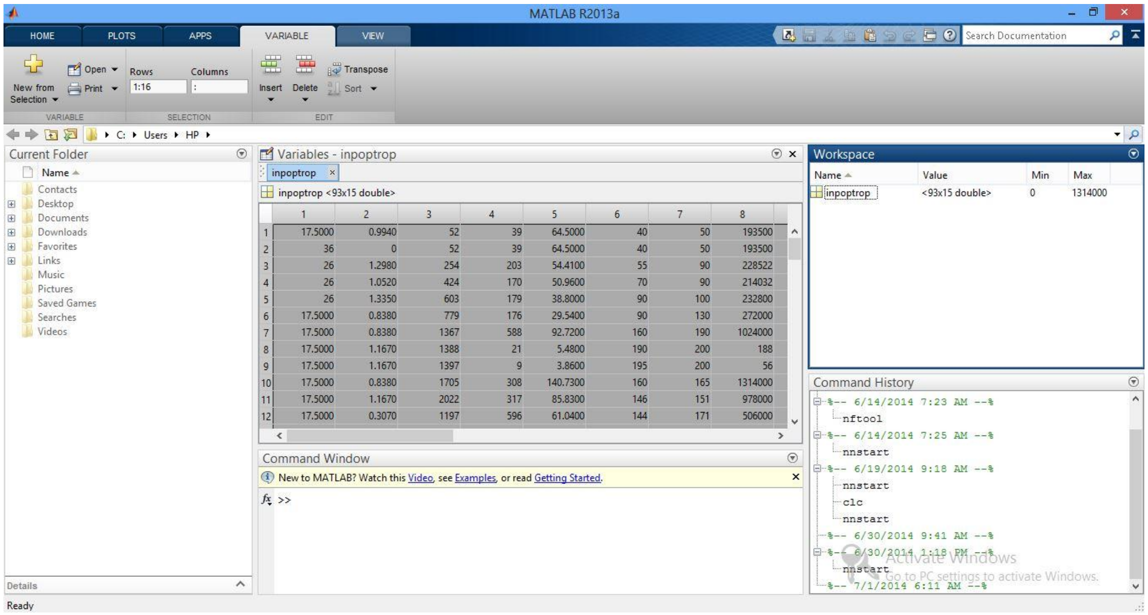


Figure 8: Process Of Using The Data As Input For Modeling.

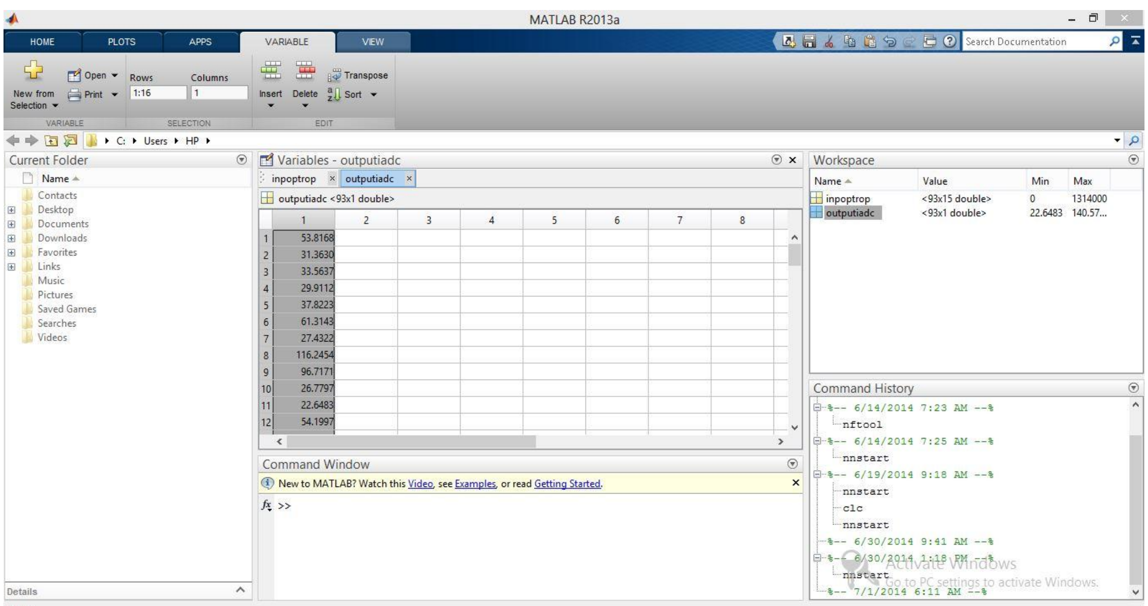


Figure 9: Process Of Using The Data As Output For Modeling.

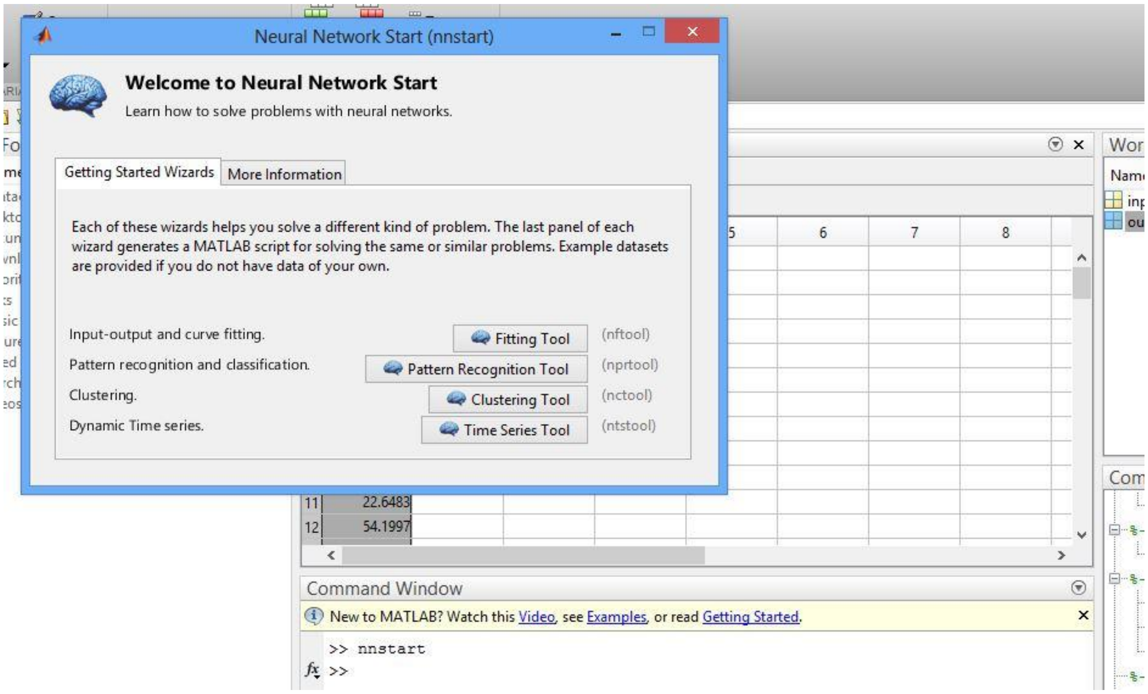


Figure 10: Neural Network Startup Program

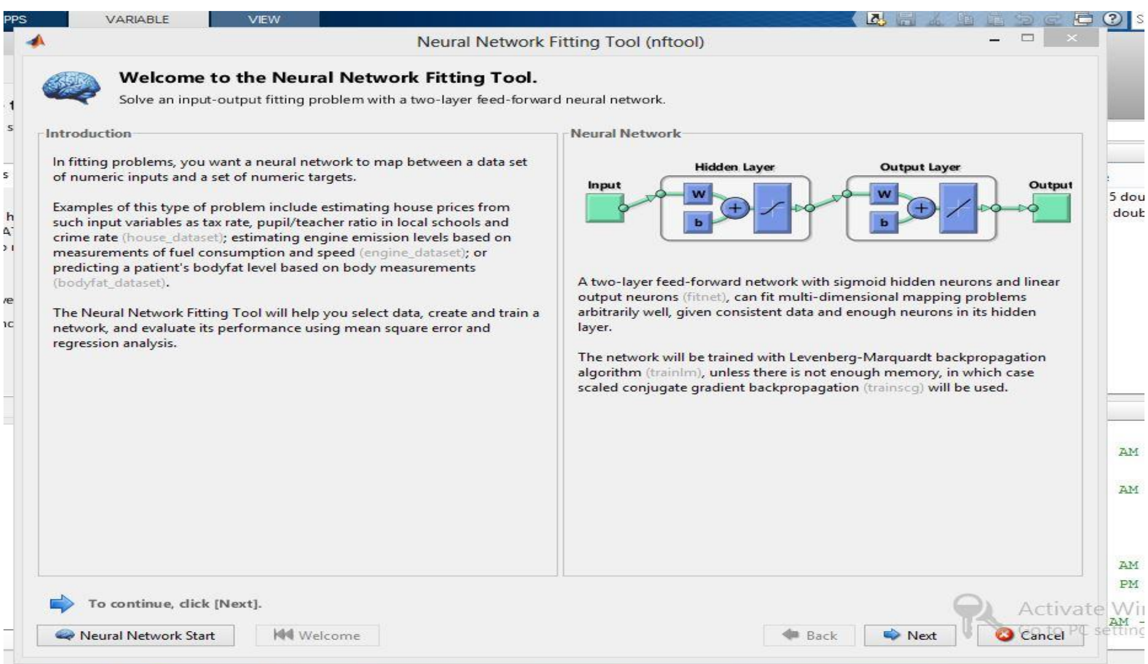


Figure 11: The Neural Network Fitting Tool

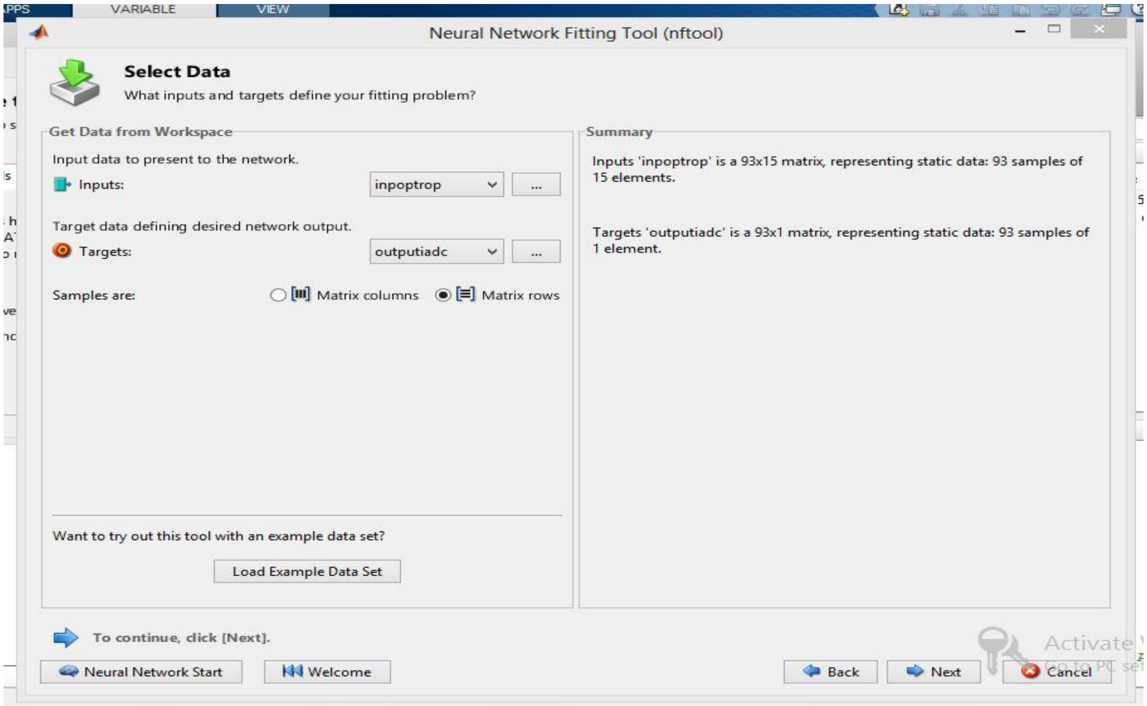


Figure 12: Neural Network Input Output Selection

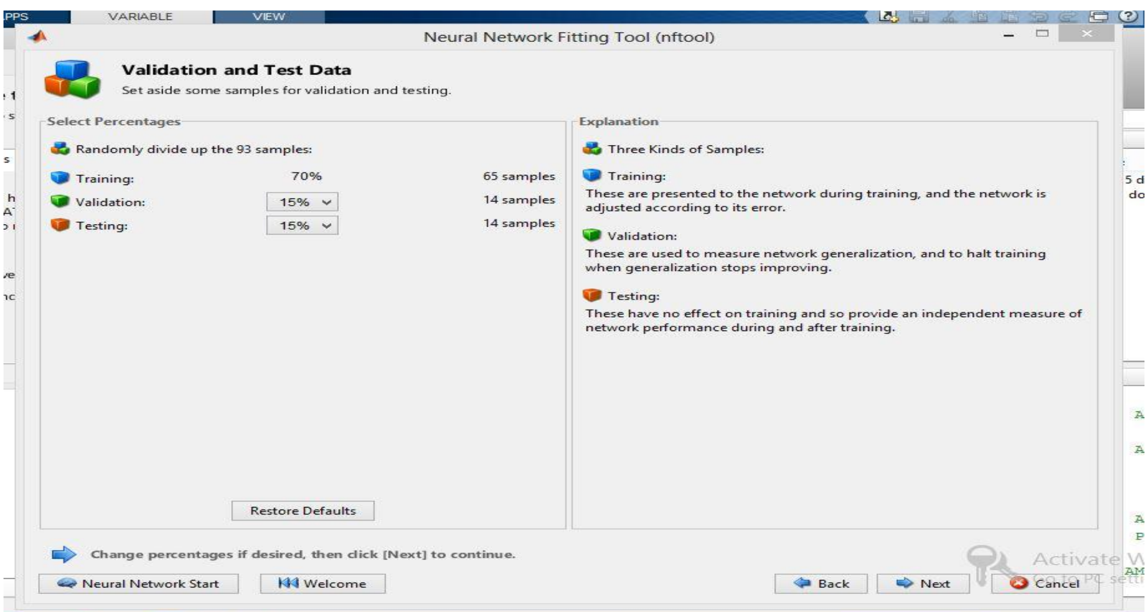


Figure 13: Training, Validation, And Testing Data.

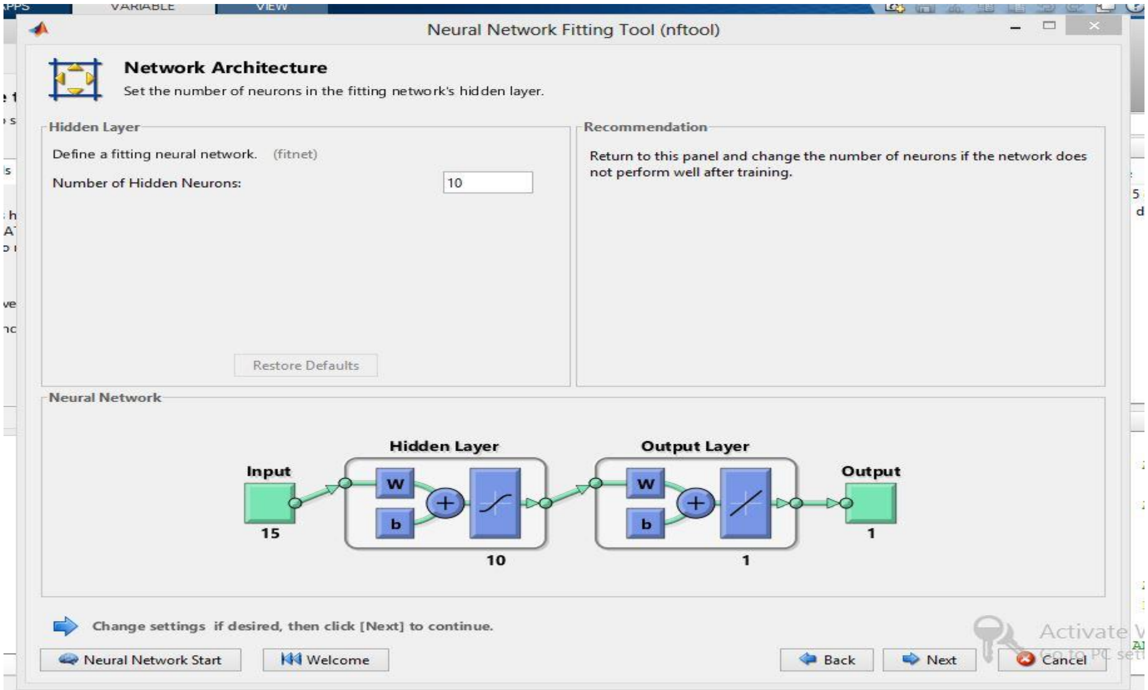


Figure 14: Number Of Hidden Neuron

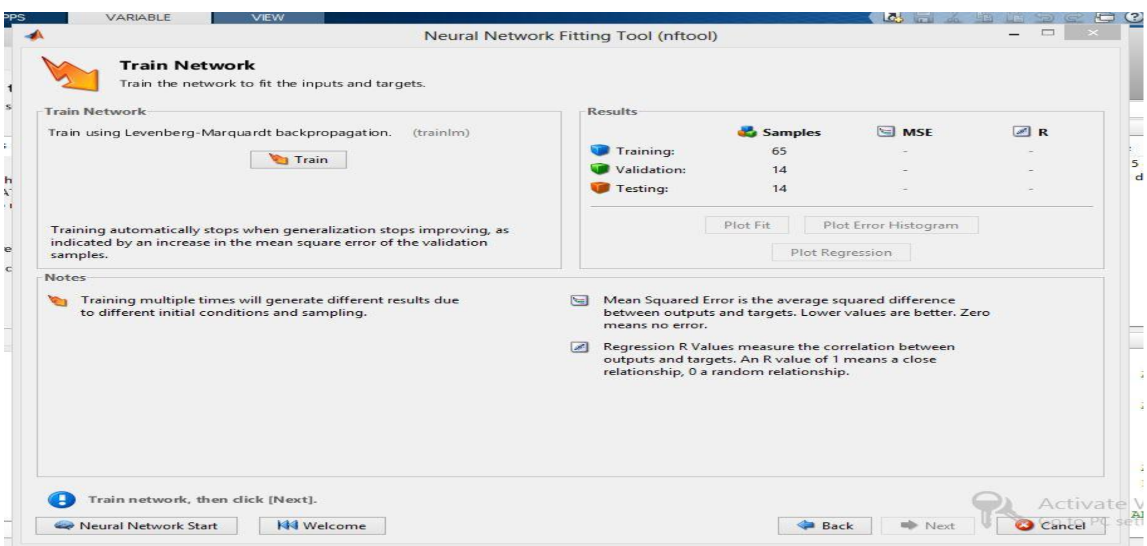


Figure 15: Training Process Of The ANN

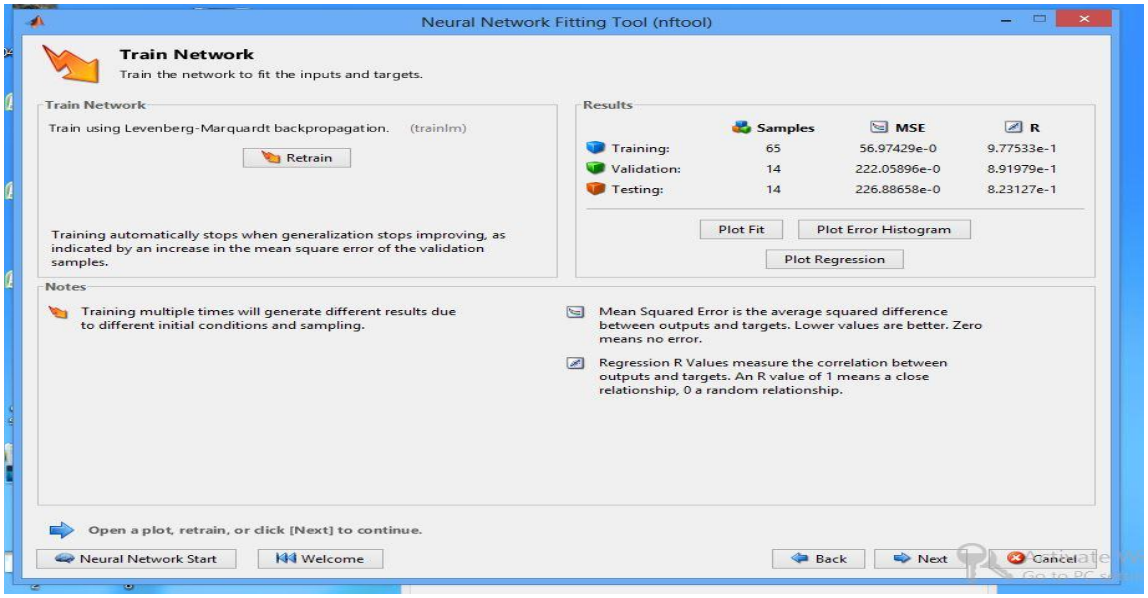


Figure 16: Training Process Of The ANN With Results

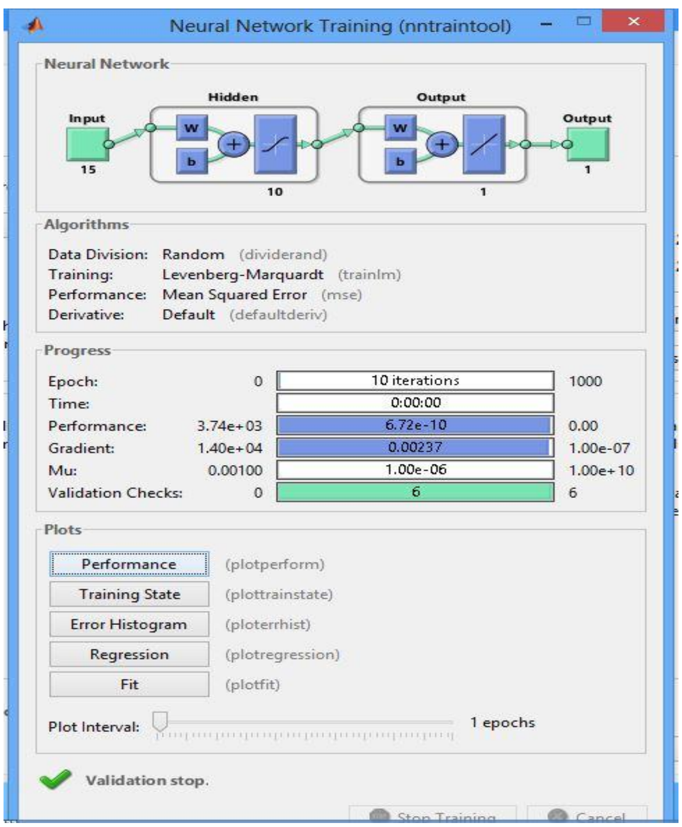


Figure 17: Performance Graphs And Regression Graphs

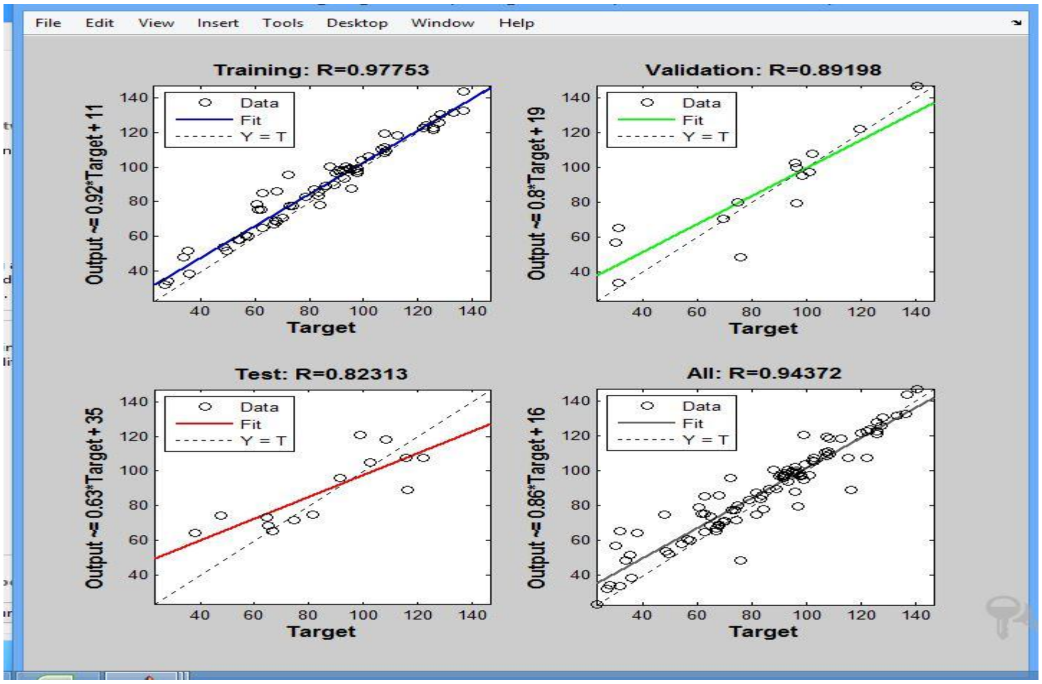


Figure 18: Example of Regression Graph Plots

The simulation part of the project activities was carried out in FYP 2. The type of data used for this project comprises of drilling data. The table below shows an example of data set that was used. The following table represents the range of the data which was used.

Table VII: Data Type Example

Type	MITO	Rotation min (rpm)	60
Size(in)	17,50	Rotation max (rpm)	60
IADC Code	115M	Total bit revolution	86400
Input For ANN	1	Weight min (kN)	20
Flow area (in^2)	0.994	Weight max (kN)	60
Depth out (m MD)	68	Flow min (l/min)	2500
Bit meter (m)	55	Flow max (l/min)	2500
Rot hours (hrs)	24,00	Pump min/max (bar)	20
ROP(m/hr)	2,3	Pump max (bar)	22

Table VIII: Data Type Range

Type	---------------	Rotation min (rpm)	0-271
Size(in)	4.13-36.00	Rotation max (rpm)	0-335
IADC Code	---------------	Total bit revol	0-1829000
Input For ANN	1-150	Weight min (kN)	0-240
Flow area (in^2)	0.000-2.227	Weight max (kN)	0-400
Depth out (m MD)	52-4762	Flow min (l/min)	0-4000
Bit meter (m)	0-569	Flow max (l/min)	0-4100
Rot hours (hrs)	0.44-190.78	Pump min/max (bar)	0-242
ROP(m/hr)	0.00-50.00	Pump max (bar)	0-297

The data set that was initially provided was from Azar Well 1 and 2. This data set consists of 103 sets of data which was completely used in the ANN Simulation process. An example of the type of parameters and a few lists of the data is shown in the table below.

Table IX: Data Set of Azar Well 1 and Azar Well 2 Examples

Type	IADC Code	Input For ANN	Size (in)	Flow area (in^2)	Depth out (m MD)	Bit meter (m)	Rot hours (hrs)	ROP (m/hr)
MITO	115M	1	17.5	0.994	52	39	64.5	0.6
ISRT	445	10	36	0	52	39	64.5	0.6
MITO	115M	1	26	1.298	254	203	54.41	3.7
MITO	115M	1	26	1.052	424	170	50.96	3.3
ISRT	415	10	26	1.335	603	179	38.8	4.6
MITO	115M	1	17.5	0.838	779	176	29.54	6
ISRT	415	10	17.5	0.838	1367	588	92.72	6.3
PDC	M323	20	17.5	1.167	1388	21	5.48	3.8
PDC	M323	20	17.5	1.167	1397	9	3.86	2.3
MITO	135	30	17.5	0.838	1705	308	140.73	2.2
PDC	M323	20	17.5	1.167	2022	317	85.83	3.7
ISRT	415	10	17.5	0.307	1197	596	61.04	9.8
ISRT	415	10	17.5	0.307	1600	403	61.28	6.6
ISRT	415	10	17.5	0.307	1987	387	73.58	5.3
MITO	115	40	14.5	1.052	2025	85	10	8.5
[redacted]								

Rotation min (rpm)	Rotation max (rpm)	Total bit revol	Weight min (kN)	Weight max (kN)	Flow min (l/min)	Flow max (l/min)	Pump min/max (bar)	Pump max (bar)
40	50	193500	10	10	3000	3000	20	22
40	50	193500	10	10	3000	3000	20	22
55	90	228522	40	120	2800	3400	36	58
70	90	214032	60	160	3200	3800	97	145
90	100	232800	20	200	3550	3750	108	126
90	130	272000	50	200	1900	3500	34	148
160	190	1024000	140	250	3500	3600	170	185
190	200	188	14	12	3600	3600	165	165
195	200	56	150	150	3625	3625	165	165
160	165	1314000	160	160	3300	3300	180	180
146	151	978000	2	20	3422	3500	165	165
144	171	506000	10	130	3325	3425	120	130
142	161	568000	10	130	3350	3380	136	140
170	183	772000	10	70	3100	3200	138	146
60	150	4900	20	20	330	330	183	183

The following was done to gain the results that will be discussed below. On receiving the raw data of the Azar well, certain values were missing. This was found by using other information given and also data of the field. The finalized data was used in the ANN modeling process. The modeling process was done in three stages. Stage 1 was to find the IADC bit code by using all the given filed data. This data includes Size(in), Flow area (in^2), Depth out (m MD), Bit meter (m), Rotation hours (hrs), ROP(m/hr), Minimum Rotation (rpm), Maximum Rotation (rpm), Total bit revolution, Minimum Weight (kN), Maximum Weight (kN), Minimum Flow (l/min), Maximum Flow (l/min), Minimum Pump Pressure (bar), and Maximum Pump Pressure (bar). The output is the Targeted IADC bit code. Stage 2 was to find the Predicted ROP values using the gained IADC bit code in Stage 1. This time, the data used as input in the ANN modeling process includes Targeted IADC bit code, Size(in), Flow area (in^2), Depth out (m MD), Bit meter (m), Rotation hours (hrs), Minimum Rotation (rpm), Maximum Rotation (rpm), Total bit revolution, Minimum Weight (kN), Maximum Weight (kN), Minimum Flow (l/min), Maximum Flow (l/min), Minimum Pump Pressure (bar), and

Maximum Pump Pressure (bar). The output is the Predicted ROP. Next is Stage 3 where the Predicted ROP value is used back again in the data set to gain Predicted IADC bit code value. The input parameters was Size(in), Flow area (in^2), Depth out (m MD), Bit meter (m), Rotation hours (hrs), Predicted ROP(m/hr), Minimum Rotation (rpm), Maximum Rotation (rpm), Total bit revolution, Minimum Weight (kN), Maximum Weight (kN), Minimum Flow (l/min), Maximum Flow (l/min), Minimum Pump Pressure (bar), and Maximum Pump Pressure (bar). The output is the Predicted IADC bit code.

4.2. RESULTS AND DISCUSSION

The results were gained and it was used to plot regression graphs. The graphs are shown below. In all the simulations done under the ANN modeling, the data was used with 70% for training data, 15% for validation data, and 15% for test data.

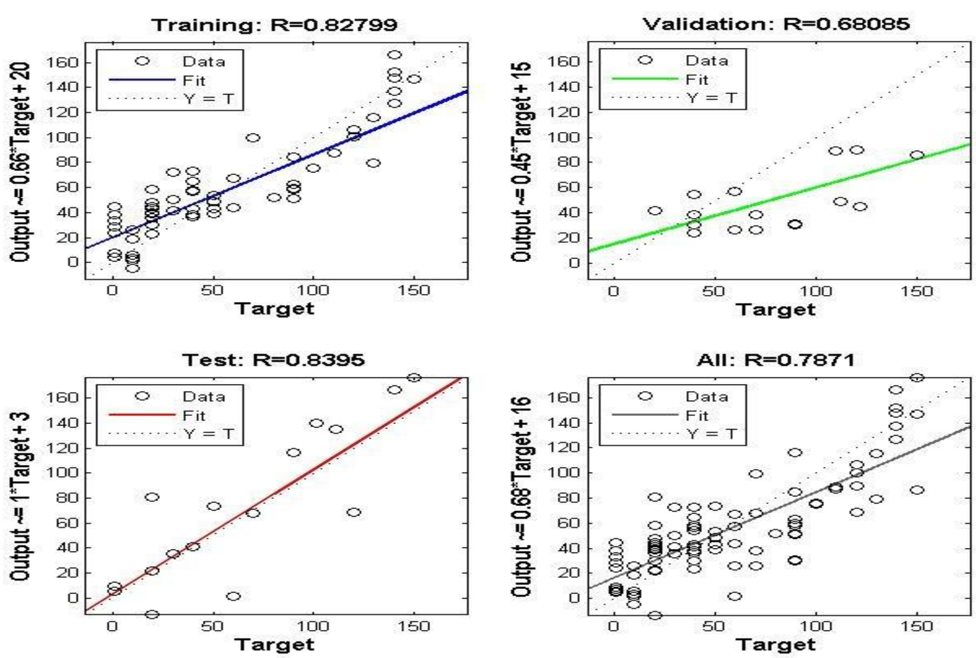


Figure 19: Results Of The Regression Graphs For Output Of Targeted IADC Bit Codes (Stage 1 of Azar Well)

For the simulation process, the number of hidden neurons can be varied from a range of 1 until 23. The best simulation results were gained when the number of hidden neurons was set to 10. The following table shows the Mean Square Error values and Regression values for Training Data, Validation Data, and Test Data.

Table X: MSE And R Value For 10 Number Of Hidden Neurons

(Stage 1 of Azar Well)

	SAMPLES	MSE	R
TRAINING	71	498.46659	0.82799
VALIDATION	16	1287.67076	0.68085
TESTING	16	2095.87942	0.83949

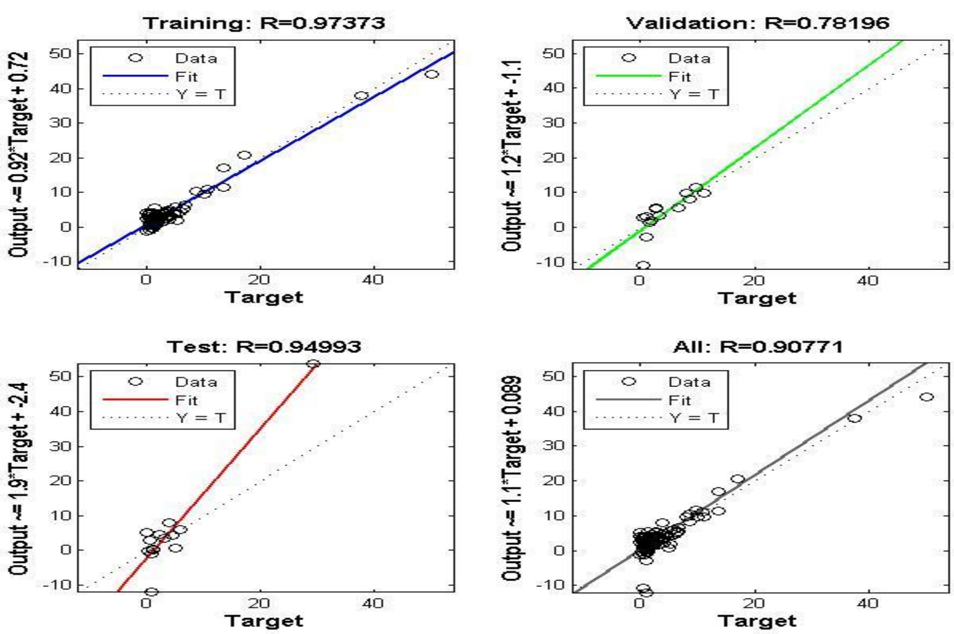


Figure 20: Results Of The Regression Graphs For Output Of Predicted ROP

(Stage 2 of Azar Well)

Table XI: MSE And R Value For 10 Number Of Hidden Neurons

(Stage 2 of Azar Well)

	SAMPLES	MSE	R
TRAINING	71	3.36574	0.97373
VALIDATION	16	12.4047	0.78196
TESTING	16	61.12097	0.94993

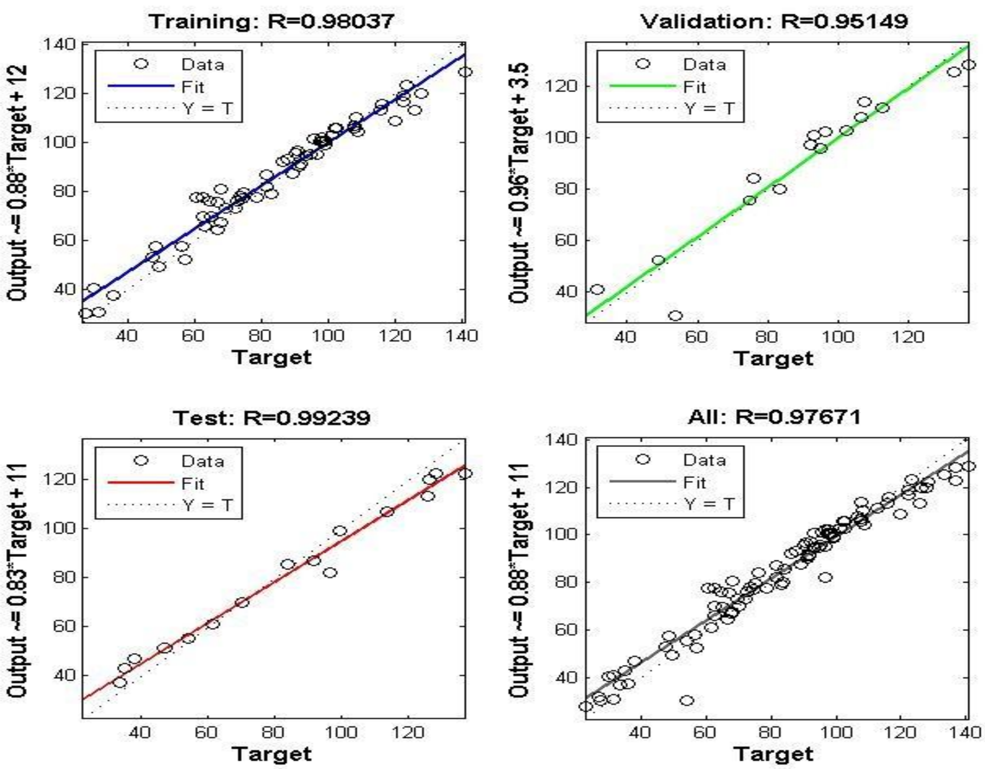


Figure 21: Results Of the Regression Graphs for Output of Predicted IADC Bit Codes (Stage 3 of Azar Well)

For the stage 3 simulation process, it is seen that the number of hidden neuron layers of 17 showed a better response compared to number of hidden neuron layers of 10.

Table XII: MSE And R Value For 17 Number Of Hidden Neurons

(Stage 3 of Azar Well)

	SAMPLES	MSE	R
TRAINING	71	34.44595	0.98037
VALIDATION	16	71.00299	0.95149
TESTING	16	59.67444	0.99239

From the graphs observed above, it is clearly seen that by using all the data given, we can optimize the ROP value through ANN modeling process and further use the Optimized ROP value to find the Optimized IADC bit code. Based on the numerical values of the graph, the accuracy of the R value is approximately 99%. There is still a small error that is due to certain reasons.

1. **Insufficient Data**

As per mentioned earlier, the data used are from the Anaran oil field and from Azar Well 1 and Azar Well 2. Thus, the data are actually limited to a certain region and the number of total data is small. If there was more data available for the simulation process of the ANN modeling, the R value can be improved further.

2. **Limited Time Frame To Complete The Project**

Since this project was given a limited time frame to be completed, the number of times the simulation was done was also limited. The simulation was done with a range of number of hidden neuron layers from 1 until 23. It was observed that the best number of hidden neuron layers is 10 and 17. However, if more time was given for the simulation, the process can be repeated until maximum best approximation can be reached.

3. **Absence Of Log Data.**

A better prediction can be gained if the drilling data is combined with log data. If there was sufficient log data to be used for the simulation process, the percentage of accuracy can be improved and the error can be reduced. Log data also will help to determine a proper bit usage as it will not only depend on drilling data.

The ANN modeling process has given out the results of Optimized IADC bit code values. However, the accuracy of these results can be further confirmed by a comparison process with other data set to see if it provides values with similar accuracy. Thus, a different set of data of Shadegan Oil Field was taken into consideration to confirm the accuracy of the ANN simulation process. This second set of data consists of 98 sets of data. Once again 70% of the data was set for training data, 15% for validation data and 15% for test data. Table below shows the example of the data set used to check the validity of the ANN simulation.

Table XIII: New Data Set For Rechecking ANN Simulation (Shadegan Oil Field)

ANN value	IADC Bit Code	3 Cone Top	ROP (m/hr)	Weight (lb)	Rotation (rpm)	Depth (m)	Mud Weight (pcf)	Drilling Interval (m)
10	1,1,1	17.5	19.263360	65	180	0	62.4	1001
10	1,1,1	17.5	16.2142857	30	160	71.5	67	794.5
70	1,3,4	17.5	7.77586207	45	150	866	68	451
90	2,1,4	17.5	3.37209302	37	150	1317	74	145
90	2,1,4	17.5	3.09090909	37	160	1462	74	34
70	1,3,4	17.5	2.80991736	35	160	1496	76.5	170
80	1,3,5	18.5	2.80991736	35	160	1496	76.5	170
90	2,1,4	17.5	1.39534884	42	160	1666	76.5	60
90	2,1,4	17.5	1.93478261	33	150	1726	76.5	89
90	2,1,4	17.5	1.90697674	33	150	1815	76.5	82
90	2,1,4	17.5	2.0000000	33	150	1897	76.5	83
90	2,1,4	17.5	1.60655738	33	150	1980	76.5	49
90	2,1,4	17.5	1.5106383	35	160	2029	76.5	71
90	2,1,4	17.5	1.41176471	33	120	2100	76.5	72
90	2,1,4	17.5	2.63157895	33	130	2172	76.5	25
10	1,1,1	17.5	13.5396825	45	160	62	69	853
10	1,1,1	17.5	6.4000000	45	160	915	69	192
10	1,1,1	17.5	4.30769231	40	155	1107	72	280
10	1,1,1	17.5	3.3800000	40	155	1387	72	169

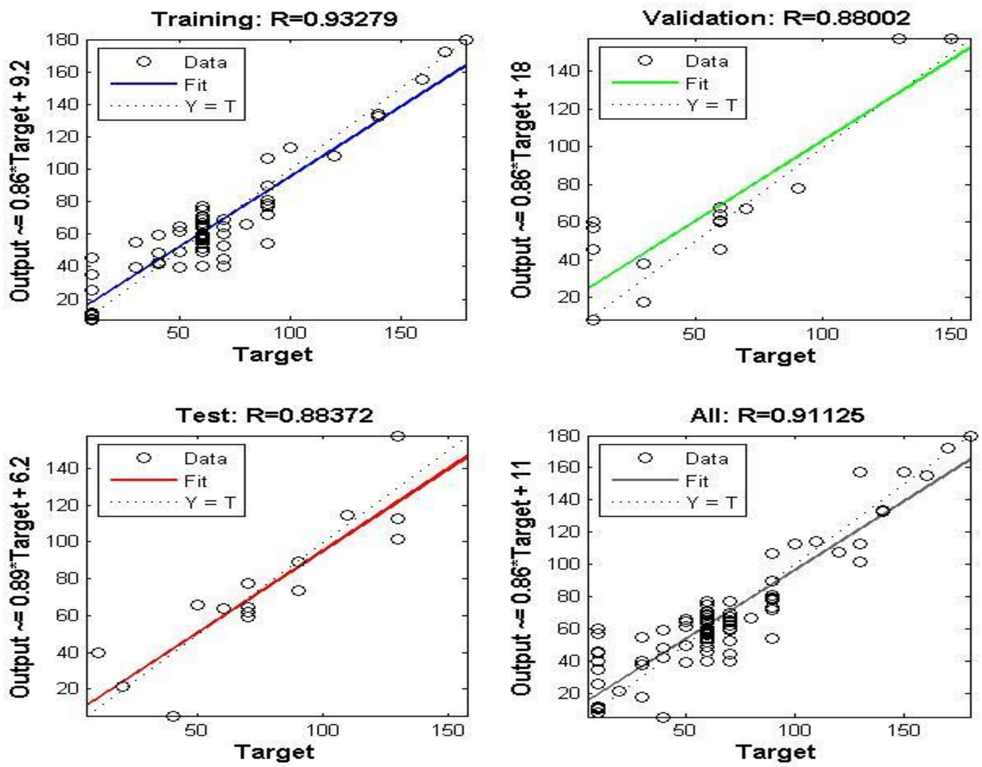


Figure 22: Results Of The Regression Graphs For Output Of Targeted IADC Bit Code (Stage 1of Shadegan Oil Field)

Table XIV: MSE And R Value For 10 Number Of Hidden Neurons (Stage 1of Shadegan Oil Field)

	SAMPLES	MSE	R
TRAINING	68	173.64249	0.932786
VALIDATION	15	492.19846	0.880015
TESTING	15	319.30662	0.883719

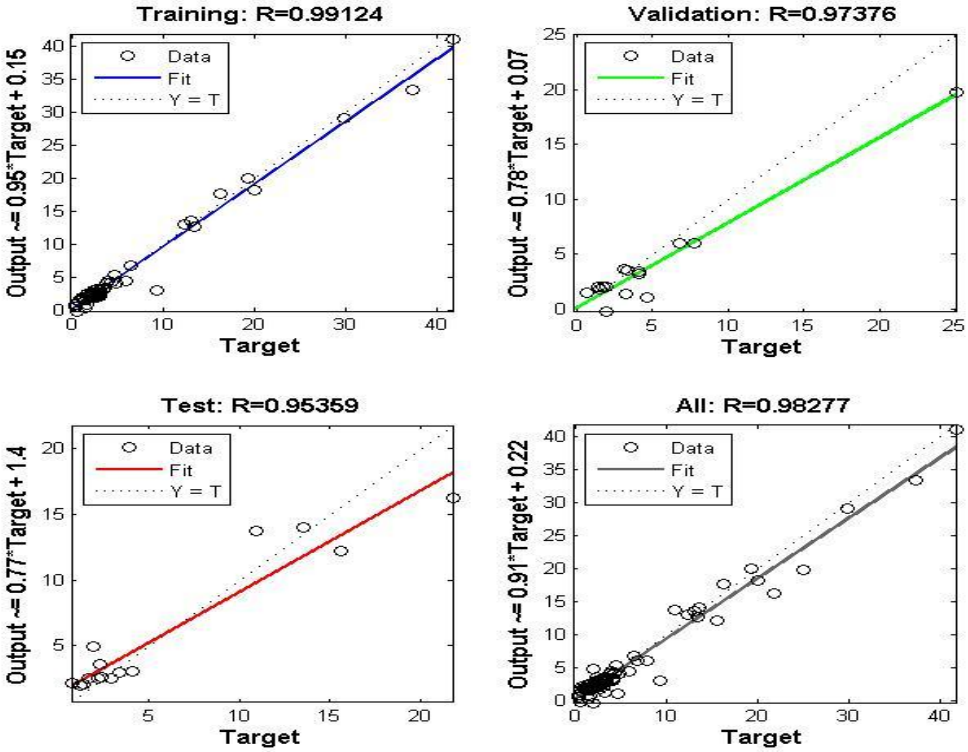


Figure 23: Results Of The Regression Graphs For Output Of Predicted ROP (Stage 2 of Shadegan Oil Field)

Table XV: MSE And R Value For 10 Number Of Hidden Neurons (Stage 2 of Shadegan Oil Field)

	SAMPLES	MSE	R
TRAINING	68	3.734661	0.966666
VALIDATION	15	7.362312	0.931656
TESTING	15	8.808993	0.958486

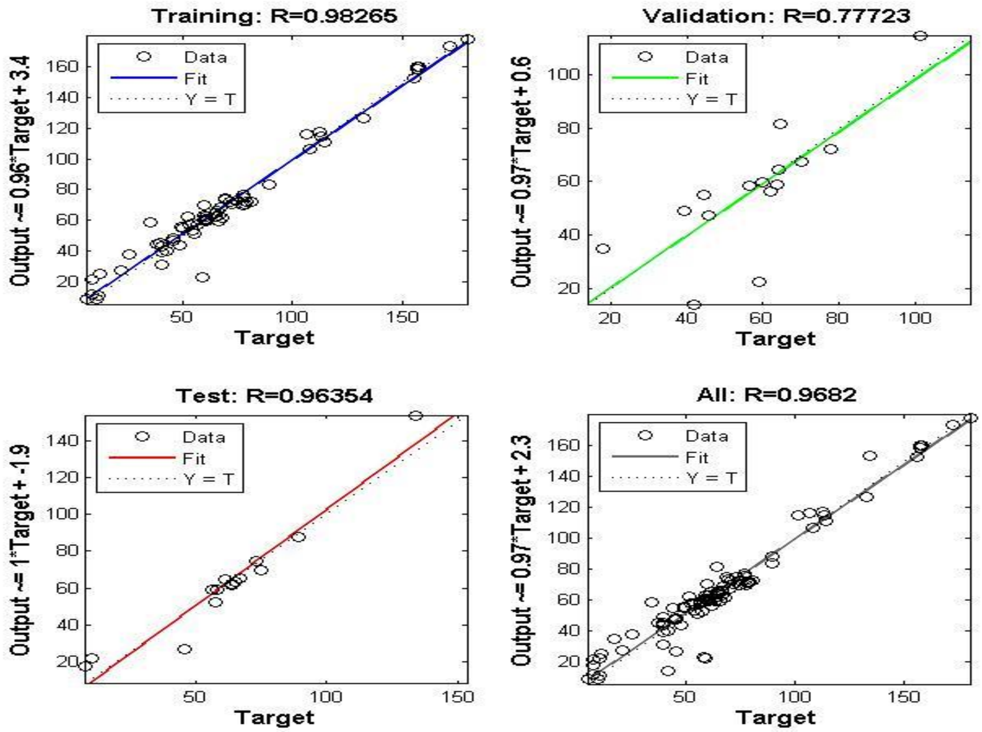


Figure 24: Results Of The Regression Graphs For Output Of Predicted IADC Bit Code (Stage 3 of Shadegan Oil Field)

Table XVI: MSE And R Value For 17 Number Of Hidden Neurons (Stage 3 of Shadegan Oil Field)

	SAMPLES	MSE	R
TRAINING	68	53.34374	0.982649
VALIDATION	15	213.67652	0.777228
TESTING	15	70.19177	0.963542

Table XVII: Predicted IADC Bit Code Value And Predicted ROP Value Examples of Shadegan Oil Field

IADC Bit Code	ANN Output	Predicted IADC Bit Code Value	ROP (ft/hr)	Predicted ROP Value (ft/hr)
1,1,1	10	8.540809	19.263360	20.03738
1,1,1	10	10.49332	16.2142857	18.74017
1,3,4	70	74.78044	7.77586207	3.43065
2,1,4	90	93.24648	3.37209302	2.866403
2,1,4	90	85.00292	3.09090909	2.379206
1,3,4	70	65.81053	2.80991736	1.642444
1,3,5	80	83.09457	2.80991736	2.324059
2,1,4	90	90.54357	1.39534884	1.711341
2,1,4	90	70.67985	1.93478261	1.633869
2,1,4	90	71.96897	1.90697674	1.499116
2,1,4	90	71.90172	2.0000000	1.35653
2,1,4	90	72.16207	1.60655738	1.455876
2,1,4	90	70.22408	1.5106383	1.02429
2,1,4	90	88.04242	1.41176471	1.29425
2,1,4	90	83.33124	2.63157895	1.329831
1,1,1	10	6.796307	13.5396825	12.9523
1,1,1	10	8.319983	6.4000000	5.959551
1,1,1	10	6.990621	4.30769231	3.70865
1,1,1	10	9.344001	3.3800000	3.596977

These values can be concluded as a good approximation as the predicted values are almost near to target values provided. The graph below shows the comparison of predicted IADC Bit Code versus the targeted IADC Bit Code.

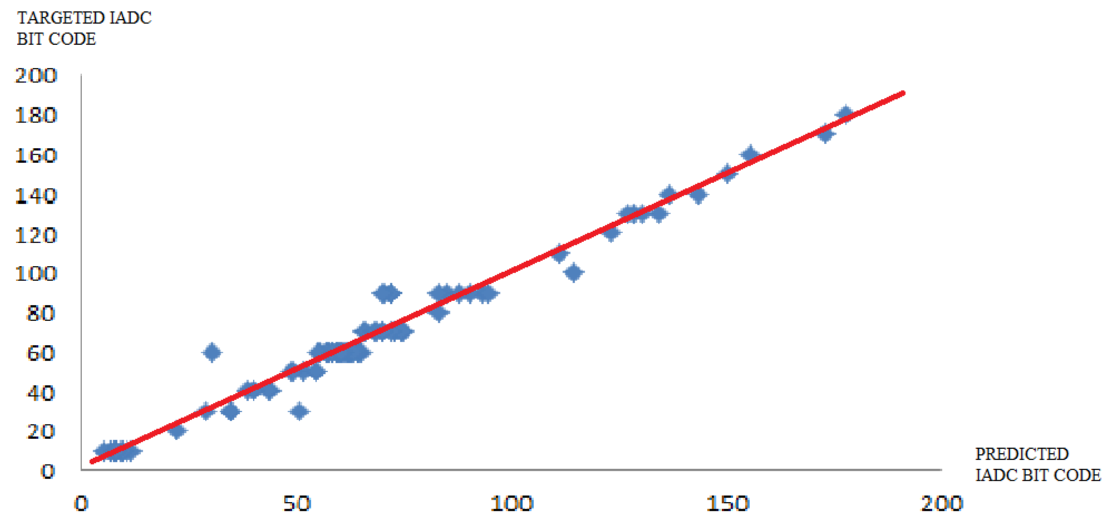


Figure 25: Results Of The Regression Graphs For Output Of Predicted IADC Bit Codes

Based on the second set of data set of Shadegan Oil Field used to recheck the accuracy of ANN simulation, it can be said that the ANN simulation process is quite accurate to be used as a prediction tool. Thus, a third set of data was taken into consideration to confirm the accuracy of the ANN simulation process whereby the results were predicted to be of atleast 95% accurate looking at the Regression values achieved from Azar Well and Shadegan Oil Field. Table below shows the example of the data set used to check the validity of the ANN simulation.

Table XVIII: New Data Set For Rechecking ANN Simulation

IADC Bit Code	ANN Output	Depth Drilled (feet)	Drilling hours	ROP (ft/hr)	WOB (klbs)	ROT (rpm)	Flow (gpm)	MW (ppg)
M614	10	2001	62.1	36	5	150	1300	9.6
S612	20	633	31.4	22.8	10	150	1300	10.5
321	30	10	4.8	4.8	20	130	1300	11
135	40	110	12.3	9.2	20	180	1340	11

M433	50	83	15.9	5.5	10	180	1340	11
S613	60	673	16.1	47.7	5	200	1340	11
S613	60	119	21.5	7.4	10	200	1340	11
M433	50	284	55.7	5.5	10	180	1340	11
435	70	337	64.5	5.8	10	100	1120	11
S232	80	732	52.6	16.5	5	140	1120	11

Based on the projects initial objective which is to gain the Predicted IADC Bit Code value and Predicted ROP value, the ANN simulation was done following the same 3 stages in order to gain the results.

Table XIX: Predicted IADC Bit Code Value And Predicted ROP Value Examples

IADC Bit Code	ANN Output	Predicted IADC Bit Code Value	ROP (ft/hr)	Predicted ROP Value (ft/hr)
M614	10	14.99148303	36	36.81820116
S612	20	25.53034541	22.8	21.95998862
321	30	34.20662463	4.8	4.305652441
135	40	44.82338565	9.2	8.556235629
M433	50	53.22414686	5.5	6.167528922
S613	60	59.32795958	47.7	45.33394708
S613	60	56.94990377	7.4	6.344683909
M433	50	50.53138095	5.5	5.009382797
435	70	74.27915875	5.8	5.360093198
S232	80	80.56945285	16.5	14.14613044

These values can be concluded as a good approximation as the predicted values are almost near to target values provided. The graph below shows the comparison of predicted IADC Bit Code versus the targeted IADC Bit Code.

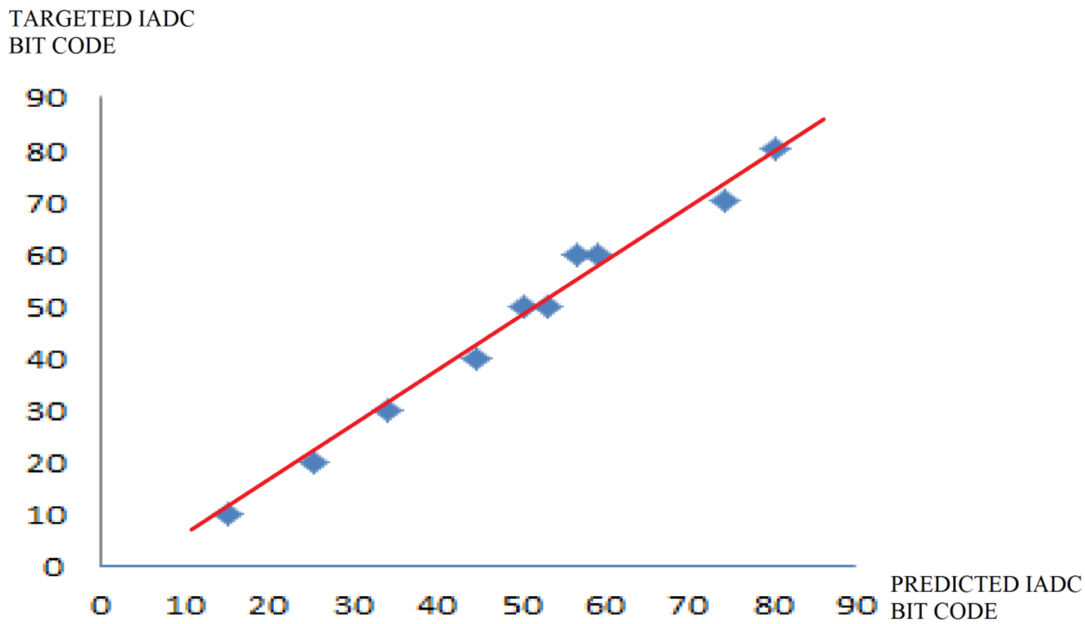


Figure 26: Results Of The Regression Graphs For Output Of Predicted IADC Bit Code (Test Data Set)

CHAPTER 5
CONCLUSION AND RECOMENDATION

5.1. CONCLUSION

In conclusion, the objective of the project has been achieved. The ANN simulation modeling process has been used to Predict ROP value and the Predicted IADC Bit Code has been found. Generally, the training is done for about 10 to 15 times for each Number Of Hidden Neurons Layers to gain the best output of Mean Square Error, MSE and Regression value, R. It has been seen during the simulation process that the most suitable hidden neuron number is 10 and 17. For the Azar Well 1 and 2 data sets, the final accuracy levels of the Predicted IADC Bit Code Values were 0.99 and the final accuracy level of the Predicted ROP Values were 0.95. This clearly shows that the usage of ANN simulation as a prediction tool can provide and accuracy level of more than 95 percent which is fairly accurate. In order to reconfirm that this values were accurate enough, a new set of data was also used to see if it gives a proper prediction. Once again, the final accuracy levels of the Predicted IADC Bit Code Values were 0.96 and the final accuracy level of the Predicted ROP Values were 0.95 for the second set of data set. Therefore, it is clearly seen that this project manage to utilize the ANN simulation to predict the IADC Bit Code and ROP values quite effectively. However there are still some errors in the prediction. This is simply due to certain reasons which are insufficient data, limited time frame to complete the project, and also the absence of Log Data. This problems can be overcome based on certain recommendations which will be discussed as per below.

5.2. RECOMMENDATIONS

Recommendation 1:

One of the problems faced in this project is insufficient data. If more time is given in the future to proceed with further research in the ANN modeling, it is suggested that more data should be taken into account. If possible, data from different field from around the globe as this will cover a wider scope and the ANN model can then be used for a wider coverage and not just for a particular region.

Recommendation 2:

Another problem faced in this project is to determine the most suitable hidden neuron layer. Simulation needs to be repeated with number of hidden neuron layers from 1 until 23 to find the result with highest accuracy. This project can be further improvised by finding the hidden process that is taking place during the ANN modeling. This might help in determining the exact process easily. Thus, the repetition of simulation to determine the number of hidden neuron layers can be avoided. This saves a lot of time. However, determination of the hidden process is not a simple task and it needs more research.

Recommendation 3:

The time period for FYP2 is limited to 14 weeks. The data that can be used are also limited as most of the data are private and confidential. Since this project has data and time limitation, there was no involvement of log data. However, it is believed that the usage of log data in combination with drilling data can further improve the Prediction accuracy of the ANN model.

Recommendation 4:

The usage of the Azar Well data and Shadegan Oil Field data was not sufficient enough. The data used should be normalized in order to gain a better result. The values obtained so far in the results and discussion section is fairly accurate up to certain extend. However, if it is viewed individually, the errors might be considerably large as well. By normalizing the data, the output data obtained will produce a better accuracy which indirectly reduces the error and improves the regression value.

APPENDIX

ARTIFICIAL NEURAL NETWORKS

Artificial Neural Network, ANN is known as a massively paralleled and disturbed processing unit which is generally known as neuron. These neurons are able to accomplish certain task as of what can be seen within a biological neurons (Feng et al., 2003).

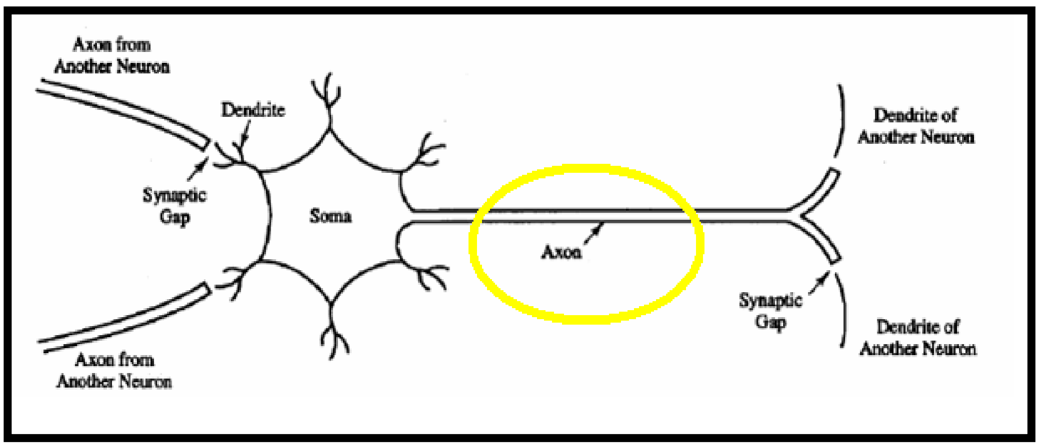


Figure 27: Simple Biological Neuron (Pinar et al., 2010)

Neural networks are known to have the capacity to learn and adapt, recognize as well as to classify ad finally o generalize various functional system. The neural network works in a direct relationship with the total number of data being fed. The more the data, the better it functions. A general neural network consists of three main layers. These are known as inputs, hidden and output (Pinar et al., 2010). A neuron will receive an input value, multiply it by connection weights from the proceeding neurons, and add up with a value known as bias, and finally feeds them to the function to produce results (Collier & Taylor, 2004).

LEARNING METHOD

TRAINLM is a systematic network training function that revises weight and bias values based on the Levernberg-Marquardt optimization process. TRAINLM is the fastest back propagation algorithm in the toolbox. However, comparing to other algorithms that are available, TRAINLM needs more memory (Demuth, Beale, & Hagan, 1992).

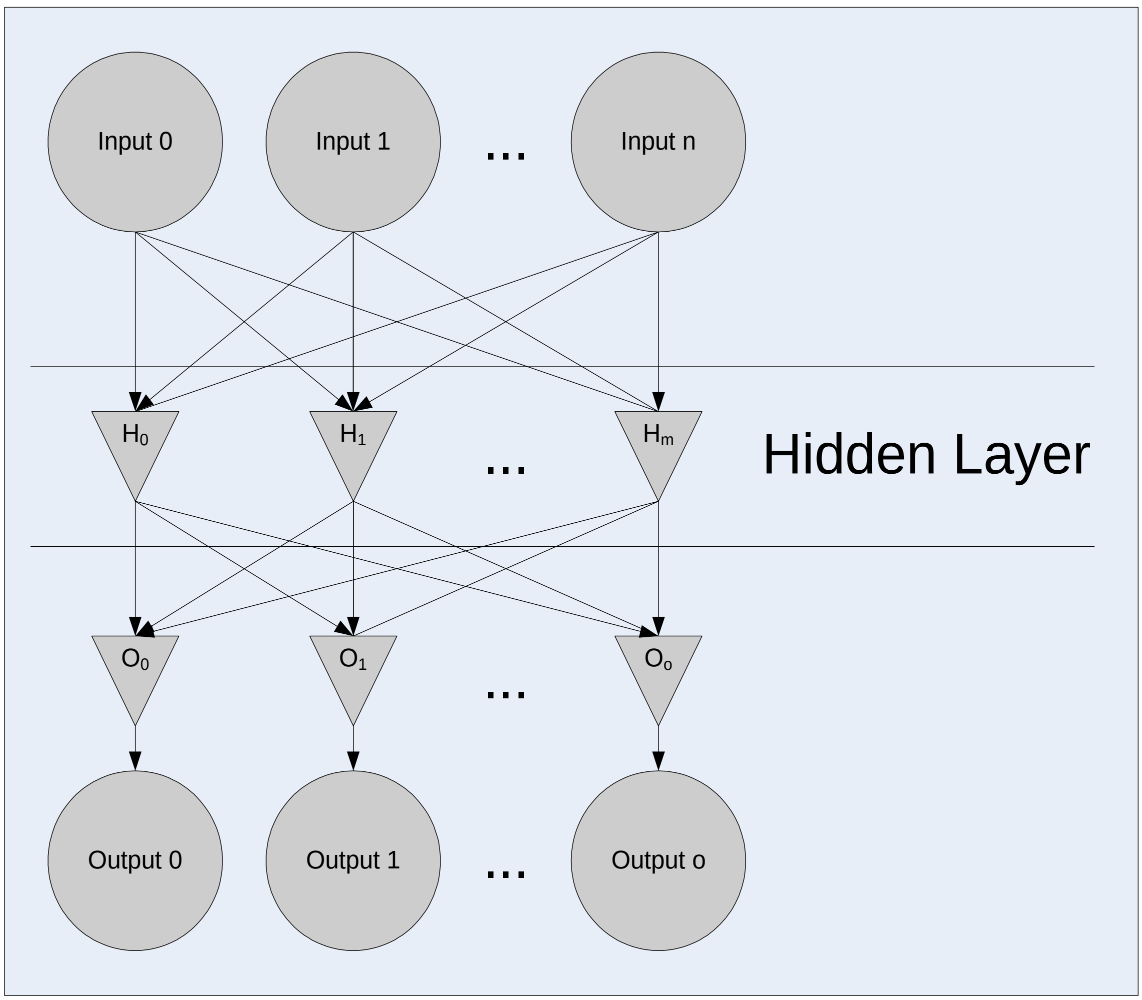


Figure 28: Typical Neural Network with Three Layers of Neurons (Demuth, Beale, & Hagan, 1992)

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