PREDICTION OF DOG-LEG SEVERITY BY USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

PREDICTION OF DOG-LEG SEVERITY BY USING ARTIFICIAL NEURAL NETWORK

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As technology growth, complexity of the drilling wells has been increasing. Directional wells have been drilling in order to deviate the well through planned targets which are at distant location from wellhead. One of the most important preliminary studies before drilling of any directional well is the prediction of Dog-leg severity. High and inconsistent Dog-leg severities can lead to high tortuosity, which may bring in high bottom torque, downhole tool failures, stuck pipe, target miss, inabilities to run casings, casing stuck and even side-track operations. Therefore, estimation of Dog-leg severity is vital for any directional wells. There are many variables affecting to DLS severity, which increases the complexity of estimation.

Artificial Neural Networks (ANN) has become useful application for drilling industry since it is able to simulate highly non-linear relationships with large data sets. It is a statistical learning model inspired by biological neurons that connected and sending signals to each other. There are many Artificial Neural Network structures available. The most common one is "Feed-Forward Back Propagation Artificial Neural Network" known as; most accurate network due to generation of low error.

This thesis is about estimation of Dog-leg severity of directional wells by Feed-Forward Back Propagation Artificial Neural Network. The study consists of two separate field drilling data, first one is an oil field located at Southeast of Turkey in Diyarbakir that has carbonates formation. Second one is a geothermal field located at the West of the Turkey in Manisa which has sandstone and claystone formation originated from metamorphic rocks. Two different ANN models have been created by considering 4290 individual drilling data of 12 wells for their 8 ½” hole sections in Diyarbakir Field and 1100 individual drilling data of 7 wells for their 12 ¼” hole sections in Manisa Field. Data sets have been prepared by dividing into 30m depth intervals. Parameters that affects Dog-leg severity are taken into account as input variables which are Sleeve Stabilizer Outer Diameter, String Stabilizer Outer Diameter, Downhole Motor Bent Angle, Rate of Penetration for bit wear effect, Depth, Inclination of the Wellbore, Tool Face Orientation, Weight on Bit, Bottom Revolution per Minute and Sliding Percentage. There are total 10 input variables drives 1 output variable which is Dog-leg Severity. Several sensitivity analyses have been made to decide network structure to obtain accurate, low error driven ANN model. It has been found that ANN Model is a proven tool for the estimation of DLS. Satisfactory results have been obtained with low Mean Squared Errors (MSE). MSE of Diyarbakir Field is 0.056 and, it is 0.057 for Manisa Field.

Keywords: Directional Drilling, ANN, DLS, Petroleum Engineering, Oil Field, Geothermal Field

ÖZ

YAPAY SİNİR AĞLARI KULLANARAK YÖNLÜ KUYULARDA DOGLEG SEVERITY TAHMİNİ

Kaymak, Sinem
Yüksek Lisans, Petrol ve Doğal Gaz Mühendisliği
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Teknoloji geliştikçe, günümüzde kazılan yönlü kuyu sayısında artış gözlemlenmektedir. Yönlü sondaj kuyuları, yüzey lokasyonundan uzakta belirtilen hedefe varmak için kazılmaktadır. Herhangi bir yönlü kuyu kazılmadan önce yapılacak en önemli çalışmalardan biri Dog-leg severity tahminidir. Değişken ve yüksek Dog-leg severity değerleri kuyuda tortuosite neden olup, beraberinde yüksek torka, dizi ekipmanının zarar görmesine, takım sıkışmasına, hedefi kaçırmaya, casing sıkışmalarına, casing indirememeye ve hatta side track operasyonlarına neden olabilmektedir. Bu yüzden, Dog-leg severity (DLS) tahmini, yönlü sondaj kuyuları için hayati önem taşımaktadır. DLS`e etki eden bir çok değişken olması, tahmin calışmalarinin kompleksliğini arttırmaktadır.

Yapay Sinir Ağları komplike lineer olmayan korelasyonları çözümleyebildiği için, sondaj alanında yararlı bir uygulama haline gelmiştir. Biyolojik nöronlardan ilham alınarak keşfedilen yapay sinir ağları, birbirine bağlı ve aralarinda sinyal gönderen nöronlardan oluşmaktadır. Günümüzde birçok yapay sinir ağları konfigürasyonu bulunmaktadır. En çok kullanılan "Feed-Forward Back Propogation Yapay Sinir Ağı" günümüzde en az hata modeli oluşturabilen bir yapay sinir ağ çeşididir

Bu tez, yönlü sondaj kuyularında Dog-leg severity tahmini için “Feed- Forward Back Propagation Yapay Sinir Ağını” kullanılması üzerinedir. Çalışmada iki ayrı sondaj sahasından elde edilen veriler kullanılmıştır. İlk saha; karbonat formasyona sahip olup, Turkiye`nin Güneydoğusunda bulunan Diyabakır ilindeki bir petrol sahasıdır. İkinci saha ise metamorfik kayaçlardan türemiş kil taşı ve kum taşı formasyonuna sahip, Turkiye`nin Batısında bulunan Manisa ilindeki bir jeotermal sahasıdır. Çalışmada iki ayrı Yapay Sinir Ağı modeli oluşturmak için Diyarbakır sahasındaki 12 kuyunun 8 ½” kuyu kesitinden elde edilen 4290 sondaj verisi ve Manisa sahasındaki 7 kuyunun 12 ¼” kuyu kesitinden elde edilen 1100 sondaj verisi kullanılmıştır. Sondaj verileri 30 metre aralıklara bölünerek hazırlanmıştır. Dog-leg Severity tahminini etkileyen değişkenler dikkate alınmış olup bunlar Sleeve Stabilizer Dış Çapı, String Stabilizer Dış Çapı, Kuyu içi Motor Bent açısı, matkap aşınma etkisi için Ilerleme Hızı, Derinlik, Kuyu Açısı, Tool Face Orientation, Matkaba Verilen Ağırlık, Kuyu Dibi Döndürme Hızı ve Sliding Yüzdesidir. Toplamda 10 girdi degişkeni bir sonuç değişkeni yani DLS severity`i oluşturmaktadır. Az hata payı ile doğru yapay sinir ağı modelleri oluşturabilmek ve modellerin dizayn parametrelerine karar verebilmek için bir çok duyarlılık analizi yapılmıştır. Yapay sinir ağı modelleri Dog-leg severity tahmininde düşük ortalama karesel hata ile birlikte ikna edici sonuçlar vermiştir. Ortalama karesel hata Diyarbakır sahası için 0.056 iken Manisa sahası için 0.057dir.

Anahtar Kelimeler: Yönlü Sondaj, Yapay Sinir Ağları, DLS, Petrol Mühendisliği, Petrol Sahası, Jeothermal Sahası

To My Father

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
BHA	Bottom Hole Assembly
BR	Bayesian Regularization
DLS	Dog Leg Severity
GD	Gradient Descent Weight
GDM	Gradient Descent with Momentum Weight
LM	Levenberg-Marquardt
$LOGSIG$	Log-sigmoid transfer function
MSE	Mean Squared Error
$MSEREG$	Mean Squared Error with Regularization
MWD	Mud Weight
MWD	Measurement While Drilling
PDM	Positive Displacement Motor
R	Correlation Coefficient
ROP	Rate of Penetration
RPM	Revolutions per Minute
TFO	Tool Face Orientation
SCG	Scaled Conjugate Gradient
SPM	Stroke per Minute

SSE	Sum Squared Error
$TANSIG$	Hyperbolic Tangent Sigmoid Transfer Function
WOB	Weight on Bit

CHAPTER 1

INTRODUCTION

1.1. Directional Wells

One of the reason for drilling a well directionally is to reach planned targets which cannot be obtain by drilling vertically due to improper surface locations like city, mountain, lake, river, road, agriculture area etc.

Another main reason is to increase the production coverage of a reservoir by landing the well with some angle or drilling multi-lateral wells. Side-tracking operation of a current well bore to avoid from fish in hole, intervention of a blow out well, keeping the well at boundary license, and collision avoidance for pad drilling are also the other reasons for drilling a directional well.

Well types are categorized into four groups shown in Figure 1.1 (Ma, Chen, & Zhao, 2016). Directional wells are also subcategorized into as S-type well consisting of build, hold, drop sections and J-type wells consisting of build and hold sections.

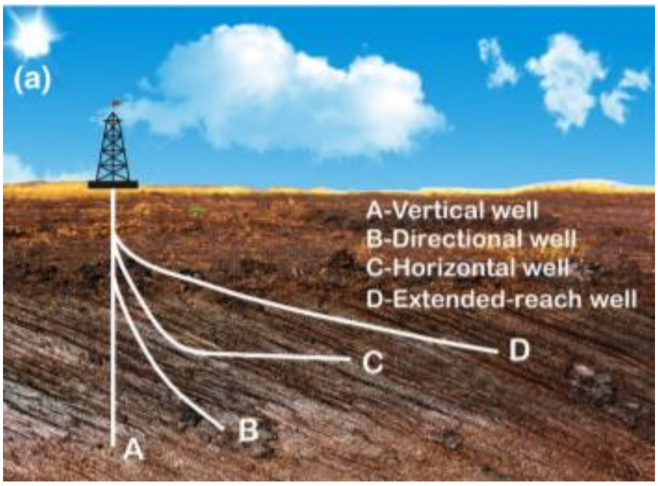

Figure 1.1 Well Types

Most important critical parameter of directional wells is called Dog-leg severity. It can be expressed as inclination change of a well in 30m depth interval (deg/30m). Unpredicted local DLS can increase tortuosity as shown in Figure 1.2 ("2015 SPE/IADC Drilling Conference Special - Drilling Contractor," n.d.) that leads high bottom torque which brings in downhole tool failures, mechanical stuck, target miss, inability to run casings, casing stuck and even side-tracks. These all unplanned events can bring in high drilling cost or even abandoning the well. (Cheatham Jr. & Ho, 1981)

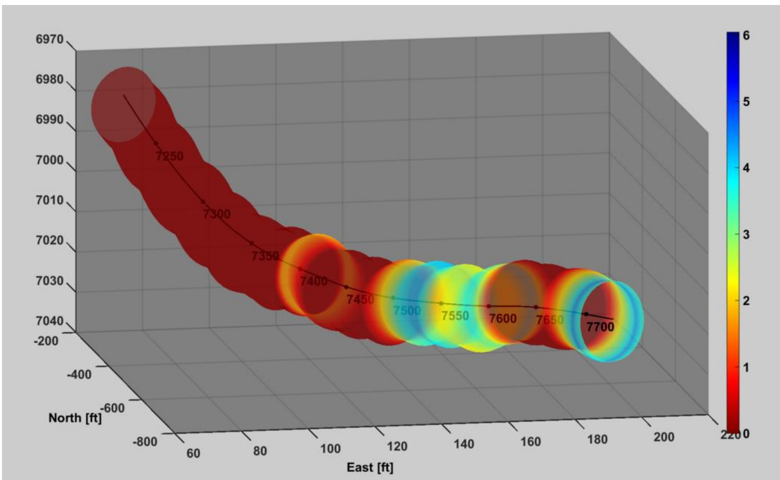

Figure 1.2 Tortuosity

In order to avoid high tortuosity, preliminary studies about Dog-leg estimation is a must.

DLS at certain depth interval can be calculated by using Radius of Curvature Method (Eq. 1.1) (Skillingstad, 2000).

$$DLS = \{\cos^{-1}[(\cos I_1\ x \cos I_2) + (\sin I_1\ x \sin I_2)\ x \cos(\ Az_2 - \ Az_1)]\}\ x\ (\frac{100}{MD}) \quad (1.1)$$

I value refers as inclination and Az is Azimuth which is the direction according to North between two survey points.

CHAPTER 2

LITERATURE REVIEW

2.1. Parameters Affecting Dog-Leg Severity

Many studies have been done to determine all factors affecting the DLS. Main parameters are bit & rock interaction, geology, wellbore inclination, Bottom-Hole-Assembly (BHA), drilling parameters and hole size.

The most difficult parameters to determine are the bit & rock interaction and geology due to existence of many controlling variables which are rock hardness, rock threshold, formation dip angle, formation anisotropy index, side force generated via bit by formation, bit specifications (Millheim, 2013). The bit specifications are mainly bit friction coefficients, back rake angle, side rake angle, cutting structures, cutting diameters, gage length and bit type. (Boualleg, Sellami, Menand, & Simon, 2006)

Current wellbore inclination is also important parameter due to hole geometry and corresponding position of bit interface angle with the formation. Natural tendencies of BHA are affected by a curved borehole and can lead to build and drop. (Rafie, Ho, & Chandra, 1986)

BHA design also plays a vital role to deviate the well and to generate DLS. Main controlling components in BHA are drill collars, position of the stabilizers, stabilizer outer diameters and other tools which can create any bending effect or creating contact points between wellbore wall and drill string (Lesso & Chau, 1999). Positive Displacement motor (PDM) is among of these tools which have a bent angle allowing well to build, drop and hold. Measurement While Drilling (MWD) tool is also part of the BHA which is hanged into a collar and acting as drill collar in the BHA. Purpose of the MWD Tool is to measure inclination and azimuth at certain depth which allows the engineers to evaluate the current situation in terms of inclination and azimuth to follow planned well path or to reach planned targets.

Drilling parameters which are Weight on Bit (WOB), Bottom RPM are also affecting the BHA dynamics and corresponding build and walk tendencies (Millheim, 2013). Azimuthal change of the wellbore with different Tool Face Orientation (TFO) is generating turn rate which also becomes important for DLS estimations (Lesso & Chau, 1999). TFO is arranged by MWD Tool in order to turn the well at desired target direction by steering the BHA with PDM. PDM has a bent house which can be set from 0-3 degree that enables to well to deviate through its target. Deviation of well is done by different drilling modes which are called as sliding and rotating, Sliding can be explained as no surface rotation but only bit rotation created by PDM by converting hydraulic energy to mechanical energy. Dropping or increasing the wellbore inclination in desired azimuth, tool face orientation requires tool face set up by using MWD and two drilling modes are applied consecutively to achieve the desired inclination and azimuth. More sliding is leading to more build up rate (BUR); therefore, sliding and rotating percentages are the one of the major factors for DLS prediction.

Additional studies also investigated the other drilling parameters like torque on bit (TOB), but it was concluded that almost no effect on BHA build and drop tendencies (Rafie et al., 1986)

A common preliminary study at drilling industry is to estimate the DLS by considering stabilizer placements, stabilizer dimensions and motor specifications. It is called as theoretical build up rate of the motor based on the specific stabilizer configuration. This preliminary study only includes Sleeve OD, Stabilizer OD, Sleeve distance from the bit, Stabilizer distance from the bit, Bit to bent distance, Motor Bent Angle and Sliding Percentage as inputs and generates a range for expected DLS.

Since there are many factors affecting the DLS, modelling or simulation of DLS prediction is quite complex. Many studies are about 3D Finite Element Models together with BHA dynamic simulations. An easy tool or estimation method is vital to predict the DLS and optimize the well programs accordingly**.**

2.2. Artificial Neural Networks

As a common practice, drilling can be optimized by using existing well data but as DLS prediction has many controlling factors, it is not easy to evaluate offset wells and draw a conclusion. A model required to simulate DLS by using previous experiences which can be used in future wells is a challenge.

Artificial Neural Network (ANN) is like human brain neurons which can create a network between input and output by connecting all neurons to each other. It tries to establish a relationship between input and output as "understand and learn". It is the data driven model that learns from the data set to determine, categorize, and generalize the relationship between input and output. Network has two outputs which are the calculated output and actual output. Aim is to converging of calculated output to desired output with iterations. (Gidh, Purwanto, Ibrahim, & Bits, 2012)

There are different network types available for ANN model, but most accurate and commonly used one in all studies due to its accuracy and fast convergent to desired output with less error is called "Feedforward Neural Network" (Bataee & Mohseni, 2011). Basic structure is shown in Figure 2.1. (Song, Zhao, Liao, & Wang, 2013)

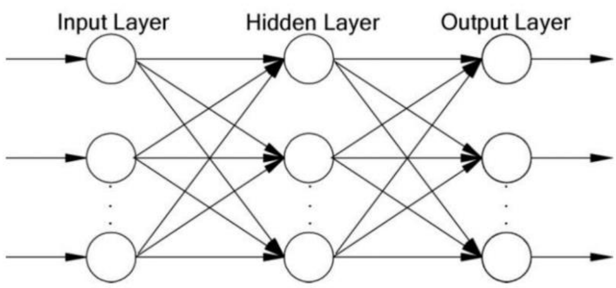

Figure 2.1 Feed Forward Neural Network Structure

The most common and accurate learning rule for ANN models is the "Back Propagation" which is performed under supervision. Back Propagation alters the weights and biases to decrease the error between calculated output and desired output by continuously feedbacking to network until error is at the acceptable range that enables network to learn from training process. (Lau, Sun, & Yang, 2019)

Structure of Back Propagation Learning Rule is shown in Figure 2.2. (Gidh, Purwanto, Ibrahim, & Bits, 2012)

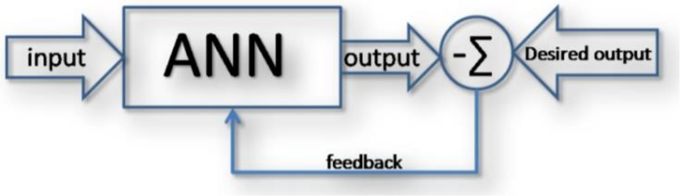

Figure 2.2 Artificial Neural Network Structure "Understand and Learn"

ANNs consists of many mathematical and statistical techniques which can be utilized at many tasks as pattern recognition, data classification, dynamic time series such as forecasting, and input-output relations with curve fitting and process modelling. (Islam, Kabir, & Kabir, 2013)

A common neural network has three layers: Input, Hidden and Output. Among the neurons, there are connection weights determines the role of each neuron in the relationship between inputs and outputs. Weighted neurons lead to a value called as bias. Weights and biases are set at the beginning of training process as randomly and subject to change during training by a learning function. Purpose is to next iteration has less error value and much more close to desired output. (Gidh et al., 2012)

Single layer network has only one hidden layer, more than one hidden layer is called as multi-layer network. In order to decrease local minima and make less training, single hidden layer is preferred for ANN Structure (Yılmaz, Demircioglu, & Akin, 2002). Increasing hidden layers in network leads to more computation time and creates the risk of overfitting. It can be a powerful network for the current training data set but when new data set is imported, high error appears since more than one hidden layer network generally memorizes the data but does not have the capability of generalizing and understand the new situations. (Wang & Salehi, 2015)

In order to obtain an accurate network, data sets are required to be divided into three groups during the process which are training, validation and testing (Bataee & Mohseni, 2011)

Design parameters of ANN are below.

1. Number of hidden layers
2. Number of neurons in hidden layers
3. Training Function
4. Learning Function
5. Performance Function
6. Transfer Function

Training Function:

To determine the input-output relation with curve fitting, there are three training functions exist.

Levenberg-Marquardt: It can be classified as hybrid technique which consists of Gauss Newton approach and gradient descent that can be applied for non-linearly related equations due to fast converging to desired target with less error and less iterations. (Lau, Sun, & Yang, 2019)

The LM is the most common training algorithm since it is considering both Newton method and descent method and solves the non-linear problems with fast convergence together with high stability by using medium data set. ("Levenberg-Marquardt Algorithm - an overview | ScienceDirect Topics," n.d.)

Scaled Conjugate Gradient: It is conjugate gradient method proceeding to a specific direction. The algorithm consists of a conjugate to the directions of previous steps and it does not conduct a line search for each iteration. SCG utilizes a mechanism to determine the step size to avoid high iterations and corresponding high time consumption. It is advantageous to be used for medium to large data sets. (Møller, 1993)

Bayesian Regularization: BR is statistical method which alters the non-linear regressions into "well-posed" problem. Aim is to obtain a network which has good generalization quantities by estimating the importance of each input on the result and eliminating some of them accordingly. It is advantageous to be used in very complex model with high number of inputs. (Burden & Winkler, 2008)

Learning Function: Two learning functions exist. GDM is the Gradient Descent with Momentum weight and bias learning function. On the other hand, GD is defined as Gradient descent weight and bias learning function. They are the optimization functions to change the weight and bias to make the network best fit with the training data. ("Gradient Descent with Momentum | KRAJ Education," n.d.)

Performance Function: It is used for error calculation between calculated output and desired output. MSE (Mean Squared Error), MSEREG (Mean squared error with regularization performance function, SSE (Sum squared error performance function). Most used one is the MSE which is the average of all squared errors, equation 2.1 is given below.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - X_i)^2 \qquad (2.1)$$

Where n is the number of data, Y is the actual value and X is the predicted value.

Transfer Function: Transfer function calculates output of a layer by using net inputs. There are two types of transfer functions exist: TANSIG (Hyperbolic tangent sigmoid transfer function) and LOGSIG (Log-sigmoid transfer function).

TANSIG: It considers one input and returns it between -1 and 1 as show in Figure 2.3. (Vogly et al, 1988)

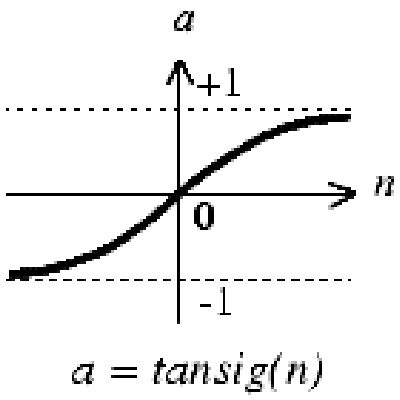

Figure 2.3 Tan-Sigmoid Transfer Function

LOGSIG: It takes one input and returns as between 0 and 1 as show in Figure 2.4. (Vogly et al, 1988)

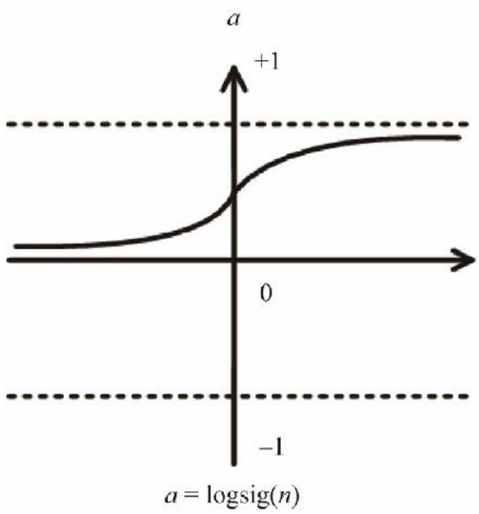

Figure 2.4 Log-Sigmoid Transfer Function

ANNs have been used at various estimations and modelling in literature.

Abdulmalek Ahmed, Elkatatny, Ali, Abdulraheem, & Mahmoud (2019) used ANN model to estimate the fracture pressure by considering WOB, RPM, Torque, ROP, MW and Pore Pressure as inputs. Studies have been conducted for 8 3/8” and 5 7/8” bit sizes. Data belongs to an onshore well which has 6 lithologies. To estimate the fracture pressure, 3925 data point are prepared. 80% of the data is used for training and 20% of them are for testing and validation. After several trainings, Feedforward Back Propagation Neural network with Bayesian Regularization training function and TANSIG transfer function with 13 neurons in 1 hidden layer gives to best fit and less error for the estimation of fracture pressure.

Wang & Salehi (2015) have estimated the pump pressure by considering ROP, depth, RPM, Torque, Differential pressure between hydrostatic mud column and pore pressure, Hook Load, SPM and mud properties as inputs. Three wells have been considered for 12 input parameters. 75 % of the data set has been used for training process, 15% of them are for validation and the rest 10% is used for testing. Feed Forward Back Propagation Artificial Network was used with Levenberg- Marquardt training function with MSE Performance function.

Bataee & Mohseni (2011) used ANN to predict ROP which is highly related to drilling cost of a well by using 15 offset wells and 1810 data points. Their study show Levenberg Marquardt training function with Back propagation learning rule gives the less error. 60% of data set is used for training, 20% is for validation and 20% is for testing. Bit size, Depth, WOB, RPM and MW considered as inputs to estimate ROP.

Jamshidi & Mostafavi (2013) created two ANN Models for the bit selection and for optimizing drilling parameters. First model is about the bit selection based on the desired ROP by applying specific drilling parameters. Second model is considering optimum drilling parameters to achieve maximum ROP with a specific drilling bit. The correlation coefficients are 0.95 and 0.90 respectively with Feed Forward Artificial Neural Network with the input variables as WOB, ROM, Flow Rate, Total Flow area of the bit, Standpipe pressure, Unconfined Compressive Strength, Drilling Interval, Bit Size and corresponding ROPs. 2000 data set has been used from 9 different offset wells. 60% are used for training, 20% is for validation and the rest 20% is for testing purposes.

Yilmaz, Demircioglu and Akin (2002), used ANN model to select the best bit which gives less cost per foot value. They used Feed Forward Back propagation ANN Model with input variables as sonic log, gamma ray log, depth, location, and IADC codes of the bits. They used single hidden layer network in their study for fast convergence and low local minima.

CHAPTER 3

STATEMENT OF THE PROBLEM

DLS estimation for directional wells are depends on many controlling factors which make any model or computer simulation complicated. Purpose of this study is to use ANN application at directional wells to predict DLS. For this purpose, two fields have been selected in Turkey. First field is an oil field at Diyarbakir, southeast of Turkey; second field is a geothermal field at Manisa, west of the Turkey.

Diyarbakir Field has southeast carbonates formation and 12 wells have been drilled so far. 8 ½" Hole sections of this field have same formation through all wells, and all are drilled with PDC bits. Depth range of the 8 ½" section is 541m to 1757m. Data set has been prepared by dividing depth range as 30m interval and 11x 390 data points are selected.

Manisa Field has metamorphic originated rock with sandstone and clay stone formation and 7 wells have been drilled. 12 ¼" hole section of the all wells have same formation and all wells are drilled by TCI bits. Depth range of 12 ¼" hole is starting at 460m and ending at 1985m. Data set has been prepared by dividing 30m depth interval and 11x 100 data points are selected.

Several sensitivity analyses have been conducted to decide network structure of ANN Model. 300 ANN models have been created and trained with 1000 iterations individually for Diyarbakir Field to decide on design parameters of network and continue further training accordingly. Same process has been followed also for Manisa Field: 300 ANN models have been created and each model has been trained with 1000 iterations. The results have been evaluated by considering various combinations of Training function, numbers of neurons in hidden layer, learning function and transfer functions according their Regression fit coefficient (R). After decision on the model structure, further training has been done until R coefficient becomes stable. 60% of the data set was used for training, 20% was used for validation and 20% was utilized for testing. For each field, one well data is kept as untrained to test the accuracy of the network. Untrained data set are 10x10 data points for Manisa Field and 10x 39 data points for Diyarbakir Field. Results of the calculated DLS have been compared with actual ones by MSE performance function.

CHAPTER 4

METHODOLOGY

Aim of this chapter is to explain the data set preparation of both Diyarbakir and Manisa Fields. Data classification and preparation has been made based on the literature surveys which enable to determine all controlling parameters for DLS prediction. Well information has been taken from actual drilling reports and divided as 30m depth range as all corresponding inputs and together with outputs. Feed-Forward Back Propagation ANN have been developed by deciding of number of hidden layers, training Function, learning Function, Performance Function and Transfer Function.

ANN models have been created for each field as separately due to decreasing the number of input variables such as hole size, rock & bit interaction, geology and bit specifications.

"Matlab nntool" has been used to create 600 ANN models. Selection of the best two network structure has been done by considering correlation fit coefficient and further training has been conducted under supervision.

Detail information is given as below for data preparation and ANN Model Development.

4.1. Input Data

Inputs have been determined as per literature review which are bit & rock interaction, geology, wellbore geometry, Bottom-Hole-Assembly (BHA), drilling parameters and hole size.

Bit & Rock Interaction and Geology: Side forces are created by bit and rock interaction depends on many bit and rock properties which cannot be easily determined from the actual drilling records (Maidla & Sampaio, 1989). Geologic features of the formation are also affecting prediction of Dog-leg severity, which are rock hardness, rock threshold, formation dip angle and formation anisotropy index. Bit & Rock Interaction and geological features of the formation are affecting the BHA build & drop tendency which is called generally as formation tendency. The BHA and formation tendencies are affected also by azimuthal changes that create additional turn rates and bit walks. Daily drilling records do not consist of such information. However, when the well is drilled by only rotating drilling mode through the certain depth interval, DLS is generated due to formation& BHA reaction. It explains although sliding percentage is 0%; there is a change on the wellbore inclination and azimuth which are generating DLS. Drilling data set consist of Tool face orientations which affects the azimuthal changes together with sliding percentages and corresponding actual DLS values vs depth, which means formation tendencies are also included in the data set. 8 ½” hole wells in Diyarbakir Field and 12 ¼” wells in Manisa Field have been drilled in same formation with same PDC bits and same TCI bits. Bit features are eliminated as input variables due to utilization of same brand and same type of bits. Bit Dull conditions or bit wear affects can be included as input by considering instantaneous ROP vs Depth values. Therefore, ROP and depth are considered as inputs.

Wellbore Geometry: Hole geometry is playing also important role to predict BHA tendencies. Initial inclination of the wells at beginning of the 30m interval has been considered as input.

BHA (Bottom-Hole-Assembly): BHA tendency is affected by drill collars, position of the stabilizers, stabilizer outer diameters and PDM specifications.

For Diyarbakir Field, same rig with same drill collars have been used for all wells. Likewise, in Manisa Field. Drill collars are eliminated from the inputs.

Position of the Stabilizers: Location of the stabilizers is vital to design BHA as pendulum (drop assembly), build assembly or hold assembly. Both Manisa and Diyarbakir Fields have same assembly with two stabilizers. First stabilizer is on

Positive Displacement Motor act as near bit stabilizer. Second stabilizer is called as Integral Blade Stabilizer located at above of Positive Displacement Motor. Therefore, position of the stabilizers is not considered for input.

Stabilizer Outer Diameters (OD): There are 2 stabilizers are available in BHAs. Different ODs exist for each well. Stabilizer Diameter is taken as input as Sleeve (Near-Bit Stabilizer) OD and String Stabilizer OD.

PDM Specification: There are various bent angles available at data sets. Downhole Motor Bent is considered as input.

Drilling Parameters: Controlling parameters are WOB, Bottom RPM, TFO and sliding percentage (%). Sliding percentage is defined as sliding footage divided by total footage. For each 30m depth interval, WOB, Bottom RPM, Sliding Percentage and TFO are considered as inputs.

Hole Size: Diyarbakir wells has same hole section as 8 ½" and Manisa wells has 12 ¼". For each field, different ANN model has been created. Therefore, hole size is not considered as input.

Below tables from 4.1 to 4.5 shows the units of all parameters and descriptive statistics of data sets.

Table 4.1 Inputs with Units

Inputs	Units
Sleeve OD	Inch
String OD	Inch
Downhole Motor Bent Angle (BH)	Degree
ROP	m/h
Depth	m
First Inclination	Degree
Tool Face	Degree
WOB	Klb
Bottom RPM	Revolution per Minute
Sliding Percentage	%

Table 4.2 Diyarbakir Field Descriptive Statistics (Part1)

	Sleeve OD	String OD	BH	ROP	Depth	First Inclination
Mean	8.34	8.19	1.06	14.01	1115.55	22.66
Standard Error	0.00	0.01	0.01	0.24	13.95	0.60
Standard Deviation	0.07	0.12	0.12	4.75	275.57	11.87
Minimum	8.125	7.875	0.78	3.22	541	0.38
Maximum	8.375	8.375	1.27	33.66	1757	50.95
Count	390	390	390	390	390	390

Table 4.3 Diyarbakir Field Descriptive Statistics (Part2)

	Tool Face	**WOB**	**Bottom RPM**	**Sliding (%)**	**DLS**
Mean	7.47	11.94	215.86	13.79	1.06
Standard Error	5.01	0.24	1.01	0.83	0.05
Standard Deviation	98.90	4.74	19.91	16.34	1.01
Minimum	-179.8	3.4	148	0	0
Maximum	180	25.71	275	86.67	5.64
Count	390	390	390	390	390

Table 4.4 Manisa Field Descriptive Statistics (Part1)

	Sleeve OD	**String OD**	**BH**	**ROP**	**Depth**	**First Inclination**
Mean	12.12	12.02	1.14	8.97	968.52	13.78
Standard Error	0.00	0.01	0.01	0.55	35.93	0.46
Standard Deviation	0.02	0.13	0.12	5.50	359.27	4.61
Minimum	12.091	11.75	1.03	1.9625	460	1.26
Maximum	12.138	12.13	1.27	25.3	1985	22.53
Count	100	100	100	100	100	100

Table 4.5 Manisa Field Descriptive Statistics (Part2)

	Tool Face	WOB	Bottom RPM	Sliding %	DLS
Mean	8.04	15.88	150.18	24.43	1.12
Standard Error	11.84	0.48	0.96	2.29	0.08
Standard Deviation	118.44	4.75	9.56	22.88	0.81
Minimum	-178.5	9.25	118.5	0	0.03
Maximum	179.2	29.67	169	100	3.5
Count	100	100	100	100	100

4.2. ANN Model Development

In order to design an ANN model, there are 6 design parameters requires to be considered: Number of hidden layers, Number of neurons in hidden layers, Training Function, Learning Function, Performance Function, and Transfer Function.

Number of Hidden Layers: 1 hidden layer is enough to establish relationship between input and output for small to medium data sets which will require training conducted in less time and will provide less error. 1 hidden layer is considered as design parameter.

Number of Neurons in Hidden Layers: Sensitivity analysis has been conducted to decide on the number of neurons in hidden layer. Starting from 1 neuron to 25 neurons, Correlation fit (R) have been compared and evaluated.

Training Function: Scaled Conjugate Gradient, Levenberg-Marquardt and Bayesian Regularizations are used for input- output relationship and curve fitting. Sensitivity analysis has been made to select best fit training function.

Learning Function: Both GDM and GD learning functions are taken into account for sensitivity analysis.

Performance Function: As a standard, MSE is considered as performance function.

Transfer Function: Both LOGSIG and TANSIG transfer functions are the part of the sensitivity analysis.

CHAPTER 5

RESULTS AND DISCUSSIONS

5.1. ANN Design

As stated by Wang and Salehi (2015), there is no rule to decide design parameters of a neural network in order to find best model.

Many sensitivity analyses have been conducted to select best training function, learning function, and transfer function for each field. 600 ANN models have been created and each model has been trained with 1000 iterations starting from 1 neuron in hidden layer up to 25 neurons. Total 600000 iterations have been done to decide network structure. 12 different possible combinations of the network functions are summarized at below Table 5.1 which is considered for two fields separately. Below figures from Figure 5.1 to 5.3 shows the regression fit charts of training function together with different learning and transfer function combinations with 1000 iterations for Diyarbakir Field. Result tables are available at Appendices A. Figure 5.4 to 5.6 shows the regression fit charts of training functions together with different learning and transfer function combinations with 1000 iterations for Manisa Field. Result tables are available at Appendices B.

Table 5.1 Network Functions for Sensitivity Analysis

Training Function	Learning Function	Transfer Function	Number of Neurons in Hidden Layer
LM	GDM	TANSIG	1-25
	GDM	LOGSIG	1-25
	GD	TANSIG	1-25
	GD	LOGSIG	1-25
SCG	GDM	TANSIG	1-25
	GDM	LOGSIG	1-25
	GD	TANSIG	1-25
	GD	LOGSIG	1-25
BR	GDM	TANSIG	1-25
	GDM	LOGSIG	1-25
	GD	TANSIG	1-25
	GD	LOGSIG	1-25

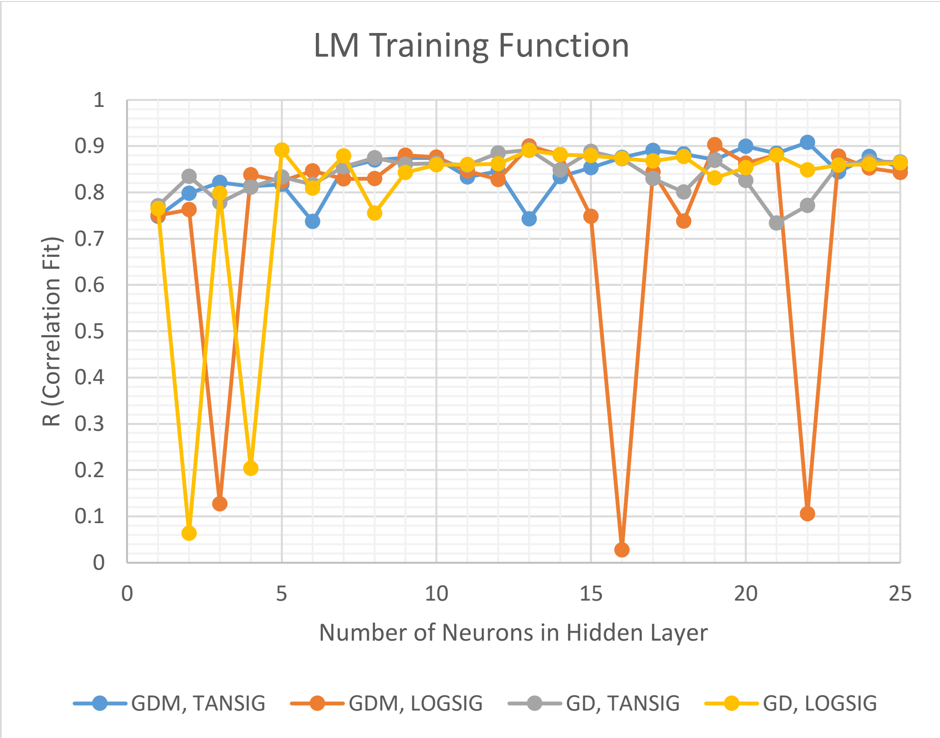

Figure 5.1 Sensitivity Analysis of LM Training Function for Diyarbakir Field

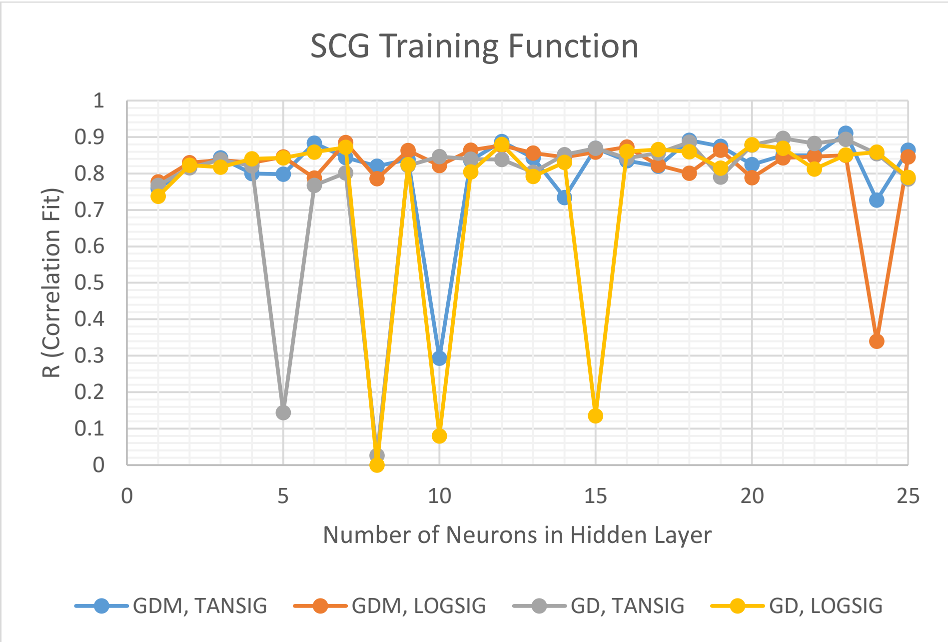

Figure 5.2 Sensitivity Analysis of SCG Training Function for Diyarbakir Field

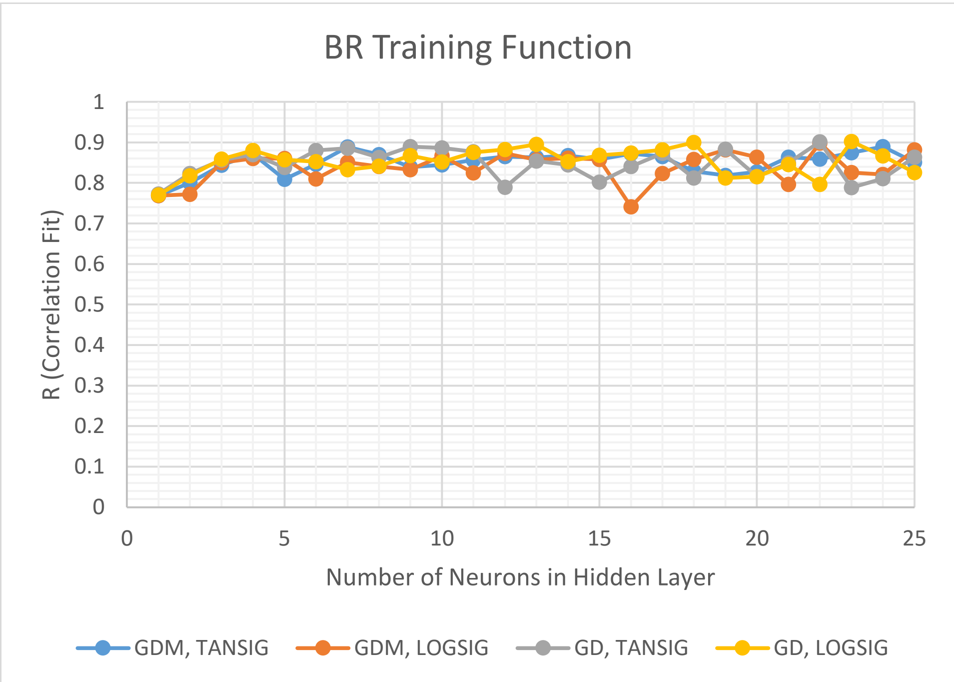

Figure 5.3 Sensitivity Analysis of BR Training Function for Diyarbakir Field

Below figures from

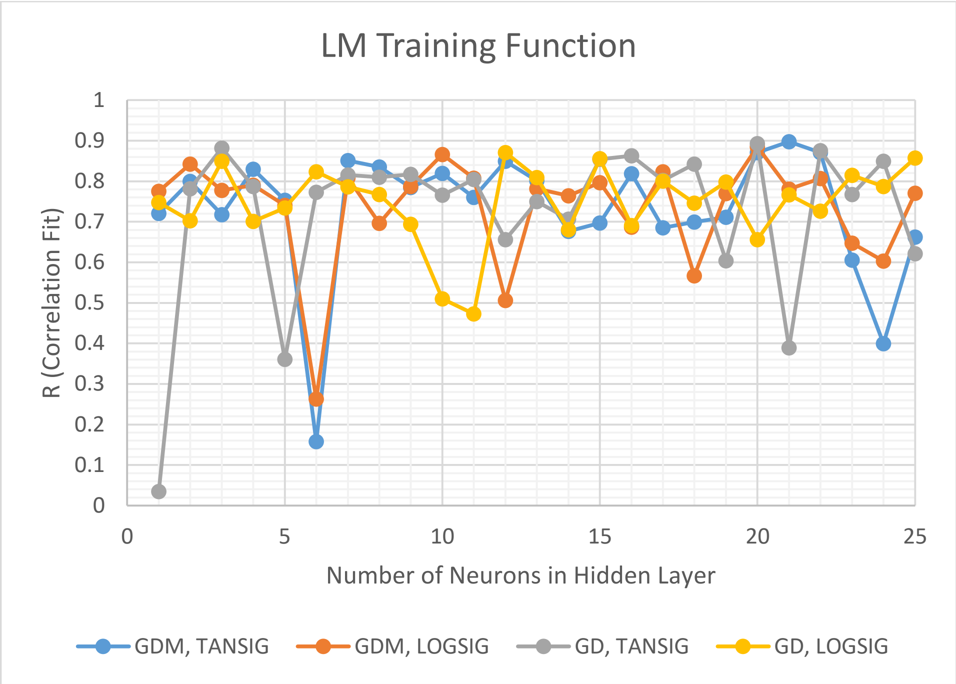

Figure 5.4 Sensitivity Analysis of LM Training Function for Manisa Field

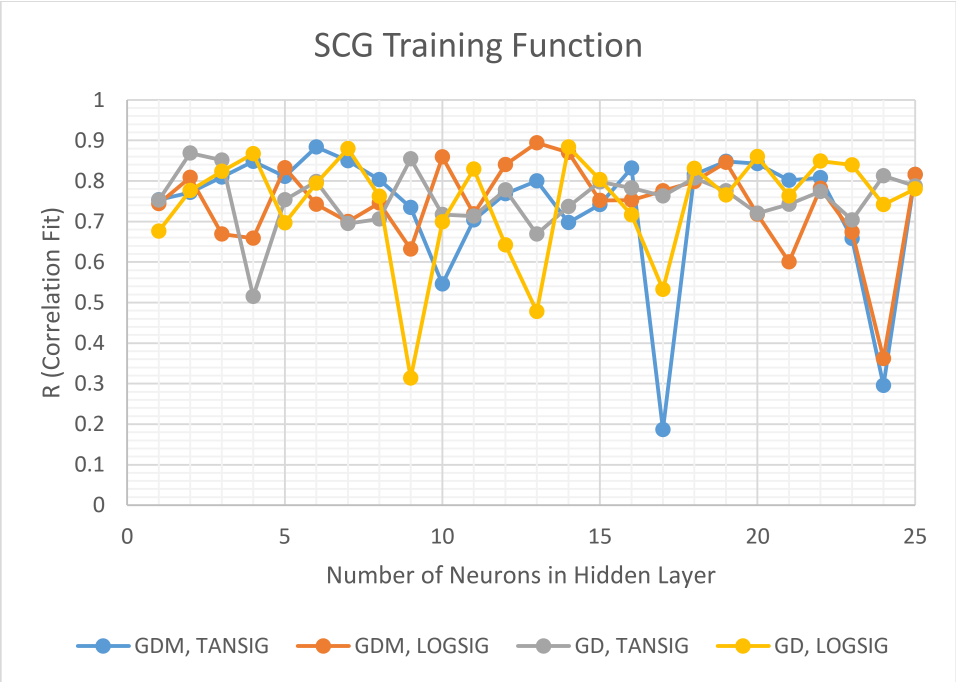

Figure 5.5 Sensitivity Analysis of SCG Training Function for Manisa Field

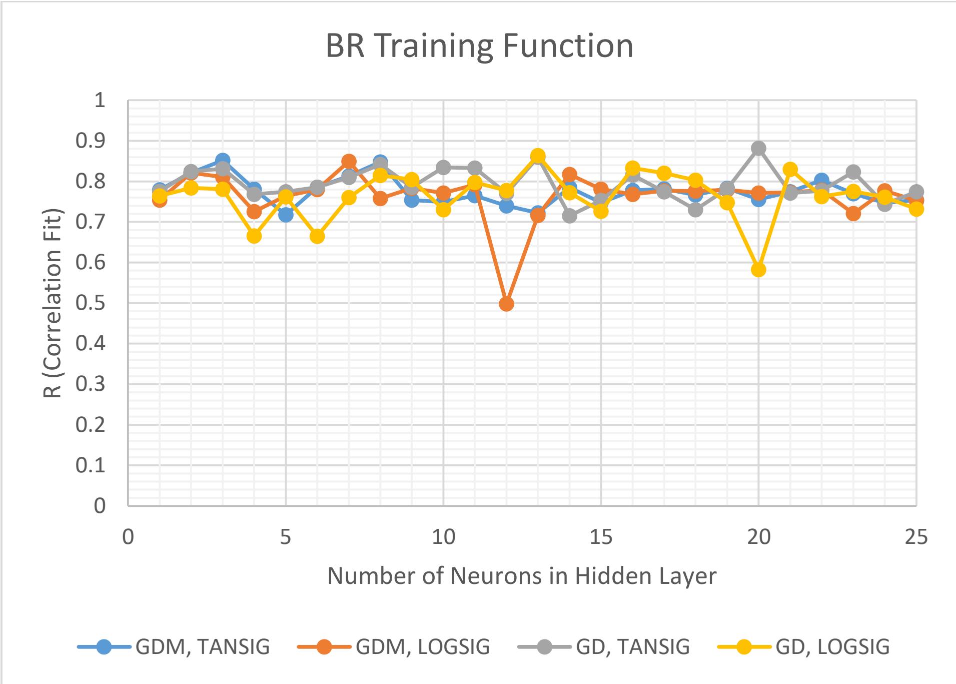

Figure 5.6 Sensitivity Analysis of BR Training Function for Manisa Field

As seen above figures, changing the number of neurons, learning function or transfer functions seems not changing R value hysterically for BR Training Function. Although BR training function gives less deviation on correlation fit coefficient, R value cannot be improved since it is eliminating some inputs variables to make model simpler as "well posed" and converging to desired target with less iterations.

SCG and LM training functions are more sensitive at different network structures. Changing any function or number of neurons leads to remarkable change on correlation fit coefficient.

According to results based on 1000 iterations, LM train function gives best R with 22 neurons in hidden layer, GDM Learning function and TANSIG Transfer function for Diyarbakir Field. For Manisa Field, it generates highest R value with 21 neurons in

GDM Learning function and TANSIG Transfer function. Corresponding R coefficients are 0.90781 for Diyarbakir Field and 0.8974 for Manisa Field.

Network architectures of Diyarbakir Field and Manisa Field are given at Figures 5.7 and 5.8.

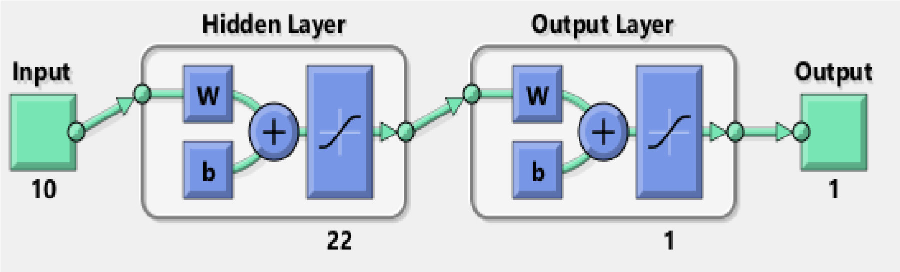

Figure 5.7 Diyarbakir Field ANN Structure (Matlab)

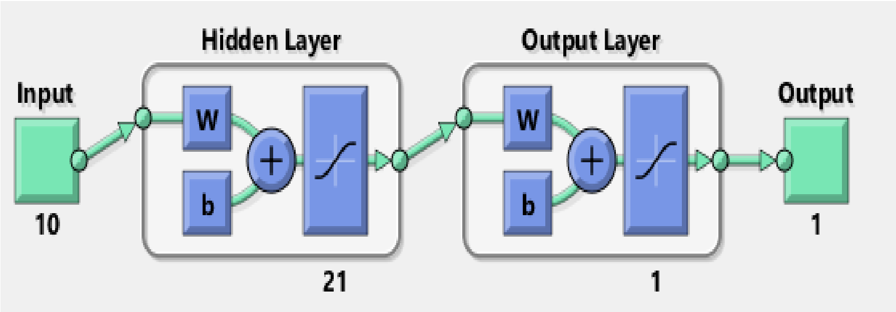

Figure 5.8 Manisa Field ANN Structure (Matlab)

5.2. Training

After the decision of the network structures, further training has been done under supervision. “Matlab nntool” randomly set connection weights and biases and alters them by iterations to get the output as much as close to target value. Training has been conducted for both models separately and it has been terminated once R value becomes stable. Below 5.9 and 5.10 are the results of Diyarbakir Field and Manisa Field trainings.

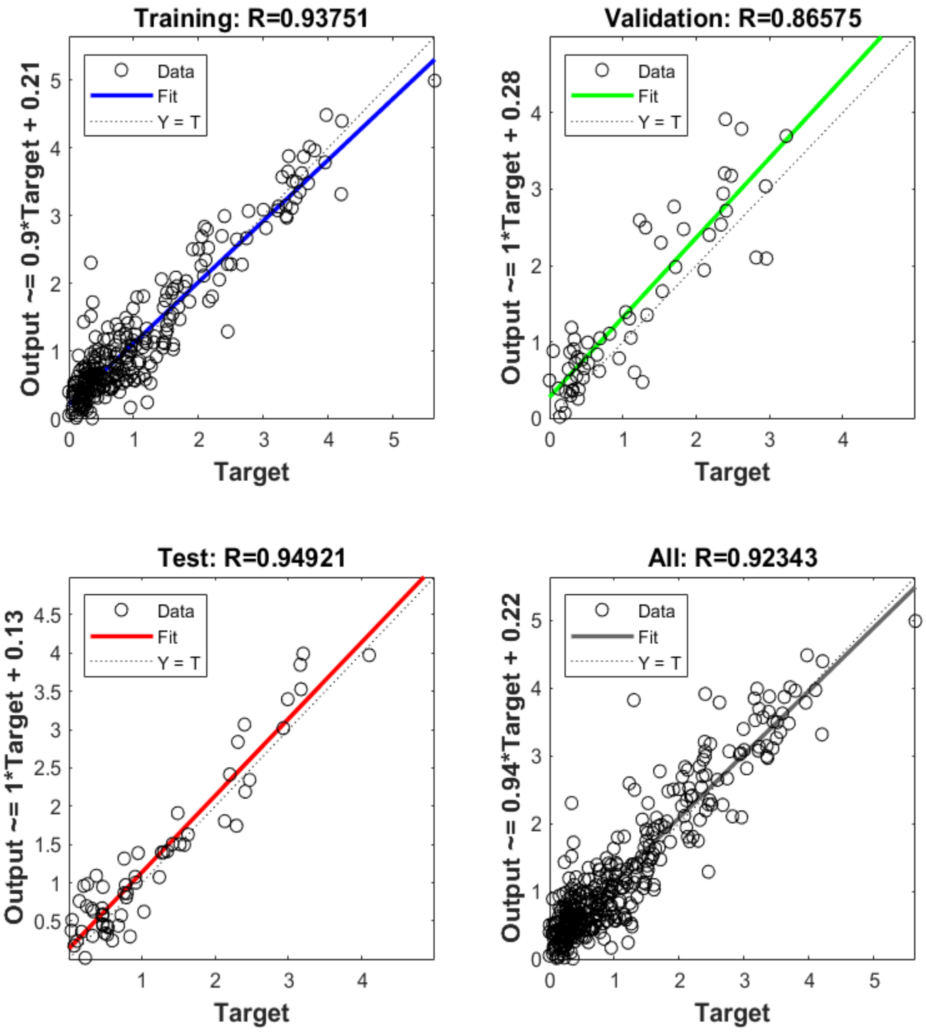

Figure 5.9 Diyarbakir Field ANN Training Regression Charts

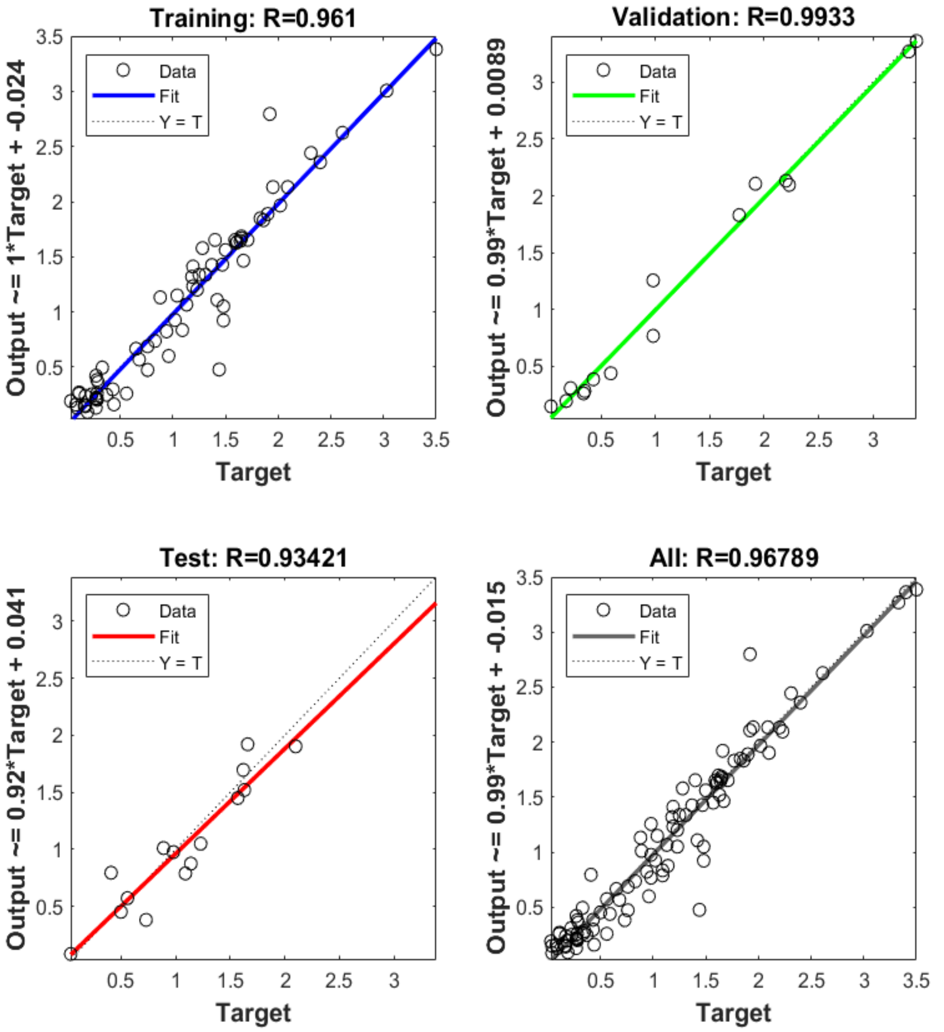

Figure 5.10 Manisa Field ANN Training Regression Charts

5.3. Testing with Untrained Data Set

From each field, a one well has not been included to training data set to test the model accuracy. Untrained data set dimensions are 10x10 for Manisa Field and 10x 39 for the Diyarbakir Field, which is equal to 10% of the total data set. Input variables of these new wells are imported to trained networks and results are driven. Below 5.11

and 5.12 shows estimated DLS values with untrained data set vs depth. Red lines represent the maximum and minimum expected DLS as per theoretical Build up rates of 8” and 6 ¾” Positive Displacement Motors according to 2 stabilizers BHA model. It is the common practice in the industry as a preliminary study before drilling any well. Predicting the DLS severity by using 2-stabilized BHA model together with theoretical build up rates of the motors produces a range for expected DLS. This model only considers motor bent, sleeve stabilizer OD, string stabilizer OD, hole size, bit to bent length, sliding percentage and distance of stabilizers according to bit.

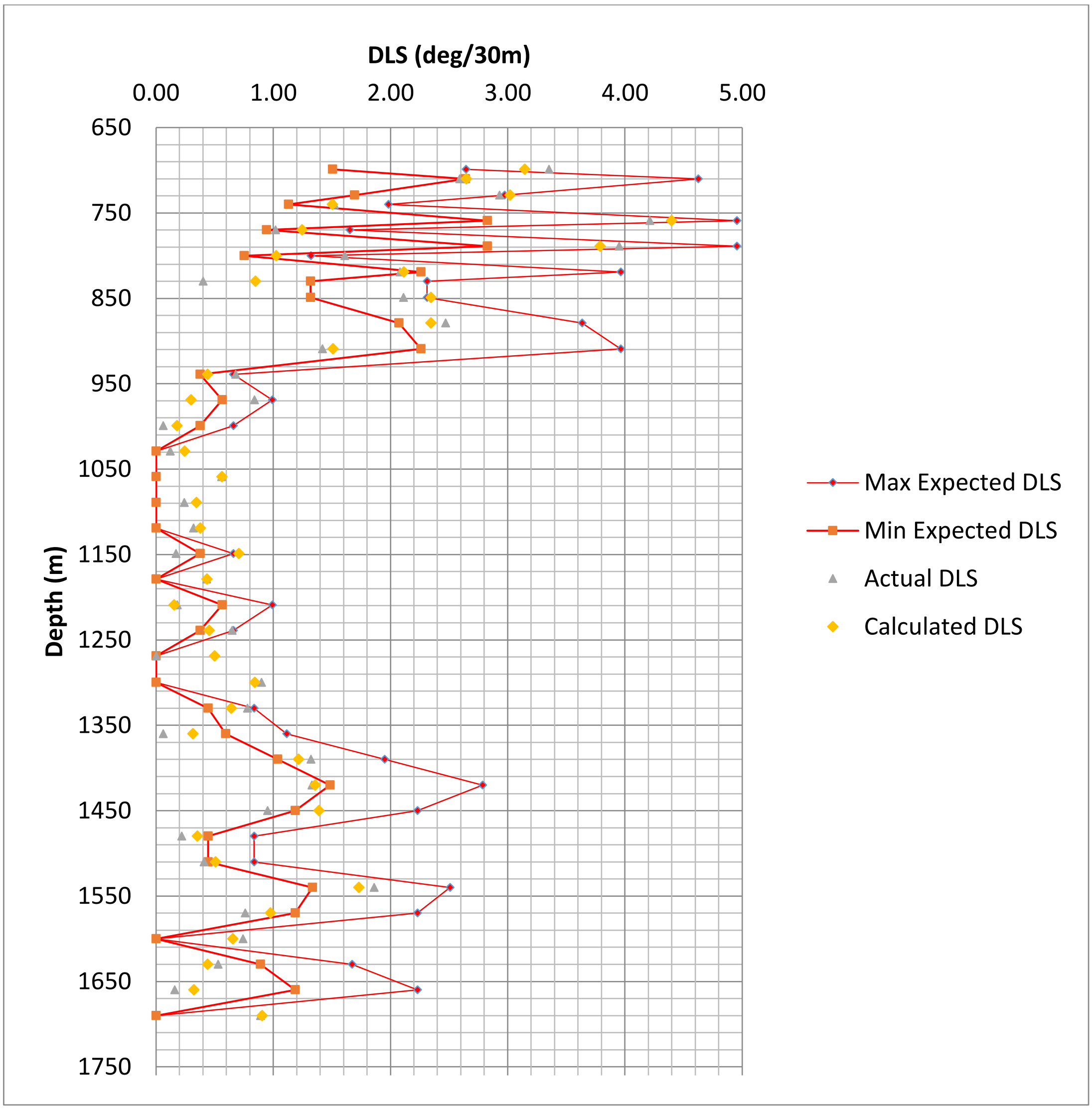

Figure 5.11 Diyarbakir Field ANN Estimated DLS vs Actual DLS

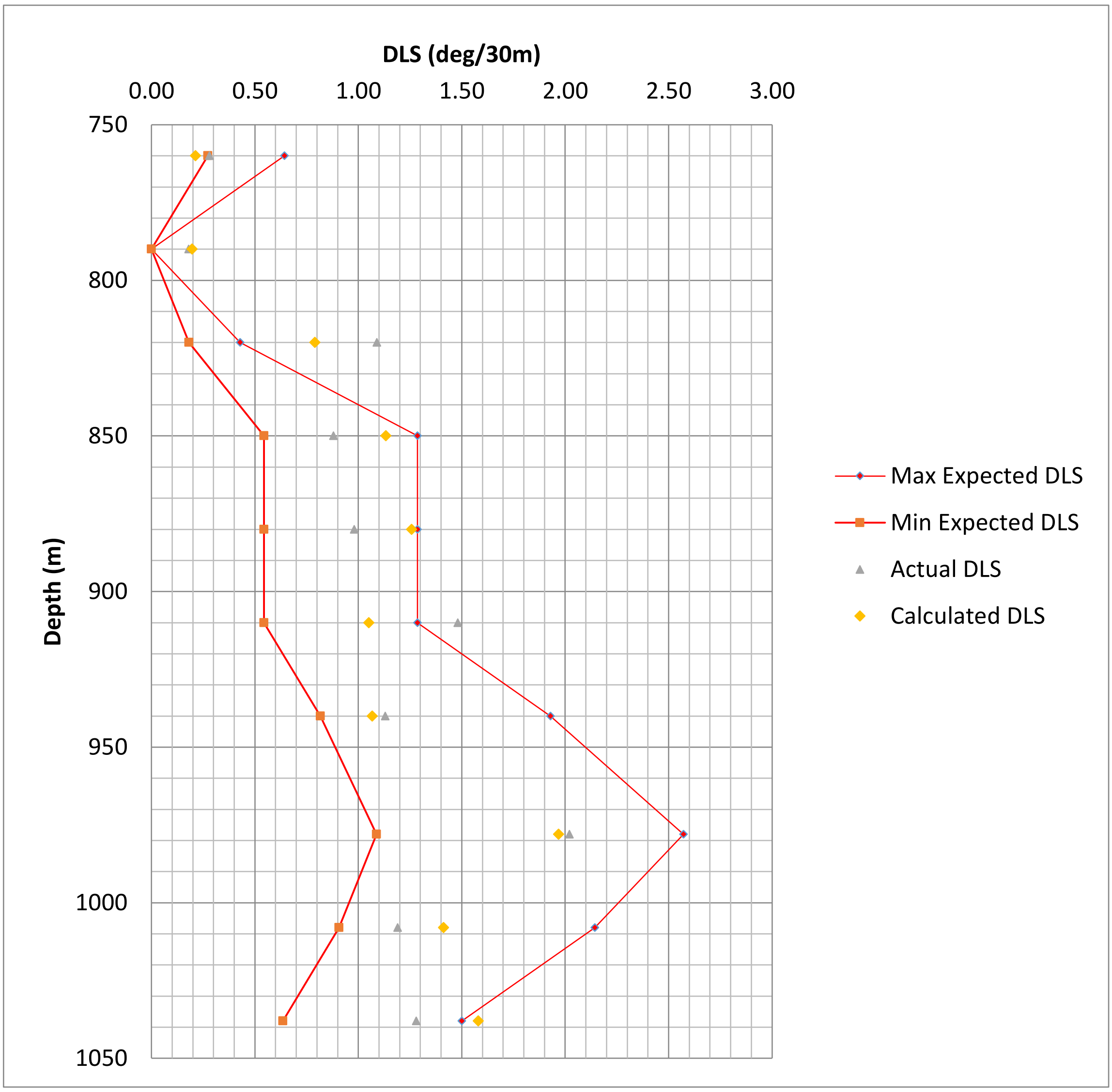

Figure 5.12 Manisa Field ANN Estimated DLS vs Actual DLS

With the untrained data set, result of MSE values for Diyarbakir Field is 0.056. And, it is 0.057 for Manisa Field. Tables which are comparing the calculated DLS and actual DLS for both fields are given at Appendices C and D.

As seen in above figures, some of the actual DLS values are outside the range of theoretical build up rates of the motors since it only takes into account the stabilizers, specifications of motor and sliding percentage. In addition, expected DLS range is quite wide to estimate the DLS. Furthermore, it is not an accurate method since these ranges are not always covering the actual DLS achieved during drilling a well since due to incapable of considering the drilling parameters such as WOB, Bottom RPM, ROP and neither the geometry of the well like; tool face orientation and wellbore inclination, nor the formation and bit & rock interaction effects.

5.4. Assumptions

Since no caliper logs available, hole size cannot be accurately determined but only assumed as drilled with the same bit size. All drilling reports are recorded by field engineers correctly. All rig components generating the data accurately such as WOB, Surface RPM, and Flow Rate. There is no downhole tool to record downhole parameters; therefore, all data have been measured from the surface.

5.5. Limitations

Two separately ANN model has been developed for separate geothermal and oil fields. Same field with same drilling bit has been selected for ANN model in order to eliminate Bit & Rock interaction and geology effect. Hole size is not an affecting parameter for each model, but the models can be used in future wells separately for 8 ½” sections in Diyarbakir Field and 12 ¼” sections in Manisa Field. BHA is limited with the 2-stabilizers design placed at same positions with respect to bit.

CHAPTER 6

CONCLUSION

In order to decrease drilling cost of a directional well and avoid unplanned incidents due to high tortuosity, Dog-leg severity (DLS) estimation is one the critical preliminary study. Therefore, predicting and optimizing DLS before any drilling operation is vital by changing the Bottom Hole Assembly Design (BHA) or optimizing drilling parameters according to specific Bit & Rock Interaction model along with the current wellbore geometry, In this study, same bits are used for 8 ½” hole sections in Diyarbakir wells and 12 ¼” hole sections in Manisa wells; therefore, bit features are not included except for bit wear effects. Bit & Rock interaction and formation effect have been introduced to model as rotating tendencies. BHA components which are controlling DLS are Sleeve Stabilizer OD, String Stabilizer OD, and Downhole Motor Bent angle since other BHA components are same in all wells that are drilled by same rigs. Drilling parameters are also included into the model as WOB, Bottom RPM, Sliding Percentage and Tool Face Orientations.

A single hidden layer Feed Forward Back Propagation Artificial Neural Network with Levenberg Marquardt Training Function (LM), Gradient Descent with Momentum weight and bias (GDM) Learning function and Tan Sigmoid Hyperbolic transfer function has been created to predict Dog-leg severities of directional wells drilled in Diyarbakir and Manisa Field. Networks have 10 inputs variables with 1 output variable for 12 Diyarbakir wells and 7 Manisa wells. Result shows the network accuracy of Diyarbakir Field as R^2 0.923 with 5.6% MSE and accuracy of Manisa Field as R^2 0.968 with 5.7 % MSE.

It is also concluded that that common preliminary studies before drilling any well in the industry is inadequate, which gives a wide range of predicted DLS and not always covers the actual DLS obtained in the field.

Study is under the limit with same hole section and drilled by identical drilling bits and same stabilizer positions in the BHA. It is recommended also train the network with normalized data set and evaluate the accuracy with different performance functions.

This study shows an ANN model can be developed and can be used in the future wells to avoid from high and unpredicted DLS and gives a practical approach to Drilling Engineers and Directional Drillers to predict or optimize the DLS.

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APPENDICES

A. SENSITIVITY ANALYIS OF DIYARBAKIR FIELD

LM TRAINING FUNCTION				
	GDM, TANSIG	GDM, LOGSIG	GD, TANSIG	GD, LOGSIG
1	0.7479	0.75	0.7708	0.76464
2	0.79828	0.76261	0.83486	0.063158
3	0.82151	0.12716	0.77799	0.79827
4	0.81299	0.83817	0.81102	0.20375
5	0.81743	0.82409	0.83342	0.89097
6	0.73701	0.84622	0.81759	0.80898
7	0.85242	0.82921	0.8551	0.87865
8	0.8701	0.83	0.87484	0.75512
9	0.87459	0.88	0.86114	0.84259
10	0.87412	0.87594	0.86271	0.8596
11	0.83305	0.84658	0.85867	0.86043
12	0.845518	0.8274	0.88517	0.86176
13	0.74281	0.90009	0.89219	0.89067
14	0.83423	0.881	0.84863	0.88171
15	0.85356	0.74803	0.88859	0.87937
16	0.87544	0.027338	0.87264	0.87309
17	0.89053	0.84416	0.82946	0.86785
18	0.88321	0.73792	0.80062	0.87739
19	0.87074	0.90311	0.86889	0.83105
20	0.89951	0.86319	0.82535	0.85322
21	0.88467	0.88095	0.73387	0.8803
22	0.90781	0.10576	0.77185	0.84857
23	0.84447	0.87783	0.85963	0.85911
24	0.87724	0.85263	0.86691	0.86108
25	0.85309	0.84322	0.86577	0.86397

SCG TRAINING FUNCTION				
	GDM, TANSIG	**GDM, LOGSIG**	**GD, TANSIG**	**GD, LOGSIG**
1	0.75894	0.77701	0.76749	0.7373
2	0.81798	0.83002	0.81584	0.82273
3	0.84289	0.83637	0.83725	0.81774
4	0.79987	0.83012	0.821	0.84006
5	0.79796	0.84579	0.14382	0.84298
6	0.88357	0.788	0.767781	0.85844
7	0.84392	0.8849	0.80191	0.87211
8	0.81996	0.7862	0.026098	0
9	0.83861	0.86313	0.82216	0.82444
10	0.29327	0.82165	0.84665	0.079969
11	0.83583	0.86423	0.83914	0.80443
12	0.88816	0.87697	0.83813	0.87956
13	0.84258	0.85592	0.80357	0.79197
14	0.73375	0.84471	0.85149	0.83033
15	0.86925	0.85861	0.86893	0.13498
16	0.83492	0.87245	0.84246	0.86007
17	0.82035	0.82249	0.85638	0.86575
18	0.89149	0.80093	0.88615	0.85948
19	0.87477	0.86424	0.7899	0.81473
20	0.82455	0.78813	0.87833	0.87918
21	0.85037	0.84326	0.89682	0.86927
22	0.85032	0.84669	0.88277	0.81219
23	0.91079	0.85022	0.89386	0.85106
24	0.72658	0.3393	0.85445	0.85846
25	0.86368	0.84532	0.78499	0.78975

BR TRANING FUNCTION				
	GDM, TANSIG	GDM, LOGSIG	GD, TANSIG	GD, LOGSIG
1	0.76886	0.76848	0.773	0.77026
2	0.80022	0.77164	0.82298	0.81763
3	0.84414	0.84996	0.85662	0.85914
4	0.87129	0.86029	0.86965	0.87981
5	0.80903	0.86056	0.83812	0.85742
6	0.84577	0.81019	0.87973	0.85219
7	0.88858	0.85122	0.88545	0.83276
8	0.87004	0.84078	0.86244	0.84171
9	0.83941	0.83249	0.88974	0.86748
10	0.84445	0.86698	0.8862	0.85198
11	0.85666	0.82472	0.87673	0.8753
12	0.86512	0.87284	0.78945	0.88283
13	0.86297	0.85694	0.85396	0.8954
14	0.86763	0.86102	0.84431	0.85257
15	0.8577	0.8576	0.80191	0.86816
16	0.87227	0.74104	0.84048	0.87346
17	0.86494	0.82325	0.8726	0.88133
18	0.82883	0.85798	0.8124	0.89947
19	0.81815	0.88152	0.883	0.81249
20	0.82732	0.86341	0.81602	0.81524
21	0.86315	0.79676	0.84902	0.84509
22	0.85878	0.89848	0.90175	0.79641
23	0.87458	0.82566	0.78885	0.90208
24	0.88954	0.82117	0.81072	0.86641
25	0.85084	0.88146	0.86377	0.82591

B. SENSITIVITY ANALYIS OF MANISA FIELD

LM TRAINING FUNCTION				
	GDM, TANSIG	GDM, LOGSIG	GD, TANSIG	GD, LOGSIG
1	0.72082	0.77544	0.034522	0.74742
2	0.80003	0.84195	0.78136	0.70281
3	0.71736	0.77726	0.88197	0.84911
4	0.82978	0.79012	0.78689	0.70084
5	0.75294	0.74025	0.36068	0.73386
6	0.15753	0.26268	0.77318	0.8232
7	0.8507	0.80833	0.81566	0.78652
8	0.83561	0.69607	0.80961	0.76729
9	0.78499	0.78727	0.81698	0.69355
10	0.81977	0.86573	0.76549	0.50974
11	0.76052	0.8078	0.80422	0.47261
12	0.84924	0.5056	0.65613	0.87104
13	0.80107	0.78177	0.75003	0.80897
14	0.6766	0.76397	0.70633	0.68073
15	0.69727	0.79644	0.85422	0.85588
16	0.81852	0.68712	0.86323	0.69107
17	0.68525	0.82313	0.80193	0.80062
18	0.69965	0.56692	0.84221	0.74629
19	0.71089	0.77002	0.60421	0.79805
20	0.87113	0.88485	0.89312	0.65566
21	0.89739	0.7804	0.38937	0.76625
22	0.87065	0.80719	0.87553	0.72615
23	0.60569	0.6475	0.76694	0.81507
24	0.39926	0.60308	0.84971	0.78692
25	0.66257	0.77044	0.62092	0.85696

SCG TRAINING FUNCTION				
	GDM, TANSIG	GDM, LOGSIG	GD, TANSIG	GD, LOGSIG
1	0.75317	0.74392	0.7522	0.67625

2	0.77118	0.80868	0.86864	0.77666
3	0.80912	0.66881	0.85163	0.82357
4	0.84773	0.6587	0.51531	0.86699
5	0.81067	0.83267	0.7535	0.69635
6	0.88384	0.74259	0.7985	0.79444
7	0.84961	0.69948	0.69514	0.87987
8	0.80328	0.7453	0.70617	0.76186
9	0.73404	0.63161	0.85459	0.31397
10	0.54545	0.85896	0.71725	0.69902
11	0.70361	0.71885	0.71277	0.82914
12	0.76806	0.84028	0.77788	0.64183
13	0.80018	0.89357	0.66928	0.47776
14	0.69757	0.87055	0.73709	0.88354
15	0.7419	0.75214	0.79741	0.80305
16	0.83188	0.75227	0.7822	0.71661
17	0.18637	0.7752	0.76268	0.53203
18	0.81586	0.79872	0.80679	0.83092
19	0.84778	0.84556	0.7754	0.76541
20	0.84279	0.71804	0.72002	0.85999
21	0.80164	0.60051	0.74256	0.76299
22	0.8076	0.7817	0.77363	0.84891
23	0.65804	0.67393	0.70385	0.83908
24	0.29529	0.36171	0.81279	0.74127
25	0.81537	0.81577	0.78757	0.78011

BR TRAINING FUNCTION				
	GDM, TANSIG	GDM, LOGSIG	GD, TANSIG	GD, LOGSIG
1	0.77951	0.75412	0.77544	0.76379
2	0.8214	0.82114	0.82436	0.78403
3	0.85214	0.81047	0.83146	0.78037
4	0.78076	0.72572	0.76798	0.66522
5	0.7179	0.76411	0.77414	0.76212
6	0.78534	0.77957	0.78578	0.6645
7	0.81301	0.84964	0.80998	0.7605
8	0.84812	0.7581	0.84122	0.81443
9	0.75353	0.78335	0.78525	0.8044
10	0.74923	0.7714	0.83449	0.7301
11	0.76481	0.79208	0.83289	0.7973
12	0.74002	0.49835	0.7706	0.77775
13	0.7224	0.71622	0.85978	0.86349
14	0.78505	0.81721	0.71488	0.77241
15	0.7474	0.78053	0.75339	0.72631
16	0.77793	0.76803	0.81525	0.8331
17	0.78193	0.77708	0.77459	0.82057
18	0.76673	0.77577	0.73008	0.80317
19	0.78304	0.77899	0.7818	0.74728
20	0.75569	0.77118	0.88193	0.58282
21	0.77415	0.7727	0.77125	0.82938
22	0.80314	0.77805	0.77679	0.76278
23	0.76987	0.72105	0.82304	0.77506
24	0.74657	0.77715	0.7437	0.76085
25	0.75417	0.75208	0.77425	0.73158

C. PREDICTED DLS AND ACTUAL DLS COMPARISON FOR DIYARBAKIR FIELD

Depth (m)	DLS (deg/30m)	Predicted DLS (deg/30m)
699.000	3.35	3.14
710.000	2.59	2.65
729.000	2.93	3.02
740.000	1.52	1.50
759.000	4.21	4.40
770.000	1.02	1.24
789.000	3.95	3.79
800.000	1.61	1.03
819.000	2.08	2.11
830.000	0.40	0.85
849.000	2.11	2.34
879.000	2.47	2.34
909.000	1.42	1.51
939.000	0.68	0.44
969.000	0.84	0.30
999.000	0.06	0.18
1029.000	0.12	0.24
1059.000	0.56	0.56
1089.000	0.24	0.35
1119.000	0.32	0.38
1149.000	0.17	0.71
1179.000	0.43	0.43
1209.000	0.18	0.15
1239.000	0.65	0.45
1269.000	0.00	0.50
1300.000	0.90	0.84
1330.000	0.78	0.64
1360.000	0.06	0.31
1390.000	1.32	1.21
1420.000	1.33	1.36
1450.000	0.95	1.39

1480.000	0.22	0.35
1510.000	0.41	0.51
1540.000	1.86	1.73
1570.000	0.76	0.98
1600.000	0.74	0.65
1630.000	0.53	0.44
1660.000	0.16	0.32
1690.000	0.89	0.90

D. PREDICTED DLS AND ACTUAL DLS COMPARISON FOR MANISA FIELD

Depth (m)	DLS (deg/30m)	Predicted DLS (deg/30m)
760.000	0.28	0.21
790.000	0.18	0.20
820.000	1.09	0.79
850.000	0.88	1.13
880.000	0.98	1.26
910.000	1.48	1.05
940.000	1.13	1.07
978.000	2.02	1.97
1008.000	1.19	1.41
1038.000	1.28	1.58