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Estimation of Downhole Inclination in Directionally Drilled Geothermal Wells

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ABSTRACT

Directional drilling in naturally fractured geothermal reservoirs is a challenging task due to unexpected changes in inclination and azimuth of the well axis, which cause inefficient weight on bit transfer, decrease in penetration rate, increasing the risk of stuck pipe and problems in while running casings. To predict the sudden changes in inclination while drilling, a back propagation, feed forwarded multi layered artificial neural network (ANN) model, which uses drilling data collected from 12 J-type directionally drilled geothermal wells from Büyük Menderes Graben, Turkey was developed. The training data consisted of 7600 individual drilling data. During the training process, effects of each drilling parameter on inclination were investigated with different scenarios for different hole sizes. Moreover, inclination predictions were carried out for a field case in which kick off point to the target depth with 30 meters survey intervals and results were compared. It has been found that developed ANN model provided satisfactory results based on the mean-square-error value which was measured to check accuracy and quality of each training. It has been found out that as weight on bit (WOB), bit revolution per minute and stand pipe pressure increase, inclination increases. On the other hand, increment in flow rate leads to drop in inclination. The results indicated that, total flow area, bit hardness and WOB have the highest impact on network data compared to other drilling parameters.

1. INTRODUCTION

Directionally drilled well is defined as drilling of a well which is deviated from vertical to a proposed inclination through a specified direction (Hole, 2006). The practice of directional drilling traces its roots to the 1920s when simple wellbore surveying tools were introduced to the oil and gas industry (Mantle, 2014). Within the last few decades this technology has also been applied for geothermal wells and now the majority of high-temperature holes are directionally drilled worldwide (Hole, 2006). Geothermal energy is simply the energy derived from the earth's magmatic heat and its most important direct products are steam, minerals and hot water. Similar to the drilling companies who are drilling oil and gas wells, geothermal energy drilling companies have also been seeking to minimize their drilling costs by increasing their rate of penetration (ROP) and minimizing unnecessary trip, rig-up, rig down and set and cement casing times (Thorhallsson, 2006). Moreover, according to Hole, (2006), directional drilling enables the operator to drill several wells from single location which reduces the site construction, road construction and terrain purchase costs. However, as the geothermal reservoirs are naturally fractured formations, drilling directionally through the desired targets without any experience is very difficult. Due to parallel faulting, spontaneous deviations may cause great irregularity in the azimuth and inclination of the well axis. As a result, drilling carried out near such geological features frequently has to be in sliding mode to keep directional drilling parameters within tolerances (Duplantis, 2016). This results in slower rate of penetration and increased drilling time. Drilling through multilayered formations with bend adjusted mud motors generally create unexpected results in inclination angle and azimuth that may lead to high values of Dog-Leg Severity (DLS). Having high DLS values accelerate drilling problems such as, inefficient transfer of weight to the bit, high torque and drag due to tortuous wellbore, unacceptably low penetration rates, problems in while running casings, and side tracking because of lost tool (Rafie. S, Ho. H.S., 1986). Considering nearly all the geothermal wells are drilled with directional assemblies, uncontrollable formation properties due to faulting are very crucial in performance of the directional drilling. These unexpected and undesired results can potentially be avoided, if sudden changes in the downhole and their effect on directional parameters are previously predicted and managed.

There are many variables, which may have an effect on performance of the directional drilling and these variables can be classified as alterable or unalterable. Since drilling operators have been seeking to work efficiently, optimization of alterable variables is very important. Bit diameter, weight on bit, flow rate, downhole rotary speed, bit type, stand pipe pressure and bottom hole assembly design are alterable variables that can be used in an optimization program. On the other hand, formation to be drilled, rock properties, weather, location and characteristic hole problems are thought out as unalterable variables (Lummus, 1970). However, effects of these variables on directional drilling performance are not fully simulated and very difficult to model. Due to these reasons, an accurate and exact mathematical model for directional drilling optimization has not been developed yet.

As can be seen from the aforementioned discussion related to absence of directional drilling optimization, having a mathematical model for this problem is very crucial and complex. In this study, a different approach is suggested by applying the power of back-propagation Artificial Neural Network (ANNs), which is a biologically inspired computed scheme. ANN is a highly parallel system which has been used in many disciplines and has proven to be very useful in solving problems that requires pattern recognition. Since inclination of the well is a result of many drilling variables using the power of an ANN model for solving pattern recognition problems is suitable. The scope of this study covers field data obtained from geothermal fields in Büyük Menderes Graben at the Aegean side of Turkey. Hole size, depths which were drilled in rotary and sliding mode, RPM, WOB, Stand Pipe Pressure (SPP), flow rate, bit type (IADC code), TFA, bend of the down hole mud motor, diameter of string stabilizer in the bottom hole assembly

and diameter of the sleeve stabilizer data are used as an input to developed ANN model. Inclination values which were collected by the measurement while drilling (MWD) tool every 30 meters during drilling are used as the output of the model. Moreover, it should also be pointed out that in this study, the data were gathered from directional wells that were drilled with Positive Displacement Mud Motor (PDM) and rock bits only. ANN model accurately predicts the inclination of directionally drilled wells in Büyük Menderes Graben by using real time drilling data.

To understand the directional drilling optimization using ANN model in detail, it is very important to know optimization and ANN and which data should be used in the ANN model to obtain accurate results.

1.1 Drilling Optimization

The aim of drilling optimization using real time drilling parameters arise from the desire to reduce possible drilling problems and minimize drilling costs by examining and projecting the past drilling data. Furthermore, having a reliable model for drilling performance can also reduce the Non-Productive Time which also reduces the significant part of the drilling expenses (Wallace et al. 2015). Throughout the time, new technologies are developed in drilling industry, especially after 1970's when rigs are started to be operated with full automation systems capable of controlling and adjusting the drilling variables to maintain best possible penetration rates in oil and gas wells. Over the years, technology of rotary drilling has been improved day by day. As technology advanced, horizontal and directional drilling operations were involved into the industry in the early 1980's to drill various wells from a single location and access reserves that may not have been reached vertically. Therefore, studies related to directional drilling optimization have increased over the last decades.

1.2 Directional Drilling Optimization

The petroleum industry did not become fully aware of well problems which were caused by deviation until the development of Seminole, Oklahoma field where wells were very close to each other and had a collision problem due to down hole deviation while one of them was already producing (Carden and Grace, 2007). In earlier times, directional drilling was used mainly as a remedial operation, either to sidetrack around stuck tools, bring the well bore back to vertical, or in drilling relief wells to kill blowouts. Nowadays, with the help of directional drilling, operators can drill inaccessible locations, salt domes, multiple exploration wells from a single well bore both in onshore and offshore and multiple sands from a single well bore (Carden and Grace, 2007) as can be seen in Figure 1.1.

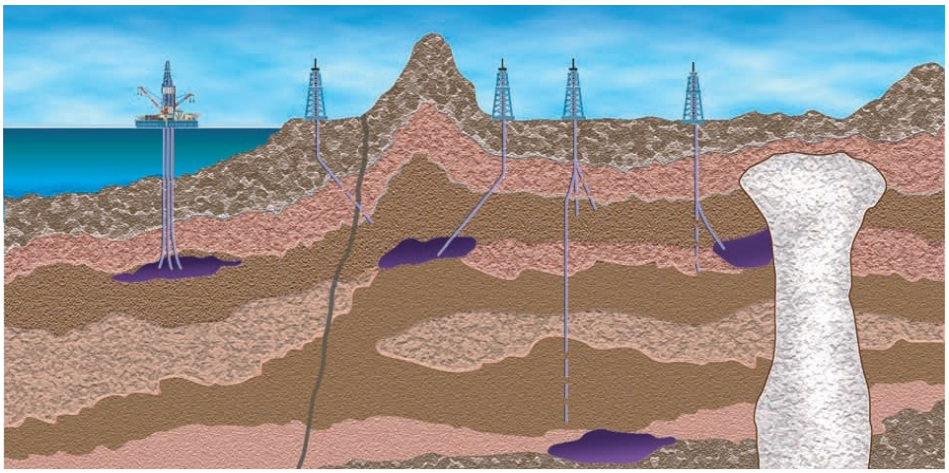


Figure 1: Applications of Directional Drilling (Giacca, 2005)

In order to drill a well directionally, directional drillers use a downhole mud motor when they kick off the well, drilling tangent sections, turn the well for sidetracking operations or building angle to maintain trajectory.

Similar to progressive cavity pumps, Positive Displacement Mud Motor uses the Moineau pump principle (Carden and Grace, 2007). Adjustable bend housing, which can be set between 0° to 3°, is the key element to steer the bit to the desired direction. By orienting that bend in desired direction, designated as tool face angle, directional driller can change the inclination angle and azimuth. To follow the well trajectory or correct the deviation caused by drilling in rotary mode, directional driller switches from rotating mode to sliding mode. In sliding mode, the bend is placed to a specific direction by the directional driller's opinion for wellbore trajectory. In order to orient the position of the bend, the drill string must not be allowed to rotate. Even though there is no rotation from the surface, the bit is turning when PDM is used. As the drilling fluid is pumped through PDM, fluid flows from the stator and turns the rotor, where hydraulic power is converted to mechanical power. In other words, drilling fluid pumped through the stator creates a pressure drop across the cavities, causing rotor to turn (Duplantis, 2016). However, the motion in the rotor cannot turn the bit because it is an eccentric motion. In order to create a concentric motion, the drive shaft is used in PDM assembly, which causes bit to rotate. Depending upon the manufacturer of the motor, the RPM's will change between 50 and 400 RPM, which varies based on the number of lobes on the rotor as compared to the number of cavities in the stator. The stator profile has one more lobe than the rotor and as the lobe count increases the RPM of the bit generally decreases. Moreover, one other important property to define the Power Section of PDM is the number of stages and it is defined as the one complete helical rotation of stator. As the number of stages increases, the differential pressure and torque increases. For example, an abbreviation of 6.5" 7-8L 5.0S PDM has a configuration of 6.5" body OD with 7 lobes in the rotor, 8 lobes in the stator and has 5 stages.

Directionally drilled wells are classified into four categories in terms of their drilling shapes. The Type I wells drilled vertically from the surface to the kickoff point where the well is smoothly deviated to the planned inclination and azimuth. As soon as the planned values for inclination and direction reached, the established values are maintained while drilling to the target depth. These wells are also called as "J-Type" wells in drilling industry. The second type is called "S-Type", which is similar to Type I wells. In S-Type wells, well is also deviated from kickoff depth through planned inclination angle and azimuth direction. However, rather than holding these parameters to target depth, in S-Type wells, after some point the angle is steadily and smoothly dropped until the well is near vertical. This type of well is generally used where multiple pay zones are encountered. Type III wells are also similar to Type I wells except the kickoff point is deeper in Type III and the well is deflected at the kickoff point with continuous build in inclination through the target interval. This type of well is especially used for multiple sand zones, salt dome drilling and fault drilling (Carden and Grace, 2007). Type IV wells are horizontal or extended reach wells, which have high inclination values that are greater than 80° with large horizontal departures.

Unlike traditional drilling systems, the directional drilling operation requires sensors, called Measurement While Drilling (MWD) system, to provide evaluations of the azimuth and inclination angle. Azimuth is defined as the deviation from the north direction in the horizontal plane and inclination angle is the deviation from the vertical plane direction (Elshafei et al., 2015).

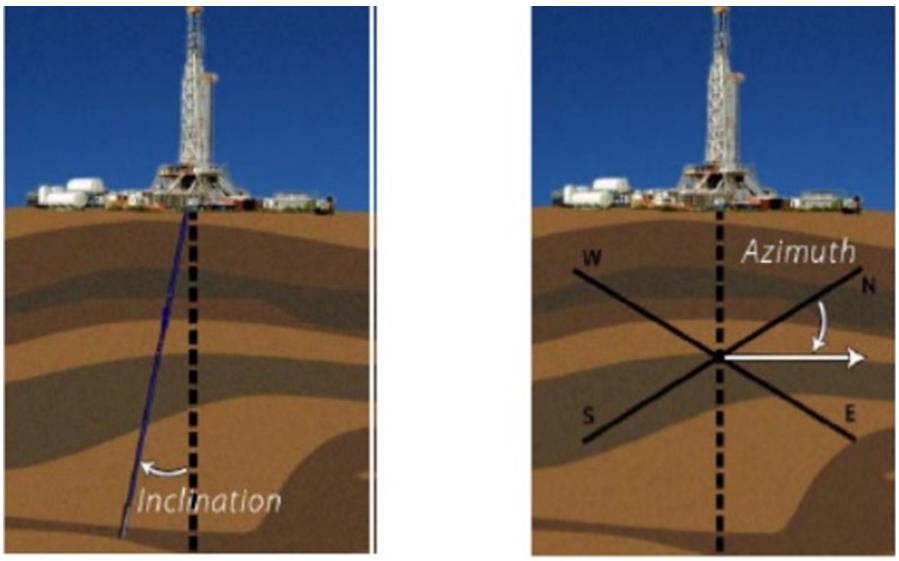


Figure 2: Visual Illustration of Inclination and Azimuth (Fouad, 2012)

As it was previously mentioned, inclination angle is measured from Direction and Inclination sensor (DNI) of any MWD tool which consist of three accelerometers and three magnetometers. Triaxial accelerometers measure 3 orthogonal axes components of the earth magnetic vector (G). Orthogonal axes of accelerometers are aligned between each other during manufacturing and assembling. It should be pointed out that, these sensors have to be calibrated after each assembling process to maintain accurate results while the tool is in the hole.

Measurement of inclination at a certain depth is called survey and accelerometers inside the DNI measures G at that survey point with the following calculation (Eq. 1.1) (Illfelder et al., 2005).

$$Inclination = \arctan\left(\frac{G_z}{\sqrt{G_X^2 + G_Y^2}}\right) \tag{1}$$

These surveys are then converted to North-South (N-S), East-West (E-W) and true vertical depth (TVD) coordinates using one of the survey calculation methods in directional drilling industry. The coordinates are then plotted in both horizontal and vertical planes. There are five methods that can be used to calculate the survey data: Tangential, Balanced Tangential, Average Angle, Radius of Curvature and Minimum Curvature Methods. Of these methods, radius of curvature and minimum curvature methods are the most common ones since tangential methods have non-negligible errors for the northing, easting and elevation (Amorin, 2010).

The conventional MWD probe is usually placed 15-20 meters away from the bit and this distance depends on the lengths of the downhole mud motor, string stabilizers and nonmagnetic drill collars. In other words, survey taken at a specified depth shows the inclination and azimuth value 15-20 meters above. Especially in highly faulted geothermal wells, 15 meters of uncertain drilling may create severe drilling problems such as high DLS, which is calculated by Radius of Curvature Method (Eq. 1.2), and high tortuosity in the wellbore which can lead to missed targets, stuck pipe and problems in running casings (Skillingstad, 2000).

$$DLS = \{\cos^{-1}[(\cos I_1 \, x \cos I_2) + (\sin I_1 \, x \sin I_2) \, x \cos(Az_2 - Az_1)]\} \, x \, (\frac{100}{MD}) \tag{2}$$

1.3 Artificial Neural Networks (ANNs)

As a result of technology progress over the last decades, Artificial Intelligence (AI) techniques like Artificial Neural Networks (ANNs) have received a massive attention. ANN systems were generated from the working principles of brain and nervous system of human body because this system mimics the human brain in learning from previous experiences and generalize to provide new outputs by abstracting main properties from inputs (Bello et al., 2016). When the problem is very complex, which require qualitative reasoning, conventional statistical and mathematical methods are inadequate, or the parameters are very difficult to create a pattern due to very noisy data. ANN modeling is a very powerful and efficient method to conduct a successful analysis (Bailey and Thompson, 1990).

One of the main superiorities of ANNs to conventional statistical analysis methods is that ANN's are data driven self-adaptive systems that can solve exquisite functional relationships even if the relationship between them is very hard to define. Moreover, according to the Rumelhart et al. (1994), ANN's capture the non-linear relationships with better accuracy. However, Boussabaine, (1996) stated that the foremost advantage of using an ANN system is their adaptability since these systems can automatically adjust their weights to optimize their behavior. Due to this reason, Saputelli et al. (2002) stated that this network system is used in wide variety of problems like nonlinear regression, discriminant analysis, nonlinear time-series, support vector machines and novel approaches to graphical models and many others. In Figure 3 a fundamental representation of ANN system is presented.

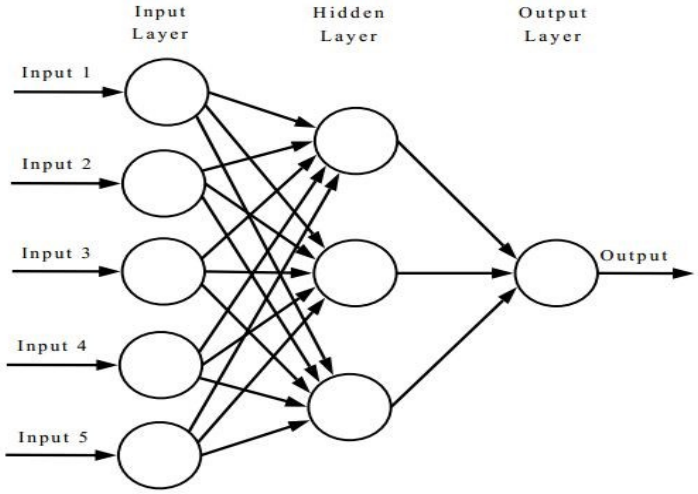


Figure 3: Representation of ANN system (Saputelli et al., 2002)

As it can be seen from the figure that, ANN is a parallel and distributed information processing structure that consist of several neurons, which receive the inputs and produce the output as a non-linear function of the inputs. The neurons are arranged in one or more hidden layers and connected in a certain way (Saputelli et al.2002). Every connection has an associated parameter, called weights and they are optimized according to the learning algorithm. The learning algorithm can be classified into two groups; supervised and unsupervised. These two groups are classified based on their outputs. If the output of the network model is known it is called as supervised and when it is not known the algorithm specified as unsupervised. Moreover, one of the main parameters of ANN is its architecture, which explains the number of units, how these units are connected and how the information flows through these units. In the literature, there are three different architectures, which describe the network and they are classified according to their layer numbers and their loops (Haykin, 2001). An architecture created with an input layer and an output layer is called Single-Layer. In this texture, information flows from the input layer to output layer but not vice versa which solves only linearly separable problems. Second architecture texture is called multilayer which has one or more hidden layers between the input and output layers. These architecture types can solve any non-linear functions and information flows in a feedforward fashion, from the input to the output going through hidden layers. Final texture, which consist of one or more layers, is called recurrent but its difference to other architecture models is, it has one feedback loop. In other words, the information can flow from input to output or output to input which creates a very difficult learning process. In this study, feedforward Multilayer Architecture with back propagation algorithm was used. This algorithm is originated when the steepest-descent method is used in order to reduce the sum of squares error between the real output and output predicted by the model.

2. METHODOLOGY

The main purpose of this study is to propose a back-propagation ANN model to determine the hole inclination during directional drilling operations of geothermal wells located in Büyük Menderes Graben. The input data is collected from the directionally drilled geothermal wells located in Büyük Menderes Graben. A total 543 sections, that corresponds to 7600 data, were used as inputs in the model. Each section corresponds to the 30 meters of drilling interval that contains 14 different drilling parameters The inputs of the model are hole size, start depth, end depth, footage of rotary and slide drilled section, WOB, downhole bit RPM, SPP, flow rate, TFA, bit IADC code, adjustable bend degree of the motor, gauge of string and sleeve stabilizers. Hole size and diameters of the stabilizers units are in inch, depth is in meters, pressure is in psi, WOB in tons and flow rate is in gallons per minute.

2.1 Feed Forward Artificial Neural Network

Feed-forward ANN is an architecture where information transmits from inputs to outputs in one direction with no back loops (Figure 4). In other words, each layer contains units, that receive their input from units of a layer directly below and transmit their output to a layer directly above the unit (Shadizadeh et al., 2010). Moreover, Krenker et al. (2011) mentioned that apart from this restriction, in feed forwarded networks, there are no limitations about the layer size, transfer function or number of connections between the artificial neurons.

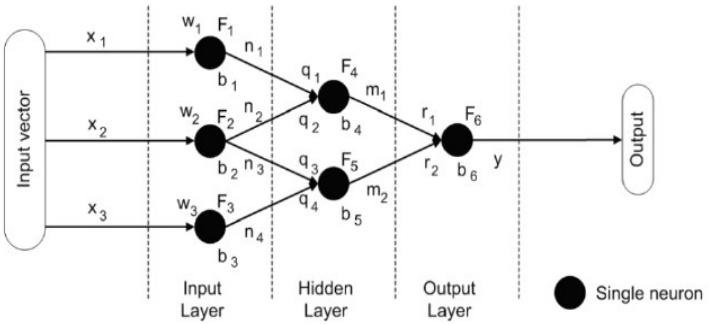


Figure 4: Architecture of Feed Forward Artificial Neural Network (Krenker et al., 2011)

Where x, n, m, y are the signals and w, q and r are the weights, F is the transfer function and finally b is the bias term. As it can be seen from the Figure 4, prediction of an output by using feed forward neural network architecture leads to complex and relatively long mathematical descriptions. In this study the network model consists of 14 input parameters, selection of training function, model parameters and data quality and data analysis are very important. Multiple layers of neurons with nonlinear transfer functions allows the network to learn nonlinear relationships between input and output vectors that makes the ANN suitable tool for complex problems (Beale et al.,2015).

2.1.1: Transfer Function

As it can be seen from Figure 4 the major unknown of an ANN model is the transfer function, which can also be stated as "activation function". Even though there are many transfer functions, linear transfer function and log-sigmoid transfer function are the most commonly used functions in the literature. In this study, log-sigmoid transfer function (Figure 5) is used to predict the inclination due to its prediction efficiency in the multilayer networks and its differentiability (Beale et al., 2015). Since inclination prediction by using directional parameters is not a linear relationship, developing a neural network without squashing function will disable the weights in the network to converge to a stable solution and would not be able to model nonlinear relationship. Equation of log-sigmoid transfer function and its curve are expressed in Eq (3) and Figure 5. As it can be seen from Figure 5, log-sigmoid transfer function receives the input and squashes the output in the range of 0 to 1.

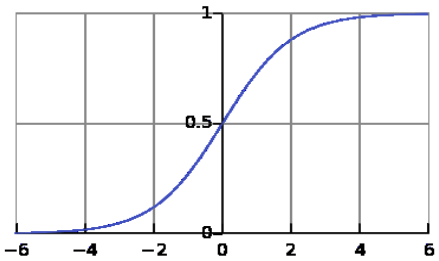


Figure 5: Log – Sigmoid Transfer Function (Beale et al., 2015)

$$f(x) = \frac{1}{(1+e)^x} \tag{3}$$

2.1.2: Backpropagation

Among other networks, backpropagation technique is the most commonly used one and it refers to the mechanism of adjusting the weights and biases of the network for error reduction, which is propagated back through the system and changes the weights and biases for a smaller MSE (Shadizadeh et al., 2010). In other words, in the beginning of the training network begins the epoch and for each training it computes the network output and error. After finishing the epoch the error is back propagated from layer to layer and the weight of the corresponding neuron is adjusted to decrease this error.

2.1.3: Learning Rule

Learning rule is the procedure of adjusting weights on connections between the nodes and biases of the network. According to Saputelli et al. (2002), learning algorithms are classified into two categories; supervised and unsupervised. Their classification is made based on the output data set. If the desired output of the network is known, the learning algorithm is supervised and when the output is not known and only input data is available, learning algorithm classified as unsupervised. Since the output of this study is

inclination and the values of inclination are included in the network dataset, the learning algorithm in this study is supervised learning.

Yilmaz et al, (2002) mentioned that, the learning rate of the ANN is adjusted by modifying the momentum factor (alpha) and learning rate modifier (eta). Momentum factor makes the $(t+1)^{th}$ update dependent on the t^{th} update, which improves convergence by keeping the weights moving in the same direction and it takes generally values in the range of 0.7 to 0.95 (Oregon State University College of Engineering, n.d.). Moreover, Doreswamy et al (2013) stated that backpropagation neural network with momentum allows the network to respond not only to local gradient, but also to recent tendency in the error surface.

2.2 Training of the Artificial Neural Network

The model has supervised learning algorithm with log-sigmoid transfer function for training. In a typical neural network training procedure, the database is divided into three different sections: training, validation and testing. Among available sets of data that consist of input and output, 80% has been used for training, 10 % has been applied in validation process and remaining 10% has been used for testing. this study, memorization and overfitting problems were minimized by training the network model using layer by layer approach, where the data is divided into layers and individually trained. When appropriate weights are obtained, performance of the network is tested with the testing data, which is real-time drilling data that is not added to the network dataset. In order to analyze the accuracy of the network, mean-square-error value (MSE) was introduced which decreases as the performance of the model to predict an output increase.

Several trainings were made to get the desired output which has no overtraining problems and has the least MSE value. Different scenarios based on the changes in momentum factor, learning rate parameter, number of hidden layers, neuron sizes of the hidden layers and number of cycles for the training were developed. Analyses were conducted to find out the optimum parameters for the ANN model. According to the results of the simulation scenarios, it was found that, program is working with a very good accuracy and without memorization problem. All the trainings, with different momentum factor, learning parameter and hidden layer sizes gave very accurate MSE values, which were less than 2%. Among all the trainings with different scenarios, the configuration that is shown in Table 1 was used for the analysis due to its low MSE, which is 0.422 and faster convergence. To avoid memorization problems and computational time limitations, number of cycles was selected as 250 even though the MSE values for different training scenarios show slightly smaller MSE results when the number of cycles is higher than 250. Since the dual hidden layer with different layer sizes gave relatively small MSE when compared to single hidden layer architecture, four layer network was used for the trainings.

Table 1: Model Parameters

Learning Parameter:	**0.9**
Momentum Factor:	0.7
Initial Weight:	0.5
First Hidden Layer Size:	20
Second Hidden Layer Size:	17
Number of Cycles:	250

In order to develop and use the model some assumptions have been made, which are divided into two main parts: Drilling conditions assumptions and model data set assumptions. In drilling conditions assumptions, the formation being drilled was considered to be homogeneous and the components of the rig are calibrated and working efficiently. On the other hand, network data set assumptions are, developed ANN model is applicable to wells to be drilled in Büyük Menderes Graben with J Type directional drilling well profile. Footages that were drilled with failure BHA components should not be used in the dataset, like failed bearing section, severe worn out in sleeve stabilizer washout in the drill string. Final two assumptions are, maximum well inclination should not exceed 30 degrees and mud properties are not included in the dataset.

3. RESULTS AND DISCUSSION

In this section, results of the ANN model for inclination angle prediction is presented with profile plots along with the quality and accuracy check of the model with the testing data that were not processed in the data sets. Moreover, sensitivity analysis of each drilling parameters was carried out and their effects on inclination were investigated with and without depth data. Then, a case study was conducted in a geothermal field to compare the ANN predicted inclination values to the actual surveys which was taken from MWD tool from the beginning of a well through the end. Finally, the model was run for different scenarios that contain different omitted drilling parameters to check the influence of each parameter on the directional drilling performance by comparing the MSE results.

As it is mentioned before, the values in Table 4.2 was used for the model parameters. According to the MSE value in training, which was calculated as 0.422 % and 1.2877 in validation, ability of the network to predict an inclination value while drilling is very good. In order to check the accuracy of the network, model was tested with the testing data that were not used in the training data set. The results indicated that, developed ANN can be used in J type directional wells for inclination prediction and optimization since calculated MSE value with testing data is 1.19 and R^2 of the plot of real inclination versus predicted inclination is 96.61%. As can be seen from the Figure 6, apart from only one point, which can be interpreted as an outlier, network can predict the inclination accurately. R^2 is a statistical measure of how close the data are to the fitted regression line. In other words, it is the percentage of the response variable variation that is explained by a linear model. As the number of R^2 percentage increases,

network explains the variability of the response data around its mean in a better way. Considering 100% explains all of the data, 96.61% can be interpreted as a reliable network for inclination prediction and directional drilling optimization.

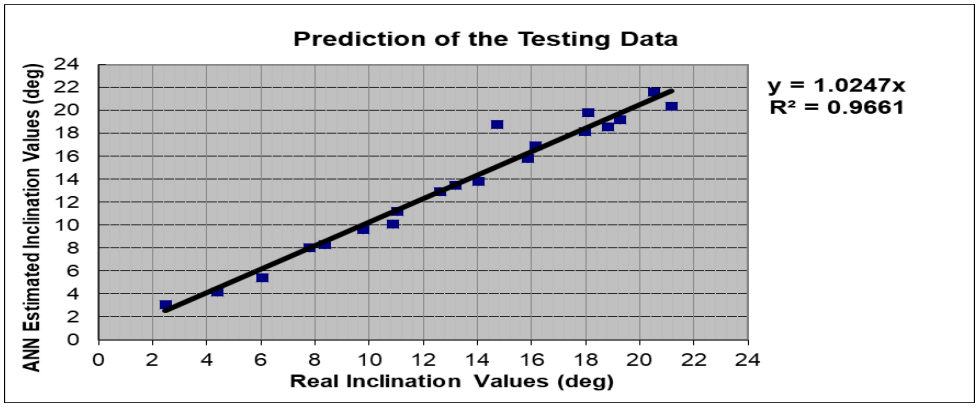


Figure 6: Plot of Real Inclination Values versus ANN Estimated Inclination Values

3.1 Sensitivity Analysis of Drilling Parameters

Once the model parameters were selected and network was evaluated with the testing data, next step is to make sensitivity analysis of drilling parameters on inclination. In this section, analyses were divided into two main parts. In the first part, effects of drilling parameters on inclination were analyzed without the depth data. Since inclination values are affected by the amount of slide and rotary footage that were made within the 30 meters drilling interval, general analysis of drilling parameters on inclination become difficult when depth data is included in training data set. On the other hand, effects of depth, sliding and rotating percentages should not be fully avoided in a program that is used for also directional drilling optimization. Due to this reason, in the second part of the analysis, effects of drilling parameters on inclination was investigated in 100 meters drilling intervals with different hole sizes.

The drilling parameters used in this study for the sensitivity analysis are WOB, bit RPM, flow rate and stand pipe pressure. The reason why these parameters were selected for the sensitivity analysis was that, these parameters are alterable by the operator as discussed before and they can be optimized in a real-time drilling operation according to the results of their influences on inclination. In order investigate the effect of a drilling parameter on inclination, the other parameters should remain constant. These parameters are called fixed parameters and they were selected based on the commonness in the data set, which can be seen in Table 2 and 3 for 12.25” and 8.5” HS.

Table 2: Fixed Parameters for 12.25” HS

WOB: 8 tons
SPP: 1500 psi.
Bit RPM: 150 rpm.
Flow rate: 700 gpm.
Total Flow Area: 0.589 in^2
Bit IADC: 437
Gauge of String Stabilizer: 12.062”
Gauge of Sleeve Stabilizer: 12.1”
Motor Bend: 1.5°

Table 3: Fixed Parameters for 8.5” HS

WOB: 6 tons
SPP: 1750 psi.
Bit RPM: 190 rpm.
Flow rate: 500 gpm.
Total Flow Area: 0.745 in^2
Bit IADC: 447
Gauge of String Stabilizer: 8.125”
Gauge of Sleeve Stabilizer: 8,375”
Motor Bend: 1.27°

According to the results of the ANN model it was found out that inclination increases as WOB increases. This is the result that we expected from the network since the most effective practices adopted in the drilling industry for rotary drilling assemblies is fanning bottom, which is drilling with very low weight on bits to avoid building (Ernst et al., 2007). Moreover, according to the sensitivity analysis of O’ Bryan and Huston (1990) BHA computer model, it was also found that, as WOB increases, the build rate of inclination increases and drop rate decreases. . Especially with the help of fulcrum assemblies increasing WOB will increase the build rate of inclination. Results indicated that, the build rate between 2 tons and 8 tons are small, but as the WOB passes 8 tons in 12.25” hole section magnitude of build rate increases. The reason of this result is that, in 12.25” hole sections, applied WOB by the directional driller is generally higher than 6 tons since the maximum allowable WOB is calculated from the buoyed weight of the BHA below jar, which is around 20 tons for typical 12.25” BHA. However, it should also be pointed out that, applying WOB between 10 and 14 tons may create accidental high DLS values in rotary drilling without careful analysis. For the 8.5” HS, as weight applied to the bit passes 8 tons, inclination starts to drop in 8.5” hole section. General idea about applying more weight for building is not suitable here. The reason of this difference could be the walk rate of azimuth such that higher WOB values can drop

the inclination angle. O' Bryan & Huston (1990) stated that, the build rate will decrease as hole size decreases since the clearance between the wellbore wall and drill collars becomes less which causes a less bit side force. Also, one other reason of this drop in inclination is a result of worn sleeve stabilizer that creates a pendulum assembly.

Moreover, the developed ANN model stated that, inclination angle increases as bit RPM increases in 12.25" HS and its influence is very similar to WOB. However, changes in the build rate and final inclination angle value are smaller when compared to the changes in WOB. The main reason of this result is that, as bit RPM increases the drill string becomes stiffer, which then decreases the build rate. Effect of the stiffness is seen especially in 12.25" hole sections since the diameter of the tools used in these sections are larger when compared to 8.5" hole tools. In other words, larger diameters create stiffer and more rigid bottom hole assemblies, which causes minor deviations. However, in this study when the bit RPM is between 140 and 170, inclination has a slight build trend which shows similar results with the experimental study of Ernst, et al (2007), where high RPM was found to be a drilling parameter that can be used to increase the build rate. For the 8.5" HS, it is seen that, as bit RPM increases, inclination increases. Especially when the bit RPM is between 160 and 200 RPM, build rate in inclination angle is very high. Since most geothermal wells drilled 8.5" hole section as hold section, directional driller needs to consider the effect of high RPM on inclination. It is safer and economical to stay below the planned inclination hole section if the bit RPM is between 160 and 200 RPM since directional driller can use the rotary tendency to his benefit and can avoid unnecessary slide time to build in inclination.

On the other hand, flowrate analysis for two hole sizes stated that, flow rate holds the inclination when the pumped drilling fluid is less than 450 gpm. However, as flow rate increases from 450 gpm. to higher values, inclination is dropping gradually to 7 degrees. Considering flow rate limitations for the downhole motors and MWD tools for the 12.25" hole section, it can be concluded that inclination is dropping in 12.25" hole section when flow rate is increasing. The profile plot that shows the analysis of flow rate in 8.5" hole section states that, inclination is holding with the flow rate when its maximum value is 450 gallons. However, as flow rate passes 450 gallons, inclination and flow rate has a reverse relationship. Finally, in 12.25" HS when the stand pipe pressure during drilling is between 900 and 1500 psi inclination is nearly constant. With this knowledge, while drilling through hold sections in 12.25" hole, directional driller can define 1500 psi as the maximum SPP value if his target inclination is a low angle. Moreover, the second part of the plot stated that, when the pressure range is between 1500 and 1900 psi, SPP and inclination have a linear relationship. This pressure range is very helpful to the directional driller while drilling the build section, where slide footages are minimized. Finally, the third part of the plot is similar to the first part, where the inclination is again holding. However, in this case the predicted inclination by the neural network at this pressure range is above 20 degrees, which make it a perfect hold section parameter for a typical J-type wells that are drilled in Büyük Menderes Graben. Similarly, for the 8.5" HS, it can be concluded that, inclination increases as stand pipe pressure increases in 8.5" hole section.

When the analysis was carried out with depth data, inclination and WOB have a linear relationship in the first 100 meters while drilling 12.25" hole section and as the depth gradually increases the build rates decrease for 12.25" HS. The linear relationship in the first 200 meters can be explained by starting the build section where inclination values are increasing after KOP and directional driller has applied high WOB values to get descent ROP to increase the drilling performance. For 8.5" HS, inclination and WOB also shows linear profile within the first 200 meters. However, analysis between 200 and 500 meters drilling clearly shows that inclination is holding as WOB increases. The reason of this profile plots is that, after 200 meters of drilling 8.5" hole section, directional driller finished the build section and continued drilling by keeping the inclination constant for successful J-Type drilling.

Furthermore, inclination is building in 12.25" hole section as bit RPM increases especially after 100 meters drilling. In the first 100 meters, inclination values are similar as RPM values are increasing. However, as depth passes 100 meters, inclination starts to build, which could be a result of softer formation. According to the analysis of Ernst et al., (2007) when the formation hardness decreases effects of bit RPM on build rate increases. On the other hand, analysis of bit RPM on inclination is different while drilling 8.5" hole section. Inclination is almost holding as RPM increases at different depth intervals, which could be the result of drilling through hold section with the hold BHA.

As it was mentioned earlier, results of the trained network for the flow rate without depth data, has a hold and drop effect to the inclination for 12.25" and 8.5" hole sections. However, the flow rates that were used in these sections stated that as flow rate increases inclination decreases. Sensitivity analysis of this parameter is also made with the depth data for two different hole sections and profile plots of these analysis stated also the same output. Finally, the profile plot of pressure versus predicted inclination angle for 12.25" hole section states that influence of SPP on inclination is not high. SPP will slightly build the inclination angle within the first 200 meters of 12.25" hole section. However, after 200 meters, higher SPP will drop the inclination as drilling continues in this region. Similar results can be obtained from the analysis for the 8.5" hole section. It should be pointed out that, in literature, effect of SPP has not been studied on inclination since it is affected by flow rate, mud weight, pressure losses in the drill string, annulus and the bit and WOB if PDM is used. Due to this reason, power of each drilling parameter on inclination tendency will change the effect of SPP on inclination.

3.2 Case Study to test the ANN

In this section, the quality of ANN to predict the hole inclination angle was tested in a geothermal field which is located in Büyük Menderes Graben. The well was drilled as J-type and kicked off from 880 m-MD and drilled directionally to 2394 m-MD by keeping the hole inclination at 20.5 degrees with a hole size of 8.5". As it was already explained in the methodology part of this paper, the accuracy of the neural network was tested with testing data. However, rather than using random test data, in this case the capability of the ANN to predict the hole inclination was tested for the entire well. During drilling, 62 surveys were taken by the MWD tool to follow the well trajectory and the developed ANN was tested 62 times in the same survey station points by using the same drilling parameters which had been applied by the directional driller during drilling this geothermal field. According to the results, the developed neural network is successfully predicting inclination of a typical inclined geothermal well in Büyük Menderes Graben from the beginning of inclination to the end. MSE value between actual inclination values and ANN predicted ones among 62 comparisons is 0.59 with an R^2 value of 0.9705 (Figure 7).

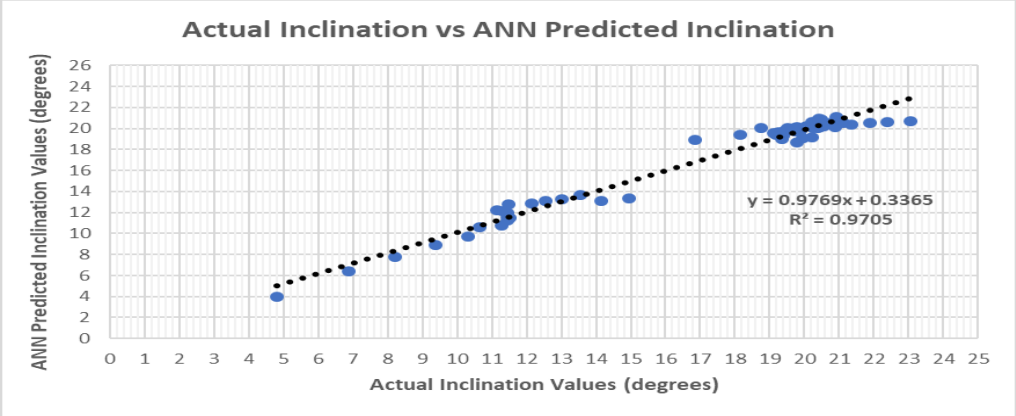


Figure 7: Actual Inclination Values vs. ANN Predicted Inclination values of the Case Study

3.3 Results of the Network when Parameters were Omitted

In the final part of this study, importance of the drilling parameters for the network were tested by comparing MSE values after removing them from the input dataset. According to the results of Table 5.6 it is clearly seen that, absence of IADC code and TFA gave the highest MSE value when the network was trained. Since these parameters were used as categorical data rather than continuous data in the network, first idea for the high MSE value without them was that, impact of categorical parameters on training accuracy is higher than continuous parameters. However, when the other two categorical parameters, which are hole size and motor bend, removed from the dataset it was seen that accuracy of the network was not affected by the absence of these parameters. It was found out that removal of TFA, IADC and WOB from the dataset gives the highest MSE values. The reason of this result can be the high influence of TFA on hydraulics and jet impact force of the bit. Changes in hydraulics and jet impact force effect the drilling profile of the bit which creates different outcomes in inclination while drilling a directional well. Moreover, selection of the appropriate bit for the appropriate formation is also very important. For example, using a 5-series IADC bit for a soft formation does not give effective result when 3 or 4 series bits are used. Moreover, wrong bit selection not only effects the ROP but also effects the directional drilling parameters because the bit will wear faster when it is used in the wrong formation which creates an uncontrollable drilling environment for the directional driller. Since the MSE of the original network is 0.422 omitting the gauge of sleeve stabilizer data from the input dataset does not affect the network accuracy, which may be a result of using same diameters for many wells that cause repeated data. Similarly, removal of other drilling parameters from the dataset do not affect the network accuracy as much as it was expected. However, it should also be pointed out that, even though removal of these parameters is giving small MSE values, an ANN without these drilling parameters cannot be evaluated as inclination prediction tool by using real time data, which helps to optimize the drilling parameters for safer and more economical operations.

4. CONCLUSION

A back propagation layered feed forwarded ANN that consist of one input layer, two hidden layers and one output layer was proposed to predict the downhole inclination in directionally drilled geothermal wells that are located in Büyük Menderes Graben. The accuracy and quality of the developed ANN model that contains data from 12 previously drilled geothermal wells was tested with without depth data. The inclination prediction results of both scenarios were very satisfactory based on their training MSE results. Using this model effects of the drilling parameters, such as WOB, bit RPM, flow rate and pressure, on inclination were analyzed for 12.25” and 8.5” hole sizes without depth data. A similar analysis was carried out with different depth intervals to analyze their influences in detail. The accuracy of the model to predict the hole inclination was checked with a case study field which located in the Menderes Fault region. Rather than using random testing data, the model was trained to predict all the inclination values of one well from beginning to end that resulted less than 1% MSE value and R^2 of 0.97. Finally, the effects of input parameters of the model were investigated by making comparisons of MSE values after omitting them from the dataset. The results showed that, TFA and IADC have the highest influence on inclination along with the WOB.

In addition to theoretical contributions mentioned above, this study has also practical implications for the directional driller in the drilling field to predict the hole inclination by using the real time drilling data. Future studies should develop a model to predict both inclination and azimuth simultaneously which may give a chance to detect the position of the bit three dimensionally.

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