APPLICATION OF ARTIFICIAL NEURAL NETWORKS TO PREDICT THE DOWNHOLE INCLINATION IN DIRECTIONALLY DRILLED GEOTHERMAL WELLS

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APPLICATION OF ARTIFICIAL NEURAL NETWORKS TO PREDICT THE DOWNHOLE INCLINATION IN DIRECTIONALLY DRILLED GEOTHERMAL WELLS

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ABSTRACT

APPLICATION OF ARTIFICIAL NEURAL NETWORKS TO PREDICT THE DOWNHOLE INCLINATION IN DIRECTIONALLY DRILLED GEOTHERMAL WELLS

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Drilling directionally through naturally fractured geothermal reservoirs is a challenging task due to unexpected changes in inclination and azimuth of the well axis, which causes 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 was developed. The training dataset 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 (MSE) value which was measured to check accuracy and quality of each training. The MSE of the training data set is 0.42% and the neural networks predicts the testing data with 1.19% MSE value. According to the sensitivity analysis, it has been found out that as WOB, Bit Revolution Per Minute (RPM) and Stand Pipe

Pressure (SPP) increase, inclination increases. On the other hand, increment in flow rate leads to drop in inclination. Moreover, the result of the case study was 0.59% MSE which concludes that network is not memorizing the data. In addition, different ANN's were created by omitting some drilling parameters to analyze individual effects of each parameter on network accuracy. The results indicated that, Total Flow Area (TFA), International Association of Drilling Contractors (IADC) code and Weight on Bit (WOB) have the highest impact on network dataset when compared to other drilling parameters.

Keywords: Neural networks, directional drilling, inclination prediction, geothermal

ÖZ

YÖNLÜ SONDAJ YÖNTEMİ İLE DELİNEN JEOTERMAL KUYULARDA YAPAY ZEKA KULLANILANARAK TABAN KUYU EĞİMİNİN SAPTANMASI

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Doğal yollar ile kırılmış olan jeotermal rezervuarlarını yönlü sondaj yöntemi ile delmek çok zordur çünkü bu doğal kırılmalar sondaj esnasında kuyunun eğiminde ve azimutunda ani değişikliklere sebep olmaktadır. Bu ani değişimler matkaba iletilen ağırlığın yetersiz olmasına, sondaj hızının düşmesine, sondaj dizisini sıkıştırma olasılığının artmasına ve koruma borularının indirilmesi esnasında oluşabilecek sorunların artmasına yol açmaktadır. Sondaj esnasında kuyu eğiminde oluşabilecek ani değişiklikleri önceden tahmin edebilmek için bu çalışmada geri yayılımlı, çok katmanlı yapay zekâ modeli oluşturulmuştur. Modelin veri tabanı 14 tane sondaj parametresinin 7600 verisinden oluşmaktır. Bu veri tabanı daha önceden Büyük Menderes Graben'i bölgesinde kazılmış olan 12 tane jeotermal sondaj kuyusundan toplanmış olup her bir sondaj parametresinin kuyu eğimi üzerindeki etkisi hazırlanmış modeli kullanarak farklı senaryo ve farklı kuyu çaplarında incelenmiştir. Bunlara ek olarak, test edilen bir örnek kuyunun yönlendirilmeye başlandığı derinlikten son derinliğine kadar ki sondaj aralığında tüm 30 metrelik kuyu eğimi ölçümleri modeli kullanarak bulunmuş ve gerçek ölçümlerle karşılaştırılmıştır. Modelin doğruluğu ve kalitesini ölçmek için kullanılmış olan ortalama karesel hata verileri incelendiğinde bu çalışmada kullanılan yapay zekâ modelinin kuyu eğimini ölçmede çok başarılı olduğu ve sonuçların memnun edici olduğu görülmüştür. Sonuçlar incelendiğinde modelin kuyu açısını 0.42% ortalama karesel hata ile tahmin ettiği ve test

verisi kullanıldığında bu değerin 1.19% olduğu gözlemlenmiştir. Ek olarak, sondaj parametrelerinin kuyu eğimi üzerindeki etkisini detaylı olarak incelendiğinde, matkaba uygulanan ağırlık, matkabın bir dakikadaki devri ve basınç arttığında, kuyu eğiminin arttığı gözlemlenmiştir. Ancak, debideki artışın kuyu eğimini düşürdüğü görülmüştür. Örnek sondaj kuyusunun da kuyu eğimini 0.59% ortalama karesel hata ile tahmin ettiği görülmüştür ve modelin veri tabanını ezberlemediği sonucuna varılmıştır. Ayrıca, her bir sondaj parametresinin model üzerindeki etkisini incelemek için model sırasıyla bu parametrelerin veri setinden çıkartılması sonrasında çalıştırılmıştır. Sonuçlar incelendiğinde matkabın toplam akış alanı, IADC kodu ve matkaba uygulanan ağırlığın model üzerindeki etkisinin diğer parametrelere göre daha fazla olduğu gözlemlenmiştir.

Anahtar Kelimeler: Yapay zekâ, yönlü sondaj, kuyu eğimini tahmin edebilme, jeotermal

To My Beloved Family and My Wife

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NOMENCLATURE

ROP Rate of Penetration (m/hr)

DLS Dog Leg Severity (degree/30m)

RPM Revolutions per minute

WOB Weight on bit (tons)

SPP Stand pipe Pressure (psi)

$IADC$ International Association of Drilling Contractors

TFA Total Flow Area (in^2)

PDM Positive Displacement Motor

MWD Measurement While Drilling Tool

BHA Bottom Hole Assembly

MSE Mean Square Error (%)

$RMSE$ Root Mean Square Error (%)

R Correlation Coefficient

HS Hole Size (inch)

TVD True Vertical Depth (meters)

MD Measured Depth (meters)

A Azimuth (degrees)

AZ_1 Azimuth at upper survey point (degrees)

AZ_2 Azimuth at lower survey point (degrees)

I Inclination (degrees)

I_1 Inclination at upper survey point (degrees)

I_2 Inclination at lower survey point (degrees)

KOP Kick off Point (meters)

N Nozzle Size (1 / 32 of an inch)

G_x Gravitational Strength at the x-axis

G_y Gravitational Strength at the y-axis

G_z Gravitational Strength at the z-axis

F Transfer Function in the Neural Network

b Bias Term

$w_i(k)$ Weight value in district time k

$x_i(k)$ Input value in district time k

α Momentum Factor

η Learning Rate Modifier

δ_j Factor depending on whether node j as an input node

$\Delta w_{ij}(t+1)$ Weight alter in epochs (I+1)

$\Delta w_{ij}(I)$ Weight alter in epoch in (I)

CHAPTER 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). Apart from higher ROPs due to the usage of mud motors, directional drilling has many advantages for the operator. Giacca (2005) stated that, with the help of directional drilling it is possible to reach deep mining targets even at an appreciable horizontal distance from the rig location. 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.

CHAPTER 2

LITERATURE REVIEW

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.

2.1 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). As it is understood from the purpose of drilling optimization, one of the main research parameters is the penetration rate. In 1974 Bourgoyne and Young proposed one of the most important studies related to drilling optimization. They demonstrated a relation between drilling rate and parameters that affect it by using linear drilling penetration rate model and select the optimized drilling parameters by performing multiple regression analysis. Optimization in drilling industry is not always related to ROP. Operator can also save money from the other disciplines in drilling. In fact, one of the early drilling optimization methods, which was established by Graham and Muench in 1959, was about the downhole rotary speed and weight on bit combinations to derive empirical mathematical expressions for bit life prediction.

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.

2.2 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 2.1.

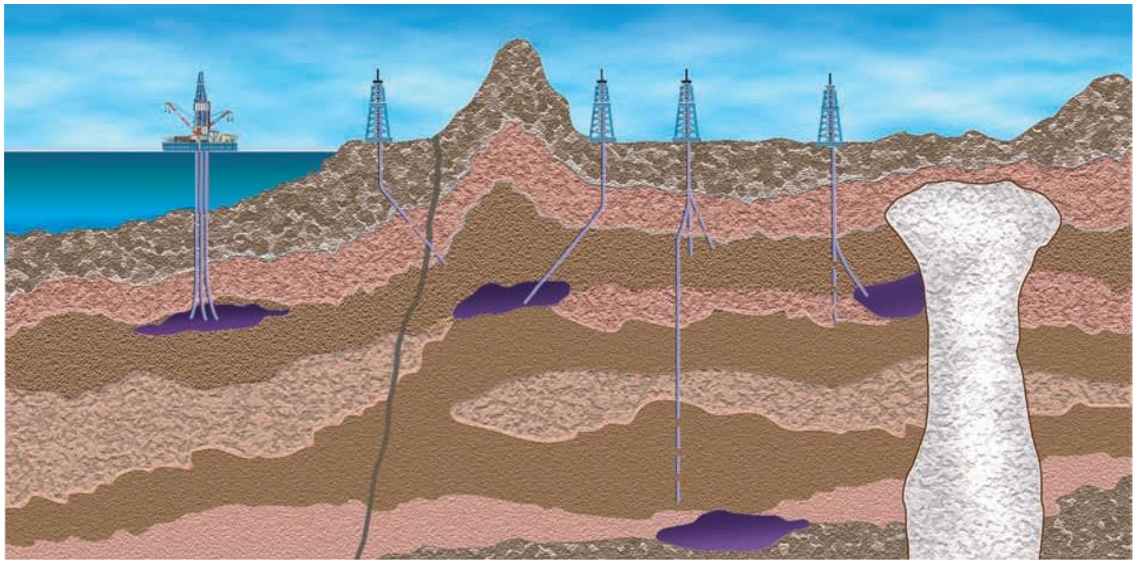

Figure 2.1: Applications of Directional Drilling (Giacca, 2005)

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.

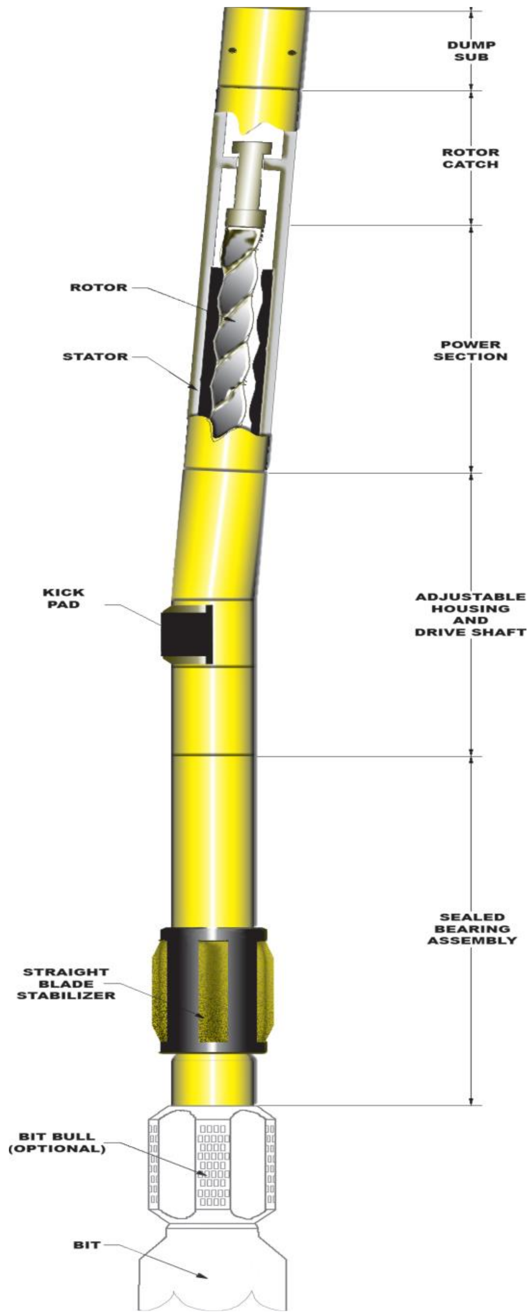

Figure 2.2: Configuration of Positive Displacement Motor (Cougar Drilling Solutions, 2012)

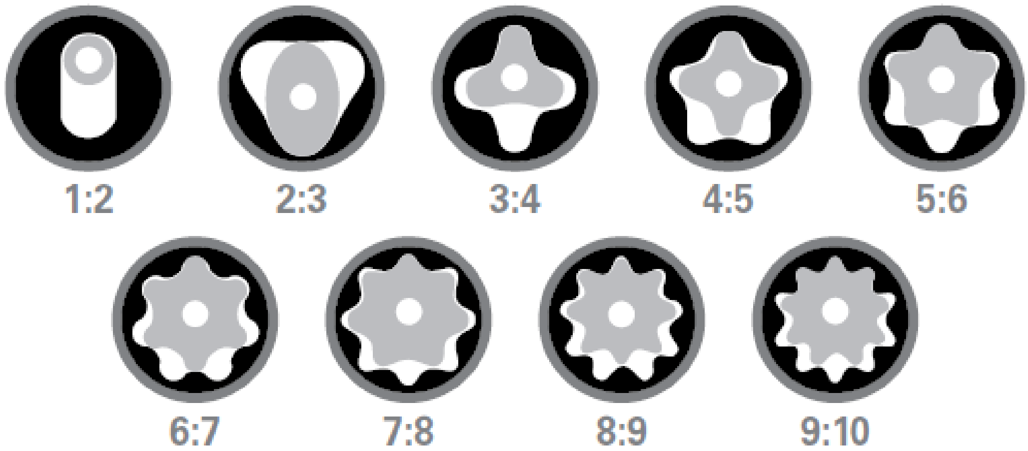

Figure 2.3: Illustration of Rotor/Stator Lobes Configuration (SperryDrill Technical Information Handbook, 2009)

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).

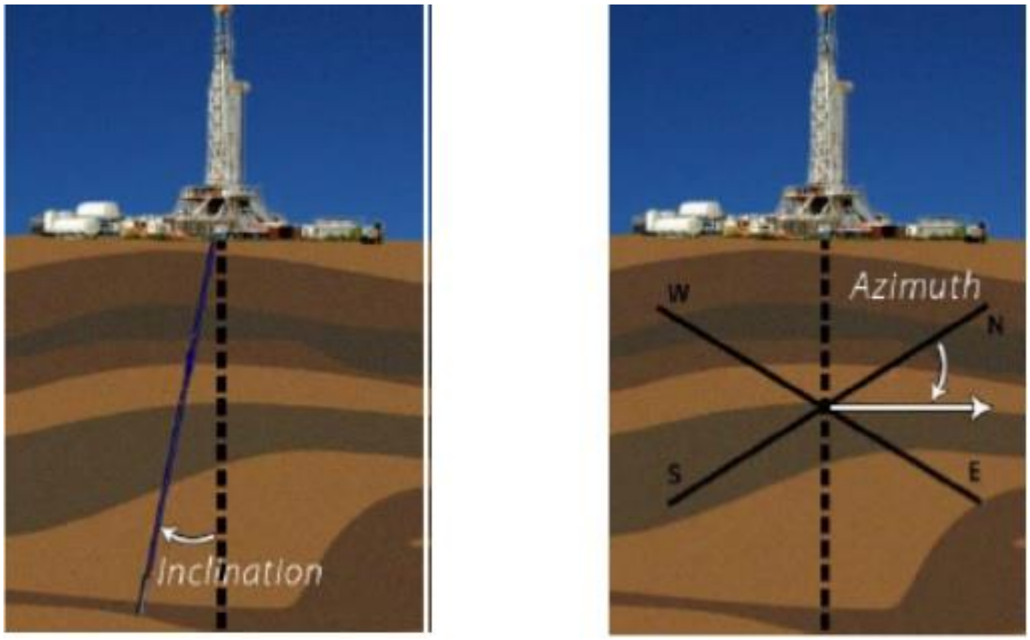

Figure 2.4: Visual Illustration of Inclination and Azimuth (Fouad, 2012)

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. 2.1) (Illfelder et al., 2005).

$$Inclination = \arctan\left(\frac{G_z}{\sqrt{G_X^2 + G_Y^2}}\right) \tag{2.1}$$

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. 2.2), and high tortuosity in the wellbore which can lead to missed targets, stuck pipe and problems in running casings (Skillingstad, 2000).

$$DLS = \{\cos^{-1}[(\cos I_1 \; x \cos I_2) + (\sin I_1 \; x \sin I_2) \; x \cos(Az_2 - Az_1)]\} \; x \left(\frac{100}{MD}\right) \tag{2.2}$$

where, I_1 and I_2 are the inclination angles at first and second survey points and Az_1 and Az_2 are the azimuth directions at first and second survey points. Finally, MD corresponds to the measured depth between survey points in terms of feet.

To overcome this problem, Lesso et al (2001) described a technique to predict the real time directional tendency of the Bottom Hole Assembly (BHA). He used continuous inclination, direction and tool face information from a MWD tool or Rotary Steerable System (RSS) to predict the drilling system. With the help of the surface systems, downhole and surface drilling data, which were surface and downhole WOB, surface and downhole torque, hook load, bit RPM, ROP, azimuth and inclination at the bit, were received continuously. To predict the tendency of the BHA he used a numerical model that contains weight, dimensions, internal and external diameters of the drill string and BHA. Moreover, he added the position and gauge of the stabilizers, borehole geometry, casing information and the gauge and hole size as a function of depth. Finally, for proper inclination measurements he used the relative location of the DNI with respect to the bit. In order to avoid noisy data for his numerical model, a pre-processing module was used. When all these real-time data are used as an input, bit anisotropy index, formation stiffness and hole enlargement are calibrated by the model. When the model parameters are calibrated continuously, a prediction is made of the expected build rate for the next meters to be drilled and present the projected trajectory. Thus, slide and rotate sequences can be optimized by the directional driller before severe drilling problems occurred.

Menand et al. (2016) presented a drill string model to figure out the borehole tortuosity and evaluate the down hole drilling efficiency in a better way. He used continuous survey measurements to evaluate the wellbore trajectory since standard minimum curvature approach links two survey points which are 30 meters away from each other and misleads the directional driller about the smoothness of the well. For the continuous survey measurements, a new technology MWD probe was used and to predict the BHA tendency a 3D Rock-Bit-BHA model was prepared. He used two main parameters to describe the bit behavior, bit steerability and walk angle. He calculated the bit steerability as the ratio of lateral versus axial drillability since steerability is the main parameter of the bit's ability to build or drop angle at a specified formation. He described the walk angle (ώ) as the angle between bit side force direction and the direction of lateral displacement of the bit. He used step-by-step approach to calculate the deflection of BHA at different bit depths with a reference of 1 ft. step length. As all these parameters were entered to the model, he found the calculated wellbore trajectory, caught the unexpectedly local dog legs which eliminates high levels of torque and drag, and reduced tortuosity.

Similarly, Lowdon et al. (2015) used a finite-element drill string model to analyze the wellbore tortuosity by comparing between standard 30 m. (90 ft.) surveys and high-resolution continuous surveys in different drive mechanisms. The aim of his study derived from the uncertainty of 30 meters spacing between surveys because especially in highly deviated and interbedded formations high differences in survey points may create severe changes in inclination and azimuth that lead to high levels of tortuosity and vibration while drilling. Eighteen wells with different trajectories and drive mechanisms were selected for analysis and they were evenly distributed between rotary steerable systems, high DLS rotary steerable systems and positive displacement mud motors. Final narrowing down process categorized the wells in terms of build, tangent and actively geosteered lateral sections. The High-Density Survey (HDS) software was designed to combine the continuous and static survey data from MWD tools and use the bending moment (M) for the evaluation factor of tortuosity rather than DLS. He used a Finite Element Analysis drilling dynamics software platform to use all these data for plotting and evaluating of bending moment in lateral planes in the wellbore. By using this software combinations rotary steerable system gave the benevolent result in terms of total tortuosity.

Pastusek et al. (2005) developed a fundamental model for the hole curvature prediction and BHA behavior on measured bit response in a directionally drilled well. In his study, he emphasized on accurate prediction of achievable bit-BHA build rate. To measure this, he combined the results of laboratory study that he designed with a finite element model. In his laboratory, he developed an artificial drilling system with PDC bit, bearing collar and drill stem. The system was fixated to apply a side load to the bit while drilling into rock samples from Cordova, Gabbro and Carthage limestones. His outputs were, depth drilled, torque, WOB and lateral deflection and by using these data he made a plot of depth drilled versus lateral displacement. By calculating the arctangent of the slope of the linear line in the plot, he found the bit tilt, which is the difference between axis of bit and borehole. Furthermore, he modelled the BHA with a finite element analysis software package to analyze various BHA scenarios. The output of the model was bit tilt and bit side force obtained by adding various parameters like stabilizer placement, diameter and gravitational effects. Once he measured the results, he plotted the data on the same axis with the bit response that he measured from laboratory testing. Resulting tilt at the bit calculated from the hole curvature and stiffness of the BHA. It defined the amount of side cutting capability. When the sign of the side force is below zero BHA has a dropping tendency and when it is above zero it has a building tendency. He then compared the formations based on their build rate vs steering force and found out that as the steering force increases with given drilling parameters build rate will increase in Cordova and Bedford formation all the time. On the contrary, Carthage formation build rate will be decreased after 25% steering force and start inclination will drop after 75%.

Muritala et al (2000) analyzed the use of near bit inclination on a different perspective. He compared the production performance of horizontal wells that had been drilled with standard MWD tools and the wells drilled with near bit inclination tool. His idea derived from the review of Kuchuk et al. (1998) study about performance evaluation of horizontally drilled wells. He believed that due to long snakelike, high tortuous well bores, cleanup is ineffective and many of the reservoirs produced below their potential. Moreover, according to the field studies of Lenn (1998) unpredictable changes in formation anisotropy creates tortuous horizontal wells which resulted in undulated well bores. In the long term, this undulation creates permanent water sumps that reduces oil entry and drop the inhibit performance about 30 to 50% of full potential. He believed that, a few feet variation from the sweet spot may lead to largely under-performing reservoirs and drilling without at-bit inclination measurement tool or model to predict the inclination and azimuth at interbedded formations will lead to this problem. To analyze this idea, he presented two field cases in Nigeria that had been drilled by Shell Nigeria and investigated the relationship between production performance and lateral profile. One of the wells drilled directionally with near bit inclination tool and the other one had already been drilled with conventional MWD tools. When the production rates of both wells were compared it was found out that in homogeneous reservoirs, the undulation, which caused by sudden changes in inclination and azimuth, had a significant effect on production rates due to frictional and pressure losses assuming all other conditions are same.

As it can be seen from previous studies sudden changes in inclination creates DLS and tortuosity that lead to severe drilling problems. Due to this reason, in most expensive drilling environments, such as offshore and deep-water operations, the RSS and near bit inclination MWD tools have almost replaced positive displacement mud motors with conventional MWD assemblies. However, these high technological and efficient drilling systems are not preferred in geothermal operations in Turkey due to their extremely high costs. Yet drilling through faults and interbedded layers with different formation anisotropies make this problem non-negligible and reveal the need of an optimization that will eliminate potential problems.

In order to predict the inclination at the bit while drilling directionally and optimize drilling without any high technological tools, selection of data for the analysis is very important. With the improvements in MWD tools and mud logging services, large amount of data from downhole is available for analysis. Each parameter that is collected from the rig site is very important for successful analysis. However, selection of quality data and eliminating noisy ones is the first important step for a quality and reliable optimization program. As it is mentioned before, in this study 14 parameters, hole size, start depth, end depth, depth of slide and rotary drilled, weight on bit, pressure, flow rate, downhole bit RPM, bit IADC, total flow area, adjusted motor bend, string and sleeve stabilizer outer diameter were used as input data. Finally, inclination values that were taken from 30 meter survey depth intervals were used as output for prediction. As the relationship between inputs and output variables is implicit, complex and nonlinear, Artificial Neural Network (ANN) modeling approach is used. It is superior compared to traditional statistical models for the predictions of linear or nonlinear multiple regressions.

2.1.1 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 superiority 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 2.5 a fundamental representation of ANN system is presented.

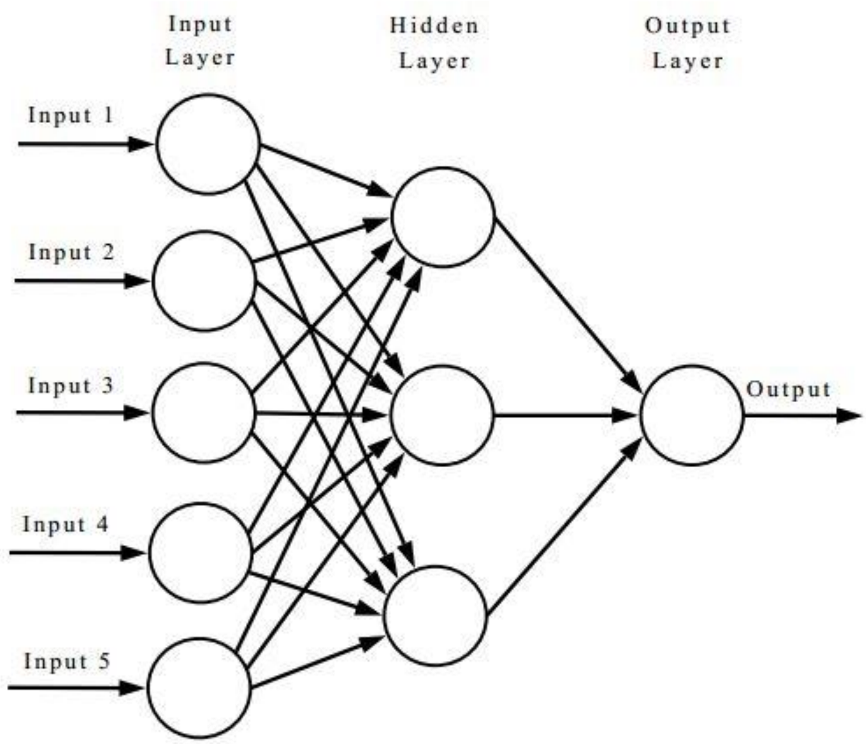

Figure 2.5: Representation of ANN system (Saputelli et al., 2002)

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 parameter 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.

ANNs have been used to solve and optimize many problems in petroleum industry in terms of exploration and production like reservoir characterization, drill bit selection, optimization of field operations and many more to reduce the total cost of the operations. Akhlaghi (2012), used an ANN model to optimize the drilling parameters in directional well and the rate of penetration. In his ANN model, he used depth, weight on bit, bit diameter, rotation per minutes, mud weight, formation pressure gradient, bit wear and nozzle impact force as inputs. He used the Bourgoyne and Young's equation (Eq. 2.3) for his model and calculations of the neural network were made in MATLAB software with the field data of 6 wells that are located in Ahwaz Field, Iran. By using the least square error method, percent error of network training, validation of the network was close to one. With the help of the ANN, operator found the best weight on bit and rotation per minute in their field over 300 real data.

$$ROP = F_1 * F_2 * F_3 * F_4 * F_5 * F_6 * F_7 * F_8 \tag{2.3}$$

Yilmaz, Demircioglu, and Akin (2002), used an ANN model for the optimum bit selection by using the data that were collected from a carbonate field located in southeast Turkey. The idea was to minimize the overall cost by improving drilling performance which is related with the appropriate bit selection in the appropriate formation. Generally, the classical way to select the optimum bit is based on the result of cost per foot (CPF) equation (Rabia, 1985) which affects the drilling economics, not the overall drilling performance. To analyze the performance, an ANN model with back-propagation layered feed-forward network that contained three layers was developed. Six parameters, sonic log, gamma ray log, depth, location and rock bit data, which was designated with IADC code were used as input data. In order to minimize memorization and over fitting problems, ANN was trained by layer-by-layer approach and a sigmoid function was used for feed forward calculations. By changing the momentum factor and learning parameter, model was adjusted based on the lowest total error. Apart from these two parameters, number of hidden layers and initial weights are also important for sensitivity analysis. As a result, a single hidden layer with 360 inputs, 0.20 learning parameter was developed to find the optimum rock bit for a well that will be drilled outside the known boundaries of the field and for wells within the known boundaries of the field. In the sensitivity analysis it was found out that, the model gives correct results in terms of formation hardness and slightly underestimated results for further rock bit details in the wells that will be drilled outside the known boundaries and propose reliable rock bit programs for a wildcat or exploration well to be drilled within the known and nearby field.

Similarly, Akin and Karpuz (2008) used ANN to estimate major drilling parameters for diamond bit drilling operations using a back-propagation layered feedforward network that consisted of an input layer, two hidden layers and an output layer. The input data was gathered from the six years of exploration drilling activities of Mineral Research and Exploration of Turkey (MTA) in Zonguldak hard coal basin at Kilimli, Bartın and Kandilli regions. For the analysis, bit load, bit rotation and mud pump circulation rates were used. Moreover, for rock mass classification, rock quality designation (RQD) methodology was used because geological information and compressive strength of the formation are very important for drill bit selection. Since rock strength is not a direct measurement and it is a derived parameter using the theory of elasticity sonic logs from these wells fails to define this parameter. The RQD is defined as the cumulative length of core pieces higher than 10 centimeters in a run divided by the whole length of the core run (Eq. 2.4).

$$RQD = 100 \frac{L_1}{L_2} \tag{2.4}$$

The final input of the study is the discontinuity frequency index (DFI) which is found by counting the number of fractures per unit length and it was used to define the quality and expected behavior of the rock masses (Zhou & Maerz, 2002). In order to minimize memorization and over fitting problems in the network, layer-by-layer training approach was used. To check the network accuracy 10% of the data, which were randomly selected, were kept during the training process and called as validation data. To minimize the total error, two hidden layers were used even though it may create local minima or difficult training process. The results of the study stated that as RQD increased ROP increased but decreased as DFI increased. It was reported that the most important parameter that affects the ROP is elastic limit and ultimate strength of the formation. On the other hand, mineral composition of the formation has a significant effect on ROP. As a result, a new approach for the estimation of RPM, bit load and ROP in diamond drilling operation with promising and accurate results for increasing compressive strength but non-abrasive formations was developed.

Bataee et al. (2010) compared artificial neural network and other methods in terms of bit optimization based on log analysis applied in Shadegan Oil Field. Latest analysis of bit selection was made from sonic and other lithology logs to estimate the rock compressive strength. However, the disadvantages of using logs and complexity of drilling parameters, increase the necessity of ANN model for bit selection in drilling industry. In the first model, the bit was selected based on the desired ROP. Bit size, total flow area, depth in, depth out, drilling interval, WOB, RPM, ROP, flow rate pressure and average unconfined compressive strength of formation (UCS) were used as inputs and IADC of the bit was used as output. Among the other architectures 3 layered back propagation feed-forward algorithm showed the lowest error where 60% percent of the total 1200 sets of data from five wells had been used for the training, 20% of the total data had been used for the validation process and the remaining 20% had been used for testing of the model. The results of the network were compared with the results that had been gathered in log analysis. The results indicated that, ANN can estimate third digit of IADC while log analysis can only find first two digits. The general analysis indicated that as depth is increasing, ROP values are decreasing due to increasing compressive strength of the formation. Log analysis was found the IADC code 22 which was same with ANN.

Bilgesu et al. (1998), presented an ANN model that predicted the bit tooth and bit bearing wear for tricone bits under different operating conditions. The study used 8000 field measured and simulated data that were recorded using a rig floor simulator to understand the wear in tooth and bearings during drilling since the only option to analyze the bit condition when pulling out of hole is finished. Three neural networks were modelled with three-layer feed forward back propagation architecture. First and second ANNs were modeled to predict bit tooth and bearing wears by using all available input data and the third network predicted both bit tooth and bearing wears at the same time while drilling. The inputs used in the model were, bit type, bit diameter, WOB, RPM, ROP, footage, formation type and the mud circulation rate and bit life in hours was selected as the output parameter in the model. The results of the network were very successful to predict the bit tooth and bit wear with 0.997 correlation coefficient (r). The results from the neural network that was used in the prediction of both bit tooth wear and bearing wear had correlation coefficients of 0.996 and 0.994 which were near perfect.

Shadizadeh et al. (2010), developed an ANN model for the prediction of differentially and mechanically stuck pipe problem in Iranian oil fields due to major drilling trouble cost for the drilling industry. The used feedforward back propagation architecture in their model. Similar to previous studies, sigmoid function was used as transform function and 8:1:1 partitioning ratio was considered for the neural data processing procedure. In other words, 80% percent of the total data were used as training data and the other 20% was divided into two for validation and testing data. The data consisted of 275 cases, 115 stuck and 160 non-stuck cases collected from Iranian oil fields. The stuck pipe cases were divided into two types, static and dynamic, based on the circulation of the drilling fluid. From 115 cases in the study, 40 of them was dynamic, whereas the remaining 75 cases occurred during static conditions, when there is no circulation. The problem was to narrow down the input parameters since introducing more input parameters to the model resulted in a large network size and gradually decreased learning speed and efficiency. Due to this reason, a new dimensionless parameter called Geometric Factor which is function of open hole length, bottom hole assembly length, outside diameter of the drill collar, hole size and inclination angle which are key factors for stuck pipe reasons, was defined. One final step before training was the normalization of inputs and targets for them to fall a specified range of 0 to 1 by using Eq 2.5 (Goda et al. 2005)which improved the network accuracy significantly.

$$X_n = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{2.5}$$

Where X_n is the normalized value and X_{max} and X_{min} are the minimum and maximum of original values and finally X is the original value. In order to eliminate the unnecessary parameters, different parameters were removed to check the accuracy of the network performance which reduced the parameters to six out of twelve with a very good accuracy. As a result, final architecture for dynamic case analysis was six inputs, three hidden layers and one output with sigmoid type activation function. On the other hand, static case analysis was made with six inputs, three hidden layers and one output with activation functions in hidden and output layers. Among 155 cases for dynamic condition, the ANN model predicted 149 correctly with 96% accuracy. Moreover, for validation and testing data the model gave 19 correct responses out of 20 cases. Similarly, for the static condition the network predicts the stuck pipe above 95% accuracy.

Bilgin et al. (2006) compared the performance of ANN method to predict the performance of conical cutters of rock samples with conventional statistical analysis. They developed multi layered perception ANN model consisting of three layers, input, hidden layer and output, to predict the cutting force, normal force and optimum specific energy from data that were gathered from rock cutting experiments, which measured uniaxial compressive strength, Brazilian tensile strength, Schmidt hammer rebound value, dynamic elastic modulus and static elastic modulus. Back propagation training algorithm was used in all models and root mean square error (RMSE) was utilized to evaluate the performance of the model. Then, estimated performance parameters of conical cutters from ANN model were plotted against measured values and RMSE of the model was compared with the errors of statistical regression analysis. The results were very promising for the ANN with less errors when compared to statistical model.

Wang and Salehi (2015) developed an ANN model for pump pressure prediction by considering formation parameters to diagnose major problems like, circulation problems, washout, underground blowout and kicks early. Twelve drilling parameters, which are torque, RPM, flow rates, active PVT, strokes speed of pumps, total pump speed, hook load, ROP, differential pressure and depth, were used as input and pump pressure was selected as the only output. Several networks were trained with increasing complexity using a learning subset of the training data that were collected from three oil wells and the training with the lowest validation error was selected. Seventy five percent of the data were used for network learning process, 15% was for validation and the remaining 10% was used for testing the network. The model architecture was three layered feed forward network coupled with back propagation algorithm and Levenberg-Marquardt training function for full connection topology. The performance of the model was evaluated using MSE and efficiency coefficient “R”. The results indicated that, the network can predict accurate pump pressure values and matched actual field data.

Elkatany et al. (2017) investigated the effects of mud properties on rate of penetration by using ANN. He developed his model by using 3333 data points from wells that were drilled in an offshore carbonate field. The data were collected from a real-time sensor that measures string rotation per minute, WOB, flow rate, standpipe pressure and drilling torque. In addition to these drilling parameters, drilling fluid density and plastic viscosity (PV) were used as inputs of the model. Among input data points, 2333 of them (70%) was used to train the ANN model. Moreover, the remaining 30% was used to test the model to predict ROP with a correlation coefficient of 0.993 and 5.6% average absolute error that corresponded to 0.99 coefficient of determination when the predicted ROP values were plotted versus real data. Furthermore, the model was compared with Bourgoyne and

Young Model and Maurer and Bingham models. The results of the comparison indicated that the ANN model outperformed published ROP models with much more accuracy.

Ozbayoglu and Miska (2002) developed an ANN model to analyze the bed height in horizontal and highly inclined wellbores. Since cutting transport is one of the main problems in horizontal drilling, knowing the amount of cuttings that creates cutting beds will minimize the risks of stuck pipe and controls the bottom hole pressure. Two statistical models were developed to estimate the height of the cutting bed. First one was traditional least-squares method and the other one was ANN. Both models used the same data that were gathered from dimensional analysis of pump rates, fluid densities, viscosity, drilling rate and wellbore geometry. By using these drilling parameters, three dimensionless groups, which are Reynolds Number, Froude Number and feed cutting concentration at the bit, were calculated and used as inputs of the model. The architecture of the ANN model was backpropagation feed-forward network with single hidden layer. The results indicated that conventional statistical model predicts cutting bed height less than 20% error by using least square method. On the other hand, the total error of the ANN model is less than 10% which was proven to be a successful tool for measuring the cutting bed height.

Salehi et al. (2009) modelled an artificial neural network to estimate the potential casing collapse for the current producing wells and wells to be drilled in large carbonate oil field located in Iran. It was reported that the field is producing from Asmari reservoir formation and the number of casing collapses at this field has been increasing since 1974 due to reservoir compaction, poro elastic effects and corrosion. Generally, reservoir compaction results in four different collapse mechanisms and bucking and shear mechanisms are the main collapse problems in Asmari formation. Moreover, there is high pressure saltwater in this formation which creates electro potential external corrosion. In this study ANN was developed to predict the expected collapse depth and the probability of casing collapse in the next five years. Latitude and longitude of the well, total depth of the well, corrosion weight factor, failure time factor and zone factor were selected as the inputs of the model. The structure of the network was five layers with back propagation neural network algorithm. The results of the network were very good with 5% error to analyze the relation between previous collapsed wells with collapsed depths.

Hegeman et al. (2009) presented an ANN model for Downhole Fluid Analysis (DFA) with the help of DFA-tool measurements of fluid composition to optimize the production strategies. Varotsis et al. (2002) pointed out that the use of simple correlations to provide single-points prediction of PVT properties gave relatively low accurate results. Due to this reason, an ANN model was developed to predict the gas oil ratio (GOR) using the data of DFA tool that can provide five component compositions, which are C_1, C_2, C_3-C_5, C_{6+} and CO_2 with mass fraction basis from 650 reservoir fluids from all around the world. Moreover, the data for the model had been improved in the laboratory with "derivative" fluids from intermediate steps of differential-vaporization studies for oil samples and depletion studies for gas condensates. As a result, the database of the model contained 1834 discrete samples. For the analysis of these samples, feedforward multilayer perceptron ANN model was selected and data were normalized with Eq. 2.4 to avoid numerical difficulties. For the training phase, the model used 80% percent of the total data at random training, 10% was used for calibration set and final 10% was used for validation of the model. The backpropagation method with a batch-learning algorithm and Broyden-Fletcher- Goldfarb-Shanno algorithm for optimization was selected for the analysis. The results of the model were very accurate with 1.6% mean relative error and 10.6% mean absolute error where conventional statistical was 23.2%. Moreover, to check the regional dependency of the model, its performance was examined in various geographic regions and the errors of the ANN GOR model indicated that it has no regional dependency and it can be used all around the world.

Similarly, Al-mashhad et al. (2016) investigated average oil flow rate of 29 different multilateral wells by using ANN. Multilateral wells are defined as wells that has more than one branch radiating from the mother bore which allows higher drainage of reservoirs and increases production of reserves with the combination of multiple targets. An ANN was modelled to calculate the average oil flow rate from a group of 174 data sets that were collected from an onshore field in Middle East. Effective length, open-hole size, choke size, reservoir pressure, flowing wellhead pressure, average permeability and number of laterals were used as inputs of the model. Gradient Descent with Adaptive Learning Rate Backpropagation algorithm was selected for the architecture of the model to calculate lateral average oil rate. Among these data sets, 70% of it was used for the training and the remaining 30% was used for testing and validation of the model. Moreover, in order to quantify the effectiveness of the ANN method, Borisov's correlation for single phase oil multilateral well has been utilized for comparison. Furthermore, the results of both models were evaluated using statistical error analysis by calculating correlation coefficient and overall error from actual field data. The results indicated that, while the errors in Borisov's correlation reached to more than 50% with a coefficient of 0.3, same parameters were close to exact in ANN with 0.97 and 7.85%.

Sadiq and Nashawi (2000) developed an ANN model to predict the formation fracture gradient by using the actual field data from several fields. His idea was derived from the well problems, which are lost circulation and kicks that leads to blowout, while drilling. In order to obtain best result, two ANN models were created with different architectures, which were Back Propagation Neural Network (BPNN) and the General Regression Neural Network (GRNN). Among several training algorithms, Levenberg-Marquard algorithm was used for BPNN architecture due to its faster convergence and two hidden layers were selected to avoid learning algorithm to be trapped in local minima. On the other hand, for the GRNN architecture, which is based on non-linear regression theory, four layers were used. The input layer, the pattern layer, the summation layer and finally the output layer. The activation function was radial basis function, which is typically Gaussian Kernel function. For BPNN model, depth, overburden stress gradient and Poisson's ratio were used as inputs while the output was the fracture gradient. 90% percent of the total data was used for the training and the remaining 10% was used for testing. However, the result of the BPNN model gave 47% absolute error which led to define it as failure. On the contrary, the GRNN model was predict the fracture gradient within 6% error that provides a reliable and a practical alternative for the prediction of the fracture gradient.

CHAPTER 3

STATEMENT OF THE PROBLEM

The main objective of a successful directional drilling operation is to hit the given targets within the least time and at a minimum cost. Especially drilling in highly faulted geothermal reservoirs, controlling the wellbore trajectory is very difficult due to sudden changes in the directional parameters, which is the main reason of severe drilling problems, like stuck pipe, excessive torque and drag forces and problems in running casings.

The aim of this study is to develop a back-propagation ANN model, which will predict the downhole inclination by using real time directional drilling parameters. For this purpose, the inclination values and drilling parameters of 12 directionally drilled geothermal wells, in several geothermal fields located in Büyük Menderes Graben are used in the program data set. More than 16000 meters of drilling data were divided into 30 meter intervals for proper and accurate optimization, which was quantified by MSE value. Moreover, the influence of each drilling parameter on the model was investigated. Finally, sensitivity analysis of each drilling parameter was conducted in every 100 meters with respect to hole inclination to analyze the effects of each parameter on hole deviation.

CHAPTER 4

METHODOLOGY

The main purpose of this study is to propose an ANN modeling approach to determine the hole inclination during directional drilling operations of geothermal wells located in Büyük Menderes Graben. The aim of this chapter is to give information about the location where data were collected and describe the inputs of the model that were gathered from the surveys, daily drilling reports and daily parameters sheet of 12 directionally drilled J-Type geothermal wells. 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 (Table 4.1). Each parameter was divided to 30-meter sections which is the differences between two survey points. Moreover, in this section the architecture and the training mechanism of the neural network model is explained.

4.1 Location

According to the geological studies, most important geothermal reservoirs of Turkey are located in the Büyük Menderes Graben which is located on the active Alpine Himalayan tectonic belt (Tureyen, et al., 2014) (Figure 4.1). The field was discovered by General Directorate of Mineral Research and Exploration in 1968 and since then the field is developing by several drilling operators (Tureyen et al., 2014).

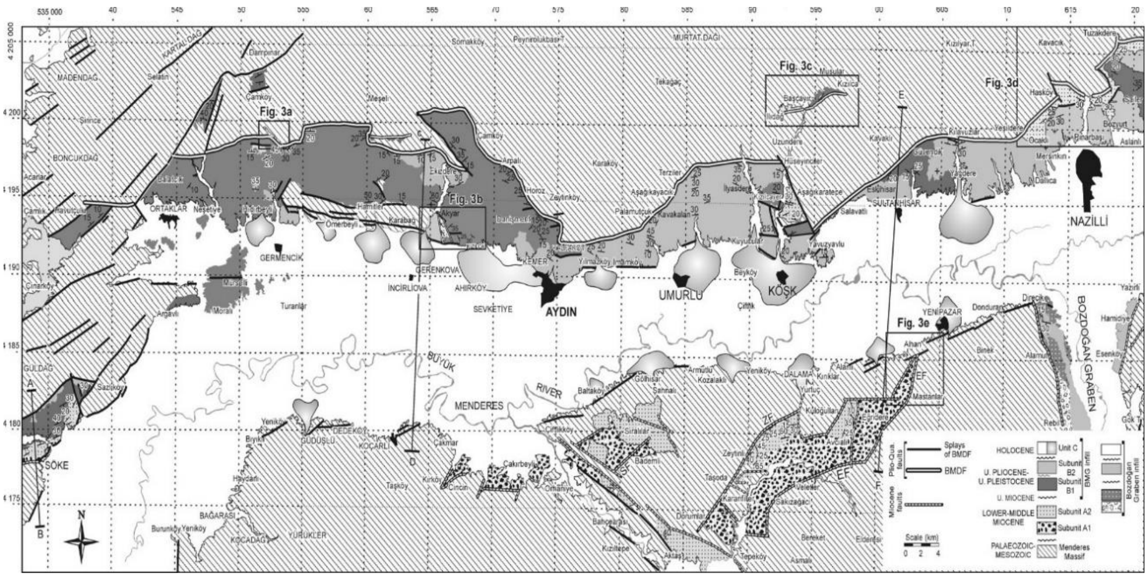

Figure 4.1: Geological map of Büyük Menderes Graben (Gürer et al., 2009)

According to the Gürer et al., (2009), Büyük Menderes Graben is bounded to the north and to the south by the Menderes Massif metamorphic rocks that forms an arc-shaped structural pattern as can be seen in Figure 4.1. Lithology logs from past drilling data stated that, the field consists of two reservoirs that composed of sandstones and conglomerates in the shallow reservoir and gneiss, marble and schist in the deep reservoir (Tureyen et al., 2014). Moreover, Yal et al., (2017) stated that, marble layers in the deep reservoir considered as the reservoir rock and the schistic levels serve as the cap rock. A sample lithologic log of a well drilled in this reservoir is shown in APPENDIX A (Şimşek, 1984) and a sample J-Type well profile is presented in Figure 4.2.

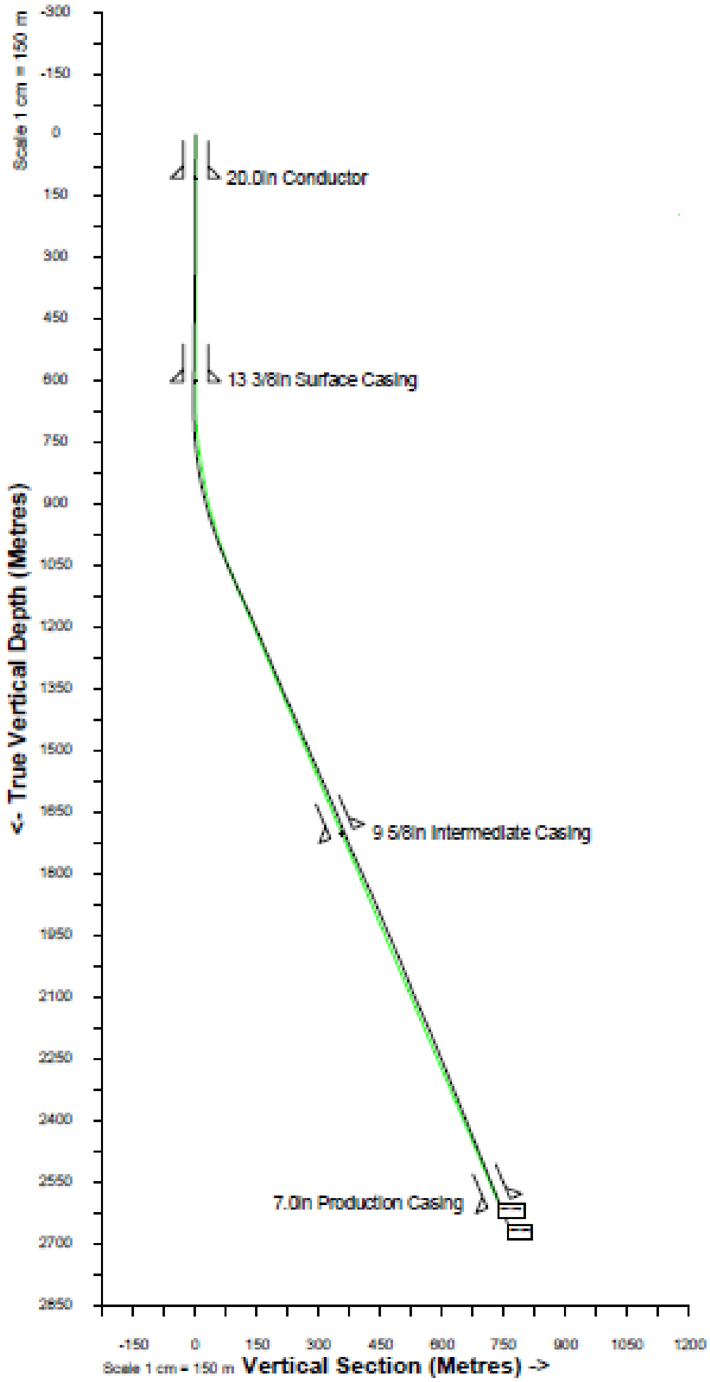

Figure 4.2: J-Type Directional Well Profile

4.2 Input Data

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 (Table 4.1). Each parameter that is collected from the rig site has a big impact on the overall optimization and prediction process. Also, the success of inclination angle prediction and directional drilling optimization depends on the quality and reliability of the input data. Due to this reason, brief description of these parameters should be made.

Table 4.1: Model inputs

Hole Size (inch)	WOB (tons)
Start Depth (m.)	TFA (in^2)
End Depth (m.)	Bit RPM
Footage of Rotary Drilled (m.)	Bend degree of the Motor
Footage of Slide Drilled (m.)	Bit IADC
Flow rate (gal.)	Gauge of String Stabilizer (inch)
Stand Pipe Pressure (psi.)	Gauge of Sleeve Stabilizer (inch)

Hole Size: Hole size, which can also be stated as the bit size, is the diameter of formation to be drilled. As the drilling continues to the deeper sections, hole size becomes smaller. Four different hole sizes from top to bottom 26",17.5",12.25" and 8.5" are usually used in the geothermal wells. Since the 26" and 17.5" hole sizes are nearly at the surface level, there are no directional drilling operations at these hole sizes. That's why the data set consists of two particular hole sizes, 12.25" and 8.5".

Start Depth & End Depth: Start depth denotes the depth where the directional drilling operation commences. Since the drilling data of each well is divided into 30 meter intervals, start depth corresponds to the beginning of the corresponding 30 meter section and end depth denotes the final depth of the 30 meter interval. For example, if one of the wells were drilled 1200 meters directionally, there will be 40 rows of start depth and end depth, like 0-30, 30-60, 60-90 and continues to 1200 meters.

Footage of Rotary Drilled: Footage of rotary drilled corresponds to the amount of rotary drilled within the 30 meters interval. The ratio between slide footage and rotary footage is decided by the directional driller. In order to avoid big DLS values directional driller may increase the footage of rotary when compared with the slide if strong rotary tendency had not been observed. One other reason is to give more rotary than slide is drilling through hold section. The objective of a directional driller is to continue with rotary as much as possible in the hold section where inclination and azimuth values should be same. In other words, if the directional driller decides to continue with rotary in the hold section, it means that directional drilling parameters are close to the plan and sliding is not required for correction.

Footage of Slide Drilled: Similar to previous input, footage of slide drilled denotes the amount of slide drilled within the 30 meters interval. Especially while drilling the build section and facing aggressive directional tendencies, the value of this parameter can be increased by the directional driller. Having too much slide intervals may decrease the ROP, increase the risks of getting stuck and increase the torque and drag in the hole (Skillingstad, 2000).

Flow rate: Flow rate is defined as the volume of mud that is pumped to the drill string and annulus from rig pumps. It is also a very important parameter for directional drilling since MWD and PDM have minimum and maximum flow rate limits for optimal and beneficial operation. Since most of the MWD systems in directional drilling industry are Mud Pulse Telemetry systems (Duplantis, 2016), which generate pressure pulses in the mud system, pumping the optimum flow rate for good signal is very crucial. Moreover, working within the optimum flow rate ranges will increase the performance and lifetime of PDM which creates higher ROPs. In this study, the unit of flow rate is represented as gallons.

Stand Pipe Pressure: Standpipe pressure is the total pressure loss in a system which occurs because of fluid friction (Chowdhury and Rahman, 2009). In drilling, standpipe pressure is the summation of pressure loss in the annulus, pressure loss inside the drill string, pressure loss across the bit and finally the pressure loss in the bottom hole assembly. Its general equation is described in Eq. 4.1.

$$\begin{aligned} SPP = {} & Pressure\ Loss\ Across\ the\ Surface\ Installations \\ & + Annulus\ Pressure\ Loss + Drill\ String\ Pressure\ Loss \\ & + BHA\ Pressure\ Loss + Pressure\ Loss\ Across\ the\ Bit \end{aligned} \tag{4.1}$$

As it can be seen from the Eq. 4.1, SPP depends on the drilling parameters such as TFA, Flow rate, WOB and mud properties. It is an important drilling parameter for the selection of bit nozzles, pump liners and required flow rate determination for the proper hole cleaning, which will minimize the risk of stuck pipe.

Weight on Bit: Weight on Bit (WOB) is defined as the amount of downward force that applied onto the bit. In vertical drilling, WOB is calculated from the subtraction of hookload from the string weight, however when the well is drilled directionally this equation cannot be used due to wellbore friction (Lei, 2014). Due to the friction between drillstring and the wellbore, applying the required WOB is more difficult in directionally drilled wells. It is applied by the driller and it is expressed either in tons or kilo pounds. In this study WOB is denoted in tons.

Total Flow Area: Total flow area (TFA) is summation of nozzle areas where the drilling fluid passes through. Bit nozzles are manufactured with a maximum diameter of 32 inch and can be adjusted according to the hydraulics and maximum allowable stand pipe pressure. TFA is calculated from Eq. 4.2.

$$Total\ Flow\ Area = \frac{N^2}{1303.8} \tag{4.2}$$

Where;

N: Nozzle size in number/32 inch

For example, if a tricone bit that has 3 nozzles with 16/32 inch is used in drilling, its TFA will be;

$$Total\ Flow\ Area = \frac{16^2 + 16^2 + 16^2}{1303.8} = 0.589\ inch^2$$

Bit RPM: RPM is the abbreviation of revolutions per minute which is defined as the amount of time the bit rotates in one minute. In other words, when there is no PDM in the BHA, RPM stands for the rotational speed of the drill string. However, with the enhancement of the mud motors, bit is not only turned from the surface, but also turned from the drive shaft of the mud motor. Apart from directional drilling, PDMs are also used for better drilling performance. As it is mentioned before, power section converts hydraulic power into rotary motion. When the drilling fluid is pumped through the stator, it creates a pressure drop across the cavities, causing bit to turn. Each PDM has its own rev/gal constant, which varies from their sizes and configuration. In this study, two motor sizes were used for three different hole sizes. Sizes of the motors are 8" and 6.5" respectively and their revolutions per unit volume constants are; 0.166 rev/gal and 0.292 rev/gal.

For example, a 6.5" Mud Motor with 6-7 Lobe and 5.0 Stage has 0.292 rev/gal constant and if the working drilling parameters are 450 gallons flow rate and 40 RPM from the rig, downhole bit RPM with this motor will be;

$$Bit\ RPM = 40\ RPM + (0.292 * 450) = 171.4\ RPM$$

Bend degree of the Motor: Bend degree of the motor is configured from the adjusted rings which connects the stator to the housings of the bearing assembly. Bend of the motor, which varies from 0 to 3 degrees, can be adjusted at the rig site according to build rates of the well plan. As bend increases build rate output of the motor increases. However, using bends higher than 2 degree creates large DLS values in rotary mode and generally used for horizontal drilling. In this study, PDMs between 1.27 degree and 1.5 degree were used.

Bit IADC Code: IADC is the abbreviation of "International Association of Drilling Contractors", where milled tooth and insert type roller cone bits are classified (http://www.iadc.org/). The IADC Roller Cone Bit Classification Method is a four-character long design and application related code, which makes it easier for drilling engineers to decide what kind of bits should be used for the projected drilling operation. The first digit of the code refers to the series of the bit, which defines the general formation characteristic and separates millet tooth and insert type bits. Series from 1 to 3 refers to milled tooth bits and series 4 through 8 is applicable to insert types. As the code number increases, application of the bits for harder and abrasive rock type increases. In other words, series 1 through 4 represents the softest and easiest drilling application for milled tooth and insert bits. Also, series 3 and 8 stands for the hardest and most abrasive application for milled tooth and insert bits. The second digit in IADC code is the further breakdown of formation with 1 being the softest and 4 the hardest. Third digit will classify the bit according to its bearing design and gauge protection, which classifies from 1 to 7 based on their configuration. Finally, the last category is a letter rather than a number and it corresponds to the definition of features available which considered to be an optional.

Gauge of String and Sleeve Stabilizer: These two parameters are defined as the diameter of the string and sleeve stabilizer. The main purpose of a stabilizer is to centralize the BHA in the borehole mechanically to avoid unintentional sidetracking, vibrations and excessive torque by reducing collar contact with the side of the hole. Moreover, it helps to transmit the weight of the BHA to the bit and minimize the risk of differential sticking. Above all, stabilizer is a very important tool for the effectiveness of the directional drilling operation. By varying stabilizer placement and diameter selection in the drill string, directional driller can adjust the forces acting on the bit, which results in additional help to increase, hold or decrease the inclination. Placing the variable stabilizer with the right gauge to the right place increases the build or drop rate of inclination 1° to 2° per 30 meters

(Skillingstad, 2000). Woods and Lubinski (1955) stated that, the optimum position and diameter of the stabilizer in the BHA depends upon the size of the collars, hole size, planned inclination and WOB. Moreover, Woods and Lubinski (1955) mentioned that, the most important factor that determines the directional drilling tendency is the bit side force. There are three main types of BHAs that controls the direction and magnitude of the bit side force, which are build assembly, drop assembly and hold assembly (Mantle, 2014).

A building assembly, which can also be stated as fulcrum assembly, is constructed by placing a full gauge stabilizer near the bit. When there is a PDM in the BHA, this type of stabilizer is called “Sleeve Stabilizer”. Moreover, by placing a string stabilizer 30 meters above the bit and sleeve stabilizer will exert a positive side force to the bit, which will build in inclination (Carden et al., 2007). There are several stabilizer placement examples for fulcrum assemblies in terms of their impact on building in inclination. These assemblies are illustrated in Figure 4.3.

On the other hand, to drop in inclination by using the help of stabilizers is called pendulum assembly where BHA stabilizers are placed 30,45, or 60 feet (9 to 27 m.) away from the bit. One other method to create a pendulum assembly configuration is using an under-gauge sleeve stabilizer and in gauge string stabilizer. With this BHA type, inclination will drop with the help of the gravity force in rotary. Other configurations to decrease inclination angle is also shown in Figure 4.3.

Finally, holding assembly is constructed by placing same gauge stabilizers closer, so that the collars are more rigid and bit side force is minimized (Mantle, 2014). Apart from fulcrum and pendulum BHAs, holding the inclination is very difficult especially in directional drilling without any sliding. Since in this study all wells were J- type, at the beginning of each well fulcrum assembly was used with one sleeve stabilizer near the bit and one under gauge string stabilizer above the motor, which was 10 meters away from the bit. While drilling through hold section, selected sleeve and string stabilizers diameters were very close to each other to minimize accidental deviation.

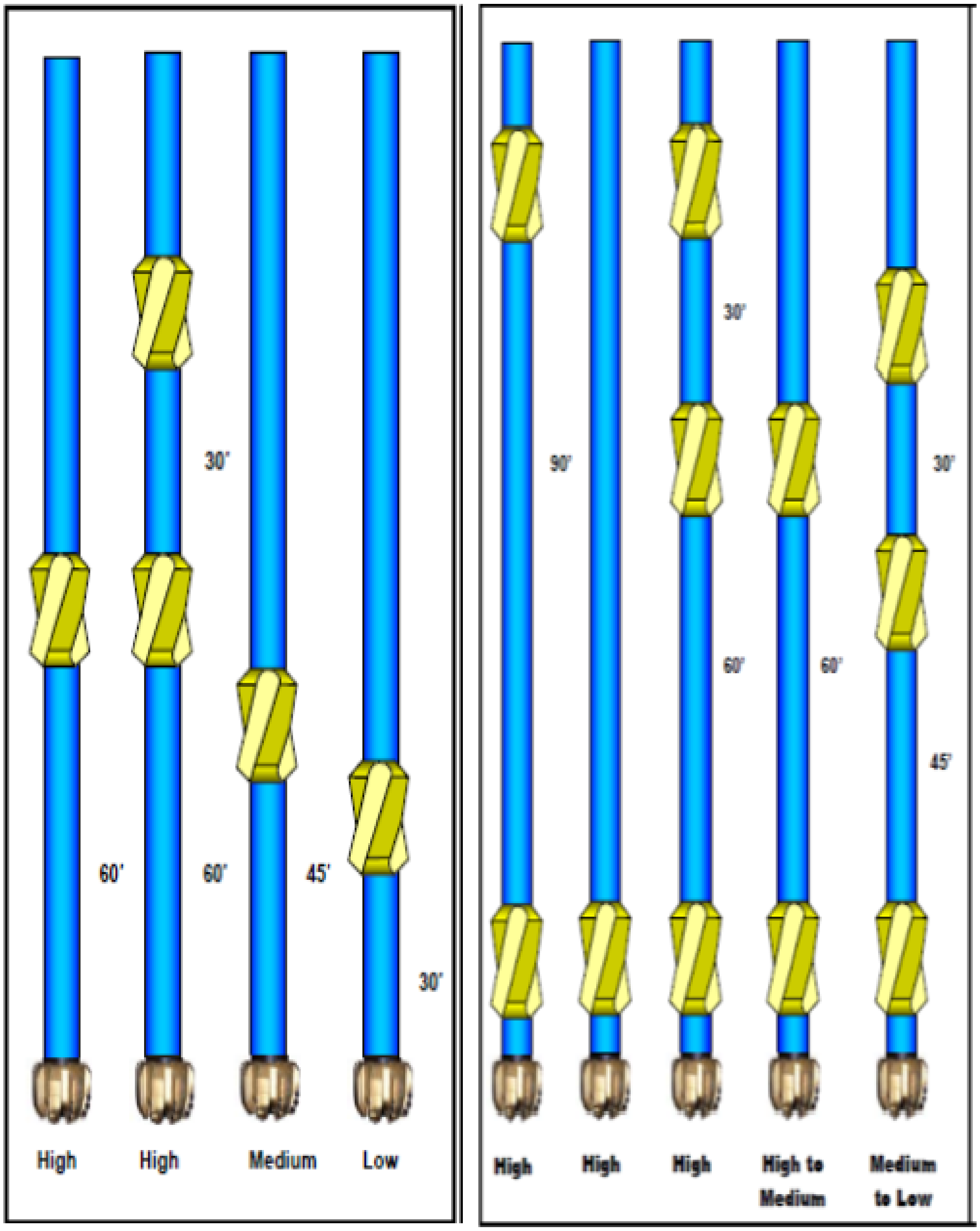

Figure 4.3: Dropping (1) and Building Assemblies (2) (Carden & Grace, 2007)

4.3 Model Development

As it is mentioned before, an ANN is a mathematical model which tries to simulate the structure and functionalities of biological neural networks. Similar to the biological neuron (Figure 4.4), where information is transferred by dendrite, processed by the soma and delivered it on by the axon, artificial neuron receives the information from inputs that are weighted, sum it with a transfer function and produce the output (Krenker et al., 2011) (Figure 4.5).

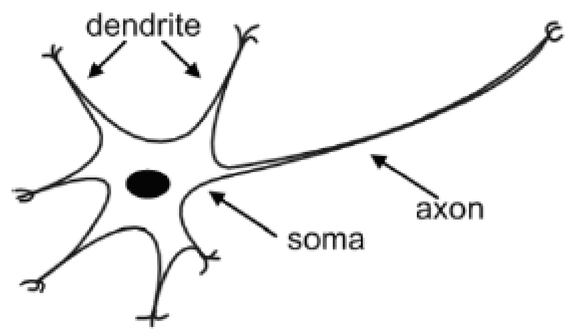

Figure 4.4: Biological Neuron Design (Krenker et al., 2011)

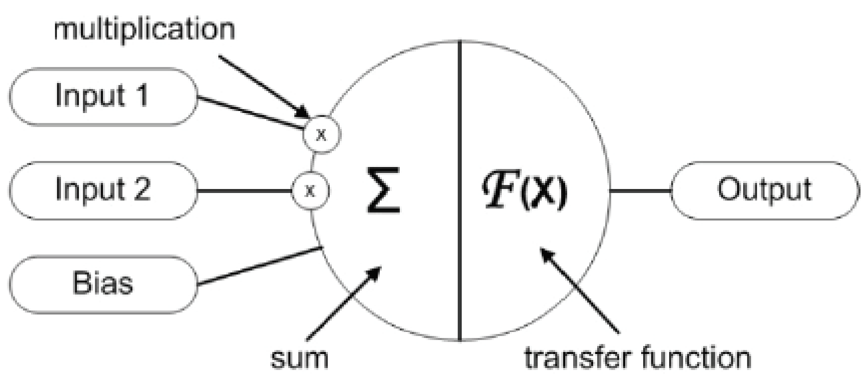

Figure 4.5: Artificial Neuron Design (Krenker et al., 2011)

Mathematical representation of Figure 4.5 is explained in Eq. (4.3).

$$(k) = F(\sum_{i=0}^{m} w_i(k) * x_i\ (k) + b) \tag{4.3}$$

Where $x_i\ (k)$ is input value in district time k where i goes from 0 to m, $w_i(k)$ is weight value in district time k where i goes from 0 to m, b is bias, F is the transfer function and $y_i\ (k)$ is output value in district time k.

In this study, the developed ANN is a back propagation layered feed forward network which contains four layers: input, two hidden and one output layer. Each layer connects with other layers with the help of weights and receives its inputs from the previous layer and forwards it to the output. As it can be seen from the Eq. (4.3), artificial neuron needs a transfer function to produce an output after an activation threshold is added to the sum. Generally, three types of transfer functions are used in ANN models, which are step function, linear function and non-linear (Sigmoid) function. The training function used in this study is, non-linear, logistic sigmoid function, that can also be stated as "squashing" function (Haykin, 2001).

4.3.1 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 4.6). 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. Mathematical background of the feed forward ANN is explained in Eq. (4.4) through Eq. (4.7).

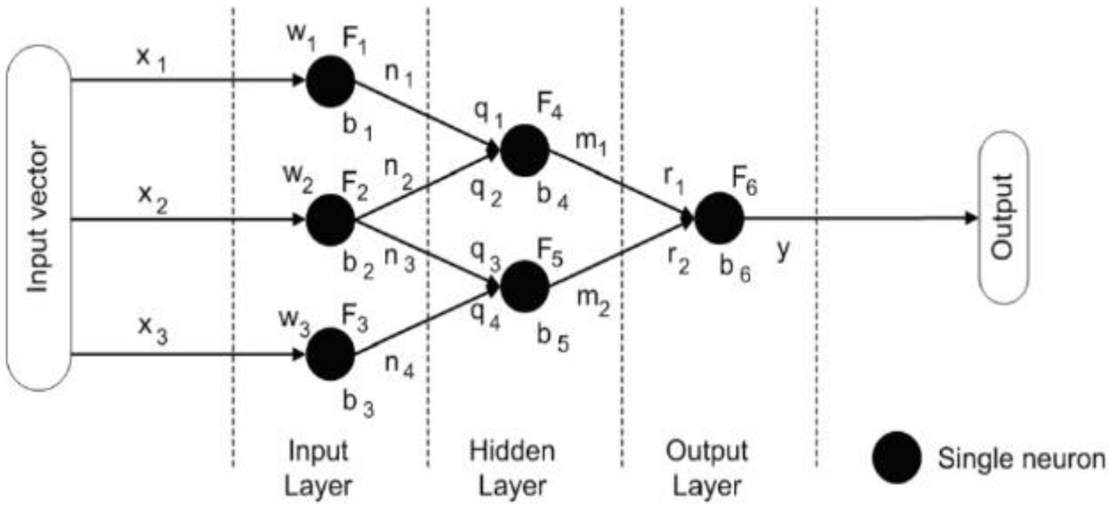

Figure 4.6: Architecture of Feed Forward Artificial Neural Network (Krenker et al., 2011)

$$
\begin{aligned}
n_1 &= F_1\,(w_1x_1 + b_1)\\
n_2 &= F_2\,(w_2x_2 + b_2)\\
n_3 &= F_3\,(w_3x_3 + b_3)\\
n_4 &= F_4\,(w_4x_4 + b_4)
\end{aligned} \tag{4.4}
$$

$$m_1 = F_4\,(q_1n_1 + q_2n_2 + b_4) \tag{4.5}$$

$$m_2 = F_5\,(q_3n_3 + q_4n_4 + b_5)$$

$$y = F_6\,(r_1m_1 + r_2m_2 + b_6)$$

$$
\begin{aligned}
y = F_6\big[\,F_4\,[q_1F_1[\,w_1x_1 + b_1] + q_2F_2[w_2x_2 + b_2]] + b_4\big)\\
+ r_2(F_5[q_3F_2[w_2x_2 + b_2] + q_4F_3[w_3x_3 + b_3] + b_5])\\
+ b_6]
\end{aligned} \tag{4.6}
$$

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 Eq. (4.6) 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).

4.3.2 Backpropagation

In this study backpropagation technique is used for the ANN model. 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.

4.3.3 Transfer Function

As it can be seen from Figure 4.5 and Eq. (4.3) 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 4.7) 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. (4.7) and Figure 4.7.

$$f(x) = \frac{1}{(1+e)^x} \tag{4.7}$$

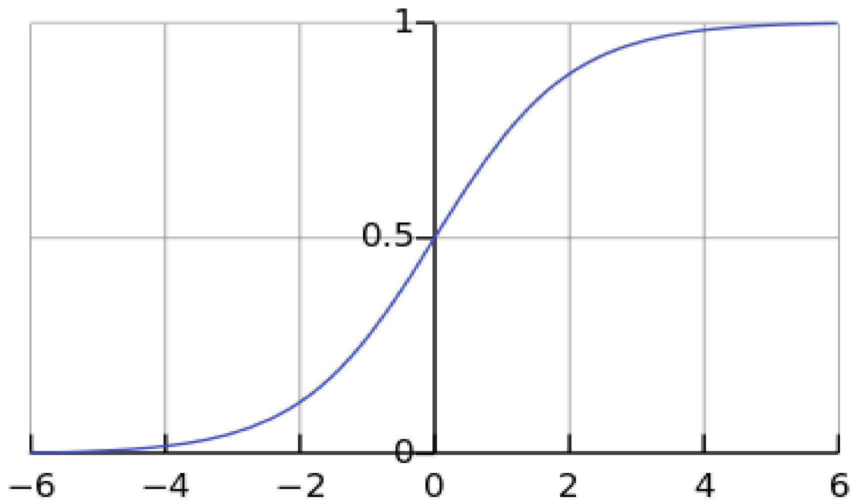

Figure 4.7: Log-Sigmoid Transfer Function Curve (Beale et al., 2015).

As it can be seen from Figure 4.7, log-sigmoid transfer function receives the input and squashes the output in the range of 0 to 1.

4.3.4 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 tth 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. Mathematical representation of this statement is presented in Eq. (4.8). Without momentum factor the network may get stuck in a shallow local minimum.

$$\Delta w_{ij}(t+1) = \eta\ \delta_j x_i +\ \alpha \Delta w_{ij}(I) \qquad (4.8)$$

Where, α corresponds to the momentum factor and η is the learning rate modifier, δ_j is a factor depending on whether node j as an input node, $\Delta w_{ij}(t+1)$ and $\Delta w_{ij}(I)$ are weight alters in epochs $(I+1)$ and (I).

4.4 Training of the Artificial Neural Network

As it is mentioned earlier, the developed ANN in this study is back propagation layered feedforward network which consist of an input, two hidden layers and an output layer. 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. Shadizadeh et al. (2010) mentioned that, in the training process, the desired output in the training set is used to help the network to adjust its weight between its neurons to minimize error. In other words, network weights which produce the minimum error are determined in the training section by the working principle of back propagation. Moreover, according to Elkan (2012), even though the portioning of validation set is different, it can also be regarded as a part of training set since it is usually used for parameter selection and avoid overfitting problems. Overfitting is a circumstance where the neural network has memorized the training example and fails to generalize on a new situation (Shadizadeh et al.,2010). It generally occurs, when data set for training is small. However, large and complex data sets may also cause overfitting problems due to noise in the data. There are several solutions to overcome the overfitting problems, which are adding more training examples, early stopping and regularization. If the network is over trained it will memorize the dataset and it will be incapable of making generalizations even though it perfectly fits. In 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 as explained in Eq.4.9. To sum up, training set is used to fit the parameters, validation set is used to tune the parameters and finally testing set assesses the performance of neural network model.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\widehat{X_i} - X_i)^2 \tag{4.9}$$

As can be seen from Eq. (4.9), MSE value is calculated from the differences in squares between estimated value and estimator. As the performance of the model to predict an output increase, MSE value decreases.

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 4.2 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 cycle is higher than 250 as can be seen in APPENDIX B. 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 4.2: 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

CHAPTER 5

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

5.1 Assumptions in the Network

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.

5.1.1 Drilling Conditions Assumptions

- The formation being drilled is considered to be homogeneous
- The components of the rig are calibrated and working efficiently

5.1.2 Network Dataset Assumptions

- Since the data used in the dataset is gathered from the Büyük Menderes Graben, the directional drilling ANN model is applicable to wells to be drilled in this graben.
- Directional wells should be drilled J-Type, which consist of a KOP, build section and hold section until well TD.
- Footages that were drilled with a failure BHA component should not be used in the dataset, like failed bearing section, severe worn out in sleeve stabilizer and washout in the drill string.
- Maximum well plan inclination should not exceed 30 degrees.
- Mud properties are not included

5.2 Results of the Neural Network with the Testing Data

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%. (Figure 5.1).

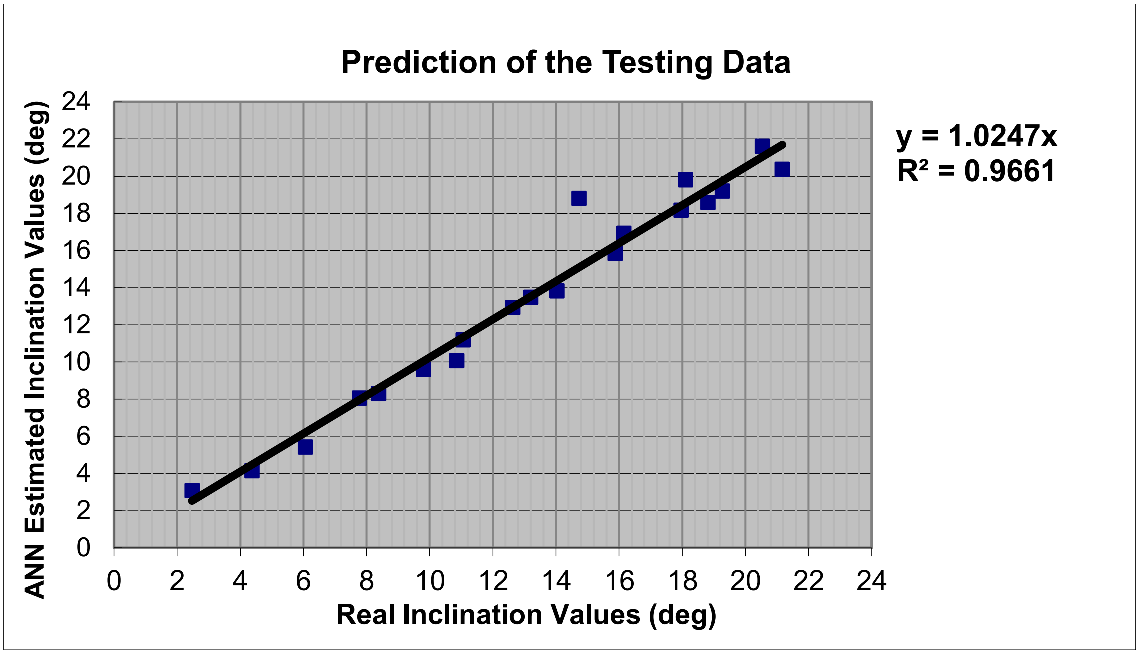

Figure 5.1: Plot of Real Inclination Values versus ANN Estimated Inclination Values

As can be seen from the Figure 5.1, 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.

5.3 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.

5.3.1 Sensitivity Analysis of Drilling Parameters without Depth Data

In this chapter, analysis of controllable drilling parameters was made to understand their effects on inclination. 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 this chapter, sensitivity analysis of drilling parameters without depth data is divided into two parts, based on the hole sizes. The MSE value of the trained network without any depth data is 1.71%.

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 5.1 and 5.2.

Table 5.1: 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 5.2: 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°

5.3.1.1 Effects of WOB on Inclination in 12.25” Hole Section

As seen in Figure 5.2, 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 (Figure 4.3) increasing WOB will increase the build rate of inclination. As can be seen from the Figure 5.2, 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. Due to this reason, directional driller needs to adjust the WOB for a better ROP and minimum DLS values that can be caused by rotary drilling. Considering 12.25” hole sections are the beginning of build section in J-Type directional wells, applying 8 tons and more will increase the build rate and minimize the slide ratio to reach the desired inclination while drilling in Büyük Menderes Graben. 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. In directional drilling operations in geothermal wells, maximum WOB should not exceed 14 tons for safer drilling. Applying higher than 14 tons may worn out the bit easily and increase the risk of getting stuck if there is no drill off. Due to this reason, sensitivity analysis of WOB was conducted up to 14 tons.

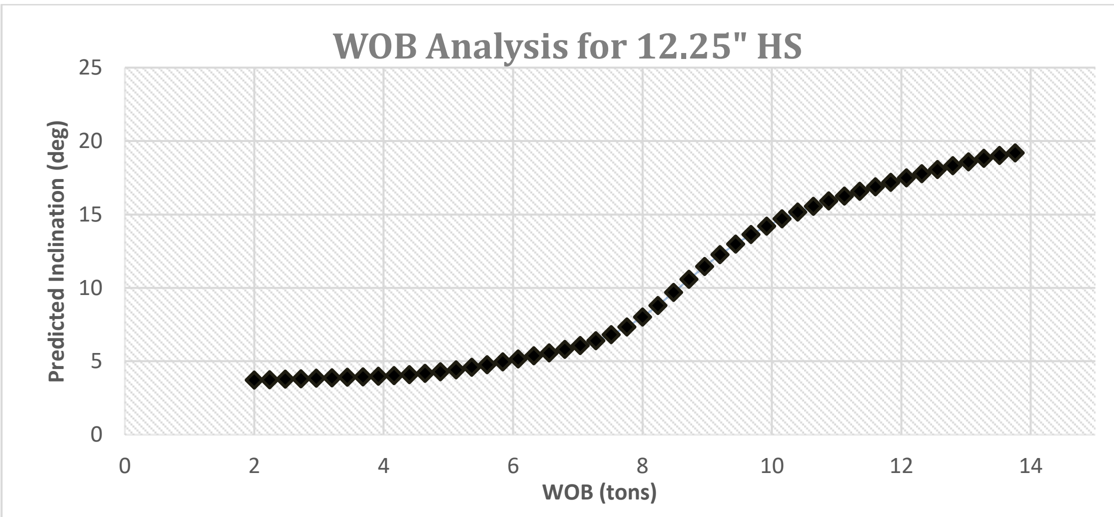

Figure 5.2: WOB Analysis for 12.25” HS

5.3.1.2 Effects of Bit RPM on Inclination in 12.25” Hole Section

According to the results of the ANN model, it was found out that inclination angle increases as bit RPM increases and its influence is very similar to WOB. However, as can be seen from Figure 5.3 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. The experiments that were conducted by Ernst et al (2007) stated that, increment in the RPM will increase the build rate, but its influence will decrease when the formation hardness increases.

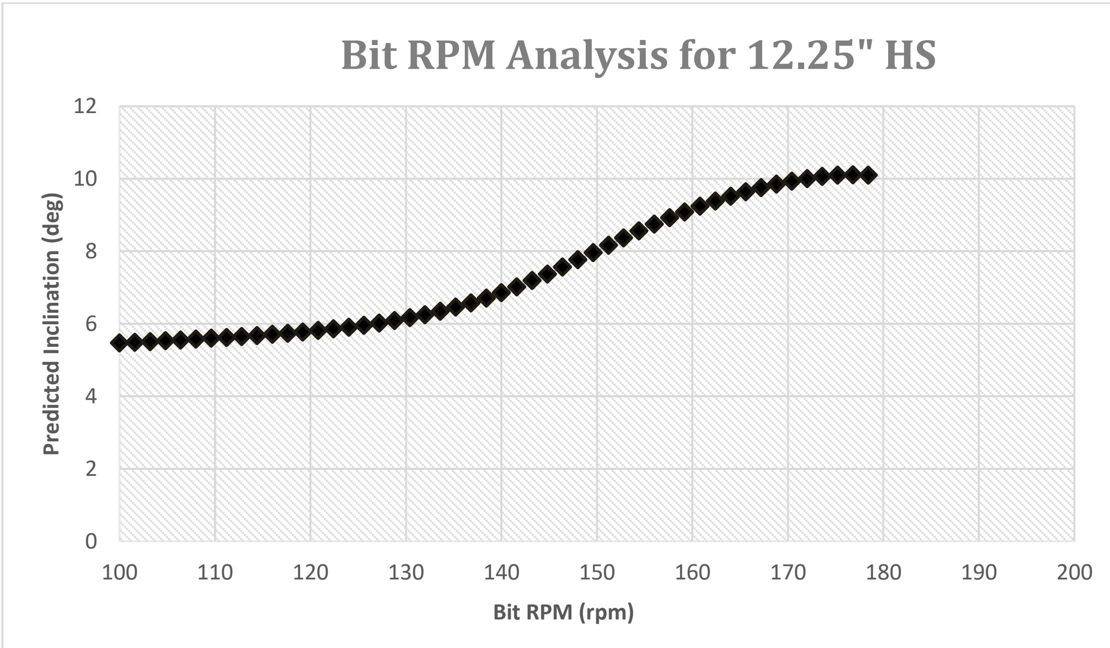

Figure 5.3: Bit RPM Analysis for 12.25” HS

5.3.1.3 Effect of Flow Rate on Inclination in 12.25” Hole Section

As can be easily seen from the Figure 5.4, 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. Note that the minimum flow rate requirement for directional tools in this section is 400 gpm. Increasing the flow rate can also be considered as creating a stiffer BHA, that may hold or drop the inclination angle. As a result, it can be concluded that higher flow rates will decrease the inclination angle rather than holding it while drilling in Büyük Menderes Graben. However, it can also be stated that when there is a drop trend in rotary drilling, directional driller may decrease the flow rate to keep inclination steady.

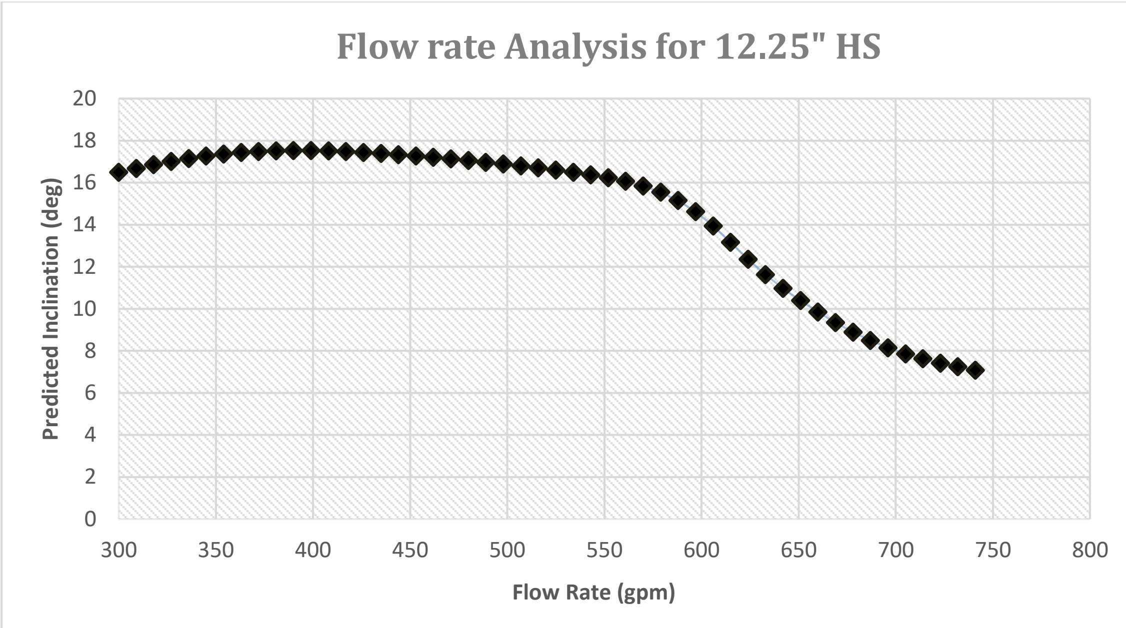

Figure 5.4: Flow rate Analysis for 12.25" HS

5.3.1.4 Effects of Stand Pipe Pressure on Inclination in 12.25" Hole Section

In order to check the effect of pressure on inclination angle while keeping other parameters constant the model is run for several different pressures. As can be seen in Figure 5.5, 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. Since as it can be seen from Figure 5.5 that, at 1500 psi inclination values are stable at 5 degrees which can considered to be a low inclination value. 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.

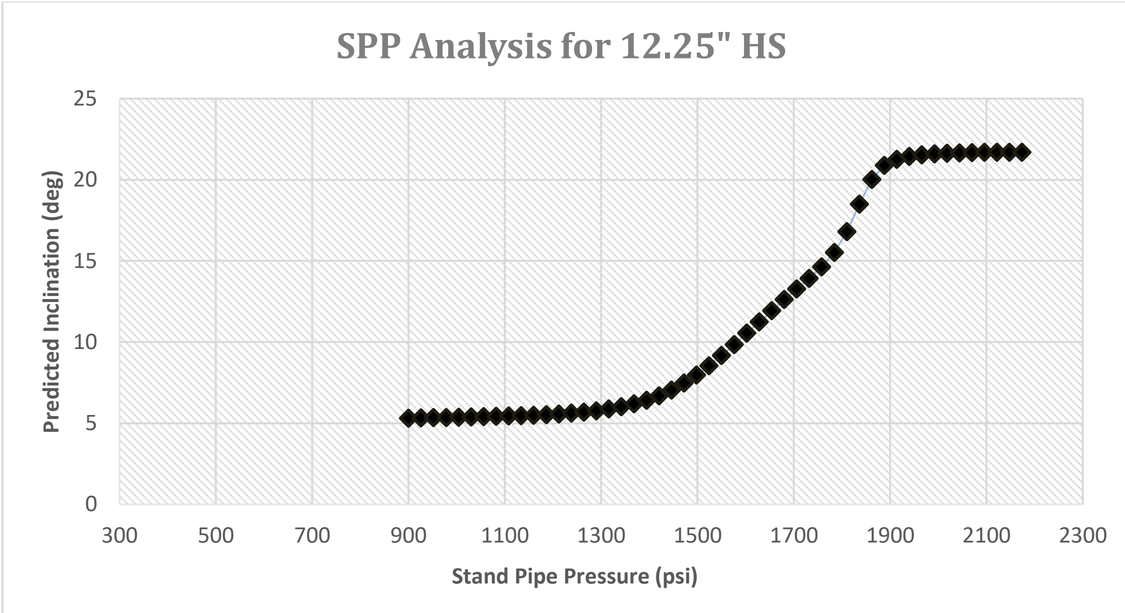

Figure 5.5: Stand Pipe Pressure Analysis for 12.25” HS

5.3.1.5 Effects of WOB on Inclination in 8.5” Hole Section

It can be observed that effect of WOB on inclination in 8.5” hole section has similarities when compared to that of 12.25” hole section (Figure 5.6). Increasing bit side force acting on the bit, which is caused by higher WOB, increase the build rate of inclination (O’ Bryan & Huston, 1990). However, the differences between two sections is that, 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. Pendulum assemblies applying more weight will drop the inclination with the help of the gravity force exerted at the bit.

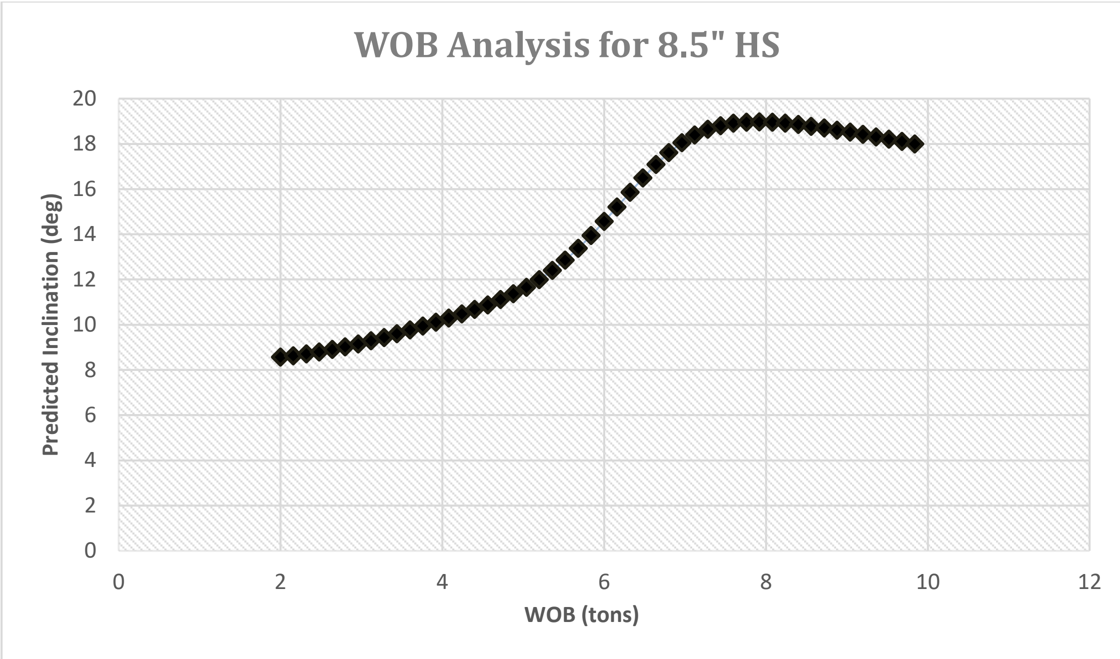

Figure 5.6: WOB Analysis for 8.5” HS

5.3.1.6 Effects of Bit RPM on Inclination in 8.5” Hole Section

Bit RPM has a slight build and hold in inclination trend for 12.25” hole section but after examining the profile plot for 8.5” hole section (Figure 5.7) 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. As can be seen from the Figure 5.7, when the RPM values are smaller than 160, inclination has a very slight build trend. However, in 8.5” hole sizes it is very rare to drill with smaller RPM values because rev/gal constant for positive displacement mud motors increases as hole size decreases. If the rig pumps are effectively working typical average rev/gal constant for 8.5” hole size is 0.28 and optimum flow rate for this section is 450 gpm. to 500 gpm. In addition to the eccentric motion from the motor, bit is also turned from the surface from 40 to 50 RPM, which makes the minimum bit RPM 160 in optimum drilling conditions. So, it can be easily said that, for 8.5” hole section inclination increases as bit RPM increases.

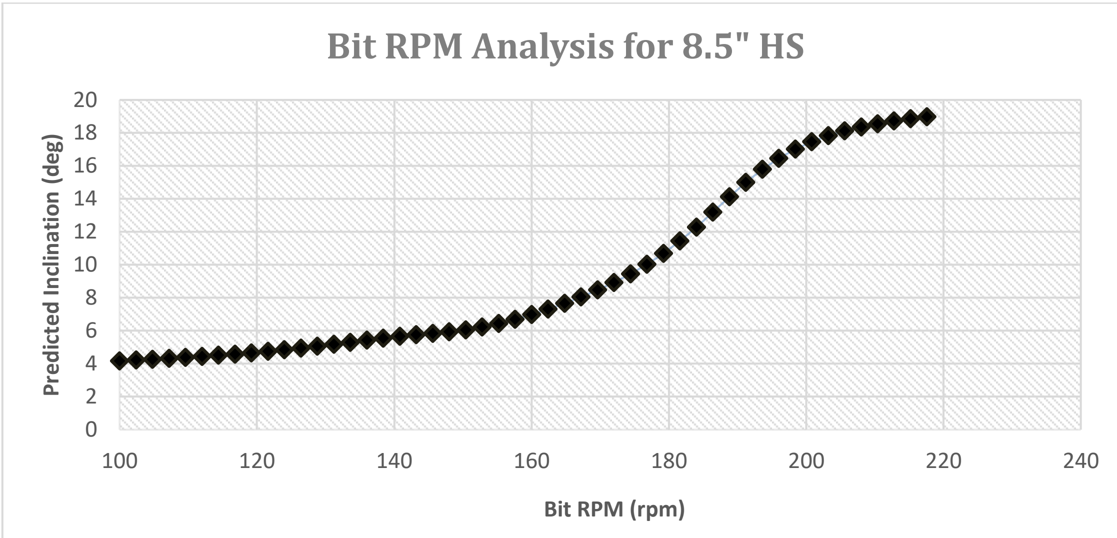

Figure 5.7: Bit RPM Analysis for 8.5” HS

5.3.1.7 Effects of Flow rate on Inclination in 8.5” Hole Section

The profile plot that shows the analysis of flow rate in 8.5” hole section (Figure 5.8) 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. Even though flow rate and bit RPM has a linear relationship, their effects on inclination is different when the flow rate is higher than 450 gallons. The reason of this difference is a result of the stiffness assembly, which is caused by the high flow rate. High RPM creates a stiffer profile at the bit whereas high flow rate creates a stiffer profile at the drill string. Due to this reason, stiffness of the BHA increases more with higher flow rates which can avoid building inclination. However, O’ Bryan & Huston, (1990) found different results in their study. According to them, as stiffness decreases, the build or drop tendency of the BHA increases since the drill collars will bend more when the stiffness decreases, it will create a higher side force acting on the bit.

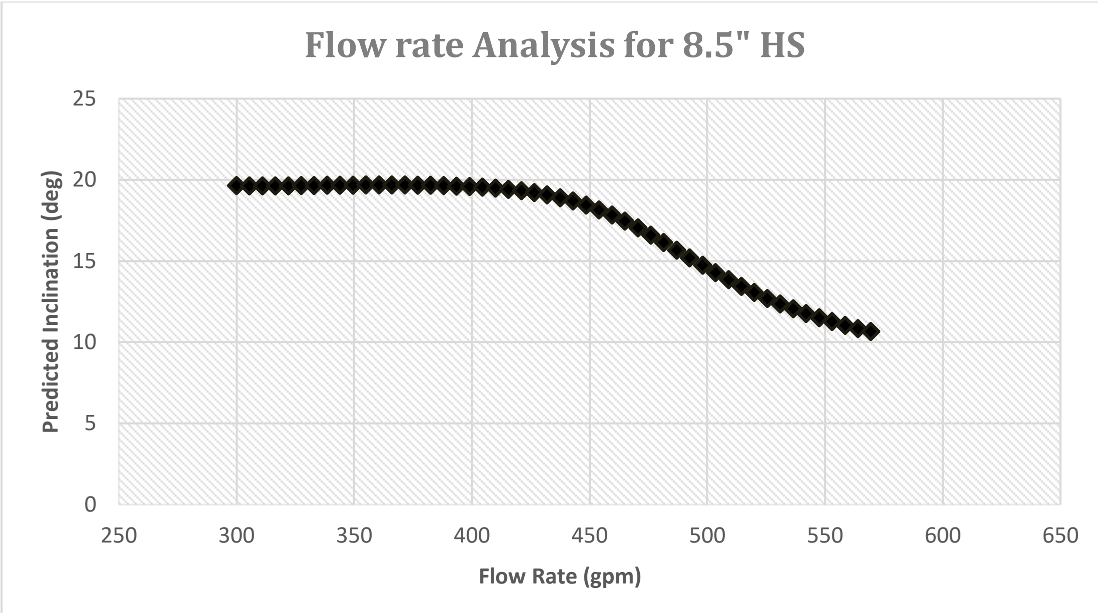

Figure 5.8: Flow Rate Analysis for 8.5” HS

5.3.1.8 Effects of Stand Pipe Pressure on Inclination in 8.5” HS

According to the profile plot (Figure 5.9) there is a direct relationship between SPP and inclination for 8.5” hole section. In 8.5” hole section impact of SPP on inclination is similar to 12.25” hole section after 1500 psi. However, before 1500 psi, inclination is building in 8.5” hole section rather than holding. Since SPP is increasing as the hole size gets smaller, common standpipe pressure values while drilling through 8.5” hole section is higher than 1500 psi if there is no pump problem. So, according to the results of the neural network it can be concluded that, inclination increases as stand pipe pressure increases in 8.5” hole section.

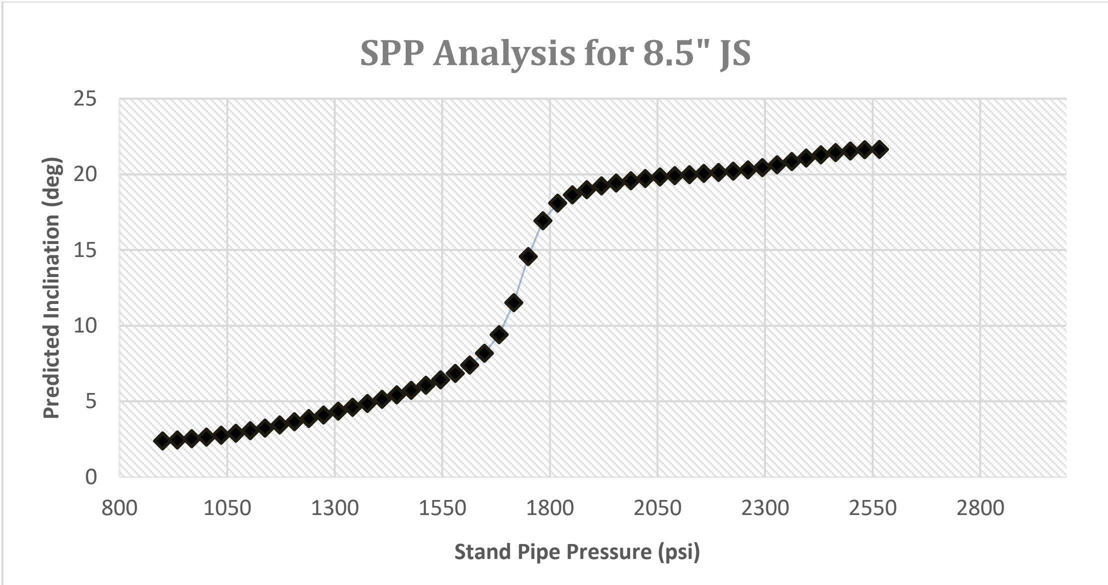

Figure 5.9: Stand Pipe Pressure Analysis for 8.5" HS

5.3.2 Sensitivity Analysis of Drilling Parameters with Depth Data Included

In this section, effects of drilling parameters were analyzed on inclination in 100 meters of drilling intervals. Apart from start depth and end depth, footage of slide and rotary drilled sections were added to the neural network training dataset as input parameters. Neural network analysis of directional drilling will be incomplete without the influence of slide footage and depth. Since formation is considered to be homogeneous in this study, effect of depth is very important for the directional driller and the quality of the directional drilling operation. The reason of assuming homogeneous formation for this study is that, in geothermal wells there are many interbedded layers and changes in formation occurs less than a meter. In fact, according to the core samples that were gathered from Büyük Menderes Graben, at some depths there are more than three formation changes in a meter. Since most of the companies that are drilling geothermal wells do not use the mudlogging technology, which shows the formation lithology in detail, formation is considered to be homogeneous in this study. However, the dataset used in the neural network contains drilling and survey data from the wells that were drilled in the same region, effects of formation on directional drilling will be very close as long as the depth value is used in the training dataset.

Table 5.3 and Table 5.4 shows fixed parameters for the training. Slide and rotary footages were selected based on their average value in the dataset. Analysis of drilling parameters in 12.25” hole section is divided to four sections with 100 meters drilling intervals. On the other hand, for the analysis of drilling parameters in 8.5” hole section, profile plots were generated from 500 meters which divided into five sections since after 500 meters of drilling there is minor changes in inclination because of drilling hold section.

Table 5.3: Fixed Parameters for 12.25” hole size

WOB: 8 tons
SPP: 1500 psi.
Bit RPM: 150 rpm.
Flow rate: 700 gpm.
Footage of Rotary Drilled: 20 m.
Footage of Slide Drilled: 10 m.
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 5.4: Fixed Parameters for 8.5” hole size

WOB: 6 tons
SPP: 1750 psi.
Bit RPM: 190 rpm.
Flow rate: 500 gpm.
Footage of Rotary Drilled: 25 m.
Footage of Slide Drilled: 5 m.
Total Flow Area: 0.745 in^2
Bit IADC: 447
Gauge of String Stabilizer: 8.125”
Gauge of Sleeve Stabilizer: 8,375”
Motor Bend: 1.27̊

5.3.2.1 Analysis of WOB on Inclination with Depth

As can be seen from the profile plots, which are shown in Figure 5.10, 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. Between 100 and 200 meters linear profile between WOB and inclination has collapsed but the build rates within these depths is still higher than the remaining 200 meters. Especially inclination starts to hold between 200 and 300 meters when the applied WOB is higher than 8 tons. On the other hand, between 300 and 400 meters inclination starts to build as weight applied to the bit increases. 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.

Similarly, while drilling 8.5” hole section, inclination and WOB also shows linear profile within the first 200 meters. The only difference between profile plots of depths are the values of predicted inclination and build rates. As depth increases the value of inclination that are predicted by the neural network increases in the first 200 meters, but analysis between 200 and 500 meters drilling clearly shows that inclination is holding as WOB increases, similar to the results that were found by the study of Jogi, Burgess, & Bowling, (1988). 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. By using the fixed parameters in Table 5.4, maximum inclination angle is predicted as 20.5 degrees which states that this inclination value is the target well plan inclination angle and directional driller performed sliding operation to keep this value within the range if there are undesired changes in the directional parameters.

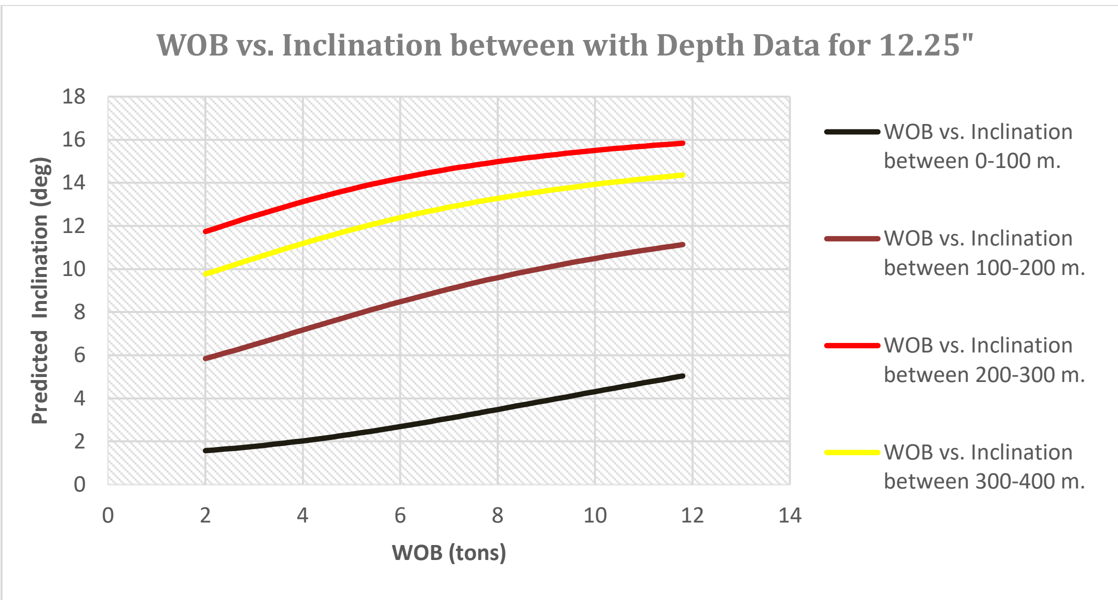

Figure 5.10: Analysis of WOB on Inclination with Depth Data in 12.25" hole section

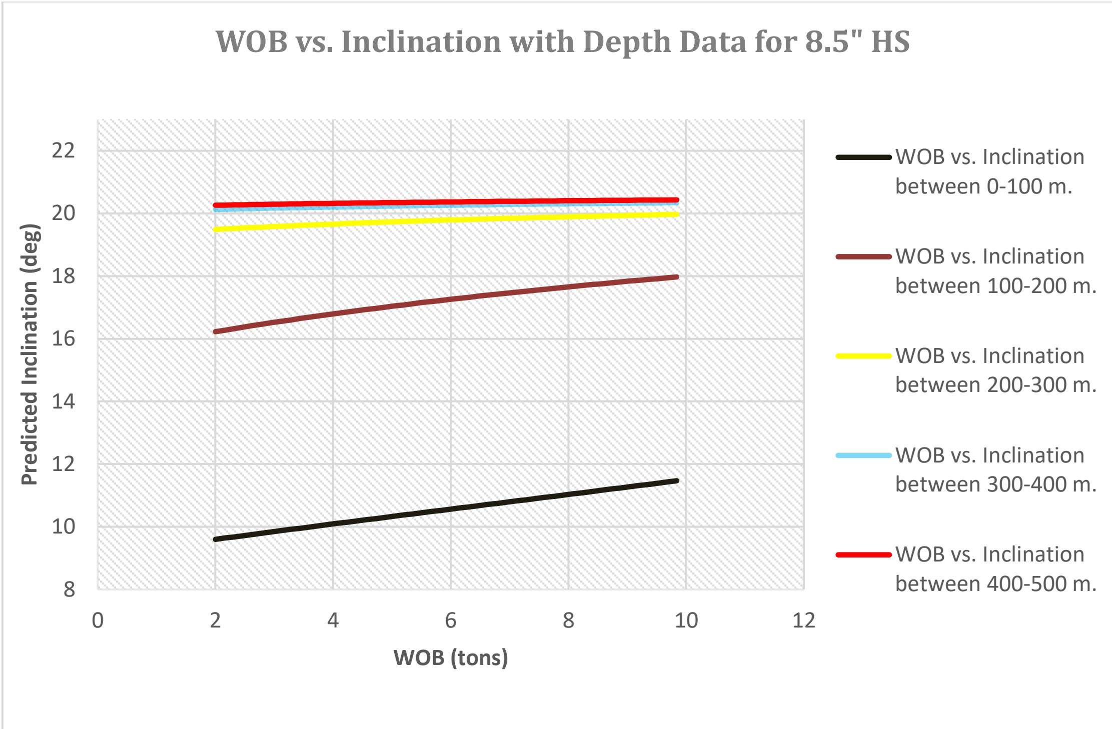

Figure 5.11: Analysis of WOB on Inclination with Depth Data in 8.5" hole section

5.3.2.2 Analysis of Bit RPM on Inclination with Depth

As the profile plots shown in Figure 5.12 and Figure 5.13 are investigated it was found out that 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. Especially, the profile plot in Figure 5.13 clearly shows that after 200 meters in 8.5" hole section build section is finished and drilling continues in hold section which is similar with the WOB analysis for 8.5" hole section.

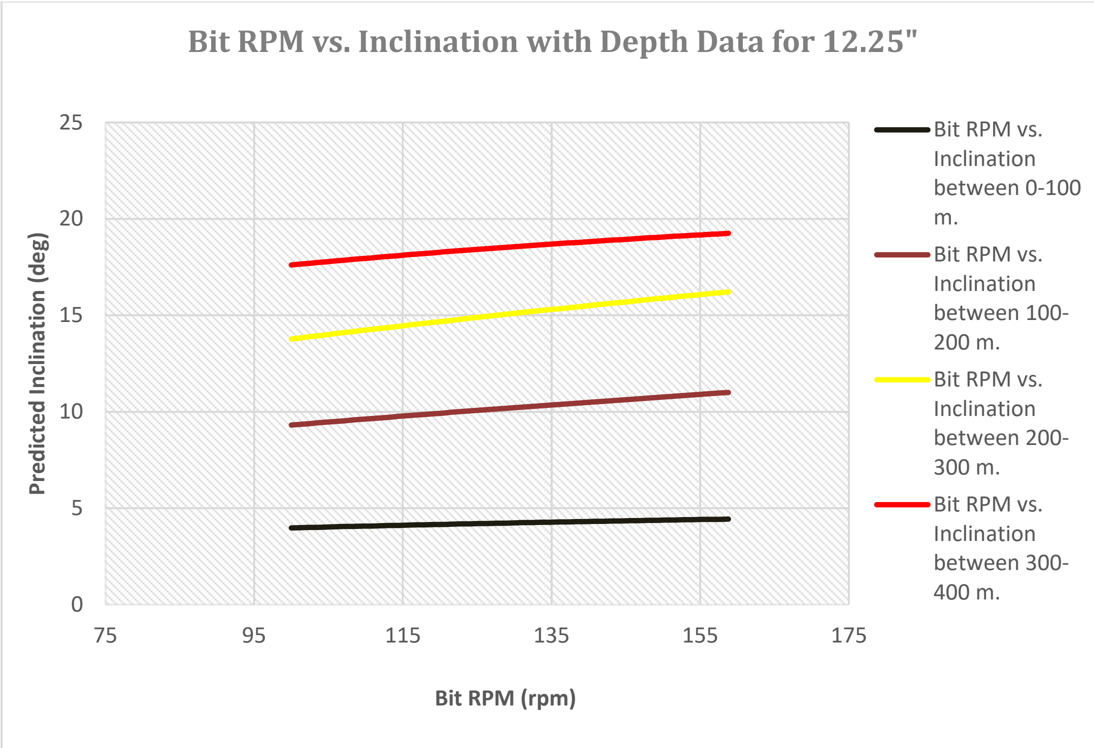

Figure 5.12: Analysis of Bit RPM on Inclination with Depth Data in 12.25” hole section

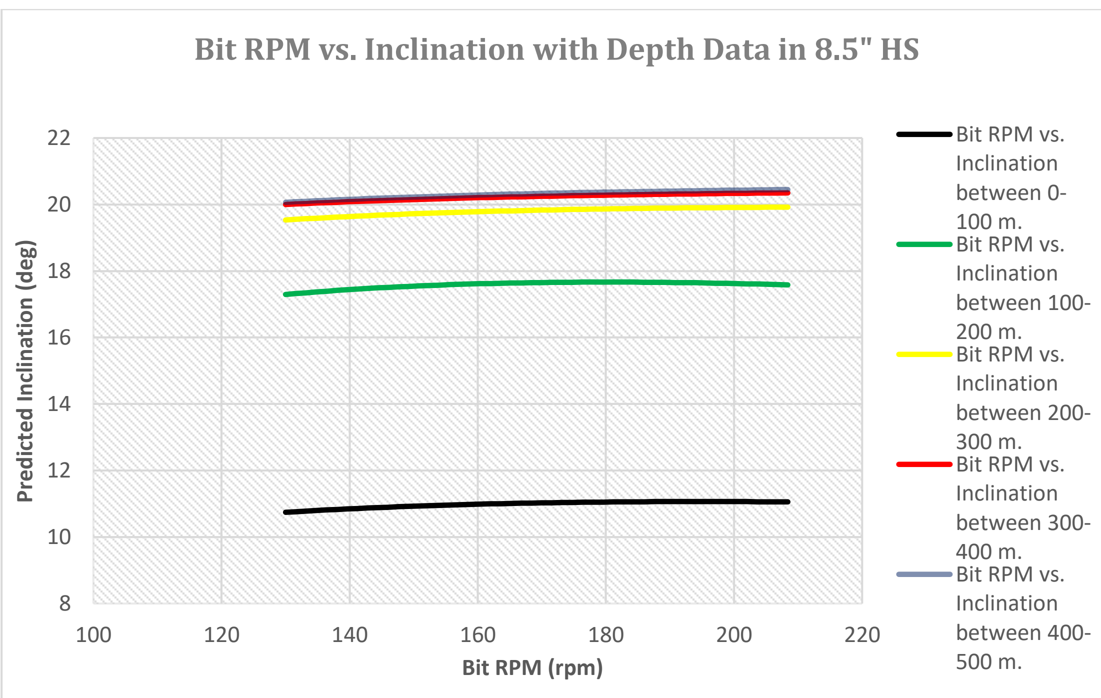

Figure 5.13: Analysis of Bit RPM on Inclination with Depth Data in 8.5” hole section

5.3.2.3 Analysis of Flow Rate on Inclination with Depth

As it is mentioned in sections 5.3.1.3 and 5.3.1.7 flowrate 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. Detail study of Figure 5.14 shows that increment in flow rate will drop the inclination angle for the entire 12.25” hole section drilling, but the drop rates are reduced as depth increases. On the other hand, Figure 5.15 states that, especially in the first 100 meters of 8.5” hole section, increasing flow rate reduce the inclination rapidly. The reason of higher drop rates in 8.5” hole section when compared to 12.25” hole section is the reduction of stiffness, that cause an uncontrollable BHA (O’ Bryan and Huston, 1990). As the drilling continues, effect of flow rate to drop the inclination is reduced and diminishes after 200 meters, which is caused by drilling through the hold section at these intervals.

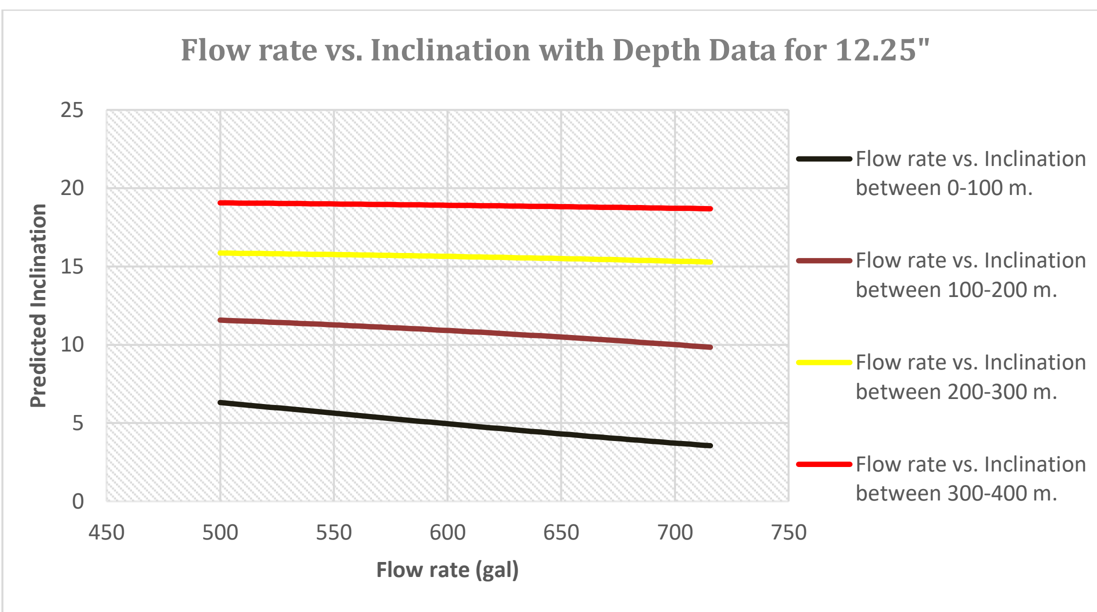

Figure 5.14: Analysis of Flow Rate on Inclination with Depth Data for 12.25” hole section

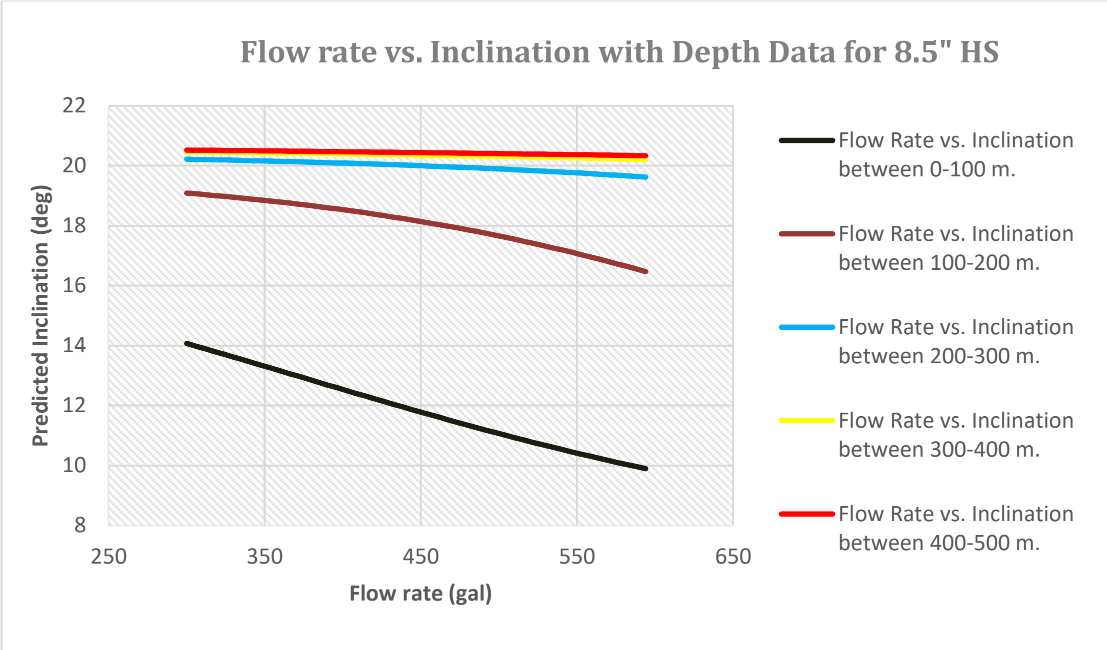

Figure 5.15: Analysis of Flow Rate on Inclination with Depth Data for 8.5” hole section

5.3.2.4 Analysis of Stand Pipe Pressure on Inclination with Depth

The profile plot of pressure versus predicted inclination angle for 12.25” hole section (Figure 5.16) states that influence of SPP on inclination is not high. Inclination angle changes between two points shows that increasing 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. Figure 5.17 clearly shows that, in the beginning of the section small build rates in inclination can be obtained by increasing the SPP for the first 200 meters. Similar to the results of other drilling parameters, increment in the SPP does not affect the results of sliding to keep inclination constant for the hold 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. When the profile plots are analyzed, it can be concluded that, for the first 200 meters, power of WOB and bit RPM to build the inclination are higher when compared to the drop effect of flow rate, but as drilling continues effect of flow rate becomes slightly higher than the effect of WOB and RPM due to drop result of inclination.

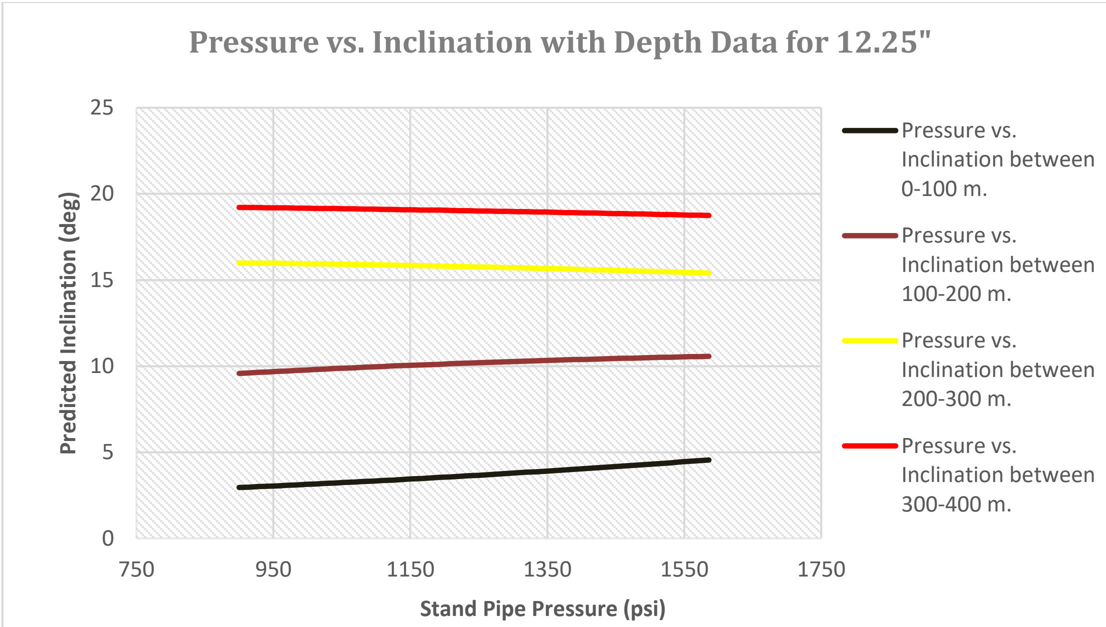

Figure 5.16: Analysis of SPP on Inclination with Depth Data for 12.25” hole section

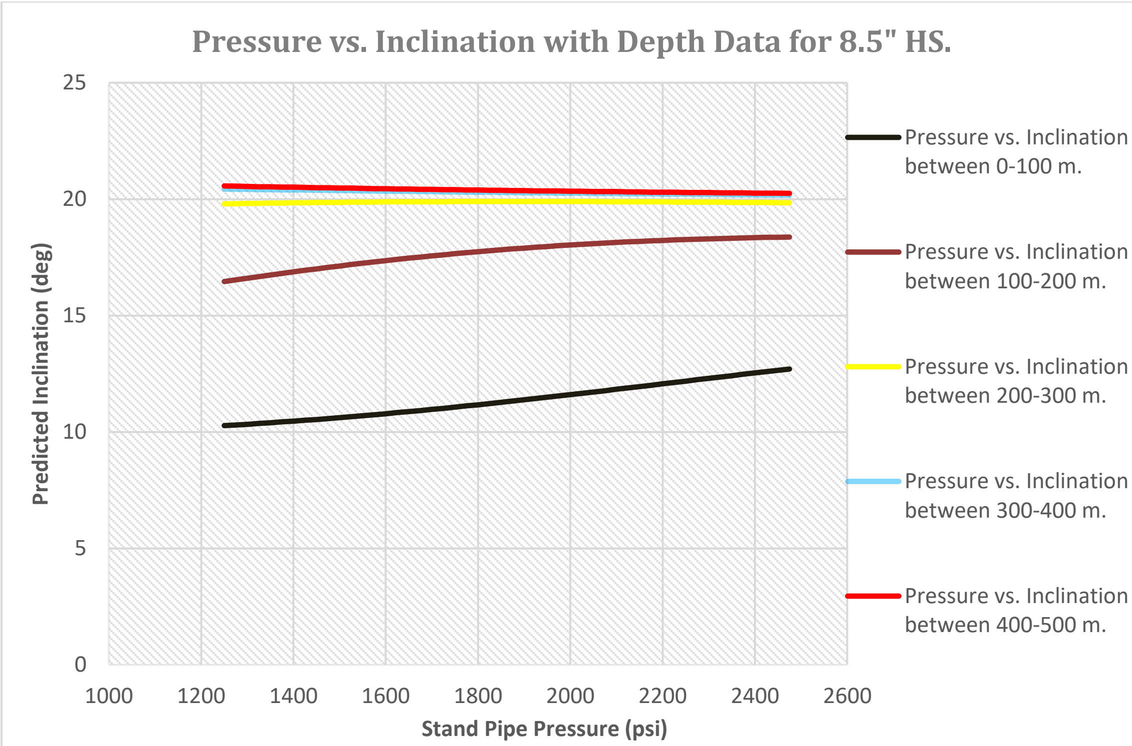

Figure 5.17: Analysis of Stand Pipe Pressure on Inclination with Depth Data for 8.5” hole section

5.4 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” (Table 5.5).

Table 5.5: Information of the Case Study Field

Location: Aegean Side of Turkey (Büyük Menderes Graben)
Hole Size: 8.5”
Start Depth (KOP): 880 m.
End Depth (Well TD): 2394 m.
Target Inclination: 20.5 degrees
Number of BHA Runs: 4 BHA
Number of Surveys: 62

As it was already explained in Chapter 5.2 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, which are shown in APPENDIX C, 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 valuee between actual inclination values and ANN predicted ones among 62 comparisons is 0.59 with an R^2 value of 0.9705 (Figure 5.18). Detailed results of the actual and predicted surveys are presented in APPENDIX C.

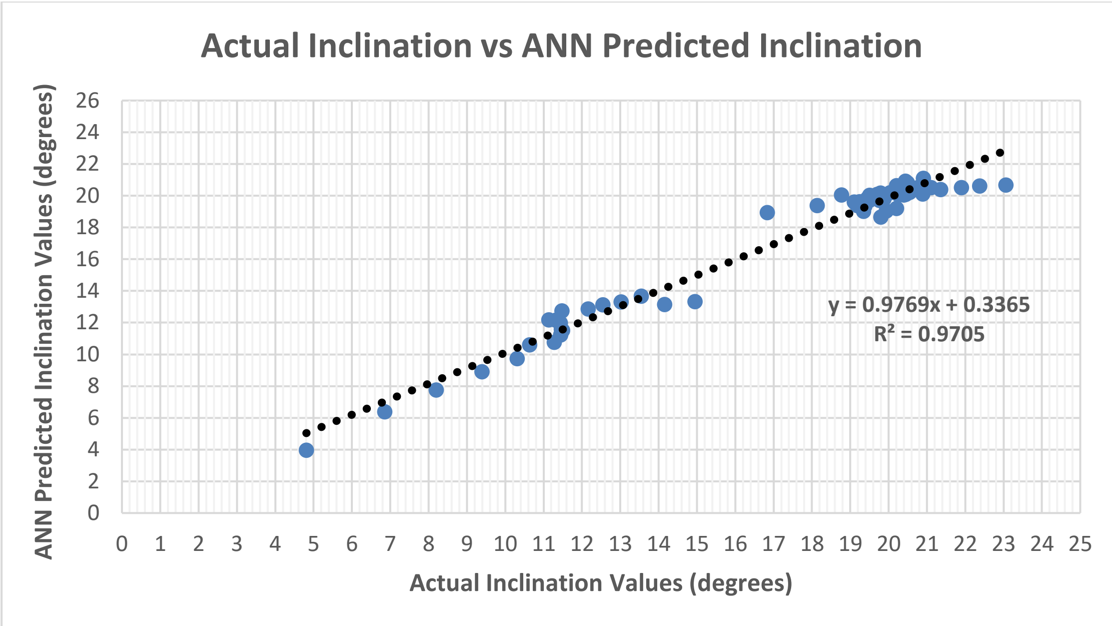

Figure 5.18: Actual Inclination Values vs. ANN Predicted Inclination values of the Case Study

5.5 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.

Table 5.6: MSE Value of the Training when Parameters Omitted

	MSE (Training) (%)	MSE(Validation) (%)
Original Training	0.422	1.287
WOB Omitted	0.442	1.4998
Flow rate Omitted	0.449	1.4889
Bit RPM Omitted	0.464	0.6906
Pressure Omitted	0.444	0.9341
Gauge of Sleeve Stabilizer Omitted	0.42	1.3275
Gauge of String Stabilizer Omitted	0.462	0.8053
TFA Omitted	0.449	1.4178
IADC Omitted	0.895	1.2523
Hole Size	0.44	0.9151
Motor Bend Omitted	0.536	0.6568
TFA & IADC Omitted	1.797	3.3393
TFA & IADC & Bit RPM Omitted	2.387	2.6943
TFA & IADC & Flowrate Omitted	2.325	2.5955
TFA & IADC & WOB Omitted	3.218	5.2993
TFA & WOB Omitted	0.716	1.6653
IADC & WOB Omitted	1.944	2.1261
Pressure, WOB, Flowrate Omitted	0.551	0.6056
Pressure & Flowrate Omitted	0.461	0.895
RPM, WOB, Flowrate Omitted	0.551	0.7888

CHAPTER 6

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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APPENDIX A

LITHOLOGY LOG OF BUYUK MENDERES GRABEN

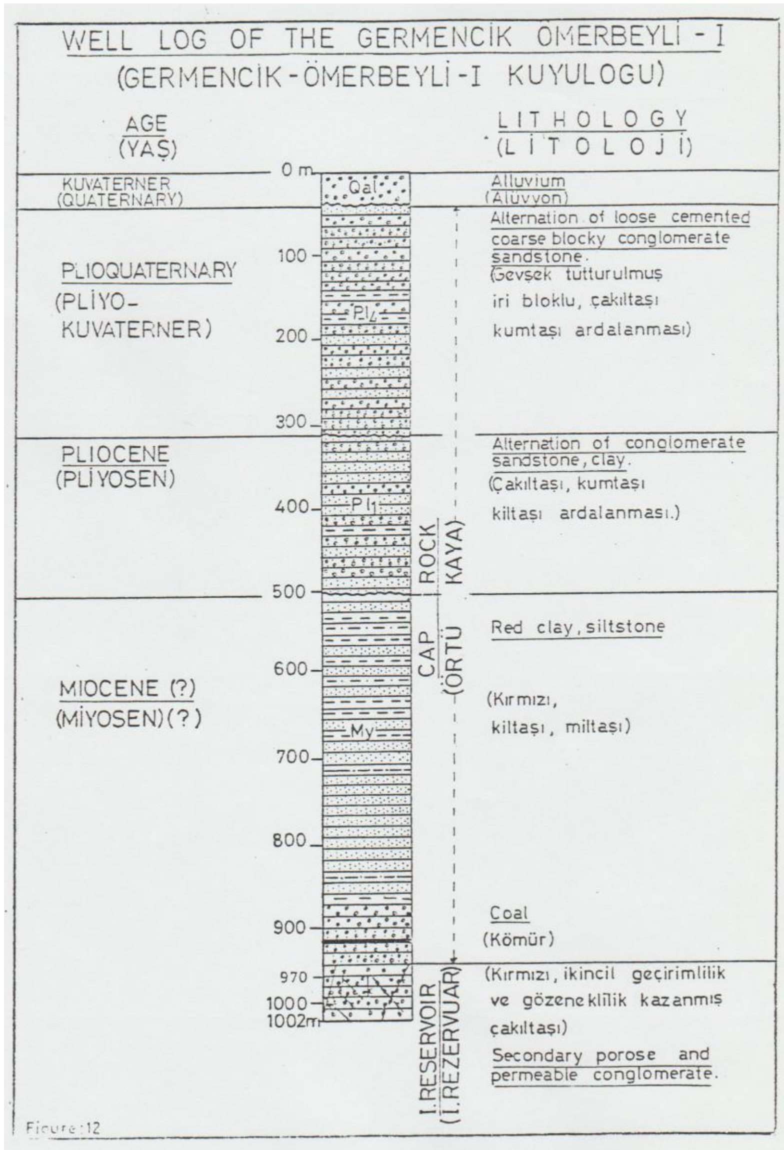

Figure A.1: A sample lithology log for a deviated well drilled in Büyük Menderes Graben (Simsek, 1984)

APPENDIX B

SIMULATIONS RESULTS TO CHECK THE OPTIMUM NEURAL NETWORK CONFIGURATION

Hidden Layer Number	Learning Parameter	Momentum Factor	Initial Weight Range	First Hidden Layer Size	Second Hiden Layer Size	MSE (Training)	MSE Validation	Number of Cycles
2	0.6	0.2	0.5	20	20	0.364	0.71	500
2	0.9	0.2	0.5	20	20	0.364	0.87	500
2	0.9	0.6	0.5	20	20	0.334	0.59	500
2	0.9	0.8	0.5	20	20	0.308	0.54	500
2	0.8	0.8	0.5	20	20	0.304	0.58	500
2	0.7	0.5	0.5	20	20	0.361	0.65	500
2	0.9	0.9	0.5	20	20	0.283	0.82	500
2	0.6	0.8	0.5	20	20	0.337	0.80	500
2	0.9	0.7	0.5	20	20	0.314	0.50	500
2	0.9	0.5	0.5	20	20	0.339	0.97	500
2	0.9	0.7	0.5	20	20	0.341	0.64	500
2	0.9	0.7	0.5	20	15	0.284	0.99	500
1	0.9	0.7	0.5	20		0.505	1.39	500
2	0.9	0.7	0.5	20	17	0.281	1.19	500
2	0.9	0.7	0.5	17	15	0.383	0.89	500
2	0.9	0.7	0.5	20	17	1.440	2.80	500 (No start depth)
2	0.8	0.6	0.5	20	15	0.364	1.95	500
2	0.8	0.9	0.5	20	17	0.275	1.95	500
2	0.9	0.8	0.5	20	17	0.456	1.54	500
2	0.9	0.7	0.5	20	17	0.422	1.29	250
2	0.9	0.8	0.5	20	17	0.458	0.47	200
1	0.9	0.8	0.5	20		0.668	1.57	250
1	0.9	0.9	0.5	20		0.620	0.75	250
2	0.8	0.9	0.5	20	17	0.481	1.42	250

Table A 1: Simulations to check MSE Values for Different Configurations

APPENDIX C

COMPARISON OF ACTUAL SURVEYS VERSUS ANN PREDICTED SURVEYS OF CASE STUDY

Depth (m)	Recorded Inclination in the Survey	Predicted Inclination by using ANN
900	4.81	3.95
919	6.86	6.37
938	8.2	7.74
958	9.39	8.91
977	10.31	9.72
986	10.64	10.6
1005	11.28	10.75
1024	11.45	11.22
1043	11.46	11.58
1062	11.5	11.51
1081	11.44	11.96
1100	11.14	12.18
1119	11.32	12.15
1138	11.48	12.74
1158	12.16	12.85
1177	12.55	13.12
1196	13.02	13.3
1215	13.55	13.67
1233	14.16	13.14
1243	14.95	13.32
1262	16.84	18.94
1280	18.14	19.37
1300	19.25	19.62
1319	19.5	19.71
1347	19.88	19.8
1366	20.26	20.06
1385	20.45	20.09
1404	20.4	20.04
1423	19.79	20.16
1451	19.57	19.98
1480	19.45	19.82
1499	19.55	19.9
1518	19.51	20.03
1537	19.47	19.78
1566	19.77	19.7
1585	19.77	19.83
1604	19.27	19.5
1623	19.18	19.38
1651	19.35	19.02
1689	20.91	21.09
1709	21.36	20.39
1728	22.38	20.6
1747	23.06	20.67
1766	21.9	20.5
1785	20.49	20.82
1861	19.8	18.66
1899	20.55	20.21
1918	20.21	20.62
1953	20.04	20.19
1975	20.44	20.92
1995	20.77	20.51
2014	21.11	20.51
2052	20.37	20.2
2090	20.89	20.11
2128	19.71	20.08
2166	20.29	20.09
2204	18.77	20.04
2242	19.11	19.59
2261	19.32	19.52
2299	19.38	19.33
2337	19.94	19.04
2375	20.21	19.19

Table A-2: Comparison of Actual Surveys vs ANN Predicted Surveys