Prediction of Sonic Shear Wave Using Artificial Neural Network

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Abstract

Shear wave time is an important parameter participating in the calculation of rock mechanics properties. Many evaluation processes including wellbore stability analysis and sand production prediction are based on rock mechanics properties so these processes are directly related to the estimation of shear wave time. Several empirical correlations have been developed to predict shear wave time using regression analysis and artificial neural network techniques for the estimation of relationships between a dependent variable and one or more independent variables for certain conditions of the reservoir. However, they are not appropriate for reservoirs with different conditions as well as all effective parameters are not considered in previous relationships. In this study, the artificial neural network is adopted for predicting shear wave time using datasets consisting of 1922 data points for a certain directional oil well from Iraqi Fauqi oil field wells. Two sets of input parameters are tried: the first trial includes the readings of seven logs (Gamma-ray, caliper, compressional sonic wave, density, neutron, deep resistivity, true vertical depth), while the second trial includes the azimuth and the inclination angles in addition to the above seven readings. The optimum structure for both datasets is obtained using 12 neurons in a single hidden layer (ANN-7-12-1 and ANN-9-12-1). The statistical results reveal that an improvement is achieved when the well azimuth and inclination are included in the ANN model. A mathematical model with high performance using an artificial neural network has been developed. The mean square error and the determination coefficient for the developed model were 14.22 and 0.952 for ANN-7-12-1, while they were 9.62 and 0.966 for ANN-9-12-1, respectively. This study presents a simple mathematical model for further determination of shear wave velocities using ANN techniques which can be then integrated with the existent petroleum software programs.

Keywords: Sonic shear wave; Artificial neural network; Empirical correlations; Wellbore deviation; Azimuth and inclination; Rock mechanics

1. Introduction

Compressional sonic and shear waves (DTS and DT) are important factors affecting exploratory geophysical characterisation, production, and drilling. Sonic waves are key parameters in predicting the elastic and strength rock properties (Edlmann et al., 1999) such as Poisson's ratio, bulk modulus, Young's modulus, unconfined compressive strength and others (Abdulraheem et al., 2009) as critical parameters in risk evaluation.
along drilling and wellbore stability, likewise production optimization, well placement (Chang et al., 2006; Moos et al., 2003) and assessing sand potential (Santarelli et al., 1989). They are either measured by a dipole sonic imager (DSI) or laboratory core experiments (Asodeh and Bagheripour, 2011). DSI log contains both monopole and dipole acquisition capabilities that are based on the determination of sonic compressional, shear and stoneley slowness waves, where waves, the transmitting section in DSI, consist of perpendicular to each other piezoelectric monopole and two electrodynamics dipoles. Shear and compressional waves propagating in the formation are excited by the electric pulse of the monopole transmitter (Al Malik and Al-Najim, 2018; Al-Banna et al., 2022). Restrictions on core samples' availability, time, and cost determine rock mechanics properties from shear wave logs better than direct core measurements (Maleki et al., 2014). Occasionally, DT is running only without DTS according to financial aspects (Alkinani et al., 2019), so many empirical correlations have been developed for predicting DTS (Pickett, 1963; Carroll, 1969; Castagna et al., 1985; Greenberg and Castagna, 1992; Freund, 1992; Brocher, 2005; Ameen et al., 2009; Al-Kattan, 2015; Allawi and Al-Jawad, 2022). All these developed correlations were (1) for specific reservoirs with special properties, and (2) multiple variables had effects on the DTS that weren’t accounted. Therefore, the existing empirical correlations do not apply to all reservoir types (Akhundi et al., 2014).

Recently, authors have begun utilizing AI methods in reservoir characterization (Mohaghegh, 2000) and DTS prediction (Ataee et al., 2018). AI techniques were applied to account for as many parameters impacting the DTS estimation as possible. Many influencing parameters on DTS can be summarized as follow (Kassab and Weller, 2015) as (1) pore pressure, lithology, porosity, and even the rock framework's elastic factor of grain density; (2) density and compressibility of fluid enclosed in pore spaces; (3) reservoir temperature, where variations in temperature between 25 and 150 °C produce changes in the DTS of dry rocks like shale or sandstone in terms of wave velocity reduction range of 5–7% for water saturated media with pressure equal to the water column, so dry rocks have DTS greater than fluid saturated rocks.; (4) depth as an influencing parameter in terms of overburden pressure, with DTS decreasing logarithmically as depth increases.; and (5) clay content in the reservoir layers that resulting an increasing in DTS.

A number of previous studies that used various AI methods examined the effects of parameters on DTS prediction. Utilized AI methods examples as artificial neural network (ANN), feedforward back propagation neural network (FFBP), The Least Square Support Vector Machine (LSSVM) in conjunction with Particle Swarm Optimization (PSO), the Genetic Algorithm (GA), and Cuckoo Optimization Algorithm (COA), fuzzy logic, and neuro-fuzzy are powerful methods for prediction DTS in term of shear wave velocity (Vs) where the last is reciprocal of DTS (Rezaee et al., 2007; Tabari et al., 2011; Tariq et al 2016; Hadi and Nygaard, 2018; Anemangely et al., 2019; Al Ghaithi and Prasad, 2020; Shi and Zhang, 2021). The better decisions for adopting AI techniques are approved based on massive historical datasets available in the petroleum industry (Mohaghegh, 2000). Above mentioned AI studies correlated DTS with many variables such as photo electric effect (PEF), shale volume (VSH), true vertical depth (TVD), measured depth (MD), gamma-ray (GR), caliper (CAL), neutron log (NPHI), density log (RHOB), deep resistivity log (RD) and DT. None of these AI studies investigated the effect of the wellbore inclination (INC) and azimuth (AZI) angles in the calculations of DTS. Changes in INC and AZI have a significant effect on wellbore stability (Paiaman et al., 2008). The main objective of this study is to construct an ANN model to predict DTS for an Iraqi directional oil well based on datasets consisting of 1922 data points; and to investigate the effect of inclination and azimuth angles on the DTS prediction.

2. Area of Study and Reservoir Stratigraphy

Fauqi oil field is located in the south of Iraq, specifically in Missan, 50 km northeast of Ammara city and 175 km north of Basrah city, as shown in Fig.1. The field extends along the Iraq-Iran border from the east. It is a few kilometers away from the Buzrgan oil field. Fauqi oil field has two domes with north-west and south-east anticlines in the north and south, respectively. Some field parts and the majority of the north dome
stretch are in Iran. The field length is approximately 23 km and the width is approximately 7 km. (Fox and Ahlbrandt, 2002; Abdul-Aziz and Abdul-Hussain, 2021).

Two main formations feed this field: Asmari, also known as (Jeribe-Euphrates, Upper Kirkuk and Middle-Lower Kirkuk reservoirs), and Mishrif. The first well drilled in 1974 reached the Nahar Omer Formation at a depth of 4683 m, but oil is found in tertiary reservoirs, which comprise Asmari and Mishrif. Actual production began in 1979 with eight wells. Until 1980, twenty four wells were drilled with target production from each reservoir alone or both two together, but the operations were not completed and the field closed with the shutdown of production due to war conditions in 1980. In August 1998, the field was put back into service and had been in production ever since (Taher et al., 2012). In 2021, the number of producing wells will increase to more than 65. (Abdul-Aziz and Abdul-Hussain, 2021).

There have been a number of studies conducted in this field, including (Al Dalawy, 2012) who calculated the petrophysical properties of the Asmari reservoir and created a 3D structural model for their distribution; (Taher et al., 2012) who built static and dynamic models for the Asmari reservoir and obtained the value of total oil in place of 1655.28 MMSTB; (Al-Baldawi, 2015), which made a 3D structural model for porosity and water saturation modeling by using datasets of five wells produced from Asmari reservoir; and the last study on this field was performed by (Abdul-Aziz and Abdul-Hussain, 2021) for coupling between geomechanical and petrophysical modeling to estimate rate of penetration.

![Fauqi oil field](image)

**Fig.1.** Major Iraqi oil fields and tectonic regions (Area of study is Fauqi oil field).

Jeribe–Euphrates Formation is the upper part of the Asmari reservoir that was deposited during the Neogene geological period. It is represented as A unit has three sub layers A1, A2 and A3 with a lithology that is primarily composed of 85% Dolomite alternated with a moderately 15% thin Shale. It has an average thickness of 40 m. Upper Kirkuk Formation is a middle sub-reservoir of the Asmari formation, deposited during the Paleogene geological period. It is denoted as the B unit and consists basically of thick shale, alternated with thin sandstone, argillaceous limestone, calcareous shale, and limestone. The sandstone portion is gray, poorly consolidated, fine to medium grained, subangular to sub-rounded, moderately sorted, predominantly quartz, argillaceous, and loose. The formation has a local 5-35% faint yellow direct fluorescence and a moderately streaming milky white cut fluorescence. Average interval of 120 m and also has four subclassifications: B1, B3, B3 and B4. Middle-Lower Kirkuk Formation is a lower sub-reservoir of
the Asmari formation. This reservoir was deposited during the Paleogene geological epoch, the Oligocene series and stage of the Aquitanian to lower Oligocene. It is represented in (Taher et al., 2012; Al Dalawy, 2012) as C and D units, but modern studies evaluate it as one unit C according to water submerge. Its lithology is composed mainly of thick shale and argillaceous siltstone, alternated with moderately thick argillaceous limestone and sandstone, with an average thickness of 200 m. Fig.2 shows the generalized Fauqi oil field stratigraphy with the average thickness of each reservoir.

According to the last available information about the field in 2021, the water oil contact of southern and northern Fauqi was -3048 and -3033 m, respectively. The pay intervals A and B are edge aquifer reservoirs with a large oil-water transition zone= the producing subzones are edge water-flooded. The natural energy of the reservoir is strong. The initial formation pressure of the north block in the Asmari reservoir is about 4900 psi. The crude oil of the Asmari reservoir is heavy oil 19.8° API with a low formation oil viscosity of 1.8 cp. The original GOR was about 491 scf/bbl. Fauqi field is a non-saturated reservoir in the initial conditions, with a bubble point pressure of 2530 psi (Abdul-Aziz and Abdul-Hussain, 2021).

<table>
<thead>
<tr>
<th>Series</th>
<th>Stage</th>
<th>Member</th>
<th>GR (σ)</th>
<th>Oil (σ)</th>
<th>GOR (σ)</th>
<th>Lithology Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Upper Fars</td>
<td>M85</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Alternation of aragonite and biodegraded huite.</td>
</tr>
<tr>
<td>Lower Fars</td>
<td>M84</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Alternation of aragonite and biodegraded huite.</td>
</tr>
<tr>
<td>Upper Kirkuk</td>
<td>B</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Alternation of aragonite and biodegraded huite.</td>
</tr>
<tr>
<td>Lower Mio</td>
<td>Burdigalian</td>
<td>Jeribe-Euphrates A</td>
<td></td>
<td></td>
<td></td>
<td>Alternation of aragonite and biodegraded huite.</td>
</tr>
<tr>
<td>Middle-Lower Kirkuk</td>
<td>C</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Alternation of aragonite and biodegraded huite.</td>
</tr>
<tr>
<td>Aalij</td>
<td>Jaddala</td>
<td>B4</td>
<td></td>
<td></td>
<td></td>
<td>Alternation of aragonite and biodegraded huite.</td>
</tr>
<tr>
<td>Sadi</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Alternation of aragonite and biodegraded huite.</td>
</tr>
<tr>
<td>Tanuma</td>
<td>Khasib</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Alternation of aragonite and biodegraded huite.</td>
</tr>
<tr>
<td>Lower Turonian to Upper Cenomanian and Lower Campanian</td>
<td>Lower Turonian to Upper Cenomanian and Lower Campanian</td>
<td>MA MA1 MA2 MB MB1 MB2 MC MC1 MC2</td>
<td></td>
<td></td>
<td></td>
<td>Beige compact limestone with biodegraded and bitumen stains.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Alternation of argillaceous siltstone and biodegraded huite.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Alternation of argillaceous siltstone and biodegraded huite.</td>
</tr>
</tbody>
</table>

Fig.2. Fauqi oil field reservoirs' stratigraphy with average thickness (Abdul-Aziz and Abdul-Hussain, 2021).
3. Materials and Methods

This study has been conducted on datasets of five wells, four of them are vertical wells while the another one is a directional well. According to the donor’s instructions, the vertical wells are renamed as X1, X2, X3, and X4 while the directional well is renamed as XD. Fig. 3 shows the distribution of these five wells based on the top of the A zone contour map of the North Fauqi oil field. The XD well was chosen over others because (1) DTS measurements were available, whereas other vertical wells did not; and (2) one of the main goals of this paper is to demonstrate the effectiveness of INC and AZI angles on DTS prediction, which only exists in directional wells. Asmari was re-evaluated by using one of commercial softwares based on the datasets of these five well logs and then classified into six units: A, B1, B2, B3, B4, and C, where the three subzones of zone A is merged together since the zone A does not contain any sand. Several well logs that measured in 2021 of the XD well are used in the present study. It is made up of 1992 data points of DTS as input parameter, while TVD, DT, GR, CAL, NPHI, RHOB, and RD are output parameters of the proposed ANN with and without INC and AZI. A total of 1922 data points were used for the training, testing, and validation stages of ANN. The used data of XD well are summarized in Table 1 and illustrated in Fig. 4 with zonation tops.

![Fig. 3. Top of A unit of the Asmari reservoir contour map with five wells location](image)

Table 1. Summary of datasets ranges covered in this study

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>DTS, (us/ft)</td>
<td>89.04998</td>
<td>156.9364</td>
</tr>
<tr>
<td>TVD, (m)</td>
<td>2993</td>
<td>3185.1</td>
</tr>
<tr>
<td>DT, (us/ft)</td>
<td>48.583</td>
<td>114.3</td>
</tr>
<tr>
<td>GR, (GAPI)</td>
<td>6.559</td>
<td>132.011</td>
</tr>
<tr>
<td>CAL, (in)</td>
<td>8.428</td>
<td>14.698</td>
</tr>
<tr>
<td>NPHI, (dimensionless)</td>
<td>0.301</td>
<td>44.6</td>
</tr>
<tr>
<td>RD, (ohm.m)</td>
<td>0.311</td>
<td>461.538</td>
</tr>
<tr>
<td>RHOB, (gm/cc)</td>
<td>2.15</td>
<td>2.94</td>
</tr>
<tr>
<td>INC, (deg°)</td>
<td>44.5483</td>
<td>48.29247</td>
</tr>
<tr>
<td>AZI, (deg°)</td>
<td>321.1377</td>
<td>323.4384</td>
</tr>
</tbody>
</table>
Fig. 4. XD well logs tracks and units tops

The seven parameters (TVD, DT, GR, CAL, NPHI, RHOB, and RD) were chosen for the input layer of the ANN based on their demonstrated effects on DTS estimation by various researchers (Akhundi et al., 2014; Anemangely et al., 2019; Shi and Zhang, 2021; Asoodeh and Bagheripour, 2011; Maleki et al., 2014; Rezaee et al., 2007). These studies indicated that seven parameters could be classified into direct and indirect effects on DTS. Direct effect parameters are (1) DT and NPHI have a positive effect on DTS because it is highly affected by porosity, so lithogy type, and (2) RHOB has a negative effect on DTS, while GR has a dual
effect depending on lithology type. Indirect influencing parameters on DTS are: (1) TVD has a negative impact in terms of overburden pressure if combined with RHOB; (2) CAL has a dual impact in terms of wellbore size as an indication of lithology type; and (3) RD has a negative influence as an indicator of fluid type in porous media. In this paper, we trained ANN in two approaches, first by using the seven parameters mentioned above, and the second by using seven parameters in addition to AZI and INC to study the impacts of these two parameters on DTS prediction for directional wells.

The multi-layer perceptron (MLP) is the prevalent function approximation in a network structure with three layers of construction: input, hidden, and output. The first and last layers are designed for entering parameters and determining network result outputs, respectively. The hidden layer with one or more sub layers is used for connecting between the input and output layers. Several neurons make up each layer that is connected with other neurons related to the next layer by weights (W). Likewise, an extra degree of freedom is introduced by a variable named bias (b) that is associated with each neuron (Abdul-Majeed et al., 2022). The input and output parameters are correlated with the number of input and output layers in neurons. Ordinarily, ANN accomplishes three processes: training, validation, and testing subsequently. In most ANN researches, available data measurements are classified into three parts: 70% for training, 15% for validation, and 15% for testing. Using the following Eq.1, each neuron in the hidden layer or output layer will be affected like a cross summation to influence the quality of each neuron’s inputs from the preceding layer (Jorjani et al., 2008):

$$S_j = \sum_{i=1}^{n} X_i \cdot W_{1ij} + b_{1j}$$  \hspace{1cm} (1)

Where $W_{1ij}$ is weight connecting between the hidden layer neurons $j$ and input vector $X_i$, $S$ is a weighted summation of biases, $b_{1j}$ and inputs, at the same time, $n$ represents the neurons’ number of the input layer. The values of $S_j$ are passing over an appropriate stimulating function to calculate its outputs (Razavi et al., 2003). The hyperbolic tangent sigmoid (tansig) function is widely used as an activation function in the hidden layer, while the linear function is often employed in the output layer. In this study, we adopt these two functions, which give values of outputs in range between $[-1, 1]$. The tansig function has the form of:

$$f(S_j) = \frac{2}{1 + e^{-2S_j}} - 1$$  \hspace{1cm} (2)

The linear function deals with the output of the tansig function to calculate the output as shown below:

$$Y_p = \sum_{j=1}^{K} W_{2j} \cdot f(S_j) + b_{2j}$$  \hspace{1cm} (3)

Where $Y_p$ is the estimated DTS result value, $W_{2j}$ is the weight of output hidden layer, $b_{2j}$ is the output layer bias, while K is the hidden layer neurons.

To avoid randomness of measured points, the ANN system converts data points to normal distribution before training, and we analyze these measured points before use. The two ANN architectures tried in this study are depicted in Fig.5. In the first ANN, seven inputs are selected (TVD, DT, GR, CAL, NPHI, RHOB, and RD), whereas in the second structure, the variables INC and AZI are added to the seven inputs.

158
4. Results and Discussion

The mean square error (MSE) and correlation coefficient ($R^2$) are found for each suggested ANN using the following equations

\[ \text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (Y_{m,i} - Y_{P,i})^2 \]  \hspace{1cm} (4)

\[ R^2 = 1 - \frac{\sum_{i=1}^{n} (Y_{m,i} - Y_{P,i})^2}{\sum_{i=1}^{n} (Y_{m,i} - \bar{Y_{m}})^2} \]  \hspace{1cm} (5)

Where $Y_{mavg}$, $Y_P$, and $Y_m$ are average predicted, predicted and measured values of DTS. Based on the values of MSE (minimum) and $R^2$ (maximum), for both ANNs, an optimum structure obtained in this paper have single hidden layer with twelve neurons. That is, the suggested structures are 7-12-1 and 9-12-1 to simplify the implementation of the developed ANNs, we derived the following mathematical equations by amalgamation Eqs. 1 through 3 with inputs and outputs parameters substituting:

\[ DTS = \sum_{j=1}^{12} W_j \left( \frac{2}{1 + e^{-2(W_{j1} TVD + W_{j2} DT + W_{j3} GR + W_{j4} CAL + W_{j5} NPHI + W_{j6} RD + W_{j7} RHOB + b_j)} - 1} + b2 \right) \]  \hspace{1cm} (6)

\[ DTS = \sum_{j=1}^{12} W_j \left( \frac{2}{1 + e^{-2(W_{j1} TVD + W_{j2} DT + W_{j3} GR + W_{j4} CAL + W_{j5} NPHI + W_{j6} RD + W_{j7} RHOB + W_{j8} INC + W_{j9} AZI + b_j)} - 1} + b2 \right) \]  \hspace{1cm} (7)

Fig.6 and Fig.7 demonstrates the performance of the two proposed ANN. The first look at these figures reveals that Eq.7 is better than Eq.6 for the training, validation, and testing datasets.
Fig. 6. Performance evaluation of the developed ANN that ignoring the effect of AZI and INC

Fig. 7. Performance evaluation of the developed ANN that considering the effect of AZI and INC

The statistical results of both structures are listed in Table 2. As shown, inclusion the effect of INC and AZI results in a clear improvement in the prediction of DTS. The decrease in average percent error demonstrates the improvement (APE), absolute average percent error (AAPE), standard deviation (SD), MSE, and increase in $R^2$; therefore, Eq.7 is recommended for estimating DTS for directional oil wells by using weights and biases are listed in Table 3.

Table 2. Performance evaluation of proposed ANNs using 1922 measured data.

<table>
<thead>
<tr>
<th>Proposed ANN</th>
<th>APE</th>
<th>AAPE</th>
<th>SD</th>
<th>MSE</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN without effect of AZI and INC, Eq.6</td>
<td>1.56</td>
<td>4.441</td>
<td>5.181</td>
<td>14.22</td>
<td>0.952</td>
</tr>
<tr>
<td>ANN with effect of AZI and INC, Eq.7</td>
<td>-0.006</td>
<td>2.168</td>
<td>2.686</td>
<td>9.62</td>
<td>0.966</td>
</tr>
</tbody>
</table>
Table 3. Weights and biases of recommended ANN for DTS estimation

| TVD  | W1j | W1j,DT | W1j | W1j | W1j | W1j | W1j | W1j | W1j | W1j | b1j | W2j | b2  |
|------|-----|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
|      |     |        |     |     |     |     |     |     |     |     |     |     |     |
| 1.547 | -6.385 | 3.107 | 4.66 | -0.938 | 5.056 | -4.332 | 1.003 | 1.13 | 3.488 | -0.16 |
| 0.603 | -0.567 | 0.591 | 0.455 | 0.497 | 2.959 | -0.013 | 0.598 | -0.98 | -3.94 | 0.58 |
| 1.117 | -1.055 | 2.383 | 19.42 | -3.598 | -8.034 | -4.075 | 1.539 | -7.75 | 15.16 | 0.38 |
| 3.7   | 3.088 | -2.798 | -1.775 | 3.655 | -16.18 | -3.027 | 4.316 | -2.07 | -19.72 | 0.11 |
| -0.709 | 0.2396 | -0.84 | -1.375 | -0.565 | 9.056 | -0.346 | -0.348 | 0.79 | 7.869 | -0.74 |
| -5.465 | -9.212 | -5.083 | 7.27 | 3.058 | 6.371 | -15.546 | -11.23 | 0.75 | 12.45 | 0.08 |
| -2.326 | -0.749 | 0.991 | 1.715 | -1.051 | -3.229 | -1.419 | 16.49 | -10.83 | -4.42 | 0.58 |
| -19.582 | 7.553 | -7.629 | 4.557 | 1.941 | 19.58 | 3.476 | 0.821 | 17.76 | 21.86 | -0.133 |
| 1.805 | -3.608 | 1.336 | 1.612 | 1.311 | -6.774 | -1.252 | -6.347 | 2.7 | -1.79 | -0.23 |
| 1.808 | 3.937 | -0.914 | 1.473 | -1.629 | 3.678 | -2.646 | 1.773 | -8.73 | 0.78 | 0.17 |
| 7.043 | 0.634 | 0.949 | -1.104 | -1.802 | -3.921 | -1.334 | 5.821 | -8.47 | -4.01 | 0.65 |
| 2.589 | -0.912 | 0.643 | 1.908 | -0.162 | -1.138 | -0.412 | 3.676 | -5.11 | -0.39 | -1.48 |

For completeness, we create Fig.8, which shows a graphical comparison between measured and predicted DTS with TVD as x-axes for the adopted directional well. As can be seen a very good agreement is shown between the measured and predicted DTS if considering INC and AZI.

![Fig.8. DTS measured and predicted versus TVD](image)

Since the proposed ANN model is derived from only one dataset, therefore, it is recommended to check it’s validation against other datasets with different flow geometry, when available.
5. Conclusions

This paper presents the application of ANN in prediction of DTS in directional oil well. A datasets of 1922 measured data points are made available for training, validation and testing of ANN. We tried two ANN structures to investigate the effect of inclination and azimuth angles. The first two angles do not consider predicting DTS, while the second structure accounts for these two parameters. For both cases, the best performance was achieved with 7–12–1 and 9-12-1 structures using tansig activation function in the hidden layer and purelin in the output layer. The statistical results show that the inclusion of inclination and azimuth angles significantly improved DTS prediction. To simplify the calculations of the DTS using the proposed ANNs and to integrate with other petroleum software, we derived two mathematical models for representing these ANNs.

Nomenclatures

AAPE = Absolute average percent error.
ANN = Artificial neural network.
APE = Average percent error.
AZI = Azimuth angle (deg\(^{\circ}\)).
CAL = Caliper (in).
COA = Cuckoo Optimization Algorithm.
DSI = Dipole sonic imager.
DT = Compressional sonic wave (us/ft).
DTS = Sonic shear wave (us/ft).
FFBP = Feedforward back propagation neural network.
GA = Genetic Algorithm.
GR = Gamma ray (GAPI).
INC = Inclination angles (deg\(^{\circ}\)).
LSSVM = Least Square Support Vector Machine.
MD = Measured depth (length unit).
MSE = Mean square error.
NPHI = Neutron log (dimensionless).
PEF = Photo electric effect (B/F).
PSO = Particle Swarm Optimization.
\( R^2 \) = Correlation coefficient.
RHOB = Density log (gm/cc).
RS = Deep resistivity log (ohm.m) T
SD = Standard deviation.
T = Temperature (temperature unit)
TVD = True vertical depth (m).
Vs = Shear wave velocity (ft/us)
VSH = Shale volume (dimensionless).

References


