



# Using Artificial Neural Network to Predict Rate of Penetration from Dynamic Elastic Properties in Nasiriya Oil Field

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## Abstract

The time spent in drilling ahead is usually a significant portion of total well cost. Drilling is an expensive operation including the cost of equipment and material used during the penetration of rock plus crew efforts in order to finish the well without serious problems. Knowing the rate of penetration should help in speculation of the cost and lead to optimize drilling outgoings. Ten wells in the Nasiriya oil field have been selected based on the availability of the data. Dynamic elastic properties of Mishrif formation in the selected wells were determined by using Interactive Petrophysics (IP V3.5) software based on the log files and log record provided. The average rate of penetration and average dynamic elastic properties for the studied wells was determined and listed with depth. Laboratory measurements were conducted on core samples selected from two wells from the studied wells. Ultrasonic device was used to measure the transit time of compressional and shear waves and to compare these results with log records. The reason behind that is to check the accuracy of the Greenberg-Castagna equation that was used to estimate the shear wave in order to calculate dynamic elastic properties. The model was built using Artificial Neural Network (ANN) to predict the rate of penetration in Mishrif formation in the Nasiriya oil field for the selected wells. The results obtained from the model were compared with the provided rate of penetration from the field and the Mean Square Error (MSE) of the model was  $3.58 \times 10^{-5}$ .

*Keywords:* Rate of penetration, artificial neural network, Dynamic elastic properties, Nasiriya Oil Field

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## 1- Introduction

Oil field developments are subject to drill wells in economical manners. For that reason, future management of oil field will face new obstacles to reduce overall costs, increase performance and reduce the probability of encountering problems[1]. Drilling for energy search from the ground has shown considerable technological advances in the recent years[2]. Different methods from different disciplines are being used now in drilling activities in order to obtain a safe and cost-effective well construction[3].

The first well drilled in a new field (a wildcat well) generally will have the highest cost. With increasing familiarity to the area optimized could be implemented in decreasing costs of each subsequent well to be drilled until a point is reached at which there is no more significant improvement.

The relationship among drilling parameters are complex, so the efforts is to determine what combination of operating conditions result in minimum cost drilling[4].

The rate of penetration is important in drilling the wells that are required in the development process of the oil field. It is likely to finish the well as soon as possible without problems [5].

So in order to implement the optimization concept for drilling parameters and reducing the cost of drilling, data from the drilled wells in areas that have the same geological properties of the area that is going to be drilled and nearby wells are gathered and analyzed to start drilling the well at the lowest cost as possible[6].

The drilling process is a complex process including many factors some of them can be adjusted at a time to enhance the drilling process and they are changeable with time, these parameters called controllable parameters, for instance, rotary speed and weight on bit.

The other parameters are difficult to control like depth and formation pressure. These parameters called uncontrollable parameters. Predicting penetration rate includes some difficulties because it relies on both the controllable and uncontrollable parameters. Many mathematical models have been proposed by several researchers to predict the penetration rate and to investigate the relationship between different drilling parameters and the penetration rate. Teale [7] presented the concept of mechanical specific energy and the equation concluded in term of the operational parameters as follows:

$$MSE = WOB * \left[ \frac{1}{Ab} + \frac{13.33 * \mu * N}{db * ROP} \right] \quad (1)$$

Where MSE is the mechanical specific energy, WOB is the weight on bit, N is the rotary speed, Ab is the borehole area,  $\mu$  is bit specific coefficient of sliding friction and

Bourgoyne and young [8] .ROP is the penetration rate developed a model based on the multiple regression analysis of the field data gathered. The model describes the ROP as a function of formation strength, formation compaction, formation depth, differential pressure, bit diameter, bit weight, bit wear, and bit hydraulics. The equation for predicting the penetration rate takes into account various drilling parameters as follows

$$ROP = \exp (a_1 + \sum_{j=2}^8 a_j x_j) \quad (2)$$

Where  $a_1$  to  $a_8$  are constants that estimated by multiple linear regression. Hareland and Motahhari [9] developed a model for PDC bit ROP model based on Hareland assuming 100% cleaning efficiency:

$$ROP = W_f \left( \frac{G N^{\gamma} WOB^{\alpha}}{db \sigma} \right) \quad (3)$$

Where: G is a coefficient determined based on bit and blade geometry.  $W_f$  is the wear function calibrating ROP values for a worn bit.  $\sigma$  Unconfined rock strength. And it's a function of WOB, RPM, and rock strength at the drilling depth. All the previous models to predict ROP were based on operational parameters and rock strength and did not include the dynamic elastic properties of rocks. In this research, the model focuses on this area to relate these properties with ROP. Artificial neural network design was inspired by the human brain. ANN is applied in different fields, for instance, financial services, biomedical applications, time series prediction. Due to neural network ability in solving non-linear problems, they were used widely in petroleum engineering.

Such application of neural network includes bit selection, reservoir characterization and enhanced oil recovery (EOR)[10]. The perceptron was introduced by Rosenblatt[11]. The perceptron receives many inputs ( $X_1, X_2, X_3, \dots, X_N$ ) from all the neurons in the previous layer. And one output is coming out from it ( $y$ ). Moreover, the perceptron has a bias weight denoted as ( $w_0$ ).

During the training stage, the weights will be changed continuously. So, it is possible to reduce or to strengthen some neurons' weight to get different outputs. A linear combination which is the sum of the product of the weight of each previous neuron by their inputs and adding to the summation the bias value as follows:

$$y = \sum_{i=0}^n x_i \cdot w_i + w_0 \quad (4)$$

Where: ( $x_i$ ) is the output from the previous neuron or from the input layer, ( $w_i$ ) Is the weight connecting the ( $i^{th}$ ) neuron from the previous layer to the ( $j^{th}$ ) neuron in the Current layer, ( $w_0$ ) is the bias, ( $y$ ) is the weighted sum. After the weighted sum computed, this value should be entered in a function called activation function ( $\sigma_z$ ) [12]. This concept is demonstrated in Fig. 1.

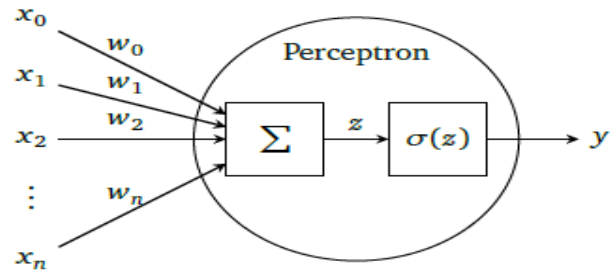


Fig. 1. Concept of the Perceptron with  $n$  Inputs and One Output[12]

The sigmoid function is one type of activation function which has the shape of the "S" curve. Sigmoid function  $\text{sig}(z)$  is sometimes called 'squashing' function, because it squashes the input to a value range between (0 and 1). This function is applied to the weighted sum of the outputs of the previous neuron to get the input of the present node [13]. To get the right outputs from the network we need to train the network in an iterative process. The network must be fed with a data set that contains the inputs and the outputs. The output from the network is called "predicted output". The output from the data set is called "desired output" or the "target". The predicted outputs are compared with the targets to estimate the error between the calculated and the actual output, subsequently, evaluating the performance of the network, for each iteration the weights are adjusted in order to get better results (closer to desired outputs). For this purpose, learning algorithms are used to get the job done[14].

There are two types of neural networks due to their learning techniques, supervised and unsupervised. In supervised neural networks, the output values are known. And in the case of unsupervised, the output is unknown. The backpropagation algorithm (BP) and Marquardt-Levenberg are the most familiar learning algorithms[15].

## 2- Aim of This Study

In this study, an intelligent model was developed in order to be used in rate of penetration prediction based on bulk modulus, shear modulus and Poisson's ratio as inputs. This model was built and developed based on the data provided from Nasiriya oil field which is the case study of this paper. Thus, predicting the ROP helps in speculating drilling cost in the study area.

## 3- Materials and Methods

### 3.1. Study Area Description

Nasiriya oil field is located on the Arabian platform in Dhi-Qar governorate, southern of Iraq, a zone with a gentle fold. The field is about 38 kilometers northwest the Nasiriya, west of the Zagros fold belt. The area of the field is located on an unstable shelf close to the Arab platform (Mesopotamian zone).

This zone characterized by the presence of subsurface anticlines and domes with variable extension. Arabian shield suffered from erosion that put in a lot of clastic sediments (Zubair formation). Nasiriya oil field has reserves in the late cretaceous (Mishrif limestone formation) and early cretaceous (Yammama limestone formation). The Mishrif Formation (Cenomanian-Early Turonian) represents a heterogeneous formation primarily characterized as organic detrital limestones, capped by limonitic freshwater limestones. It is thickest in the Rumaila and Zubair fields (270 m), in the NahrUmr and Majnoon fields along the Iraq - Iran border it becomes (435 m) thick. And in Abo Amud field between kut and Amara it is (380 m) thick. Other isolated occurrences lie near Kifl (255 m) and Samarra (250 m)[16].

### 3.2. Data Collection and Research Methodology

The first step in the research methodology is the selection of wells in the Nasiriya oil field. In this field, there are two sets of open hole logs for different depth intervals provided by Schlumberger Company (INOC, 1985; INOC, 2007).

The first one from 1924 m to 2532 m and the other one from 2528 m to 3430 m. The first set is passed through Mishrif carbonate formation which is the most important formation. Whereas, the second set is passed through Yammama carbonate formation which is one of the deepest reservoirs in the NS oil field. NS-1, NS-3, NS-4, NS-5, NS- 9, NS-15, NS-16, NS-18, NS-19, and NS-21 are selected for this study. Five exploratory wells drilled in the Nasiriya oil field with in the period 1978 -1987. All the picked wells are production wells and scattered to overlay wide area of the Nasiriya oil field.

This distribution gives a high stiffness in the field data. All logs are present for these wells (INOC, 2007). Core samples were used in this research. Laboratory measurements were conducted on the core samples to compare log reading and lab measurements. James Instrument V-Meter Mark IV Ultrasonic device was used for measuring the compressional waves' velocities.

The samples dimensions were (1) inch in diameter and (2) inches in length. After the samples preparation process, dynamic elastic properties which include bulk modulus, shear modulus, and Poisson's ratio are computed. Then, the data were used to build an intelligent model using ANN to predict the rate of penetration. The data set was divided into three categories training, testing and validation by 70%, 15%, and 15% respectively. The steps of developing (ANN) model are as follows:

- 1- Selecting the data: after the dynamic elastic properties have been calculated by IP software and the rate of penetration records has been organized and listed with depth. The data must be analyzed and processed.
- 2- Building neural network model: the model is built by selecting properties of the network such as network topology, training algorithms and minimum accepted error between predicted and actual.

- 3- Testing the model: the model was tested by new data that wasn't used in the training stage and within the range of training data.

### 4- Implementing Neural Network

The artificial neural network is used in many applications to model highly non-linear problems. Sometimes ANN models fast to build and give accurate results. The neural network model was built using the Marquardt-Levenberg training algorithm. Two hidden layers were used; each layer has twenty hidden neurons with the sigmoid transfer function for the two hidden layers. One output layer and a linear transfer function between the last hidden layer and the output layer. The dynamic elastic properties (KB, MU, and PR) data from five wells (NS-1, NS-3, NS-4, NS-5, NS-18) were averaged and listed with depth. After averaging the data, they have been arranged in a form that the network accepts it in order to be used as input data for training the network. The number of epochs was set to 1000 iteration. The performance of the neural network model for ROP prediction should be evaluated. In order to do this evaluation, a regression analysis between network outputs (ROP predicted) and actual (ROP) was hired.

Fig. 2 demonstrates regression analysis with a straight line stand for best regression between the net output (ROP predicted) and the desired output (ROP actual).

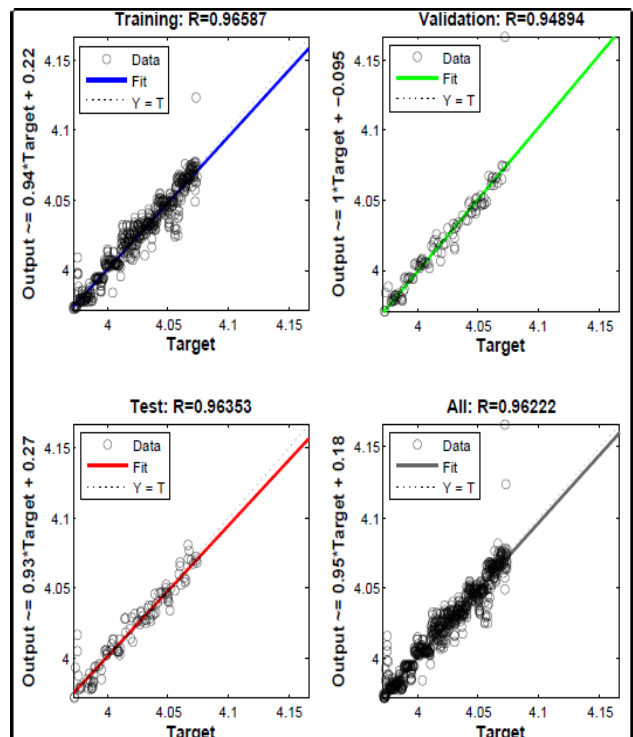


Fig. 2. Regression for the ROP model at Training, Validation, and Testing

To get an excellent fit line the slope must be one and the intercept must be zero.

Good correlation coefficients (R) were obtained from the trained network which they were  $R = [0.96, 0.96, 0.94]$  during the training, testing and validation stages respectively. The mean square error between predicted and desired (ROP) was  $(3.58 \times 10^{-5})$  as shown in Fig. 3.

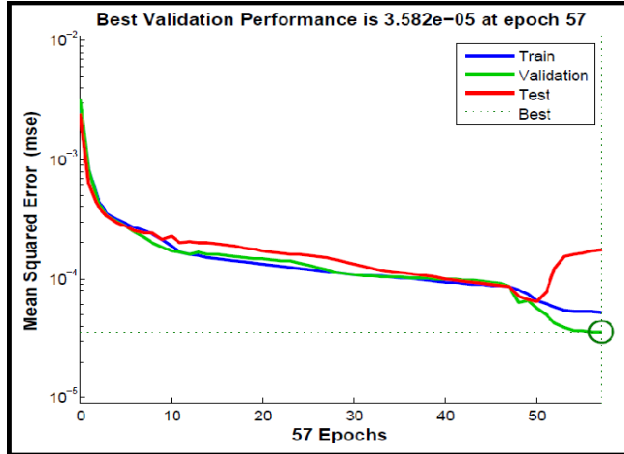


Fig. 3. Mean Square Error for the Network

### 5- Results and Discussion

After the clay volume and the type of lithology have been identified. Shear wave velocity (VS) can be obtained by using the Greenberg-Castagna model which depends on the type of formation and clay volume calculations. Then, Bulk modulus, Shear modulus and Poisson's ratio are computed and listed against depth for Mishrif formation of the studied wells. Dynamic elastic properties were calculated for the ten selected wells. These results are in agreement with Fjaer et al [17] and Gercek [18]. The Table 1 illustrates the average values of the dynamic elastic properties for the selected wells. The average values of (VP/VS) range from (1.87) to (1.91) where the velocity in (ft/s). These values agree with Pickett [19], Fadhil [20] and Zinszner and Pellerin [21] results for (VP/VS) values for limestone. The results of dynamic elastic properties are shown in Fig. 4 for NS-16.

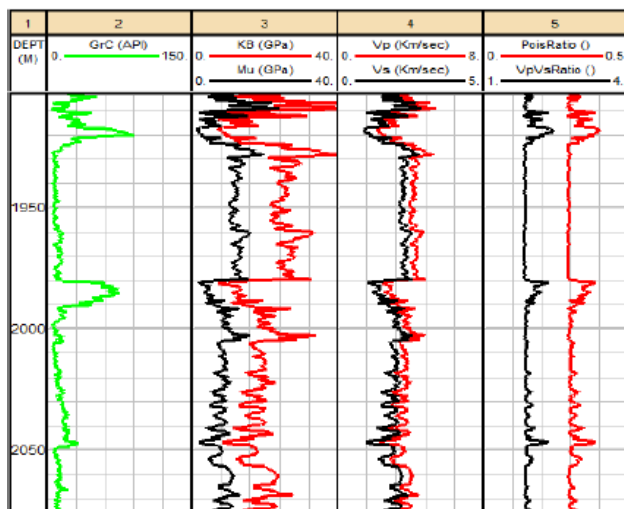


Fig. 4. Dynamic elastic properties for Mishrif formation (NS-16)

Laboratory measurements were conducted on samples of cores taken from NS-3 and NS-18 to measure compressional and shear waves velocities and to compare it with the results from the sonic log at the same depth. The non-destructive ultrasonic test was used to measure transit time for compressional and shear waves. James instrument V-meter mark IV device used for these measurements and it has an advanced microprocessor and equipped with the S-wave response (shear wave transducers). The results showed good agreement between laboratory measurements and log records with maximum absolute percentage error (APE) is 20% and minimum (APE) is 1%. Due to convenience between the lab measurements and the shear waves obtained from Greenberg-Castagna model. Greenberg-Castagna model was used to estimate the shear wave velocities curve.

Table 1. Average results for dynamic elastic properties

| FM                | WELL  | VP/VS | KB <sub>GPa</sub> | St.de <sub>v</sub> | MU <sub>GPa</sub> | Std <sub>ev</sub> | PR    | St.dev |
|-------------------|-------|-------|-------------------|--------------------|-------------------|-------------------|-------|--------|
| MISHRIF FORMATION | NS-1  | 1.88  | 23.7              | 5.7                | 11.1              | 2.9               | 0.300 | 0.018  |
|                   | NS-3  | 1.88  | 25.8              | 8.8                | 12.0              | 4.1               | 0.300 | 0.014  |
|                   | NS-4  | 1.87  | 23.4              | 6.0                | 10.9              | 3.0               | 0.299 | 0.011  |
|                   | NS-5  | 1.88  | 22.1              | 6.3                | 10.2              | 2.7               | 0.301 | 0.015  |
|                   | NS-9  | 1.90  | 20.6              | 8.5                | 8.6               | 4.0               | 0.305 | 0.017  |
|                   | NS-15 | 1.88  | 21.1              | 4.7                | 9.8               | 2.5               | 0.301 | 0.013  |
|                   | NS-16 | 1.91  | 20.7              | 6.4                | 9.4               | 3.5               | 0.307 | 0.019  |
|                   | NS-18 | 1.87  | 25.5              | 8.4                | 11.9              | 3.7               | 0.299 | 0.013  |
|                   | NS-19 | 1.88  | 24.8              | 7.7                | 11.6              | 3.6               | 0.300 | 0.015  |
|                   | NS-21 | 1.87  | 27.6              | 9.0                | 13.0              | 4.0               | 0.297 | 0.009  |

Table 1 lists the dynamic elastic properties values for the studied wells. Highest average value of bulk modulus was (27.6) GPa from NS-21. The minimum average value of bulk modulus was (20.6) GPa from NS-9. For the shear modulus, the minimum average value was (8.6) GPa from NS-9. The maximum average value was (13) GPa from NS-21. For the Poisson's ratio, the values were close together for the all wells.

The minimum average value was (0.297) from NS-21 and the maximum was (0.307) from NS-16. Standard deviation gives an idea about how the data are spread out around the mean (average). Low standard deviation means that most of the numbers are close to the mean.

Higher standard deviation was obtained from NS-21 with a value of (9) for bulk modulus. In the other hand, the minimum value of standard deviation was obtained from NS-15 which was (4.7). The deviation around the mean was smaller for the shear modulus. Largest deviation around the mean was (4.1) from NS-21. NS-15 gave low standard deviation around (2.5). In case of Poisson's ratio the highest value of standard deviation was (0.019) which gained from NS-16, while the lowest value of standard deviation obtained from NS-21 was (0.009).

The ROP values were supported as discrete points in drilling reports. Then, linear regression was used to predict the values of ROP along the depth of interest in all studied wells.

The correlation coefficient was ( $R^2 = 0.91$ ). Dynamic elastic properties were plotted against rate of penetration for the wells (NS-1, NS-3, NS-4, NS-5, and NS-18) as shown in Fig.5. The bulk modulus is reciprocal of rock compressibility. So, as the value of this modulus increase, the rock resistance to penetration also increases. In the result, if the other operational parameters and rock properties held constant, low rate of penetration will be obtained. Fig. 5 does not show a clear trend between bulk modulus and ROP because of wide range of variety in bulk modulus. This is due to the heterogeneity of carbonate reservoirs. For the shear modulus, it's the rock resistance for the applied shear force. Its effect was the same as the effect of bulk modulus. From Fig.5, at the top of formation where the values of bulk modulus and shear modulus were at minimum the ROP was at its highest value. ROP started to decrease as the elastic properties started to rise up along the depth of interest.

The plot of bulk modulus and shear modulus versus ROP for the wells (NS-9, NS-15, NS-16, NS-19, and NS-21) is shown in Fig. A1 in Appendix- A

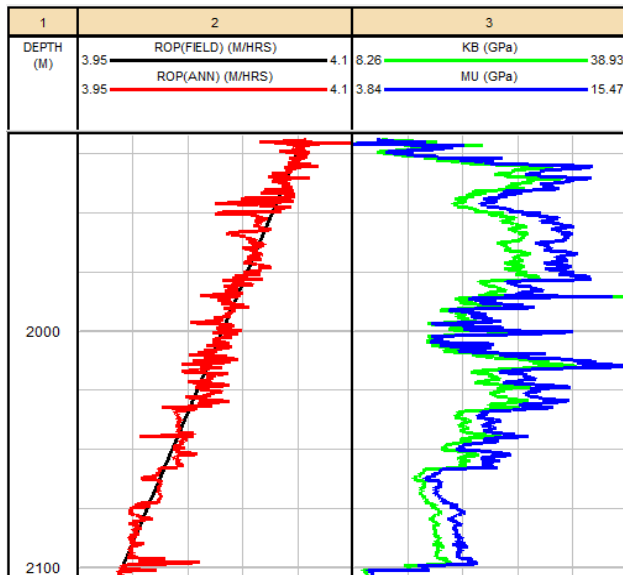


Fig. 5. Bulk modulus and shear modulus vs average rate of penetration (NS-1, NS-3, NS-4, NS-5, and NS-18)

Fig. 6 demonstrates the relationship between the Poisson's ratio and the rate of penetration for the wells (NS-1, NS-3, NS-4, NS-5, and NS-18). Poisson's ratio is the negative ratio of lateral strain to longitudinal strain. High Poisson's ratio means the rock has lateral strain higher than longitudinal strain.

This means that the rock has more resistance to penetration process. As shown in Fig. 6, the penetration rate was highest at the top of the Mishrif formation where the Poisson's ratio was at its minimum values.

As moving downward, the ROP started to decrease as the Poisson's ratio increased. All curves have large deflections and non-clear trend.

There are a lot of parameters that lead to change in the ROP. Also, the Poisson's ratio was plotted against ROP in Appendix-A2. The same behavior was obtained for these wells

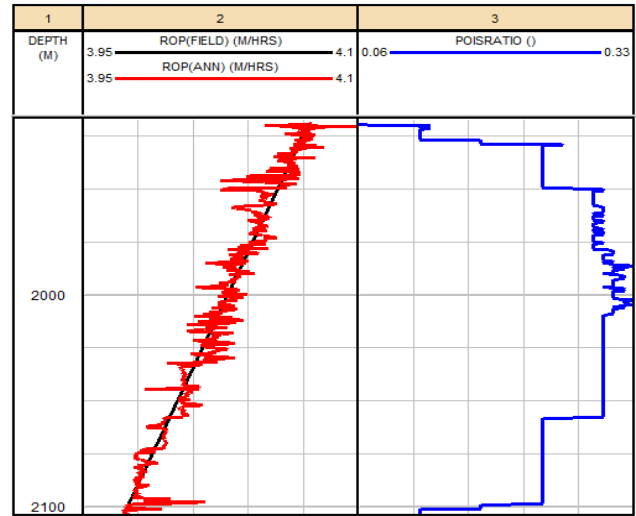


Fig. 6. Poisson's ratio vs average rate of penetration (NS-1, NS-3, NS-4, NS-5, and NS-18)

Fig. 7 shows a plot between ROP from field and the predicted ROP by the ANN model for the wells (NS-1, NS-3, NS-4, NS-5 and NS-18).

The data from these wells where used to train and build the ANN model. Fig. 8 shows the predicted ROP by the ANN model for the wells (NS-9, NS-15, NS-16, NS-19 and NS-21).

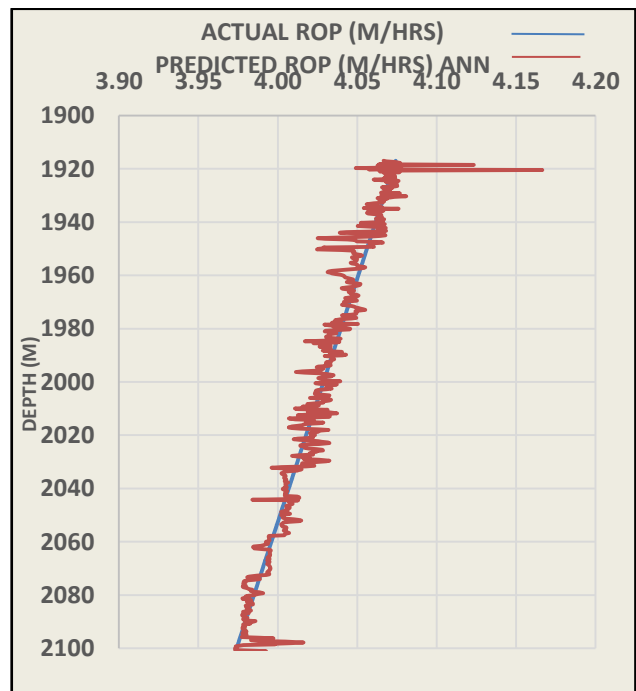


Fig. 7. ROP predicted by ANN model versus ROP actual (NS-1, NS-3, NS-4, NS-5, and NS-18)

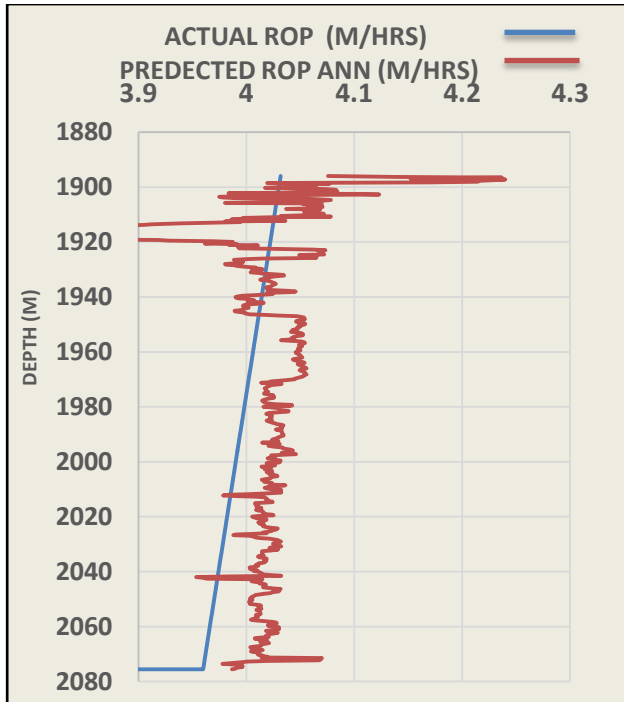


Fig. 8. ROP predicted by ANN model versus ROP actual (NS-9, NS-15, NS-16, NS-19, and NS-21)

## 6- Conclusions

The results did not show strong dependency of ROP on dynamic elastic properties. Because the rate of penetration does not depend on the elastic properties only other properties has direct effect on ROP like rock compressive strength, porosity, operational parameters, and bit hydraulics.

As shown in Fig. 5 and Fig. 6, there are large variations in the values of dynamic elastic properties due to heterogeneity of carbonate reservoirs. The ROP was inversely proportional with dynamic elastic properties. When the values of dynamic elastic properties decrease the ROP values rise up. A low rate of penetration was obtained in Mishrif formation which was between (3.7) and (4.1) m/hrs.

Based on the values of (VP/VS) ratio, the lithology of Mishref formation was limestone with some shale points scattered. The ANN model has a mean square error about  $3.58 \times 10^{-5}$ . As a result, the model gave close results to the real data and can be used in (ROP) prediction in similar area.

Highest average value of bulk modulus in Mishrif formation was (27.6) GPa estimated from NS-21 while the lowest average value was (20.6) GPa from NS-9. For the shear modulus, the highest average value was (13) GPa observed from well NS-21 and the lowest average value was (8.6) GPa estimated from well NS-9.

As for the Poisson's ratio, the highest average value in the Mishrif formation was (0.307) from well NS-16 and the lowest average value was (0.297) from well NS-21. The Bulk modulus showed high distribution of the values around the mean.

The highest value of the standard deviation was (9) obtained from NS-21. In case of shear modulus, the highest value of standard deviation was (4.1) from NS-3. For the Poisson's ratio, the values were close and the distribution was not major. Highest value of standard deviation was (0.019) obtained from NS-16. Fig. 7 and Fig. 8 display the difference between the predicted and the actual ROP.

## Nomenclature

|          |                                                        |
|----------|--------------------------------------------------------|
| db       | Bit diameter                                           |
| $\mu$    | Bit specific coefficient of sliding friction           |
| Ab       | Borehole area                                          |
| G        | Coefficient determined based on bit and blade geometry |
| N        | Rotary speed                                           |
| $\sigma$ | Unconfined rock strength                               |
| $W_f$    | Wear function calibrating ROP values for a worn bit    |

## Abbreviations

|        |                           |
|--------|---------------------------|
| APE    | Absolute percentage error |
| ANN    | Artificial Neural Network |
| BP     | Backpropagation           |
| KB     | Bulk modulus              |
| VP     | Compressional wave        |
| MSE    | Mean square error         |
| NS     | Nasiriya                  |
| PR     | Poisson's ratio           |
| ROP    | Rate of Penetration       |
| MU     | Shear modulus             |
| VS     | Shear wave                |
| St.dev | Standard deviation        |
| WOB    | Weight on Bit             |

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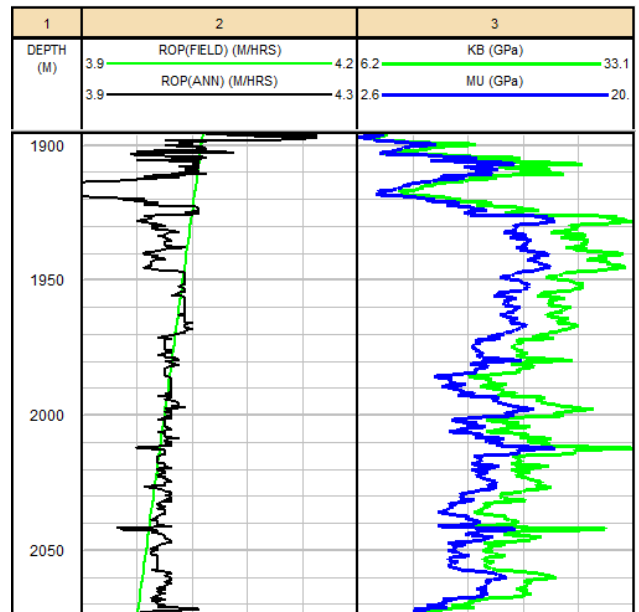
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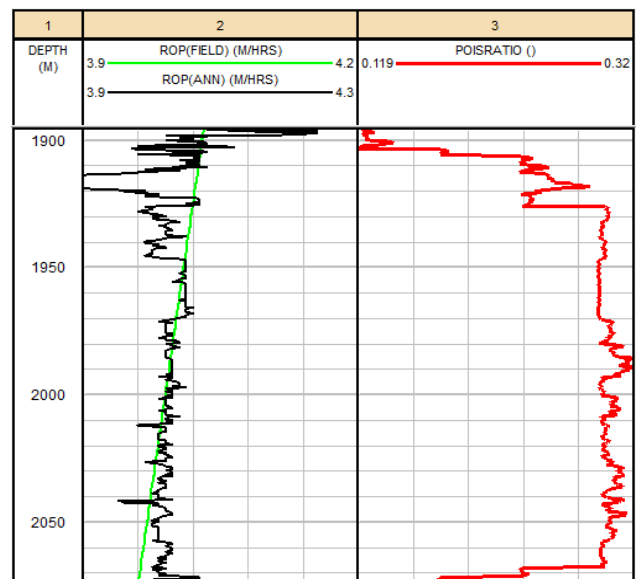
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## Appendices



Appendix-A1. Bulk modulus and shear modulus vs average rate of penetration (NS-9, NS-15, NS-16, NS-19, and NS-21)



Appendix-A2. Poisson's ratio vs average rate of penetration (NS-9, NS-15, NS-16, NS-19, and NS-21)

## استخدام الشبكة العصبية الاصطناعية للتنبؤ بمعدل الاختراق من الخصائص المرنة الصخرية الديناميكية

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### الخلاصة

يمثل الوقت المستغرق في تقدم عملية الحفر جزءاً كبيراً من إجمالي تكلفة البئر. حفر الآبار عملية باهظة الثمن بما في ذلك تكلفة المعدات والمواد المستخدمة أثناء اختراق الصخور بالإضافة الى جهود الطاقم من أجل إنهاء البئر دون مشاكل خطيرة. معرفة معدل الاختراق من شأنه أن يساعد في تخمين التكلفة لذلك معرفة معدل الاختراق في المنطقة التي على وشك ان تحفر يساعد في عملية تخمين كلفة الحفر في تلك المنطقة. تم اختيار عشرة آبار في حقل الناصرية النفطي بناءً على توفر البيانات. تم تحديد الخصائص المرنة الديناميكية لتكوين المشرف في الآبار المحددة باستخدام برنامج Interactive Petrophysics (IP V3.5) واستناداً إلى ملفات las وتسجيلات اللوكات المقدمة من قبل الشركات. تم تحديد معدل اختراق الآبار التي تمت دراستها وإدراجها مقابل العمق مع معدل الخصائص المرنة الديناميكية. أجريت قياسات مختبرية على عينات أساسية مختارة من بئرين. تم استخدام جهاز Ultra-sonic لقياس وقت العبور لموجات الضغط والقص ولمقارنة هذه النتائج بتسجيلات اللوك. السبب وراء ذلك هو التحقق من دقة معادلة الموديل المستخدم Greenberg-Castagna التي تم استخدامها لحساب موجات القص لحساب الخصائص المرنة الديناميكية للصخور. تم بناء الموديل باستخدام تقنية الذكاء الاصطناعي والالية المستخدمة كانت الشبكة العصبية الاصطناعية للتنبؤ بمعدل الاختراق في تكوين مشرف في حقل نفط الناصرية النفطي للآبار المختارة. تمت مقارنة النتائج التي تم الحصول عليها من الموديل مع معدل الاختراق المقدم من تقارير الحفر وكان متوسط الخطأ التريبيعي  $(3.58 * 10^{-5})$  لموديل الشبكة العصبية الاصطناعية.

الكلمات الدالة : معدل الاختراق ، الشبكة العصبية الاصطناعية، الخواص الديناميكية المرنة، حقل الناصرية النفطي.