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Prediction of penetration Rate and cost with Artificial Neural Network for Alhafaya Oil Field

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Abstract

Prediction of penetration rate (ROP) is important process in optimization of drilling due to its crucial role in lowering drilling operation costs. This process has complex nature due to too many interrelated factors that affected the rate of penetration, which make difficult predicting process. This paper shows a new technique of rate of penetration prediction by using artificial neural network technique. A three layers model composed of two hidden layers and output layer has built by using drilling parameters data extracted from mud logging and wire line log for Alhalfaya oil field. These drilling parameters includes mechanical (WOB, RPM), hydraulic (HIS), and travel transit time (DT). Five data set represented five formations gathered from five drilled wells were involved in modeling process.Approximatlly,85 % of these data were used for training the ANN models, and 15% to assess their accuracy and direction of stability. The results of the simulation showed good matching between the raw data and the predicted values of ROP by Artificial Neural Network (ANN) model. In addition, a good fitness was obtained in the estimation of drilling cost from ANN method when compared to the raw data.

Keywords: Rate of Penetration, Artificial Neural Network

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1- Introduction

During the last decades, drilling operations have witnessed significant progress to improve down hole drilling techniques. Drilling optimization techniques have been extensively used to minimize drilling operation costs by reducing nonproductive time **[1]**.

At the present time, there is no representative mathematical relationship between rate of penetration and drilling parameters due to large number of uncertain drilling variables that influenced the drilling rate and also the complex and nonlinearity relationship between them **[2]**.

Rate of penetration is affected by two types of parameters, which are controllable and uncontrollable parameters .The controllable parameters are related to mechanical (WOB, RPM), hydraulic, drilling fluid properties, well configuration, and type of bit, while the uncontrollable parameters are related to formation properties **[3]**.

During the last decades, drilling optimization techniques adopted new methods for solving drilling optimization problems.

These new methods include Artificial Intelligence (AI) such as Genetic Algorithm (GA), and Artificial Neural Network (ANN) methods.

M.H.Bahari et al (2008) applied GA method to calculate constant coefficients of Bourgoyne and Youngs ROP model for solving problems where the model had proven to be meaningless in some cases .The results of simulation had proven to be proficient to determine that coefficients of Bourgone and Young ROP model **[4]**.

Jahanbakhshi,R,et al.(2012) developed an ANN model to investigates and predict the ROP in one of Southern Iran's oil field, by considering type of formation , mechanical properties of rock, hydraulics factors, bit type, and mud properties. The results showed the efficiency of ANN model for field application, and for drilling planning for any oil and gas wells in the related field **[5]**.

M.Bataee et al (2011) developed an ANN model to determine complex relationship between drilling variables. Their model predicted the exact penetration rate, optimization of drilling parameters, time of the drilling of wells, and lowering the drilling cost for future wells **[6]**.

In this study, a new model of rate of penetration based on the Artificial Neural network (ANN) is build using the MATLAB programming computer.

Results of predicted model showed good convergence when compared with others model and a good estimation of drilling cost.

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2- Artificial Neural Network Approach

Artificial Neural Network are powerful techniques used in modeling complex systems that seeks to simulate human brain behavior by treatment of data on the basis of trial and error. ANN has been identified as tool to determine and optimize complicated nonlinear relationships between parameters **[6]**.

In petroleum industry, Artificial Neural Networks (ANNs) has accepted a wide applications such as prediction of hole pressure, fracture pressure, pore pressure, and the instability of wellbore.

ANN is massively parallel –distributed treatment units called neurons. These simple neurons have specific performance characteristics in common with biological neurons.

Artificial Neural network is usually consisted of multilayers. These layers are input layer, one or more hidden layers, and one output layer. The number of input neurons is usually corresponds to the number of parameters that are being presented to the network as inputs, also, the same thing for the output layer.

For the hidden layers and neurons, their number is unknown and can be unlimited.

The neurons are arranged and organized in different forms depending on the type of the network (architecture).The layers of neurons are linked by the connection weight, which then formed the ANN. The most common ANN architecture is the feed forward with back propagation artificial neural network, in which the information will propagate in one direction from input to output **[7]**. The structure or topology of feed forward ANN is shown in Fig. **1**.

The first step in ANN modeling is the training or learning process. The training process is a procedure to estimate the weights and thresholds by using an appropriate algorithm (activation function).

Each neuron has different activation functions, which are used to process data. Generally, the data is divided randomly in three sets, training set, validation set, and testing set. The validation set is used to stop training process to prevent the network from over fitting the data.

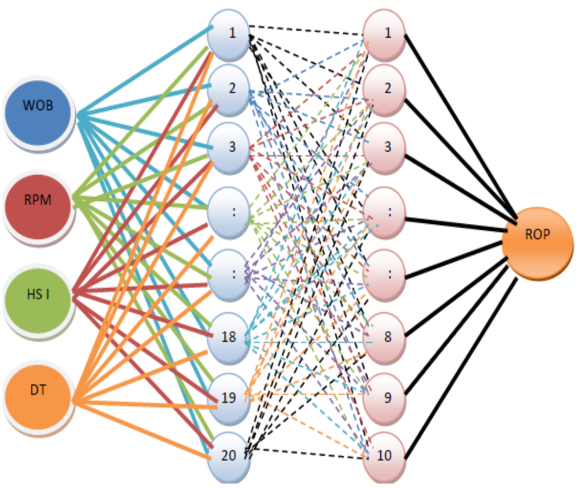

Fig. 1. Structure of ANN model

3- Region of Study

In order to build the model, field data from AL-Halfaya oil field was extracted from mud logging unit and sonic log. AL-Halfaya oilfield is located in Missan province in the southeast of Iraq, 35 kilometers southeast to Amara city.

The data used in this study are provided by Petro China Company Limited (from Contractor Bohai Mudlogging), that working in AL-Halfaya oil field. Modeling data are extracted from five vertical wells called (HF004-M272, HF051-N051, HF109- N109, HF195-N195and HF004-N004) for five formation called (fars formation, Kirkuk formation, Hartha formation, Mishraf formation and Nahar Umar formation). Each formation represented dataset.

For ANN modeling purpose, the ROP was considered as dependent variable, while the (WOB, RPM, HSI and DT) were considered as independent variable. The interval transit time (DT) is the reciprocal of sonic speed in the rock and express in (μsec/ft).

Five data sets are considered in the modeling which represented five formations. These parameters represented the mechanical, hydraulic and formation strength, which are the most important parameters. Table **1** depicts the final input parameters for ANN modeling.

Table 1. Input parameters for ANN modeling

Parameter	Unit
Weight on Bit	ton
Rotary Speed	rpm
Hydraulic	HSI
Transit Time	$Msec^{-1}$

Before the input data is applied to the network, it should processed by normalization function .To scale the data for each input variable, a known method called min-max normalization method, which linearly scales the data to values between 0 and 1 using the following equation:

$$Xmin - max = (X - Xmin) / (Xmax - Xmin) \quad (1)$$

Where X is the value of the parameter to be noramalized, X_{min} and X_{max} are minimum and maximum values respectively. With this method, the output of network will always falls into a normalized range.

4- Training the Network

It's well known that using of powerful nonlinear regression models is associated with the possibility of over fitting data. In order to obtain the optimal size of the neural network model, a heuristic approach was applied.

Here, there is possibility to increase the number of hidden layers to two or three if the results with one are still not adequate.

However, increasing the numbers of neurons in the hidden layers or increasing the number of hidden layers will increase the power of the network model, but will required more computation processes and lead to produce over fitting **[7]**.

In order to avoid over fitting data during the developed stage of the model, the field data of five sets was divided into three subsets which are training subset, validation subset, and testing subset. The set of training is used to calibrate the model. It is used for calculating the gradient and updating the network weights and biases. The set of validation is used to verification the generalization of the developed model during the learning phase.

The validation errors will decrease normally during the initial phase of training, which also the training set error. The set of testing is used to examine the final calculation of the network and compare different models. For the model building process, the available dataset consisted of 85% for the pure network leaning process, and 15% for validation.

5- Results of Simulation

While developing ANN model, the three layered network showed the lowest network error. Also, different structures in the three layered have been tested as well and the comparison between these structure showed that the three layered with 20 hidden neurons in the hidden layer is the best model. As it shown in the Fig. **1**, a three layer feed forward network which use activation function for the hidden layer and pure line for output layer and full connection topology between layers is used. This algorithm can approximate any nonlinear continuous function to an arbitrary accuracy [7].
The performance of the ANN model can be evaluated on the basis of efficiency coefficient(R). Table **2** gives the R values for the five data sets from A to E as follows:

Table 2. Results of network model for five data sets in term of R

Dataset	No.of Data	Training
		R
A	1800	0.91261
B	550	0.96893
C	374	0.83361
D	469	0.94061
E	397	0.92163

Performance of the best ANN model for each data sets are shown in Fig. **2** through Fig. **6**.

As it seen in all figures, an increase in number of training attempts would accompany by an improvement in performance of ANN model due to reduction of mean square error (mse) values and thereby could obtained good predicted values of rate of penetration (ROP).

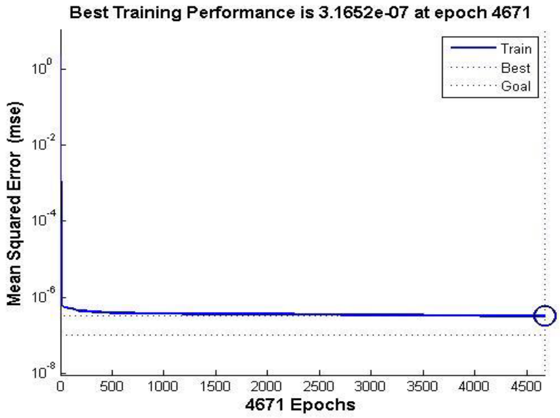

Fig. 2. Neural network training performance for dataset A

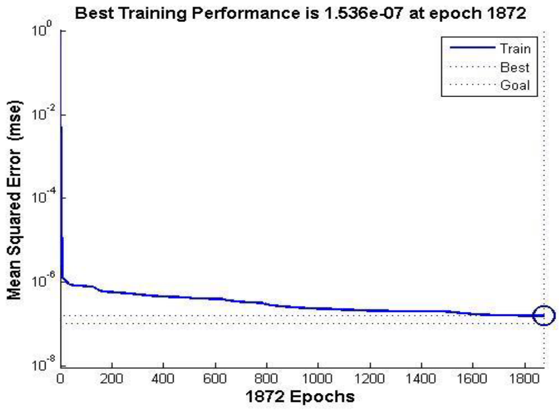

Fig. 3. Neural network training performance for dataset B

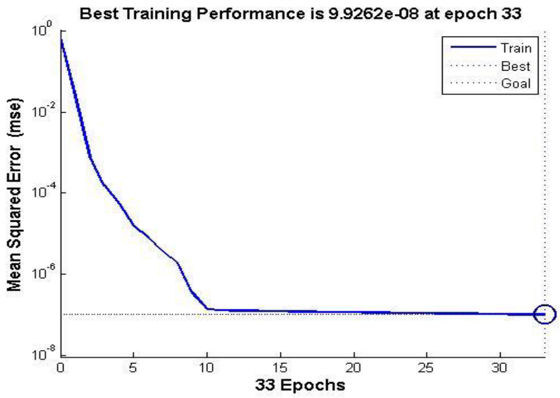

Fig. 4. Neural network training performance for dataset C

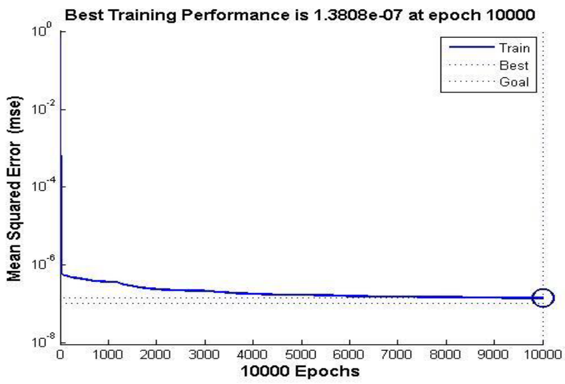

Fig. 5. Neural network training performance for dataset D

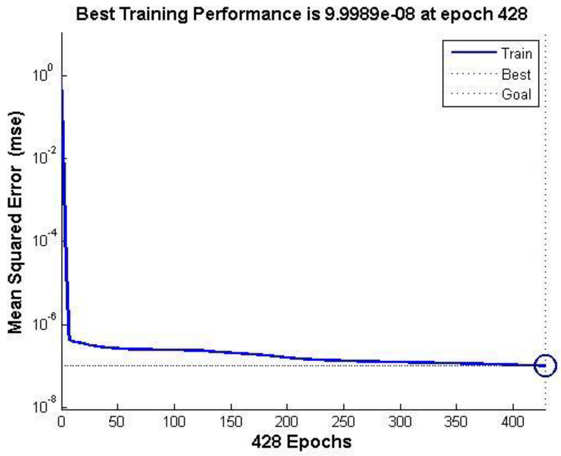

Fig. 6. Neural network training performance for dataset E

The regression analysis of ANN model for five data sets (A, B, C, D, and E) could be seen in Fig. **7** through Fig. **11**.

These figures show the regression plots of predicted rate of penetration against field data. The efficiency coefficient values (R) for training process shows excellent convergence between the predicted and actual values of ROP for all data sets. Also each data set has special regression equation as shows on y-axis.

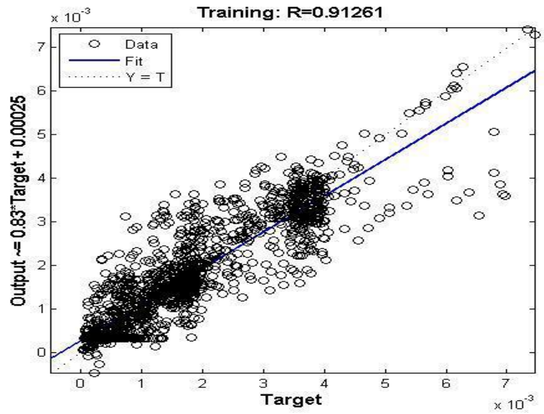

Fig. 7. Neural network regression for dataset A

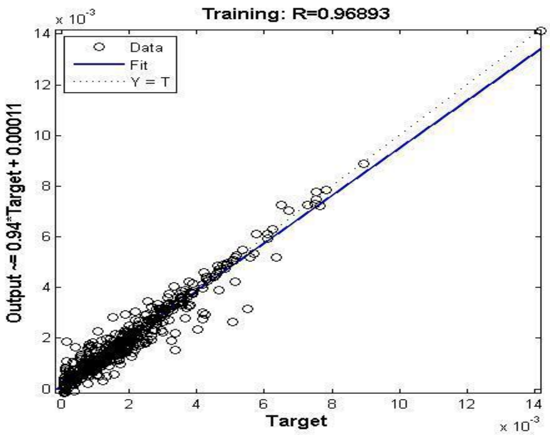

Fig. 8. Neural network regression for dataset B

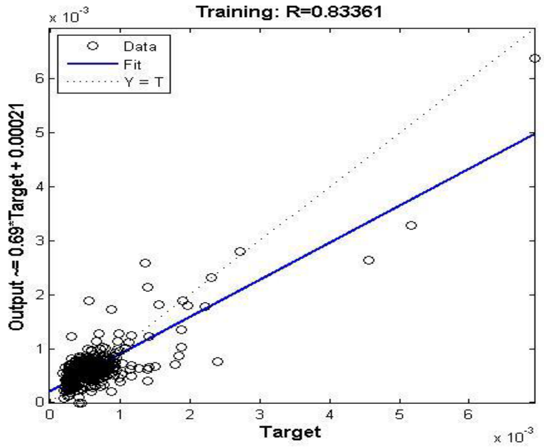

Fig. 9. Neural network regression for dataset C

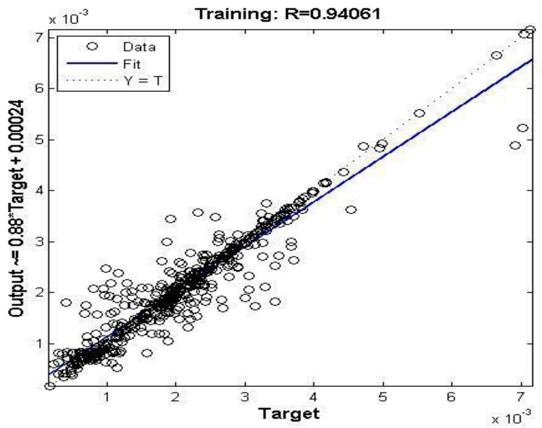

Fig. 10. Neural network regression for dataset D

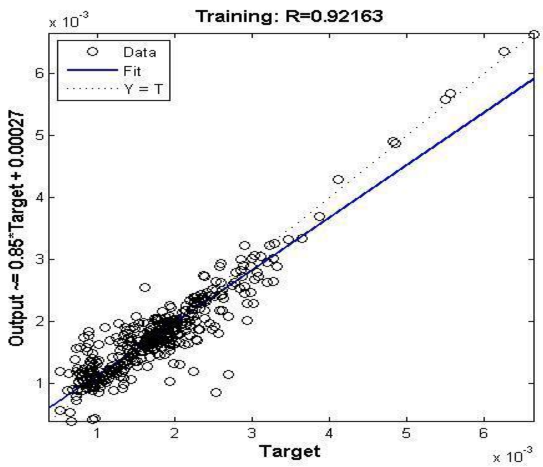

Fig. 11. Neural network Regression for Dataset E

Fig. **12** through Fig. **16** shows the matching between the predicted and measured data in term of ROP for the five datasets.

The output of the ANN model shows a good agreement matching at wide range of depth with the raw data.

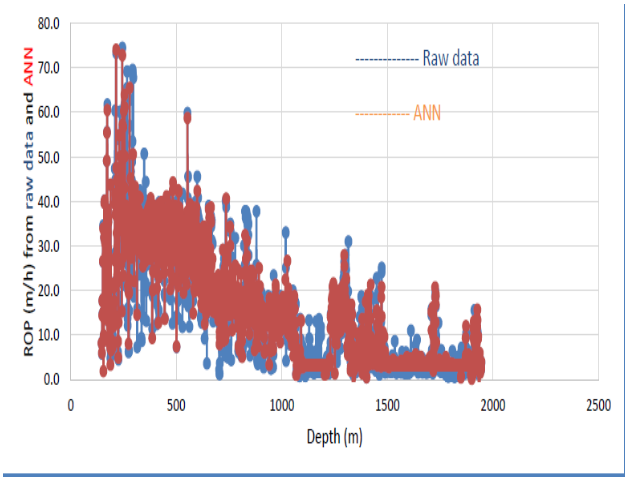

Fig. 12. Training data comparison between field and ANN model of dataset A

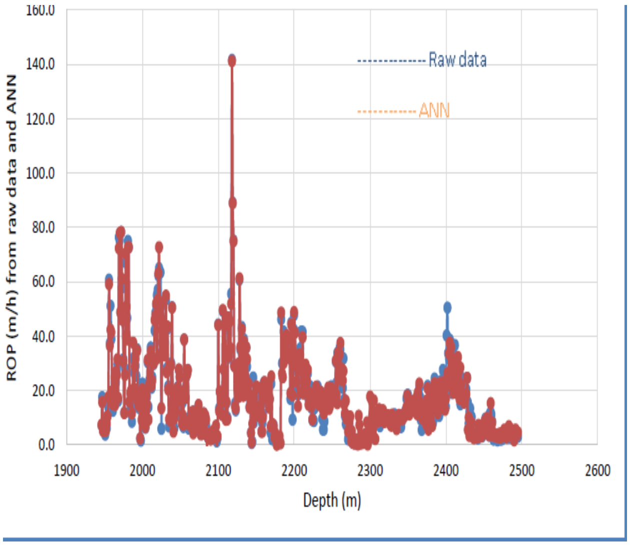

Fig. 13. Training data comparison between field and ANN model of dataset B

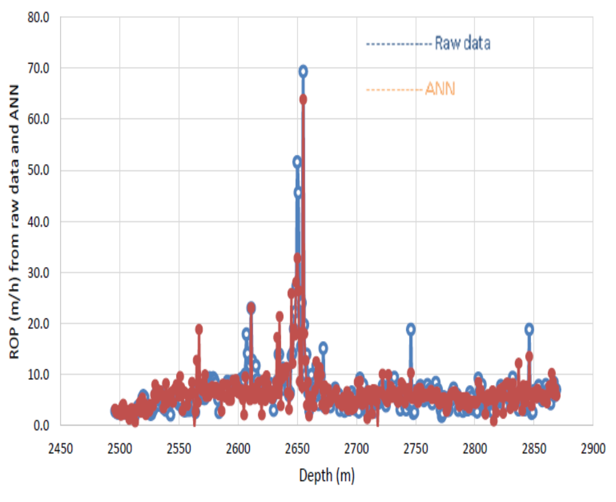

Fig. 14. Training data comparison between field and ANN model of dataset C

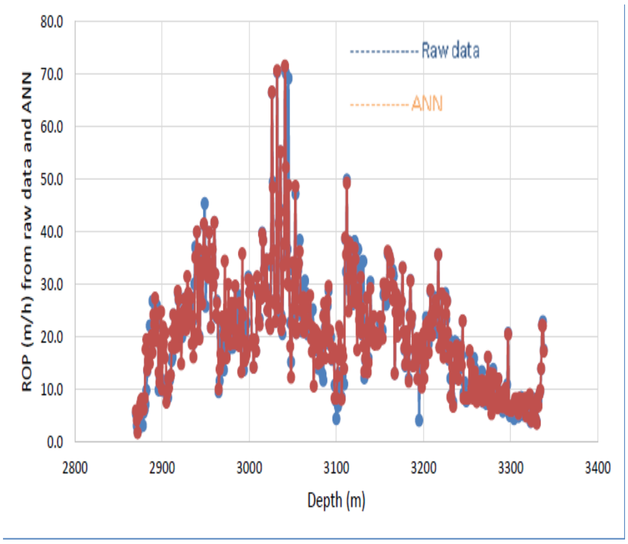

Fig. 15. Training data comparison between field and ANN model of dataset D

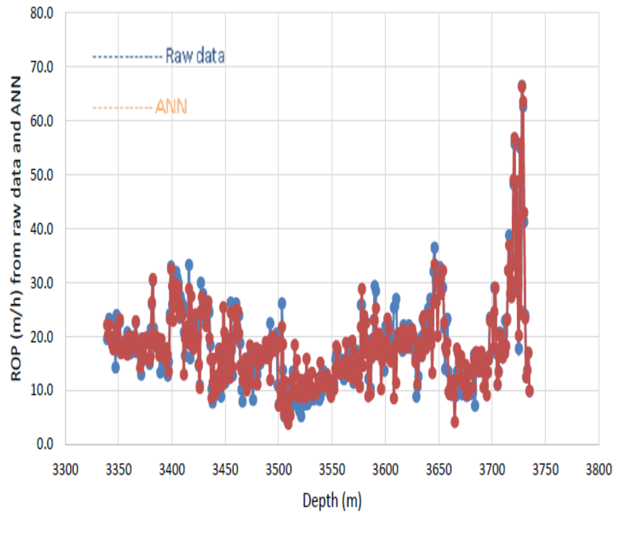

Fig. 16. Training data comparison between field and ANN model of dataset E

6- Estimation of Drilling Cost

As mentioned earlier, the objective of drilling optimization is to reduce the drilling operation cost. In this section the proposed ANN model was tested again by estimation of drilling cost for certain well (HF004) and specific depth (from depth 147 m to1390 m) for each dataset. The following information in Table **3** is obtained from field operating company.

Table 3. Data of cost estimation

Cost of Rig, $/d	30000
Cost of Bit,$	5000
Rotating time,hr	16
Trip time,hr	1.5
Connection time,min	1

The estimation of cost of drilled footage was done with following equation:

$$cpm = \frac{cb+cr(Tr+Tt+Tc)}{f} \quad (2)$$

Where cpm is cost per meter, cb is bit cost, cr is rig cost, Tr is rotation time, Tt is trip time, Tc is connection time, and f is the number of drilled footages.

The performance of proposed ANN model in term of estimation of drilled footage is presented in Fig. **17** through Fig. **21** for five datasets.

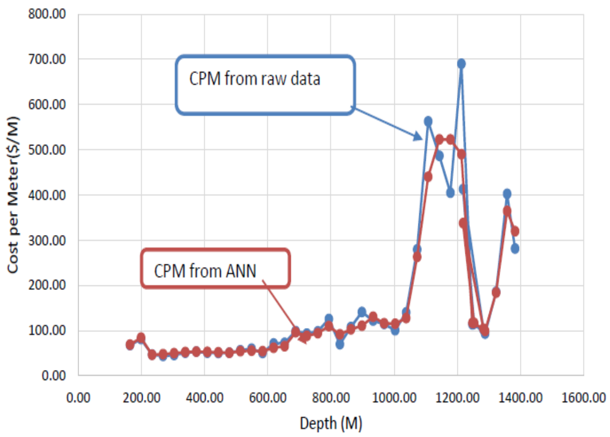

Fig. 17. Comparison between predicted drilled cost by ANN model and actual data for data set A

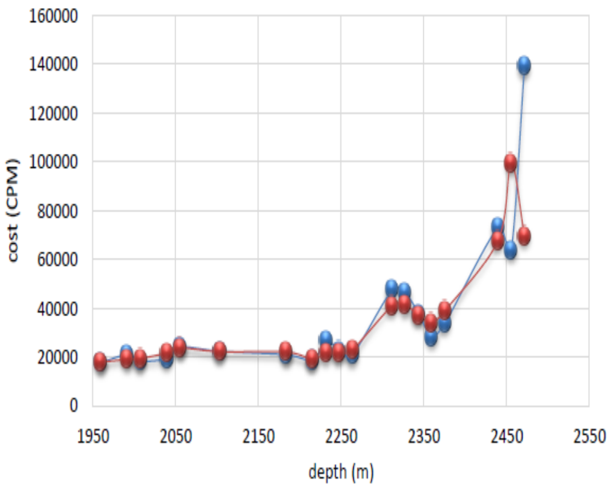

Fig. 18. Comparison between predicted drilled cost by ANN model and actual data for data set B

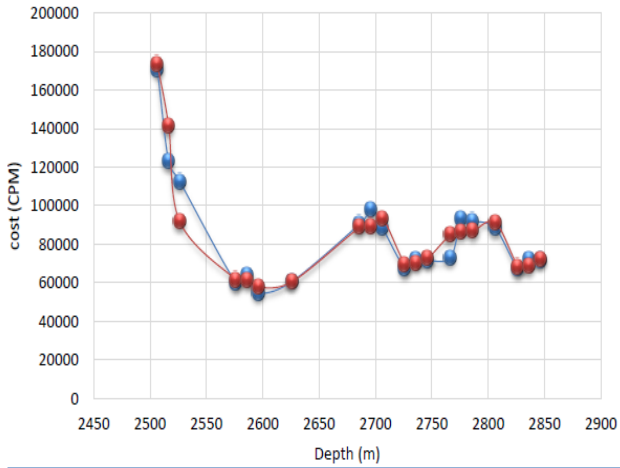

Fig. 19. Comparison between predicted drilled cost by ANN model and actual data for data set C

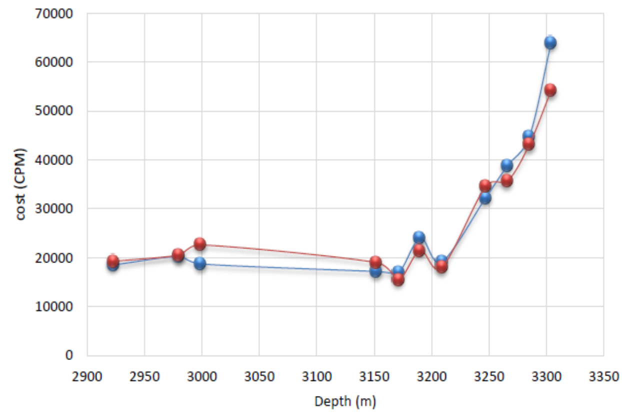

Fig. 20. Comparison between predicted drilled cost by ANN model and actual data for data set D

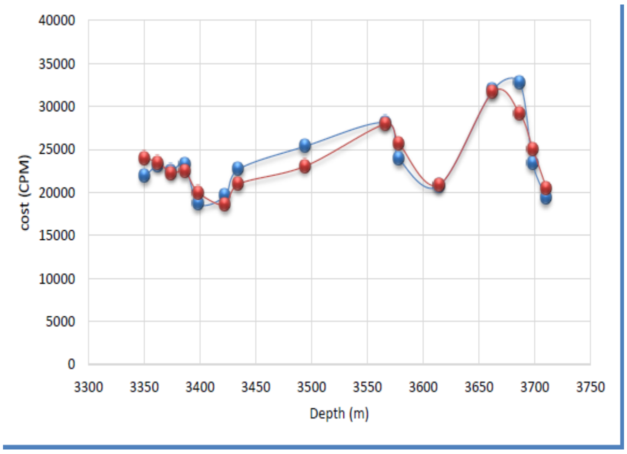

Fig. 21. Comparison between predicted drilled cost by ANN model and actual data for data set E

All these results demonstrated that the cost of drilled footage predicted by the proposed ANN model has accurate drilled cost and matched concisely with the actual field data. So, these calculations support the accuracy of the neural network model.

7- Conclusions

Based on the previous calculation, an Artificial Neural Network model of three layers for estimating rate of penetration of Alhalfaya oil field could be constructed with aid of five data sets from mud and wire line logs. A large training process for each data set were conducted due to high quantity of field data and could be obtained high performance of ANN model by reducing the mean square error to minimum level, and improving the value of efficiency coefficient.

The ANN proposed model showed good feasibility and accuracy when it applied for estimation the rate of penetration in five formations due to high matching with the raw data. Also, economic application of the proposed ANN model for estimation the cost of drilled footage in five data sets showed their capability for yielding quite accurate outcome.

Nomenclature

Cpm:	cost per meter,$/m
Cr:	rig cost, $/hr
F:	No of drilled meter,m
R:	Efficiency coefficient
Tc:	connection time,hr
Tr:	rotation time, hr
Tt:	trip time, hr

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تخمين معدل الحفر والكلفة بواسطة الشبكة العصابية الصناعية لحقل الحلفاية النفطي

الخلاصة

التخمين الدقيق لمعدل الحفر ذو اهمية كبيرة في الحفر الامثل بسبب تاثيره المحوري على كلفة عمليات الحفر. وعادة يكون هذا التخمين صعب بسبب تداخل العوامل التي تؤثر على عملية الحفر.في هذا البحث تم استخدام طريقة الشبكة العصابية الصناعية كاسلوب جديد لتخمين معدل الحفر والكلفة, حيث تم بناء موديل الشبكة العصابية من ثلاثة طبقات اثنان مخفية وواحدة للنواتج باستعمال بيانات مجسات الطين والمجسات الاخرى لحقل الحلفاية النفطي. العوامل التي تم استخدام قيمها هي العوامل الميكانيكية (الوزن المسلط, سرعة الدوران),العوامل الهيدروليكية,وزمن انتقال الموجة الصوتية .

تم استخدام خمس مجاميع للبيانات والتي نمثل خمس تكوينات في الحقل حيث تم استخدام 85%من البيانات لتدريب الموديل و15% لاختبار صلاحيته. بينت النتائج التطابق الجيد لقيم معدل الحفر المحتسبة من الموديل مع القيم المقاسة وكذلك لقيم الكلفة المحتسبة مع القيم الاصلية.