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Original Research Article

Drilling Cost Optimization for Extended Reach Deep Wells Using Artificial Neural Networks

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Abstract

Global Petroleum reserves are currently getting depleted. Most of the newly discovered oil and gas fields are found in unconventional reserves. Hence there has arisen a need to drill deeper wells in offshore locations and in unconventional reservoirs. The depth and difficulty of drilling terrains has led to drilling operations incurring higher cost due to drilling time. Rate of Penetration is dependent on the several parameters such as: rotary speed(N), Weight-On-Bit, bit state, formation strength, formation abrasiveness, bit diameter, mud flowrate, bit tooth wear, bit hydraulics e.t.c. Given this complex non-linear relationship between Rate of Penetration and these variables, it is extremely difficult to develop a complete mathematical model to accurately predict ROP from these parameters. In this study, two types of models were developed; a predictive model built with artificial neural networks for determining the rate of penetration from various drilling parameters and an optimization model based on normalized rate of penetration to provide optimized rate of penetration values. The Normalized Rate of Penetration (NROP) more accurately identifies the formation characteristics by showing what the rate should be if the parameters are held constant. Lithology changes and pressure transition zones are more easily identified using NROP. Efficient use of Normalized Penetration Rate (NROP) reduces drilling expenses by: Reducing the number of logging trips, minimizing trouble time through detection of pressure transition zones, encouraging near balanced drilling to achieve faster penetration rate.

Keywords: Artificial Neural Networks, Extended Reach Drilling Normalized Rate of Penetration, Optimization model, Rate of Penetration.

INTRODUCTION

Since drilling time and drilling cost have a directly proportional relationship as a decrease in drilling time would also result in a decrease in drilling cost, it should be considered that the best way to optimize drilling operations is by finding ways to decrease drilling time. Drilling time is dependent on both drilling depth and Rate of Penetration, equation 1.0.

$$\text{Drilling time} = \frac{\text{Drilled Depth}}{\text{ROP}} \quad \ldots\ldots(1.0)$$

Where ROP= Rate of Penetration (ft/hr or ft/min)

Since drilled depths in this case are large for deep wells and cannot be changed, drilling time can only be reduced by increasing the rate of penetration of drilling operations. The cost per footage drilled is given by the general equation 1.1:

$$C = [R(t + t_d) + C_b] / F, \quad \ldots\ldots(1.1)$$

Where, C = Total cost per footage drilled ($/ft)
R = Rig Operating Cost ($/hr)
t = total trip time (hrs)
t_d = total drilling time (hrs)
C_b= Total bit cost (hrs)
F = Footage drilled (ft)

The Rig operating cost is known as well as the footage drilled, the total drill time depends on the Penetration rate. For a given footage drilled, the total time can be expressed as shown in the equation 1.2

$$t = \int_0^f 1/ROP \quad \ldots\ldots(1.2)$$

Where t is the total drill time(hrs)
ROP = Penetration rate(ft/hr)
f= footage drilled

Drilling depth is more or less fixed and not much can be done to affect it, the rate of penetration is the only variable parameters on which drilling time is dependent and it would be the major parameter considered in this study. Rate of penetration is however dependent on the following parameters: Weight on Bit (WOB), Rotary speed (N), drilling fluid properties, bit hydraulics and formation properties. These parameters would serve as the input layer for my Artificial Neural Network model while Rate of Penetration would be the output layer.

According to field data, there are several methods to reduce the drilling cost of new wells. One of these methods is the optimization of drilling parameters to obtain the maximum available rate of penetration (ROP). There are too many parameters affecting ROP like hole cleaning (including drill string rotation speed (N), mud rheology, weight on bit (WOB) and floundering phenomena), bit tooth wear, formation hardness (including depth and type of formation), differential pressure (including mud weight) and etc. Therefore, developing a logical relationship among them to assist in proper ROP selection is extremely necessary and complicated though. In such a case, Artificial Neural Networks (ANNs) is proven to be helpful in recognizing complex connections between these variables.

There are various applicable models to predict ROP such as Bourgoyne and Young's model, Bingham model and the modified Warren model. To optimize the drilling parameters, it is required that an appropriate ROP model be selected. Since the 1970s, various works have been done in the aspects of predicting penetration rate from drilling parameters and optimizing these parameters with the objective of maximizing footage drilled and decreasing drilling cost simultaneously. Some researchers performed some pilot tests on exploration wells which revealed communications, improved interventions and made the advices much more clear, limiting downtime [1]. A new and innovative drilling automation and monitoring system named Drilltronics has been developed, and it was observed that preventing stick-slip occurrences by means of activating one of the introduced algorithms increased ROP by 15 to 30% [2]. Results from a laboratory investigations on the effect of drilled solids on drilling performance was analyzed, among the penetration rate models, the model proposed by Bourgoyne and Young [3] was perhaps the most complete and widely accepted one. Eight functions are used in their equation to model the effect of most important drilling variables

A study on a drilling cost optimization in a hydrocarbon field by combination of comparative and mathematical methods to predict Rate of Penetration while creating Mathematical models based on a comparative analysis on the Iranian Khangiran gas field was conducted [4]. A multiple regression analysis to obtain the regression coefficients of the pre-defined general ROP model in order to predict ROP was examined This gives the flexibility of ROP follow-up as a function of drilling parameters specifically for subject formation. Any diversion from the predicted value should indicate a change, either in formation or drilling condition that an action could be necessary to be taken [5].

The application of Artificial Neural Network (ANN) methods for estimation of ROP among drilling parameters obtained from one of Iranian southern oil fields was conducted, In the study, both the dependent parameters and those that result in higher training error were eliminated in order to decrease the number of inputs. The selected input parameter for the neural network included: Drill collar Outside diameter, Drill Collar Length, Kick off point, Azimuth, Inclination angle, WOB, flowrate of mud, bit rotation speed, mud weight, Solid percentage, Plastic viscosity, Yield point and measured depth [6].

The prediction and optimization of drilling rate of penetration using response surface methodology and bat algorithm were examined. Effect of six variables on penetration rate using real field drilling data were also investigated simultaneously using the Response surface methodology (RSM). A mathematical relation between penetration rate and six factors. The important variables were well depth (D), weight on bit (WOB), bit rotation speed (N), bit jet impact force (IF), yield point to plastic viscosity ratio (Yp/PV), 10 minute to 10 second gel strength ratio (10MGS/10SGS). Next, bat algorithm (BA) was used to identify optimal range of factors in order to maximize drilling rate of penetration. Results indicate that the derived statistical model provides an efficient tool for estimation of ROP and determining optimum drilling conditions. Sensitivity study using analysis of variance shows that well depth, yield point to plastic viscosity ratio, weight on bit, bit rotation speed, bit jet impact force, and 10 minute to 10 second gel strength ratio had the greatest effect on ROP variation respectively. Cumulative probability distribution of predicted ROP shows that the penetration rate can be estimated accurately at 95% confidence interval. In addition, study shows that by increasing well depth, there is an uncertainty in selecting the jet impact force as the best objective function to determine the effect of hydraulics on penetration rate [7].

While using a typical extreme learning machine (ELM) and an efficient learning model, upper-layer solution-aware (USA) to predict Rate of Penetration, the results obtained indicated that ANN, ELM, and USA models are all competent for ROP prediction, with both of the ELM and USA model showed the advantage of faster learning speed and better generalization performance [8].

A study using a combination of Artificial Neural Networks (ANN) and Ant Colony Optimization (ACO) to determine optimal Rate of Penetrationwas carried out. The Bayesian regularization neural network was trained using the modified Warren model for ROP for rolling cutter bits. The trained network was capable of accurately predicting ROP for rolling cutter bits and was compared to the modified warren model. The ACO algorithm was then used to optimize the drilling parameters by brute force. Ideally, real time data should be used to train the network, but in the absence of data, they made use of ROP values estimated by the modified warren model known to estimate ROP with high accuracy [9].

A new approach to predicting and optimizing rate of penetration using Artificial Neural Networks. Rate of Penetration depends on many variables such as drilling parameters [flow rate (Q), RPM, torque (T), weight on bit (WOB), stand pipe pressure (P)], fluid properties (mud density and plastic viscosity), and formation strength (UCS) was developed. The developed ANN model was able to estimate ROP with high accuracy (R of 0.99 and AAPE of 5.6%). The developed empirical correlation for ROP prediction outperformed the previous models. The high accuracy of the developed correlation (AAPE of 4%) confirmed the importance of compiling the drilling parameters and the drilling fluid properties [10].

A new methodology of predicting drilling rate of penetration using a combination of Artificial Neural Network and Optimization algorithm was introduced to predict penetration rate during drilling process, Results showed that the model is accurate enough for being used in the prediction and optimization of ROP in drilling operations [11].

Considering the optimization of Penetration rate using Real Time Measurements from Machine Learning and Meta-Heuristic Algorithm. an Artificial Neural Network (ANN) was developed to predict ROP by making use of the offset vertical wells' real-time surface parameters while drilling. In the ANN, the input-output mapping was designed with interconnected feed-forward back propagation neural network so that the ROP was efficiently predicted at the drilling bit [12]. The present study is aimed at optimizing the drilling parameters, predicting the proper penetration rate, estimating the drilling time of the well and eventually reducing the drilling cost for future wells

METHODOLOGY

Developing the Predictive Model

The first step was in choosing the predictive model that would be used to determine Penetration rate from given drilling parameters For the purpose of this study, a deep regression neural network using C, C++ and Java based MATLAB software are employed.

Building the Predictive Model

To develop this model, drilling reports were obtained from an extended reach horizontal well in the offshore deep wells region in the Niger Delta Region, Nigeria.

The following parameters to serve as the input data for the neural network and the prediction of penetration rate. Obtained from the drilling reports the values of the following: Inclination angle, Bit Number, Depth, Viscosity, Rock strength, Bit Diameter, Nozzle diameter, Lithology, Rotary speed, Weight-On-Bit, Viscosity, Bit wear, Mud Flowrate

Training the Network

The data was divided into 3: this include the Training set, Validation set and Testing set. This model used are both Levenberg Marquadt and Bayesian Regularization algorithm of which Bayesian Regularization was observed to have a higher accuracy. The model was developed using 9994 data points with 8994 (90%) used for training, 500 (5%) used for validation and 500 (5%) used for testing the model. The number of epochs was set to 100 at one iteration and the number of iterations was equal to 5000The value of the Coefficient of regression for this study was optimized to be as close to 1.0 (i.e 100%) as possible.

Building the Optimization Model

The Rate of Penetration is dependent on several factors, some of which are weight-on-bit, rotary speed, mud weight, bit type, lithology and so on. This makes predicting rate of penetration more complicated but not less important. The ability to predict rate of penetration precisely is vital for most rig cost optimization algorithms. For the purpose of this study the Normalized Rate Of Penetration, (NROP) equation (1.3) was used for the evaluation.

The formular for Normalized Rate of Penetration is given below:

$$NROP = ROP * \frac{(W_n - M)}{(W_O - M)} * \left(\frac{N_n}{N_o}\right)^r * \frac{(Pb_n * Q_n)}{(Pb_o * Q_o)} \ldots\ldots\ldots(1.3)$$

Where; ROP = observed rate of penetration.
W_n = normal bit weight.
W_o = observed bit weight.
M = formation threshold weight.
N_n = normal rotary speed.
N_o = observed rotary speed.
r = Rotary exponent.
Pb_n = normal bit pressure drop.
Pb_o = observed pressure drop.
Q_n = normal circulation rate.
Q_o = observed circulation rate.

RESULTS AND DISCUSSION

The results were generated by the use of Using MATLAB. The figures 1.0, 2.0 and 3.0 present the various training algorithm result for Levenberg Marquadt, Bayesian Regularization and Scaled Conjugate Gradient algorithms respectively, while the predicted model for the Levenberg Marquadt, Bayesian Regularization and Scaled Conjugate Gradient algorithms, is presented in the figures 4.0, 5.0 and 6.0, respectively. The Error histogram for Levenberg Marquadt, Bayesian Regularization and Scaled

Conjugate Gradient algorithms are presently in the figures 10.0, 11.0 and 12.0, respectively. According to this results and the value of the R^2 coefficient, it can be deduced that the Levenberg Marquadt training algorithm was 87% accurate, Conjugate Gradient training algorithm was 59% and the Levenberg Marquadt training algorithm was 96% at predicting the Rate of Pentetration.

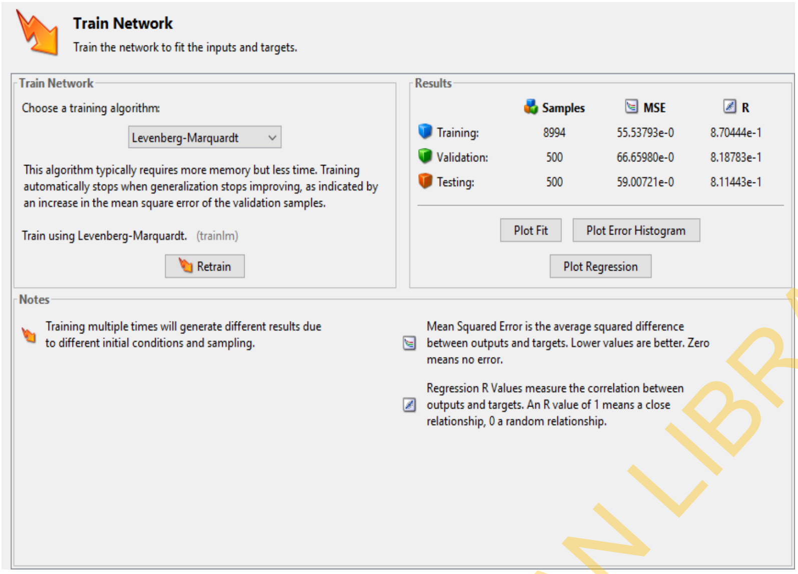

Fig-1: Levenberg marquadt algorithm prediction model (generated in MATLAB)

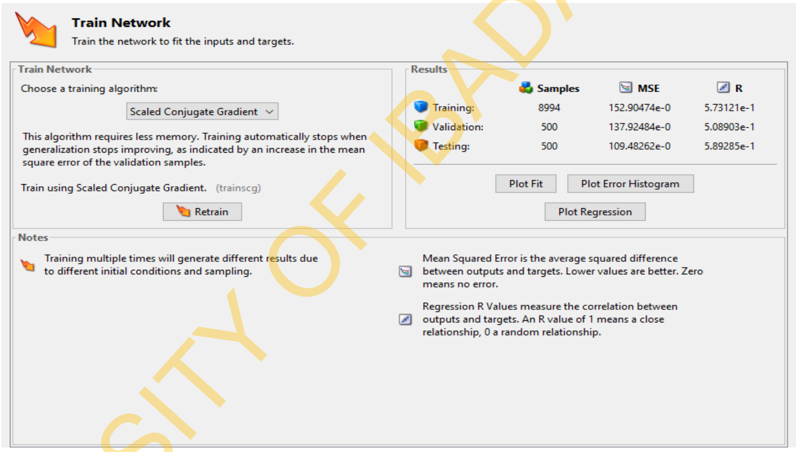

Fig-2: Scaled Conjugate Gradient Algorithm Prediction Model. (Generated in MATLAB)

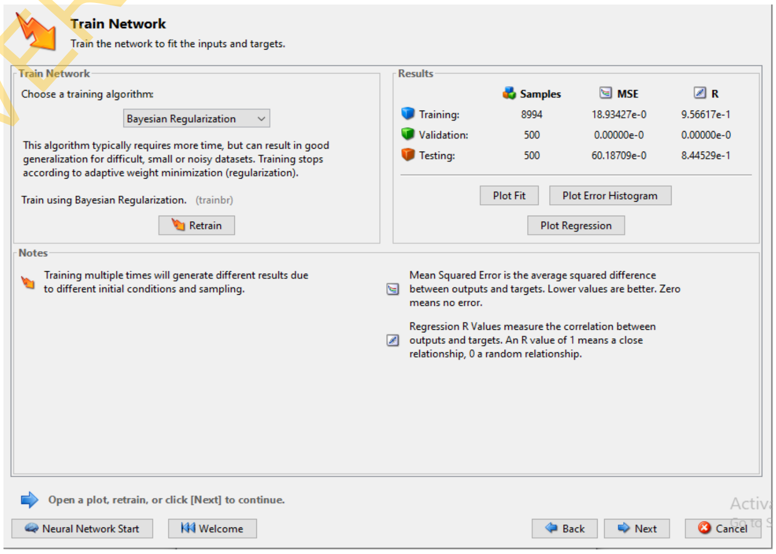

Fig-3: Bayesian Regularization algorithm prediction model. (Generated in MATLAB)

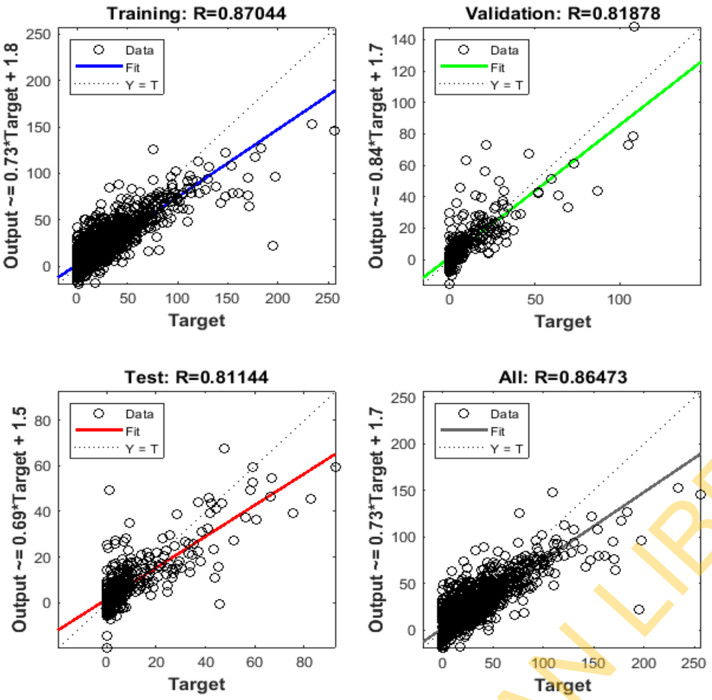

Fig-4: Regression plot of Levenberg Marqaudt Predictive Algorithm

Table-1: Summary of Results

	Levenberg Marquadt	**Scaled Conjugate Gradient**	**Bayesian Regularization**
Mean Square Error	55.53	152.90	18.90
RMSE	7.45	12.365	4.35
Mean Absolute error	2.87	1.43	0.97
R^2 Coeff.	0.82	0.573	0.844
Coeff. of Regression	0.87	0.589	0.96

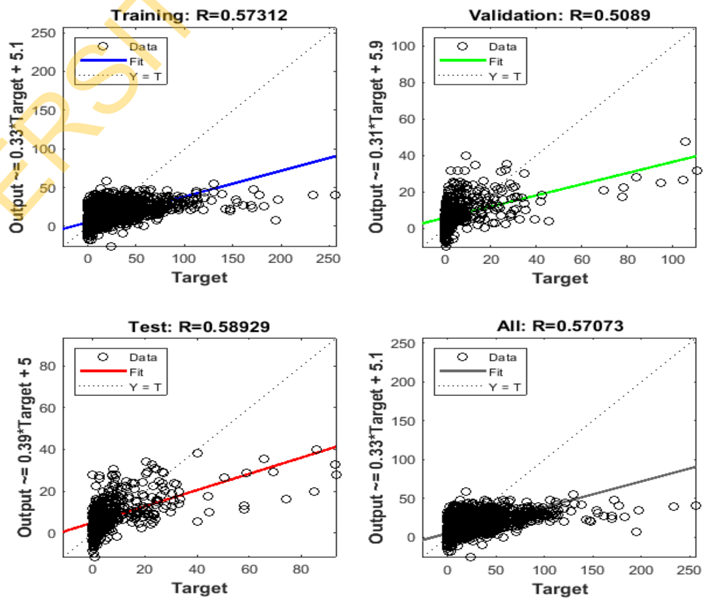

Fig-5: Regression plot of Scaled Conjugate Gradient Predictive Algorithm

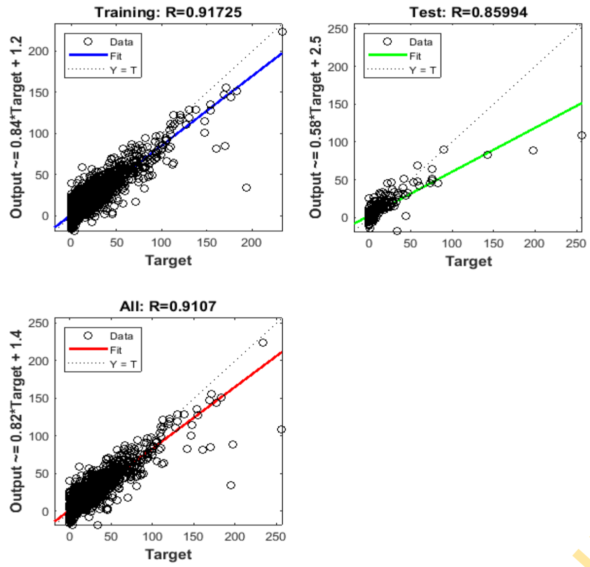

Fig-6: Regression plot of Bayesian Regularization Predictive Algorithm

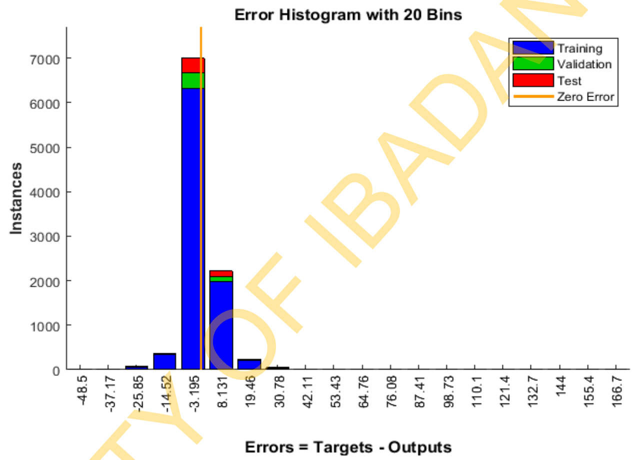

Fig-7: Error histogram of Levenberg Marquadt Predictive Algorithm

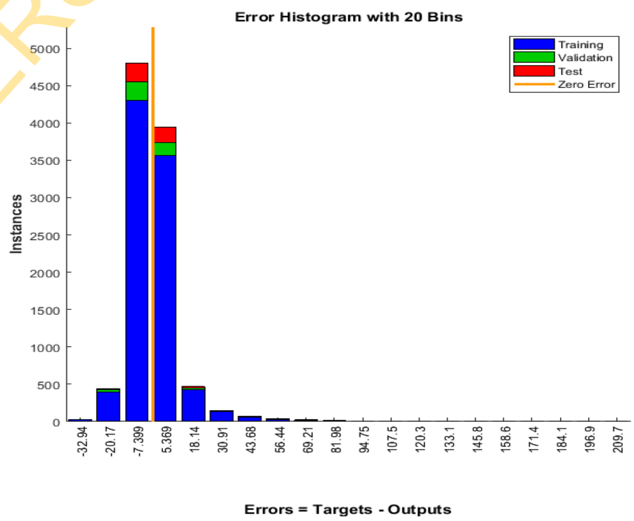

Fig-8: Error of Scaled Conjugate Gradient Predictive Algorithm

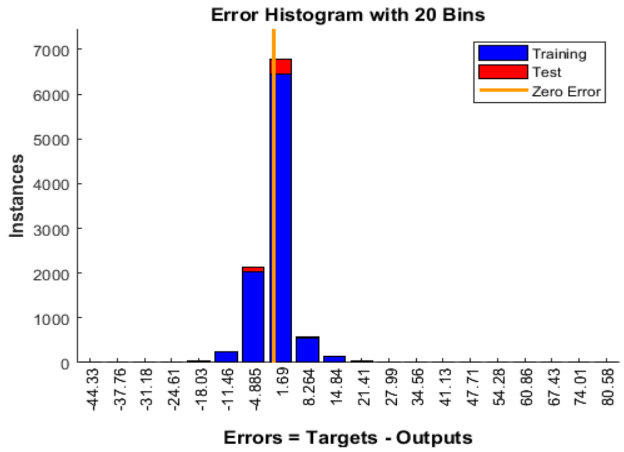

Fig-8: Error of Bayesian Regularization predictive algorithm

COMPARISON OF RESULTS

The Table 1 present the summary of the results obtained from the training algorithms used to develop the predictive model. And Bayesian Regularization is the best training algorithm to be used for the predictive model and would therefore be the basis for the Optimization model

PERFORMANCE OF THE OPTIMIZATION MODEL

The results obtained from the Normalized Rate of Penetration equation can be used to create a plot which is not affected by how the driller changes bit weight, rotary speed, or hydraulics. Drilling Extended Reach wells requires the latest innovations in drilling engineering principles; such wells are more interrelated and sensitive to smaller changes than conventional wells. An integrated approach for both planning and execution becomes more critical due to the high operational risks and all uncertainties must be properly assessed by solid engineering planning. In addition to that, it brings engineering challenges from many disciplines, which must be met and addressed for proper execution. Integration of drilling and real time evaluation allows engineers and geoscientists to take the proper drilling decisions and lead to reduce operational risk. It will also provide an accurate well placement; improve drilling efficiency and maximum recovery.

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APPENDIX A

MATLAB codes for Predictive neural network

```
function [Y,Xf,Af] = myNeuralNetworkFunction(X,~,~)
%MYNEURALNETWORKFUNCTION neural network simulation function.
%
% Generated by Neural Network Toolbox function genFunction, 12-Jan-2020 06:24:40.
%
% [Y] = myNeuralNetworkFunction(X,~,~) takes these arguments:
%
%   X = 1xTS cell, 1 inputs over TS timesteps
%   Each X{1,ts} = Qx11 matrix, input #1 at timestep ts.
%
% and returns:
%   Y = 1xTS cell of 1 outputs over TS timesteps.
%   Each Y{1,ts} = Qx1 matrix, output #1 at timestep ts.
%
% where Q is number of samples (or series) and TS is the number of timesteps.

%#ok<*RPMT0>

% ===== NEURAL NETWORK CONSTANTS =====
 % Input 1
x1_step1.xoffset = [0;0;0;0;0;0;0;0;0;0;0];
x1_step1.gain = [0.000133422281521014;0.166666666666667;6.66688889629654e-05;0.125;0.0625;0.738007380073801;0.00573065902578797;0.0338983050847458;0.952425965846243;2.00017282093225;0.00222229034727358];
x1_step1.ymin = -1;

% Layer 1
b1 = [-0.87581815939626739276;6.7690205442213935427;6.2096342167954778901;40.56144276520762304;-1.8389147135984769132;1.4293704162361366983;0.063205624508442179166;-2.6650528171956713308;-6.4902354413846810033;1.9397892753036272l4;-43.799839355665056928;5.8914543449280518672;-6.8390075761985036351;1.4527567916441208595;-5.7895513650893990487;-1.3955735631855741286;0.59690981094636952342;0.99532576000923567161;-9.1140010053837876569;11.120926585472847847;11.232964832446626247;-6.4529268091644338412;-1.9115362416272390078;0.99941621672403180288;-1.3843300839939196578;-6.3099702815189608884;0.26418928708023059482;-9.5667201405404860282;-14.671955228906384l5;1.0591081295898510106;-1.4207933821720377665;3.5651634519686004055;16.294996972127016477;-6.0188097428738283057;-2.5479285280035335326;10.094493008242006127;-0.22056095606710368617;-15.319165124194352501;-5.6049007180122476512;-3.5857581512914520339;-1.5355983789347924517;-0.70213907050011958866;10.020917392325054962;0.66750258359718672718;11.190282813865200851;1.5702175975156917875;-6.5040094536804486935;1.9457349630023275111;11.325405223392627008;7.5483722758584699264];
IW1_1 = [11.412862676430830078 -2.8947172221460935049 0.61298174397393545565 -1.8163389272605892089 -7.9685882270807502081 -0.77836816978415701573 -1.4446373788904491864 -1.0236458708137037288 -4.8285050885133182774 8.7122687045443285569 4.2700539540079551 77;0.97067375850485626554 0.41130487768172535601 -0.21739409727708128295 0.75673670941070125817 0.16419474206028339403 -0.23824734093264676726 4.5891663392572228375 -0.47865735906268375155 0.26907659002487199773 -1.2179519387622332882 0.36433831079400141872;8.7584691899000848281 0.34046663145860289745 3.1583506512671459809 1.1659937302749876498 0.53517566202368882511 -1.1202924849625390813 -0.26688623629568480888 -0.81452553091416202147 -0.19196555504113888002 -0.40520995557273337129 0.13437848229911458775;34.557240464380392098 0.71910427777024921 17 -0.49281649297658125519 -1.3027372888581940646 -1.3192606026204212188 -5.922152372240160112 -1.2162388443961624773 1.0466722891578859045 1.8670401897924371326 0.84405312628256912166 -1.5597272829057955423;-
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```
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2.8114768461602719363 0.21051202917899505818 -2.9531988472496522036 -3.2344127115123724181];

% Layer 2
b2 = 1.3353888721779751947;
LW2_1 = [2.9985915289918834148 -5.6829936803668710255 3.1075735066274567941 4.5741489828318080413
0.67120136232146698774 -1.4163733951770762776 -2.7110113905992641037 1.2628815226433540708 -
2.3415910762082674523 -4.7055742955006092387 4.5203904630058655556 -2.0293209618359164814
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1.5711989521771194678 2.8913028895437209442 -0.69059722060056405457 3.5512943770371436791 -
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0.51093139788027497339 2.1472496922529700214 4.3239810495446677763 0.79341852279477609322
2.2358676320784534042 -6.763580491937383421 -2.0952937218840563816 -3.4092311578152081353
6.8056104487938062775 2.7628676487698857756 -5.7248729688873059018 0.76417533072077892253 -
2.2223961572978736534 -0.99047217119907371 43 -1.7650453713859726168 -0.97695656233985150863
10.313233170956495499 2.4278789830031692887 -0.95849805643415908474 3.8981603976303160763 -
5.8156836583699869081 -1.9871769428469245877];

% Output 1
y1_step1.ymin = -1;
y1_step1.gain = 0.00778876106110971;
y1_step1.xoffset = 0;

% ===== SIMULATION ========
 % Format Input Arguments
isCellX = iscell(X);
if ~isCellX
   X = {X};
end

% Dimensions
TS = size(X,2); % timesteps
if ~isempty(X)
   Q = size(X{1},1); % samples/series
else
   Q = 0;
end
% Allocate Outputs
Y = cell(1,TS);
 % Time loop
for ts=1:TS
  % Input 1
   X{1,ts} = X{1,ts}';
   Xp1 = mapminmax_apply(X{1,ts},x1_step1);
  % Layer 1
   a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*Xp1);
   % Layer 2
   a2 = repmat(b2,1,Q) + LW2_1*a1;
   % Output 1
   Y{1,ts} = mapminmax_reverse(a2,y1_step1);
   Y{1,ts} = Y{1,ts}';
end
 % Final Delay States
```

```
Xf = cell(1,0);
Af = cell(2,0);
 % Format Output Arguments
if ~isCellX
    Y = cell2mat(Y);
end
end

% ===== MODULE FUNCTIONS ========

% Map Minimum and Maximum Input Processing Function
function y = mapminmax_apply(x,settings)
y = bsxfun(@minus,x,settings.xoffset);
y = bsxfun(@times,y,settings.gain);
y = bsxfun(@plus,y,settings.ymin);
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n,~)
a = 2 ./ (1 + exp(-2*n)) - 1;
end

% Map Minimum and Maximum Output Reverse-Processing Function
function x = mapminmax_reverse(y,settings)
x = bsxfun(@minus,y,settings.ymin);
x = bsxfun(@rdivide,x,settings.gain);
x = bsxfun(@plus,x,settings.xoffset);
end
```

Code for Optimization model built with Python

```
Print ('This program was developed to Optimize the Normalized Rate of Penetration')
Print ('During realtime drilling operations.')
ROP = float (input ('Enter the current/predicted Rate of Penetration: '))
Wn = float (input ('Enter the normal bit weight: '))
Wo = float (input('Enter the observed bit weight: '))
M = float (input ('Enter the formation threshold weight: '))
Nn = float (input ('Enter the normal rotary speed: '))
No = float (input ('Enter the observed rotary speed: '))
r = float (input ('Enter the rotary exponent: '))
Pbn = float (input ('Enter the normal bit pressure drop: '))
Pbo = float (input ('Enter the observed bit pressure drop: '))
Qn = float (input ('Enter the normal circulation rate: '))
Qo = float (input ('Enter the observed circulation rate:'))
NROP = ROP*((Wn-M)/(Wo-M))*((Nn/No)**r)*((Pbn*Qn)/(Pbo*Qo))
Print ('Your Optimized normalized Rate Of Penetration is:')
Print  (NROP)
```