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Field Application of a Particle Swarm Optimization (PSO) and a Rate of Penetration (ROP) Model Routine to Reduce Overall Drilling Cost by Finding Optimal Bits, Pull Depths and Operating Parameters

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Abstract

Drilling optimization can reduce drilling costs but is challenging due to the number of operational parameters and the large search space of the combined variables. The approach presented herein, applies a swarm algorithm to a rate of penetration (ROP) model with the goal to decrease overall drilling cost. Drilling optimization becomes more complicated when considering the potential use of multiple bits. An advanced search algorithm can help assist by searching the infinite search space of control variables and narrowing on the global optimum point. The optimized variables include depth based operational parameters, weight on bit (WOB), rotary speed (RPM), best bit combination, and optimal bit pull depth. The validity of the optimization algorithm shows great promise as it did when applying it to a previously drilled offshore 12.25" hole section, and the approach can be generalized and applied to any drilling operation or location. An offshore 12.25" hole section was analyzed using the proposed approach. The 12.25" hole sections had previously been drilled with two bits with an overall 127.8 $/ft. Different optimization criteria were tested and integrated to obtain the potential lowest cost. The resultant lowest $/ft. simulation used two drill bits with an optimized pull depth and operating variables resulting in 78.1 $/ft. for the section, a reduction of 39 percent from the offset.

Introduction

Models are established in almost all fields in science to help scientists come up with efficient designs and to reduce overall costs. In the drilling domain, the rate of penetration (ROP) models are used to find out how the different parameters such as weight on bit (WOB), revolution per minutes (RPM), bit designs and hydraulics effect the ROP. In drilling, there are several models which are used to calcuate the drilling rate of penetration (ROP) based on numerous variables.

Cunningham in 1960, showed that the roller cone bit ROP is a function of WOB and RPM (Cunningham, 1978). His model suffers from some shortcomings such as ignoring the effects of hydraulics, bit design and formation properties. In 1962, Maurer suggested a model and incorporated the effect of rock strength into the ROP. The Maurer model was developed for ideal hydraulics which assume perfect hole cleaning (Maurer, 1962). Later in 1974, Bourgoyne and Young developed a model for roller cones bits (Bourgoyne et al, 1974). They incorporated not only the effect of operational parameters such WOB, RPM but the hydraulic, bit geometry and formation properties such as rock strength.

Today utilizing Polycrystalline Diamond Compact (PDC) bits in drilling industry is common due to the fact the PDC enhance the performance through faster ROP and longer bit life. In addtion, they are stable in both vertical and horizontal wells, and they can withstand high pressure, temperature, hardness, and toughness. In 2014, Kerkar et al., developed a model to estimate the ROP of PDC bits. This model is one of the most accurate and comprehensive models for estimating ROP of PDC bits. The model utilizes key parameters, such as operational parameters, hydraulic, bit design, formation rock strength and abrasiveness to estimate the ROP. The model is provided in the Eq. 1 – 6. Analyzing these equations, it can be seen that some parameters have integrated effects on drilling ROP, such as WOB and RPM in Eq. 1 and Eq. 6. In addition, like most real models, this equation is non-linear, multidimensional, and complex constraints are applied to the feasible solutions, which make it difficult to solve using analytical methods. Metaheuristic algorithms were developed to help find the optimum solution of such complex equations. In this study, the PSO agorithm was applied to the ROP model with the overall goal to reduce the cost of drilling by finding the optimum parameters for WOB, RPM, bit arrangments, and pull depths.

$$ROP = \left[\frac{K1.WOB^{a1}.RPM^{b1}.COS(SR)}{CCS^{c1}.D_{Bit}.TAN(BR)}\right].W_f.h(x).b(x), \ldots (1)$$

$$W_f = 1 - a_3.\left[\frac{\Delta BG}{8}\right]^{b_3}, \ldots (2)$$

$$h(x) = a_2.\frac{(HSI.\frac{JSA}{2.D_{bit}})^{b_2}}{ROP^{c_2}}, \ldots (3)$$

$$HSI = \frac{\frac{Q.\Delta P_{bit}}{1714}}{\left(\frac{\pi}{4}\right).D_{bit}{}^2},...(4)$$

$$b(x) = \frac{RPM^{1.02-0.02N_b}}{RPM^{0.92}},...(5)$$

$$\Delta BG = W_c.\sum_{i=0}^{n} \Delta D_i\,.WOB_i{}^{a_4}.RPM_i{}^{b_4}.CCS_i.ABR_i,...(6)$$

PSO Algorithm

Particle swarm optimization (PSO) is a stochastic method developed by Eberhart and Kennedy in 1995, and was designed to mimic the behavior of animals, bird flock, fish school, in nature (Eberhart and Kennedy, 1995). This algorithm creates a population of solutions and it tries to improve those iteratively using simple mathematical equations. In this algorithm, each solution, which are considered particles, iteratively update the position by adding an updated velocity term to the particles previous position, as seen in Eq. 7. The velocity value for each particle is then updated using inertial, cognitive and social components and the new velocity is used to update the position using Eq. 8. The inertial component (ω) helps each particle stay in the problem boundary by applying a degree of continuity to the solutions (Atashnezhad et al, 2014). The cognitive component (φ_1) determines the degree of force that is applied to each particle to move to its best previous position, while the social component (φ_2) determines the degree of force that is applied to each particle and moves to the best global particle. The best particle in the new generation replaces the best global particle if it is evaluated at a higher fitness value.

$$V^{k+1}{}_i = \omega V^k{}_i + \varphi_1 r^k{}_1 * \left(p^k{}_i - x^k{}_i\right) + \varphi_2 r^k{}_2 * \left(p^k{}_g - x^k{}_i\right),...\,(7)$$

$$x^{k+1}{}_i \leftarrow x^k{}_i + V^{k+1}{}_i\,,...\,(8)$$

There are several ways that the particles share their information with the neighbors in the PSO algorithm, which are referred as topology. Four common topologies are: single-sighted, ring, fully connected and isolated. In the single-sighted, each particle shares the information with the next best. In the ring topology, each particle shares the information with the left and right particles. In the fully connected topology, the particles share all information with each other, while the isolated topology, everyone is compared to a predetermined group. The topology definition helps the algorithm find the optimum answer efficiently and helps the algorithm avoid getting caught in a local minimum. In this study, the PSO algorithm used the fully connected topology. The four common topologies are provided in the Figure 1.

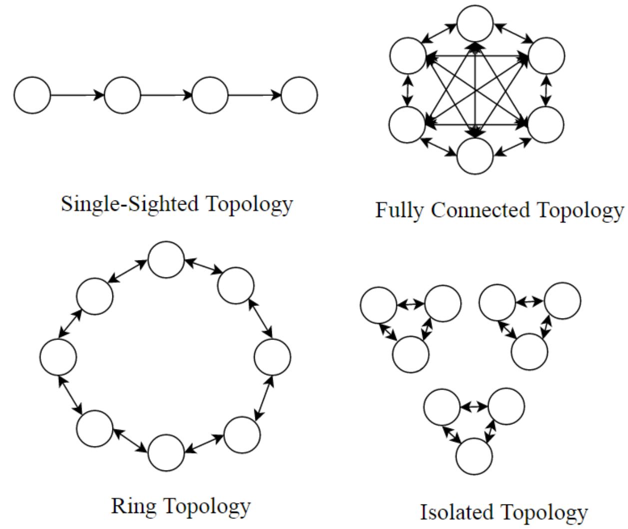

Figure 1: Four common topologies for PSO algorithm

Results

To prove the validity of the algorithm, field case data was taken from a 12.25" well drilled in the North Sea (Gjelstad et al., 1998, Bratli et al., 1997). The research herein, optimizes the first two PDC bit runs, 9379 ft. – 13832 ft. Before optimizing, the rock strength was converted to confined compressive strength (CCS) and then discretized to be input into the algorithm. Figure 1 below shows both the actual rock strength data, along with the discretized rock strength overlay

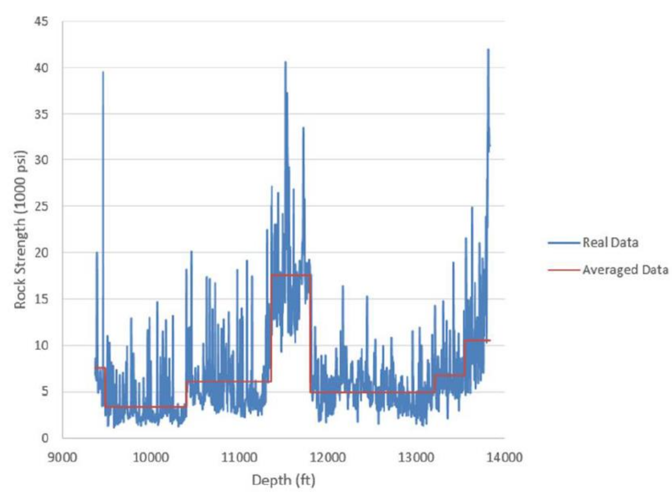

Figure 2: Rock Strength from 12.25" well in North Sea

The two bits used during this section of the well are detailed below in Table 1.

	Bit A	Bit B
Bit Type	PDC	PDC
Bit Diameter	12.25 in.	12.25 in.
Depth In	9379	11814
Depth Out	11814	13832
Wear In	0	0
Wear Out	4.4	1.4
Cost	$48,062	$57,876
Number of Cutter	69	107
Back Rake	20°	20°
Side Rake	15°	0°
Number of Blades	6	6
Junk Slot Area	28 in^2	28 in^2

Table 1: Bit Description from 12.25" well

Both bits A and B were input into the algorithm, to allow the program to choose the optimal bit combination between the two available bits. The two bits were correlated to drilling data for their respective sections, resulting in both Bit A and Bit B having different W_c and K values for the algorithm to weigh the cost vs. performance.

For any optimization routine, there needs to be a clear objective function (OF) to optimize upon. The OF for this optimization routine was to minimize the equation set shown below in Eq. 9 – 11

$$OF: Cost = \frac{Cost_{Rig}(t_{Rotating} + t_{Tripping}) + Cost_{Bit}}{Footage\ Drilled}, \ldots (9)$$

$$t_{Tripping} = (D_1 + D_2)t'_{Tripping}, \ldots (10)$$

$$t_{Rotating} = \sum_{n=1}^{n} \frac{\Delta D_i}{ROP_i}, \ldots (11)$$

The above set of equations is used for one bit; therefore, these calculations were performed twice and totaled to get the overall cost. The tripping rate estimation, $t'_{Tripping}$, used was 0.75 hr. / 1000 ft., and the cost of the rig rate is assumed to be $100,000 per day. D_1 is the start depth for the bit, and D_2 is the depth when the bit is pulled.

For this optimization algorithm, there was a maximum allowable ROP set to 350 ft./hr. Theoretically, the well could be drilled with much higher ROP values, however, this constraint was implemented to ensure realistic results, due to practical limitations.

WOB, RPM, Pull Depth, and Bit Selection Optimization

Below show the optimum results for WOB and RPM found from the algorithm, along with the resultant ROP, Figures 3 – 5. The two different bits the algorithm selected are shown with the different textures.

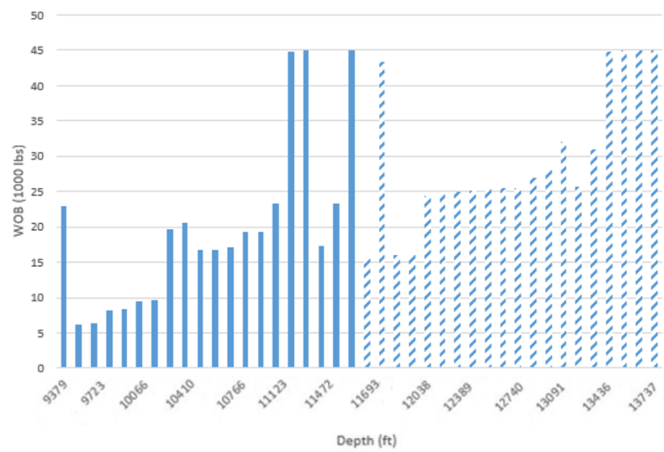

Figure 3: Optimal WOB for 12.25" well

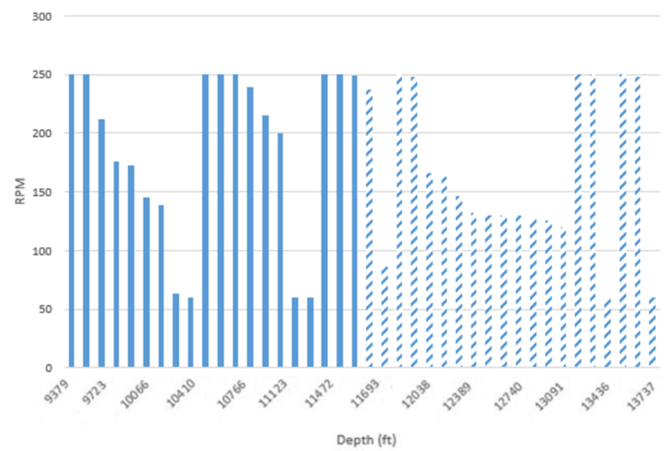

Figure 4: Optimal RPM for 12.25" well

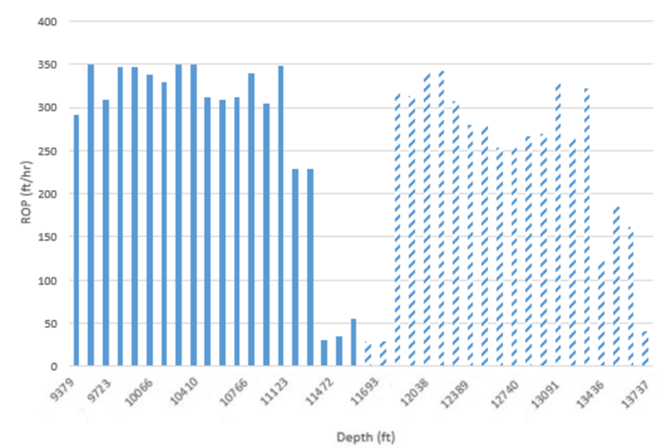

Figure 5: Optimal ROP for 12.25" well

In addition to the simulation shown above, there were two more optimization scenarios performed for comparison purposes. The first was optimizing only the operational parameters WOB and RPM. The depth to change out bits was held constant, along with the bit combinations and final bit wear for both bits were all kept the same as performed in the field. The second scenario was optimizing WOB, RPM, and the optimal depth to change bits. The bit combination was chosen to be the same as performed in the field.

Below, Figure 6, shows the overall cost and ROP for each optimization scenario.

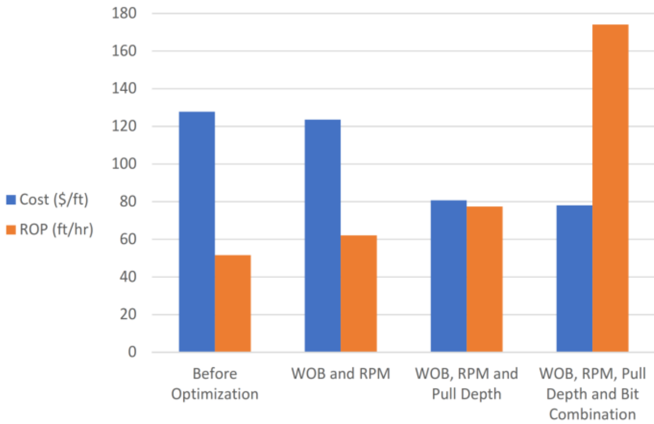

Figure 6: ROP and Cost comparison for different optimization scenarios

Discussions

Before optimization, the actual cost of drilling was $569,093, or 127.8 $/ft., which resulted in an overall average ROP of 51.55 ft./hr. This was the result of using Bit A from 9379 ft. until 11814 ft., then using Bit B from 11814 ft. to 13832 ft. Optimizing only WOB and RPM, the overall cost of drilling the well was $550,836, or 123.7 $/ft., with an average ROP of 62.17 ft./hr. This optimization resulted in a slight decrease in cost, however, the algorithm was restricted to optimizing only on operational parameters. When optimizing on WOB, RPM, and depth to change the bits, the cost was reduced to $359,802, or 80.8 $/ft., with an average ROP of 77.51 ft./hr. For this scenario, the algorithm selected to use Bit A once, and for this single bit to drill the entire interval. This optimization did not result in a big increase in performance in terms of ROP, only an increase of 26 ft./hr., but the cost was reduced significantly. This result is due to the cost of only using one bit, along with eliminating the cost of tripping out to change the bit. Finally, for the complete optimization scenario of the drilled section, WOB, RPM, bit combination and depth to change bits, the cost of the well reduced to $347,779, or 78.1 $/ft., which results in an overall average ROP of 174.11 ft./hr. For the full optimization, the algorithm selected to use Bit A twice and not use Bit B in either section. The chosen pull depth for this scenario was 11600 ft., resulting in a significant increase in performance and significant reduction in cost. Analyzing the results from all the optimizations in Figure 6, the algorithm shows a decrease in overall cost per foot with an increase in allowable optimized parameters. Extending this further, it would be conceivable that the cost would continue to decrease with the incorporation of more parameters for optimization. This would continue until the cost can no longer be decreased and eventually level out to the lowest possible drilling cost.

Conclusions and Future Work

Applying this algorithm to a field case drilling scenario proves the validity of the algorithm and the potential for future use. Additionally, the results are very encouraging due to the continuous decrease in cost with the increase in allowable optimized parameters.

There is some future work to be done for this algorithm to make it more functional. Some of this work will include applying both PDC and roller cone ROP models, incorporating drill string torque and drag analysis to integrate the results to obtain downhole parameters from surface measurements, and allow the algorithm to generically create bit designs.

Nomenclature

$a_1, a_{2,} a_3, a_{4,},$: Empirical Coefficient
ABR: Relative Abrasiveness
$b_1, b_{2,} b_3, b_{4,},$:: Empirical Coefficient
c1, c2: Empirical Coefficient
ΔD: Depth Step Size
ROP: Rate of Penetration
WOB: Weight on Bit
RPM: Revolution per Minute of the Bit
BR: Back Rake
SR: Side Rake
CCS: Confined Compressive Strength
W_f: Wear function
h(x): Hydraulic efficiency function
b(x): function for the effect of Number of Blades
D_{bit}: Bit Diameter
HSI: Horsepower per Square Inch
JSA: Junk Slot Area
K1: Calibrated Constant
N_b: Number of Blades
Pbit: Bit Pressure Loss
Q: Flowrate
Wc: Wear Coefficient
V: Velocity of each Particle
φ_1: Cognitive component
φ_2: Social component
ω: Weighted Inertia Constant
r1, r2: Random value from 0 to 1
p_i: Previous Best for each Particle
p_j: Global Previous Best for each Particle
x: Position of the Particle
i: vector index
k: iteration number

References

1. Cunningham, R.A., 1978. An empirical approach for relating drilling parameters. Journal of Petroleum Technology, 30(07), pp.987-991.
2. Maurer, W.C., 1962. The" perfect-cleaning" theory of rotary drilling. Journal of Petroleum Technology, 14(11), pp.1-270.
3. Bourgoyne Jr, A.T. and Young Jr, F.S., 1974. A multiple regression approach to optimal drilling and abnormal pressure

detection. Society of Petroleum Engineers Journal, 14(04), pp.371-384.

4. Kerkar, P. B., Hareland, G., Fonseca, E.R., and Hackbarth, C. J., 2014. Estimation of Rock Compressive Strength Using Downhole Weight-on-Bit and Drilling Models. In IPTC 2014: International Petroleum Technology Conference.
5. Eberhart, R. and Kennedy, J., 1995, October. A new optimizer using particle swarm theory. In Micro Machine and Human Science, 1995. MHS'95., Proceedings of the Sixth International Symposium on (pp. 39-43). IEEE.
6. Atashnezhad, A., Wood, D.A., Fereidounpour, A. and Khosravanian, R., 2014. Designing and optimizing deviated wellbore trajectories using novel particle swarm algorithms. *Journal of Natural Gas Science and Engineering*, *21*, pp.1184-1204.
7. Bratli, R. K., Hareland, G., Stene, F., Dunsaed, G. W., & Gjelstad, G., 1997. Drilling optimization software verified in the North Sea. SPE 39007 presented at SPE LACPEC Conference in Rio De Janeiro, Brazil, August.
8. Gjelstad, G., Hareland, Gl, Nikolaisen, K. N., & Bratli, R. K., 1998. The method of reducing costs more than 50 percent. SPE 47342 presented at SPE/ISRM Eurock 98 in Trondheim, Norway, 8–10 July.