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Machine Learning Application in Enhancing Drilling Performance

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Abstract

Drilling Oil and Gas wells is an expensive operation, where the cost for drilling a single shallow offshore HP-UHT well may exceed 30 million USD easily. Due to the huge cost involved, companies are eager to accomplish the drilling operations in a minimal time frame, by increasing the drilling rate or rate of penetration (ROP) and reducing the downhole tool failures. The Mechanical Specific Energy (MSE) concept addresses these two drilling performance measures in totality as it provides maximum ROP which can be achieved with the existing drilling system (i.e., Drill Bits, Drilling Tubular, Well Profile, and Mud weight) without causing downhole tool failures. ROP is a function of Weight on Bit, Rotation per Minute, and Flow rate for an existing drilling system, optimization of these parameters results in increased ROP, whereas unharmonious values lead to shock and vibration in drilling assembly. Machine Learning algorithms facilitate this optimization of drilling parameters for enhancing drilling performance, by the development of an accurate ROP prediction and optimization model. The ROP prediction model was developed using Artificial Neural Network and Random Forest, and the optimization model was developed using evolutionary optimization algorithms like particle swarm optimization and genetic algorithms. The result of the optimization model depends upon the accuracy of the ROP prediction model and the upper and lower limits of drilling parameters defined in the optimization model. Machine learning applications in improving the Drilling Performance can be easily quantified in terms of saving days, where one day of operational cost for the company is approximately 0.2 million USD per Offshore – HP-UHT well.

Keywords: Neural Network; Random Forest; Genetic Algorithm; Drilling Performance; Rate of Penetration; Mechanical Specific Energy

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1. Introduction

Oil and Gas are trapped beneath the earth's surface ranging from a few hundred meters to thousands of meters. Complexity and cost of drilling a well increase with the increase in geological difficulties to access oil and gas-bearing locations, commonly known as reservoirs. Drilling a well requires a detailed understanding of Drilling Principles, Geological and Petro-physical characteristics of the formation, Drilling Fluid characteristics, etc. The rate at which the formation is drilled depends upon several factors like the strength of the formation which is quantified by Confined Compressive Strength (CCS), the indent of the drill bit cutter which depends upon cutter size and placement, torque at the bit (actual rotational energy), availability of sufficient hydraulic energy to remove the cutting from hole effectively, etc. make drilling a complex activity to understand and increase the overall Drilling Performance. Initially, drilling performance was only evaluated based on Rate of Penetration (ROP), however with in-depth knowledge of drilling operations, it was understood that parameters like Weight in Bit (WOB) and Rotation per Minute (RPM) if increased beyond a certain limit with a view of increasing the ROP, would rather have an adverse effect on ROP and may also lead to drilling tool and bit failures. To attain maximum ROP without drilling tool failures, the concept of Mechanical Specific Energy (MSE) is to be implemented while addressing the drilling optimization problem. MSE is the energy required to remove the unit volume of rock, it is related to input energy and ROP as mentioned in equation 1. It implies that for a given rock of particular compressive strength, the energy required for removing a specific volume of rock remains constant and this was experimentally derived by Teale [1]. MSE is a function of ROP, WOB, RPM, Diameter of Bit (D), and Torque on Bit (TOB) as mentioned in equation 2, among the same RPM, TOB and WOB are independent variables, whereas ROP is dependent on these independent parameters and other geological and operational factors exhibiting complex inter-relationships. Experimentally, it has been established that the MSE value is equal to the Confined Compressive Strength (CCS) of the formation. In order to enhance the drilling performance, ROP should be maximum and MSE should be minimum, as higher MSE compared to CCS value signifies that energy is getting lost in wellbore walls due to drill string vibrations, buckling, etc., leading to downhole tool failures

$$MSE \approx Input\ Energy \div Output\ ROP \quad (1)$$
$$MSE = ((480 \times TOB \times RPM)/(D\hat{}2 \times ROP)) + ((4 \times WOB)/(\pi \times D\hat{}2\ )) \quad (2)$$

As MSE is a basis of an optimization model for providing the optimal drilling parameters for attaining the maximum ROP without downhole tool failures, thus the most important aspect of the Drilling Performance model is to develop an accurate ROP prediction Model. Various numerical and physical models can predict ROP, but each method presumes some ideal constants, thus the prediction of ROP is not accurate with traditional methods. Machine Learning's ability to decipher the actual relations between Drilling Parameters and ROP enables it to predict the results based on the actual interaction of input parameters with the environment resulting in accurate ROP prediction.

Subsequently, the ML optimization model initially calculates ROP for each combination of drilling parameters as iterated within the optimization model between the pre-defined drilling parameter range, then using the iterated values of WOB, TOB, RPM, and predicted value of ROP at each instance, MSE can be calculated and compared with CCS value of the formation for the corresponding depth. The iterated drilling parameters which give MSE value close to CCS can be considered the optimum solution. The pre-defined drilling parameter range or upper and lower limit of drilling parameters required in the optimization model is dependent upon the equipment limits or operational parameters, these need to be carefully specified to obtain realistic results.

The paper comprises six sections, the first section is an introduction, the second section is a review of research carried out by various researchers in the development of ROP prediction models and/or optimization models, the third section is a brief on Machine Learning algorithms used for developing ROP prediction and Optimization Models, the fourth section is a rationale of setting upper and lower limits of drilling parameter for optimization model, the fifth section is results and discussion and the sixth section is the conclusion.

2. Literature Survey

Data-Driven Methodology was used by various authors for the prediction of ROP and subsequently, an optimization technique for identifying the input parameters which may lead to enhancement of ROP.

Soares and Gray [2] developed an ML model using Artificial Neural Network (ANN), Support Vector Machine (SVM), and Random Forest (RF) focusing on ROP as a parameter for enhancing drilling performance. The authors used WOB, RPM, Flow Rate, and Depth as drilling parameters for model development and a 10-fold cross-validation technique in training the data to check the accuracy and generic nature of the model. Authors cited that hyperparameter selection is the most critical part of any model to achieve the highest accuracy, based on the hyperparameter grid search method, authors observed that Gaussian Kernel Function, 1 Epsilon (ε), 100 Budget (C), 0.1 Kernel Co-efficient (γ) for SVM model, Limited memory Broyden–Fletcher–Goldfarb–Shanno algorithm (LBFGS) Solver, 4 neurons in 2 hidden Layer, Logistic Activation function, 0.0001 Regularization (α) for NN model, Decision tree as a base learner for ensemble model with 25 trees, 2 maximum feature per split, 2 minimum samples split gave most accurate results. Among the three ML models, authors cited that the accuracy of the RF model is maximum.

Koopialipoor and Noorbakhsh [3] have developed an ANN model for the prediction of ROP and used Artificial Bee Colony (ABC) algorithms for optimizing the input values for ROP enhancement. They have highlighted the ability of evolutionary optimization technique over gradient-based optimization technique in achieving global optima, approximate optimization algorithm over exact algorithms to find a close optimal solution in a short time, and meta-heuristic approximate algorithm over heuristic in view of the latter being subject to performance degradation over the complex problems. Parameters considered for the development of the model were MD, WOB, RPM, YP/PV, and 10 m Gel Strength (GS)/10 SGS. Authors developed an ANN model with three different transfer functions viz. Levenberg-Markvart (LM), scaled conjugate gradient (SCG), and one-step secant (OSS). Based on theory and practice that one hidden layer is optimum for handling non-linear function, optimum neuron ranges were selected based on the rules proposed by various other researchers involving the number of input (Ni) and output variables (No) like (Ni + N0)/2, 2Ni/3, 2Ni, <=2 x Ni+1, etc. The neuron envisaged for ANN model development were in-between 2 and 16. Depending upon R2 and RSME value, the authors depicted that the ANN model with 1 hidden layer, 16 neurons, and LM transfer function results in the best performance. Subsequently optimizing input parameters using ABC optimization algorithms with a population of 40 and 500 iterations author concluded that ROP has increased by 20-30 % on test cases at various depths.

Ashena et al. [4] developed an ANN-FFBP model for the prediction of ROP and a combination of two optimizing algorithms viz. Genetic Algorithms (GA) and Pattern Search (PS) optimize the parameters in order to achieve the highest ROP. Parameters considered for model development were MD, WOB, TRQ, RPM, SPP, Flow Rate, Mud Weight, Mud Temperature, and formation type. Post-pre-processing, the available dataset of 15285 collected from 6 wells was used for two models development comprising two hidden layers, one with 15 neurons and the other with 10 neurons, the model tuned was planned for 200 epochs and it was observed that RSME reached 2.9734 in 195 epoch. Subsequent to model acceptance, authors used evolution computation Genetic Algorithms for drilling optimization citing its ability to reach global optima in complex problems and construct fitter solutions using selection, crossover, and mutation techniques, however owing to its stochastically working nature sometimes it may not lead to global optimum, which necessitates the use of Pattern Search once GA has completed its processes. Authors set target ROP and limits of Drilling parameter in GA, subsequently fixed population size to 500 and varied generation size between 50 and 150 to achieve the minimum MSE values.

Takbiri-Borujeni et al. [5] developed an ANN-FFBP model with 1 hidden layer, 50 neurons, Adam Solver, and Rectified Linear Unit (ReLu) activation function for prediction of ROP and subsequently addressed the bit balling, bit dysfunctional diagnosis, and bit failure based on predicted ROP, new bit performance factor and actual ROP. The authors initially considered SPP, RPM, FLOW RATE, WOB, Bottom Hole Pressure (BHP), SPP, Choke Pressure, TRQ, Penetration, and Depth of Cutting. Authors split the data set into 50:50 with an understanding that when a bit is new mainly in the first half dataset the bit performance is optimum and the model was trained and validated with the same, this trained model is used for the prediction of ROP in the second half of the data set, if the predicted ROP matched the actual ROP, it may be inferred that Bit is optimum for use however any deviation of predicted ROP signifies bit balling, wear or dysfunctionality and necessary changes in drilling parameters may be undertaken to enhance the drilling efficiency, in case no promising further result, the bit may be pulled out of a hole. Authors preferred to use Lasso Regression analysis for evaluating the impact of various input parameters on ROP prediction, over linear support vector regression, linear least square regularization, and uni-variate linear F-regression test citing its higher accuracy over other methods to rank the parameters. The authors concluded that WOB and BHP have the maximum influence on ROP.

Singh et al. [6] developed eight machine learning models viz. multivariate linear regression (MLR), least absolute shrinkage selector operator (LASSO) regression, ridge regression (RR) under linear models, random forest (RF)/ decision trees (DT), ANN/ deep learning, and recurrent neural networks (RNN)) under non-linear models, Principal Component Analysis (PCA) under decomposition techniques, and multivariate adaptive spline regression (MASR) model, for the prediction of ROP using the dataset from 45 wells comprising 15 parameters viz. TRQ, RPM, SPPA, HKL, FLOW, MD, WOB, Differential pressure (ΔP), Mechanical Specific Energy (MSE), Bit Hydraulic Horse Power per square Inch (HSI), Mud Weight (MW), Plastic Viscosity of Mud (PV), Yield Point of Mud(YP), Bit Size, and Total Flow Area (TFA). In comparing the eight models based on Mean Absolute Percentage Error (MAPE) authors cited that the spline regression model, which gives an error of 13% is the most accurate. Authors highlighted the pros and cons of each model as DT and Random Forest models were good on training data but underperformed on blind data (comprising additional 5 well data) due to overfitting, Deep learning and ANN models predicted the result with acceptable accuracy but owing to their black-box nature resulted in poor interpretability, Shrinkage methods such as LASSO and Ridge Regression have high interpretability however due to linear relationship results in poor accuracy, it was observed that multivariate adaptive spline regression provides the best accuracy, interpretability and computationally inexpensive for real-time drilling operations. They performed feature selection techniques on input parameters and observed that ΔP, WOB, and Flow have maximum influence on ROP and the same need to be considered for optimization for enhancing the drilling performance.

3. Machine Learning and Optimization Algorithms

Machine learning is a subfield of artificial intelligence that enables a computer to learn from historical data and make a prediction on a new dataset without human intervention. ROP prediction is a regression problem and drilling performance enhancement is an optimization problem. ML Optimization approach gives the user an upper hand over traditional methods to select the input parameters automatically using computer computation power, resulting in the best output and enhancing the efficiency of operations to the maximum extent. Among various optimization techniques viz, Gradient Descent, Stochastic Gradient Descent (SGD), Bayesian Optimization, evolutionary optimization, etc. evolutionary optimization is widely used for finding an optimal solution to drilling problems. Traditional models solve the problem of optimization by using the gradient-based method to reach the global maxima, but since most of the drilling problems are complex and may have many local maxima, the objective function may be stuck at local maxima only rather than reaching the global maxima of the situation, which causes the method to fail. There are various types of Evolutionary Optimization techniques such as Genetic Algorithms (GA), Artificial Bee Colony Algorithms (ABC), Bees algorithm, Ant Colony Optimization, Particle swarm optimization, etc. which may be employed for optimization problems with a high degree of success.

ROP prediction and optimization are categorized under the supervised machine learning technique. In supervised learning, the algorithm gets trained using the labeled dataset. The input variable i.e drilling parameters are called an independent variable and the output/target variable i.e ROP is called a dependent variable as depicted in equation 3 (Kotsiantis et al. [7]).

$$Y = f(X) \tag{3}$$

In the above equation, X, Y, and f(X) are the Input variable, Output variable, and Target function respectively. A supervised learning algorithm finds a mapping function that maps the input variable with the output variable using the target function. The target function is best approximated by the mapping function so that for any value of the input variable (X) the function can be able to predict the output variable (Y). Supervised learning algorithms can solve both, Classification and Regression problems. In a classification problem, the ML algorithm finds the mapping function that can map the input variables (X) to the discrete output variable (Y) like a stuck pipe prediction problem, whereas in Regression problems algorithms establish a relationship (either linear or non-linear) among the variables and try to plot them in a best-fit line or curve. The best-fit line or curve should pass through the points in such a way that the distance of the points should be minimum from the line or curve. They are used to solve problems where the output variable is continuous i.e ROP prediction. Regression algorithms find the mapping function which can map the input variable (X) to the continuous output variable (Y). Commonly used supervised algorithms used for ROP prediction are ANN and RF.

Artificial Neural Network (ANN) algorithm is inspired by the functionality of the human brain. ANN comprises the input layer, hidden layer, and output layer. The input layer introduces the attributes or features into the ANN model, which gets multiplied by the randomized weights, and bias is added before entering into each neuron of the hidden layers. Weights represent the importance between the units i.e., input and hidden layer, thus zero weight signifies that no relation exists between the units, whereas any float value and its magnitude represent the importance of that particular input in determining the output (Schmidhuber [8]). In the hidden layer, summation of weights and bias are calculated and forwarded to activation functions viz. Sigmoid, Tansig, ReLU, etc. which determines whether the neuron will be fired or not for feature extraction. In the output layer, the summation of output from the hidden layer is processed and the outcome is prepared and delivered. Thereafter as per the feedforward and back-propagation technique, the output is back propagated to adjust the weights and minimize the error. This is done by comparing the predicted output with the actual output values while training the model at each iteration, which ultimately results in improved accuracy of the model (Jain et al. [9]). There are various types of neural networks, and the selection of each type of neural network depends upon the types of problems, parameters available, and output type i.e., discrete-valued, real-valued, etc. The most commonly used neural network are Modular Neural Network (MNN), Feed Forward Neural Network (FF-NN), Radial Basis Function Neural Network (RBF-NN), Kohonen Self organizing Neural Network, Recurrent Neural Network, Convolutional Neural Network, and Long short-term memory networks. Intrinsic advantages of ANN are the ability to generate output even with incomplete information, output generation not disrupted by mal-functionality of one cell in ANN, and parallel processing ability.

Random Forest is an ensemble machine learning method. The base learners of Random Forest are decision trees. The principle of Random Forest is the selection of random samples from the dataset, then constructing a decision tree for each sample and obtaining the prediction result from each tree. The prediction results are evaluated through either voting or averaging the final results of all base learners, which then predicts the final output for the classification/regression problem (Cutler et al. [10]). The accuracy of RF increases with an increase in the number of trees but up to a certain limit. As RF builds prediction models on random forest regression trees, in which parameters are randomly selected to grow the tree at each node, the tree is grown until the decisive prediction is reached using the bootstrap aggregation sampling method, also known as the bagging method. The independency among the tree also increases using the bootstrap sampling method. Optimal nodes are sampled from total nodes in the tree to form an optimal splitting feature. Random sampling technique in selecting optimal splitting feature lowers the correlation, correspondingly the variance of regression trees, which improves the prediction performance of individual trees in the forest. Though the individual decision trees may produce errors, the majority of the group are correct, leading to the overall outcome of the RF model in the right direction. The important hyperparameters to enhance the accuracy of prediction are n_estimators (i.e., the number of trees the algorithm builds before averaging the predictions), max_features (i.e., the maximum number of features RF considers before splitting a node), and min_sample_leaf (i.e., the minimum number of leaves required to split an internal node). The hypermeters to enhance the speed of the model are n_jobs (i.e., number of processors available), random_state (i.e., the randomness of the sample), and oob_score (i.e., Out of the bag, it is a cross-validation method for RF, one-third of the data set is used to evaluate the performance of the model). The advantages of RF are that there is less probability of overfitting the model, as RF requires large data set, accuracy is generally high, and missing values can be estimated more precisely by substituting the variable appearing most in a particular node. Scaling of data is not required in the RF algorithm, it predicts accurate results even without scaling. RF is capable of handling datasets with high dimensionality and works well with both categorical and continuous values. Further normalizing of a dataset is not necessary for RF as it uses a rule-based approach.

Genetic Algorithm optimization technique comprises five phases viz. Initial population, Fitness function, Selection, Cross over, and Mutation, (as illustrated in Figure 1), each phase has a significant role in reaching an optimal solution. The initial population is a set of present solutions available, each solution is known as an individual, which comprises chromosomes. Chromosomes are the parameters or features that define the individual. Further, each chromosome has a set of genes which is represented by a string of 0's and 1's. These initial populations are used to generate a new random solution, then perform a gradient search to understand the behavior of convergence. The fitness function scores each individual, it is a qualitative measure that enables optimization model to select the best solution for problem. A higher fitness function value means a high-quality solution. The fitness value calculation of each individual is called evaluation. After scoring the solutions, high-quality individuals or parents are selected for the mating pool, based on the fitness value (up to a threshold limit) to generate the next generations or offspring, which can be able to reach an optimal solution. This process removes the bad individuals from generating bad offspring. Repetition of this process of selecting and mating high fitness value individuals results in a good chance of retaining the good properties of an individual and leaving out bad ones. Crossover is important to create new unique solutions, as new generations of offspring generated just by selecting and mating parents have characteristics of the parent, which may also include some drawbacks, to overcome the same thus mutation process is necessary. The Mutation increases the diversity in the solution, by introducing a pre-determined change user wants to introduce in the population. It is to be noted that in absence of a crossover step the offspring is identical to parents and without mutation offspring possess similar characteristics to parents, which may restrict to reach the optimal solution. Some of the major advantages of GA are that they do not require any derivative information, are fast and efficient in comparison to the traditional optimization methods, optimize continuous function/discrete functions and multi-objective problems, and are also useful when a large number of features are involved and searching optimal parameters combination for the objective function. In the optimization model, the lower and upper range of each input parameter is to be defined, so the optimization model searches for the optimum value of each input parameter within a specified range that results in achieving the maximum output as targeted by the user. It is necessary because mechanical equipment or operational parameters have pre-defined working ratings or range, any value of input parameters predicted by the optimization model which is beyond the prescribed range would be unrealistic and the practicality of the model is unjustified. Subsequent section brief about the major input parameters affecting ROP and their limit based on the operational and mechanical aspects.

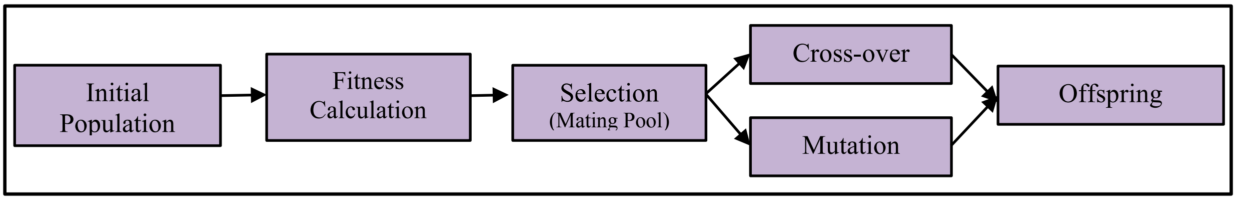


Fig. 1 Phases of Genetic Algorithm

4. Drilling Mechanics, Parameters, and Limiters for Machine Learning Optimization Model

The aim of improving drilling performance is related to completing the drilling activity in minimal time and ideally reaching the Technical Drilling Limit (TDL) with operations optimization, re-engineering the well design, and utilizing innovative and advanced equipment (Marshall [11]). ROP majorly depends upon the formation type (measured usually with its compressive strength), type of bits, BHA design, wellbore trajectory, and surface control parameters. Among the same, formation is a natural factor, well trajectory is predefined to reach reservoir target and bit design is an engineering parameter pre-decided during well planning, thus ROP alteration in real-time majorly depends upon surface parameters viz WOB, Over-balance, RPM, TRQ, and FLOW RATE. The important formation and drilling parameters are summarized below, along with the rationale for setting the various drilling parameter limits for the optimization model.

1.1 Confined Compressive Strength (CCS)

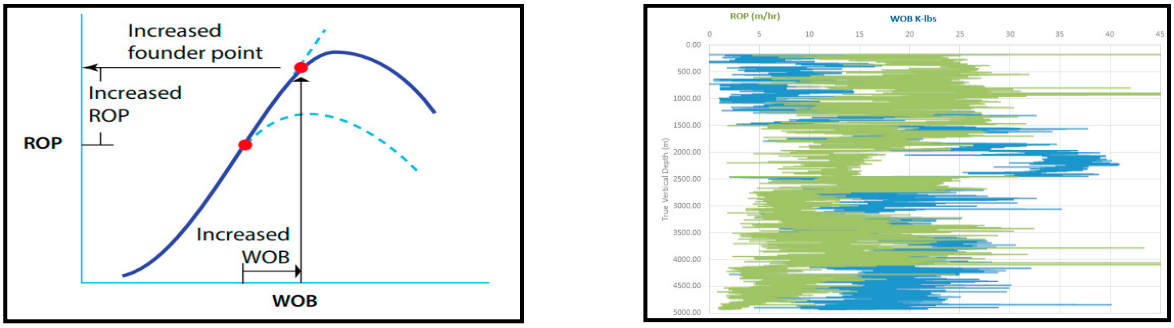
It is a measure of rock strength. High CCS formations like shale are difficult to drill owing to high density and compactness, thus ROP is reduced significantly, whereas in sandstone formation high ROP is recorded due to low CCS value. Likewise, increasing the WOB in the shale section does not result in high ROP, rather it may result in an increase of lateral and axial vibrations in drill string resulting in downhole tool failures. Depending upon the type of formation to be drilled, the ML model needs to be re-trained with the historical data of that particular formation and corresponding depth.

1.2 Mud Weight (MW)

Mud weight is necessary for maintaining geo-mechanical stresses after removal of rock and to prevent formation fluids viz. oil and gas entering into the wellbore leading to a well control situation, whichever condition has a higher mud weight requirement, the same is selected for drilling operations and set as a lower limit in optimization model (Nautiyal and Mishra [12]). The upper limit of the mud weight is usually set based on case histories at which differential sticking occurred in the static condition or in conjunction with the flow rate at which formation breakdown occurs in dynamic conditions.

1.3 Weight on Bit (WOB)

Weight on bit is weight transferred to bit so that the bit cutters indent the formation to break it. WOB is one of the major factors in increasing the ROP, but only up to a particular point known as the founder point as illustrated in Figure 2a, increasing the WOB beyond that limit may result in vibrations, bit balling, etc., leading to damage the drill string, downhole tools or even the bits cutters. WOB is varied throughout the various sections of a wellbore in order to achieve maximum ROP as illustrated in Figure 2b. The lower limit of WOB can be as low as possible, but the upper limit is governed by Bottom Hole Assembly design, jar setting, Bit, and Directional tools limit. The WOB is governed by the evaluation of MSE values in the optimization model.



(a) (b)

Fig. 2. (a) WOB vs. ROP curve; (b) WOB & ROP vs. Depth across wellbore

1.4 Revolution per Minute (RPM)

RPM usually has a direct relation with ROP up to a certain limit in conjunction with WOB, however higher RPM also results in BHA whirl, drill string vibrations, high wear and tear of drilling components especially in abrasive formations, etc. The offset well record of RPM at which BHA, Bit, and directional tool failure is occurring due to lateral vibrations may be used for setting the upper limiting of RPM in the optimization model otherwise Top drive rotation capability is set as the upper limit. The lower limit of RPM may be set as zero. The RPM is to be adjusted as per downhole tools response and the same may be optimized based on MSE values.

1.5 Flow Rate

Flow rate is a governing factor in cleaning the wellbore, in case of insufficient flow, the cutting may not be removed beneath the bit, resulting in grinding actions of formation cutting which leads to a significant loss of bit performance and correspondingly the ROP. The lower limit of Flow rate is guided by critical hole cleaning flow rate requirement i.e., minimum flow rate to circulate out cuttings from the wellbore and the upper limit is guided by either downhole losses based on Equivalent Circulating Density (ECD) or surface equipment handing capability of shakes, augers, and Mud Pump Pressure limitations.

1.6 Torque

Torque is a rotational force generated between the BHA and formation. The lower limit may be set to zero, whereas the upper limit is governed by the makeup torque limit of the drill pipe in use for drilling operations.

5. Results & Discussions

MSE provides a means for monitoring the efficiency of the Drilling System. It provides a way to optimize drilling parameters by finding the founder point with the current drilling system and also indicate the area where the engineering application is required with respect to equipment for reaching the technical drilling limit of operations viz. BHA modelling to reduce the vibration losses, Bit design, etc. (Chen et al. [13]). MSE is a ratio of input energy and ROP as depicted in equation 1, it is also represented as the slope of Figure 2a, which remains constant throughout the linear portion of the curve, and if the system is foundering, which is reflected from a non-linear portion of the curve indicate that MSE value is increasing and drilling efficiency is reducing. It is illustrated in Figure 3 that means when MSE is minimum, ROP is maximum.

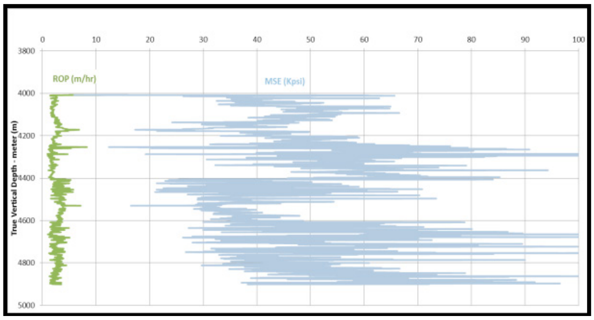


Fig. 3. ROP and MSE trend analysis.

Table 1. Comparison of earlier optimization models with the proposed model

Author(s)	Research Aim	ML algorithms	Evaluation method	Highest accuracy	Comparison with proposed methods in paper.
Koopialipoor and Noorbakhsh [3]	ROP prediction and Optimization	ANN- LM, ANN-SCG, ANN-OSS ABC for optimization	R2- 0.912 and RSME- 0.0779	ANN-LM with 1 hidden layer and 16 neurons	ANN models require feature scaling, noise, and outlier removal, as drilling data is prone to the above, RF model is recommended for developing ROP prediction Model in this paper. The authors did not address drill string vibrations, energy losses, bit inefficiency issues, etc., in the ROP optimization model, which is not an actual case. In the present paper, MSE evaluation criteria is proposed to be incorporated into the optimization model to address the above issues.
Ashena et al. [4]	ROP prediction and Optimization	ANN GA and PS for optimization	RSME: 2.97	ANN with 2 hidden layers, one with 15 and the other with 10 neurons	RF models are found to have lower mean absolute error for Drilling Problems in comparison to ANN models. Thus, RF is recommended in this paper for ROP prediction. Drill string vibrations, energy losses, etc., issues are not addressed in the ROP optimization model by the author, which is not an actual case. MSE evaluation criteria is incorporated in the optimization model of the present paper to address the above issues, optimize drilling parameters and practically maximize ROP.
Takbiri-Borujeni et al. [5]	ROP prediction and identifying bit dysfunctionality	ANN-MLP (ReLu – ADAM)	MAE	ANN-MLP	The MAE for RF models is lower as compared to ANN models for ROP prediction. The authors only addressed the bit dysfunctionality in the paper as an optimization method, which partially addresses the drilling optimization. MSE criteria in the optimization model address bit dysfunctionality, drill string vibrations in the present work

Among various machine learning algorithms, ANN and RF were widely used by researchers for developing the model for ROP prediction, between the same RF is preferred owing to their intrinsic nature of possessing higher accuracy, robustness to overfitting, and working with high dimensionality, noisy and outlier datasets which are usually associated with drilling data recorded on field. ANN with 1 hidden layer is capable of handling a non-linear dataset, but the accuracy of the ANN model largely depends upon the number of hidden layers, the neuron in each layer, the type of activation function, and the type of optimizer used, which can be obtained by hit and trial methodology or using a deep learning KerasTuner function. The hyperparameter tuning is necessary to increase the accuracy of the prediction model. Further, to reduce the computation time, complexity and dimensionality stuck issues, it is recommended to perform feature selection using Pearson Correlation Coefficient, Z-score, Analysis of variance (ANOVA), F-score, etc. techniques on drilling dataset. Evolutionary optimization methods specifically genetic algorithms and particle swarm optimization techniques are recommended for drilling optimization problems. It is to be noted that optimization models without MSE criteria would be unrealistic and unable to address the drilling performance enhancement in totality as mentioned in comparison table 1. Additionally, in the optimization model, the upper and lower limit of each drilling parameter should be defined based on operational limits and equipment ratings, otherwise, the optimization model results may be impractical to achieve in the field. Drilling engineer guidance is required for setting the drilling parameter limits in the optimization model. The model workflow for the development of the ROP prediction model using Random Forest Regressor is illustrated in 4a and the optimization model is illustrated in 4b.

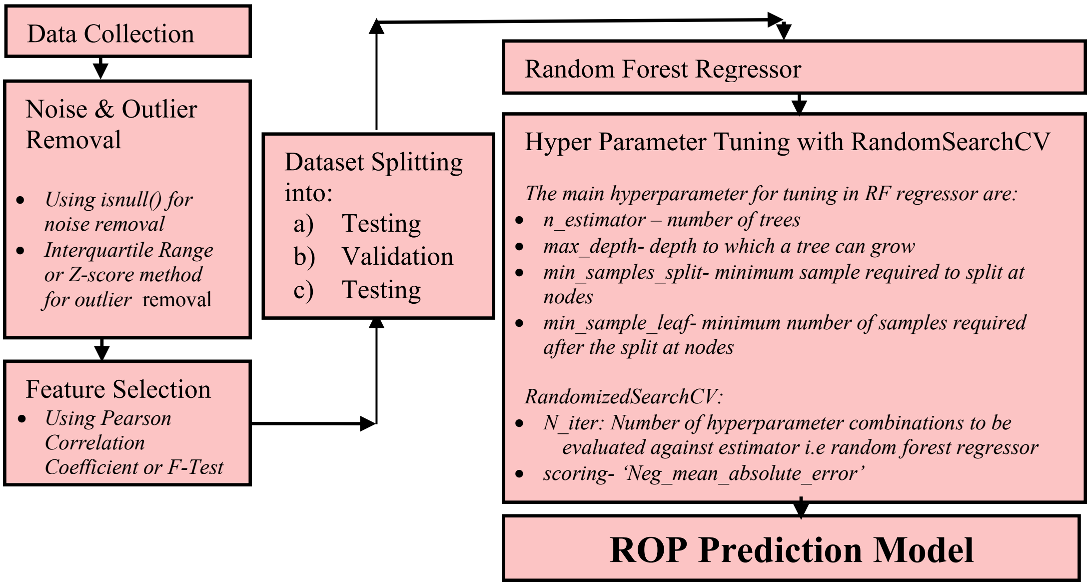


Fig 4a. Flow chart for development of ROP prediction model

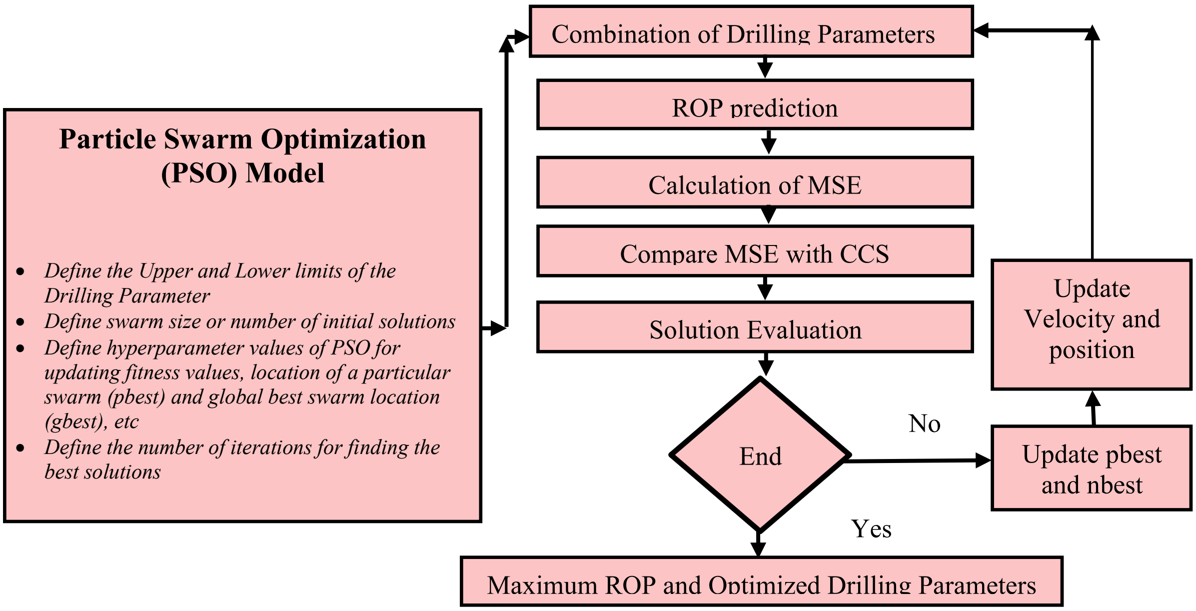


Fig 4b. Flow chart for development of Drilling Optimization Model Development with MSE

6. Conclusion

The machine learning aided Drilling Optimization has higher accuracy over the traditional empirical methods, numerical methods, statistical methods, etc. RF algorithms for ROP prediction and evolutionary optimization algorithms for drilling parameters optimization are recommended for developing a drilling performance enhancement model. RF algorithm is preferred over other ML algorithms as it is robust to noise, outliers and high dimensionality stuck issues which are usually associated with drilling datasets. Additionally in the RF model feature scaling is not required even though several drilling parameters vary significantly in magnitude. Earlier ROP optimization models do not include any criteria for addressing energy loss and downhole tool failure owing to vibrations, etc., thus optimized results may be impractical and cannot be applied on the field to attain maximum drilling performance. The coupling of MSE criteria in the optimization model as discussed in this paper may result in attaining maximum ROP, without inducing any downhole vibrations or energy loss. The upper and lower limits of the ML optimization model ensure the practical applicability of results in optimizing the drilling performance in the field. MSE provides a quantitative measure for improving and evaluating the drilling performance, additionally, it highlights the region where advanced engineering in equipment design/selection is to be implemented to reach the technical drilling limit. Machine Learning provides a tool for the drilling engineers, to optimize the drilling operations in real-time, which not only helps to reduce the operational time but also saves significant Capital Expenditure (CAPEX) for the company.

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