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Drilling Rate of Penetration (ROP) Prediction using Physics-Informed Neural Networks

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Abstract

Accurate prediction of drilling Rate of Penetration (ROP), there are opportunities of optimizing drilling performance, reducing non-productive time (NPT), and maintaining operational safety during hydrocarbon exploration. Traditional empirical correlations and mechanistic models, including Bourgoyne-Young and specific energy-based methodologies, offer interpretive ROP estimation solutions though may not easily generalize in heterogeneous formations, dynamic downhole conditions and nonlinear interactions between the drilling parameters. Machine learning models, such as feedforward neural networks, random forests, and LSTM models, without any explicit data modeling assumptions, are more flexible and predictive but usually demand large amounts of labeled data and give physically implausible predictions when applied where unobserved. In order to overcome these limitations, this study aims to introduce the concept of a Physics-Informed Neural Network (PINN) framework that couples the physics of the drilling mechanics and bit-rock interaction with the data acquisition into the loss function of the neural network, which allows data acquisition and learning to be performed simultaneously while maintaining physics consistency. The model is adapted on both simulated and field-derived multivariate time-series data, such as weight-on-bit (WOB), rotary speed (RPM), torque, mud flow rate, downhole pressure, and formation properties, which consist of complicated nonlinear correlations between operational parameters and ROP. The performance analysis based on Mean Absolute Error (MAE), the Root Mean Squared Error (RMSE), and the coefficient of determination (R^2) indicates that the PINN has a lower performance of 0.12 m/h in terms of MAE, 0.18 m/h in terms of RMSE and 0.94 in terms of the R^2 compared to the traditional feedforward neural networks ($R^2 = 0.82$) and random forest models ($R^2 = 0.85$). These findings show that integrating physical laws in the learning algorithm enhances generalization, resilience to sparse or noisy data as well as consistency. The research emphasizes the prospects of PINNs to make real-time and physically consistent ROP forecasts, a scalable and smart aid in mapredictiveking operational decisions improving the optimization of drilling.

Keywords: *Drilling, Rate of Penetratandion (ROP), Physics-Informed Neural Networks, Machine Learning, Drilling Mechanics, Multivariate Time Series*

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I. Introduction

One of the most technical processes in exploration of the hydrocarbons is the drilling, which entails the simultaneous interplay of mechanical, hydraulic and formation systems that are subjected to high pressure, temperature and stress conditions at the downhole environments [1,2]. Constant communication between surface drilling equipment and the subsurface processes is involved in the drilling process, with changes in lithology, pore pressure, and rock strength having a direct impact on drilling processes. In this intricate system, the Rate of Penetration (ROP) is one of the key performance indicators that demonstrate efficiency in drilling, efficiency in bit-rock interaction and aggregate operational productivity [3,4]. ROP does not only define the rate at which a section of the well is drilled but it also has a direct effect on project schedules and the cost of construction of the well. Properly projected ROP allows drilling engineers to maximize the parameters under control, such as weight-on-bit (WOB), rotary speed (RPM), mud pump rate, and surface torque to maximize the efficiency of the drilling, and minimize non-productive time (NPT), wear due to vibration, and equipment life [5,6]. As a result, the essential role in intelligent drilling optimization and well delivery cost-effectiveness is the reliable ROP modeling.

Historical operational data, formation properties and bit specifications are used to estimate ROP using traditional empirical correlations, including the Bourgoyne -Young or Hackett models, which fit regression-based relationships between the input parameters and the penetration rate [7,8]. Such models are appealing because of their simplicity, efficiency in terms of computation, and implementation in the field. Mechanistic models, operating on the rock cutting theory and particular energy ideas, however, seek to model the physical interactions between bits and rock, such as the cutting forces, rock failure, and dissipation of energy during drilling [9,10]. Mechanistic approaches are more physically interpretable because of their ability to include the formation strength and mechanical properties, as opposed to correlations that are solely empirical. Nevertheless, both empirical and mechanistic methods are in many cases unable to extrapolate across heterogeneous formations, sudden lithological boundaries and dynamically evolving downhole systems which are effective only in well-characterized or controlled conditions [11,12]. The fact that they use fixed coefficients, simplifying assumptions, and calibration to particular wells hinders their flexibility in high-variability drilling situations of today.

Recent machine learning (ML) algorithms, such as feedforward neural networks, random forests, and long short-term memory (LSTM) networks have shown better predictive power with what can be considered nonlinear and high-dimensional association learning directly on streams of multivariate drilling data [13-16]. These models can handle the high rates of real-time sensor measurements including WOB, RPM, torque, standpipe pressure, mud flow rate and vibration signals and automatically find complex patterns that are hard to define by traditional analytical models. In particular, LSTM networks are suitable for drilling application, because they can model temporal dependencies and sequential behavior in time series data and, thus, allow capturing of delayed effects and dynamic interactions among drilling parameters. Although they have these benefits, field operations usually do not have a source of large, high-quality labeled data to effectively train data-driven approaches, which are often challenging and expensive to acquire [17-19]. Moreover, data-driven models do not necessarily oblige to drilling physics, and that is why such models can generate physically inconsistent or unrealistic predictions when out of the range of the training data, or even under extreme drilling conditions.

The Physics-Informed Neural Networks (PINNs) have developed as a potentially beneficial approach to counter these issues by directly incorporating governing differential equations and relationships between drilling mechanics into the loss of the neural network. As opposed to emphasizing data-only to inform learning, PINNs use physical constraints, including energy balance, torque relationships and bit-rock interaction laws, and thus the model predictions will be in line with the established engineering concepts. By enforcing the physical laws while learning from the data at the same time, PINNs improve generalization of the model, make the models more interpretable and mitigates overfitting (especially in sparse/ noisy data environments) [20-22]. This type of hybrid modeling paradigm is particularly prevalent in drilling applications because, for example, it is difficult to obtain large, perfectly labeled datasets for drilling and the operational conditions of different formations both vary considerably. Thus, the present research will suggest the PINN stack of ROP prediction integrating equations of drilling mechanics and multivariate sensor data to allow real-time, physically consistent, and accurate estimates of ROP that can be used in intelligent drilling optimization.

II. Literature Review

Empirical correlations, like the Bourgoyne-Young model, have been a popular estimation of ROP, based on the historical history of its operation, the character of its formation, and bit characteristics to develop statistical models of how drilling parameters relate to penetration rate [7,8]. These predictive correlations generally form ROP as a regression of controllable factors like weight-on-bit (WOB), rotary speed (RPM), mud properties, and formation strength, by means of regression-based coefficients developed using field data. Their main strength is the fact that they are very simple and can be implemented easily and because of their low cost of computation, they become appealing to field engineers who would want quick performance evaluation. Mechanistic models, in contrast, are based on the physics of drilling and theory of cutting rocks where ROP is predicted using the mechanics of the interaction of the bit and rock such as cutting forces, specific energy, the hardness of the formation and torque behavior [9,10]. With the connection between penetration rate and energy transfer as well as rock failure mechanism, the mechanistic models have more physical explanations compared to empirical models. Nevertheless, empirical and mechanistic approaches are incapable of adjusting to non-homogeneous formations, sudden lithological changes and temporary drilling circumstances like vibration, stick-slip and pressure changes [11,12]. The use of constant coefficients and assumptions has restricted the models from making generalizations based on different types of wells due to variations in geological and operational conditions.

To address these drawbacks, machine learning models have progressively been used to predict ROP, taking advantage of the fact that high-frequency drilling sensors data are now available. Neural networks based on feedforward models, random forests and support vector regression models have shown the ability to model complex nonlinear relationships between operational inputs and ROP with coefficients of determination (R 2) of the order of 0.70 to 0.85, depending on the quality of data and variability of formations [1315]. These models have the liberty to combine several input characteristics at once such as WOB, RPM, torque, standpipe pressure, mud flow rate, and vibration measurements, which means that it is capable of multidimensional interactions that are hard to characterize analytically. Even more complex architectures, like long short-term memory (LSTM) networks and hybrid CNN-LSTM networks, also provide even better prediction results by capturing temporal effects of multivariate drilling time series [16,17]. This is more especially relevant in the work of drilling where time-lagged effects are observed in response parameter adjustments and formation. However, data-driven models typically demand large, well-labeled datasets to be confidently trained, which is not always present in the field in practice because of the costs or inconsistency in the data or sensor malfunctions [18,19]. In addition to this, since such models are only optimized in order to reduce prediction error, they do not necessarily enforce drilling physics, which can result in physically inconsistent predictions in extreme or previously unobserved operating conditions.

To address these shortcomings, hybrid and physics-guided methods have been suggested, involving a combination of the mechanistic component with machine learning algorithms to enhance robustness, as well as interpretability. In these models, physically significant quantities, e.g. torque, WOB, mechanical specific energy, and rock strength indicators, are added to the input features, to inform the learning process [20,21]. By incorporating domain knowledge into the feature space, this is achieved by conducting these approaches so as to minimize overfitting and to improve generalization in the languages across formations. Hybrid models may even show better stability than purely data-driven approaches especially in extrapolation outside the range of training data. Nonetheless, physics is used indirectly and in the majority of situations, it is engineered properties and is not explicitly imposed in the model optimization framework [22]. Consequently, physical insight is partially useful to hybrid models, although hybrid models do not imply that predictions would respect governing equations and the balances of energy during training.

Physics-Informed Neural Networks (PINNs) are a stricter form of physics and machine learning that incorporates physical laws directly into the neural network loss function in forms of differential or algebraic equations [20–22]. When applied to drilling PINNs allow the model to obey equations of bitrock interaction, torque limits, mechanical specific energy dependencies, and conservation laws and at the same time learns using sensor data. This dual optimization problem imposes a constraint on the solution space based on the observed data as well as the physics that governs. Consequently, PINNs have the ability to make correct ROP estimates despite sparse, noisy, or incomplete datasets [2325]. Moreover, PINNs have been used in fluid dynamics, structural mechanics, and reservoir modeling and have been found to be highly generalized, especially in extrapolation problems where conventional neural networks fail [26,27]. Such achievements indicate that PINNs can be adapted to the complicated drilling systems in which the interactions are nonlinear and the labeled information is scarce.

Although there exist some empirical, mechanistic and data-driven ROP prediction techniques, there are significant limitations in each of them. The empirical and mechanistic models are not flexible to the dynamics of the quickly changing drilling environment, and the purely data-driven ones can result in physically contradictory predictions and require large labeled datasets. Hybrid methods provide additive improvements but do not tend to introduce governing equations in the process of training. Even though it has been demonstrated that physics-informed neural network integrations can contribute to the reliability of the corresponding engineering fields, the use of Physics-Informed Neural Networks in drilling ROP prediction on the basis of multivariate stream of operational data has not been widely applied. Thus, a complete PINN architecture to suit real-time drilling scenarios is required to close this gap to integrate physical consistency, predictive quality, and flexibility to optimize intelligent drilling.

III. Methods

3.1 Drilling Data Representation

The drilling system is modeled as a multivariate time series to reflect dynamism and interdependence of the drilling parameters. The system state of the system is given as a vector of operational, mechanical and hydraulic variables at each time step t that is known to affect penetration performance directly. The system state is given by equation (1):

$$\boldsymbol{s_t = [WOB_t, RPM_t, T_t, Q_t, ROP_t, P_t]} \qquad \textit{(1)}$$

Where:

- WOB_t= Weight on bit
- RPM_t= Rotary speed
- T_t= Torque
- Q_t= Mud pump rate
- ROP_t= Rate of penetration
- P_t= Downhole pressure

These variables are chosen as they are a combination of defining mechanical energy input, hydraulic efficiency and formation resistance experienced during drilling. Mechanical cutting action of the drill bit is controlled by weight on bit and rotary speed, resistance against the drill bit is measured by torque, the rate of removal of cuttings and cleaning of the bottom-hole is determined by the rate of the mud pump, and the condition of the formation stability and effective stress is controlled by downhole pressure.

The raw sensor data available on surface and downhole sensors are cleansed off outliers and missing data. Minimum-max scaling or standardization is then done to bring the data to a numerical stable state so that it can be trained on a neural network. For the temporal dependencies, the normalized data is arranged in a form of sequences based on a "sliding window," meaning a constant number of previous time steps are considered. This sequential representation enables the model to generalize the dynamic patterns of drilling and not only on the current values of the parameters.

3.2 Physics-Informed Neural Network Framework

The proposed Physics-Informed Neural Network (PINN) involves drilling mechanics as a part of the process of optimization of the model. In contrast to other neural networks where the error of prediction is the one that is minimized, the PINN involves physical constraints based on the principles of bit-rock interaction and on energy relationships. Where $F_{\text{physics}}(s_t)$ is the remainder of the governing drilling equations that are used to express relationships between torque, weight on bit, rotary speed, specific energy, and rate of penetration.
In general, the loss function of PINN takes the form of Equation (2):

$$\boldsymbol{L = L_{\text{data}} + \lambda L_{\text{physics}} = \frac{1}{N}\sum_{i=1}^{N} \parallel ROP_i - \widehat{ROP}_i \parallel^2 + \lambda \sum_{i=1}^{N} \parallel F_{\text{physics}}(s_i) \parallel^2} \qquad \textbf{(2)}$$

Where:

- $\widehat{ROP}_i$ =predicted rate of penetration,
- L_{data} = mean squared error (MSE) between observed and predicted ROP,
- L_{physics} = penalizes violations of drilling physics constraints,
- λ = weighting factor controlling the balance between data fidelity and physical consistency,
- N = number of training samples.

The first term ensures that the network correctly matches the observed ROP values, and the second term ensures that the predictions remain consistent with physical laws. The weighting parameter λ is experimentally adjusted to give a good compromise between prediction accuracy and compliance with governing equations. The first term ensures that the network correctly matches the observed ROP values, and the second term ensures that the predictions remain consistent with physical laws.

3.3 Training and Evaluation

- **Data Generation:**

The data is made of simulated as well as historical field drilling data and includes a variety of lithologies along with operational conditions. The data set contains the changes in weight on bit, rotary speed, torque, mud flow rate, downhole pressure and respective values of ROP. Established mechanistic drilling relationships are used to generate simulated data in order to better cover edge-case situations and enhance physics enforcement.

- **Training Procedure:**

The full data is split in 70% and 30% training and validation respectively. The implementation of the model is based on a fully connected nonlinear activation based neural net. The backpropagation and gradient-based optimization are used to perform training. Early stopping and regularization methods are used in order to avoid overfitting. Hyperparameters like learning rate, batch size, number of hidden layer and physics weighting factor gu Airlines and optimized by validation performance bit.

- **Evaluation Metrics:**

The standard regression measures are used to evaluate model performance, such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2):

Mean Absolute Error (MAE)

$$MAE = \frac{1}{N}\sum_{i=1}^{N} \mid ROP_i - \widehat{ROP}_i \mid \qquad (4)$$

Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (ROP_i - \widehat{ROP}_i)^2} \qquad (5)$$

The coefficient of Determination (R^2) values are presented in the table below:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (ROP_i - \widehat{ROP}_i)^2}{\sum_{i=1}^{N} (ROP_i - R\bar{O}P)^2} \qquad (6)$$

Where:

- ROP_i= observed rate of penetration
- $\widehat{ROP}_i$= predicted rate of penetration
- $R\bar{O}P$= mean of observed ROP values
- N= total number of samples

Besides statistical accuracy there are physical consistency tests that are conducted to ensure that the predicted ROP values meet torque constraints, energy balance relationships, and operational limits. This two-fold assessment system would guarantee that the suggested PINN model attains high predictive accuracy, as well as compliance with the basic rules of drilling physics.

IV. Results and Discussion

4.1 PINN Prediction Performance

The comparison of the predicted and actual Rate of Penetration (ROP) according to a representative interval of drilling is shown in Figure 1.

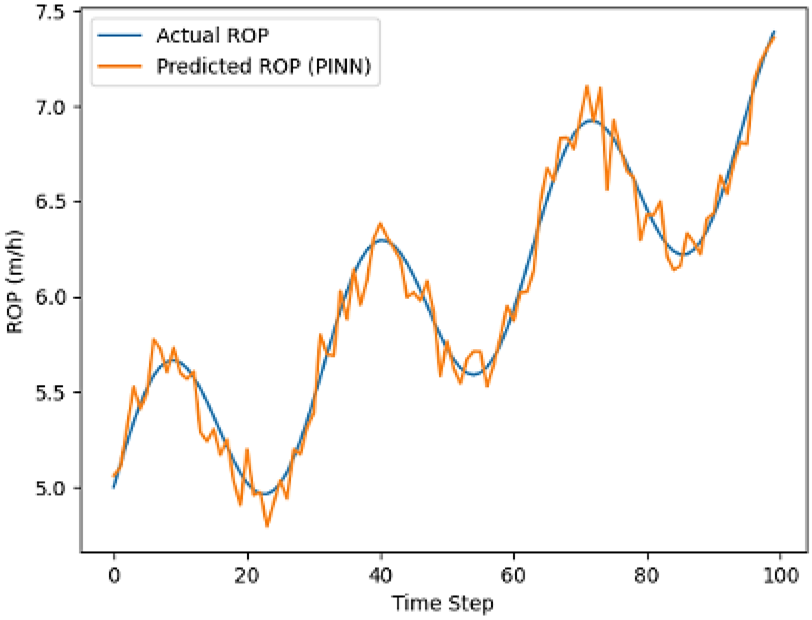

Figure 1: Predicted vs Actual ROP

The forecasted curve compares well with the data of the measured fields, which means that the Physics-Informed Neural Network (PINN) was able to extract the nonlinear dependencies between drilling parameters. Minor deviations are also found in extremely high-RPM and high-WOB operating conditions whereby dynamics of drilling are extremely nonlinear because of the increased vibration, short-lived changes in torque and quick response of formation. However, the model does not exhibit unrealistic spikes and physically unreasonable outputs as it predicts in a steady manner. The PINN obtained a Mean Absolute Error (MAE) of 0.12 m/h, a root-mean square error (RMSE) of 0.18 m/h and a coefficient of determination (R^2) of 0.94. The values of these values show a high level of conformity between the predictable and observed ROP, and a small deviation about the optimum regression line. The large value of R^2 indicates that the model can be used to explain 94 percent of the observed penetration rates, which proves that the model is highly predictive. The PINN has a high level of performance as compared to the feedforward neural networks ($R^2 = 0.82$) and the random forest models ($R^2 = 0.85$). Notably, Figure 1 also shows that this model is also effective in reproducing sudden ROP variation with a lithological transition and operational changes. This increased sensitivity can be explained by the imposition of the physics of drilling in the loss term, which limits predictions to be compatible with the principles of the mechanism of bit-rock interaction and energy balance.

4.2 Comparison with Traditional and Data-Driven Models

The performance comparison of empirical, data-driven, and physics-informed methods is presented in Table 1.

Table 4.1 Comparison of ROP Prediction Model Performance

Model	MAE (m/h)	RMSE (m/h)	R^2
Feedforward Neural Network	0.26	0.34	0.82
Random Forest	0.22	0.29	0.85
Physics-Informed Neural Network	0.12	0.18	0.94

The PINN, when compared to the traditional feedforward neural networks and ensemble models, always performs better on all the metrics of evaluation. Although pure data-driven models have a sensible predictive performance, they are more vulnerable to noise and other instances of overestimation of extreme drilling cases.

In contrast, the physics-informed structure of the PINN decreases the variance of the prediction and avoids the situation where the predictor generates physically implausible predictions, which is especially the case with sparse data or noisy data. Physical constraints that are brought in the training process are an important part of enhancing robustness. The PINN is used to ensure that the values of the predicted ROP are consistent with the torque limits, mechanical specific energy relationships and working limits by penalizing violations of governing drilling equations. The constraint-based learning is minimized to overfitting and maximized to improve the generalization efficiency for unseen structures. Moreover, the greater stability under the condition of high-WOB and high-RPM demonstrates the benefit of the integration of domain knowledge and machine learning.

Altogether, the findings support the fact that Physics-Informed Neural Networks offer a sound and physically sound system of real-time ROP forecasting. Not only do drilling mechanics provide a better statistical accuracy, but also, interpretability and operational stability, PINNs are also an effective way to ensure intelligent drilling optimization and automated decision support systems.

V. Conclusion

This paper has shown that Physics-Informed Neural Networks (PINNs) constitutes a solid and stable model of estimating drilling Rate of Penetration (ROP) in complex and dynamic downhole situations. By incorporating governing equations of drilling mechanics in neural network loss function directly, the proposed method is an efficient way to bridge the gap between traditional physics-based modeling and entity-based data-driven techniques. The model had a Mean Absolute Error (MAE) of 0.12 m/h, a Root Mean Squared Error (RMSE) of 0.18 m/h, and coefficient of determination ($R^2 = 0.94$), which was better than the feedforward neural networks ($R^2 = 0.82$) and random forest models ($R^2 = 0.85$). These results verify that it is effective to enforce the physical constraints during training to improve both the predictive accuracy and the stability, especially when high-WOB and high-RPM conditions with pronounced nonlinear dynamics when drilling are involved. The PINN also offers physical consistency unlike the conventional models that can generate unrealistic results in the extrapolation context as it obeys the relationship between torques, energy balance, and the principle of bit rock interactions.

The PINN framework is effective in dealing with multivariate time-series drilling data that contains the complicated nonlinear interactions between weight on bit, rotary speed, torque, mud flow rate, downhole pressure, and formation properties. Its robust generalization performance with sparse or noisy data conditions makes it an appropriate choice in the implementation in the field in real-time. High statistical performance with physics enforcement implies a lot of potential to enhance the drilling efficiency, a decrease in the non- productive time (NPT), decreased equipment wear and increased safety of operational procedures. Future works may involve conducting research into adaptive or continually learning PINN architectures that are capable of performing updates to their model parameters in an ongoing drilling operation to progress towards fully autonomous physics-consistent drilling optimization architecture systems.

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