Engineering Applications of Artificial Intelligence 126 (2023) 107035

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Enhancing the drilling efficiency through the application of machine learning and optimization algorithm

Farouk Said Boukredera [a,*], Mohamed Riad Youcefi [b], Ahmed Hadjadj [c], Chinedu Pascal Ezenkwu [d], Vahid Vaziri [a], Sumeet S. Aphale [a]

[a] Centre for Applied Dynamics Research, University of Aberdeen, UK
[b] Faculty of Technology, University of Amar Telidji Laghouat, Algeria
[c] Petroleum Equipment and Materials Reliability Laboratory, Faculty of Hydrocarbons and Chemistry, M'Hamed Bougara University, Algeria
[d] Business and Data Analytics, School of Creative and Cultural Business, Robert Gordon University, UK

ARTICLE INFO

Keywords:
Drilling optimization
Drilling vibrations
Artificial neural network
Machine learning
Rate of penetration

ABSTRACT

This article presents a novel Artificial Intelligence (AI) workflow to enhance drilling performance by mitigating the adverse impact of drill-string vibrations on drilling efficiency. The study employs three supervised machine learning (ML) algorithms, namely the Multi-Layer Perceptron (MLP), Support Vector Regression (SVR), and Regression Decision Tree (DTR), to train models for bit rotation (Bit RPM), rate of penetration (ROP), and torque. These models combine to form a digital twin for a drilling system and are validated through extensive cross-validation procedures against actual drilling parameters using field data.

The combined SVR - Bit RPM model is then used to categorize torsional vibrations and constrain optimized parameter selection using the Particle Swarm Optimization block (PSO). The SVR-ROP model is integrated with a PSO under two constraints: Stick Slip Index (SSI<0.05) and Depth of Cut (DOC<5 mm) to further improve torsional stability. Simulations predict a 43% increase in ROP and torsional stability on average when the optimized parameters WOB and RPM are applied. This would avoid the need to trip in/out to change the bit, and the drilling time can be reduced from 66 to 31 h.

The findings of this study illustrate the system's competency in determining optimal drilling parameters and boosting drilling efficiency. Integrating AI techniques offers valuable insights and practical solutions for drilling optimization, particularly in terms of saving drilling time and improving the ROP, which increases potential savings.

1. Introduction

Optimizing the efficiency of drilling operations (which accounts for half of the budget of any exploration and development project) is essential in reducing overall costs and time, maximizing equipment reliability, and minimizing the adverse impact of hazardous situations. Certainly, the improvement of drilling efficiency and operational safety has become vital for improving efficiency and reducing the carbon footprint of the oil and gas industry.

Unwanted drill-string vibrations are the main cause of performance failures (Bavadiya et al., 2017). They are detrimental as they take away the mechanical energy aimed at drilling, lead to borehole instability, and cause premature wear of downhole equipment (Pllácido et al., 2002). These vibrations are of great concern critical due to the ease with which they creep in and their persistent nature. The main causes of these vibrations are nonlinear bit-rock interactions, mass imbalance, poor management of drilling parameters, and improper selection of the downhole equipment (Yigit and Christoforou, 2006). These drill-string vibrations can be classified into three modes: torsional, axial, and lateral (Spanos et all, 2003).

It can be observed that the occurrence of one type of vibration mode during drilling operations often leads to the induction of other types due to dynamic coupling (Boukredera et al., 2021). For instance, the occurrence of axial vibration can induce lateral shocks, and torsional vibrations can trigger both bit bounce and whirl. Despite this cross-coupling, torsional vibrations are widely regarded as the most severe type of vibration due to their gravity and frequency characteristics (al Dushaishi et al., 2018). The main problem is associated with the

* Corresponding author.
E-mail address: farouk.boukredera@abdn.ac.uk (F.S. Boukredera).

https://doi.org/10.1016/j.engappai.2023.107035
Received 21 May 2023; Received in revised form 20 August 2023; Accepted 22 August 2023
Available online 27 August 2023

high-speed peaks during the slip phase, which lead to extreme accelerations and forces in both the axial and lateral directions, causing bit bounce and whirl (Fig. 1-b). During the Stick phase, there will be excessive friction on the cutters, which causes the stuck bit situation. In this case, the Top Drive continues to apply a constant torque to the drill-string, which has a certain degree of elasticity, causing the drill-string to buckle and the drill pipe to twist (Fig. 1-a). Therefore, the drilling optimization process must consider the mitigation of drill-string vibrations to improve the drilling efficiency and decrease non-productive time (NPT).

Traditional physical-based models have limitations due to unreliable assumptions resulting from variations in downhole equipment, well angle, and geological passage. To overcome these restrictions, scholars have turned to data-driven models trained with enormous amounts of data. In particular, the use of AI algorithms has shown promising results in predicting drilling outcomes. The intelligent drilling systems, which employ innovative workflow and tools, are based on AI algorithms and smart equipment. The nonlinear modelling and optimization workflow offer necessary instructions and support for smart equipment, which provides the data to model and validate the AI systems. The optimization algorithms used to enhance ROP, while easing the drill-string vibration are presented.

Although the application of AI has made significant progress, most models address different challenges. For instance, a real-time DL-based high-performance damage detection model and VHD detection frameworks have been presented by (Roy and Bhaduri, 2023; Jamil and Roy, 2023) to address the shortcoming of the current models in complex and noisy environments. The novel deep learning (DL)-based high-performance outperformed current state-of-the-art models by providing at least 89.51% accuracy in more superficial network structures. Multiple Graph Learning Neural Networks (Jiang et al., 2022) have been recently presented and experimented on several datasets to demonstrate that MGLNN outperforms other related methods on semi-supervised classification tasks and the results are fairly stable in some parameter range even when the hyperparameters are changed.

Iterative learning control (ILC) algorithms have been used by (C. Zhou et al., 2022; Zhuang et al., 2022) to introduce a robust and optimal ILC for constrained systems. Their work extends the existing framework of ILC, utilizing the design degree of freedom to optimize performance beyond tracking accuracy. These algorithms showcase the potential for enhanced control in constrained conditions and improve the algorithm's constraint handling capability compared to conventional counterparts.

In addition to its prominent roles in classification and prediction with iterative learning, AI is also extensively employed in optimization. Many-Objective Teaching-Learning-Based Optimizer (MaOTLBO) has been introduced as a potential solution for addressing the complexities of the Optimal Power Flow (MaO-OPF) challenges (Jangir et al., 2023). The algorithm evaluation encompasses both the DTLZ test suite, encompassing 5, 7, and 10 objectives, and the IEEE-30 test systems highlight its performance and adeptness with various operational constraints. Another Many-Objective Weighted Optimization Algorithm (MOWOA) subjected to a 17 comprehensive evaluation and tests, comprising 8 unconstrained problems, 5 constrained problems, and 4 multi-objective engineering design challenges (Pandya et al., 2022). By doing so, the algorithm's capabilities are substantiated, with both quantitative and qualitative evidence highlighting its adeptness. This substantiation encompasses numerical performance metrics, as well as its convergence and coverage of the Pareto optimal front.

Significant research has been aimed at addressing the challenge of predicting ROP and mitigating the effect of drilling vibrations using innovative AI solutions such as the risk assessment method based on neural network backpropagation (Chen et al., 2018), the average accuracy of prediction for BPNN based on the wellhead torque signals is more than 90%. A workflow that combines ROP optimization with ML based vibration models (Hegde et al., 2019), the approach offered an improvement of ROP by 14.1% on average across all formations. Real-time workflows that detect and characterize drill-string shock and vibration using historical data and ML methods (Millan et al., 2019), The trained model performed on classification of the testing data had an accuracy of 93% to distinguish periods with and without lateral shocks. The efficacy of these approaches depends on the presence of downhole measurement tools (MWD) within the drill-string, to detect excessive vibrations. These MWD tools are included only for deviation objectives.

The optimization scheme should be constrained by factors that mitigate drilling vibrations, such as mechanical specific energy (Rashidi et al., 2010) or stick slip index (Hegde et al., 2019). Simply using the maximum WOB and RPM can induce drilling vibrations, which prevents achieving the optimal ROP (Bataee and Mohseni, 2011). To achieve this (Abbas et al., 2019), propose AI based scheme using the ANNs model and genetic algorithm (GA) to obtain operating parameters WOB and RPM that lead to an ROP minimum of 15,8 m/h with the bit selection. In addition, AI based workflow has assisted the bit selection and ROP optimization (Batruny et al., 2021; Tortrakul et al., 2021), The application of trained ROP models in conjunction with various drilling bits yields noteworthy outcomes, including a remarkable 50% increase in ROP when compared to the original field data. This approach also

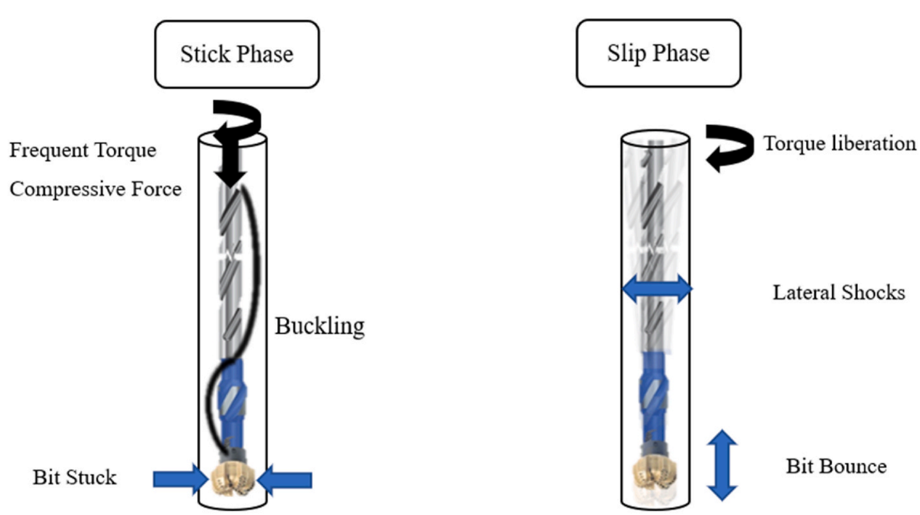

Fig. 1. Stick and slip situations, (a) The elasticities of the drill-string cause the buckling during the stick phase. (b) Extreme accelerations and forces in both the axial and lateral directions causing bit bounce and whirl during slip phase.

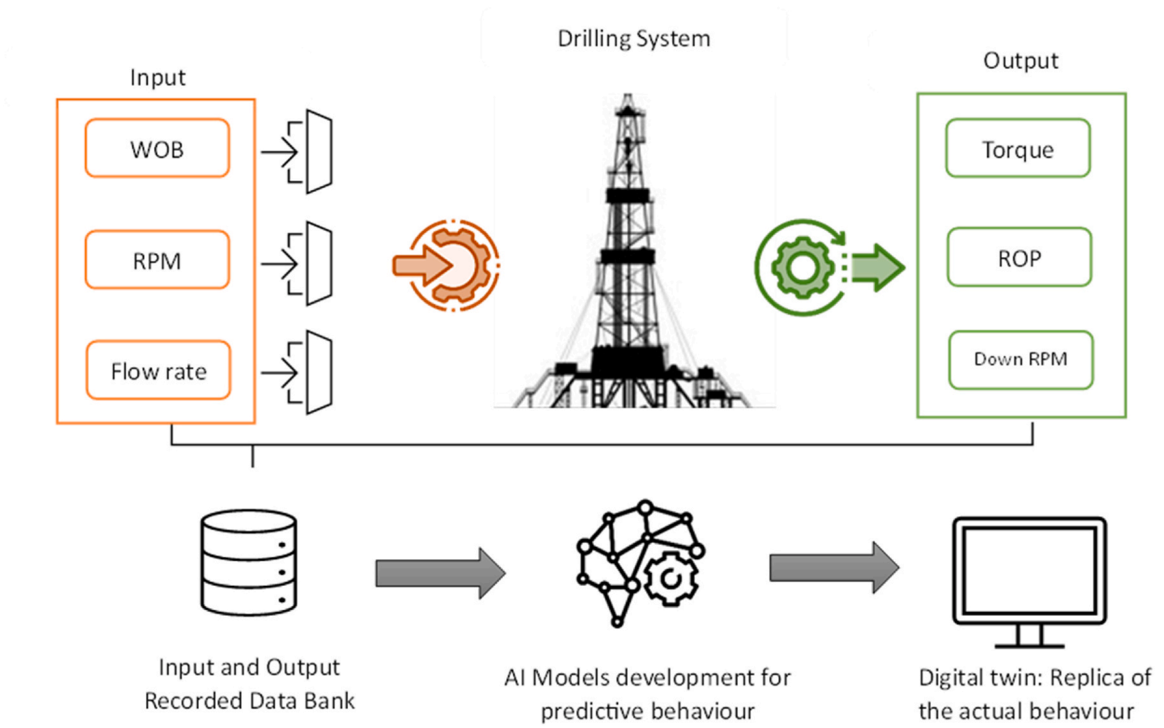

Fig. 2. The operational framework used in creating the Digital twin using ML and field data. The field data collected from actual behavior are employed to create a predictive behavior.

enables the selection of the most suitable bit while effectively avoiding detrimental vibrations. The cost of these practical experiments is very high, and several bits and runs are required for the training and decision making, which will be impossible in daily or footage contract type scenarios.

In contrast (Koulidis and Ahmed, 2023), have combined AI with in-cutter sensing data to improve drilling efficiency and mitigate axial vibrations. Although this research is currently limited to a small dataset of 100 points and laboratory experiments, it offers a promising direction for future research. Other review papers highlight the potential of AI to address the industry challenges such as stuck pipes and hydrate formation (D'Almeida et al., 2022).

Among them, the model related to vibrations has primarily focused on characterizing and detecting drill-string vibrations rather than mitigating them. Additionally, these models often do not consider important parameters such as depth-of-cut and the severity of torsional vibrations, which are critical in maintaining the dynamic stability of the bottomhole assembly and the drill-string (Y. Zhou et al., 2017). However, recent research has shown that managing these parameters by adjusting DOC can significantly improve drilling efficiency and reduce non-productive time and bit failures (Alkhazal et al., 2022). Therefore, there is a need for more advanced AI models that incorporate these factors to optimize drilling parameters and mitigate vibrations.

The current state-of-the-art in drilling optimization involves finding controllable drilling parameters, such as the WOB and RPM, to achieve a maximum ROP while minimizing drill string vibrations. However, traditional drill-off testing methods for different drilling bits can be costly and time consuming; this approach involves manually changing the DOC by applying several WOB/RPM. The present paper proposes a novel solution in the drilling optimization field to improve the drilling bit aggressiveness with virtual tests. Compared to the existing studies, which include measurement equipment and require massive data sets, the proposed solution is based on an updating system that can build real time sub-models at every 9 m drilled interval, to maintain the generalization capability of the ML models. The existing studies and solutions are applicable only to specific regions and formations.

This research presents a novel AI-based workflow that improves drilling efficiency and minimizes vibrations. It presents the first workflow that considers the depth-of-cut during the application of ML models for ROP optimization with bit tests and the selection of the optimal drilling parameters. The proposed method provides an effective solution to reduce time, cost, and effort, compared to the current state-of-the-art models and workflows. Additionally, the proposed workflow offers a cost-effective and safer alternative to traditional field-testing methods by allowing for the testing of different depths-of-cut as a constraint in a virtual optimization system built on field data, without requiring the use of new bits in the field. Simulations predict an average 43% increase in ROP and torsional stability when the optimized parameters WOB and RPM provided are applied. This would avoid the need to trip in/out to change the bit, and the drilling time can be reduced from the initial 66 to 31 h.

The aims of this study are as follows:

- The development of the system model and the open loop dynamics to digitally replicate the behaviour of the drilling system virtually

Table 1
The inputs data for each feedback and the model development techniques.

Model	Inputs	Output (Predictive Models)	Technique
Bit RPM	WOB, RPM, Depth, Torque	Bit RPM $_{SVR}$ Bit RPM $_{MLP}$ Bit RPM $_{DTR}$	MLP, SVR, DTR
ROP	WOB, RPM, Torque, Depth, flowrate	ROP $_{SVR}$ ROP $_{MLP}$ ROP $_{DTR}$	
Torque	WOB, RPM, depth, flowrate	Torque $_{SVR}$ Torque $_{MLP}$ Torque $_{DTR}$	

Table 2
The Initial configurations and hyperparameters for the machine learning techniques.

Machine learning Algorithms	Initial Configuration/Hyperparameters
Multi-layers Perceptron (MLP)	**Number of hidden Layers:** 1 **Number of neurons: 7** **Learning rate:** 0.001 **Activation function:** Sigmoid **Optimization Algorithm:** Levenberg Marquart
Support Victor Regression (SVR)	**kernel function:** Sigmoid **Kernel parameter λ:** 0.1 **C parameter:** 1
Decision Tree Regression (DTR)	**Max depth:** 8 **Min samples split:** 10 **Min samples leaf:** 5 **Max leaf nodes:** 100

(Digital Twin). The ML methods and the data used are detailed in Section 2.
- The breakdown of the optimization workflow with the objective function (ROP) utilizing the PSO method with DOC/SSI constraints. This is also covered in Section 2.
- The accuracy of the prediction models is evaluated numerically by means of the statistical measures NRMSE and R^2, and qualitatively using cross-validation scatter plots (Section 3, part 1).
- The implementation of the proposed strategy to demonstrate its effectiveness in improving drilling efficiency and reducing drill-string vibrations. The success of the optimization workflow is demonstrated when applied in the digital twin, and the results are provided in Section 3, part 2.
- The Field deployment is suggested in Section 3, part 3 to boost safety and minimize operational costs.

2. Methodology

The digital twin of a drill-string is a computational model that mimics the physical behaviour of an actual drilling system. The system uses real-time data collected from sensors such as WOB, RPM and flow rate for a virtual representation of the drilling process. The input parameters have an immediate feedback signal, such as torque, bit RPM, and standpipe pressure (SPP). The system's overall output is measured by the ROP, a metric that reflects the drilling performance. In addition to the WOB, RPM, and flow rate inputs, it should be noted that the system also employs depth as a parameter. The role of depth, along with the updating system, will be detailed on in the following section.

The operational framework which relies on the inputs and outputs parameters collected from the rig are represented in Fig. 2. These data are processed and analysed using machine learning algorithms to enable the digital twin to simulate and forecast the behaviour of the drilling system.

Therefore, for the best replica of the system, the digital twin should have essential models for immediate and global feedback, including Bit RPM, torque, and ROP. These models will be used to optimize the drilling system's performance. The hydraulic model for SPP is not included in this digital twin.

2.1. Data acquisition and processing

To develop accurate predictive models for drilling parameters, it is crucial to have a reliable and comprehensive database. In this study, field data collected through surface sensors with varying frequencies were utilized, comprising a total of 10998 data points. The drilling data were sampled continuously at different rates from 1 to 50 Hz, corresponding to the sensor types employed in the drilling rigs. The data was subsequently processed to obtain an average value every 1 s. Typically, drilling rigs are equipped with Electronic Data Recorder (EDR) systems that capture measurements from the rig's sensors. These systems typically record surface data at frequencies ranging from low to medium (0.1–10 Hz), it is presented in Fig. 2 as a Data bank.

These data points were utilized in the learning and validation process to develop the Down RPM models along with the ROP and drilling torque models. The input data included various drilling parameters, such as depth, bit position, hook position, flow rate, ROP, WOB, RPM, SPP, and Surface Drilling Torque. Data pre-processing was performed by

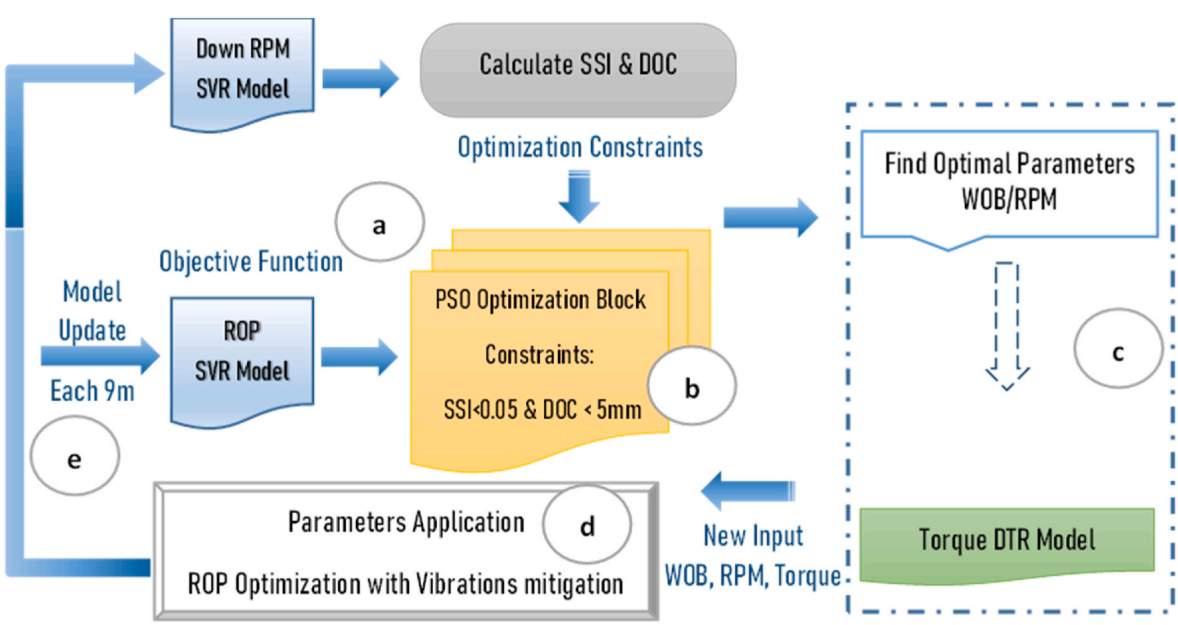

Fig. 3. Drilling optimization workflow utilizing PSO and the digital twin. The objective function in the optimization block is the ROP model, subject to two constraints measured with the Down RPM model (a). The PSO algorithm creates sets of candidates and tests them in the ROP model to determine the optimal WOB/RPM (b). The optimal parameters are then introduced in the torque model (c), which serves as an input in (d) where all parameters are implemented to assess the ROP enhancement. The system collects inputs during drilling every 9m and updates the prediction of the models utilized (e).

Table 3
Drilling process optimization formulation.

	Parameters/Functions	Objective formulation/constraints
Objective function	*ROP* (*WOB*,*RPM*)	Maximize *ROP*
Constraint	SSI	<0.05
	DOC	<5 mm

removing tripping Out/In data, reaming data, and unrealistic data. Wrong measurements and noise due to sensor malfunctions, wellbore friction, buoyancy, lift induced by flow, and nozzle jetting can pollute the drilling data. These data points containing unrealistic values, such as null and negative values, were discarded. The box plot diagram, which is a powerful graphical technique for outliers detection, was then used to detect and eliminate the abnormal values that can drastically affect the training process and bias the fit predictions.

The data were then normalized between 1 and -1 to. The field data were then divided into two subsets using the learn/validate the split approach. This approach involved randomly dividing the data into a training set (80% of the data) and a test set (20% of the data). These latter evaluate the generalization ability of the system.

2.2. Model development

The feedback from the drilling system (Bit RPM, Torque and ROP) are modelled in this section using the MLP, SVR, and DTR. These machine learning algorithms are a type of artificial neural network and require a large amount of data to train effectively. The MLP, which consists of multiple layers of nodes, can handle complex nonlinear relationships between inputs and outputs (Youcefi et al., 2020). The SVR, which deals effectively with high-dimensional data, can be used for regression tasks to find the hyperplane that best fits the data. The objective of SVR is to minimize the distance between the predicted values and the actual values while also minimizing the complexity of the model. The DTR works effectively for categorical variables and handles both linear and nonlinear relationships between inputs and outputs by partitioning the input space into a hierarchy of binary splits until a stopping criterion is met.

In this research, the models use the control parameters WOB and RPM and the drilling torque and depth, as input data, as depicted in Table (1):

An initial effective configuration had been set for each machine learning technique and used in the first interval. The hyperparameters presented in Table 2 will be updated at fixed intervals as more data is available. The ML performance was evaluated by the normalized root mean square error (NRMSE).

The Levenberg Marquart Algorithm was employed to optimize the weight and bias for the MLP within a range of learning rate between 0.001 and 0.01. The Sigmoid function was selected after a series of runs testing all the functions and the performance was evaluated by the normalized root mean square error (NRMSE). The initial MLP topology consisted of a single hidden layer with seven neurons, and this configuration will be updated at fixed intervals as more data is acquired from the sensors.

Training SVR models involves solving an optimization problem. The approach aims to minimize the distance between the points from the hyperplane and the closest point in the data. The sigmoid kernel function had been selected to improve the SVR model's performance based on its accuracy and capability to be tailored to specific characteristics. The choice of the regularization parameter C and Kernel parameter λ impact the model's precision by avoiding misclassifying each training example and to minimize the distance between the hyperplane and the data points.

Table 4
PSO Initial Configuration and parameters.

Hyperparameters	Initial Value
Swarm size	50
learning rates C_1	2.05
learning rates C_2	2.05
Inertia weight (ω)	0.729
Random numbers r'_1 and r'_2	[0; 1]

In addition, training a DTR model is done by building the tree by recursively portioning the data into subsets. The RMSE criterion hyperparameter was used to measure the quality of a split in the DTR. The hyperparameters shown in Table 2 aim to avoid overfitting and to ensure that nodes are only split when enough data is available to make reliable predictions. The maximum depth limits the tree depth to avoid overfitting and is set to allow for a relatively complex model. The minimum sample splits sets to ensure that nodes are split when enough data is available. The leaf is set to 5 to prevent overfitting by ensuring that each leaf node has enough samples to make reliable predictions. The maximum leaf nodes sets the maximum number of leaf nodes to avoid overfitting by limiting the complexity of the tree.

After the second interval of data collecting, a empirical evaluation of several parameter choices was used to find the ideal configuration for each parameter separately. This method allowed the dynamics and fluctuations of each parameter to be captured.

After the model's validation, the most accurate Bit RPM model was employed to measure the DOC and SSI using equations (1) and (2) for the prediction and classification of torsional vibrations.

$$DOC = \frac{ROP}{Bit\ RPM} 16.67\ \left(\mathrm{mm}/_{Rev}\right) \tag{1}$$

and

$$\mathrm{SSI} = \frac{\mathrm{Max}\ Bit\ RPM - \mathrm{Min}\ Bit\ RPM}{\mathrm{AVG\ Bit}\ RPM} \tag{2}$$

The severity of the torsional vibration is then classified using DOC and SSI into three groups: low [SSI<0, 05], medium [0,05<SSI<0,35], and high [0,35<SSI< 1]. The DOC for low torsional vibration severity is recorded for optimization reasons and will be used as a constraint in the optimization block via PSO methods. The PSO block outputs will be used as inputs in the drilling digital twin system to verify its correctness.

It is essential to apply optimal control parameters during the optimization process to ensure the enhancement of the drilling efficiency. To achieve this, the digital twin (physical system) should have ROP and torque as outputs. The ML techniques were utilized to build ROP and drilling torque models using the inputs shown in Table 1. After applying the parameters, the best model with the minimum error was selected to evaluate the optimization system.

2.3. Model validation

Cross-validation is a validation approach used in machine learning model verification in which the scatter plots (cloud diagrams) between the recorded and predicted values of the test and validation datasets are compared with the unit line (x = y). Furthermore, statistical parameters such as NRMSE and coefficient of determination (R^2) are used to numerically validate the ANN models and assess the prediction accuracy.

Equations (3)–(5) define the formulae used to determine NRMSE and R^2. As a result, NRMSE and R2 values near 0 and 1, respectively, indicating a successful prediction model.

$$NRMSE = \frac{RMSE}{(Max\ Y_{real} - Min\ Y_{real})} \tag{3}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Y_{real,i} - Y_{predicted,i}\right)^2} \tag{4}$$

Table 5
Statistical parameters.

	SVR			MLP			DTR		
	Bit RPM	ROP	Torque	Bit RPM	ROP	Torque	Bit RPM	ROP	Torque
R^2	0.987342	0.99886	0.970054	0.970368	0.811692	0.969302	0.981762	0.698786	0.970404
NRMSE	0.017	0.070	0.066	0.020	0.196	0.070	0.029	0,.335	0.064

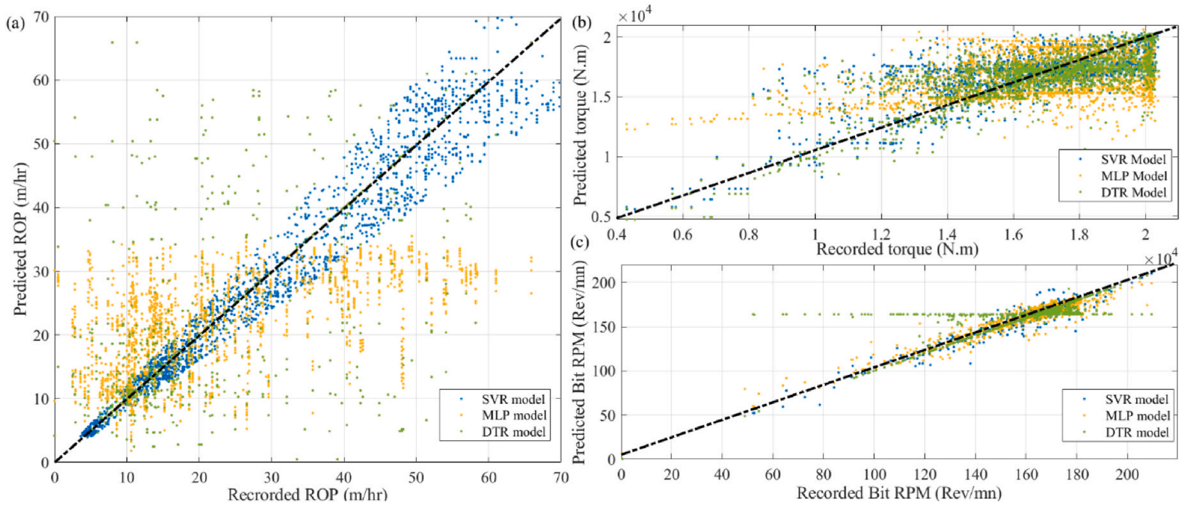

Fig. 4. Cross-Validation illustrating the ability of the models to predict the ROP, Torque and Bit RPM using new data points that were not used during the training phase. The scatter plot is compared to the unit line (y = x). The outcomes of the predictive ROP models are depicted in (a), and the Torque cloud diagrams using SVR, MLP and DTR model is illustrated in (b). The results of the ML models are shown in (c) for the Bit RPM. all three scatter plots drawn together is a good practice to facilitate a decision on which model to work with in the digital twin.

$$R^2 = 1 - \frac{\sum_i^N \left(Y_{real,i} - Y_{predicted,i}\right)}{\sum_i^N \left(Y_{predicted,i} - \overline{Y}\right)} \quad (5)$$

2.4. Optimization workflow

The developed ROP model represents a function of controllable drilling parameters such as WOB, RPM, depth, flow, and torque, and is considered the objective function (Fig. 3, Step (a)). PSO algorithms are used to provide ideal control of the drilling process by determining the correct values for the controllable drilling parameters WOB and RPM, which can be modified at the rig surface to maximize ROP. The established SSI formula and DOC formula measured from the Bit RPM model is used to define the constraints of the optimization process. The optimization process shown in Fig. 3, Step (b) is designed to maximize ROP while keeping SSI at the desired interval, keeping the DOC within an acceptable range during drilling, this range is provided from the classification of vibrations severity and represents the low severity torsional vibrations which ensures that the optimized WOB and RPM do not

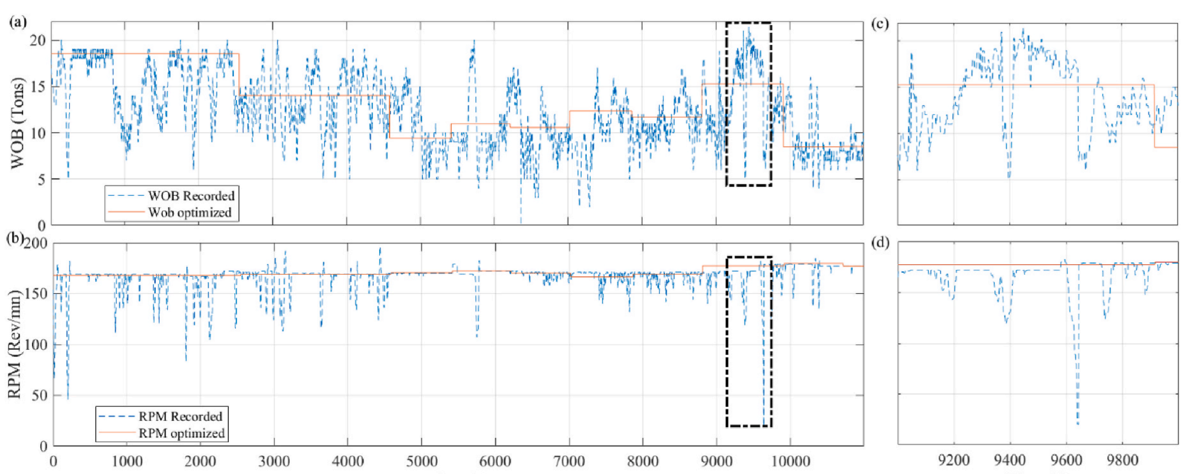

Fig. 5. Variation of Controllable Parameters for the field Case and for the PSO Outcomes. (a) depicts the WOB fluctuation in a drilling scenario. The highlighted area in (a) is zoomed in (c) exhibits cases of axial vibration and steady values for the optimization outcomes. (b) illustrates the RPM fluctuation in the real case, showing torsional vibration. The highlighted area in (b) zoomed in (d) shows severe stick slip with steadiness of optimized RPM values.

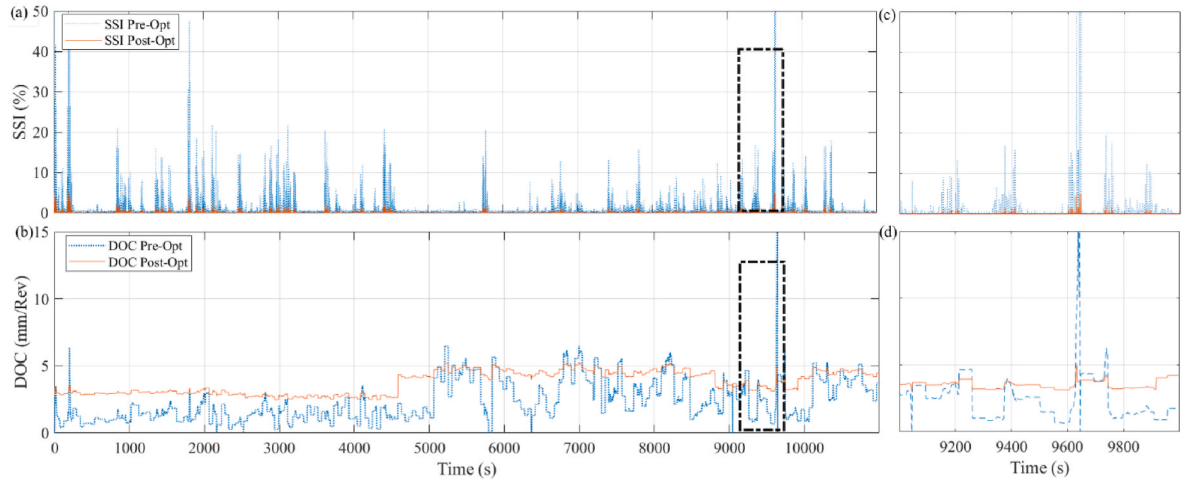

Fig. 6. Variation of SSI and DOC before and after the optimization. (a) depicts high severity of the preoptimization SSI and exhibits low severity for the post optimization SSI, the highlighted area is zoomed in (c) to show that the maximum value of SSI after the optimization is limited to 5%. (b) illustrates high severity of the real DOC measured by Bit RPM model and exhibits new DOC with steady values after implementation of new parameters. The highlighted area in (b) is zoomed in (d) to show the efficacy of the system to keep the DOC at acceptable range.

introduce drilling vibration. Table 3 summarizes the formulation of this optimization problem.

The PSO effectiveness on many hard problems is no longer to be proven (Flori et al., 2022). The PSO optimization block (Kennedy and Eberhart, 1995) has several key parameters including the swarm size, learning rates (C_1 and C_2), and the inertia weight (ω) introduced by (Shi and Eberhart, 1998), each of which plays a crucial role in the PSO algorithm's ability to find optimal solutions based on the following equation:

$$V_i^{t+1} = \omega V_i^t + C_1 r_1^t \left(pbest^t - X_i^t\right) + C_2 r_2^t \left(gbest^t - X_i^t\right) \tag{6}$$

Three key terms in Equation (6) are used to define the particle trajectory in the search area. The inertial component ωV_i^t is the memory of the previous direction of motion, designed to prevent the particle from drastically changing its path. The cognitive component $C_1 r_1^t (pbest^t - X_i^t)$ pulls the particle back to its sweet spot. The Social term $C_2 r_2^t (gbest^t - X_i^t)$ transfer each particle to the best region where the swarm has found so far in the domain space (Chiou et al., 2012). PSO algorithm is proposed and successfully applied to design an efficient Maximum Power Point Tracking (MPPT) controller (Dziri et al., 2022) and emotion recognition (Kouka et al., 2023). The PSO parameters are listed in Table 4.

After the first interval was fully drilled (which we can consider between 9m or 27m) and the Bit RPM, ROP, and drilling torque models were developed; the optimization phase began. The ROP model was input into the optimization block to define the optimal control parameters (WOB/RPM) to maximize the ROP using the PSO algorithm while limiting the SSI and DOC as seen in Table 3. Once the optimal WOB and RPM are determined, they can be recommended to the Driller for implementation (Step (c)). The Fig. 3, Step (e) represents the update of the models with the new training data collected while drilling 9 m and to be introduced again in the PSO to find ideal RPM and WOB values for the next part (the second optimization stage). This procedure is repeated until the entire formation is drilled. Fig. 3 shows the full workflow of the proposed drilling optimization strategy.

Field data were employed to test the accuracy of the predictive models and the optimization workflow. These offline data were

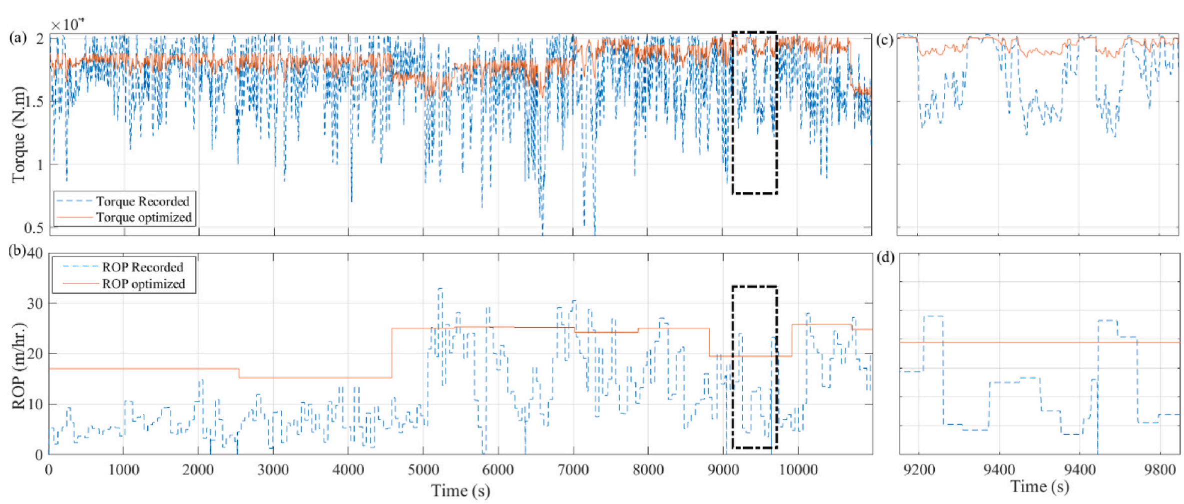

Fig. 7. The variation of torque and ROP before and after optimization. (a) exhibits managed new torque, the highlighted area is zoomed in (c) to show torsional stability. (b) illustrates the recorded ROP versus optimized ROP after implementation of new parameters. The highlighted area is zoomed in (d) to show that fixed WOB/RPM provide both torsional stability and high ROP in this case.

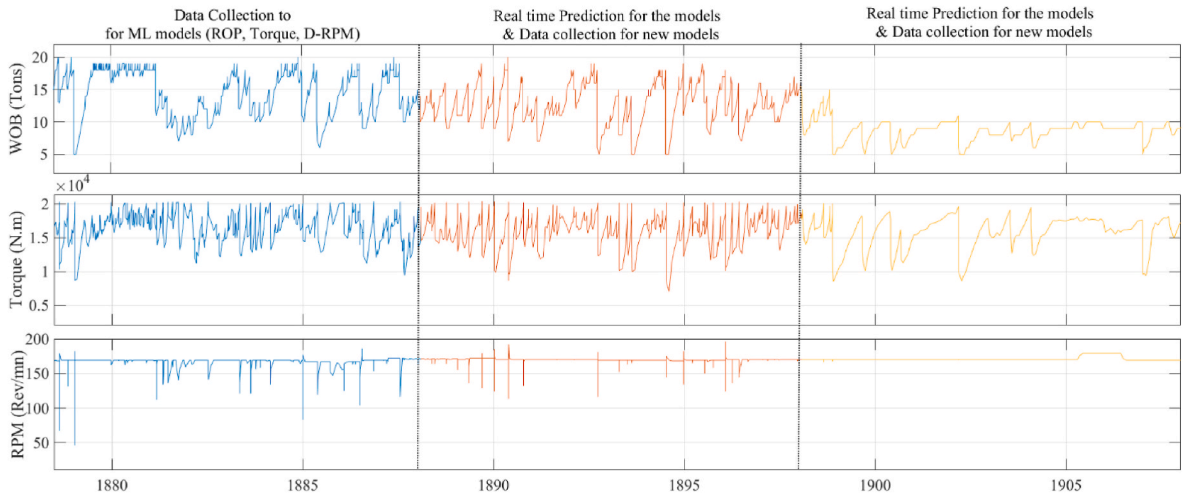

Fig. 8. Multi-interval approach for continuous learning. Data is collected in the first interval and used in the learning process and the optimized model is used in the second interval, and new data is collected to develop a new model for the following optimization cycle. The image emphasises the continuous learning technique's iterative nature and its capacity to adapt to changing data patterns over time.

segregated, filtrated, and provided to the system in real time synchronization where the collected data of the first interval were employed to build the models. In the field, the models will be trained and developed during the connection time which take generally 7 min. This technique shall overcome the impact of the changing variable sauch as formation and drilling programs by updating the models' parameters each connection.

The execution time depends on the computing resources. It took almost a minute to complete this process (modelling and optimization) on a laptop with 8 GB RAM and an 11th Gen Intel i5-11400U 2.70 GHz CPU. With this computing power, the ROP model can be optimized to select the best operating parameters every minute, but changing drilling parameters is often impractical in practice. For this, the frequency of model updates is set to the time required for drilling 9m. However, the ROP model can be retrained at any time, even before drilling through the entire interval. If the drill sees too much vibration or a sharp increase in torque, these parameters will be changed.

3. Results, analyses and discussion

In this section, a detailed discussion and analysis of the results are presented. These will clearly demonstrate the efficacy of the proposed algorithm and lead to meaningful conclusions.

3.1. Predictive models evaluation

The evaluation of digital twin models is presented in this section. Specifically, ML algorithms (SVR, MLP, and DTR) have been developed for Bit RPM, ROP, and torque, and their accuracy is showcased through the statistical parameters NRMSE and R^2 in Table 5.

Cross validation was used in addition to statistical characteristics to evaluate the prediction model's ability. Fig. 4 displays the cloud diagrams (Scatter plots) between the field data and predicted values for each of the developed models. These data points are picked at random from the 20% of data set aside for testing and validation. This is applicable to real-world scenario and is advantageous for generalising these predictive models.

Based on the cross plots presented in Fig. 4, it can be observed that the MLP and DTR models exhibit a poor level of precision in predicting ROP (Fig. 4-a). This is evident from the disorderly distribution of ROP values in the testing charts for the MLP and DTR models. This suggests that the model may not be effective in predicting ROP values for new data points. On the other hand, the SVR algorithm appears to be the best predictive model for ROP, as demonstrated by the matching between the unit line and the tendency line. This indicates a high level of accuracy in predicting ROP values for the test/validation subsets. Moreover, the statistical parameters of the SVR model confirm its precision in predicting ROP values. With an R^2 value of 0.99886 and an NRMSE of 0.070, the SVR model outperforms the other models considered in this study. Fig. 4-a clearly indicates that the SVR model outperforms the DTR and MLP models, as it is closer fit to the unit line. This comparison with the unit line is critical, as all the results must be close to it for accurate predictions. Therefore, the SVR model has great potential for practical applications in the optimization strategy of drilling operations.

Surface torque is often challenging to model accurately. However, minor differences in the models can be observed in the cross plots presented in Fig. 4-b. In this case, the DTR model appears to be the best model for surface torque, as it shows a relatively tight clustering of data points around the unit line. While the lack of small torque values due to filtration processes may have led to some imperfections in the tendency line, the DTR model still demonstrates a good level of precision.

The Scatter plots for the torque show that both the SVR and MLP models exhibit a distribution of data points around the unit line indicating a lack of precision in their predictions. In addition, the DTR torque model shows a comparable level of precision to the other developed models, with an R^2 value of 0.970404 and a NRMSE of 0.064. These statistical parameters fall within an acceptable range, particularly when compared to the SVR and MLP models. Where the SVR model have R^2 value of 0.970054 and a NRMSE 0.066 and the MLP have an R^2 value of 0.969320404 and a NRMSE 0.070 as presented in Table 5. The presentation of all cloud diagrams together is a good practice to facilitate a decision on which model to work with in the digital twin; The DTR model is closer fit to the unit line. This DTR model appears to offer a promising solution for predicting torque values in real-world drilling scenarios.

According to the outcomes, the Bit RPM model developed using SVR displays the best results compared to the MLP and DTR models. The SVR model exhibits a perfect fit between the unit line and tendency line, as shown in Fig. 4-c. While the MLP model shows a small deviation in the cross plot, it can be overlooked as the tendency line for test remain stable. In contrast, the DTR model displays the lowest accuracy with a greater deviation from the unit line in the scatter plot illustrated in Fig. 8-c. Furthermore, the SVR model for Bit RPM exhibits the lowest error in statistical parameters (NRMSE = 0.017 and R2 = 0.987342), which are within an acceptable range (as highlighted in Table 5). These results indicate that the developed SVR model performs well in predicting Bit RPM based on new data not seen during training. Hence, the SVR model will be employed further in the optimization process to estimate the SSI and DOC.

3.2. Drilling process optimization

Optimization PSO algorithm was employed to determine the optimal values of WOB and RPM that improve torsional stability by minimizing torque fluctuation while maximizing aggressiveness. The Fig. 5 represents the block outcomes for both RPM and WOB compared to real scenario in drilling operation.

The population of candidate solutions is iteratively updated during the PSO optimization process by modifying the values of WOB and RPM based on the best solutions found thus far. The method employs a swarm approach, in which each solution is represented as a particle that moves around the search space in pursuit of the best reaction. Through a process of evaluation and adjustment, the PSO algorithm identifies the best values of WOB and RPM that satisfy the constraints of DOC and SSI while maximizing the ROP. The process continues until the desired level of optimization is achieved or a stopping criterion is met.

Fig. 5-b reveals that sharp fluctuations in surface RPM are a consequence of severe torsional vibrations. Under these circumstances, the SSI ranges superior to 15%, causing the top drive to be unable to overcome the reactive torque with programmed RPM due to the drilling limit torque constraint (20000 N.m.). As a result, the RPM decreases each time (i.e.: Fig. 5-d) with frequent applied torque (Fig. 7-a) until either the bit is liberated, or a total stuck situation is assumed. Severe fluctuations in the WOB occur due to bit bounce, as demonstrated in Fig. 5-a. The Fig. 5-c shows the presence of these vibrations in the highlighted area from Fig. 5-a and the successful mitigation achieved through the implementation of new parameters.

After the classification process of vibrations and the localization of the optimal DOC with continual training after each 9 m drilled, two constraints are introduced to the system. The Bit RPM model is effectively used to calculate the severity of stick slip index, which classifies the severity of vibrations into three ranges: low, medium, and high (Fig. 6). Most SSI values are less than 5%, representing high reactive torque that the top drive can easily overcome by increasing the motor torque. In this range, RPM fluctuation is acceptable (i.e., from 160 to 148 rpm), and the vibrations are less harmful (Both Fig. 5-a and 6-a).

The ANN model determines the optimal drilling parameters for avoiding harmful drilling vibrations. The Fig. 5a-b show the optimal RPM and WOB under the constraints of DOC and SSI. The system provides stable parameters every 9 m drilled, and the optimized WOB/RPM differs from the real WOB/RPM selected in the drilling program Fig. 5c-d. These optimized parameters are used to measure new post-optimization parameters, such as optimized SSI, new DOC, optimized torque, and optimized ROP, presented in Figs. 6 and 7, respectively. PDC cutters' principal mission is to remove formation to boost the ROP. When the cutters penetrate deeply into the formation, the blades can rub against the formation, resulting in a severe stick-slip situation. Stick-slip is the unpredictable movement of the drill-string that can damage the bit and reduce drilling efficiency.

In the Fig. 6-b, it seems that when the DOC exceeds 6 mm, the torsional stability of the drill-string decreases, and the SSI surpasses 15% like the example presented in Fig. 6-d. This indicates a strong relationship between the DOC and torsional stability. Therefore, to optimize drilling efficiency and reduce bit wear, a maximum DOC of 5 mm is fixed as a constraint in the optimization block with low SSI (SSI$<$5%) to avoid undesirable friction with the formation.

The system output provides steady DOC with high torsional stability, as observed in Fig. 6-c the post optimization SSI is low, and the maximum is 5%. The torsional stability is noticed in Fig. 7-a, where the torque fluctuations have been managed without stick slip situation, the maximal torque reach the drilling limit torque in few cases where both optimized RPM and WOB reach the maximum values. This is due to the training process, where these parameters show high ROP without any dysfunctions. This is the only situation where the optimized WOB and RPM are too high. All the parameters are not either maximized or minimized, they are optimized depend on the data used in the machine learning and collected each 9m drilled, new parameters will be given from the system and new Torque is calculated continuously.

The recorded WOB and RPM during drilling operations (real scenario) often show various vibrations, such as stick slip and bit bounce. However, these inefficiencies and vibration issues were eliminated in the digital twin outcomes through the use of new optimized parameters, as depicted in Figs. 6 and 7. The optimized parameters were able to mitigate these issues by taking into account the relationship between the DOC and reactive torque.

By using the minimum DOC necessary to pierce the bottom hole, the bit cutters were able to penetrate the borehole without inducing axial vibrations, such as bit bounce. This, in turn, helped control and mitigate lateral vibrations, such as whirl and shocks, since all types of vibrations can induce each other. Additionally, since the cutters were not deeply penetrating the formation, the reactive torque did not reach the drilling limit torque (Fig. 7-a), resulting in a constant RPM and avoiding torsional vibrations. Therefore, by maintaining the DOC within an acceptable range, torque fluctuation was minimized, leading to greater torsional stability as shown in the highlighted area presented in Fig. 7-c.

It's important to note that the optimized ROP is higher than the actual ROP at several points (Fig. 7- b and d), indicating that the optimization workflow has the potential to significantly decrease drilling time. If the open-loop results are implemented in a real drilling scenario, the optimized WOB and RPM values predicted by the PSO are expected to result in a significant improvement in ROP as resulted in the drilling digital twin. For example, in a 16″ phase (1560 m) that was drilled using three bits (3 runs), the average ROP was 23.5 m/h. However, if the optimization workflow is implemented, the average ROP is expected to increase to 41 m/h, as shown in Fig. 7-b. Assuming that the entire section can be drilled with a single bit rather than three, the incorporation of all parameters could reduce drilling time from the initial 66 h to just 31 h. This would also provide the added benefit of avoiding the need to trip in/out to change the bit. Hence, this optimization workflow could enhance ROP by 43%.

3.3. Discussion

The appropriate choice of machine learning algorithms was based on their suitability for nonlinear modelling tasks. SVR and DTR demonstrated their handling capability of complex high-dimensional data and effective learning processes, making them a reasonable choice for predicting the drilling parameters in real time based on unseen data. However, the MLP model performed poorly compared to other proposed SVR and DTR models in this study. Even if the MLP is widely used for pattern recognition, it did not fit the research purpose due to the extensive variation in the data, overfitting issue, and unsuitability with iterative learning in a short period during the connection time after the drilled formation.

For the modelling task, the SVR exhibited the best performance even on predicting the drilling parameters based on the unseen data. These results reveal the generalization capacity of the established models and the importance of the steps that were followed in this paper for building ML models. The box plot was employed as a tool for detecting the outlier data, thus eliminating this abnormal data that could negatively affect the training process and model fit. In addition, the hyperparameters tunning process via empirical evaluation of several parameter choices approach and cross validation was a crucial step for building robust models.

For the optimization workflow, the PSO demonstrates its power and speed for exploring the search space and finding the optimal drilling parameters, resulting in an average 43% increase in net ROP from 23.5 m/h to 41 m/h. The integration of PSO as a metaheuristic optimization and its ability to iteratively explore the data allowed the workflow to find the optimal parameters effectively, together with the digital twin creation that provides a suitable testing environment. In addition, incorporating DOC as a constraint was a key differentiator compared to the current state of the arts models. Considering the DOC control strategy based on ML models, the process efficiency was improved with an additional bit selection option.

Although updating the ML models make the workflow more efficient regardless of the geological conditions and the data quality that restricts the model's performance, it can be challenging when implemented in real time. Delays in real time data collection may hinder the system's ability to optimize the WOB/RPM. The sub-models development is conducted during the connection time; therefore, any complexities or dysfunctions during the stand drilling (stuck pipe, fluid loss) can limit the workflow performance. Finally, the system requires a new generation of drilling equipment to be integrated, such as Top drive, draw works, and mud pumps.

3.4. Field implementation

The continuous learning technique utilized in this work is notably beneficial for drilling operations since various variables might affect the drilling process. The models can adjust to changes in drilling conditions, such as modifications in geology, rheology qualities, or BHA design, by being continuously updated in real-time. The data collected within the first interval of Fig. 8, across the depth range of 1879–1888 m, were utilized for training the first models. These models were subsequently employed to forecast critical drilling parameters, including the ROP, RPM, and torque, within the second interval (1888–1897 m). Concurrently, the system collected pertinent data from the second interval to facilitate the training of a subsequent model, intended to enable the accurate prediction of the aforementioned parameters within the third interval of the drilling.

The implementation of the bit RPM predictive model to monitor the SSI and DOC enables the detection of severe malfunction and the prevention of operational challenges such as bit wear and tear, which need tripping out operation and cause NPT. The system highlights how drilling operations can be improved for optimal efficiency, particularly cost reduction and enhanced drilling productivity (ROP).

Several advanced drilling software use AI based workflow and physical based model are available in the market. These solutions advice the user on the best drilling parameters, give recomandation and provide early warning when predicting dysfunctions. Drilling Advisory System (DAS) (Payette et al., 2015) and Optidrill (Hbaieb et al., 2018) are examples of these software. Nonetheless, the updating system proposed in this research can improve all of these software programmes that require top-formation detection algorithms to pass from model to model for each drilled section.

The ability of the PSO-based AI system to automatically customise and adapt to different drilling operations and changing drilling conditions constitutes one of its most significant features. This means that, depending on input from sensors and other sources, the AI system may adjust drilling parameters in real time, resulting in a more efficient and effective drilling operation. Furthermore, the presented AI system can be embedded with PLCs for both Drawworks and Top drive, allowing precise control over motor torque/speed as well as axial displacement (WOB). This level of precision and efficiency allows for even more precise and efficient drilling operations, which can improve drilling performance, reduce drilling time, and boost safety.

4. Conclusion

In this work, Artificial Neural Network models were developed to predict various drilling parameters and to digitally replicate the drilling system's behavior virtually (Digital Twin). SVR was found to be the most accurate model for predicting Bit RPM and ROP, while Decision Tree Regression was the best model for predicting surface torque. The resulting models demonstrated high accuracy, with R2 values of 0.9 or higher and NRMSE values of 0.07 or lower.

The success of the optimization workflow is demonstrated when applied in the digital twin. The PSO algorithms demonstrate their power and speed in identifying the optimal drilling parameters (WOB and RPM) under DOC/SSI constraints. With the objective function was set to maximize the ROP, increase torsional stability, minimize torque fluctuation, and improve bit aggressiveness; simulations predict an average 43% increase in net ROP from 23.5 m/h to 41 m/h. This would avoid the need to trip in/out to change the bit and save the drilling time from 66 to 31 h for the drilled section (1560 m). The proposed digital twin can automatically adapt to different drilling operations and most PLC equipment, ensuring high precision, effective optimization and smooth operation to increase ROP, reduce downhole vibrations, and save drilling costs. Future research will aim at applying AI algorithms to early warning of potential problems and recommending corrective actions.

CRediT authorship contribution statement

Farouk Said Boukredera: Conceptualization, Methodology, Study design, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Mohamed Riad Youcefi:** Methodology, Study design, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft. **Ahmed Hadjadj:** Validation, Resources, Writing – review & editing, Supervision, Project administration. **Chinedu Pascal Ezenkwu:** Software, Formal analysis. **Vahid Vaziri:** Methodology, Study design, Formal analysis, Investigation, Writing – review & editing, Visualization, Supervision. **Sumeet S. Aphale:** Methodology, Study design, Formal analysis, Writing – review & editing, Visualization, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Acknowledgment

We would like to acknowledge the collaborative efforts of SONATRACH Group, and the universities involved in this research (Université de Boumerdes, Université de laghouat and University of Aberdeen).

References

Abbas, A.K., Assi, A.H., Abbas, H., Almubarak, H., Al Saba, M., 2019. Drill bit selection optimization based on rate of penetration: application of artificial neural networks and genetic algorithms. In: Abu Dhabi International Petroleum Exhibition & Conference. https://doi.org/10.2118/197241-MS. D032S207R002).

al Dushaishi, M.F., Nygaard, R., Stutts, D.S., 2018. An analysis of common drill stem vibration models. Journal of Energy Resources Technology, Transactions of the ASME 140 (1). https://doi.org/10.1115/1.4037682.

Alkhazal, S.A., Mahdi, M.J., Barrera, J.L.Q., Aljishi, M., 2022. Improving drilling efficiency through heterogeneous formations and reduce stick slip levels after the implementation of self-adjust depth of cut technology in oil well. ADIPEC, Abu Dhabi, UAE. October 2022. https://doi.org/10.2118/211503-MS (ISBN: 978-1-61399-872-4).

Bataee, M., Mohseni, S., 2011. Application of artificial intelligent systems in ROP optimization: a case study in shadegan oil field. In: SPE Middle East Unconventional Gas Conference and Exhibition. https://doi.org/10.2118/140029-MS. SPE-140029-MS).

Batruny, P., Zubir, H., Slagel, P., Yahya, H., Zakaria, Z., Ahmad, A., 2021. Drilling in the digital age: machine learning assisted bit selection and optimization. In:

International Petroleum Technology Conference. https://doi.org/10.2523/IPTC-21299-MS. D012S045R137.

Bavadiya, V.A., Alsaihati, Z., Ahmed, R., Gustafson, K., 2017. Experimental Investigation of the Effects of Rotational Speed and Weight on Bit on Drillstring Vibrations, Torque and Rate of Penetration. Abu Dhabi International Petroleum Exhibition & Conference.

Boukredera, F.S., Hadjadj, A., Youcefi, M.R., 2021. Drill string torsional vibrations modeling with dynamic drill pipe properties measurement and field validation. J. Energy Resour. Technol. 144 (2), 24502.

Chen, C., Zhang, S., Zhang, H., Li, X., 2018. RESEARCH ON RISK ASSESSMENT METHOD OF STICK-SLIP VIBRATION OF THE BIT BASED ON BP NEURAL NETWORK ALGORITHM. In: https://proceedings.asmedigitalcollection.asme.org.

Chiou, J.-S., Tsai, S.-H., Liu, M.-T., 2012. A PSO-based adaptive fuzzy PID-controllers. Simulat. Model. Pract. Theor. 26, 49–59.

D'Almeida, A.L., Bergiante, N.C.R., de Souza Ferreira, G., Leta, F.R., de Campos Lima, C. B., Lima, G.B.A., 2022. Digital transformation: a review on artificial intelligence techniques in drilling and production applications. Int. J. Adv. Des. Manuf. Technol. 119 (9–10), 5553–5582.

Dziri, S., Alhato, M.M., Bouallègue, S., Siarry, P., 2022. Improved particle swarm optimizer-based MPPT control of PV systems under dynamic partial shading. In: 2022 19th International Multi-Conference on Systems, Signals & Devices. SSD, pp. 1603–1608.

Flori, A., Oulhadj, H., Siarry, P., 2022. QUAntum Particle Swarm Optimization: an auto-adaptive PSO for local and global optimization. Comput. Optim. Appl. 82 (2), 525–559.

Hbaieb, S., Converset, J., Foster, J., Arevalo, Y., 2018. Technology update: well construction performance service bridges planning-execution gap to boost efficiency. J. Petrol. Technol. 70 (4), 20–22.

Hegde, C., Millwater, H., Pyrcz, M., Daigle, H., Gray, K., 2019. Rate of penetration (ROP) optimization in drilling with vibration control. J. Nat. Gas Sci. Eng. 67, 71–81.

Jamil, S., Roy, A.M., 2023. An efficient and robust phonocardiography (pcg)-based valvular heart diseases (vhd) detection framework using vision transformer (vit). Comput. Biol. Med. 158, 106734.

Jangir, P., Manoharan, P., Pandya, S., Sowmya, R., 2023. MaOTLBO: many-objective teaching-learning-based optimizer for control and monitoring the optimal power flow of modern power systems. Int. J. Ind. Eng. Comput. 14 (2), 293–308.

Jiang, B., Chen, S., Wang, B., Luo, B., 2022. MGLNN: semi-supervised learning via multiple graph cooperative learning neural networks. Neural Network. 153, 204–214.

Kennedy, J., Eberhart, R., 1995. Particle swarm optimization. In: Proceedings of ICNN'95-International Conference on Neural Networks, vol. 4, pp. 1942–1948.

Kouka, N., Fourati, R., Fdhila, R., Siarry, P., Alimi, A.M., 2023. EEG channel selection-based binary particle swarm optimization with recurrent convolutional autoencoder for emotion recognition. Biomed. Signal Process Control 84, 104783.

Koulidis, A., Ahmed, S., 2023. Advisory system for drilling optimization using artificial intelligence and in-cutter sensing data. In: SPE Symposium: Leveraging Artificial Intelligence to Shape the Future of the Energy Industry. https://doi.org/10.2118/214468-MS. D021S005R004.

Millan, E., Ringer, M., Boualleg, R., Li, D., 2019. SPE/IADC-194061-MS Real-Time Drillstring Vibration Characterization Using Machine Learning.

Pandya, S.B., Ravichandran, S., Manoharan, P., Jangir, P., Alhelou, H.H., 2022. Multi-objective optimization framework for optimal power flow problem of hybrid power systems considering security constraints. IEEE Access 10, 103509–103528.

Payette, G.S., Pais, D., Spivey, B., Wang, L., Bailey, J.R., Pastusek, P., Owens, M., 2015. Mitigating drilling dysfunction using a drilling advisory system: results from recent field applications. In: International Petroleum Technology Conference.

Pllácido, J.C.R., Santos, H.M.R., Galeano, Y.D., 2002. Drillstring vibration and wellbore instability. J. Energy Resour. Technol. 124 (4), 217–222. https://doi.org/10.1115/1.1501302.

Rashidi, B., Hareland, G., Tahmeen, M., Anisimov, M., Abdorazakov, S., 2010. Real-time bit wear optimization using the intelligent drilling advisory system. In: SPE Russian Oil and Gas Conference and Exhibition. https://doi.org/10.2118/136006-MS. SPE-136006-MS).

Roy, A.M., Bhaduri, J., 2023. DenseSPH-YOLOv5: an automated damage detection model based on DenseNet and Swin-Transformer prediction head-enabled YOLOv5 with attention mechanism. Adv. Eng. Inf. 56, 102007.

Shi, Y., Eberhart, R., 1998. A modified particle swarm optimizer. In: 1998 IEEE International Conference on Evolutionary Computation Proceedings. IEEE World Congress on Computational Intelligence (Cat. No. 98TH8360), pp. 69–73.

Tortrakul, N., Pochan, C., Southland, S., Mala, P., Pichaichanlert, T., Tangsawanich, Y., 2021. Drilling performance improvement through use of artificial intelligence in bit and bottom hole assembly selection in gulf of Thailand. In: IADC/SPE Asia Pacific Drilling Technology Conference. https://doi.org/10.2118/201079-MS.

Yigit, A.S., Christoforou, A.P., 2006. Stick-slip and bit-bounce interaction in oil-well drillstrings. Journal of Energy Resources Technology, Transactions of the ASME 128 (4), 268–274. https://doi.org/10.1115/1.2358141.

Youcefi, M.R., Hadjadj, A., Bentriou, A., Boukredera, F.S., 2020. Rate of penetration modeling using hybridization extreme learning machine and whale optimization algorithm. Earth Science Informatics 13 (4), 1351–1368.

Zhou, C., Tao, H., Chen, Y., Stojanovic, V., Paszke, W., 2022. Robust point-to-point iterative learning control for constrained systems: a minimum energy approach. Int. J. Robust Nonlinear Control 32 (18), 10139–10161.

Zhou, Y., Zhang, W., Gamwo, I., Lin, J.-S., 2017. Mechanical specific energy versus depth of cut in rock cutting and drilling. Int. J. Rock Mech. Min. Sci. 100, 287–297.

Zhuang, Z., Tao, H., Chen, Y., Stojanovic, V., Paszke, W., 2022. An optimal iterative learning control approach for linear systems with nonuniform trial lengths under input constraints. IEEE Transactions on Systems, Man, and Cybernetics: Systems.