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Real-time Bit Wear Prediction and Deployment Validation in Challenging Hard and Heterogeneous Sandstones using 3D Detailed and Simplified Physics-Based Progressive Wear Models

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ABSTRACT

Drill bits experience significant cutter wear in hard and abrasive drilling applications, leading to high drilling cost. Therefore, the accurate prediction of bit progressive wear and its influences on drilling performance is crucial for bit design and drilling optimization in such sandstones. This paper presents two high fidelity bit wear models and how these drill bit wear tools were applied and validated in real-time tests in abrasive sandstone drilling.

Two advanced drilling prediction software models were trained on drilling parameter, bit design, cutter dulls, and formation evaluation data from past runs in the of interest. The models predict forces on both sharp and worn states, and also use these forces, the drilling parameters, and the rock properties to calculate the current wear state while drilling, and predict future wear state of the bit. Cutting force and thermomechanical wear formulas based on decades of drilling mechanics research are implemented. The detailed physics-based model was used in the design workflow to simulate target drilling. The simplified physics-based wear model was developed based on this detailed model. In the simplified model, the cutting structure is represented by an equivalent single cutting element and validated against both lab and drilling data.

Multiple offset well data is cleaned and processed to build a pre-well training database. The two wear models are first trained using offset bit runs in the database and then tested on another selected target run in pre-well. The training and testing results show both wear models captured the progressive wear and the corresponding drilling responses very well. The pre-trained wear models were then deployed in the real-time trials. The predicted real-time bit wear and drilling performance matches with the well measurement reasonably well. While the detailed model considering the bit cutting structure is used in the bit design, the simplified wear model implements the equivalent single cutting element and reduces the simulation time by more than 90%. It is observed the physics and the learning transfer of the lab data improves the generalization capacity of the model and overcomes the overfitting issue due to the limited scarcity or data bias in the real-time application.

This study presents two high fidelity progressive wear models by combining drilling physics and data learning approach. The hybrid physics and data learning approach is applicable to the real-time applications in challenging drilling formations. The simplified wear model improves the simulation speed significantly without losing the prediction accuracy, thus opening new pathways for real-time applications and drilling automations.

EXTENDED ABSTRACT

Introduction

Drilling optimization is critical in hard rock applications. PDC bits experience significant wear in abrasive hard rock applications. When PDC bits wear significantly, it can drastically reduce ROP in harder rock, which adds days on well, increasing drilling costs. Because of this, it is important to have tools that allow engineers to design wear-resistant PDC bits, plan for drilling parameters before the run, and make adjustments to drilling parameters during the run. PDC bit wear models have existed for a quite some time. Physics-based wear models (Glowka D. a., 1986; Glowka D. A., 1986; Yang, 2020; Rashidi, 2008) and data-driven wear models (Agostini, 2020; Gidh Y. K., 2012; Gooneratne, 2020) for bit wear and ROP predictions have been around for nearly 40 years. However, challenges remain in applying these models to the applications for pre-well planning and real-time operations. The main difficulties are: 1) developing cutting force equations that cover all scenarios, 2) calibrating cutting forces for new drilling s, and 3) calibrating wear characteristics for these new s and various PDC cutter chemical make-ups. In recent studies (Matthews III, 2021; Zhan, 2021), 3D drilling models using a hybrid physics and lab/ data learning approach successfully predicted the bit drilling parameters and in a test. In this paper, the progressive wear of individual cutter is included in this 3D drilling model to simulate the evolution of wear flats with the distance drilled. Thermomechanical wear modeling is based on decades of cutting mechanics research and laboratory findings. The progressive wear model was first trained and validated on multiple offset training wells. Then the pre-trained wear model was deployed in real-time tests. The results show the wear model reliably predicted both the progressive drilling response and final dull state in multiple real-time trial tests.

Detailed 3D and Simplified Progressive Wear Model

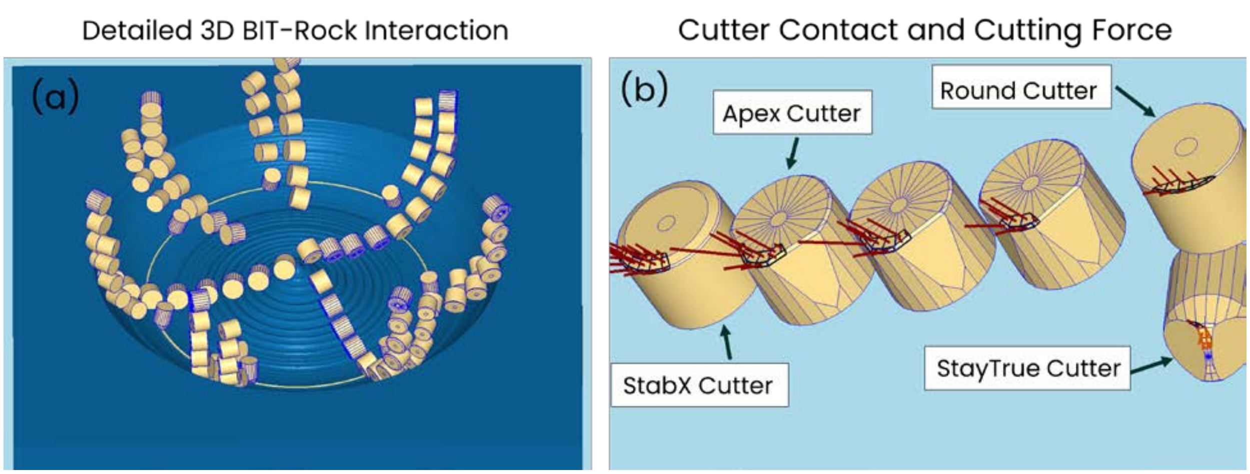

Figure 1 Detailed 3D representation of bit-rock interaction

A detailed 3D progressive wear model is developed to predict the bit wear in real-time. In the detailed model, the 3D geometry of the bit body, cutters, and rock is represented by a 3D mesh studies (Matthews III, 2021; Zhan, 2021). The geometric interaction between the cutting elements and the rock is calculated using a Boolean engine (Figure 1(a)). Figure 1(b) shows the cutting areas of various shaped cutters on the same bit blade. The red arrow indicates the cutting force magnitude and its orientation. In progressive wear simulation, the wear flat is modeled as a planar surface orientated along the local tangent of the drill bit profile. The evolution of the wear flat is accomplished by incrementally increasing the wear flat depth. Figure 2 demonstrates the wear evolution from the sharp state at the beginning of the run to the final dull state.

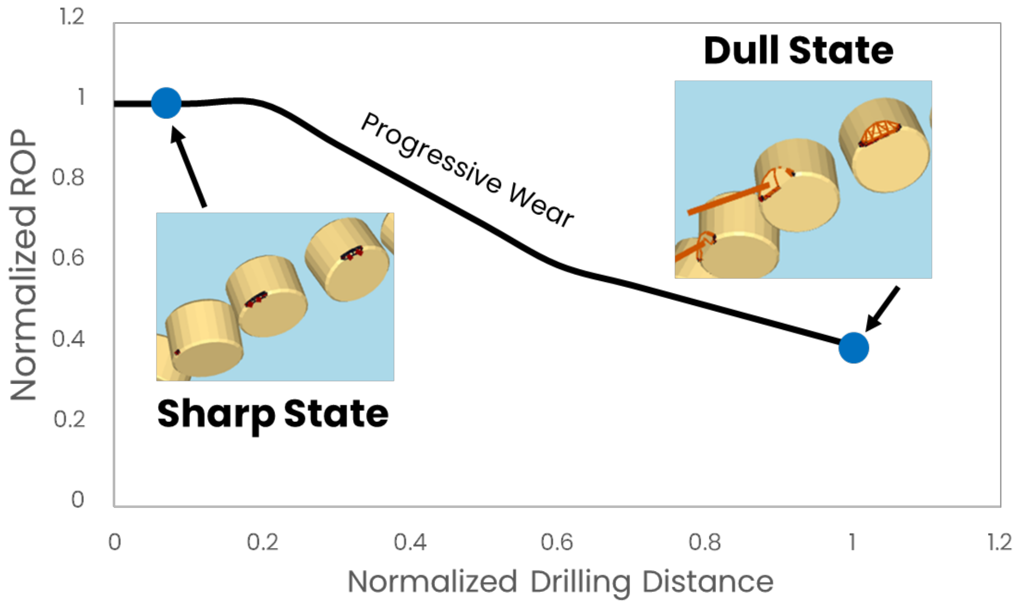

Figure 2 Wear evolution from sharp state to dull state

The cutting forces are calculated using a unified cutting force model library built on decades of cutting mechanics research studies (Matthews III, 2021; Zhan, 2021). The wear flat cutting force considers the effect of the depth of cut and local confinement due to the wear flat contact (Zhou & Detournay, 2014; Alehossein, Detournay, & Huang, 2000; Rostamsowlat, 2017). The force model formulas are evaluated against hundreds of controlled full-scale lab drilling tests under the downhole pressurized condition (Ledgerwood & Kelly JR., 1991). The highest ranking force model with the least training error and the least number of model fitting parameters is selected by the ensemble for performance prediction and bit design optimization. The progressive wear rate is calculated at each drilling depth using a thermomechanical wear model (Archard, 1953). The wear rate is a function of cutting force, cutting velocity, surface friction, cooling rate, and material abrasivity (Glowka D. a., 1986). The parameters of the wear rate model are determined by combining the results from finite element analysis, computational fluid dynamics modeling, and lab wear tests. In real-time applications, the wear parameters are further refined by training on the offset well data of the target well. A robust differential evolution algorithm is employed for the model parameter optimization (Storn & Price, 1997). The error metric includes both drilling response error such as WOB/TOB (Warren & Sinor, 1986) and the final wear area distribution error. During the model training process, it is observed transferring the lab data learning to the data training is critical for the model generalization capacity (Magana-Mora, 2017).

While the 3D mesh model captures the detailed cutting structure and bit-rock interaction, its real-time application is limited by the high computational cost. To improve the model efficiency, a simplified progressive wear model is developed. The simplified wear model (SWM) converts the detailed cutting structure into a simplified equivalent single cutting element. The bit diameter and bit total penetration rate is utilized to calculate the equivalent cutting area of the single cutting element. An equivalent radial position, averaged back rake angle, and chamfer size is implemented in SWM to capture the geometry effect on the in-situ rock cutting strength (Rajabov, Miska, Mortimer, Yu, & Ozbayoglu, 2012; Detournay, Richard, & Shepherd, 2008). Different from the detailed progressive wear model, the SWM calculates the total wear area on the bit, instead of per-cutter wear.

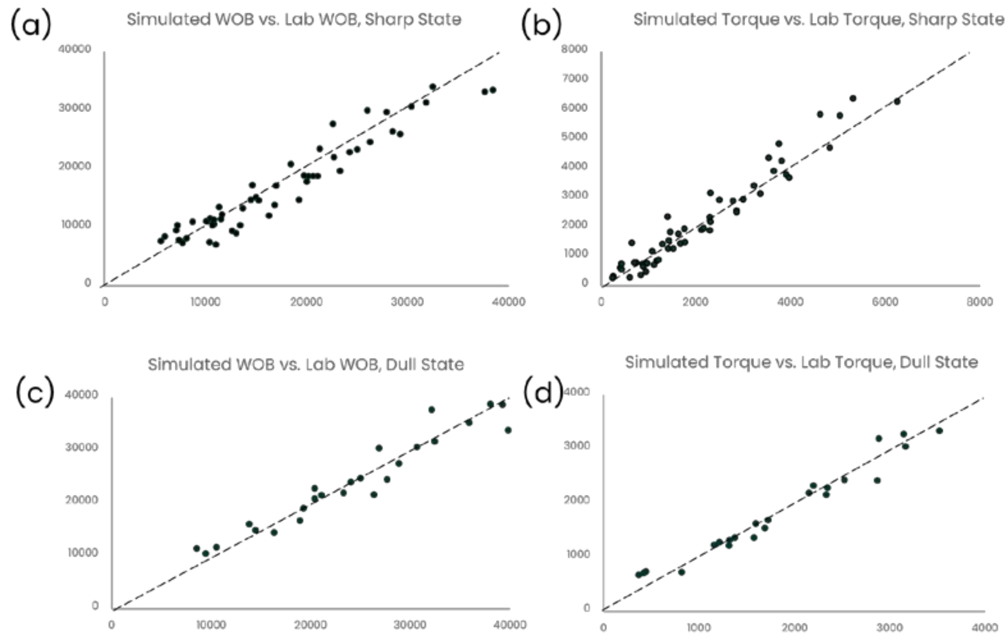

Figure 3 Simulation results of SWM versus lab drilling results after model training at both sharp and dull states (a) sharp state WOB (b) sharp state TOB (c) dull state WOB (d) dull state TOB

The same unified cutting force model and thermomechanical wear model is applied in SWM. To verify the geometry simplification and assumptions in SWM, the SWM is trained using the same lab dataset as the detailed wear model. Figure 3 shows the lab training results of the SWM on both sharp and dull states. The simulation is performed under ROP control and the simulated WOB/TOB response is compared with the lab measurements. Each data point in the figure represents one stable drilling state extracted from the full-scale downhole drilling tests. The training results show the SWM can capture the drilling response reasonably well for both sharp state and dull state. The training accuracy of the SWM is comparable to the detailed 3D model. It should be noted though SWM improves the simulation speed with a comparable model accuracy, the SWM doesn't consider the detailed cutting structure of the bit. Thus, the application of the SWM should focus on the real-time bit wear prediction, and the detailed 3D wear model is required for the bit design optimization.

Multi-Well Model Training and Validation in Pre-Well

Lab-trained detailed 3D and SWM models are re-trained using the offset well data in the target application. It is found the learning transfer from the lab training to the well is crucial to improve the model generalization capacity and avoid model overfitting. The lab learning transfer involves two aspects. The first aspect is the model parameter transfer such that selected model parameters trained using the lab analogy rock remains the same in the application. The second aspect of the learning transfer is to apply the searching boundaries learned from the lab to constrain the parameter optimization in the model training. It not only improves the training speed, but also avoids non-physical solutions. This section presents the pre-well training and validation results of the 3D detailed model and SWM using multiple offset well runs in the target hard and abrasive sandstone application.

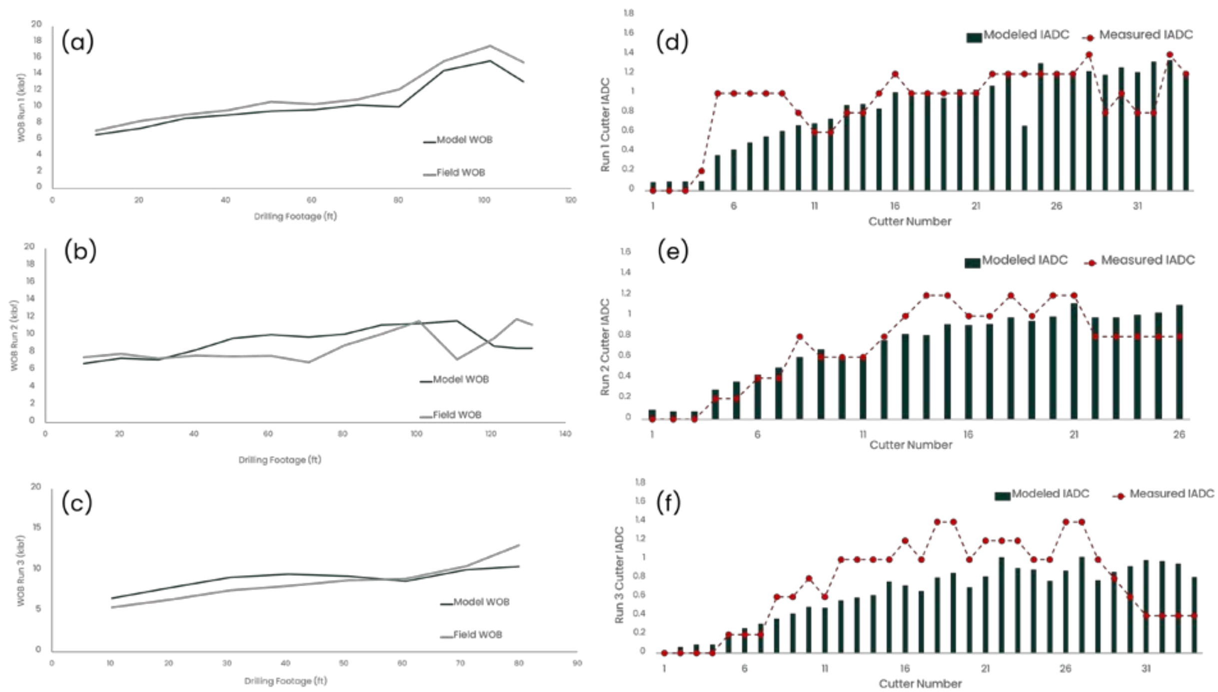

Figure 4 Detailed model: simulation results vs. results after model training on three offset well runs 1 to 3

Figure 4 (a) to (c) shows the simulated WOB of the detailed wear model vs. the WOB after the model training on three offset bit runs. To improve the training efficiency, a stand-alone parameter optimization engine is developed and coupled with the detailed 3D progressive simulation engine. The progressive wear rate and the cutting force is calculated in every 10ft and the wear flat geometry is updated accordingly. The training results show the detailed progressive wear model captured the WOB response very well for all three offset runs. As expected, the simulated WOB increases gradually as increasing the drilling distance due to the progressive wear effect. Figure 4 (d) to (f) shows the wear comparison of the detailed model. It is observed the simulated wear matches with the wear very well in terms of both the distribution shape and the wear magnitude. To validate the model, the pre-trained model is set in the prediction mode and applied to predict another offset run, run #4. The predicted WOB agreed with the WOB reasonably well with an overall error of ~11%. The predicted wear matches with the wear as shown in Figure 5. It is observed the dull grade of the measurement jumped suddenly from IADC 0.2 to 1.0 from the fourth cutter, indicating a non-abrasive impact damage probably due to the bit vibration.

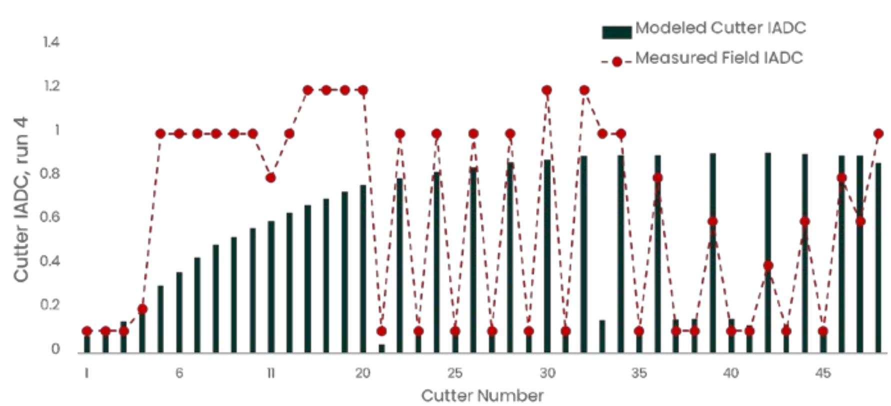

Figure 5 Detailed model: Predicted wear distribution vs. wear distribution on test run 4

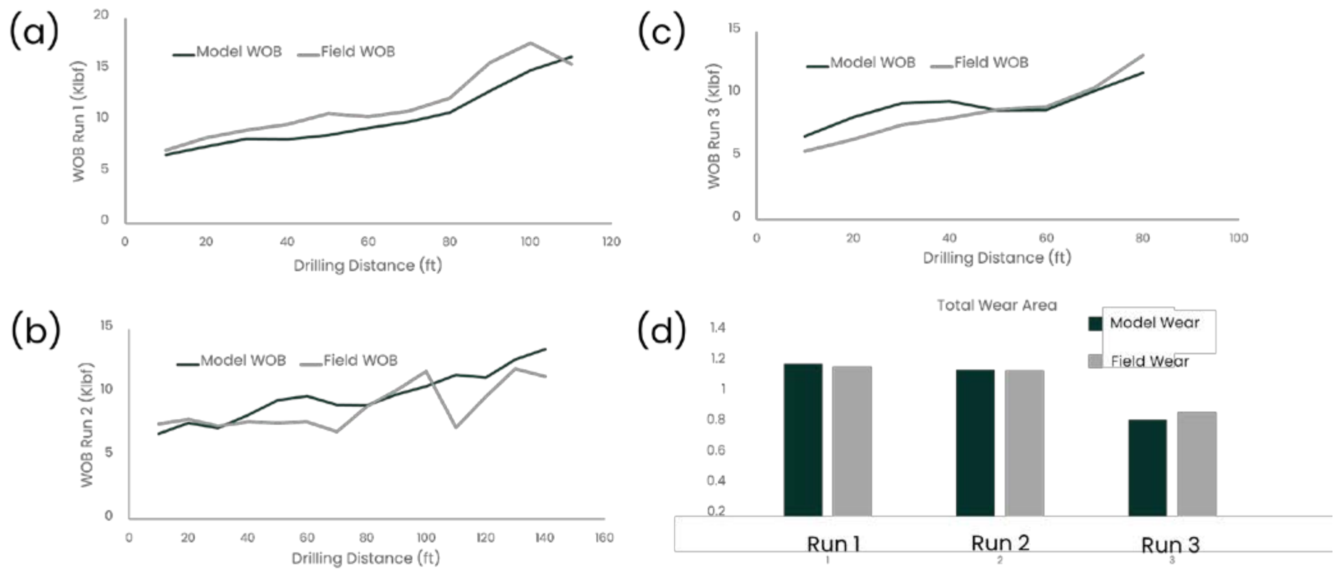

Figure 6 SWM: simulation results vs. results after model training on three offset well runs 1 to 3

The same pre-well training runs (run #1 to run #3) and validation run (run #4) are used to train and test the SWM. Figure 6 shows the simulated WOB of SWM vs. the WOB on the three training runs, run #1 to #3. After the model training, the SWM captured the progressive WOB (Figure 6(a) to (c)) with a reasonable accuracy. The model training time of the SWM is less than 5% of the time required for the detailed model. Figure 6(d) shows the total wear area comparison between the SWM and the measurement. Note the SWM approximates the bit cutting structure as an equivalent single cutting element, instead of the detailed 3D cutting geometry. Thus, only the total wear area is available and outputted for the comparison. The training results show the simulated total wear area agrees with the wear area decently well on all three training runs.

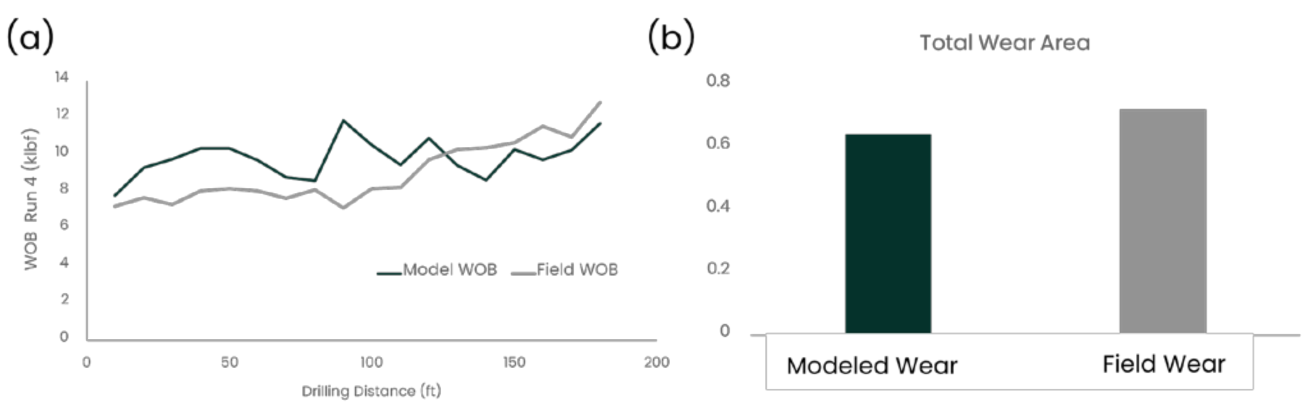

Figure 7 SWM: predicted results vs. results on test run 4

Figure 7 shows the validation results of SWM on run#4. Figure 7(a) shows the predicted WOB vs. the WOB. The overall error of the predicted WOB is ~15%. The predicted total wear area matches with the measurement very well as shown in Figure 7(b). Overall, the SWM captured both the WOB response and the final wear state very well in the validation run #4 and the wear model is ready for the real-time trial.

Wear Model Real-Time Trial

The pre-trained detailed 3D wear model and SWM were tested in real-time for a selected target well. During the real-time trial, the surface drilling data and downhole logging data is cleaned and processed in real-time. The averaged rock properties from the offset wells are used as the initial input and fine adjusted if needed (Sherbeny, et al., 2016; Sherbeny, Nuic, & Richards, 2015). The predicted wear and projected ROP in the next 50ft were reported daily as a drilling guidance. The simulated WOB was monitored and compared to the WOB to verify the drilling response of the model. Once the bit run was completed, the reported final bit wear before the bit was pulled out of the hole was compared to the measured wear based on the dull photos.

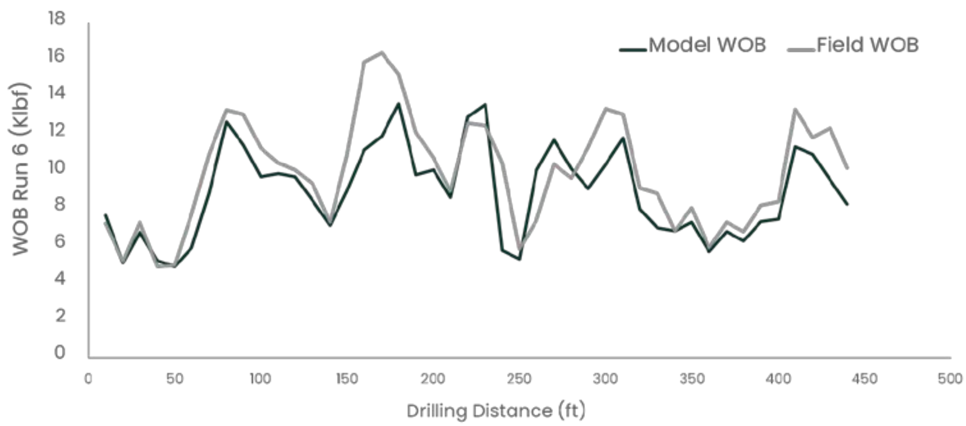

Figure 8 Real-time detailed model: modeled WOB vs. WOB on real-time run 6

Figure 8 shows the real-time simulated WOB vs. the WOB of the detailed 3D model. The comparison results show the detailed 3D model captured the WOB very well in real-time. Figure 9 shows the final bit wear comparison. The model predicted wear (blue bar) matched with the wear (red dot) excellently. Note, to improve the comparison accuracy, a refined IADC grade with a resolution of 0.2 is implemented as shown in the figure, instead of the standard IADC resolution of 1.0. It is observed the wear shows a wear jump at cutter number 7, 10 and 34 probably due to the downhole vibration.

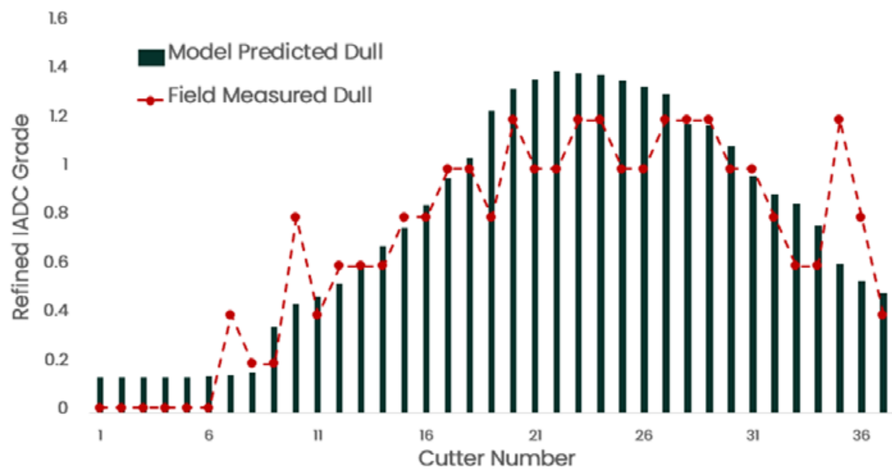

Figure 9 Real-time detailed model: predicted wear distribution vs. wear distribution on real-time run 6

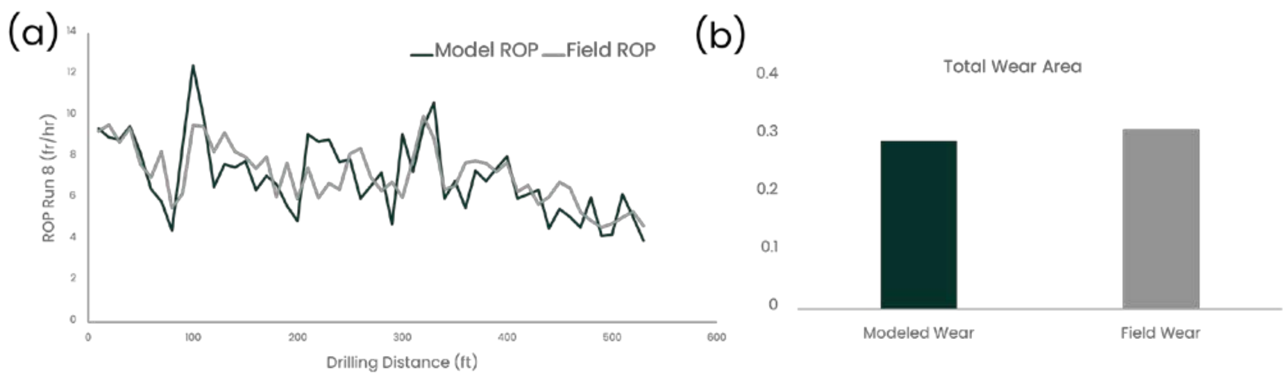

Figure 10 Real-time SWM: predicted results vs. results on real-time run 6

The same run was utilized to test the SWM in real-time. Figure 10 shows the real-time simulated ROP vs. the ROP. It should be noted the ROP, instead of WOB, is used for the drilling response comparison in real-time SWM. The ROP calculation under the WOB control is usually more time consuming. Numerical iterations are required to obtain a converged solution and the optimization of the PID parameters are needed. The low computational cost of SWM enables the real-time ROP calculations. As shown in Figure 10(a), the real-time simulated ROP matched with the ROP. The decreasing trend of the ROP due to the progressive wear is captured by the SWM very well. Figure 10(b) shows the final wear area predicted in real-time vs. the measured final wear area. The prediction error of the total wear area is smaller than 10%. Both the detailed model and SWM were real-time tested in multiple runs in this well and good matches were observed. Overall, the real-time results validated the real-time application of both the 3D detailed model and SWM.

Conclusions

This paper presents two high fidelity bit wear models and how these drill bit wear tools were applied and validated in real-time tests. The two wear models are first trained using three offset bit runs and then tested on another selected target run in pre-well. The pre-trained wear models were then deployed in real-time trials. The predicted bit wear and drilling performance in real-time matches with the measurement reasonably well for both the detailed 3D model and SWM. While the detailed wear model considers the bit cutting structure and is used for the bit design, the simplified wear model implements the equivalent single cutting element and reduces the simulation time by more than 90%.

It is observed the physics and the lab data learning transfer improves the generalization capacity of the model and overcomes the overfitting issue due to the limited scarcity or data bias in the real-time application. The simplified wear model improves the simulation speed significantly without losing the prediction accuracy, thus opening new pathways for real-time applications and drilling automations.

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