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Real-Time Physical Models with Learning Feedback as a Digital Twin Architecture

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Abstract

The use of numeric simulation tools has been a traditional approach for determining the behavior of equipment and complex engineering operations. These same techniques have been used in the oil & gas industry over the years to help improve efficiency and reduce cost, allowing the exploration of areas that were previously economically unfeasible. Currently, with the increasing development of sensors and communication technologies, real-time numerical simulation is becoming a key tool for a better understanding of drilling dynamics, allowing the prediction of critical events and making operations more efficient and secure. The goal of this work is to present a computational tool that applies the concept of digital-twin to oil drilling systems by proposing the use of physical models to simulate, in real-time, phenomena such as well hydraulics, torque and drag, cuttings concentrations and bed formation. Data collected in real-time from the rig is used as input to the physical models, whose outputs can flow into other models, allowing a multi-physics analysis. The data collected from the sensors and the results provided by the digital-twin tool are stored in a time series database, which is used for the continuous evaluation of errors and efficiency improvement, implementing a learning feedback into the physical model calculations of drilling operations. Enhancements on the accuracy of model calculations are shown, leveraging the aforementioned architecture to monitor well operations, such as hydraulic, torque and drag and cuttings transport, and by the validation of the results by subject matter experts. This work presents how the proposed approach incrementally improves closing equations coefficients with learning feedback, i.e. having historical data from sensors and calculated data continuously being stored into the system, using big data technologies for handling the large volume data.

Introduction

The depreciation of oil prices has increased the demand for solutions that optimize drilling operations, with the usage of tools for monitoring and evaluating those operations in real-time. For many years, phenomenological equations have been used in all projects that demand complex engineering processes, and serve to promote safety, quality and to avoid the use of unnecessary resources. In the oil & gas industry, drilling development projects are extremely complex, requiring numerous steps and a great multidisciplinarity for their technical elaboration. Engineering concepts are constantly being improved and the increasing computational power allows more and more mathematical complexity to be tackled for achieving better results.

A digital twin refers to a digital replica of physical assets (physical twin), processes, people, places, systems and devices that can be used for many goals [Parrott A., Warshaw L. 2017]. The definition of Digital Twin technology is based on two main characteristics: the emphasis on the connection between the real entity and its correspondent virtual model, and the fact that this connection shall be established through the acquisition of data from sensors and its processing in real-time.

In literature, studies have proposed the analysis of drilling conditions in real-time both for optimizing the operation as to allow preventive actuation for avoiding operational problems. However, the massive amount of data generated by sensors that are present both at the rig and at the Bottom Hole Assembly (BHA) has to be interpreted by specialized personnel through systems for real-time monitoring, which in general have complex user interfaces that don't promote a good cognitive experience for the users to promote real-time situational awareness for drilling operations. According to [M. R. Endsley 1995] situational awareness is "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future". It involves the capture and cognitive understanding of real-world situations, and the capacity to effectively perform actions that will affect the situation in the desired matter. To the best of our knowledge, current research and development is still being made to achieve systems with a comprehensive approach for providing such situational awareness in real-time and with the appropriate performance.

This work presents a big data computational tool that applies the concept of digital-twin to oil drilling systems by proposing the use of physical models to simulate, in real-time, phenomena such as well hydraulics, torque and drag, cuttings concentrations and bed formation. Data collected in real-time from the rig is used as input to the physical models, whose outputs can flow into other models, allowing a multi-physics analysis. The data collected from the sensors and the results provided by the digital-twin tool are stored in a time-series database and can be constantly consolidated and queried, enabling a learning feedback to physical models, i.e. the continuous evaluation of errors and efficiency improvement of drilling operations.

The proposed system architecture includes the following aspects: real-time or historical data collection from sensors available in drilling operations generated by the drill rig and the drill string; processing this data on dedicated servers using real-time and batch processing jobs and artificial intelligence algorithms; modeling of drilling mechanics through physical models such as solids loading and dragging; and finally, the visualization of the results in a user-friendly application.

In this work, various technologies from different areas of computer science are employed to leverage solutions to the problems mentioned here for the optimization of support systems for well drilling operations. Software Engineering principles were applied to the development of all calculation modules using automated testing and integration tools. These tools, in addition to ensuring quality and correctness, enable AI model training to be improved and deployed in a structured and modularized manner. Event-driven computational paradigms with declarative rules, i.e. real-time stream processing and complex event processing are used [D. Carney, et.al., 2002; B. Babcock, et. al, 2002; G. Cugola and A. Margara, 2010; D. C. Luckham 2001; D. McCarthy and U. Dayal, 1989; O. Etzion and P. Niblett 2010; Eugster, et.al, 2003]. Thus, situations of interest can be expressed quickly and ad-hoc, without the need for a long development cycle.

The large volume of data generated by such well operations poses challenges to the design of the system's architecture and infrastructure, which must present scalability in the flow of real-time data ingestion, processing, and persistence; as well as performance in viewing this data for a growing number of client applications [N. Marz and W. James, 2015]. Therefore, part of this project takes into consideration aspects of state-of-the-art technologies in the areas of cloud computing, software container orchestration, scalable inter process communication and distributed stream and complex event processing, which are detailed in the Digital Twin Architecture Section.

Objectives

Equations that describe the behavior of physical properties or coefficients in regions of transfer of momentum, heat or mass, the so-called closure equations, are normally developed using data produced in laboratories, keeping controlled conditions that provide the expected behavior. Therefore, using those equations in real-world situations is, in the great majority of cases, not appropriately accurate. There are many reasons for these equations to present such imprecision, which stem from the laboratory setting not being able to reproduce real conditions to the need of simplification of independent variables that are difficult to be applied in such an artificial environment.

With the increasing number and quality of sensors in oil and gas drilling operations, the used models can be better calibrated. However, this is still limited to two specific regions, the surface and the bottom of the well, where the drill bit is located. In addition, there are limitations on the amount of data that can be obtained from the region near the drill bit in real-time due to interruptions on the transmissions of data, which is dependent of pressure pulse data transmission technology that needs flow rate of pumped fluid to reach the surface.

The goal of this work is to present a big data computational and visualization tool that implements a digital-twin which uses physical models to simulate in real-time, phenomena such as well hydraulics, torque and drag, cuttings concentrations and bed formation. Real-time data collected from the rig is used as input to the physical models, whose outputs can flow into other models, allowing a multi-physics analysis. A history of the collected data is stored and used during real-time calculations, by continuously evaluating errors and improving accuracy, to which we refer to herein as a Learning Feedback for the physical model calculations.

Physical Model Benchmarking

In order to develop and validate physical models, an industry-proven well engineering analysis and simulation tool was used as reference. The first module developed implemented the torque & drag model, which calculates mechanical stress acting upon the drill string during drilling operations.

First, the benchmark mirrored the reference tool's capabilities and functionalities by applying many of the same scientific theoretical principles, which are based on the work of well-established authors in the field of torque and drag analysis in tubulars [Dawson, R. and Paslay, P.R., 1984; Johancsik et al., 1984; Brett et al., 1987]. This was achieved by using the same equations as the tool outputs and establishing a computational framework. Then, to verify the consistency of our model results, a series of cases were proposed, which simulated common drilling operations being performed in a set of wellbore geometries.

The chosen geometries were: vertical, build up to 60°, horizontal well, S-shaped, build up to 60° inclination and 120° azimuth and a slant well, with 60° inclination from top to bottom. The operations performed in these wells were tripping in, tripping out, rotating on bottom and rotating off bottom. The purpose of using this wide variety of scenarios was to verify whether the model was capable of considering the many different variations of results produced by the tool.

After a series of adjustments, the physical model was able to replicate almost perfectly the reference tool results, indicating that it was able to perform at the same industry proven standards. As such, it can be concluded that the developed model is appropriate to be used as base for the calibration methodology employed in this study.

Learning Feedback Mathematical Modelling

In order to improve the accuracy of the calculated models from the substitution of closure models, techniques or error minimization from a parameter are required, such as Newton based methods: Levenberg-Marquardt, Gauss-Newton, among other minimization or regression techniques that go from the most simplistic like linear regression to neural networks. The idea is to calculate the phenomenological models like quantum momentum, heat and mass and the error between the simulated and real data choosing the set of closure equations that will be substituted or calibrated.

As a study for the proposed approach, we take real data for the calibration of values, friction and drill pipe weight factors. By using data from hook load, rotation, fluid properties, etc., to adjust a non-dimensional parameter which is multiplied by the weight or drag terms in the torque and drag equation. Figure 1 shows the proposed mechanism for the minimization of error from an adjustment parameter.

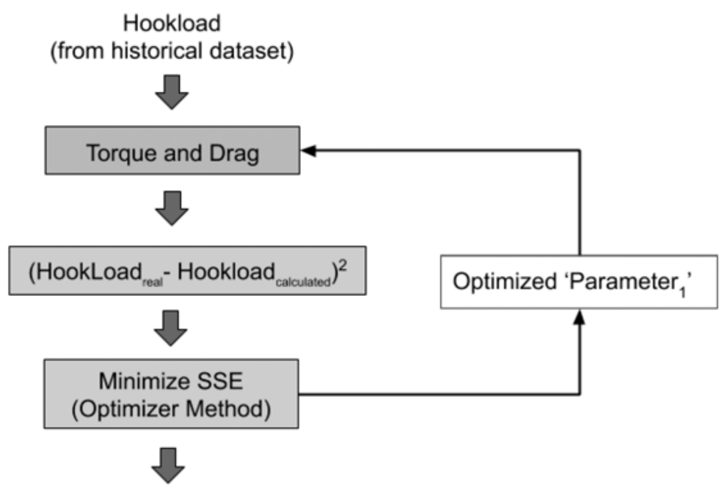

Figure 1—Learning Feedback 1: Optimization of adjustment parameter for friction factor

A case being studied is the acquisition of values for drill bit weight, to improve the friction factor solid fluid models. For each step on historical time, the value of Hook load is used in the torque and drag equations for the regression to only friction factor, and the values for this property is created in a new dataset keeping the historical data such as rotation, column velocity, weight on bit, throughput, fluid characteristics. We also perform the addition of simulated data, such as fluid average temperature, average pressure, cuttings concentration, etc. With the creation of this new database, the new equation for friction factor is calculated. The methods used for the learning range from linear regression to neural networks, as shown in Figure 2.

Therefore, the mathematical modelling can be summarized by the two techniques as the following:

- Calculation of the parameter one from historical data, to be multiplied by the most appropriate friction factor for the scenario of the well at hand, which is already specified in the reference literature, e.g. open or cased hole respectively have already recommended friction factors [Bourgoyne et al].
- Calculation of the friction factor through a regression equation generated from historical data of sensors and simulated data.

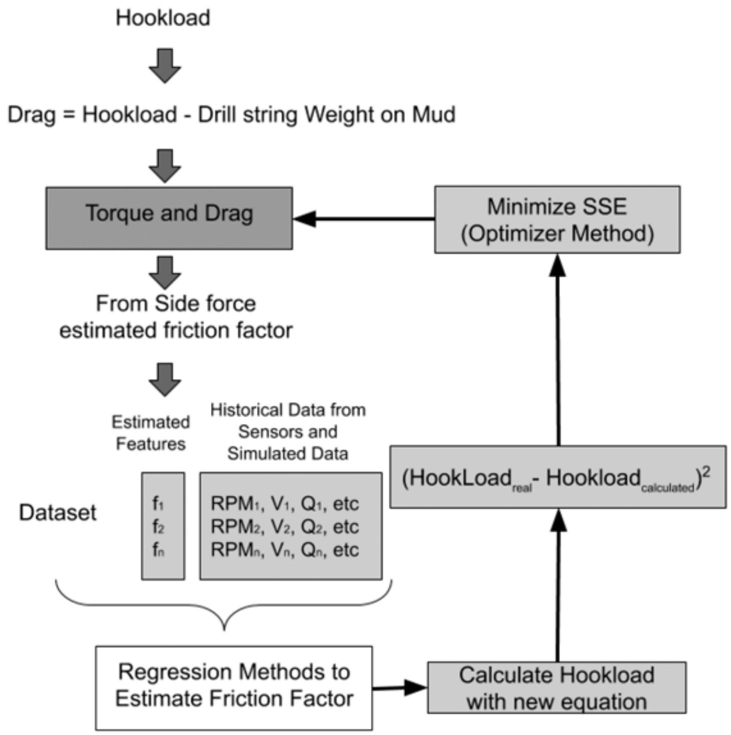

Figure 2—Learning Feedback 2: Closure equation for friction factor calculation from regression

By using the aforementioned techniques, it is possible to learn the behavior of these past phenomena and to apply this learning in future situations, to which we refer to as a ***Learning Feedback*** for physical models.

Optimization

Optimization methods, e.g. Levemberg-Marquardt and Gauss-Newton, were used for the optimization of parameters from equations or sets of nonlinear equations. These methods are based on Newton's, whose successive approximations through derivatives make the solution minimize the problem as shown in Figure 3.

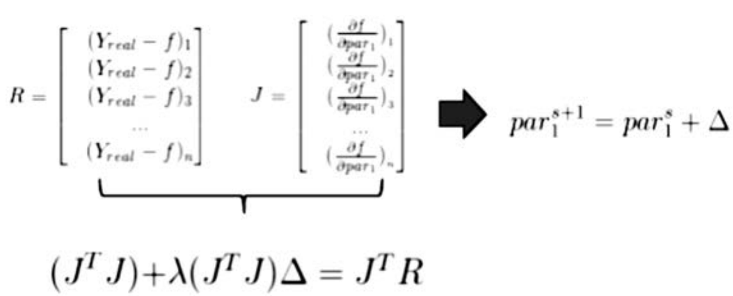

Figure 3—Optimization mechanism – Levemberg-Marquardt

Among the regression methods used were multi-linear regression, support vector machines and neural networks. All these methods used existing mathematical software libraries, since the focus of this work is not the implementation of such methods. Figure 4 depicts this idea which is, from the regression data it is possible to evaluate the behavior of each variable on the variation of the independent variable, which in our case is the friction factor, for a decrease in the error between the calculated and real values.

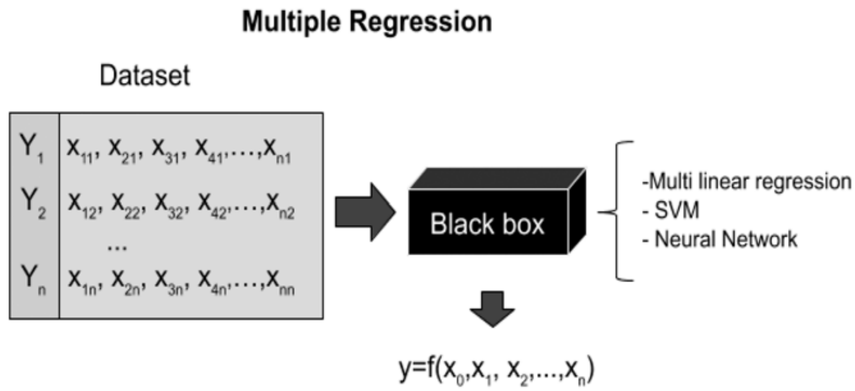

Figure 4—Multiple Regression flowchart

Intelie LIVE is a real-time stream analytics platform that enables visualization and monitoring of high volumes of data. It is a Complex Event Processing (CEP) system. CEP is a technology for online situation detection in event streams, whose usage has rapidly grown over the last decade since it is very well suited to support real-time monitoring applications in many domains. It provides an asynchronous processing model, where CEP rules, which are Event-Condition-Action (ECA) rules, are set-up in a rule-based CEP engine to continuously process event streams. Figure 5 shows the Intelie LIVE processing model.

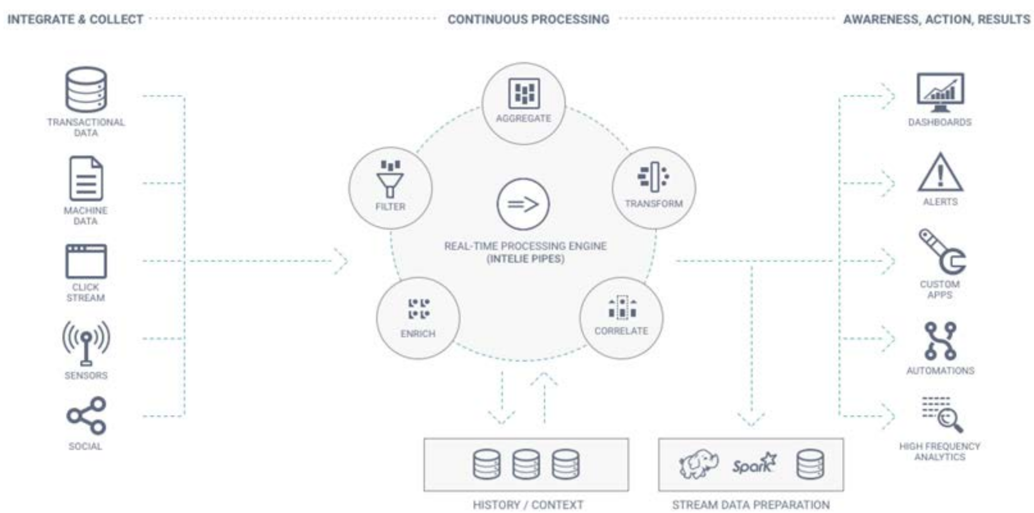

Figure 5—Intelie LIVE processing model

The CEP rules use operators (e.g. logical, quantifiers, counting, temporal, spatial and sequencing operators) and apply them to received events seeking correlations among them, and generating the corresponding complex, or composite, events that summarize the combination of constituent elementary events. A complex event is thus a higher-level abstraction representing a situation derived from the occurrence of simple events (i.e. events not composed by other events), for example, a complex event c1 representing the occurrence of an event e1 followed by an event e2 ($c1 = e1 \rightarrow e2$). Defining such causality relations allows the tracking of events that caused a specific event to happen. The ability to express temporal properties among events allow CEP rules to establish temporal relationships among them (e.g. to detect event sequences), and to process events within specified time windows (e.g. to detect the events that happened in the last few minutes, or to detect the absence of an event, which requires a time-bound for the negation rule to match). It is also possible to define aggregation functions over event attributes observed in sets of events, such as the average, maximum or minimum attribute values of observed event sets [D. C. Luckham 2001; O. Etzion and P. Niblett 2010].

By using declarative rules and event-based capabilities of Intelie LIVE, situation detections can be rapidly expressed without a large development cycle. By leveraging high-performant data ingestion and normalization mechanisms, business rules can be expressed in an ad-hoc fashion on the fly, providing great flexibility to users to compose real-time analytics visualizations.

Digital Twin Architecture

The Intelie LIVE platform, as mentioned above, consists of a stream processing/CEP system with a declarative ad-hoc declarative rules engine for real-time stream processing. In this work, in order to achieve a Digital Twin architecture, additional system components were developed that implement the appropriate storage of static structural data, large scale real-time and historical data and the execution of physical models and machine-learning algorithms that implement the digital twin capabilities. Figure 5 shows the different subsystems that are combined for providing the required digital twin capabilities. Intelie LIVE EDGE is a daemon application that runs on the rig for collecting data from sensors and sending it to the Intelie LIVE instance at the cloud. Intelie LIVE provides data ingestion and real-time stream processing using the PIPES event processing language. Intelie Well Suite (IWS) is the well planning tool, providing a large set of information about the well structure and the operation planning. Figure 6 shows an overview of the architecture's main modules.

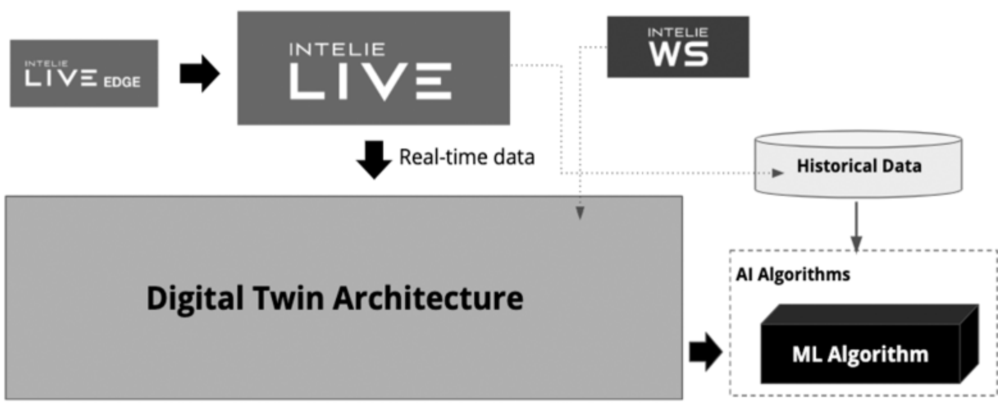

Figure 6—Leveraging Intelie LIVE for achieving Digital Twin capabilities

In order to support the collection, processing and storage of a large volume of sensor data from well operations, a big data architecture was designed. Figure 7 shows the main components of the architecture. This architecture consists of two main layers. The first consists of the real-time or historical data collection component from sensors available in drilling operations generated by the drill rig and the drill string, which periodically sends sensor data to the infrastructure provided with technology to handle a variable number of collectors (Scalable Data Ingestion). This data is input to an event processing machine with declarative ad-hoc rules engine.

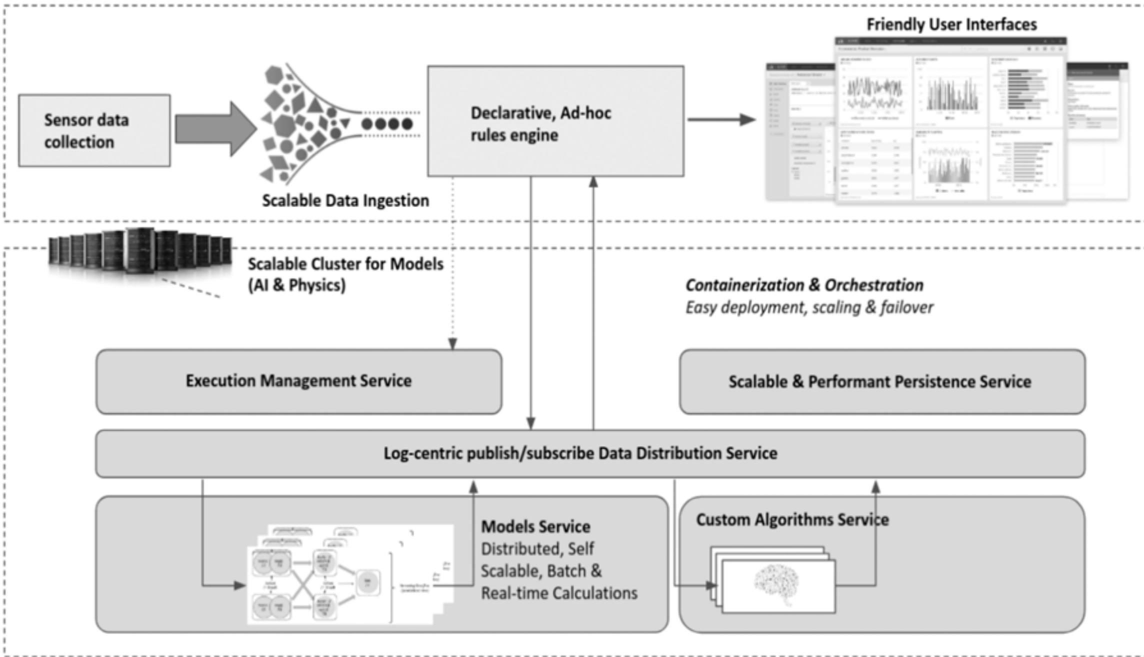

Figure 7—Proposed Digital Twin Architecture

The second tier, which can be provisioned on the cloud (cloud computing) or client premises, implements a cluster for scalable execution of algorithms for calculating physical models, KPIs, and AI, consuming raw data from ingested data, sensor data and real-time or historical processing. This architecture allows the dynamic instantiation of processes for these calculations, allowing to meet a variable number of sensors (i.e. wells, platforms, etc.) in a scalable and elastic manner (i.e. that can be increased or decreased as needed). Dynamic instantiation of these algorithms is enabled by the latest technologies for containerization and orchestration of software components (Containerization & Orchestration) [K. Hightower et. al., 2019]. An execution management service is provided in the architecture to allow all types of algorithms to be executed. In order to have asynchronous and decoupled communication between all components, a log-centric publish/subscribe model [Eugster, et.al, 2003; O. Papaemmanouil, 2009, J. Kreps, 2013] is used, which offers several guarantees and properties of eventual consistency in distributed systems (Publish/subscribe Data Distribution Service). A service responsible for the persistence of large volumes of historical data [E. Hewitt, J. Carpenter. 2020] is used, allowing subsequent queries to time-indexed data ranges or another desired dimension [T. Persen, R. Winslow. 2016] (Scalable & Performant Persistence Service). A service for distributed algorithm execution (Models Service) is used for real-time stream processing, complex event processing and batch historical data processing [V. Kalavri, F. Hueske. 2019].

Results

The optimization methods which use historical data of directional wells were used for obtaining the calibration parameters for minimizing the error between the calculated and real hook load values. Figure 8 shows the non-calibrated curves versus real hook load values, the distances between real and calculated are bigger.

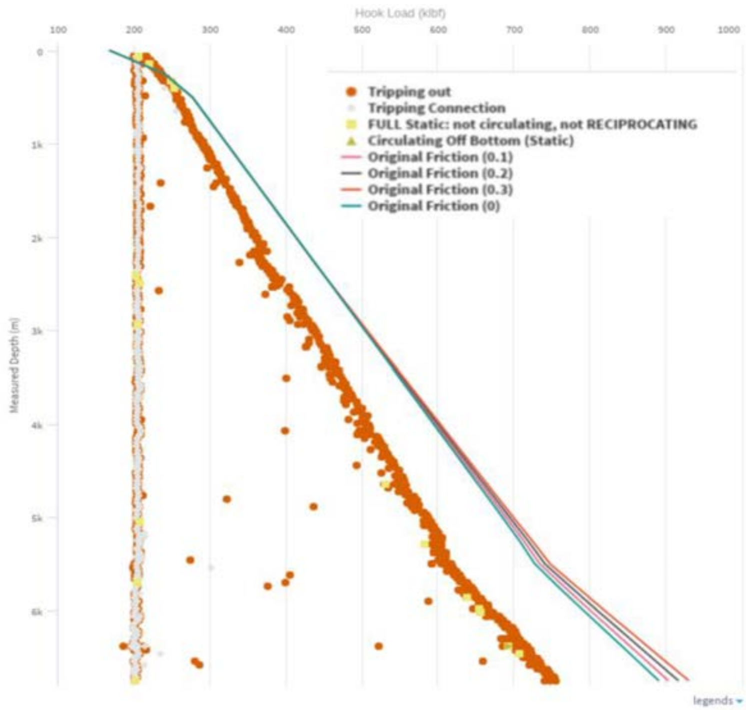

Figure 8—Real Hook load (dots) vs Non calibrated hook load curves

In. addition, Figure 9 shows the results obtained from the optimization. In this example, the calibration adjusted the parameter value (equal to 0.78) that changes the drill pipes linear weight on the vertical range, improving the behavior of the torque and drag model and of the most important ranges which is the angle gain region.

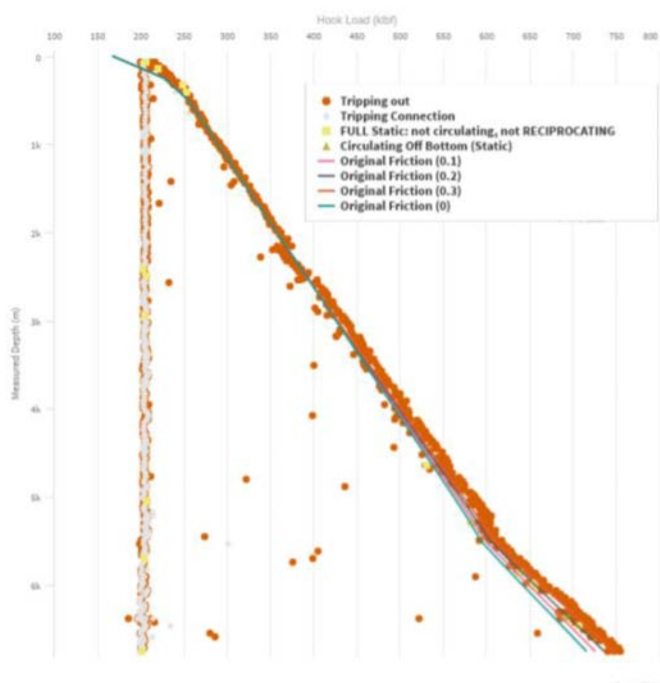

Figure 9—Real Hook load (dots) vs Calibrated hook load curves

In these tests, regressions for the substitution of closure equations still haven't been applied. In the future, work will be finished using the methodology to apply regression from historical data to create new closure-equations.

Final Remarks

- In this work we have presented a computational tool implementing the concept of a digital-twin supporting oil drilling operations by using physical models to simulate phenomena in real-time.
- In order to provide a multi-physics analysis, the ingestion and input of these physical models are performed in an orchestrated manner.
- Sensor and model results are then stored in a time series database, which is used for the continuous evaluation of errors and efficiency improvement, implementing a learning feedback into the physical model calculations of drilling operations.
- An approach for enhancing the accuracy of model calculations was proposed, leveraging the software architecture to monitor well operations and to incrementally improve closing equations coefficients with learning feedback.

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References

1. Bourgoyne, A. T., Millheim, K. K., Chenevert, M. E., & Young, F. S.. Applied Drilling Engineering. *Society of Petroleum Engineers*.
2. Brett, J.F., Bechett, A.D. Holt, C.A., and Smith, D.L. *Uses and Limitations of Drillstring Tension and Torque Model to Monitor Hole Conditions*. SPE 16664
3. B. Babcock, S. Babu, M. Datar, R. Motwani, and J. Widom, "Models and issues in data stream systems," Proc. twenty-first ACM SIGMOD-SIGACT-SIGART Symp. Princ. database Syst. - Pod. ‘02, p. 1, 2002.
4. Coelho, A.C.D., Camargo C., Kato, E.T. and Legrand, V.M.Q.F, 2005, "Utilizing Mini-DST for Formation Evaluation", SPE Latin American and Caribbean Petroleum Engineering Conference, SPE 94963, Rio de Janeiro, Brazil, 20-23 June 2005.
5. Dawson, R. and Paslay, P. R., September 1982. *Drillpipe Buckling in Inclined Holes*. SPE 11167
6. D. C. Luckham, *The Power of Events: an introduction to complex event processing in distributed enterprise systems*. Addison-Wesley Longman Publishing Co., Inc. Boston, MA, USA, 2001.
7. D. Carney, U. Cetintemel, M. Cherniack, C. Convey, S. Lee, G. Seidman, M. Stonebraker, N. Tatbul, and S. Zdonik, "Monitoring streams: A new class of data management applications," in Proceedings of the 28th VLDB Conference, 2002, pp. 215–226.
8. D. McCarthy and U. Dayal, "The architecture of an active database management system," *ACM Sigmod Rec.*, 1989.
9. E. Hewitt, J. Carpenter. "Cassandra: The Definitive Guide, 3rd Edition", O'Reilly Media, Inc. July 2020
10. G. Cugola and A. Margara, "Processing flows of information: From data stream to complex event processing," *Technical report, Politecnico di Milano, 2010*. Submitted for Publication, 2010.

11. Johancsik, C.A., Friesen, D.B., and Dawson, R., June 1984. Torque and Drag in Directional Wells – Prediction and Measurement. *Journal of Petroleum Technology*, p. 987–992
12. J. Kreps, "The Log: What every software engineer should know about real-time data's unifying abstraction", LinkedIn Engineering, December 16, 2013.
13. K. Hightower, J. Beda, B. Burns; "Kubernetes: Up and Running, 2nd Edition". October 2019, O'Reilly Media, Inc.
14. M. R. Endsley, "Toward a theory of situation awareness in dynamic systems," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. **37**, no. 1, pp. 32–64, 1995.
15. Nathan, Marz and Warren, James. 2015. *Big Data-Principles and best practices of scalable realtime data systems*
16. O. Etzion and P. Niblett, *Event processing in action*. Manning Publications Co., 2010.
17. O. Papaemmanouil, U. Cetintemel, and J. Jannotti, *"Integrating Pub-Sub and Stream Processing for Internet-Scale Monitoring,"* 2009.
18. Parrott A., Warshaw L. *Industry 4.0 and the digital twin*, Deloitte University Press, 2017
19. P. T. H. Eugster, P. A. Felber, R. Guerraoui, and A. M. Kermarrec, "The Many Faces of Publish/Subscribe," *ACM Comput. Surv.*, vol. **35**, no. 2, pp. 114–131, 2003.
20. T. Persen, R. Winslow. "Influx db vs. cassandra for time-series data, metrics & management." *Tech. rep.*, September 2016
21. V. Kalavri, F. Hueske. *"Stream Processing with Apache Flink"*. O'Reilly Media, Inc. April 2019