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Digital Twins for Real-Time Scenario Analysis during Well Construction Operations

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Abstract: Well construction is a complex multi-step process that requires decision-making at every step. These decisions, currently made by humans, are inadvertently influenced by past experiences and human factor issues, such as the situational awareness of the decision-maker. This human bias often results in operational inefficiencies or safety and environmental issues. While there are approaches and tools to monitor well construction operations, there are none that evaluate potential action sequences and scenarios and select the best possible sequence of actions. This paper defines a generalized iterative methodology for setting up a digital twin to address this shortcoming. Depending on its application, the objectives and constraints around the twin are formulated. The digital twin is then built using a cyclical process of defining the required outputs, identifying and integrating the necessary process models, and aggregating the required data streams. The twin is set up such that it is predictive in nature, thus enabling scenario analysis. The method is demonstrated here by setting up twinning systems for two different categories of problems. First, an integrated multi-model twin to replicate borehole cleaning operations for stuck-pipe prevention is developed and tested. Second, the creation, implementation, and testing of a twinning system for assisting with operational planning and logistics is demonstrated by considering the time it takes to drill a well to total depth (TD). These twins are also used to simulate multiple future scenarios to quantify the effects of different actions on eventual outcomes. Such systems can help improve operational performance by allowing more informed human, as well as automated, decision-making. Development of a system for well construction operations that integrates multiple sources of information with process and equipment models to quantify the system state and analyzes different scenarios by evaluating action sequences is a novel contribution of this paper. The approach presented here can be applied to the construction of digital twins for any well construction operation.

Keywords: digital twinning; well construction; drilling automation; hole cleaning; scenario analysis; well planning

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1. Introduction and Background

Well construction is the process of drilling and completing a well on the subsurface for some specific purpose, such as extracting hydrocarbons, accessing geothermal energy, storing waste, or collecting rock samples. Drilling a well is typically an uncertain and high-cost operation due to the irreducible complexity of the geological environment deep below the earth's surface, leading to an inherent degree of variability and unpredictability in well construction operations. Drilling operations can pose safety hazards and therefore require careful monitoring of the equipment and process variables. Process or (and) equipment failures during any of the various steps involved in well construction can result in non-productive time (NPT) and associated trouble cost. Such failures could also lead to potentially catastrophic wellbore failures or well control issues, as was shown by the blowout on the Macondo well in the Gulf of Mexico in 2010 [1]. Monitoring, however, is only the first step to ensure safe and efficient well construction operations. Monitoring needs to be followed by appropriate actions, which today, are largely driven by the knowledge and experience possessed by the humans involved in the operation. Tools do not exist in well construction for scenario tracking and analysis in real-time, and this drastically reduces the chances of an optimum response. A major objective of this paper is detailing a process to perform real-time scenario analysis and to demonstrate the process with examples.

In general, recent advances in sensors and data processing technologies at the well construction rig site have now made access to operational and equipment data more reliable. This data, when used in conjunction with historical data and appropriate system models, can be used to improve the overall safety and efficiency of well construction. This improvement in safety and efficiency can be accomplished by developing what are referred to as 'digital twins'. Literature describes the digital twinning process as having three main components [2,3]:

- The real physical system (process or equipment) and the associated sensors for data collection;
- Virtual representation of integrated models of the system to digitally replicate its behavior to enable performance tracking and scenario analysis;
- A data-stream to exchange data and information between the real system and its twin.

Note, however, that not everyone applies the above strict definition when calling a system a digital twin. The capability for scenario analysis is missing in the digital twins published in the well construction digital twin literature, and that is the shortcoming that this paper will address. Given that no such scenario analysis digital twin exist in the well construction literature to date, we briefly introduce one from a different domain as an example. Figure 1 demonstrates the three components of digital twinning through an application for Formula One racing strategy planning and management. The physical system is the race car interacting with other competitors' race cars and the racetrack. The race car itself has over 300 sensors that stream data about different aspects of the car (such as engine and tire temperatures, racetrack conditions, etc.) in real-time to the team's control room at their headquarters [4,5]. This data is then fed into an integrated multi-model system (the digital twin) representing the car and its interaction with the environment, to run many thousands of simulations per second. These simulations analyze multiple scenarios and decide on the best race strategy going forward. Furthermore, throughout the race weekend, starting from the practice sessions on Friday until the final race on Sunday, many hundred gigabytes of data are collected. This data is used to update the understanding of the environment and the car, thereby improving the digital twin's performance for future racing events (a process known as enrichment).

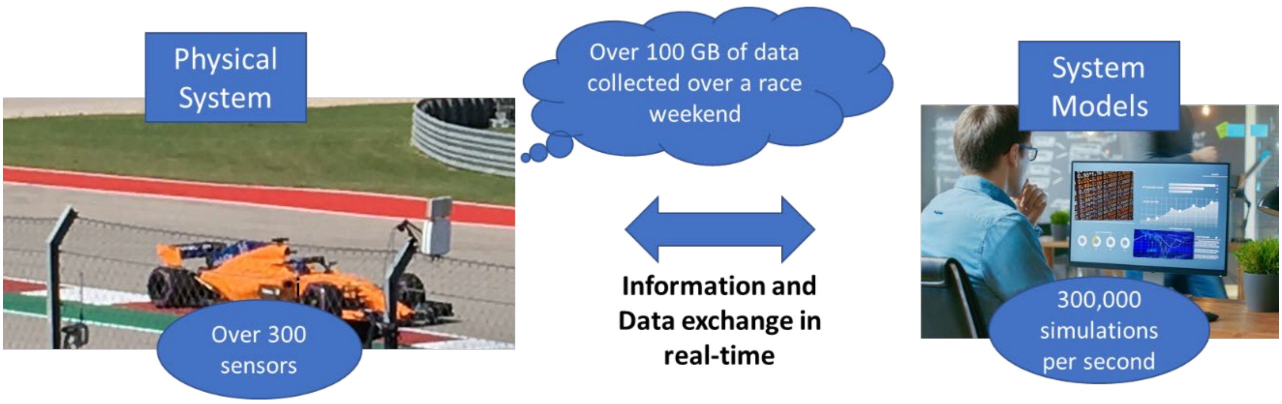

Figure 1. The three components of digital twinning demonstrated through application in auto racing strategy planning, based on information from [4].

Although the domains are entirely different, Formula One racing is actually an appropriate analog for well construction when it comes to the topic of digital twinning and pro-active scenario analysis/action planning. In both cases, we have a dynamic system (the car during racing; the rig and the well during well construction) that is outfitted with sensors collecting real-time data at various frequencies. For rigs and wells, these are the surface sensors and downhole measurements provided by an instrumented drillstring. Whereas the data in racing is used to inform the racing headquarters to take proactive actions, the rig and well data can be used for the same purpose by the rig team and/or a remote monitoring team. In both cases, the ultimate goal of digital twinning is twofold. First, the aim is performance optimization, which in racing is related to optimized speed and reduced lap time, whereas in drilling this is typically the optimized rate of penetration (ROP) and reduced time per footage drilled (e.g., a typical indicator used is days per 1000 ft drilled). Drilling inefficiently typically leads to so-called invisible lost time (ILT). Secondly, in both cases it is important to prevent unforeseen and catastrophic events. In racing, these are engine failures, tire punctures because of non-optimum tire wear management strategy, and avoidable crashes. By analogy, in drilling, one aims to prevent well control incidents and lost circulation events, as well as borehole instability and stuck pipe incidences. The latter can be a major source of non-productive time (NPT) and trouble cost on any well construction project. Excessive ILT and NPT often lead to well construction projects not meeting economic and environmental, safety, and governance (ESG) goals. Their avoidance and minimization are therefore major motivators for considering and implementing digital twinning with associated scenario analysis and action planning.

A very valuable property of digital twins is their ability to be updated in real-time (RT) based on the most recent data. This feature allows for their application in building and applying RT decision-making systems [6–8]. Apart from Formula One racing simulations and strategy planning, the concept of digital twinning has been successfully implemented in various other industries across a variety of applications. Some practical applications include twinning wind turbines for digital wind farm management [9,10], twinning gas turbines to predict failures [9,11], aerospace asset maintenance [12,13], product lifecycle management [14–16], and developing integrated models for weather forecasting [17,18].

In this paper, we first document the state of the art in well construction monitoring and support. We can call these weak digital twins, as they all lack real-time scenario analysis capabilities. Then we propose a generalized methodology for constructing a well construction digital twin that allows for scenario analysis. We subsequently illustrate the process by two applications, hole cleaning and logistical optimization, as representative examples of well construction processes.

2. Digital Twins in the Well Construction Domain

Well construction is guided by an engineering plan called the drilling program, which includes information about the current well's directional plan, the bottom hole assembly (BHA) design, subsurface geology, fluid and hydraulics plan, well control measures, casing design, and cementing plans, as well as relevant information from offset wells [19]. Apart from specifying making the hole with a drill bit attached to a hollow flexible drillstring and rotated via a motor at the surface (top drive or rotary table), the drilling program guides many other processes, such as [20–22]:

- tripping the drillstring in and out of the borehole using a drilling rig's hoisting system (drawworks, hook, traveling block, etc.)
- making or breaking connections, to add or remove discrete drillstring elements called stands using pipe handling systems (hydraracker and hydratongs)
- directional drilling, to control the trajectory of the well using either mud motors (rotary and slide drilling operating modes) or rotary steerable systems
- circulating the drilling fluid (or drilling mud), to maintain its equivalent circulation density (ECD) within a drilling margin using the rig's hydraulics system (reciprocating positive displacement mud pumps, standpipe, etc.)
- hole cleaning, to remove the drilled cuttings from the borehole by controlling the mud flowrate, mud properties, and surface drilling parameters

- well logging, to make high-fidelity downhole measurements, such as formation evaluation logs, near-bit drilling parameter measurements, and directional surveys using measurement and logging while drilling (MLWD) tools.

Throughout the process, various drilling parameters, such as weight on bit (WOB), drillstring rotation speed (RPM), applied torque, and standpipe pressure, are measured directly or calculated using a suite of sensors installed on the drilling equipment [23]. Once a section of the well has been drilled, the next steps involve securing it by running casing and then cementing the casing in place [20].

As can be seen, well construction is a highly involved multi-step process wherein each step has multiple co-occurring sub-processes and various systems interacting with each other. Over the past few decades, much research has been conducted to manage this complexity. For instance, process modeling [24–26] and advanced data analytics [27–31] have assisted in the monitoring of well construction operations for improving its efficiency and safety. Table 1 shows the many areas within the well construction domain wherein progress has been made. While all of these approaches use models (physics or data-based) and partially satisfy the requirements for being called a digital twin, none of them have a framework for scenario analysis, which is an important component of digital twinning (as shown in the example on race strategy planning) and is essential to be able to optimize the selection of appropriate future actions. The goal of this paper is to advance the state of the art in the digital twinning of well construction operations by formulating a step by step process for building digital twins that are also capable of real-time scenario analysis.

Table 1. Current applications for improving operational efficiency and safety and in well construction.

Application Type	Value Addition	Potential Applications
Non-productive time identification (diagnostics) and prevention	• Real-time process monitoring and diagnostics • Improved and faster decision making • Event detection • Drilling optimization	• Mitigating well control issues (e.g., kicks and losses) [27,32,33] • Drilling dysfunction identification and mitigation [34,35] • Wellbore quality degradation identification and mitigation [36–38] • Hole cleaning and stuck pipe prevention [39,40]
Prognostics for equipment failure and detection	• Reduce downtime associated with operational failures • Early diagnosis of failures • Condition-based maintenance (CBM) of drilling tools and equipment • Optimizing drilling tool performances within their operating windows	• CBM of subsea blowout preventer (BOP) pipe rams [41] • Estimating the remaining useful life of downhole components (MLWD tools, mud motors, and drill pipes) [42–45] • CBM of surface equipment, such as top drive, mud pumps, drawworks, and pipe handling equipment [46–48] • CBM of artificial lift systems [49,50]
Invisible lost time evaluation and mitigation	• Improve operational efficiency for various processes • Key performance indicator (KPI) monitoring and tracking • Identification of performance gaps in different processes	• Rig crew performance monitoring and improvement [51–53] • Defining KPIs for quantifying rigs' operational performance for various auxiliary tasks [54–56]

Table 1. *Cont.*

Application Type	Value Addition	Potential Applications
Logistics and planning	• Forecasting and planning • Ability to run what-if scenarios on multiple processes • Delivery of safe, cost-effective wells • Improved well planning and more efficient oilfield development	• Predicting bit degradation and RT downhole drilling fluid properties for optimizing drilling parameters [57–59] • Replication of well construction operations such as drilling, casing, tripping, and cementing (short- and long-term operational planning) [37,60]
Training and development	• Training drilling crew on specific technology • Preparing college students • Testing new technology in a safe environment	• Replicating surface drilling operations (and equipment) and downhole process behavior [61–64] • Developing and testing drilling programs and operation manuals [65,66] • Beta-testing software before rolling them out to the field [67]

3. Digital Twinning Methodology

The methodology developed consists of the following steps:

a. The first step is to determine the objectives of the system being twinned. For instance, the goal of an 'RT drilling dysfunction mitigation twin' would be to detect signatures of dysfunctions (such as vibrations, bit balling, stick-slip), and suggest drilling parameters (such as RPM, WOB, torque, flowrate) to optimize the rate of penetration (ROP) while minimizing dysfunctions.

b. The next step is to set up the twinning system and requires a compromise between the desired and the practical outputs. This compromise depends on the system's objectives, the available data, and the computation capacity for model implementation. The following three steps are iterated repeatedly:

   1. Based on the twin's objectives, the metrics or outputs required to quantify the state of the system are identified. For the dysfunction mitigation twin, parameters such as mechanical specific energy (MSE), depth of cut, and stick-slip index, would be required to quantify the drilling performance and dysfunctions.
   2. Once these metrics are recognized, the next step is the identification and implementation of the different models (data- or physics-based, or a combination of both) to calculate them, i.e., building the digital twin. The selection of these models depends on the application type and the associated temporal and computational constraints. For instance, since online action planning applications require balancing accuracy with runtime speed, analytical model implementations may be acceptable in certain cases. On the other hand, for offline planning or more detailed post-job analysis, wherein computation time or capacity may not be a constraint, numerical models may be used.
   3. Subsequently, based on the input requirements of the various models (twin), the necessary data streams are identified and aggregated; the data is filtered and processed (data wrangling) and integrated with the twin. If the available data stream does not support the calculation of a desired output component, the required system outputs or the underlying models are tweaked accordingly.

c. The twinning system thus set up is then used for performance tracking and scenario analysis. The goal of scenario analysis is to make predictions about future system states and to understand the different driving factors and how they might influence the system behavior [68].

Figure 2 illustrates the different steps and the cyclical relationships between them. The following two sections demonstrate the application of this methodology on two important well construction tasks: one for optimizing hole cleaning operations (NPT diagnostics and mitigation) and the other for predicting and optimizing operational times to evaluate the time remaining to well total depth (logistics and planning).

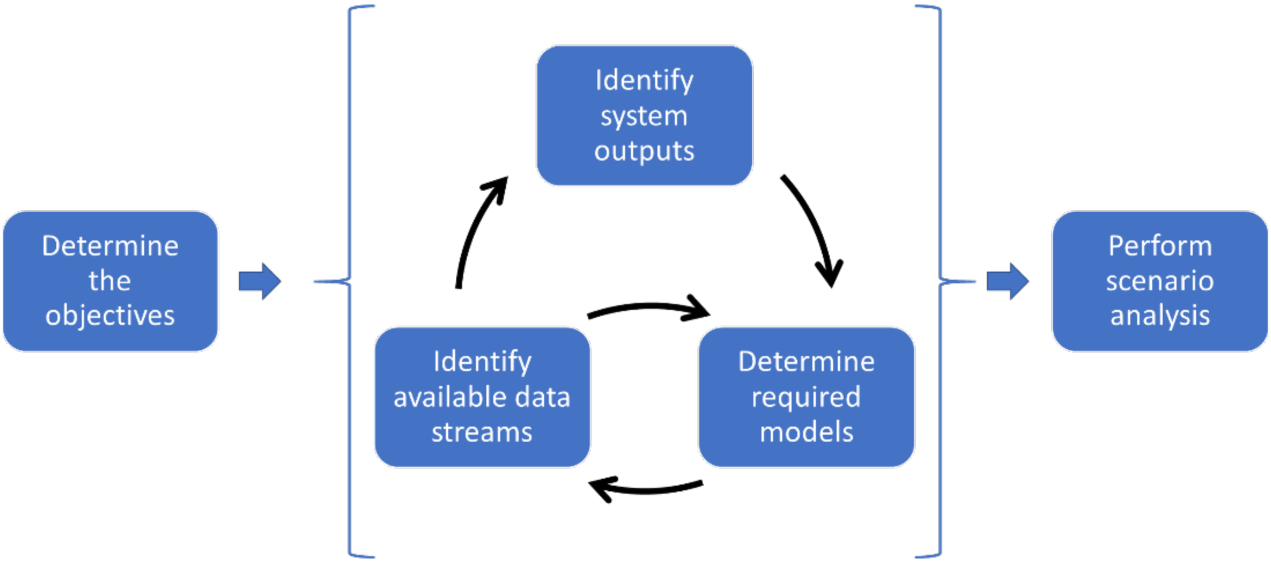

Figure 2. Digital twinning methodology.

4. Development of a Digital Twin for Hole Cleaning Advisory

In this section, we will demonstrate how the process identified in the previous section is used for developing a hole cleaning twin. Inadequate or poor hole cleaning can lead to a series of costly drilling issues such as stuck pipes, formation damage, downhole tool damage, reduction in drilling speed, difficulty tripping out of the hole, or issues while running casing [69]. Well problems such as stuck pipes and wellbore instabilities can halt drilling operations for days and cost millions of dollars in NPT [70]. Therefore, it is of value to digitally twin the hole cleaning system to understand the progression of the borehole condition in real-time and track the outcomes of different actions. Such a digital twin can serve as a baseline for developing an automated intelligent decision-making system for hole cleaning.

4.1. Determining the Objective of the Twinning System

The primary objective of hole cleaning is to remove solids from the wellbore to the extent that different operations such as drilling, tripping, casing, and cementing can be performed efficiently and safely. The solids may include cuttings, cavings, metal shavings, or cement. The following sections discuss the construction and application of a twin for hole cleaning monitoring and action planning.

4.2. Building the Digital Twin

Since a well can be many thousands of feet in depth, hole cleaning measures directed towards one interval of the well may not necessarily result in effective hole cleaning in another interval. Thus, it is essential to quantify and monitor the condition of the borehole in real-time for the entire well.

4.2.1. Identification of the System Outputs

The purpose of modeling cuttings transport is to understand the process of removal of solids (cuttings, cavings, or metal shavings) from the borehole. Removal of solids is critical to ensure that different well construction operations (such as tripping, casing, and cementing) are performed safely and efficiently. The solids in the borehole can be quantified using a combination of the cuttings bed height and the concentration of cuttings in the flow. Furthermore, not maintaining the ECD within the drilling margin can result in wellbore instability issues, such as kicks or lost circulation events. Therefore, the following metrics may be used to describe the state of the borehole for a hole cleaning system [24,71]:

- Height of the cuttings bed at different depths along the wellbore;
- Concentration of cuttings in suspension along the wellbore;
- ECD along the length of the wellbore;
- The average friction factor of the wellbore.

The mechanics of cuttings transport are different in different sections of the wellbore; they depend on wellbore inclinations and wellbore geometry. The cuttings generated during the drilling of non-vertical sections (borehole inclination angles greater than 30 degrees) can start building on the low side of the borehole, resulting in a cuttings bed of some height. More energetic cuttings that do not settle are suspended and carried up hole by the drilling mud [72]. ECD at any depth is calculated as the gradient of the total pressure drop at that depth. The total pressure drop is calculated by summing the hydrostatic head exerted by the drilling mud to the circulating frictional pressure losses in the annular space between the drillstring and the wellbore [20]. Torque and drag, respectively, are rotational and axial forces acting between the drillstring and the casing or the formation. These forces are primarily caused by a combination of the side forces and frictional forces acting on the drillstring [73]. The torque and drag forces are used to estimate a friction factor for the wellbore.

4.2.2. Determining the Required Models

The next step is to identify the models required to calculate these metrics. Analytical implementations, to balance accuracy and runtime speed, of the following models need to be adapted, integrated, and implemented to build the twin [74]:

- Hydraulics model to calculate the frictional pressure losses and ECD throughout the well;
- Torque and drag model to evaluate the friction factor of the well using rotary, slack-off, and pick-up weights;
- Cuttings transport model to estimate cuttings bed height and cuttings concentration in the flow throughout the well.

For hydraulics, an adaptation of the analytical narrow slot approximation model for yield power law (YPL) fluids proposed by Erge et al. [25] was implemented with some modifications to account for the effects of cuttings bed height and cuttings concentration in flow on the mud density. For torque and drag, an analytical soft string model was implemented based on Aadnoy et al.'s work [75,76]. For cuttings transport, a quasi-transient analytical model was derived and implemented based on a combination of concepts from work by Larsen et al. [77], Jalukar [78], Bassal [79], Duan and Miska [72], Rubiandini [80], and Naganawa et al. [81], along with further modifications to account for mass conservation and the physics of fluid flow.

4.2.3. Identification of the Data

The next step is the identification and aggregation of the required data streams to implement the above models. This data can be grouped into the following categories:

- Information about the well profile, obtained from pre-drill well plans and near real-time directional survey data;
- Details about the BHA such as the geometry and unit weights of the individual components, obtained from pre-drill well plans;
- Casing information, such as geometry and casing setting depths for different casing strings and liners, derived from wells' operational data and pre-drill well plans;

- Real-time drilling data obtained from surface and downhole sensors, such as drillstring RPM, surface torque, drilling ROP, flowrate, hookload, tripping velocity, mud rheology, downhole near-bit sensor data, and downhole pressure data.

Datasets comprising the above-mentioned field data were made available for this study by an oil and gas operator. Data from an unconventional well drilled directionally in a shale reservoir is used in the following to illustrate our digital twinning approach to hole cleaning.

Figure 3 summarizes the structure of the proposed digital twin for the hole cleaning system. Initially, well profile and well geometry information are utilized for segmenting the well into smaller discrete control volumes. These segments represent any changes in well dimensions (changes in inner or outer diameter) or different survey intervals. Solving each control volume with time and depth generates an estimate of the state of the system (hole condition quantification metrics for the well). The actual state of the system is determined by utilizing downhole tools, such as a pressure while drilling (PWD) tool for calculating ECD and near-bit MLWD tools for estimating the friction factor. The differences between the actual and the predicted state values can then be used to update the system models.

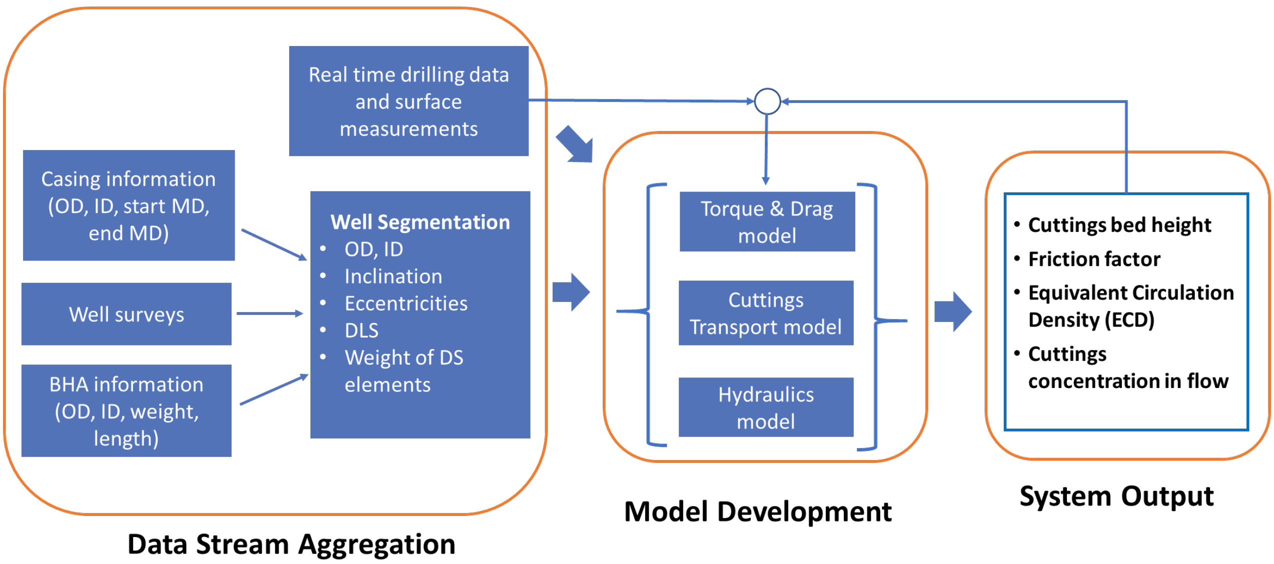

Figure 3. Final structure of the proposed digital twin for the hole cleaning system, see also [82].

4.3. Application of the Twin for Performance Tracking and Scenario Analysis

The methodology was applied for a set of wells to develop a variant of the proposed hole cleaning digital twin, as shown in Figure 4. The data stream did not include tripping information such as tripping rig states or tripping velocities; therefore, the twin's desired output was adjusted not to incorporate the friction factor. Furthermore, since the available data streams did not include downhole tool data (no PWD or near-bit MLWD data), no immediate feedback about the actual system state was possible. This resulted in a digital twin with only the cuttings bed height, ECD, and cuttings concentration in the flow as the outputs. The developed twin was used as a tool for performance tracking by continuously evaluating the state of the wellbore. This twin also offers the capability of performing scenario analysis and action planning.

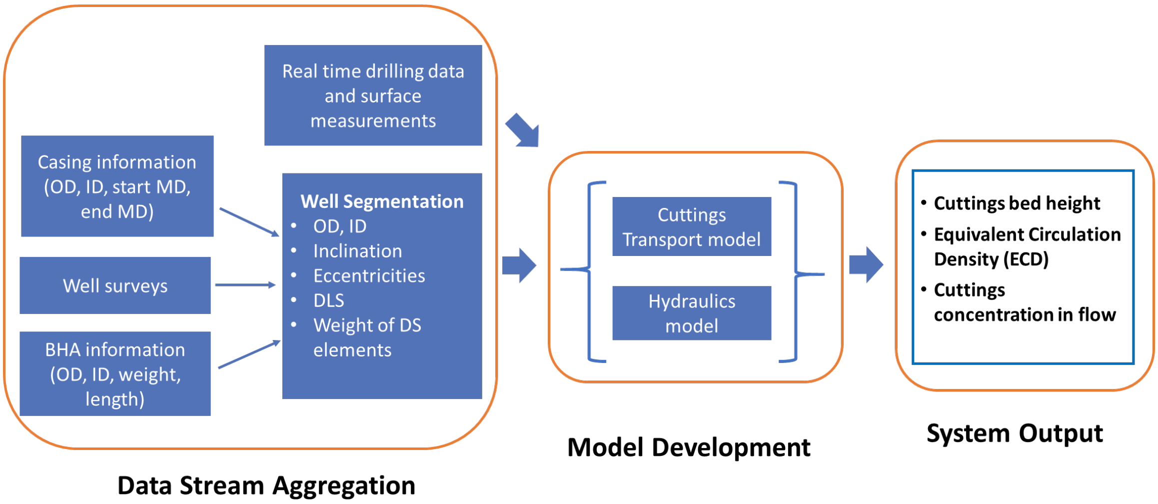

Figure 4. The developed variant of the digital twin for the hole cleaning system, see also [82].

4.3.1. Performance Tracking

The digital twin was deployed to replicate the hole cleaning performance of multiple wells. For one well, Figure 5 represents the state of the borehole after tracking its evolution from the surface in 10 min intervals. In this case, the well has been drilled to a hole depth of 10,000 feet. In the prior 10 min interval, the drilling operation involved slide drilling at an ROP of 93 feet per hour, with an average surface rotational speed of 14 RPM (slide drilling mode) and a flowrate of 598 gallons per minute (GPM). Properties of the drilling mud for this system are stated in the figure. For this system, the table (inset Figure 5) shows some of the required initializations regarding cuttings properties, thermal properties, and thermal gradients. The plots of ECD, cuttings concentration in the flow, and cuttings bed height versus hole depth are displayed in the figure. In the horizontal section at depths greater than 7500 feet, there exist cuttings beds approximately 3 to 4 inches high (in a 7.875-inch open hole). The ECD at 10,000 feet is around 13.1 ppg for drilling mud with a surface density of 12.5 ppg. The cuttings concentration in the flowstream for most of the well is under 5 percent. A relatively high cuttings concentration near the bit is due to cuttings that have not yet been deposited.

4.3.2. Scenario Analysis

The system from its current state (Figure 5) was used to simulate multiple scenarios or actions (a combination of changes in action variables, such a flowrate, RPM, and ROP) to evaluate the outcomes of each. Figure 6 describes the different actions and their predicted consequences on the hole cleaning system state. For the system at 10,000 feet, its state is represented by cuttings concentration, cuttings bed height, and ECD. Then, five different actions over the next 10 min interval were simulated using the digital twin. As expected, different actions lead to different future system states, some more desirable than the others. Some actions lead to minimal improvement in hole condition; actions 1 and 2 result in only a slight reduction in the cutting bed height and the ECD. Some actions (such as actions 3 and 4) lead to an improved hole condition by reducing the bed height while minimally affecting the ECD. On the other hand, more aggressive actions (such as action 5) result in a significantly reduced bed height, but simultaneously result in a high ECD value. Although such actions assist with cuttings removal, an increase in the ECD closing the distance to the fracture gradient can result in induced wellbore fracturing and lost circulation issues.

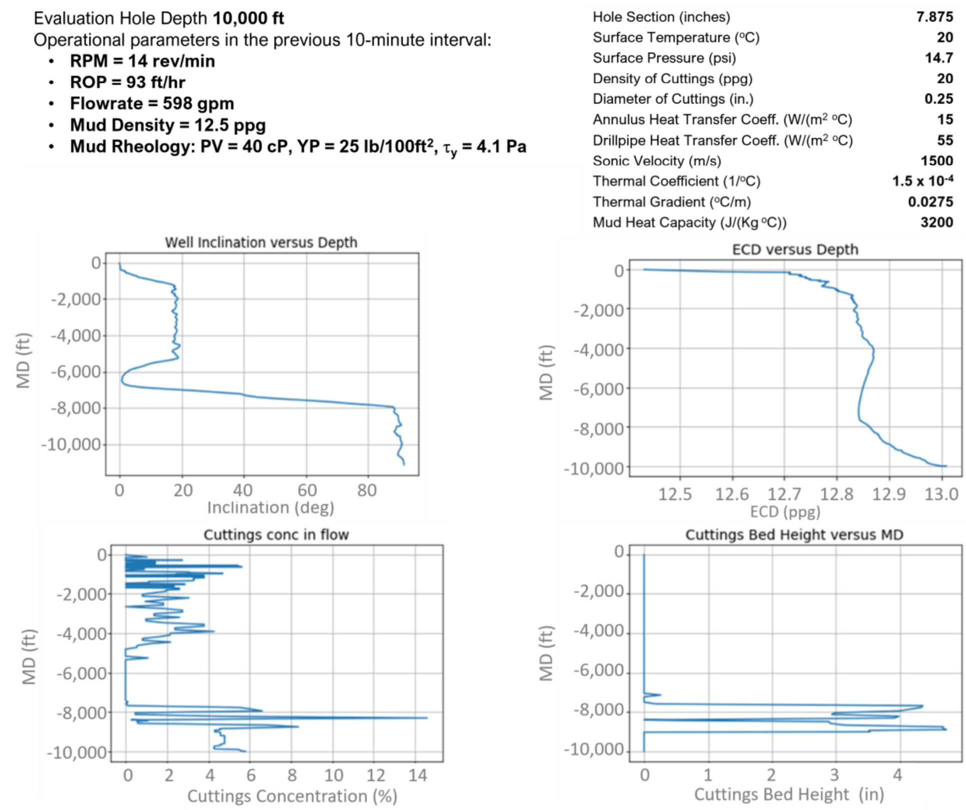

Figure 5. State of the system at a 10,000 foot hole depth after tracking its evolution from the surface.

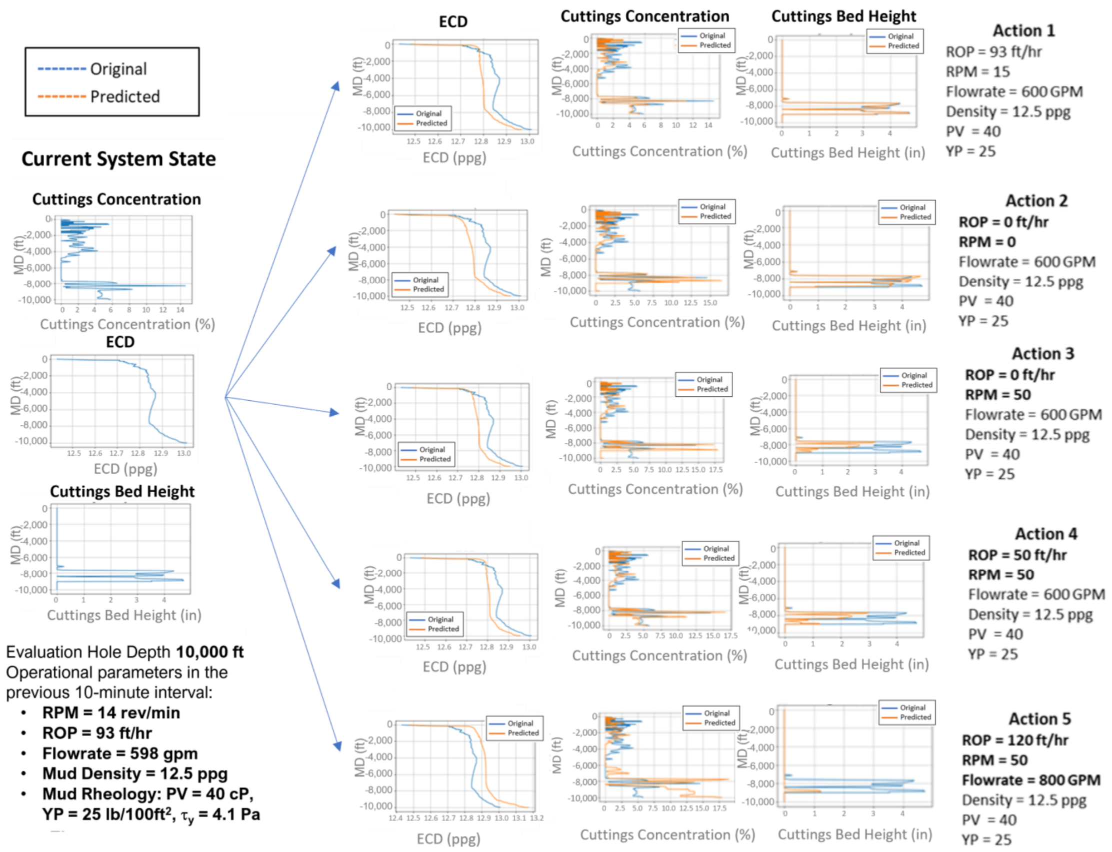

Figure 6. Scenario analysis for predictive action planning.

This concept of a single-step scenario analysis can easily be expanded to multi-step analysis, as shown in Figure 7. This digital twin, therefore, can be used to evaluate multiple action sequences over several time steps (evaluation intervals) to find the optimal way of traversing through the system, i.e., coming up with an optimal plan (action planning). Such short- and long-term scenario analysis is only possible with a predictive model and is a prime requirement for any twin.

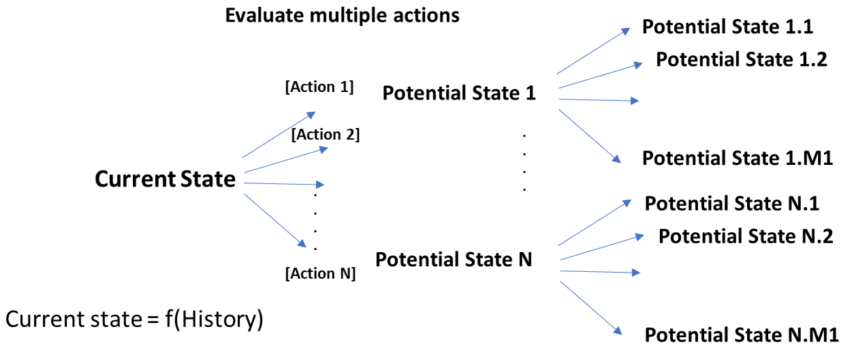

Figure 7. Simulating multiple action sequences.

5. Development of a Digital Twinning System for Optimizing Logistics and Planning

In this section, we will demonstrate how the methodology described in Section 3 is used for developing a twin for optimized logistics and well planning. During well construction, the drilling of a well section or interval is generally followed by circulation cycles for hole cleaning, then casing and cementing operations, and in some cases, by clean-out operations and casing/formation integrity tests. These steps are repeated until the objectives laid out in the drilling program are met, which includes drilling the well to its planned total depth (TD). The unpredictability in reaching TD affects the overall logistics and completion schedule of the well, which, in turn, affects the drilling program. It is therefore essential to be able to estimate and optimize the times required for the different well construction operations.

5.1. Determining the Objective of the Twinning System

This section discusses the development of a digital twin for predicting, updating, and optimizing in real-time, the time remaining to drill a section or reach well TD, referred to as 'time to TD'. This time prediction can be made using information such as:

- The operational performance of the offset (historical) wells;
- The current position of the drill bit relative to the well plan;
- The operational performance of the current well up to its present depth;
- Degradation in performance of drilling tools, equipment, or drill bit.

5.2. Building the Digital Twin

The following sections describe the different steps involved in building this digital twin.

5.2.1. Identification of the System Outputs

The first step in estimating time to TD is the identification of components that comprise this time and the factors affecting these individual components. Time to TD from the standpoint of rig activities is the sum of anticipated times spent performing the different operations (or time spent in different rig states). The following generally comprise time to TD:

- Total anticipated on-bottom drilling time ($T_{Drilling}$);
- Total time for acquiring the directional surveys ($T_{Surveys}$);
- Total expected time for making connections ($T_{Connections}$);

- Total tripping time (including times for tripping in, tripping out, making up and laying down BHAs) ($T_{Tripping}$);
- Total circulation time ($T_{Circulation}$);
- Total miscellaneous time to capture the times for all other activities and operations not considered above ($T_{Miscellaneous}$).

The anticipated on-bottom drilling time further depends on the following:

- Total distances to be drilled individually by rotary and slide drilling;
- The remaining formations to be drilled through and the approximate depths of each;
- The estimated average drilling speeds (for both slide and rotary drilling modes) through each remaining formation.

The approximation of the total connection and the total survey times requires estimating the remaining number of connections and surveys until the planned TD is reached. Similarly, metrics are designed to extrapolate the estimated circulation and tripping times until the planned TD is reached. To summarize, the time to TD can be calculated as follows:

$$T_{well\ TD} = T_{Drilling} + T_{Surveys} + T_{Connections} + T_{Tripping} + T_{Circulation} + T_{Miscellaneous} \quad (1)$$

5.2.2. Determining the Required Models

The next step is the identification of the models required to calculate the individual components. Knowledge derived from offset wells is used in combination with the current well's performance, along with the information about planned tasks, to anticipate future events and estimate the different time components. The following models need to be implemented to accomplish this:

- Rig state detection engine, to classify the real-time data into different operational categories such as on-bottom drilling (slide and rotary drilling), tripping (in and out), circulating, reaming, and making connections;
- Slide and rotary drilling predictive models, to predict relative amounts of slide and rotary drilling required until the TD, based on the well plan and the learnings from offset wells;
- Predictive data-based models, to estimate different component times by utilizing an adaptive weighed scheme for combining statistics obtained from real-time data and offset well data, as shown in Figure 8. For example, the connection times between the more recent time interval $t = t_2$ to $t = t_{current}$ would likely be given a higher weight in comparison to the connection times between the interval $t = t_1$ to $t = t_2$ when coming up with an expected connection time in the future.

In the adaptive weighted scheme, the most recently acquired data has the highest weight (W1), while historical data is assigned the lowest weight (W4). The sum of all the weights is 1, and the various times (t_1, t_2, etc.) are not fixed; instead, they are functions of the number of data points collected thus far.

5.2.3. Identification of the Data

The following data streams are required for implementing this digital twin:

- Real-time drilling data obtained from the surface sensor measurements, specifically data channels such as drillstring RPM, applied WOB, drilling ROP, flowrate, standpipe pressure, tripping speed, and surface torque and hookload measurements;
- Geologic formation top information (anticipated start and end depths of different formations);
- BHA and bit information, obtained from the well plan;
- Well trajectory information, derived from the well plan and the well survey data, quantified using azimuth and inclination angles at different depths along the well;
- Descriptive statistics, derived from offset well data, to quantify past performances for the various operations.

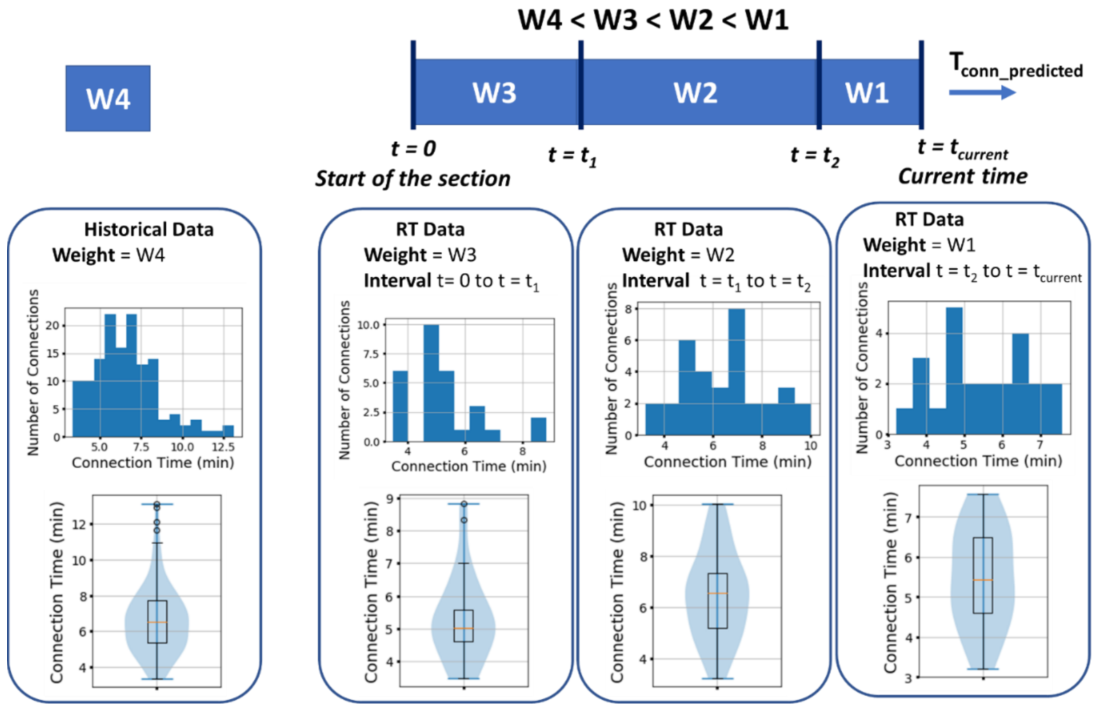

Figure 8. Adaptive weighted scheme for combining data collected at different times (for average connection time approximation).

Here again, datasets comprising the above-mentioned data were made available for this study by an oil and gas operator. Figure 9 summarizes the structure of the designed digital twin. First, the offset well data in combination with the current well's well plan, and formation top information is used to derive pre-drill or 'a priori' initializations. Subsequently, these initializations, in conjunction with RT drilling data, are fed into the multi-model digital twin. The twin then estimates the different time components that are summed together to make a time-to-TD prediction. As a new real-time data point is collected, the various statistics are re-calculated, and a new prediction is made. The differences between this prediction and the actual time are then utilized for tuning the adaptive weights of the prediction model. Therefore, the structure of the developed digital twin ensures that the system is continuously learning and updating itself based on the latest data.

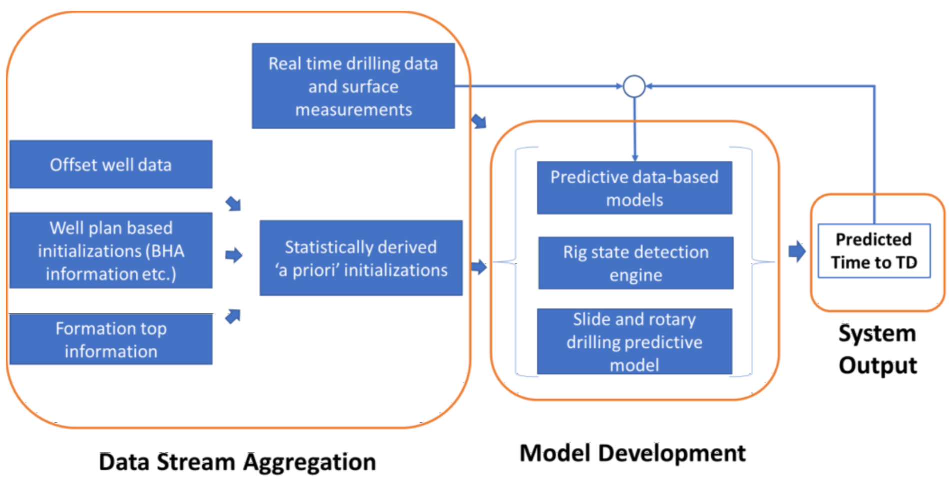

Figure 9. Final structure of the designed digital twin for making time to TD predictions, see also [82].

5.3. Application of the Twin for Performance Tracking and Scenario Analysis

The developed digital twin was implemented on a dataset comprising four wells; three were used as 'offset wells', and the fourth was treated as the 'test well'. Figure 10 illustrates a subset of the data collected from each of the offset wells to derive a priori initializations for the twin. Initially, the number of collected data points from the test well is low. This results in the times and weights associated with the adaptive weighting being tuned to give more importance to the offset well data for making predictions. However, as more real-time data is collected, the twin starts learning, thereby updating the different weights and times.

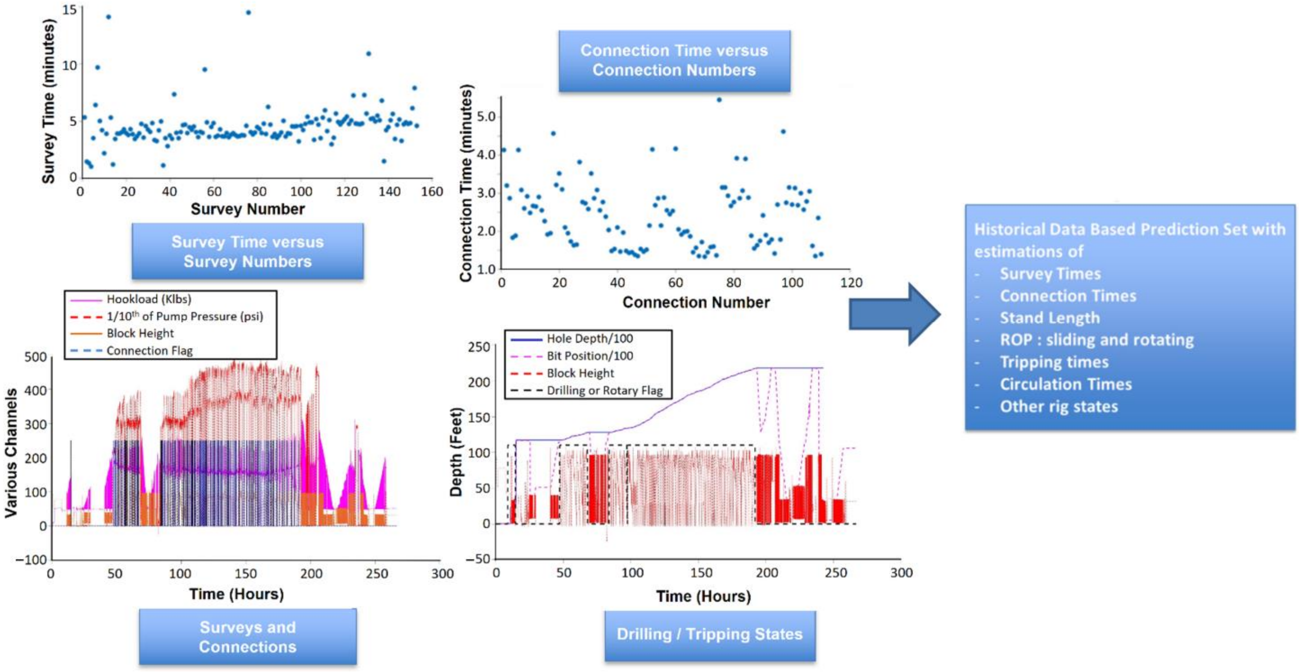

Figure 10. Subset of the data collected from each offset well for deriving a priori initializations.

5.3.1. Performance Tracking

The twin was used to make real-time predictions for the time required to reach TD for drilling the horizontal lateral section of the test well. As per the well plan, the lateral section was scheduled to be drilled with a single bit run starting at approximately 11,500 feet till the planned TD of 20,700 feet. However, unexpected tool failures mandated three bit runs (or consequently two trips in and out of the borehole to replace the failed tools). Since these trips were not planned, the initial predictions made by the twin were optimistic. However, the predictions became more realistic once the rig state engine identified the unexpected trips. Figure 11 shows the results of the predictions on plots between the predicted time versus the actual operation times. Figure 11a details the individual time predictions for different operations. Figure 11b shows the total time to TD predictions, along with the three bit runs. Another feature of the various time predictions is their ability to adapt rapidly due to:

- Different weights being assigned to different data points at different times (adaptive weighting);
- Continuous real-time re-evaluation of the slide and rotary drilling requirements.

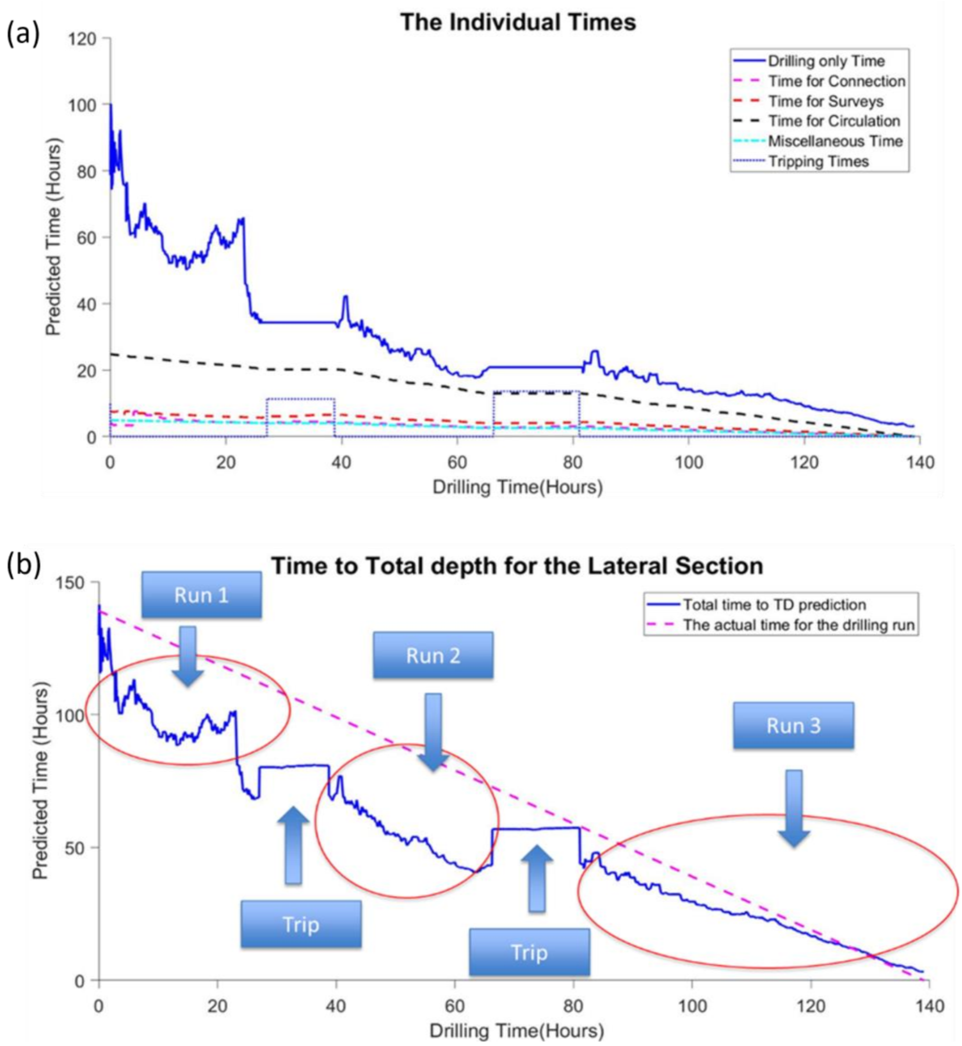

Figure 11. (**a**) Estimated individual times for different rig states versus time; (**b**) total time to TD predictions versus time.

Figure 12 is another way to visualize the predictions by overlaying the predicted and actual remaining times to TD versus the drilled hole depth. The two "time jumps" around 13,250 feet and 15,850 feet represent the trips to change the failed tools. Spikes are visible in the predicted times in both these instances, as soon as the algorithm identifies the beginning of tripping operations. Since a spike accounts for the time related to completing the tripping procedure from the given depth, it is directly proportional to the depth at which tripping starts.

5.3.2. Scenario Analysis

Similar to the hole cleaning advisory twin, this twin also permits scenario analysis to estimate the outcome of different logistical actions on the time to reach TD. Some examples of such logistical decisions include:

- Analyzing the effect of tripping out at a certain depth to change the drill bit;
- Examining the impact of different drilling parameters on the various operational times;
- Inspecting 'what-if' scenarios with varying values of time components such as tripping speeds or connection times.

Some examples of scenarios that were analyzed using basic CBM models and data are summarized in Figure 13.

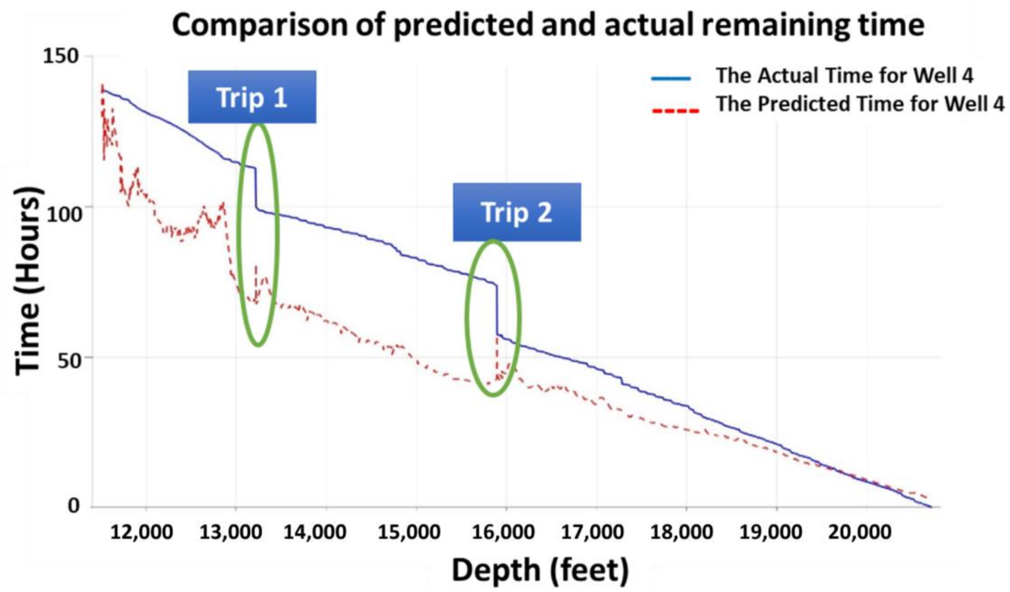

Figure 12. Comparison of the predicted and actual remaining times to TD versus drilled hole depth.

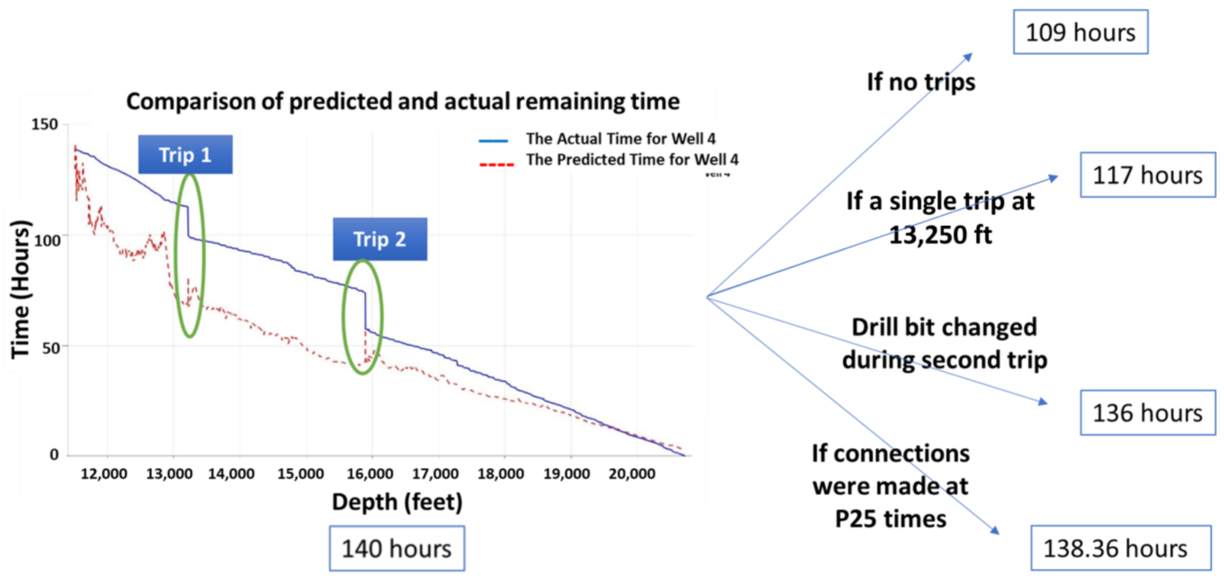

Figure 13. Analyzing post-run 'what-if' scenarios.

Observations include:

- Integrating CBM models, such as for estimating bit degradation, provides the twin with the ability to estimate the bit condition and remaining useful bit life in RT. This, in turn, allows for evaluating the benefits of continued drilling with a potentially worn bit, versus the time cost of tripping operations to change to a newer bit. The entire horizontal section (over 9000 feet) was drilled using a single drill bit. However, if the drill bit were changed (to a newer bit) during either of the trips, it would have resulted in reducing the total drilling time. Assuming linear bit degradation as a function of the depth drilled would have resulted in finishing the last section almost 4 h faster if the bit were changed during the second trip.
- Operationally, the average time for making a connection while drilling the well was 171 s, while the P25 time was 112 s (Figure 14). Making all connections throughout drilling at 112 s would have resulted in ILT reduction, with the total operation time being reduced by 1.64 h.

- This twin is a good starting point for making initial time predictions and estimations and can be further enhanced by using advanced process models. Integrating more comprehensive CBM models for, for instance, mud motor failure would not only have allowed for the prediction of 'unexpected' tool failures, thereby saving the extra downhole trips (NPT prevention), but also suggested optimal drilling parameters to prolong tool life.

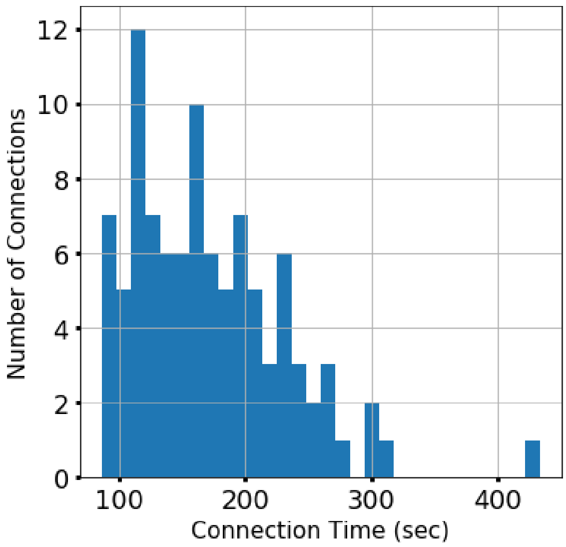

Figure 14. Variation and distribution of connection times for the drilling operation.

6. Summary and Conclusions

This paper proposes a three-step methodology (identification of the objectives, building the digital twin, and performance tracking and scenario analysis) for setting up twinning systems for well construction operations such that they can be utilized for RT performance tracking and scenario analysis. There are many models available in the drilling literature, included in conventional "weak" digital twinning approaches, to address drilling efficiency and safety issues; however, to the best of our knowledge, none of these provide a systematic framework for analyzing scenarios or action planning described in this paper. On the other hand, scenario analysis is common in other domains such as gaming artificial intelligence engines (chess and go), race strategy planning, wind farm management, etc. To enable scenario analysis in a stronger digital twinning approach for well construction, the methodology proposed in this paper addresses the following aspects of digital twinning:

- The defined cyclic process of development of the digital twin ensures that the final built twin is a compromise between the application type, the available data, and the memory and computational constraints.
- The integrated multi-model nature of the twin results in more realistic constraints around the permitted action values; for instance, as shown for the hole cleaning system, an aggressive increase in the flowrate would result in faster cuttings removal but lead to increased ECD, which could be detrimental to wellbore quality.
- Scenario design and selection is highly dependent on the twin and the available computation time. Thus, domain-knowledge can be employed to intelligently structure scenarios and build action sequences.

Due to their short- and long-term decision-making capability, digital twins that are able to perform scenario analysis can be utilized for setting up intelligent decision-making frameworks, which can be used as an advisory system for the rig teams taking improved actions but can also be coupled directly with the rig control systems to automate the control of drilling parameters such as flowrate, RPM, WOB, tripping speeds, and mud rheology. This paper provides a process for the creation of digital twins focused on scenario analysis, which, when implemented either through advisory systems or automation, will help drilling engineers and well construction managers in reducing time and cost through minimized ILT and avoided NPT events (e.g., well control, lost circulation, wellbore instability, and stuck pipes), making operations more reliable and safer by removing human bias and inconsistency.

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Unit Conversion

1 meter (m)	3.28 feet (ft)
1 meter/second (m/s)	11,811 feet/hour (ft/h)
1 psi	6894.76 Pa
1 ppg	119.83 kg/m^3
1 radian	57.2958 degrees
1 ft^3	0.02832 m^3
1 GPM	0.0000631 m^3/s

Nomenclature

CBM	Condition-based maintenance
ECD	Equivalent circulation density (ppg)
ESG	Environmental, safety, and governance
ILT	Invisible lost time
MLWD	Measurement and logging while drilling
NPT	Non-productive time
PV	Plastic viscosity (cP)
PWD	Pressure while drilling
ROP	Rate of penetration (ft/h)
RPM	Surface rotation rate of the drillstring (revs/min)
RT	Real time
$T_{Drilling}$	Total anticipated on-bottom drilling time (h)
$T_{Circulation}$	Total circulation time (h)
$T_{Connections}$	Total expected time for making connections (h)
$T_{Miscellaneous}$	Total miscellaneous time for all other operations (h)
$T_{Surveys}$	Total time for acquiring the directional surveys (h)
$T_{Tripping}$	Total tripping time, including times for tripping in, tripping out, making up, and laying down BHAs (h)
$T_{Circulation}$	Total circulation time (h)
$T_{well\ TD}$	Total time to TD prediction (h)
WOB	Weight on bit (Klbs.)
YP	Yield point (lb./100ft^2)

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