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# Statistical Optimization of PDC Bit Designs Based on 3D Simulations Applied to Demanding Directional Applications

Gilles Pelfrene, Varel International Energy Services; Hadi Al-Ajmi, Jomah Bashir, Fahad Al-Otaibi, Ahmad Al-Nuaimi, Hamad Al-Jiran, Ahmad Baroun, Abdulaziz Al-Kandari, and Talal Huseen, Kuwait Oil Company; Boktor Mikhail, Ehab El-Genidy, Sebastien Reboul, and Julien Carlos, Varel International Energy Services

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## Abstract

Simulating the mechanical response of PDC drill bits contains a lot of uncertainties. Rock and fluid properties are generally poorly known, complex interactions occur downhole and physical models can hardly capture the full complexity of downhole phenomena. This paper presents a statistical approach that improves the reliability of the PDC bit design optimization process by ensuring that the expected directional behavior of the drill bit is robust over a well-defined range of drilling parameters.

It is first examined how uncertainty propagates through an accurate bit/rock interaction model which simulates numerically the interaction between a given PDC drill bit geometry and a given rock formation, both represented as 3D meshed surfaces. Series of simulations have been launched with simulation parameters defined as probability density functions. The focus has been set on directional drilling simulations where the drill bit is subjected to significant variations in contact loads on gage pads along its trajectory. A global sensitivity analysis has also been performed to identify the key parameters which control drilling performance.

Directional system parameters are critical in terms of steerability and tool face control, particularly in high dogleg severity applications. Based on these simulations, a statistical optimization strategy has then been implemented to ensure that the directional performance of the drill bit remains effective under a given uncertain drilling environment. Statistical analysis combined with drilling simulations indicated that ROP improvements could even be achieved without compromising steerability. A balanced bit design was selected and manufactured in an 8 1/2-in. model to drill a 714 ft section of a Kuwait field. The bit was run on a high dogleg rotary steerable system and directional assembly. The bit achieved the high steerability goals required by the application while showing a good compatibility with the directional tool. Moreover, ROP was increased by approximately 27% compared to offset wells, setting a record rate of penetration in the field.

Whereas statistical analyses are commonly conducted in the field of geosciences, it has rarely been applied in the field of drilling applications. The statistical bit design optimization strategy deployed in this work has allowed to improve both the drilling performance of the drill bit and its reliability.

## Introduction

### Parameter uncertainty and variability in directional drilling

Rotary steerable systems are among the most advanced technologies in the drilling industry. They are designed to achieve directional goals with accuracy and reliability, in deep and harsh drilling environments. High dogleg severity (DLS) applications increase the complexity of these operations.

Among the major sources of perturbation to the planned well trajectory are the BHA components involved in the directional behavior of the drilling structure: the directional system itself can exhibit a variable mechanical response (Spencer et al., 2013). Other BHA components can also impact the variability of this response, like the drillbit, the stabilizers and the drillcollars interacting with the borehole wall (Chen et al., 2007; Barton et al. 2009).

A second major source of variability is the rock. Although the average lithology of a well is generally known, rock characteristics are highly variable over a sedimentary basin and along a drilling section (Cuillier et al., 2017). Rock characteristics are also uncertain at a smaller scale (Amri et al., 2016). Depending on the heterogeneity or the anisotropy of the rock, its mechanical characteristics may vary significantly (Boualleg, 2006).

### Statistical tools used to optimize the bit design process

Under these constraints, the simulation of the mechanical response of PDC drill bits is an inherently uncertain and variable process. In this paper, a statistical approach has been developed in order to grasp the complexity of these interactions by accounting for parameter uncertainty and variability as described in Begg et al. (2014). Whereas statistical analyses are commonly conducted in the field of geosciences (Rodriguez et al., 1988; Tague, 2000; Li and Bai, 2012, Bazargan et al., 2013), it is less common to tackle drilling problems (Spanos et al., 2002; Gradl et al., 2008). In this study, two main statistical tools have been implemented to ensure that the directional performance of an optimized bit design was achieved over wide range of drilling conditions.

The first of these tools is called uncertainty propagation. It basically consists in defining a space of Nd input parameters of the model. Each parameter is considered as a random variable following a given distribution law, also called probability density functions (PDF).

A common example of a PDF is the uniform law which states that a given random variable can take values within a given range with the same probability. This law can be used for example to describe the variability of a parameter which evolves in time or space without any particular value to be reached. Another common example is the normal law, also known as the gaussian distribution, which is used to describe a wide variety of physical processes. It can be used to describe the variability of a measurable parameter which is known with some degree of uncertainty. This parameter is given an average value and a standard deviation which fully define the PDF. The most probable value taken by the parameter is its average. The probability that the parameter takes another value decreases exponentially as it departs from the average. The standard deviation determines the percentage of the population of values of this parameter which lie within a given range around the average. For example, assuming the given parameter follows a normal law of average $\mu$ and standard deviation $\sigma$ implies that 68.25% of its values range within $[\mu-\sigma, \mu+\sigma]$ and 95.45% range within $[\mu-2\sigma, \mu+2\sigma]$. These percentages refer to the theoretical normal law. In practice, they may vary depending on how many samples of this parameter are picked. The higher this number, the more accurate these percentages.

Once each PDF is determined, a dedicated algorithm is used to generate a given number of samples N of the parameter space. Each of these samples consists in a combination of Nd randomized values which serve as inputs to the given model. Simulations are repeated N times to generate an output sample. In this paper, the model refers to a drill bit simulator and the output of the model consists in a set of directional drilling performance indicators described in the next sections. The higher the size of the sample N, the better the statistical convergence of the outputs. In other words, computing the average or the standard deviation of a given performance indicator over a range of input parameters is all the more accurate as N increases.

Since this is one of the main goals of this study to estimate the average and the standard deviation of several of these indicators, N plays a critical role. Indeed, in this study, Nd may range between 10 and 15 depending on the assumptions made. The typical sample size corresponding to such a parameter space dimension is 10k-100k. Knowing that a directional simulation ran with a 3D bit simulator like the one described in Pelfrene et al. (2019) typically lasts 1-10 minutes on a standard laptop, the total simulation time to obtain accurate statistical results ranges between 1 week and 2 years depending on the complexity of the simulation.

Fortunately, the second statistical tool implemented in this study, the sensitivity analysis, allows to optimize the dimension of the parameter space by focusing on the most influential input parameters and fixing the less influential ones. There are different classes of sensitivity analyses which have been described in the literature (Saltelli et al., 2008; Baudin et al., 2015). In this study, 2 of them have been used: the Morris sensitivity analysis, which belongs to the class of the screening methods; and the Sobol analysis which belongs to the class of global sensitivity analyses.

Screening methods are a class of sensitivity analyses which is used to obtain a relatively fast and qualitative assessment on the influence of the different parameters of the problem (Baudin et al., 2015). In particular, the Morris analysis exhibits linear dependencies between inputs and outputs. In this method, the parameter space is sampled as a regular grid containing a given number of levels between the minimum and the maximum range for each parameter. For example, 3 levels correspond to sampling the minimum, the maximum and the mid-point for each parameter of the parameter space. Based on this grid, the effect of each parameter is computed along a given number of trajectories Nt, typically 10. The typical number of simulations for such an analysis is Nd * Nt, i.e. roughly 100.

Whereas the Morris analysis may exhibit major trends, it does not provide a quantitative assessment on the influence of the different input parameters. This is provided by the global sensitivity analyses (Saltelli et al., 2008). Among them, the Sobol sensitivity analysis is widely used. It basically allows to estimate which percentage of the variability of an output, a given input parameter variability is responsible for. Hence, this is a very powerful tool to rank parameters' influence. However, this method usually requires to heavily sample the parameter space. Assuming for example Nd = 10, a typical Sobol analysis is performed with N = 10k-100k.

**Content**

In the first section of this paper, the directional model and its parameters are presented. Then, the statistical approach developed to select the cutting structure is described, from the parameter space description to the results of the Sobol sensitivity analysis. The uncertainty propagation leading to the selection of the optimal cutting structure is then presented. In the third section, the statistical approach developed to select the gage configuration is described. A different strategy is presented from the parameter space description to the results of the Morris sensitivity analysis. The uncertainty propagation leading to the selection of the optimal gage configuration is then described. In the last section, the application of the whole statistical approach to the targeted bit run in a high dogleg application in a Kuwait field is presented.

## Directional simulations with a 3D bit simulator

The 3D bit simulator used to conduct directional simulations presented in this paper has been described in detail in Pelfrene et al. (2019). In the following section, we focus on describing the directional model parameters that will be used by the different statistical analyses presented in the next section. The model follows a kinematic approach which relies on two distinct submodels.

## Geometric model

The first submodel aims at computing the geometry of the bit/rock interaction, including the geometry of the hole drilled, the interactions between the cutters and the hole and the interactions between the non-cutting parts of the drill bit (i.e. the gages, the blades and other tool face contact elements) and the hole.

To compute these interactions, it is necessary to prescribe the well trajectory and the bit movement relative to this trajectory. To simplify the analysis, the trajectory is assumed to be two-dimensional (i.e. no turn considered). Thus, the well trajectory can be simply defined by 4 parameters allowing to model most common trajectories (straight/vertical, build/drop or kick-off sections). These parameters are the depth at the top of the section (depth in), the depth at the bottom of the section (depth out), the build rate at the top (build rate in) and the build rate at the bottom (build rate out). The trajectory mathematical definition can be reduced to only 2 independent parameters, which are the build rate and the rate of increase of the build rate along the section. In the analyses presented below, it is further assumed that the build rate is constant throughout the section, so that only one parameter is required to describe the well trajectory: the build rate. It is added to the parameter space (PS) of the analysis:

$$PS = \{build\ rate\} \tag{1}$$

Well trajectories described above can be achieved by a variety of directional systems like bent-motors, rotary steerable systems (RSS) or hybrid systems. Directional drilling systems involve complex, proprietary mechanical components which makes them difficult to model with accuracy. Rather than trying to model the complexity of these systems knowing that most of their core parameters are simply unknown, the approach followed in this paper consists in using a simplified 4-parameters model for the directional system. And to account for the complexity of it by making these 4 parameters evolve as random variables. These 4 parameters are the rotary RPM, the motor RPM, the bit tilt and the distance between the bit and the pivot point. As shown in Fig. 1, it applies differently depending on the drive. In accordance with the drive used in the field application presented in the last section of the paper, we will focus on the point-the-bit model.

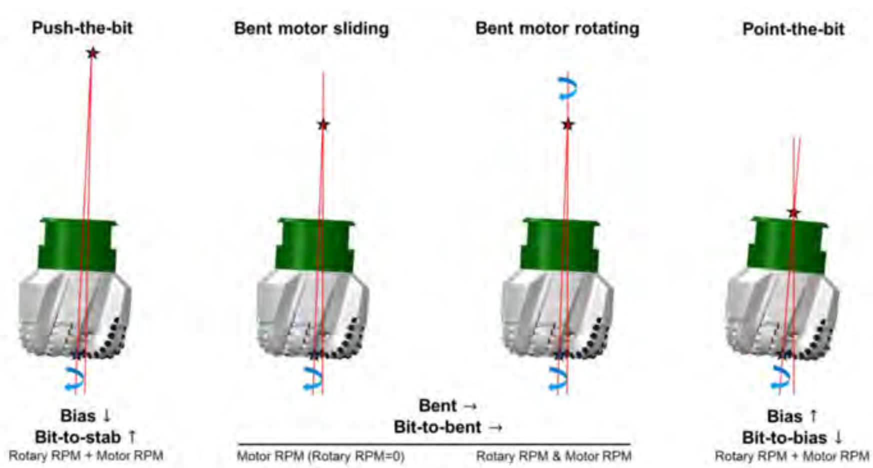


**Figure 1—the 4-parameters directional model applied to 4 distinct directional drilling contexts**

The point-the-bit model is defined by 3 parameters, which are thus added to the parameter space defined in (1):

$$PS = \{build\ rate,\quad bit\ RPM,\quad bias,\quad bit\ to\ bias\} \tag{2}$$

In a kinematic approach, the build rate and the bias are independent. In reality, the former is determined by the latter. Hence, it is up to the modeler to decide which combination of these parameters is representative of the reality. It strongly depends on the directional system mechanical behavior, but it can be approximated by using a 3-point geometry formula or some other kind of empirical relationship (Marchand and Kalantari, 2013). Again, this simplification of the model will be somehow compensated by letting these parameters evolve as random variables. Then, a high number of simulations will be run trying to make the statistical estimators converge.

### Physical model

Based on the computation of local geometric interactions, local forces can be computed. Fig. 2 shows the negative view of the hole geometry (in brown) drilled by a given bit design, the cutting volumes removed by each cutter (in orange) with the associated cutting forces (blue vectors) and the contact volumes (in red) with the associated contact forces (blue vectors). This kind of interactions where the gages of the bit significantly engage the borehole wall is typical from a directional simulation. Once the local forces are determined, they can be summed in order to provide global forces like the WOB (red-straight vector along Z axis), the side force (red-straight vector in the X-Y plane) and the TOB (red-circular vector).

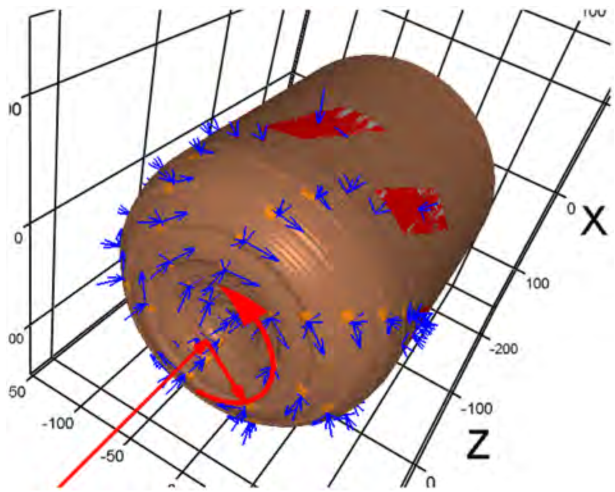


**Figure 2—view of all bit-rock interactions computed by the 3D bit simulator**

A variety of models are available in the literature to compute local cutting forces (Zijsling, 1987; Detournay and Defourny, 1992; Pelfrene et al., 2011; Amri et al., 2018). For the purpose of this study, local cutting forces have been computed based on a modified version of the cutting model developed by Gerbaud (1999) (Fig. 3).

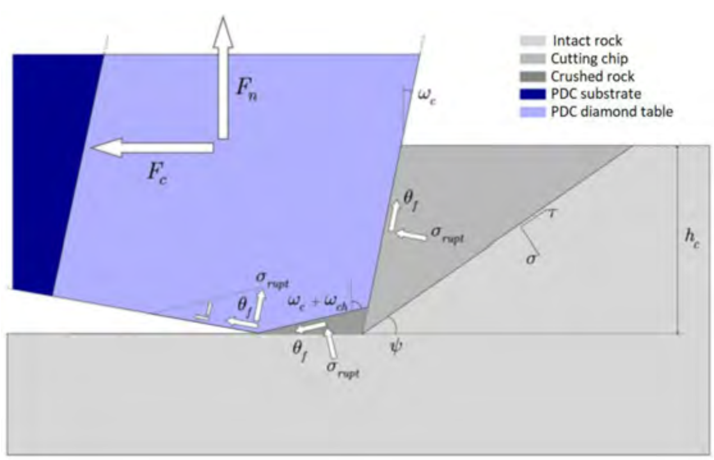


**Figure 3—schematic description of the cutting model**

The main modification consists in neglecting the so-called back cutter forces arising from an elasto-plastic upward deformation of the rock at the back of the cutter. Except for this effect, the equations of the cutting model are very similar and involve the following physical parameters: the unconfined compressive strength of the rock (UCS); its internal friction angle (IFA); the cutting friction angle (cufa) which measures the friction between the cutter face and the cutting chip; the bit depth and the mud density (dmud) which both contribute to determine the hydrostatic mud pressure which tends to strengthen the rock. Adding these parameters to (2) leads to:

$$PS = \{build\ rate,\ \ bit\ RPM,\ \ bias,\ \ bit\ to\ bias,\ \ UCS,\ \ IFA,\ \ cufa,\ \ bit\ depth,\ \ dmud\} \quad (3)$$

Just like cutting models, several contact models exist in the literature to compute local contact forces. For the purpose of this study, local contact forces have been computed based on the Hertz contact model with the assumption that bit contact parts are infinitely rigid in comparison to the rock. Equations of the model are described in Pelfrene et al. (2019) and involve 2 parameters which have been considered as random variables in this study, the Young's modulus of the rock (E) and its contact friction angle (cofa). Adding them to (3), gives:

$$PS = \{build\ rate,\ \ bit\ RPM,\ \ bias,\ \ bit\ to\ bias,\ \ UCS,\ \ IFA,\ \ cufa,\ \ bit\ depth,\ \ dmud,\ \ E,\ \ cofa\} \quad (4)$$

### Conclusion

The directional model used in this study involves a variety of geometrical and physical parameters. Whatever the complexity of such model, applying it to a 3D bit simulator in order to simulate actual field conditions generally exhibits significant discrepancies with downhole measurements.

These discrepancies can be either due to the assumptions of the model (simplifications); to the inherently uncertain nature of rock parameters; to the change in lithology along the drilling section; to a lack of knowledge on the specifications of the mechanical systems modeled; or to a simple variability of drilling and directional parameters set by the driller.

The main task of this paper is to account for the variability of the parameters identified above in order to understand how it impacts the directional performance of a given bit design. The operational objective is to make the bit design optimization process more robust by ensuring the performance of a given bit design is guaranteed over a statistically representative range of downhole conditions.

## Statistical analysis for cutting structure selection

### Cutting structures description

The first step of the bit design process consists in selecting a cutting structure which will achieve a good ROP while delivering a high steerability with an optimal tool face control.

Since the formation to be drilled is known for its heterogeneity, hardness and abrasiveness, a relatively heavy-set cutting structure is needed to ensure its durability along the run. 2 cutting structures that would fit the objectives of the application have been pre-selected: V716P (A20874) and V713P (A20629):

– V716P (A20874) is a 7 bladed bit design with a majority of 16mm PDC cutters and a double row of underexposed PDC cutters on each blade.
– V713P (A20629) is also a 7 bladed bit design mainly with 13mm PDC cutters and a double row of PDC cutters on each blade.

Fig. 4 shows the associated 2D bit profiles and main characteristics as well as the 3D views of the cutting structure.

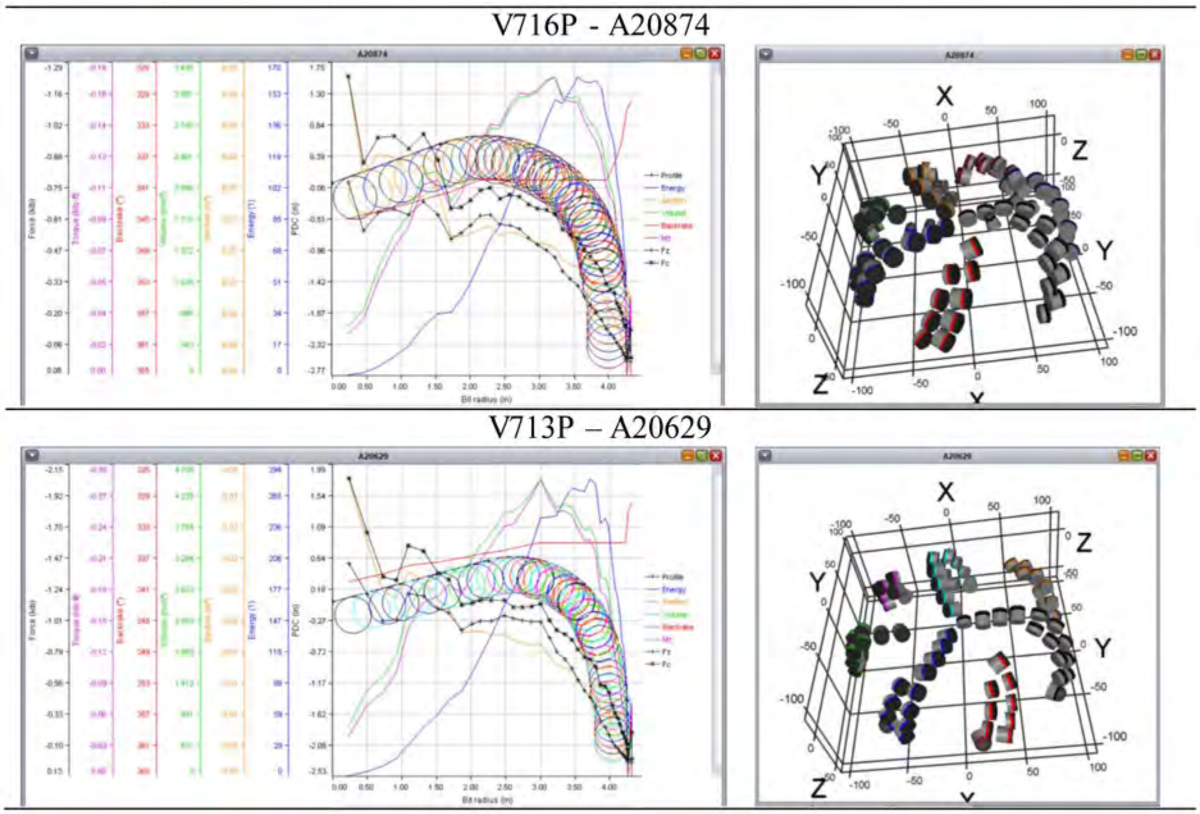


Figure 4—A20874 / A20629 2D bit profiles, characteristics and 3D views

## Statistical approach

Prior to running heavy simulations in a directional context, a preliminary set of simulations have been run in a straight drilling context with a proprietary 2D bit simulator described in detail in Carlos (2017) and Cuillier et al. (2017). In this context, the parameter space (4) reduces to 7 independent parameters listed in Table 1.

Table 1—parameter scenario for Sobol sensitivity analysis on the straight drilling model

| | Distribution | Unit | Avg | Sthev | Min | Max |
|---|---|---|---|---|---|---|
| ROP | Uniform | ft/hr | - | - | 30.0 | 50.0 |
| RPM | Fixed | RPM | 100.0 | - | - | - |
| Bit Depth | Uniform | kft | - | - | 9.0 | 11.0 |
| Mud density | Fixed | lb/gal | 11.6 | - | - | - |
| UCS | Normal | ksi | 12.0 | 1.0 | - | - |
| IFA | Normal | ° | 30.0 | 1.0 | - | - |
| cufa | Normal | ° | 11.0 | 0.5 | - | - |

The statistical approach consists first in setting the PDF for each of them. The type of law as well as its characteristics has a significant influence on results. Hence, it must be defined with care while accounting for the reality of the application of interest and the actual knowledge we may have on it (Begg et al., 2014).

Additionally, some of these parameters interact with eachother. This does not mean that these parameters depend on eachother, it means that the model is impacted by a combination of them rather than each of them independently. The first set of interacting parameters are RPM and ROP. Indeed, the parameter that drives the hole geometry is the ratio ROP/RPM rather than ROP and RPM independently. It allows to make only one of them vary while fixing the other. Thus, the RPM has been fixed to its average value. And the

ROP, which varies in time, has been defined as a uniform distribution within a target range of maximum achievable ROP representative of the application.

The second set of interacting parameters are bit depth and mud density. Indeed, the parameter that drives the mud pressure in the model involves the product (bit depth x mud density). Thus, the mud density has been fixed to its average value. And just like the ROP, the bit depth parameter, which varies in time, has been defined as a uniform distribution within the section drilled.

Other parameters have been defined as standard normal distributions, with their average values corresponding to the average values of the section drilled and their standard deviation corresponding to a reasonable uncertainty.

A statistical sample of this parameter space has then been generated. Just like other statistical tools used in this study, the algorithm used to generate this sample belongs to the Python OpenTurns library (Baudin et al., 2015). This algorithm is based on an implementation of a random design of experiment named 'Sobol indices experiment'. The size of the experiment was set to 5000, which, with Nd = 5 independent variable parameters considered, led to a total of 80k samples. The diagonal of the crossplot in Fig. 5 shows how the size of the experiment allows the empirical distributions to converge well towards the theoretical distributions. The empirical statistical moments (average, standard deviation, min, max) of these distributions have also been compared to the theoretical ones set in Table 1, and they match closely. From the non-diagonal terms, it can also be noted that the chosen design of experiment evenly fills in the parameter space, without exhibiting any gaps or anisotropy. From these observations, we thus expect the results of the statistical analysis to fairly represent the reality of the selected parameter scenario.

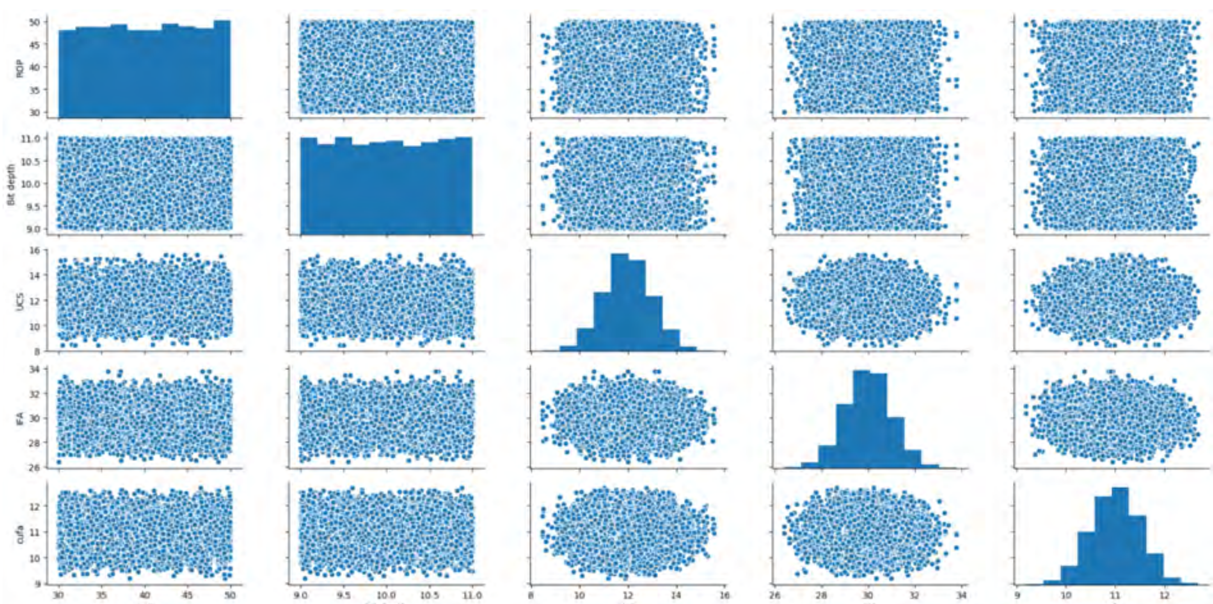


**Figure 5—crossplot of the input parameters used for the Sobol sensitivity analysis on the straight drilling model**

## Uncertainty propagation through the 2D model

For each bit design and for each of the 80k parameters combinations, one straight drilling model simulation has been run. The comparative performance of A20874 vs A20629 has been done based on 3 classically used performance indicators: the WOB and the TOB to estimate the aggressiveness of the cutting structure in axial mode and torsional mode respectively. The % imbalance (imb), which is defined as the ratio (in %) of the side force to the WOB and which measures the tendency of the bit to drill off-center. These 3 indicators have been computed by the simulator. The corresponding crossplots and statistical moments are shown in Fig. 6.

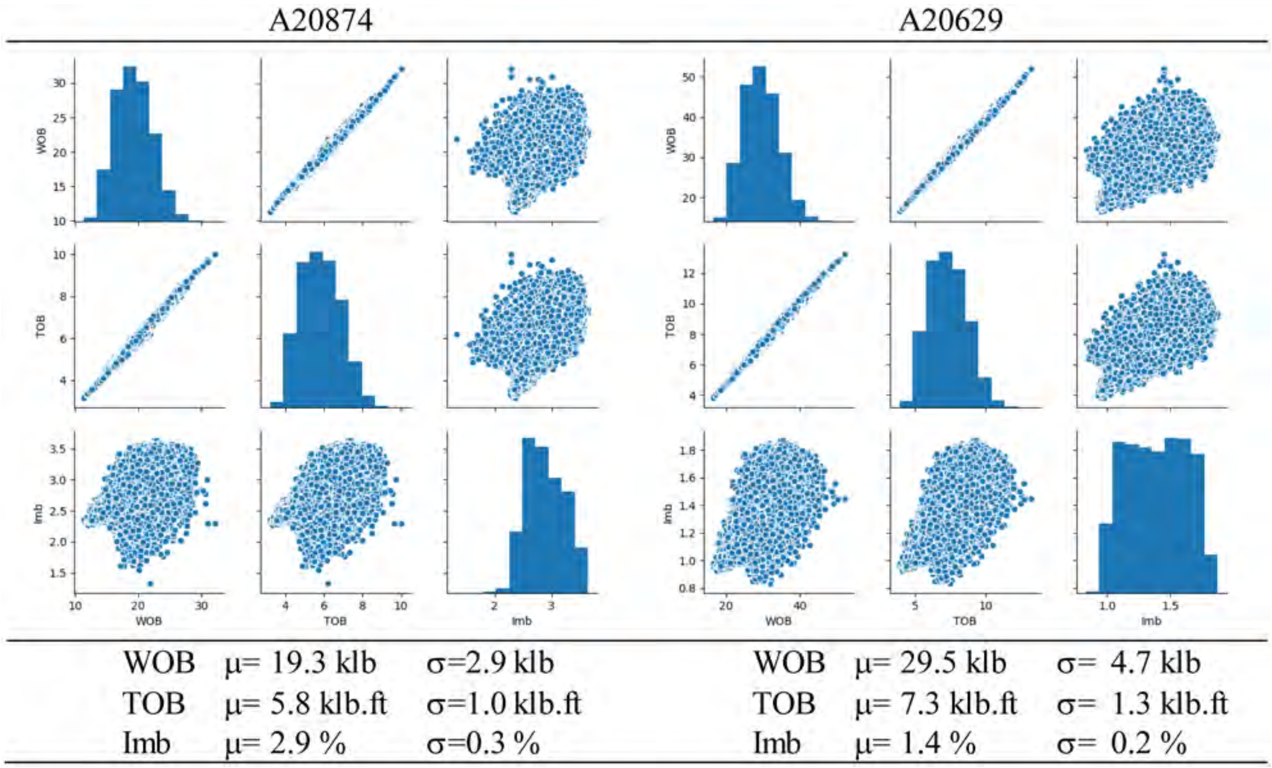


**Figure 6—A20874 / A20629 performance comparison based on statistical straight drilling simulations**

These results show that A20874 is in average more aggressive than A20629 both axially and torsionally since, in average, it requires significantly less WOB and TOB in the range of given ROP. On the contrary, A20629 is better balanced in average than A20874. Considering that around 95% of the values reached by the imbalance range within [μ-2σ, μ+2σ], we can also confirm that both cutting structures remain well below the disqualifying 5 % imbalance in the whole range of the parameter space. Moreover, although the imbalance of A20874 is about twice the imbalance of A20629, the variability of the former is quite close to the variability of the latter. Interestingly, the distribution of the former roughly follows a normal distribution, whereas the distribution of the latter roughly follows a uniform law. Based on these observations, we can deduce that the imbalance response of A20874, yet higher than A20629's one, is relatively more reliable in the range of variation of the parameter space.

## Global sensitivity analysis on the 2D model

Based on the same design of experiment, a global sensitivity analysis (Sobol analysis) has been performed on both bit designs in order to determine the most influential parameters and estimate whether it was possible to fix some of them to reduce the dimension of the parameter space. The results of this analysis are shown in Fig. 7, for A20874 only, since A20629 shows exactly the same trends.

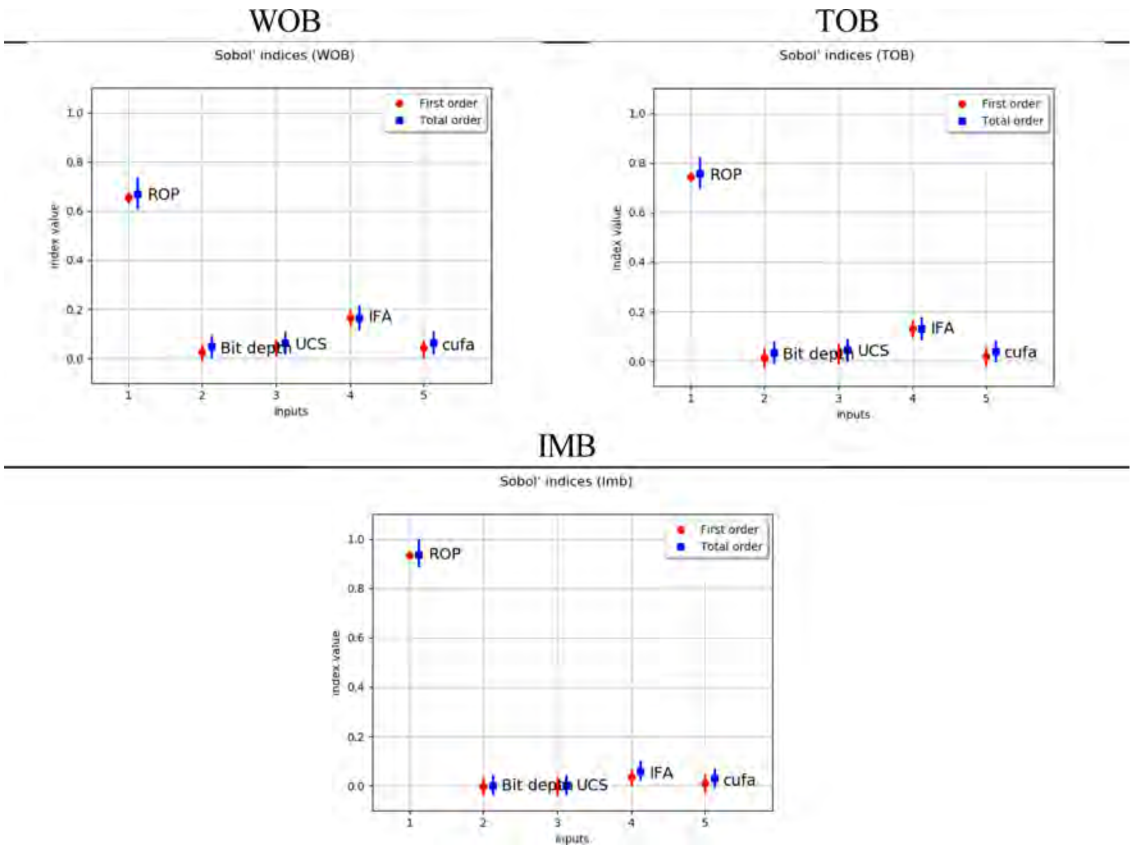


**Figure 7—Sobol indices computed based on the statistical straight drilling model (A20874)**

First, the relatively small error bars surrounding each data points on these plots indicates a good statistical convergence of the computation. Second, the relatively small differences between the first order Sobol indices (red dots) and the corresponding total order Sobol indices (blue dots) indicates that there is no significant interactions between the 5 variable parameters (Saltelli et al., 2008).

Based on these preliminary observations, results mainly show that between 70% and 95% of the variability of the 3 performance indicators are explained by the variability of the ROP alone. All other parameters correspond to physical model parameters and are much less influential. Unfortunately, the only parameter which significantly affects the computation time of a 3D bit simulator is the ROP. Consequently, these results are not sufficient to allow us to fix the ROP in the directional drilling scenario considered in the next section.

**Conclusion**

Results obtained with the statistical analysis implemented in this section show that selecting the A20874 cutting structure represents a good trade-off between a good aggressiveness allowing to reach elevated ROP and a good balancing well below the disqualifying standards. The statistical approach also tends to show that A20874 balancing should be relatively robust within the wide range of parameters considered.

## Statistical analysis for gage configuration selection

Based on the A20874 cutting structure selected in the previous section, 4 different gage configurations have been pre-selected and a statistical analysis has been implemented to select the optimal one. The primary goal of the application is to deliver a high steerability bit design able to provide an optimal tool face control in a demanding short radius well.

## Description of gage configurations

In order to best match the gage configuration selection to the given RSS drive system of the application, 4 different geometries were pre-selected (Fig. 8):

- Stepped Gage (SG) – A20874: 2″ full diameter + 1″ undercut, to provide some space for a bit tilt mechanism to activate and reduce lateral reactive forces.
- Full Gage (FG) – A20820: 3″ full diameter gage configuration usually adapted to non directional application but which can be used in certain tangent trajectory with soft formation to prevent dropping tendency.
- Undercut Gage 1 (UG1) – A21110: 2″ undercut gage to allow for maximum lateral displacement and low reactive forces.
- Undercut Gage 2 (UG2) – A20717: 1″ undercut + 1″ undercut + 1″ undercut to allow both maximum lateral displacement and maximum bit tilt.

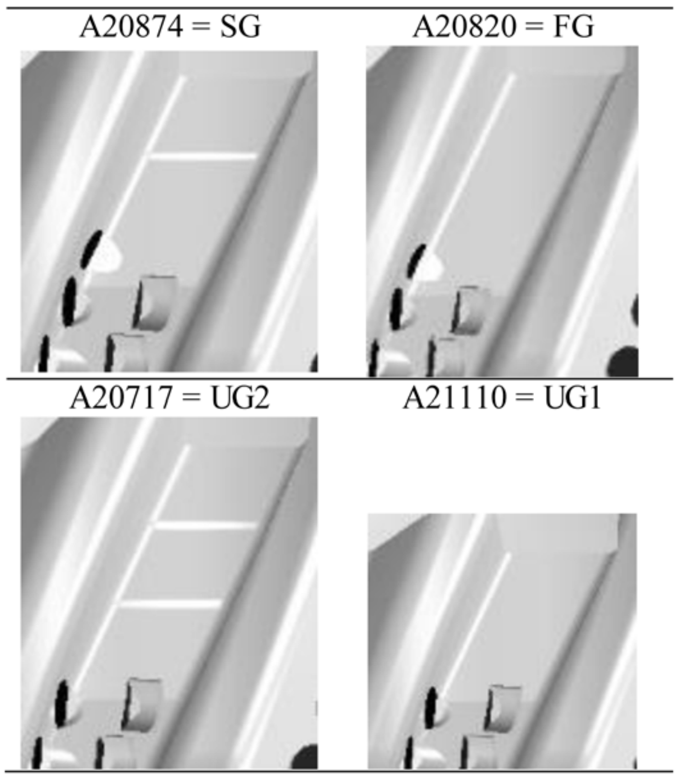


Figure 8—the 4 pre-selected gage configurations

## Directional simulations and directional performance indicators

Due to the intrinsically three-dimensional nature of the directional problem, simulations are conducted with the 3D bit simulator described at the beginning of this paper, which is based on the same physical models as the 2D bit simulator presented in the previous section. In this section, some of the results provided by the 3D bit simulator are described and a set of directional performance indicators used in the statistical analysis are defined.

Fig. 9 compares the bit/rock interactions computed for a single sample of directional parameters defined in (4), applied to the 4 gage configurations. It shows that A20874-SG and A20820-FG significantly engage the borehole wall as revealed by the large contact geometry on their gage pads and the associated local contact forces (blue vectors). In comparison, A20717-UG2 and A21110-UG1 do not engage it significantly.

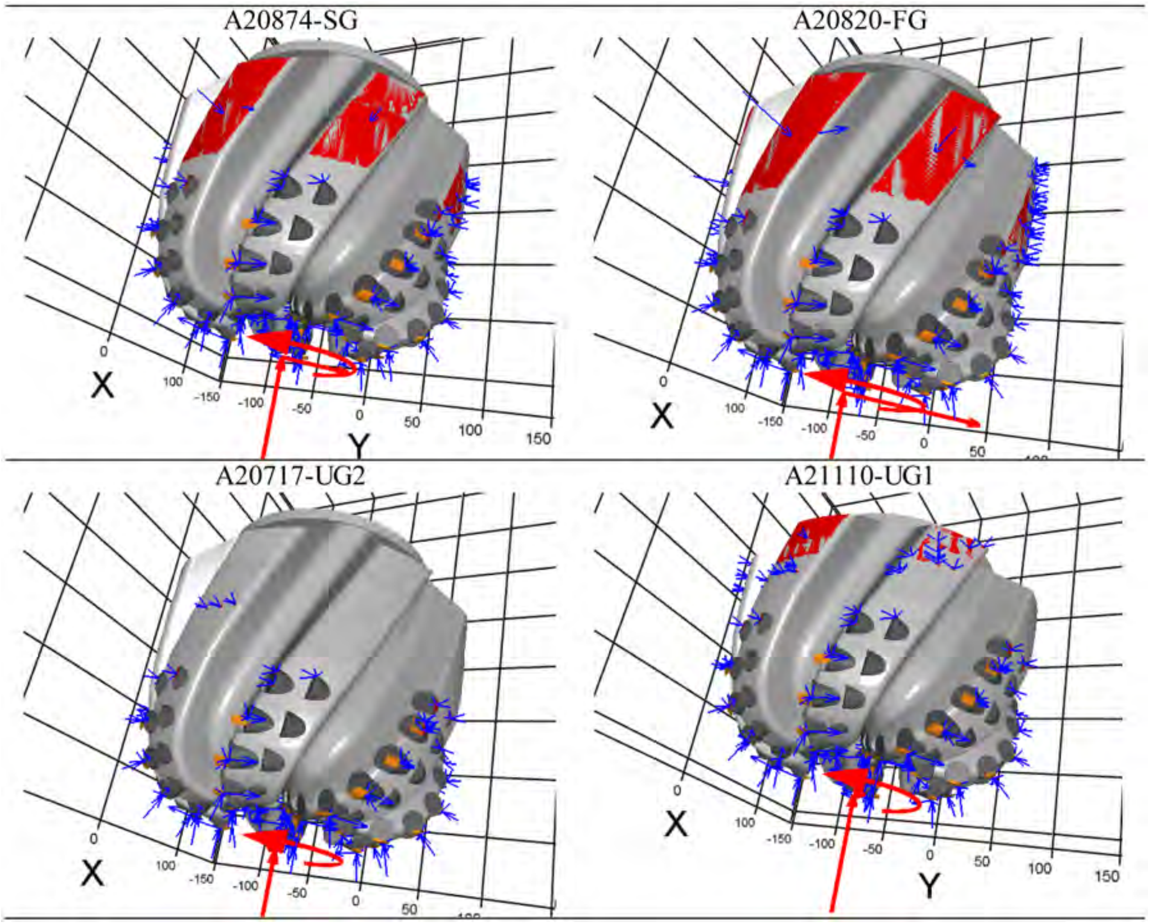


**Figure 9—comparison of bit/rock interactions for the 4 gage configurations**

In the following, two major outputs of these computations will be used: the total side force and the walk angle (Ho, 1995). The total side force is defined as the projection of the total force exerted on the drillbit on the X-Y plane, the Z-axis pointing parallel to the well axis. The side force vector can be seen in Fig. 9 (A20874-SG and A20820-FG) as a red vector at the bottom of the bit. Note that in a directional context, most of the side force vector intensity comes from the contacts on the gage pads rather than from the cutting forces. Note also that the side force for A20717-UG2 and A21110-UG1 is too small to be observed.

The walk angle is defined as the angle between the side force vector and the direction of the bit side movement. As the 3D bit simulator is based on a kinematic approach, the latter corresponds to the direction in which the bit is tilted, and the orientation of the side force is an output of the simulation. Most bit designs walk left, or in other words have a negative walk angle. Fig. 10 shows the evolution of these 2 directional outputs over a bit revolution.

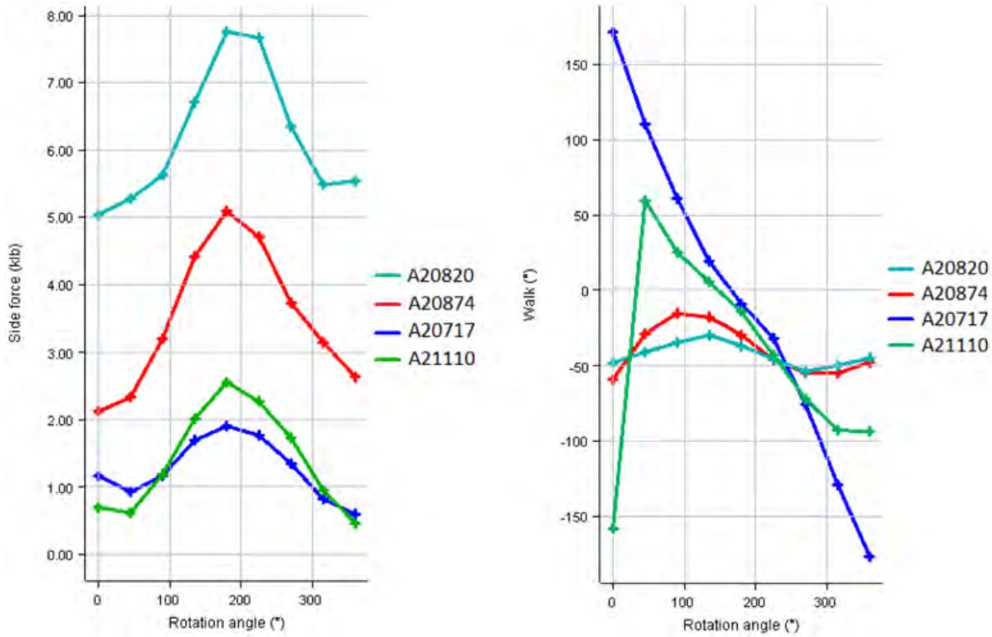


**Figure 10—evolution of the side force and the walk angle over a bit revolution for the 4 gage configurations**

These plots show that the side force and the walk angle vary much over a bit revolution. This observation led us to analyse both the average of the side force and the walk angle, but also the variability of these outputs over a bit revolution. Four directional drilling performance indicators have thus been defined:

- "Average steerability": simply defined here as the average side force over a bit revolution. Indeed, under a given directional movement (kinematic approach), a first drill bit generating less side force than a second one, can be considered as more steerable. Note that this definition is valid provided that drillbits are compared with respect to the same parameter scenario, which is the case in this study.
- "Average walk tendency": defined as the average walk angle over a bit revolution
- "Instantaneous steerability": defined as the standard deviation of the side force over a bit revolution and subjected to the same remark as the average steerability.
- "Instantaneous walk tendency": defined as the standard deviation of the walk angle over a bit revolution

These 4 directional performance indicators have been used in the statistical analysis presented in the next sections to compare the directional response of the 4 gage configurations.

**Morris sensitivity analysis on the 3D directional model**

The directional parameter space (4) contains 11 independent parameters which makes a statistical analysis impractical to run in the limited time frame of the bit manufacturing process. In this section, a sensitivity analysis is performed to reduce the dimension of the model.

We focus on parameters which strongly influence the simulation time: rop, bias, bit-to-bias and build rate. As a global sensitivity analysis would have been too long to perform with the 3D bit simulator, a screening method has been chosen to reduce the simulation time while providing valuable qualitative results. The Morris method has been selected, with a standard grid setting of 4 levels and 10 trajectories, leading to a total number of 50 simulations. The corresponding parameter scenario is shown in Table 2.

**Table 2—parameter scenario for Morris sensitivity analysis on the directional model**

| | Distribution | Unit | Avg | Sthev | Min | Max |
|---|---|---|---|---|---|---|
| Depth in | Fixed | kft | 9.0 | - | - | - |
| Depth out | Fixed | kft | 11.0 | - | - | - |
| Build rate in | Uniform | °/100ft | - | - | 5.0 | 10.0 |
| Build rate out | = Build rate in | °/100ft | - | - | - | - |
| Bias | Uniform | ° | - | - | 0.5 | 0.7 |
| Bit-to-bias | Uniform | ft | - | - | 1.5 | 3.0 |
| ROP | Uniform | ft/hr | - | - | 10 | 50 |
| RPM | Fixed | RPM | 100 | - | - | - |
| Bit Depth | Fixed | kft | 10.0 | - | - | - |
| Mud density | Fixed | lb/gal | 11.6 | - | - | - |
| UCS | Normal | ksi | 12.0 | - | - | - |
| IFA | Normal | ° | 30.0 | - | - | - |
| Cufa | Normal | ° | 11.0 | - | - | - |
| E | Uniform | GPa | 3.0 | - | - | - |
| Cofa | Uniform | ° | 40.0 | - | - | - |

This scenario sets the distribution of the 4 parameters listed above as uniform in order to determine their respective influence on the directional drilling performance indicators with minimal assumptions on their actual field values.

The results of the Morris analysis performed on the directional model with bit design A20874-SG are plotted in the Morris diagram ($\mu^*$, $\sigma$) in Fig. 11. In this diagram, $\mu^*$ designates the average of the absolute value of the effect of each individual parameter on the output. The higher this value, the higher the effect. $\sigma$ designates the standard deviation of the effect of each individual parameter on the output. When $\sigma$ is low (typical lower than $0.5\mu^*$, i.e. the dashed line of the diagram), it means that the effect of the input on the output is linear and that the input does not interact with another input. When $\sigma$ is high, it means that the effect is non-linear or that the input interacts with another input. Only the 4 directional drilling performance indicators defined above have been plotted.

Fig. 11 (top left) indicates that the average steerability is mainly influenced by the bias and varies linearly with it in the range of values set by the scenario. Fig. 11 (bottom left) indicates that the instantaneous steerability is mainly influenced by the ROP and varies linearly with it. Fig. 11 (top right and bottom right) shows some non-linearities in the model or some interactions between the input parameters with respect to the average and the instantaneous walk tendency. A more advanced sensitivity analysis would help to discriminate between non-linearities and interactions. But it is believed that there are some significant interactions between the bias, the bit-to-bias and the build rate because the three of them directly impact the relative tilting movement of the bit inside the borehole.

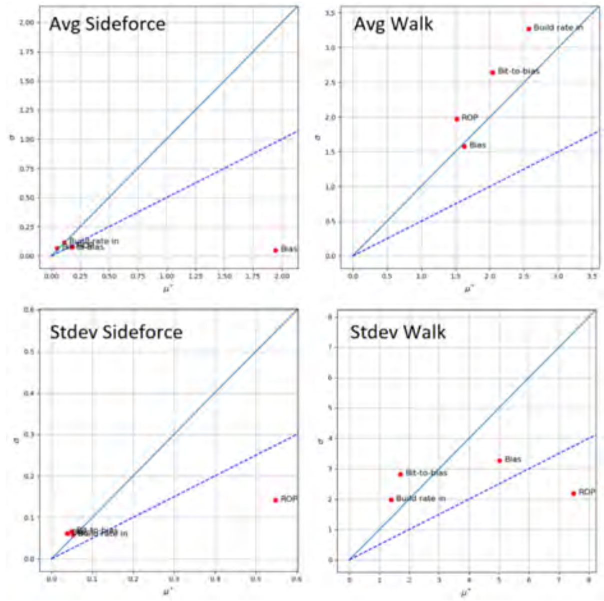


Figure 11—Morris diagrams of the directional drilling model (A20874-SG)

Besides, Fig. 11 (top right) shows that the effect of these parameters on the average walk tendency is limited in amplitude. This is confirmed by Fig. 12 which illustrates the variability of the 4 directional drilling performance indicators with the help of crossplots. The variability of the average walk is indeed limited to a small 5° range. On the contrary, the variability of the instantaneous walk tendency is significantly higher [4.0°-18.0°]. However, Fig. 11 (bottom right) shows that the most influential parameters on the instantaneous walk tendency are the rop and the bias.

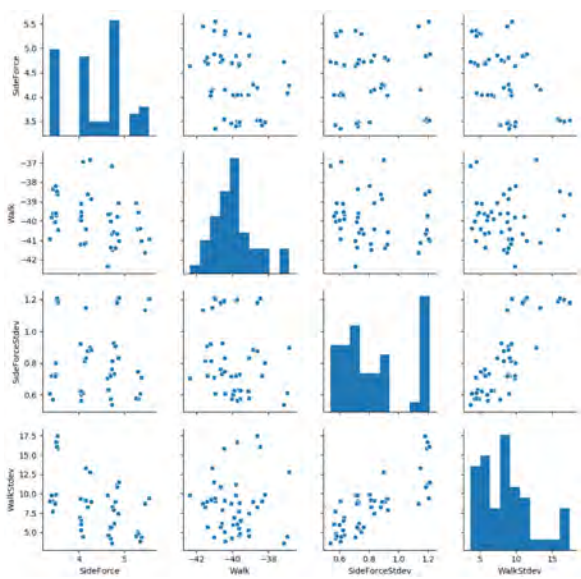


Figure 12—crossplots of the directional performance indicators in Morris analysis parameter scenario (A02874-SG)

In conclusion, the Morris analysis and the associated uncertainty propagation through the 3D directional model, although being conducted on a very limited number of samples (50), tend to show that the bias and the ROP are the most influential parameters of the 4 parameters considered on the directional performance indicators. Build rate and bit-to-bias can thus be fixed as having a limited influence. Although being very influential, ROP shows some strong linearity with the outputs. Hence, it should only impact the gage selection process by amplifying the tendencies and not by altering them. ROP will thus be fixed too in order to limit further the simulation time.

## Uncertainty propagation through the 3D directional model

The Morris analysis has allowed us to reduce the model dimension. Among the parameters significantly influencing the simulation time, only the bias remains. In this section, other parameters of the parameter space (4) are injected back into the analysis and listed in Table 3.

**Table 3—parameter scenario used for the uncertainty propagation through the directional model**

| | Distribution | Unit | Avg | Sthev | Min | Max |
|---|---|---|---|---|---|---|
| Depth in | Fixed | kft | 9.0 | - | - | - |
| Depth out | Fixed | kft | 11.0 | - | - | - |
| Build rate in | Fixed | °/100ft | 8.0 | - | - | - |
| Build rate out | Fixed | °/100ft | 8.0 | - | - | - |
| Bias | Discrete Uniform | ° | - | - | 0.5 | 0.7 |
| Bit-to-bias | Fixed | ft | 2.0 | - | - | - |
| ROP | Fixed | ft/hr | 50 | - | - | - |
| RPM | Fixed | RPM | 100 | - | - | - |
| Bit Depth | Uniform | kft | - | - | 9.0 | 11.0 |
| Mud density | Fixed | lb/gal | 11.6 | - | - | - |
| UCS | Normal | ksi | 12.0 | 1.0 | - | - |
| IFA | Normal | ° | 30.0 | 1.0 | - | - |
| cufa | Normal | ° | 11.0 | 0.5 | - | - |
| E | Uniform | GPa | - | - | 2.0 | 4.0 |
| cofa | Uniform | ° | - | - | 30.0 | 50.0 |

The decision to fix some parameters in this table has been justified above in this paper. Among the remaining variable parameters, some of them are poorly known in the application, like the Young's modulus and the contact friction angle (cofa). Some others simply vary much within the drilling interval, like the bit depth. For both these parameters, a uniform distribution law has been used. Some others are well known measurable and do not vary much within the drilling section, like the UCS, the IFA and the cutting friction angle (cufa). The last one, the bias, has a major effect on the simulation time. In order to further reduce the simulation time, it has been decided to use a discrete uniform distribution rather than a continuous one to account for the uncertainty of the directional system. The discrete set of values the bias can randomly take has been sized to 10.

The design of experiment chosen to generate the statistical sample is the Latin Hypercube Sampling. This quasi-random algorithm allows to efficiently sample the whole range of the parameter space without requiring as many samples as the Monte Carlo experiment for example. The size of the experiment was set to 1000. Fig. 13 shows how empirical distributions converge well towards theoretical distributions. On the first row and column of the plot, it can be noticed the typical pattern of the bias discrete uniform distribution in the min/max range given the table above. Although the whole sample is much less dense than the one used in the statistical analysis of the straight drilling model (Fig. 5), we still expect the results of the statistical analysis to fairly represent the reality of the selected parameter scenario.

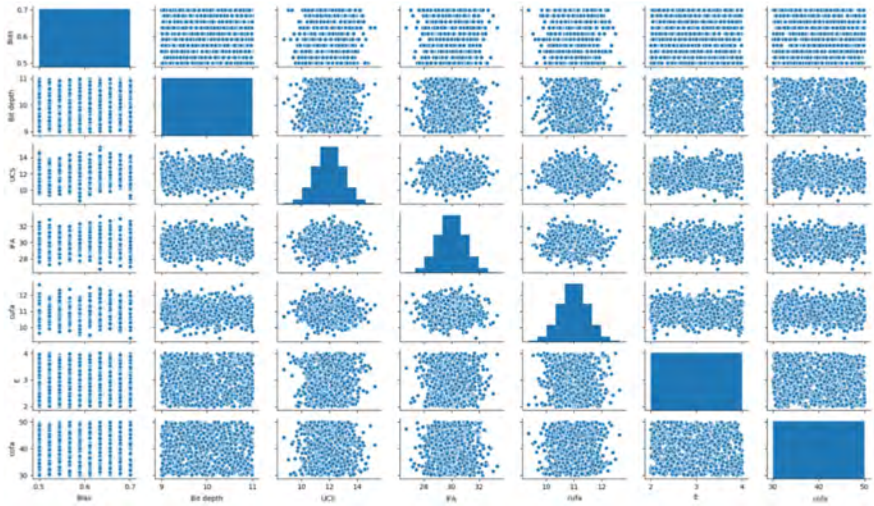

**Figure 13—crossplots of the input parameters used for the uncertainty propagation through the directional model**

For each of the 4 gage configurations and for each of the same 1000 parameters combinations, one directional drilling simulation has been run. Based on which, the 4 directional performance indicators have been computed. The resulting crossplots are shown in Fig. 14.

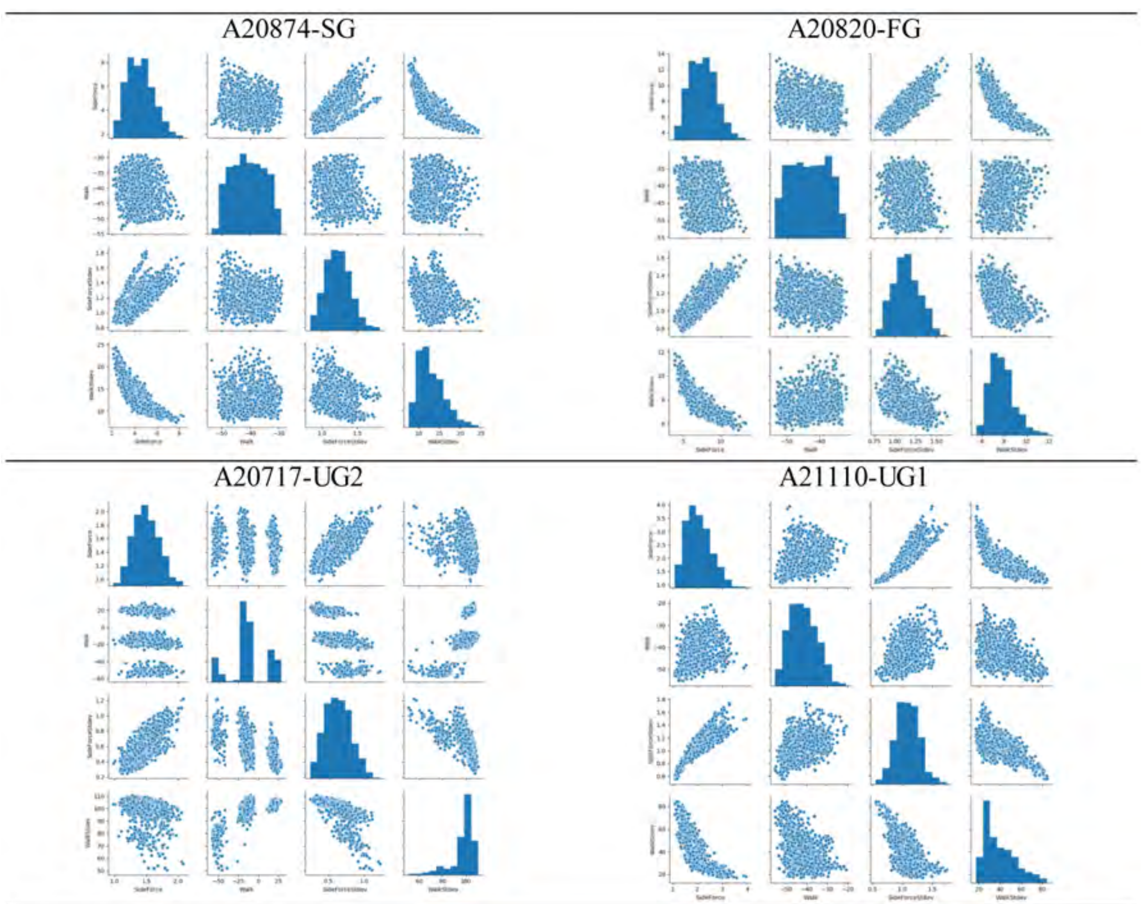


**Figure 14—crossplots of the 4 directional performance indicators for the uncertainty propagation through the directional model applied to the 4 gage configurations**

Empirical distributions for A20874-SG, A20820-FG and A21110-UG1 show very similar patterns. On the contrary A20717-UG2 exhibits a clustering pattern in the average walk tendency distribution and to a lesser extent in the instantaneous sideforce distribution. This pattern is believed to be due to 2 factors: as observed in Fig. 9 the gage pads of this design do not engage much the borehole wall whereas the bias is set to 0.6°. Now the bias is set to vary between 0.5° and 0.7°, the bit response is likely to jump between a situation of no engagement at all to a situation of continuous engagement. The second factor which could amplify this clustering effect is the fact that the distribution of the bias is discrete.

The statiscal moments corresponding to the 4 directional performance indicators and the 4 gage configurations are plotted in Fig. 15.

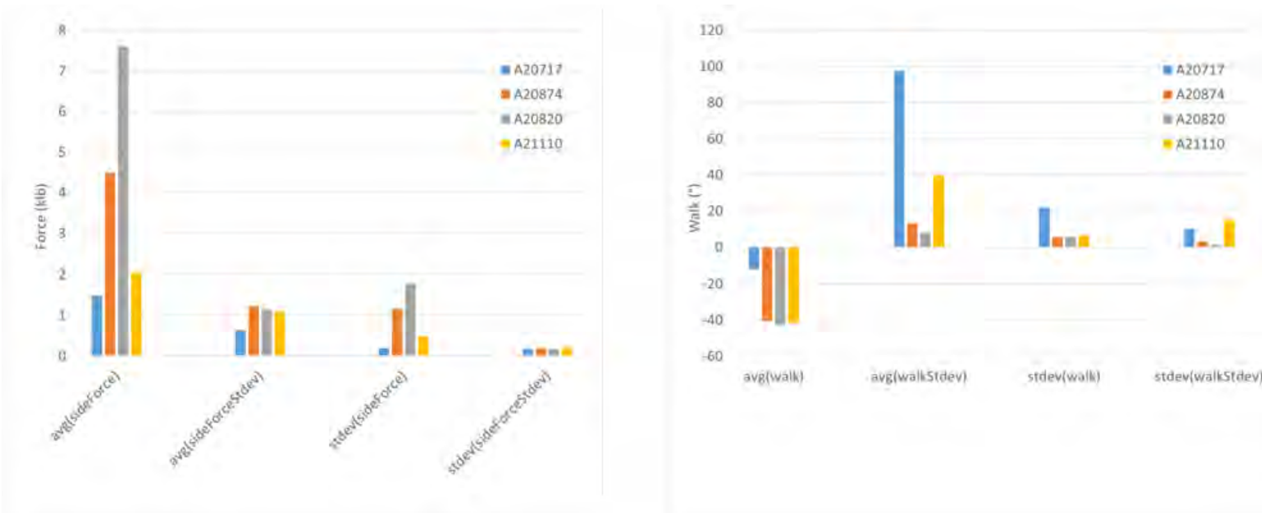


**Figure 15—statistical moments of the 4 directional performance indicators for the uncertainty propagation through the directional model applied to the 4 gage configurations**

In terms of steerability, the following results are observed:

- The ranking in terms of average steerability 'avg(sideForce)' are A20717-UG2 > A21110-UG1 > A20874-SG > A20820-FG
- 'stdev(sideForce)' interestingly indicates that the variability of the average steerability over the range of parameters simulated is significantly lower for A20874-SG than for A20820-FG.
- This result somehow compensates the higher average of the instantaneous steerability 'stdev(sideForce)' observed on A20874-SG in comparison to A20820-FG.

In terms of walk tendency:

- All gage configurations walk left around −40° ('avg(walk)'), except for A20717-UG2 which walks left at about −20°.
- A20874-SG and A20820-FG walk left steadily, i.e. with a limited variability over the range of parameters 'stdev(walk)'
- considering the average of the instantaneous walk tendency 'avg(walkStdev)', the differences between A20874-SG and A20820-FG are not significant and the values of the instantaneous walk tendency are not significant neither.

## Conclusion

The statistical analysis conducted in this section shows that the A20874-SG gage configuration is the best trade-off between a good level of average steerability and a standard average walk tendency. It also demonstrates that although the variability per revolution of A20874-SG is higher than that of A20820-FG, its variability on the whole range of parameters of the statistical experiment is lower. This unexpected result tends to show how robust the A20874-SG bit design behaves under uncertain conditions, which should ease its tool face control.

## Case study: high dogleg application in a Kuwait field

### Field Application

The 8 1/2-in. bit A20874-SG resulting from this design selection process was used to drill in an important reservoir in Kuwait. The reservoir formation drilled typically shows a variable quality and heterogeneity. It is mainly a sand base section with shale intervals. This field has been developed for many decades and is an appropriate application for this RSS PDC bit design process to further push the optimization process.

The bit was run on a non-motorized RSS BHA, and drilled using a standard oil based mud (OBM) drilling fluid. The WOB was between 10 and 22 Klb at approximately 100 RPM. The short radius wells had a secondary KOP at approximately 9,450 ft and a built angle from 46° to approximately 88.5° at 10,190 ft MD.

### Run details

An in-house petrological analysis software based on mud logs and described in Cuillier et al. (2017) has confirmed the range of UCS used in this paper (Fig. 16). The assumption of relatively homogeneous formations all along the section at around 10-15 kpsi has also been confirmed.

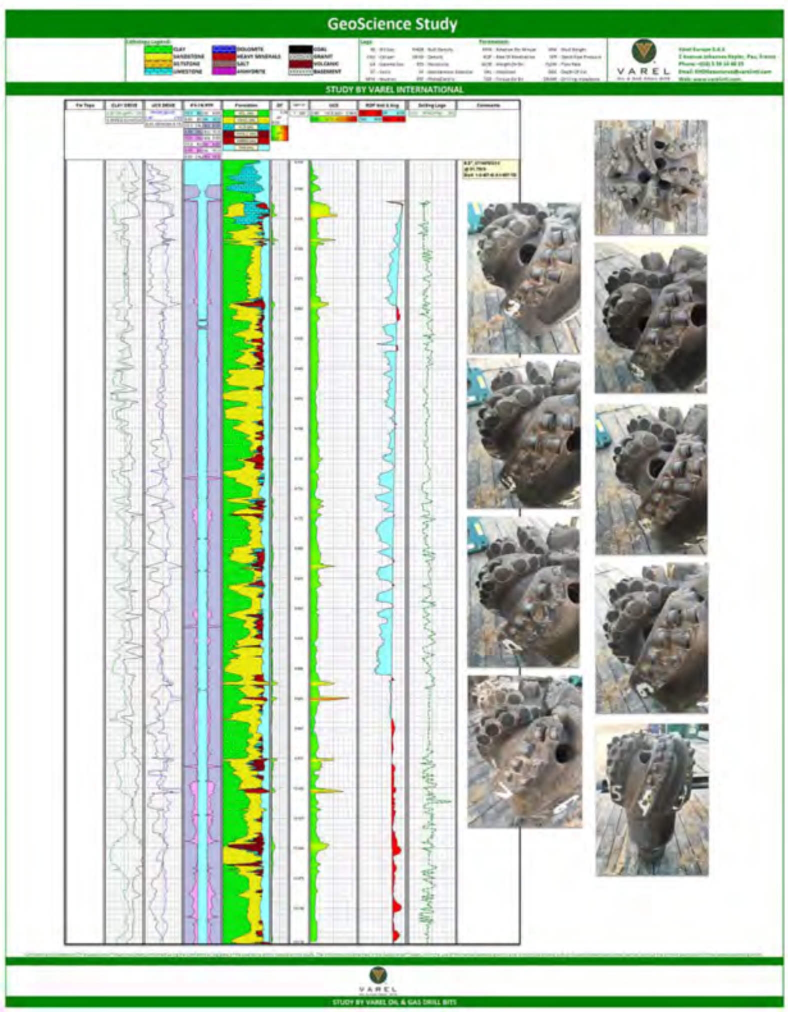


Figure 16—petrological result plot and bit dull pictures

## Directional response analysis

The observed directional reponse of the drill bit is shown in (Fig. 17) with inclination/azimuth and DLS evolution versus measured depth. It appears that downlink were regularly made along the section with different Tool Face angle orientations and different Percentage of Power transmitted to the point-the-bit system. The bit allowed the achievement of high DLS up to 8.5°/100ft when using 50% to 60% power on the RSS Point-the-bit system (Fig. 17).

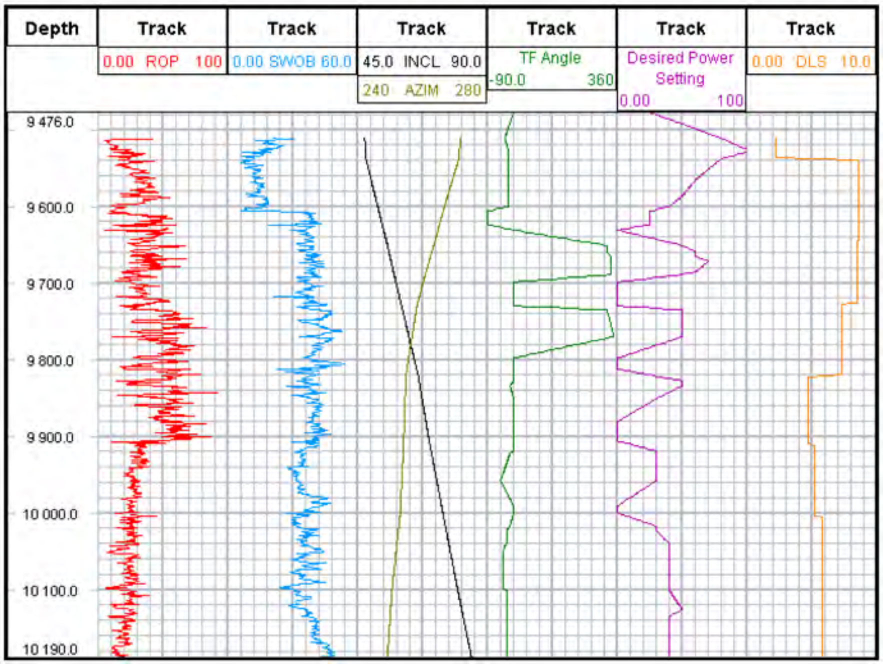


Figure 17—BHA directional response and RSS setting

## Performance results and comparison

The bit drilled 714 ft (217 m) at a record ROP of 31.7 ft/hr (Fig. 18) while building angle from 46° to 88.5° inclination and turning from 272.5° to 249°. The bit achieved a 49% ROP improvement compared to the offset average in this application. The dull grade for the bit is 1-2-BT-G-X-I-WT-TD as can be seen in the pictures above. The bit contributed to an efficient drilling coupled with an excellent directional control which resulted in a new ROP benchmark in the area (Fig. 18)

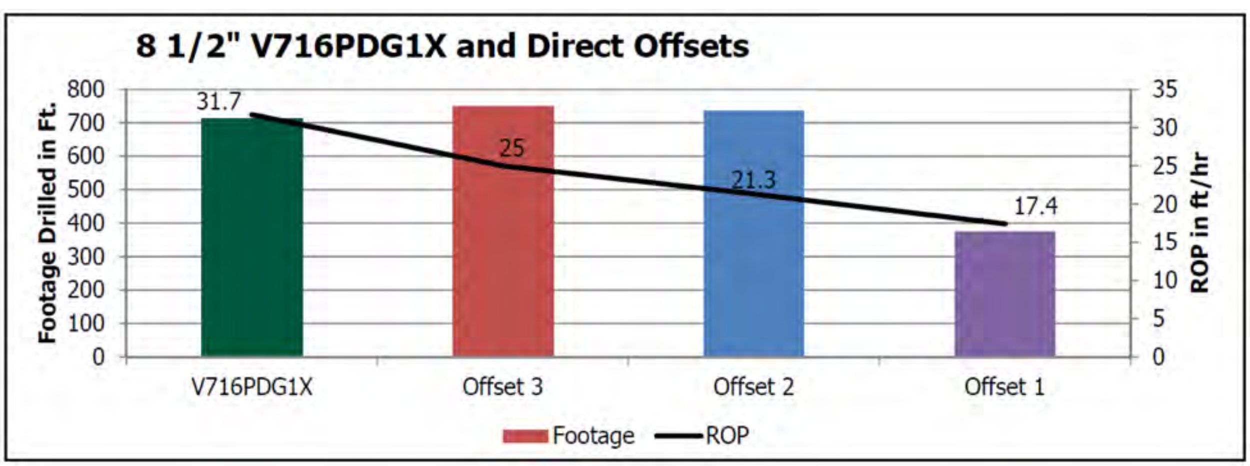


Figure 18—performance chart comparison on 8 1/2-in. section

## Conclusion

In this paper, a statistical approach has been developed to improve the reliability of the PDC bit design optimization process and ensure that the expected directional behavior of a given drill bit is robust over a well-defined range of drilling parameters.

A variety of tools have been developed in order to analyse and understand the statistical response of a directional model implemented in a 3D bit simulator. The parameter space has been defined with respect to the constraints of the field application. A sensitivity analysis has been conducted on the model to determine the most influential parameters. This has allowed to reduce the dimension of the problem and hence to compute an optimal number of simulations. Uncertainties have been propagated through the 3D directional model to determine the optimal bit design according to a set of directional performance indicators.

The statistical approach has been applied to an 8 1/2-in. bit design drilling a 714 ft section of a Kuwait field application. Based on this methodology, a bit design has been selected and manufactured. The bit was run on a high dogleg rotary steerable system and directional assembly. The bit achieved the high steerability goals required by the application while showing a good compatibility with the directional tool. Moreover, ROP was increased by 27% compared to offset wells, setting a record in the field.

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## References

Amri, M., Pelfrene, G., Gerbaud, L., Sellami, H., Tijani, M., 2016. Experimental investigations of rate effects on drilling forces under bottomhole pressure. *Journal of Petroleum Science and Engineering*, Volume **147**, 2016, Pages 585–592.

Amri, M., Pelfrene, G., Jahangir, E., Tijani, M., Sellami, H., 2018. Numerical and analytical study of rate effects on drilling forces under bottomhole pressure. *International Journal of Rock Mechanics and Mining Sciences*, Volume **110**, 2018, Pages 189–198.

Barton, S. P., May, H. S., Johnson, S., 2009. Gauge, Cutting Structure, Torque Control Components - What Really Counts for Optimal Tool Face Control With FC Drill Bits? *Society of Petroleum Engineers*.

Baudin, M., Dutfoy, A., Iooss, B., Popelin, A.-L., 2015. OpenTURNS: An industrial software for uncertainty quantification in simulation.

Bazargan, H., Christie, M., Tchelepi, H., 2013. Efficient Markov Chain Monte Carlo Sampling Using Polynomial Chaos Expansion. SPE 163663.

Begg, S. H., Welsh, M. B., Bratvold, R. B., 2014. Uncertainty vs. Variability: What's the Difference and Why is it important? SPE-169850-MS.

Boualleg, R., 2006. Modélisation des systèmes de forage en formations géologiques anisotropes. Thèse de Doctorat. Ecole Nationale Supérieure des Mines de Paris.

Carlos, J., 2017. Software solutions. *Oilfield Technology Magazine*, Issue June 2017.

Chen, S., Arfele, R., Glass, K., 2007. Modeling of the Effects of Cutting Structure, Impact Arrestor, and Gage Geometry on PDC Bit Steerability. AADE-07-NTCE-10.

Cuillier, B., Al-Enezi, D., Goswami, B., Al-Salamin, J., Sayed, S., Mikhail, B., El Genidy, E., Reboul, S., 2017. Prediction and Analysis of PDC Bit Downhole Behavior Provides Insights and Efficiencies for Directional Drilling. SPE-186885-MS.

Detournay, E., Defourny, P., 1992. A phenomenological model of the drilling action of drag bits. *Int. J. Rock Mech. Min. Sci*. **29** (1), 13–23.

Gerbaud, L., 1999. Optimisation de l'interaction PDC-roche application à la conception d'outils pour forage pétrolier en petit diamètre. Thèse de doctorat, Ecole Nationale Supérieure des Mines de Paris.

Gradl, C., Eustes, A. W., Thonhauser, G., 2008. An Analysis of Noise Characteristics of Drill Bits. SPE 115987.

Ho, H.-S., 1995. Method and system of trajectory prediction and control using PDC bits. United States Patent 5,456,141.

Li, G., Bai, M., 2012. Parametric sensitivity investigation: Analysis of wellbore stability. *Harmonising Rock Engineering and the Environment – Qian & Zhou (eds)*, 2012 Taylor and Francis Group, London. ISBN 978-0-415-80444-8.

Marchand, N., Kalantari, M., 2013. A New Approach for Build Rate Estimation of Downhole Motors. SPE 166457-MS.

Pelfrene, G., Sellami, H., Gerbaud, L., 2011. Mitigating Stick-Slip In Deep Drilling Based On Optimization Of PDC Bit Design. SPE/IADC 139839-MS

Pelfrene, G., Stab, O., Tilleman, D., Gallifet, T., Cuillier, B., Carlos, J., 2019. Modelling the 3D Bit-Rock Interaction Helps Designing Better PDC Bits. SPE/IADC 194134-MS.

Rodriguez, E., Tetzlaff, D. M., Mezzatesta, A., Frost, E., 1988. Estimating Rock Properties by Statistical Methods. SPE 17603.

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., Tarantola, S., 2008. Global Sensitivity Analysis, The Primer. John Wiley & Sons, Ltd. The Atrium, Southern Gate, Chichester, West Sussex PO19 85Q, England.

Spanos, P. D., Chevallier, A. M., Politis, N. P., 2002. Nonlinear Stochastic Drill-String Vibrations. *Journal of Vibration and Acoustics. Transactions of the ASME*, vol. **124**, October, 2002.

Spencer, R., Hanson, J., Hoffmann, O., Kulkarni, A., Allison, C., 2013. New Directional Drilling Simulation Tool Reveals Link between Dynamic Stability and Tool Face Control. SPE/IADC 163467.

Tague, J. R., 2000. Multivariate Statistical Analysis Improves Formation Damage Remediation. SPE 63004.

Zijsling, D. H., 1987. Single cutter testing - a key for PDC bit development. SPE 16529.