Value Creation with Multi-Criteria Decision Making in Geosteering Operations

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Abstract: Due to escalated drilling costs, the petroleum industry has been attempting to access the largest possible hydrocarbon resources with the lowest achievable costs. Multiple well objectives are set prior to the start of drilling. Then, a geosteering approach is implemented to help operators achieve these objectives.

A comprehensive literature survey has been performed on geosteering case histories, including many cases with multiple objectives. We found that the listed objectives are often conflicting and expressed in different measures. Furthermore, none of the cases from the reviewed literature has discussed a systematic approach for dealing with multiple objectives in geosteering contexts. Without implementing a well-structured approach, decision makers are likely to make judgments about the relative importance of each objective based on previous experiences or on approximate methods. Research shows that such decision-making approaches are unlikely to identify optimal courses of action.

In this paper, we propose a systematic method for making multi-criteria decisions in geosteering context. The method is constructed such that it is applicable for real-time operations. Results show that different decision criteria can have significant impact on well success as measured by its trajectory, future production, cost, and operational efficiency.

Keywords: Geosteering, real-time well placement, geosteering decision, multi-objective decision, decision making.

1. INTRODUCTION

Oil and gas asset developments require drilling wells, which in turn involve extensive investments as well as complex decisions in the face of uncertainties. Prior to drilling each well, a list of well objectives is determined by a multidisciplinary team and included in the well plan. These well objectives are reflections of the organization's short- and long-term goals and include technical and operational constraints. Once the objectives are set, the well location is selected and the well trajectory is designed. The well location alternatives that offer the best balance among the objectives are chosen [1]. Thus, choice of well placement is a decision problem involving multiple objectives. The objectives could include future production [2, 3], well construction cost and time [4-6], wellbore configuration [7, 8], environmental impact [7], and safety issues [9].

During pre-drilled well design, reservoir simulations are often performed to help select a reservoir wellpath that seems likely to result in maximum well production. However, once drilling starts, the pre-drilled optimal wellpath is usually altered as additional reservoir information becomes available and the operator's understanding of the geology and petrophysical parameters is updated [10]. Reservoir simulation is ordinarily too time-consuming to provide support for the real-time or near real-time decisions often encountered during drilling [11]. As a consequence, well production, or the net present value resulting from production forecast, is not used directly as an objective. Rather, a set of less computational "means" objectives is used that can produce input for real-time geosteering decisions. The next section will discuss the "means" objectives commonly used during drilling and their relationship to the fundamental objectives identified in the planning phase.

Although final well trajectories and future well performance are clearly a result of geosteering decisions, a systematic approach has not been applied that would enable these decisions to optimize the wellpath based on multiple well objectives. Rajaieyamchee et al. [12] discussed an approach for supporting well placement decisions involving multiple objectives. However, we are aware of no published study in which such an approach was applied to a real geosteering case history. Additionally, the approach proposed by Rajaieyamchee et al. [12] is limited to decisions with only a few options (direction change or sidetrack). It did not suggest an appropriate time to make directional change nor an optimal number of degrees to change the well direction. Although time constraints are a major concern during drilling, a systematic decision making method can be adapted to

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operational environments, as discussed by Giese and Bratvold [13] and Kullawan *et al.* [14].

In this paper, we develop and illustrate a consistent multi-criteria decision-making process adapted to operational geosteering decisions. The paper consists of three main contributions: (1) a review of 44 case histories regarding geosteering objectives; (2) a discussion of a decision-analytic framework for making multi-criteria geosteering decisions; and (3) a case study that applies multi-criteria decision-making (MCDM) technique to geosteering operations. From the case study, we demonstrate that using different decision criteria, and combinations of criteria, results in significant impacts on final well trajectories. As a consequence, it can strongly influence the short-term operational cost and long-term production from the wells.

This paper is organized as follows. The next section provides an overview of common geosteering objectives drawn from a survey of publications. This section focuses on a set of geosteering objectives used in the oil and gas industry and the current approach of decision-making with multiple objectives. We then discuss the importance of applying a systematic approach to making multi-objective decisions and present a structure and methodology for consistent decision-making. The penultimate section presents a case study and illustrates the impact of different combinations of objectives on the final well trajectories. The final section provides a discussion and concluding remarks.

2. MULTIPLE OBJECTIVES IN GEOSTEERING CASE HISTORIES

Well trajectory decisions during drilling operations are made under severe time pressure. After measurement while drilling (MWD) data have been gathered, the geosteering team (GST) has limited time for data interpretation, information analysis, earth model updating, and decision making.

In this section, we illustrate how operators commonly translate fundamental objectives from the pre-drilled phase into operational, "means," objectives. We also show how sets of objectives are related.

2.1. Objectives of Geosteering Operations

To characterize common industry practices related to geosteering, we extensively reviewed geosteering literature from the OnePetro database. To identify relevant papers, we searched the OnePetro database using the term "geosteering." Limiting the search to papers published from 2001 to 2013 resulted in 682 SPE paper hits. We further limited the papers to one hundred where the main focus was on real-time well placement of horizontal sections. Of those, we selected 44 papers that included a field case study where the geosteering objectives were explicitly stated.



Figure 1: Number of papers that considered a given geosteering objective: Green box – Maximize production, Red box – Minimize cost, Black box – Not actionable objective.

Figure **1** shows for each objective, the number of papers that considered it. The number of papers for each objective exceeds 44, as some papers listed multiple objectives.¹

The most frequently stated objective was avoiding reservoir exit (or maximizing reservoir contact),² followed by placing the well in an optimal location, placing the well in a high-quality reservoir zone, and reducing the cost and time of the operations. Whether because they are considered less important or because they are constrained by regulation and operational constraints that every operator must follow, the objectives of safety and environmental considerations are mentioned less frequently. None of the geosteering cases explicitly listed the use of maximum forecasted production from production simulation, or maximum net present value, as a geosteering objective.

Figure **1** summarizes the relationship between means objectives and fundamental objectives for a geosteering implementation. The means objectives for achieving maximum production are enclosed in a green box, while the means objectives for minimizing cost are enclosed in a red box. In 10 of the 44 papers selected for the review, placing the well in an optimal location was the objective of the drilling operation. As discussed earlier, well objectives generally consist of various objectives which are measured on different scales and can be in conflict with each other. Because conflicting objectives cannot be maximized simultaneously, decision makers are required to evaluate tradeoffs among the objectives. The objective of "placing the well in an optimal location," with no further definition of what this means, is neither specific nor measurable and, thus, not actionable.

Identifying and deciding on a set of appropriate objectives is essential for high-quality decision-making. Objectives are specific with measurable attributes that represent the decision maker's preferences. They can be divided into fundamental objectives and means objectives. The fundamental objectives of any decision describe why the decision maker is concerned about the decision, whereas the means objectives represent a way toward the progress of the fundamental objectives or a possible action to achieve the fundamental objectives [15, 16]. In petroleum exploration and production, well locations are selected so as to maximize the net worth of the project [17]. To achieve that, maximizing future production of the well and minimizing the well construction cost are two of the operator's main concerns in well construction activities. Thus, they are commonly used as fundamental objectives to contribute to an overall value of the well. During the planning phase, the well is designed based on simulations of production flow rate and cumulative production, which are means objectives to achieve the fundamental objective of maximizing future production. Another objective is to minimize estimated drilling cost and time of the planned well path because it is a key issue in achieving drilling projects' success [18].

Ideally, whenever data are collected during the drilling process, the earth model should be updated to be consistent with the new information, and a forward simulation of the production uncertainty given the updated earth model should be conducted. The process of updating the earth model in a consistent manner and capturing the production uncertainty through simulation is a time consuming process which, with today's models and computing power, is not achievable in real-time or near real-time. Thus, operators and service companies use a different set of objectives, called means objectives, during the drilling phase. The means objectives should be chosen so that they contribute to the fundamental objectives identified in the pre-drilled phase.

Maximizing reservoir contact and placing the well in a high-quality reservoir are means objectives believed to contribute to the objective of maximizing future production. The means objective of avoiding reservoir exit not only contributes to the production but eliminates additional cost due to an unwanted sidetrack and increased drilling time. Furthermore, minimizing dogleg severity (DLS) is a means to minimize cost because high DLS wellbores have a greater chance of resulting in difficulties when drilling and completing the wells.

To improve transparency in well placement decisions, we develop an objectives hierarchy³ [16, 19], shown in Figure **2**, to establish the relationship between the objectives in the pre-drilled planning phase and the drilling phase. The objectives hierarchy

¹ The papers included are listed in Appendix A.

² Some papers refer to this objective as "maximizing reservoir exposure," "maximizing net to gross ratio," "maximizing net sand," or "maximizing net pay." In Fig. 1, the objective of maximizing the well length within a specific distance from boundaries or fluid contacts is also included in the same category.

³ Sometimes called a value hierarchy.



Figure 2: Objective hierarchy of well placement decision, representing fundamental objectives and means objective in the planning phase and the drilling phase.

demonstrates how each objective contributes to an overall value (net worth) of the well. The attributes column refers to the scale used for measuring how each alternative meets a given objective.

The objective hierarchy in Figure **2** is generic in that it has been derived from case histories in the geosteering literature. In reality, the hierarchy developed by different operators will vary as a function of the companies' chosen value structure and operating conditions.

Unlike production or cost, there is no obvious natural scale for measuring the safety level of the operation or environmental impact. In such cases, a constructed scale is created to measure intangible quantities [16, 20].

2.2. Current Practice in Making Multi-Criteria Geosteering Decisions

In reviewing the literature for objectives used in geosteering operations, we found that 18 of 44 papers explicitly stated that they used multiple objectives for the operations. Interestingly, of the papers that applied multiple objectives, none discussed or adopted any of the well-established and consistent methods for decision making with multiple criteria.

3. MULTI-CRITERIA DECISION-MAKING METHOD

Traditionally, geosteering decisions involving multiple objectives and tradeoffs among the objectives are usually made without the support of a validated approach. It is well-documented [21-23] that under such conditions, decision makers tend to use "approximate methods" or "heuristics" to address decision problems.

Although heuristics can identify satisfactory courses of action in some cases [24], they are often affected by biases and mental errors. In petroleum exploration and production, decisions influenced by such biases and errors can lead to detrimental results [25].

Faced with the need to make decisions, decision makers generally seek reasons to justify their choice of action and resolve conflicts [26]. This "reason-based choice" method is not uncommon in geosteering operations. Real-time data gathered during drilling is used to support decision-making and provide reasons to justify choices, such as:

 Decision to steer upwards away from the lowquality (heavy oil) zone, due to repeatable low permeable pressure profiles from "formation pressure while drilling" (FPWD) tool [27].



Figure 3: A simplified case involving geosteering decisions with multiple objectives.

 Decision to steer up/down to avoid exiting the reservoir because the MWD data indicate approaching bed boundaries [10, 28].

Decision-making using "reason-based choice" is not consistent with well-established methods for multiobjective decision making [29] as the method is typically vague and decisions may be rationalized after the fact [26]. Furthermore, any chosen alternative is highly sensitive to how the decision is framed [23].

Figure **3** illustrates a simple geosteering situation with multiple objectives, where a structured approach is required for normative decision making.⁴ It depicts an operation which a horizontal well is being drilled into a reservoir that is sandwiched by shale layers on the top and bottom. Real-time data indicate higher reservoir quality in the top part of the sand layer. The GST is facing a decision involving at least these two alternatives:

- Alternative 1: Steer up to the higher-quality reservoir. If this alternative is chosen, the GST then needs to decide the extent of directional change.
- Alternative 2: Continue at the same direction to avoid exiting the reservoir.

The literature survey (Figure 1) indicates that avoiding reservoir exit is the most frequently used objective for geosteering operations and that placing the wellbore in a high-quality reservoir is the third-most frequently used objective. Alternative 1 should be selected if the objective is to place the well in the highquality reservoir, whereas alternative 2 is superior if the team is trying to avoid reservoir exit. As discussed in the section "Multiple Objectives in Geosteering Case Histories," avoiding reservoir exit equates to maximizing the well length in the reservoir. In more realistic situations, geosteering decisions may be significantly more complex. The GST may need to consider several reservoir properties, such as permeability or porosity, along with the magnitude of differences in these properties in various reservoir locations, uncertainties ahead of the drill bit, and other operating conditions. This complexity makes "reasonbased choice" particularly prone to errors and a systematic decision-making process is essential to guide decision makers in making consistent trade-offs among objectives under uncertainties.⁵

3.1. Decision Analytics for Multi-Criteria Geosteering Decision

Kullawan et al. [14] discussed an implementation of a decision-driven analytics approach to geosteering operations. The approach divides the processes into three main components: descriptive analytics. predictive analytics, and decision analytics. As the drillstring penetrates the formation and real-time data are gathered, descriptive analytics can be used for updating the formation properties up to the sensor points. The descriptive model, available data, and expert knowledge are then combined to refine the prediction model ahead of the sensor location. After that, decision analytics is used to optimize geosteering decisions. The influence diagram representing this approach in geosteering operations is shown in Figure 4.

⁴ Normative decision making refers to decisions that are logically consistent with the decision maker's preferences, alternatives, and information [30, 16].

⁵ Consistent with the decision-makers preferences, information, and alternatives.



Figure 4: Influence diagram representing a geosteering decision problem.

The use of decision analysis for drilling operational decisions has been illustrated in the SPE literature. Examples include the use of decision trees to support casing-setting-depth decisions [31], an analysis of an exploration prospect [32], applying a decision-analytic approach for autonomous geosteering [33], and decision support in integrated operations [13]. Of these, only Rajaieyamchee *et al.* [12] illustrated how to implement a consistent multi-objective decision analysis process for geosteering decisions with some limitations.

Geosteering objectives are often conflicting and trade-offs must be made. One of the techniques for evaluating tradeoffs between objectives is multiattribute utility theory (MAUT). MAUT is not new to the petroleum industry. Suslick *et al.* [34] applied this technique to evaluate exploration decisions involving financial as well as technological gain in offshore areas. Castro *et al.* [35] illustrated the application of MAUT in the selection of facilities for a deepwater production system by considering financial, environmental, safety, and technological objectives. The ability of MAUT to address multiple objectives would seem to make it suitable for supporting real-time geosteering decisions.

Most large oil and gas companies claim to be riskneutral in their decision making.⁶ Furthermore, the cost of a single well is usually low enough that even companies that are generally risk-averse would be riskneutral. We will assume that the decision maker is riskneutral and use expected value (EV) as the decision criterion. Bratvold and Begg [16] presented a simple approach for multi-objective decision making that consists of the following steps.⁷

Step 1: Define the decision context

Step 2: Set objectives

- Step 3: Identify alternatives
- Step 4: Assess alternatives against objectives
- Step 5: Apply weights to each objective
- Step 6: Determine the best alternative
- Step 7: Perform sensitivity analysis

During the planning phase, the GST implement steps 1 to 3 by determining the decision context, a set of objectives to be achieved and a list of possible alternatives, in advance. Although steps 4 to 6 will be repeatedly evaluated during drilling, the value functions of each objective and the relative weightings among the objectives can be conducted during the planning phase. Drawing on the well objectives defined in the pre-drilled phase, the GST determines value functions and their relative weightings for the geosteering operation.⁸ In the case study section below, the decision process along with its mathematical support will be described in detail, using a similar geosteering scenario that is shown in Figure **4**.

⁶ Walls [36] argued that this is not always the case.

⁷ Comparable decision processes are discussed in [25, 29, 37].

⁸ How to do this is discussed in detail in [16].

The geosteering context allows limited time for sensitivity analysis, step 7. A preliminary sensitivity analysis should be conducted in the pre-drilled phase by investigating different decision scenarios and uncertainties. Real-time sensitivity analysis while drilling will become increasingly common with the implementation of suitable analytics, inference, and operational decision support software combined with ever more-powerful computers.

The process described by Bratvold and Begg [16] was developed for making strategic decisions where the time available for analysis may be days, weeks, or months. When making geosteering and other operational decisions, the time available is more often measured in seconds, minutes, or hours. Thus, decision analysis for operational decision situations has often been dismissed with the assumption that the decision analysis processes are too computationally intensive or that such decision situations have a very small impact on the drilled well's overall value. However, geosteering and other operational decision situations can be frequent, and their cumulative impact would be immense. Therefore, making the right decision for each one would add to the bottom line.

Furthermore, whether one has ample time or little time, the decision basis and general requirements for consistent and good decision-making are still the same. However, whilst strategic decisions often are one-off type decisions with significantly different contexts, geosteering and many other operational decisions typically involve repeated decisions with essentially the same objectives (maximize production and minimize costs) and alternatives (directional changes/stopping points). Therefore, standard decision processes can be constructed in advance and embedded into everyday operations. Not only are these decisions made relatively frequently but each decision itself is also individually important and can have a crucial effect on the end results of the well. This emphasizes the necessity to implement a structured and logical process which better incorporates expert knowledge and experiences to help decision makers drive transparency, make better and faster decisions, and deal with conflicts among objectives while focusing on the organization's values.

4. CASE STUDY—IMPACT OF DIFFERENT DECISION CRITERIA ON FINAL WELL TRAJECTORIES

We now present a case study that demonstrates the use of multi-objective decision analysis for making geosteering decisions and illustrates the effect of different criteria on real-time well placement decisions and the resulting well trajectories.

While drilling in a horizontal section, real-time formation property data are gathered and interpreted for supporting well placement decisions regarding directional changes. In this case study, we demonstrate that final well trajectories can vary greatly depending on the decision criteria being used.

4.1. Problem Statement

A horizontal well is drilled in a three-layered model, with a hydrocarbon reservoir sandwiched by shale layers at the top and bottom. Based on reservoir quality, the reservoir can be divided into two zones: high-quality sand in the top 40% of the reservoir, and low-quality sand in the bottom 60% of the reservoir. The reservoir quality within each zone is assumed to be homogeneous. The key well placement



Figure 5: Time series of bed boundaries update with 80% probability intervals as the sensor (dashed blue line) passes through the formation.



Figure 6: Illustration of geosteering scenario: blue line - formulated wellpath, red line - boundary between high- and low-quality reservoirs.

uncertainties in this case are the depths of the reservoir boundaries. MWD data consist of deep directional resistivity (DDR) measurements that are gathered and transmitted topside in real-time.

zone

Using the information derived from MWD data, the geomodel is updated in real-time and well placement decisions are made based on the updated earth model. Nonetheless, only the uncertainties behind the sensor point are resolved at the time the decisions are made. Thus, inferences about the properties of the formation ahead of the drill bit should be used in making any steering decision. In this paper, we apply the Bayesian inference technique discussed by Kullawan et al. [14] to consistently update ahead-of-the-bit uncertainties using the real-time data. The updated model will then be used for supporting geosteering decisions by applying the multi-objective decision-making methodology described in the previous section. Figure 5 shows the time series of probability distributions of the bed boundaries as the well is drilled through the horizontal section. The plot at t_0 represents our prior beliefs about the bed boundaries before drilling into the horizontal section. The upper solid line is the expected depth to the upper boundary (UB), and the lower solid line is the expected depth to the lower boundary (LB). The dashed lines above and below the expected boundaries represent P10 and P90 boundary locations; there is a 10% chance that the given boundary is located above (below) the P10 (P90). At times t > t_0 , the dashed blue line represents the sensor

location. The drill bit moves from left to right and is located just ahead of the dashed line (beyond the sensor). The updated uncertainties of the bed boundaries are shown, with the uncertainty increasing with distance from the sensor. The red dotted line, between the UB and the LB, represents the boundary between high-quality and low-quality reservoir sections. The depth referred to in all figures in this paper represents true vertical depth (TVD).

Figure 6 illustrates the drilling scenario in this problem. The blue line is the wellpath calculated from a given alternative for the next 10 observation points (30 m), and the dashed, red line is the boundary between the high-quality and low-quality reservoir sections. The formation thickness is represented by h, and DTUB and DTLB represent the distance to the upper boundary and the distance to the lower boundary, respectively. V_{ii} represents the expected value of objective *i* in cell *j*.

The bed boundaries are discretized into n observation points. The depth uncertainties of the bed boundaries are updated at 3 m intervals as the sensor passes the formation. Once the probability distributions for the bed boundaries are updated using the Bayesian framework, the expected values of the bed boundaries are determined. These expected values are used to evaluate each alternative. Steering decisions are made every 30 m, and the change in wellbore inclination is constrained not to exceed 5° per 30 m. There are 11 steering alternatives, whose change in inclination ranges from building the well inclination of 5° (+5°) to



Figure 7: Schematic decision tree for geosteering decision problem.

dropping 5° (-5°), in increments of -1° .⁹ The wellpath from pursuing each alternative is calculated, and the expected value of meeting each objective is evaluated.¹⁰

The two objectives used to guide the geosteering decisions in this case are avoiding reservoir exit (Objective 1) and placing the well in the high-quality reservoir (Objective 2). To minimize the chance of exiting the reservoir, the optimal well location is in the middle of the reservoir based on the real-time ahead-of-the-bit inferences about the bed boundaries. However, to maximize Objective 2, the well should be steered up toward the upper part of the reservoir. This would result in the well being placed closer to the UB and, thus, increase the chance of drilling into the upper shale layer. Objective 1 and Objective 2 are obviously conflicting. A schematic decision tree for this decision situation is shown in Figure **7**.

To assess how each alternative performs against the objectives, we start by calculating the well trajectory that would result from pursuing each alternative.¹¹Using the calculated well trajectory, we can determine to what extent each alternative satisfy the objectives.

In this case study, the objectives are measured on different scales. To combine the objectives' payoffs measured from two different scales, we first transform the values on each scale to values on a common scale. In this work, we use a common scale from 0 to 1, where 0 indicates the worst outcome from a given objective and 1 indicates the best possible outcome. Higher number towards 1 indicates better outcome. The value functions for both objectives are constructed using *the mid-value splitting technique*.¹² After finding the mid-value points and performing a consistency check, the value functions are smoothed into curves.

3.4. Objective 1: Avoid Exiting the Reservoir

Because ahead-of-the-drill-bit boundary depth uncertainties have not yet been resolved at decision time, placing the well as close to the middle of the reservoir as possible will minimize the chance of exiting the reservoir. Using the following relationships:

$$DTUB_i = Depth of Wellbore_i - Depth of Upper Boundary_i$$
(1)

 $DTLB_i = Depth of Lower Boundary_i - Depth of Wellbore_i$ (2)

Ratio of DTUB to Reservoir Thickness_j =
$$\frac{DTUB_j}{h_i}$$
 (3)

Ratio of DTLB to Reservoir Thickness_j =
$$\frac{DTLB_j}{h_i}$$
 (4)

$$\alpha_{j} = \min\left(\frac{DTUB_{j}}{h_{j}}, \frac{DTLB_{j}}{h_{j}}\right)$$
(5)

 α_j represents the quotient of the distance between the well and the closest reservoir boundary, divided by total reservoir thickness, h_j . When the well is in the middle of the reservoir, *DTUB* equals *DTLB*, which gives $\alpha_j = 0.5$. At $\alpha_j = 0.5$, V_1 has the maximum value at $1.V_1$, decreases as α_j decreases, and approaches 0 when the well is on the bed boundary.

⁹ A set of alternative = $[-5,5] \in II$. However, if the well is outside the reservoir, the set of alternatives will include only the options that direct the well back to the reservoir.

¹⁰ The details of calculation methods for updating the bed boundaries and well trajectories are shown in Appendix B.

¹¹ Well trajectory is calculated using the Minimum Curvature Method. More details are discussed in Appendix B.

¹² See [29].

 V_1 decreases at a slower rate when α is closer to 0.5. The farther away from 0.5, the faster the rate of decrease of V_1 . This is consistent with the operator's preference that moving up or down by 10% has less impact when the well is in the middle of the reservoir than when the well is near either boundary. A possible value function for Objective 1 is represented by the line shown in Figure 8. A useful approach to creating such a value function is to first reach agreement in the GST as to how the line should look (curvature) and then develop a parametric representation of the line.



Figure 8: Value function for objective 1.

3.5. Objective 2: Stay in High-Quality Zone

Suppose that in this case study, the high-quality reservoir zone has a permeability of 200 mD. A value function constructed for Objective 2 focuses only on the permeability range of interest. Figure **9** transforms the reservoir quality, with permeability ranging from 0 to 200 mD, to a value score in the 0 to 1 range. In this case, the value score is non-linear because the difference in moving from the impermeable zone



Figure 9: Value function for objective 2.

(0 mD) to the permeable zone has higher impact than increasing the permeability of the high-quality zone.

To determine the best alternative, an overall value for each alternative is obtained by summing the alternative's weighted scores for each objective. The alternative that offers the highest value will be chosen, and the well will be steered accordingly.¹³ Given the two geosteering objectives specified in this case study; we assume that the necessary conditions for an additive value function are satisfied.¹⁴ Thus, an additive value function is used for assessing the alternatives, which is expressed in the form:

$$V_k = \sum_{i=1}^n w_i v_{ik} \tag{6}$$

$$\sum_{i=1}^{n} w_i = 1 \tag{7}$$

where V_k is the value of alternative k, w_i is the weight of the objective i, n is the number of objectives, and v_{ik} is the payoff of the alternative k. The weights describe the decision maker's relative desirability between objectives. These weights need to be carefully evaluated.

The depth uncertainties of the bed boundaries ahead of the bit are represented by the normal distributions, and the expected value for each alternative is then calculated. The alternative with the highest expected overall value will be chosen, and the wellpath will be steered accordingly.

Suppose that the well is landed in the high-quality zone at 1719 mTVD with a 90° inclination. However, the MWD data indicate that the shale layer on the top is dipping downward. Keeping the same direction means that the well has greater chance of exiting the reservoir, whereas steering down means steering towards the low-quality zone. If the GST decides to drop the angle, the rate of change also needs to be determined.

Several cases from the literature use a single objective in geosteering operations. Figure **10** compares the final well trajectories¹⁵ (represented by the green line, where the black dots show the decision

¹³ The decision procedure used in this paper is not based on Dynamic Programming (DP) decision-making policy. Future work will relax this assumption.

¹⁴ The additive form of value function can be used to combine the objectives measured on different scales. However, this form is appropriate only if the preference of the decision-maker satisfies the mutual preference independence condition. More detail about verification of this condition can be found in [29].

¹⁵ Figure 10 and Figure 11 are plotted for illustrative and comparative purposes. Thus, horizontal and vertical distances are not plotted on the same scale.



Figure 10: Comparisons of resulting well trajectories from different single objective.



Figure 11: Comparisons of resulting well trajectories from different weighting schemes applied to multiple objectives.

points) resulting from using different single objectives as decision criteria.¹⁶ In both scenarios, a high-quality zone has a permeability of 200 mD, and a low-quality zone has a permeability of 100 mD.

Scenario 1: The geosteering decisions are made based only on Objective 1 to avoid reservoir exit. $(w_1 = 1, w_2 = 0)$.

Scenario 2: The geosteering decisions are made based only on Objective 2 to place the well in the highquality zone. ($w_1 = 0$, $w_2 = 1$).

If the only objective of the operation were to avoid reservoir exit, the GST would at all times steer the well away from the boundary. In this case, the well is successfully steered within the reservoir, resulting in 100% reservoir contact. However, only 35% of the well length is in the high-quality zone. On the other hand, if the GST only focused on Objective 2, direction changes would be made such that the well is expected to be in a good reservoir although such actions lead to higher chances of drilling into shale. In this scenario, 73% of the well length is in the high-quality zone, but the reservoir contact is reduced to 86%.

For the case histories where multiple objectives are explicitly stated, none has discussed the relative importance among the objectives. Figure **11** illustrates the impact on the final well trajectories of using different weights for the objectives in two different scenarios.

Scenario 1: The difference in reservoir quality between the two zones is small, with the permeability of 200 mD in the high-quality zone and 100 mD in the low-quality zone. Thus, higher weight is placed on Objective 1. ($w_1 = 0.67$ and $w_2 = 0.33$).

Scenario 2: The difference in reservoir quality between two zones is large, with the permeability of 200 mD in the high-quality zone and 20 mD in the lowquality zone. Thus, higher weight is placed on Objective 2. ($w_1 = 0.41$ and $w_2 = 0.59$).

¹⁶ In this case study, it is assumed that once the well exits the reservoir, it can always be steered back into the reservoir without performing a sidetrack operation.

Although the same set of objectives is used for both cases, the weighting scheme significantly affects the final well trajectories. In scenario 1, where the difference in reservoir quality is lower, more weight is assigned to Objective 1 as the decision maker thinks that it is more important to avoid reservoir exit. This results in a final wellpath with 100% reservoir contact but with only 59% of the well length's staying in the high-quality zone. In scenario 2, the difference in reservoir quality between two zones is more pronounced, and more weight is assigned to Objective 2. The decision maker is willing to stay closer to the UB to ensure that the well stays in the top zone. This increases the likelihood of drilling into shale. The resulting wellpath has 92% reservoir contact, with 70% of the well length in the high-quality zone.

CONCLUSIONS

Geosteering a well involves analyzing data, drawing inferences, and making decisions in real-time. Despite the high cost of drilling wells and significant rewards achieved by successfully placing the wells, the review of many papers discussing geosteering showed that the data analysis and the inferences drawn from the analysis lack rigor and consistency. Furthermore, although operators and service companies involved in drilling often specify multiple objectives and criteria for success, none of the papers reviewed for this work indicated that consistent multi-objective decision optimization methods were being applied to

geosteering decisions. This is surprising because much literature and empirical evidence has demonstrated that trying to optimize multiple objectives in the face of significant uncertainty by using ad hoc or intuitive methods is unlikely to identify optimal courses of action. The geosteering problem is a complex, multiobjective decision problem that requires a systematic approach consistent with the decision makers' preferences, alternatives, and information.

In this work, we have demonstrated that the choice of objectives and their weighting significantly affects both well trajectory and final placement. We have introduced and discussed a general approach to multiobjective decision analysis in the context of geosteering decisions. A case study has been used to illustrate how the approach can be implemented, and the results simulated in this example have clearly shown that different decision criteria or relative weighting among the objectives has significant impact on well success as measured by its trajectory, future production, cost, and operational efficiency.

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Land well	Place well in high quality reservoir	Avoid reservoir exit/ Max. well length in reservoir/ specific zone	Reduce risk/cost/time	Well configuration	Safety	Environment	Place well in optimal location
SPE 109844	SPE 128155	SPE 71733	SPE 81026	SPE 128851	SPE 72277	SPE 128851	SPE 72277
SPE 146732	SPE 161839	SPE 87979	SPE 88531	SPE 107506	SPE164257		SPE 109844
SPE 109971	SPE 140073	SPE 88531	SPE 125881	SPE 108737			SPE 125881
SPE 107506	SPE 132884	SPE 88889	SPE 155205	SPE 132884			SPE 147941
SPE 108737	SPE 157926	SPE 110940	SPE 137137	SPE 164408			SPE 146732
SPE 155205	SPE 163538	SPE 107714	SPE 164151				SPE 153580
SPE 161430	SPE 164257	SPE 120551	SPE 164408				SPE 158395
		SPE 128155					SPE 160922
		SPE 132439					SPE 109971
		SPE 149543					SPE 164151
		SPE 153160					
		SPE 137137					
		SPE 159132					

		Avoid reservoir exit/					
Land well	Place well in high quality reservoir	Max. well length in reservoir/spec ific zone	Reduce risk/cost/time	Well configuration	Safety	Environment	Place well in optimal location
		SPE 158390					
		SPE 155056					
		SPE 151047					
		SPE 128851					
		SPE 95725					
		SPE 102637					
		SPE 107506					
		SPE 108737					
		SPE 132884					
		SPE 133431					
		SPE 157926					
		SPE 161430					
		SPE 163538					
		SPE 106790					
		SPE 128185					
		SPE 164408					

Table 1A: References that support various objectives of geosteering operations, summarized in Figure 1.

APPENDIX B

Appendix B describes the mathematical method used for updating bed boundaries as real-time data are gathered and calculating wellbore trajectories along with the parameters used in the case study.

Figure **B-1** shows the depth uncertainties at location *i* where μ and σ^2 symbolize mean and variance of the normal distribution, *N*(,), respectively. At location *i*, the depth uncertainties at *UB_i* and *h_i* are assumed to be independent. Then, the depth uncertainties at *LB_i* are modeled as the combination of *UB_i* and *h_i*.



Figure B-1: Modeling depth uncertainties of bed boundaries at location *i* using normal distributions.

Figure **B-2** displays the discretization of bed boundaries into observation points. The depth uncertainties at each observation point are characterized by the normal distribution, $N(\mu, \sigma^2)$. A multivariate normal (MVN) distribution is used to characterize the uncertainties of the bed boundaries and formation thickness. The MVN is fully specified by the mean vector and the covariance matrix.

(B-3)

(B-4)



Figure B-2: A schematic of reservoir section as the drillstring penetrates the formation.

Suppose that we partition the mean vector and the covariance matrix as follows:

mean vector;

$$\mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}$$
(B-1)

and covariance matrix;

$$\sum = \begin{bmatrix} \sum_{11} & \sum_{12} \\ \sum_{21} & \sum_{22} \end{bmatrix}$$
(B-2)

where μ_1 is a mean vector of *n* points of upper boundaries and *n* points of formation thickness (set X_1) and μ_2 is a mean vector of sensor readings (set X_2) at a particular time step.

 \sum_{11} and \sum_{22} represent variances and covariances for set X_1 and set X_2 respectively. \sum_{12} as well as \sum_{21} , gives covariances between variables in set X_1 and set X_2 .

The covariance matrix at time $t = t_0$ is generated from the correlation matrix and the vector of standard deviations. The correlation matrix contains the correlation coefficients among each point along the bed boundaries and the correlation coefficients between bed boundaries and the sensor readings.

The correlation coefficient between two points on the same bed boundaries is determined from the distance between them and the rate that the correlation decreases as the distance increases. The correlation coefficient between the m^{th} and the n^{th} observation points with the rate of change (β)¹⁷ can be determined from:

$$\rho(m,n) = \max\{1 - \beta(abs(m-n)), 0\}$$

The covariance between the m^{th} and the n^{th} observation points can then be calculated from:

$$Cov(m,n) = \rho(m,n) \times \sigma_m \times \sigma_n$$

and the correlation coefficients between the bed boundaries and the sensor readings ($\rho_{m,sensor}$) are characterized by an exponential correlogram with the sill of 0.999 and the range of 35 observation points.

The standard deviation of the sensor reading at each bed boundaries location is influenced by the correlation coefficient between the sensor readings and the location being measured. The standard deviation of the sensor reading can be calculated from:

¹⁷ Sensitivity analysis has been performed on the rate of change in correlation value. The rate is varied from 0.01 to 0.20 with no significant change in the simulation results.

$$\sigma_{sensor} = \sqrt{\sigma_m^2 \times \left(1 - \rho_{m,sensor}^2\right)} \tag{B-5}$$

where σ_m is the standard deviation of the bed boundary or thickness at location *m* and $\rho_{m,sensor}$ is the correlation coefficient between the sensor reading and the value being measured.

As the downhole sensor passes the first observation point, the mean vector of the UB and thickness is characterized from the knowledge as;

$$\mu_1 = (\mu_{11}, \mu_{12}, \dots, \mu_{1n}, \mu_{1(n+1)}, \dots, \mu_{1(2n)})$$
(B-6)

where μ_{1i} represents the mean of the UB at location *i* where $1 \le i \le n$ and μ_{1i} represents the mean of the formation thickness at location *i* where $n + 1 \le i \le 2n$.

The sensor reading is described by:

$$x_2 = (x_{21}, x_{22}) \tag{B-7}$$

where x_{21} represents sensor readings of *UB* and x_{22} represents sensor readings of *h*.

Conditional distribution of UB and h (set X_1), given sensor readings (set X_2) equal to x_2 , is also a multivariate normal with:

mean vector;

$$\mathbb{E}(X_1|X_2 = x_2) = \mu_1 + \Sigma_{12}\Sigma_{22}^{-1}(x_2 - \mu_2)$$
(B-8)

and covariance matrix;

$$Cov(X_1|X_2 = x_2) = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}$$
(B-9)

This conditional distribution will be used as a prior distribution as the drillstring continues to the next location.

Once the bed boundaries are updated, wellbore trajectory for each alternative is calculated using the minimum curvature method. In this case study, we consider the wellpath from a 2-dimensional perspective, and thus, the azimuth angles of the well are assumed to remain constant and only changes in TVD are considered. See Bourgoyne [38] for further details of the calculation. Change in TVD from a given alternative can be determined from:

$$\Delta TVD = \frac{MD}{2} \times \left[\cos(I_1) + \cos(I_2) \right] \times RF \tag{B-10}$$

where RF can be calculated from 2 following equations:

$$\beta = \cos^{-1} \left[\cos(I_2 - I_1) - \left(\sin(I_1) \times \sin(I_2) \times (1 - \cos(A_2 - A_1)) \right) \right]$$
(B-11)

and

$$RF = \frac{2}{\beta} \times tan\left(\frac{\beta}{2}\right) \tag{B-12}$$

where

MD = Measured Depth between 2 points

$$I_1$$
 = Inclination angle of the well at the initial point

- I₂ = Inclination angle of the well at the final point
- A_1 = Azimuth angle of the well at the initial point
- A_2 = Azimuth angle of the well at the final point
- B = Dogleg angle (in radians)

To limit the well's dogleg severity, the maximum change in inclination angle between 2 decisions (30 m) is controlled not to exceed 5°/30 m. We further limit operational constraints such that, at any point in the horizontal section of the well, the minimum inclination will not drop below 86° and the maximum inclination will not exceed 94°. The expected value of each alternative is calculated using Eq. 6. The alternative which offers the highest expected value and meet all the operational constraints will be chosen.

REFERENCES

- [1] Norrena KP and Deutsch CV. Automatic Determination of Well Placement Subject to Geostatistical and Economic Constraints. Proc SPE International Thermal Operations and Heavy Oil Symposium and International Horizontal Well Technology Conference, Calgary, Alberta, Canada 2002; 4-7: SPE-78996-MS. http://dx.doi.org/10.2118/78996-MS
- [2] Schulze-Riegert R, Bagheri M, Krosche M, et al. Multiple-Objective Optimization Applied to Well Path Design under Geological Uncertainty. Proc SPE Reservoir Simulation Symposium. The Woodlands, Texas, USA, 21-23 February 2011, SPE-141712-MS. http://dx.doi.org/10.2118/141712-MS
- [3] Hasan A, Gunnerud V, Foss B, et al. Decision Analysis for Long-term and Short-term Production Optimization Applied to the Voador Field. Proc SPE Reservoir Characterization and Simulation Conference and Exhibition, Abu Dhabi, UAE 2013; 16-18: SPE-166027-MS. http://dx.doi.org/10.2118/166027-MS
- [4] Coutinho MR, Abreu CE, Braga MS, et al. Horizontal Well Geosteering: The Experience in a Giant Campos Basin Deep-Water Field. Proc SPE Latin American and Caribbean Petroleum Engineering Conference, Port-of-Spain, Trinidad and Tobago 2003; 27-30. <u>http://dx.doi.org/10.2118/81026-MS</u>
- [5] Mitra PP, Joshi TR and Thevoux-Chabuel H. Real Time Geosteering of High Tech Well in Virtual Reality and Prediction Ahead of Drill Bit for Cost Optimization and Risk Reduction in Mumbai High L-III Reservoir. Proc SPE Asia Pacific Oil and Gas Conference and Exhibition, Perth, Australia 2004; 18-20: SPE-88531-MS. <u>http://dx.doi.org/10.2118/88531-MS</u>
- [6] Zimmer C, Richter D, Person J, et al. Drilling a Better Pair: New Technologies in SAGD Directional Drilling (in English). Journal of Canadian Petroleum Technology 2012; 51(2): 115-126. SPE-137137-PA. http://dx.doi.org/10.2118/137137-PA
- [7] Dawoud AM, Mahdi AE, Ayoub MR, et al. Geosteering Long Horizontal Holes in Abu Dhabi Heterogeneous Carbonate Reservoirs. Proc SPE Oil and Gas India Conference and Exhibition, Mumbai, India 2010; 20-22: SPE-128851-MS. <u>http://dx.doi.org/10.2118/128851-MS</u>
- [8] Cuadros J, Duque NO, Cuadros G, et al. Horizontal Well Placement Optimization for Heavy Oil Production in Girasol Field. Proc Trinidad and Tobago Energy Resources Conference, Port of Spain, Trinidad 2010; 27-30: SPE-132884-MS. <u>http://dx.doi.org/10.2118/132884-MS</u>
- [9] Longis C, Ferment DY, Madjidi A. Geosteering in a Complex Dolomitic Reservoir. Proc SPE/IADC Middle East Drilling Technology Conference, Bahrain 2001; 22-24: SPE-

72277-MS.

http://dx.doi.org/10.2118/72277-MS

- [10] Omovie SJ, Pearson WR. Using Deep-Azimuthal Resistivity and 3D Seismic for Optimal Horizontal Well Placement: An Integrated Approach, Nipisi Field, Western Canada. Proc IADC/SPE Drilling Conference and Exhibition, San Diego, California, USA 2012; 6-8: SPE-151047-MS. <u>http://dx.doi.org/10.2118/151047-MS</u>
- [11] Navarro ADP, Kumar S, Perez-Damas CE, et al. Simulation While Drilling: Utopia or Reality? Proc., Intelligent Energy Conference and Exhibition, Amsterdam, The Netherlands 2006; 11-13: SPE-99945-MS. http://dx.doi.org/10.2118/99945-MS
- [12] Rajaieyamchee MA, Bratvold RB, Badreddine A. Bayesian Decision Networks for Optimal Placement of Horizontal Wells. Proc., SPE EUROPEC/EAGE Annual Conference and Exhibition, Barcelona, Spain 2010; 14-17: SPE-129984-MS. <u>http://dx.doi.org/10.2118/129984-MS</u>
- [13] Giese M, Bratvold RB. Probabilistic Modeling for Decision Support in Integrated Operations. SPE Economics and Management 2011; 3(3): 173-185. SPE-127761-MS. <u>http://dx.doi.org/10.2118/127761-MS</u>
- [14] Kullawan K, Bratvold RB, Bickel JE. A Decision Analytic Approach to Geosteering Operations. SPE Drilling and Completion 2014; 29(01): 36-46. SPE-167433-PA. <u>http://dx.doi.org/10.2118/167433-PA</u>
- [15] Keeney RL. Value-Focused Thinking: A Path to Creative Decisionmaking. Harvard University Press (reprint) 2009.
- [16] Bratvold RB, Begg SH. Making Good Decisions. Society of Petroleum Engineers (reprint) 2010.
- [17] Lesso JrWG, Kashikar SV. The Principles and Procedures of Geosteering. Proc., SPE/IADC Drilling Conference, New Orleans, Louisiana 1996; 12-15: SPE-35051-MS. <u>http://dx.doi.org/10.2118/35051-MS</u>
- [18] Amar R. Drilling Performance Management System. Proc SPE/IADC Middle East Drilling and Technology Conference, Cairo, Egypt 2007; 22-24. SPE-107250-MS. <u>http://dx.doi.org/10.2118/107250-MS</u>
- [19] Parnell GS, Bresnick TA, Tani SN, et al. Handbook of Decision Analysis. Wiley (reprint) 2013.
- [20] Rudduck NP, Khurana AK, Congreve M, et al. Multi-Objective Decision Making: A Critical Analysis of The Applicability Of Renewable Energy Technologies. Proc SPE Asia Pacific Oil and Gas Conference and Exhibition, Adelaide, Australia 2006; 11-13: SPE-101770-MS. <u>http://dx.doi.org/10.2118/101770-MS</u>
- [21] Tversky A and Kahneman D. Judgment under uncertainty: Heuristics and biases. Science 1974; 185(4157): 1124-1131. 10.1126/science.185.4157.1124.
- [22] Simon HA. Models of Bounded Rationality. Cambridge, Massachusetts, MIT Press (reprint) 1982.

- [23] Goodwin P and Wright G. Decision Analysis for Management Judgment. Third edition. John Wiley and Sons, Ltd. (reprint) 2004.
- [24] Gigerenzer G and Todd PM. Simple Heuristics that Make Us Smart, ABC Research Group (reprint) 1999.
- [25] Virine L and Murphy D. Analysis of Multi-Criteria Decision-Making Methodologies for the Petroleum Industry. Proc., International Petroleum Technology Conference, Dubai, UAE 2007; 4-6: IPTC-11765-MS. <u>http://dx.doi.org/10.2523/11765-MS</u>
- [26] Shafir E, Simonson I and Tversky A. Reason-based choice. Cognition 1993; 49(1): 11-36.
- [27] Neumann PM, Salem KM, Tobert GP, et al. Formation Pressure While Drilling Utilized for Geosteering. Proc., SPE Saudi Arabia Section Technical Symposium, Dhahran, Saudi Arabia 2007; 7-8: SPE-110940-MS. <u>http://dx.doi.org/10.2118/110940-MS</u>
- [28] Reddy SK and Pitcher JL. Application of 3D Geosteering Capabilities in Geologically Complex Shale. Proc., SPE Americas Unconventional Resources Conference, Pittsburgh, Pennsylvania 2012; 5-7: SPE-153160-MS. http://dx.doi.org/10.2118/153160-MS
- [29] Keeney RL and Raiffa H. Decisions with Multiple Objectives: Preferences and Value Tradeoffs. Series in Probability and Mathematical Statistics., Wiley and Sons, New York, New York 1993.
- [30] Howard RA. The Foundations of Decision Analysis Revisited. In W Edwards, J Ralph F Miles, and Dv Winterfeldt (Editors), Advances in Decision Analysis. Cambridge University Press, New York, New York 2007; 32-56.
- [31] Turley JA. A Risk Analysis of Transition Zone Drilling. Proc., 51st Annual Fall Technical Conference and Exhibition: New Orleans, Louisiana 1976; 3-6: SPE-6022-MS. <u>http://dx.doi.org/10.2118/6022-MS</u>

- [32] Cowan JV. Risk Analysis as Applied to Drilling and Developing an Exploration Prospect. Proc 44th Annual Fall Meeting of SPE of AIME, Denver, Colorado, 28 September – 1 October 1969. SPE-2583-MS. http://dx.doi.org/10.2118/2583-MS
- [33] Rajaieyamchee MA and Bratvold RB. A Decision Analytic Framework for Autonomous Geosteering. Proc., SPE Annual Technical Conference and Exhibition, Florence, Italy 2010; 19-22: SPE-135416-MS. <u>http://dx.doi.org/10.2118/135416-MS</u>
- [34] Suslick SB, Furtado R, Nepomuceno F. Integrating Technological and Financial Uncertainty for Offshore Oil Exploration: An Application of Multiobjective Decision Analysis. Proc., SPE Hydrocarbon Economics and Evaluation Symposium, Dallas, Texas 2001; 2-3: SPE-68579-MS. http://dx.doi.org/10.2118/68579-MS
- [35] Castro GT, Morooka CK, Bordalo SN. Decision-Making Process for a Deepwater Production System Considering Environmental, Technological and Financial Risks. Proc., SPE Annual Technical Conference and Exhibition, San Antonio, Texas 2002; 29 September–2 October 2002. SPE-77423-MS.

http://dx.doi.org/10.2118/77423-MS

- [36] Walls MR. Corporate Risk Tolerance and Capital Allocation: A Practical Approach to Implementing an Exploration Risk Policy. Journal of Petroleum Technology 1995; 47(04): SPE-28281-PA. http://dx.doi.org/10.2118/28281-PA
- [37] Clemen RT and Reilly T. Making Hard Decisions with Decision Tools. Duxbury/Thomson Learning (reprint) 2001.
- [38] Bourgoyne AT. Applied Drilling Engineering. Society of Petroleum Engineers (reprint) 1986.

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