UNCERTAINTY QUANTIFICATION AND CALIBRATION IN WELL CONSTRUCTION COST ESTIMATES

A Thesis

by

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ABSTRACT

The feasibility and success of petroleum development projects depend to a large degree on well construction costs. Well construction cost estimates often contain high levels of uncertainty. In many cases, these costs have been estimated using deterministic methods that do not reliably account for uncertainty, leading to biased estimates. The primary objective of this work was to improve the reliability of deterministic well construction cost estimates by incorporating probabilistic methods into the estimation process.

The method uses historical well cost estimates and actual well costs to develop probabilistic correction factors that can be applied to future well cost estimates. These factors can be applied to the entire well cost or to individual cost components. Application of the methodology to estimation of well construction costs for horizontal wells in a shale gas play resulted in well cost estimates that were well calibrated probabilistically. Overall, average estimated well cost using this methodology was significantly more accurate than average estimated well cost using deterministic methods. Systematic use of this methodology can provide for more accurate and efficient allocation of capital for drilling campaigns, which should have significant impacts on reservoir development and profitability.

DEDICATION

This thesis is dedicated to my wife and my parents for helping me achieve the goals I have set in my life and for all the support they have given throughout the years.

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Finally, thank you to my parents for their encouragement towards continuous growth, both professionally and personally.

NOMENCLATURE

AFE	Authorization for Expenditure
BHA	Bottom Hole Assembly
C_i	Cost of AFE i
C_T	Total Well Cost
CDF	Cumulative Distribution Function
COV	Coefficient of Variance
F	Position Indicator
i	Index of AFE's Sub-costs
K	Maximum Number of Divisions
n	Number of Elements in the Dataset
NPT	Non-Productive Time
p	Fractile Desired for Calculating Percentile
P10	10th Percentile
P50	50^{th} Percentile
P90	90^{th} Percentile
R	Correlation Coefficient
ROP	Rate of Penetration
ROWC	Rate of Well Completion
SD	Standard Deviation
X_i	Historical Correction Factor

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1. INTRODUCTION

The feasibility and success of petroleum development projects depend directly on the well construction costs, which contain high levels of uncertainty. The well cost estimations provide the basis for AFE's (Authorization for Expenditures) and thus impact capital allocation in the annual budgeting process. It is necessary to accurately estimate well construction costs to provide efficient allocation of capital.

Well construction costs have traditionally been assessed using deterministic methods to obtain point estimates, which do not account for the uncertainties. In order to reliably account for uncertainty, it is necessary to apply probabilistic methods to ascertain the distribution of outcomes, which will provide more information for the decision-making process.

The use of uncertainty quantification is a key element when making decisions. Particularly in the drilling industry, by acknowledging and assessing uncertainties, it is possible to assess the probabilities of cost overruns, understand the accuracy of the estimates and provide identification of risk factors in the well construction operations.

Capen (1976) claimed we have not learned to successfully deal with uncertainty. In his work, engineers were asked to come up with 90% confidence intervals for several estimations, but instead generated 32% confidence intervals on average. This experiment demonstrated a tendency to understate the uncertainty and overestimate the accuracy of one's knowledge, which becomes the basis for decisions that are more susceptible to surprises.

The uncertainties in well construction cost estimation must be quantified and accounted for in cost predictions. These estimations will be used in other forecasts, such as cash flow analysis, forming a hierarchical structure in which the errors or inaccuracies of the well cost estimations will propagate to other forecasts, which results in a cumulative impact that leads to cost estimates that are different from the actual.

Today in the oil and gas industry, probabilistic methods are being widely used in areas such as reserves estimation, reservoir characterization and production forecasting. In these areas, stochastic models have become common practices, while their application in drilling engineering has been limited (Hariharan et.al 2006).

A survey provided by Hariharan et al. (2006), designed to discover the level of interest in probabilistic methods in the drilling industry, included questions regarding the value of using probabilistic methods, current use of probabilistic methods and reasons for not using the methods. The results from the survey reveal that 91% of the respondents believe there is value in using probabilistic methods for the estimation of drilling costs, but only 54% actually use probabilistic methods when estimating drilling costs. The reasons for not using probabilistic results were due mainly to the lack of adequate knowledge and training in statistics, and the fact that it takes more time to perform. This survey shows that deterministic methodologies that do not quantify uncertainty are still being widely used, which indicates, as Capen said, that we still have not learned to successfully deal with uncertainty.

1.1. Status of the question

The use of deterministic estimates can result in overestimation and underestimation of well costs. Overestimation implies that there was too much capital allocated to a specific well, which could have been allocated to another project. Underestimation, on the other hand, indicates that the estimations are optimistic, providing predictions that are lower than the actual well cost, which produces cost overruns at later stages of the project. Both issues contribute to inefficient capital budgeting.

Using a probabilistic methodology is not sufficient to assess the uncertainty reliably. Look-backs, which are based on the analysis of past estimations, are required to provide more reliable estimates. Calibration provides a tool to measure the degree to which the predicted values agree with the observed outcomes. In order to provide calibration it is possible to use historical well construction cost to scale the estimates, providing for more reliable results. As Capen (1976) explained, keeping records of our probabilistic estimates and comparing them with actual outcomes allows us to build our own rules for making more reliable probabilistic estimates.

A study of historical cost estimates by Loberg et al. (2008) indicates that deterministic values have been too optimistic from the engineers' point of view. Optimism, as described by McVay and Dossary (2012), is a tendency to ignore or not consider possible negative outcomes that bring cost and time overruns that could lead the project to uneconomic results.

Probabilistic well cost models have been used to provide more accurate estimations; these models consist of the well construction process modeled in different sections and activities with associated costs that can be represented by probability distributions. The following studies presented models that have different approaches for estimating well costs.

Peterson et al. (1993/1995) presented two papers that introduce a probabilistic methodology to create drilling performance predictions by generating risked AFE estimates. The first paper explains a procedure for providing a probabilistic approach to estimate total time, which consists of adding the total problem-free time and the total problem time, from parameters estimated by fitting data to a historical database. The second paper consists of the application of this same methodology to two specific case studies. The first was based on an AFE estimation for a development well, for which only the time was estimated probabilistically. The second consisted of an exploration well, for which both time and cost were estimated using distributions, in order to reflect the uncertainty of prices and the availability of services in the future.

Whelehan and Thorogood (1994) proposed an automated system for predicting drilling performance, which focuses on forecasting drilling time by using data from offset wells (historical well database). The approach consists of defining a group of offset wells that must be comparable to the designed well plan, which will be entered as a sequence of jobs. Using the performance data from the offset wells, several tasks are appointed for each of the jobs. The forecast is based on the time it took to complete the tasks of the offset wells.

Kitchel et al. (1997) introduced a combined drilling cost spreadsheet that contained a forecasting and risk analysis program to predict ranges of cost and time to drill a well, using Monte Carlo simulation and regional costs to generate the drilling estimates. Their approach is to differentiate the time, depth and fixed-cost components of the well, while focusing on the cost drivers that influence the results the most. These cost drivers are represented as distributions, while the others are denoted as point estimates.

Williamson et al. (2006) focused on the application of Monte Carlo simulation in time and cost estimation for single wells, concentrating on a cost model that calculates the average section drilling time from a distribution of rates of penetration (ROP). The paper describes how to create probabilistic models, as well as explanations of common pitfalls when creating these kinds of models. The paper also focuses on multi-well cost forecasting by single-well aggregation when estimating large drilling campaigns.

Akbari et al. (2007) proposed a similar model to the one presented by Peterson et al. (1993), which consists of using risk analysis and Monte Carlo simulation, with statistical analysis of historical drilling estimates, to improve the accuracy of AFE estimates. The model includes the calculation of the total time, based on parameters such as the total problem time and the free rig time. Additionally, it introduces a new parameter: the rate of well completion (ROWC), which consists of the depth over the total drilling time.

Loberg et al. (2008) and Merlo et al. (2009) presented an application (tool) and a methodology for performing probabilistic well cost estimates, which consists of calculating the total cost and the total duration of the different activities of the construction process. This is done by representing the different AFE sub-costs and the durations of the activities as probability distributions to reflect uncertainty. The input distributions must be created by experienced personnel using the tool, which requires the minimum, maximum and peak values chosen by the engineer. This issue reflects a weakness in the methodology, given that the reliability of the estimates will depend on the engineers' expert judgment, instead of using a historical dataset to create more representative distributions that are based on the outcomes of past well construction estimations, in the case that these are available.

These authors have presented methodologies to obtain probabilistic well cost estimates from historical data and expert judgment. The main issue presented so far resides in the lack of validation, not having evaluated the calibration of these models.

Adams et al. (2010) work focuses on several limitations presented by other authors, such as poor consistent definition of Non-Productive Times (NPT) and the importance of the validation of the model. The concept of validation is not addressed in any of the papers mentioned before, and is considered of key importance to provide assurance that the model is coming up with reliable estimates.

The validation of Adam's model consists of matching the calculated estimates to historical data, using the mean of the durations and the coefficient of variance (COV), which represents a dimensionless dispersion given by the standard deviation over the mean. The study's main weakness resides in the fact that the dependencies between the drilling activities were not included in the model.

Hollund et al. (2010) proposed a probabilistic cost model in which the user models the drilling sequence as a series of activities, estimating each of their times, and then estimates the cost from this time model, making the model time-dependent. The model focuses on three parameters: time rate, quantity associated with the activity, and the section of the well that is being estimated.

Hollund's methodology presents a calibration capability using historical data, by obtaining parameters that are calculated from a dataset of wells, based on the similarities with the wells that are being planned. The features that are compared are geography, geology and technology; those that present high similarities in these areas will provide a good candidate to be incorporated in the historical database. In this step the authors use an "outlier detection algorithm" that filters wells that present extreme conditions in terms of outcomes; by doing so, they are not taking into account the occurrence of these improbable cases, which could lead to overconfidence.

Hollund also presented a validation technique, which consists of overlapping the actual cost distribution and the distribution obtained using the methodology, in order to determine if they match. The model presented by the authors assumes the variables as stochastically independent, which could lead to unrealistic values if the variables present dependencies among one another.

The methodologies explained above provide different approaches to probabilistic well cost estimations. The use of probabilistic methodologies has been mainly in conventional reservoirs, particularly in high-cost environments such as offshore or the arctic, due to the high uncertainty present and huge economic impact caused by unwelcome surprises.

As previously mentioned, the models described present different weaknesses that should be addressed to more reliably account for uncertainty, such as the lack of validation and lack of determination of dependencies. The use of historical data could provide for more reliable estimates in comparison to those that come from the engineers' expertise alone. The use of these probabilistic models has not been greatly applied in unconventional reservoirs, which would be valuable in this area due to the large number of wells required for their development. The similarities that these wells present has led to the use of deterministic methodologies to estimate well construction costs, failing to account for uncertainty.

1.2. Research objectives

The objectives of the research are the following:

- For well construction costs that are estimated deterministically, provide a methodology to externally convert deterministic estimates into probabilistic estimates through the use of historical data.
- Determine if the probabilistic estimates generated in this manner improve the accuracy and reliability of well cost estimation and determine the magnitude of the improvement.
- Determine the economic impact, in unconventional reservoirs, of reliable probabilistic well construction cost estimation.

1.3. Historical dataset description

The historical dataset that is used in the study, from which the probabilistic estimates will be acquired, is composed of cost information from 482 horizontal wells drilled in the Fort Worth basin during a three-year period, from 2009 to the second quarter of 2011. The dataset contains 87 wells from 2009, 237 wells from 2010 and 158 wells from 2011.

The information presented in the historical dataset contains the well costs in a deterministic format, which means that the information is presented as point estimates. The total cost is divided into different AFE sub-costs. In addition, each AFE sub-cost is separated into actual cost and deterministic estimates (estimations provided by the engineers).

1.4. Overview of the methodology

The study will provide a step-by-step methodology for creating a model that will provide more accurate well cost predictions from deterministic estimates provided by engineers. The different steps that were taken during the study will be presented in the following sections, although a short explanation of each step will be described here.

The steps that comprise the methodology are the following (**Fig. 1.1**):

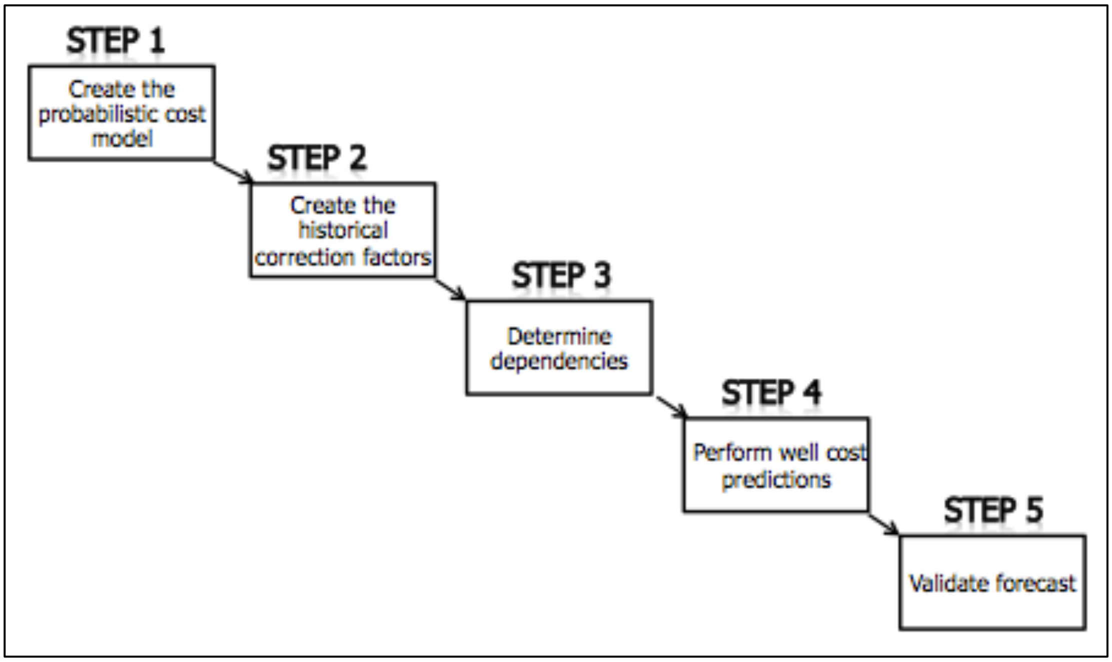

Fig. 1.1—Step-by-step methodology for the proposed model

Step 1: Create the probabilistic cost model

The model consists of taking the drilling-cost model provided, which will be the sum of the AFE sub-costs, and modifying it to obtain probabilistic outcomes. This modification will consist of the creation of probabilistic correction factors that bring the AFE estimates as closely as possible to the actual values.

Step 2: Create the historical correction factors

The creation of the correction factors is drawn from the historical dataset, which will provide a measure of error based on previous estimations from the engineers. The correction factors will also provide the conversion of the deterministic estimates to probabilistic estimates.

The proposed model will be encoded in a Microsoft Excel spreadsheet, and the correction factors will be fitted to distributions using @RISK.

Step 3: Determine dependencies

It is necessary to determine the level of dependency of the variables and include the relations, through correlation matrixes, into the cost model.

Step 4: Perform well cost predictions

The spreadsheet created in Microsoft Excel will function as an interface for the user, where the estimator can input deterministic costs in each of the drilling cost subdivisions and obtain probabilistic estimates. The well cost predictions are performed in this stage by running the simulation in @RISK and obtaining the probabilistic outcomes.

Step 5: Validate forecast

The proposed methodology must be validated to determine if the model is well calibrated, i.e., able to perform reliable future well-cost estimations. Different evaluation measures will be performed for the validation, which includes coverage rate and calibration plots.

After having validated the model, it is necessary to determine the benefit of using this methodology as a standard practice when performing well-cost predictions. The economic impact will be demonstrated by comparing the total capital from the deterministic estimates, total capital calculated from the probabilistic predictions, and the actual amount invested in the project. The comparison will show the amount by which the costs were inaccurately estimated by the engineers and what would have resulted if the proposed model had been applied.

2. STEP 1: CREATE THE PROBABILISTIC COST MODEL

This section describes the current AFE cost model and presents the proposed solution for applying a probabilistic methodology to that particular model. The subdivision of costs that comprises the AFE will also be explained in detailed to understand the variables that will be assessed during this study.

2.1. Current AFE estimation

The current cost model used in AFE estimations consists of integrating a number of AFE sub-costs to estimate the total cost of the well. The AFE sub-costs are specified as different components in the well construction process that are then added together. Traditionally, these sub-costs have been estimated deterministically (Eq. 1) in unconventional reservoirs where large numbers of wells are drilled.

$$C_T = \sum_{i=1}^{n} C_i = C_1 + C_2 + C_3 + \cdots + C_n, \qquad (1)$$

The sub-costs presented for this study are taken from the AFEs of an oil and gas operator. If these AFE sub-costs are different for each company the procedure is equally applicable to any format. The number of AFE sub-costs for this study is composed of twenty-three (23) components (**Table 2.1**).

TABLE 2.1— DETAILED DESCRIPTION OF AFE SUB-COSTS	
AFE Sub-Cost	**Description**
Tangible	
Surface Casing	Drilling - Surface Casing - New (pipe identified by materials personnel as surface casing, upper portion of casing string)
Production Casing	Drilling - Production Casing - New (including if the casing string is either a liner or full string, include liner hanging equipment if utilized)
Wellhead Equipment	Wellhead Equipment & Christmas tree - New (equipment identified by materials personnel as wellhead equipment)
Intangible	
Access Location & Roads	Costs incurred to prepare location for drilling: -Building roads & locations -Location damages -Survey crews & archaeology surveys -Rat holes & mouse holes -Setting anchors -Conductor pipe & cost to set conductor pipe -Excavating pits -Tractor cost for pulling personnel into/out of location
Rig Move	Cost to move rig on location: -Trucking charges -Day work while moving -Reduced day rates may apply -Check with Engineer
Day Work	Contractual cost of drilling company performed on a daily or hourly basis.
Bits & BHA	All costs for drill bits and BHA components (purchased or rented): -Key seat wiper, RT tools, watermelon mills -Subs for BHA -Reamers, square drill collars, stabilizers, shock subs, chert cutters
Fuel	Includes cost of any fuel types used in drilling operations: -Diesel, gasoline, fuel oil, electric power -Propane for flare lighter -Fuel for trailer houses, air compressors, water wells
Water	Water used during drilling operations: -Laying down& taking up water lines -Payments to land owner for water -Cost to drill water well for drilling purposes -Rental cost of: plastic water line, generator, water pump, water meter & tubing for water well
Mud & Chemicals	All costs for drilling fluids: -Product additives, specialty additives, mud engineering services, weight & lost circulation materials. -Chemicals: including those to protect drill string, crude oil or diesel when added to mud system. -Drayage: trucking products to & from location. -Cost should be equivalent to bill from drilling fluids company.
Cementing & Services	-Cement & cementing services including related equipment: -Float shoe & collar, Centralizers, DV tools, Scratchers -Nitrogen for cement job -Ready mix concrete for cellars
Logging & Testing	-Surveying & testing -Sidewall cores, etc. -Open hole logging -Drill stem tests
Mud Logging	Includes cost of equipment and personnel used to provide on-site geological services for mud logging and sample catching.
Transportation	General transportation of equipment, products & personnel.
Drilling Overhead	Estimate to capture overhead & indirect drilling operation costs

TABLE 2.1—CONTINUED	
AFE Sub-Cost	**Description**
	Intangible
Equipment Rental	Rental cost of all equipment & supplies related to rig operations, casing crews & equipment: -Solids Control Equipment: mud tanks, shale shakers, desilters, desanders, centrifuges, frac tanks for mud storage, mud strippers, dewatering system, degasser -Rotating head assembly & rubbers -Mud gas separator -Petron costs – daily rate provided by company -Blowout preventers -Reverse circulating units & power swivels -Drilling choke -Drill pipe, Drill collars & handling tools -Rental spools -Any repairs of rented equipment EXCEPT tubulars -Intercoms -Forklift (if kept on location) -Packer & retrievable bridge plug - PVT's monitoring equipment -Circulating pump (for reserve pit) -Pick up lay down machines -All casing crews (surface & production) -Mobile homes & fresh water systems (rental & transportation to location)
Other Expenses	-Miscellaneous items, labor or equipment -Welders -Cranes to set bar bins & other equipment -Testing BOP's -Fittings/valves for bar bins & mud gas separator -Nipple up crew -Drinking water for trailer house -Cost of lift plugs for casing pick up -Hydraulic unit to lift BOP stacks -Tandem trucks for setting BOP stacks -Forklift (not kept on location) to unload casing/tubulars -Field liner hanger supervisor on location (hang or set liner) -Thread man to witness torque make up on tubular goods
Environmental & Safety	-Trash trailer & cost to dispose of contents -Chemical toilets -Lining, fencing, filling in reserve pits -Sound abatement -Hydrogen sulfide monitoring equipment -Digging septic holes -Cleaning up spills (water, oil, mud, solid waste) -Reclaiming/reseeding access road, reserve pit, location
Directional Drilling	Directional Company Costs. Including: -Magnetic Multishot surveys -Personnel -MWD logging -Mobilization of related equipment -MWD's-Gyro surveys -Wireline single surveys -Drill collars-Whipstock -Steering tools & stabilizers -Standby time -Motors -Directional drilling tools lost in hole -MWD personnel
Supervision	Salaries of company personnel, consultants & contractors who work at supervisory level
Tubular Inspection & Handling	Inspections & repairs of drill pipe, drill collars, HWDP & subs -Cleaning & drifting tubulars -All tool inspections

TABLE 2.1—CONTINUED	
AFE Sub-Cost	**Description**
Intangible	
Disposal Cost	Disposal of: -Cuttings -Fluids during drilling -Closed loop systems include: backhoe, pump truck, dozer, open top tanks for cuttings, vacuum trucks -Cost of all equipment & transportation associated with DISPOSAL of water or mud used during drilling operation, reserve pit & cellar fluids
Title & Opinion	Legal & land permitting and project development costs incurred in acquiring lease. Project Engineer will provide cost

2.2. Proposed probabilistic model

The proposed model for this study converts point (deterministic) estimates provided by the engineers into probabilistic ranges based on the historical data provided. The model requires modification of the current cost model; this involves the insertion of probabilistic correction factors that will allow to account for the uncertainty by creating distributions of the AFE sub-costs estimates (Eq. 2). A correction factor is calculated for each of the twenty-three (23) AFE sub-costs and is estimated from historical data.

$$C_T = \sum_{i=1}^{n} X_i C_i = X_1 C_1 + X_2 C_2 + X_3 C_3 + \cdots + X_n C_n \qquad (2)$$

2.3. Historical correction factors

The historical correction factor distributions are calculated from a historical database of wells, which contains the actual well costs and the deterministic estimates. The historical database provides ratios that are fitted to estimate the behavior of the different AFE sub-costs. Eq. 3 represents the ratio that must be calculated for each AFE sub-cost to provide a dataset from which the distributions will be created.

$$X_i = \frac{Actual\ well\ cost}{Estimated\ well\ cost} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Table 2.2 is a representation of the database for the directional drilling AFE sub-cost, and also contains the ratios that have been calculated using Eq. 3. The ratios can be seen marked in red, while the historical information (actual and the deterministic estimates predicted by the engineers) is marked in yellow. Table 2.2 is a representation of ten (10) wells, which were extracted for demonstration purposes, out of the 158 wells that constitute the whole dataset for the year 2011.

TABLE 2.2—REPRESENTATION OF THE HISTORICAL DATABASE OF THE DIRECTIONAL DRILLING AFE SUB-COST

Well	DIRECTIONAL DRILLING		
	Deterministic Est.	Actual Cost	Ratio
1	$102,000.00	$113,068.00	1.11
2	$126,000.00	$128,347.50	1.02
3	$126,000.00	$166,047.50	1.32
4	$150,000.00	$149,188.00	0.99
5	$197,300.00	$160,194.10	0.81
6	$154,000.00	$177,000.00	1.15
7	$168,000.00	$179,700.00	1.07
8	$110,000.00	$177,238.00	1.61
9	$161,000.00	$114,470.94	0.71
10	$121,000.00	$96,875.00	0.80

The ratio provided in the calculation indicates an underestimation of the sub-cost if the ratio is bigger than one, which means the actual sub-cost was greater than estimated by the engineer. On the other hand, if the value of the ratio is less than one, the estimation by the engineer was greater than the actual sub-cost, indicating overestimation.

The wells comprising the historical database must be selected carefully to obtain reliable estimates. The mixture of wells must be similar in properties to the type of well that we are trying to estimate. For example, if we are trying to estimate well costs in unconventional developments, we must include recent wells from the same development project or wells from previous projects that have similar properties (e.g., well design).

3. STEP 2: CREATE THE HISTORICAL CORRECTION FACTORS

This section describes the distribution fitting process and evaluation to create the historical correction factors; it will also explain the definition of distributions in the cases where fitting does not correctly represent the dataset. After the fitting process is completed the distributions are created.

3.1. Distribution selection methodology

The distribution fitting and selection consist of the representation of the data by fitting to different types of theoretical distributions to determine the most appropriate distribution. The data that will be fitted are the ratios calculated from the actual well sub-cost and those estimated by the engineer. The outcome of this fitting process provides the correction factors that will represent each of the sub-costs of the AFE.

The fitting of the distributions must be analyzed to determine if the distributions selected appropriately represent the dataset. In this study, the analysis was performed using the Chi-square methodology and a visual inspection of each of the distribution fittings to determine if a particular distribution form is appropriate or if it is necessary to manually define the distribution. The Chi-square or "goodness of fit test" is a statistical measure to determine how well the data fit the probability density function. The smaller the value of the Chi-square, the better the fit.

In the study, the 23 AFE sub-costs were fitted and the results are classified as Good, Moderate or Bad, to determine which distributions should be chosen using the fit obtained and which have to be defined manually in @RISK to model the particular dataset.

The three levels are represented in **Figs. 3.1-3.3**. Fig. 3.1 represents the fitting of the supervision AFE sub-cost, which falls in the category of "Good" fitting. The red square to the left shows the fit ranking with a Chi-square value of 5.97. The probability density function, in the middle, and the cumulative relative frequency curve, on the right, demonstrate good fit, which confirms a good representation of the dataset.

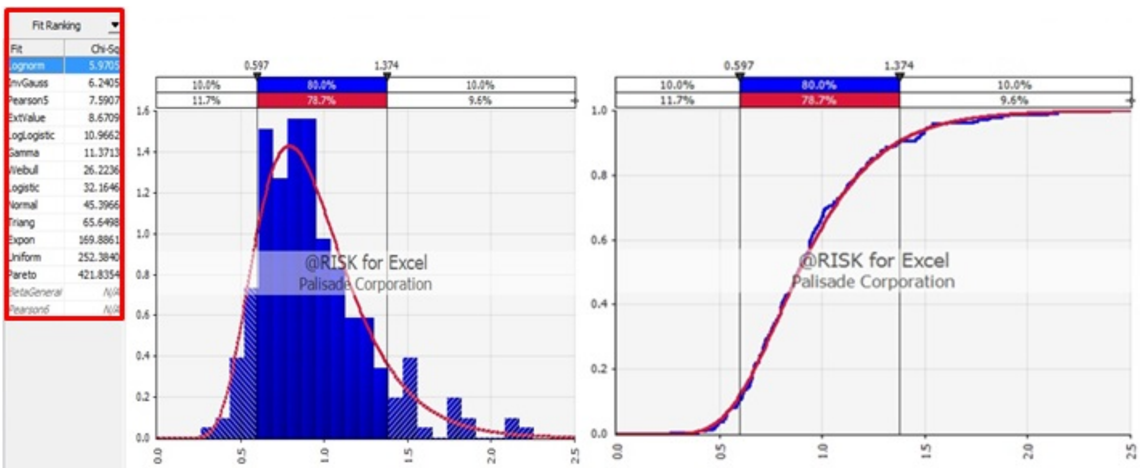

Fig. 3.1—Fit distribution of supervision cost ratio (Level: Good)

In Fig. 3.2, the fit of the drilling overhead ratio is shown. Its Chi-square value of 37.27 falls in the category of "Moderate" fitting. In addition, the cumulative distribution curves do not overlie as much as the ones for the supervision AFE sub-cost seen in Fig. 3.1. Fig. 3.3 shows the fit for the mud-logging AFE sub-cost with a Chi-square value of 121.08, which is even higher than the moderate case. The red circle in Fig. 3.3 shows that the cumulative distribution curve does not overlie at all in some parts of the curve, which places it in the category of "Bad" fitting.

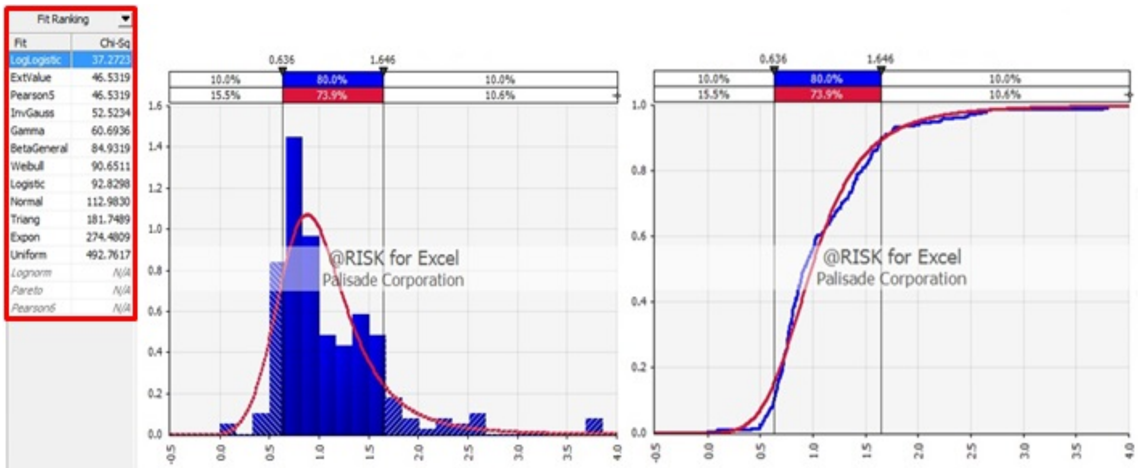

Fig. 3.2—Fit distribution of drilling overhead AFE sub-cost. (Level: Moderate)

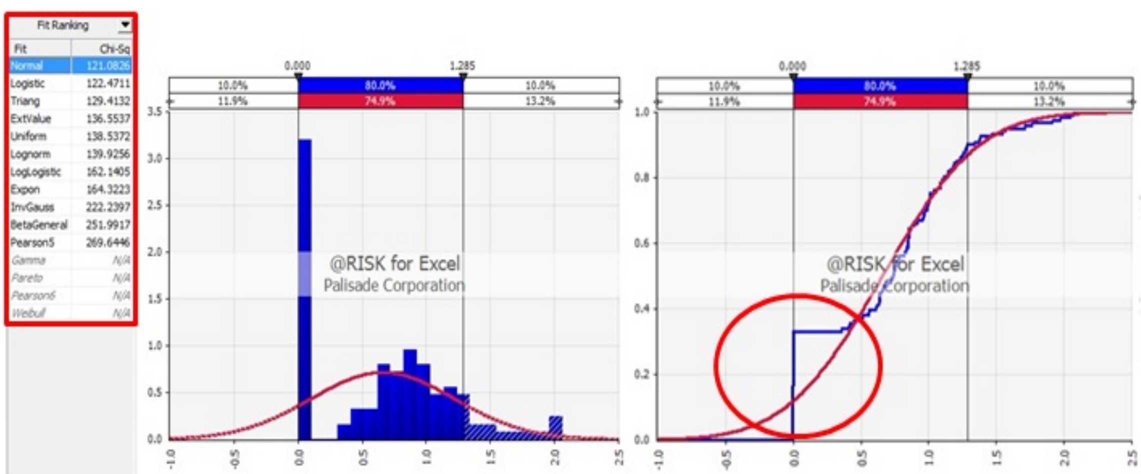

Fig. 3.3—Fit distribution of mud logging AFE sub-cost. (Level: Bad)

The results from the visual and the Chi-square fit evaluations are presented in **Tables 3.1-3.3** for the datasets using 2009 wells, 2010 wells, and 2009-2010 wells, respectively. The cases that resulted in a bad fit were entered manually into @RISK by defining their distributions, as explained more in detail in Section 3.2. Using the historical data from 2009-2010, the AFE sub-costs that required manual fitting were wellhead equipment, open-hole logging, mud logging, disposal cost and title opinion. For the other two datasets, the cases were open-hole logging, mud logging and disposal cost.

TABLE 3.1—EVALUATION OF THE FITTING DISTRIBUTIONS FOR THE HISTORICAL DATA 2009

Drilling Cost Ratios	Chi-Sq Fit	Fit
Surface Casing Ratio	7.11	Good/Moderate
Production Casing Ratio	14.00	Moderate
Wellhead Equip. Ratio	6.44	Good/Moderate
Access, Location, Roads and Survey Ratio	18.32	Good/Moderate
Rig Move Ratio	5.07	Good
Day Work Cost Ratio	14.28	Moderate
Bits and BHA Ratio	2.14	Good
Fuel Ratio	6.18	Good/Moderate
Water Ratio	3.15	Good
Mud and Chemicals Ratio	12.76	Good
Cementing Ratio	6.69	Good
Open Hole Log Ratio	9.60	Bad
Mud Log Ratio	0.00	Bad
Transportation Ratio	6.44	Good
Drilling Overhead Ratio	1.38	Good
Equipment Rental Ratio	6.69	Good/Moderate
Other Drilling Expenses Ratio	14.28	Moderate
Environmental and Safety Charges Ratio	6.44	Good/Moderate
Directional Drilling Ratio	8.31	Good
Supervision Ratio	3.66	Good
Tubular Inspec. Ratio	7.63	Good/Moderate
Disposal Cost Ratio	180.90	Bad
Title Opinion-Drill Site Ratio	12.23	Good

TABLE 3.2—EVALUATION OF THE FITTING DISTRIBUTIONS FOR THE HISTORICAL DATA 2010		
Drilling Cost Ratios	**Chi-Sq. Fit**	**Fit**
Surface Casing Ratio	17.4473	Good
Production Casing Ratio	20.2712	Moderate/Good
Wellhead Equip. Ratio	71.9958	Moderate
Access, Location, Roads and Survey Ratio	15.962	Good
Rig Move Ratio	22.443	Good
Day Work Cost Ratio	23.6582	Good
Bits and BHA Ratio	18.6441	Good
Fuel Ratio	4.7553	Good
Water Ratio	13.3966	Good
Mud and Chemicals Ratio	11.2363	Good
Cementing Ratio	7.0506	Good
Open Hole Log Ratio	85.9291	Bad
Mud Log Ratio	121.0826	Bad
Transportation Ratio	10.2911	Good
Drilling Overhead Ratio	37.2723	Moderate
Other Drilling Expenses Ratio	13.3966	Good
Environmental and Safety Charges Ratio	23.9322	Moderate
Directional Drilling Ratio	18.7975	Good
Supervision Ratio	5.9705	Good
Tubular Inspec. Ratio	13.9367	Good
Disposal Cost Ratio	375.2572	Bad
Title Opinion-Drill Site Ratio	37.2677	Good

TABLE 3.3—EVALUATION OF THE FITTING DISTRIBUTIONS FOR THE HISTORICAL DATA 2009-2010		
Drilling Cost Ratios	**Chi-Sq. Fit**	**Fit**
Surface Casing Ratio	13.6502	Good
Production Casing Ratio	40.1776	Moderate
Wellhead Equip. Ratio	76.4444	Moderate/Bad
Access, Location, Roads and Survey Ratio	26.3333	Good
Rig Move Ratio	10.0836	Good
Day Work Cost Ratio	42.3333	Moderate/Good
Bits and BHA Ratio	13.4272	Good
Fuel Ratio	15.2222	Good
Water Ratio	14.0000	Good
Mud and Chemicals Ratio	9.7778	Good
Cementing Ratio	16.1111	Good
Open Hole Log Ratio	90.0414	Bad
Mud Log Ratio	149.188	Bad
Transportation Ratio	12.1111	Good
Drilling Overhead Ratio	39.2298	Moderate/Good
Other Drilling Expenses Ratio	20.6667	Good
Environmental and Safety Charges Ratio	22.9009	Moderate/Good
Directional Drilling Ratio	21.6625	Good
Supervision Ratio	14.1111	Good
Tubular Inspec. Ratio	16.4365	Good
Disposal Cost Ratio	755.0194	Bad
Title Opinion-Drill Site Ratio	51.4161	Bad

3.2. Manual creation of distributions for required cases

As previously mentioned, in the cases where data were not properly represented, the distribution was modeled manually using the “define distributions” option in @RISK. The process requires that the minimum and maximum values of the dataset, as well as different percentiles be introduced to model the cumulative distribution curve of the AFE sub-costs.

The percentiles are calculated by first ordering the dataset in ascending values, then choosing the fractile (p) and the K value. The K value represents the number of divisions that was selected, which for this case is equal to 100 (for estimating percentiles). Eq. 4 allows to calculate the position of the desired percentile in the dataset (in ascending order), indicating the location of the specific value that corresponds to the percentile for the given dataset.

$$F = \frac{p}{K}(n+1), \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

After determining the percentiles of the dataset, it is necessary to define the distributions in @RISK by selecting the cumulative distribution option and entering the probabilities with their respective values. After completing this process the distribution will be created. **Fig. 3.4** represents the CDF of the mud-logging AFE sub-cost inputted in @RISK, which was created manually. **Fig. 3.5** shows a comparison between the actual distribution of the dataset and the manually created distribution for the mud-logging AFE sub-cost.

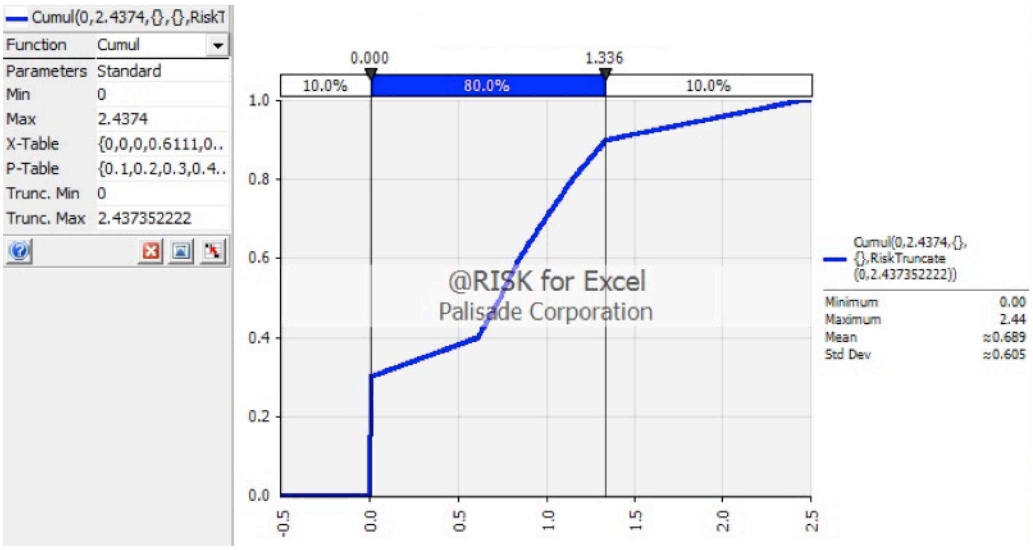

Fig. 3.4—Mud logging AFE sub-cost with manually defined distribution

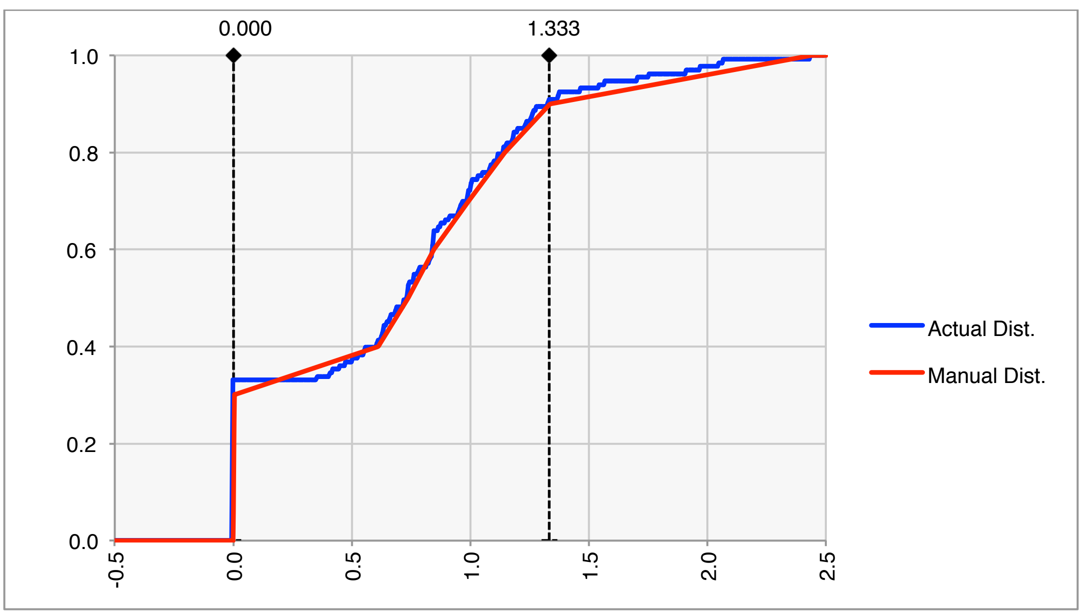

Fig. 3.5—Comparison of the actual distribution and the manually defined distribution for the mud logging AFE sub-cost

4. STEP 3: DETERMINE DEPENDENCIES

In well-cost estimation the different AFE sub-costs are often correlated. Up to this point in the model these variables have been treated as independent, which implies no relationships amongst them. Using a model assuming independence for variables that are actually correlated may result in outcomes that are unreasonable. This section describes the methodology used for calculating the level of dependency and including these relations, through correlation matrixes, into the cost model.

4.1. Dependency between well AFE sub-costs

In order to determine the relationship between two variables it is necessary to create scatter diagrams that consist of plotting a variable against another, to determine the correlation coefficient (R value) of the trend line resulting from the plot. Another approach is using the Correlation tool in the Data Analysis of Microsoft Excel, which will correlate the data from the input range selected and provide the matrix required for the analysis.

The correlation coefficients obtained in the data provided must range between -1 and +1, which represents the level of dependency of the two variables, or strength of the correlation. A value close to 0 indicates that there is no correlation between the variables. In the cases where it is close to -1, there exists an inverse correlation between the variables, denoting that one variable will sample smaller values as the other variable samples higher ones. Values close to +1 represent a positive correlation between the variables, which means that as the generated sample increases the other sample will increase as well. The values that are close to 0.5 or -0.5 represent partial correlation, with positive and inverse relationships, respectively.

4.2. Correlation matrix

The correlation matrix specifies the correlation coefficient for each pair of variables. The correlation matrix created for each model includes the coefficients for all 23 variables. **Table 4.1** presents a subset of the complete correlation matrix for the model using historical data from 2009-2010, which includes the six variables that present stronger dependencies in the model. The complete correlation matrices used for the models are presented in Appendix A.

TABLE 4.1—CORRELATION MATRIX OF VARIABLES WITH STRONGER DEPENDENCIES

@RISK Correlations	Day Work Cost Ratio in GF7	Fuel Ratio in GF9	Mud and Chemicals Ratio in GF11	Drilling Overhead Ratio in GF16	Directional Drilling Ratio in GF20	Supervision Ratio in GF21
Day Work Cost Ratio in GF7	1					
Fuel Ratio in GF9	0.41	1				
Mud and Chemicals Ratio in GF11	0.47	0.33	1			
Drilling Overhead Ratio in GF16	0.38	0.38	0.32	1		
Directional Drilling Ratio in GF20	0.53	0.49	0.37	0.40	1	
Supervision Ratio in GF21	0.12	0.34	0.21	0.14	0.33	1

The capability of creating a correlation matrix that can be applied to the distributions is provided by @RISK in the “define correlations” tab; this tool allows selection of the particular distributions between which we are looking to model the dependency and specification of the correlation coefficient that was previously calculated (Section 4.1). Using @RISK capabilities, it is also possible to visualize the scatter plots of the distributions in the correlation matrix (**Fig. 4.1**).

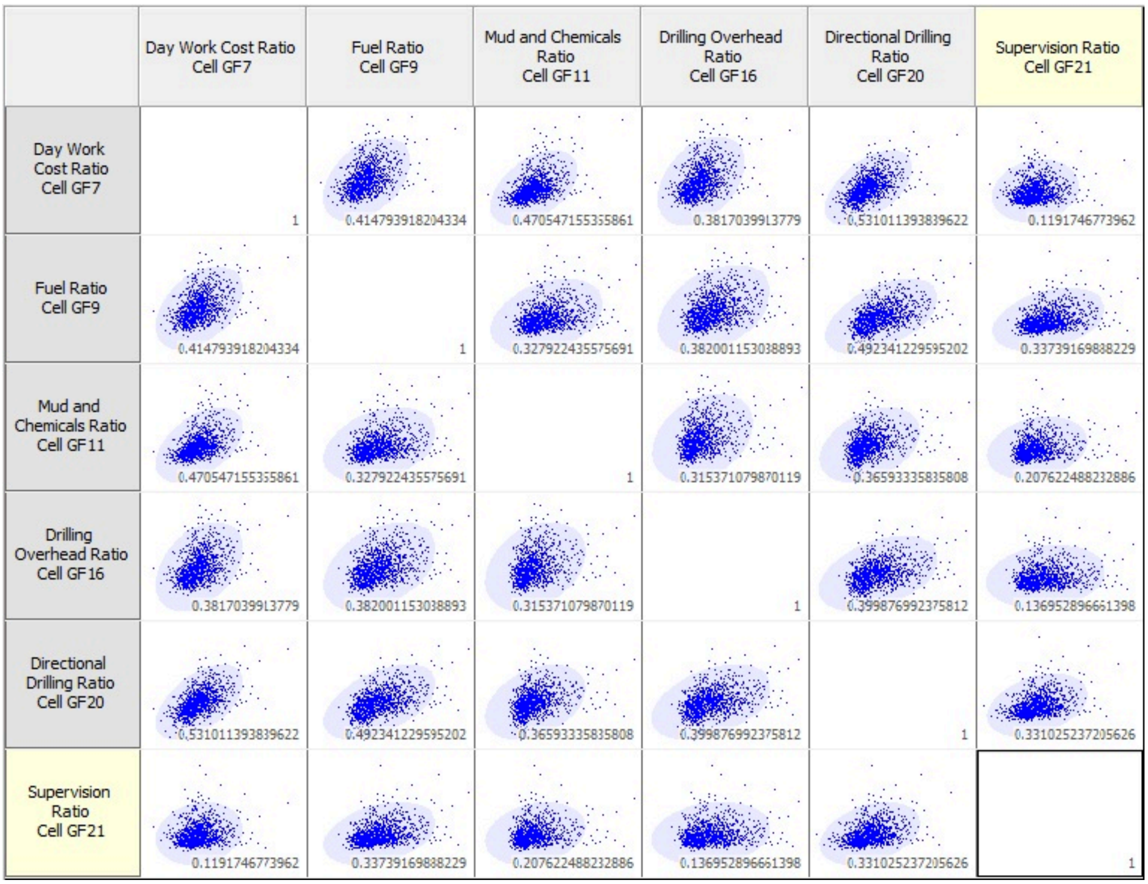

Fig. 4.1—@RISK correlation matrix with scatter plots for the variables with stronger dependencies

The dataset evaluated in this study resulted in correlation coefficients that were between the range of -0.2 and 0.53, showing mostly positive partial correlations and cases where variables are independent, having no correlation. All the variables were correlated in the model to increase the reliability of the models.

4.3. Final distributions used for calibration

The final distributions that are used in the model contain two additional specifications to those distributions obtained in the fitting process explained in Section 3; these are the “CORRMAT” and “TRUNCATE” functions. The first specifies the correlation matrix for the particular variables. The second is provided to limit the values sampled by the distributions to the minimum and maximum values of the dataset, which is necessary to avoid unrealistic values such as a negative cost.

The final distributions obtained for each of the datasets in this study can be seen in Appendix B. These distributions represent the correction factors that will be applied to the cost model to convert deterministic estimates into probabilistic estimates.

5. STEP 4: PERFORM WELL COST PREDICTIONS

The model must be represented in Microsoft Excel to be able to use @RISK, which provides the sampling capability required for the analysis. The first step must be to generate the cost model in a simple structure that contains each of the AFE sub-costs, their respective correction factor and the product of these two, which is the AFE sub-cost probabilistic estimate. This must be done for all 23 AFE sub-costs, which will be added to obtain the probabilistic estimate of the total well cost.

Once the model has been created in Microsoft Excel, it is possible to use the historical data to execute the procedure that was described in Section 3.1 to generate the correction factors. This consists of calculating the ratios of the actual well sub-cost over the estimated well sub-cost and fitting distributions to these ratios.

The correlation coefficients must then be generated, as described in Section 4.2; the correlation option of the "Data Analysis" module in Microsoft Excel provides these coefficients in a quick and efficient matter. These correlation coefficients must then be placed in matrix form, containing 23 columns and rows, in order to account for the correlations between variables. Limiting the distributions to the minimum and maximum data values complete the process. At this time, the model has been created successfully and is ready to perform predictions.

Table 5.1 is an example of the model created in Microsoft Excel. The red square contains the engineers' deterministic estimates to which the model will be applied; the blue square encloses the different correction factors for each of the AFE sub-costs; the green square contains the results of multiplying the correction factors by the deterministic estimates to obtain the probabilistic estimates for the different AFE sub-costs; and the yellow square shows the probabilistic estimate of the total well cost. The cells in the blue, green and yellow squares represent distributions, and the value shown is the mean of each distribution.

TABLE 5.1—CREATION OF MODEL IN MICROSOFT EXCEL

AFE Sub-Cost	Deterministic Est.	Correction Factor (Xi)	Probabilistic Est.
Surface Casing	$ 19,000.00	0.89	$ 16,964.83
Production Casing	$ 178,000.00	0.90	$ 160,298.28
Wellhead Equipment	$ 5,000.00	1.31	$ 6,550.57
Access, Location, Roads and Survey	$ 140,000.00	1.30	$ 182,174.02
Rig Move	$ 55,825.00	1.09	$ 60,883.65
Day Work	$ 276,300.00	1.00	$ 276,222.49
Bits and BHA	$ 50,000.00	1.02	$ 50,846.43
Fuel	$ 48,000.00	0.96	$ 46,156.79
Water	$ 5,000.00	0.99	$ 4,959.86
Mud and Chemicals	$ 130,000.00	1.18	$ 153,216.68
Cementing	$ 99,850.00	1.00	$ 100,086.48
Open Hole Logging	$ -	1.07	$ -
Mud Logging	$ -	0.67	$ -
Transportation	$ 10,000.00	1.04	$ 10,416.56
Drilling Overhead	$ 2,600.00	1.06	$ 2,767.11
Equipment Rental	$ 98,000.00	1.60	$ 156,529.42
Other Drilling Expenses	$ 10,000.00	2.13	$ 21,274.87
Environmental and Safety Charges	$ 13,000.00	1.22	$ 15,892.26
Directional Drilling	$ 102,000.00	1.03	$ 104,741.31
Supervision	$ 30,000.00	0.93	$ 28,049.06
Tubular Inspection	$ 10,000.00	1.65	$ 16,485.94
Disposal Cost	$ 5,000.00	1.00	$ 4,977.58
Title Opinion-Drill Site	$ 35,000.00	0.83	$ 28,941.08
Total Cost	$ 1,322,575.00	Total Well Cost	$ 1,448,435.25

The system provides percentiles, as well as descriptive statistics for these distributions such as mean, standard deviation and variance. **Fig. 5.1** shows the outputs that were selected to obtain the required results of the probabilistic estimates, which constitute the predictions of the well cost. The right side of the figure illustrates the result for Bits and BHA AFE sub-cost that was obtained after running the model.

AFE Sub-Cost	Deterministic Est.	Correction Factor (Xi)	Probabilistic Est.
Surface Casing	$ 19,000.00	0.89	$ 16,964.83
Production Casing	$ 178,000.00	0.90	$ 160,298.28
Wellhead Equipment	$ 5,000.00	1.31	$ 6,550.57
Access, Location, Roads and Survey	$ 140,000.00	1.30	$ 182,174.02
Rig Move	$ 55,825.00	1.09	$ 60,883.65
Day Work	$ 276,300.00	1.00	$ 276,222.49
Bits and BHA	$ 50,000.00	1.02	$ 50,846.43
Fuel	$ 48,000.00	0.96	$ 46,156.79
Water	$ 5,000.00	0.99	$ 4,959.86
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Supervision	$ 30,000.00	0.93	$ 28,049.06
Tubular Inspection	$ 10,000.00	1.65	$ 16,485.94
Disposal Cost	$ 5,000.00	1.00	$ 4,977.58
Title Opinion-Drill Site	$ 35,000.00	0.83	$ 28,941.08
Total Cost	$1,322,575.00	Total Prob. Cost	$ 1,448,435.25

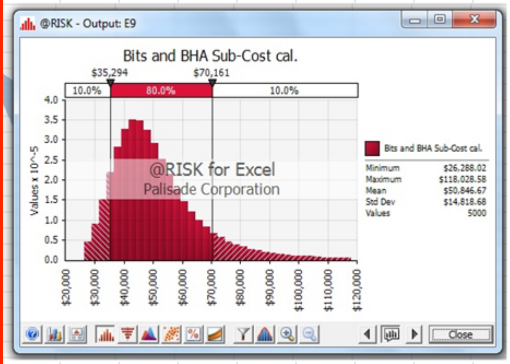

Fig. 5.1—Output selection

5.1. Random sampling methods

The use of a random sampling method is used to obtain samples for aggregating or multiplying different distributions. The process consists of generating values that are randomly drawn from input probability distributions that are defined in the model. The result is a distribution that is available for analysis and interpretation.

The manner in which the random samples are drawn from the input distributions will directly impact the accuracy of the resulting distribution, which is why it is important to allow the model to perform an appropriate number of iterations to completely sample these distributions.. The main two sampling methods are Monte Carlo sampling and Latin Hypercube sampling.

Monte Carlo sampling has been the traditional technique used when sampling variables. In this method, any given sample may fall anywhere within the range of the input distribution. The problem with this methodology resides in the fact that clustering of samples could arise when a small number of iterations is selected (**Fig. 5.2**). On the other hand, Latin Hypercube sampling consists of stratification of the input probability distributions. The cumulative curve is divided into equal intervals on the cumulative probability scale. In this sampling method, a sample is randomly taken from each interval, providing a better representation of the entire input probability distribution (**Fig. 5.3**).

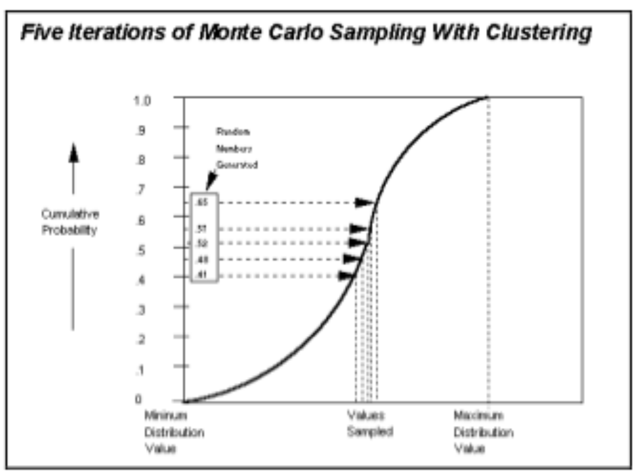

Fig. 5.2—Monte Carlo sampling method (Palisade (2010))

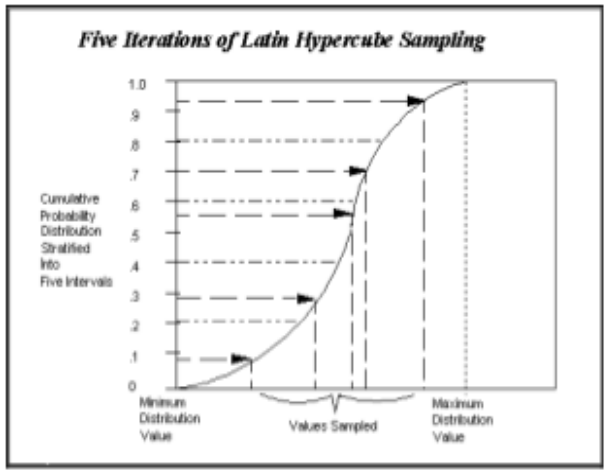

Fig. 5.3—Latin Hypercube sampling method (Palisade (2010))

Based on this difference in the way each method picks the samples, Monte Carlo will require a larger number of samples to approximate an input distribution. Latin Hypercube is able to converge faster with fewer iterations. The probabilistic model used in this study employs Latin Hypercube sampling with 5,000 iterations.

6. STEP 5: VALIDATE FORECAST

The validation of the model constitutes a necessary step that must be completed to determine if the model is well calibrated. In the validation the model predictions are compared against the actual well cost. The objective of the validation is to determine how well the distribution of the probabilistic estimates matches the distribution of the actual well costs.

The validation requires probabilistic estimates and the actual well costs, which is provided by performing well cost predictions based on historical data. The methodology is analyzed using three simulations: one that uses historical data from 2009 wells to estimate the well costs for 2010; one that uses the wells from 2010 to estimate the well costs for 2011, and the third that uses the wells from 2009 and 2010 to estimate well costs for 2011.

The validation of the forecast consists of the application of two evaluation measures: first, the coverage rate; and second, the calibration plot. The application of these measures provides a quantitative and visual evaluation of the match between the distribution of the probabilistic estimates and the actual well costs. Additionally, a comparison of cost distributions further evaluates the calibration of the model.

6.1. Coverage rate

The coverage rate is the number of wells in which the actual well cost falls within the P10-P90 range of the probabilistic estimates divided by the total number of wells. In this study, each of the wells are analyzed and classified in two categories: "Inside the range," for the wells in which the true value falls within the P10-P90 range; and "Outside the range," for those wells in which the actual value falls outside this range.

Fig. 6.1 presents an example of a well in which the true value falls inside the range, where the black line, representing the actual well cost, falls within the P10 and P90 values. **Fig. 6.2** shows a well in which the actual well cost falls outside of the P10-P90 range.

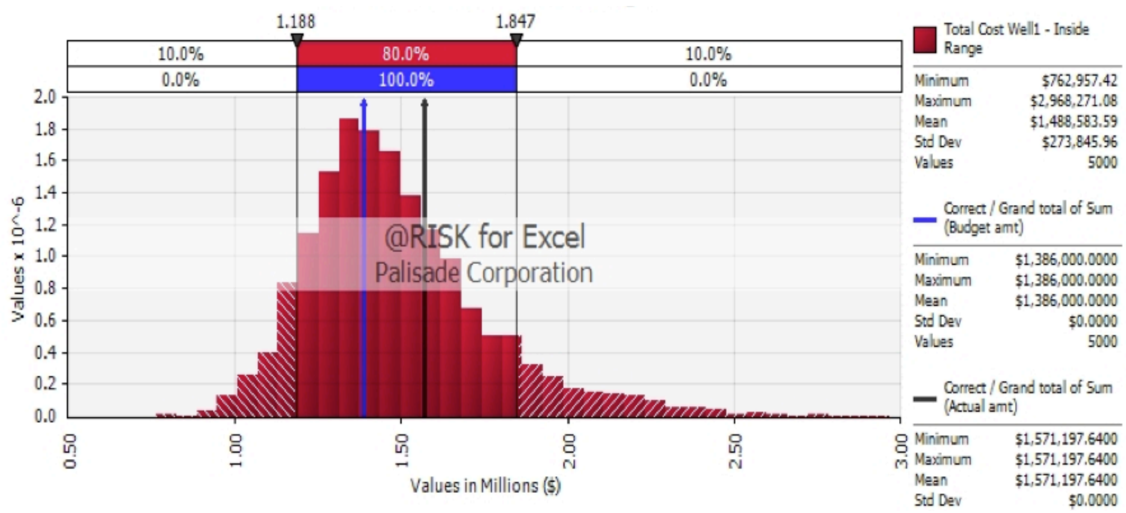

Fig. 6.1—Coverage rate. Case: inside the range

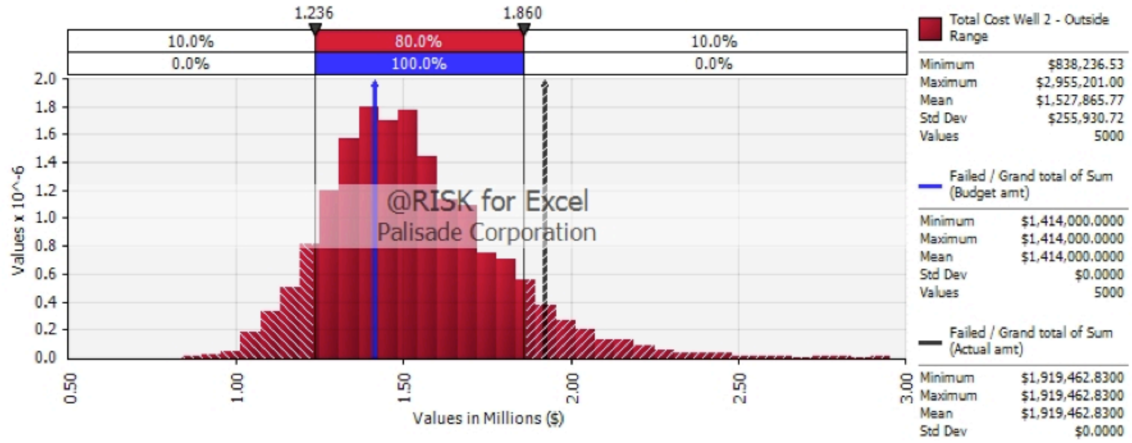

Fig. 6.2—Coverage rate. Case: outside the range

The validation of the model is based on the percentage of wells that fall inside the range. If a model is generating reliable probabilistic predictions, the expectation is that the true value would fall within the P10-P90 range about 80% of the time. Thus, the closer the coverage rate is to 80%, the better calibrated is the model.

The results obtained from the coverage rate measure are shown in **Table 6.1**, which contains the numbers of wells that fall inside and outside the ranges.

TABLE 6.1—RESULTS FROM COVERAGE RATE

Historical Data Used	Forecast	Case	Number of Wells	Percentage
2009	2010	Inside Range	206	86.92%
		Outside Range	31	13.08%
2010	2011	Inside Range	129	81.65%
		Outside Range	29	18.35%
2009-2010	2011	Inside Range	131	82.91%
		Outside Range	27	17.09%

The results show that the three models have a coverage rate that is close to 80%. The model that uses historical data from 2010 to predict costs for 2011 provided slightly better results, at 82%, than the other two models. The model using historical data from 2009 to predict costs for 2010 wells was the least well calibrated, at 87%, which is still relatively close to 80%. Thus, it is possible to conclude that all the models are reasonably well calibrated.

6.2. Calibration plots

The second measure provided to evaluate the calibration of the model is the use of calibration plots, which compares the probabilistic estimates to the actual well cost from a cumulative distribution perspective.

The creation of the calibration plot consists of taking the P10, P50 and P90 values obtained from the probabilistic estimates, and determining the number of wells in which the actual cost falls below each of these values. The x-axis in the calibration plot represents the cumulative probability assigned, i.e., the probability that the actual value falls below those specific values. These assigned probabilities are 10%, 50% and 90%. The y-axis represents the proportion of wells in which the actual value falls below these assigned probabilities (proportion correct). The model is well calibrated when the proportion correct equals the probability assigned over the entire distribution.

The calibration plot for the model that uses historical data from 2009 to predict costs for 2010 is presented in **Fig. 6.3.** The black, dashed, unit-slope line represents a perfect match of the proportion correct to the assigned probabilities; the blue diamond represents the deterministic estimates of the wells from 2010 assuming they are P50 estimates; and the orange curve corresponds to the plot for the probabilistic model using historical data from 2009 to predict costs for 2010.

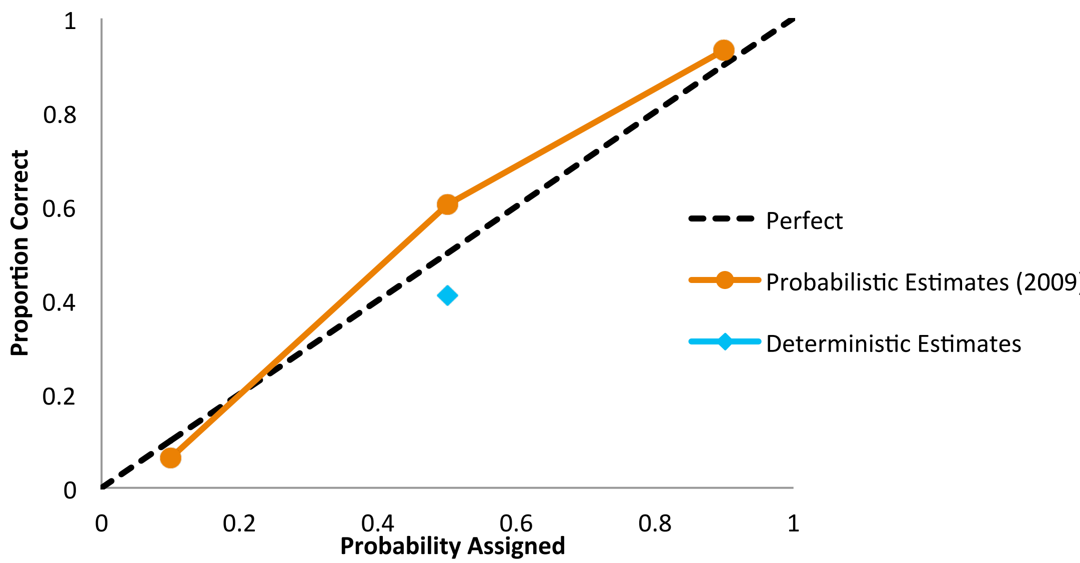

Fig. 6.3—Calibration plot for validation of the model using historical data from 2009 to predict costs for 2010

In Fig. 6.3 the P10 and P90 estimates are in close proximity to the unit-slope line, better than the P50 estimates. Overall, the plot indicates that the model is reasonably well calibrated.

The calibration plot for the models that predict costs for 2011 is presented in **Fig. 6.4.** The blue diamond represents the deterministic estimates for 2011 wells by assuming they are P50 estimates; and the green and red curves correspond to the probabilistic models using historical data from 2010 and 2009-2010, respectively.

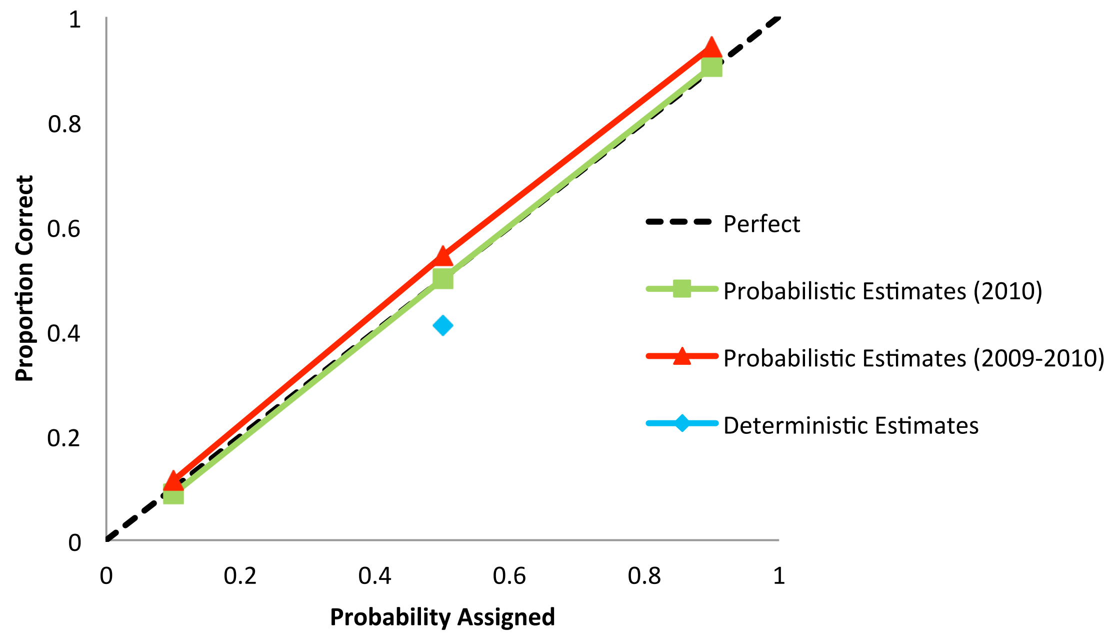

Fig. 6.4— Calibration plot for validation of the models using historical data from 2010, and 2009-2010, to predict costs for 2011

The results clearly show that both models are well calibrated, based on their close proximity to the unit-slope line, although the model using historical data from 2010 is superior. It can be observed that the two models (using historical data from 2010 and from 2009-2010) provide a better match to the actual well cost distribution than does the deterministic estimates.

Table 6.2 shows the values used for the calibration plots. For both 2010 and 2011 wells, the deterministic estimates resulted in a proportion correct of 41%, indicating the deterministic estimates underestimated the actual well costs in 59% of the wells.

TABLE 6.2—RESULTS FOR THE CALIBRATION PLOT

	Probability Assigned	Proportion Correct	Number of Wells
Probabilistic Est. Historical Data 2009	<P10	0.06	15
	<P50	0.60	143
	<P90	0.93	221
Deterministic Est. P50 (2010)	<P50	0.41	98
Probabilistic Est. Historical Data 2010	<P10	0.09	14
	<P50	0.50	79
	<P90	0.91	143
Probabilistic Est. Historical Data 2009-2010	<P10	0.11	18
	<P50	0.54	86
	<P90	0.94	149
Deterministic Est. P50 (2011)	<P50	0.41	64

The coverage rate and the calibration plot present good results and confirm the calibration of the three probabilistic models, which are able to efficiently perform well cost predictions of future wells.

7. IMPACT OF THE PROPOSED PROBABILISTIC COST MODEL

The impact of the model is demonstrated by applying the methodology to three different datasets. The first uses historical data from the year 2009 to predict costs for 2010; the second uses historical data from 2010 to predict costs for 2011; and the third uses historical data from the 2009 and 2010 to predict costs for 2011. The analysis consists of the comparison of two scenarios for each of the three cases mentioned above: one where the new methodology is used (probabilistic estimates), followed by another in which the methodology is not used (deterministic estimates).

The results are presented in four different sections. The first is comprised of crossplots of the probabilistic estimates compared to deterministic estimates in order to visualize the impact of the model. The second section analyzes the application of the methodology on an average per-well basis, by calculating the average ratio (actual/estimated) and the mean of the distribution obtained from the average of the total well costs. The third section consists of analyzing the results obtained by adding the probabilistic well cost estimates of all the wells, and comparing them against the sum of the deterministic well estimates of all the wells; this is done to simulate the use of the calibration model when predicting the cost of a drilling campaign in a development project. The fourth section shows the results from a sensitivity analysis, pointing out the advantages that this methodology provides as a common practice when estimating well cost.

7.1. Analysis of forecast using crossplots

In this section, the analysis of the forecast is conducted using crossplots comparing the actual total well cost to the estimated total well cost, for the probabilistic and deterministic estimates. The results presented in this section are mainly visual; the following sections provide more detailed numerical results of the estimations.

The crossplot consists of, on the y-axis, the actual total well cost, and on the x-axis, the estimated total well cost (**Fig. 7.2 through 7.9**). A unit-slope line is where the value of the actual total well cost equals the estimated total well cost. By using the unit-slope line, the behavior of underestimation and overestimation is illustrated, based on the side of the line on which the estimate falls. For example, an estimate that falls above the perfect line represents a case where the actual total well cost was higher than the estimated total cost, indicating underestimation of the cost. The case in which the estimate falls below the perfect line shows that the estimated total cost was higher than the actual well cost, exhibiting overestimation (**Fig. 7.1**).

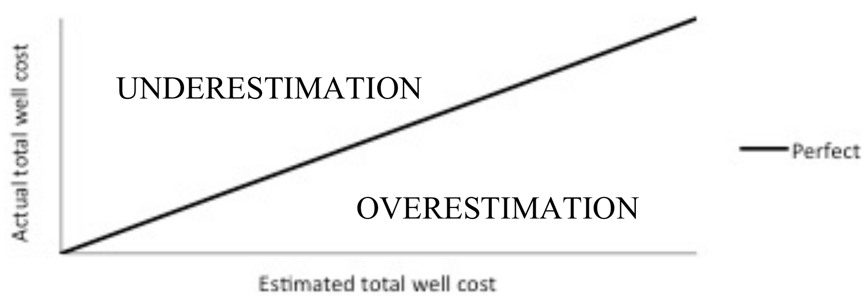

Fig. 7.1—Representation of the crossplot with perfect line

7.1.1. Analysis of estimates for 2010 well cost

The deterministic estimates are compared to the mean values of the probabilistic models. The first model consists of using historical data from 2009 to predict costs for 2010 wells.

The analysis starts by plotting the deterministic estimates from 2010 against the actual well cost. Fig. 7.2 shows the results of the deterministic dataset, in which it is possible to see the spread of the individual well costs (blue diamonds), having some values higher than the actual well cost and others lower; the solid blue diamond with the black marker line represents the average deterministic estimate, with a value of $1,493,239 and an actual value of $1,561,550. The average deterministic estimate falls slightly above the perfect line, showing slight underestimation of the well costs overall.

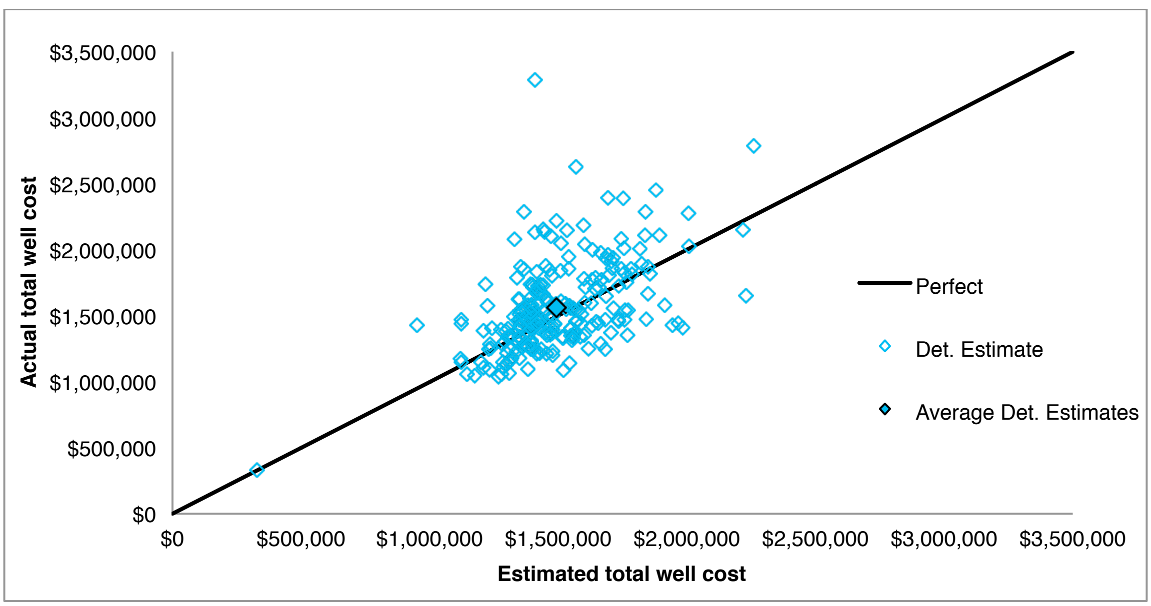

Fig. 7.2—Deterministic estimates for the 2010 wells

The mean values from the probabilistic estimates are next incorporated in the crossplot (Fig. 7.3). By applying the methodology, the cost was shifted from a case of slight underestimation to slight overestimation, but in a lower degree, indicating an improvement in the results. The average of the mean probabilistic estimates for the model that uses historical data from 2009 to predict costs for 2010 is $1,615,413 and an actual value of $1,561,550.

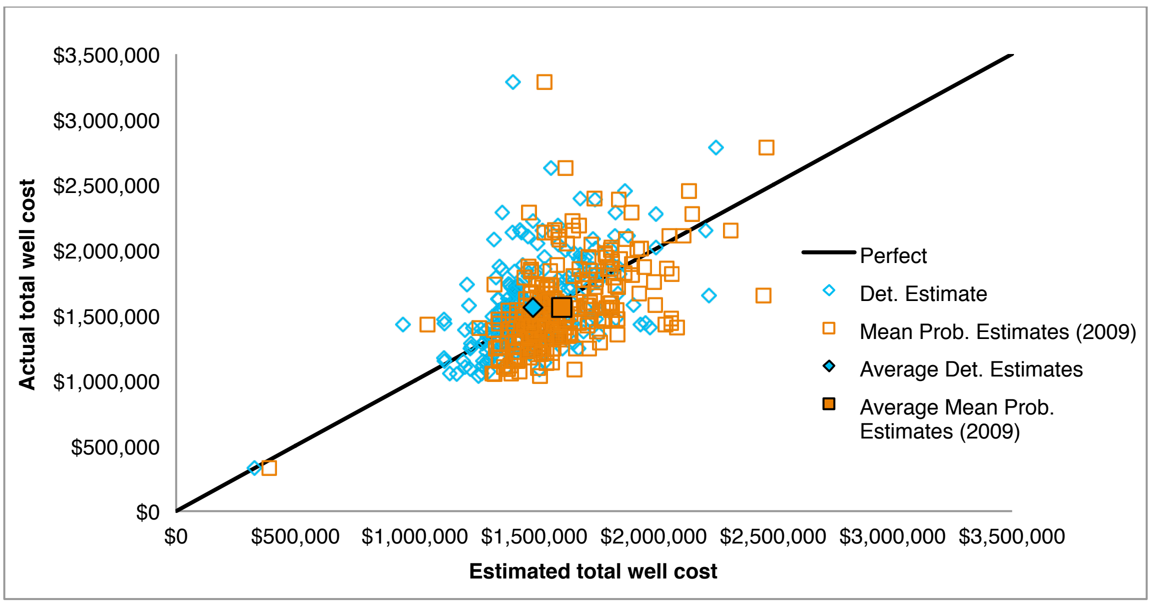

Fig. 7.3—Crossplot of deterministic and probabilistic estimates using historical data 2009 to predict wells for 2010

In Fig. 7.4, the individual wells of the deterministic estimates and probabilistic estimates are removed to provide a better visualization of the average results.

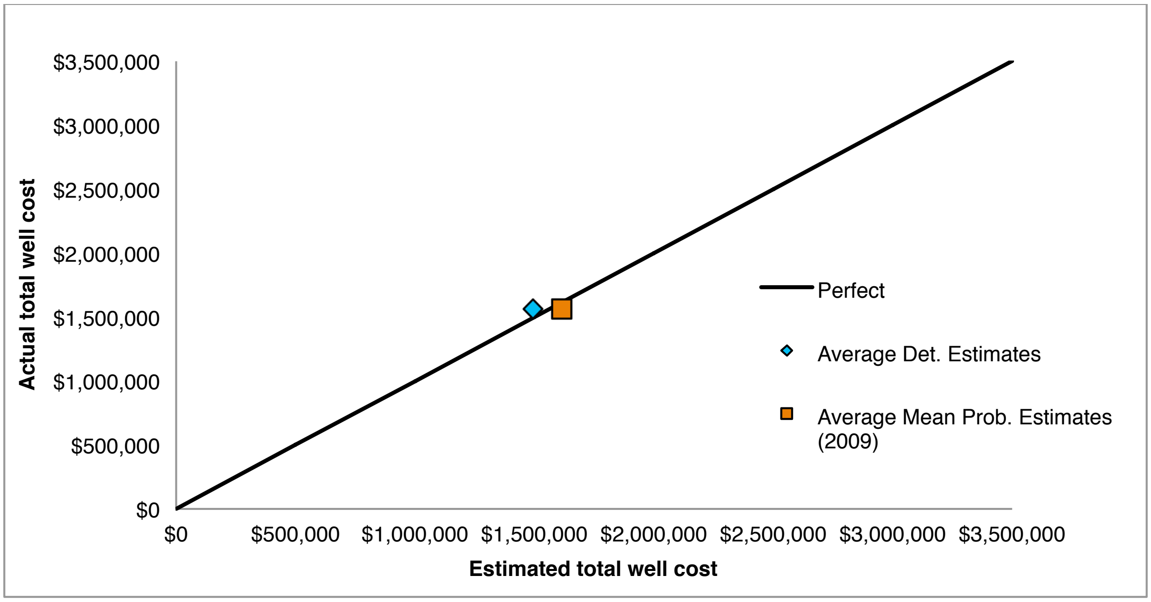

Fig. 7.4—Average of the mean deterministic and probabilistic estimates using historical data 2009 to predict wells for 2010

The comparison of the model using the historical data from 2009 to predict costs for 2010 demonstrates the ability of the methodology to shift values closer to the actual well cost. The results obtained show a slight improvement in predicting well costs, given that the deterministic estimates were already in close proximity to the actual well costs.

7.1.2. Analysis of estimates for 2011 well costs

A similar analysis is applied to the forecasts for the year 2011, comparing the deterministic estimates to the most-likely and mean values of the probabilistic models, using historical data from 2010 and 2009-2010.

As before, the analysis starts by plotting the deterministic estimates from the year 2011 against the actual well cost. Fig. 7.5 shows the results of the deterministic dataset, in which it is possible to see the spread of the individual well costs (blue diamonds), having more values higher than the actual well cost than lower; the blue diamond with the black marker line represents the average deterministic estimate, with a value of $1,437,901 and an actual value of $1,539,061. The average deterministic estimate falls above the perfect line, indicating underestimation of the cost of the wells.

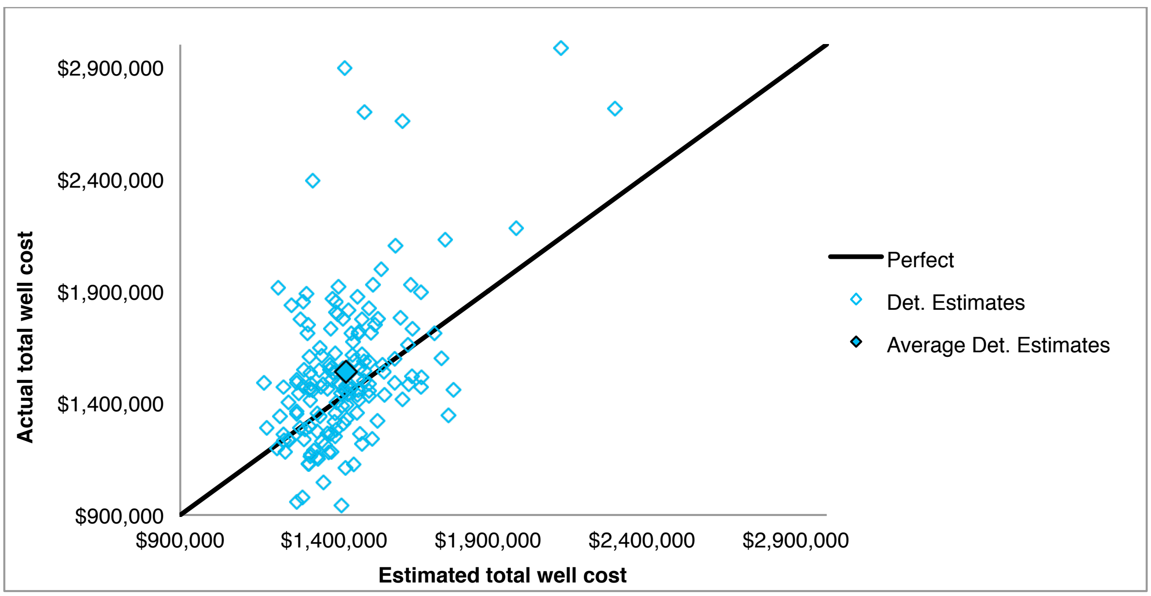

Fig. 7.5—Crossplot of deterministic estimates for the 2011 wells

The most-likely, or mode, values for the probabilistic estimates using historical data from 2009-2010 were incorporated into the crossplot with the deterministic estimates (Fig. 7.6).

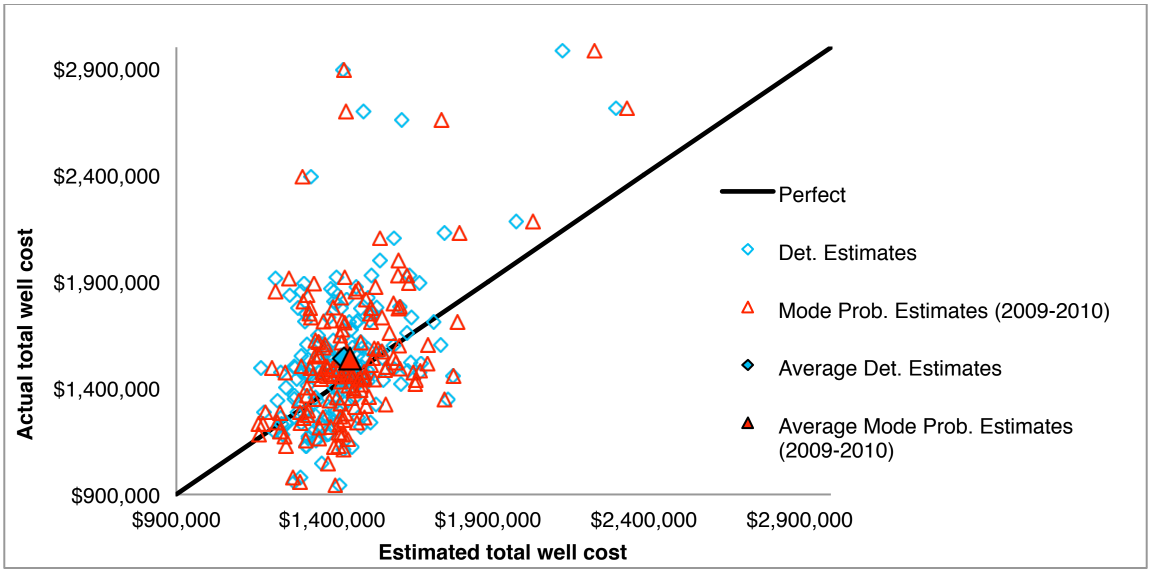

Fig. 7.6—Crossplot of deterministic estimates and mode of probabilistic estimates using historical data from 2009-2010 to predict wells for 2011

The most-likely values for the probabilistic estimates using historical data from 2010 are incorporated in the crossplot (Fig. 7.7). It is essential to point out that the average of the most-likely values for this model falls in close proximity to the other two estimates (average deterministic estimate and average mode from the 2009-2010 probabilistic model).

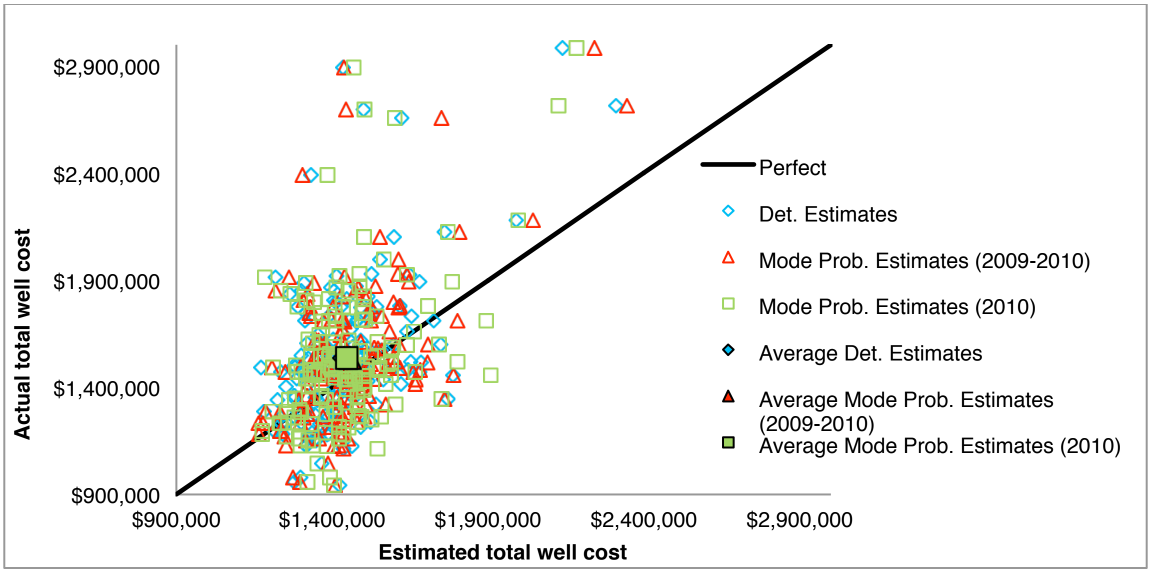

Fig. 7.7—Crossplot of deterministic estimates and mode of probabilistic estimates using historical data 2009-2010 and 2010 to predict wells for 2011

Fig. 7.8 shows the average of the deterministic estimates and the average of the modes for both probabilistic models, which clearly illustrates that the three values are in close proximity to each other. The average mode for the model that uses historical data from 2010 and 2009-2010 to predict costs for 2011 is $1,446,242 and $1,457,145, respectively; whereas the average deterministic estimate is $1,437,901 and the actual value is $1,539,061. No further information was available regarding how the engineers generated the deterministic estimates. Based on these results, it appears that the engineers' deterministic estimates represent most-likely estimates, which seems logical. If probabilistic methods were not used by the engineers, it would be difficult to calculate other statistical quantities such the median or mean.

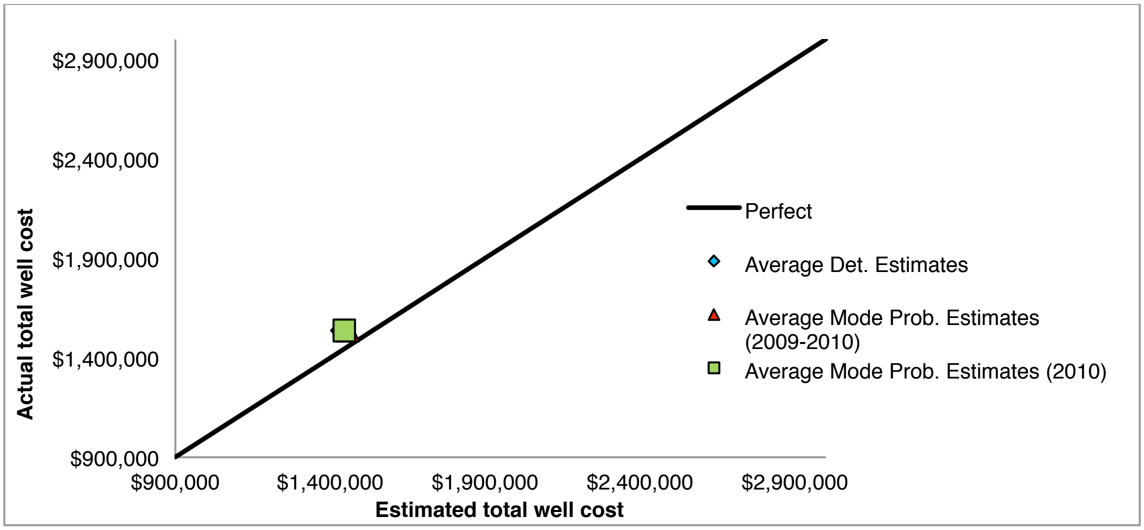

Fig. 7.8—Average of deterministic estimates and average of mode probabilistic estimates using historical data 2009-2010 and 2010 to predict wells for 2011

Similarly, I used a crossplot to compare the deterministic estimates to the mean values of both probabilistic models (Fig. 7.9). The average of the probabilistic estimates using the historical data from 2010 provide very accurate results, falling at close proximity to the perfect line, which indicates an almost perfect prediction, effectively reducing the level of underestimation. The average of the mean probabilistic estimates for the model that uses historical data from 2010 and 2009-2010 to predict costs for 2011 is $1,539,731 and $1,592,393, respectively; whereas the average deterministic estimate is $1,437,901 and the actual value is $1,539,061.

The results presented for the probabilistic estimates using historical data from 2009-2010 fall below the perfect line, having a higher estimated total cost than the actual total well cost. This result represents overestimation of the well cost; however, it provides values that are closer to the perfect line than the deterministic estimates.

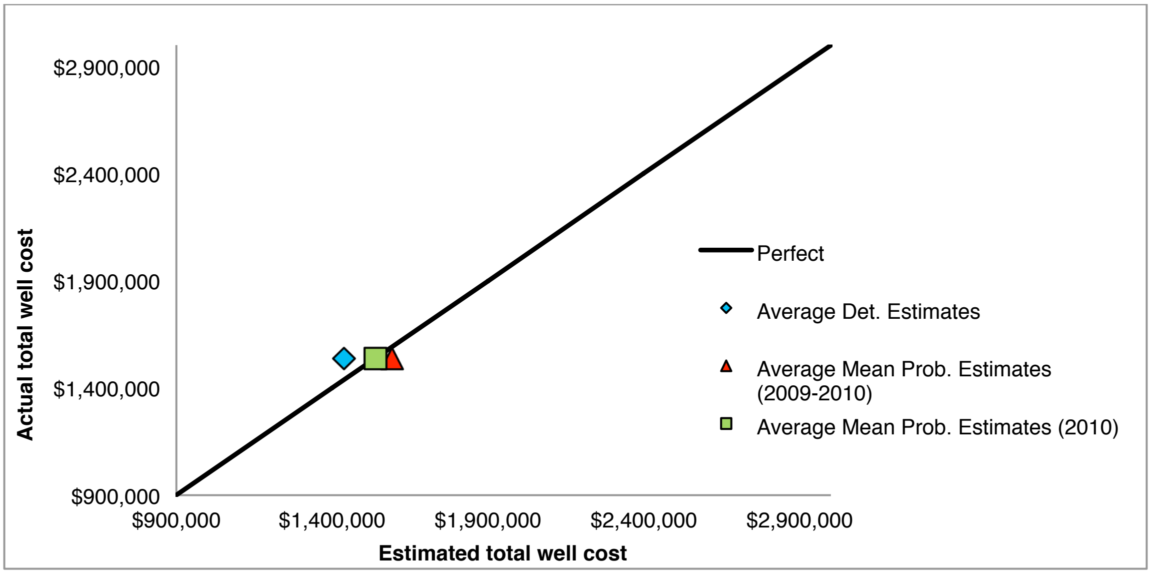

Fig. 7.9—Average of the mean deterministic and average of mean probabilistic estimates using historical data 2009-2010 and 2010 to predict wells for 2011

The total well cost distributions obtained from applying the methodology (Fig. 6.1) resulted mostly in distributions that are skewed to the right, similar to the example distribution shown in **Fig. 7.10**. In a right-skewed distribution, the most-likely estimate is a lower value than the mean of the distribution. Using most-likely values in individual well cost predictions leads to underestimation of the total well cost on average, which explains the behavior of the engineers' deterministic estimates. The use of the mean value for estimated individual-well costs better matches actual well cost on average, which is demonstrated in the results presented above. One of the advantages of the probabilistic approach proposed here is that, despite its simplicity, it provides a method for generating a mean cost estimate, which is difficult to achieve using deterministic methods.

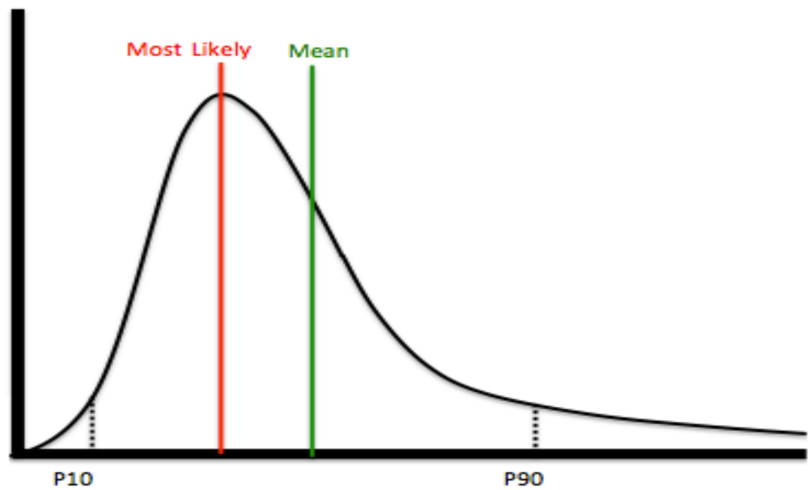

Fig. 7.10—Typical probabilistic total well cost distribution

7.2. Analysis of average per-well estimates

This analysis consists of comparing the average of the probabilistic well costs to the average of the deterministic estimates. The results are presented in two graphs: the first represents the distribution of the ratios of the probabilistic well costs (actual/probabilistic estimate), and the second represents the distribution of the average total well cost.

7.2.1. Probabilistic model using historical data 2009

The results presented in this section were derived from the probabilistic cost estimates using the historical data from 2009 to perform predictions for the 2010 wells. **Fig. 7.11** shows the distribution of the total well cost ratio, in which the orange curve represents the distribution of the ratios of the probabilistic well costs (actual/probabilistic estimate), and the blue curve represents distribution of ratios of the deterministic estimates (actual/deterministic estimate).

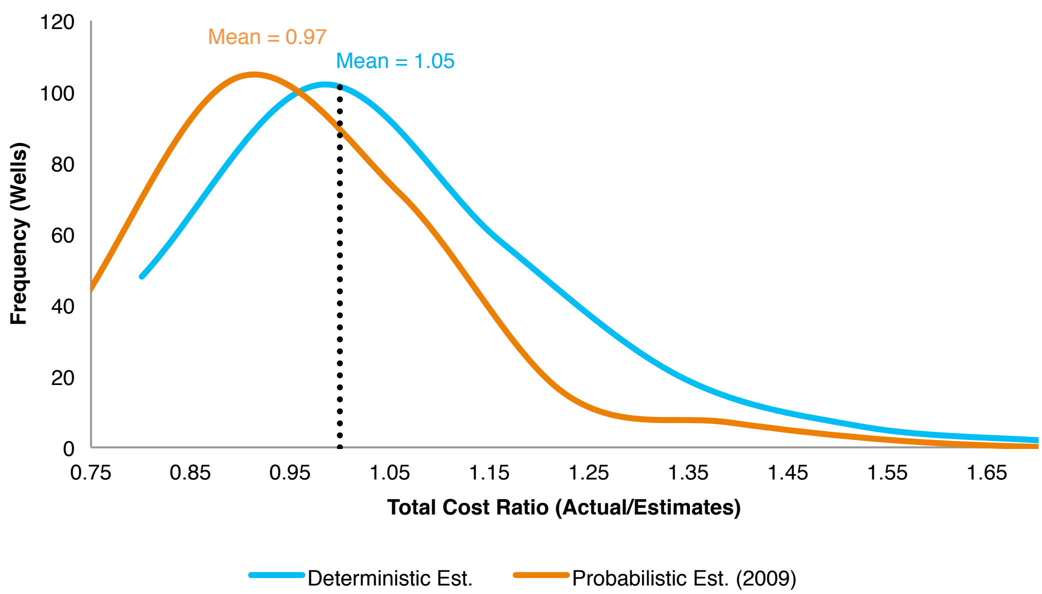

Fig. 7.11—Distribution of the total well cost ratio for probabilistic and deterministic estimates using historical data 2009 to predict costs for 2010

The results show a mean of 1.05 for the deterministic ratios and a mean of 0.97 for the probabilistic estimates (Fig. 7.11).

As shown in **Fig. 7.12**, the mean of the distribution of the average total well costs resulted in \$1,615,413 (red distribution), where as the average deterministic estimate resulted in \$1,493,239 (blue line), while having an actual value of \$1,561,550 (black line). The deterministic average estimate presents a difference of \$68,311 from the actual value, whereas the mean of the probabilistic estimates present a difference of \$53,863, being closer to the actual well cost. These results demonstrate that, even in this case where the deterministic estimates were relatively accurate, the probabilistic estimates are still able to provide even closer predictions. This illustrates the ability to produce more reliable predictions using the methodology.

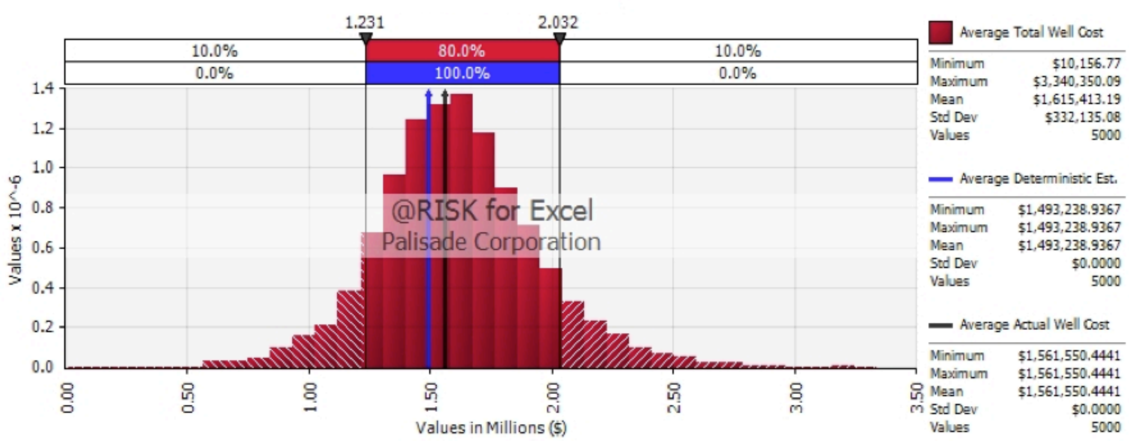

Fig. 7.12—Distribution of the average total well costs prediction for 2010 wells using historical data 2009, average deterministic estimates and average actual well cost

7.2.2. Probabilistic model using historical data 2010

The results presented in this section were derived from the probabilistic estimates using the historical data from 2010. **Fig. 7.13** shows the distribution of the total well cost ratio, in which the green curve represents the distribution of the ratios of the probabilistic well costs (actual/probabilistic estimate), and the blue curve represents distribution of ratios of the deterministic estimates (actual/deterministic estimate).

The results presented show a mean of 1.07 for the deterministic ratios; and a mean of 0.99 in the case of the probabilistic estimates (Fig. 7.13).

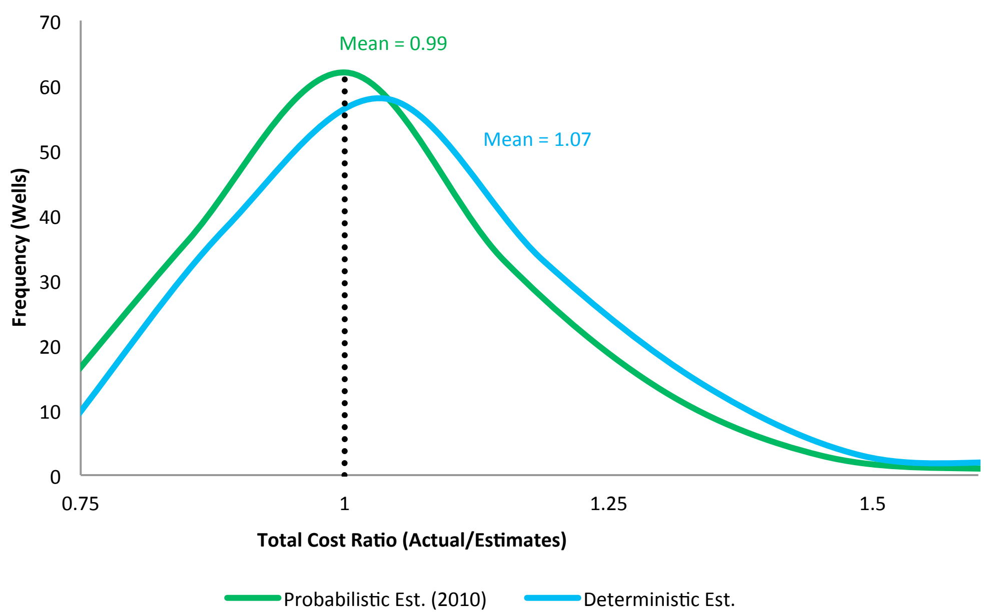

Fig. 7.13—Distribution of the total well cost ratio for probabilistic and deterministic estimates using historical data 2010 to predict costs for 2011

Fig. 7.14 shows the results for the mean of the distribution of the average total well costs, compared to the deterministic estimates and the actual well cost. The mean from the probabilistic estimates resulted in $1,539,731 (red distribution), whereas the deterministic estimates resulted in $1,437,901 (blue line), while having an actual value of $1,539,061 (black line). The deterministic average estimate presents a difference of $101,160 from the actual value, whereas the mean of the probabilistic estimates present a difference of $670, being much closer to the actual well cost and providing more accurate predictions in the case that the user wants to continue presenting a point estimate approach.

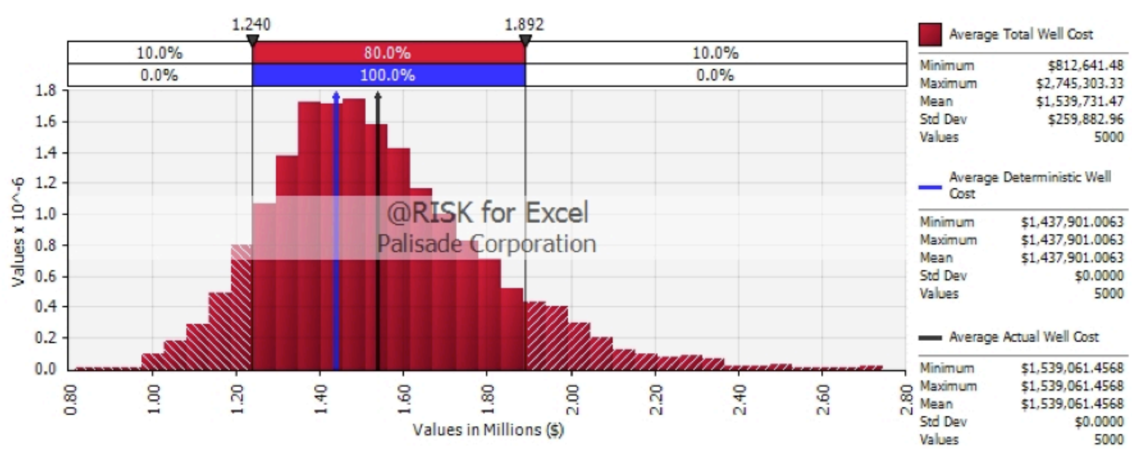

Fig. 7.14—Distribution of the average total well costs prediction for 2011 wells using historical data 2010, average deterministic estimates and average actual well cost

7.2.3. Probabilistic model using historical data 2009-2010

The results presented in this section were derived from the probabilistic estimates using the historical data from 2009-2010. **Fig. 7.15** shows the distribution of the total well cost ratio, in which the red curve represents the distribution of the ratios of the probabilistic well costs (actual/probabilistic estimate), and the blue curve represents distribution of ratios of the deterministic estimates (actual/deterministic estimate).

The results presented show a mean of 1.07 for the deterministic ratios; and a mean of 0.97 in the case of the probabilistic estimates (Fig. 7.15).

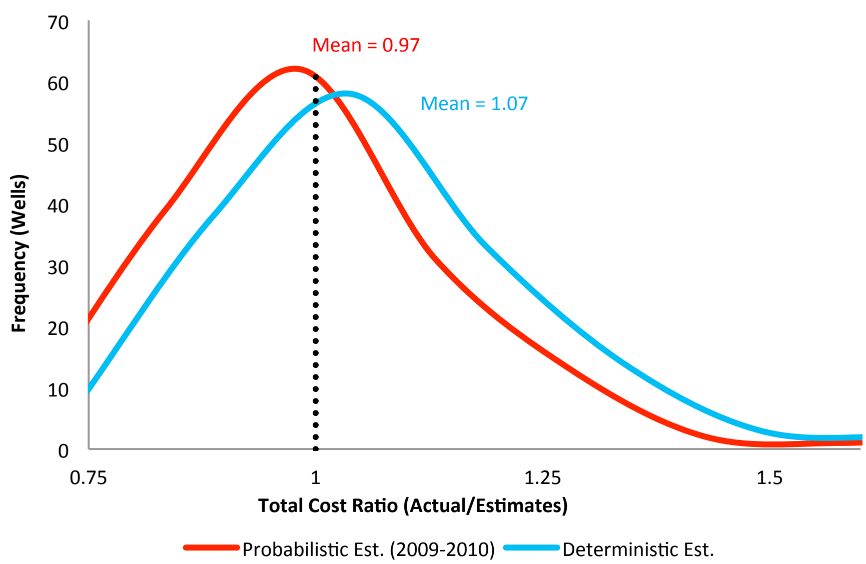

Fig. 7.15—Distribution of the total well cost ratio for probabilistic and deterministic estimates using historical data 2009-2010 to predict costs for 2011

Fig. 7.16 shows the results for the mean of the distribution of the average total well costs, compared to the deterministic estimates and the actual well cost. The results in this figure demonstrate the ability of the tool to provide more accurate values even when using the mean, which represents a "best" deterministic estimate. The mean from the probabilistic estimates resulted in \$1,593,393 (red distribution), whereas the deterministic estimates resulted in \$1,437,901 (blue line), while having an actual value of \$1,539,061 (black line). The deterministic average estimate presents a difference of \$101,160 from the actual value, whereas the mean of the probabilistic estimates present a difference of \$54,332, being much closer to the actual well cost and providing more accurate predictions in the case that the user wants to continue presenting a point estimate approach.

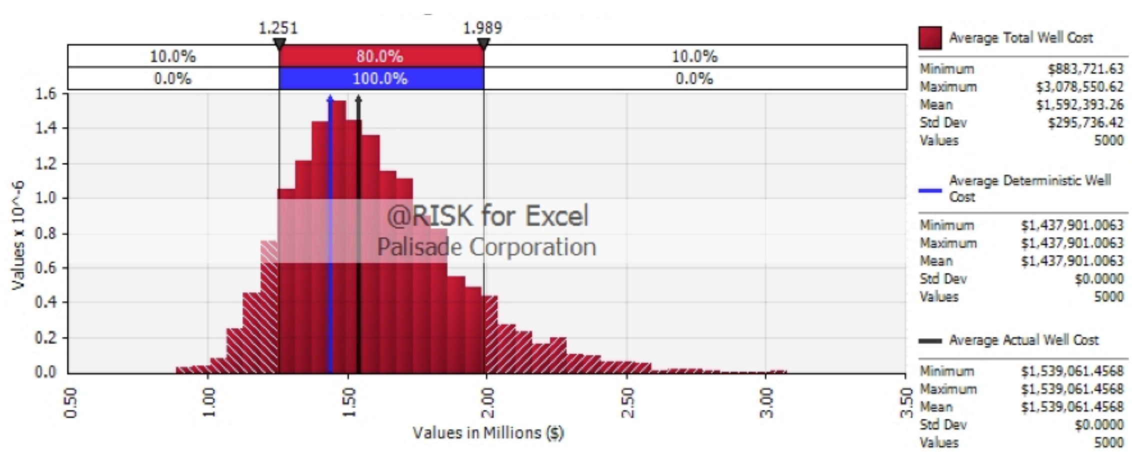

Fig. 7.16—Distribution of the average total well costs prediction for 2011 wells using historical data 2009-2010; average deterministic estimates and average actual well cost

The results obtained in the average per-well analysis show the accuracy that the use of the methodology provides when performing predictions, specifically in the case of the probabilistic estimates using historical data of 2010 to predict costs for 2011, which provided a mean that is of great proximity to the actual well cost, making this the most reliable model.

7.3. Analysis of multiple well estimates (economic impact)

The economic impact of the proposed methodology is evidenced in its application to a specific project, which makes it possible to determine the capital allocation capability of the model. The project consists of predicting the cost of a drilling campaign composed of 327 wells from 2010 and another comprised of 158 wells from 2011.

By applying this simulation we are able to test the predictive capability of the tool, not only in a single well cost, but in the prediction of a complete drilling campaign. The capital budget of the company is impacted in a more evident way by the drilling campaign as a whole, which has a direct effect on the company’s ability to undertake multiple projects, bringing the issues of overestimation and underestimation. In the case of overestimation, the engineer’s predictions bring the company to take capital from other projects to finance one that does not require such large investment; from the point of underestimation, the company will have to unexpectedly inject more capital in a project, possibly limiting the resources of other projects.

The capital investment has to be carefully planned to maintain the company's ability to undertake multiple projects. Having said this, it is of the utmost importance that the well cost be predicted as closely as possible to the actual value, in order to reduce budget conflict between projects.

The results obtained using historical data from 2009 to predict 2010 wells are shown in **Fig. 7.17**. The mean of the actual cost of the drilling campaign and the mean of the deterministic estimates are $370,087,455 and $353,897,628, respectively. In this particular project the engineers were not able to obtained accurate predictions; we can observe an error of $16,189,827, which represents a percentage error of 4.37%, also brought on by the underestimation of the cost of the different wells.

The application of the methodology resulted in a predicted mean for the 2010 drilling campaign of $382,852,926, with an error of $12,765,471, which represents an overestimation of the cost, but still providing better results than those obtained from the deterministic estimates. The application of this model provides a better allocation of capital of $3,424,356.

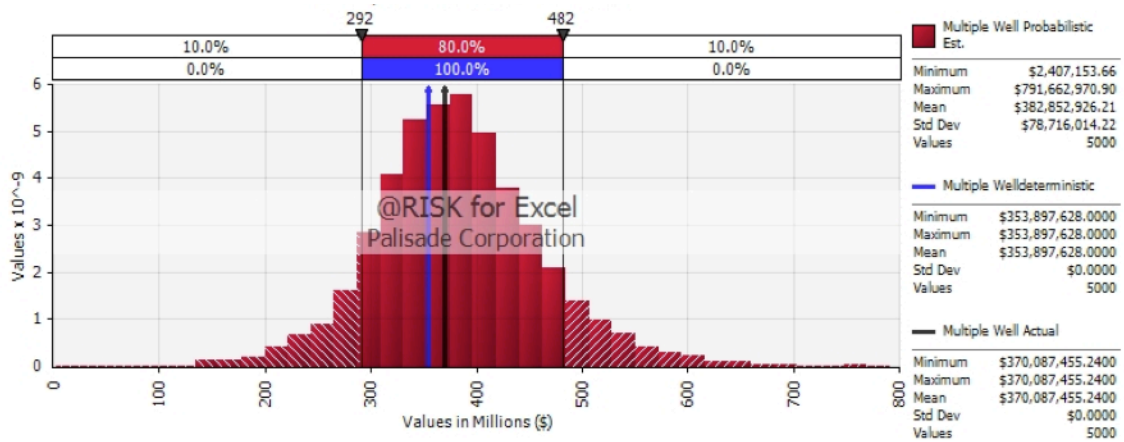

Fig. 7.17—Results of the application of the methodology for the wells of 2010 using historical data 2009

The results obtained using the probabilistic estimates with historical data from 2010 to predict 2011 wells are shown in **Fig. 7.18**, where it is possible to see the probabilistic estimates for the drilling campaign cost (red distribution); the actual cost of the drilling campaign (black arrow), and the deterministic estimates (blue arrow). The actual cost of the drilling campaign and the mean of the deterministic estimates are $243,171,710 and $227,188,359, respectively.

In this particular project, the engineers were not able to obtain accurate predictions; we can observe an error of $15,983,351, which represents a percentage error of 6.57%, brought on by the underestimation of the costs of the different wells.

The methodology proposed in this study resulted on a predicted mean of the drilling campaign of $243,277,572, which is in great proximity to the actual value, with an error of $105,862. This value indicates a slight overestimation that would not impact or limit the budget of the company as significantly as the deterministic case. Consequently, the use of the methodology provides a better allocation of $15,877,489.

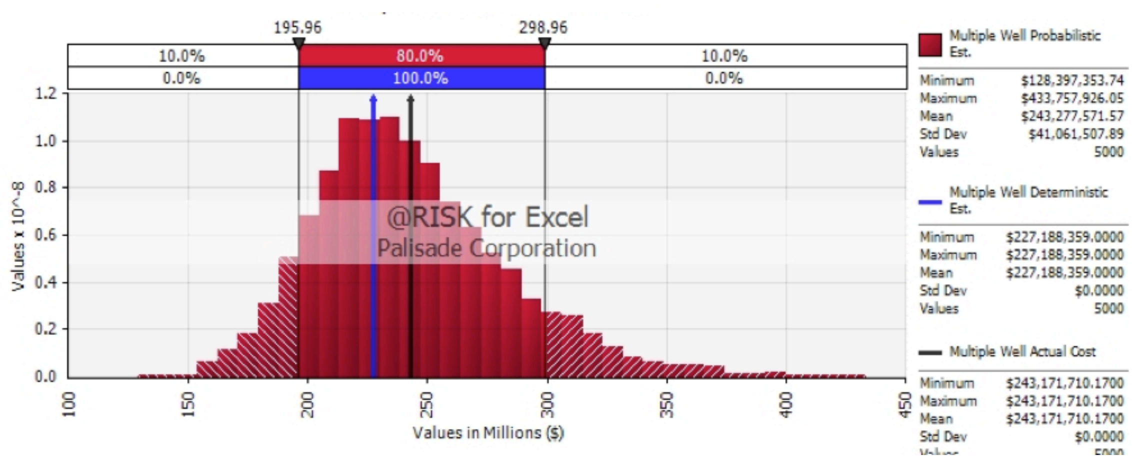

Fig. 7.18—Results of the application of the methodology for the wells of 2011 using historical data 2010

The results obtained using the probabilistic estimates with historical data from 2009-2010 to predict 2011 wells are shown in **Fig. 7.19**. For this model, the predicted mean for the drilling campaign was $251,598,136, with an error of $8,426,426, which represents an overestimation of the cost. This model still provides better results than those obtained from the deterministic estimates. The application of this model provides a better allocation of capital of $7,556,925.

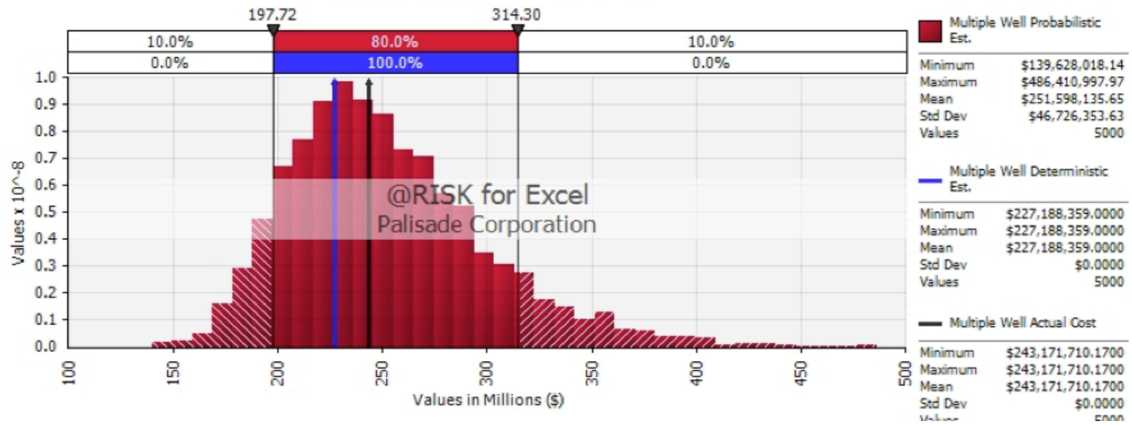

Fig. 7.19—Results of the application of the methodology for the wells of 2011 using historical data 2009-2010

The results of the methodology can further be analyzed by comparing the results having used the methodology in consecutive periods. In this case, I estimated the wells from 2010 and 2011, with an actual well cost of $613,258,925; the deterministic estimates resulted in $581,085,987, and the results from the methodology were $626,130,498, representing a better allocation of capital of 19,301,365.

In understanding the results obtained, it is of the utmost importance that we do not only focus on the mean values of the project, but also in the P10 and P90 percentiles, in order to be able to evaluate the risks associated with undertaking the project and understand the outcomes. **Table 7.1** shows the values of P10, P90 and mean for all three models. These values are calculated by adding the distributions obtained for each of the individual wells using Latin Hypercube simulation in @RISK.

TABLE 7.1—RESULTS OBTAINED FOR THE MULTIPLE WELL ANALYSES OF THE 3 SIMULATIONS				
	Mean	P10	P50	P90
Analysis of Multiple Well Estimates for 2010				
Deterministic Est.	$353,897,628	-	-	-
Actual Well Cost	$370,087,455	-	-	-
Probabilistic Est. (Hist. 2009)	$382,852,926	$291,802,567	$379,186,255	$481,621,626
Analysis of Multiple Well Estimates for 2011				
Deterministic Est.	$227,188,359	-	-	-
Actual Well Cost	$243,171,710	-	-	-
Probabilistic Est. (Hist. 2009-2010)	$251,598,136	$197,716,302	$244,744,465	$314,302,150
Probabilistic Est. (Hist. 2010)	$243,277,572	$195,964,831	$237,814,242	$298,957,715

In understanding that the well cost estimation process has great uncertainty we must understand the risk that we are taking when engaging in projects of these magnitudes, which is why we must think about these ranges if the company is willing to undertake this development project.

7.4. Sensitivity analysis of probabilistic estimates

The sensitivity analysis or "what if" analysis is a technique that indicates how much the total well cost changes in response to a given arbitrary change in an input variable. The technique consists of varying one variable while leaving all the other variables constant, in order to record how much the total cost varies depending on that specific variable. The same procedure is done for every input variable to determine which variable has the greatest impact on the total cost, indicating the one that the model is more sensitive to.

This tool is of great importance to the drilling engineer because it provides the information that allows focusing on the AFE sub-cost(s) that has the most effect on the model, by gathering more data and reducing the uncertainty of the estimate. The results of the sensitivity analysis are displayed in tornado charts, which demonstrate the amount of change in the output; the largest bar on the graph represents the most influential variable of the dataset.

The results are presented for the specific dataset used in the study, shown in **Fig. 7.20**, specifically the model of the 2011 wells that uses historical data from 2010. The three variables to which the total cost is most sensitivity are day work cost, directional drilling cost and supervision cost. These AFE sub-costs require further review when estimating well cost to reduce the uncertainty of the estimates and provide more accurate results that could bring us closer to the actual well cost.

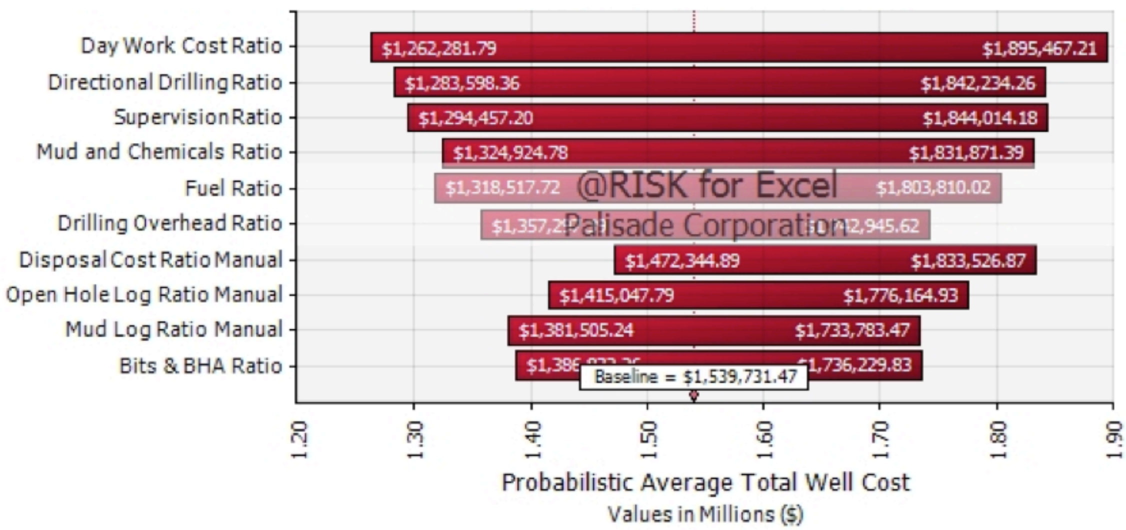

Fig. 7.20—Sensitivity analysis of the average total well cost of the probabilistic estimate

The sensitivity analysis helps the engineers define what uncertainties are critical and provides essential information that enables the creation of contingency plans that focus more on the input variables that have the highest potential impact on the total well cost.

8. CONCLUSIONS

From the development and application of the probabilistic methodology to actual well-cost estimates in an unconventional reservoir, I draw the following conclusions:

- The creation of correction factors from historical data has provided a way to successfully convert deterministic well-cost estimates into probabilistic estimates that are more accurate and better calibrated than the deterministic estimates.
- Analysis of historical data showed that well-cost distributions are typically right-skewed. Engineers' deterministic estimates typically corresponded to most-likely values, which for right-skewed distributions results in underestimation of individual well costs and overall cost of the drilling campaign.
- Mean values derived from the probabilistic estimates were closer to actual well costs than deterministic estimates, yielding more accurate predictions of overall cost of the drilling campaign.
- The use of the methodology presented in the study provides significant improvement in the 2010 and 2011 well cost predictions as compared to the deterministic estimates. The error in cost estimations for the simulation using historical data from 2009 to predict 2010 wells was reduced from $16,189,827 (deterministic estimate) to $12,765,471 (mean of probabilistic estimate). For the simulations that predict 2011 wells, the error was reduced from $15,983,351 to $105,862, for the one that uses historical data from 2010, and from $15,983,351 to $8,426,426, for the one that uses historical data from 2009-2010.

- The use of the methodology provides the ability to perform a sensitivity analysis of the total well cost. This allows one to determine the impact that each of the different AFE sub-costs has on the total well cost estimate, thus being able to focus on the more sensitive costs.
- Systematic use of this methodology could provide for more reliable and efficient allocation of capital for drilling campaigns, which should have significant impacts on reservoir development and profitability.

8.1. Recommendations for future work

The methodology should be applied in a longer-term test to validate its utility in a continuous application. This research was conducted using spreadsheets in Microsoft Excel. The methodology would benefit from the development of a relational database software application to record, modify and calibrate estimates over time.

The methodology presented in the study showed improvement in well cost estimations, but more research is required in how to further improve its application. Future studies should focus on determining the optimal amount of historical data to use in creating the correction factors. One approach would be to do a higher-resolution analysis by choosing quarterly data instead of yearly to create the correction factors, and comparing those results to the ones presented in this study. This should be done with a number of well datasets to be able to come up with conclusive results.

Other studies proposed are the application and evaluation of the methodology to the initial stage of a project, for which no historical data is available, based on data obtained from another project with similar characteristics, in order to create the necessary correction factors.

The methodology could be applied to a probabilistic cash flow, comparing its impact against using deterministic well costs, in order to measure the change in the NPV caused by not accounting for the uncertainty in well cost estimates. The methodology could also be applied to time estimation in well construction operations, which are very difficult to predict and are directly connected to the well cost, in order to further improve the estimates.

The future contributions explained up to this point have been focused on the area of well construction, but the methodology is potentially applicable to any type of forecasting, such as production forecasting or oil-price forecasting. As long as there is actual data and deterministic estimates, the methodology is applicable. The methodology should be tested on other types of datasets.

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APPENDIX A

TABLE A.1—CORRELATION MATRIX OF THE MODEL USING HISTORICAL DATA 2009

	Surf. Casing Ratio	Prod. Casing Ratio	Wellhead Equip. Ratio	Acces, Location Roads and Survey Ratio	Rig Move Ratio	Day Work Cost Ratio	Bits and BHA Ratio	Fuel Ratio	Water Ratio	Mud and Chemicals Ratio	Cem. Ratio	Open Hole Log Ratio	Mud Log Ratio	Transp. Ratio	Drilling Overhead Ratio	Equip. Rental Ratio	Other Drilling Expenses Ratio	Env. and Safety Charges Ratio	Directional Drilling Ratio	Sup. Ratio	Tubular Inspec. Ratio	Disposal Cost Ratio	Title Opinion-Drill Site Ratio
Surf. Casing Ratio	1.00																						
Prod. Casing Ratio	0.22	1.00																					
Wellhead Equip. Ratio	0.49	0.22	1.00																				
Roads and Survey Ratio	0.02	0.36	0.10	1.00																			
Rig Move Ratio	0.12	0.08	0.08	0.13	1.00																		
Day Work Cost Ratio	0.04	-0.22	0.05	-0.06	-0.25	1.00																	
Bits and BHA Ratio	-0.06	-0.26	-0.07	-0.09	0.06	0.30	1.00																
Fuel Ratio	-0.05	-0.14	0.04	0.06	-0.01	0.28	0.33	1.00															
Water Ratio	0.11	-0.02	-0.04	0.08	0.18	0.20	0.14	0.09	1.00														
Mud and Chemicals Ratio	0.13	-0.02	-0.01	-0.01	-0.06	0.42	0.21	0.26	0.21	1.00													
Cementing Ratio	0.23	0.05	-0.02	-0.09	0.26	0.14	0.20	-0.17	0.14	0.00	1.00												
Open Hole Log Ratio	0.17	0.15	0.16	0.00	0.42	-0.33	-0.09	-0.29	0.18	-0.20	0.10	1.00											
Mud Log Ratio	0.36	-0.04	0.03	-0.15	0.20	0.43	0.03	-0.28	0.07	0.56	0.34	-0.67	1.00										
Transportation Ratio	0.00	0.19	0.10	0.11	0.00	0.20	0.20	0.02	0.02	0.03	0.27	-0.26	0.21	1.00									
Drilling Overhead Ratio	0.18	-0.10	0.19	-0.01	0.03	0.28	0.33	0.19	0.33	0.35	0.18	-0.18	0.16	0.04	1.00								
Equip. Rental Ratio	0.04	-0.08	0.06	-0.04	0.02	0.47	0.19	0.37	0.12	0.48	-0.12	-0.16	0.09	0.15	0.17	1.00							
Other Drilling Expenses Ratio	0.09	0.11	0.10	0.11	0.10	0.30	0.17	0.05	0.01	-0.04	0.28	-0.06	0.35	0.58	0.11	0.02	1.00						
Safety Charges Ratio	0.27	0.08	0.00	0.10	0.10	-0.04	-0.04	-0.03	0.23	0.24	0.08	0.37	0.45	-0.20	0.24	-0.05	-0.13	1.00					
Directional Drilling Ratio	0.07	-0.03	-0.01	-0.04	-0.17	0.26	0.14	0.45	0.19	0.44	-0.35	-0.16	-0.71	-0.08	0.20	0.48	-0.31	0.01	1.00				
Supervision Ratio	-0.03	-0.19	-0.01	0.03	-0.07	-0.07	0.21	0.37	0.08	0.15	-0.14	-0.03	0.61	0.01	0.05	0.25	-0.01	-0.01	0.34	1.00			
Tubular Inspec. Ratio	0.06	0.16	0.27	-0.08	-0.03	0.09	-0.01	-0.04	-0.05	0.11	0.36	-0.16	0.14	0.30	0.15	-0.03	0.06	-0.11	0.10	0.03	1.00		
Disposal Cost Ratio	0.20	0.14	0.16	0.13	-0.01	-0.14	-0.03	-0.01	-0.22	-0.16	0.02	-0.16	-0.06	-0.07	-0.07	-0.28	0.01	0.25	-0.21	-0.07	-0.05	1.00	
Title Opinion-Drill Site Ratio	0.15	0.17	0.17	0.19	0.16	-0.14	-0.11	0.13	0.25	-0.10	-0.06	-0.02	-0.22	0.04	-0.16	-0.11	0.02	0.13	0.00	-0.04	-0.06	0.09	1.00

TABLE A.2—CORRELATION MATRIX OF THE MODEL USING HISTORICAL DATA 2010

	Surf. Casing Ratio	Prod. Casing Ratio	Wellhead Equip. Ratio	Acces, Location Roads and Survey Ratio	Rig Move Ratio	Day Work Cost Ratio	Bits and BHA Ratio	Fuel Ratio	Water Ratio	Mud and Chemicals Ratio	Cem. Ratio	Open Hole Log Ratio	Mud Log Ratio	Transp. Ratio	Drilling Overhead Ratio	Equip. Rental Ratio	Other Drilling Expenses Ratio	Env. and Safety Charges Ratio	Directional Drilling Ratio	Sup. Ratio	Tubular Inspec. Ratio	Disposal Cost Ratio	Title Opinion-Drill Site Ratio
Surf. Casing Ratio	1.00																						
Prod. Casing Ratio	0.19	1.00																					
Wellhead Equip. Ratio	0.00	0.06	1.00																				
Roads and Survey Ratio	0.08	0.04	0.05	1.00																			
Rig Move Ratio	0.02	-0.06	-0.04	0.14	1.00																		
Day Work Cost Ratio	-0.01	-0.12	0.01	0.05	0.05	1.00																	
Bits and BHA Ratio	0.07	0.00	0.05	0.03	-0.10	0.33	1.00																
Fuel Ratio	-0.09	-0.13	0.11	0.03	0.13	0.50	0.34	1.00															
Water Ratio	-0.02	-0.09	0.11	0.15	0.08	0.18	0.16	0.15	1.00														
Mud and Chemicals Ratio	-0.11	-0.13	-0.07	-0.11	0.07	0.49	0.21	0.37	0.10	1.00													
Cementing Ratio	0.02	0.05	0.08	0.05	0.07	0.13	0.05	0.27	0.12	0.16	1.00												
Open Hole Log Ratio	0.03	-0.02	-0.04	0.04	0.21	0.08	-0.04	0.04	0.02	0.09	0.13	1.00											
Mud Log Ratio	-0.14	-0.12	0.01	0.16	0.09	0.31	0.26	0.23	0.21	0.28	0.11	0.22	1.00										
Transportation Ratio	0.04	0.03	-0.05	0.06	0.02	0.12	0.00	0.12	0.09	0.07	0.13	0.01	0.07	1.00									
Drilling Overhead Ratio	-0.05	-0.14	-0.06	0.05	0.19	0.43	0.26	0.48	0.14	0.27	0.11	0.05	0.06	0.09	1.00								
Equip. Rental Ratio	-0.10	0.01	0.07	-0.01	0.01	0.20	0.13	0.28	0.21	0.18	0.24	-0.02	0.06	0.05	0.17	1.00							
Other Drilling Expenses Ratio	-0.09	-0.05	0.07	-0.02	0.07	0.30	0.05	0.22	0.22	0.28	-0.04	0.00	0.08	0.18	0.14	0.19	1.00						
Safety Charges Ratio	0.08	0.03	0.08	0.22	0.09	0.09	0.19	0.06	0.13	-0.06	0.00	0.08	0.19	0.08	0.06	0.03	0.08	1.00					
Directional Drilling Ratio	0.05	-0.06	0.00	0.14	0.08	0.68	0.34	0.51	0.16	0.31	0.14	0.10	0.25	0.19	0.47	0.12	0.11	0.23	1.00				
Supervision Ratio	0.10	-0.14	0.09	0.18	0.16	0.62	0.29	0.43	0.30	0.40	0.13	0.13	0.39	0.23	0.37	0.16	0.34	0.23	0.51	1.00			
Tubular Inspec. Ratio	-0.02	0.05	-0.22	-0.02	0.02	0.19	-0.07	0.22	0.06	0.17	0.04	0.06	0.16	0.20	0.18	0.02	0.22	-0.07	0.15	0.09	1.00		
Disposal Cost Ratio	0.10	0.00	0.04	-0.02	0.01	0.02	0.14	-0.11	0.04	-0.04	0.06	0.45	0.04	0.00	-0.04	-0.11	-0.11	0.13	-0.01	0.02	-0.17	1.00	
Title Opinion-Drill Site Ratio	-0.10	-0.10	-0.03	0.10	-0.01	-0.05	-0.01	0.07	-0.01	0.06	-0.03	-0.02	0.07	0.08	-0.01	-0.04	-0.05	-0.03	-0.12	-0.02	0.11	-0.08	1.00

TABLE A.3—CORRELATION MATRIX OF THE MODEL USING HISTORICAL DATA 2009-2010

	Surf. Casing Ratio	Prod. Casing Ratio	Wellhead Equip. Ratio	Acces, Location Roads and Survey Ratio	Rig Move Ratio	Day Work Cost Ratio	Bits and BHA Ratio	Fuel Ratio	Water Ratio	Mud and Chemicals Ratio	Cem. Ratio	Open Hole Log Ratio	Mud Log Ratio	Transp. Ratio	Drilling Overhead Ratio	Equip. Rental Ratio	Other Drilling Expenses Ratio	Env. and Safety Charges Ratio	Directional Drilling Ratio	Sup. Ratio	Tubular Inspec. Ratio	Disposal Cost Ratio	Title Opinion-Drill Site Ratio
Surf. Casing Ratio	1.00																						
Prod. Casing Ratio	0.22	1.00																					
Wellhead Equip. Ratio	0.17	0.19	1.00																				
Roads and Survey Ratio	0.07	0.16	0.08	1.00																			
Rig Move Ratio	0.05	-0.01	0.00	0.14	1.00																		
Day Work Cost Ratio	-0.01	-0.21	-0.01	0.00	-0.04	1.00																	
Bits and BHA Ratio	0.03	-0.10	0.00	-0.01	-0.06	0.31	1.00																
Fuel Ratio	-0.08	-0.17	0.06	0.03	0.09	0.41	0.34	1.00															
Water Ratio	0.01	-0.06	0.08	0.14	0.10	0.16	0.15	0.12	1.00														
Mud and Chemicals Ratio	-0.04	-0.15	-0.08	-0.08	0.02	0.47	0.20	0.33	0.11	1.00													
Cementing Ratio	0.10	0.10	0.07	0.01	0.12	0.10	0.10	0.08	0.13	0.06	1.00												
Open Hole Log Ratio	-0.02	-0.06	-0.05	0.02	0.31	-0.12	-0.05	-0.09	0.03	-0.05	0.04	1.00											
Mud Log Ratio	-0.11	-0.11	0.01	0.12	0.09	0.33	0.23	0.13	0.20	0.33	0.15	0.19	1.00										
Transportation Ratio	0.00	0.00	-0.04	0.05	0.00	0.19	0.08	0.10	0.05	0.10	0.14	0.00	0.11	1.00									
Drilling Overhead Ratio	0.01	-0.17	0.00	0.02	0.14	0.38	0.28	0.38	0.17	0.32	0.11	-0.04	0.09	0.10	1.00								
Equip. Rental Ratio	-0.07	0.00	0.06	-0.01	0.01	0.23	0.13	0.27	0.20	0.22	0.16	-0.04	0.06	0.06	0.16	1.00							
Other Drilling Expenses Ratio	-0.02	-0.01	0.05	0.03	0.07	0.31	0.11	0.13	0.12	0.11	0.10	0.01	0.15	0.43	0.13	0.10	1.00						
Safety Charges Ratio	0.13	0.04	0.05	0.19	0.09	0.04	0.12	0.03	0.14	0.04	0.03	0.05	0.20	-0.02	0.11	0.02	-0.01	1.00					
Directional Drilling Ratio	0.04	-0.10	-0.03	0.08	0.02	0.53	0.27	0.49	0.16	0.37	-0.04	-0.03	0.15	0.11	0.40	0.16	-0.08	0.17	1.00				
Supervision Ratio	0.01	-0.18	0.00	0.06	0.02	0.12	0.20	0.34	0.12	0.21	-0.06	0.05	0.42	0.08	0.14	0.12	0.07	0.06	0.33	1.00			
Tubular Inspec. Ratio	-0.02	-0.01	-0.03	-0.06	-0.01	0.17	-0.04	0.11	0.01	0.18	0.11	0.00	0.16	0.31	0.19	0.00	0.15	-0.08	0.16	0.06	1.00		
Disposal Cost Ratio	0.11	0.08	0.09	0.00	0.01	-0.04	0.10	-0.11	0.02	-0.08	0.08	0.13	0.03	-0.07	-0.07	-0.12	-0.08	0.13	-0.06	-0.03	-0.17	1.00	
Title Opinion-Drill Site Ratio	0.01	0.00	0.06	0.11	0.05	-0.08	-0.06	0.11	0.06	-0.01	-0.06	0.05	0.03	0.08	-0.06	-0.05	0.01	0.04	-0.03	-0.03	0.03	-0.05	1.00

APPENDIX B

TABLE B.1—FINAL DISTRIBUTIONS OBTAINED FROM THE DATASET 2009	
AFE Sub-Cost	**Distributions**
Surface Casing	RiskLogistic(0.83663,0.10923,RiskTruncate(FV31,FU31),RiskName("Surface Casing"),RiskCorrmat(NewMatrix2,1))
Production Casing	RiskNormal(0.77612,0.17592,RiskTruncate(FV32,FU32),RiskName("Production Casing"),RiskCorrmat(NewMatrix2,2))
Wellhead Equipment	RiskLoglogistic(-0.30766,1.1681,3.719,RiskTruncate(FV33,FU33),RiskName("Wellhead Equipment"),RiskCorrmat(NewMatrix2,3))
Access, Location, Road & Survey	RiskLoglogistic(-0.4715,1.6322,6.9914,RiskTruncate(FV34,FU34),RiskName("Acces/Location"),RiskCorrmat(NewMatrix2,4))
Rig Move	RiskLognorm(1.0574,0.70607,RiskShift(-0.03471),RiskTruncate(FV35,FU35),RiskName("Rig Move"),RiskCorrmat(NewMatrix2,5))
Day Work Cost	RiskLaplace(1.0547,0.40102,RiskTruncate(FV36,FU36),RiskName("Day Work"),RiskCorrmat(NewMatrix2,6))
Bits & BHA	RiskExtvalue(0.88309,0.24379,RiskTruncate(FV37,FU37),RiskName("Bits/BHA"),RiskCorrmat(NewMatrix2,7))
Fuel	RiskPearson5(7.2917,7.4712,RiskShift(-0.12481),RiskTruncate(FV38,FU38),RiskName("Fuel"),RiskCorrmat(NewMatrix2,8))
Water	RiskWeibull(1.4618,0.86442,RiskShift(0.16434),RiskTruncate(FV39,FU39),RiskName("Water"), RiskCorrmat(NewMatrix2,9))
Mud and Chemicals	RiskLaplace(1.2768,0.77988,RiskTruncate(FV40,FU40),RiskName("Mud/Chemicals"),RiskCorrmat(NewMatrix2,10))
Cementing	RiskLaplace(0.8962,0.33573,RiskTruncate(FV41,FU41),RiskName("Cementing"),RiskCorrmat(NewMatrix2,11))
Open Hole Log	RiskCumul(0,17.129,{0.156,0.734,0.949,1.011,1.068,1.248,1.728,2.31,3.775},{0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9})
Mud Log Ratio	RiskCumul(0,2.4374,{0,0,0,0.5299,0.6873,0.8675,1.1186,1.1888,1.3331},{0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9})
Transportation Ratio	RiskLognorm(1.4734,1.7725,RiskShift(0.14734),RiskTruncate(FV44,FU44),RiskName("Transportation"),RiskCorrmat(NewMatrix2,12))
Drilling Overhead	RiskLognorm(1.0436,0.62327,RiskShift(0.23607),RiskTruncate(FV45,FU45),RiskName("Drilling Overhead"),RiskCorrmat(NewMatrix2,13))
Equipment Rental	RiskLoglogistic(-0.32378,1.8008,5.1127,RiskTruncate(FV46,FU46),RiskName("Equipment Rental"),RiskCorrmat(NewMatrix2,14))
Other Drilling Expenses	RiskLognorm(2.6455,2.5986,RiskShift(0.033761),RiskTruncate(FV47,FU47),RiskName("Other Drilling Expenses"),RiskCorrmat(NewMatrix2,15))
Environmental and Safety Charges	RiskExpon(1.3553,RiskShift(0.015375),RiskTruncate(FV48,FU48),RiskName("Enviromental"),RiskCorrmat(NewMatrix2,16))
Directional Drilling	RiskLoglogistic(-1.245,2.3582,11.587,RiskTruncate(FV49,FU49),RiskName("Directional Drilling"),RiskCorrmat(NewMatrix2,17))
Supervision Ratio	RiskLoglogistic(0.12489,0.73883,3.2339,RiskTruncate(FV50,FU50),RiskName("Supervision"),RiskCorrmat(NewMatrix2,18))
Tubular Inspection	RiskLoglogistic(0.11469,1.5807,2.7193,RiskTruncate(FV51,FU51),RiskName("Tubular Inspection/Handling"),RiskCorrmat(NewMatrix2,19))
Disposal Cost	RiskCumul(0,3.0303,{0,0,0,0,0,0.0257,0.0816,0.2141,0.385},{0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9}, RiskCorrmat(NewMatrix2,20))
Title Opinion Drill Site	RiskInvgauss(1.7194,0.18275,RiskShift(-0.039028),RiskTruncate(FV53,FU53),RiskName("Title Opinion"),RiskCorrmat(NewMatrix2,21))

TABLE B.2—FINAL DISTRIBUTIONS OBTAINED FROM THE DATASET 2010	
AFE Sub-Cost	**Distributions**
Surface Casing	RiskLoglogistic(-0.75459,1.6366,15.773,RiskTruncate(0,3.883428713),RiskName("Surface Casing Ratio"),RiskCorrmat(HistDataDist2010Matrix,1))
Production Casing	RiskLogistic(0.900603,0.054801,RiskTruncate(0,1.411042412),RiskName("Production Casing Ratio"),RiskCorrmat(HistDataDist2010Matrix,2))
Wellhead Equipment	RiskInvgauss(2.1952,40.0078,RiskShift(-0.88483),RiskTruncate(0.133924615,5.01713),RiskName("Wellhead Equip. Ratio"),RiskCorrmat(HistDataDist2010Matrix,3))
Access, Location, Road & Survey	RiskLoglogistic(-1.1946,2.4513,9.6826,RiskTruncate(0.109020133,4.1234089),RiskName("Access, Location, Road & Survey Ratio"),RiskCorrmat(HistDataDist2010Matrix,4))
Rig Move	RiskLoglogistic(-0.22076,1.1244,3.3165,RiskTruncate(0,12.14881),RiskName("Rig Move Ratio"),RiskCorrmat(HistDataDist2010Matrix,5))
Day Work Cost	RiskLoglogistic(-0.14248,1.1188,8.7746,RiskTruncate(0.17469933,2.53890167),RiskName("Day Work Cost Ratio"),RiskCorrmat(HistDataDist2010Matrix,6))
Bits & BHA	RiskLoglogistic(0.40215,0.55683,3.5723,RiskTruncate(0.52571833,2.364004762),RiskName("Bits & BHA Ratio"),RiskCorrmat(HistDataDist2010Matrix,7))
Fuel	RiskLoglogistic(-0.72446,1.6506,8.4793,RiskTruncate(0,2.776634444),RiskName("Fuel Ratio"),RiskCorrmat(HistDataDist2010Matrix,8))
Water	RiskExtvalue(0.73736,0.42478,RiskTruncate(0.0845,9.989544),RiskName("Water Ratio"),RiskCorrmat(HistDataDist2010Matrix,9))
Mud and Chemicals	RiskLoglogistic(0.18013,0.92175,4.2877,RiskTruncate(0.376057273,3.614390933),RiskName("Mud and Chemicals Ratio"),RiskCorrmat(HistDataDist2010Matrix,10))
Cementing	RiskLoglogistic(-0.38213,1.3706,12.864,RiskTruncate(0.337368778,3.743988659),RiskName("Cementing Ratio"),RiskCorrmat(HistDataDist2010Matrix,11))
Open Hole Log	RiskCumul(0,11.00488,{0,0,0.147543,0.47125,0.56114,0.71694,0.827594,1.013424,1.472904},{0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9},RiskName("Open Hole Log Ratio Manual"),RiskCorrmat(HistDataDist2010Matrix,12))
Mud Log Ratio	RiskCumul(0,2.06724,{0,0,0,0.61111,0.73875,0.84575,0.992691,1.141705,1.336},{0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9},RiskName("Mud Log Ratio Manual"),RiskCorrmat(HistDataDist2010Matrix,13))
Transportation Ratio	RiskGamma(1.8738,0.44994,RiskShift(0.14839),RiskTruncate(0.15849,8.27352),RiskName("Transportation Ratio"),RiskCorrmat(HistDataDist2010Matrix,14))
Drilling Overhead	RiskLoglogistic(-0.14783,1.1312,4.621,RiskTruncate(0,3.859723333),RiskName("Drilling Overhead Ratio"),RiskCorrmat(HistDataDist2010Matrix,15))
Equipment Rental	RiskLoglogistic(0.18165,1.2467,3.6488,RiskTruncate(0.384369176,18.76712),RiskName("Equip. Rental Ratio"),RiskCorrmat(HistDataDist2010Matrix,16))
Other Drilling Expenses	RiskPearson5(7.0095,16.585,RiskShift(-0.61604),RiskTruncate(0.372953333,9.81736),RiskName("Other Drilling Expenses Ratio"),RiskCorrmat(HistDataDist2010Matrix,17))
Environmental and Safety Charges	RiskLoglogistic(-0.047215,1.0034,2.5187,RiskTruncate(0.017035,9.283653333),RiskName("Enviromental and Safety Charges Ratio"),RiskCorrmat(HistDataDist2010Matrix,18))
Directional Drilling	RiskLoglogistic(-0.90599,1.9113,11.859,RiskTruncate(0.025757576,2.664472444),RiskName("Directional Drilling Ratio"),RiskCorrmat(HistDataDist2010Matrix,19))
Supervision Ratio	RiskLognorm(0.91866,0.3234,RiskShift(0.020221),RiskTruncate(0.264106508,2.255958444),RiskName("Supervision Ratio"),RiskCorrmat(HistDataDist2010Matrix,20))
Tubular Inspection	RiskGamma(2.6126,0.38307,RiskShift(0.46799),RiskTruncate(0.493689,9.034073),RiskName("Tubular Inspection Ratio"),RiskCorrmat(HistDataDist2010Matrix,21))
Disposal Cost	RiskCumul(0,10.13638,{0,0,0,0.128604,0.426,0.807901,0.956362,1.079779,1.488322},{0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9},RiskName("Disposal Cost Ratio Manual"),RiskCorrmat(HistDataDist2010Matrix,22))
Title Opinion Drill Site	RiskPearson5(1.1518,0.39975,RiskShift(-0.11644),RiskTruncate(0,10.548004),RiskName("Title Opinion Drill Site Ratio"),RiskCorrmat(HistDataDist2010Matrix,23))

TABLE B.3—FINAL DISTRIBUTIONS OBTAINED FROM THE DATASET 2009-2010	
AFE Sub-Cost	**Distributions**
Surface Casing	RiskLogistic(0.8733,0.10828,RiskName("Surface Casing Ratio"),RiskTruncate(0,3.883428713),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,1))
Production Casing	RiskLogistic(0.875494,0.072344,RiskName("Production Casing Ratio"),RiskTruncate(0,1.411042412),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,2))
Wellhead Equipment	RiskCumul(0,5.01713,{0.563,0.7003,0.887,1.0731,1.2162,1.2418,1.4762,1.6476,1.9407},{0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9},RiskName("Wellhead Equipment Ratio Manual"),RiskTruncate(0,5.01713),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,3))
Access, Location, Road & Survey	RiskLoglogistic(-0.93907,2.1691,8.6868,RiskName("Access, Location, Road & Survey Ratio"),RiskTruncate(0.109020133,4.1234089),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,4))
Rig Move	RiskLoglogistic(-0.19683,1.0891,3.3206,RiskName("Rig Move Ratio"),RiskTruncate(0,12.14881),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,5))
Day Work Cost	RiskLoglogistic(-0.41075,1.4107,9.5468,RiskName("Day Work Cost Ratio"),RiskTruncate(0.068266667,2.846538267),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,6))
Bits & BHA	RiskExtvalue(0.88715,0.23255,RiskName("Bits & BHA Ratio"),RiskTruncate(0.514955375,3.065937714),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,7))
Fuel	RiskExtvalue(0.80885,0.33162,RiskName("Fuel Ratio"),RiskTruncate(0,3.0234975),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,8))
Water	RiskPearson5(6.0777,6.5883,RiskName("Water Ratio"),RiskShift(-0.31369),RiskTruncate(0.0845,9.989544),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,9))
Mud and Chemicals	RiskLoglogistic(0.21068,0.92176,3.6252,RiskName("Mud and Chemicals Ratio"),RiskTruncate(0.376057273,4.4910222),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,10))
Cementing	RiskLogistic(0.97088,0.1292,RiskName("Cementing Ratio"),RiskTruncate(0.313888933,3.743988659),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,11))
Open Hole Log	RiskCumul(0,17.1288125,{0,0,0.3306,0.5261,0.6806,0.8216,0.9989,1.2026,1.8837},{0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9},RiskName("Open Hole Log Ratio Manual"),RiskTruncate(0,17.1288125),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,12))
Mud Log Ratio	RiskCumul(0,2.4374,{0,0,0,0.6111,0.7374,0.8458,0.9927,1.1453,1.336},{0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9},RiskName("Mud Log Ratio Manual"),RiskTruncate(0,2.437352222),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,13))
Transportation Ratio	RiskInvgauss(1.0969,1.6576,RiskName("Transportation Ratio"),RiskShift(0.045882),RiskTruncate(0.15849,8.27352),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,14))
Drilling Overhead	RiskPearson5(11.679,17.769,RiskName("Drilling Overhead Ratio"),RiskShift(-0.51973),RiskTruncate(0,3.9234),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,15))

TABLE B.3—CONTINUED	
AFE Sub-Cost	**Distributions**
Equipment Rental	RiskLoglogistic(0.054272,1.3881,4.0196,RiskName("Equip. Rental Ratio"),RiskTruncate(0.291296296,18.76712),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,16))
Other Drilling Expenses	RiskLoglogistic(0.0055298,1.8748,3.0201,RiskName("Other Drilling Expenses Ratio"),RiskTruncate(0.287472,18.63467),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,17))
Environmental and Safety Charges	RiskLoglogistic(-0.077562,1.0224,2.2167,RiskName("Environmental and Safety Charges Ratio"),RiskTruncate(0.017035,9.283653333),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,18))
Directional Drilling	RiskLoglogistic(-0.91031,1.9413,11.156,RiskName("Directional Drilling Ratio"),RiskTruncate(0,2.664472444),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,19))
Supervision Ratio	RiskPearson5(8.8204,8.2646,RiskName("Supervision Ratio"),RiskShift(-0.098785),RiskTruncate(0.234480882,14.55977267),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,20))
Tubular Inspection	RiskLoglogistic(0.23376,1.1594,3.162,RiskName("Tubular Inspection Ratio"),RiskTruncate(0.328872269,9.034073),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,21))
Disposal Cost	RiskCumul(0,10.1364,{0,0,0,0.0257,0.176,0.4669,0.8328,1.0093,1.4234},{0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9},RiskName("Disposal Cost Ratio Manual"),RiskTruncate(0,10.13638),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,22))
Title Opinion Drill Site	RiskCumul(0,31.87474,{0.0069,0.0614,0.186,0.2886,0.4452,0.6221,0.9339,1.3453,2.3774},{0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9},RiskName("Title Opinion Drill Site Ratio Manual"),RiskTruncate(0,31.87474),RiskCorrmat('WellCost Prob. Estimation (2009-2010 HistData)(Sim23)(Correlated)Curves.xlsx'!HistDataDist20092010,23))