Reservoir Uncertainty Assessment

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A reliable estimate of the uncertainty in the amount of oil or gas in a reservoir affects resource/reserve classification, investment decisions, and development decisions. There is a need to make the best decisions with an appropriate level of technical analysis considering all available data. Current methods of estimating resource uncertainty use spreadsheets or Monte Carlo simulation software using specified probability distributions for each variable. 3D models may be constructed, but they rarely consider uncertainty in all variables. This research develops appropriate 2D and 3D models of heterogeneity and uncertainty. This research improves reserve evaluation in the presence of geologic uncertainty. Guidelines are developed to: a) select the best modeling scale for making decisions, b) understand parameters that play a key role in reserve estimates, c) investigate how to reduce uncertainties, and d) show the importance of accounting for parameter uncertainty in reserves assessment. The parameters addressed in this research are those required in the assessment of uncertainty including statistical and geological parameters. This research shows that fixed parameters seriously underestimate the actual uncertainty in resources. A methodology for the assessment of uncertainty in the structural surfaces of a reservoir, fluid contacts levels, and petrophysical properties is developed with accounting for parameter uncertainty in order to get a fairly global uncertainty. Parameter uncertainty can be quantified by several approaches such as conventional bootstrap (BS), spatial bootstrap (SBS), and conditional-finite-domain (CFD). Real data from a large North Sea reservoir dataset is used to compare those approaches. The CFD approach produced less uncertainty in distributions of the resource than those obtained from the BS or SBS approaches. The results are considered more realistic since they consider the correlation between the input data and the conditioning data.

Introduction

An accurate estimate of the reservoir volume is important for selecting number of wells to be drilled, deciding their locations, and making other reservoir development decisions. The first choice to make in any geostatistical study is the modeling scale. High resolution 3-D models are appropriate for modeling heterogeneity and providing input to flow simulation; however, they cannot be used effectively for uncertainty quantification. Global statistical analysis is appropriate for checking and providing input to parameter uncertainty, but it does not permit uncertainty assessment for specific locations or well patterns. Reserves estimations may be undertaken with 2-D modeling, which can be used in early stages of life reservoir and account for uncertainty in structural surfaces.

Hydrocarbon reserves are calculated as the product of gross rock volume, net/gross ratio, porosity, hydrocarbon saturation, formation volume factor, and recovery factor. A single resource/reserve figure (deterministic case) can be computed if the value of each parameter is well known. It is more realistic to represent individual parameters by a range of values, or a probability distribution. This leads to a probability distribution for the reserves and improved decisions. It is important to have a narrow and fair estimate of uncertainty at the early stages of field life; otherwise, designed production facilities might be underestimated or overestimated.

The uncertainty is due to limited data, measurement errors, and an imperfect model. Limited data leads to incomplete knowledge of the complex subsurface structure, petrophysical properties, and fluid properties. Errors in the measured data lead to increased error. It is difficult to generate a model that represents the real reservoir. With all these sources of uncertainty, a reasonable numerical model is needed to relate available data and understand the subsurface.

Reserves volumes have significant uncertainty due to sparse well data and uncertainty in structural surfaces. In this report, reservoir data was used to develop a classical geostatistical approach to surface simulation and uncertainty assessment. The top surface structure of a reservoir, subsequent layer thickness, and oil water contact depths are uncertain. The main controls on the uncertainty assessment are (1) the possible deviations from the base case seismic predicted surfaces, that is, a distribution of the possible deviations from the base case, and (2) a variogram that specifies how fast the uncertainty increases away from the well locations.

Reservoirs consist of stratigraphic layers constrained by a top seal. The Gross Rock Volume (GRV) is the volume of a reservoir trapped between the top and bottom surfaces above the oil water contact (OWC), see Figure-1. Generally, the top and bottom structure surfaces are obtained from seismic interpretation, while the OWC can be estimated from the available wells. Seismic interpretation is performed in the time domain and transferred to depth with a time-to-depth conversion using some type of velocity model. There is no unique surface in units of depth because of uncertainties in the interpretation (in time) and uncertainties in the time-to-depth conversion. In general, the further away from the well locations is, the larger the uncertainties in the surfaces are, see Figure-2. Therefore, the calculated GRV is uncertain. This uncertainty is often recognized but not quantified. Simulation methods are implemented to assess the uncertainty in the GRV calculation.

Methodology

The estimation of Hydrocarbon Initially in Place (HIIP) can be calculated by multiplying GRV by Net-to-Gross ratio (NTG) by porosity (ϕ) by hydrocarbon saturation (1-Sw). A reserve requires an estimate of recovery and an economic feasibility study. There is interdependence between these parameters. For example, the NTG is often correlated with thickness (h), porosity (ϕ), and water saturation (Sw). Another consideration is the uncertainty in parameters, plus the disparate data types such as seismic and sparse well data.

Four steps have to be done. The first step is to quantify the uncertainty in the structure surfaces (such as Top/Bottom surfaces and reservoir thickness). Second one is to quantify the uncertainties in fluid contacts levels (such as GOC, GWC, and/or OWC). Third step is to quantify uncertainties in some petrophysical properties (such as NTG, ϕ, and Sw). Fourth step is to find the uncertainty in HIIP calculated from the results of the first three steps combined to quantify full uncertainty. These steps will be conducted to quantify uncertainties without parameter uncertainty (without parameter uncertainty means a mean of zero for parameter uncertainty).

Uncertainty with Parameter Uncertainty

It is important to account for parameter uncertainty in the uncertainty calculations to get a fairly global uncertainty. There are several techniques for calculating parameter uncertainty in a required input histogram. These techniques include conventional bootstrap (BS), spatial-bootstrap (SBS), and Condition finite-Domain (CFD). A comparison between these approaches has been conducted and published by Babak and Deutsch (2006).

Any of the three techniques can be applied to quantify the uncertainty in the mean of each variable. Uncertainty in the mean is of primary importance; the details of the histogram are of second order importance compared to the mean. Uncertainty in the variogram is sometimes considered; however, it is also of second order importance. Uncertainty in the mean of each parameter was quantified with the three techniques mentioned above and was compared to choose the optimum technique for quantifying full uncertainties in HIIP with parameter uncertainty for this case study.

The procedure for quantifying the uncertainties in estimating the reserve/resource volumes in the presence of geologic uncertainty involves five steps. The first step is to calculate the means for variables of interested based on correlation coefficients between the variables. Second step is to quantify the uncertainty in the structure surfaces (such as Top/Bottom surfaces and reservoir thickness). Third one is to quantify the uncertainties in fluid contacts levels (such as GOC, GWC, and/or OWC). Fourth step is to quantify uncertainties in some petrophysical properties (such as NTG, ⍰⍰, and Sw). Last step is to find the uncertainty in HIIP calculated from the results of the first three steps combined to quantify full uncertainty. These steps will be conducted to quantify uncertainties with parameter uncertainty. These scenarios will be run many times using different parameter uncertainty approaches.

Uncertainties in Reservoir Structure Surfaces

The methodology to quantify uncertainty in reservoir structure surfaces with accounting for parameter uncertainty is similar to that done without parameter uncertainty except that the parameter mean for each realization will be variable; and it can be obtained from the parameter distribution generated by one of the three approaches mentioned above. The following steps were done to quantify the uncertainty in top and bottom surfaces and thickness:

- the top and bottom surfaces from seismic interpretation were considered as reference surfaces, which have been fitted to well data.
- the deviations from the reference surfaces are assumed to follow a known distribution (Gaussian as mentioned above).
- the standard deviation of the parameter mean was determined by quantifying the mean uncertainty by one of the three approaches, BS, SBS, or CFD.
- deviations can be simulated by a Sequential Gaussian Simulation with conditioning data at the well locations to be equal to dx_l , which is calculated by the following equation:

$$dx^l = \frac{m_p^l - m_o}{\sigma_o} \qquad (1)$$

where l = 1 , …, L (L = Number of realizations)

m_p^l = parameter mean drawn from parameter uncertainty distribution for the variable of interest;

m_o = a mean obtained from 2D original data for the variable of interest;

σ_o = a standard deviation obtained from 2D original data for the variable of interest;

Each realization has different value of dx^l since the standard deviation of the parameter mean was varying for each realization.

- to reset the values at well locations to be zeros, the results of each realization has to be shifted by a value of (- dx^l).
- the deviations can be multiplied by the assumed correcting standard deviation then added to the reference surfaces/layer thicknesses.

Uncertainties in GOC/OWC

The uncertainty in GOC/OWC level is investigated by determining its minimum, mode, maximum levels and assuming a triangle distribution to quantify the uncertainty in GOC/OWC, then so many realizations can be generated by drawing the value of GOC/OWC at all nodes randomly from the triangle distribution where the mode value will be variable in each realization.

Uncertainties in Petrophysical Properties

The methodology of quantifying uncertainty in petrophysical properties with parameter uncertainty is similar to that without parameter uncertainty except the reference distribution that is used in the *ultimatesgsim* program was changed for each realization. The changing in the procedure was as the following:

- The original data was used as reference distribution but it has to be shifted to fit a new parameter mean based on the mean and standard deviation of the parameter as a result of using one of the three approaches to quantify the parameter uncertainty. A program called *shift_pdf* was created for this purpose.
- Each shifted reference distribution was used as an input file in the cosimulating process using an *ultimate_sgsim* code.

CASE STUDY

The following case study is based on data set of Hekla reservoir, a portion of a large North Sea fluvial deposit offshore Norway. The Hekla data set is suitable for demonstrating the proposed approach. The data are available in two data files. The first file contains seismic data defining reservoir geometry, while the second file contains 20 well data including Well ID, X-Coordinate, Y-Coordinate, Depth, Log Porosity, and Log Permeability.

The reservoir consists of two major layers, H1 and H2. It is also gridded horizontally into a 101 by 131 cells, and each cell represents 50 meters in two directions, X and Y. From the seismic data, 2D and 3D views of H1 top surface are shown in Figures 3 to give an idea about the field structures and trends. Figure 3 also shows the contour maps for the top surface depth of both H1 and H2 with the distribution of the twenty well locations. From the 3D view, it was noticed that the low thickness-thin areas crossing the field have two faults.

Well No. 8 was eliminated from the data since it is a horizontal well with length of about 1000 m. Therefore, the thickness found doesn't reflect the actual vertical thickness in the layers especially H2 layer since H3 top structure is unknown. So, the study will be based on data of 19 wells only.

The histograms for all top structure depths from logs/well data were generated for the three top structures, H1, H2, and H3 layers. There were no data about any fluid contacts levels; therefore, it was assumed that the reservoir is oil bearing with no Gas Cap while the Oil Water Contact (OWC) was assumed to be at 2150m depth as a base case.

In this study, the uncertainties of eight parameters and their effects on HIIP with and without parameter uncertainty were investigated individually and combined all together in a ninth case with full uncertainty. First case studied the effects of structure surface uncertainties on HIIP. Second and third cases studied the effects of first and second layer thickness uncertainties on HIIP individually. While the effects of OWC level uncertainties were studied in the fourth case. The fifth and sixth cases investigated the effect of NTG uncertainties for the two layers on HIIP individually. While the seventh and eighth cases investigated the effect of porosity uncertainties for the two layers on HIIP individually. The last case combined the effects of all parameter uncertainties on HIIP. The study results were as the following:

Uncertainty Without Parameter Uncertainty

CASE-1: Uncertainty of Top/Bottom Surfaces

This case investigated the effects of Layers structures, top and bottom surfaces uncertainties on HIIP. GSLIB software was used first in the method to generate the variogram of the well data using a *gamv2004* code for the Top structure of H1 Layer. The variograms were calculated in the omnidirection due to sparse data. Then the *vmodel* code was used to obtain the best variogram model fitting the variogram result trends. The equation of the H1 Top Surface variogram model, as shown in Figure 12, is:

$$\gamma(h) = 0.001 + 0.999 * sph \qquad (2)$$

$$av = 1$$
$$ah1 = 2400$$
$$ah2 = 2400$$

By getting the variogram model parameters, the conditional Gaussian simulation was ran using a *sgsim* code with conditioning data at the well locations to be zeros. 100 realizations were generated where each realization gives a Gaussian distribution with a mean of zero and a standard deviation of one. The results then were analyzed with *OOIP* program by multiplying the results with some standard deviations then adding the new results to the reference data, see Equation (3). The program was created for this purpose. The standard deviation of the distributions should be estimated by referring to seismic interpretation, and it was assumed to be 15 meters for the reference top and bottom surfaces in this study. Finally, the uncertainties in HIIP were estimated by calculating the HIIP of each realization and generating a distribution plot.

$$z^l(u) = z_b(u) + y^l(u) * \sigma_\Delta * f(u) \qquad (3)$$

Three runs were conducted with different assumed OWC level; its level depth was assumed at 2050m in the first run, 2100m in the second run, and 2150m in the third one in order to investigate the impact of OWC level depth on the calculations; since calculating HIIP relays not only on the top and bottom surfaces, but also on OWC level. The influence of surface deviations on HIIP is restricted by OWC level. By comparing the results, it was obvious that the HIIP is higher with increasing OWC level depth, which is expected. From these three runs, it was determined to fix OWC at 2150m in all cases studying uncertainties in other parameters. In reality, OWC should be determined by logs or should be assumed at the lowest known hydrocarbon level, if not detected.

CASE-2: Uncertainty in H1-Layer Thickness

In this case, the effects of H1 layer thickness uncertainties on HIIP were investigated. Simulated thicknesses are obtained for each layer by adding the reference thicknesses and normally distributed deviations. Similarly to what have been done in investigating the top/bottom surfaces structures, the deviations can be generated by a *sgsim* code with zero values at well locations. The problem in running this case is that the variogram model could not be generated due to a decreasing trend of the experimental variograms obtained from H1 layer thicknesses at well locations. Therefore, the variogram model obtained from top surface structure was used in case-2 to generate the Sequential Gaussian simulation conditioned to be zero at well locations. The standard deviation for H1 layer thickness was assumed to be 3m. 100 realizations were run to get the HIIP distributions. The results of HIIP distributions were obtained and summarized.

CASE-3: Uncertainty in H2-Layer Thickness

It was similar to what was conducted in the previous case, but the variogram model used in this case was generated using H2-Layer thickness data at all well locations, see the second plot in Figure-12; where the equation of the H2 Thickness variogram model is:

$$\gamma(h) = 0.001 + 0.999 * sph \qquad (4)$$

$$av = 1$$
$$ah1 = 4000$$
$$ah2 = 4000$$

Then the deviations were generated by a *sgsim* code with a zero mean value and a standard deviation of one and conditioning values at well locations to be zeros. The standard deviation was assumed in this case to be 3m; and by generating 100 realizations, the HIIP distributions were obtained and summarized.

CASE-4: Uncertainty in Oil/Water Contact Level

In this case, the effects of OWC level uncertainties on HIIP were investigated by generating deviations randomly assuming a triangular distribution (minimum = 2148, mode = 2150, and maximum = 2152). 100 realizations were run with different seed number to get the HIIP distributions above OWC.

CASES-5 and 6: Uncertainty in NTG for H1 and H2 Layers

The NTG data on well locations was inferred from well logs. It was based on assuming a porosity cutoff of 10% in this study. 100 NTG realizations were generated by cosimulating NTG and Porosity simultaneously with thickness obtained from seismic data using an *ultimate_sgsim* code. The HIIP distributions were obtained and summarized for the effects of H1 layer NTG uncertainty and H2 layer NTG uncertainty individually.

CASES-7 and 8: Uncertainty in Porosity (ϕ) for H1 and H2 Layers

As mentioned in above that porosity cutoff was assumed to be 10% in this study. 100 porosity realizations were generated for each layer using an *ultimate_sgsim* code by cosimulating NTG and porosity with thickness data obtained from Seismic data for each layer. The HIIP distributions were also obtained and summarized for the uncertainty effects of H1 and H2 layer porosities on HIIP, individually.

CASE-9: Full Uncertainty Quantification

In this case, multiple realizations should be drawn with uncertainty attached to all parameters, surface structures, layer thicknesses, OWC levels, NTG, and Porosity for each layer. The deviations were generated without parameter uncertainty (with a mean of zero) for all parameters and standard deviations of 15m for surface structure depths and 3m for each layer thicknesses. 100 realizations were generated to get the HIIP distributions above OWC level of 2150m. Tornado charts of P90-Mean and P10-Mean for all parameters affecting HIIP distribution for both H1 and H2 layers. The results showed H1-layer thickness uncertainty was the most effective parameter on HIIP distribution followed by the uncertainty in top and bottom structure surfaces, the uncertainty of H2-layer thickness, the uncertainty in petrophysical properties, and last the uncertainty in OWC level surface. From these results, it is obvious that ignoring the uncertainty in reservoir structure surfaces might lead to underestimating of the global uncertainty and making bad decisions. The thickness and structure surface uncertainties were more effective on HIIP distribution than uncertainties of Petrophysical properties and OWC depth level, separately.

Uncertainty with Parameter Uncertainty

Three different methods, Conventional Bootstrapping method (BS), Spatial Bootstrapping method (SBS), and Conditional Finite Domain (CFD) method were used in this research to account for parameter uncertainty. Each of these three methods will be described briefly.

The BS method is a popular application of MCS technique. It is a statistical resampling technique that permits the quantification of uncertainty in any calculated statistics by resampling from the original data. It is based on two important assumptions: the data set is representative of the entire population and the data are independent, which is acceptable in early reservoir appraisal with widely spaced wells.

The independence assumption is unrealistic when the data are correlated. Therefore, SBS was developed to account for the spatial correlation in the input data. Its program used LU simulation for generating the realizations (Deutsch; 2004).

The third method, CFD method was developed by Babak, Olena and Deutsch, Clayton V. (2006). CFD is based on a multivariate Gaussian distribution. It is the first approach that accounts for the two important factors related to the study area: size of domain and conditioning data. It is shown to be convergent in the sense of limiting uncertainty calculation, design independent and parameterization invariant. Table-4 summarizes the means and standard deviations obtained for all variables of interest using the three different parameter uncertainty approaches.

CASE-1: Uncertainty of Top/Bottom Surfaces

This case investigated the effects of Layers structures, top and bottom surfaces on HIIP with accounting for parameter uncertainty. The variogram was already generated in the previous scenario of calculating HIIP without parameter uncertainty. The standard deviation of the original data, σ_o and mean and standard deviation of H1 top depths were used as mentioned in the methodology above.

The conditional Gaussian simulation was ran using a *sgsim* code with conditioning data at the well locations to be dx^l, which is calculated as shown in equation (1). The value is different in each realization.

100 realizations were generated where each realization gives a Gaussian distribution with a mean of zero and a standard deviation of one with conditioning data at well location to be dx^l. Then the results of each realization were reset at well locations to be zeros by adding ($-dx^l$) value to the realization results. Then the deviation results were nonstandardized by multiplying them by some standard deviations, which was assumed to be 15 meters in this case then added to the reference seismic data. Finally, the uncertainties in HIIP were estimated by calculating the HIIP of each realization and generating a distribution plot.

Three runs were conducted with different parameter uncertainty techniques, BS, SBS, and CFD, please see Table-5. By comparing the results the HIIP has more uncertainty with SBS approach to quantify the uncertainty in Top/Bottom Structure Surfaces while using CFD gave almost similar results compared to those obtained from BS approach; but the importance of accounting for parameter uncertainty is clear.

CASE-2: Uncertainty in H1-Layer Thickness

In this case, the effects of H1 layer thickness with parameter uncertainty on HIIP were investigated. Simulated thicknesses are obtained for each layer by adding the reference thicknesses and normally distributed deviations. Similarly to what have been done in investigating the top/bottom surfaces structures, the deviations can be generated by a *sgsim* code with conditioning values at well locations to be equal to dx^l. where dx^l was based on standard deviation of original thickness data at well locations and mean and standard deviation of H1 thickness mean using BS, SBS, and CFD, as shown in Table-4. The results were reset at well locations to be zeros by adding ($-dx^l$) to each realization data. Then the standard deviation for H1 layer thickness was assumed to be 3m. 100 realizations were run to get the HIIP distributions using each of parameter uncertainty approaches. The results of HIIP distributions were obtained and summarized. The results show the importance of accounting for parameter uncertainty; even though, the results were almost the same with using all three approaches.

CASE-3: Uncertainty in H2-Layer Thickness

It was similar to what was conducted in the previous case, but the variogram model used in this case was generated using H2-Layer thickness data at all well locations. Then the deviations were generated by a *sgsim* code with a zero mean value and a standard deviation of one and conditioning values at well locations to be dx^{l} (based on H2-layer data). The standard deviation was also assumed in this case to be 3m; and by generating 100 realizations, the HIIP distributions were obtained and summarized in Table 1 for all three parameter uncertainty approaches..

CASE-4: Uncertainty in Oil/Water Contact Level

In this case, the effects of OWC level uncertainties on HIIP were investigated by generating deviations randomly assuming a triangular distribution (minimum = 2148 and maximum = 2152). 100 realizations were run with different mode to get the HIIP distributions above OWC as shown in Table-5.

CASES-5 and 6: Uncertainty in NTG for H1 and H2 Layers

To quantify the parameter uncertainty in NTG, different reference distributions were obtained where each reference distribution has a mean matching a mean drawn from parameter uncertainty for the same parameter of interest. There were 100 reference distribution used separately as an input file to get 100 NTG realizations by cosimulating NTG and Porosity simultaneously with thickness obtained from seismic data using an *ultimate_sgsim* code. In other words, the same methodology used in Cases 5 and 6 without parameter uncertainty were used but with changing the reference distribution for each realization. The uncertainty in HIIP due to uncertainty in NTG of each layer was obtained using three different parameter uncertainty methods. SBS and CFD were repeated for the same data but with higher variogram range upto 2500m to investigate the effect of dependency on the results of using SBS and CFD methods.

The HIIP distributions for the three approaches were obtained and summarized in Table-5 and Figures-21 and 22 for the effects of H1 and H2 layer NTG uncertainties individually. SBS and CFD approaches were used again but with a high arbitrary variogram range, 2500m.

CASES-7 and 8: Uncertainty in Porosity (ϕ) for H1 and H2 Layers

As mentioned in last two cases, 100 porosity realizations were also generated for both layers using an *ultimate_sgsim* code by cosimulating NTG and porosity with thickness data obtained from Seismic data for each layer in each approach with using different reference distribution as mentioned above. The HIIP distributions were also obtained and summarized in Table 5 for the uncertainty effects of H1 and H2 layer porosities on HIIP, individually.

CASE-9: Full Uncertainty Quantification

In this case, multiple realizations should be drawn with uncertainty attached to all parameters, surface structures, layer thicknesses, OWC levels, NTG, and Porosity for each layer. The value of parameter mean in each realization was obtained from using correlation coefficient among all parameters of interest and using LU simulation (using *correlate* code). Each parameter mean was used as described in Cases-1 to 3 to get the nonzero value that the conditional SGS will be equal at the well location. The deviations were generated with parameter uncertainty for all parameters and standard deviations of 15m for surface structure depths and 3m for each layer thicknesses.

100 realizations were generated to get the HIIP distributions as shown in Table-5 with assuming triangular distribution with a different mode value in each realization.

T he means of parameter uncertainty for NTG and porosity were also obtained using the correlation coefficient among the variables as mentioned above where those parameter means were used to get shifted reference distributions that were used in the cosimulation of NTG and porosity with thickness obtained from Seismic Data (as described in Cases 5-8 with parameter uncertainty).

Discussion

The orders of the parameters affecting HIIP uncertainty from the most effective parameter to the least effective one were summarized for all seven scenarios in Table 2. Two observations can be inferred from the comparison between those results. First, quantifying the uncertainty in HIIP without parameter uncertainty was more sensitive to structural surfaces parameters, then petrophysical properties, and last to the OWC. The other six scenarios quantifying the uncertainty in HIIP with parameter uncertainty were more sensitive to petrophysical properties, then structural surfaces parameters, and last to the OWC.

Second observation was about the order of the parameters in the six scenarios quantifying the uncertainty in HIIP with parameter uncertainty. It was almost the same except the porosity of H1 and H2 layers that were exchanged in those six scenarios because their effects on the HIIP uncertainty were almost close to each other.

The effects of changing parameter uncertainty approach on all parameters of interest were investigated and summarized based on the HIIP distribution uncertainty. In all cases, it was obvious that ignoring parameter uncertainty gives always the narrowest HIIP distribution. By comparing the results of using different parameter uncertainty approaches, the order of the approaches was SBS, BS, and CFD as the results had more uncertainty distribution to less uncertainty distribution except case-2 where the order was reversed, CFD, BS, and SBS. The effects of using different parameter uncertainty approaches were almost the same in cases 1 to 3, but cases 5 to 8 showed a significant difference between the HIIP distributions.

In cases 5 to 8, increasing the variogram range affected on the HIIP distributions with using SBS and CFD approaches, while the results with using the BS approach were almost the same because SBS and CFD are based on the spatial correlation between the data but BS approach is based on the independency assumption between the data.

The standard deviations of the HIIP distributions obtained from using parameter uncertainty approaches were related to the standard deviations of the parameter uncertainty distributions used. For example in case 1, the order of the standard deviations of HIIP distributions was SBS, BS, and CFD, descendingly. As the order of the standard deviations of the parameter uncertainty was SBS (26.9m), BS (18.8m), and CFD (15.79m). This comment was applied for all cases.

The results of using different parameter uncertainty approaches were compared using the tornado chart. The narrowest HIIP distribution was obtained from estimating HIIP without parameter uncertainty. Using SBS approach gave the most uncertain distribution with a low/high variogram range compared to those obtained from using BS or CFD approaches. The BS approach results were almost the same with low/high variogram ranges. The result of using CFD approach was narrower than those obtained with using BS and SBS approaches but with high variogram range, the result of using BS approach became the narrowest compared to those obtained from using SBS and CFD approaches.

The probability and cumulative distribution frequencies of HIIP with full uncertainty were compared. Using BS approach produced more uncertainty in the HIIP estimates compared to the result without parameter uncertainty but BS approach was ignoring the spatial correlation between the data. Using SBS approach considered the spatial correlation between the data and produced more uncertainty in the HIIP distribution with high standard deviation compared to all other approaches. The CFD approach considered the correlation between the input data and the conditioning data, so it can be more realistic; even though, it is not such well known and popular as SBS approach.

BS approach might be recommended in the early stages of the reservoir life because of its simplicity. CFD approach might give the same results in that stage of the reservoir life plus it will give more realistic results as more data are gathered. The only disadvantage of using the CFD is the significant time required to generate a parameter uncertainty that might reach to a few hours depending on the input data and the CPU and this time is unwanted to make quick decisions.

Conclusions and Future Work

We would wish for the lowest uncertainty possible. However, too narrow uncertainty due to ignoring the uncertainty in the present geology leads to a false confidence in reserves and resources. Our aim is to obtain a realistic and fair measure of uncertainty. Decisions of stationarity and a modeling methodology are the most important factors in determining output uncertainty in any practical modeling study.

In this study, a methodology for the assessment of uncertainty in the structure surfaces of a reservoir, fluid contacts levels, and petrophysical properties was developed and investigated. A complete setup was considered with accounting for parameter uncertainty in order to get a fairly global uncertainty. There is no question that uncertainty in the input histogram main parameter, such as the mean, must be considered for realistic global uncertainty characterization. There are several techniques for calculating parameter uncertainty in a required input histogram. These techniques include conventional bootstrap (BS), spatial-bootstrap (SBS), and Condition finite-Domain (CFD).

Any of the three techniques can be applied to quantify the uncertainty in the mean of each variable. Uncertainty in the mean is of primary importance; the details of the histogram are of second order importance compared to the mean. Uncertainty in the variogram is sometimes considered; however, it is also of second order importance. Uncertainty in the mean of each parameter was quantified with the three techniques mentioned above. The results of uncertainty in HIIP distribution with/without parameter uncertainty were analyzed and assessed to show the importance of accounting for parameter uncertainty in estimating HIIP and choose the optimum technique for quantifying full uncertainties in HIIP with parameter uncertainty for this case study.

By comparing the results with using higher variogram ranges, it was obvious how important is to incorporate the dependency of data. Although, the more correlated the data are, the more uncertainty the HIIP has. Last, a complete setup for the assessment of uncertainty with parameter uncertainty in the presence of structural uncertainty was developed in order to get a fairly global uncertainty.

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Both Layers OOIP with/without Parameter Uncertainty Statistics											
Case	PU Approach	Mean	Std	Minimum	Maximum	P90	P50	P10	P90-Mean	P50-Mean	P10-Mean
1 - Uncertainty in Top Structures	No PU	92.8086	0.7745	90.942	94.824	93.931	92.7975	91.8315	1.1224	92.023	0.8895
	BS	92.8966	0.9583	90.984	94.993	94.1325	92.873	91.6285	1.2359	91.9147	0.6445
	SBS	92.896	0.9868	90.883	95.046	94.236	92.8745	91.4965	1.34	91.8877	0.6135
	CFD	92.8968	0.9498	91.006	94.991	94.1205	92.8825	91.6505	1.2237	91.9327	0.6445
2 - Uncertainty in H1 Thickness	No PU	93.1718	0.8546	91.303	95.799	94.378	93.138	92.118	1.2062	92.2834	0.815
	BS	93.2473	1.0217	91.144	95.361	94.588	93.2185	91.8395	1.3407	92.1968	0.6955
	SBS	93.2491	1.0482	91.184	95.422	94.5925	93.275	91.8495	1.3434	92.2268	0.6655
	CFD	93.247	1.0176	91.115	95.348	94.596	93.221	91.8285	1.349	92.2034	0.7135
3 - Uncertainty in H2 Thickness	No PU	92.9618	0.4405	92.032	94.23	93.5755	92.9585	92.454	0.6137	92.518	0.422
	BS	93.0053	0.507	91.877	94.006	93.704	92.9905	92.314	0.6987	92.4835	0.437
	SBS	93.0052	0.5077	91.906	94.018	93.71	92.9685	92.3125	0.7048	92.4608	0.4065
	CFD	93.0053	0.5069	91.872	94.004	93.702	92.995	92.315	0.6967	92.4881	0.443
4 - Uncertainty in OWC	No PU	92.9115	0.0048	92.903	92.924	92.9185	92.911	92.906	0.007	92.9062	0.003
	PU in the mode	92.918	0.0644	92.808	93.029	93.0075	92.918	92.829	0.0895	92.8536	0.021
5 - Uncertainty in H2 NTG	No PU	90.841	0.3374	90.189	92.911	91.2345	90.8005	90.4765	0.3935	90.4631	0.2875
	BS	93.3908	6.3876	76.697	109.926	101.5115	93.4365	85.12	8.1207	87.0489	8.423
	BS with high range	93.3908	6.3876	76.697	109.926	101.5115	93.4365	85.12	8.1207	87.0489	8.423
	SBS	90.3157	6.9903	72.103	108.318	99.427	90.3545	81.2595	9.1113	83.3642	9.1565
	SBS with high range	90.9277	8.036	69.972	111.7	101.12	90.9735	80.5245	10.1923	82.9375	10.5525
	CFD	91.5688	5.0386	78.447	104.485	98.117	91.584	85.0455	6.5482	86.5454	6.5985
	CFD with high range	92.2973	6.7492	74.699	109.758	100.7715	92.332	83.559	8.4742	85.5828	8.86
6 - Uncertainty in H1 NTG	No PU	91.4682	0.2131	91.064	92.911	91.674	91.45	91.262	0.2058	91.2369	0.198
	BS	94.1744	3.8429	84.223	104.136	99.1265	94.173	89.2195	4.9521	90.3301	4.9965
	BS with high range	94.1744	3.8429	84.223	104.136	99.1265	94.173	89.2195	4.9521	90.3301	4.9965
	SBS	92.6174	3.9092	82.48	102.746	97.66	92.6265	87.576	5.0426	88.7173	5.096
	SBS with high range	93.8443	5.0619	80.724	106.963	100.377	93.8465	87.313	6.5327	88.7846	6.589
	CFD	94.8937	3.1845	86.636	103.143	99.01	94.8845	90.7785	4.1163	91.7	4.1425
	CFD with high range	97.0139	4.3152	85.83	108.197	102.5865	97.0065	91.45	5.5726	92.6913	5.62
7 - Uncertainty in H1 Porosity	No PU	90.8585	0.2242	90.561	92.911	90.9635	90.829	90.7245	0.105	90.6048	0.1635
	BS	92.8095	2.352	86.691	98.904	95.8545	92.808	89.774	3.045	90.456	3.083
	BS with high range	92.8095	2.352	86.691	98.904	95.8545	92.808	89.774	3.045	90.456	3.083
	SBS	91.7472	2.6677	84.832	98.657	95.201	91.7315	88.3045	3.4538	89.0638	3.4725
	SBS with high range	92.0927	3.0365	84.206	99.963	96.027	92.0915	88.1635	3.9343	89.055	3.9575
	CFD	93.1311	1.8491	88.341	97.929	95.5255	93.136	90.7595	2.3944	91.2869	2.4185
	CFD with high range	94.3798	3.5927	85.07	103.682	99.0225	94.365	89.747	4.6427	90.7723	4.677
8 - Uncertainty in H2 Porosit	No PU	91.4708	0.1555	91.312	92.911	91.53	91.455	91.378	0.0592	91.2995	0.066
	BS	92.3249	2.2224	86.559	98.096	95.197	92.3305	89.461	2.8721	90.1081	2.902
	BS with high range	92.3249	2.2224	86.559	98.096	95.197	92.3305	89.461	2.8721	90.1081	2.902
	SBS	91.1167	2.4022	84.87	97.335	94.205	91.1125	88.011	3.0883	88.7103	3.141
	SBS with high range	91.2068	3.0622	83.277	99.16	95.15	91.21	87.2585	3.9432	88.1478	3.9815
	CFD	92.9032	1.8826	88.024	97.775	95.3275	92.9035	90.469	2.4243	91.0209	2.445
	CFD with high range	92.6851	2.0242	87.441	97.947	95.301	92.685	90.0685	2.6159	90.6608	2.6275
9 - Uncertainty in H1 NTG	No PU	93.099	1.1415	90.402	95.829	94.4935	93.05	91.4405	1.3945	91.9085	1.0385
	BS	95.0838	11.1202	68.966	125.566	109.5415	93.779	81.624	14.4577	82.6588	12.658
	BS with high range	95.0838	11.1202	68.966	125.566	109.5415	93.779	81.624	14.4577	82.6588	12.658
	SBS	89.0134	13.191	64.264	132.802	107.366	86.403	74.3275	18.3526	73.212	10.0635
	SBS with high range	91.5967	15.7863	58.378	137.669	113.5846	89.4915	72.3795	21.9879	73.7052	14.0015
	CFD	95.7294	9.5482	73.984	126.575	107.617	95.2865	84.13	11.8876	85.7383	10.146
	CFD with high range	100.569	13.5197	69.659	137.087	117.9896	99.286	84.9505	17.4207	85.7663	15.2915

Table 1: HIIP analysis for Both Layers; values are in million cubic meters.

Scenarios	Most effective parameters ⟵⟶ Less effective parameters							
No PU	Thickness of H1	Top&bottom surfaces	Thickness of H2	NTG of H1	NTG of H2	Porosity of H1	Porosity of H2	OWC
BS	NTG of H1	NTG of H2	Porosity of H1	Porosity of H2	Thickness of H1	Top&bottom surfaces	Thickness of H2	OWC
SBS	NTG of H1	NTG of H2	Porosity of H1	Porosity of H2	Thickness of H1	Top&bottom surfaces	Thickness of H2	OWC
CFD	NTG of H1	NTG of H2	Porosity of H2	Porosity of H1	Thickness of H1	Top&bottom surfaces	Thickness of H2	OWC
BS with high range	NTG of H1	NTG of H2	Porosity of H1	Porosity of H2	Thickness of H1	Top&bottom surfaces	Thickness of H2	OWC
SBS with high range	NTG of H1	NTG of H2	Porosity of H2	Porosity of H1	Thickness of H1	Top&bottom surfaces	Thickness of H2	OWC
CFD with high range	NTG of H1	NTG of H2	Porosity of H1	Porosity of H2	Thickness of H1	Top&bottom surfaces	Thickness of H2	OWC

Table 2: Order of parameters affecting on HIIP distribution from the most effective parameter to the least effective one in all seven scenarios.

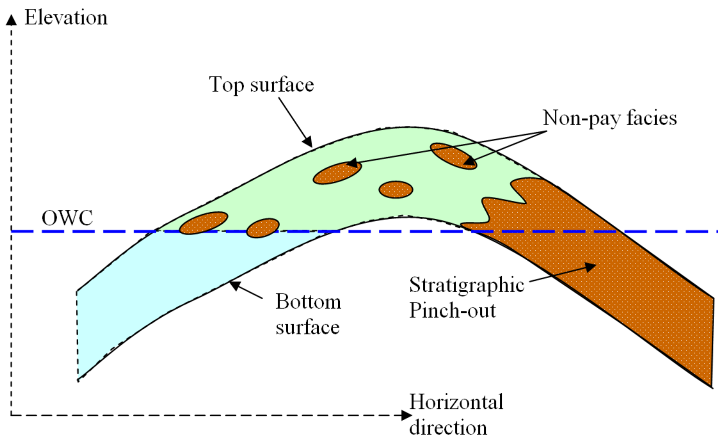

Figure 1: Reservoir Cross-section: The reservoir is bounded by the top and bottom structure surfaces and above the OWC level as shown in the green area and excluding the non-pay facies.

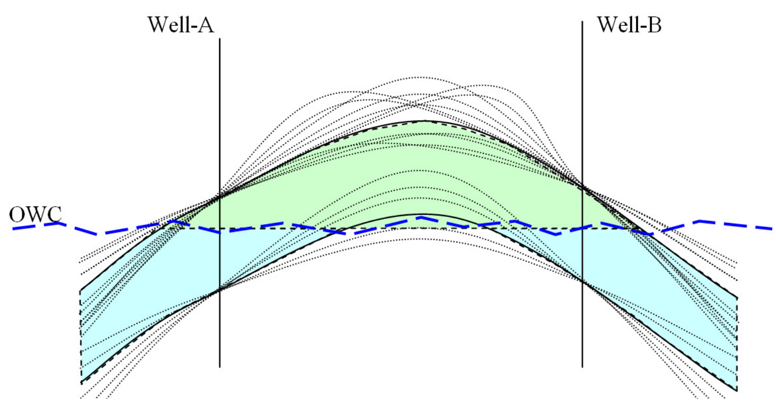

Figure 2: The uncertainty of the values of top/bottom surface structure and reservoir thickness increases as goes far from well locations.

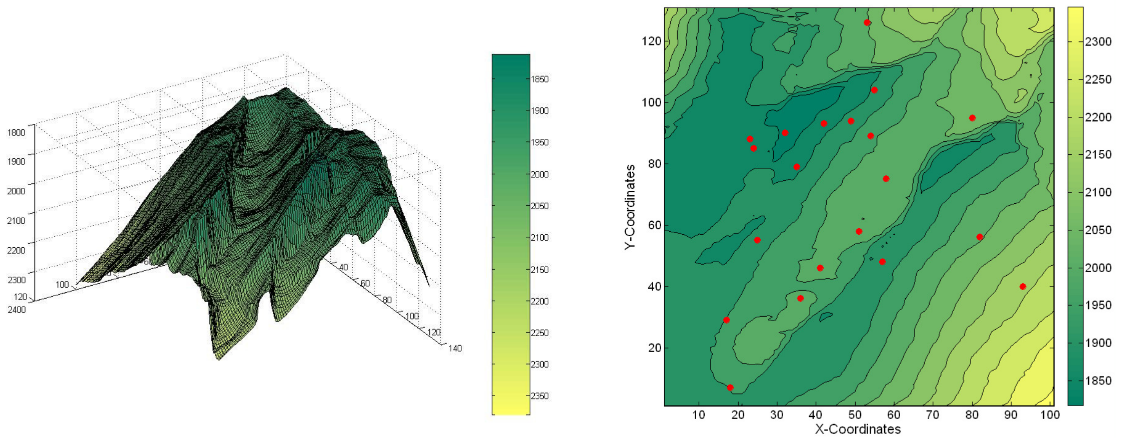

Figure 3: 3D view of Hekla field, top structure of H1 layer. Contour map of H1 layer depth in Hekla field with showing the distribution of twenty well locations.

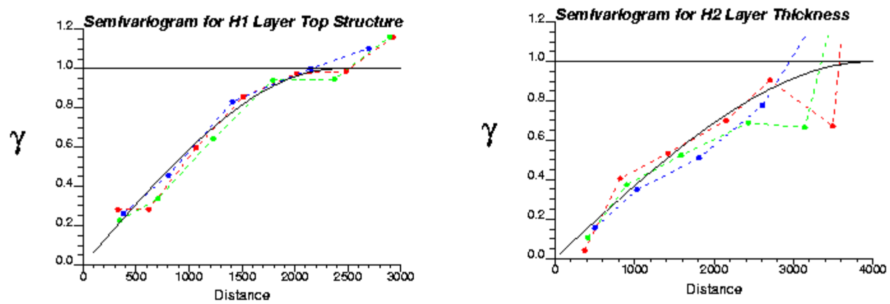

Figure 4: The variogram models for H1 Top Structure Depths and H2 Layer Thicknesses.

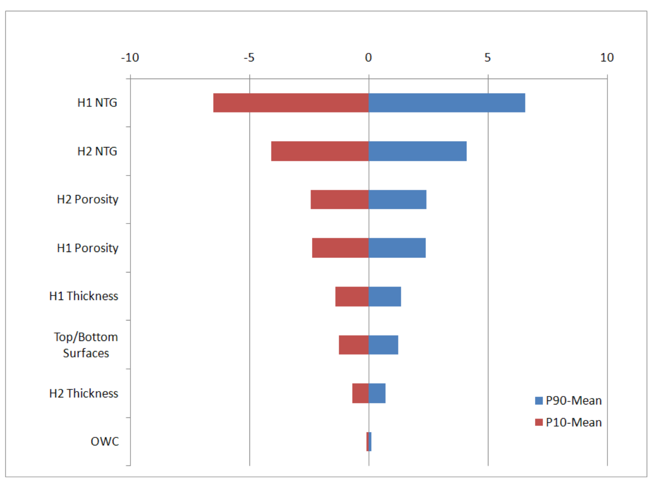

Figure 5: Sensitivity analysis for quantifying HIIP with parameter uncertainty using CFD approach; the results are in millions m^3.