

Bias in geophysical interpretation—the case for multiple deterministic scenarios

PETER ROWBOTHAM, PETER KANE, and MARK BENTLEY, AGR Petroleum Services

Oil exploration and production business decisions need accurate forecasts derived from a description of the subsurface combined with a statement of the uncertainty associated with that description. However, we commonly observe biases in the quantification of uncertainty due to cultural influence and overconfidence in our ability to estimate uncertainty, leading to disappointment when reality lies outside predictions. In tandem, a lack of insight into the value that uncertainty holds on the business case can lead to a mismatch between the effort expended on deriving a single “best” guess versus that on understanding the uncertainty range associated with that guess. Generating stochastic results around a “best technical case” can give a seemingly plausible range of uncertainty but typically fails to explore the uncertainty space.

We promote the use of multiple deterministic scenario modeling, and argue for the extension of this approach into the early stages of data processing and interpretation. We demonstrate common pitfalls in the quantification of uncertainty using three examples: (1) time-depth conversion, (2) populating reservoir properties, and (3) volumetrics.

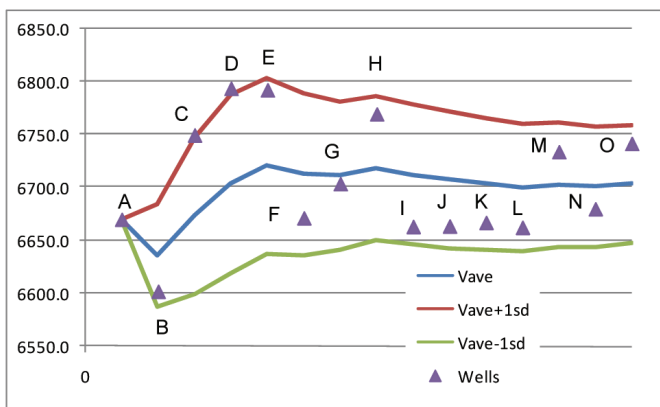
Common problems

Baddeley et al. (2004) review the causes of bias and error in information derived from the probabilistic judgments made by people. Using their observations, we consider here the types of issue that lead to difficulties in uncertainty assessment. The following examples are common and are often the result of strong cultural bias or influence (upbringing, education, etc.) which standard uncertainty workflows seem unable to negate:

- *Need to get the “right” answer.* This results in a disproportionate effort in producing a best technical case and not enough on assessing and characterizing the uncertainty range.
- *Instinct driven.* Despite or because of our education, we may trust our instincts more than statistical results. The effect of this bias can be beneficial, for example when we mistrust and question data that fall outside of our range of expectation or experience, or detrimental such as when data are ignored because they don’t fit the prevailing paradigm.
- *Box ticking.* In other words, running an uncertainties workflow (e.g., black-box stochastics) to satisfy a prescribed procedure. Although superficially thorough, a false sense of security (overconfidence) will have been generated by the act of completing the procedure rather than a thorough consideration of all elements in the process, and the uncertainties that surround them.
- *Focusing on the wrong thing.* When we follow tried and tested procedures, there is a danger of not looking for new ideas that explain the data (the complacency effect).
- *Herding.* This is being unduly influenced by others and can manifest itself as an organizational imprint, if company standardization overrules independent thought. This behavior may be exhibited during the initial working of the data set, but can also be shown by experts in review sessions, which will inevitably reinforce the sense that the technical case and uncertainty bounds presented capture all eventualities.

Well	TVDSS (ft)	TWT (s)	Vapp (ft/s)	Vave (ft/s)	SD (ft/s)
A	-7258.5	2.177	6669.5	6669.5	
B	-7347.8	2.226	6601.8	6635.6	47.9
C	-7303.9	2.164	6748.8	6673.4	73.6
D	-7248.9	2.134	6792.8	6703.2	84.7
E	-6968.2	2.052	6791.4	6720.9	83.3
F	-7170.8	2.150	6670.8	6712.5	77.2
G	-7244.7	2.162	6703.0	6711.2	70.6
H	-7294.8	2.155	6768.7	6718.4	68.5
I	-7207.8	2.164	6662.8	6712.2	66.7
J	-7211.3	2.165	6663.2	6707.3	64.7
K	-7175.4	2.153	6666.5	6703.6	62.6
L	-7188.5	2.158	6662.0	6700.1	60.9
M	-7251.5	2.154	6733.1	6702.6	59.0
N	-7240.4	2.168	6679.4	6701.0	57.1
O	-7230.9	2.145	6740.9	6703.6	55.9
		Average	6703.6		
		SD	55.9		

Figure 1. Time-depth table for wells in the study area and a graph showing the apparent velocity for each well and the progressive average velocity (± 1 SD) for all wells as they are drilled in order.



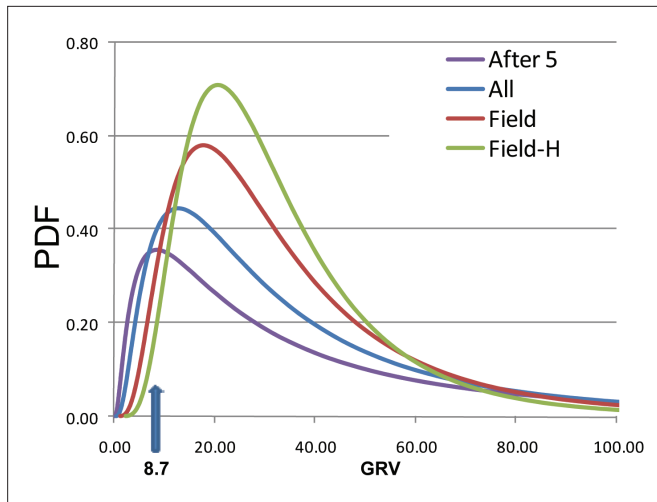


Figure 2. Volumetrics distribution for the four cases modeled with lognormal distributions. The “correct” solution of 8.7 is indicated.

The above factors can lead to:

- **Overconfidence.** Baddeley et al. identify overconfidence as one of two main sources of cultural bias that affect our ability to make probabilistic judgments. As an example, Rankey and Mitchell (2003) report on an interpretation exercise conducted by six independent workers of varied levels of experience over a Canadian Devonian pinnacle reef. The critical point in the exercise came where a key reflector split. The spread of interpretations was significant and yet all interpreters were fairly confident of their own interpretation. They had correctly identified this area as being one of the critical decision points of the interpretation, yet had assumed they had made the right choice.
- **Anchoring on a best technical case.** Bentley and Smith (2008) demonstrate the limitations of using a best guess as a best technical case with a range of uncertainty (\pm percentage) added to that guess. The weak point is that the best guess is reliable only when the system being described is well ordered and well understood, to the point of being highly predictable (e.g., the accuracy range of a porosity measurement device is well quantified whereas the distribution of porosity away from the measurement point is not). Self-evidently, the technique can yield a valid uncertainty range only if the best guess is very close to the mean.
- **Lack of understanding of impact.** Contradicting the advice that one should never answer a question with a question, to the question “What’s the uncertainty?”, we should reply “Why do you want to know and what are you going to use the result for?” The uncertainty in a product will be tightly related to its purpose (e.g., whether the question is posed during the exploration or development phases, for well planning or for modeling). Understanding the sensitivity of the business decision to the uncertainties is of prime importance.

Example 1: Time-depth conversion

We illustrate how bias affects technical conclusions using a

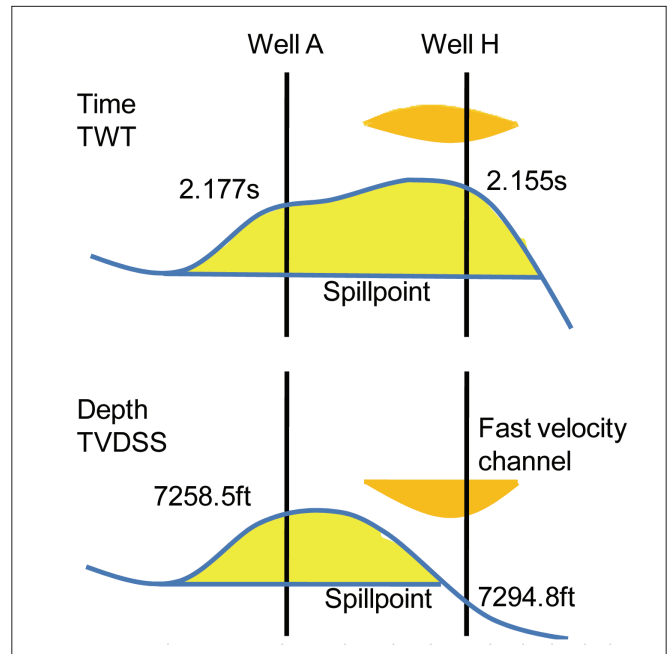


Figure 3. Schematic demonstrating how a channel in the overburden has had a pull-up effect in time at well H.

spreadsheet common to an interpreter’s repertoire, the time-depth sheet (Figure 1). This synthesized data set has the characteristics often encountered in a North Sea field exercise. Column 1 lists 15 wells, A-O drilled in that order, and column 2 the true vertical depth subsea (TVDSS) of a marker horizon seen in each of the wells. Column 3 shows the seismic two-way time (TWT) of the interpreted seismic horizon corresponding to the marker at the wells. From these data columns are derived apparent velocities (V_{app}) per well (column 4). As the wells are drilled from A to O, the spreadsheet computes the running average apparent velocity (V_{ave} , column 5) and standard deviation (SD, column 6) for the wells drilled to date. This progression is displayed in the chart in Figure 1. (V_{0k} has been run but, for this relatively flat structure, does not bring extra insight.)

Note that, after the first phase of drilling (wells A–E), V_{ave} is 6720.9 ft/s with SD of 83.3 ft/s. We call this the “after 5” case. Having drilled all 15 wells (the “all” case), and without further information, a best guess depth conversion could be to use the final V_{ave} of 6703.6 ft/s, and high and low maps generated with ± 1 SD (reduced to 55.9 ft/s). However, wells B, C, D, and E are regional wells outside the area of interest. These wells represent the outliers, and excluding them from the population gives a V_{ave} of 6692 ft/s and SD of 38.0 ft/s (the “field” case). Well H is now an outlier, lying at +2 SD from the mean; excluding this on the assumption of a suspect depth pick results in a V_{ave} of 6688.1 ft/s and SD of 30 ft/s (the “field-H” case).

To understand how these velocity cases impact business, the 12 depth conversion maps (four cases, each with high, mid, low) are tied locally to wells, and gross rock volumes (GRV) are computed above a nominal flat fluid contact and within a bounded polygon to mimic a four-way dip-closed

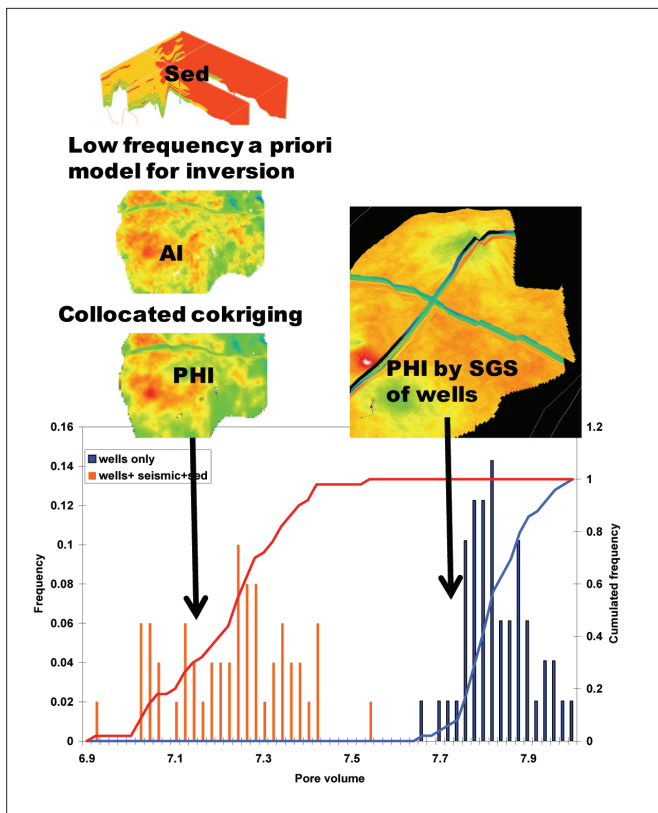


Figure 4. Workflow for generating volumetrics constrained by wells only and by wells, sedimentary model, and seismic inversion data.

field. For each case, a reality and plausibility check on log-normal distributions of GRV lead to the results in Figure 2. Also shown on Figure 2 is the “correct” solution of this synthetic case. With further study of the field, it becomes apparent that there are channels of anomalous velocity in the near overburden of our structure (Armstrong et al., 2001). These anomalies are faster than the background velocities and therefore have a pull-up effect on TWT, resulting in an overly optimistic view of the structure in the time domain (Figure 3). What we took to be an anomalous time-depth pair at well H was due to these anomalies. Seismic processing velocities may have been of benefit in identifying this anomaly, but were of insufficient quality in this example.

Consider the human behavior demonstrated by the evaluation described above; the need to get to the right answer and trust in instinct over statistics led to overconfidence in the initial answer and a focus on the horizon rather than the overburden. The correct solution sits at the P50, P70, P85, and P93 percentile of our progressively narrower and more optimistic GRV distributions. Would this have been picked up at review, or would a convincing presentation herd the audience into a financially damaging drilling decision?

Example 2: Reservoir properties constrained by seismic

Figure 4 shows two workflows for generating multiple realizations of reservoir properties in a reservoir model, firstly from well properties only by sequential Gaussian simulation (SGS), and secondly using the wells, a sedimentary model

and geostatistical seismic inversion data. The results of these two processes were reported by Rowbotham et al. (2003). The two approaches share the same a priori model for porosity (stratigraphic grid, porosity distribution from wells, variograms), but whereas the “wells only” model by definition has a porosity distribution mimicking that of the wells, the addition of the sedimentary model and seismic impedances allows the porosity distribution to move away from a priori distribution.

For any cell, the second approach can reduce or widen the range of possible reservoir models. For the model overall, it was found that the use of seismic and sedimentological data tended to reduce pore volume and increase the uncertainty range (SD multiplied by 2). Note that there is no overlap of volumetric distributions from each of the methods. This suggests that the a priori constraints used to generate the porosity models constrained by well data only were too simplistic and optimistic, and including seismic and sedimentary constraints gives more meaningful control on uncertainties in reservoir models. These results remind us that since wells are drilled for economic reasons, they are aimed deliberately at the best part of the reservoir, and so tend to sample better quality and less diverse reservoir properties than may be present in the reservoir as a whole. Likewise, in a structural sense, wells consciously sample high structures rather than low, and thus our well stock is a biased data set. Taking a model whose rock properties are based on well data alone through to development design could have led to an expensive oversizing of facilities. In this example, we observe overconfidence when we fit to our well populations, box-ticking in the use of SGS to address uncertainties and a lack of understanding of the impact of the result.

Tackling the problem: the case for scenario modeling

The two preceding examples demonstrate what Bentley and Smith refer to as a rationalist approach. When faced with uncertainty, we rationalize a best guess, base case, or best technical case solution. Adopting this approach assumes that enough data are available from past activities to predict a future outcome. Statistical/stochastic modeling (adding ranges around a most probable prediction) also falls into the rationalist category, since it is rooted in the available data and therefore anchored in the same starting assumption as the simple forecast. In other words, what may seem to be an extensive uncertainty analysis is in fact exploring only a very limited area of uncertainty space. All such rationalist forecasts go adrift if any essential data are lacking (Example 2).

Scenario modeling is free from this limitation; the built scenarios must honor, but are not limited to, the available data. Each scenario is a complete and internally consistent static/dynamic subsurface model (Figure 5) with an associated plan tailored to optimize its development. The choice of deterministic models is driven by an understanding of those factors that may impact the particular issue being studied. This approach is inherently nonstatistical, based instead on deterministic conceptual models, although stochastic modeling can have a place within this overall framework (e.g., Figure 5 models 1-3). Alternative scenarios are not incrementally

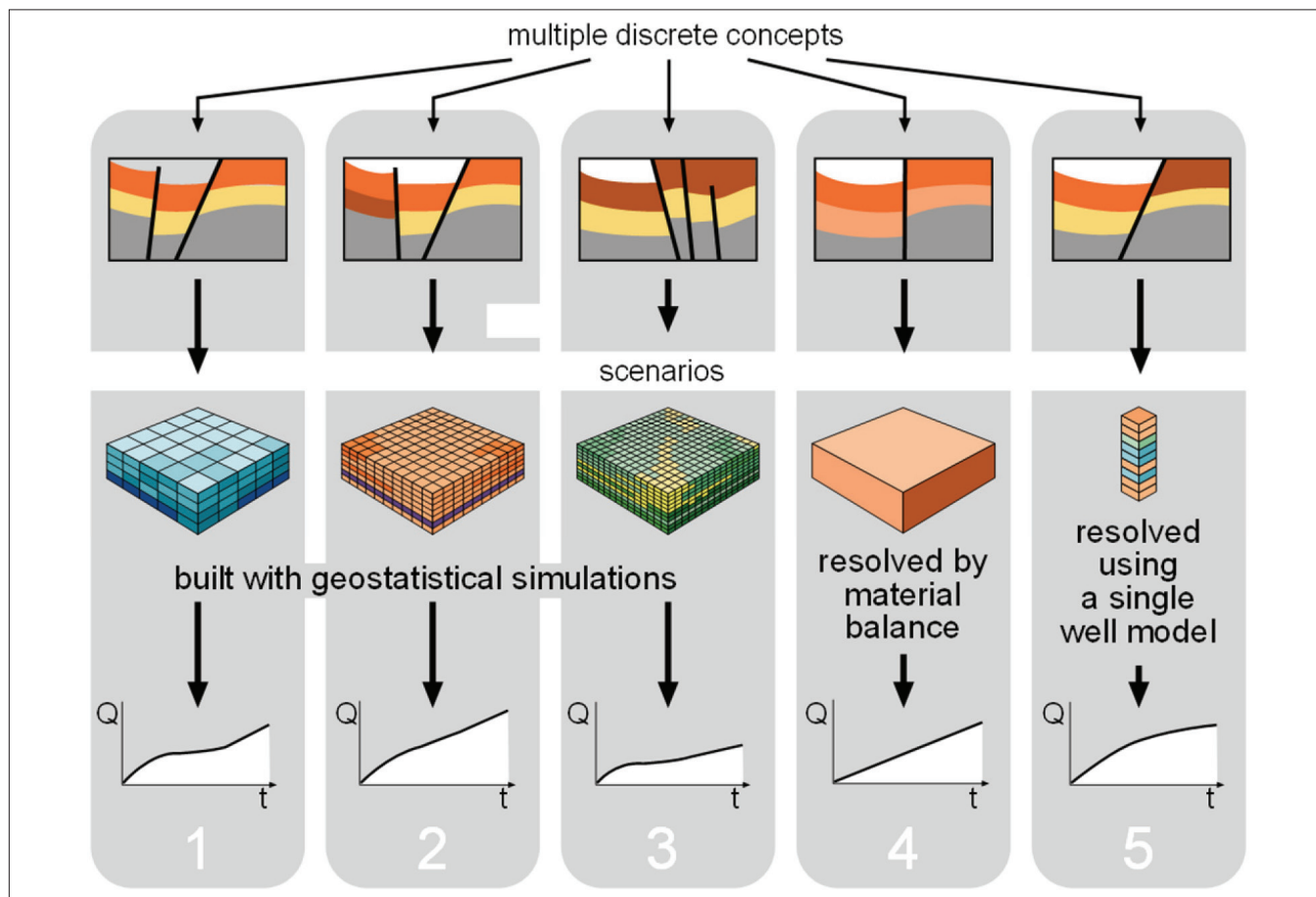


Figure 5. Representation of the multiple deterministic, “scenario-based” approach. The spread of outcomes is generated by multiple, deterministically defined starting concepts, some of which may require differing modeling techniques. There is no selection of an initial base case; the technique is not anchored.

different realizations, but are structurally distinct, plausible outcomes based on some design criteria. Revisiting Example 1, scenarios could be constructed with alternative top structure maps assuming (1) no overburden variation, (2) a single overburden channel, and (3) several possible channels. Top structure is just one of several inputs to the model; the number of deterministic models to construct will be determined by the number of uncertain input parameters that are being combined and the number of variations for each parameter. If that sounds like a recipe for an endless modeling exercise, help is at hand. Experimental design (ED) offers a way of generating probabilistic results from a limited number of deterministic scenarios, and of relating individual scenarios to specific positions on a cumulative probability S curve. In turn, this provides a rationale for selecting specific models (e.g., P90, P50, P10) for screening development options. ED expresses uncertainties as end members and therefore the need for base case, best guessing is reduced or removed. A more detailed review of this approach is offered by Bentley and Smith.

Example 3: Volumetric assessments using multiple deterministic scenarios

In another field example, two different depth-conversion

methods were considered as best technical cases (A and B) with two less likely alternatives also considered (L and H); GRV was computed for all four cases and carried through to volumetrics. Figure 6 shows an example of how these top structure maps could be combined with other deterministic choices for each factor in the STOIIP equation ($STOIIP = GRV * porosity * saturation * formation\ volume\ factor$). As the first stage of a multiple deterministic scenario modeling exercise, STOIIP was computed for each combination in a spreadsheet. This quick exercise can reveal the sensitivity of STOIIP to each choice, and is a tool for the subselection of parameter combinations for a full 3D modeling exercise.

Figure 7 shows the results of this exercise as an expectation curve, with the sorted results of each parameter combination displayed as blue triangles. The orange squares are the two best guess depth conversions (A and B) with identical combinations of porosity, saturation and FVF choices. This plot demonstrates that the overall volumetrics result is fairly insensitive to the difference in the two preferred depth mapping approaches. For building 3D deterministic reservoir models for volumetrics purposes, emphasis should instead be placed on maintaining the uncertainty range with the choice of the red squares for P90, P50 and P10 representative models. The

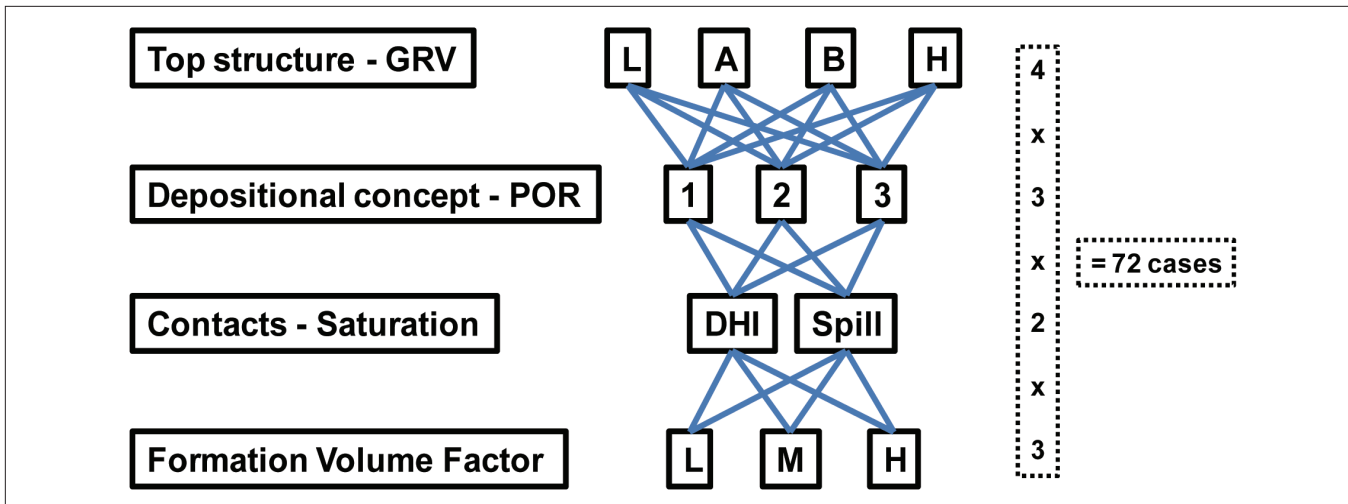


Figure 6. An example combination of concepts for multiple deterministic STOIP realizations. Some parameter combinations may be mutually exclusive such as a High Top structure and Fill-to-Spill saturation, so in reality fewer cases are run.

alternate best technical case depth conversion routes may have impact in the realms of well targeting, but this example illustrates an initial lack of understanding of the importance and impact of geophysical choices. The multiple deterministic approach avoids the problem of anchoring the result around an initial best technical case and therefore maintains a realistic range of uncertainty through the modeling lifecycle.

Conclusions

We have presented several common issues that plague the understanding and use of uncertainties in geophysical and other subsurface work. The lack of insight into the potential impact of uncertainty on business decisions leads to a mismatch between the effort expended on uncertainty analysis and its value. Practical examples have demonstrated that overconfidence, wrong emphasis of study and the cultural bias of oneself and others make it difficult to form rational, logical, and independent judgments. These examples have also shown that use of a best guess with uncertainty bounds is potentially damaging and multiple deterministic scenario modeling is instead a better way of maintaining a realistic uncertainty range from the geophysical domain and through the modeling lifecycle.

Discussion: Relevance to geophysical workflows

In the reservoir modeling teams of some operating companies, deterministic scenario modeling has become a common technique; therefore, the interpretation or asset geophysicist is more likely to have actively contributed to a deterministic scenario modeling exercise than say, the acquisition, processing, or quantitative/inversion geophysicist. Herein lies a problem—without clear communication of the fundamental uncertainties from each geophysical specialty into the reservoir modeling domain, only a subset of the true uncertainty domain is available to scenario building.

Flicking through a seismic processing report on a recent project, we noted over 20 separate stages in the workflow, most of which represent incremental improvements to the

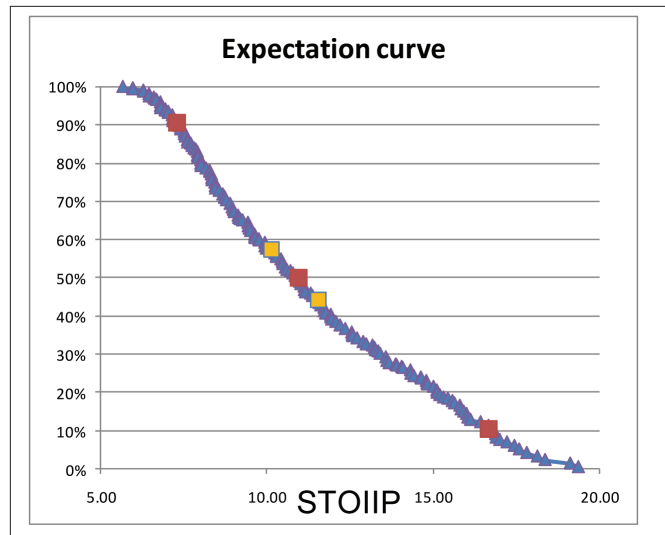


Figure 7. STOIP expectation curve for multiple deterministic scenario-based realizations. Red squares are realizations chosen to represent a P90, P50, P10 case. Orange squares were two original best guesses for time-depth conversion, with identical combinations of other parameters.

final data quality (imaging time, frequency content, and amplitude preservation). As nonprocessing specialists, we suggest that the choices made in just three of those steps—noise reduction (random, multiples), velocity analysis (quality, spacing), and migration (parameters)—make significant difference in the seismic output, and thus reservoir model input. The processing report concluded that the optimal choice of parameters has delivered a clear image; however, once seismic volumes have been delivered, report written and data archived, it becomes extremely difficult to test this conclusion, or to describe how the processed seismic may have looked if an alternative flow had been followed. The uncertainty that existed in the mind of the processor and which triggered parameter testing at key stages of the processing project is essentially lost to the interpreter and to other downstream recipients of seismic products.

One such recipient is the seismic inversion specialist who performs deterministic–simultaneous AVO, full band, 4D, relative AI (e.g., Tuttle et al., 2009)—or stochastic inversion (e.g., Leguit, 2009). In the deterministic inversion workflow, subjective choices are made regarding which wavelets to use, what matching parameters, what level of SNR is acceptable with an objective in mind to best match the seismic and well data. The stochastic approach incorporates uncertainties in these inputs in multiple realizations. However, whether deterministic or stochastic, both workflows start from the premise that the input seismic volumes are accurate, single representations of the subsurface. It is only when we are able to combine the key uncertainties from the processing domain with those from inversion that we can maintain our uncertainty bounds in the inverted impedance and other related attribute volumes. A full stochastic processing/inversion workflow is beyond the realms of current computer power and storage, and besides would soon become unmanageable.

We therefore call for the identification and communication of representative, alternative, multiple deterministic outcomes to capture those key elements from each specialty, including processing geophysics, that may fundamentally affect the business decision. **TLE**

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Corresponding author: peter.rowbotham@agr-ps.com