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Scenario-based reservoir modelling: the need for more determinism and less anchoring

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Abstract: The scenario-based reservoir modelling method places a strong emphasis on the deterministic control of the model design, contrasting with strongly probabilistic approaches in which effort is focused on the 'richness' of a geostatistical algorithm to derive multiple stochastic realizations. Scenario-based approaches also differ from traditional 'rationalist' modelling, which often involves the construction of only a single, best-guess or base-case model. The advantage of scenario modelling is that there is no requirement to anchor on a preferred, base-case model, and it is argued here that selection of a base case is detrimental to achieving appropriately wide uncertainty ranges. Multiple-deterministic scenario modelling also carries the advantage of maintaining explicit dependency between model parameters and the ultimate model outcome, such as a development plan. The approach has been applied widely to new fields, where multiple deterministic reservoir simulations of a suite of static models can be easily handled. The approach has also been extended to mature fields, in which practical approaches to multiple-history matching are required. Mature field scenario modelling, in particular, illustrates the weaknesses of base-case modelling, and delivers a strong statement on the non-uniqueness of modelling in general. Current issues are the need to develop better methodologies for multiple-history matching, and for linking discrete, deterministic, scenario-based outcomes to probabilistic reporting. Experimental design methods offer a solution to the latter issue, and a simple, practical workflow for its application is described.

Scenario-based modelling has become a popular means of managing subsurface uncertainty, although opinions differ on the nature of the 'scenarios', particularly with reference to the relative roles of determinism and probability. The idea of alternative, discrete subsurface scenarios (analogous to the concept of 'multiple working hypotheses') followed on logically from the emergence of integrated reservoir modelling tools (Cosentino 2001; Taylor 1996). These emphasized the use of 3D 'static' reservoir modelling, ideally fed from 3D seismic data and leading to 3D 'dynamic' reservoir simulation, generally on a full-field scale (Fig. 1).

When appreciating the numerous uncertainties involved in constructing such field models, the desire for multiple models naturally arises. Although not universal (see discussion in Dubrule & Damsleth 2001), the application of multiple modelling techniques is now widespread, with the alternative models described variously as 'runs', 'cases', 'realizations' or 'scenarios'.

The multiple terminologies are more than semantic. The notion of multiple modelling has been explored differently by different workers, the essential variable being the balance between deterministic and stochastic inputs. This is reflected in differing applications of geostatistical algorithms, and differing ideas on, and expectations of, the role of the probabilistic component of the modelling.

The contrasting approaches broadly fall into three groups (Fig. 2):

1. *Rationalist approaches*, in which a preferred model is chosen as a base case. The model is either run as a technical best guess, or with a range of uncertainty added to that guess. This may be either a +/− percentage in terms of the model output, often volumes in-place (Fig. 3a), or separate low case and high cases flanking the base case (Fig. 3b). This is the modelling approach which most closely maintains the pre-3D modelling approach to reservoir characterization – 'traditional' determinism.
2. *Multiple stochastic approaches*, in which a large number of realizations or outcomes are probabilistically generated by geostatistical simulation (Fig. 4). The deterministic input lies in the setting of the boundary conditions for the simulation based on a conceptual geological model.
3. *Multiple deterministic approaches*, which avoid making a single best-guess, or choosing a preferred base-case model (Fig. 5). A smaller number of models are built, each one reflecting a different, manually defined reservoir concept. Geostatistical simulations may be applied in the building of the 3D model but the *selection* of the model realizations

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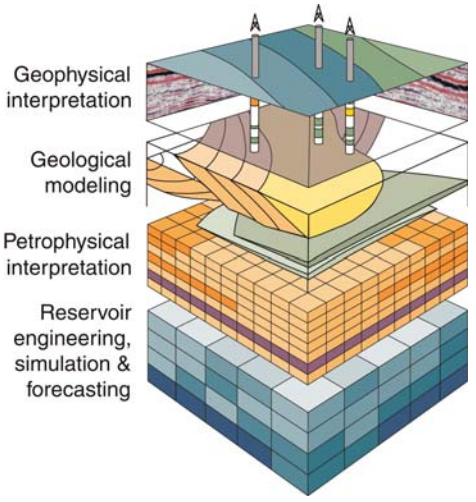

Fig. 1. The 3D reservoir modelling process for a single model realization. The key element which is captured is the point-to-point dependency between static and dynamic model elements.

is made manually rather than by statistical simulation (van de Leemput *et al.* 1995).

Any of the above have been referred to as 'scenario modelling' by different workers. It is proposed here that although all three approaches have application in subsurface modelling, multiple-deterministic scenario-building is the preferred route in most circumstances. In order to make this case, the underlying philosophy of uncertainty assessment will briefly be recalled and a definition of 'scenario modelling' will be offered. Based on a review of three applications of multiple-deterministic scenario modelling, strengths and weaknesses will be summarized, and a recommendation as to how to address two current weak points will be made.

Approaches to model-based uncertainty-handling

The limits of rationalism

The traditional rationalist approach described above is effectively simple forecasting – making a 'best guess' – and puts faith in the ability of an individual or team to make a reasonably precise judgement. If presented as the best judgement of a group of experts, then this appears reasonable. The weak point is that the best guess is only reliable when the system being described is well ordered and well understood, to the point of being highly predictable (Mintzberg 1990). It must be assumed that enough data is available from past activities to predict a future outcome with confidence, and this applies equally to production forecasting, exploration risking, volumetrics or well prognoses. In practice, this is rarely the case in the subsurface, except perhaps fields with large (>100) well stocks. There is, nevertheless, a strong tendency for individuals, particularly managers, to desire

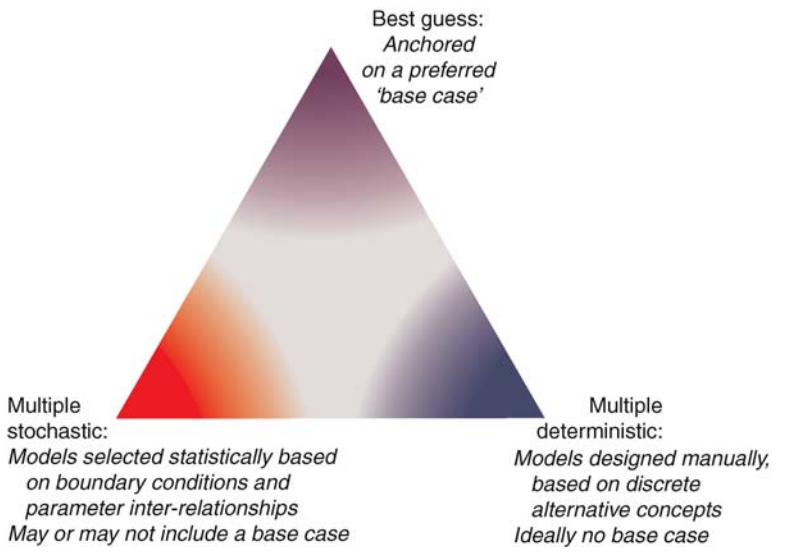

Fig. 2. Ternary diagram summarizing three end-member approaches to uncertainty-handling: multiple deterministic, multiple stochastic and the single 'best guess'. Many modelling studies blend these techniques; all can be mapped within this spectrum.

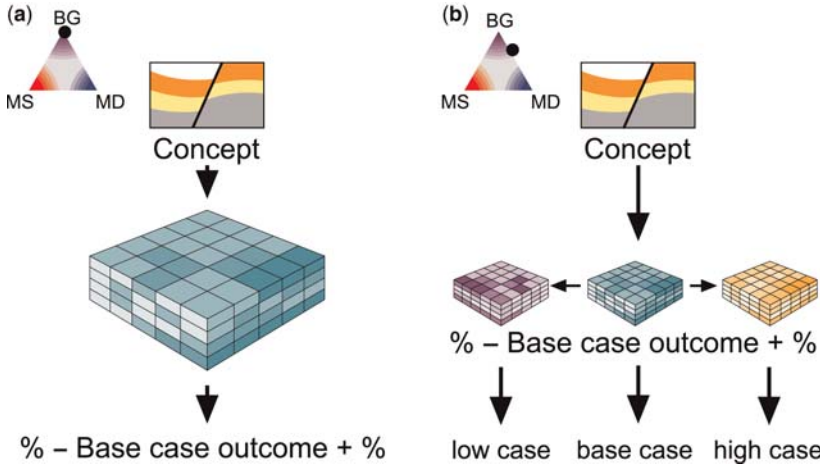

Fig. 3. Diagramatic representation of base-case, or strongly 'rationalist', approaches: **(a)** the extreme end-member case is the single best guess; **(b)** even with the addition of a +/− spread, the approach is still anchored on the initial best guess, and therefore lies to the base-case end of the spectrum of possible approaches.

a best guess, and to subsequently place too much confidence in that guess (Baddeley *et al.* 2004).

It is often stated that for mature fields, a simple, rationalist approach may suffice because uncertainty has reduced through the field lifecycle. It is suggested here that this is a fallacy. The *magnitude* of the initial development uncertainties tends to decrease with time but as the lifecycle progresses new, more subtle uncertainties arise. For example, the subtleties of a heterogeneous but broadly connected sand-rich reservoir may not be a major issue during the early lifecycle, but will be highly significant as the final infill wells are placed later in field life. The impact of uncertainties in terms of their

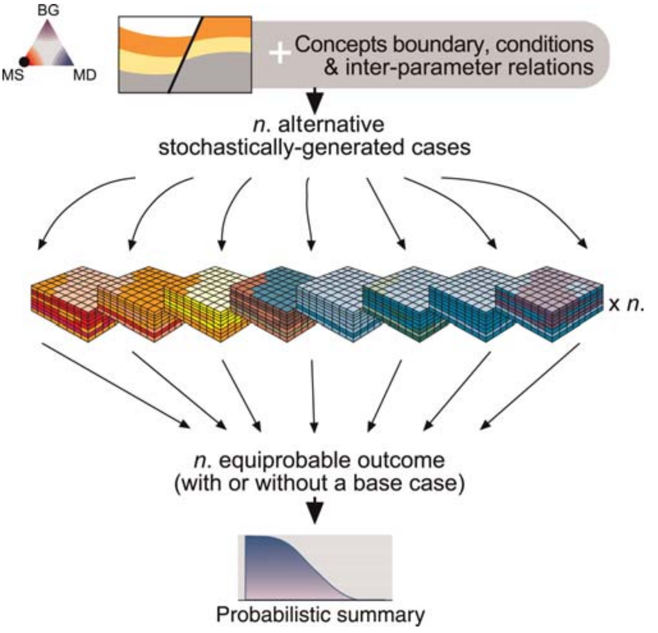

Fig. 4. Diagramatic representation of the multiple stochastic approach. The spread of outcomes is generated by statistcally sampled multiple realizations of an initial base case.

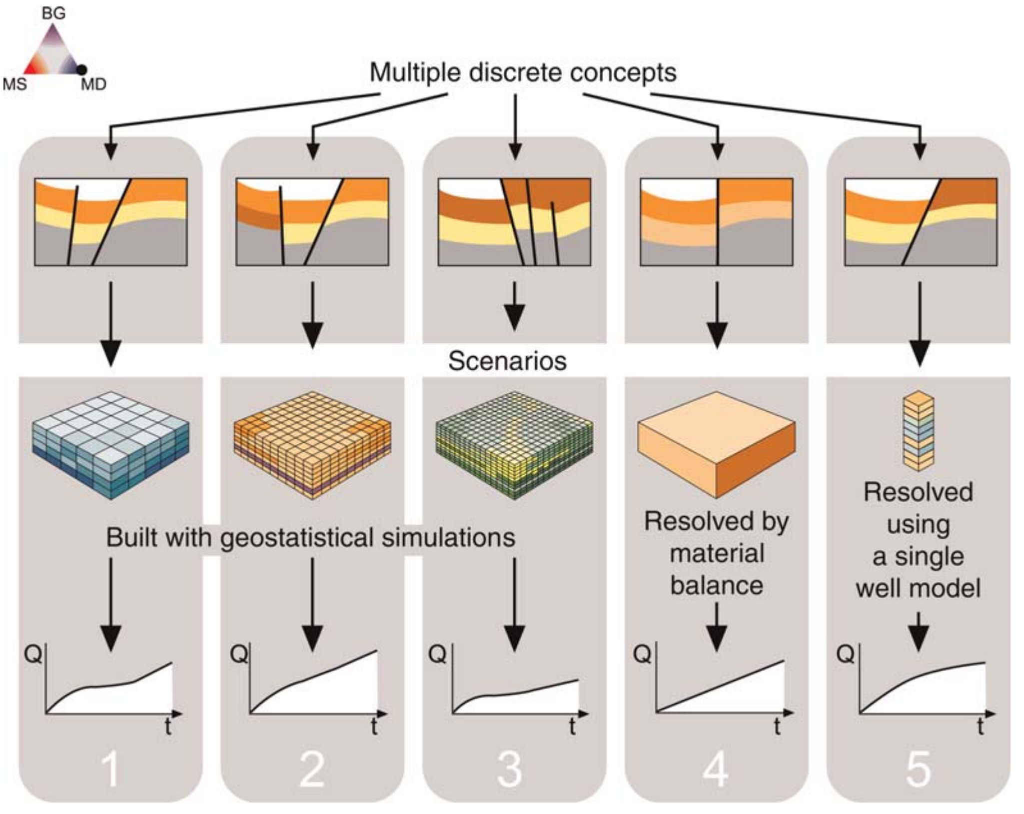

Fig. 5. Diagramatic representation of the multiple deterministic, 'scenario-based' approach. The spread of outcomes is generated by multiple, deterministically defined starting concepts, some of which may require differing modelling techniques to evaluate. There is no selection of an initial base case; the technique is not anchored.

ability to erode value may therefore be as great near the end of the field life as at the beginning.

Despite the above, rationalist, base-case modelling remains common across the industry. In a review of 90 modelling studies conducted by the authors and colleagues across many companies, field modelling was based on a single, best-guess model in 36% of the cases (Smith *et al*. 2005). This is despite a bias in the sampling from the authors' own studies, which tend to be scenario-based. Excluding the cases where the model design was influenced by the authors, the proportion of base case-only models rose to 60%.

Anchoring and the limits of geostatistics

The process of selecting a best guess in spite of wide uncertainty is referred to as anchoring, and is a well-understood cognitive behaviour (Baddeley *et al.* 2004). Once anchored, the tendency to fully explore the uncertainty range reduces as the outcomes become overly influenced by the anchor point. This often occurs in statistical approaches to uncertainty-handling, as these tend to be anchored in the available data and may therefore make the same rational starting assumption as the simple forecast, although adding ranges around a 'most probable' prediction.

Geostatistical simulation allows definition of ranges for variables, followed by rigorous sampling and (ideally) combination of parameters to yield a range of results, which can be interpreted probabilistically. If the input data can be specified accurately, and if the combination process maintains a realistic relationship between all variables, the outcome may be reasonable. In practice, however, input data are imperfectly defined and the 'reasonableness' of the automated combination of variables is hard to verify. Statistical rigour is applied to datasets which are not necessarily statistically significant and an apparently exhaustive analysis may have been conducted on insufficient data sources.

The validity of the outcome may also be weakened by centre-weighting of the input data to variable-by-variable best guesses. Although this can be avoided by careful definition of potentially irregular probability density functions to describe complex data distributions, this is not necessarily undertaken. Centre-weighting of the input data creates an inevitability that the 'most likely' probabilistic outcome will be close to the initial best guess – the geostatistical simulation itself is 'anchored'.

It is therefore argued that the application of geostatistical simulation does not in itself compensate for a natural tendency towards a rationalist best guess – it often tends to simply reflect it. The crucial step is to select a workflow which removes the opportunity for anchoring on a best guess; this requires deterministic intervention and is what scenario modelling, as defined here, attempts to address.

Scenarios defined

The definition of 'scenario' adopted here follows that described by van der Heijden (1996), who discussed the use of scenarios in the context of corporate strategic planning. Scenarios are: *'a set of reasonably plausible, but structurally different futures*'. Alternative scenarios are not incrementally different models based on slight changes in continuous input data (as with multiple probabilistic realizations), but models which are *structurally* distinct, based on some design criteria. Translated to oil and gas field development, a 'scenario' is a plausible development outcome, and the 'scenario approach' to modelling is defined as *the building of multiple, deterministically driven models of development outcomes*.

Each scenario is a complete and internally consistent static/dynamic subsurface model with an associated plan tailored to optimize its development. In an individual subsurface scenario, there is clear linkage between technical detail in a reservoir model, and an ultimate commercial outcome; a change in any element of the model detail prompts a quantitative change in the outcome and the dependency between *all* parameters in the chain between the changed element and the outcome is unbroken. This contrasts with many probabilistic simulations, in which model design parameters are statistically sampled and combined, and in which dependencies between variables may be lost, or collapsed into simple correlation coefficients.

The scenario approach therefore places a strong emphasis on deterministic representation of a subsurface concept: geological, geophysical, petrophysical and dynamic. Without a clearly defined concept of the subsurface – clear in the sense that a geoscientist could represent it as a simple sketch – the modelling cannot progress meaningfully. Geostatistical simulation may be intrinsic to the modelling workflow but the design of the scenarios is determined directly by the modeller. Multiple models are based on multiple, deterministic designs. This distinguishes the workflows for scenario modelling, as defined here, from multiple stochastic modelling which is based on statistical sampling from a single initial design. The two approaches are *not* mutually exclusive. A thorough workflow may involve the deterministic definition of multiple scenarios, followed by multiple probabilistic realizations (changing the seed number only) within a given scenario. This can be done to check for sensitivities in the model building, for example whether volumetrics are sensitive to the chance positioning of sand bodies above or below a hydrocarbon–water contact. In the experience of the authors, however, the spread of results from multiple stochastic sensitivities tends to be less than that between the deterministic scenarios – hence the argument here that the key to addressing a full uncertainty range lies in an awareness of the large-scale deterministic controls on the reservoir models.

Scenario-based approaches therefore place emphasis on a listing and ranking of uncertainties, from which a suite of scenarios will be deterministically designed, with no attempt being made to select a best guess case up-front.

Basis of design

The key to success in scenario modelling lies in deriving a 'correct' list of key uncertainties, a matter of experience and judgement. However, there is often a tendency to conceptualize key uncertainties for at least the static reservoir models in terms of the parameters of the STOIIP equation (Stock Tank Oil Initially In Place). For example, when asked to define the key uncertainties in the field, modellers will often quote parameters such as 'porosity' or 'net sand count' as key. If the model building progresses with these as the key variables to alter, this will most likely be represented as a range for a continuous variable, anchored around a best guess.

A better approach is to question why porosity is a significant uncertainty. It will either emerge that the uncertainty is not that significant or, if it is, then it relates to some underlying factor, such as heterogeneous diagenesis, or some local facies control which has not been extracted from the data analysis. For example, in Figure 6 a probability density function (PDF) of net-to-gross is shown. A simplistic approach would involve taking that PDF, inputting it to a geostatistical algorithm and allowing sampling of the range to account for the

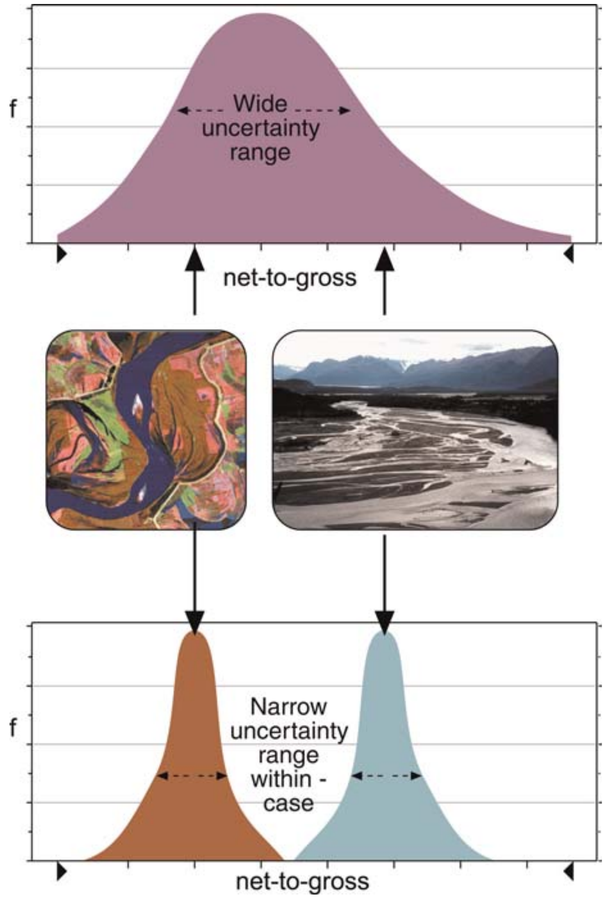

Fig. 6. Determining underlying causative uncertainties to populate the uncertainty list. In this case, net-to-gross is presented as an uncertainty (upper diagram). However, the underlying driving issue is the uncertainty over the depositional architecture, and alternative scenarios should be generated for this underlying factor. Within each scenario, the net-to-gross spread may be a second order issue rather than a principal uncertainty (lower diagram).

uncertainty. As the data in the figure illustrate, this would be misleading, because the range is reflecting mixed facies types. The need is to understand the facies distribution and isolate the facies-based factors – in this case the proportion of different channel types – and then establish whether this ratio is known within reasonable bounds. If not known, the uncertainty can be represented by building contrasting, but realistic, facies models (the basis for two alternative scenarios) in which these elements specifically contrast. The uncertainty in the net-to-gross parameter within each scenario is probably a second-order issue.

In defining key uncertainties, the need is therefore to chase the source of the uncertainty to the *underlying causative factor* and model the conceptual range of uncertainty of that factor with discrete cases, rather than simply input a data distribution for a higher-level parameter such as net-to-gross.

Application – greenfield

The application of scenario modelling has been most successfully reported in the case of new or ‘greenfield’ cases. Van der Leemput *et al*. (1995) described an application of scenario-based modelling in the context of an LNG field development plan (FDP). Once sufficient proven volumes were established to support the scheme, the commercial structure of the project focused attention of the issue of the associated capital expenditure. CAPEX therefore became the prime quantitative outcome of the modelling exercise, driven largely by well numbers and the requirement for and timing of gas compression.

The model scenarios were driven by a selection of principal uncertainties summarized in Figure 7. Five static and six dynamic uncertainties (three related to well productivity) were identified, based on the judgement of the project team and input from peers. Maintaining the uncertainty list became a continuing process, iterating with new well data from appraisal drilling, and the changing views of the group.

For the FDP itself, the uncertainty list generated 22 discrete scenarios, each of which was matched to the small amount of production data, then individually tailored to optimize the development outcome over the life of the LNG scheme. The outcomes, in term of impact on CAPEX, are shown in Figure 7.

A key learning from this exercise was that a list of 11 uncertainties was unnecessarily long to generate the ultimate outcome, although convenient for satisfying concerns of stakeholders. The effect of statistical dominance meant that the range was not driven by all 11 uncertainties, but by 2–3 key uncertainties to which the scheme was particularly sensitive (to well productivity in particular) (Fig. 7).

Contrary to common expectations, gross rock volume on the structures was not a key development issue, even though the fields were large and each had only 2–3 well penetrations at the time of the FDP submission. The key issue was the potential enhancements of well deliverability offered by massive hydraulic fracturing – not a factor typically at the heart of modelling studies. The majority of the issues normally addressed by modelling: sand body geometries, relative permeabilities, aquifer size etc., were certainly poorly understood, but could be shown to have no significant impact on the scheme. In hindsight, the dominant issues were foreseeable without modelling.

In the light of the above, continued post-FDP modelling became more focused, with a smaller number of scenarios fleshing out the dominant issues only. Tertiary issues were effectively treated as constants. The above was conducted without selecting a ‘base-case’ model. A development scheme was ultimately selected by the surface engineering team, but this was based on a range of outcomes defined by the subsurface team.

Scenario modelling for greenfields has been conducted many times since the publication of this example. In the experience of the authors, the

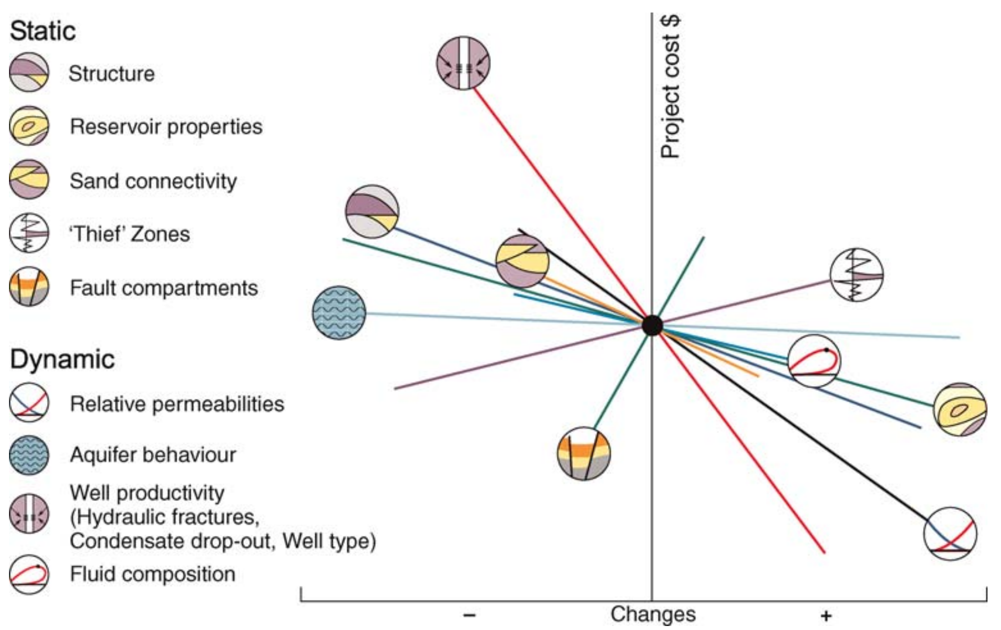

Fig. 7. Summary of the Barik greenfield case study. The uncertainty list (represented by the column of icons) generated a suite of multiple-deterministic scenarios, the impact on project cost (the issue of interest) is shown on the spider plot. In hindsight, the issue was overanalysed. The outcome was predictably insensitive to a number of uncertainties, and dominated by the well performance uncertainty. The study delivered an outcome range, with no base case selected up-front.

early learnings described above have held true, notably:

- large numbers of scenarios are not required to capture the range of uncertainty;
- the main uncertainties can generally be identified through cross-discipline discussion prior to modelling – if not, these can be established by running quick sensitivities;
- the dominant uncertainties on a development project do not always include the issue of gross rock volume, even at the pre-development phase; and
- it is not necessary to select a base-case model.

Application – brownfield

Two published examples are summarized here which illustrate the extension of scenario modelling to mature ('brown') fields.

The first concerns the case of the Sirikit Field in Thailand (Bentley & Woodhead 1998). The requirement was to review the field mid-life and evaluate the potential benefit of introducing water injection to the field. At that point, the field had been on production for 15 years, with 80 wells producing from a stacked interval of partially connected sands. The required outcome was a quantification of the economic benefit of water injection, to which a scenario-based approach was to be applied.

The uncertainty list is summarized in Figure 8. The static uncertainties were used to generate the suite of static reservoir models for input to simulation. In contrast to the greenfield cases, where production data are limited, the dynamic uncertainties were used as the history-matching tools – the permissible parameter ranges for those uncertainties being established *before* the matching began. A longer account of the study is given in Bentley & Woodhead (1998), notably the workflow for multiple–history matching and scaling of results.

A compiled production forecast for the 'no further drilling case' is shown in Figure 8. The difference between that spread of outcomes and the spread from a parallel set of outcomes which included water injection, were used to quantify

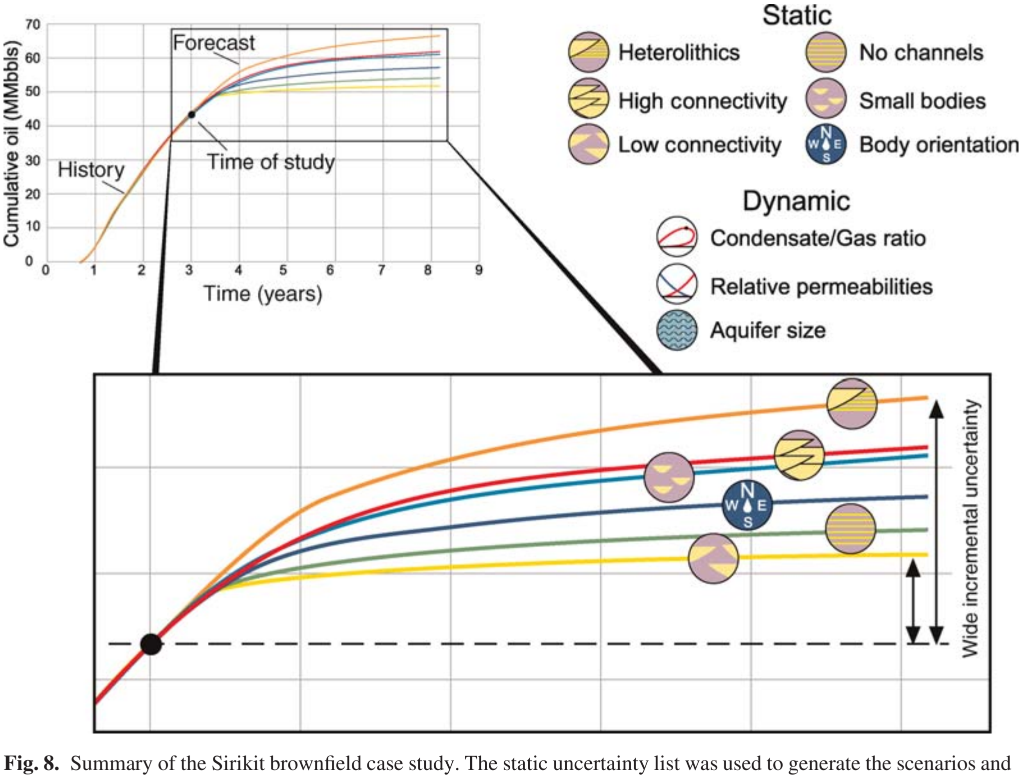

Fig. 8. Summary of the Sirikit brownfield case study. The static uncertainty list was used to generate the scenarios and the dynamic uncertainties used as variables in history matching. With all models matched, the incremental production forecasts varied by several factors. With all models plausible, there was no requirement to select a base case.

the value of the injection decision. Of interest here is the nature of that spread. Although all models gave reasonable matches to history, the incremental difference between the forecasts was larger than that expected by the team. It was hoped that some of the static uncertainties would simply be ruled out by the matching process. Ultimately, none were, despite 80 wells and 15 years of production history.

The outlier cases were reasonable model representations of the subsurface, none of the scenarios was strongly preferred over any other, and all were plausible. A base case was not chosen. The outcome makes a strong statement about the non-uniqueness of simulation model matches. If a base-case model had been rationalized based on preferred guesses, any of the seven scenarios could feasibly have been chosen – only by chance would the eventual median model have been selected. Sirikit also confirmed that multiple deterministic modelling was achievable in reasonable study times, and gave a surprisingly wide range of model forecasts.

A second example of scenario-based logic to mature fields, using a modified workflow, is a case from the Gannet B Field in the Central North Sea (Bentley & Hartung 2001; Kloosterman *et al.* 2003). The issue to model in Gannet B was the risk and timing of potential water breakthrough in one of the field's two gas producers, and placing value on alternative contingent activities post-breakthrough. As with the cases above, the study started with a listing and qualitative ranking of principal uncertainties in a cross-discipline forum. Unlike the previous cases, it proved not to be possible to match all static reservoir models with history. The lowest volume realization would not match. The model outcome – a range of water-cut breakthrough times, is illustrated in Figure 9.

The Gannet B study offered some additional insights into mature field scenario modelling:

- although the truism is offered that multiple models can match production data (there is no uniqueness to history matches), the converse is not necessarily true; – not everything can be matched;
- the above may be more likely to be true in smaller fields, where physical field limitations play a role earlier in a field history; and
- in the specific case of Gannet B, the principal matching tool was 4D seismic data, not production data; it was the matching of simulated acoustic impedance changes *versus* the observed seismic amplitude changes which was the matching target for the multiple model scenarios.

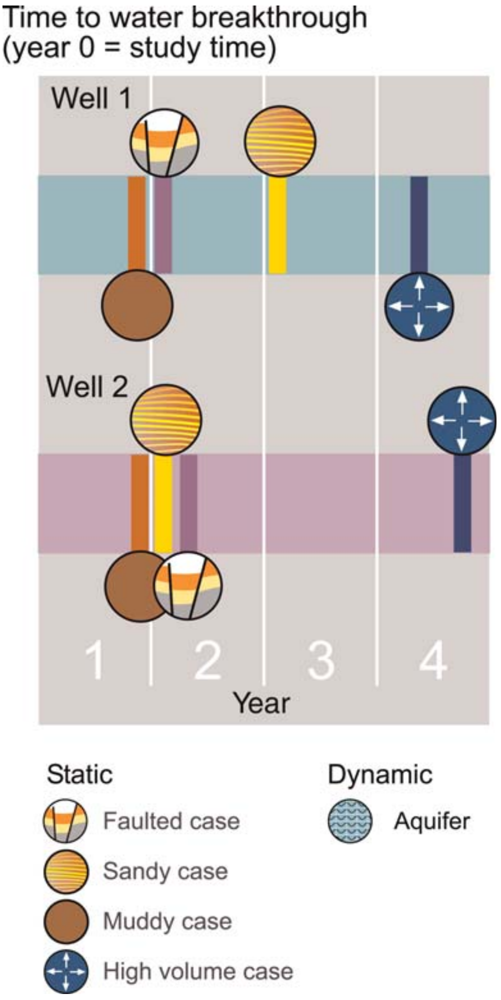

Fig. 9. Summary of the Gannet B brownfield case study. The static uncertainty list was used to generate the scenarios, which were history matched using the single principal dynamic uncertainty. With all models matched, the time to water breakthrough was forecast for the two wells in the field. The study outcome was the time range shown and there was no preferred base case; selection of a base case would have significantly distorted the result.

Scenario modelling – benefits

The scenario-based approach as defined here offers specific advantages over base-case modelling and multiple probabilistic modelling:

1. *Determinism*: the dominance of the underlying conceptual reservoir model, which is deterministically applied via the model design. Although the models use any required level of geostatistical

simulation to recreate the desired reservoir concept, the geostatistical simulation results are not used to select the cases to be run, nor to quantify the uncertainty range in the model outcome.

2. *Lack of anchoring*: the approach is not built on the selection of a base case or best guess. Qualitatively, the natural tendency to underestimate uncertainties is less prone to occur if a best guess is not required – the focus lies instead on an exploration of the uncertainty range.

3. *Dependence*: direct dependence between parameters is maintained through the model process; a contrast between two model realizations is fed through directly to two quantitative, generally commercial outcomes, which allow the significance of the uncertainty to be evaluated.

4. *Transparency*: although the models may be internally complex, the workflow is simple, and feeds directly off the uncertainty list, which may be no more complex than a short list of the key issues which drive the uncertainty range. If the key issues which could cause a project to fail are identified on that list, the modelling process will evaluate the outcome in the result range. The focus is therefore not on the intricacies of the model build (which can be reviewed by an expert, if required), but on the uncertainty list, which is transparent to all interested parties.

Scenario modelling – issues to resolve

Two potential weak points of the scenario approach need to be addressed:

1. It is generally assumed that more effort will be required to manage multiple models than a single model, particularly when brownfield sites require multiple history matching; and

2. As each scenario is qualitatively defined, the link to statistical descriptions of the model outcome (e.g. P90, P50, P10 definitions) is similarly qualitative. As some common model outputs, notably volumetrics, are reported in the form of cumulative probability distributions, the issue of mapping deterministic cases onto a probabilistic distribution arises.

Possible ways forward on these issues are discussed below.

Multiple model handling

Multiple model handling in greenfield sites is not necessarily a time-consuming process. Figure 10 illustrates results from a recent unpublished study involving 120 discrete development scenarios. These were manually constructed from permutations of six underlying static models and dynamic uncertainties in fluid distribution and composition. The static models were deemed feasible, and the permutations were defined based on combining uncertainties which could be deemed independent (e.g. sand architecture and fluid compositions). This was an exhaustive approach in which all combinations of key uncertainties were assessed. The final result could have been achieved with a smaller number of scenarios, but the full set was run simply because it was not particularly time-consuming (the whole study ran over roughly five person-weeks, including static and dynamic modelling). The case illustrates the efficacy of multiple

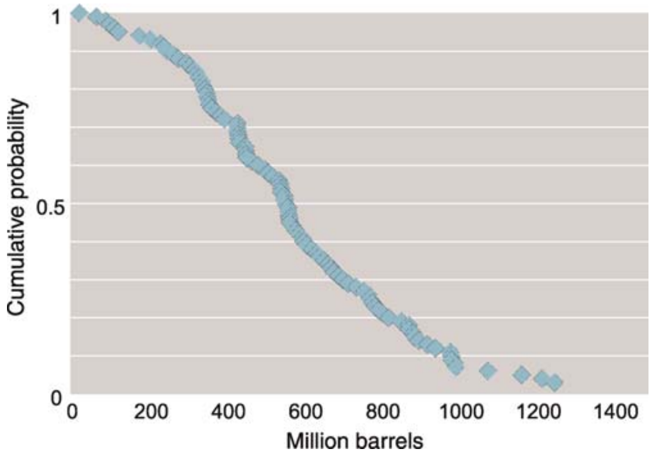

Fig. 10. An exhaustive route to the definition of a probabilistic S-curve; over 100 deterministically created static/dynamic simulations, considered equally plausible.

static/dynamic modelling in greeenfields, even when the compilation of runs is manual.

This issue is more pressing for brownfield sites, although the cases described above from Sirikit and Gannet illustrate that workflows for multiple model handling in mature fields can be made practical. This is being improved further by the emergence of a new breed of automatic history-matching tools which achieve model results according to input guidelines that can be deterministically controlled.

It is suggested that the running of multiple models is not a barrier to scenario modelling, even in fields with long production histories. Once the conceptual scenarios have been clearly defined, it often emerges that complex models are not required, and this comes with a significant time-saving. Cross-company reviews by the authors indicate that model-building exercises which are particularly lengthy are typically those where a very large, detailed, base-case model is under construction. History matching is often pursued to a level of precision disproportionate to the accuracy of the static reservoir model it is based on. By contrast, multiple modelling exercises tend to be more focused and, perhaps paradoxically, may be quicker to execute than the very large, very detailed base-case model-builds.

Linking deterministic models with probabilistic reporting: experimental design

A recent development has been the merging of deterministically defined scenario models with probabilistic reporting using a collection of approaches broadly described as 'experimental design'. This methodology offers a way of generating probabilistic distributions of hydrocarbons in place or reserves from a limited number of deterministic scenarios, and of relating individual scenarios to specific positions on a cumulative probability, or 'S' curve. In turn, this provides a rationale for selecting specific models (e.g. P90, P50 and P10) for screening development options.

Experimental design is a well-established technique in the physical and engineering sciences where it has been used for several decades (e.g. Box *et al.* 1978). It has recently become popular in reservoir modelling and simulation (e.g. Egeland *et al.* 1992; Yeten *et al.* 2005; Li & Friedman 2005). It offers a methodology for planning experiments so as to extract the maximum amount of information about a system using the minimum number of experimental runs. In the subsurface, this can be achieved by making a series of reservoir models which combine uncertainties in ways that are specified by a theoretical template or 'design'. The type of design depends on the purpose of the study and on the degree of interaction between the different variables.

One of the simplest approaches is the Plackett–Burman formulation (Plackett & Burman 1946). This design assumes there are no interactions between the uncertain variables and that a relatively small number of experiments are sufficient to approximate the behaviour of the system. More elaborate designs, for example D-optimal or Box-Behnken (Alession *et al*. 2005; Peng & Gupta 2005) attempt to analyse different orders of interaction between the uncertainties and require a significantly greater number of experiments.

A key aspect of experimental design is that the uncertainties are generally expressed as end-members. The emphasis on making a base case, best guess for any variable is reduced, and can be removed.

The combination of Plackett-Burman experimental design with the scenario-based approach is shown by the case below from a mature field redevelopment plan involving multiple-deterministic scenario-based reservoir modelling and simulation. The purpose of the modelling was to build a series of history-matched models that could be used as screening tools for a field development.

As with all scenario-based approaches, the workflow started with a listing of the uncertainties, thought in this case to be:

- *Top reservoir structure*: caused by poor quality seismic and ambiguous depth conversion. This was modelled using alternate structural cases capturing plausible end-members.
- *Thin-beds*: the contribution of intervals of thin-bedded heterolithics was uncertain as these intervals had not been produced or tested in isolation. This uncertainty was modelled by generating alternative net-to-gross logs.
- *Reservoir architecture*: uncertainty in the interpretation of the depositional model was expressed using three conceptual models: tidal estuarine, proximal tidal-influenced delta and distal tidal-influenced delta models (Fig. 11). Each model was built as a complete geocellular model realization involving both deterministic and probabilistic components (deterministic for structure, stratigraphy and facies associations; probabilistic infill for facies and facies-dependent reservoir properties).
- *Sand quality*: this is an uncertainty simply because of the limited number of wells and was handled by defining alternative cases for facies proportions, the range based on the best and worst sand quality seen in wells to date.

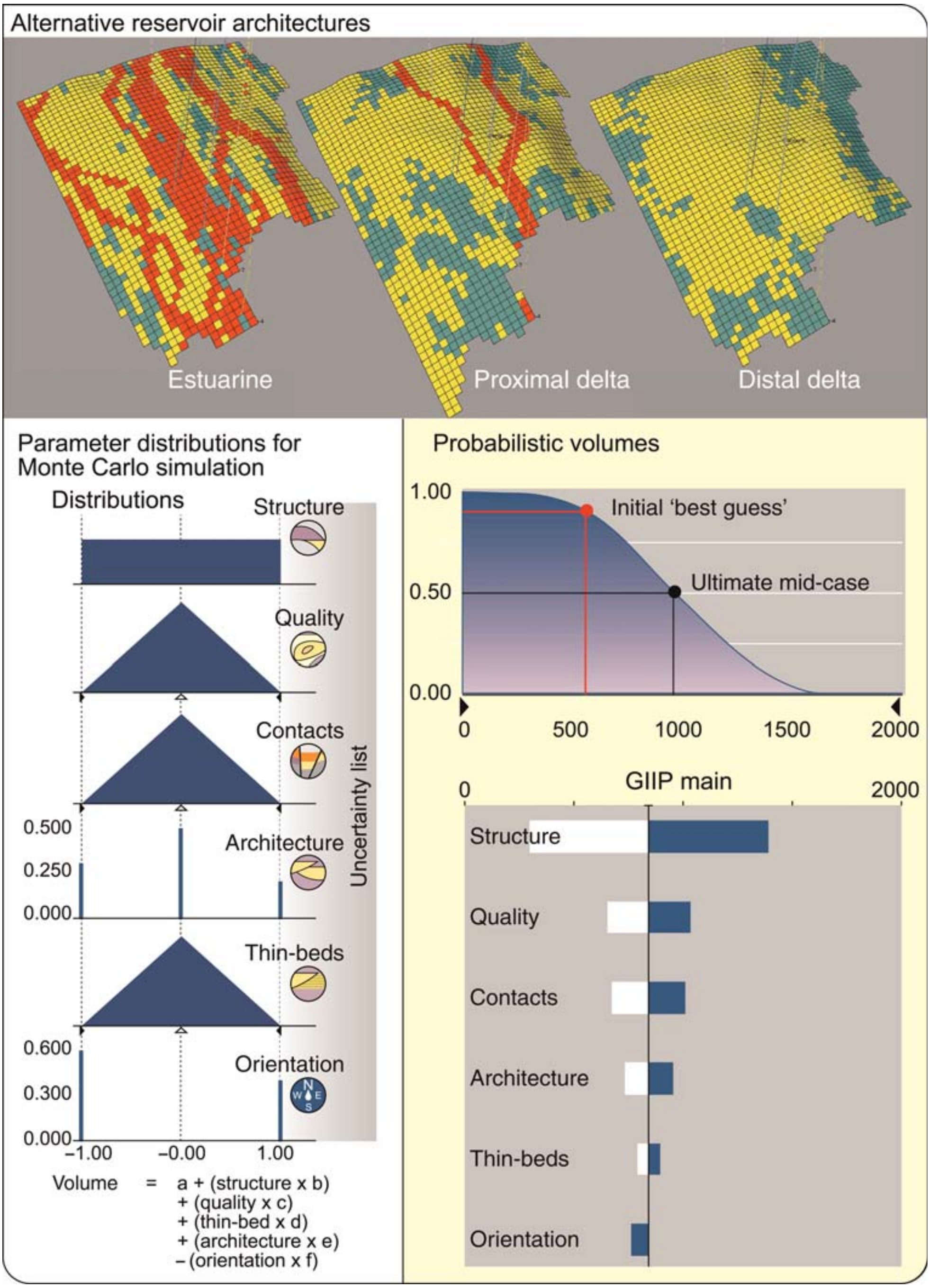

Fig. 11. Compound summary of the application of experimental design to link deterministic, scenario-based models with probabilistic output. **Top image**: discrete deterministic cases for reservoir architecture; **left**: weightings used for each uncertainty in the Monte Carlo sampling of the response variable function; **right centre**: output of the Monte Carlo run expressed as a probabilistic S-curve, showing the P50 compared with an initial 'best guess'; **bottom right**: tornado plot showing sensitivity of the outcome to the input variables (the principal uncertainties).

- *Reservoir orientation*: modelled using alternative orientations of the palaeodip.
- *Fluid contacts*: modelled using plausible end-members for fluid contacts.

These six uncertainties were combined using a 12-run Plackett-Burman design. The way in which the uncertainties were combined is shown in the Table 1 where the high-case scenario is represented by +1, the low-case scenario by −1 and a mid-case by 0. Two additional runs have been added, one using all the mid-points and one using all the lows. Neither is theoretically necessary but they serve as useful reference points in the analysis of the results.

The 14 reservoir models were built and the hydrocarbon volumes determined for each reservoir unit. In this case, the hydrocarbon volume is the output parameter of interest: the 'response data'. A linear least squares 'response function' for that data was derived, expressing the volumetric outcome as a function of the six identified uncertainties. The quality of the fit could be quantified using statistical measures or simply as a plot of modelled versus predicted volumes. Once the functional relationship between the model outcome (volumes in this case) and the underlying uncertainties had been established, a spread of volumes could be generated by Monte Carlo analysis to generate a probabilistic distribution. To generate the spread, the distribution shape for each uncertainty between the end-member possibilities (represented by the deterministic selection of the −1 and +1 realizations) was defined in the Monte Carlo simulator. If the nature of the given uncertainty was such that all cases between the end-members were possible and equally likely, then a uniform distribution was selected; if the uncertainty was a choice between discrete alternatives, such as between alternative facies association models, then a discontinuous distribution was chosen, and so on. The choices made for this case are shown in Figure 11. The Monte Carlo simulation was then run on the function, sampling these distributions, which are effectively acting as weights in the regression. As the weighting on the uncertainties changes from run to run, the volumetric outcome changes, and the result is a spread of outcomes which can be represented as a probabilistic, or S-curve, distribution. The analysis was conducted using standard commercially available software.

Three advantages of this workflow are highlighted. First, it makes a link between probabilistic reporting and discrete multiple-deterministic models. This can be used to provide a rationale for selecting models for simulation. For example, P90, P50 and P10 models can be identified from this analysis and it may emerge that models reasonably close to these probability thresholds were built as part of the initial experimental design. Alternatively, it may show that new models need to be built. This is easy to do now that the impact of the different uncertainties has been quantified, and is an improvement on an arbitrary assumption that a high-case model, for example, represents the P10 case. Secondly, the workflow focuses on the end-members and on capturing the range of input variables, avoiding the need to make an erroneous best guess. Finally, the approach provides a way of quantifying the impact of the different uncertainties via tornado diagrams or simple spider plots, which can in turn be used to steer further data-gathering in a field. Moreover, having

Table 1. *Plackett-Burman design for a suite of deterministic reservoir models involving six uncertainties. For this case, the response data values represent in-place gas volumes in Billion Standard Cubic Feet*

Run order	Structure	Quality	Contacts	Architecture	Thin beds	Orientation	Response
1	−1	1	1	1	−1	1	1178
2	−1	−1	1	1	1	−1	380
3	−1	−1	−1	−1	−1	−1	109
4	1	−1	1	1	−1	1	1105
5	−1	−1	−1	1	1	1	402
6	1	−1	1	−1	−1	−1	1078
7	1	1	−1	1	1	−1	1176
8	1	−1	−1	−1	1	1	1090
9	−1	1	−1	−1	−1	1	870
10	−1	1	1	−1	1	−1	932
11	1	1	−1	1	−1	−1	1201
12	1	1	1	−1	1	1	1245
13	0	0	0	0	0	0	956
14	1	1	1	1	1	1	1656

conducted an experimental design, it may emerge that the P50 outcome is significantly different from any initial best guess, as illustrated in Figure 11.

Conclusion

1. Scenario-based approaches are a better approach to base-case modelling, as results from the latter are anchored around best-guess assumptions. The latter are invariably misleading because knowledge of the subsurface is insufficiently predictive.

2. 'Scenarios' are defined here as 'multiple, deterministically driven models of development outcomes', and are preferred to multiple stochastic modelling exercises for uncertainty-handling, the application of which is limited by the same data-insufficiency issue which limits base-case modelling. Each 'scenario' is a plausible development future based on a specific concept of the subsurface, the development planning response to which can be optimized.

3. The application of geostatistical techniques, and conditional simulation algorithms in particular, is wholly supported as a means of building a realistic subsurface model – usually infilling a strongly deterministic model framework. Multiple probabilistic models also have a role in the QC of the model-building process, notably to check for sensitivity of the outcome to random selections made during a conditional simulation. However, geostatistical modelling techniques are not seen as the principal tool for uncertainty-handling. Deterministic techniques are preferred for reasons of transparency, relative simplicity, and because each scenario can be individually validated as a plausible subsurface outcome.

4. Scenario-based modelling is readily applicable to greenfield sites but, as the examples shown here confirm, it is also practical at mature brownfield sites, where multiple-history matching may be required at the simulation stage.

5. One current area of improvement which benefits from continuing attention in scenario-based workflows is the approach to multiple-history matching. This is aided by increased computing power but benefits more from rethinking modelling workflows.

6. A second area of current research is the marrying of deterministically selected scenarios with probabilistic reporting. The preferred option presented here is a simple, pragmatic application of experimental design formulation. The technique can be applied to a small number of deterministic scenarios, and makes no requirement to pre-select a base-case or 'best-guess' model. The approach therefore avoids the pitfall of model anchoring, the avoidance of which is believed to be the key to maintaining a wide, but plausible, range of uncertainty in the modelling workflow.

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