Application of the ‘Design of Experiments’ method to estimate hydrocarbon-in-place volumes

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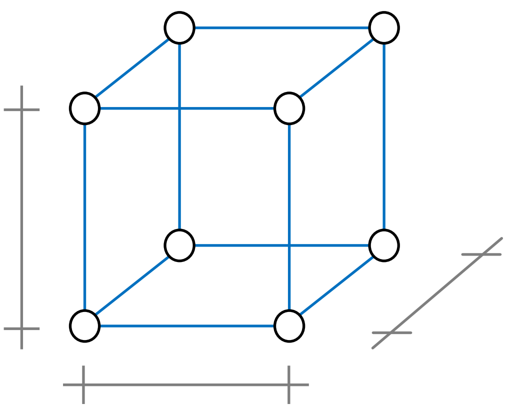
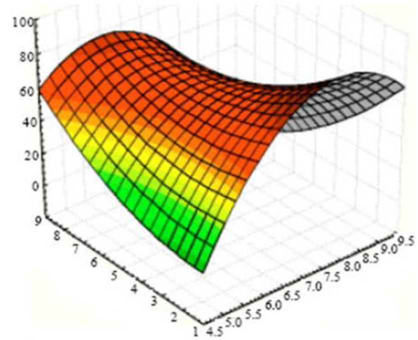
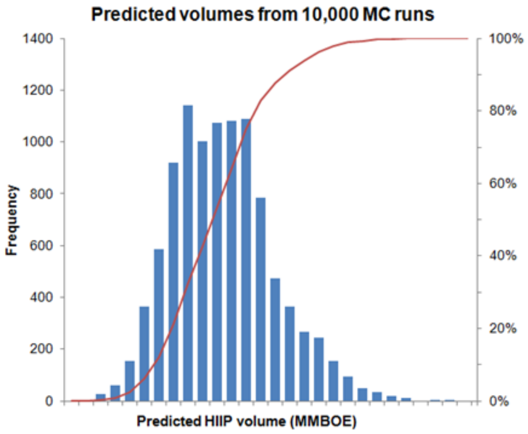
DEVEX, May 2014







Overview

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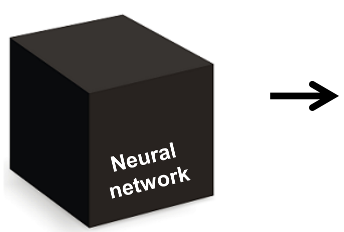
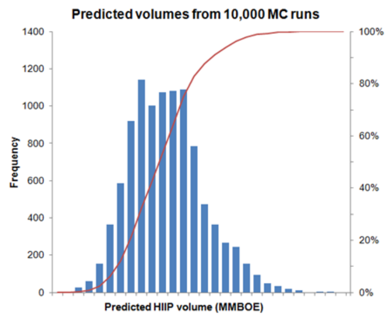
- Objective of case study was to obtain a range of Hydrocarbon Initially In Place (HIIP) volumes for a small reservoir, fully accounting for all identified uncertainties
  - i.e. using Design of Experiments to cover the uncertainty space with a reduced number of geomodels

Workflow:

1. Expert elicitation of uncertain factors, factor levels and their probabilities
2. A Design of Experiments method was used to generate an 'optimal' dataset, from which a proxy model could be built
3. The proxy model was then used in a Monte Carlo analysis to generate a distribution of possible HIIP volumes

Sequence number	Top surface	Presence of fault	Internal architecture	N/G cut-off	Porosity range	Sand proportion	OWC scenarios	FVF	Channel orientation	*response variable* HIIP volume
1	-1	-1	-1	-1	-1	1	1	1	1	
2	1	-1	-1	-1	-1	1	-1	-1	-1	
3	-1	1	-1	-1	-1	-1	1	-1	-1	
4	1	1	-1	-1	-1	-1	-1	1	1	

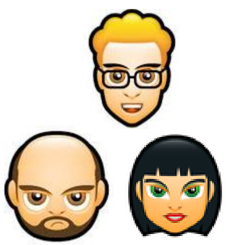




I – Relevant theory

Expert elicitation

- One of the biggest challenges is eliciting the input factors (uncertainties) properly
- If the input factors are elicited poorly, the analysis and results will be inherently flawed. Considerations include:



Group vs. individual

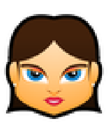
How questions are phrased

? ? ?

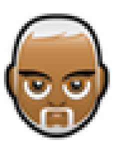
Personality of expert(s)

Available time

Not all experts are equal



Experience of moderator



Expert elicitation (2)

- Individual biases (e.g. anchoring, overconfidence, confirmation) and group biases (e.g. herding) affect us when making judgements
  - our intuition can mislead us[1,2]
  - cognitive biases can impact geoscience interpretation[3,4]

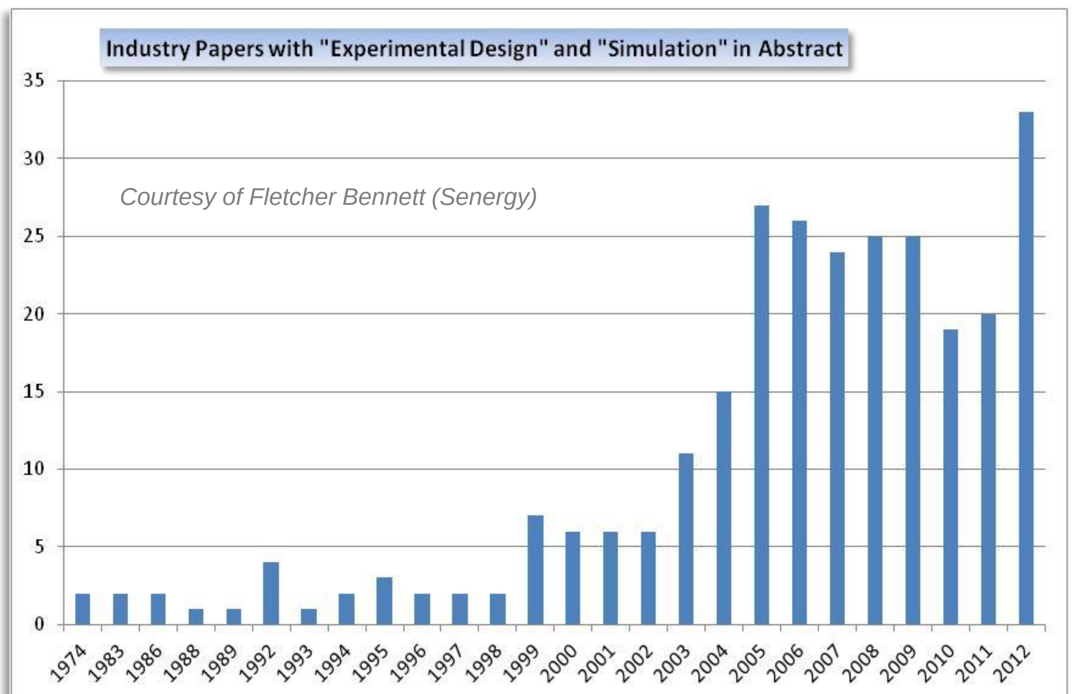
What we did in this study:

- Conducted individual elicitations (one expert per factor)
- Discussed the impact of biases on the experts
- Asked ‘open’ questions and tried to consider alternative explanations
- Talked about assumptions
- Discussed the problem in words and later translated it into probabilities
- Compared experts’ probabilities relatively

[1]Tversky and Kahneman (1974); [2]Capen (1976); [3]Baddeley et al. (2004); [4]Bentley and Smith (2008)

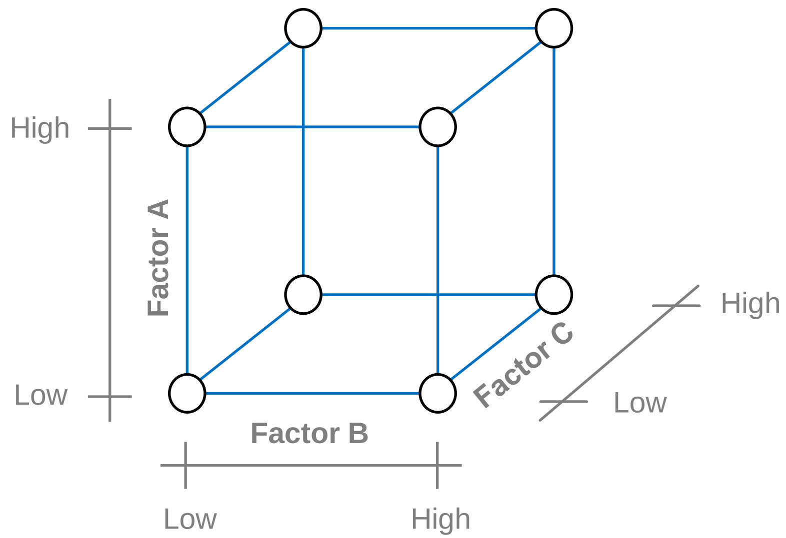
Design of Experiments (DoE) background

- First reference to a designed experiment is from 1747 (reducing the prevalence of maritime scurvy – James Lind, HMS Salisbury)
- Method first published in 1926 (agriculture) by statistician Sir Ronald Fisher
- Advanced during and after World War II
- Now used in many science and engineering disciplines and by the military
- Used less in oil and gas industry, but more common since 2005



Why DoE is beneficial...

- Cube below represents the experimental domain of 3 factors each with “low” and “high” settings



2^3 = 8 possible experiments, represented by the 8 dots

If we include mid case points as well, there are 3^3 = 27 possible experiments

4 factors = 81 experiments

5 factors = 243 experiments

6 factors = 729 experiments

...

- We want to capture maximum information at a minimum cost
  - *For example, which 4 experiments best cover the domain?*
- **Design matrices, by formulation, give maximal coverage using a selected subset of experiments**

Design matrices

- In experimental design, uncertain factors are varied simultaneously
  - this is more robust and efficient than traditional one-factor-at-a-time analyses
- Below is a 2-level (high and low case) fractional factorial design matrix (Box et al., 1978)
  - we can analyse 9 factors with only 32 experiments – 1/16th of full 2^9 matrix

										response variable
Sequence number	**Top surface**	**Presence of fault**	**Internal architecture**	**N/G cut-off**	**Porosity range**	**Sand proportion**	**OWC scenarios**	**FVF**	**Channel orientation**	**HIIP volume**
1	-1	-1	-1	-1	-1	1	1	1	1	
2	1	-1	-1	-1	-1	1	-1	-1	-1	
3	-1	1	-1	-1	-1	-1	1	-1	-1	
4	1	1	-1	-1	-1	-1	-1	1	1	
5	-1	-1	1	-1	-1	-1	-1	1	-1	
6	1	-1	1	-1	-1	-1	1	-1	1	
7	-1	1	1	-1	-1	1	-1	-1	1	
8	1	1	1	-1	-1	1	1	1	-1	
9	-1	-1	-1	1	-1	-1	-1	-1	1	
10	1	-1	-1	1	-1	-1	1	1	-1	
11	-1	1	-1	1	-1	1	-1	1	-1	
12	1	1	-1	1	-1	1	1	-1	1	
13	-1	-1	1	1	-1					

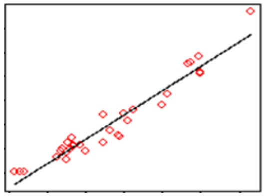
http://www.itl.nist.gov/div898/handbook/pri/section3/eqns/2to9m4.txt

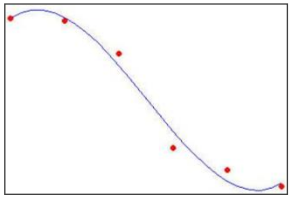
Proxy models

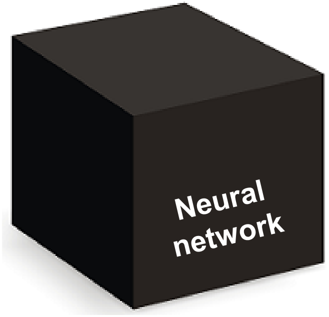
- A proxy model is an equation that mathematically represents the relationship between input variables (e.g. a geomodel) and a response variable (hydrocarbon volume)
- Monte Carlo (MC) simulations are run on the proxy model using the factor level probabilities that were originally elicited from the experts
- It is much faster to run the proxy model than the geomodel workflow
  - we can complete 10,000 MC runs on the proxy model very quickly
- However, proxy models vary in their ability to represent nonlinearity and variable dependencies
  - the more flexible the model, greater numbers of experiments are required

Examples:

- Linear
- Polynomial
- Nonlinear methods, e.g. artificial neural networks







Artificial neural networks (ANNs)

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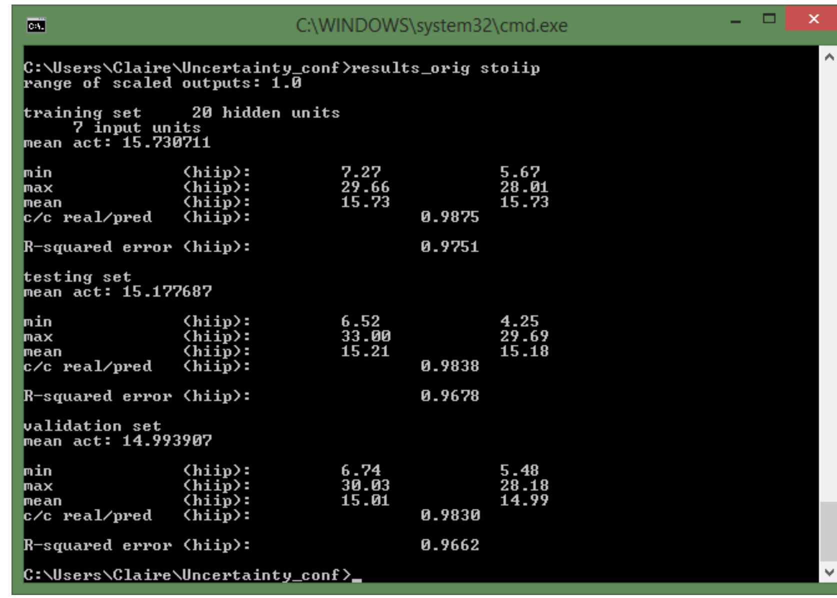
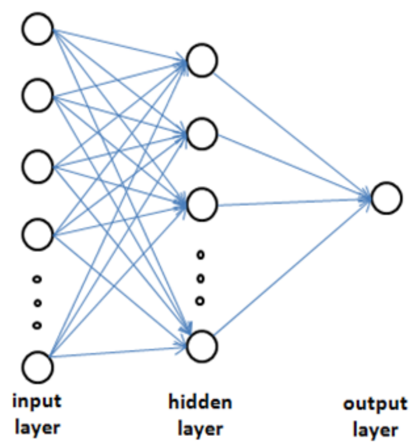
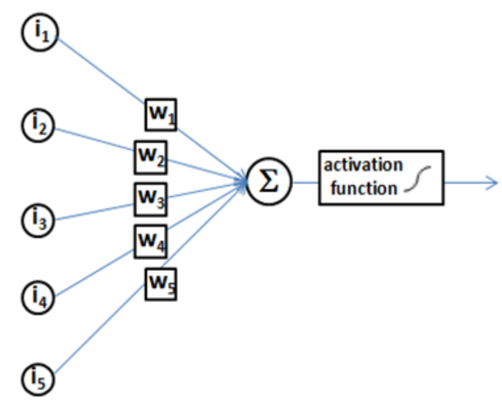
- An ANN was used as the proxy model in this study
  - ANNs capture nonlinearity and account for dependencies
  - we have in-house expertise
  - adaptive algorithm based on Fahlman and Lebiere (1989)
- It is a “black box” technique...
  - a type of machine-learning computer model that uses interconnected and weighted nodes to empirically solve numerical problems
- However, it may be hard to explain to stakeholders







II – The case study

Overview of method

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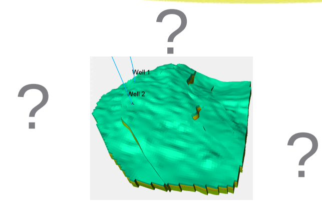
1. Specify problem – choose response variable and input factors

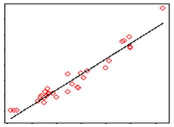


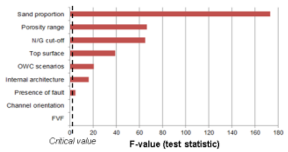
2. Elicit factor levels and their probabilities

3. Use a ‘screening’ design matrix

Sequence number	Top surface	Presence of fault	Internal architecture	N/G cut-off	Porosity range	Sand proportion	OWC scenarios	FVF	Channel orientation	*response variable* HIIP volume
1	-1	-1	-1	-1	-1	1	1	1	1	
2	1	-1	-1	-1	-1	1	-1	-1	-1	
3	-1	1	-1	-1	-1	-1	1	-1	-1	
4	1	1	-1	-1	-1	-1	-1	1	1	

4. Analyse screening results with a linear statistical model





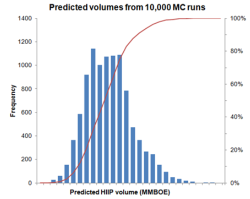
5. Use an ‘optimisation’ design matrix with 3 levels

Sequence number	Top surface	Presence of fault	Internal architecture	N/G cut-off	OWC scenarios	FVF	Channel orientation	*response variable* HIIP volume
1	-1	-1	-1	-1	1	1	1	
2	1	-1	-1	-1	-1	-1	-1	
3	-1	1	-1	-1	1	-1	-1	
4	1	1	-1	-1	-1	1	1	

6. Create proxy model from ~16% of total experiments

7. Validate proxy model using further 16% of experiments

8. Use Monte Carlo analysis to predict the range of HIIP



Introducing the dataset

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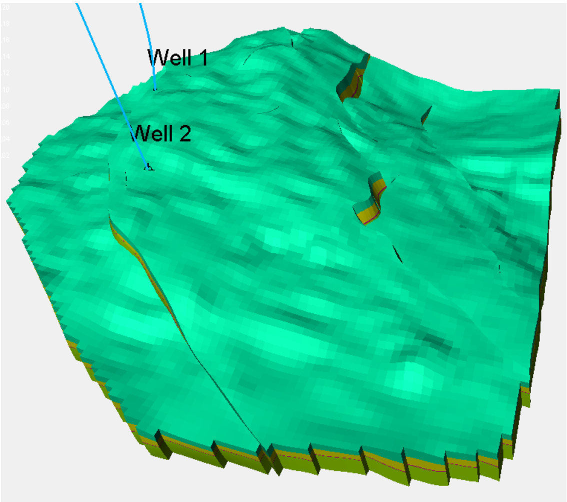
- A real dataset from a hydrocarbon field
- Field is sealed on one side by a fault and has two reservoir zones:
  - a channelised zone
  - a relatively homogeneous sandy zone
- There are two wells penetrating the crest of the field
  - little well control
- Seismic data are of poor quality
  - increased structural uncertainty
- RFT/MDT and fluid saturation data are ambiguous
- Objective was to estimate the range of potential HIIP volumes



Uncertain factors

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- 9 factors that could impact HIIP were identified via expert elicitation
- Each factor could be varied between low, mid and high values
- Total possible experiments was $3^9 = 19,683$

	-1	0	+1
Top surface	deep	medium	shallow
Separate fault segment?	sealing fault	some fault degradation	no fault
Internal architecture	more channelised zone	intermediate	more homogeneous zone
Channel orientation	SW-NE	W-E	NW-SE
NTG cut-off	higher permeability	medium	lower permeability
Porosity	low	well log average	high
Sand proportion	less sand	well log proportions	more sand
Fluid contacts	shallow	measured in one well	deeper in upper zone
Formation volume factor	high	latest measurement	low

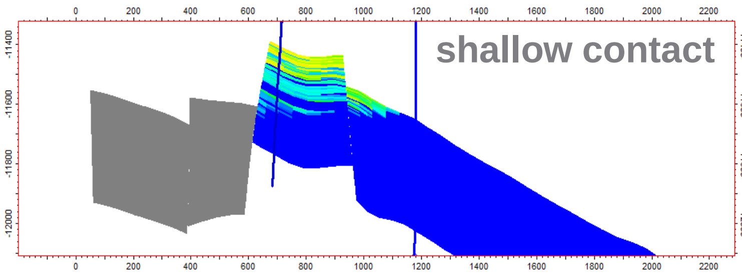
- A volumetric calculation workflow was built in Petrel™

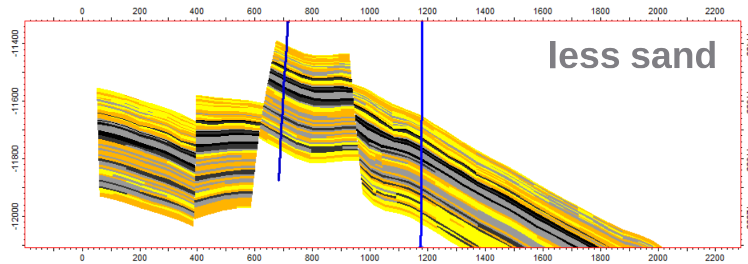
Example factors and their probabilities

fluid contacts | sand proportion

probability

0.2

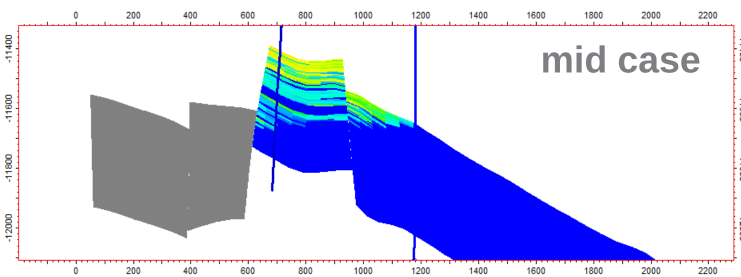


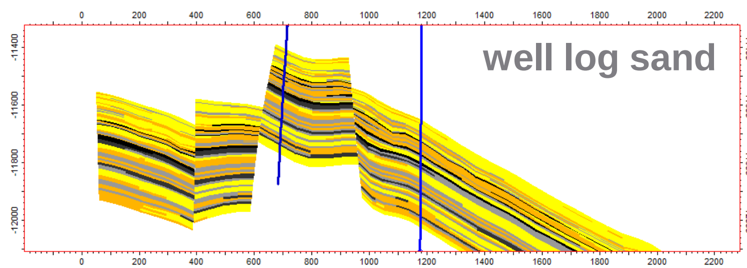


probability

0.15

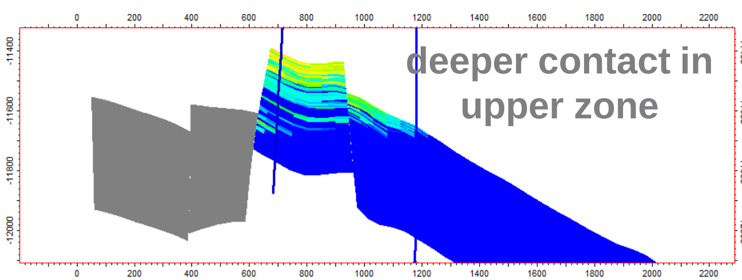
0.6

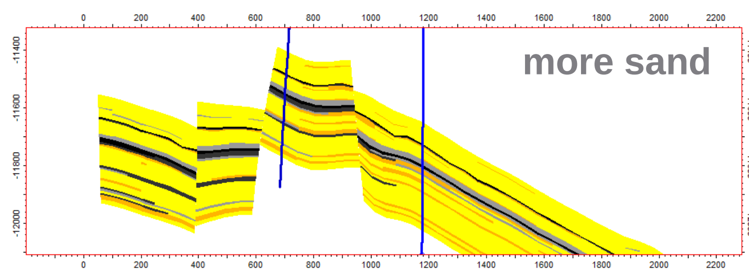




0.7

0.2





0.15

Factor screening

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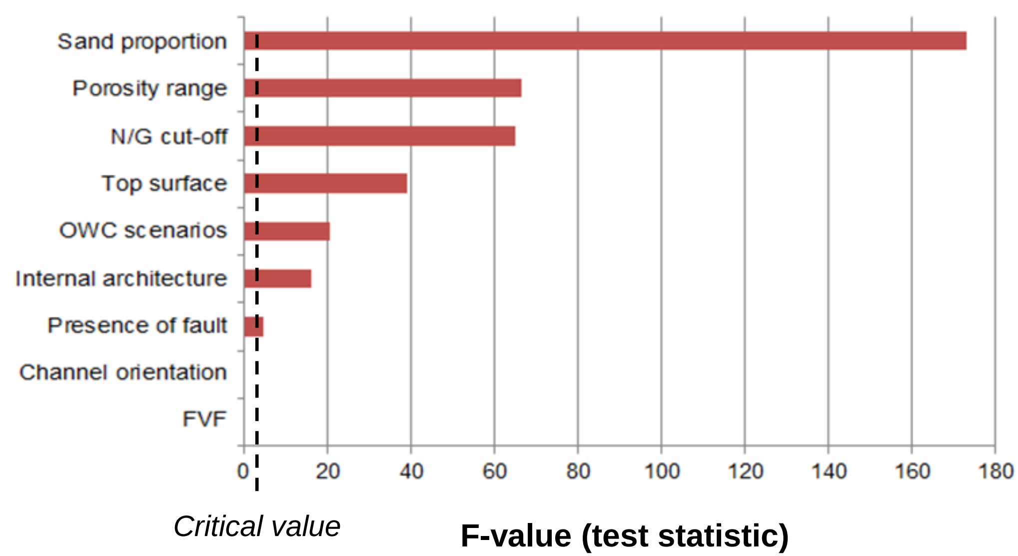
- Design matrix with 2 levels was used for screening
- Only 32 experiments required to analyse 9 factors
- A HIIP volume was calculated for each experiment

Sequence number	Top surface	Presence of fault	Internal architecture	N/G cut-off	Porosity range	Sand proportion	OWC scenarios	FVF	Channel orientation	*response variable* HIIP volume
1	-1	-1	-1	-1	-1	1	1	1	1	
2	1	-1	-1	-1	-1	1	-1	-1	-1	
3	-1	1	-1	-1	-1	-1	1	-1	-1	
4	1	1	-1	-1	-1	-1	-1	1	1	
5	-1	-1	1	-1	-1	-1	-1	1	-1	
6	1	-1	1	-1	-1	-1	1	-1	1	
7	-1	1	1	-1	-1	1	-1	-1	1	
8	1	1	1	-1	-1	1	1	1	-1	
9	-1	-1	-1	1	-1	-1	-1	-1	1	
10	1	-1	-1	1	-1	-1	1	1	-1	
11	-1	1	-1	1	-1	1	-1	1	-1	
12	1	1	-1	1	-1	1	1	-1	1	
13	-1	-1	1	1	-1	1	1	-1	-1	
14	1	-1	1	1	-1	1	-1	1	1	

- Linear model was fitted to the results to analyse the 9 factors

Results

- 'Channel orientation' and 'FVF' were removed from the analysis
- 'Sand proportion' seems to be the most significant factor



Optimisation stage

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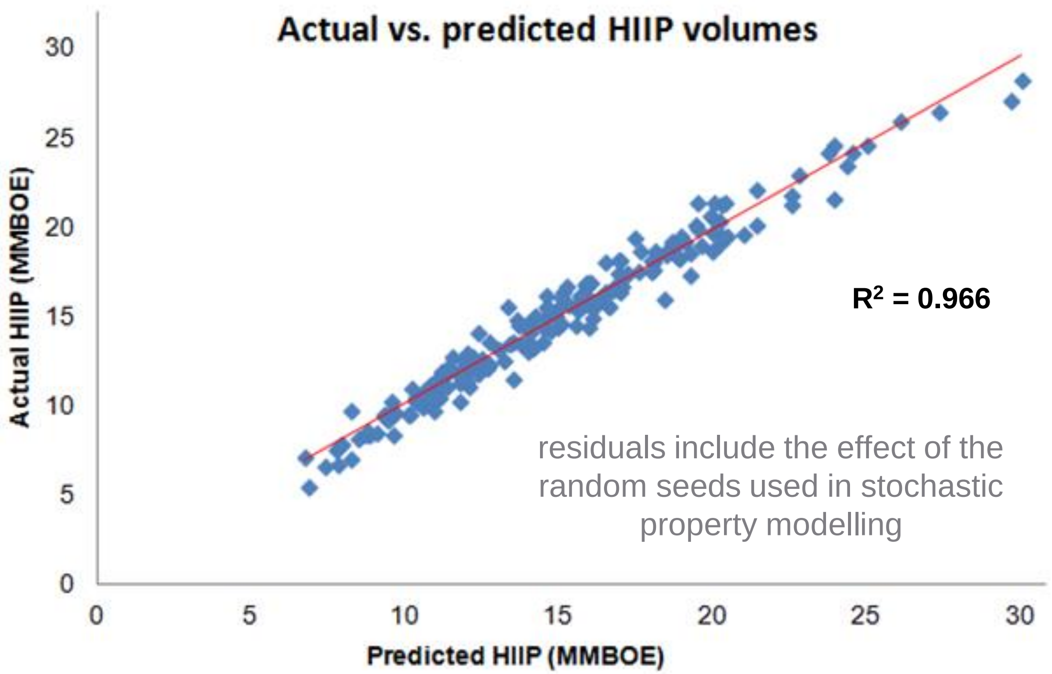
- A 3-level 'optimisation' design matrix was created for the 7 factors that passed the screening stage
- Since the field was small, it was possible to conduct $3^6 = 729$ experiments overnight using the volumetrics workflow

Proxy modelling

- 50% of the dataset used to train ANN
- The other 50% used to validate model
- Results were excellent
- Method worked almost exactly as well with 25% of the data used for ANN training

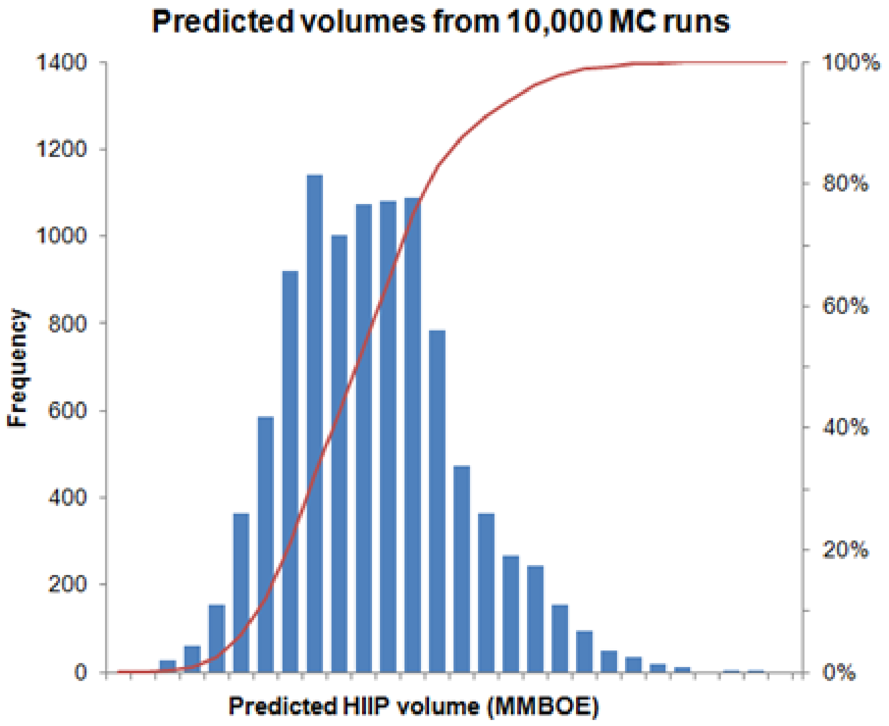


Monte Carlo analysis

- 10,000 Monte Carlo (MC) simulations of the ANN proxy model were run to generate a distribution of HIIP volumes (using the prior probabilities elicited from the experts)

Results

- The range was wider than that reported in a previous study



Potential implications

- Reduction in decision risk
- Specific models can be selected to pass to RE for dynamic simulations

III – Conclusions

Conclusions

- The method presented allowed a comprehensive treatment of uncertainty, accounting for discrete as well as continuous variables
  - including: structural uncertainties, errors associated with well log measurements, and natural variation between the wells
  - uncertainty space was adequately covered with the use of 729 experiments from a total of 19,683
    - good results were achieved with fewer experiments

- Further work could be focused on
  - screening factors more robustly (i.e. accounting for nonlinearity) while still using a limited number of experiments
  - determining the relative impacts of the input factors in a nonlinear and probabilistic analysis
  - selection of models for dynamic simulations

Any questions?

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