

Aims

The ability to generate geologically realistic reservoir models that honour the available well and seismic data is an important step in predicting reservoir behaviour. A new class of “compression” object models have successfully modelled net:gross and amalgamation ratios seen in natural turbidite systems (Zhang, 2015), however like conventional object-based modelling they struggle to honour the well data. The main aim of the present work is to devise a workflow combining the compression method with multiple-point statistical methods for creating geologically realistic models, conditioned to well data, with high net:gross and low amalgamation ratios typical of natural turbidite reservoirs.

1. Introduction

Many deep marine turbidite reservoirs consist of sandstones interbedded with low permeability shales and in most instances the flow behaviour of such reservoirs is strongly dependant on the connectivity of the sandstone bodies. Outcrop data suggests that natural systems have an amalgamation ratio (AR) that is usually significantly lower than their net:gross ratio (NTG; Manzocchi et al. 2007; Figure 1.1a). The amalgamation ratio of a sequence is defined as the fraction of sandstone bed bases eroded into an underlying sandstone bed when measured on a vertical line sample (Chapin et al. 1994). AR at the bed scale has been demonstrated to be a key control on reservoir connectivity and flow behaviour (Manzocchi et al. 2007).

A new class of object-based model, which uses a so-called “compression” method in order to reproduce poorly amalgamated but high net:gross ratio sequence typical of many lobe reservoirs, was developed by Manzocchi et al. (2007). The compression method allows the NTG and AR to be separate inputs into the modelling workflow. In conventional object-based models, the object-placement algorithm results in realisations in which AR = NTG; it is clear (Figure 1.1) that the individual sand beds in these models are too connected. A major limitation of the method, however, is that the models cannot honour particular observations made at wells.

The recently-developed multiple-point statistics (MPS) approach (Strebelle 2002) is pixel-based so models can be easily conditioned, and uses a training image to recreate the desired geological architecture. We have developed a new workflow that combines the compression algorithm with the MPS method in order to create geologically realistic models that have realistic levels of sand amalgamation yet honour the available well data. Section 2 centres around how the training image is constructed. In section 3, model realisations constructed in various ways are compared to a target scenario to test quantitatively the methods in terms of static connectivity and dynamic flow behaviour. MPS modelling was performed in Petrel 2015.6, and flow simulation modelling in Eclipse 100.

2. Conditioning compression-based models to wells

A number of modelling experiments have been applied in order to identify a successful workflow, these are outlined below and in Figures 2.2-2.4. In each experiment, uniform circular sand bodies (diameter 2.5km, thickness 1m) were modelled within a 5km x 5km x 20m model volume and conditioned to a single well at the centre of the model. The conceptual geological model we are trying to reproduce in these experiments is a system with NTG of 0.7 and AR of 0.1 (Figure 2.1a). The accuracy of the various results are tested visually by a qualitative comparison of the resultant geomodels, and quantitatively, by comparing the statistical distributions of the connected sandstone volumes within the models (Figure 2.1b). The conditioning well was extracted from an unconditioned compression-method model with the target AR and NTG values (Figure 2.1c). The examples of each method (Figures 2.2-2.4) honour exactly the sequence at this location.

Experiment 1: Using a training image with the target net:gross ratio

The training image (TI) (Figure 2.2a) was generated with the standard object-based modelling method, which places objects within the model volume until the target NTG is reached. The AR value of the training image is therefore unconstrained and will tend to approximate to the NTG value (Manzocchi et al. 2007). Hence the sands in the training image are more connected than they are in the low AR conceptual model we are considering. The MPS realisation (Figure 2.2b) honours the low AR conditioning well (Figure 2.2c), but because the training image is not representative of the conceptual geological model, the 3D connectivity of the MPS model is too high overall (Figure 2.2d).

Experiment 2: Using a training image with the target amalgamation and net:gross ratios

The training image input for this experiment was an unconditioned compression based model where the target NTG and AR values were predefined inputs (Figure 2.3a). The resulting MPS models failed to reproduce the static connectivity modelled in the original compression-based object models (Figure 2.3b). The circular sand bodies depicted in the training image were not replicated in the MPS models, and the connected volumes in the realisation are larger than in the conceptual model or the training image (Figure 2.3c & d). The compression-based models have an irregular grid cells thickness (Figure 1.1b, 2.3a), and this appears to affect how the MPS algorithm reads the patterns. Therefore, though conceptually this should be the simplest method for generating a low amalgamation ratio models conditioned to a well, use of an unconditioned compression based model as a training image has proven to be an unsuitable solution.

Experiment 3: Using a ‘decompressed’ well and training image with the target connectivity

Because of the difficulty of reproducing low connectivity at high NTG even when this is a characteristic of the training image, we decided to use a “decompressed” training image and a “decompressed” conditioning well, and then apply the compression algorithm to resultant MPS realisation. The “decompressed” training image object model (Figure 2.4a) uses the same initial object characterisation as previously, however both the net:gross and the object thickness are reduced in such a way that the later expansion of the sand bodies and compression of the shale layers to reach the desired NTG will result in the target object thickness. The MPS model is then generated based on the decompressed training image conditioned to the decompressed wells. The compression algorithm is then applied to the MPS model to achieve the desired net:gross ratio (Figure 2.4b). Initial results (Figure 2.4c & d) indicate that this workflow produces models with similar connected volumes as the target conceptual models, but that can be easily conditioned to well data.

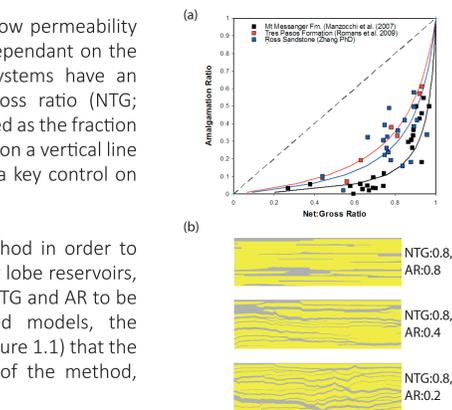


Figure 1.1(a) Net:gross v Amalgamation ratio for three different natural turbidite systems. The coloured curves represent a representative relationship between AR and NTG for each system, while the dashed line (NTG=AR) indicates the relationship present in an unconstrained object-based model (after Manzocchi et al. 2007). (b) Three cross sections of models with identical NTG but different AR. It is clear how AR is related to reservoir connectivity, and that the sands in the unconstrained model (AR = 0.8) have an unnaturally high connectivity (sand yellow, shale grey).

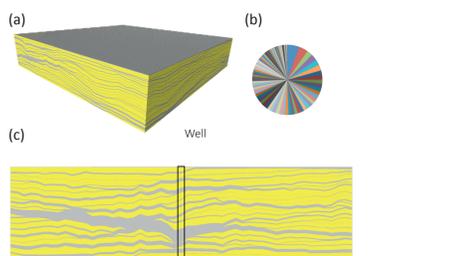


Figure 2.1(a) Unconditioned compression-based object model target NTG = 0.7, AR = 0.1 (sand yellow, shale grey). (b) Pie chart of the connected sand volumes. The largest connected volume occupies 5.5% of the total sand volume. (c) The conditioning well was extracted from an unconditioned compression model.

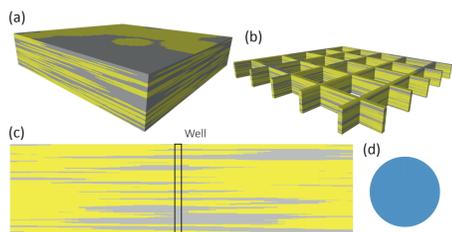


Figure 2.2. Experiment 1. (a) The training image is an object based model with NTG = 0.7. (b, c) The resulting MPS model, with the conditioning well highlighted on the cross-section. (d) The connected volume distribution. The largest cluster occupies 99.9% of the total volume.

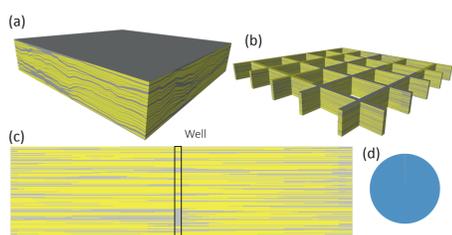


Figure 2.3. Experiment 2. (a) The training image is an unconditioned compression based object model, with NTG = 0.7 and AR = 0.1. (b, c) The resulting MPS model, with the conditioning well highlighted. (d) The connected volume distribution. The largest cluster occupies 99.9% of the total volume.

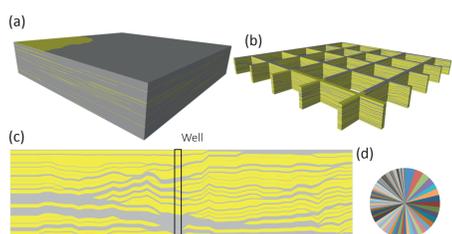


Figure 2.4. Experiment 3. (a) The training image is a ‘decompressed’ object model with NTG = 0.1 and AR = 0.1. (b, c) The resulting MPS model, with the conditioning well highlighted. (d) The connected volume distribution. The largest cluster occupies 5% of the total volume.

3. Results

For each of the experiments, 30 realisations were created in order to quantitatively compare the static connectivity and the dynamic flow properties of the target compression-based object models to the MPS models built using different training images. Each of the 30 realisations created for the three groups of MPS models were conditioned to a well extracted from the centre of a compression-based target model, i.e. there is a pairing between the target models and the output MPS models.

The following cross plots (Figure 3.1, 3.2 & 3.3) compare net:gross (NTG), largest volume of connected sand, and the dynamic flow properties in the form of the recovery factor (RF) and water break through time in years. In each instance the plots show the four model sets and their 30 realisations. The scatter of dots for each model set is indicative of the natural variability of the 30 different realisations. Results indicate the MPS models built in Experiment 3 show similar behaviour to the target compression-based object models. Experiment 1 and 2, by contrast yielded, MPS models with higher sand connectivity (Figure 3.2), resulting in greater recovery factors and early water break through (Figure 3.3).

The Kolmogorov-Smirnov test was used to compare each group of MPS models to the compression-based models (Figure 3.4). The K-S test was used to determine how statistically different the MPS models are to the target compression-based models. The results show that the static connectivity and dynamic flow performance of the MPS models created in Experiment 1 and 2 compared to the target models are statistically significant. The MPS models built using the new decompression workflow (Experiment 3) show statistical similarities to the target models in terms of static connectivity and water breakthrough time, however net:gross and recovery factor show statistically different distributions. The variation in net:gross may be a result of the difference in the tradition object-based method used as the training image input in Experiment 3 and the compression-method. The difference in recovery factor appears to be a result of difference in the drainable volume of each model realisation in the group of target compression-based models and those built using the decompression workflow.

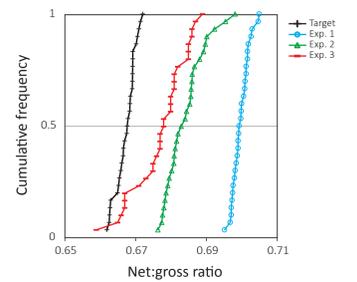


Figure 3.1 Comparison of net:gross ratio results for the four groups of models. Median NTG ratio for the target compression-based models, Exp. 1, Exp. 2, and Exp. 3 groups of MPS models is 0.668, 0.7, 0.683 and 0.678 respectively.

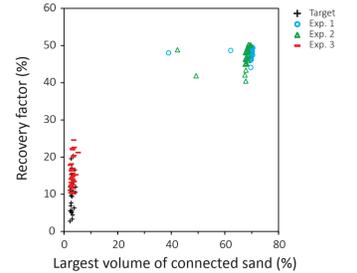


Figure 3.2. Largest volume of connected sand (%) against recovery factor (%) for the four model groups. In general there is higher recovery when the sand is more connected. The MPS models from Exp. 1 and 2 (green and blue) show the highest recovery between 40-50%, and greater volumes of connected sand (40-70%). The compression models (black) show much lower rates of recovery (5-20%) with largest connected volume of sand between 2-5%. The MPS models from Exp. 3 in red compare well with the target compression-based models in terms of largest connected volume of sand. Recovery factors are slightly higher, between 10-25%.

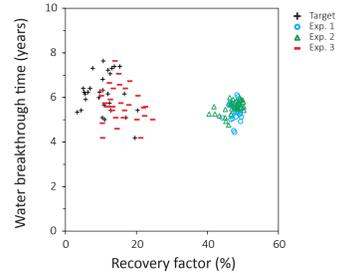


Figure 3.3. Recovery factor (%) plotted against water break through time (years). The MPS models from Exp. 1 and 2 (green and blue) show the highest recovery between 40-50% and in general an earlier water break through time (4-6 yrs). The compression models (black) show much lower rates of recovery (5-20%) the MPS models from Exp. 3 in red compare well with the target compression-based models, with recovery factors between 10-25% and water break through times 4-8 yrs.

	Exp. 1	Exp. 2	Exp. 3
net:gross	X	X	X
largest volume of connected sand (%)	X	X	✓
recovery factor (%)	X	X	X
water breakthrough time (years)	X	X	✓

Figure 3.4 Comparison matrix for net:gross, largest volume of connected sand, recovery factor and water breakthrough time in years for each of the MPS groups compared to the target compression-based object models using the K-S test.

4. Initial findings and conclusions

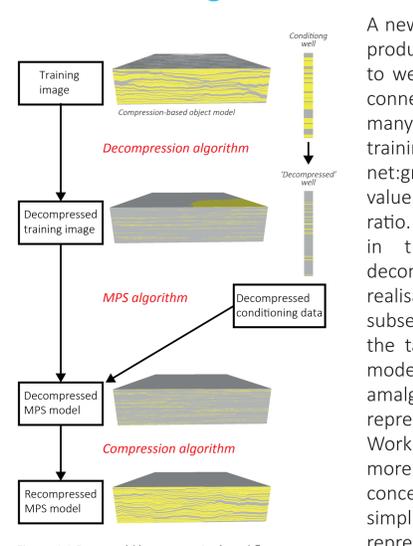


Figure 4.1 Proposed ‘decompression’ workflow.

A new workflow (Figure 4.1) has been established to produce multiple-point statistics models conditioned to well data able to honour also the poor reservoir connectivity at high net:gross ratio characteristic of many reservoirs. This workflow uses a ‘decompressed’ training image and ‘decompressed’ wells, in which the net:gross ratio is much lower than the ultimate target value and instead is equal to the target amalgamation ratio. This decompressed training image is then used in the MPS simulation and conditioned to decompressed wells in order to create an MPS realisation. The compression algorithm is subsequently applied in order to rescale to model to the target net:gross ratio. This workflow results in models which have high net:gross ratios but poorly amalgamated sand bodies which are more representative of natural turbidite systems. Work is ongoing to apply to method to geologically more realistic models than the extremely simple conceptual model discussed here, but despite the simplicity of the models presented, the workflow represents a significant modelling advance by allowing the generation of models with realistic user-defined amalgamation ratios conditioned to well data.

5. Future work

The aim of this project is to test if the compression-based object modelling method (Manzocchi et al. 2007) can be combined with the multiple-point statistical facies modelling method in order to create hierarchical facies models that quantitatively reproduce net:gross and amalgamation ratio at different hierarchical scales (Zhang 2015) but that can be conditioned to well and seismic data. The ultimate outcome is to test findings on a case study.

References

Chapin, M. A., Davies, P., Gibson, J. L. and Pettigill, H. S. [1994] Reservoir architecture of turbidite sheet sandstones in laterally extensive outcrops, Ross Formation, western Ireland. In: Weimer, P., Bouma, A. H. and Perkins B. F. (eds.), Submarine Fans and Turbidite Systems. Sequence Stratigraphy, Reservoir Architecture and Production Characteristics, Gulf of Mexico and International, Gulf Coast Section, SEPM, 15th Annual Research Conference, 53-68.
Manzocchi, T., Walsh, J. J., Tomasso, M., Strand, J., Childs, C. and Haughton, P. D. W. [2007] Static and dynamic connectivity in bed-scale models of faulted and unfaulted turbidites. Structurally Complex Reservoirs 292, 309-336.
Stephens, K. D., Clark, J. B. and Gardiner, A. R. [2001] Outcrop-based stochastic modelling of turbidite amalgamation and its effects on hydrocarbon recovery. Petroleum Geoscience 7(2), 163-172.
Strebelle, S. [2002] Conditional simulation of complex geological structures using multiple-point statistics. Mathematical Geology 34(1), 1-21.
Zhang [2015]. Quantitative characterisation and hierarchical modelling of deep-water lobes. PhD Thesis, University College Dublin.
Zhang, L., Manzocchi, T., Haughton, P. D. W. and Pönten, A. [2015] Hierarchical parameterisation and modelling of deep-water lobes. Petroleum Geostatistics, Biarritz, France.