

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; Fig. 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).

Recent work which focused on understanding the internal architecture of deep-water lobes, has recognized a general four-fold hierarchical geometrical arrangement of lobe complex, lobes, lobe elements and beds for these reservoirs (e.g. Pr elat 2009) (Fig. 1.2). The hierarchy is based on the characteristics of the fine-grained units that bound the sand prone bodies (i.e. the interlobe elements, interlobes and interlobe complex).

In conventional object-based models, the object-placement algorithm results in realisations in which AR = NTG; it is clear (Fig. 1.1) that the individual sand beds in these models are too connected. A new class of object-based model, which uses a so-called "compression" method in order to reproduce poorly amalgamated but high NTG sequences 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. A major limitation of the method is that the models cannot honour particular observations made at wells. This limitation is addressed by the current work.

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 "decompression" workflow that combines the compression algorithm with the MPS method to create geologically realistic models that have realistic levels of sand amalgamation yet honour the available well data. Section 2 centres around the experiments testing the basic decompression workflow. In section 3, the decompression workflow has been adjusted to allow for hierarchical MPS modelling. MPS modelling was performed in Petrel 2016, and flow simulation modelling in Eclipse 100.

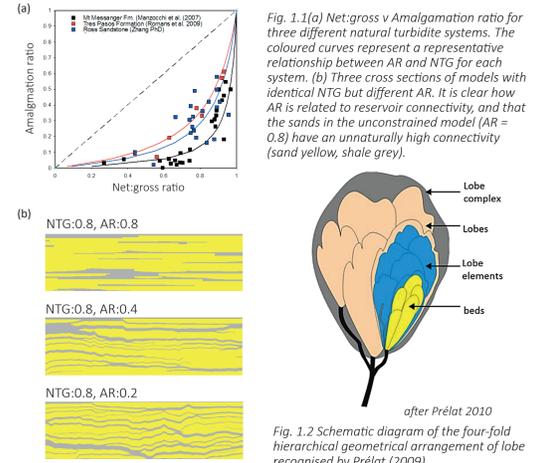


Fig. 1.1 (a) Net:gross v Amalgamation ratio for three different natural turbidite systems. The coloured curves represent a representative relationship between AR and NTG for each system. (b) Three cross sections of models with identical NTG but different AR. It is clear how AR is related to reservoir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

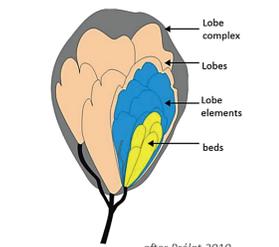


Fig. 1.2 Schematic diagram of the four-fold hierarchical geometrical arrangement of lobe complex, lobes, lobe elements and beds (after Pr elat 2010). The hierarchy is based on the characteristics of the fine-grained units that bound the sand prone bodies (i.e. the interlobe elements, interlobes and interlobe complex).

2. The basic decompression workflow

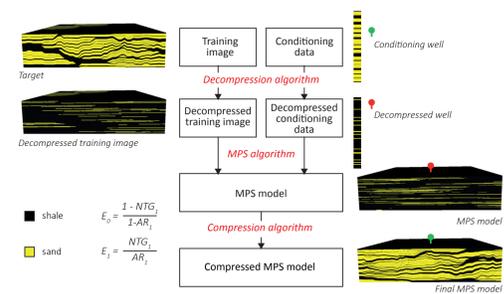


Fig. 2.1 The basic decompression workflow that has been established.

A new decompression workflow (Fig. 2.1) has been established to produce MPS models conditioned to well data able to honour also the poor reservoir connectivity at high NTG characteristic of many lobe reservoirs (Walsh and Manzocchi 2016).

First the training image and well data must be decompressed (i.e. the cells containing sand and shale are divided by their associated expansion factors, E_i). The decompressed training image represents the target AR at reduced NTG. The decompressed training image is used as the input into the MPS workflow conditioned to the decompressed wells to create an MPS realisation. The compression algorithm is subsequently applied to rescale the model to the target NTG. This workflow results in models which have high NTG but poorly amalgamated sand bodies which are more representative of natural turbidite systems.

The decompression workflow was tested to investigate if the output MPS model have statistically similar properties to models generated using the compression-based object modelling method, where NTG and AR are predefined inputs, but conditioned to well data. For each experiment a group of 30 MPS models were generated using the decompression workflow as well as a corresponding group of 30 compression-based object models with the same target NTG, AR and object dimensions.

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. The dynamic flow behaviour of the various experiments are also considered in terms of recovery factor and water break through time.

The decompression workflow was applied to a number of conceptual models. The NTG, AR, object dimensions and the number of conditioning wells were varied to test if the decompression workflow is capable of building MPS models that have statistically similar properties to compression-based object models, but conditioned to well data, regardless of the initial target properties. The conditioning wells have appropriate AR and NTG for the conceptual model being tested. A decompressed training image was built for each experiment and conditioned to the decompressed wells. Fig. 2.2a shows example MPS realisations output from each experiment and Fig. 2.2b shows the conditioning well data. The input well data is compared to the well data after the workflow is applied. There is a reasonably good correlation between the target and final wells, there is some minor offset and sand bed thickness difference where the well intercepts the edge of a sand unit in the MPS realisation. The cross plots in Fig. 2.3 compares the static connectivity and the dynamic flow properties of the MPS models to the compression-based object models. In each instance, the mean value for the group of MPS models is plotted against corresponding group of object models. The error bars reflect the natural variability seen across 30 realisations. Results indicate the MPS models built using the decompression workflow show statistically similar behaviour to the compression-based object models.

The basic decompression workflow shows the ability to generate reservoir models conditioned to well data with user defined amalgamation ratios, however this workflow is limited to conceptual models containing only one hierarchical level.

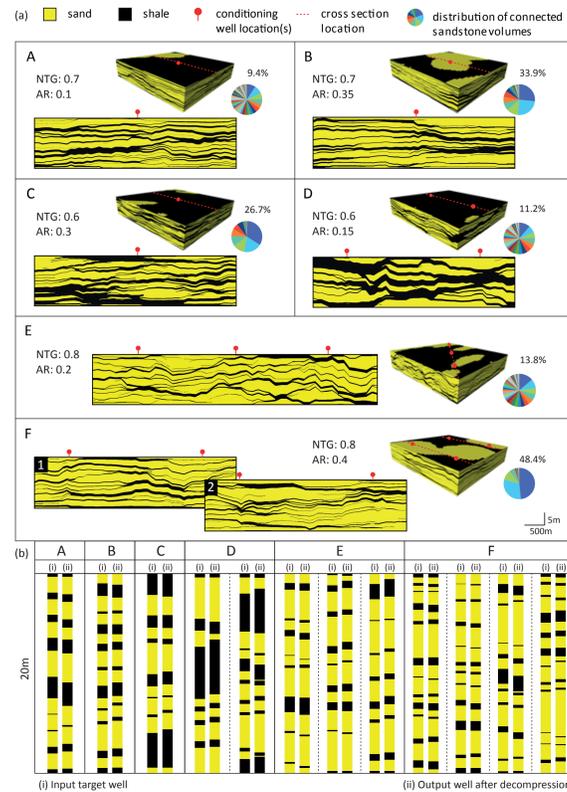


Fig. 2.2 (a) Example outputs from the decompression workflow for each of the experiments (A-F), with variable NTG, AR, object dimensions and number of wells. The conditioning wells are highlighted on the resulting MPS models and on the corresponding cross section. The pie charts indicated the connected volume distributions with the largest cluster of sand highlighted in each example. (b) The conditioning wells for each of the examples in (a) are shown, with (i) the input target well on the left and (ii) the final well after the decompression workflow is applied on the right.

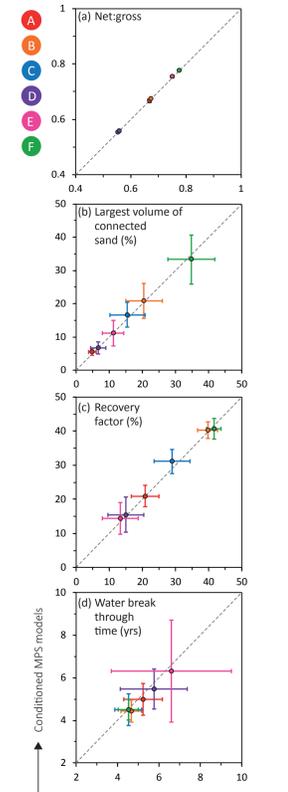


Fig. 2.3 Comparison of (a) NTG, (b) largest volume of connected sand, (c) recovery factor and (d) water break through time for the mean value of each group of MPS models compared to the corresponding object models. The error bars reflect the natural variability of 30 realisations.

3. The hierarchical decompression workflow

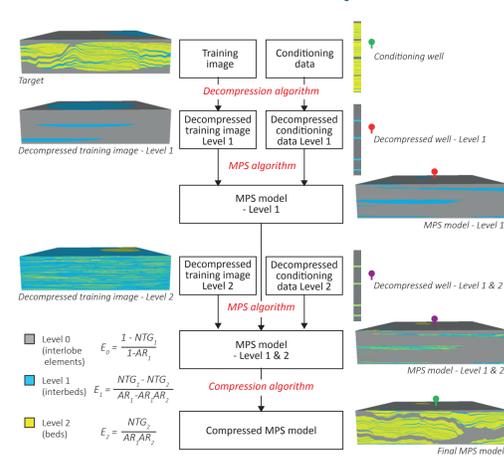


Fig. 3.1 The proposed workflow for generating hierarchical MPS models with high net:gross and user defined amalgamation ratios at each hierarchical level conditioned to well data.

The aim of this project is to test if the compression-based object modelling method (Manzocchi et al. 2007) can be combined with the MPS method (Strebelle 2002) to create hierarchical facies models that quantitatively reproduce NTG and AR at different hierarchical scales (Zhang 2015) but that can be conditioned to well and seismic data.

The proposed hierarchical decompression workflow is outlined in Fig. 3.1 and considers two hierarchical levels. A decompressed training image is required for each hierarchical level. The conditioning wells must also be interpreted for each hierarchical level and then decompressed. The highest hierarchical level, "Level 1" is modelled first in a "Level 0" background. The Level 1 decompressed training image is input into the MPS workflow conditioned to the decompressed Level 1 wells. This MPS model is then used as the 'container' for the smaller level, "Level 2". The Level 2 decompressed training image is input into the MPS workflow conditioned to the corresponding decompressed well, constrained by Level 1 in the first MPS model. The resulting MPS model has modelled Level 2 patterns in Level 1 patterns in a Level 0 background. The compression algorithm is applied to this MPS model until the target NTG is reached without impacting on the static connectivity and also honouring the original conditioning wells. This workflow in principal can be repeated to include any subsequent hierarchical levels, but due to the number of cells in the model it may become impractical to model more than a couple of hierarchical levels.

This hierarchical decompression workflow was tested on a conceptual geological model with two hierarchical levels, "beds in lobe elements". Four model sets with a bed-scale target NTG of 0.7 and the same target object dimensions were used (Fig. 3.2). AR is varied at both the lobe element and bed-scale. A set of decompressed training images are input into hierarchical workflow to generate 30 compressed MPS models for each case conditioned to a single well at the centre of the model. The final conditioning wells show a good correlation to the original input wells (Fig. 3.2b). Fig. 3.3 summarizes the results, comparing the static connectivity and dynamic flow behaviour of the conditioned MPS models to unconditioned compression-based object models. Results indicate that the hierarchical MPS models show statistically similar behaviour to models built using the compression-based object modelling approach, but conditioned to well data. The slightly higher recovery factor and earlier water break through times of the MPS models, we believe to be a result of differences in the grids and how transmissibility is calculated between grid cells during flow simulation compared to the object models.

Although the experiments outlined above have focused on simplistic conceptual models, the results indicate that the hierarchical decompression workflow can generate reservoir models conditioned to the well data also able to reproduce high NTG and low AR at different hierarchical levels. The next step will be to apply the method to a case study.

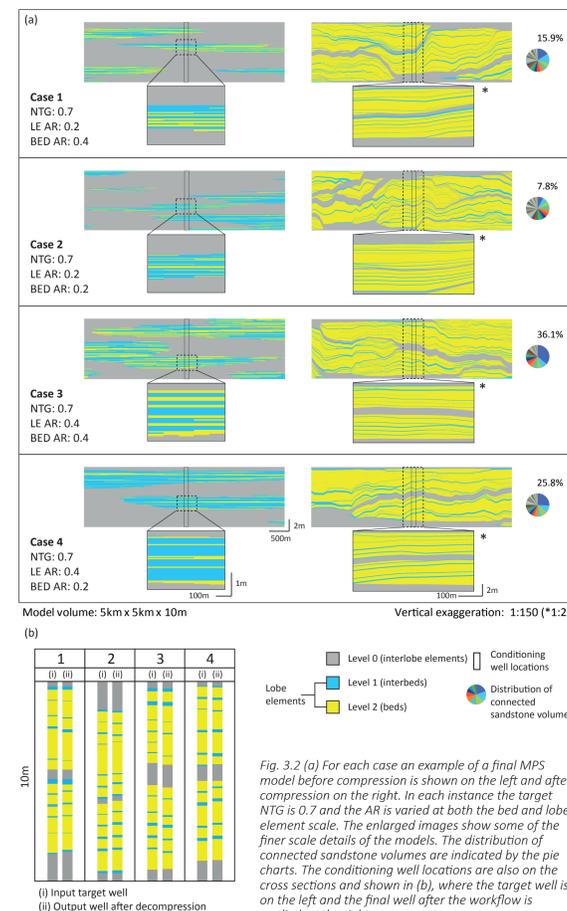


Fig. 3.2 (a) For each case an example of a final MPS model before compression is shown on the left and after compression on the right. In each instance the target NTG is 0.7 and the AR is varied at both the bed and lobe element scale. The enlarged images show some of the finer scale details of the models. The distribution of connected sandstone volumes are indicated by the pie charts. The conditioning well locations are also on the cross sections and shown in (b), where the target well is on the left and the final well after the workflow is applied on the right.

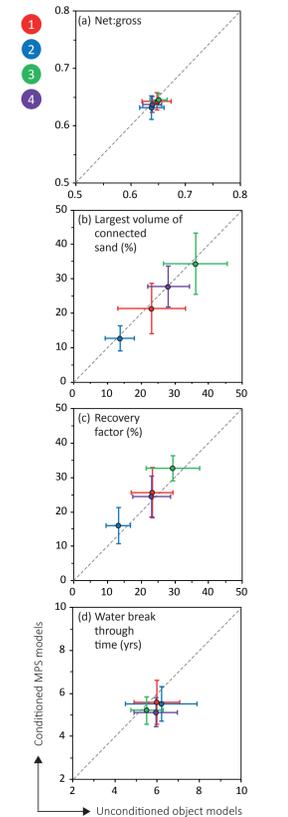


Fig. 3.3 Comparison of (a) NTG, (b) largest volume of connected sand, (c) recovery factor and (d) water break through time for the mean value of each group of MPS models compared to the equivalent group of object models. The error bars reflect the natural variability of 30 realisations.

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