Recent developments in object modelling opens new era for characterization of fluvial reservoirs

Markus L. Vevle[1*], Arne Skorstad[1] and Julie Vonnet[1] present and discuss different techniques applied to fluvial reservoir characterization and modelling.

Introduction

Fluvial depositional environments play a major role as hydrocarbons reservoirs around the world and have therefore received considerable attention in the domain of reservoir modelling (Keogh et al., 2007). Modelling of fluvial reservoirs represents a vast research field. The wide range of scales, the heterogeneity of deposits, the complex geometry has made them highly challenging to incorporate into subsurface models to replicate the reservoir behaviour in 3D.

Multiple facies modelling techniques have been used to mimic these deposits and their geometries in the most realistic way. However, algorithmic limitations may sometimes render oversimplified models, reducing their predictive power. Furthermore, more detailed and abundant well information as well as seismic data are now often available, and honouring this information is crucial to ensure models will support long-term decision making.

In this article, we look at the different techniques applied to fluvial reservoirs characterization and modelling, reviewing both the algorithms and some of the limitations faced during the modelling steps, and we'll finally introduce a new algorithm that can incorporate different landforms into the reservoir model for improved representation of fluvial depositional environments. We will also investigate how this next generation object-based modelling method can handle data from a real reservoir case.

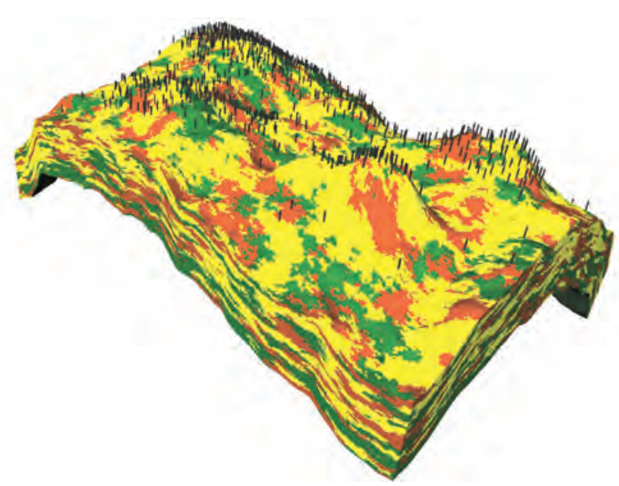

Figure 1 An indicator model for a mature giant oilfield.

The importance and challenges of fluvial systems

In an article in the *Journal of Petroleum Technology* as far back as 1993, Donald C. Swanson stated that 'fluvial/deltaic deposits may be the most important hydrocarbon reservoirs in the world' and that 'many large fields have reservoirs of varying combinations of braided-stream, point-bar, distributary-fill, and valley-fill deposits.'

25 years on and it is clear that fluvial depositional environments are present in many of today's reservoirs and, even if significant progress has been made since 1993, portraying these deposits in a 3D grid can still be challenging. Indeed, the main goal of facies modelling is to obtain an accurate numerical representation of the reservoir geology, suitable for subsequent allocation of petrophysical properties, while honouring the data provided by seismic and drilling campaigns.

If we consider the main elements of a fluvial system, we quickly realize that representing the heterogeneity is here a key factor for successful predictive models. Meandering fluvial systems are generally described as composed of several facies (channels, levees, crevasse splays, etc). Each facies produces different bodies, which is a result of the depositional processes, leading to specific geometry as well as specific rock properties. Modelling these structures implies an accurate representation of the heterogeneity of such systems as well as respecting the changes observed in channel thickness, amplitude or sinuosity. Additional processes such as amalgamation will often result in highly variable distribution and shapes of the fluvial deposits. Understanding the bed-scale architecture in 3D and the effect that has on reservoir dynamic behaviour is all too often overlooked in fluvial systems.

Another challenge is the data available to build the model and populate the grid to be used for decision-making. Increased density of drilled wells in addition to sophisticated well geometries will potentially provide a large and complicated set of well data which needs to be honoured in the model.

As we will see in the next section, multiple facies modelling techniques can be applied to respect both the geological reality of the deposits and the data available as input information for the algorithms to populate 3D grids.

A review of current modelling methods

Current facies modelling methods for fluvial reservoirs characterization tend to be based around pixel- or object-based algorithms.

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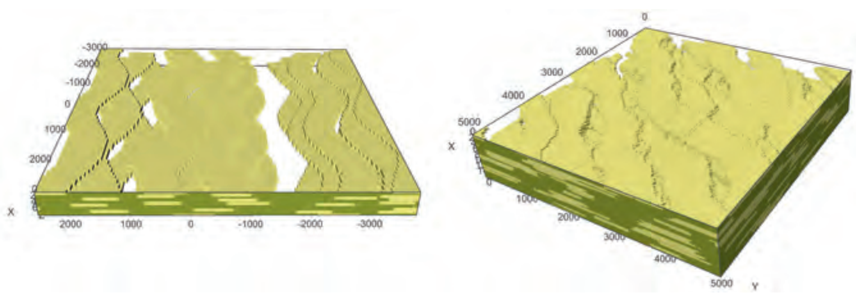

Figure 2 MPS simulation created using the training image. Left shows the training image and right the MPS simulation created using the training image.

The following section aims at describing the basics of the most popular techniques used for modelling fluvial environments as well as presenting the limitations of these algorithms.

Pixel-based methods

Sequential indicator simulation

An often used facies modelling method today, also for fluvial reservoirs, is sequential indicator simulation (SIS). SIS is a stochastic simulation method that populates facies between observations, and relies on indicator kriging to obtain some facies continuity beyond just neighbouring cells.

The sequential simulation works by visiting each point on the grid to be simulated, calculating the conditional distribution at that point and sampling from that distribution. The conditional distribution is the probability distribution for the facies at the point, given knowledge of the facies at nearby well locations and of previously simulated points near by (within the search neighbourhood of the point to be simulated).

It is applicable to a wide range of data sets and provides fast and accurate results of any number of facies. Figure 1 shows an SIS model generated for a mature giant oilfield with more than 25 million cells and a thousand wells.

Yet, while the tool can run with minimal user data, using additional geological information and accommodating unlimited amounts of well data, fluvial sediments and multi-scale channels are difficult to model using sequential indicator simulation.

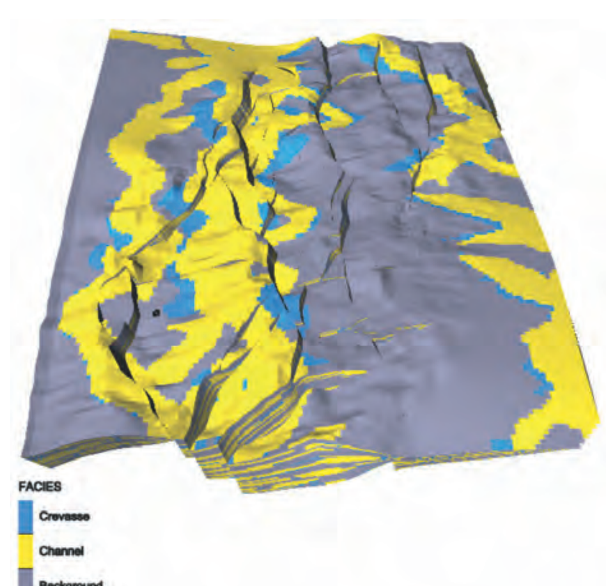

Figure 3 An example of application of object modelling to represent a fluvial system.

This particularly applies to the danger of oversimplification and the limitations in capturing long continuous bodies, thereby missing important geological representations of the reservoir important for predicting the actual flow pattern in the reservoir. In such cases, sequential indicator simulation is best suited to model undefined shapes of particular facies bodies or used in combination with secondary data input.

Multipoint statistics

Another method is Multipoint Statistics (MPS), a set of sequential simulations algorithms that uses a pixel-based approach for building stochastic facies realisations based on training images/ pattern recognition. MPS offers another way to model complex and heterogeneous geological environments through the use of a training image describing the geometrical characteristics of the facies to model and allowing the capturing of geological elements, such as channels and reefs.

While SIS algorithms reproduce variograms, multi-point statistics algorithms reproduce training images by extracting pattern probabilities from the training image.

The MPS method enables the generation of flexible and geometrically more realistic patterns for multiple facies than SIS methods. It also allows the user to condition the results to multiple sources of hard data, such as well data and seismic.

Still there are limitations. The construction of a training image that captures the true geological variability, as well as for the user to deal with the parameters controlling the algorithms, poses practical problems. In addition, MPS methods will be computationally more expensive than SIS methods, somehow limiting their use in a fast-paced decision-making environment.

Object-based methods

Object modelling

Object models are one of the earliest geostatistical approaches to facies modelling, originating with (Bridge & Leeder, 1979). Object-based modelling is very often used when the models to be populated need to represent realistic complex geometries of deposits. These methods are based on drawing objects from user-defined distributions controlling the geometric shapes, into the reservoir while fitting all observations. One of the greatest benefits of this method is that the geometric shapes are realistic, another is that relationships between objects can be controlled. E.g. a crevasse-splay will always be related to a channel object, as in nature, rather than being independently generated. Therefore, object model realizations are also commonly the training images to be used in combination with Multipoint statistics, as described in (Strebelle, 2002).

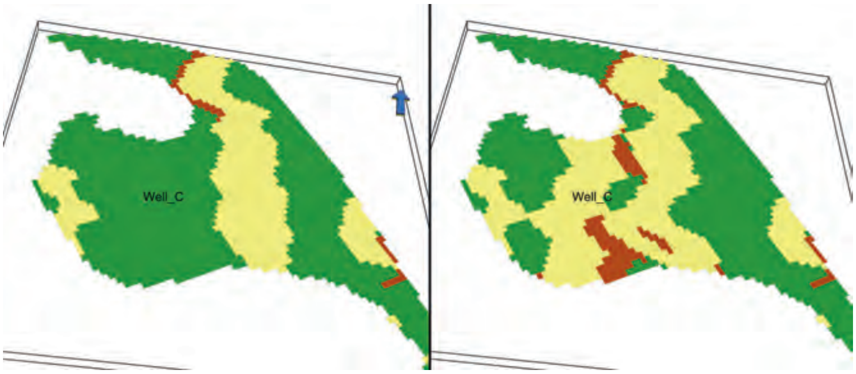

Figure 4 Illustration of a locally updated channel model. Left shows the original facies model where channel objects have been modelled, prior to Well_C being drilled. Right shows the locally updated facies model where the newly drilled Well_C is conditioned to.

Object modelling has always been central to fluvial reservoirs characterization. One of the earliest breakthroughs in addressing fluvial channel deposits was to represent them as objects, allowing the stochastic models to honour geologically realistic geometries, which in turn greatly improved the predictive power in the reservoir flow communications (e.g. Georgsen et al., 1994). Introducing intrabody trends also made it possible to take into account the bed-scale architecture when modelling the petrophysical properties, as shown in Figure 3, where the model generated reflects the channel geometry and the related crevasse-splays.

It is also possible to condition the model to newly acquired well data without changing the model around existing wells with the algorithm automatically detecting where an update is needed.

Figure 4 provides an example map view of a locally updated channel model in the case of newly drilled data. Conditioning to real data has proven to be more difficult than with pixel-based algorithms, especially in the cases where the number and density of wells to be honoured gets high.

The next generation object modelling algorithm

As detailed in (Hauge et al., 2017), object-modelling methods could not cover enough observations primarily because the algorithm generally failed to sample the prior in a way that would enable all the hard data to be honoured. In comparison, Multipoint statistics-based simulation keeps running realizations until all observations are respected, leading to a better convergence even for densely drilled areas. However, as a result, multipoint algorithms tend to sacrifice geometry in case of complex settings in order to respect both the well data and the probability of occurrence of a given facies, given by the training image. Object models cannot sacrifice geometry as the shape of the object is the conditioning factor. To improve the convergence, the sampling algorithm used for object-modelling has been enhanced as described in (Hauge et al., 2017) and is now available as a commercial state-of-the-art object model method.

This new technique provides the possibility to model meandering fluvial deposits, and its associated levee and crevasse facies, in one single tool. It provides a high degree of flexibility, where a multitude of trends, well data and geological knowledge is combined into a single facies model allowing intrabody trends to be used in subsequent petrophysical modelling. The intrabody trends for levee and crevasse are now also separated, making it possible to capture the different heterogeneities caused by their different depositional processes. It can address both meandering channel bodies, and more straight channel belts.

Each modelled body, being a channel, levee or crevasse, will be modelled individually with input given by the user, as seen on Figure 5. All the geometric definitions are given as distributions from which the values for one body are taken. By setting up correlations between the facies, it is possible to correlate the geometries between the channels and their associated levees and crevasses.

Figure 6 shows an example from a synthetic case with over 300 densely spaced wells and demonstrates the effectiveness of the new algorithm in conditioning on many observations of an object, while avoiding areas with background observations (i.e. other facies types).

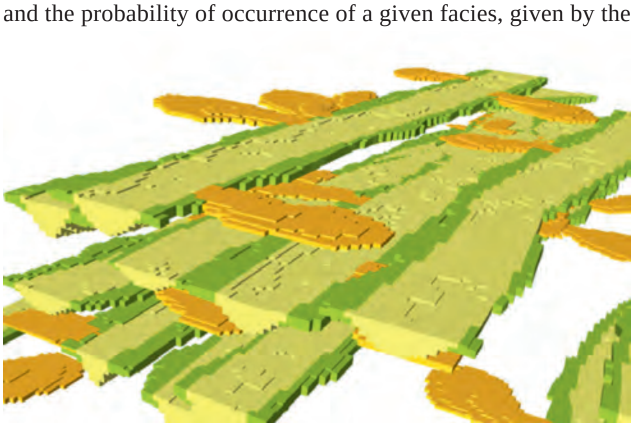

Figure 5 The new Next Generation Object Modelling Algorithm can model meandering channels and channel belts.

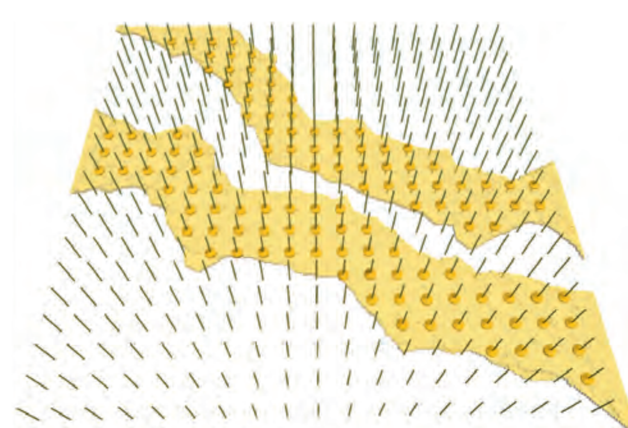

Figure 6 A synthetic case with more than 300 densely spaced wells demonstrating the effectiveness of the new algorithm in conditioning on many observations of an object, while avoiding areas with background observations (after Hauge et al., 2017).

Figure 7 One realization with crevasse and levee facies coupled to the channel deposits.

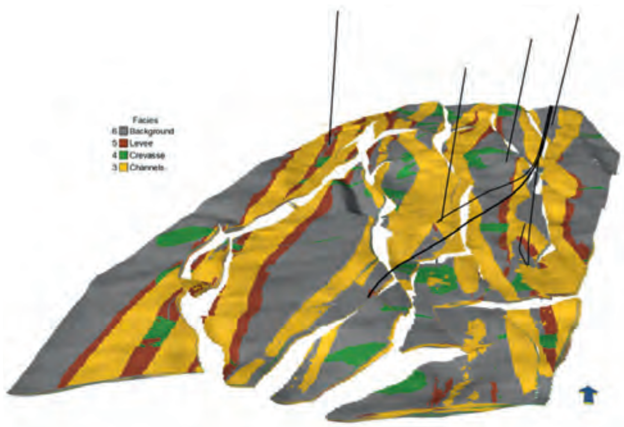

Figure 8 Channel, levees and crevasses are all linked together with an erosional hierarchy, which leads to geologically realistic facies deposits consistent with well data.

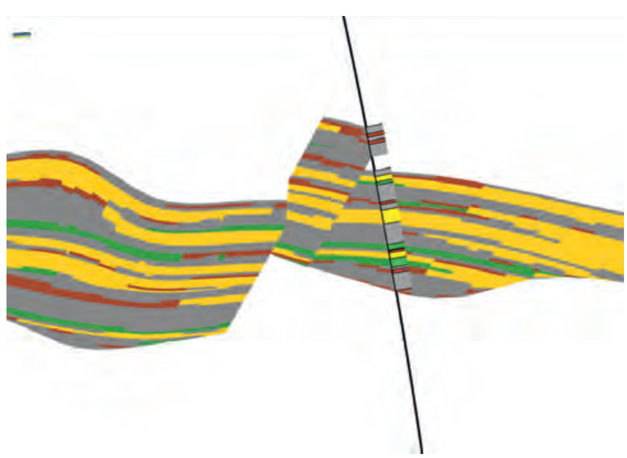

Figure 9 Examples of how the new algorithm also handles complex situations, such as wells crossing faults — The figures show intersections with the well with logs and the grid.

Using this new method, the channels can be modelled with or without levees and crevasses and crevasses will not occur in the inner bends. The channel and levee cross-sectional shape, and the crevasses plane view outline can also be edited with polygons.

When performing object modelling it is possible to include different trends describing a variety of the input in the model. This makes it possible to capture the uniqueness of a reservoir, the effect of depositional influences, including erosion, all the way to compactional effects by using the intrabody trends in the output from the facies model.

Illustration on real data

Using real open source data from the North Sea, we investigated how the next generation object-based algorithm handles data from a real fluvial channel system, including crevasse and levee facies associations.

Facies data from seven representative wells in the area, which include deviated wells, and wells crossing faults, have been interpreted. Corresponding to the geological setting, we have defined three object types: channels, levees and crevasses. These are connected, with levees flanking the channels, and crevasses breaking out through the levee from the channel, as shown in Figure 7.

We parameterise channels along a centre line, with horizontal edges described by 1D Gaussian fields, and top and base described by Gaussian 2D fields with a channel shape as expectation. These Gaussian fields serve the double function of providing stochastic variability, and enabling well conditioning in dense well patterns.

The levee parameterisation is very similar to the channel parameterisation. As levees are always connected to a channel, they follow the same centre line. Furthermore, one horizontal edge is given by the channel edge, whereas the other edge is defined by a 1D Gaussian field describing the levee width.

Crevasses are modelled slightly differently. These are parameterised around a backbone, consisting of two connected straight-line segments, one describing the breakout direction from the channel, and one describing the flow direction for the crevasse after the breakout. The leftmost channel in Figure 7 illustrates how the crevasses (green) are breaking through the levees out from the channel margins.

Modelling the results

We then calculate the well match for a conditional realisation.

This match is exact for all wells used in this study. The realisation is shown in Figure 8, which also shows the well pattern. As one can see, channel, levees and crevasses are all linked together with an erosional hierarchy, which leads to geologically realistic facies deposits consistent with well data. As the figure shows, the new algorithm makes realizations in accordance with geological specifications as well as honouring the well data. In Figure 9 we show in more detail how the conditioning of objects looks in an intersection view along the more complex wells. Note how the objects are picking up their respective conditioning points, while carefully avoiding the observations of other facies types.

Conclusions

This article has illustrated the variety of techniques available in fluvial reservoir characterization and how recent developments and modern object-based algorithms can generate geologically realistic realisations, including the coupling of levee and crevasse objects to their associated channel objects, while also correctly conditioning these objects to well data even when dealing with high numbers of observations.

The ability to condition all data correctly means that the new object-based modelling algorithm for fluvial reservoirs can run in an automated setting without manual edits. For multi-realization settings relying on automated workflows to generate large ensembles of realistic reservoir models, this feature marks a paradigm shift. There is now a realistic alternative to the commonly used pixel-based methods, allowing geometric control of large-scale features crucial for representing the reservoir flow pattern.

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