Marine and Petroleum Geology 61 (2015) 56–68

Contents lists available at ScienceDirect

Marine and Petroleum Geology

journal homepage: www.elsevier.com/locate/marpetgeo

Research paper

Towards process-based geological reservoir modelling: Obtaining basin-scale constraints from seismic and well data

Quinto Sacchi [a], Gert Jan Weltje [b, 1], Francesca Verga [a, *]

[a] Politecnico di Torino, Engineering Faculty, Department of Environment, Land and Infrastructure Engineering, Corso Duca degli Abruzzi 24, 10129, Torino, Italy

[b] Delft University of Technology, Department of Geoscience and Engineering, Stevinweg 1, NL-2628CN, Delft, The Netherlands

ARTICLE INFO

Article history:
Received 20 December 2013
Received in revised form
24 October 2014
Accepted 20 November 2014
Available online 27 November 2014

Keywords:
Process-based stratigraphic simulation
Model inversion
Uncertainty
Inference approach
Sub-grid parameterization

ABSTRACT

Forward stratigraphic modelling aims at representing the spatial distribution of lithology as a function of physical processes and environmental conditions at the time of deposition so as to integrate geological knowledge into the reservoir modelling workflow, thus increasing predictive capabilities of reservoir models and efficient exploitation of hydrocarbons. Application of process-based models in inverse mode is not yet well-established due to our limited insight into the information content of common subsurface data and the computational overhead involved.

In this paper we examine inverse modelling of stratigraphy by using a typical dataset acquired in the hydrocarbon industry, which consists of seismic data and standard logs from a limited number of wells. The approach is based on the use of a forward model called SimClast, developed at Delft University of Technology, to generate facies distribution and architecture at the regional scale. Three different goodness of fit functions were proposed for model inversion, following an inference approach. A synthetic reservoir unit was used to investigate the impact of the uncertainty affecting the input parameters and the information content of seismic and well data.

The case study showed that the model was more sensitive to the initial topography and to the location of the sediment entry point than to sea level. The depth of the seismic reflector corresponding to the top-reservoir surface was the most informative data source; the initial and boundary conditions of the simulation were constrained by evaluating the depth of this reflector across the whole basin area. In the reservoir area, where the seismic-to-well tie was established, the depth of the reservoir top does not give enough information for constraining the model parameters. Our results thus indicate that evaluation of basin-scale data permits reduction of uncertainty in (geostatistical) reservoir models relative to the current workflow, in which only local data are used. Effective use of well data to generate reservoir models conditioned to basin-scale scenarios requires post-processing methods to downscale the output of the forward model used in the experiments.

1. Introduction

The current workflow for obtaining static reservoir models relies on integration of quantitative well and seismic data by geostatistical (geometric–stochastic) methods. Kriging-like procedures are used to build a “best-guess” static reservoir model, from which an ensemble of equiprobable realizations is produced by conditional simulation (Deutsch, 2002). Conditional simulation implies that the large-scale geometry of a reservoir (and its enveloping geological unit) as derived from seismics is respected and well data are honoured. Each realization is transformed into a continuous 3-D porosity and permeability field by appropriate averaging (upscaling) procedures to serve as boundary conditions for dynamic models of reservoir behaviour. Uncertainties associated with reservoir behaviour are modelled by regarding the ensemble of equiprobable realizations obtained by conditional simulation as a representative sample of a population of (geologically realistic) subsurface models that is consistent with the observations. The underlying geological scenario is in most cases the main source of uncertainty (Deutsch, 2002; Bentley and Smith,

* Corresponding author. Tel.: +39 0 110907644; fax: +39 0 110907699.
E-mail address: verga.francesca@polito.it (F. Verga).

[1] Present address: University of Leuven, Department of Earth and Environmental Sciences, Geology Division, Celestijnenlaan 200E, 3001 Leuven-Heverlee, Belgium.

http://dx.doi.org/10.1016/j.marpetgeo.2014.11.002
0264-8172/

2008) and therefore multiple scenarios should be subjected to this geostatistical modelling workflow for any reservoir.

In the geostatistical approach to geological reservoir modelling, the aim is to mimic the present-day spatial distribution of geological entities without taking into account how a particular spatial distribution of lithology (porosity and permeability) has been generated. Geological objects, such as channel belts, shale lenses, and sandy lobes are introduced into such models by invoking templates, so called “analogues” taken from outcrops of rocks inferred to have formed under similar conditions (Deutsch, 2002). This “product-based” approach to prediction of reservoir architecture does provides limited opportunities for incorporating knowledge of the physical laws which govern basin filling into the modelling workflow (Karssenberg et al., 2001; Imhof and Sharma, 2006; Charvin et al., 2009, 2011; Weltje et al., 2013). A recently conducted experiment in which a continuous outcrop was sparsely sampled to mimic subsurface data (Deveugle et al., 2014) illustrates the limitations of state-of-the-art geostatistical algorithms for prediction of lithology between wells.

The use of process-based stratigraphic simulation models facilitates the integration of basin-scale geological constraints into static reservoir models by providing quantitative predictions of the spatial distribution of lithology (stratigraphic architecture) based on geological information that is in principle independent of the local data to which reservoir models are typically conditioned.

The capability to predict stratigraphic architecture is relevant to reservoir modelling because high-resolution sequence-stratigraphic representations of (local) basin-fill architecture may be used to guide different stages of the reservoir-modelling workflow: from the early phase of stratal pattern reconstruction by well correlation and definition of possible depositional scenarios (Wendebourg and Harbaugh, 1997; Burgess et al., 2006; Falivene et al., 2014) to the final stage of constraining stochastic lithofacies distributions for the assessment of reservoir volumes and connectivity, and the planning of infill wells (Doligez et al., 1999). Instead of building inferences about reservoir architecture solely upon models which honour the well data of a particular reservoir, which may not contain enough information to constrain stochastic models (Karssenberg et al., 2001), process-based stratigraphic modelling allows us to reduce the solution space of reservoir architecture to a subset of models which also honour basin-scale geological constraints. For practical purposes, however, the added value of stratigraphic modelling relies on our capability to condition these highly non-linear models to case-specific observations, such as seismic and well data (Burton et al., 1987; Heller et al., 1993; Lessenger and Cross, 1996; Cross and Lessenger, 1999; Bornholdt et al., 1999; Wijns et al., 2004; Imhof and Sharma, 2006; Falivene et al., 2014). If this can be accomplished, we may narrow down the range of possible scenarios (realizations) in the exploration stage, which should result in more reliable uncertainty estimates associated with reservoir-architecture models.

In this study we focus on the first step of the workflow, i.e. conditioning of a process-based model to seismic and well data. We carry out stratigraphic simulations with SimClast, an aggregated basin-scale process-based model of a fluvio-deltaic system with sub-grid parameterizations of fluvial channel networks and coastal dynamics (Dalman and Weltje, 2008, 2012). SimClast is a so-called 2DH model (depth-averaged model of flow in the two-dimensional horizontal plane). The term sub-grid parameterization originated in the field of computational fluid dynamics (Meneveau, 2010). In the case of SimClast, it refers to the implementation of processes which govern the evolution of drainage networks (such as avulsions) as sub-grid scale routines into the large-scale basin-filling model. The visualization and investigation of the sub-grid alluvial stratigraphy generated implicitly by the model may be performed by post-processing of model output in order to attain the level of detail required for geological reservoir modelling.

It is well known that the parameters of a model can be inferred by means of inverse methods (optimization or sample based). Inversion of highly non-linear models of sedimentary systems is an iterative process in which the stratigraphic model is run, the output is compared with the data according to an objective function (or likelihood function in Bayesian approaches), the parameters are adjusted by means of the selected technique and the model is run again until a satisfactory match with the target has been reached (Lerche, 1992, 1996; Bornholdt et al., 1999; Wijns et al., 2004; Charvin et al., 2009; Karssenberg et al., 2001, 2007; Verga et al., 2013). One of the potential problems in stratigraphic inversion is the non-uniqueness of the solution, i.e. multiple solutions which fit the data equally (or nearly) as well, even in cases where a good match between model and data has been achieved. Moreover, the inversion of sedimentary models tends to be computationally expensive and is sometimes regarded as unfeasible (Wijns et al., 2004; Burgess, 2012). An alternative method, suited for situations in which limited data are available (Heller et al., 1993; Burgess et al., 2006) consists of systematically searching the likely parameter space in order to form a map of the model properties (e.g. spatial distribution of net to gross). In the approach adopted in this study, each input parameter was assumed to follow a uniform distribution over a given interval. The solution space was explored with a Quasi-Monte Carlo method in order to obtain a set of solutions corresponding to each possible combination of input parameters. Conditioning of the model to well and seismic data was achieved by an inferential approach, using different goodness of fit functions, i.e. functions expressing the misfit between simulated data and a reference case mimicking real data. Because the solution space contained a ‘reference case’, the effectiveness of the goodness of fit functions could be evaluated in the light of possible limitations of the forward model and/or the data. This approach allowed exploration of the parameter space and robust assessment of the uncertainty in a fully non-linear manner. This approach differs from local (i.e. gradient methods) and global (i.e. Genetic Algorithm) optimization methods, which are primarily designed to find a single ‘best-fit’ solution (Lerche, 1996), in that it was aimed at identifying multiple scenarios of input parameters characterized by a likely stratigraphic realization. Systematic exploration of the parameter space provided the analysis of the influence of each of the parameters, and allows us to evaluate how the uncertainty of input parameters propagated to the modelled stratigraphy.

In a follow-up study of the present paper we intend to use the obtained basin-scale results to constrain sedimentary architecture at the reservoir scale. This will allow us to assess how the associated uncertainty propagates to the reservoir scale, opening the way to a full-risk analysis on the hydrocarbons initially in place and the recoverable reserves as a function of a given field development plan.

1.1. Process-based stratigraphic simulators

Stratigraphic forward models may be subdivided into two main categories: geometric and dynamic models (Paola, 2000; Burgess, 2012). Geometric models are relatively simple as they do not aim at describing the physical processes involved, but instead focus on direct simulation of the resulting stratal geometries (Burton et al., 1987; Bowman and Vail, 1999; Cross and Lessenger, 1999). Dynamic models are more complex as they attempt to simulate time-dependent erosion and sedimentation processes using empirical and/or process-based equations. Two main approaches can be distinguished within the latter method: hydraulic models and diffusion-based models. Hydraulic models use flow laws based on