Marine and Petroleum Geology 35 (2012) 20–27

Contents lists available at SciVerse ScienceDirect

Marine and Petroleum Geology

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

Non-Gaussian gas hydrate grade simulation at the Mallik site, Mackenzie Delta, Canada

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ARTICLE INFO

Article history:
Received 7 December 2011
Received in revised form
23 February 2012
Accepted 24 February 2012
Available online 3 March 2012

Keywords:
Gas hydrate
Stochastic simulation

ABSTRACT

For the past decades, gas hydrate reservoirs have beneficiated from an increasing attention in the academic and industrial worlds. As a result, there is a growing need to develop specific and comprehensive gas hydrate reservoir characterization methods. This study explores the use of a stochastic Bayesian algorithm to integrate well-logs and 3D acoustic impedance in order to estimate gas hydrate grades (product of saturation and total porosity) over a representative volume of the Mallik gas hydrate field, located in the Mackenzie Delta, Northwest Territories of Canada. First, collocated log data from boreholes Mallik 5L-38 and 2L-38 are used to estimate the statistical relationship between acoustic impedance and gas hydrate grades. Second, conventional stochastic Bayesian simulation is applied to generate multiple gas hydrate grade 3D fields integrating log data and lateral variability of 3D acoustic impedance. These equiprobable scenarios permit to quantify the uncertainty over the estimation, and identify zones where this uncertainty is greater. Contrary to conventional stochastic reservoir modeling workflows, the proposed method allows integrating non Gaussian and non linear distributions. This permits to handle bimodal distributions without using complex stochastic transforms. The results present gas hydrate grade values that are in accordance with well-log data. The relatively low standard deviation calculated at each pixel using all realizations suggests that gas hydrate grades is well explained by acoustic impedance and log data.

1. Introduction

Gas hydrates occurring in permafrost regions are known to represent a large volume of the global natural gas resources (Expert panel on gas hydrates, 2008). However, actual gas hydrate volume estimates vary over many orders of magnitude reflecting the numerous assumptions and the lack of reliable volume calculation methods, at the global or at the site scale (Collett, 2000). Reservoir characterization in terms of the spatial distribution of gas hydrate (GH) saturation and porosity is a key step prior to any exploitation project. Conventional investigation tools used to infer these properties include 3D seismic surveys that have a large spatial coverage but low spatial resolution (mostly vertical) and downhole logging data with high vertical resolution but poor lateral coverage (Le Ravalec-Dupin, 2005). In addition to conventional reservoir characterization obstacles, the multiple choice of petrophysical relationships possibly linking large scale acoustic attributes to small scale physical properties complexifies accurate gas hydrate modeling (Helgerud et al., 1999; Dai et al., 2004).

It has been shown that gas hydrate saturation presents a strong statistical relation with acoustic impedance (Lu and McMechan, 2002; Dai et al., 2004; Bellefleur et al., 2006). This relation, observed on well data, motivates the use of 3D acoustic impedance inversion of seismic data as well as log data, to estimate gas hydrate grades (product of saturation and porosity) over a large area of the Mallik gas field. Thus, we propose a simulation algorithm which combines 3D acoustic impedance data with acoustic impedance log and grade data estimated using porosity and gas hydrate saturation (Takayama et al., 2005). Similar simulation approaches were first applied by Doyen et al. (1996) and Gastaldi et al. (1998) to constrain 3D oil reservoir porosity models using 3D seismic and log data. More recently, Grana and Della Rosa (2010) presented a probabilistic Bayesian approach combining in situ petrophysical relationships with inverted 3D seismic acoustic attributes to estimate the distribution of petrophysical parameters (effective porosity, clay content, and water saturation) as well as litho-fluid classes.

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0264-8172/$ – see front matter
doi:10.1016/j.marpetgeo.2012.02.020

Statistical simulation approaches have the advantage of quantifying and providing the spatial distribution of the uncertainty of the estimates.

Previous works on Mallik gas hydrate field modeling were presented by Bellefleur et al. (2006) and Riedel et al. (2009). They showed that a strong relationship exists between gas hydrate saturation and acoustic impedance. An important step in this research is to consider gas hydrate as a mining resource, hence to consider grades instead of saturation, as it is typically done in the petroleum industry. The grades are defined as the product of saturation and porosity but can calculated at the wells by the subtraction of the NMR porosity to the total porosity, as described later in this paper. Starting from this point, this study aims at estimating the in-place volume of methane trap within hydrates and to address the continuity of the high gas hydrate grades layers observed at the wells with its uncertainty. In an exploitation point of view, these results can play an important role in the decision process of the future drilling locations.

2. Methodology

This study investigates the use of in situ well-log statistical relationship between acoustic impedance and gas hydrate grades through a non-linear Bayesian simulation algorithm to simulate the gas hydrate grades (G) over the 3D seismic data from Mallik. The available seismic data consists of a 3D acoustic impedance (AI) cube inverted using conventional least-square algorithm (Bellefleur et al., 2006). Time-to-depth conversion chart is built from a zero-offset Vertical Seismic Profile (VSP) measured at borehole 2L-38 (Sakai, 1999) located in the center of the 3D seismic cube and reaching the base of the gas hydrate stability zone. Multiple properties were obtained from logging data from both wells including bulk density, neutron porosity, NMR porosity, and P-wave velocity (Collett et al., 1999, 2005). From these properties, fine scale ($\sim$15 cm) 1D acoustic impedance was calculated by multiplying the density and the velocity of P-wave whereas gas hydrate grades were calculated by multiplying the gas hydrate saturation with the total porosity.

Grades were preferred over standard gas hydrate saturation since, in its natural form, gas hydrate occurs as a solid rather than a fluid as it is typically in conventional reservoir (Gabitto and Tsouris, 2010). Consequently, the characterization tools for gas hydrate reservoirs are closer to those used in mining rather than the ones used in oil and gas reservoir study. Moreover, the grades are an additive variable. Therefore, upscaling and downscaling can be done by simple averaging. Following this property, log data have been re-sampled at the coarse seismic scale (2 m) using sliding window arithmetic mean.

2.1. Gas hydrate grades calculation

The two log parameters included in the present BSS algorithm are acoustic impedance and gas hydrate grades. Acoustic impedance is calculated by multiplying the bulk density and P-wave velocity.

The bulk density of gas hydrate bearing sediments (ρ_b) can be expressed by (Lee and Collett, 2011)

$$\rho_b = \rho_{ma}(1-\phi) + \rho_w\phi(1-C_h) + \rho_h\phi C_h \tag{1}$$

where ϕ is the total porosity and ρ_{ma}, ρ_w and ρ_h are the densities of grains, water, and gas hydrate, respectively. C_h is the gas hydrate saturation filling the pore space.

In addition, NMR well-logging tools respond quantitatively to pore-space liquid water (bound, capillary, and free water) but not to gas (Kleinberg et al., 2005). Thus, the NMR porosity (ϕ_{NMR}) can be written as

$$\phi_{NMR} = \phi(1-C_h) \tag{2}$$

From equations (1) and (2), the total porosity, which corresponds to the pore space occupied by water and gas hydrate, is

$$\phi = \frac{\phi_D + \lambda_h\phi_{NMR}}{1+\lambda_h} \tag{3}$$

where

$$\lambda_h = \frac{\rho_w - \rho_h}{\rho_{ma} - \rho_w} \quad \text{and} \quad \phi_D = \frac{\rho_{ma} - \rho_b}{\rho_{ma} - \rho_w} \tag{4}$$

From equations (2) and (3), the gas hydrate saturation and grades can be expressed as

$$C_h = \frac{\phi - \phi_{NMR}}{\phi} \tag{5}$$

$$G = \phi \times C_h = \phi - \phi_{NMR} \tag{6}$$

Gas hydrate grades, estimated from NMR and density logs are considered as the most accurate since it only depends on the accuracy of the NMR tool as well as the density log and not on a model or parameters (Takayama et al., 2005; Lee and Collett, 2011).

2.2. Kernel estimation

The first step of our methodology consists in inferring the statistical petrophysical relationship between G and AI using collocated log data. The joint probability function was then estimated using the non-parametric kernel density estimator (KDE) (Rosenblatt, 1956; Parzen, 1962). The joint probability function $f(G,\mathrm{AI})$ for n collocated data points (G_i,AI_i) and for $i = 1,\ldots,n$ the KDE is expressed by Wand and Jones (1995).

$$f(G,\mathrm{AI}) = \frac{1}{nh_1h_2}\sum_{i=1}^{n} K\left(\frac{G-G_i}{h_1}\right)K\left(\frac{\mathrm{AI}-\mathrm{AI}_i}{h_2}\right) \tag{7}$$

where h_1 and h_2 are the kernel bandwidths and K is the kernel function. Among all possible kernel types (uniform, triangle, Epanechnikof,…), we selected a Gaussian kernel as it is routinely used for continuous variables (Silverman, 1986).

The determination of the optimal bandwidth is not straightforward; too much smoothing decreases the resolution of the relationship between variables whereas not enough smoothing leads to an unstable relationship. Many empirical equations exist to help making this choice (Silverman, 1986). However, since the relationship includes only two variables, a visual bandwidth determination is preferred.

2.3. Bayesian sequential simulation

This section presents the BSS algorithm as illustrated on Figure 1. This algorithm comprises five steps and allows the integration of the seismic attributes with the in situ petrophysical relationship in a stochastic and flexible manner. The first step consists in defining a random path visiting each cell of the 3D grid once. All the subsequent steps presented below aim at simulating the gas hydrate grades of voxel n.

The second step defines the a priori distribution of the gas hydrate grades. This is done in two sub-steps (Fig. 1, Steps 2.1 & 2.2). Since the gas hydrate grades and acoustic impedance present a bimodal distribution, it is necessary to statistically infer a family for