STOCHASTIC BAYESIAN ALGORITHM TO ESTIMATE GAS HYDRATE GRADE AT THE MALLIK FIELD, MACKENZIE DELTA, CANADA

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ABSTRACT
Gas hydrates occurring in permafrost regions are known to represent a large volume of the global natural gas resources. However, actual estimates of gas hydrate volumes vary from many orders of magnitude reflecting the lack of reliable calculation methods. In order to overcome these difficulties, this study explores the use of a stochastic Bayesian algorithm to estimate gas hydrate grade over a representative area of the Mallik gas hydrate field, located in the Mackenzie Delta, Northwest Territories of Canada. The approach aims at integrating acoustic impedance inversion of 3D seismic data and log data to obtain a large scale gas hydrate grade over the seismic grid. Firstly, collocated log data from boreholes Mallik 5L-38 and 2L-38 are used to estimate the statistical relationship between acoustic impedance and gas hydrate grade. Secondly, conventional stochastic Bayesian simulation is applied to generate multiple 3D gas hydrate grade fields integrating log data and lateral variability of 3D acoustic impedance. These scenarios permit to quantify the uncertainty over the estimation and identify zones where this uncertainty is greater. The results present gas hydrate grade values that are in accordance with core data. The relatively low variance over 50 realizations suggests that gas hydrate grade is well explained by acoustic impedance and log data.

Keywords: gas hydrate, stochastic simulation.

NOMENCLATURE
AI Acoustic impedance [Pa·s/m]
G Grade [unitless]
h Kernel bandwidth
K Kernel function

INTRODUCTION
Gas hydrates occurring in permafrost regions are known to represent a large volume of the global natural gas resources [1]. However, actual gas hydrate volume estimates vary from many orders of magnitude reflecting the lack of reliable volume calculation methods [2]. In addition, reservoir characterization in terms of permeability, gas hydrate grade, porosity and its associated heterogeneity is a key step prior to any exploitation project. Conventional investigation tools used to infer these parameters include 3D seismic surveys that have a large spatial coverage but low spatial resolution and downhole logging data with high vertical resolution but poor lateral coverage. In addition to conventional reservoir characterization obstacles, the absence of reliable petrophysical relationships that link large scale acoustic attributes to small scale physical properties complexifies GH accurate modeling [3].

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It has been shown that GH presents a strong statistical relation with acoustic impedance [4]. This relation, observed on well data, motivates the use of 3D acoustic impedance inversion of seismic data as well as log data, to estimate GH grade over a large area of the Mallik gas field. Thus, the proposed simulation algorithm combines 3D acoustic impedance data with acoustic impedance log and grade data estimated using porosity and gas hydrate saturation [5]. Similar approaches were first applied by [6] and [7] to constrain 3D oil reservoir porosity models using 3D seismic and log data. More recently, [8] presented a stochastic Bayesian approach combining in situ petrophysical relationships with inverted 3D seismic acoustic attributes to estimate the distribution of petrophysical parameters. In relation to gas hydrate, [9] developed a means of representing heterogeneity at different scales based on log statistics. The method was then applied to the Mallik reservoir and highlighted the impact of heterogeneity on gas hydrate volume estimates. Previous works on Mallik gas hydrate field modeling were presented by [4] and [10]. They showed that a strong relationship exists between gas hydrate saturation and 3D acoustic impedance.

A first important step in this research was to consider gas hydrate as a mining resource, hence to consider grades instead of saturation like in petroleum industry. This statement is more in agreement with the nature of the gas hydrate as its saturation is not directly linked to the exploitation. Moreover, since the relation between GH grade and AI is highly non linear and bimodal, the use of conventional simulation methods like cosimulation are excluded [11]

**METHODOLOGY**

In this study, a Bayesian sequential simulation algorithm (BSS) is used to simulate the gas hydrate grade (G) over a 3D seismic data grid from Mallik. These seismic data have previously been inverted into acoustic impedance (AI) in order to evaluate the distribution of gas hydrate and provide a volume estimate [4]. Time-to-depth conversion for seismic-to-well correlation was done using a Vertical Seismic Profiling (VSP) acquired in a borehole (Mallik 2L-38) located in the center of the 3D seismic cube and reaching the base of the gas hydrate stability zone. In that borehole and in a second one (Mallik 5L-38) 94 meters away, multiple logs were measured including bulk density, neutron porosity, NMR porosity, and sonic logs [12; 13]. From these data, fine scale (~15 cm) 1D acoustic impedance and gas hydrate grade were calculated multiplying the density by the velocity of P-wave and gas hydrate grades were calculated multiplying the GH saturation by 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 like in conventional reservoir [14]. This is an important change of paradigm and the characterization tools for GH reservoirs are closer to mining's than oil and gas one. In addition, as soon as GH changes phase (solid to gas), it will naturally moves between the open pores as its volume expands as in the case of shale gas. The grade variable also eliminates the dependency to porosity unlike the saturation and makes it an additive variable that discards a lot of problems in up and down scaling. Thanks to that property, log data have been resampled at the coarse seismic scale (2 m) using sliding window arithmetic mean.

**Kernel estimation**

The first step of our methodology consists in inferring a statistical petrophysical relationship between G and AI, using collocated log data. The joint probability density function was calculated with the non-parametric kernel density estimator (KDE). Thus, the joint pdf, \( f(G, AI) \), for \( n \) collocated data points \((G_i, AI_i)\) and for \( i=1,\ldots,n \) the KDE is expressed by [15].

\[
f(G, AI) = \frac{1}{n h_1 h_2} \sum_{i=1}^{n} K\left(\frac{G - G_i}{h_1}\right) K\left(\frac{AI - AI_i}{h_2}\right)
\]

where \( h_1 \) and \( h_2 \) are the kernel bandwidths also known as smoothing parameters and \( K \) is the kernel and corresponds to a weighting function for which the integral is 1. Among all possible kernel types (uniform, triangle, Epanechnikof,...), we selected a Gaussian kernel as it is routinely used for continuous variables [16].

The determination of the optimal bandwidths is not straightforward; too much smoothing leads in a decrease of 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 [16].
However, since the relationship includes only two variables, a visual bandwidth determination is possible.

**Bayesian sequential simulation**
This section presents the BSS algorithm as illustrated on Figure 1. The first step consists in defining a random path visiting each cell of the 3D grid once. All the subsequent steps aim at simulating the gas hydrate grade of voxel $n$.

The second step aims at defining the a priori distribution of the gas hydrate grade. This is done in two sub-steps (Figure 1, Steps 2.1 & 2.2). Firstly, since the gas hydrate grade presents a bi-modal distribution, it is necessary to statistically infer in which family the voxel to simulate belongs to, i.e. family 1 corresponding to low gas hydrate grade or family 2, corresponding to high gas hydrate grades.

The known AI value at the voxel to simulate as well as the joint pdf linking gas hydrate grades to AI, allows the extraction of a likelihood function $f(AI_n|G_n)$. This latter is then modeled by a sum of two Gaussians functions, using the Gaussian Mixture Models [17]. The area under the curve of Gaussian corresponding to family 1 over the total area under the curve gives the probability of belonging to that family. A random probability value finally stochastically select the family the voxel belongs to. Step 2.2 consists in performing, at voxel $n$, a simple kriging of the known log data and all the previously simulated grade values of family 2 to obtain the prior distribution $f(G_n|G_1,...,G_{n-1})$.

Under multivariate Gaussian assumption, the parameters required to estimate a Gaussian distribution (the conditional mean $\mu_n$ and variance $\sigma_n$) are given by the simple kriging parameters [11]. In the last step, the data are separated into two families so that individually, each family presents a Gaussian-type behavior. Each family has its own mean and variance. The vertical range required in the simple kriging algorithm is determined fitting an exponential model on the experimental variogram of the log data. Since only two boreholes are available at the study site, the horizontal ranges are inferred from the 3D acoustic impedance data, assuming that the latter parameter reflects the spatial structure of the gas hydrate grade.

Step 3 (Figure 1) simply consists in extracting the same likelihood function as previously from the joint pdf.

Based on Bayes theorem, the posterior distribution is computed by updating the prior with the likelihood. Finally, a grade value is randomly picked from the posterior distribution and assigned to the voxel $n$. The simulated value is now considered as a measured data for the next voxel to be simulated. Steps 2 to 5 are repeated until all voxels have been visited once.
STUDY SITE

The Mallik gas hydrate field is located onshore the Arctic permafrost in the areas of the Beaufort Sea, in the Mackenzie Delta, Northwest Territories, Canada (Figure 2). Three internationally partnered research well programs have intersected three intervals of gas hydrate and allowed successful extraction of subpermafrost core samples with a significant amount of gas hydrate [18].

The gas hydrate intervals are up to 40 m thick and have high gas hydrate saturation, sometimes exceeding 80% of pore volume in unconsolidated clastic sediments with average porosities ranging from 25 to 40%. The three gas hydrate intervals are located in the crest of a faulted anticline structure [19]. In 2002 and 2008, depressurization and thermal stimulation of targeted gas hydrate layers have been successfully conducted. This world premiere opens a promising door for future exploitation of this abundant resource.

3D seismic data

In this study we use the upper two seconds of a 3D seismic reflection data set acquired and processed by Veritas DGC Land in 2002. The acquisition geometry for the 3D was designed to image conventional hydrocarbon accumulations located beneath the gas hydrate zones (deeper than 1100 m). The processing also focused on the imaging of the conventional gas-bearing structures rather than gas hydrate; permafrost (< 600 m) and low CDP fold in the gas hydrate depth range (900–1100 m). The chosen data set was reprocessed to maintain the relative true-amplitude of the data. A complete processing description is given in [19]. The data used in this study is a subset of the 3D cube (41 x 41 traces) centered on wells 2L-38 and 5L-38 and selected by [4] and [10] for detailed acoustic impedance inversion. The inversion was computed by matching a reflectivity model to seismic data.

Well data

Data from wells Mallik 2L-38 and 5L-38 are used in this study. All these data were acquired with Schlumberger probes during the research well programs. Both wells, 94 m apart, crosses the entire gas hydrate stability zone resulting in continuous data from 850 m to 1160 m deep. Previous work on Mallik well log analysis has allowed the identification of two continuous high saturation gas hydrate horizons (Zones B and C), confirmed by various measurement types (resistivity, P- and S-wave velocity, NMR), and a shallower one (Zone A) presenting less spatial continuity between wells [10]. These horizons are composed of high porosity sand located between 850 and 1100 m, the depth documented to be the base of the gas hydrate stability zone. Zone C, located at the base of the gas hydrate stability zone is known to be the most continuous horizon and to extend over a large area compared to Zone B, documented to be discontinuous and patchy and located at about 950 m. Zone A, considered as the top of the gas hydrate occurrence (~890 m) is not present at all on the inverted seismic section due to complex interference patterns of the highly variable stratigraphy and inappropriate seismic imaging [4].

The two log parameters included in the present BSS algorithm is acoustic impedance and gas hydrate grade. Acoustic impedance is calculated multiplying the bulk density and P-wave velocity. The gas hydrate grade is obtained multiplying the gas hydrate saturation by the total porosity. Saturation was calculated using CMR porosity and standard resolution density porosity, as explained in details in [5]. All log data were then upscaled, by arithmetic mean, at the 3D acoustic impedance resolution in order to take into account the measurement support. This is possible as grades are used rather than saturation values.
RESULTS

The 3D acoustic impedance inverted data as well as the upscaled grade log data of borehole Mallik 2L-38 and 5L-38 are combined to generate 50 BSS realizations.

The variogram model used to compute the simple kriging is exponential with horizontal ranges of 400 m and a vertical range of 40 m. Family 1 has a mean grade value of 0.005 and a variance of 1.54x10^{-3}, including a nuggets effect of 1.4x10^{-4}. Family 2 has a mean of 0.21 and a variance of 7.7x10^{-3}, including a nugget effect of 7x10^{-4}. The vertical range as well as the two means and variances were inferred from the well data whereas the horizontal ranges were estimated from the 3D acoustic impedance data. This latter estimation is valid under the hypothesis that the acoustic impedance respects the main structural behavior.

One realization among 50 is presented in Figure 3. The two continuous gas hydrate horizons ( Zones B and C) detected on the log data are visible. In these horizons, gas hydrate occupies from 20 to 33% of the total volume. Zone A is not apparent on the slide presented here, however, it is present over the volume in a rather sparse way, as documented by previous works [4; 10]. The black lines added to the image show the northwest-southeast anticline structure present in the area.

Gas hydrate volume estimation

The total volume of gas hydrates within the seismic cube can be calculated for each realization. It is calculated multiplying the grade of each voxel by its volume. The 3D grid is composed of 184 910 rectangular voxels of 30 m x 30 m x 2.7 m.

At standard atmospheric temperature (20°C) and pressure (1 atm) conditions, 1 m$^3$ of solid methane hydrate is equivalent to 164 m$^3$ of free gas [21]. Thus, the total volume of methane of our study site is approximated by $1 4 6 4 \times 1 0^6 \pm 2 4 6 x 1 0^6$ m$^3$ of natural gas, considering that approximately 90% of all clathrates are documented to be filled with gas. The obtained natural gas volumes are consistent with previous volume estimates [4; 9; 10; 12].

Figure 3 One realization of gas hydrate grade at Mallik gas hydrate field, Northwest Territories, Canada. The black line follows the northwest-southeast anticline structure.

Furthermore, the standard deviation for each voxel is calculated using the 50 realizations (Figure 4). This parameter allows quantifying the uncertainty of the grade estimation. This analysis is of great importance at many stages of project process since it defines the geological risk associated with the estimation tool. It also permits to guides the decision of optimal new well positions [20]. The relatively low standard deviation of the gas hydrate grade over the 50 realizations (around 20%) suggests that gas hydrate grade is well explained by acoustic impedance and log data and also reflects the low dispersion of the in situ statistical relation between G and AI.
CONCLUSION
This study presents the first step of the use of a Bayesian sequential simulation algorithm to model the Mallik gas hydrate field. The approach is based on an in situ petrophysical relationship between gas hydrate grade and acoustic impedance, at a seismic scale. This statistical relationship is used to extrapolate the gas hydrate grades over a 3D acoustic impedance cube. It allows estimating the total in situ gas hydrate volume and assessing the continuity of the gas hydrate horizons. Furthermore, this stochastic algorithm allows estimating the spatial uncertainty among a set of equiprobable realizations. This study presents the preliminary results of a larger project where the next step aims at taking into account the uncertainty linked with the seismic inversion.

REFERENCES
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