Sedimentary Microfacies and Porosity Modeling of Deep-Water Sandy Debris Flows by Combining Sedimentary Patterns with Seismic Data: An Example from Unit I of Gas Field A, South China Sea

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Abstract: Sandy debris flow deposits are present in Unit I during Miocene of Gas Field A in the Baiyun Depression of the South China Sea. The paucity of well data and the great variability of the sedimentary microfacies make it difficult to identify and predict the distribution patterns of the main gas reservoir, and have seriously hindered further exploration and development of the gas field. Therefore, making full use of the available seismic data is extremely important for predicting the spatial distribution of sedimentary microfacies when constructing three-dimensional reservoir models. A suitable reservoir modeling strategy or workflow controlled by sedimentary microfacies and seismic data has been developed. Five types of seismic attributes were selected to correlate with the sand percentage, and the root mean square (RMS) amplitude performed the best. The relation between the RMS amplitude and the sand percentage was used to construct a reservoir sand distribution map. Three types of main sedimentary microfacies were identified: debris channels, fan lobes, and natural levees. Using constraints from the sedimentary microfacies boundaries, a sedimentary microfacies model was constructed using the sequential indicator and assigned value simulation methods. Finally, reservoir models of physical properties for sandy debris flow deposits controlled by sedimentary microfacies and seismic inversion data were established. Property cutoff values were adopted because the sedimentary microfacies and the reservoir properties from well-logging interpretation are intrinsically different. Selection of appropriate reservoir property cutoffs is a key step in reservoir modeling when using simulation methods based on sedimentary microfacies control. When the abnormal data are truncated and the reservoir properties probability distribution fits a normal distribution, microfacies-controlled reservoir property models are more reliable than those obtained from the sequence Gauss simulation method. The cutoffs for effective porosity of the debris channel, fan lobe, and natural levee facies were 0.2, 0.09, and 0.12, respectively; the corresponding average effective porosities were 0.24, 0.13, and 0.15. The proposed modeling method makes full use of seismic attributes and seismic inversion data, and also makes the property data of single-well depositional microfacies more conformable to a normal distribution with geological significance. Thus, the method allows use of more reliable input data when we construct a model of a sandy debris flow.

Key words: sandy debris flow deposit, seismic attribute and inversion, geological modeling controlled by micro-facies, data truncated process

1 Introduction

Haldorsen and Larry (1982) proposed a geological modeling approach to reservoir prediction: this was a significant advance in predicting the distribution of reservoirs within a three-dimensional space in the early stage of stochastic modeling techniques. Weber and Van (1990) then classified reservoir architecture on the basis of sedimentary facies, converting different reservoir architectures into specific models used in deterministic modeling. Depositional patterns were then associated with reservoir modeling techniques. Soon after, Damsleth et al.

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reservoir property models using geostatistics (Doyen, 1988; Fournier and Derain, 1995) or using multiple-point geostatistics incorporating wells and seismic data (Liu et al., 2004). Seismic data and reservoir models can be integrated using the collocated cokriging alternative method (Xu et al., 1992; Behrens, 1998; Grötsch and Mercadier, 1999). Furthermore, sedimentary patterns can initially be obtained from seismic data. From this, sedimentary facies models can be constructed, followed by construction of reservoir property models, i.e., a two-stage stochastic model (Damsleth et al., 1992). To achieve a realistic model while simultaneously avoiding the effect of drilling data deficiencies, integration of sedimentary microfacies with seismic data remains a preferred approach for reservoir model building. In this study, we described a feasible workflow for deep submarine fan reservoirs with few well data incorporating both sedimentary-microfacies-controlled reservoir modeling and seismic data. In the sedimentary microfacies modeling, seismic attributes were optimized to obtain the functions of sedimentary parameters, similarly to the relationship between the seismic root mean square amplitude and sand percentage. Sequential indicator simulation and assigned value simulation methods were applied simultaneously to construct a sedimentary microfacies model incorporating the sedimentary parameters (such as sand percentage), thus obtaining sedimentary microfacies properties for each single well. On the basis of the sedimentary microfacies model, utilizing the sequential Gaussian collocated cokriging stochastic simulation method, reasonable cutoff values of reservoir properties of different sedimentary microfacies were applied to construct a reservoir porosity model under the control of sedimentary microfacies. The model was subsequently coupled with seismic inversion data. Therefore, the results of the reservoir modeling in our study are comparable with the actual geological conditions.

2 Geological Setting

2.1 The study area and stratigraphy

The Baiyun Depression is a third-order tectonic belt in the Pearl River Mouth Basin of the South China Sea. The gas field A is located in the eastern part of the Baiyun Depression and contains four separately drilled exploration wells (Fig. 1). This gas field has four intervals from Oligocene to Miocene (Units I, II, III, and IV) of economic importance, of which Unit I is the most commercially important. This unit is formed in a deep-water submarine fan (Pang et al., 2008); this is the basis for the reservoir model in this study.
2.2 Sedimentary facies patterns

As there are only four wells in the study area, seismic data are required to elucidate the sedimentary facies patterns. When well control is limited, 3D seismic attributes or acoustic impedance inversion data are needed to construct a reliable reservoir model (e.g., Hart and Balch, 2000; Habibnia and Momeni, 2012). Five types of seismic attributes correlating well with sand percentage were used to describe the sedimentary facies: seismic wave are length (AL), root mean square (RMS) amplitude, effective belt width (EBW), instantaneous frequency (IF), and total absolute amplitude (TAA). Because the relative proportions of sand and shale in a set of clastic reservoirs can affect the spatial distribution of depositional environment (Issautier et al., 2012), the correlations between sand percentage and every seismic attribute were analyzed (Fig. 2): RMS showed a good correlation with sand percentage (Figs. 2-C, -D). The four wells were classified into two groups to allow analysis of the correlations between well position and gas-bearing characteristics. One group contains two wells, W1 and W3; the other group consists of wells W2 and W4.
The seismic attribute codes are as follows: AL, seismic wave are length; RMS, root mean square amplitude; TAA, total absolute amplitude; IF, instantaneous frequency; EBW, effective belt width. Except for RMS, the correlations of sand percentage versus those selected seismic attributes are not favorable. NB: There are six data points in each crossplot (from two wells and three Units, i.e., Unit I, II and III). Therefore, 12 data points (four wells and three Units) were used to analyze the relationship between seismic attributes and sand percentage. RMS was selected because of its good correlation with sand percentage and four data points (four wells, Table 1) in one Bed (Unit I, the study interval) were collected.
Table 1 Relationship of sand percentage versus RMS in Unit I

<table>
<thead>
<tr>
<th>Well name</th>
<th>RMS</th>
<th>Sand percentage (%)</th>
<th>Equation of sand percentage versus RMS</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>W1</td>
<td>60</td>
<td>45.7</td>
<td>y = 2.299098x - 86.8543</td>
<td>0.98</td>
</tr>
<tr>
<td>W2</td>
<td>70</td>
<td>77.1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>W3</td>
<td>40</td>
<td>6.4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>W4</td>
<td>72</td>
<td>77.8</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Sand percentages were obtained from four drilled wells and the values of RMS were determined from seismic data gathered at the well site. These two parameters show a linear positive correlation, \( R^2 \) is about 0.98. Therefore, the sand percentages of the points without the use of drilling can be calculated by RMS (root mean square amplitude).

The numerical values of sand percentage and RMS for each well position show a very good correlation (Table 1); therefore, RMS can be used to calculate the sand percentage of each pseudo-well site using seismic data. However, because the presence of gas will affect the seismic attributes, it is necessary to reduce these effects and obtain a more reliable relationship between lithology and seismic attributes. Different lithologies or gas-bearing features will show different seismic attribute values (Fig. 3). To allow more effective analysis of the seismic data, Unit I and Unit II were both subdivided into two layers, and Unit III was subdivided into three layers on the basis of interval thickness. The lithology and gas saturation were determined from well data, and could be of one of three possible types: gas-bearing sandstone, sandstone with water, and mudstone (shale). TAA and RMS were determined from the seismic lines that cross those wells. The RMS value of mudstone is less than 60, that of sandstone with water is between 55 and 85, and that of gas-bearing sandstone is between 75 and 120. The difference in RMS value between gas- and water-bearing sandstones is in the range 20 to 35 and the amount of impact is between 36% and 41%, with an mean value of 38%. Thus, the RMS value should be reduced by 38% when calculating the sand percentage.

The sand percentage values for all the pseudo-well sites were used to obtain the sand percentage distribution (Fig. 4). Subsequently, using the sand percentage distribution characteristics and classical deep-water submarine fan patterns, such as the 12 types of deep-water submarine fan models summarized by Reading and Richards (1994), the sedimentary facies distribution pattern of the study area was obtained (Fig. 5).

The sedimentary microfacies of the deep-water submarine fan in the study area mainly included channels, fan lobes, natural levees, and crevasse splay. Debris channels were the prevailing sedimentary facies. Channels situated in the west showed considerably less erosion than those situated in the east, and crevasse splay mainly developed along the eastern channel. Natural levees tended to form along the channels, and fan lobes were developed in front of terminal channels (Fig. 5).

3 Reservoir Modeling Methods

Using sedimentary microfacies patterns (Fig. 5), reservoir modeling was conducted as follows. First, sedimentary microfacies from drilled well(s) in Unit I were identified using electrofacies. The sedimentary microfacies model was constructed with sedimentary facies control boundaries using the sequential indicator simulation method. Subsequently, using constraints from sedimentary microfacies, reservoir properties were manipulated to ascertain suitable reservoir property cutoff values. Finally, the sequential Gaussian collocated co-kriging stochastic method was used to construct a reservoir property model controlled by the sedimentary microfacies model and seismic inversion data.

In general, in reservoir modeling, seismic data are considered to be soft data (i.e., not very reliable) because other factors may also affect the main variables. In the case of few wells, the use of a collocated stochastic seismic data reservoir model can increase the level of deterministic information and decrease the uncertainty between well locations. The collocated co-kriging stochastic approach is a type of geological statistical method suitable for use in these situations. The combination of this method with the sequential Gaussian simulation method (Isaaks, 1990) is termed the sequential Gaussian collocated co-kriging stochastic approach (SGCCS; Dehghani et al., 1999). The SGCCS method is suitable for analyzing continuous variables such as porosity and permeability.

For SGCCS, the stochastic variables should be normally distributed. Therefore, if the distribution of a variable is not normal, it must be transformed to a normally distributed variable for analytical purposes. The normally distributed variable was applied during modeling and then
and an indirect parameter (such as a seismic attribute) are applied to construct a reservoir property model, the parameters must be transformed to become normally distributed as follows:

\[ x(u) = \Phi[X(u)], \quad y(u) = \Phi[Y(u)] \]

Where \( X(u) \) is a direct parameter and \( Y(u) \) is an indirect parameter, and \( x(u) \) and \( y(u) \) are the results of the normal transformation. Using the normal transformation, the SGCCS method was adopted to construct a workable reservoir property model.

4 Reservoir Modeling Controlled by Facies

The structural model was constructed using a deterministic modeling method, i.e., the kriging method, combined with the uppermost horizontal information of the interval (interpreted from well and seismic data). The reservoir structural horizons were constructed using this method (Fig. 6). The horizon grid scale is 100 m\(^2\), the vertical resolution is sufficient for the identification of even the thinnest sandbody. This structural model is the basis for the other reservoir models, such as the sedimentary microfacies model and reservoir porosity model.

4.1 Process of sedimentary microfacies modeling

Although well data are available, it is difficult to construct a good sedimentary facies model without reasonable information on sedimentary patterns. During modeling, the assigned value method was adopted to provide the initial sedimentary model, which largely reflects the sedimentary patterns. Subsequently, sequential indicator simulation with control from the sedimentary facies distribution probability was carried out to obtain the final sedimentary model (Ma et al., 2009). Sequential
indicator simulation was adopted for construction of the sedimentary microfacies model because it allows for discontinuous properties. However, sedimentary microfacies were not observed in drilled wells, which should also be accounted for in the model (Fig. 7). As such, assigned value simulation was applied to the sedimentary microfacies pattern (Fig. 5). Sequential indicator simulation is a type of stochastic modeling method that has been adopted to construct sedimentary microfacies reservoir models, such as of debris channels, natural levees, and fan lobes, because of their strong reservoir heterogeneities. Assigned value simulation is a type of deterministic modeling method that can be used to construct models of stable or undrilled sedimentary microfacies. By integrating these two methods and applying the three types of available data, a reservoir sedimentary microfacies model was obtained (Fig. 7). Note that mudstone and shale are widespread, and their distribution varies very little, i.e., there is few uncertainty with respect to the mudstone for the area; thus, the assigned value simulation method is applicable to modeling of mudstone.

4.2 Probability of sedimentary microfacies distribution

In general, sedimentary microfacies modeling must be carried out with reference to the sedimentary sequence and the probability and patterns of sedimentary microfacies distribution. In this case, however, reliable statistical information could not be established solely from the four wells available. Therefore, we applied the assigned value simulation method to construct a conceptual sedimentary facies model and calculate the probabilities of different microfacies. The results show that debris channels are the most common facies in the study area, with a probability of more than 40.4%. Fan lobes and natural levees are very well developed, with probabilities of approximately 17.2% and 14.4%, respectively. The drilled wells were subdivided into 40 layers with an average thickness of approximately 1 m. Using data of these layers, the vertical distribution of sedimentary microfacies was reliably obtained. In general, debris channels are dominant and most widely developed in Unit I. The development of sandbodies in the lower section of Unit I is very poor, as a result of early marine transgression. Mudstone is dominant in the section, particularly in the outer fan area. The distribution probability of debris channels increases further to 50% while that of fan lobes decreases (Fig. 8).

4.3 Results of sedimentary facies modeling

As sedimentary facies are discrete variables, the most suitable modeling method is sequential indicator simulation, which is widely used for analysis of discrete variables (Seifert and Jensen, 1999; Deutsch, 2002). Constrained by sedimentary sequences and the patterns and probability of sedimentary facies distribution, the initial model for the major sedimentary microfacies was applied using the sequential indicator simulation. The undrilled sedimentary microfacies were also estimated using the assigned value simulation. Finally, by suitable integration of these two models, the final sedimentary microfacies model was obtained (Fig. 9).

The result of sedimentary microfacies modeling (Fig. 9) shows that the distribution of the major facies, debris channels, natural levees, and fan lobes is consistent with the sedimentary microfacies patterns (Fig. 5). Furthermore, the probabilities of these main factors show good agreement with the statistical results described above, in which the probabilities of debris channels, fan lobes, and natural levees are 34.9%, 15.6%, and 14.9%, respectively, and that of mudstone is more than 32% (Fig. 10).

4.4 Porosity modeling

4.4.1 Porosity statistic of major sedimentary microfacies

The initial reservoir modeling porosities are based on the statistics derived from the continuous well log data. The porosity values from the log data should display a positive correlation with the sedimentary microfacies. Such correlations will affect the final porosity model when discrete data, e.g., sedimentary microfacies, are adopted as constraints in the modeling process. Essentially, the amounts of the main sedimentary microfacies will directly affect the quality of the reservoir porosity model. However, abnormal values obtained during correlation between the continuous porosity and discrete microfacies may affect the quantitative statistics of the final porosity model. Therefore, any abnormal values must be excluded when we calculate and characterize the reservoir, making the distribution of the porosity of the geological model a
Fig. 8. Sedimentary micro-facies probability distribution according to the statistics of drilled well. Vertically, the debris channel facies developed most effectively.

Fig. 9. The process and controlled conditions of sedimentary micro-facies modeling. The top left graph shows a vertical sedimentary sequence, the top right graph vertically shows probabilities of each sedimentary micro-facies, and the middle diagram is a sedimentary micro-facie pattern. These three conditions were adopted to build a facies model at the bottom left with the sequential Gaussian simulation method. The bottom right diagram displays the assign value simulation results and these two models will be integrated to form the final sedimentary micro-facies model.
better fit to reality.

Suitable porosity cutoff is very important for a reservoir model (Wang et al., 2014). The correlation between sedimentary microfacies (discrete data) and porosity (continuous data) can be obtained from the statistical relationship between sedimentary microfacies and porosity using the interpreted cutoff values of effective sand (i.e., gas-bearing sand) and the average log porosity values. From the data obtained from the log curve, Unit I in well W4 may indicate that the debris channels have the best (i.e., highest) porosity, and the porosity values of the fan lobe and natural levee are also quite favorable (Fig. 11), in good agreement with the geological parameters.

Data analysis and processing were carried out on the three types of microfacies (debris channel, fan lobe, and natural levee) in Unit I. The final porosity model was mainly constrained by the three sedimentary microfacies and was suitable for use in quantitative modeling. The distribution of porosity obtained from the well logs should have a similar statistical trend to that obtained from the geological model.

The properties and flow currents of debris channels are intrinsically complex and contain the best reservoir quality in the deep fan reservoir with high-amplitude blocky gamma ray readings. Abnormal porosity values (less than the cutoff value) arising from inaccurate correlation between porosity and log microfacies, may affect the porosity model, resulting in a poor-quality geological model. Therefore, the porosity model can be more accurately constrained by incorporating assigned cutoff values and log statistics before constructing the model. If the porosity probability distribution is close to a normal distribution, the modeling result controlled by the microfacies is more credible with the sequence Gaussian simulation method. The porosity of the debris channel is mainly greater than the cutoff value (0.2) in the study area, and the average value of debris channel porosity is 0.24 throughout the cutoff treatment (Fig. 12).

The fan lobe is located at the entrance of the main debris channel, where the flow current has different flow power and characteristics from the current in debris channel. The fan lobe was deposited in a lower-power environment, and contains finer and more thinly bedded sediments, showing a sheet-like or lobate distribution. The porosity of the fan lobe (with a cutoff value of 0.09) has a lower overall value. The average porosity of the fan lobe is 0.13, which is markedly lower than that of debris channel (Fig. 13).

The natural levee is located on both sides of the debris channel, and is formed of thin-bedded sediments that were transported by turbulent currents. The porosity of the
natural levee (with a cutoff value of 0.12) has a mean value around 0.15 after excluding the abnormal values (Fig. 14).

From the results of the data analysis and processing, the percentages and effective porosities of these three types of major sedimentary microfacies (debris channels, fan lobes, and natural levees) can be calculated (Table 2). The sedimentary microfacies distribution was taken into account, and the correlation between porosity and each sedimentary microfacies was normalized for use as the geostatistical basis of the reservoir model.

4.4.2 Results of porosity modeling

The porosity model is the most important property model for quantitative reservoir characterization. It was constructed using constraints from the structural model and sedimentary microfacies model. The well log data have higher vertical resolution and can reflect the characteristics of the thin layers of sediments. In addition, because the drilling data are sparse, it is necessary to apply the lateral prediction function of seismic inversion data. We chose the sequential Gaussian algorithm for simulation of continuous variables, from which porosity model could be constructed.

In the process of constructing the porosity model, seismic inversion values at well sites were extracted for Unit I; then a correlation between the well porosity data and seismic inversion data was established. Finally, the
most appropriate geological modeling method was selected on the basis of its goodness of fit. Because of the poor correlation between seismic inversion data and porosity, the sedimentary microfacies model was required to control the porosity modeling with seismic inversion data. The sequential Gaussian method was then adopted to perform random simulation, as well as to construct the final 3D porosity model (Fig. 15A).

Integrated with the sedimentary microfacies model controlled by sedimentary microfacies with seismic inversion data, it is suggested that the final porosity model is in good agreement with the sedimentary geological patterns and can reflect the spatial distribution of deep-water submarine fan. However, because seismic data have a low resolution and a high degree of uncertainty, there is a poor correlation with the porosity values from well log interpretation. Therefore, the porosity model constructed using only seismic inversion data cannot reflect spatial variations of porosity, and does not accurately reflect the real geology. In the study area, the porosity model constructed by seismic inversion data could only approximately simulate the physical property distribution of the structural crest. In contrast, for other parts of the reservoir with more complex spaces the model could not provide adequate forecasts; for example, the porosity distribution of lobes in the south and the channel in the east were not predicted clearly (Fig. 15B and Fig. 5). By integrating both sedimentary facies patterns with seismic data, the porosity model controlled by microfacies can provide more detailed information (Fig. 15A and Fig. 5).

<table>
<thead>
<tr>
<th>Type</th>
<th>Debris channel</th>
<th>Fan Lobe</th>
<th>Natural Levee</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effective porosity</td>
<td>0.24</td>
<td>0.13</td>
<td>0.15</td>
</tr>
<tr>
<td>Probability of sedimentary micro-facies</td>
<td>34.9%</td>
<td>15.6%</td>
<td>14.9%</td>
</tr>
</tbody>
</table>

Fig. 14. The porosity histograms of natural levees. (A), Statistic showing total porosity of natural levees; (B), Statistic showing porosity truncation of the natural levees.

Fig. 15. The two porosity models in Unit I of Gas Field. (a), The porosity model is controlled by the sedimentary micro-facies model collocated seismic inversion data; (b), The porosity model with seismic inversion data only.
5 Discussion

We proposed a reservoir modeling strategy integrating sedimentary facies with seismic data to address the problem of inadequate data with rare wells. To obtain a perfect reservoir model, seismic attributes should be optimized to ensure good correlation between sedimentary parameters and seismic data. Suitable modeling methods should be chosen for different reservoir models. In this study, the Gaussian collocated cokriging stochastic simulation method and reasonable cutoff values of reservoir properties were selected to construct satisfactory reservoir models for an example of a deep-water sandy debris flow. Uncertainties in the models resulted from the presence of gas in the reservoirs. Differences in sedimentary facies recognition will also result in different reservoir models.

6 Conclusions

A two-step reservoir modeling method was proposed and adopted to construct a reservoir model incorporating the advantages of both stochastic and deterministic modeling. The final reservoir model is in good agreement with the three constraints: the sedimentary sequence, sedimentary patterns, and probability of sedimentary microfacies distribution.

For an exploration area with few drilled wells, collocated seismic data are adequate to create a reservoir model constrained by sedimentary microfacies. However, the credibility of the model will be reduced by using only seismic data to construct the reservoir model, particularly when the correlation between reservoir properties and seismic data is not accurate or appropriate.

To ensure that the porosity model is consistent with the subsurface reservoir, the porosity cutoff value of the major sedimentary microfacies should be determined before the reservoir porosity modeling process using collocated seismic data and controlled by a sedimentary microfacies model. Otherwise, the final porosity model will not be credible. Suitable truncation treatments were used to obtain more reasonable porosity cutoff values for the three major sedimentary microfacies; therefore, the final porosity model shows good consistency with the subsurface reservoir geology.

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