



Uncertainty in estimation of coalbed methane resources by geological modelling



Fengde Zhou ^{a,*}, Zhenliang Guan ^b

^a School of Petroleum Engineering, University of New South Wales, NSW 2052, Australia

^b Key Laboratory of Tectonics and Petroleum Resources of Ministry of Education, China University of Geosciences, 430074, China

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ABSTRACT

This paper presents an uncertainty analysis of coalbed methane resources estimation for a coal seam gas field containing multiple coal seams. Firstly, logs from nine wells and laboratory data from nine coal seams were used to predict the coal thickness, ash content and gas content at nine boreholes. Secondly, the structural models were determined using the well correlation, structural contour and coal seam thicknesses maps from coal mine data by the convergent gridded and sequential Gaussian simulation methods. Then, distributions of coal density and ash content were generated in 3D by using sequential Gaussian simulation based on the well log interpretations. Then, the distributions of gas content for each cell were built by two methods; one is multivariable regression analysis in 3D and the other is sequential Gaussian simulation based on the log interpreted gas content. Finally, coalbed methane resources were estimated based on the cell volume, coal density, net to gross ratio and gas content. In coalbed methane resources estimation, four different density cutoffs were used to define the net to gross ratio of coal in 3D. Results show that the gas contents decreases with increase in depth though with increases of vitrinite reflectance ratio, fixed carbon content and pressure. Calculated gas content from linear multivariate regression by using parameters of ash content, volatile matter content and fixed carbon content and sample's burial depth matches well with laboratory measured values. The total coalbed methane resources estimated are similar by the two geological modelling processes, the multivariable regression analysis in 3D and the sequential Gaussian simulation. It has been found that the effects of coal density cutoffs on coalbed methane resources for different coal seams are different.

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1. Introduction

Coalbed methane (CBM) resources Estimation is a complex process (Jenkins, 2008) but it is important for planning and design of coal seam gas production (Zhou et al., 2012). The resource estimation is highly uncertain because it depends on the distributions of coal thickness, coal quality, gas content, gas saturation, etc. But the distribution predictions for those parameters are uncertain. Hence, the uncertainty associated with the estimation of CBM resource must be assessed (Zhou et al., 2012, 2015).

Three techniques, field analogs, volumetric methods and probabilistic methods were used in CBM resources estimation (Jenkins, 2008). For the volumetric method, the CBM resources are

calculated based on the 3D distributions of coal quality and gas content. Coal seam thickness, coal density, and gas content are considered to be major parameters that introduce the uncertainty in resource estimation (Wang et al., 1997; Zuo et al., 2009). Hence, the uncertainty in calculating of CBM resources comes mainly from two sources, well log interpretation and predicted distributions of coal thickness, coal quality and gas content (Zhou et al., 2012). Note that parameters related to 3D modelling, e.g. drilling density, structural uncertainty (well correlation errors, fault geometry, isopach/isochore issues) and gas saturation are also important for uncertainty analysis but beyond the range of this paper.

Log interpretation by integrating laboratory and log data is carried out firstly to estimate the coal quality and gas content at boreholes. Next, the statistical analysis is carried out to characterise coal quality and gas content in horizontal and vertical. Thus the generated data are used in geological modelling. In laboratory, coal gas content, weight percent of moisture, fixed carbon and volatile matter content, desorption time and coal bulk density are normally

* Corresponding author. University of Queensland, School of Earth Sciences, QLD 4072, Australia.

E-mail address: f.zhou@uq.edu.au (F. Zhou).

measured for each sample. Coal maceral compositions, e.g. vitrinite reflectance ratio (VRO, %), vitrinite, liptinite and inertinite, are measured in separate experiment. Coal ash and sodium content (Heriawan and Koike, 2008a), volatile matter content (Hagelskamp et al., 1988), sulfur content (Bancroft and Hobbs, 1986; Beretta et al., 2010) need to be studied as part of the assessment of coal quality. The coal quality parameters were used to predict gas content (Zhou et al., 2012). Nolde and Spears (1998) calculated the gas content using a linear regression equation in which the depth is the only independent variable. According to Nolde and Spears, the gas content increases with increase in depth. The authors presented a model equation based on the desorption values for the 61 low volatile bituminous coal samples. Fu et al. (2009) estimated the gas content using multivariable regression analysis by relating data, such as burial depth, resistivity, sonic slowness and density log (RHOB) with measured gas contents from 64 samples. Only one of the five reported equations by Fu et al. (2009) shows that the gas content decreases with increase in burial depth but the reason was not represented. Gas content was also estimated by relating with the pressure, temperature, and the ratio of fixed carbon over volatile matter content in wt% (Kim, 1977).

The log derived data is geostatistical analyzed to estimate distributions of coal thickness (Jakeman, 1980; Mastalerz and Kenneth, 1994), coal quality (Cairncross and Cadle, 1988; Hagelskamp et al., 1988; Liu et al., 2005; Heriawan and Koike, 2008b; Beretta et al., 2010; Hindistan et al., 2010) and coal tonnage (Heriawan and Koike, 2008a). Sequential Gaussian simulation (SGS) and ordinary Kriging methods are used to predict the distribution of coal thickness and coal quality (Beretta et al., 2010). Zhou et al. (2012) presented an uncertainty analysis of CBM resources using the stochastic reservoir modelling for a CBM field in southeast Qinshui Basin from China. They reported that the heterogeneities in coal seam thickness and coal quality lead to increasing uncertainty in estimating CBM resources. The authors also reported that the density variogram and coal seam roof surface contribute less to the uncertainty estimation of CBM resources. But sufficient data, sound log interpretation models and appropriate geological methods can improve the reliability of resource estimation.

In this paper, the uncertainty in CBM resources estimation is analyzed for a producing CBM field containing multiple coal seams. Well logs, laboratory data and the data obtained from coal mining are used to predict the coal structure, coal thickness, coal quality and gas content. Noteworthy is that the gas content distribution is estimated by using two different techniques: the multivariable regression analysis in 3D and the SGS. The uncertainty is assessed firstly by analyzing the effects of coal density cutoffs on resource estimation, secondly comparing the resource estimation based on the distributed gas content by the multivariable regression analysis in 3D and the SGS analysis and finally, analyzing the relationships of coal bulk density with ash, fixed carbon, and volatile matter contents. It is assumed that the statistics of gas content, proximate analysis and logging data from the nine wells can be taken as representative for the study area.

2. Data

2.1. Field data

Fig. 1 shows the litho-stratigraphic succession of coal seam XVIII to coal seam I from top to bottom. These coal seams dip gently with dip angles ranging from 5° to 15° except in the vicinity of fault and the seams dip towards the basin centre in general (Saikia and Sarkar, 2013). The mining methods for gently dip seam are the same as in flat seams but mining conditions are a little more

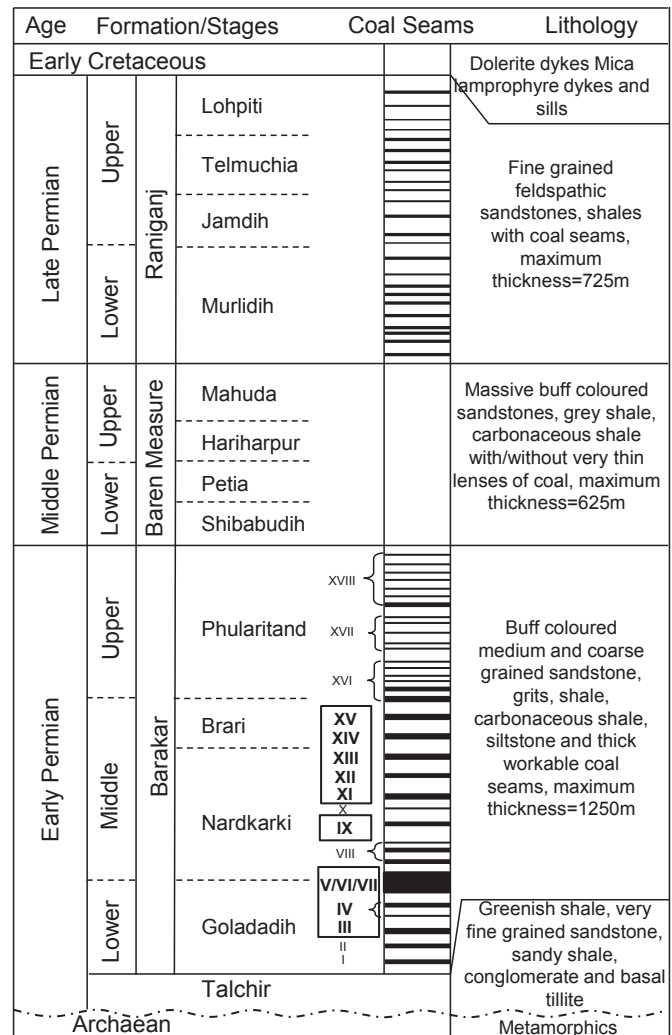


Fig. 1. A schematic of the stratigraphic succession showing coal seams. Coal seams numbers in rectangles are objectives of this study (After Saikia and Sarkar, 2013).

difficult (Jeremic, 1985). The fault's opening ability affect the gas saturation in coal and the dewatering process because the open fault will be a conduit for gas and water flow.

In the study area, logs are used to correlate coal seams with their characteristics, namely stratigraphic sequence, thickness, variation of log attributes etc. Fig. 2 shows two cross sections of the nine wells. Results show that the coal seams can be identified by typical values of bulk density (RHOB) and gamma ray (GR). The sandstone sequences are characterized by lower GR response, however, higher RHOB, which is similar to that of the mudstone; GR response in mudstone is the highest of the three. Archaean gneiss is located at the south of the study area (Paul and Chatterjee, 2011; Singh et al., 2013; Saikia and Sarkar, 2013) which was intersected by the well #F (Fig. 2) at its deepest section. The Archaean gneiss is granite gneiss and characterized by high RHOB and low GR.

Structural map on the roofs of each coal seam and the thickness contour maps of each coal seam were drawn by using coal mining and coal seam gas boreholes. Fig. 3 shows the maps of structure and coal seam thickness for one of the coal seam No. III–IV. It shows that there are 17 faults and 14 of them are normal faults. Three reverse faults are located in tectonic transition area. Coal seam No. III–IV is thicker in the middle and north part of the study area.

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