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Use of a Variable Shape Distribution (VSD) Model to Populate Reservoir Properties in Tight Fractured Reservoirs for Numerical 3D Modeling

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Use of a Variable Shape Distribution (VSD) Model to Populate Reservoir Properties in
Tight Fractured Reservoirs for Numerical 3D Modeling

by

John Freddy Ramirez Vargas

A THESIS

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Abstract

Hydrodynamic plots of tight formations in the Deep Basin of the Western Canada Sedimentary Basin (WCSB) indicate the lack of a water leg and the presence of water on top of gas; quite unconventional. Furthermore, experience indicates that in many instances properties such as matrix and fracture density in these tight formations cannot be modeled using conventional statistical distributions. Widely used approaches such as normal, geometric and fractal distributions do not reproduce accurately the behaviour of such properties in many cases. Thus it could be said that the unconventional fluids distribution meets the unconventional rocks distribution in unconventional formations. These occurrences have led to the development of the research presented in this work. Original contributions are as follows:

- 1) Reservoir simulation covering over 1.5 million years that corroborates the presence of a block of water on top of gas in the tight gas Nikanassin formation of the WCSB.
- 2) Implementation of a new methodology to populate matrix and fracture density properties in reservoir simulation with the use of a Variable Shape Distribution (VSD) model.

The question is if it is reasonable to think that gas can be trapped for hundreds of years and more by an updip water block. A reservoir simulation model has been created as indicated in item 1 above in order to answer this question. The water seal is shown to be the result of very low permeability and high capillary pressures, properties that are generally found in tight gas formations. The model is defined by a geometry that mimics the geologic interpretation of the Nikanassin Basin Center Gas Accumulation (BCGA) in the Western Canada Sedimentary Basin (WCSB) and rock properties that provide a good representation of the real behavior of the reservoir in the Deep Basin of Alberta. Reservoir simulation has been used historically to model in the order of 10 to 40 years of production. But to our

knowledge this is the first reservoir simulation that goes beyond 1.5 million years. The results lead to the conclusion that updip water blocks provide good seals in the Deep Basin. The new methodology mentioned above in item 2 introduces an extension of the VSD approach for reservoir simulation purposes. In the original methodology when matching input information in the VSD equation, each data point is assigned an integer according to its ranking (N_t) in the overall sample population. If these integers are used in a normal score transformation for reservoir simulation, the hard data (for example permeability) will not be honoured. As a result, in order to honour the hard data, the integers have been replaced with real numbers found by calculating the values that produce the exact data points when input into the VSD equation. Since this equation has an exponential form it cannot be solved directly for N_t and it is necessary to perform an iterative process to find the exact values.

The new methodology is demonstrated with data from the WCSB tight gas Nikanassin Group and Cadomin formation. The result is a good comparison between wells with the best cumulative gas production and areas with the largest fracture density in Township 65 Range 09, located in the Rocky Mountains in Alberta. The results lead to recommendations to drill and multi-stage hydraulically fracture horizontal wells in specific areas of such Township.

It is concluded that the VSD is a valuable tool that has significant potential for applications in conventional, low and ultra-low permeability formations and for evaluating distribution of rock properties at the micro and nano-scale. In the case of reservoir simulation the VSD can be extended to generate more rigorous static models.

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Thanks to Schlumberger and CMG for providing the software and training required for the completion of my work.

Finally I want to thank my wife for her support and for accompanying me during the conduction of this research.

Dedication

I dedicate this thesis to my wife Sonia Plazas for her love and encouragement, to my mother Aura Lilia Vargas for being my inspiration, to my family for the support they have given to me, and to God for being my all.

“The fear of the Lord is the beginning of knowledge, but fools despise wisdom and instruction”.

Proverbs 1:7

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List of Symbols, Abbreviations and Nomenclature

Nomenclature

a = Semivariogram Range (m)

a_p = Pareto slope

CDARCY = Darcy's constant, 8.527×10^{-3} (metric units) or 1.127×10^{-3} (field units).

D = fractal dimension

FD = Fracture density, fracture area (m^2) per unit volume (m^3)

h = Lag, or separation distance between data points (m)

k = Semivariogram lag

K = Matrix permeability

l = matrix block size

N_m = minimum number of samples (= 1)

N_t = cumulative number of samples

N_x = maximum number of samples

NSD = Normalized standard deviation of well cumulative gas production (dimensionless)

R^2 = Coefficient of determination (dimensionless)

S = severity exponent that controls the steepness of the slope of the estimated VSD curve where it separates from the Pareto straight line (on the right hand side of the distribution, near the largest values)

TR = Matrix-fracture transmissibility

V = Matrix cell bulk volume

V_i = Size of a sample

V_m = minimum size of a sample

V_s = approximate size which the data begins to deviate from the Pareto straight line (on the right hand side of the distribution, near the largest size). This is a good starting point for the calculations but it can change during the fitting procedure of the real data

V_{tf} = final, estimated size of a sample

V_x = maximum size given by the Pareto straight line (at $N_m = 1$)

Z_i = Data points taken from a sample

$\bar{Z}$ = Mean of a sample

$\hat{Z}$ = Estimator for a property Z

Greek Symbols

α = slope of Pareto straight line

γ = Semivariance (dimensionless)

λ_i = Kriging weights

σ_0^2 = Semivariogram nugget

σ^2 = Semivariogram sill

σ_0^2 = Variance of a variable

σ_{0i}^2 = Covariance of a variable with measured points

σ_{ij}^2 = Covariance between measured points

σ_{SK}^2 = Simple kriging variance

σ_{OK}^2 = Ordinary kriging variance

σ = Shape factor to account for the matrix/fracture interface area per unit volume

ψ = separation ratio that controls the amount of separation between the Pareto straight line and the estimated VSD curve (on the right hand side)

Abbreviations

2D = two-dimension

3D = three-dimension

AAPG = American Association of Petroleum Geologists

APOGCE = Asia Pacific Oil & Gas Conference and Exhibition

BCGA = Basin Centered Gas Accumulation

BHP = Bottom Hole Pressure

CDF = Cumulative Distribution Function

DFN = Discrete Fracture Network

GFREE = Geoscience G), Formation Evaluation (F), Reservoir drilling, completion and stimulation (R), Reservoir Engineering (RE), Economics and Externalities (EE). The GFREE team researches an integrated approach for optimizing rates and recoveries from low permeability reservoirs

MMSM3 = Million Standard Cubic Meter

NSERC = Natural Sciences and Engineering Research Council of Canada

PRA = = Peace River Arch

PRE = = Peace River Embayment

SCFD = Standard Cubic Feet Day

SPE = Society of Petroleum Engineers

USGS = United States Geological Survey

UWI = Unique Well Identifier

VSD = Variable Shape Distribution

WCSB = Western Canada Sedimentary Basin

Chapter One: **Introduction**

Exploitation of unconventional resources has become a key issue in the world energy market; this is mostly due to production decline of conventional oil and gas. In the United States production of tight and shale gas and oil have led to predictions of energy self-sufficiency in the near future. However, the understanding of these kinds of reservoirs is still under development with the bulk of the work performed from roughly 2005 to date concentrating on the quest for operational efficiency. This has led to the revival of some ‘unconventional plays’ and to the development of new ones. This has been called Shale 1.0 by Meisenhelder (2013).

Meisenhelder (2013) further describes “Shale 2.0: The Coming Revolution in Effectiveness.” In here he describes upgrading his Shale 1.0 model “by understanding the rock first” before drilling 100s or 1,000s of wells.

This was the same idea of the GFREE research program introduced at the University of Calgary in 2006. GFREE refers to a program that integrates geoscience (G), formation evaluation (F), reservoir drilling, completion and stimulation (R), reservoir engineering (RE), and economics and externalities (EE) with a view to finding means of improving production rates and ultimate recoveries from unconventional reservoirs.

The kernel of the GFREE is the proper understanding of rocks (Aguilera and Harding, 2011) as well as their regional variability of fracture distribution, mineralogy and diagenesis. Previous research on understanding the rocks in ‘unconventional reservoirs has been performed by GFREE members (for example, Solano (2010), Ortega (2012), Ortega and Aguilera (2013 and 2014), Olusola (2013), Olusola et al. (2013), Zambrano et al. (2013) and Zambrano (2014)).

This thesis advances the previous findings by investigating problems associated with the distribution of fractures and petrophysical properties in unconventional reservoirs. For example, it has been found that some of these properties cannot be modeled using any conventional statistical distribution. Even the widely used fractal distribution for naturally fractured reservoirs does not reproduce accurately the behaviour of such properties.

Therefore it was necessary to develop and implement a new methodology to model the properties of tight naturally fractured reservoirs more accurately. This goal was achieved in this thesis with the use of a Variable Shape Distribution (VSD) model. **Figure 1.1** shows how the mega-scale gas endowment volumes published by the United States Geological Survey, USGS (2000) can be matched with the VSD model ($R^2 = 0.98$). **Figure 1.2** shows how the VSD method can be extended to a micro-scale of fracture apertures. The graph includes a good fit of micro and macro-fractures without any data truncation ($R^2 = 0.99$).

Figure 1.1 World conventional natural gas endowment calculated with variable shape distribution (VSD) model (After Aguilera, 2006).

Figure 1.2 Cozzette aperture size distribution for microfractures (purple squares), macrofractures (green circles) and all fractures (black diamonds); and insert published by Hooker et al. (2009). VSD distribution shown by the red line provides a good fit of the real macrofracture and microfractures data with only one equation ($R^2 = 0.994$) (After Aguilera et al., 2012).

1.1 Objectives

The key objectives of this thesis are the implementation of the VSD model for reservoir characterization of the Nikanassin formation (Late Cretaceous, Early Jurassic) in the Western Canada Sedimentary Basin (WCSB), and the rigorous construction of a static model for numerical 3D simulation. The VSD distribution worked very well for modeling the world petroleum endowment (Aguilera, 2006) and is shown in this thesis to provide very precise matches for different petrophysical and fracture properties. Research objectives are defined as follows:

1. Develop a methodology that integrates the VSD model with recognized geostatistical methods in order to build more rigorous static models. The Nikanassin Group in Township 65 – Range 9 (Alberta) is used for illustration purposes. This is referred to as the ‘study area’ in this thesis. However, the methodology is developed in sufficient detail in such a way as to allow easy implementation in other areas around the world where the same ‘properties distribution’ problems might be present.
2. Evaluate the impact of the methodology in history matching and production forecasting. The VSD model is shown to be capable of capturing the behaviour of tight fractured reservoir properties in the whole scale spectrum without any truncation. This is a significant improvement over previous approaches.
3. Identify areas with high fracture intensity that are more favourable for drilling horizontal wells as they present the best potential in terms of well productivity and recovery.

1.2 Study Area

The area selected for this research is Township 65R09W6 in Alberta, and the strata of interest is the Nikanassin Group that belongs to the Alberta Deep Basin in the WCSB. The area is located within the Red Rock field and it covers an area of 36 mi² (approximately 100 km²). **Figure 1.3** shows the location of the study area. The Cadomin formation was also included in the study given the fact that most of the wells in the area produce commingled from these two formations.

Figure 1.3 Location of the Deep Basin (part of the Western Canada Sedimentary Basin) in Alberta and British Columbia (area shaded with yellow). The red square highlights the study area. Source: (Gonzalez et al., 2012)

The Nikanassin Group, as many other reservoirs in the Deep Basin, falls in the category of an unconventional reservoir due to its very low permeability. It is also considered to be part of a Basin Centered Gas Accumulation (BCGA). These accumulations are characterized by being regionally pervasive, with continuous gas or oil saturation, are abnormally pressured, they lack a downdip water contact, and have low permeability throughout the reservoir (Law, 2002).

The BCGA's jointly with tight gas, tight oil, coalbed methane, shale oil, shale gas, gas hydrates, and shallow biogenic gas form part of a wider group called Continuous Petroleum Accumulations. In addition to the geologic features already mentioned above common characteristics include large areal extent, lack of obvious trap and seal, and close association with source rocks. Furthermore, "these accumulations share production characteristics that include a large in-place petroleum volume, low recovery factor, absence of truly dry holes, dependence on fracture permeability, and sweet spots within the accumulation that have generally better production characteristics" (Schmoker, 2005).

An important characteristic of the study area is that gas is trapped by an updip water block. The question is if it is reasonable to think that gas can be trapped over millions of years by a water block. To answer this question a reservoir simulation model was created as part of this thesis. The water seal is shown to be the result of very low permeability and high capillary pressures, properties that are generally found in tight gas formations.

1.2.1 The Nikanassin Group and Cadomin Formation

"The stratigraphic group corresponds to the Upper Jurassic/Lower Cretaceous strata currently present in the subsurface of west-central Alberta and east-central British Columbia" (Solano et al., 2011). Nikanassin strata can be stratigraphically subdivided in

three main units: Monteith, Beattie Peaks, and Monach from older to younger, respectively (Miles et al., 2009).

Among the three units the Beattie Peaks has the least potential for production as it consists mainly of shale and siltstone. Completions in this unit have been failures in terms of production. The Monteith formation is the thickest unit within the study area with an average thickness of 130 m. It has an average permeability of 0.05 mD, and is considered the most important in terms of production (Gonzalez, 2012). The Monach formation has high sandstone/shale ratios (89-95%), and its mineralogical composition is predominantly characterized by litharenites (Miles et al., 2009). Monach's thickness was affected by an unconformity with the overlying formations and as a result the average thickness is only around 40 m in the study area.

“The Cadomin Formation marks an erosional unconformity that truncates older Mesozoic and Paleozoic beds throughout a large part of the region” (Stott, 1998). It consists of conglomerate and conglomeratic sandstones with better permeability and porosity than the Nikanassin Group units.

Exhaustive geological description of the area of interest has been done by different members of the GFREE research group at the University of Calgary (see for example Solano et al., 2011, Zambrano et al., 2013, Zambrano, 2014).

1.3 Thesis Chapters

This thesis has been divided into seven chapters as follows:

Chapter one provides an introduction to the thesis, describing the objectives and the organization.

Chapter two presents a literature survey of basic statistical and geostatistical concepts and an overview of petrophysical modeling methods widely used in the industry to construct static reservoir models. These methods include deterministic approaches as well as stochastic simulation methods.

Chapter three describes the models used to corroborate that gas can be trapped by a water block in the Deep Basin of the WCSB, and that the Nikanassin Group presents this feature characteristic of BCGA. The models are defined by a geometry that mimics the geologic interpretation of the Nikanassin BCGA in the WCSB and rock properties that provide a good representation of the real behavior of the reservoir in the Deep Basin. Different models were created trying to understand sensitivities to permeability and capillary pressure in the distribution of downdip gas and updip water over more than a million years. The results obtained appear consistent and reliable when compared with factual information from the Deep Basin. The information included in this chapter was adapted from a previous publication presented during the development of this research; the title of the paper is “Updip Water Blockage in the Nikanassin Basin Centered Gas Accumulation, Western Canada Sedimentary Basin” (Ramirez and Aguilera, 2012).

Chapter four describes the mathematical derivation of the VSD model for estimating the distribution of the world petroleum endowment (Aguilera, 2006), and the utilization of this model for characterizing different reservoir properties. The latter is a micro-scale application that contrasts with the original use of the model which was at the macro and mega scale of global petroleum resources. This chapter is adapted from a SPE paper that was presented during the development of this study. The title is “A Variable Shape Distribution (VSD) Model for Characterization of Pore Throat Radii, Drill Cuttings,

Fracture Apertures and Petrophysical Properties in Tight, Shale and Conventional Reservoirs” (Aguilera et al., 2012).

Chapter five describes the methodology proposed in this research for the construction of the static model required in numerical simulations; it also includes the results of the application of the methodology in the study area and a comparison with the various input data available. This chapter was also taken from the SPE paper: “Use of a Variable Shape Distribution (VSD) Model to Populate Reservoir Properties in Tight Fractured Reservoirs for Numerical 3D Modeling” (Ramirez and Aguilera, 2013).

Chapter six presents the numerical 3D model description and the results obtained when using the VSD model in the petrophysical modeling. This chapter also includes proposals for drilling horizontal wells in areas that show the highest potential for production.

Chapter seven states the conclusions reached in this study and recommendations for future research.

1.4 Technical Publications

Parts of the results of this research have been presented at the following international conferences of the Society of Petroleum Engineers (SPE):

- “A Variable Shape Distribution (VSD) Model for Characterization of Pore Throat Radii, Drill Cuttings, fracture apertures and petrophysical properties in Tight, Shale and Conventional Reservoirs,” SPE 158808 presented at the Asia Pacific Oil & Gas Conference and Exhibition (APOGCE) in Perth, Australia (22 - 24 October 2012) by Roberto F. Aguilera, Camilo Ortega, John F. Ramirez and Roberto Aguilera.
- “Updip Water Blockage in the Nikanassin Basin Centered Gas Accumulation, Western Canada Sedimentary Basin,” SPE-162774-PP presented at the SPE

Canadian Unconventional Resources Conference in Calgary, Canada (October 30-November 1, 2012) by John F. Ramirez and Roberto Aguilera.

- "Use of a Variable Shape Distribution (VSD) Model to Populate Reservoir Properties in Tight Fractured Reservoirs for Numerical 3D Modeling," paper SPE 167290-MS presented at the 2013 SPE Kuwait Oil and Gas Show and Conference held at Kuwait International Fair, Mishref, Kuwait (7-10 October, 2013) by John F. Ramirez and Roberto Aguilera

Chapter Two: Literature Survey

2.1 Basic Statistics and Geostatistics Concepts

Statistic tools have been widely used to analyze, describe, and model data. Use of statistics in the petroleum industry has had a transition from description to modeling, leading to geostatistics, a branch which is focused on the behavior of random variables in space.

The objective of modeling is basically to predict the values that a variable can take, based on collected data and the information that can be obtained from it. Those predictions can be deterministic or stochastic. Deterministic predictions are, by far, superior to stochastic since they leave no place for uncertainty, but uncertainty from models theory and data input. However, in reality there are not completely deterministic systems, in fact most properties seem to have a random behavior. This randomness is defined as the behavior of a system or process which produces uncertain results, which might show extreme sensitivity to initial conditions. The randomness is given by two main properties; a non-linear physical law and iterative processes. These properties can be found in petroleum reservoirs; the equations for Darcy flow and two phase fractional flow are clear examples of non-linear physical law, and some processes in geology such as growth of clays, cementation, sedimentation, erosion and breakage are iterative.

Given the stochastic nature of the petroleum reservoir physical properties, there is a restriction to use stochastic predictions to model such properties.

2.1.1 Heterogeneity

Normally, heterogeneity and variability are used indiscriminately. But from the petrophysical point of view, heterogeneity is defined as the property of a permeable

medium that causes a flood front to distort and spread. The property of the media with the largest contribution to flood front distortion and spread is permeability (Jensen et al., 2000).

Heterogeneity measures are divided in two groups:

- Static measures: These are measure of reservoir properties of a sample from the formation that require a flow model to interpret their effect in the flow.
- Dynamic measures: Are direct measures of how the heterogeneity affects the flow.

2.1.2 Correlation

According to the definition of Jensen et al. (2000), “correlation is the expression of how two or more random variables are related.” It is less powerful than regression given that it does not develop a predictive relationship. Correlation is also known as co-variation, and since it is a dimensionless quantity, it can be used to compare relationships between variables with different units.

The purpose of the correlation in geostatistics is to help in the study and understanding of spatial relationships, so in data analysis correlation is divided in three types(Jensen et al., 2000; Montgomery and Runger, 2003). These types are shown in figure 2.1.

- Simple correlation: Relationship between two different variables of different sample spaces, but at the same location. An example is provided by porosity and permeability in Well No. 1 in Figure 2.1.
- Crosscorrelation: Relationship between samples of the same variable, but taken at different locations. This type is shown on Figure 2.1 for the case of permeability.
- Autocorrelation: Relationship between variables of the same sample space taken at different locations. Figure 2.1 shows this type of correlation in Well No. 1.

Figure 2.1 Schematic illustration of correlation types for porosity and permeability
Source: (Jensen et al., 2000).

The last type, autocorrelation, is used to measure and find how data points close to each other correlate, and the strength of the correlation is given by the autocorrelation coefficient, r , that can be obtained from the following equation (Jensen et al., 2000):

$$r(k) = \frac{1}{1-k} * \frac{\sum_{i=1}^{1-k} [(Z_i - \bar{Z})(Z_{i+k} - \bar{Z})]}{\sum_{i=1}^I (Z_i - \bar{Z})^2} \dots (2.1)$$

Where:

k : Lag, or separation distance between data points

Z_i : Data points

$\bar{Z}$: Mean of the sample

2.1.3 Semivariance and Semivariogram

Contrary to the autocorrelation, the semivariance is a measure of dissimilarity, and it gets its maximum value when there is not any correlation between data points. The estimator for the semivariance is given by Equation 2.2 (Jensen et al., 2000).

$$\hat{\gamma}(k) = \frac{1}{2*(I-k)} * \sum_{i=1}^{I-k} (Z_i - Z_{i+k})^2 \dots (2.2)$$

Semivariance is always greater than zero, and as indicated by the expression, it does not involve the mean value. The main use of the semivariance is to construct the semivariogram that is one of the most important tools for different geostatistical methods. The semivariogram is a function that accounts for the spatial continuity of variables; it assumes second-order stationarity. An experimental semivariogram can be obtained by plotting semivariance vs. lag. In order to describe the semivariogram three parameters are often used: range, sill and nugget. Range is the maximum separation distance between two data points for them to be correlated; further than this distance data points have a random relationship. Sill is the variance where the separation distance is greater than the range, and the nugget is the extrapolation value of the variance at the origin, it characterizes the short scale variation of the data.

The process of obtaining the semivariogram model for a given variable of a reservoir is of paramount importance to produce a reliable estimation of the variable at locations where samples are not taken, given that geostatistical methods strongly rely on the assumption that the semivariogram provides an accurate representation of the variable continuity in space (Campozana, 1997).

Semivariograms can be experimental or theoretical. Experimental semivariograms are constructed with the measured data and the distance between the locations and are

restricted to the number of data points that are available. Figure 2.2 shows an example of an experimental semivariogram. The theoretical semivariograms refer to different models developed to fit the shape and trends of the experimental semivariogram. There are several theoretical semivariograms, but the most commonly used are: Spherical, Exponential, Gaussian and Hole.

Figure 2.2 Experimental semivariogram of porosity in vertical direction.

- Spherical: This three parameter model is the most popular among the autocorrelation models, given the robustness and stability it provides when solving the kriging equation system, it also has a linear behavior at short separation distances and a sharp transition to the sill. The equation that defines this model is the following (Jensen et al., 2000):

$$\gamma(h) = \begin{cases} \sigma_0^2 + (\sigma^2 - \sigma_0^2) * \left[1.5 * \left(\frac{h}{a} \right) - 0.5 * \left(\frac{h}{a} \right)^3 \right] & \text{for } h \leq a \\ \sigma^2 & \text{for } h > a \end{cases} \dots (2.3)$$

Where:

σ_0^2 : Nugget

σ^2 : Sill

a : Range

h : Lag

- Exponential: This model approaches asymptotically to the sill as the separation distance goes to infinity; the range is defined at an effective distance where variance is 95% of the sill (Jensen et al., 2000).

$$\gamma(h) = \sigma_0^2 + (\sigma^2 - \sigma_0^2) * \left[1 - \exp\left(-\frac{h}{a}\right) \right] \dots (2.4)$$

- Gaussian: This model is best suited for variables that are extremely continuous, at least in the short scales; at larger distances it approaches asymptotically to the sill. Range is defined in the same way than in the exponential model (Jensen et al., 2000).

$$\gamma(h) = \sigma_0^2 + (\sigma^2 - \sigma_0^2) * \left[1 - \exp\left(-\frac{h^2}{a^2}\right) \right] \dots (2.5)$$

- Hole effect: Many variables present a certain degree of cyclicity; the hole effect model accounts for this characteristic. The main feature of the model is that it presents troughs or holes and it does not reach a flat sill as other models. The holes represent data points that have some correlation even at long separation distances. It is given by the Equation 2.6 (Jensen et al., 2000).

$$\gamma(h) = \sigma_0^2 + (\sigma^2 - \sigma_0^2) * \left[1 - \frac{a}{h} * \sin\left(\frac{h}{a}\right) \right] \dots (2.6)$$

A graphic comparison between the semivariogram models explained above can be observed in Figure 2.3.

Figure 2.3 Schematic of the most common semivariograms; with nugget=0.3, sill=1.0 and range=20ft.

2.2 Petrophysical modeling methods

The objective of petrophysical modeling methods is to interpolate (all types of kriging) or to simulate (sequential Gaussian simulation, sequential indicator simulation, simulated annealing, among others) the values of a given property through the reservoir model. The input for these methods usually comes from well data, but it is necessary to perform a statistical analysis before the data can be used. Procedures involved in this analysis are construction of semivariograms, trends identification, normal score transformation (it can

include other type of transformations), among others. The most common methods of interpolation and simulation are explained below.

2.2.1 Kriging

Kriging was first developed to determine ore grade in gold mines. It is basically a statistical estimation technique, and the fundamental procedure for interpolating data. Despite the several types of Kriging that have been established, all of them share the same fundamentals and are related to regression.

Since Kriging is an interpolator, it uses known values of the random variable at sampled locations to estimate the value at an unsampled location. This is done by assigning weights to the known values according to the distance to the point of interest and the variance, and then combining the known values linearly to obtain the estimate. Equation 2.7 shows the common interpolator or estimator for a property Z (Jensen et al., 2000).

$$\hat{Z} = \sum_{i=1}^I \lambda_i Z_i \dots (2.7)$$

Where the λ_i 's are the Kriging weights, Z_i 's the known values and $\hat{Z}$ is the estimate. From the equation it is deduced that if the weights are found, it is possible to calculate the $\hat{Z}$.

Although the linearity of Equation 2.7 simplifies the procedure, it also means that the estimates $\hat{Z}$ are going to have a Gaussian or normal distribution. This is supported by the Central Limit Theorem, which states that “any random variable that is a sum of a large number of independent, additive events will become Gaussian, regardless of the underlying probability density function or distribution of the events” (Jensen et al., 2000). For the case of the kriging estimator, the sum of the independent events, $\lambda_i Z_i$, is going to be normally distributed even if the Z_i 's are not. This effect makes necessary the transformation of the data to a normal distribution before performing the analysis and estimation of the data.

The main objective of all kriging types is to produce estimates of a certain property at unsampled locations, and the way it is done is by calculating the Kriging weights. The procedure to find the weights is minimizing the error variance of the estimations; the error of the estimations can be defined as the difference between the estimated value and the true value. The definition and constraints of the error variance is what distinguished the different types. The most common types of kriging are briefly described next.

2.2.1.1 Simple kriging

This is the most basic type; error variance does not have any additional constraint and is defined by Equation 2.8. Since the expected value of the difference between the estimates and the true values is different than zero it is said that simple kriging is a biased estimator (Jensen et al., 2000).

$$\sigma_{SK}^2 = \sigma_o^2 + \sum_{i=1}^I \sum_{j=1}^I \lambda_i \lambda_j \sigma_{ij}^2 - 2 \sum_{i=1}^I \lambda_i \sigma_{oi}^2 \dots (2.8)$$

Where:

σ_o^2 : Variance of the variable

σ_{oi}^2 : Covariance of the variable with measured points

σ_{ij}^2 : Covariance between the measured points

The usual procedure to minimize a function of n variables is to take the n partial first derivatives and setting them to zero; which produces a system with n algebraic equations and n variables, which can be solved with no trouble.

2.2.1.2 Ordinary kriging

The main difference with simply kriging is that the bias is removed by adding a constraint to the problem: that the sum of the weights is equal to one. When minimizing the error variance this constraint increases the system of algebraic equations by one, as well as the

number of variables. The new variable is called the Lagrange parameter, represented by μ . The error variance is now defined as (Jensen et al., 2000).

$$\sigma_{OK}^2 = \sigma_o^2 - \sum_{i=1}^I \lambda_i \sigma_{oi}^2 + \mu \dots (2.9)$$

2.2.1.3 Indicator kriging

Indicator kriging follows the same procedure as simple kriging. The difference lies in the use of the indicator semivariogram instead of the usual one. It uses cutoff values of the property and an indicator variable to construct the semivariogram to be used; the semivariogram is not strongly dependant on the distribution of the original variable and is not affected by extreme values. It also provides an estimate of the conditional cumulative distribution function at the desired cutoff, and it does not require the transformation of Z.

2.2.1.4 Advantages and drawbacks of kriging

Since kriging is a deterministic method, *i.e.*, it provides a unique realization for a given set of data points; the computation time is relatively low. Kriging also yields the minimum error variance, is an unbiased estimator and uses the data structure. However, it has some disadvantages; one of them is that because of its deterministic nature it is not suitable to evaluate uncertainty. The variables end up with a Gaussian distribution and since the method is strongly dependant of the mean, the estimation surfaces are too smooth overlooking the existence of extreme values.

2.2.2 *Stochastic simulation*

Given the fact that is not possible to evaluate uncertainty with kriging, stochastic methods with the ‘uncertainty’ feature have been developed. Stochastic simulation procedures, defined as “the process of building alternative, equally probable, high-resolution models of the spatial distribution of a desired variable; the simulation is said to be conditional if

the resulting realizations honor data values at their locations” (Deutsch and Journel, 1994).

The most commonly used simulation methods are described next.

2.2.2.1 Sequential Gaussian Simulation

This method follows the sequential simulation principle, which conditions not only the measured data, but the previously simulated values within a neighborhood, to simulate new values. The procedure to generate a field of J cells from I data points, as defined by Jensen et al. (2000) is as follows:

1. Transform the sampled data to be Gaussian. The most common technique is the normal scores technique. This is a natural precursor to any Gaussian technique.
2. Assign each of the $(J-I)$ unconditioned cell values to be equal to those at the nearest conditioned cells. The values in the conditioned cells do not change in the following.
3. Define a random path through the field such that each unconditioned cell is visited once and only once.
4. For each cell along the random path, locate a pre-specified number of surrounding conditioning data. This local neighborhood, which may contain data from previously simulated cells, is selected to roughly conform to the ellipse range on the semivariogram model.
5. Perform ordinary Kriging at the cell using data in the local neighborhood as conditioning points. This determines the mean of the Gaussian distribution $\hat{Z}$ and the variance σ_{OK}^2 . The local cumulative distribution function is now known since the mean and variance completely determine a Gaussian distribution.

6. Draw a random number in the interval $[0, 1]$ from a uniform distribution. Use this value to sample the Gaussian distribution in step 5. The corresponding transformed value is the simulated
7. Add the newly simulated value to the set of "known" data, increment I by 1, and proceed to the next cell as in step 4.

Repeat steps 4 to 7 until all cells have been visited. This constitutes a single realization of the procedure. Multiple realizations are carried out by repeating steps 3 to 7. All the values in all realizations are back-transformed to their original distribution before subsequent use (Jensen et al., 2000).

2.2.2.2 Indicator Based Procedures

These procedures are designed to model binary indicator variables, which are set to 1 if a given event occurs at a certain location and zero if not. Therefore, indicator algorithms are most widely used to simulate categorical variables; probably facies being the most representative variable of this kind in a petroleum reservoir.

Although it is better suited to simulated categorical variables, indicator procedures can be used in simulation of continuous variables. This is done by discretizing the continuous variable into a given number of mutually exclusive classes.

2.2.2.3 Simulated Annealing

The core of this technique is the utilization of an objective function that can incorporate one or several constraints of any nature; it can honor variogram data, descriptive statistics (mean, median, and mode), a histogram, or a correlation coefficient among others. The procedure can be divided in a few steps: initialize the model with random values from the population distribution, choose the objective function (that must be non-negative), then the

value of the property in a randomly chosen cell is changed; if the objective function decreases the change is accepted, if increases it has a certain probability to be accepted (this is in order to avoid local minima). This is done until a low objective function state is achieved.

There are different algorithms for simulated annealing, including the Metropolis Algorithm, the Heat Bath Algorithm, among others (Deutsch and Journal, 1994).

2.2.2.4 Variable Shape Distribution Model

The Variable Shape Distribution (VSD) model is a new approach (Aguilera, 2006; Aguilera et al., 2012) for estimating the distribution of properties that cannot be properly matched with other methods, such as fracture aperture size, pore throat radii, porosity, permeability, among others. The model has been used in the past at the macro and mega scale for estimating the global endowment of oil, natural gas and natural gas liquids. In this thesis the VSD method is shown to also have application at the field scale for simulation of tight gas naturally fractured reservoirs and at the micro and nano scale for estimating the distribution of properties such as fracture aperture and fracture length, pore throat aperture and properties determined from drill cuttings. Mathematical derivation of the VSD is covered in detail in **Chapter 4** of this thesis.

Chapter Three: Updip Water Blockage in the Nikanassin Basin Centered Gas Accumulation, Western Canada Sedimentary Basin

A basin centered gas accumulation (BCGA) is a “continuous petroleum accumulation” characterized by low permeability, the absence of downdip water, the absence of obvious traps and seals, the presence of pervasive gas or oil saturation over very large areas, abnormal pressures (either high or low), and the relative proximity to source rocks. This is the case of the Nikanassin Group, a tight gas formation located in the WCSB, chosen as study area for this research.

In fact, this chapter shows a reservoir simulation model that corroborates not only the absence of downdip water in the chosen area, but also the possibility of having water acting as a seal on top of gas, something very interesting that had not been verified before. The water seal is shown to be the result of very low permeability and high capillary pressures, properties that are generally found in tight gas formations.

The model is defined by a geometry that mimics the geologic interpretation of the Nikanassin BCGA in the Western Canada Sedimentary Basin (WCSB) and rock properties that provide a good representation of the real behavior of the reservoir in the Deep Basin. Different models were created trying to understand sensitivities to permeability and capillary pressure in the distribution of downdip gas and updip water over thousands of years. The results obtained appear consistent and reliable when compared with factual information from the Deep Basin.

3.1 Theoretical Background

The qualifier “unconventional” for tight gas reservoirs is certainly valid. The lack of water leg, the seal provided by a “water block” updip in the gas reservoir, the porosity associates

with slots and dissolution secondary pores, the abnormal pressure (high or low with respect to a normally pressured reservoir) and the very large continuous areas where they are found make them certainly “unconventional”. The terminology associated with these types of reservoirs is presented next.

3.1.1 Basin Centered Gas Continuous Accumulation

Basin centered gas accumulations, tight gas formations; coalbed methane, oil and gas shales, and gas hydrates are generally categorized as “continuous petroleum accumulations”. Those continuous accumulations have two key geologic features in common: first, they consist of very large areas with pervasive oil or gas saturation, and second they do not depend upon the buoyancy of oil or gas in water for their existence. Petroleum as defined by the United States Geological Survey is the sum of oil, natural gas and natural gas liquids.

In addition to the key features mentioned above, there are other important characteristics of continuous accumulations including the lack of down dip water, absence of obvious trap and seal, large areal extent, low matrix permeability, abnormal pressure (either high or low), and close proximity to source rocks.

Beside the geological features mentioned above, there are some important engineering and production characteristics that include large in-place gas volumes, low recovery factors (most of the times between 2 to 10% of the original gas in place in the whole continuous accumulation), strong dependence on fracture permeability, lack of true dry wells (there are always gas shows) as it is virtually impossible to drill a well without contacting a gas charged reservoir in the continuous gas accumulation. Nearly all wells require hydraulic fracturing stimulation to establish commercial production. But in spite of hydraulic

fracturing there are vertical and horizontal wells that result in economic fiascos. Another interesting aspect is the existence of the so called “sweet spots”. These are zones within the continuous accumulation where the rock quality is better and therefore the deliverability is larger than in the rest of the accumulation. In these cases the gas recovery can be larger than 50% of the original gas-in-place in the sweet spot region.

3.1.2 Tight Gas

These types of reservoirs are included in the continuous accumulation definition stated above, and consequently have the same geologic, production and engineering characteristics. On the other hand, apart from the geologic and production features these reservoirs are defined by government regulations that include a permeability cut-off of 0.1mD. Reservoirs with lower permeabilities are considered as “tight gas sands”.

The work presented in this thesis focuses on the Western Canada Sedimentary Basin (WCSB), and more precisely on the Deep Basin located in front of the Foothills overthrust.

3.1.3 Alberta Deep Basin

In the Deep Basin, the Mesozoic rock section thickens gradually westward. This increase of thickness is accompanied by a reduction in rock quality (i.e. porosity and permeability) and progressively increasing depths. When examining the eastern part of the province of Alberta, there are conventional gas reservoirs on top of water. Moving west and down dip there are areas where the rock is totally saturated with water. Further west and deeper it is found what Masters (1979) called “Gas Packages”, i.e., very large bulk volumes of rock mostly saturated with gas. The technical basis for Masters’ statement was the increase of resistivity he observed in well logs from east to west. In the east part the average resistivity

is around 5 ohm-m and in a denominated transition zone the resistivity increases considerably, starting from a minimum of 20 ohm-m and reaching values of 200 ohm-m. In the western part of the Deep Basin where the ‘tight gas’ is contained, permeabilities and porosities are much lower than in the eastern part of the basin. In the transition zone with water saturated rock up-dip and gas saturated rock down-dip there are two phenomena that allow the gas to accumulate deeper than water: one is the hydrodynamics that might create a back pressure against the buoyant force of the gas, so that as the water flows down dip the gas is not able to enter in the fined grained rock; the other phenomena has to do with relative permeabilities, and is based on the effect that high water saturation has on permeability to gas in very low-permeability rocks. This causes a water block that does not allow the gas to flow.

The main objective of this work is to corroborate (or deny) the possibility of having a water bearing zone updip from a gas zone and the integrity of the “water seal”.

3.1.4 Seal and Trapping

Law (2002) has presented a reasonable theory that explains how gas-reservoirs in BCGA systems were created. Law indicates that these gas systems require gas-prone source rocks and low-permeability reservoirs in proximity to each other. As both, source and low permeability rocks, suffer further burial and exposure to increasing temperatures, the source rock reaches an optimum window to begin generating natural gas. Observing the burial history curve of the WCSB in **Figure 3.1**, it is evident that the period when the source and reservoir rocks experienced the highest stresses and temperatures, around 60 million years ago, occurred during the Paleocene.

Accompanying the gas generation are expulsion and migration of gas. Thus gas begins to flow into the adjacent, water-wet sandstones. Due to the low permeability of the sandstones, the rate at which gas is generated and accumulated in the reservoir is greater than the rate at which gas is lost. With time the gas that is continuously generated accumulates in the pore space, and eventually the capillary pressure of the wetting phase (i.e. water) is exceeded. When this stage is reached free, mobile water is expelled from the pore system. This whole process results in an overpressured, gas-saturated reservoir with little or no free water. In this study it is theorized that the underpressured condition, also present in the Deep Basin, emanates from leakage of gas updip and the creation of slot porosity during uplifting of the basin, i.e., the creation of additional pore space results in diminishing reservoir pressures.

Figure 3.1 Burial history diagram at 10-35-71-13W6, located in the Deep Basin of Alberta. Source: Ness (2001).

Now that the process of generation and accumulation of gas has been explained, the focus is on the provenance of the seal and trapping mechanisms that do not allow gas to migrate

further. It is known that in the zone of interest there is a lack of typical structural and/or stratigraphic trapping mechanisms. Therefore a couple of theories were developed by Masters (1979) that offer reliable explanations for the entrapment. One is related to hydrodynamics and the other one to relative permeabilities and capillary pressure which are combined to create a “water block”.

Some of the characteristics of the Deep basin are similar to other zones, where hydrodynamic conditions seem to provide entrapment. Updip in the Deep basin it is possible to find water in fairly porous and permeable sandstones which grades into downdip gas in tighter sandstones as shown in the schematic presented in **Figure 3.2**. The effect of hydrodynamics is the creation of a back pressure against the buoyancy force of gas that does not allow the gas to flow. However the clearest evidence is the lack of a downdip water flow in the formations belonging to Lower Cretaceous to Triassic periods. The “water block” is caused by the high water saturation and its effect on the relative permeability to gas in low permeability zones. This effect is also present in the case of damage near wellbore resulting from water coning. For a typical relative permeability curve of sandstone of 1mD, at 10% water saturation relative permeability to gas has the same value that relative permeability to water at 100% water saturation. The interesting fact is that the gas permeability falls really fast, to the point that at 65% water saturation the rock is almost completely impermeable to gas flow. The schematic of **Figure 3.2** illustrates the transition zone and the assumption that in the gas-water interface, the rock reaches a water saturation of 65%, at which a rock with very low permeability is not permeable to gas.

In addition there is the capillary pressure effect. For these kinds of reservoirs the pore throats are very small and the capillary pressure increases rapidly to a point that is very difficult to move water.

Figure 3.2 Schematic of the transition zone in a Basin Centered Gas Accumulation.
Source: Masters, 1979.

3.2 Simulation Model

The main objective of this chapter is to verify, through a numerical model, if it is possible to have water updip and gas downdip in a tight formation. To accomplish this goal a reservoir model was built to simulate a gas reservoir in proximity to a water bearing zone with a gas water transition zone. This is referred in this paper as to the base model. How the base model was created using a commercial software package and its characteristics are explained next.

Dimensions: The area of the WCSB is very large, with a NE-SW length of 300 miles length (close to 480 km). The total area exceeds 60,000 square kilometers. A model with these dimensions was too big and difficult to handle because of the detail required in the model

and the running time as the simulation time was planned to be over one million years. After some experimentation it was decided to use the geometric properties presented in **Table 3.1** by striking a balance between performance and detail. For the case of the time step it was decided to use a value of 100 years; this value was chosen in the basis that simulation runs performed with smaller time steps (one year) for a period of 100,000 years showed identical results, and the computation time was more than a week. The software used

Table 3.1 Geometric properties of the base model.

PROPERTY	VALUE
Length	120,000ft (22.73 mi) in 200 grid blocks
Width	30,000ft (5.68mi) in 50 grid blocks
Thickness	200ft in 20 grid blocks
Top depths	12000-14000ft

Three zones were defined; a lower one that represents the tight sandstone containing natural gas, a second intermediate one where the gas-water transition zone is located, and a third upper one that represents the conventional rock with 100% water saturation. In this paper, those zones are denoted as Zone 1, Zone 2, and Zone 3 respectively. The permeabilities, porosities and pressure gradients used for each zone are presented in the **Table 3. 2**.

Table 3.2 Rock properties of the base model.

ZONE	PERMEABILITY	POROSITY	PRESSURE
1	Uniformly distributed [0.0001-0.01] md	0.04	Underpressured with a gradient of 0.32 psi/ft.
2			
3	Uniformly distributed [0.01-1] for the first half and [1-10] for the second half	0.15	Normally pressured with a gradient of 0.43 psi/ft.

To mimic the fluid distribution at the beginning of the simulation, with water updip and gas downdip, the water saturation in each zone was defined differently. Thus at time zero in the simulation the reservoir is not in equilibrium. In the downdip gas zone water saturation was set at an irreducible value, in the gas side of the transition zone it was set at around 15% and in the water side at about 85%, and for the updip water bearing zone the water saturation was set at 100%. The pressure gradients were defined according to information available in underpressured zones of the Deep Basin in the basin centered gas accumulations of the WCSB.

Relative permeabilities and capillary pressure curves had to be defined in order to complete the simulation model. For relative permeabilities, the curves were constructed following the description of tight gas sandstones given by Masters as explained above. The curves are shown in **Figure 3.3**.

Figure 3.3 Relative permeabilities used in the base model, showing the permeability jail concept. a) Shows Kr's in a Cartesian plot, and b) in a semilog plot. The curves were constructed based on the Masters (1979) description of tight gas formations in the Deep Basin of the WCSB.

Figure 3.4 Gas water capillary pressures calculated on the basis of drill-cuttings measurements in the laboratory (Source: Ortega, 2012; Ortega and Aguilera, 2012).

Permeability and porosity measurements from drill cuttings (Ortega, 2012; Ortega and Aguilera, 2012) performed on samples of the Jurassic Nikanassin Group were used for calculating mercury-air capillary pressure curves that were subsequently converted into gas-water capillary pressures for use in this simulation study (**Figure 3.4**). Research on the use of drill cuttings for a combination of qualitative and quantitative analysis is being carried out by the GFREE research team at the University of Calgary. Although the optimum is to determine these curves from laboratory work on cores, the amount of available core capillary pressure data are rather limited. But the data generated, started with only drill cuttings, did provide realistic measures of the capillary pressures in the study area and helped to meet the objectives of this work.

Although developed for different conditions and formations, it is interesting to compare the cuttings-based data with capillary pressures published by Holditch (1979) for tight gas formations in high pressure reservoirs (**Figure 3.5**). The comparison shows a nearly perfect match of the drill cuttings values with the curve for 0.01 md published by Holditch.

Figure 3.5 Capillary pressure curves. Smooth lines for different permeabilities are taken from Holditch (1979). Squares are capillary pressures calculated from the analysis of drill cuttings (Ortega, 2012; Ortega and Aguilera, 2012).

Since the migration of fluids takes a long time, a typical reservoir lifetime (for example 30 years) is not enough to see an appreciable change in the fluids distribution in tight formations. To get a good idea with respect to the validity of the updip “water block” seal the simulation was conducted for a time larger than 1 million years. Although this is a long time compared with a reservoir lifetime it is not really comparable to geological ages that

may cover several millions of years. However, from the point of view of simulation this is long enough to observe if the fluids distribution changes.

In order to verify that changes in the distribution of fluids in the tight formation under consideration are not significant, three control models were created. The first one has similar characteristics to the base model, but the permeability is 1,000 times larger and is somewhat more comparable to a conventional reservoir, i.e. permeabilities range between 1 and 10 md (Control model 1). The second (Control model 2) uses a capillary pressure curve published by Holditch for the case of a sample with permeability equal to 1 md (**Figure 3.5**). The third one has both permeability and capillary pressure properties changed (Control model 3)

3.3 Results and Discussion

From the base simulation model, results show that after more than one and a half million years of dynamic activity in the reservoir, gas saturation in the water side of the transition zone rises from the initial 15% to 45%. Although this is a significant increase it occurs only in the first row of cells of the interface. In the second row updip gas saturation reaches 40%, in the third row and the other rows updip close to the interface the increase is only in the order of 1%. For rows of cells that are further updip there is no increase in the gas saturation.

The comparison of fluids distribution at initial conditions (time zero) and after more than one and a half million years of dynamic activity in the reservoir is shown in **Figures 3.6** and **3.7**. The comparison shows clearly that although there is some movement of fluids, the updip “water block” provides an effective seal that prevents gas from escaping from the downdip Jurassic tight gas formation.

The cases that were created to verify if one and a half million years are enough time to observe changes in fluids distribution, show clearly an updip movement of gas while water goes down as in the case of conventional gas reservoirs. The movement is more accentuated in control models 1 and 3 than in the control model 2. **Figures 3.8, 3.9 and 3.10** show displacement of the gas going up and water coming down based on Control models 1, 2 and 3, respectively.

When examining the results of the control models, there is something that draws particular attention, and it is the fact that the difference between the base model simulation (**Figure 3.7**) and the model with low capillary pressure is not significant. On the other hand, when the reservoir has a higher permeability the difference is very large as the fluids distribution changes drastically in a relative short time. This suggests that the main component of the seal is the low permeability.

Figure 3.6 Phases distribution at time zero using base model. Red corresponds to gas and blue to water.

Figure 3.7 Phases distribution after one and a half million years of simulation using the base model show that there has been very little movement of fluids and corroborates that the water block updip is an effective seal in tight gas formations. Red corresponds to gas and blue to water.

Figure 3.8 Phases distribution after one and a half million years of simulation. Control model 1 indicates that by increasing permeability one thousand times, water moves down and gas goes up. In this case there is not a “water block” seal. Red corresponds to gas and blue to water.

Figure 3.9 Phases distribution after one and a half million years of simulation. Control model 2 indicates that by decreasing the capillary pressure and maintaining the same low permeability of the base case the fluids movement at the interface is very limited. This corroborates the presence of an updip “water block” seal. Red corresponds to gas and blue to water.

Figure 3.10 Phases distribution after one and a half million years of simulation. Control model 3 indicates that by increasing permeability and decreasing capillary pressures, water moves down and gas goes up. In this case there is not a “water block” seal. Red corresponds to gas and blue to water.

Based on results shown in the different saturation graphs (**Figures 3.6 to 3.10**) it is concluded that the “water block” in basin centered gas accumulations can act as a very effective seal. Control cases 1 and 3 showed a change in the distribution of the fluids that became visually apparent during the first 5000 years of simulation, and in these cases gas even reached the water-bearing zone that was located further updip from the transition zone. On the other hand in the base case there was a restricted exchange of fluids that affected only a couple of rows in the model after one million years simulation. The comparison suggests that one million years of simulation is long enough to provide definitive conclusions with respect to the effectiveness of the “water block” seal.

To corroborate the characterization of the base model, a well was placed randomly in the gas zone to determine its gas production capability. Gas production was low at about 10,200 SCF/D as anticipated due to the poor characteristics of the rock, and water production was negligible. This is what is generally observed in tight gas reservoirs, i.e., uneconomic gas rates unless the well is hydraulically fractured to attain commercial production. Therefore, it can be concluded that the characterization of the zone was done properly.

Figure 3.11 shows a classic geological cross section of the Deep basin published by Masters (1979) and a cross section of the base simulation model developed in this study. The comparison between the Jurassic Nikanassin Group and the simulation model is very good. The simulation model mimics closely the geological cross section and corroborates the updip “water block” theory developed by Masters.

Summarizing, the bulk of the fluids remained in their original positions (water on top of gas) for over one million simulated years. Thus natural gas in the Jurassic tight formation

considered in this study is not trapped by conventional seals. The seal is provided an updip “water block”.

Examination of the control cases indicates that very low permeabilities have a stronger effect on the “water block” as compared to capillary pressures. When permeabilities were increased 1,000 times from 0.0001-0.1 md to the range of 0.1-10 md the conventional phase displacements stemming from gravity forces were evident even with high capillary pressures.

Figure 3.11 Results show a very good comparison between geological cross section of the Jurassic in the Deep Basin as published by Masters (1984) and the cross section of the Jurassic model developed in this study after one and a half million years of simulation. The simulation corroborates the effectiveness of the “water block” as a seal capable of stopping updip migration of gas. Red corresponds to gas and blue to water.

Chapter Four: A Variable Shape Distribution (VSD) Model for Characterization of Pore Throat Radii, Drill Cuttings, Fracture Apertures and Petrophysical Properties in Tight, Shale and Conventional Reservoirs

Fractal and power law distributions have been found in the past to be useful for modeling some reservoir properties following the assumptions of constant shape and self-similarity. The work included in this chapter shows, however, that pore throat apertures, fracture apertures, petrophysical and drill cuttings properties of unconventional formations are better matched with a variable shape distribution model (as opposed to constant shape). This permits better reservoir characterization and forecasting of reservoir performance. Pore throat apertures, fracture apertures, petrophysical properties and drill cutting sizes from tight and shale reservoirs are shown to follow trends that match the variable shape distribution model (VSD) with coefficients of determination (R^2) that are generally larger than 0.99. The good fit of the actual data with the VSD allows more rigorous characterization of these properties for use in mathematical models. Data that could not be described previously by a single equation can now be matched uniquely by the VSD. Examples are presented using data from conventional, tight and shale formations found in Canada, the United States, China, Mexico and Australia.

In addition, the chapter shows that the size of cuttings drilled in vertical and horizontal wells can also be matched with the VSD. This allows the use of drill cuttings, an important direct source of information, for quantitative evaluation of reservoir and rock mechanics properties. The results can be used for improved design of stimulation jobs including multistage hydraulic fracturing in horizontal wells. This is important as the amount of information collected in horizontal wells drilled throughout tight formations, including cores and well logs, is limited in most cases.

4.1 Introduction

Fractal geometry was introduced by Mandelbrot (1982) in his seminal work “The Fractal Geometry of Nature.” He indicated that this type of geometry applies to many irregular objects in nature. Since then, fractals have been shown to be useful in many disciplines including geology, petroleum engineering, earthquakes, and economics to name a few. In geology, the approach has been used, for example, to evaluate the distribution of natural fractures in outcrops and reservoir rocks; also for evaluating stratigraphic units. In petroleum engineering, they have been used in efforts to capture the distribution of natural fractures for well test analysis. In the case of telluric movements, fractals have been used to evaluate very small to very large earthquakes. In economics, fractals have been used to analyze the distribution of income amongst populations. In the case of the oil and gas industry as a whole, fractal geometry has been used for estimating the spatial distribution of hydrocarbon accumulations (Barton and La Pointe, 1995).

In essence, fractal geometry indicates that a log-log crossplot of cumulative frequency of a number of objects vs. the size of the object should result in a straight line with a constant slope a_p (usually known as Pareto slope) and an intercept C . Thus, the fractal distribution can be represented by a power law. The Pareto slope allows estimating the fractal dimension depending on the type of problem under evaluation. The straight line implies self-similarity and constant shape of the sampling population. More than one straight line in the log-log plot indicates multi-fractal geometry (Han et al., 2006).

The problem is that in many instances there are combinations of fractal and non-fractal behaviour in nature. For example Hooker et al. (2009) indicate that “the aperture-size distribution of a set of opening-mode fractures in the Cozzette Sandstone is complex and

cannot be described uniquely by a single equation.” Thus they used in their analysis a combination of power law and log normal distributions. In many cases samples that are not fractal are usually not considered in further evaluations or are dismissed as noise. This can happen for very large and/or very small sample sizes. In several instances in the literature, truncation of data is required to end up with a reasonable straight line on log-log coordinates.

This fractal and non-fractal behaviour was observed by Aguilera (2006) while researching the global endowment of oil, natural gas and natural gas liquids. In all cases he observed curves (with some segments that were straight or approximate straight lines) when cross plotting cumulative number of petroleum provinces vs. hydrocarbon endowments. This indicated that hydrocarbon accumulations did not necessarily have a constant or approximately constant shape as required by a fractal distribution, but rather variable shapes. This led him to develop a variable shape distribution (VSD) model that properly fit all the global hydrocarbon endowment data he evaluated. His work went up to trillions of barrels of oil and quadrillions of cubic feet of gas contained in provinces around the world (Aguilera et al., 2009).

As the VSD worked so well at those very large scales, the question is: is it possible that the VSD might also apply at the micro and nano scales observed, for example, in pores and pore throats? The answer is positive based on the results shown in this research. To validate the approach data published previously in the fractal literature for sandstones, carbonates, tight and shale reservoirs from different countries around the world was used. Data generated by the GFREE research team at the University of Calgary was also included.

This work does not discuss how the data was collected and/or elaborated by various researchers. The objective is to demonstrate the usefulness and advantages of the VSD model over previous work for evaluating rock data at the micro and nano scale for both fractal (constant shape, self-similarity) and non-fractal structures (variable shape). Furthermore, this work does not assume that data that does not fall on a straight line on log-log coordinates are necessarily of poor quality or associated with noise.

4.2 Theoretical background

Following the work of Pareto, Mandelbrot (1982), and Barton and Scholz (1995), Aguilera (2006) developed the VSD model for estimating the distribution of global fossil energy resources successfully at scales that go into the trillions of barrels oil equivalent (BOE). In this paper the VSD is extended from the macro-scale of global resources to the micro and nano-scale of reservoir properties such as the size of pores in different types of rocks including those found in tight and shale reservoirs. Development of the VSD model follows closely the original work of Aguilera (2006) and is explained with the use of **Figures 4.1 to 4.3** developed for the case of petroleum resources.

The fractal distribution equation (with a constant shape) is given by (Mandelbrot, 1982; Barton and Scholz, 1995):

$$N(r) = Cr^{-D} \dots (4.1)$$

Where:

D = constant shape (fractal) dimension.

C = constant of proportionality.

r = some quantity (for example, pore throat aperture).

$N(r)$ = number of objects with a quantity equal to or greater than r .

Equation 4.1 indicates that a log-log crossplot of $N(r)$ vs. r should result in a straight line with a slope equal to $-D$. In reservoir engineering, Equation 4.1 has been used for evaluation of properties at the micro and nano-scale. The observation by various researchers that a single straight line does not fit the data accurately has led to the use of multi-fractal evaluations, i.e., the use of 2 or more straight lines in a single log-log crossplot, which implies the use of different values of D . The VSD does not present this limitation. Rather the VSD (a single equation) can be used for fitting the complete population of the data. Aguilera's (2006) VSD equation is given by:

$$N_t = \frac{I}{r_t^{a_t}} \dots (4.2)$$

Where:

a_t = unknown, variable shape exponent (as opposed to the constant shape exponent in the fractal equation).

N_t = cumulative number of samples.

r_t = estimated normalized size of the sample.

The VSD equation above is somewhat similar to the fractal equation. The significant difference is that the shape exponent in the fractal equation is a constant, while the shape exponent in the VSD model can vary. However, the constant in the VSD model can also remain constant if needed as shown later. When the shape exponent in the VSD model is constant, the VSD equation is a fractal equation. By using normalized sizes, the constant of proportionality, C , is equal to 1. Since there are two unknowns in Equation 4.2, a_t and

r_t , Aguilera (2006) proposed an auxiliary equation for calculating the two unknowns. The equation has the form:

$$N_t = \frac{1}{r_t^{a_t}} = \frac{1}{r_v^{a_p} + r_m^{a_m}} \dots (4.3)$$

Where:

a_m = slope of line between (1) point of maximum number of samples or some function of the maximum number of samples (N_x) and minimum size of the sample (V_m) and (2) point of minimum number of samples or function of the minimum number of samples (N_m) and maximum size of the sample (V_x) given by the fractal straight line (for example, $N_m = 1$ as shown in **Figure 4.1**, where cumulative number of samples correspond to petroleum provinces and the size of the samples correspond to size of known petroleum provinces).

a_p = slope of straight line approximated from data points with larger sizes; same as slope of fractal distribution (see **Figure 4.1**).

r_m = normalized, minimum sample size ($r_m = V_m/V_x$, where V_m is the minimum size, and V_x is the maximum size given by the fractal straight line at a number of samples equal to 1 or equal to the smaller value in a given population normalized to 1).

r_v = estimated normalized size of a sample minus the normalized minimum size of the sample.

Figure 4.1 Cumulative number of provinces versus size of ‘known petroleum’ provinces (Source: Aguilera, 2006).

The right hand side of Equation 4.4 was established empirically. Since the slopes a_p and a_m can be determined from the graphed data, it is possible to re-arrange Equation 4.3 to determine r_v , as follows:

$$r_v = \left(\frac{1}{N_t} - r_m^{a_m} \right)^{\frac{1}{a_p}} \dots (4.4)$$

Equation 4.4 gives the estimated normalized size of a sample minus the normalized minimum of the sample (r_m). The minimum size must be added to r_v to get the estimated, normalized size of a sample, as follows:

$$r_t = r_v + r_m \dots (4.5)$$

Then, to ‘de-normalize’ r_t , and get the estimated size of a sample, the following equation is used:

$$V_t = r_t V_x \dots (4.6)$$

Where:

V_t = estimated size of a sample.

V_x = maximum size given by Pareto straight line at number of samples = 1.

After calculating r_v and r_t using Equations 4.4 and 4.5, respectively, it is possible to rearrange Equation 4.4 to solve for the variable shape exponent (a_t), as follows:

$$a_t = \frac{\log[r_v^{a_p} + r_m^{a_m}]}{\log r_t} \dots (4.7)$$

Where:

a_t = variable shape exponent; slope of line between point of any estimated size and the maximum size point given by the Pareto straight line at number of samples equal to 1 (see

Figure 4.2 for an example, which has been made using the case of ‘known petroleum’ published by the USGS, 2000).

Figure 4.2 Cumulative number of provinces versus size of ‘known petroleum’ provinces, including VSD estimate (Source: Aguilera, 2006)

Note that in **Figure 4.1**, the data point for the largest sample, V_L , does not lie on the Pareto straight line. In other cases, more than one of the large size samples will not lie on the line. To get a more accurate, estimated curve that adjusts the right tail of VSD, an exponential function has been incorporated empirically into the VSD model. The function has the effect of smoothly bending the estimated curve in the direction of the actual data. The exponential function is as follows:

$$f(V_t, V_s) = (1 - \exp(-V_t/V_s))^S \dots (4.8)$$

Where:

S = severity exponent that is determined by trial and error. It controls the extent to which the estimated VSD curve will separate from the Pareto straight line (on the right tail of the distribution, near the largest sizes).

V_s = parameter that corresponds approximately to the point at which the largest samples begin to deviate from the Pareto straight line, on the right tail of the distribution, near the largest sizes (see **Figure 4.2**). This a good starting point for the calculations but it can change during the matching process of the actual data.

V_t = estimated size of a sample.

As can be seen in **Figure 4.2** (based on the ‘known petroleum’ case), the approximate size (V_s) at which the largest samples begins to deviate from the Pareto straight line is approximately equal to 320,000 MMBOE. This is however a starting point and the value of V_s can be changed subsequently in order to better fit the actual data, either manually or using non-linear regression. **Figure 4.3** is a graph showing the results of Equation 4.8 on the vertical axis, and the estimated size of the samples (V_t) on the horizontal axis (in this case, the estimated ‘known petroleum’ size). As shown in **Figure 4.3**, severity exponents

(S) equal to 1, 8 and 30, and a value of V_s equal to 320,000 MMBOE, are used in Equation 4.8. Notice that Equation 4.8 also uses the estimated ‘known petroleum’ size of the provinces, V_t .

Figure 4.3 Exponential function for $V_s = 320,000$ MBOE with varying severity exponents. Source: (Aguilera, 2006)

Figure 4.3 illustrates that the conventional use of Equation 4.8, using $S = 1$, leads to a smooth curve where the function goes from nearly 0 to 1. The value of the function is always equal to approximately 0.63 when $V_t = V_s$. When S is greater than 1 (for example, 8 and 30, as seen in **Figure 4.3**) the increase from 0 starts later and the slope of the transition to 1 is steeper. In **Figure 4.2**, the severity exponent (S) is estimated, by trial and error, to be 8 for the ‘known petroleum’ case. The details of how the exponential function is incorporated into the VSD model follow later in this section.

Another parameter incorporated into the VSD model to get a more accurate fit of the largest samples is approximated by:

$$\psi = \frac{V_L}{V_x} \dots (4.9)$$

Where:

ψ = separation ratio that controls the amount of separation between the Pareto straight line and the estimated VSD curve (on the right tail of the distribution, near the largest size samples).

V_L = size of the largest sample.

V_x = maximum size given by Pareto straight line.

In the ‘known petroleum’ example, there is only one data point that deviates significantly from the Pareto line: the West Siberian Basin, with a known petroleum size of 354,730 MMBOE (see **Figure 4.2**). This point is also the largest size, V_L , from the USGS (2000) data. Visual inspection of **Figure 4.2** shows that V_x is approximately 800,000 MMBOE. Dividing V_L by V_x (354,730 MMBOE / 800,000 MMBOE) gives 0.4, which is a good initial approximation for ψ . This value has been adjusted to 0.3, which gives a slightly better fit of the USGS (2000) data.

Three parameters (V_s , ψ , and S) may require adjustments until the estimated VSD curve gives the best possible fit of the data. These three parameters only affect the right tail of the VSD curve, near the largest size samples. They are incorporated so that the VSD curve will fit over the largest size samples that do not lie on the Pareto straight line.

The exponential function (see Equation 4.8) and the separation ratio (ψ) are used to improve the estimate of a sample’s size as follows:

$$V_{tf} = \frac{V_t \times \psi}{\psi + (1 - \psi) \cdot f(V_t, V_s)} \dots (4.10)$$

Where:

V_{tf} = final, estimated size of a sample.

Expanding the exponential function, $f(V_t, V_s)$, in Equation 4.10, Equation 4.11 is obtained:

$$V_{tf} = \frac{V_t \times \psi}{\psi + (1 - \psi) \cdot (1 - \exp(-V_t/V_s))^S} \dots (4.11)$$

Where, as shown earlier in Equation 4.6:

$$V_t = r_t V_x = \left[\left(\frac{1}{N_t} - r_m^{a_p} \right)^{\frac{1}{a_p}} + r_m \right] \cdot V_x \dots (4.12)$$

By further expanding Equation 4.12, the following expression is obtained:

$$V_t = \left[\left(\frac{1}{N_t} - \left(\frac{V_m}{V_x} \right)^{\left(\frac{\log N_x - \log N_m}{\log V_x - \log V_m} \right)} \right)^{\frac{1}{a_p}} + \frac{V_m}{V_x} \right] \cdot V_x \dots (4.13)$$

When substituting V_t , from Equation 4.13, into Equation 4.11, all the terms are expanded, resulting in the following:

$$V_{tf} = \frac{\left\{ \left[\left(\frac{1}{N_t} - \left(\frac{V_m}{V_x} \right)^{\left(\frac{\log N_x - \log N_m}{\log V_x - \log V_m} \right)} \right)^{\frac{1}{a_p}} + \frac{V_m}{V_x} \right] \cdot V_x \right\} \times (\psi)}{(\psi) + [1 - (\psi)] \cdot \left[1 - \exp \left(- \left\{ \left[\left(\frac{1}{N_t} - \left(\frac{V_m}{V_x} \right)^{\left(\frac{\log N_x - \log N_m}{\log V_x - \log V_m} \right)} \right)^{\frac{1}{a_p}} + \frac{V_m}{V_x} \right] \cdot V_x \right\} \div V_s \right) \right]^S} \dots (4.14)$$

Equation 4.14 is used to generate the estimated VSD curve shown in **Figure 4.2**, for ‘known petroleum’ (size of sample), using the following control parameters:

Maximum number of samples (N_x) = 117

Minimum number of samples (N_m) = 1

Minimum size of sample data (V_m) at N_x equal to 117 = 3 MMBOE

Maximum size of sample data given by Pareto straight line (V_x) at N_m equal to 1 = 800,000 MMBOE

Pareto shape exponent (a_p) = 0.897

Size of separation (V_s) = 320,000 MMBOE

Separation ratio (ψ) = 0.3

Severity exponent (S) = 8

The validity of the parameters can be confirmed by visual inspection of **Figure 4.2**. Further confirmation is provided by the coefficient of determination ($R^2=0.99$). The VSD method (Equation 4.14) is robust as it allows matching actual data when the shape of the curve on log-log coordinates is concave, convex, or straight as shown in the examples below. For the straight line case, $\psi = 1.0$, N_x is very large (for example, $N_x = 1E+50$), and V_m is very small (for example, $V_m = 1E-50$). This is because Pareto’s straight line can theoretically reach infinitesimally small sizes and an infinite number of samples. For this situation, the V_s and S values do not have any significance (Aguilera and Aguilera, 2012).

Example applications of the VSD are shown next for the case of micro and nano scales in sandstone, carbonate, tight and shale reservoirs. The original legends and units in the ordinate and abscissa of graphs published by the referenced authors are used in this paper.

This is done in **Figures 4.4 –4.13** for ease of comparison with their original work.

4.2.1 Sandstones

The first example presents sandstone data from the Lamadian oil field in Daqing, China (Shen et al., 1995, 1998). **Figure 4.4** shows a crossplot of pore throat number vs. pore throat radius (microns) on log-log coordinates. The pore throat number is obtained by counting the pores with certain radius in a sample, and scaling it to a given length. In this graph the pore throat number corresponds to N_t and the pore throat radius to V_t in Equation 4.14. The black diamond symbols represent the data published by Pingping et al. The solid continuous red line has been calculated with the VSD model. Pingping et al. divided their data into 2 parts. The first one is a pore radius smaller than approximately 10 microns (signaled in the graph by r_0). Pingping et al. indicate that these are fractal pore throats characterized by self-similarity. On the other hand the radii larger than 10 microns are non-fractal. Their interpretation is reasonable and compares with fractal evaluation of sandstones carried out by Krohn and Thompson (1986) who also found two segments in sandstones using SEM techniques. The segment with the short length pores was characterized by fractal distribution. The segment with the long length pores was assigned a non-fractal behaviour.

The question is how to handle all the pore throats so that their distribution can be input realistically into mathematical models. The answer is provided by the VSD model as the whole distribution from the largest to the smaller pore throat can be modeled with a single equation with a nearly perfect fit ($R^2 = 0.999$) as shown in **Figure 4.4**.

Figure 4.4 Pore throat radii distribution for sandstone in Lamadian oil field, China. Black diamonds correspond to data published by Pingping et al. (1995). Solid red line is calculated with the VSD model. $R^2 = 0.999$.

The initial step is normalizing Pingping et al.'s pore throat numbers. This is done dividing each of the pore throat numbers by the smallest pore throat number (0.000565) in such a way that N_m is equal to 1. Then Equation 4.14 and the data shown in **Table 4.1** are used to generate the VSD line. As the smaller pore radii form a Pareto straight, the value of V_m is very small (for example, $1E-14$) and N_x is very large (for example, $1E42$) (Aguilera and Aguilera, 2012). Once the normalized best fit is obtained, the normalized pore throat aperture is multiplied by the actual smallest pore throat number (0.000565) to revert to the data published by Pingping et al.

Table 4.1 Data Used for Generation of Variable Shape Distribution (VSD) Curves in the graphs presented in this study. The first column shows the identification of the figure. The second column shows the Pareto slope (a_p). The third column shows maximum size (V_x) given by the Pareto straight line (at $N_m = 1$). The fourth column shows approximate size (V_s) at which the data begin to deviate from the Pareto straight line (on the right hand side of the distribution, near the largest size). This is a good starting point for the calculations but it can change during the fitting procedure of the real data. The fifth column (ψ) is a ratio that controls the amount of separation between the Pareto straight line and the estimated VSD curve (on the right hand side). The sixth column shows the severity exponent (S) that controls the steepness of the slope of the estimated VSD curve where it separates from the Pareto straight line (generally on the right hand side of the distribution, near the largest values). The seventh columns shows the maximum number of samples (N_x). The last column shows the minimum size (V_m) of the sample population.

Figure	a_p	V_x	V_s	ψ	S	N_x	V_m
4.4	2.55	590	37	0.12	2.2	1.00E+42	1.00E-14
4.5	0.615	150	160	0.2	1	1.00E+50	1.00E-50
4.6	2.2	65	7	0.33	2	1.00E+32	1.00E-12
4.7	2.1	69	13	0.21	2	1.00E+32	1.00E-12
4.8	2	100	41	0.21	2	1.00E+32	1.00E-12
4.9	3.51	1.10E+09	4.50E+08	0.02	0.72	1.00E+41	1.00E-11
4.10	3.49	0.129	0.1	1	1	1.44E+16	1.00E-07
4.11	0.285	52.715	8.68	728.482	311.415	1.00E+10	1.00E-40
4.12	0.8	51.652	23.882	0.111	21.823	1.00E+18	1.00E-21
4.13	1.435	0.449	0.146	3.133	2.256	1.00E+16	1.00E-12
4.14	4	1.395	0.14	2.124	972.498	73	0.5
4.15	1.8	396	129	0.364	7.539	14	33
4.16	2.565	0.465	0.026	0.74	4320.605	14	0.038
4.17	1.177	1.736	0.139	0.56	473.195	14	0.092
4.18	3.489	0.357	0.311	2.124	972.498	14	0.237
4.19	1.34	10.7569	17.1185	0.08784	1.26799	26.4724	0.5062
4.20	1.5	0.07	0.0068	30	130	201.34	0.0015
4.21	3	0.03	0.015	0.3	8	4747.56	0.000568
4.22	0.625	1.0901	0.045	0.11	1.41255	28.94	0.001
4.23	1.95	0.032	0.0045	200	130	100.72	0.00116
4.24	4.33	0.0121	0.00059	180	800	1544.2	0.0011
4.25	1.116	102.202	31.792	0.497	23.431	7	61
4.26	1.116	32.211	21.208	0.577	30.358	12	40.708

The same approach was used in **Figure 4.5** that presents data from the United States Blackhawk sandstone published by Krohn and Thompson (1986). In this case the authors cross plotted a feature size in microns (corresponding to V_i in Equation 4.14) vs. Number of features per micron (N_i). For features smaller than approximately 10 microns, Krohn and Thompson calculate a fractal dimension (D) equal to 2.66. Features larger than 10 microns are non-fractal. The VSD model is capable of fitting all the data points, fractal and non-fractal, with the use of the data presented in **Table 4.1**. The Pareto slope is -0.615 leading to a fractal dimension equal to $3 - 0.615 = 2.385$ as explained by Krohn and Thompson. The last data points yield a negative slope equal to 1 as pointed out by Krohn and Thompson. In this example the coefficient of determination (R^2) using the VSD is equal to 0.998.

Figure 4.5 Feature size distribution for Blackhawk sandstone. Black diamonds correspond to data published by Krohn and Thompson (1985). Solid red line is calculated with the VSD model. $R^2 = 0.998$.

Li (2004) discussed the evaluation of 3 sandstone core samples to investigate fractal behavior in an oil reservoir. His results are presented as log-log crossplots of number of

pore (N_i in Equation 4.14) vs. pore radius (V_i) in **Figures 4.6, 4.7 and 4.8** where the black diamonds represent Li's data as extracted from capillary pressure measurements. Again the same approach discussed above was used for the VSD evaluation of Li's 3 core samples. As in the case of Pingping et al. (1995) and Krohn and Thompson (1986), Li indicates that the smaller pore radii conform to fractal behavior and the largest pores are non-fractal. In all 3 core samples the VSD model provides very good fits for small, intermediate and large pores; and the coefficients of determination (R^2) are larger than 0.99. The data used in the VSD analysis are shown in **Table 4.1**. The fractal dimensions (D) published by Li are equal to 2.45, 2.18 and 2.06, for his core samples. This compares with 2.2, 2.1 and 2.0 evaluated with the VSD model.

Figure 4.6 Pore radius distribution for Sample 1. Black diamonds correspond to data published by Li (2004). Solid red line is calculated with the VSD model. $R^2 = 0.999$.

Figure 4.7 Pore radius distribution for Sample 2. Black diamonds correspond to data published by Li (2004). Solid red line is calculated with the VSD model. $R^2 = 0.999$.

Figure 4.8 Pore radius distribution for Sample 3. Black diamonds correspond to data published by Li (2004). Solid red line is calculated with the VSD model. $R^2 = 0.999$.

The same methodology was used in **Figure 4.9** that presents data from a Daqing, China siltstone reservoir published by Han et al. (2006) who cross plotted pore radius in Angstroms (corresponding to V_i in Equation 4.14) vs. the probability density of the pore size distribution (N_i). Their pore characterization was carried out using a combination of image analysis and mercury porosimetry. For pore radii smaller than approximately 700,000 Angstroms, Han et al. calculate a fractal dimension (D) equal to 2.51. Larger pores are non-fractal. The VSD model is capable of fitting the complete sequence of data points, fractal and non-fractal using the data presented in **Table 4.1**. The Pareto slope is $-3.51 = -(D - 1)$ leading to a VSD fractal dimension (D) equal to 2.51, the same value published by Han et al. The coefficient of determination (R^2) using the VSD is equal to 0.993.

Figure 4.9 Pore radius distribution for Daqing, China sandstone. Black diamonds correspond to data published by Han et al. (2006). Solid red line is calculated with the VSD model. $R^2 = 0.993$.

Figures 4.4 to 4.9 have shown cases where the smaller size samples are fractal, which means a straight line in log-log coordinates. For the straight line case, the VSD model is applicable using $\psi = 1.0$, N_x is very large (for example, $N_x = 1\text{E}+50$), and V_m is very small (for example, $V_m = 1\text{E}-50$). This is because Pareto's straight line on log-log coordinates can theoretically reach infinitesimally small sizes and an infinite number of samples.

Figure 4.10, however, presents an opposite case where the larger size samples remain in a log-log straight line and the smaller size samples form a tail that deviates to the left of the straight line. Black diamonds in the graph shows data from Daqing, China published by Han et al. (2006) of magnitude of the scattering vector (Q) on $\text{\AA}^{-1}$ vs. scattering intensity $I(Q)$ in cm^{-1} . The reader is referred to the original paper by Han et al. for explanations on the development of their data, including how it was collected and the physical meaning. The best fit, represented by the red continuous line, is calculated with data shown in **Table 4.1**. The Pareto slope is -3.49 from which the fractal dimension is $6 - 3.49 = 2.51$ as explained by Han et al. The coefficient of determination (R^2) using the VSD model is equal to 0.999.

Figure 4.10 Pore radius distribution for Daqing, China sandstone. Black diamonds correspond to data published by Han et al. (2006). Solid red line is calculated with the VSD model. $R^2 = 0.999$

Figure 4.11 also presents an opposite case as compared to **Figures 4.4 to 4.9**. In **Figure 4.11** the tail associated with the largest size sample deviate to the right of the Pareto straight line. The black diamonds are based on data from the Coconino sandstone (Utah, United States) and was published originally by Katz and Thompson (1984) as a log-log crossplot of the pore – pore density autocorrelation based on SEM images of polished-rock thin sections. The slope of the straight line was taken from the feature size distribution collected on a fracture surface. The VSD line was developed using the data shown on **Table 4.1**. The fit is excellent with a coefficient of determination equal to 0.985.

Figure 4.11 Feature length distribution for Coconino sandstone (Arizona, United States). Black diamonds correspond to data published by Han et al. (2006). Solid red line is calculated with the VSD model. $R^2 = 0.985$.

4.2.2 Carbonates

An example using data collected in a naturally fractured carbonate outcrop of the Sierra Madre Oriental, Mexico by Ortega et al. (2006) is used to explain the VSD methodology. Although Ortega et al. do not discuss explicitly fractal distributions their methodology is based on a power law, which for practical purposes is associated with fractal geometries. The black diamonds in **Figure 4.12** show their real data (fracture apertures) for fracture set A. Ortega et al. indicate that they applied a truncation bias in order to generate their log-log straight line. Visual inspection of their original fit shows a good result. Their coefficient of determination (R^2) is equal to 0.981. So certainly their analysis is good. In the case of the VSD model, however, truncation is not required. The red continuous solid line in **Figure 4.12** was developed with the use of Equation 4.14 and the data presented in **Table**

4.1. The non-truncated fit is good with a coefficient of determination (R^2) using the VSD model equal to 0.998. Note that the larger fracture apertures are also matched by the VSD model, something that cannot be done with the fractal approach.

Figure 4.12 Fracture aperture distribution for set A in Mexican carbonate outcrop. Black diamonds correspond to data published by Ortega et al. (2006). Solid red line is calculated with the VSD model. $R^2 = 0.998$.

A second carbonate example taken from Ortega et al. is presented in **Figure 4.13**. In this case the authors fit again their data using a power law straight line. Their coefficient of determination (R^2) is equal to 0.993 indicating a good comparison with the real fracture apertures. Careful examination of their data points (black diamonds), however, suggests a trend that is slightly concave downwards. The VSD model takes this trend into account without having to force a straight line through the data points. Information used for generating the VSD line is presented in **Table 4.1**. The coefficient of determination (R^2) is equal to 0.996.

Figure 4.13 Fracture aperture distribution for set C in Mexican carbonate outcrop. Black diamonds correspond to data published by Ortega et al. (2006). Solid red line is calculated with the VSD model. $R_2 = 0.996$.

4.2.3 Tight Reservoirs

The same methodology described above for sandstone and carbonate reservoirs has been used for evaluation of tight gas formations particularly using data from the Nikanassin Group collected in vertical and horizontal wells in the Western Canada Sedimentary Basin (WCSB). The information has been used to assist in optimization of hydraulic fracturing jobs in vertical wells ((Leguizamon and Aguilera, 2011; Leguizamon, 2011) and multi-stage hydraulic fracturing jobs in horizontal wells (Ortega, 2012; Ortega and Aguilera, 2012, 2013). In addition to the properties described in the previous section, which concentrate on pore apertures and fracture length, the VSD model can be used for evaluating other properties such as drill cuttings size, grain size, permeability, brittleness index and water saturation. Some of the data presented in this section has been developed

by the GFREE research team at the University of Calgary; the balance of the data was published originally by Hooker et al. (2009).

The quality of drill cuttings is important for determination of permeability particularly in the absence of core (Solano, 2010). A good quality cutting has a diameter of 2 mm or more. Contreras (2011) and (Contreras et al., 2012) have presented methods for optimizing the quality of drill cuttings in the Nikanassin Group without sacrificing the rate of penetration. Good quality cuttings can be used for developing estimates of geomechanical properties (Ortega, 2012; Ortega and Aguilera, 2012), and petrophysical properties (Ortega and Aguilera, 2013). **Figure 4.14** shows the best fit with the VSD model using data presented in **Table 4.1**. As the number of samples in this graph starts with 1.0, the data do not have to be normalized. The coefficient of determination (R^2) is equal to 0.999.

Figure 4.14 Drill cuttings size distribution for the Monteith formation, Nikanassin Group, WCSB. Black diamonds correspond to actual data (Contreras, 2011). Solid red line is calculated with the VSD model. $R^2 = 0.999$.

Grain size, an important property for geologic and engineering evaluations, can also be modeled with the VSD equation. An example is presented in **Figure 4.15**, which shows a crossplot of grain size in microns vs. cumulative number of samples for a vertical well drilled in the Monteith Group in Canada. The VSD uses data presented in **Table 4.1** and provides again a very good fit with a coefficient of determination (R^2) equal to 0.992.

Figure 4.15 Grain size distribution for the Monteith formation, Nikanassin Group, WCSB. Black diamonds correspond to average of actual data (Solano, 2011). Solid red line is calculated with the VSD model. $R^2 = 0.992$.

Permeabilities from drill cuttings (Lenormand and Fonta, 2007) in the Nikanassin are generally smaller than permeabilities from cores due to the milling effect of the drilling bit that tends to destroy microfracture and slot porosity in tight gas formations (Ortega, 2012, Ortega and Aguilera, 2012). A log-log crossplot of permeability (from cuttings) vs. cumulative number of samples is presented in **Figure 4.16**. The graph shows a good comparison between actual data and VSD results calculated with parameters shown on **Table 4.1**. The coefficient of determination (R^2) is equal to 0.963.

Figure 4.16 Permeability (from drill cuttings) distribution for the Monteith formation, Nikanassin Group, WCSB. Black diamonds correspond to average of actual data (Ortega, 2012). Solid red line is calculated with the VSD model. $R^2 = 0.963$.

Nikanassin water saturation, calculated starting with only drill cuttings (Ortega and Aguilera, 2013), has also been modeled with the VSD equation. The approach is important particularly in the case of horizontal wells where the amount of well logs can be quite scarce in many instances. Results are presented in **Figure 4.17**. The black diamonds represent real data. The red continuous line has been calculated with the use of the VSD model. Input data are shown in **Table 4.1**. The fit is very good with a coefficient of determination equal to 0.994.

Figure 4.17 Water saturation (based on petrophysical analysis of drill cuttings) distribution for the Monteith formation, Nikanassin Group, WCSB. Black diamonds correspond to average of actual data (Ortega and Aguilera, 2013). Solid red line is calculated with the VSD model. $R^2 = 0.99$.

Figure 4.18 Pore throat apertures at 35% cumulative pore volume (based on analysis of drill cuttings) distribution for the Monteith formation, Nikanassin Group, WCSB. Black diamonds correspond to actual data (Ortega and Aguilera, 2013). Solid red line is calculated with the VSD model. $R^2 = 0.982$.

Pore throat apertures at 35% cumulative pore volume (r_{p35}) have been found to provide a continuum between conventional, tight and shale reservoirs (Aguilera, 2010). This allows the determination of flow units and to make estimates of initial production rates from individual wells (Deng, Leguizamon, et al., 2011). Values of r_{p35} determined on the basis of drill-cuttings are crossplot as shown on **Figure 4.18**. The data are matched properly by the VSD model ($R^2 = 0.985$) using data presented in **Table 4.1**.

Hooker et al. (2009) have presented an excellent study where they discuss “the aperture-size distribution of a set of opening-mode fractures in the Cozzette sandstone.” They further indicated that the Cozzette “is complex and cannot be described uniquely by a single equation.” Hooker et al.’s data thus present a unique challenge for the VSD model (one equation) as the Cozzette’s distribution is certainly complex and difficult to handle with one equation. In this study the VSD is used to model the Cozzette macro and microfractures distribution published by Hooker et al. Input data for these evaluations are presented in **Table 4.1** and the graphical results are shown in **Figures 4.19 to 4.24**. An insert is presented in all these Figures with a graph of the original interpretation.

Figure 4.19 shows the Cozzette actual macrofracture aperture size distribution (black diamonds) as published by Hooker et al. (2009). Included is an insert by the same authors that allows comparing the VSD and other types of distributions. The VSD distribution, shown by the red line, provides a good fit of the real fracture apertures ($R^2 = 0.975$).

Figure 4.20 presents Cozzette transgranular microfracture aperture size distribution. The actual data (black diamonds) and insert were published by Hooker et al. (2009). Note that the data are limited by two theoretical distribution shown in the insert. Referring to the insert Hooker et al. indicate that “log-normal curves fit the plots with the lowest statistical

error, but visual inspection suggests the real size distribution is more complicated than any single equation.” The statement was certainly valid up to the moment of their publication. However, the VSD distribution method presented in this paper advances the characterization so that the data can be fit with only one equation. The VSD shown by the red line in the graph provides a good fit of the real data ($R^2 = 0.967$).

Figure 4.21 displays Cozzette intragranular microfracture aperture size distribution. Actual data (black diamonds) and insert published by Hooker et al. (2009). The same comment by Hooker et al. applies in this case, i.e., “log-normal curves fit the plots with the lowest statistical error, but visual inspection suggests the real size distribution is more complicated than any single equation.” The single equation VSD distribution shown by the red line provides a good fit of the real data ($R^2 = 0.942$). Last data point with a question mark in the graph is probably an outlier but in any case is included in the coefficient of determination R^2 .

Figure 4.22 illustrates Cozzette aperture size distribution for all transgranular microfractures measured along scanlines. The actual data (black diamonds) and insert were published by Hooker et al. (2009) without showing a fit of the data. The VSD distribution shown by the red line provides a good fit of all the transgranular microfractures data ($R^2 = 0.995$).

Figure 4.23 shows Cozzette aperture size distribution for transgranular microfractures. Actual data (black diamonds) and insert published were published by Hooker et al. (2009). The authors indicate that “a truncation bias is more plausible for the transgranular microfracture rollover, but a power law (straight-line) segment is not likely present; the aperture-size distribution swings down and then up again at larger sizes, suggesting a

power law is not present at all scales.” In our opinion the statement is on target.” There are variations away from the power law that are handled with good accuracy using the VSD distribution model shown by the red line. The fit is good with a coefficient of determination $R^2 = 0.975$.

Figure 4.24 presents a very interesting case that is a challenge for any type of distribution available in the geologic and petroleum engineering literature. The data published by Hooker et al. (2009) includes Cozzette aperture size distribution for microfractures (purple squares) and macrofractures (green circles). The complete fracture aperture population is represented by black diamonds. The insert published by Hooker et al. indicates a good fit provided by “extrapolation of a power law from the largest microfractures measured towards larger fracture sizes.” They highlight the “close fit to smallest macrofractures.” The power of the VSD distribution is shown by the red line which provides a good fit of the real macrofracture and microfractures data with only one equation ($R^2 = 0.994$).

Figure 4.19 Cozzette macrofracture aperture size distribution. Actual data (black diamonds) and insert published by Hooker et al. (2009). VSD distribution shown by the red line provides a good fit of the real data ($R^2 = 0.975$).

Figure 4.20 Cozzette transgranular microfracture aperture size distribution. Actual data (black diamonds) and insert published by Hooker et al. (2009). VSD distribution shown by the red line provides a good fit of the real data ($R^2 = 0.967$).

Figure 4.21 Cozzette intragranular microfracture aperture size distribution. Actual data (black diamonds) and insert published by Hooker et al. (2009). VSD distribution shown by the red line provides a good fit of the real data ($R^2 = 0.942$). Last data point with the question mark is probably an outlier but in any case is included in the R^2 .

Figure 4.22 Cozzette aperture size distribution for all transgranular microfractures measured along scanlines. Actual data (black diamonds) and insert published by Hooker et al. (2009). VSD distribution shown by the red line provides a good fit of the real data ($R^2 = 0.995$).

Figure 4.23 Cozzette aperture size distribution for transgranular microfractures. Actual data (black diamonds) and insert published by Hooker et al. (2009). VSD distribution shown by the red line provides a good fit of the real data ($R^2 = 0.975$).

Figure 4.24 Cozzette aperture size distribution for microfractures (purple squares), macrofractures (green circles) and all fractures (black diamonds); and insert published by Hooker et al. (2009). VSD distribution shown by the red line provides a good fit of the real macrofracture and microfractures data with only one equation ($R^2 = 0.994$).

4.2.4 Shale Reservoirs

Shale gas formations have long posed challenges to petrophysicists because of the presence of clays and organic matter, complex mineralogy and their complicated impact on well log responses. Many times, to solve this problem, advanced logging tools and sophisticated interpretation methods have been used. However, the qualitative and quantitative examination of rock samples collected in the reservoir remains a key direct source of information.

Permeabilities from the first well drilled in a shale gas reservoir in the Perth Basin, Australia have been presented by Gödeke and Hossain (2012). The permeabilities are very small with a limited spread and the amount of information is very limited. This results in a log-log crossplot where the distribution actual data (black diamonds in **Figure 4.25**) results

in a very steep line. In spite of these limitations the VSD equation has been used to try to model the available laboratory data. Results are represented by the red line in **Figure 4.25**.

The fit is good with a coefficient of determination (R^2) equal to 0.989.

A segment of permeabilities in the Utica shale, Quebec, measured in cores cut in a vertical well present a similar steep distribution as shown in **Figure 4.26**. The amount of information is larger in the Utica and there are some permeabilities that are larger and some that are smaller than the range shown in **Figure 4.26** (Lavoie et al., 2011). Results from the VSD model show a coefficient of determination equal to 0.991. Input data for generating the VSD curves in **Figures 4.25 and 4.26** are presented in **Table 4.1**.

Figure 4.25 Shale gas permeability distribution for available data in the Perth basin, Australia. Black diamonds correspond to actual data (Godeke and Hossain, 2012). Solid red line is calculated with the VSD model. $R^2 = 0.989$.

Figure 4.26 Shale gas permeability distribution for portions of available data in the Utica shale, Quebec, Canada. Black diamonds correspond to actual data (Lavoie et al., 2011). Solid red line is calculated with the VSD model. $R^2 = 0.991$.

4.3 Discussion

The VSD was developed originally for evaluating the distribution of hydrocarbon endowments in petroleum provinces of the world that have been tested by drilling and production. The method further allowed estimation of endowments for provinces that have not been produced up to this point. The global endowments ranged in the trillions of barrels of oil and quadrillions of cubic feet of gas. In this thesis the VSD was extended for evaluations at micro and nano scales. In efforts to make the comparisons of real data and the VSD as rigorous as possible data available in the literature was used. The data was interpreted by the original authors as fractal. It was demonstrated that the VSD provides a better fit of data in conventional rocks (for example, calculating pore radii and pore throat apertures) and naturally fractured rocks (for example calculating fracture aperture) without

having to recur to truncation in order to obtain a straight line fit on log-log coordinates. This is significant in practice because with the use of only Equation 4.14 it is possible to input the complete distribution of the data (fractal and/or non-fractal) into mathematical models. For example, fractals are included in well testing under the assumption of fractal distribution of natural fractures in some current models.

Chapter Five: Use of a Variable Shape Distribution (VSD) Model to Populate Reservoir Properties in Tight Fractured Reservoirs for Numerical 3D Modeling

The importance of unconventional resources is increasing every day; according to the Energy Outlook 2013 in Canada the unconventional gas accounts for an estimated 46% of the total gas production. In the United States the estimate is 60%. And it is anticipated that the contribution of unconventional resources throughout the world will become significant in decades to come.

Most unconventional reservoirs are naturally fractured and also need to be hydraulically fractured to attain commercial production. But inputting natural fracture data accurately in the simulator at different scales is challenging. Thus, as mentioned before one of the objectives of this research is the use of a variable shape distribution (VSD) model, which has never been utilized in the past in reservoir simulation, to build a more rigorous static model with a view to improve history matching, production forecasting, and modeling of tight fractured reservoirs. While other statistical models are not capable of fitting the whole scale spectrum of fracture properties without truncating the data, the VSD fits the complete set of non-truncated fracture data with a coefficient of determination (R^2) of at least 0.97. This improves reservoir characterization and geostatistical modeling. Although application of the method concentrates only on a tight gas formation of the Western Canada Sedimentary Basin (WCSB) the workflow is presented in detail so that it can be reproduced in other tight naturally fractured reservoirs around the world.

5.1 Introduction

Unconventional gas includes shale gas, coalbed methane, natural gas hydrates and tight gas reservoirs. A distinction between tight gas and conventional reservoirs is given

by a government regulation that established a permeability cut-off of 0.1 mD. Reservoirs with permeabilities below this value are considered as 'tight gas sands'. Tight reservoirs are considered as continuous petroleum accumulation. They are characterized by very large areas with pervasive oil or gas saturations and do not depend upon the buoyancy of oil or gas in water for their existence (Law, 2002).

Although the gas volumes in place are gigantic, estimates have been reported as high as 1311 Tcf for tight gas in Canada (Heffernan and Dawson, 2010), recovery factor for the whole accumulation are very low (around 10%). There are exceptions where the recovery can be as high as 50%, these zones are called "sweet spots" and have better rock quality (porosity and permeability). It is believed that a proper reservoir characterization would allow placement of new wells in key zones of the reservoir and therefore lead to an increase in the recovery factor.

The Variable Shape Distribution (VSD) model was developed by Aguilera (2006) for estimating the world petroleum endowment distribution. This distribution is somehow similar to the fractal or Pareto distribution, but instead of using a constant fractal dimension the VSD is based on a shape exponent that is variable. The VSD encompasses the constant shape fractal distribution.

The macro-scale estimation of global petroleum endowment was performed successfully with the VSD model (Aguilera, 2006). Subsequently, Aguilera et al. (2012) extended the VSD application to the micro and nano-scale of reservoir properties such as grain size, pore size, fracture apertures, and permeability, among others. The fractal and VSD formulations are given by Equations 4.2 and 4.14, respectively (Aguilera, 2006):

Figure 5.1 Porosity distributions for the Nikanassin Group and Cadomin formation combined. Blue diamonds correspond to actual data (Deng, 2011). Red squares are calculated with the VSD model, green line is calculated with a log-normal distribution, and purple line is calculated with a normal distribution. Correlation coefficients are 0.9161 for normal, 0.9566 for log-normal, and 0.9941 for the VSD distribution.

An example application of the VSD to model reservoir properties distribution is shown next. In one case matrix porosity data from the Nikanassin Group and Cadomin Formation in the Western Canada Sedimentary Basin is used. **Figure 5.1** shows a crossplot of cumulative number of samples vs. porosity in log-log coordinates. In this graph the cumulative number of samples corresponds to N_i , and porosity to V_i in Equation 4.14. For this case the data range between 0.00085 and 0.20, a difference of more than two orders of magnitude. The distribution presents a very particular signature that can only be partially matched when using conventional distributions such as normal and log-normal. It would require a multi-fractal distribution to obtain a better match. However, a nearly perfect match ($R^2 = 0.994$) was obtained without multi-fractals with the use of a single equation

given by the VSD model. This is a significant advantage for handling data of heterogeneous reservoirs.

5.2 Methodology

The proposed procedure to populate the reservoir model consists basically of integrating the VSD model with conventional geostatistical methods. The latter are applied without any changes in the standard algorithms. The insertion of the VSD is done in the pre-processing of the data prior to the application of the preferred geostatistical method in the final stage. **Figure 5.2** shows a schematic of the implemented workflow for developing this methodology. The steps are as follows:

- 1) Data are upscaled into the grid blocks that are located along the path of the different wells.
- 2) Once the upscaling is done, the values corresponding to the grid blocks are fitted with the VSD model using Equation 4.14. The parameters of the equation are calculated using least squares.
- 3) The fitted data is then transformed into a normal distribution by using the normal score transformation. This step is also part of several geostatistical methods that need the data to be normally distributed in order to produce reliable realizations.
- 4) Estimate experimental or sample semivariograms in X, Y, and Z directions; then match the experimental semivariograms with one of the different theoretical models (Spherical, Exponential, and Gaussian, among others).
- 5) Proceed with the chosen geostatistical method and obtain values for each grid block, specifying the desired number of realizations. These values are distributed normally (same procedure as the input data).

- 6) Transform the produced data back to the original distribution with the VSD fit found in step 2.

The methodology described above starts with data in the form of well logs in step 1 (usually the most abundant resource of information available in field studies), but the procedure can be implemented for any kind of data such as cores and drill cuttings, or data obtained from correlations.

When population of the model is done, the history match is performed by using different combinations with realizations of the modeled properties. Once a history match is obtained, the model can be used to forecast production under diverse development strategies, and to propose the trajectory for optimized horizontal wells (Ramirez and Aguilera, 2014).

Figure 5.2 Schematic of the implemented workflow and methodology for populating reservoir properties in tight fractured reservoirs with the use of the VSD distribution model (best fit in the upper right hand corner).

5.3 Case Study

Members of the GFREE research team in the University of Calgary have worked in the characterization and modeling of the Western Canada Sedimentary Basin, more

specifically in the Nikanassin group and have focused particularly in township 65-09W6. This township has been selected as the study area in this paper. Data from a previous numerical model (Gonzalez, 2012; Gonzalez et al., 2012) have been adapted for use in the VSD model. **Figure 5.3** shows the location of the study area.

Figure 5.3 Location of the Deep Basin (part of the Western Canada Sedimentary Basin) in Alberta and British Columbia (area shaded with yellow). The red square highlights the study area. Source: (Gonzalez et al., 2012)

5.3.1 Matrix Properties

The methodology for the population of reservoir properties was first applied to matrix porosity and permeability data obtained by Deng (2011) and Deng et al., (2011). Deng gathered permeability data from cores available in the study area, and used a triple porosity model (composed by microfracture and slot porosity, non-connected porosity, and intergranular porosity) porosity to calculate effective porosity for some of the wells in study area. The upscaled values were exported to a spreadsheet and the fit with the VSD was performed for the Nikanassin group and the Cadomin formation. The analysis was conducted first with both zones commingled, and then individual analyses were carried out for each formation of the Nikanassin Group (Cadomin, Monach, Beattie Peaks, and Monteith) and the Monteith formation. **Table 5.1** contains the VSD parameters used to fit matrix properties for each of the formations and all the data combined. Also shown are the correlation coefficients (R^2) for the VSD and for a conventional distribution that could be log-normal or normal, depending on which one provides the best result. Comparisons between correlation coefficients for VSD and for conventional distributions, along with visual inspection of the generated curves (**Figure 5.4** for porosity and **Figure 5.5** for permeability) corroborate the potential of the VSD model for characterization of reservoir properties distributions. In addition to have larger values of correlation coefficients, the VSD captures all the features of the properties distributions in the whole scale spectrum without any data truncation.

Although the VSD showed good results when dealing with real data of all the formations combined, it was decided to divide the data according to the formations. Considering the

data individually for each formation ensures a more appropriate modeling of the reservoir properties from a geological point of view.

Table 5.1 Parameters used for generation of Variable Shape Distribution (VSD) curves corresponding to matrix porosity and permeability. Coefficients of determination (R^2) shown in the last column are always superior to R^2 from the log-normal distribution. Asterisks* indicate R^2 for normal distribution instead of log-normal.

PROPERTY	FORMATION	ap	Vx	Vs	ψ	S	Nx	Vm	R2(log-normal)	R2 (VSD)
PERM	MONTEITH	1.232	0.780	0.2612	0.2070	3.73	268	0.000003	0.9489	0.9970
	BEATTIE PEAKS	2.235	0.055	0.0025	1.2000	150.00	45	0.001554	0.9936	0.9893
	MONACH	1.480	4.555	0.4042	0.4700	1414.36	135	0.000895	0.9702	0.9902
	CADOMIN	2.673	100.642	6.4736	3.0093	8176.41	54	3.467572	0.9071	0.9865
	NIKANASSIN GROUP AND CADOMIN	1.469	0.394	0.0041	737.4378	1.08	502	0.000003	0.9485	0.9727
PORO	MONTEITH	1.380	0.600	0.6473	0.0513	1.40	274	0.000845	0.9377	0.9951
	BEATTIE PEAKS	5.702	0.110	0.0017	0.3025	241.37	45	0.006699	0.9931*	0.9765
	MONACH	1.165	3.000	2.5930	0.0201	1.06	122	0.002137	0.9876*	0.9965
	CADOMIN	3.990	0.086	0.0055	1.7995	1800000	54	0.016420	0.9112	0.9858
	NIKANASSIN GROUP AND CADOMIN	1.289	3.000	0.7608	0.0624	1.23	495	0.000845	0.9566	0.9937

Figure 5.4 Porosity distributions for the study area. Blue diamonds correspond to actual data (Deng, 2011). Red squares are calculated with the VSD model. Coefficients of determination (R^2) shown at the top of each graph correspond to the VSD model. Green triangles are calculated with a log-normal distribution for the Nikanassin and Cadomin combined (graph a), Monteith (graph b), and Cadomin (graph e); and a normal distribution for Beattie Peaks (graph c) and Monach (graph d). Visual inspection shows that superior results are obtained with the VSD distribution.

Figure 5.5 Permeability distributions for a) the Nikanassin Group and Cadomin formation, b) Monteith formation, c) Beattie Peaks formation, d) Monach formation, and e) Cadomin formation. Blue diamonds correspond to actual data (Deng, 2011). Red squares are calculated with the VSD model and green triangles are calculated with a log-normal distribution. Values of the coefficient of determination (R^2) at the top of each graph apply to the VSD model.

5.3.2 Fracture Properties

Fracture flow and fracture storage properties such as permeability and porosity can be obtained from intrinsic properties of the fractures within the reservoir. These properties include density, aperture, length, dip, and azimuth, and can be used to generate a Discrete Fracture Network (DFN) from which is possible to calculate porosity and permeability of the natural fractures (Schlumberger, 2012).

Different authors have discussed the nature of natural fractures; some say that fracture generation is a random process while others affirm that there are different well known processes involved in the creation of natural fractures. For example, fractional production-variability plots (Nelson, 2001) have been used with the objective of estimating heterogeneity in naturally fractured reservoirs.

This tool was used in a sensitivity study (Gonzalez and Aguilera, 2013) aimed at determining which of the fracture properties have the largest effect on production variability of individual wells in the Nikanassin Group. Results showed that the fracture property with the greatest impact was fracture density (m^2/m^3). After an exhaustive sensitivity analysis, Gonzalez and Aguilera (2013) obtained an expression that correlates fracture density with a normalized standard deviation of well cumulative gas production for the Nikanassin Formation (Equation 5.1). In a more recent study, Gonzalez et al. (2012) proposed a procedure to obtain an average fracture density per well. The final result was a fracture density surface used as main input for the DFN. That procedure was adapted to this study in order to generate realizations of fracture properties. The VSD model was used to generate the fracture density surfaces instead of generating the permeability and porosity directly:

$$FD = 0.18 * \exp(-3.56 * NSD) \quad (5.1)$$

Where:

FD: Fracture density, fracture area (m²) per unit volume (m³).

NSD: Normalized standard deviation of well cumulative gas production (dimensionless).

Data obtained by Gonzalez and Aguilera (2013) were fitted with the VSD model in the present study. **Figure 5.6** shows the match obtained for the two sets of data available, one for Monteith formation, and the other for the joint Monach and Cadomin formations. Monach and Cadomin share the data set since most of the wells in the area produce comingled from these formations. Once again the VSD shows very good correlation coefficients; for this case the VSD was compared with a log-normal distribution, and the matches for the VSD were superior. **Table 5.2** shows the VSD parameters used to fit fracture density values for the two data sets. Also included are the correlation coefficients for the VSD model and for a log-normal distribution.

Based on the VSD matches, the proposed methodology was applied to the fracture data. Sequential Gaussian Simulation was the chosen geostatistical method in order to give a stochastic element in the generation of the surface. The resulting surfaces for both sets of data are shown in **Figure 5.7** (Monteith) and **Figure 5.8** (Monach and Cadomin). Fracture density is the main input for the DFN generation, but other parameters also have to be input including fracture aperture, length, dip, and azimuth. These input data were taken from the study by Gonzalez et al. (2012) and correspond to the data that gave the best history matching results (production and well bottom hole pressures). **Table 5.3** contains the data used as input for the DFN simulator.

Figure 5.6 Fracture density (area/volume) distributions for a) Monteith formation, and b) the Monach and Cadomin formation. Blue diamonds correspond to actual data (Gonzalez et al. 2012). Red squares are calculated with the VSD model and green triangles are calculated with a log-normal distribution. Values of the coefficient of determination (R^2) at the top of each graph apply to the VSD model.

Table 5.2 Parameters used for generation of Variable Shape Distribution (VSD) curves corresponding to fracture density (area/volume).

FORMATION	ap	Vx	Vs	ψ	S	Nx	Vm	R2(log-normal)	R2 (VSD)
MONTEITH	1.232	0.780	0.2612	0.2070	3.73	293	0.000003	0.9352	0.9964
MONACH AND CADOMIN	1.532	4.568	0.4043	0.4700	1414.36	134	0.001357	0.9782	0.9950

Table 5.3 Fracture parameters in the sensitivity analysis by Gonzalez et al. (2012). SEED: parameter that indicates the starting point of the stochastic fracture generation process. ELONGATION: horizontal to vertical aspect ratio of the fracture planes. CONCENTRATION: relative alignment of the fractures to the specified orientation. SD APERTURE: standard deviation of fracture aperture. Source: Gonzalez et al. (2012)

Parameter	Cadomin	Monach	Montieth
SEED	901593	417240	424504
ELONGATION	32.95	10.00	245.94
MEAN LENGTH (m)	1268.75	1232.88	2414.77
MEAN DIP	87.74	89.18	66.29
MEAN DIP AZIMUTH	42.06	42.88	46.22
CONCENTRATION	58.78	98.40	22.36
MEAN APERTURE (mm)	0.807	0.909	0.521
SD APERTURE (m2)	1.61344E-06	1.81841E-06	1.04127E-06

The red and yellow areas in **Figures 5.7** and **5.8** correspond to zones of intense fracturing, while purple corresponds to areas where fractures are practically inexistent. Red and yellow areas are more prospective for horizontal wells.

5.4 Preliminary Results

The static model obtained from the methodology proposed in this study and the procedures explained are in good agreement with the input data. The comparison with the input data is done in terms of histograms and cumulative distribution function (CDF) of each property as explained next.

Figure 5.7 Fracture density (m^{-1}) surface obtained for the Monteith formation. Red and yellow areas correspond to zones of intense fracturing, while purple corresponds to areas where fractures are practically inexistent. Red and yellow areas are more prospective for horizontal wells.

Figure 5.8 Fracture density (m^{-1}) surface obtained for the Monach and Cadomin formation. Red and yellow areas correspond to zones of intense fracturing, while purple corresponds to areas where fractures are practically inexistent. Red and yellow areas are more prospective for horizontal wells.

5.4.1 Matrix Properties

Results for porosity and permeability show a very good agreement. **Figure 5.9** and **Figure 5.10** show the comparison between the input data and the data modeled with the VSD for porosity and permeability respectively. The figures show that the histogram matches very well throughout the whole scale spectrum and that the CDF curves for the calculated data are almost on top of the input data curves. This indicates that the methodology is reproducing the statistical behavior of the properties modeled without any truncation, which is the main objective of any reservoir characterization tool.

Figure 5.9 Histograms (represented by bars) and CDF curves (represented by open squares) of the matrix porosity from logs. Comparisons of input data from logs and a VSD realization are reasonable.

Figure 5.10 Histograms (represented by bars) and CDF curves (represented by the squares) of the matrix permeability derived from logs. Comparisons of input data and a VSD realization are reasonable.

5.4.2 Fracture Properties

The input used to generate these properties was the fracture density determined from the cumulative gas production variations obtained by Gonzalez et al. (2012). Thus, the comparison is not for porosity and permeability directly, but for the generated fracture density surfaces. **Figure 5.11** shows the comparison for the Monteith formation, and **Figure 5.12** for the joint Monach and Cadomin formations. For this case the VSD results show some minor differences with the input data. The VSD distributions appear to be smoother than the input data, but this behavior is common for both surfaces. But in general, the VSD results are quite close to the input data.

Figure 5.11 Histograms (represented by bars) and CDF curves (represented by open squares) of Monteith fracture density. Input data (Gonzalez et al. 2012) and a VSD realization provide a reasonable comparison.

Figure 5.12 Histograms (represented by bars) and CDF curves (represented by open squares) of Monach and Cadomin fracture density. Input data (Gonzalez et al. 2012) and a VSD realization provide a reasonable comparison.

Chapter Six: **Numerical 3D Model of the Nikanassin Tight Gas Reservoir**

Modeling of tight gas reservoirs cannot be done by following conventional procedures as petrophysical properties are affected by different processes that alter their distributions and correlations among them. Deng (2011) conducted extensive state-of-the-art work on the methodologies and techniques developed by many different authors on how to model these types of reservoirs. In his study he included procedures for calculation of matrix permeability, effective porosity, pore throat aperture, net to gross, and flow units, among others. Deng (2011) utilized some of the standard methods stated in his research and introduced some modifications in order to characterize the Nikanassin Group. All the properties mentioned above were first obtained for individual well locations, since data available was in the form of well logs and cores. The data was then extended to all the grid blocks in the reservoir model by performing facies and petrophysical modeling.

The purpose of the present research is to go one step forward by implementing the VSD distribution for characterizing and modelling naturally fractured reservoirs including tight gas sands.

This chapter describes the model obtained by using the methodology described in Chapter four. Input data for the matrix system used in this study was developed as part of the GFREE research program by Deng (2011). Fracture system data, primarily fracture density at well locations, was obtained by Gonzalez et al. (2012). Gonzalez et al. found a relation between the natural-fracture density and individual wells production variability in the Nikanassin tight gas formation. With production history of the area was able to obtain values of fracture density for all the wells in the area.

6.1 Reservoir Model

The constructed model encompasses the area covered by Township 65 Range 09, located in the Rocky Mountains in Alberta. The strata included in the model were the Nikanassin Group and the Cadomin formation. As the reservoir produces dry gas and no water, the simulation is conducted with a dual porosity (matrix and fractures) single phase flow model. Relative permeability curves, fluid data and initial conditions are the same utilized in a previous study (Gonzalez, 2012). **Table 6.1** shows general geometric properties of the model. The average size in the z-axis shown in the table is for the whole model, this is including the Beattie Peaks formation. Grid block thickness for the formations of more interest are as low as 1m. Given the fact that the minimum spacing of the wells with hard data in the study area is larger than 400m, it was concluded that a 200m grid block size was adequate for the gridding without losing detail in the data distribution. **Table 6.2** shows petrophysical properties obtained with the VSD model. Since there is no fracture density data available for the Beattie Peaks formation, no fracture properties were modeled for this strata.

Table 6.1 Geometric properties of the model for the Nikanassin Group and Cadomin Formation.

PROPERTY	VALUE
Length X-Axis	10000 m in 72 grid blocks
Length Y-Axis	10000 m in 69 grid blocks
Average Thickness	220 m in 56 grid blocks
Grid Block Size	200 m, 200 m, 3.93m
Top Depth	1912 - 2131 m

Table 6.2 Average petrophysical properties obtained with the VSD model for the different layers.

Property		Value / Formation			
		Cadomin	Monach	Beattie Peaks	Monteith
Average Matrix Porosity (fraction)		0.0561	0.0301	0.0211	0.0148
Average Matrix Permeability (md)		29.18	0.2935	0.0151	0.0179
Average Fracture Porosity (fraction)		1.88 E-6	1.93 E-6	*	1.9 E-7
Average Fracture Permeability (md)	X	24.18	7.22	*	0.51
	Y	72.18	122.67	*	2.14
	Z	74.75	128.13	*	1.84

6.1.1 Matrix System

The input data used for the matrix porosity and permeability were obtained by Deng (2011) at individual well locations. Values of effective porosity and permeability were available at nine well locations. The next section shows how the methodology proposed in **Chapter 5** was applied in this thesis and how the key reservoir properties were modeled in the grid that represents the reservoir of interest.

6.1.1.1 Well Log Data Upscaling

The main issue when upscaling well logs is that it is possible to lose some detail if the thickness of the grid cells is not appropriate. As a result it is recommendable to check if the distribution of the log data is similar to the distribution of the upscaled grid blocks. **Figure 6.1** shows a comparison between distribution of well logs and upscaled grid blocks for porosity. **Figure 6.2** shows the same type of comparison for permeability. It can be observed that there is a good agreement in both cases, which is indicative that the layering was performed correctly.

6.1.1.2 Modeling Input Data with the VSD

This step consists mainly in finding the appropriate parameters of the VSD distribution model to fit the input data. Since the final values of the parameters are refined using least squares, it is important to introduce precise initial values in order to reproduce accurately the shape of the data distribution. Recommendations on how to calculate proper initial values at the macro and mega scale of global oil and gas endowment can be found in Aguilera (2006).

Figures 5.4 and 5.5 in the previous chapter show the match obtained with the VSD model for porosity and permeability. Note the significant improvement obtained with the VSD as compared with conventional statistical distributions.

6.1.1.3 Normal Score Transformation

Normal score transformation is a common procedure for many recognized geostatistical methods. It is a crucial step in the proposed methodology because it is here where the VSD model is integrated with property modeling. When matching the input information, each data point is assigned an integer according to its ranking (N_t) among the overall sample. If these integers are used in the transformation the hard data will not be honoured. In order to honour the hard data, the integers have to be replaced with real numbers found by calculating the value that produce the exact data points when input in Equation 5.2. Since this equation has an exponential form it cannot be solved directly for N_t and it is necessary to perform an iterative process to find the exact values. In this study this process was realized using Matlab. Once the new values for N_t are calculated they are used to perform the transformation.

6.1.1.4 Semivariograms

Experimental semivariograms are constructed using the transformed data to find the autocorrelation of the data. Theoretical models for semivariograms fit the experimental ones to be able to calculate the variance at any distance. Both experimental and theoretical semivariograms for all data modeled can be found in Appendix A. The parameters for the theoretical semivariograms are shown in **Table 6.3**.

Table 6.3 Semivariogram models used in the geostatistical analysis.

Property	Variogram Description	Cadomin	Monach	Beattie Peaks	Monteith
Matrix Porosity	Type	Spherical	Spherical	Spherical	Spherical
	Major direction (degree)	300	300	300	300
	Minor direction (degree)	210	210	210	210
	Major range (m)	4002.17	2760.49	2856	1709.84
	Minor range (m)	1359.62	2760.49	2760.49	1423.3
	Vertical Range (m)	10.06	7.511	18.02	18.18
	Nugget	0.118	0.118	0.118	0.118
Matrix Permeability	Type	Spherical	Spherical	Spherical	Spherical
	Major direction (degree)	45	45	45	45
	Minor direction (degree)	315	315	315	315
	Major range (m)	5403.04	2728.65	4097.68	2824.17
	Minor range (m)	5339.36	1359.62	2792.33	2824.17
	Vertical Range (m)	10.22	7.67	7.35	20.41
	Nugget	0.239	0	0	0.18
Fracture Density	Type	Spherical	Spherical	-	Spherical
	Major direction (degree)	100	100	-	135
	Minor direction (degree)	10	10	-	45
	Major range (m)	4512.7	4512.7	-	3019.17
	Minor range (m)	1505.37	1505.37	-	1526.67
	Nugget	0.2515	0.2515	-	0.1946

6.1.1.5 Realizations and Back Transformation

For many cases it is necessary to perform several realizations of different properties in order to match the input data. However, for matrix porosity and permeability a single realization was enough to reproduce the behaviour of the well logs. Since the input data is transformed to a normal distribution, it has to be back transformed to its original distribution; this is done by using an inverse method to the one mentioned in step 3 of the methodology stated in **Chapter 5**. Results of the property modeling of the matrix properties compared with the data from logs are shown in **Figures 5.9 and 5.10**.

6.1.2 Fracture Network

The main input data to construct the fracture discrete network and model fracture properties is fracture density. A strong correlation between fracture density and production variability in the area was found by Gonzalez and Aguilera (2013), and is represented by Equation 5.3. Since the input data is not in the form of well logs, upscaling is not necessary. In fact the fracture density is not modeled in the 3D grid, but as a 2D surface that is part of the input for the discrete fracture network simulator.

6.1.2.1 Modeling Input Data with the VSD

The procedure followed to model the fracture density distribution was the same as used for the matrix properties. **Table 5.2** shows the VSD parameters calculated for the two data sets that were available, one for Monteith formation, and one for Monach and Cadomin formations. Since all the completed zones in the Beattie Peaks formation have resulted in production failures there is no data available for this strata and fractures were not modeled in there.

6.1.2.2 Normal Score Transformation

As discussed previously the normal score transformation is a very important step in the proposed methodology. The procedure used for the matrix data to correct the values of N_t was also followed for the fractures. **Figure 6.3** shows a comparison between the original values of N_t (using the standard VSD procedure), and the corrected ones calculated with the method proposed in this thesis using data from Monach and Cadomin formations. **Figure 6.4** shows the values of fracture density and their equivalent after the transformation for the same data.

Figure 6.3 Blue diamonds represent the corrected N_t values for fracture density in Monach and Cadomin formations. Solid orange line is a 45° line.

Figure 6.4 Original fracture density data points (red circles), and equivalent transformed values (orange circles). F is cumulative frequency. FD is the fracture density.

6.1.2.3 Semivariograms

For the case of fractures there are only two sets of semivariograms, experimental and theoretical, and both can be found in Appendix A. The parameters for the theoretical semivariograms are shown in **Table 6.3**.

6.1.2.4 Realizations and Back Transformation

Fracture density realizations are in the form of 2D surfaces as mentioned above; the initial approach obtained with the VSD was reasonable (**Figures 5.11** and **5.12**), but as concluded at the end of **Chapter 5** there is room for improvement. It was considered that the difference between the modeled data and input data distributions was not related to the methodology itself, thereby the solution adopted was to perform more realizations and select the one that reproduces more accurately the behaviour of the input data. **Figure 6.5** and **6.6** show the input data and the two best realizations distributions (histogram and CDF)

for the Monteith formation, and the joint Monach and Cadomin formations, respectively. Fracture density surfaces from **Figures 6.7** and **6.8** served as input for the Discrete Fracture Network (DFN) Simulator. **Table 6.2** shows some of the properties obtained from the DFN; in addition to these properties the simulator provides the fracture spacing in all directions and the shape factor (sigma). These additional properties are required to calculate the flow interaction between the matrix and fracture systems, also called matrix-fracture transmissibility. This transmissibility is shown in Equation 6.1 (Schlumberger, 2012a, 2012b).

$$TR = CDARCY * K * V * \sigma \dots (6.1)$$

Where:

CDARCY: Darcy's constant, 8.527 e-3 (metric units) or 1.127 e-3 (field units).

K: Matrix permeability.

V: Matrix cell bulk volume.

σ : Shape factor to account for the matrix/fracture interface area per unit volume. Given by Equation 6.2 (Kazemi et al., 1976).

$$\sigma = 4 * \left(\frac{1}{l_x^2} + \frac{1}{l_y^2} + \frac{1}{l_z^2} \right) \dots (6.2)$$

Where l represents the fracture spacing or matrix block size.

With fracture properties calculated with the DFN simulator and matrix properties calculated with the VSD distribution, the static model for the reservoir of interest is finally constructed.

6.1.3 Wells

Production history was available for 54 wells that produce at present or produced in the past from the reservoir in the study area. Among these wells there is only one that produces exclusively from the Nikanassin formation and is identified with the UWI 100/13-14-065-09W6/0. There are also bottom hole pressure (BHP) data available for 14 wells (out of 54) in the area including well 100/13-14-065-09W6/0. Matching the bottom hole pressure of this well was considered of great importance given the fact that it is the only well that does not produce commingled in the study area. Therefore matching BHP of this well was a key objective as well as the matching of production data.

Figure 6.5 Histograms (represented by bars) and CDF curves (represented by open squares) of Monteith fracture density. Input data (Gonzalez et al., 2012) and the two best VSD realizations provide a very good comparison.

Figure 6.6 Histograms (represented by bars) and CDF curves (represented by open squares) of Monach and Cadomin fracture density. Input data (Gonzalez et al., 2012) and the two best VSD realizations provide a very good comparison.

Figure 6.7 Best fracture density (m2/m3) surface obtained for the Monteith formation. Red and yellow areas correspond to zones of intense natural fracturing, while purple corresponds to areas where fractures are practically inexistent. Red and yellow areas are more prospective for horizontal wells.

Figure 6.8 Best fracture density (m²/m³) surface obtained for the Monach and Cadomin formations. Red and yellow areas correspond to zones of intense natural fracturing, while purple corresponds to areas where fractures are practically inexistent. Red and yellow areas are more prospective for horizontal wells.

6.2 Results

One of the objectives of this research was to evaluate the impact that the implementation of the VSD model for populating reservoirs properties had in history matching and production forecasting.

With the static model complete and other elements such as fluid properties, initial conditions, and relative permeability curves taken from previous simulation studies performed in the area (Deng, 2011; Gonzalez, 2012), all the requirements for the simulation model were complete. The model was run for ten years commencing in April 2001 when gas production from the area started.

6.2.1 History Matching

Production history was used as constraint to control the wells in the model, and the BHP was monitored. After modelling more than ten years, simulated gas production rate for the field was very close to the history (**Figure 6.9**), and most of the 54 wells in the area were matched properly. As mentioned above special attention was given to well 100/13-14-065-09W6/0 as this is the only well in the study area that is producing only from the Nikanassin. All other wells are commingled with the Cadomin formation. **Figure 6.10** shows gas production and field measured bottom hole pressure history data for this well. **Figure 6.11** includes the simulated gas flow rate and bottom hole pressure. For this well the gas production was used as a simulation constraint and it matches perfectly; the BHP presents some important differences but in general it follows the trend of the measured data, until the simulation reaches the period where the field data shows contradictory behaviour (January 2010). After this point the simulated BHP follows expected trends, i.e. BHP drops with an increase in gas flow rate and

Although gas production was matched, the simulated BHP is constantly larger than the measured pressure for most of the wells with field data available. These results are similar to the ones obtained in a preceding study (Gonzalez, 2012) previous to coupling with a geomechanical model, and the explanation is thought to be the same. The fracture properties of the reservoir are stress dependant, and there is some fracture closure stemming from an increase in effective stresses that reduces fracture porosity and permeability; this reduction in fracture properties makes it necessary to increase the drawdown to keep the gas production constant. Since the present model is not taking into account the effect of stress in the fracture network, it calculates larger BHP's than the

measured at field. The effect of stresses on the fracture network is beyond the scope of this study. However, this is of paramount importance. As a result it is recommended to pursue this study by coupling the VSD reservoir model with a geomechanical model.

However, the main objective of this thesis, i.e., the use of the VSD distribution for populating the simulation model, proved to simplify the process of history matching over previous approaches. This is shown by the fact that it is possible to produce a static model that reproduces more accurately what is in the subsurface before proceeding to run many simulation cases.

Figure 6.9 Solid green line represents the simulated field gas production and the blue line with empty circles accounts for the history production data. Comparison between the real and simulated data is reasonable.

Figure 6.10 Historical gas flow rate (red circles) and bottom hole pressures (black circles) for well 100/13-14-065-09W6/0. BHP data shows some inconsistencies after January 2010.

Figure 6.11 Measured BHP (black circles) versus simulated BHP for well 100/13-14-065-09W6/0 (solid blue line). Larger simulation pressures starting around October 2009 are interpreted to be the result of partial fracture closure emanating from increases in net stresses due to reservoir depletion.

6.3 Prospective Zones for Future Wells

Fracture density was selected as the criterion for determining prospective zones for drilling horizontal wells as it is anticipated that these areas will provide the largest deliverabilities. Net sand thickness was used to take into account possible reserves. **Figure 6.12** shows the wells included in this study (blue), and highlights (empty black circles) those wells with individual cumulative gas production greater than 15 MMSM³. **Figure 6.13** shows the same wells and the surfaces that were used to generate fracture properties (yellow and red colors correspond to areas with more intense natural fracturing).

Observing the wells that have more cumulative production, it is evident that nearly all of them are located in areas of intense natural fracturing in both the Monteith and Monach/Cadomin commingled formations.

Of particular importance is that there are areas of intense fracturing where no wells have been drilled. These areas are highlighted with dashed ellipses, and are interpreted to be prospective areas where it is recommended to drill horizontal wells that should be hydraulically fractured in multiple stages.

Figure 6.14 shows a map of net sand thickness for the Monach formation (Zambrano, 2014). Also placed in the map are the ellipses that marked the intense fractured zones in the top graph of **Figure 6.13**. In the areas inside the ellipses the thickness is larger than the average for that formation, especially in the western part of the township. This suggests that the selected areas have large amounts of gas in place. This combined with the high deliverability contributed by the natural fractures discussed previously, supports the recommendation presented above to drill horizontal wells in the areas encircled by the dashed ellipses.

Figure 6.12 Location of wells included in the simulation study. Wells with gas cumulative production greater than 15 MMSM³ are highlighted with large black circles. Data taken from public domain (Accumap).

Figure 6.13 Wells with cumulative gas production larger than 15 MMSM³ on top of fracture density surfaces for Monach and Cadomin formations (top), and for Monteith formation (bottom). Ellipses show areas where it is recommended to drill horizontal wells. Yellow and red colors inside the ellipses correspond to areas with more intense natural fracturing.

Figure 6.14 Net sandstone map for the Monach formation at Township 65 Range 09. Ellipses are located in the defined prospective areas from the simulation work developed in this thesis (map after Zambrano, 2014).

Chapter Seven: **Conclusions and Recommendations**

The study of the VSD model, its implementation in property modeling, the impact that it has in reservoir modeling, and the simulation study of the Nikanassin Group as a BCGA have led to the following conclusions:

1. A new methodology has been developed to populate reservoir properties in naturally fractured tight gas formations. The new methodology is demonstrated with data from the WCSB tight gas Nikanassin Group and Cadomin formation.
2. Even though drilling in the study area (Township 65 Range 09) has been relatively intense, there are areas in the Nikanassin Group and Cadomin formation where wells have not been drilled, which present attractive hydrocarbon potential. These areas located particularly in the western part of the Township are characterized by zones of intense fracturing and relatively thick layers of clean sandstone. These are prime areas for drilling horizontal wells and performing multi-stage hydraulic fracturing.
3. The VSD model shows improved performance over conventional statistical distributions such as normal, lognormal and fractal, and it does not require truncation of data. It can handle straight lines on log-log coordinates as required by fractal geometry or a combination of fractal and non-fractal geometries.
4. Implementation of the VSD in property modeling improves the history match and reduces the time required to achieve it given that reservoir properties can be modeled with more accuracy. This results in a more rigorous static model.
5. The new methodology can be coupled with any conventional geostatistical method in the pre and post-processing of the data.

6. The VSD model is a valuable tool for applications in low and ultra-low permeability formations and for evaluating distribution of rock properties at the micro and nano-scale, for example, fracture apertures and pore throat radii. But it can also probably be applied in conventional reservoirs.
7. The VSD model has been corroborated using data from sandstones, carbonates, tight and shale reservoirs from various places around the world. For ease of comparison, various data sets used for the VSD analysis had been published previously in the literature.
8. A “water block” provides an adequate seal for basin centered gas accumulations in the Deep Basin of the WCSB. This is based on results obtained from different simulation cases run over 1.5 million years using a model that mimics rock properties and fluid distribution of Jurassic and Cretaceous tight gas formations.

Experience gained during the realization of this research, accompanied by lessons learned by other researchers of the GFREE research group at the University of Calgary, has led to the following recommendations for future work:

1. Drill horizontal wells and perform multi-stage hydraulic fracturing in the areas of more intense natural fracturing and larger clean sand thickness in Township 65 Range 09. These areas are found mostly in the western side of said township.
2. Use the new proposed methodology and couple the reservoir model with a geomechanical model for the area of interest. This will allow investigating the reduction in properties such as fracture porosity and permeability due to increases in effective stresses.

3. Most steps of the new methodology were carried out independently using different software packages and spreadsheets. A program should be coded to integrate all the steps thus reducing time in the characterization and modeling.
4. Extend the methodology for determining prospective zones for drilling horizontal wells in areas that combine the largest fracture densities and clean sand thicknesses to other areas in the Deep Basin in Alberta.

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APPENDIX A

Appendix A Semivariograms for Geostatistical Analysis

Figure A.1 Experimental semivariogram represented by black squares, and theoretical semivariogram represented by solid blue line for matrix permeability in the Cadomin formation. Top: Major direction, Center: Minor direction, Bottom: Vertical direction.

Figure A.2 Experimental semivariogram represented by black squares, and theoretical semivariogram represented by solid blue line for matrix permeability in the Monach formation. Top: Major direction, Center: Minor direction, Bottom: Vertical direction.

Figure A.3 Experimental semivariogram represented by black squares, and theoretical semivariogram represented by solid blue line for matrix permeability in the Beattie Peaks formation. Top: Major direction, Center: Minor direction, Bottom: Vertical direction.

Figure A.4 Experimental semivariogram represented by black squares, and theoretical semivariogram represented by solid blue line for matrix permeability in the Monteith formation. Top: Major direction, Center: Minor direction, Bottom: Vertical direction.

Figure A.5 Experimental semivariogram represented by black squares, and theoretical semivariogram represented by solid blue line for matrix porosity in the Cadomin formation. Top: Major direction, Center: Minor direction, Bottom: Vertical direction.

Figure A.6 Experimental semivariogram represented by black squares, and theoretical semivariogram represented by solid blue line for matrix porosity in the Monach formation. Top: Major direction, Center: Minor direction, Bottom: Vertical direction.

Figure A.7 Experimental semivariogram represented by black squares, and theoretical semivariogram represented by solid blue line for matrix porosity in the Beattie Peaks formation. Top: Major direction, Center: Minor direction, Bottom: Vertical direction.

Figure A.8 Experimental semivariogram represented by black squares, and theoretical semivariogram represented by solid blue line for matrix porosity in the Monteith formation. Top: Major direction, Center: Minor direction, Bottom: Vertical direction.

Figure A.9 Green squares represent experimental semivariogram in the major direction, blue squares represent experimental semivariogram in the minor direction, and red circles represent theoretical semivariogram for fracture density in the Monteith formation.

Figure A.10 Red squares represent experimental semivariogram in the major direction, blue squares represent experimental semivariogram in the minor direction, and green circles represent theoretical semivariogram for fracture density in the Monach and Cadomin formations.