MULTI-POROSITY MODELING FOR UNCONVENTIONAL RESERVOIRS (CASE STUDY: EAGLE FORD)

Mohammadreza Ghasemi
Texas A&M University

Timothy McNealy
Halliburton

ABSTRACT

One of the primary challenges in unconventional gas/oil reservoirs is characterization and modeling. There are different models for describing the production in an unconventional reservoir (e.g., dual porosity, triple porosity, etc.). This paper generalizes the solution for a multi-porosity model (MPM). This model assumes there are multiple fracture groups in the reservoir and each type of fracture group has varying properties. Different MPMs are considered and an appropriate measure for selecting the best model that describes production data using any known reservoir properties is discussed. The MPM is used to characterize and evaluate a horizontal well in an unconventional reservoir with multistage fracturing.

After selecting the best model, sensitivity analysis can be performed to determine the primary parameters affecting production. These parameters can be estimated by matching the MPM to the well's production history. The MPM uses rate data, no pressure data is necessary, which makes it a perfect tool for analyzing daily production or public production data collected daily or monthly. This data is used to history match the MPM by minimizing the weighted root mean squared (RMS) between the model and the true production data.

Most reservoir models have the inherent flaw of generating non-unique solutions, with more than one correct answer. A plausible solution to this challenge could be achieved by randomizing the input variables and generating a statically probability of a unique solution.

Two wells in the Eagle Ford, oil/condensate window, have been analyzed using the proposed MPM. The MPM was validated through history matching and used for forecasting production. The recent production data is compared to the model's predictions.

INTRODUCTION

Fractures contribute to production significantly by providing the primary pathways for hydrocarbon migration in oil and gas reservoirs. These fractures can exist naturally or can be induced by a hydraulic force. In the case of unconventional reservoirs (shale), these hydraulic fractures are the primary driving mechanism in hydrocarbon production. Unconventional reservoirs are characterized by ultralow permeability, high organic content, multiple porosity types, complex fluid storage, and flow mechanisms. Additionally, unconventional reservoirs tend to be naturally fractured, micro or macro fracturing, caused by hydrocarbon expulsion or geological forces, and contain secondary or induced porosity in addition to their original primary porosity.

It is essential to have an accurate computational model to help design stimulation treatments that can maximize production from an oil and/or gas well in a fractured reservoir. A computational model generally refers to a mathematical model that simulates the behavior of a system, such as the production from an oil and/or gas well, and allows the behavior of the stimulated system to be analyzed. However, fractured oil and gas reservoirs can be challenging to characterize and model because such reservoirs comprise the combination of interacting natural reservoir media and the fractures contained therein, each of which has different parameters, such as porosity and permeability (Serra et al. 1983; McNealy 2013).

Fractured reservoirs can be characterized using a multiple porosity model. For example, a triple porosity model can be used to represent one fracture system and two matrix systems or one matrix system and two fracture systems, each having different properties (Abdassah and Ershaghi 1986). First, Warren and Root (1963) solved this problem, assuming sugar cube idealization of the fractured reservoir, as shown in **Figure 2**. They also extended this model to well test analysis and introduced it to the petroleum literature. Their model was primarily developed for transient well test analysis in which they introduced two main dimensionless parameters, the storativity of the fractures system and fracture-matrix interporosity flow. The analytical solution in Laplace space and the approximation solution of the flow in log-log plots were introduced by Cinco-Ley and Meng (1988). They assumed pseudo steady state flow between the matrix and fracture systems.

Different techniques have been recently proposed in literature for modeling fractured reservoirs. Microscale multiphase flow is suggested to model the complex dynamics in an unconventional reservoir (Alfi et al. 2014; Yan et al. 2013). Shabro et al. (2011) combined a pore-scale model with a reservoir simulation algorithm to predict gas production in gas-bearing unconventional reservoirs. There are some issues that hinder these models from being practical, (i.e., lack of data to initialize these models, complexity of tuning and history matching them, and they are also computationally expensive to run). The latter issue can be mitigated by using some model order reduction techniques as proposed in the literature (Gildin et al. 2013; Ghasemi and Gildin 2014; Ghasemi et al. 2015).

Additionally, an analytical model of fractured reservoirs has been suggested, assuming the reservoir has homogeneous permeability and the fractures are uniformly distributed. In other words, to avoid having two partial derivatives in one equation (making the equation underdetermined), one of the variables, pressure or flow rate, can be made constant. This can be considered a significant difference between an analytical solution and a numerical solution. That is, in a numerical solution, both variables can change over time; but, during a single time step, one must be constant.

Dual porosity was proposed by Bello (2009) to model hydraulically fractured reservoirs. The author assumed linear flow in the reservoir matrix and fractures and identified five different flow regimes in the lifetime of a well. Al-Ahmadi and Wattenbarger (2011) and Dehghanpour and Shirdel (2011) suggested a triple porosity model, wherein not only induced hydraulic fractures are considered, but also a network of natural fractures connected by main hydraulic fractures are assumed. Tivayanonda (2012) compared single, dual, and triple porosity models and suggested a guideline for interpretation of the results.

MPMs proposed in this study were developed to model naturally and hydraulically fractured reservoirs with multi-scale fractures. This model is based on an analytical solution of a fractured reservoir in Laplace transform. It allows for either linear or radial flow. Also, one can easily consider any number of fractured media with different porosity in the model.

After obtaining a proper model, it is advantageous to match the model to the actual reservoir production history, referred to as history matching. History matching, however, can be a nonlinear problem and mathematically accurate models might have multiple solutions (Kalakkadu et al. 2013). Therefore, there is a need for improved methods and systems for determining reservoir properties and fracture properties in wells, such as oil and gas wells.

Conventional models typically rely on well pressure for history matching and determining reservoir properties. There are different web services that provide well production information that can be used in the MPM. The data from these sources can be used to determine a flow rate, but it typically does not provide the daily pressure data for the well, which can be a requirement in some computational models.

This paper suggests a new approach to generalize the fractured reservoir and for the MPM to be used for determining reservoir and fracture properties from data sources where daily and/or monthly rates are available, but the flowing pressure is not available. This allows a well engineer to compare wells in terms of the number of open fractures, porosity, and permeability close to the wellbore. In the new workflow, one can start with a generalized fractured model and run the assisted history match to match the model to the existing production data, then the best model will be selected based on statistical analysis of the results. After obtaining this model, one can perform more analysis of the solution to investigate the non-uniqueness of the solution. This workflow is illustrated and discussed in detail later.

This work is organized as follows.

- First, the mathematical model and proposed MPM are discussed.
- Second, this model is discussed in addition to some sensitivity analysis with respect to different parameters in the model. These results are used in the following section for assisted history matching of the model to production data.
- Third, the statistical methods are discussed to select the best model from all possible solutions. The best model is then used to analyze two production wells in the Eagle Ford and to identify the reservoir and fracture properties.
- Finally, the non-uniqueness of the solution is discussed and an approach to investigating the trend of the solutions is discussed.

UNCONVENTIONAL RESERVOIR MODELING

Modeling unconventional reservoirs with conventional models can present several challenges. Some of these challenges include determining properties and scale of fractures and the reservoir, understanding the interaction between the fractures and the matrix, secondary and/or tertiary fracturing and porosity not available in the model, lack of pressure data during production, computational resources, and the time necessary to process the model. Using an analytical dimensionless rate, constant pressure solution can resolve several issues and these models typically are magnitudes faster and less resource intensive than numerical models.

In general, MPMs can be solved considering multiple media with different permeability and porosity. **Figure 2** is a schematic perspective view of an exemplary triple porosity model. In this model, multiple differential forms (one for matrix and one for fracture) of diffusivity equations should be solved simultaneously at any point in the reservoir model.

There are different types of flow with respect to spatial derivative or time derivative. With respect to time, the flow solution in each media can be transient or pseudo-steady state flow. With respect to spatial derivative, the solution can be linear in Cartesian coordinates or radial in cylindrical coordinates.

In general, one can convert the time and production data to dimensionless time and rate by defining the following time and pressure variables, given it is slightly compressible fluid [for derivation and description, refer to Bello (2009)]

$$t_{DAc} = \frac{0.00633 k_f t}{(\phi \mu c_t)_{f+m} A_{cw}} \qquad (1)$$

$$\frac{1}{q_{DL}} = \frac{k_f \sqrt{A_{cw}} (p_i - p_{wf})}{141.2 q B \mu}, \textit{liquid reservoir} \qquad (2)$$

$$\frac{1}{q_{DL}} = \frac{k_f \sqrt{A_{cw}} \left(m(p_i) - m(p_{wf})\right)}{1422 q_g T}, \textit{gas reservoir} \qquad (3)$$

The analytical dimensionless rate solution for linear flow constant bottomhole pressure (BHP) in the Laplace domain is as follows

$$\frac{1}{\overline{Q_{DL}}} = \frac{2\pi s}{\sqrt{s f(s)}} \coth\left(-2\sqrt{s f(s)}\, y_{De}\right) \qquad (4)$$

where $f(s)$ is the function derived based on different flow regimes in a reservoir, which is explained in detail at the end of this section.

There are two dimensionless parameters used in any analytical solution. These parameters help interpret different flow regimes in a reservoir. The first one is storativity ratio, ω_i, which relates the total expansion in the fracture network to the total expansion in the system. This parameter accounts for the amount of fluid in a fracture system and is defined as

$$\omega_i = \frac{\phi_i c_i}{\sum_i^n \phi_i c_i} \quad (5)$$

where ϕ_i and c_i are porosity and compressibility in media i, respectively. The second parameter is interporosity flow, λ_i, that describes the fracture-matrix interaction and is defined as

$$\lambda_i = \sigma \frac{k_i}{K_F} A_{cw} \quad (6)$$

where k_i is the permeability of the *i*th fracture, K_F is the permeability of the main fracture, $A_{cw} = 2x_F h$ is cross-sectional area at well face, h reservoir thickness, and x_F fracture half-length.

In Equation 6, σ is the shape factor that reflects the geometry of the matrix elements and controls the flow between porous media; for example, if the reservoir model is composed of slabs, as shown in Figure 2, then $\sigma = 12/L_F$, where L_F is the main fracture spacing distance.

Starting from the innermost fracture, and assuming the flow is from reservoir matrix to the natural fractures, and then from those to the main fractures (hydraulic fractures), until it gets to wellbore, $f(s)$ can be found as

$$f_i(s) = \frac{3}{\lambda_{i-1}}(\omega_i + F_i) \quad (7)$$

$$\sum_{i=1}^{N} \omega_i = 1, \lambda_0 = 3, F_N = 0 \quad (8)$$

where F_i for slab matrix blocks is defined as

$$F_i = \begin{cases} \frac{\lambda_i}{3s}\sqrt{sf_{i+1}(s)}\tanh\left(\sqrt{sf_{i+1}(s)}\right), pseudo \\ \frac{\lambda_i f_{i+1}(s)}{3+sf_{i+1}(s)}, transient \end{cases} \quad (9)$$

The model can be one of several models—dual, triple, or generally multi-porosity. In the dual porosity model, there is only the hydraulic fracture. In the triple porosity, natural fracturing and hydraulic fractures exist. In the quad porosity model, there are two types of natural fractures and hydraulic fractures, and so on. It should be noted that each of these models includes the matrix properties in addition to fracture properties.

SENSITIVITY ANALYSIS

One of the primary tasks after obtaining a model is to determine the importance of each parameter in the model. This can help improve not only the understanding of the model, but also helps provide some intuition in terms of determining whether a reservoir is profitable.

A sensitivity analysis should be performed on the important parameters in the model separately. However, one should keep in mind that some parameters might be related proportionally or inversely; thus, the results will be related. In the sensitivity analysis, one parameter is changed at a time in specific range, and the output of the model is compared for different values. Although this approach is useful, another approach was chosen, a tornado chart (for the sake of space), to compare the significance of each parameter in the model.

In a tornado chart, the model is run by assuming a set of values for each parameter that are typical values for a specific case. Then, each parameter is changed by relatively the same amount (e.g., $\pm 10\%$), and the new value of the output is compared with the base case. This comparison is usually shown as a horizontal bar for each value. For example, a tornado chart for triple porosity model is shown in **Figure 3**. To generate this figure, each parameter was varied $\pm 10\%$, except permeabilities that were changed one order of magnitude, and cumulative production was compared with the base case. The difference for each is shown as a bar in Figure 3.

As it can be seen, the reservoir porosity, permeability, pressure drawdown, and thickness have the largest effect on production and fracture half-length. On the contrary, fluid pressure/volume/temperature (PVT) [e.g., viscosity and formation volume factor (FVF)] also have great impact on the production. Conversely, the fracture porosity does not play that significant of a role. It is believed to be because of the small volume of the fractures compared to total stimulated volume (SRV) of the reservoir.

MPM WORKFLOW

In general, an MPM can be solved considering multiple media with different permeability and porosity. In this case, multiple differential equation forms of diffusivity equations are solved with proper boundary condition at wellbore and fractures.

MPMs appear to cover a wide range of unconventional models. This case study investigates the results of this model in a new workflow for unconventional reservoir to determine its accuracy.

To understand the process used for the MPM workflow, **Figure 4** was developed. The first step is to import reservoir data to initialize the model. The production data in the form of oil rate, gas rate, or barrel of oil equivalent (BOE) are needed for history matching the model. This data also includes reservoir properties, such as average reservoir pressure, average formation volume factor, and viscosity. The initial estimation for reservoir permeability and initial hydraulic and natural fractures properties are also included. If the initial estimation for the fracture parameters is not accurate enough, the production from the model will be very different than true production data. One should modify these parameters to achieve the model output close to real production data to obtain a more reliable solution after history matching.

The next step is to match the model with the production data using assisted history matching. During this step, one of the MPMs is selected, for example, triple porosity. A computer program is used to minimize the error between the model output and the true measured data. This is an iterative process and, upon the end of this regression, reservoir parameters can be estimated. Early production data can be noisy and inaccurate. Also, the recent production is more important in terms of forecasting future production. One should weigh the data points accordingly before running assisted history matching. The error is calculated as a root-mean-squared rate according to the following formula

$$Err(x) = [Q_{model}(x) - Q_{actual}(x)]^T * W * [Q_{model}(x) - Q_{actual}(x)] \quad \text{..........(10)}$$

where x is a set of all unknown reservoir parameters, $Q_{model}(x)$ is the value calculated by a computational model, $Q_{actual}(x)$ is the actual value of production derived from historical data, and W is the weighting matrix influence of a data point on the error, which affects the history match. An initial weight matrix is an identity matrix; however, the diagonal elements corresponding to noisy data or outliers are set to very small values.

The error function in Equation 10 is quadratic with some inequality constraints for each parameter. This function can be minimized using automated regression routines that can handle constraints. This paper used a nonlinear solver function, where the solution converges with good initial estimation.

The assisted history matching should be accomplished for all the relevant MPMs, (i.e., dual, triple, and quad porosity models). After gathering all the history matching results of different models, one should compare them using statistical tools to select the best model that captures the production data. The typical tests are Akaike information criteria (AIC), Baysian information criteria (BIC), F-testing, etc.

The AIC parameter is calculated using the following formula

$$AIC = n\ln\left(\frac{SSR}{n}\right) + 2k + \frac{2k(k+1)}{n-k-1} \quad \text{......(11)}$$

where n is the number of data points, SSR is the sum of squared residual as defined in Equation 10 , and k is the number of parameters used in the model (i.e., K_m, K_f, K_F, etc.). The models can be also compared using an F-test, which can be calculated according to the following formula

$$F = \left(\frac{SSR_1 - SSR_2}{SSR_2}\right)\left(\frac{n-p_2}{p_2-p_1}\right) \quad \text{......(12)}$$

where n is the number of data points, SSR_1 and SSR_2 are the sum of squared residuals for the first and the second model, respectively, and p_1 and p_2 are the number of parameters in the first and the second model, respectively.

It should be noted that the F-test is a comparison between two nested models to determine if the model with more parameters yields a significantly lower error. Models with more parameters can result in a better fit to the actual data, but can add complexity to the task of resolving a unique solution.

Ultimately, after selecting the best model, one can investigate the non-uniqueness of solutions from history matching and find a trend in the parameter solutions. This process is necessary because the system of equations used to define the model is nonlinear and the nonlinear regression used in history matching can yield non-unique solutions. This nonlinear problem is anticipated to generate multiple local minima solutions and it is anticipated that only one local minima solution yields the lowest error or best history match to the actual production. Non-unique solutions can be problematic because different parameter combinations can result in solutions that satisfactorily match the historical data, but yield different values for the iteratively computed parameters in a model, such as matrix permeability, main hydraulic fracture permeability, porosity etc. For example, there is an inverse relationship between a hydraulic fracture's length and permeability, which can be observed in a dimensionless fracture conductivity equation.

Understanding these relationships and the impact that false solutions can have on forecasting actual well production are the reasons why a probability distribution on the initial guess of the unknown parameters is necessary. This can be accomplished by randomly initializing all of the parameters with a uniform distribution and finding all of the local minima, which can quantify the extent of any non-unique solutions. Without using a uniform random sampling on the initial unknown parameters, it is possible that some local minima will never be detected.

Knowledge and experience in a specific reservoir are necessary to set limits on the range of values that a property can have. For example, in the Eagle Ford, it is expected that the permeability of the matrix will be between 10 milidarcies (md) and 10 nanodarcies (nd). If the model outputs a matrix permeability of 1 darcy (D) and still yields a low error, it is safe to assume that the results of the model are not valid. This validation should be applied to all of the properties being solved for to help ensure the validity of the results.

CASE STUDY RESULTS

Production data for two adjacent wells (Wells 1 and 2) in the Eagle Ford, oil/condensate window, are available. The goal is to analyze these two wells with the proposed MPM to estimate some unknown reservoir and fracture parameters. The MPM results were validated through history matching and by comparing recent production data with the model's forecasting results.

The initial parameter estimation is the same for both wells. **Figure 5 and 6** show a comparison of three exemplary models (e.g., dual, triple, and quad porosity) with the corresponding historical production data for Well 1. Differences in the models can be observed, for example, in the slope of the data and the accuracy of the history matching.

Visually inspecting the output of the models can be helpful in terms of validating the overall accuracy of the output, as each model can use the same input that might have been weighted for various reasons. Additionally, the use of a log-log plot can help visualize the slopes of actual and modeled data, and can help determine when each flow regime occurred.

Table 1 shows the results of AIC calculation based on Equation 11 for the case study. Here, dual, triple, and quad porosity models were compared. It is apparent that, in this example, the best model for this particular well would be the triple porosity model because the probability of that model being correct was found to be approximately 79.7% (i.e., a higher probability than those for the remaining models).

The results of an F-test for the case study are calculated using Equation 12 and the results are shown in **Table 2**. These results also verify that the triple porosity is superior to either the dual or quad porosity models. The P-value is a probability measure of the sum of squares over the degrees of freedom to determine the significance of one model compared to the other.

This comparison was conducted in the same manner for Well 2, and the triple porosity model also appeared to be the best representative model.

After selecting the triple porosity model and history matching both wells' production data to the triple porosity model, the unknown reservoir parameters are extracted and shown in **Tables 3 and 4** for Wells 1 and 2, respectively. The estimated parameters are close, just as the locations of these two wells are close and in the same type of reservoir rock.

Now that the triple porosity model was opted as the best model and parameters were extracted using assisted history matching, the production data for Wells 1 and 2 are compared to the model results in **Figures 7 and 8,** respectively. Additionally, the cumulative production data is compared with the triple porosity model for both wells, and the results are shown in **Figures 9 and 10**, revealing that the model matches the data accurately.

To validate this model, one can use it to forecast the production and then compare this forecast with recent production data that has not been used during history matching process. Because the public data was only available for both wells combined, the results from both models were combined and compared with recent production data in **Figure 11**. This figure shows the daily production data that has been used for history matching and the monthly production data that are available publicly. As it can be seen, the model forecast and cumulative production match very closely.

Figure shows a distribution of initial parameters in their plausible range. This is a biplot or matrix plot showing relationships of each variable to all other variables. Each row header in this example identifies the variable for the y-axis along the corresponding row; similarly, each column header identifies the variable for the x-axis along the corresponding column. The plots along the diagonal show an initial histogram for the variable corresponding to the respective row/column intersections. The histograms in this figure illustrate that the initial parameters are close to uniform distribution.

In this figure, five variables were used, namely, kF (main or hydraulic fracture permeability), kf (natural fracture permeability), km (reservoir or matrix permeability), Lf (distance between natural fractures), and ye (main or hydraulic fracture half-length). However, other variables and numbers can be used in accordance with a particular application.

A set of initial values can be chosen based on any information that is available regarding the corresponding variable. For example, a model can benefit from (i.e., by becoming more likely to be accurate) a set of initial values for a variable chosen from as narrow of a range as possible for that value. Also, one can choose any other distribution, such as Gaussian, Poisson, etc., if any a priori information is available about the corresponding variable.

In this case study, 200 initial values were selected for each variable from a range of possible values. Assisted history matching of this model using every set of initial conditions can identify values that might be more probable than others. This can be identified as a trend.

Figure shows a matrix plot for the case study and parameters discussed after each set was used for initial estimation during history matching and the new parameters were obtained. The histogram for each parameter, along the diagonal of the matrix plot, demonstrates the frequency for each parameter.

Further, the two trends between k_f and L_f and k_m and L_f in this figure indicate that there can be two solutions for a value of L_f. Under such circumstances, one can determine the best option for a particular application based on other information available about the project at hand and experience or knowledge in the field, etc.

Because a triple porosity model is underdetermined, the solution to the inverse problem is not unique. This problem can be avoided by holding some parameters constant. For example, in this case study, a more likely value for k_f is approximately 75 md, and approximately 65 hydraulic fractures are open. One should remember that sometimes more information is necessary to help determine a unique solution for all of the parameters.

CONCLUSIONS

This paper introduces a new workflow for fast evaluation of unconventional reservoirs. This process is based on matching different MPMs, dual, triple, quad, etc., to historical production data (no pressure information is necessary). It was suggested that statistical tools, (e.g., AIC, F-test, etc.) be used for selecting the best model. After such a selection and history matching, the unknown parameters of the reservoir or fractures can be estimated.

This workflow was verified in a case study of two wells in the Eagle Ford shale reservoir. A triple porosity model was selected as the best model. It agrees that these wells are located in naturally fractured reservoirs. Also, the model forecast recent production data was very close to the public monthly production values.

Finally, an approach to investigate non-uniqueness of the history matching solution based on determining the final distribution of parameters with respect to each other after history matching was proposed. These results were compared in a matrix plot to help determine the final histograms and possible trends between parameters.

NOMENCLATURE

$\boldsymbol{k}$	Permeability $[\boldsymbol{md}]$
$\boldsymbol{\phi}$	Porosity
$\boldsymbol{x_r}$	Reservoir (SRV) length $[ft]$
$\boldsymbol{y_f}$	SRV half length (main fracture half-length) $[ft]$
$\boldsymbol{L}$	Spacing between two adjacent elements (fractures) $[ft]$
$\boldsymbol{w}$	Width $[in]$
$\boldsymbol{h}$	Reservoir thickness $[ft]$
$\boldsymbol{\mu_o}$	Oil viscosity $[cp]$
$\boldsymbol{B_o}$	Formation volume factor $[\frac{\mathrm{rbbl}}{\mathrm{stb}}]$
$\boldsymbol{c_t}$	Total compressibility
$\boldsymbol{\Delta p}$	Pressure drawdown between reservoir and bottom-hole
n	Total number of fractures

SUBSCRIPTS

$\boldsymbol{F}$	Main fracture
$\boldsymbol{f}$	Secondary fracture
$\boldsymbol{m}$	Matrix (reservoir)

REFERENCES

Abdassah, D. and Ershaghi, I. 1986. Triple-Porosity Systems for Representing Naturally Fractured Reservoirs. *SPE Form Eval* **1** (2): 113–127. SPE-13409-PA. http://dx.doi.org/10.2118/13409-PA.

Al-Ahmadi, H.A. and Wattenbarger, R.A. 2011. Triple-porosity Models: One Further Step Towards Capturing Fractured Reservoirs Heterogeneity. Presented at the SPE/DGS Saudi Arabia Section Technical Symposium and Exhibition, Al-Khobar, Saudi Arabia, 15–18 May. SPE-149054-MS. http://dx.doi.org/10.2118/149054-MS.

Alfi, M., Yan, B., Cao, Y. et al. 2014. How to Improve Our Understanding of Gas and Oil Production Mechanism in Liquid-Rich Shale. Presented at the SPE Annual Technical Conference and Exhibition, Amesterdam, The Netherlands, 27–29 October. SPE-170959-MS. http://dx.doi.org/10.2118/170959-MS.

Bello, R.O. 2009. *Rate Transient Analysis in Shale Gas Reservoirs With Transient Linear Behavior.* PhD Thesis, College Station, Texas A&M University (2009).

Cinco-Ley, H. and Meng, H.-Z. 1988. Pressure Transient Analysis of Wells with Finite Conductivity Vertical Fractures in Double Porosity Reservoirs. Presented at the SPE Annual Technical Conference and Exhibition, Houston, Texas, 2–5 October. SPE-18172-MS. http://dx.doi.org/10.2118/18172-MS.

Dehghanpour, H. and Shirdel, M. 2011. A Triple Porosity Model for Shale Gas Reservoirs. Presented at the Canadian Unconventional Resources Conference, Alberta, Canada, 15–17 November. SPE-149501-MS. http://dx.doi.org/10.2118/149501-MS.

Ghasemi, M. and Gildin, E. 2014. A New Model Reduction Technique Applied to Reservoir Simulation. Presented at the European Conference on the Mathematics of Oil Recovery, Catania, Italy.

Ghasemi, M., Yang, Y., Gildin, E.. et al. 2015. Fast Multiscale Reservoir Simulation Using POD-DIM Model Reduction. Presented at the SPE Reservoir Simulation Symposium. Houston, Texas, 23-25 February. SPE-173271-MS. http://dx.doi.org/10.2118/173271-MS.

Gildin, E., Ghasemi, M., Romanovskay, A. et al. 2013. Nonlinear Complexity Reduction for Fast Simulation of Flow in Heterogeneous Porous Media. Presented a the SPE Reservoir Simulation Symposium, The Woodlands, Texas, 18–20 February. SPE-163618-MS. http://dx.doi.org/10.2118/163618-MS.

Kalakkadu, S., Devegowda, D., Civan, F. et al. 2013. History Matching and Production Data Analysis for Shale Gas and Oil Reservoirs: The Relevance of Incorporating. Presented at the Unconventional Resources Technology Conference*.* Denver, Colorado, 12–14 August. SPE-168822-MS. http://dx.doi.org/10.1190/URTEC2013-054.

McNealy, T. 2013. Proppant economics in the Eagle Ford formation. *Hart Energy Exploration and Production*.

Serra, K., Reynolds, A.C., and Raghavan, R. 1983. New Pressure Transient Analysis Methods for Naturally Fractured Reservoirs (includes associated papers 12940 and 13014) . *J Pet Technol* **35** (12):2271–2283. SPE-10780-PA. http://dx.doi.org/10.2118/10780-PA.

Shabro, V., Torres-Verdin, C., and Javadpour, F. 2011. Numerical Simulation of Shale-Gas Production: From Pore-Scale Modeling of Slip-Flow, Knudsen Diffusion, and Langmuir Desorption to Reservoir Modeling of Compressible Fluid. Presented at the North American Unconventional Gas Conference and Exhibition, The Woodlands, Texas, 14–16 June. SPE-144355-MS. http://dx.doi.org/10.2118/144355-MS.

Tivayanonda, V. 2012. *Comparison of Single, Double, and Triple Linear Flow Models for Shale Gas/Oil Reservoirs.* MSc Thesis, Texas A&M University, College Station, Texas (2012).

Warren, J.E. and Root, P.J. 1963. The Behavior of Naturally Fractured Reservoirs. *SPE J.* **3** (3): 245–255. SPE-426-PA. http://dx.doi.org/10.2118/426-PA.

Yan, B., Alfi, M., Wang, Y. et al. 2013. A New Approach for the Simulation of Fluid Flow In Unconventional Reservoirs Through Multiple Permeability Modeling. Presented at the SPE Annual Technical Conference and Exhibition. New Orleans, Louisiana, 30 September–2 October. SPE-166173-MS. http://dx.doi.org/10.2118/166173-MS.

Table 1 - Comparing different models' match based on AIC.

Model	No. of Parameters	SSR	AIC	Correctness Probability (%)
Dual porosity	4	1.9446e5	964.98	9.9
Triple porosity	6	1.8220e5	960.81	79.7
Quad porosity	8	1.8161e5	964.88	10.4

Table 2 - Comparing different models' match based on F-test.

Comparison	F-Test Value	P Value
Dual vs. triple porosity	4.2	$1.7\% < 5\%$
Triple vs. quad porosity	0.18	$83.8\% > 5\%$

Table 3 - Reservoir parameters for Well 1.

Matrix Permeability (nd)	Hydraulic Fracture Permeability (md)	No. of Hydraulic Fractures	Fracture Half-Length (ft)	Natural Fracture Permeability (md)	Total No. of Natural Fractures
1900	184	60	348	0.8	60*10

Table 4 - Reservoir parameters for Well 2.

Matrix Permeability (nd)	Hydraulic Fracture Permeability (md)	No. of Hydraulic Fractures	Fracture Half - Length (ft)	Natural Fracture Permeability (md)	Total No. of Natural Fractures
2260	86	60	533	0.5	60*18

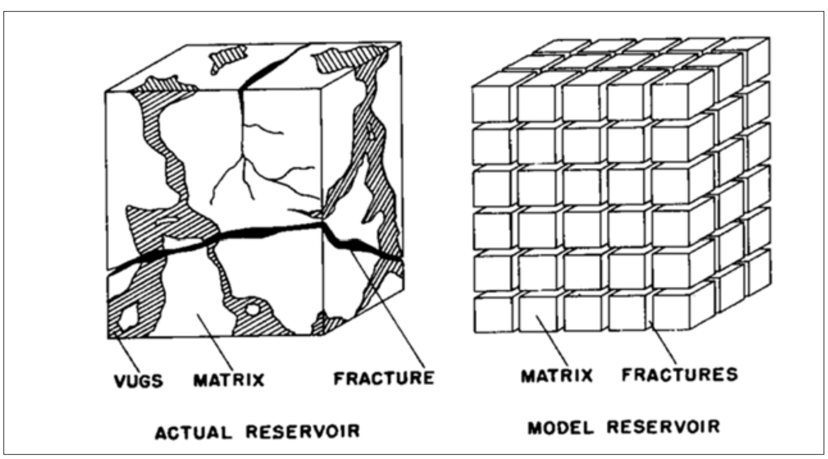

Figure 1 - Idealization of the heterogeneous porous medium (Warren and Root 1963).

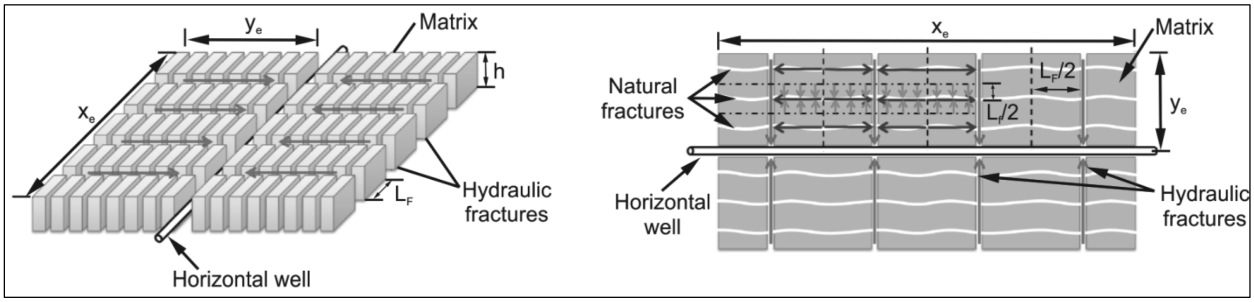

Figure 2 - Triple porosity model (Al-Ahmadi et al. 2011).

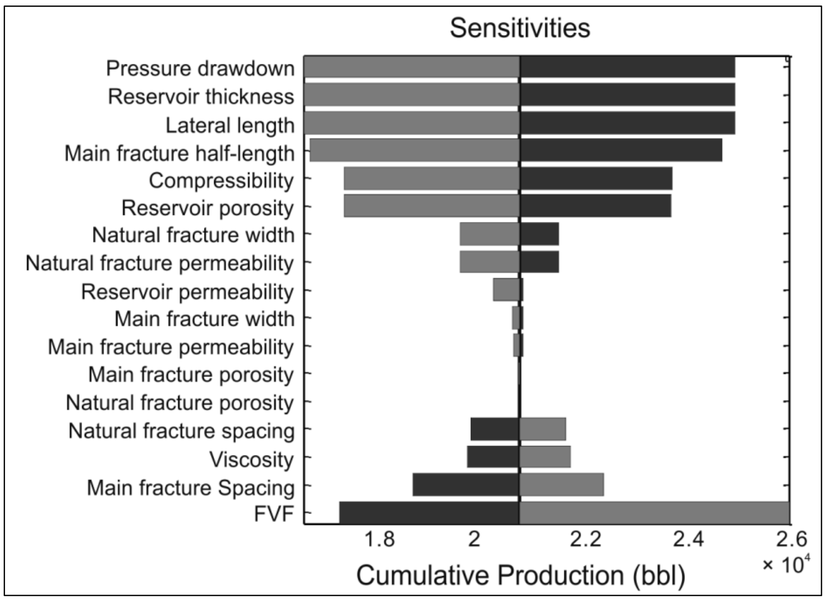

Figure 3 - Tornado chart shows sensitivity of different parameters.

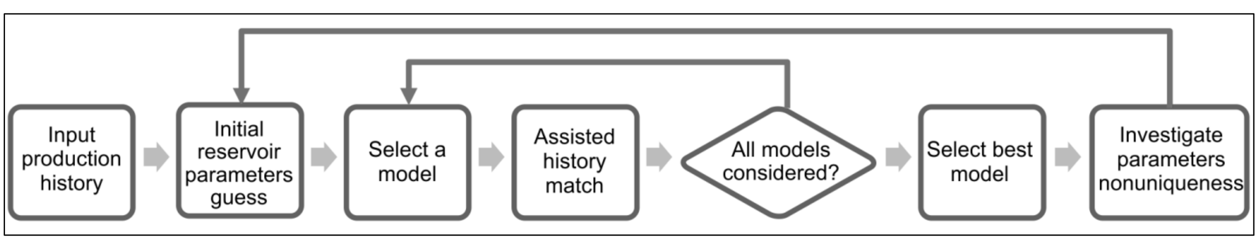

Figure 4 - Multi-porosity workflow.

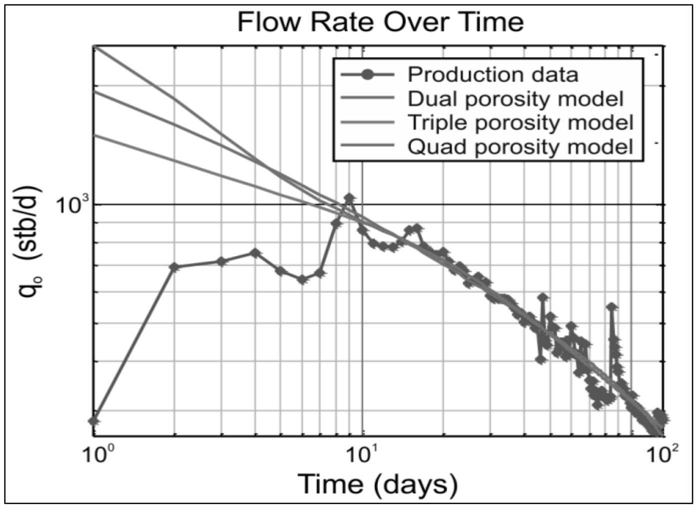

Figure 5 - History matching results compared to daily production rate for different models.

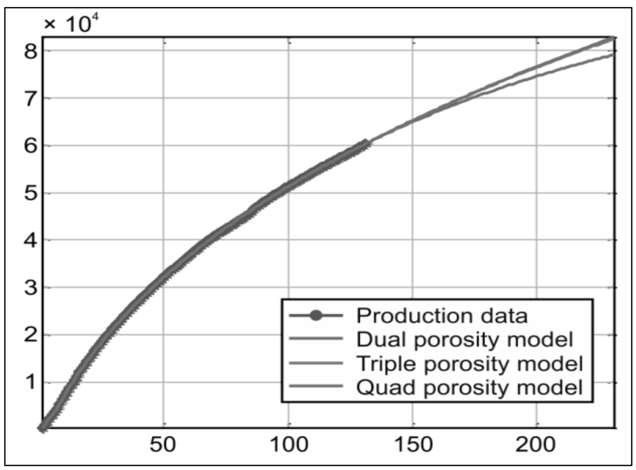

Figure 6 - History matching results compared to cumulative production for different models (stb vs. days produced).

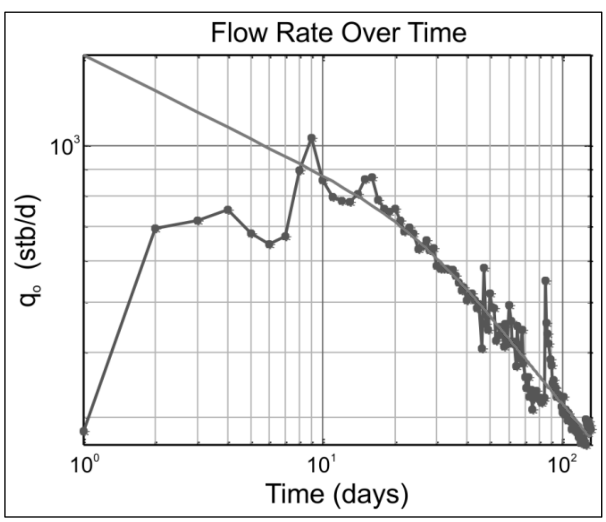

Figure 7 - History matched Well 1 production rate.

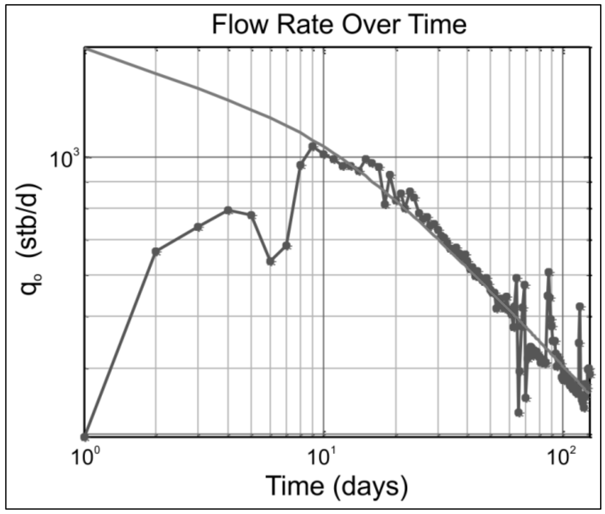

Figure 8 - History matched Well 2 production rate.

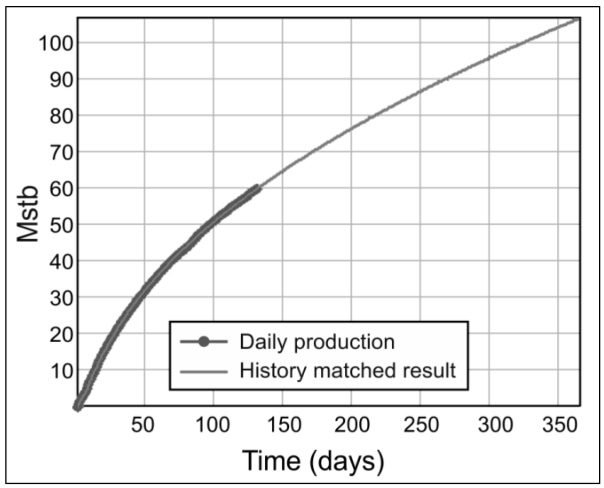

Figure 9 - History matched Well 1 cumulative production.

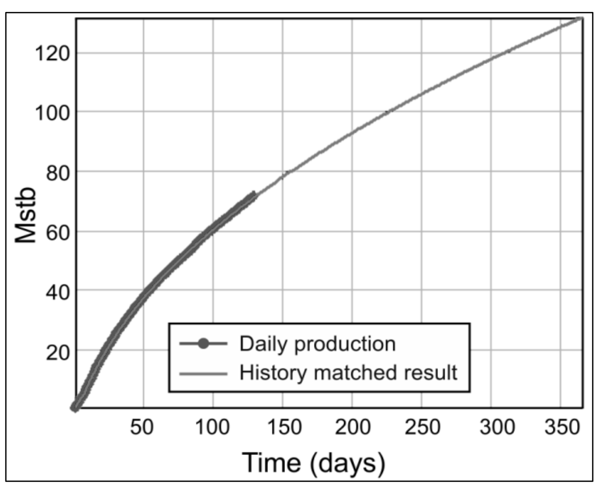

Figure 10 - History matched Well 2 cumulative production.

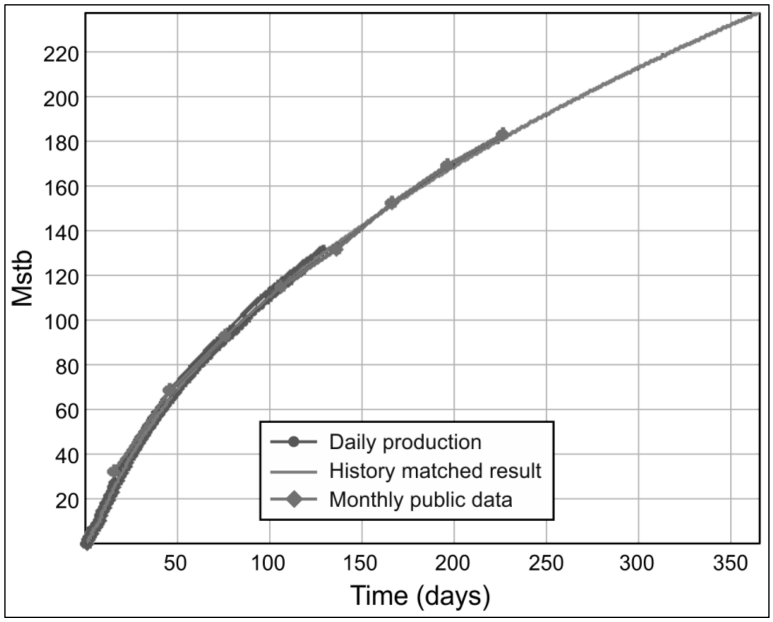

Figure 11 - Monthly production data compared to history matched model. The triple porosity model shows good prediction in this example.

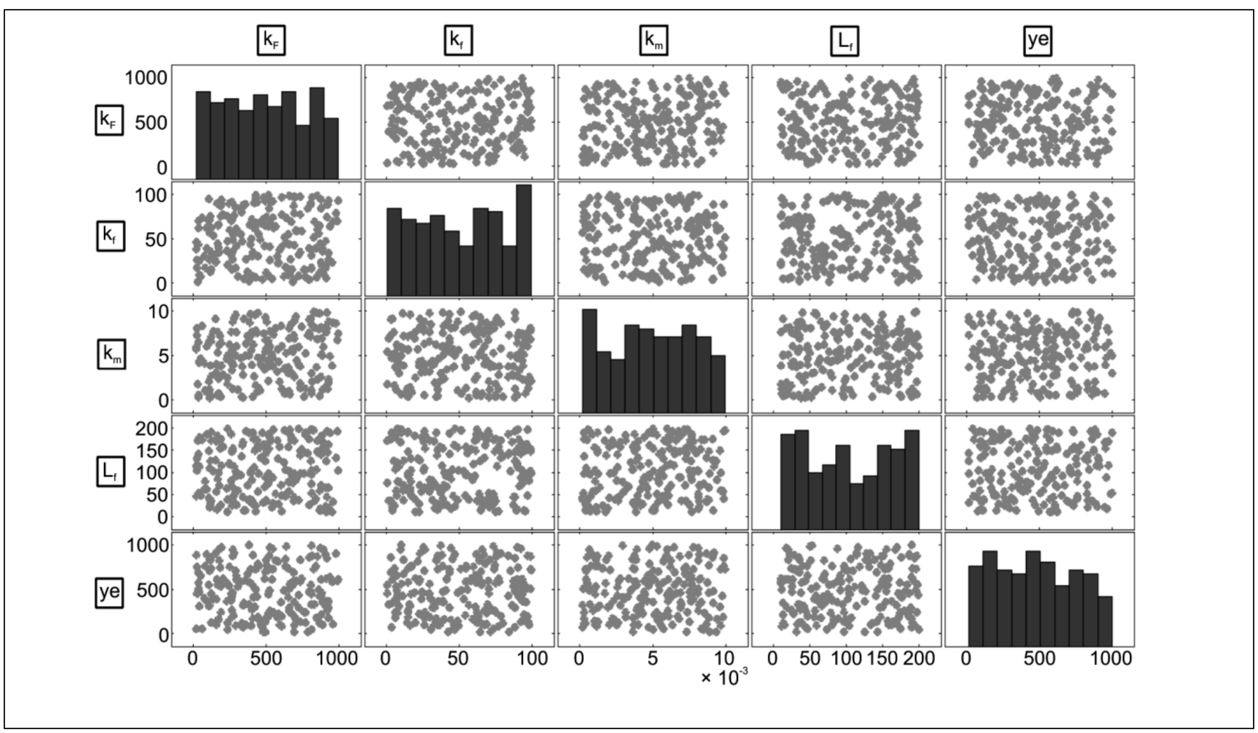

Figure 12 - Cross plot of initial parameters from uniform distribution.

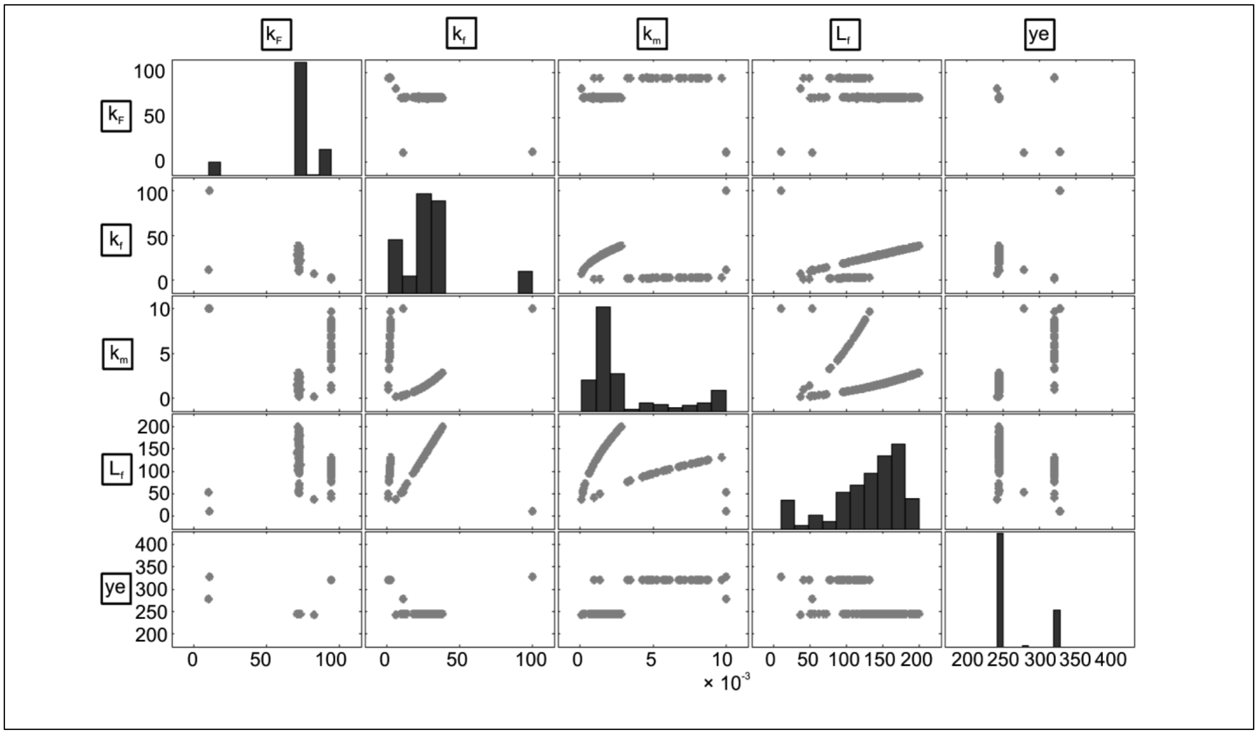

Figure 13 - Parameters extracted from matched triple porosity model to production history. Each history match was initiated from a set of uniform distributed points in Figure .