Proposal for Modeling Naturally Fractured Reservoirs

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This paper proposes a methodology for modeling naturally fractured reservoirs. The new methodology is based on previous works but offers several unique improvements. A new method for calculating a robust correlation coefficient in the presence of sparse data has been proposed. The sampling distribution for the correlation coefficient is implemented in order to examine its uncertainty and its effect on geostatistical models. The proposed methodology also considers the discrete fracture network generation techniques that simulate more geologically realistic inter-relationships between parameters such as fracture length, aperture, location and density. Flow simulation sensitivity studies have been proposed that would derive flow sensitivity coefficients allowing faster and more accurate history matching.

Introduction

Research shows as much as 60% of the world's petroleum reserves are known to be in naturally fractured reservoirs (NFRs) (Waldren and Corrigan 1985, Beydoun 1998, Roxar 2009) where the fractures in the reservoir rock have, or are predicted to have, a significant effect on the reservoir fluid flow. As most convenient and economical reserves decline, producers are increasingly turning toward non-traditional sources of petroleum such as oil sands and NFRs.

In order to optimize the management of NFRs, detailed information on the behavior, attributes and properties of the fracture network and rock matrix must be determined. The main challenge facing geologists and geostatisticians is that fracture networks in NFRs are extremely complex. As a result, it is impractical to gather enough data to make meaningful direct estimates of fracture size, orientation, permeability and flow response. Despite these challenges, the uncertainty in the prediction of reservoir performance can be reduced by integrating as much data as possible. The reduction in uncertainty is proportional to the amount of historical data and the interference between wells (Reza 2003). As such, there is a need to integrate all available information such as: formation micro-images (FMI), well-test data, production data, seismic surveys, seismic geophysical log data, outcrop data and geological measurements of fractures (orientation, intensity, permeability, size, etc.).

This research will offer a new methodology for modeling NFRs using geostatistics that incorporates data from many different sources. The proposed methodology is based on previous works, but will offer several unique improvements that will result in a significant contribution to the field of research, resulting in more accurate and efficient NFR models.

Background

A framework for integrated modeling of NFRs is presented by Baker and Kuppe (2000) and Bogatkov and Babadagli (2008) and is summarized in Figure 1. In general, modeling work flows combine direct and inverse approaches for characterization of NFRs. In a direct approach, data is used to create a geological model in a forward manner. In an inverse approach, a geological model is modified so that its simulated flow response matches production or well-test data.

Micro-scale static geological data from core analysis and various well logs can be used in a direct approach to create a fracture and facies model. The goal is to establish relationships between fracture attributes and porosity, lithology, structure and rock brittleness. The initial conceptual fracture model is usually limited by fracture connectivity and lengths, which are not well defined (Baker and Kuppe 2000). Macro-scale engineering data (such as tracer tests and build-up and drawdown tests) and production data can be used in an inverse approach to determine the effective permeability of the fractures as well as fracture connectivity and length (Baker and Kuppe 2000).

When used in isolation, neither the direct or inverse approaches to modeling NFRs are capable of characterizing the fracture system in a manner that allows reliable and accurate predictions of future reservoir performance. It is only when the two approaches are used in tandem that the uncertainty in reservoir performance predictions can be reduced to the point where the analysis can be used to make reservoir management decisions (Baker and Kuppe 2000).

Many recent studies concerning NFRs present a similar integrated work flow that accounts for different types of static and dynamic data (Bourbiaux et al. 2002, Basquet et al. 2004, Jenni et al. 2004, Fonta et al. 2007, Guaiquirian et al. 2007, Lohr et al. 2008). Many of these studies are based on Bourbiaux et al. (2002), who, propose a four step integrated workflow to account for multi-scale fractures in reservoir simulation models:

1. Generate a geological fault/fracture network based upon data from core, seismic and outcrops:
    a. Characterization of fracture intensity and orientation from FMI, seismic, core and well-log data;
    b. Fracture modeling, which refers to interpolating the fracture intensity and orientation in between measurement locations.
2. Characterize the hydrodynamic properties of the network from flow-related data;
3. Choose an appropriate flow simulation model for the reservoir using upscaled parameters derived from the flow-calibrated geological fracture model;
4. Simulate reservoir flow behavior considering multiphase flow mechanisms existing within fractures and between rock matrix blocks.

The first two steps combine direct and inverse approaches based on geosciences and reservoir engineering, respectively. The last two steps involve flow upscaling procedures that ensure consistency between the flow-calibrated geological model and the modeling approach chosen for field simulation.

The Proposed Methodology

The background section summarizes the general common workflow, as presented in the literature, for characterizing NFRs. However, modeling NFRs is a complex task and there remain areas for improvement and avenues for research. The proposed research will offer a new methodology for modeling NFRs using geostatistics. The proposed methodology is based on previous works but will offer several unique improvements that will result in a significant contribution to the subject. Figure 2 summarizes the proposed workflow

Data Collection

As is the case in any methodology for modeling NFRs, the first step is data collection. Several sources of data may be gathered including drill core, formation micro-images, geophysical logs, outcrop and well-test data. This portion of the modeling workflow remains unchanged compared to the literature.

Problem Formulation and Preliminary Analysis

Many NFR modeling methodologies ignore (or don’t present) the steps between data collection and static modeling. The proposed methodology will include a preliminary analysis of the collected data. The preliminary analysis will involve building the distributions of fracture attributes and checking the data for errors. Next, the problem formulation will include calculating appropriate effective properties and the choice of a conceptual permeability model (single porosity, dual porosity, dual porosity / dual permeability, etc.) and representative elementary volume (REV) along with its effective parameters. One can imagine that the treatment of a reservoir that is highly fractured over the entire modeling domain would be treated differently than one with few fractures other than a few large-scale faults which conduct most of the flow. Bourbiaux et al. (2002) present guidelines for choosing a permeability model depending on the fracture size, connectedness and dispersion throughout the reservoir.

Static Modeling

Next, static modeling of fracture attributes such as fracture intensity and orientation is undertaken. Static modeling involves regionalization of primary variables such as fracture intensity, permeability and porosity. The static data can be regionalized using traditional geostatistical techniques such as kriging and sequential Gaussian simulation to obtain estimates or realizations of fracture intensity (Isaaks and Srivastava 1989, Deutsch and Journel 1997, Deutsch 2002).

In an attempt to improve geostatistical models and reduce their associated uncertainty, geostatisticians usually try to incorporate all available information into their models. When a physically justifiable relationship between a secondary and a primary variable can be demonstrated, the uncertainty of inter-well predictions can be significantly reduced. Thus, fracture intensity modeling can be improved by available secondary information. Examples of secondary data include seismic, geometric (distance to faults and elevation), mechanical (lithology and rock strength), petrophysical (porosity) and kinematic (surface restoration for back calculation of in-situ stresses) data.

Secondary data can be incorporated into the geostatistical model by relying on the correlation between the primary and secondary variables. However, in the presence of sparse data (as is often the case with NFRs), the uncertainty in those correlations can be very large (Kalkomey 1997). In addition, the traditional Pearson's correlation coefficient is known to be heavily influenced by outliers (Abdullah 1990, Shevlyakov 1997, Jeongtae Kim and Fessler 2004).

The proposed methodology considers the effects of outliers on the correlation coefficient and determines a way to calculate a correlation that is more resistant to outliers and assess its uncertainty so that its effect on geostatistical models can be evaluated. Research into robust correlations with small samples and uncertainty in the correlation coefficient has been previously reported (Niven and Deutsch 2008a, Niven and Deutsch 2008b).

Discrete Fracture Network Generation

A discrete fracture network (DFN) is usually simulated to model the fractures in a reservoir. Although some researchers (Dowd et al. 2007) still use grid based approaches to represent fracture networks, DFNs have the advantage of portraying both the fracture spatial distribution and details of individual fracture characteristics such as location, orientation, size, density and conductivity (Tran et al. 2002).

Large scale faults and some large scale fractures show up on seismic surveys and are explicitly specified in the DFN. Small and medium scale fractures (those that do not show up on seismic surveys and are referred to as being sub-seismic) are modeled probabilistically. Cacas et al. (2001) generated synthetic sub-seismic faults by assuming a seismic fault length distribution.

Many studies use the Poisson process to randomly generate fracture locations and properties. However, fractures and their properties do not occur randomly. Fracture attributes such as orientation, aperture and size are location dependent and there may be relationships between these characteristics. Some researchers have used a heterogeneous Poisson process, which uses a non-uniform potential, to simulate fracture locations (Cacas et al. 2001). However, in areas with few data, the potential is uncertain. A Cox process (Cox 1955) could be used to simulate the fracture characteristics in an integrated fashion. A Cox process is also known as a doubly stochastic Poisson process and is a generalization of the Poisson process where both event locations and the potential are stochastic processes. Using a Cox process, fracture locations may be simulated randomly using a randomly changing intensity function. Multivariate data may be incorporated into the potential used to simulate fracture locations (Jaquet et al. 2008).

The Cox process has already been used by some researchers in geostatistics (Lantuejoul 2002, Brown et al. 2008, Jaquet et al. 2008), but has not been used in the simulation of DFNs. Regardless of the actual process used to generate fracture attributes, that there is an opportunity to better consider the correlations and inter-relationships between characteristics like fracture size, orientation, aperture, intensity, distance to faults, etc. The proposed research would represent a significant contribution by allowing more realistic generation of DFNs with inter-correlated fracture attributes.

Dynamic Modeling

Dynamic modeling is similar to static modeling, except that the aim is to regionalize fracture properties such as porosity and permeability instead of attributes like fracture intensity and orientation. Relationships between porosity and permeability and secondary variables such as seismic impedance and fracture intensity will be investigated. Similar to the static modeling, the incorporation of secondary data into the geostatistical models reduces uncertainty at interwell locations when a relationship between a primary and secondary variable can be demonstrated. As was the case with static modeling, the proposed research will investigate new methods for regionalizing dynamic data such as porosity and permeability that incorporate multivariate data.

Flow Simulation at the Well-Test Scale

Although we have a geo-cellular model of the petrophysical properties of the reservoir and a model of the fractures in the reservoir (the DFN), certain parameters like fracture aperture and length, in particular, are not well known. As a result, the first pass flow simulation at the well-test or full-field scale will not match the observed well-test or production data.

The geometry of the DFN must be validated and its hydraulic conductivity quantified and calibrated by history matching the flow simulation results with well-test data. The estimates of fracture length and aperture are refined by this history matching procedure at the well-test scale.

For small scale problems, such as flow simulation at the well-test scale, the DFN approach is often used. The permeability of the rock matrix is generally assumed to be negligible and flow simulation is conducted on the discrete fractures themselves (Elsworth 1986, Golder Associates 2001).

The flow simulation at the well-test scale includes a variety of information including: mud loss data, caliper logs or leak-off tests, the distribution of productivity/injectivity indices at field-scale, production logs and transient well-tests including drawdown, buildup and interference tests. In Bourbiaux et al. (2002) a local-scale DFN is flow simulated by discretizing the fracture network using nodes at fracture intersections and matrix blocks around each fracture. This simulation method accounts for the actual distribution of matrix block sizes compared to more traditional continuum based flow simulations.

History matching and flow simulation calibrations can be slow; however, Pourpak et al. (2008) use the “gradual deformation” method, globally then locally, to deform the distribution of facies, speeding up the model calibration and preserving the spatial variability of the model.

The proposed research will use the equations that describe flow through porous media to derive sensitivity coefficients that will allow determination of those factors that have the greatest impact on flow simulation. In addition, the effectiveness of the fracture variables in capturing the flow system will be studied. This will result in a decrease in the number of scenarios that need to be considered in sensitivity studies. Reservoir flow simulation is computationally expensive, especially for fractured reservoirs where a dual porosity / dual permeability simulator is used. Thus, this proposed research represents a significant contribution in that the key parameters that drive flow simulation results will be determined, reducing the computational burden of flow simulation sensitivity studies. The beginnings of this research can be seen in Niven and Deutsch (2009).

Flow Simulation at the Full-Field Scale

At the reservoir scale the complex DFN cannot be directly flow simulated due to computational limitations. Flow simulation must be conducted on a simplified version of the geological model. Essentially, the fractures are homogenized into gridblocks with an “equivalent” permeability tensor. The size of the gridblocks depends upon the representative elementary volume (REV). The REV is the minimum volume of a material that can be used as a representation of the whole volume. However, there is no guarantee that an REV actually exists for a given fractured rock mass (Neuman 1987, Kulatilake and Panda 2000). Oda (1985) investigated the REV concept with the statistically homogeneous fracture data and suggested that side lengths of square REV models can be 3 times the mean fracture trace length.

Bourbiaux et al. (2002) present guidelines for choosing an appropriate flow simulation approach (i.e. single-porosity, dual-porosity single-permeability, dual-porosity dual-permeability) depending on those aforementioned factors. In some instances a dual-porosity reservoir can be modeled successfully using a single-porosity flow simulator (Bahar et al. 2003).

A single-porosity flow model has only one the flow medium (the reservoir rock matrix). A dual-porosity (or dual-porosity, single-permeability) flow model is used to describe flow of fluids in a fractured porous medium and was introduced by Warren and Root (1963). In a dual-porosity system, the reservoir has a complex porosity system with two components: 1) the porosity of the fractures and 2) the smaller scale porosity existing in the pore spaces of the intact rock matrix.

In a dual-porosity, single-permeability model the matrix acts as storage and supplies fluid to the fractures where all fluid flow takes place. Flow may occur from matrix to fracture and along fractures but may not occur from fracture to matrix or matrix to matrix. In a dual-porosity, dual-permeability model, flow may occur from matrix to matrix, matrix to fracture or fracture to matrix.

Once the flow simulation approach is chosen, equivalent flow properties are assigned to each grid cell. The method for determining equivalent properties is based on the type of flow simulator chosen and many studies discuss methods to calculate the equivalent permeability tensor for a fracture network (Jensen et al. 1998, Nakashima et al. 2000, Park and Sung 2000, Sutopo et al. 2001) although some studies involved a discretization of each fracture (Koudina et al. 1998). The final full-field simulation must consider the complexity of multiphase flow transfers in fractured media. The effects of physical mechanisms such as fluid and pore volume compressibility, capillarity, gravity, viscous drive and compositional effects must be considered.

The sensitivity coefficients will also be used at the full-field scale. The flow simulation is even more computationally expensive at the full-field scale compared to the well-test scale. Therefore, the derived sensitivity coefficients will result in a decrease in the number of full-field flow simulation scenarios that need to be tested.

After flow simulation is complete, the resulting DFN and permeability models can be used to optimize reservoir management decisions. The analysis may lead to decisions about the viability of proposed well locations, future reservoir performance predictions and decisions about whether or not to pursue future development.

Conclusions

The proposed research outlines modeling methodology for NFRs based on the noted literature and offers several improvements over existing methodologies. A new method for calculating correlation between variables has been proposed (Niven and Deutsch 2008b) that is more robust to outliers in small samples than either the Pearson or Spearman correlation coefficients. Next, the sampling distribution for the correlation coefficient will be implemented. An assessment of the uncertainty in the correlation between primary and secondary variables has rarely been considered although it can have a significant impact on resulting geostatistical models (Niven and Deutsch 2008a). Literature on NFRs rarely considers estimation or simulation techniques that incorporate multivariate data. The proposed research will examine new or modified techniques for regionalizing static data (such as rock matrix porosity). Techniques for incorporating data in a multivariate framework that includes all available data will be developed. Another important area of proposed research is integration of the inter-relationships between fracture attributes in the generation of DFN models. Current DFN codes simulate fracture attributes (such as location, orientation, aperture, etc.) independently and as a Poisson process. However, these fracture attributes do not occur randomly. The proposed research will implement a fracture simulation algorithm that considers the inter-relationships between all fracture attributes and their correlations with all other available data. Flow simulation, and subsequent history matching, is integral to the modeling of NFRs due to their extreme complexity compared with other conventional reservoirs. Flow simulation sensitivity studies must be carried out to assess the impact of the choice of modeling parameters on the simulated result. The flow simulation itself is CPU intensive. Thus, the proposed research will derive flow sensitivity coefficients that will allow assessment of the most important parameters for flow simulation. This will result in a significant decrease in computational burden during flow simulation.

References

Abdullah, M.B. 1990. On a robust correlation coefficient, The Statistician, **39**: 455-460.

Bahar, A., Ates, H., Al-Deeb, M.H., Salem, S.E., Badaam, H., Linthorst, S., and Kelkar, M. 2003. An innovative approach to integrate fracture, well-test, and production data into reservoir models. *In* SPE International Improved Oil Recovery Conference, Kuala Lumpur, Vol. SPE 84876, pp. 325-336.

Baker, R.O. and Kuppe, F. 2000. Reservoir characterization for naturally fractured reservoirs. *In* SPE Annual Technical Conference and Exhibition, Dallas, Texas, Vol. SPE 63286.

Basquet, R., Jeannin, L., Lange, A., Bourbiaux, B.J., and Sarda, S. 2004. Gas-flow simulation in discrete fracture-network models, SPE Reservoir Evaluation & Engineering, **SPE 88985**: 378-384.

Beydoun, Z.R. 1998. Arabian plate oil and gas; why so rich and so prolific? Episodes, **21**(2): 74-81.

Bogatkov, D. and Babadagli, T. 2008. Integrated modeling and statistical analysis of 3-D fracture network of the midale field. *In* International Petroleum Technology Conference, Kuala Lumpur, Malaysia.

Bourbiaux, B.J., Basquet, R., Cacas, M.C., Daniel, J., and Sarda, S. 2002. An integrated workflow to account for multi-scale fractures in reservoir simulation models: Implementation and benefits. *In* 10th Abu Dhabi International Petroleum Exhibition and Conference, Abu Dhabi, Vol. SPE 78489.

Brown, G., Ferreira, J., and Lantuejoul, C. 2008. Conditional simulation of a cox process using multivariate supports. *In* Proceedings of the Eighth International Geostatistics Congress, Santiago, Chile, Vol. 1, pp. 459-468.

Cacas, M.C., Daniel, J.M., and Letouzey, J. 2001. Nested geological modelling of naturally fractured reservoirs, Petroleum Geoscience, **7**(S): S43-S52.

Cox, D.R. 1955. Some statistical methods connected with series of events, Journal of the Royal Statistical Society.Series B (Methodological), **17**(2): 129-164.

Deutsch, C.V. 2002. Geostatistical reservoir modeling. Oxford University Press, Inc., New York, New York.

Deutsch, C.V. and Journel, A.G. 1997. GSLIB: Geostatistical software library and user's guide. Oxford University Press, .

Dowd, P.A., Xu, C., Mardia, K.V., and Fowell, R.J. 2007. A comparison of methods for the stochastic simulation of rock fractures, Mathematical Geology, **39**(7): 697-714.

Elsworth, D. 1986. A model to evaluate the transient hydraulic response of three-dimensional sparsely fractured rock masses, Water Resources Research, **22**(13): 1809-1819.

Fonta, O., Al-Ajmi, H., Verma, N.K., Matar, S., Divry, V., and Al-Qallaf, H. 2007. The fracture characterization and fracture modeling of A tight carbonate reservoir: The najmah sargelu of west kuwait, SPE Reservoir Evaluation & Engineering, **10**(6): 695-710.

Golder Associates. 2001. MAFIC: User documentation. Redmond, Washington.

Guaiquirian, L., Gonzalez, P., Gonzalez, A., Hernandez, M.M., Le Maux, T., Mattioni, L., and Rouvroy, P. 2007. Use of discrete fracture network "DFN" to characterise and model a naturally fractured sandstone reservoir: A case study of orocual field, san juan formation, venezuala. *In* 2007 SPE Latin American and Caribbean Petroleum Engineering Conference, Buenos Aires, Vol. SPE 108052.

Isaaks, E.H. and Srivastava, R.M. 1989. An introduction to applied geostatistics. Oxford University Press, Inc., New York.

Jaquet, O., Lantuejoul, C., and Goto, J. 2008. Estimation of long-term volcanic hazard using a cox process with a multivariate potential. *In* Proceedings of the Eighth International Geostatistics Congress, Santiago, Chile, Vol. 1, pp. 167-176.

Jenni, S., Hu, L.Y., Basquet, R., de Marsily, G., and Bourbiaux, B.J. 2004. History matching of stochastic models of field-scale fractures: Methodology and case study. *In* SPE Annual Technical Conference and Exhibition, Houston, Texas, Vol. SPE 90020.

Jensen, C.L., Lee, S.H., Milliken, W.J., Kamath, J., Narr, W., Wu, H., and Davies, J.P. 1998. Field simulation of naturally fractured reservoirs using effective permeabilities derived from realistic fracture characterization. *In* SPE ATCE, Vol. SPE 48999.

Jeongtae Kim and Fessler, J.A. 2004. Intensity-based image registration using robust correlation coefficients, Medical Imaging, IEEE Transactions on, **23**(11): 1430-1444.

Kalkomey, C.T. 1997. Potential risks when using seismic attributes as predictors of reservoir properties, The Leading Edge, : 247-251.

Koudina, N., Gonzalez Garcia, R., and Thovert, J.-. 1998. Permeability of three-dimensional fracture networks, Physical Review E, **57**(4): 4466-4479.

Kulatilake, P.H.S.W. and Panda, B.B. 2000. Effect of block size and joint geometry on jointed rock hydraulics and REV, Journal of Engineering Mechanics, **126**(8): 850-858.

Lantuejoul, C. 2002. Geostatistical simulation: Models and algorithms. Springer, .

Lohr, T., Krawczyk, C.M., Tanner, D.C., Samiee, R., Endres, H., Thierer, P.O., Oncken, O., Trappe, H., Bachmann, R., and Kukla, P.A. 2008. Prediction of subseismic faults and fractures: Integration of three-dimensional retrodeformation, and well data on an example of deformation around an inverted fault, AAPG Bulletin, **92**(4): 473-485.

Nakashima, T., Sato, K., Arihara, N., and Yazawa, N. 2000. Effective permeability estimation for simulation of naturally fractured reservoirs. *In* SPE Asia Pacific Oil and Gas Conference and Exhibition, Brisbane, Australia, Vol. SPE 64286.

Neuman, S.P. 1987. Stochastic continuum representation of fractured rock permeability as an alternative to the REV and fracture network. *In* 28th US Symposium on Rock Mechanics, Tucson, pp. 533-561.

Niven, E.B. and Deutsch, C.V. 2009. A sensitivity analysis for equivalent permeability tensors calculated from 2D discrete fracture networks. *In* Centre for Computational Geostatistics: Report 11.

Niven, E.B. and Deutsch, C.V. 2008a. Application of the sampling distribution for the correlation coefficient. *In* Centre for Computational Geostatistics: Report 10.

Niven, E.B. and Deutsch, C.V. 2008b. A robust method for updating the correlation coefficient in the presence of outliers. *In* Centre for Computational Geostatistics: Report Ten, University of Alberta, pp. 116-1-116-6.

Oda, M. 1985. Permeability tensor for discontinuous rock masses, Geotechnique, **35**(4): 483-495.

Park, Y.C. and Sung, W.H. 2000. Development of FEM reservoir model equipped with effective permeability tensor and its application to naturally fractured reservoirs. *In* SPE Oil and Gas Conference and Exhibition, Beijing, China, SPE 64793.

Pourpak, H., Bourbiaux, B.J., Roggero, F., and Delay, F. 2008. An integrated methodology for calibrating a Heterogeneous/Fractured reservoir model from wellbore flow measurements: Case study. *In* SPE Europec/EAGE Annual Conference adn Exhibition, Rome, Italy, Vol. SPE 113528.

Reza, Z.A. 2003. Some aspects of production data integration in reservoir modeling. PhD Thesis, University of Alberta, .

Roxar. 2009. Naturally fractured reservoirs: An introduction to their appraisal and management [online]. Available from http://www.roxar.com/category.php?categoryID=2141 [cited April 22 2009].

Shevlyakov, G.L. 1997. On robust estimation of a correlation coefficient, Journal of Mathematical Sciences, **83**(3): 434-438.

Sutopo, Arihara, N., and Sato, K. 2001. Simulation of naturally fractured reservoirs with effective permeability. *In* SPE Asia Pacific Oil and Gas Conference and Exhibition, Jakarta, Indonesia, Vol. SPE 68705.

Tran, N.H., Rahman, M.K., and Rahman, S.S. 2002. A nested neuro-fractal-stochastic technique for modeling naturally fractured reservoirs. *In* Proceedings SPE Asia Pacific Oil and Gas Conference and Exhibition, pp. 453-464.

Waldren, D. and Corrigan, A.F. 1985. An engineering and geological review of the problems encountered in simulating naturally fractured reservoirs. *In* SPE Middle East Oil Technical Conference and Exhibition, Bahrain, pp. 311-316.

Warren, J. and Root, P. 1963. The behavior of naturally fractured reservoirs, SPE Journal, : 245-255.

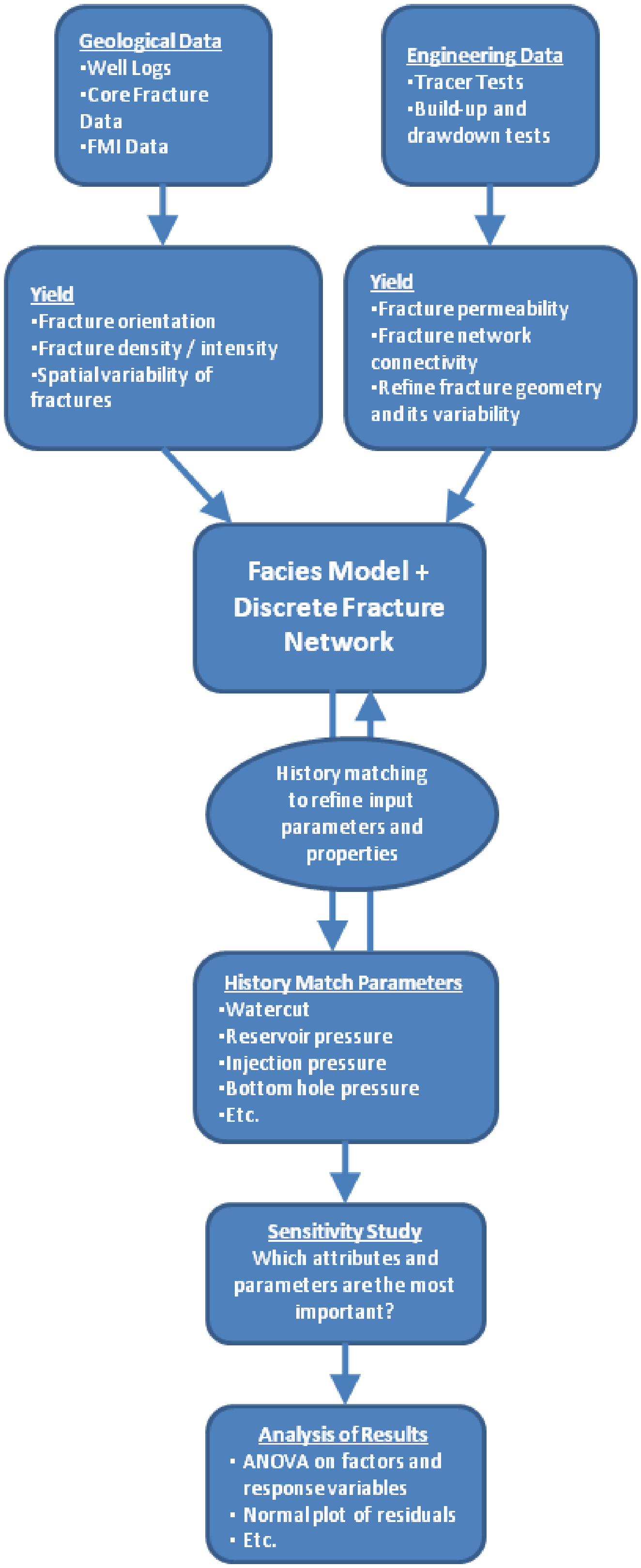

Figure 1: Integrated modeling and sensitivity study for NFR

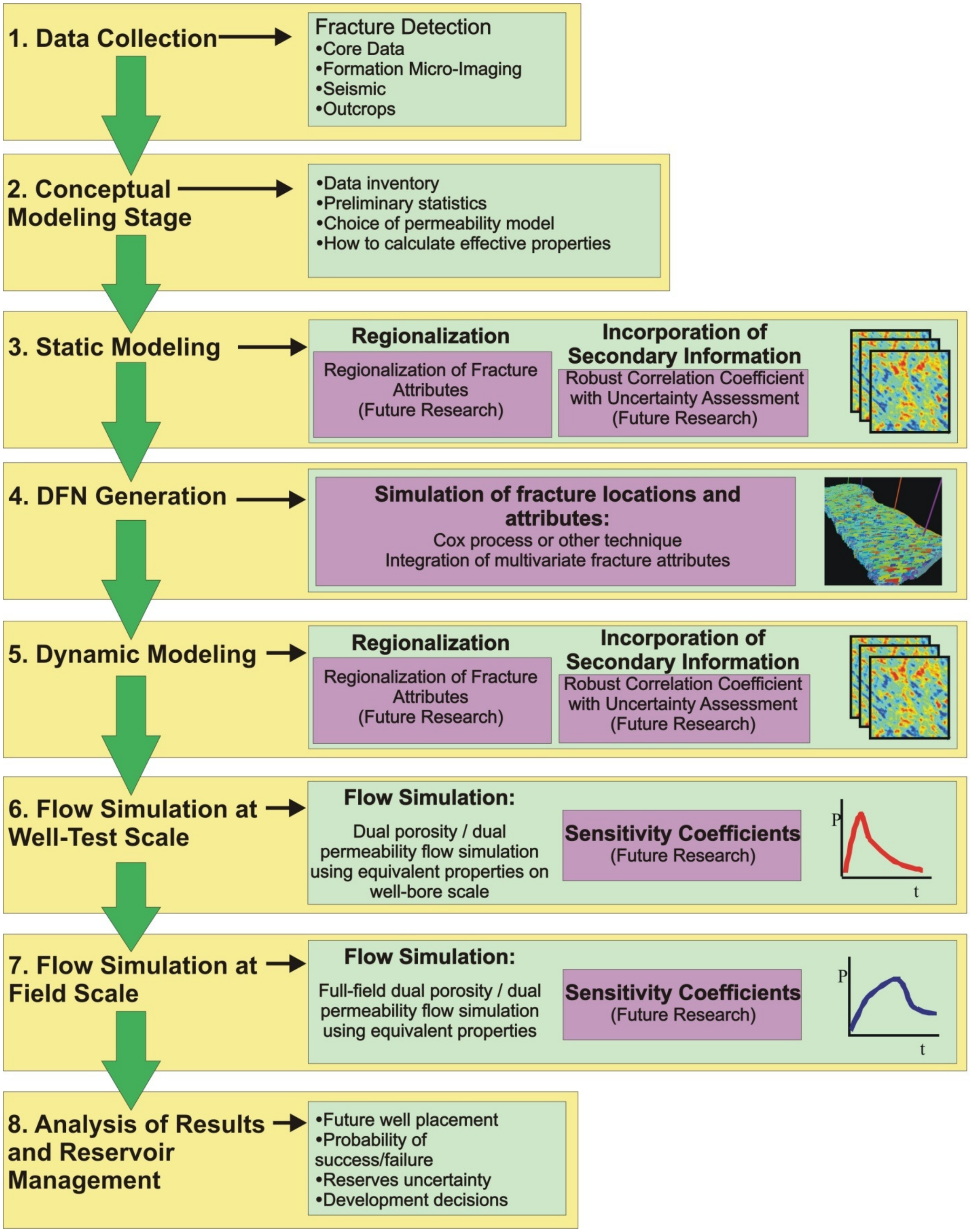

Figure 2: Proposed workflow for Naturally Fractured Reservoirs