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Uncertainty Estimation in Production Predictions Constrained by Production History and Time-Lapse Seismic in a GOM Oil Field

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Abstract

Successful uncertainty quantification requires many reservoir models matching field production data and time lapse seismic. We have been able to automatically generate nearly 50 history matched models for a GOM oil field using the Neighbourhood Approximation stochastic sampling algorithm. This allows us to produce uncertainty forecasts for various production scenarios.

Geostatistical simulation constrained by well log, core, and seismic data is applied for building geological and reservoir models. The parameters of the geostatistical simulation (channel directions, channel dimensions, variogram parameters, etc.) are considered as uncertain parameters. Additionally, end points of relative permeability curves, dependencies of compressibility factors and permeability on effective stress, transmissibility multipliers across faults, and water aquifer size are varied in the history matching process.

A misfit function is selected to quantify history match of model results with field measurements of water cut, gas-oil ratio, and reservoir pressure in production wells in different moments of time. Trends and variances of the observation data are determined and incorporated in the objective function.

The position of the water-oil contact at the beginning of the field development and after three years of production is estimated from time lapse seismic. Differences in the water-oil contact positions determined from the reservoir simulation and time lapse seismic are quantified and incorporated in the objective function.

The reservoir model has been run nearly 2400 times in the history matching process. The Neighbourhood Algorithm is applied for the selection of the values of the history matching parameters in each run. The high quality of the history match is demonstrated,

An ensemble appraising procedure based on a Bayesian framework is used to determine probability distributions of the history matching parameters and to assign probabilities to the simulation models (runs). About 50 models with the highest probabilities (which cover 99% of the cumulative probability range) are selected for the predictions. A general tool has been developed for the definition of statistical parameters of production predictions (mean values, confidence interval, etc) and their changes in time. Uncertainty estimations for the base case predictions and several production scenarios are demonstrated.

Introduction

Our objective is the estimation of uncertainties in production predictions caused by uncertainties in reservoir model parameters. The prediction uncertainties can be significantly reduced if only reservoir model realizations which have a reasonable match with field production data and time lapse seismic are applied. In the paper, we present a methodology for the estimation of uncertainties in production profiles constrained by field production data and time-lapse seismic. The methodology is based on the Neighbourhood Approximation algorithm developed by M. Sambridge¹⁻² and significantly advanced by M. Christie and others³⁻⁵ as part of the Heriot-Watt Uncertainty project. Ideas from the BP's Top Down Reservoir Modeling (TDRM) methodology⁶⁻⁸ have been applied. Software tools for the definition of a misfit function and the statistical treatment of simulation results have been incorporated.

The methodology has been very successfully applied in several GOM reservoir simulation studies. Examples for one GOM oil field are presented in the paper.

The methodology is designed for two objectives: first, model history matching, second, definition of uncertainties in model predictions.

In the history matching step, uncertain parameters of the reservoir model and their prior probability distributions should be selected. It is also required to properly define a misfit function which quantifies a match between simulation results and field production data as well as 4-D seismic. Uncertainties in observation data should be taken into account. Less emphasis should be put on matching field production data with larger noise level. We incorporated the methodology for the misfit function definition described in References 3-5. A software program has been developed for the definition of the misfit

function using simulation results from plot files generated by a commercial reservoir simulator and observation data. The program determines statistical parameters of the observation data (linear trends, variances, covariance matrix, etc. in different time intervals). Then it calculates misfits for any variables (pressure, rates, water cut, gas-oil ratio, etc) and any management level (perforations, wells, gathering centers, flow stations, areas, field, nodes, etc.) included in the plot and observation files. Also, a software tool has been developed for the definition of the 4-D seismic misfit. The final misfit is determined as a linear combination of the misfits for the different variables, time intervals, and 4-D seismic with user specified weighting coefficients.

Values of model uncertain parameters which yield reasonable history match are selected running a reservoir simulator model multiple times in the history matching time interval. The Neighbourhood Algorithm (NA) is applied to select values of the history matching parameters in each run.

The major advantageous feature of the applied methodology is its capability to predict probability distributions of the history matching parameters and prediction results. The ensemble appraising procedure (NAB) developed by M. Sambridge² is applied. The Bayesian framework is used to determine posterior probability distributions of the history matching parameters and to assign probabilities to the simulation models (runs).

A software program has been developed for the definition of statistical parameters of production predictions (mean values, confidence interval, etc) and their changes in time. The program reads the plot files generated by a commercial reservoir simulator in multiple simulation runs. Then, it creates the statistical parameters of reservoir production predictions in the standard plot file format. Therefore, the statistical parameters of the production/injection from individual wells, layers, regions, and whole reservoir can be displayed using commercial post processing packages. The statistical parameters are calculated based on probabilities assigned to the simulation runs. The program provides capabilities to define the statistical parameters of production predictions for each prediction case and for differences between selected and base cases.

Modeling Methodology

Major steps of the applied modeling methodology are as follows (see Figure 1):

- Define a static reservoir model constrained by available seismic, well log, and well core data.
- Define a dynamic reservoir model for field production predictions. Models of reservoir and surface facilities are integrated in this stage.
- Select uncertain parameters of the static and dynamic reservoir models and their prior probability distributions.
- Select a misfit function to quantify history match of model results with field measurements and time lapse seismic.
- Build multiple realizations of the static and dynamic reservoir models. Apply the Neighbourhood Algorithm (NA) to select values of the uncertain parameters for each realization. Run the dynamic reservoir models multiple times in the history matching time interval. Determine the misfit function in each history matching run.

- Apply the ensemble appraising procedure (NAB) to predict the probability distributions of the uncertain parameters and the simulation runs.
- Select the history matching realizations with the high probabilities.
- Run prediction model multiple times for the selected history matching realizations. Repeat this step for each prediction scenario.
- Run the statistical program (for each production scenario) to create the statistical parameters of production predictions and incremental recovery.

The brief description of the above steps is provided below.

Integrated Model of Reservoir and Surface Facilities

The methodology that we use for the construction of the static and dynamic reservoir models in GOM oil fields is described in References 9-11. Short summary is provided below.

Structural mapping (construction of top/base surfaces of reservoir zones and fault surfaces) is the first modeling step. We use a geostatistical simulation to construct the structural maps constrained by well markers and surfaces derived from seismic interpretations.

We use a static reservoir description consisting from three dimensional models of facies and rock properties. Object based geostatistical modeling tools are applied for the construction of the 3-D facies models constrained by seismic, well data, and consistent with depositional environment. Three-dimensional models of reservoir properties (net-to-gross ratio, porosity, permeability, and initial fluid saturations) are built using geostatistical methods with seismic and well constraints. Correlations from rock physics are applied to directly derive rock properties from seismic attributes (separately for each facies). The seismically derived rock properties are used as the 3-D trends in the geostatistical modeling.

We use a dynamic integrated model of reservoir and surface facilities for production profile predictions. *The reservoir module* of the integrated model is used for the prediction of the pressure, fluid composition, oil, gas, and water saturations in each reservoir grid cell at every time step during the simulation. *Well tubing string and surface pipeline network modules* are applied for the determination of the well production rates by simultaneous solution of reservoir and surface pipeline flow equations. Well production rates are allocated from pressure constraint, oil, gas, and water capacity limits at individual nodes of the surface pipeline network system.

Model Uncertain Parameters

Uncertain parameters of the geological and reservoir models selected in the GOM reservoir simulation study are described in this section.

We have built multiple realizations of the static reservoir model applying the geostatistical simulation for the construction of the structural maps and three dimensional volumes of facies and rock properties. Parameters of the geostatistical simulation (channel directions, channel dimensions, and variogram ranges) have been considered as uncertain parameters.

The following parameters of the integrated reservoir model have been considered as uncertain parameters: transmissibility multipliers across fluid flow barriers and faults; end points of relative permeability curves; dependencies of compressibility and permeability on pressure; water aquifer size; Kv/Kh ratio; parameters of fluid flow modeling near wellbore (well indices); parameters of fluid flow modeling in well tubing strings and surface pipeline network system (SPN).

A priori, we assume that the history matching parameters are equal probable within the specified ranges. The posterior probability density functions of these parameters are calculated by the NAB program.

Fluid flow barriers shown in Figure 2 have been identified from a seismic interpretation. However, we do not know how these barriers restrict fluid flow in reservoir. For this reason, transmissibility multipliers across the barriers have been used as the history matching parameters.

Relative permeability curves have been measured for preserved core samples. However, the laboratory tests have been terminated well before residual oil saturation and residual water saturation have been achieved. For this reason, end points of the relative permeability curves have been used as the uncertain parameters. Range of residual water saturation has been selected from water saturation well logs.

There have been large uncertainties in permeability and compressibility dependencies on pore pressure derived from core measurements. For this reason, we consider parameters of applied correlations between rock compressibility/permeability and effective stress as uncertain parameters.

The delineation of channels in water aquifer has been very difficult, because limited amount of well data and poor seismic contrast in the water aquifer area. For this reason, a pore volume multiplier in the water aquifer has been considered as an uncertain parameter.

Total seventeen uncertain parameters of the static and dynamic reservoir models (besides well indices, well tubing strings, and surface pipeline network parameters) have been selected.

Misfit Function Definition

The misfit function is applied to quantify history match of model results with field production data and time lapse seismic. Procedure that we applied for the misfit function definition is described in this section.

The misfit function is defined as the sum of misfit functions for different elements and variables of well management levels with the user specified weight coefficients. The seismic misfit is also incorporated (see next section). The following well management levels are considered: perforations, wells, gathering centers, areas, flow stations, regions, and field. Misfit functions for different time dependent variables (oil, gas, water production rates, cumulative production rates, gas-oil ratio, water cut, pressure, etc) are incorporated. Mismatch of water breakthrough times and/or gas breakthrough times in production wells also can be included in the misfit function.

The variances of the observation variables can be automatically calculated for each time subinterval or they can be input by the user. For the definition of the observation variances, time dependant trends of the observation variables

are automatically calculated. It is assumed that the trend of any observation variable is the piecewise linear function of time.

The following formula is used for the objective function definition:

$$F_m = \sum_l \sum_e \sum_v \sum_t c_{levt} \left[\sum_i \frac{(S_{levti} - O_{levti})^2}{\sigma_{levt}^2} \right] + c_{4d} F_{4d}$$

Where: F_m is the misfit function; S_{levti} and O_{levti} are the calculated and measured values of the v-th variable in the e-th element from from the l-th level on the i-th time point in the t-th time subinterval; σ_{levt} is the variance; F_{4d} is the time lapse seismic misfit; c_{levt} , c_{4d} are the user specified coefficients.

As an example, we describe below the misfit function definition on the GOM reservoir simulation study. In this case, production and pressure data have been available in history matching time interval from November 11, 1997 to March 1, 2004 for five production wells. Oil, gas, and water well production rates have been measured monthly in a test separator. Pressure gauges have been installed in bottomholes of most production wells for continuous pressure measurements.

Oil production rates are specified in the history matching time interval. Gas-oil ratio does not change in time because reservoir pressure is much higher than bubble point pressure. For these reasons, we try to match water breakthrough times; water cut; shutin bottomhole pressure; flowing bottomhole pressure; and tubinghead pressure changes versus time in production wells. We also try to match pressure measurements in inlet and outlet of flowlines in the surface pipeline network system.

The following procedure has been used:

Step 1: Adjust reservoir model parameters to match water breakthrough times, water cut changes, and shutin bottomhole pressure changes versus time in production wells.

Step 2: Adjust well indices to match flowing bottomhole pressure in production wells.

Step 3: Adjust parameters of well tubing string and flowlines models to match tubinghead in production wells and flowline pressure.

In Steps 2 and 3: we have used an automatic tuning procedure for adjustments of well indices and flowline parameters. This procedure is described in Reference 12.

Water breakthrough times in production wells have been included in the misfit function as separate parameters.

Observations and trends of shutin bottomhole pressure and water cut for a production well are demonstrated in Figures 3 and 4.

Matching Water-Oil Contact Movement Derived from 4-D Seismic

An important objective of the history matching procedure is matching simulation results with 4-D seismic observation. Below we describe a procedure that we applied in the GOM reservoir simulation study to match water oil contact movement derived from 4-D seismic.

The 4D seismic monitor survey in Year 2000 observed that the oil-water contact (OWC) had moved updip from the

original OWC on the pre-production survey in Year 1990. This OWC map was compared to the OWC extracted from reservoir simulation runs, by scanning up each column of simulation cells from the bottom to the top of the reservoir, and picking an OWC at the top of the last (shallowest) cell with water saturation (S_w) larger than 0.3. The OWC mapped from 4D was subtracted from the simulated OWC at each seismic trace location, to make a map of the elevation difference, with logic to exclude areas without meaningful simulated OWC data. These differences were squared and summed to give a measure of how well the simulation matched the OWC from 4D. The seismic mismatch is incorporated as an additional term in the misfit function.

Logic was used to exclude (i.e. set OWC difference to 0) locations where all cells were oil-filled and above the OWC from 4D, and where all cells were water-filled and below the OWC from 4D (using the $S_w=0.3$ threshold to distinguish oil-filled and water-filled cells).

Figure 5 shows maps of the OWC difference for several time steps, and the sum-of-squares mismatch measure. The minimum mismatch is at 973 days, about the time of the 4D monitor survey. The maps are colored with blue indicating simulated OWC too deep (+ve difference) and red too shallow, with gray for zero difference or excluded data. Green is offscale blue, at +750 feet; red would go offscale to yellow at -750 feet (not shown, but the 1338-day map is close).

Sampling and Ensemble Appraising Procedures

We run the multiple realizations of the static and dynamic reservoir models with randomly selected model parameters for the estimation of the uncertainties in the production predictions. We apply the Neighbourhood (NA) sampling procedure (see Reference 1) for the selection of model parameters in each realization. The NA procedure samples more frequently in areas of the model parameter space with reasonable history match of the simulation results with field production data and time lapse seismic (near local and global minima of the misfit function). We apply the ensemble appraising procedure NAB (see Reference 2) for the definition of probability distribution functions of the uncertain parameters and realizations. The NA and NAB procedures are described in References 1, 2. Short summary is included below.

Assume that we selected d uncertain model parameters and we made n realizations of the static and dynamic reservoir models. The NA procedure selects values of the model parameters for each realization. It uniquely divides d -dimensional parameter space into n Voronoi cells with one realization in a center of each grid cell. The NA procedure can be formulated as follows:

Step 1. Generate an initial set of n_s realizations uniformly distributed in the parameter space.

Step 2. Calculate the misfit function for the most recently generated n_s realizations. Determine the n_r realizations with the lowest misfit values of all realizations generated so far.

Step 3. Generate n_s new realizations by performing a uniform random walk in the Voronoi cell of each of the n_r chosen realizations (i.e. n_s/n_r realizations in each cell). Go to Step 2

Step 1 corresponds to the initial iteration. Steps 2 and 3 are executed in all further iterations. The procedure is terminated when the number of the iterations exceeds the user specified number.

The NAB procedure is based on a Bayesian approach. We make some initial guess and define the prior probability density function of the model parameters $\rho(m)$. Then, we select n model realizations using the NA sampling procedure, construct the Voronoi grid with n cells, and determine misfits of the simulation results with field observations. Bayes theorem provides a tool to determine the posterior probability density function $P(m)$ (PPD) of the model parameters based on the information that we learned from the n realizations (the misfits in the n simulation runs). PPD is approximated in the NAB procedure by the function $P_{na}(m)$, which is equal to the PPD value in i -th realization for all points of the Voronoi cell containing the realization:

$$P(m) \cong P_{na}(m) = P(m_i), m \in \Gamma_i,$$

where m_i is the i -th realization; Γ_i is the i -th Voronoi cell.

The Gibbs sampler with multiple independent starting points is applied in the NAB procedure (see Pages 731-732 of Reference 2) for the definition of one dimensional and two dimensional marginal probability density functions of the model parameters. Probabilities of the model realizations are also calculated.

Uncertainty Estimations in the GOM Reservoir Simulation Study

As an example, we demonstrate below the application of the uncertainty estimation methodology in the GOM reservoir simulation study.

The following parameters of the NA procedure have been used: Parameter n_s has been set to 96, because 96 CPUs have been available. The number of iterations has been set to 24. 48 model realizations have been run in the initial iteration. Therefore, total $48 + 24 * 96 = 2352$ jobs have been run in the history matching process. The uniform random walk was conducted in 24 cells ($n_r = 24$) in each iteration.

Scatter plot of the misfit function values versus realization numbers is presented in Figure 6. It demonstrates that the misfit function values have been reduced significantly with the application of the NA procedure.

Cumulative probabilities of the model realizations calculated in the NAB procedure are presented in Figure 7 (failed runs are not included in this plot). Realizations have been ordered based on increasing probability values.

47 simulation history matching runs with the cumulative probability larger than 0.01 have been selected for the statistical treatments and for prediction runs.

Comparisons of mean, maximum, and minimum values of simulation results with observation data of water cut in a production well are presented in Figure 8. Reasonable match of simulation results and field measurements have been achieved for water breakthrough times and water cut changes in time for all production wells. The confidence intervals are narrow and observation data are within these intervals. Match of mean values of simulation results with field observations of shutin

bottomhole pressure, flowing bottomhole pressure, and tubinghead pressure in a production well are presented in Figures 9. Reasonable match of simulation results and pressure measurements have been achieved.

One-dimensional and two-dimensional marginal probability density functions of the model uncertain parameters and their covariance matrix have been determined using the NAB procedure. The marginal probability density function for the porosity multiplier in the water aquifer is shown in Figure 10.

Uncertainties in a base case prediction have been estimated. Uncertainty estimations of incremental oil recovery with infill drilling and gas injection have been also provided. The following prediction cases have been considered:

- Base case prediction. Infill drilling and gas injection are not included in this case;
- Two infill drilling cases. Two potential locations of an infill drilling well have been evaluated in these cases;
- Fourteen cases with gas injection. Different number of gas-injection wells, their locations, gas injection rates, have been evaluated in these cases.

Uncertainty estimations in each of the 17 prediction cases have been based on simulation results of 47 prediction runs restarted from the selected history matching realizations. Therefore, $17 * 47 = 799$ jobs have been run in the prediction stage of the reservoir simulation. The statistical parameters of the production predictions have been determined based on probabilities assigned to each model realization. Mean values and confidence intervals of the normalized cumulative oil production from a production well in the base prediction case are presented in Figure 11.

Conclusions

1. A general methodology for the estimation of uncertainties in production predictions constrained by field production history and 4-D seismic is presented.
2. Static and dynamic reservoir models are run multiple times to select model realizations with reasonable history match of simulation results with field production data and 4-D seismic. The Neighbourhood sampling procedure (NA) is applied for the selection of model parameters in each realization.
3. Probability distributions of the model uncertain parameters and simulation runs are determined using the ensemble appraising procedure (NAB) based on a Bayesian framework.
4. Application of the uncertainty estimation methodology in the GOM reservoir simulation study is presented.

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Figure 1: Modeling Methodology



Figure 2: Fluid Flow Barriers Derived from Seismic

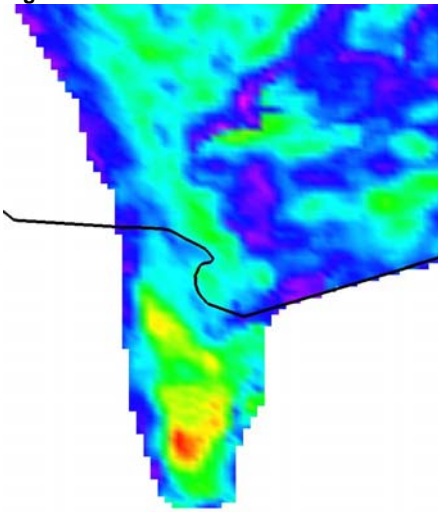


Figure 3: Observations and Trend of Shutin Bottomhole Pressure in a Production Well

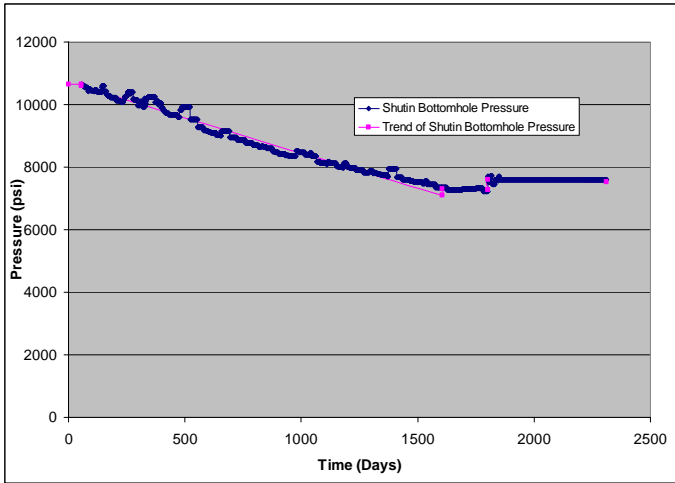


Figure 4: Observations and Trend of Water Cut in a Production Well

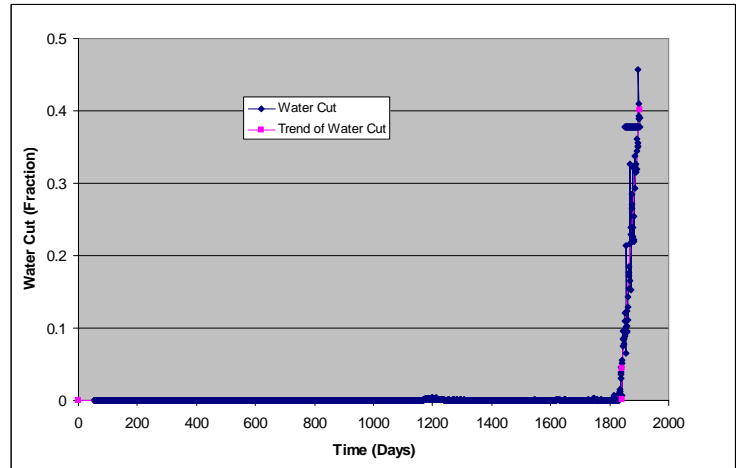


Figure 5: Mismatch of OWC Derived from 4-D Seismic and Simulation Results

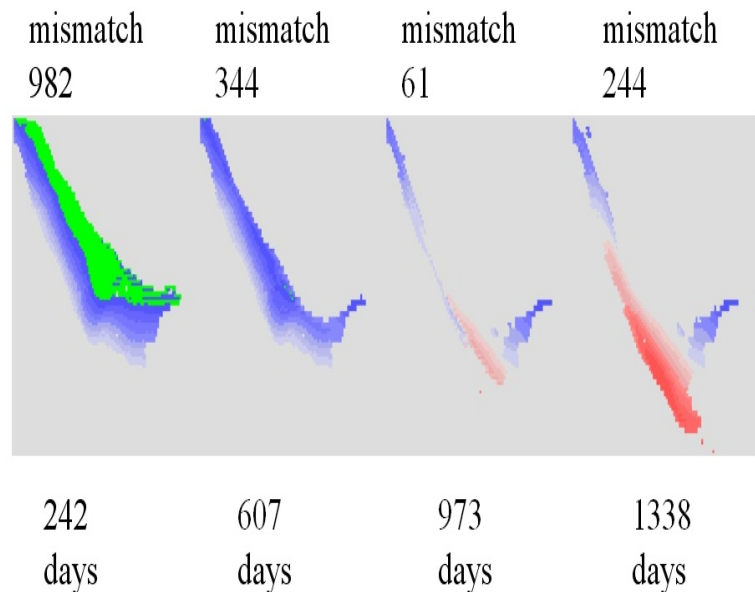


Figure 8: Comparison of Mean (red solid line), Maximum, and Minimum (blue dashed lines) Values of Simulation Results with Observation Data (cyan circles) of Water Cut in a Production Well



Figure 6: Misfit Values for Model Realizations

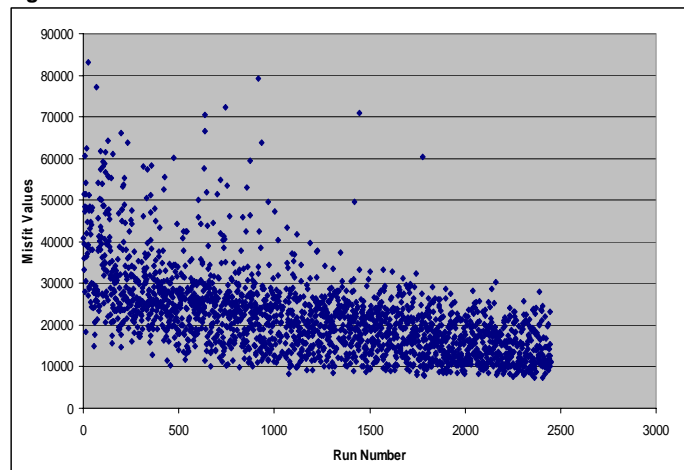


Figure 9: Comparison of Mean Values of Simulation Results with Observation Data for Shutin Pressure, Flowing Bottomhole Pressure, and Tubinghead Pressure in a Production Well

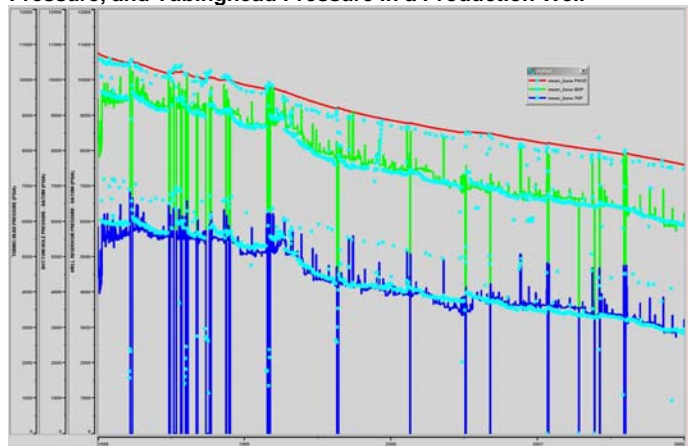


Figure 7: Cumulative Probabilities of Model Realization

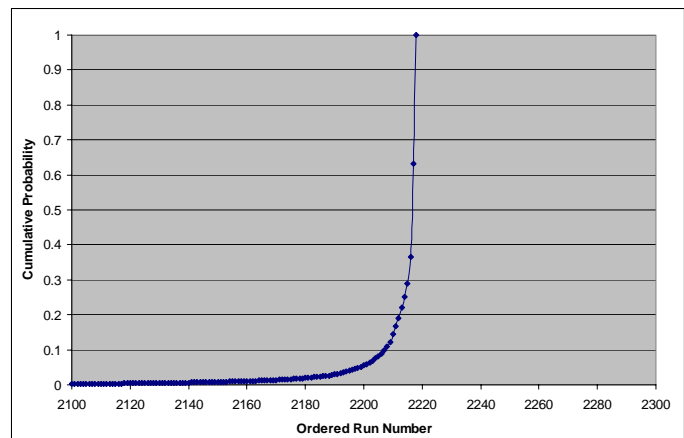


Figure 10: Marginal Probability Density Function For Porosity Multiplier in Water Aquifer

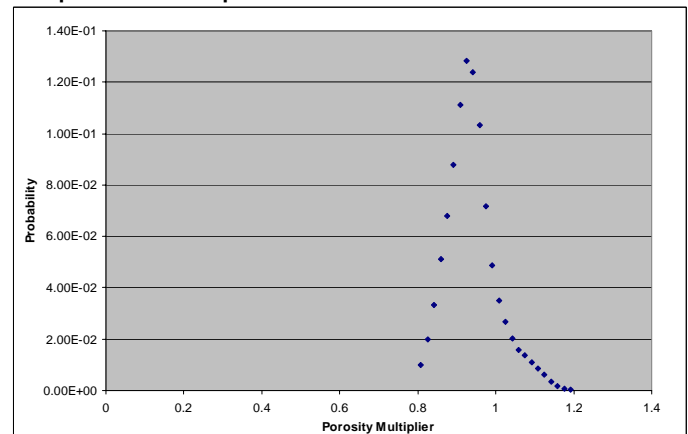


Figure 11: Mean Values and Confidence Interval of Normalized Cumulative Oil Production Predictions from a Production Well in Base Case

