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Quantifying Uncertainties Associated with Reservoir Simulation Studies Using Surrogate Reservoir Models

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Abstract

Reservoir simulation is routinely used as a reservoir management tool. The static model that is used as the basis for simulation is the result of an integrated effort that usually includes the latest geological, geophysical and petro-physical measurements and interpretations. As such, it is inherently a model with some uncertainty. Analysis of these uncertainties and quantification of their effects on oil production and water cut using a new and efficient technique is the subject of this paper.

Typical uncertainty analysis techniques require many realizations and runs of the reservoir model. In the day and age that reservoir models are getting larger and more complicated, making hundreds or sometimes thousands of simulation runs can put considerable strain on the resources of an asset team. This paper summarizes the results of uncertainty analysis on a giant oil field in the Middle East using a new technique that incorporates a Surrogate Reservoir Model (SRM).

A Surrogate Reservoir Model that runs and provides results in real-time is developed to mimic the capabilities of a full field model that includes about one million grid blocks and takes 10 hours to run on a cluster of twelve 3.2 GHz CPUs. This Surrogate Reservoir Model is used as the objective function of a Monte Carlo Simulation to study the impact of the uncertainties associated with several parameters on the model outcome, i.e. oil production and water cut is analyzed. The analysis can be performed individually on each of the 165 horizontal wells.

During the analyses of uncertainty, the Surrogate Reservoir Model will serve as an objective function for the Monte Carlo Simulation. In this study, uncertainties associated with several reservoir parameterts and their quantitative effect on cumulative oil production and stantaneous water cut are examined.

Introduction

Reliance on supercomputing facilities and the long processing times required for high-performance simulations make the use of complex simulation studies impractical in situations where real-time or near real-time information processing is required. Real-time decision making, real-time optimization and analysis under uncertainty are three of such situations. Accurate simulation of complex physical processes usually takes much longer than the actual physical time of the process. This is especially true for complex fluid flow through porous media, fluid-dynamics and general multi-physics processes. This makes the advanced CFD (Computational Fluid Dynamics) methods and some of the solutions for PDEs (Partial Differential Equations) virtually useless in predicting the course of events or making real-time decisions and optimizations of events which are in progress. A similar situation in the oil and gas industry is the smart field initiative currently being entertained by many majors and national oil companies where real-time decision making, real-time optimization and real-time analysis under uncertainty become vital.

If simulators are to be used effectively for real time analysis, they must be capable of processing potential scenarios much faster than their current speed. For mission critical processes such as those mentioned here, comparison of multiple scenarios becomes essential. To accomplish such tasks successfully simulators must approach real-time or near real-time speeds and be capable of providing results in fraction of a second instead of minutes, hours or days. The set of techniques that, when effectively integrated, is capable of providing such performance is hybrid intelligent systems and includes, but is not limited to, artificial neural networks[1], genetic algorithms[2] and fuzzy logic[3]. Using intelligent systems, it is now possible to build Surrogate Intelligent Models (SIMs) that can mimic functionalities of complex simulators in real-time. The subject of this paper is a version of SIMs that are developed for numerical reservoir simulators used in the oil and gas industry called Surrogate Reservoir Models. This paper demonstrates the use of SRMs for quantification of uncertainties associated with input parameters in a full field model.

The conventional approach in our industry for quantification of uncertainty is mainly based on geostatistics. One such method that is used quite often is Response Surfaces[4-6]. Response Surfaces are statistical interpolations (based on fitting some type of pre-determined model – linear or quadratic –) of model responses to different geological, geophysical and petro-physical realizations[7,8]. Another method that has been used more in other industries is Reduced Models. Reduced Models are approximations of full three dimensional numerical simulation models that essentially approach an analytical model for tractability[9].

We introduce a new approach for quantification of uncertainty that has been named Surrogate Reservoir Models[10]. Surrogate Reservoir Models are approximations of the full three dimensional numerical reservoir models that are capable of accurately mimicking the behavior of the full field models. The approach used during the development of the Surrogate Reservoir Models fits more appropriately within the approach summarized in the system theory[11] (as shown in Figure 1) rather than the approach commonly used in our industry that is essentially based on geostatistics.

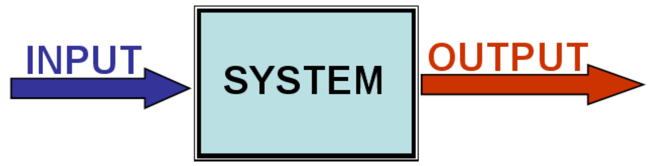

Figure 1. The three components involved in the System Theory, Input, System and Output.

Considering the full field reservoir model within the realm of the System Theory, different reservoir parameters such as permeability, porosity, and capillary pressure from the geologic model are input to the system while the production from the well would be the system output (sytem being the full field reservoir model). During analyses that are categorized as response surface, hundreds of combinations of the input parameters are generated (realizations) and used as input to the full field model and upon completion of hundreds of runs results in hundreds of outputs (production from wells in the field). These outputs are then used to generate a surface of all the possible responses that can result from the predetermined realizations.

Selection of the realizations is usually made in a way that maximizes the coverage of anticipated range of input parameters while requiring the minimum number of simulation runs. Usually techniques such as Latin Hyper Cube[13] and Design of Experiments[14] are used to optimize this process. Nevertheless, most of the serious studies require hundreds of runs to provide meaningful coverage. Furthermore, once the hundreds or thousands of the required simulation runs are made and the response surface is generated, the input parameters no longer play any role in the process. In other words, the approach mentioned in the System Theory will not be in effect upon completion of the simulation runs.

The major difference between Surrogate Reservoir Models with the previously mentioned techniques is that SRMs require a significantly smaller number of runs. For example, the Surrogate Reservoir Model that is the subject of this technical paper was developed using only 10 simulation runs (please note that design of these runs is an important step in the development process and is a direct result of the main objective for which the SRM is being built). This is due to the fact that during the development of the Surrogate Reservoir Model a new, non-physics-based and non-deterministic relationship between the resulting outputs and the input parameters are established in a way that the integrity of the entire process is preserved within the definition of the System Theory. Furthermore, it should be noted that a pre-determined functional model (such as linear, exponential, or quadratic) is not identified for this relationship. In other words, upon completion of the development, and during the application of SRM, one can perturb any selected parameter from the input space and observe the corresponding results in the system output, just like the actual reservoir model, with the major difference being that such a task can be accomplished in real-time by the SRM.

Methodology

In a recent SPE paper Lu and Zhang[12] make an interesting observation about the Monte Carlo Simulation, its capabilities for quantification of uncertainty and why it is rarely performed in our industry for performance prediction when it comes to large scale reservoir simulators. To quote them directly, they mention that

> *Monte Carlo Simulations entails generating a large number of equally likely random realizations of the reservoir fields with parameter statistics derived from sampling, solving deterministic flow equations for each realization, and post-processing the results over all realizations to obtain sample moments of the solution. This approach has the advantages of applying to a broad range of both linear and nonlinear flow problems, but has a number of potential drawbacks. To properly resolve high frequency space-time fluctuations in random parameters, it is necessary to employ fine numerical grids in space-time. Therefore, the computation effort for each realization is usually large, especially for large-scale reservoirs. As a result, a detailed assessment of the uncertainty associated with flow performance predictions is rarely performed.*

In this paper the author will show how a computationally expensive, yet technically accurate and desirable analysis of uncertainty based on Monte Carlo Simulation can be performed in a short period of time using a Surrogate Reservoir Model on a full field reservoir model simulating a giant oil field in the Middle East. It will be demonstrated that a Monte Carlo Simulation study for the analysis of uncertainties associated with several reservoir parameters can now be quite attainable using SRM while it would have been impractical using the full field model.

A single run of the full field model (developed using ECLIPSE™) for this particular filed takes 10 hours on twelve 3.2 GHz CPUs. Assuming that all 12 CPUs will be available to the asset team at all times a Monte Carlo Simulation study that requires 5000 runs will take more than 5 years and 8 months to be completed. Same study using 1000 runs will take 1 year and 2 months. Upon the development of the Surrogate Reservoir Model for the filed several Monte Carlo Simulation studies were performed at about 6 seconds per study that included 5000 runs.

Details on the development and the subsequent validation (using blind data) of this particular Surrogate Reservoir Model were discussed in a previous SPE paper[10] and will not be covered here. This paper discusses the application of this Surrogate Reservoir Model in analysis and quantification of uncertainties.

The field that is the subject of this Surrogate Reservoir Model includes 165 producing horizontal wells. Figure 2 (located at the bottom of this article) shows the location of these wells within this field. The lines identifying a potential and hypothetical drainage area for each of the wells were drawn using Voronoi Graph Theory[15].

Identification of Key Performance Indicators (KPIs) of the fluid flow and production process in a particular reservoir is an important step during the development of the Surrogate Reservoir Models. Figure 3 shows the KPIs identified for the full field model that is the subject of this study. The KPIs are calculated separately for each of the SRM outputs, namely cumulative oil production and instantaneous water cut. Once properly calculated, KPIs play three distinct and important roles in different analyses:

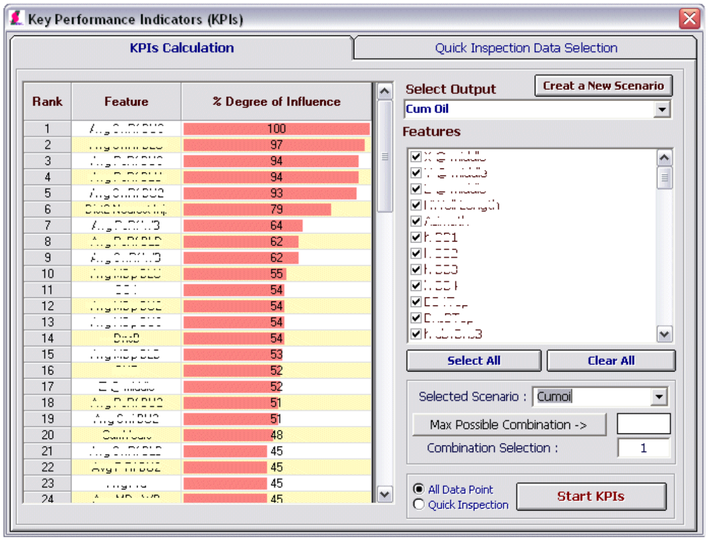

Figure 3. Identification of Key Performance Indicators as an important step during the SRM development.

1. During the development of SRM, KPIs serve as an important indication for decision making during the dimensionality reduction before the actual modeling process starts.

2. Once the SRM development is completed and the model is used for analysis, KPIs are used to identify the parameters that should be considered during the quantification of uncertainties as demonstrated in this paper. Even small amounts of uncertainties in very important parameters play more important role in the well productivity than large amounts of uncertainties in parameters that play minor role in the production process.

3. It has been noted that one of the major uses of SRMs is during the history matching process. KPIs can guide the reservoir engineers in modification of key parameters to achieve history matches. For example in a post-development exercise it was identified that to match the oil production and water cut of a particular well in this field the horizontal permeability in the well blocks had to be modified several folds in order to achieve the desirable match. Looking at the KPIs it was observed that in order to achieve similar results (match) the capillary pressure function of two of the layers above the well had to be modified slightly. A 10% modification in a targeted location and parameter is far more justifiable than several folds modification of another parameter.

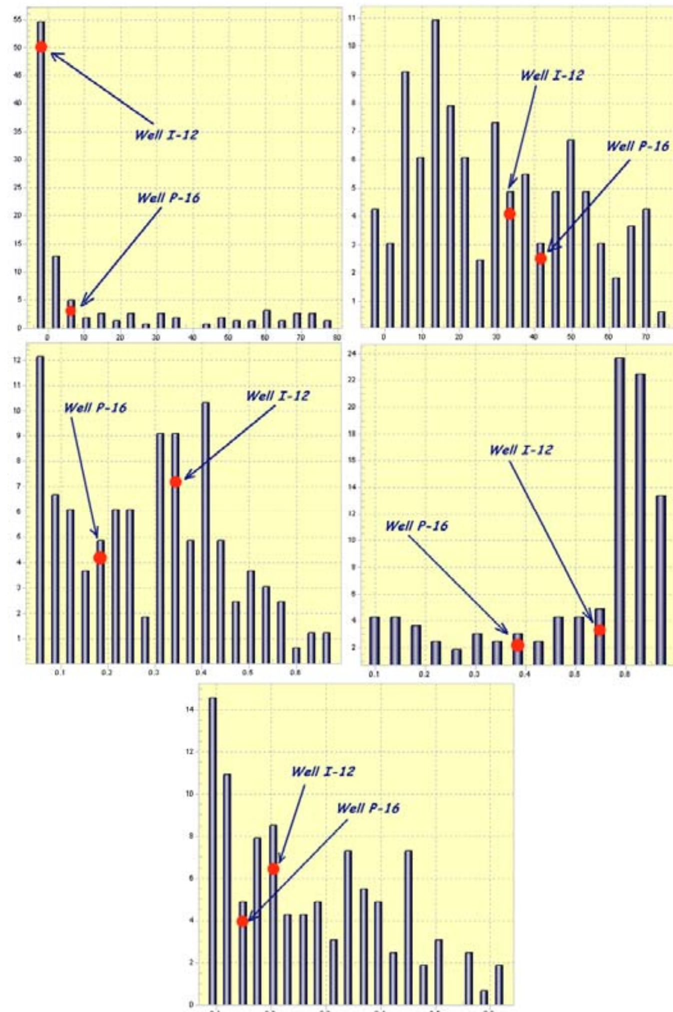

Figure 4. Distribution of the top five KPIs for the reservoir being studied.

In this paper we concentrate on the second use of KPIs as was mentioned above. We use the information in order to guide our uncertainty analysis. In this exercise we select the top five parameters from the KPI list and assign probability distributions to them and perform Monte Carlo Simulation to quantify the uncertainties that are introduced to the oil production and instantaneous water cut by this modifications.

Results & Discussions

The top five parameters that were ranked during the identification of Key Performance Indicators were used for the analysis and quantification of uncertainties. Figure 4 shows the distribution of each of the parameters in the data set.

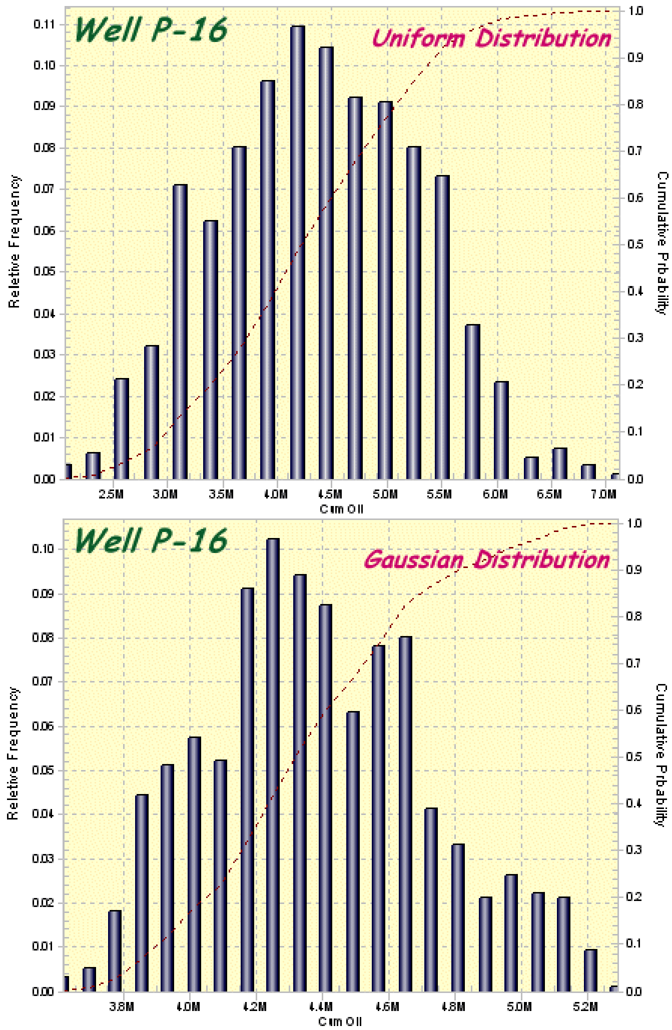

Figure 5. Probability distribution of cumulative oil production (5 years) for well P-16 when uniform and Gaussian distribution is used for the top 5 KPIs.

The data set here represents the geological model of the reservoir used during the simulation process. The reservoir model includes almost one million grid blocks that include 40 layers of producing formations. Therefore these distributions represent the distribution of each of the parameters in the total number of grid blocks present in the geologic model. Here the analyses performed on two different wells are presented. These wells are identified as P-16 and I-12. The red dots on the distributions (Figure 4) show the value of the parameter for each of these two wells.

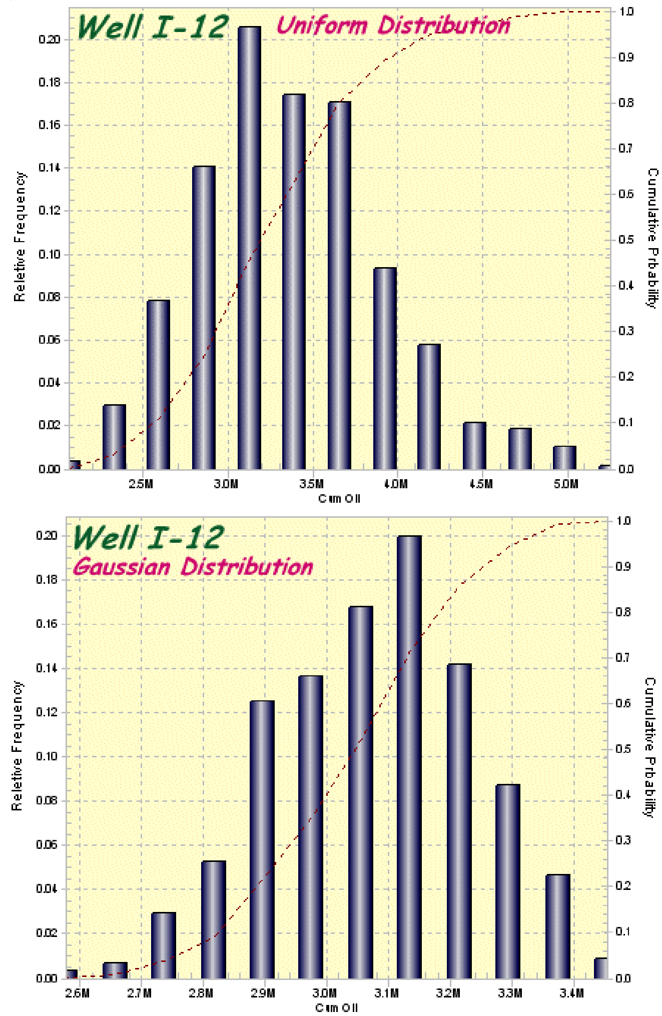

Figure 6. Probability distribution of cumulative oil production (5 years) for well I-12 when uniform and Gaussian distribution is used for the top 5 KPIs.

In this exercise Monte Carlo Simulation is performed to calculate and quantify the effect of uncertainties associated with top ranked Key Performance Indicators on cumulative oil production and instantaneous water cut. Two types of distributions were assigned to each of the KPIs. During the first exercise uniform distribution was assigned to the top 5 KPIs and during the second exercise Gaussian distribution was assigned to the top 5 KPIs.

All other parameters for each well were kept constant during each simulation run while the values for the top 5 KPIs were selected from the identified distribution. The model was run 5000 times calculating the 5 year cumulative oil production and the instantaneous water cult at the end of the 5th year. The 5000 results were plotted in the form of a probability distribution. This process was repeated for each well in the field. Results for two of the wells are shown in Figures 5 through 8.

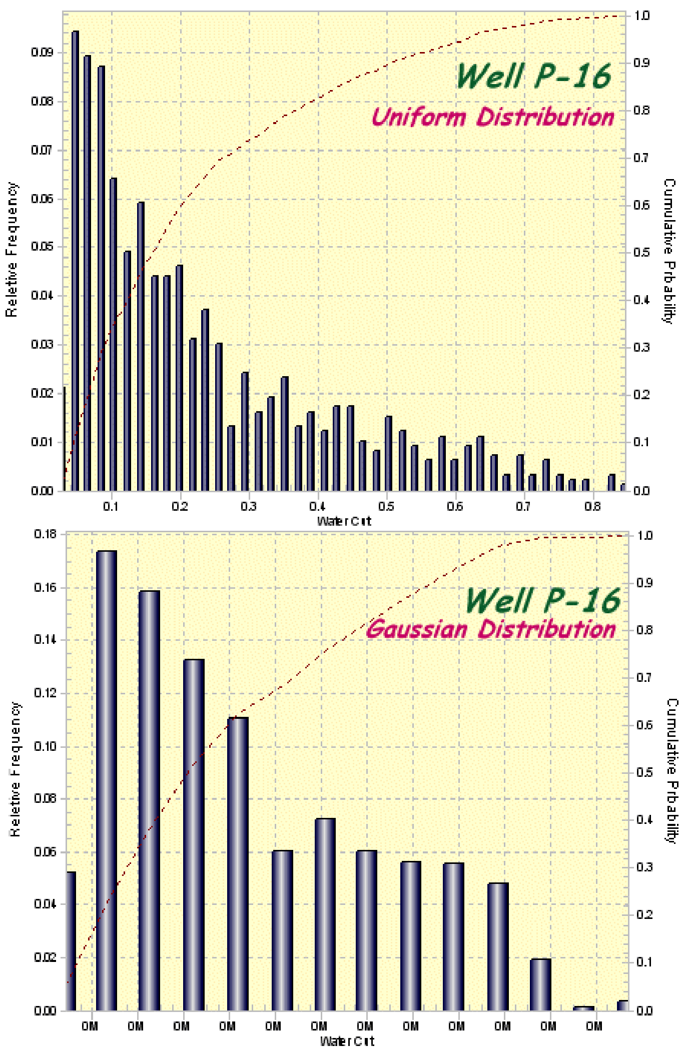

Figure 7. Probability distribution of instantaneous water cut (5th year) for well P-16 when uniform and Gaussian distribution is used for the top 5 KPIs.

Figure 5 shows the results of the analysis for 5 year cumulative oil production of well P-16. The graph on the top corresponds to the probability distribution of cumulative oil production generated when uniform distribution was used during the Monte Carlo Simulation for the top 5 KPIs. The graph on the bottom corresponds to the probability distribution of cumulative oil production generated when Gaussian distribution was used during the Monte Carlo Simulation for the top 5 KPIs.

Although the probability distributions shown in this figure have the general shape of a normal distribution the range of the top graph is much larger than the one at the bottom. The top graph has minimum value of 2 and a maximum value of 7 million barrels for 5 year cumulative oil production from this particular well (range of 5 million barrels), while the minimum and maximum values of the bottom graph (Gaussian distribution) are 3.5 and 5.5 million barrels (range of 2 million barrels), respectively. Nevertheless, the highest frequency in both cases occurs at around 4.2 to 4.3 million barrels. These graphs show the sensitivity of the 5 year cumulative oil production of well P-16 to combined uncertainties associated with the top five most influential parameters in this reservoir study.

Figure 6 shows the same analysis for well I-12. In this well, distributions of the 5 year cumulative oil production that have been generated from uniform and Gaussian distribution of input parameters are skewed in opposite directions, with the top one starting from 2 million barrels to 5.5 million barrels (range of 3.5 million barrels) and the bottom one from 2.6 to 3.6 million barrels (range of 1 million barrels). But again the highest frequency in both cases occurs at around 3 to 3.5 million barrels. Similar observation can be made on Figures 7 and 8 where instantaneous water cut is analyzed for both wells.

The most important issue here is that performing such analysis for each well using the Surrogate Reservoir Model takes less than one minute where performing such analysis using the actual reservoir model would be practically impossible.

In the above analysis the top 5 KPIs were studied in a combinatorial fashion. Now we demonstrate similar analysis for one particular parameter at a time to quantify the effect of such uncertainty on the oil production and water cut. Figure 9 (at the bottom of the article) shows the results of a Monte Carlo Simulation study performed on well B-19. In this exercise, two input parameters were selected to be studied separately. The analysis was performed first on one of the most inflenial input parameters (top ranked KPI) and then on a parameter that had been ranked low in the KPI study. Similar distribution was assigned to both of these parameters and Monte Carlo Simulation was performed to quantify the uncertainties that are introduced to 5 year cumulative oil production and water cut as a result of uncertainties associated with each of these parameters. The top two graphs in Figure 9 show 5 year cumulative oil production and water cut distributions when the uncertain parameter is the top ranking KPI and the two graphs at the bottom of Figure 9 are the results when the lowest ranking KPI is analyzed.

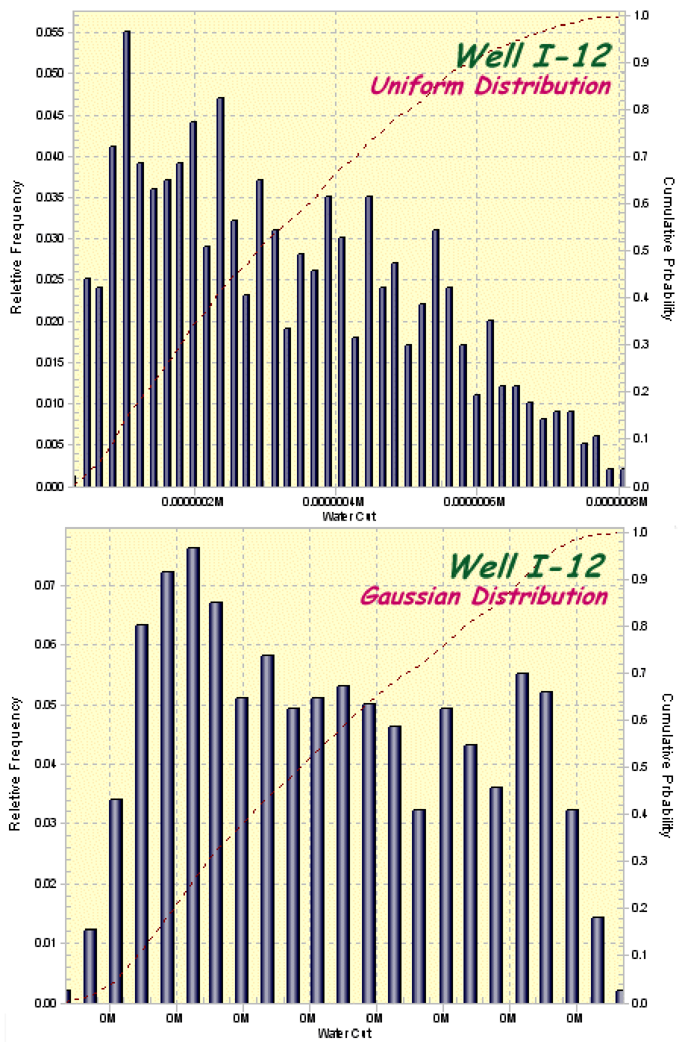

Figure 8. Probability distribution of instantaneous water cut (5^{th} year) for well I-12 when uniform and Gaussian distribution is used for the top 5 KPIs.

Graphs in this figure show that uncertainties associated with the top ranked KPI introduce a much larger range in 5 year cumulative oil and water cut values as compared to the uncertainties associated with the lower ranked KPI. This shows the validity of the KPI analysis and its contribution to a detail reservoir study.

The range of 5 year cumulative oil production when the top ranked KPI (graph on the top left) is used as the uncertain parameter is between 1.6 to 3.6 million barrels (range of 2 million barrels) while it is between 3 and 3.3 million barrels (range of 0.3 million barrels) when the low ranking KPI is used as the uncertain input parameter (graph on the bottom-left). The distribution of the top graph indicates much more uncertainties than the lower graph.

Similar results can be observed on the two graphs on the right where the results for the water cut are shown. The range of the uncertainties for water cut when the top ranking KPI is used as the uncertain input parameter is about 35% (minimum 10% and maximum 45%) while it is about 7% (minimum 38% and maximum 45%)for the bottom graph where the uncertainties associated with a low ranking KPI is analysed.

Conclusions

Performing Monte Carlo Simulation for the uncertainty analysis of reservoir simulation studies is impractical due to the fact that they require hundreds or thousands of simulation runs to provide meaningful results. Surrogate Reservoir Models are replicas of full field reservoir models that can be run in fraction of a second rather than in minutes, hours, or days. A Surrogate Reservoir Models that was developed and validated for a giant oil field in the Middle East was used to perform several Monte Carlo Simulation studies.

Accuracy and speed of Surrogate Reservoir Models in analysis and quantification of uncertainties associated with input parameters in a reservoir simulation study was demonstrated. This shows that Surrogate Reservoir Models are indispensible tools for uncertainty analyses in complex hydrocarbon reservoirs.

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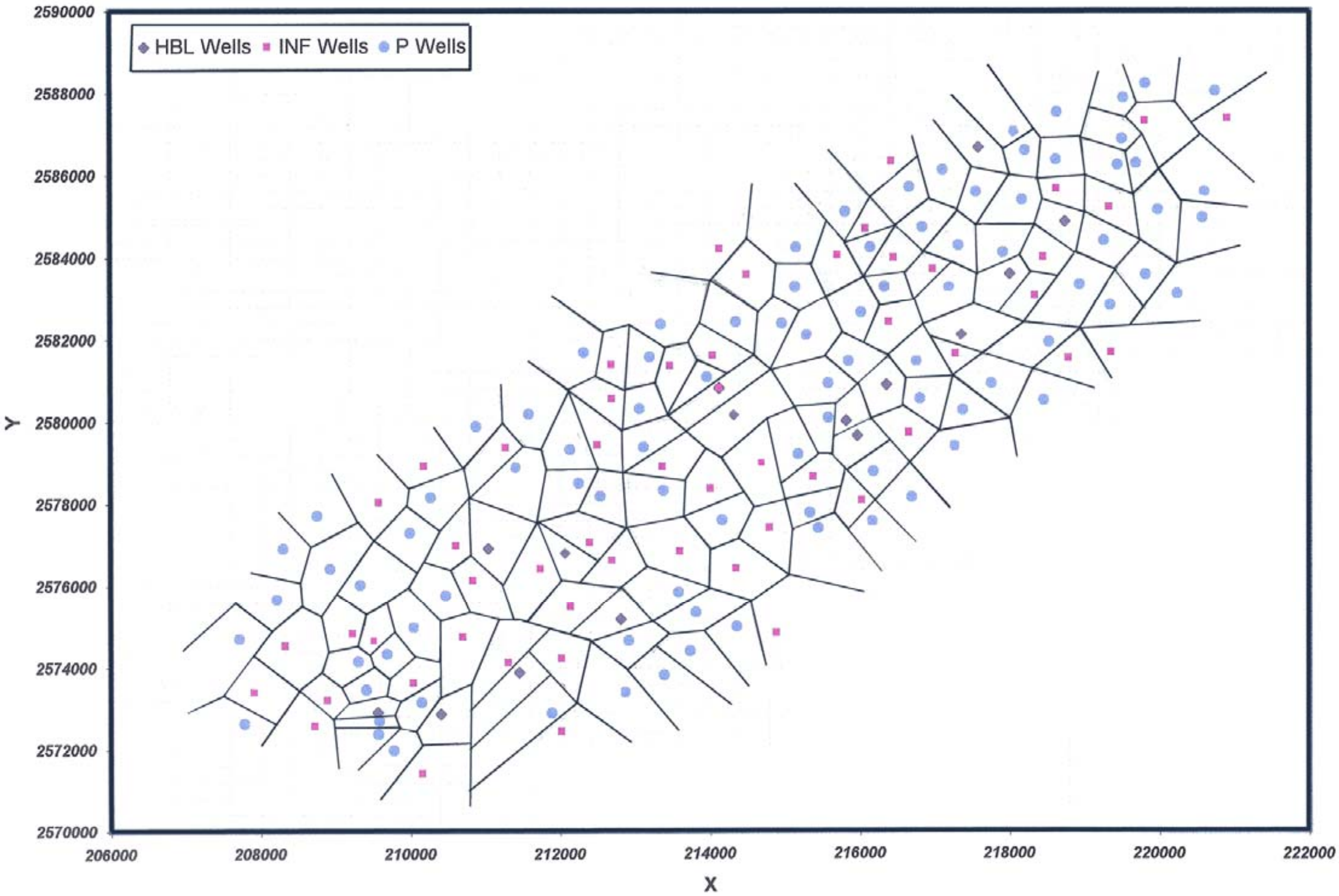

Figure 2. Location of 165 wells in the field. Well identified within colored drainage area are used as blind wells for validation of the analysis.

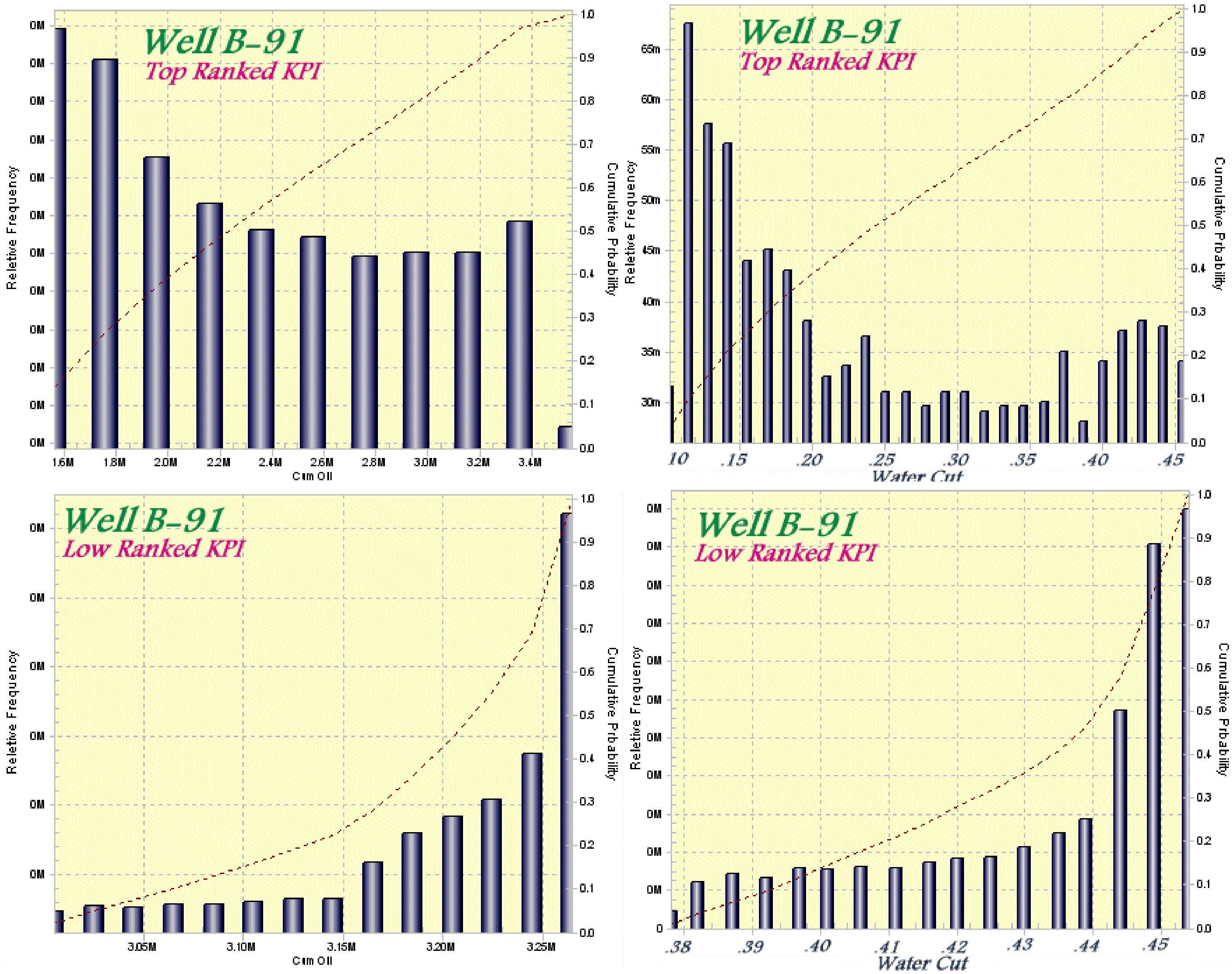

Figure 9. Probability distribution of instantaneous water cut (5th year) and 5 year cumulative oil production for well B-91. Monte Carlo Simulation performed analyzing uncertainties associated with two different reservoir parameters.