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Development of Surrogate Reservoir Models (SRM) For Fast Track Analysis of Complex Reservoirs

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Abstract

Reservoir simulation has become the industry standard for reservoir management. It is now used in all phases of field development in the oil and gas industry. The full field reservoir models that have become the major source of information and prediction for decision making are continuously updated and major fields now have several versions of their model with each new version being a major improvement over the previous one. The newer versions have the latest information (geologic, geophysical and petro-physical measurements, interpretations and calculations based on new logs, seismic data, injection and productions, etc.) incorporated in them along with adjustments that usually are the result of single-well or multi-well history matching.

A typical reservoir model consists of hundreds of thousands and in many cases millions of grid blocks. As the size of the reservoir models grow the time required for each run increases. Schemes such as grid computing and parallel processing helps to a certain degree but cannot close the gap that exists between simulation runs and real-time processing. On the other hand with the new push for smart fields (a.k.a. i-fields) in the industry that is a natural growth of smart completions and smart wells, the need for being able to process information in real time becomes more pronounced. Surrogate Reservoir Models (SRMs) are the natural solution to address this necessity. SRMs are prototypes of the full field models that can run in fractions of a second rather than in hours or days. They mimic the capabilities of a full field model with high accuracy. These models can be developed regularly (as new versions of the full field models become available) off-line and can be put online for automatic history matching and real-time processing that can guide important decisions. SRMs can efficiently be used for real-time optimization, real-time decision making as well as analysis under uncertain conditions.

This paper presents a unified approach for development of SRMs using the state-of-the-art in intelligent systems techniques. An example for developing an SRM for a giant oil field in the Middle East is presented and the results of the analysis using the SRM for this field is discussed. In this example application SRM is used in order to analyze the impact of the uncertainties associated with several input parameters into the full field model.

Introduction

Over the past several years computer simulation has made major advances in terms of scope and complexity. Today they can reach the levels of accuracy, which make it possible to play realistic scenarios of complex mechanical and geo-physical processes. The success of computer simulation techniques is due to the development of efficient algorithms and solution methods for general partial differential equations (PDE), the advancement of modern computational fluid dynamic (CFD) and multi-physics simulation technologies, as well as due to the availability of increasingly capable hardware platforms, such as supercomputer facilities, and Beowulf clusters.

Reservoir Simulation is now an industry standard. No serious alternative to the conventional reservoir simulation and modeling is in the horizon. It is a well understood technology that usually works well in the hand of experience modelers incorporating reasonably good geological, geophysical, and petro-physical interpretations and measurements with the reasonably sophisticated simulators that are currently available in the market. The reservoir models that are built for an average size field with tens and sometimes hundreds of wells tend to include very large number of grid blocks. As the number of reservoir layers or the thickness of the formations increase the number of cells included in the model approaches several millions. Technologies such as Local Grid Refinements[1-2] have been developed to dampen the geometric increase of the number of grid blocks required for detail and focused simulation and modeling around the wellbore and locations in the reservoir where more detail is required, but the size of the models remains in the several millions of cells.

As the size of the reservoir models grow the time required for each run increases. Schemes such as grid computing and parallel processing helps to a certain degree but cannot close the large gap that exists between simulation runs and real-time processing. On the other hand with the new push for smart fields (a.k.a. i-fields) in our industry that is a natural growth of smart completion and smart wells, the need for being able to process information in real time becomes more pronounced. Surrogate Reservoir Models – SRMs are the natural solution to this necessity. In this article authors will introduce a detail process for successful development of SRMs. The potential pitfalls for such developments will also be discussed.

First attempt in developing a surrogate model in the oil and gas industry was concentrated on developing a surrogate model for a hydraulic fracturing simulator. In 1999 Mohaghegh and Popa[3-4] developed a surrogate model that was able to accurately mimic the capabilities a hydraulic fracturing simulator called FracPro[5]. They used the surrogate model for real-time optimization of hydraulic fracture design of tight formations. If we define surrogate modeling in the context of model development that can replicate results of complete reservoir, hydraulic fracturing, and/or other comprehensive numerical simulators, then authors were unable to find other serious efforts that can be sited in the literature. Other attempts for surrogate model developments[6-9] can be found in the literature that does not necessarily fit the definition that is presented in this paper.

The next attempt in developing surrogate models (being discussed in this paper) was on a major oil field in the Middle East. In this research and development effort, a full filed reservoir model that included close to a million grid blocks and more than 165 horizontal wells was the target. During this study a Surrogate Reservoir Mode – SRM that was able to successfully mimic the behavior of the full field reservoir model was developed and validated. The SRM was then used for candidate well selection and analysis under uncertainty. The results were used for important decision making on the future of the field and optimum operation of the horizontal wells.

One of the major issues that must be addressed as we approach the smart field era is the bottleneck that currently exists between high frequency data streams coming from the field through permanent downhole gauges and the major reservoir management tools, specifically reservoir models. While the data streams have the potential to provide data at a time scale of seconds, the reservoir simulators or the Full Field Models (FFM) run in time scales of several hours or even days, in some cases. The problem intensifies when we realize that in many cases in order to make reservoir management decisions, several FFFM runs must be made.

A similar problem exists when one decides to use the FFM in order to perform uncertainty analysis. Due to the same problem that was mentioned above (length of time required for a single FFM run) uncertainty analysis becomes a painful and time consuming process. Most of the techniques used for uncertainly analysis call for development and analysis of several realizations. In order for the uncertainty analysis to be meaningful, the number of realizations must be statistically significant. As the number independent parameters involved in a problem increase, so does the number of realizations needed for statistical significancy. It can be argued that each grid block in a FFM represent a set of several independent variables. Given the high number of grid blocks in even a moderate size FFM, one can imagine that the number of realizations needed in order to have a statistically significant dataset will be relatively large. There have been many advances in the statistics and geostatistics that contribute to decreasing the number of realizations required for such analysis while keeping the integrity of the analysis intact. Nevertheless, even after all the approximations and techniques such as Latin Hyper Cube[10] and Design Of Experiment[11] that are used, the number of the FFM runs required for a reasonably accurate uncertainty analysis remains quite high.

Surrogate Reservoir Models – SRMs play an important role in addressing problems such as those mentioned here. They provide the means for making hundreds and even thousands of FFM runs in matter of seconds. In the problem that is presented in this article we demonstrate a Monte Carlo simulation study for uncertainty analysis on several parameters that were making significant contribution in the outcome of the FFM. The Monte Carlo simulation used the FFM of a giant oil filed in the Middle East as its objective function. The Surrogate Reservoir Model that was built to represent this FFM was validated using a significant number of blind data and had proven to be quite accurate. During the uncertainty analysis using Monte Carlo simulation, the Surrogate Reservoir Models (essentially the FFM) was run 5000 times in less than 10 seconds.

Field of Dreams

There is a famous phrase from a movie called “Field of Dreams” that says, “If we build it, they will come”. In that movie the main character was referring to building a baseball field and was hoping that once it was built, then the legends of baseball will show up to play in it. It seems that today the smart fields have become the “Field of Dreams” of the oil industry.

Much effort has been concentrated on hardware, manily permanent downhole tools and gauges and the communication infrastructure that can capture and transmit high resolution data streams into offices where engineers and managers are located.

This is the brain that is indeed a significant and essential component of the “Field of Dreams”. But in order to have a complete entity and have actual “intelligentce”, smart fileds need more than just brain (hardware). They need “mind” or enabling software. Many scientists around the world are currently working on this problem using different tools such as kalman filters[12,13] and other techniques, we claim that in order to successfully address this complex issue intelligent systems must be a significant contributer to any serious effeorts. To realize the merit of this claim one needs to observe that not a single industry (from aerospace to automotive to household appliances) has been able to increase its products IQ (Intelligence Quotient) without significant use of intelligent systems. Here the term intelligent system is referred to a series of techniques that include but are not limited to artificial neural networks[14], genetic optimization[15] and fuzzy logic[16].

This paper presents an example of developing such application that is considered to be an enabling technology for the smart fields. Here we describe the steps that need to be taken in development of a Surrogate Reservoir Model and present the results.

The Full Field Model

The Full Field Flow Model (FFFM) that was the target of this study is a reservoir simulation model build for a giant oil field in the Middle East. Figure 1 shows a cross section of the reservoir in order to demonstrate the complexity of this model. The FFM represented the formation that is indentified by XXX in Figure1.

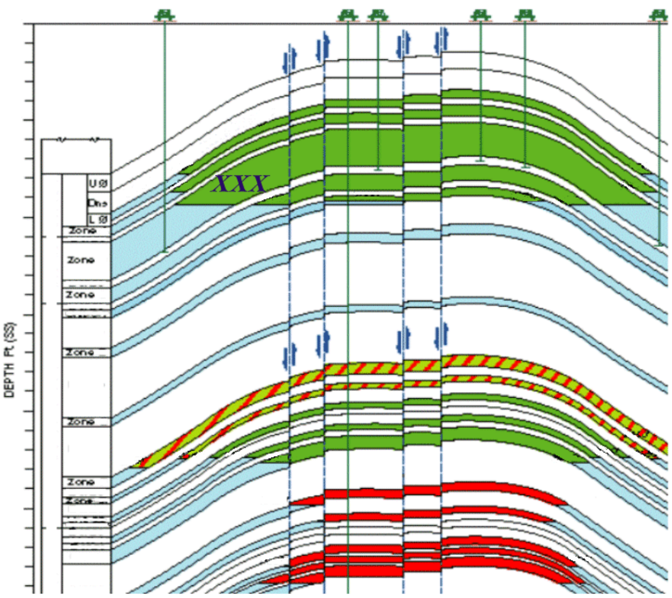

Figure 1. The crosssection of the reservoir that the Full Filed Flow Model is based on.

There are more than 165 horizontal wells drilled in this field that are currently producing at a capped production rate. The field is certainly capapble of producing more but the cap is imposed for reservoir management purposes.

Figure 2 shows an approximate top view of the field with approximate locations of the horizontal wells. As it is shown in Figure 1, this reservoir is multi-layered. Most of the wells are completed in one particular layer and layers above and below the layer in which the wells are completed contribute to the production.

The operation in this filed includes water injection into some of the layers for pressure maintenance and sweep purposes. Gas injection is also taking place in some areas of the filed. The reservoir includes many major and minor faults (Figure 2) that have been detected by geo-scientists and are part of the earth model that has been used to build the FFM. Several rock types have been identified in this reservoir and have played an important role in developing the model. The Full Field Model has been developed using ECLIPSE[17] and includes less than one million grid blocks. A single run of the version of the FFM used for this study took about 10 hours on a cluster of tweleve 3.2 Ghz Intel Xeon CPUs.

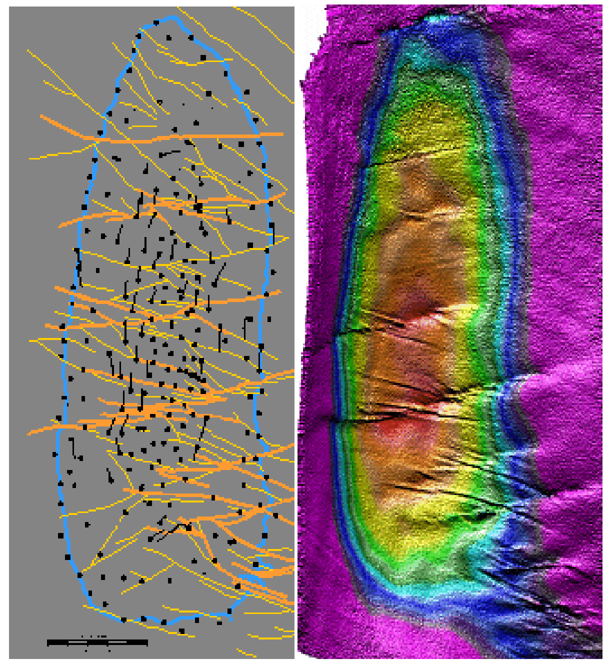

Figure 2. Top view of the reservoir with approximate location of more than 165 horizontal wells.

The Curse of Dimensionality

The first step in developing a Surrogate Reservoir Model (SRM) is to identify the FFM that it is going to represent. The FFM include two sets of information that need to be represented in the SRM. These two sets of information are the static, earth model and the dynamic flow characteristics.

To fulfill the objectives of this study it was decided to represent the static model only around the wellbore. Furthermore only horizontal wells in this field were being studied. After carefully studying the characteristics of the reservoir and its multi-layered nature, it was decided to represent the reservoir characteristics around the wellbore using five layers. This is shown in Figure 3 where there is a bottom layer representing the layers below the wellbore, the layer that includes the wellbore, and three distinct layers above the wellbore known as top layer I, that is immediately above the wellbore and layers II, and III that represent the rest of the layers in the reservoir.

Furthermore, each layer is divided into eight equal sections. The size of each section is a function of well's length and therefore may not be the same from well to well. Another schem that was tried included dividing the length of the horizontal well into three sections called heel, middle and toe. In cases where reasonable amount of production log is available, or when this technique is being used for single-well history matching, this scheme may prove to be more appropriate.

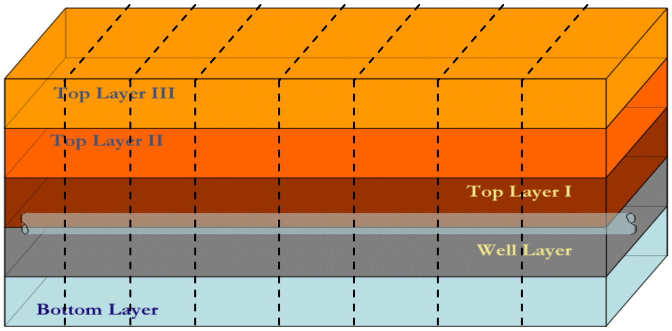

Figure 3. Schematic diagram of the reservoir representation around horizontal wells.

List of parameters that have been identified to be used in the SRM development from the static model are shown in Tables 1 and 2. As it is shown in Figure 3 the model for the SRM includes 5 layers with 8 segments per layer adding up to a total of 40 segments per well. While data shown in Table 1 is collected on a "per-segment" basis, data in Table 2 need to be collected on a per well basis.

Parameters Used on a per segment basis	
Mid Depth	Thickness
Relative Rock Ttype	Porosity
Initial Water Saturations	Stylolite Intensity
Horizontal Permeability	Vertical Permeability
Sw @ Reference Point	So @ Reference Point
Capillary Pressure/Saturation Function	Pressure @ Reference Point

Table 1. List of parameters used in the SRM development on a per segment basis.

Now let's try to calculate the number of parameters contributed by the static model that should be used during the SRM development. There are 12 parameters in Table 1 and one value per segment is needed from this table. That would add up to 480 parameters. Plus there are 16 parameters identified in Table 2 and we need one value for each well from this table.

This makes the total number of parameters from the static model to add up to 496. To this number of course we have to add the dynamic parameters that will be identified and needed during the SRM development. It goes without saying that 496 are too many parameters. Some may argue that SRMs arethe same as reduced order models. Authors are of the opinion that this may not necessarily be a correct assessment of this technology. This is due to the fact that we are starting with a reservoir model that has almost a million grid block, averaging about 15 (to be on the safe side, the actual number is higher than 15) parameters per grid block. Therefore, the original order of the FFM (only static parameters) is about 15,000,000. Going from 15,000,000 to 496 may be considered a well designed reduced order model (of course if the reduced order model has acceptable performance). But we make the argument that at 496 parameters we already have too many parameters to develop a SRM. This is called the "Curse of Dimensionality" and is common whenever complex phenomena are to be modeled accurately.

Parameters Used on a per well basis	
Latitude	Longitude
Deviation	Azimuth
Horizontal Well Length	Productivity Index
Distance to Free Water Level	Water Cut @ Reference Point
Flowing BHP @ Reference Point	Oil Prod. Rate @ Reference Point
Cum. Oil Prod. @ Reference Point	Cum. Water Prod. @ Reference Point
Distance to Nearest Producer	Distance to Nearest Injector
Distance to Major Fault	Distance to Minor Fault

Table 2. List of parameters used in the SRM development on a per well basis.

Figure 4 shows the actual behavior of two typical parameters that are being considered, namely Azimooth and Distant to Nearest Injector. From this figure it is clear that there are no apparent patterns that can be readily detected. Of course this was clearly expected, since if otherwise, this would not have been a challenging problem to solve.

Once the parameters that represent the static model are identified, the next step is the identification of the dynamic parameters that need to be considered. This is an important step in the development since it controls the number of simulation runs that has to be performed.

One of the key issues in SRM development is to realize that it is impractical to develop a global SRM. A global SRM is a SRM that is capapble of performing all the functions of a reservoir simulator. Developing a global SRM is a trap that many fall into. To be practical one needs to identify the specific objectives of a project and then design and develop the appropriate SRM for that project. In other words, many SRMs, with different capabilities can be developed to represent the same FFM. For the purposes of this project we needed to build a SRM capable of accurately predicting simultaneous water cut, cumulative oil production and cumulative water production for every horizontal well at any given time.

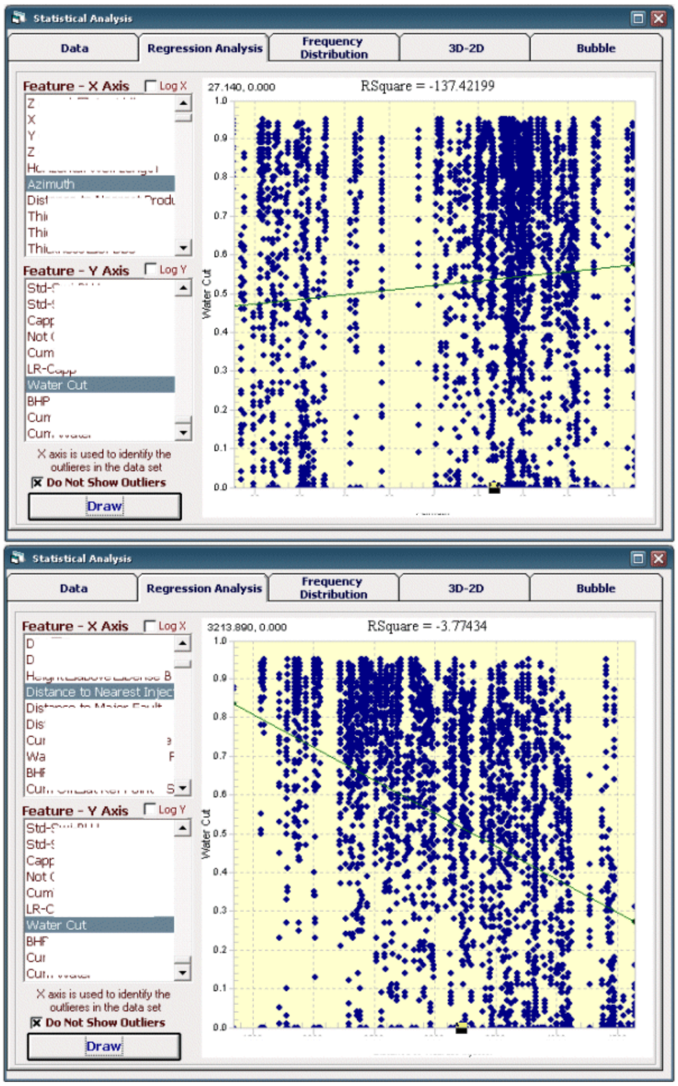

Figure 4. Behavior of instantenous water cut as a function of well Azimooth and Distance to the Nearest Injector for 165 horizontal wells at several different times.

In order to satisfy these objectives, ten runs were designed and performed on the Full Field Model. The ten runs included five runs with a predetermined cap on the total field production and five similar runs where no cap was imposed on the total production from the field. The five runs included:

- Imposing a nominal production cap of 1,500 barrels of fluid per day on each well.
- Imposing a nominal production cap of 2,500 barrels of fluid per day on each well.
- Imposing a nominal production cap of 3,500 barrels of fluid per day on each well.
- Imposing a nominal production cap of 4,500 barrels of fluid per day on each well.
- Changing the imposed nominal production cap according to Figure 5.

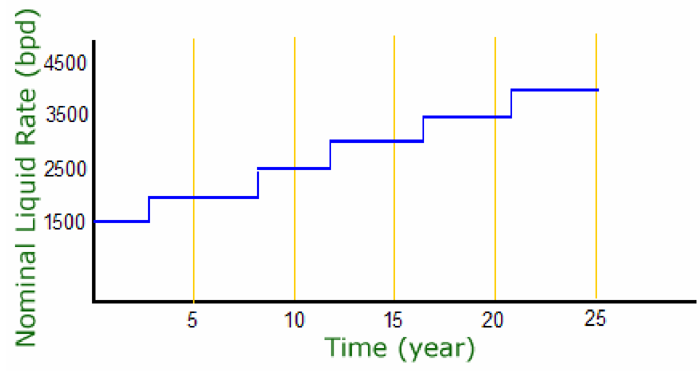

Figure 5. The Imposed production cap scheme on the FFM to generate dynamic data for the development of SRM.

Once the total number of parameters (static and dynamic) that must be used in the development of the SRM were identified, the first order of business for the development of the SRM is reducing the dimensionalityof this problem to a manageable and reasonable number. We do this by using Fuzzy Pattern Recognition[16,18].

This technology can be used to identify the Key Performance Indicators (KPI) in any process. The idea is that when we look at all the 165 horizontal wells in our field, given the specific flow characteristics of the field being studied, some of the parameters will have more significant contribution to the well behavior than others.

The objective is to identify these key parameters and use "them" during the development of the SRM. This task is much more complex than it may appear. Nevertheless, Key Performance Indicators can be identified.

The first challenge of developing a SRM for this reservoir was to reduce the dimensionality of the problem to a manageable number. Using the Key Performance Indicator (KPI) feature of IDEA™ [18], the software application that was used during the development of the SRM, the top 33 paramters were selected for the development.

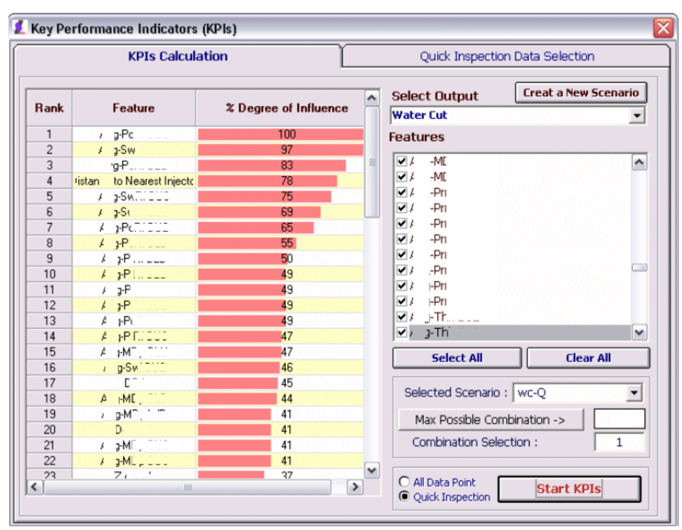

Figure 6. Key Performance Indicators identified for the SRM development.

As mentioned before, this feature of the software application uses a Fuzzy Pattern Recognition technology to identify the KPIs for a given system. Figure 6 shows the top 23 parameters that were identified through the KPI procedure. Using the same feature we were able to identify the overall contribution of each of the layers to the production from the horizontal wells. Figure 7 shows the contribution of each layer to the instantaneous water cut. In this figure contribution of all the existing parameters were used in order to calculate the overall contribution of each layer to the production from the horizontal well. In this figure higher values on the fuzzy pattern recognition scale represent lower contribution and visa versa. It is interesting to note that the layer containing the wellbore has the lowest contribution to the production.

This seems to be counter-intuitive since most of the time during the history matching process engineers tend to modify the paramters closest to the wellbore inorder to achieve a match. Figure 7 shows that in this particular multi-layer reservoir, by the time the fluids have made their way to the layer where the horizontal well is located, it is too late to modify any parameters. The top three layers control the water production in this reservoir and must be dealt with during a history matching procedure before the parameters in the layer where the wellbore is located.

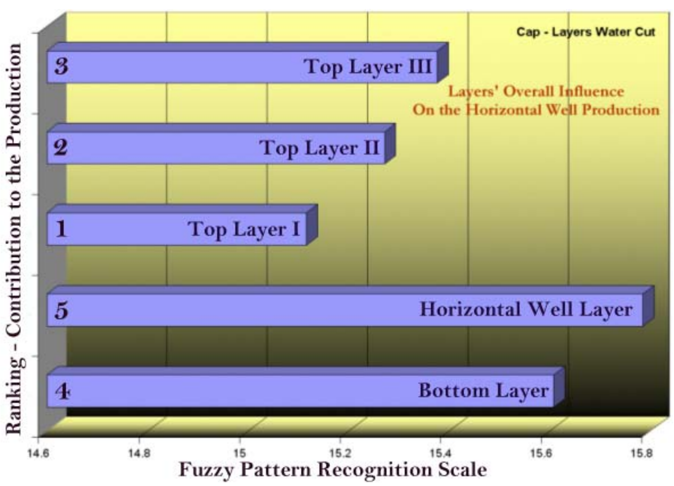

Figure 7. Contribution of each layer to the production from the horizontal wells.

Validation of the Surrogate Reservoir Model

Once the SRM is developed it must be validated with data that has not been used during its development. For this project 40% of the original data was set aside for the validation purposes. Once the SRM's development was completed its predictions were plotted agains FFM's results for cumulative oil production and instantaneous water cut from many wells at different times. In both cases the results were acceptable and therefore the analysis could continue. Figure 8 shows the validation plots for cumulative oil production and simultaneous water cut.

It should be noted, that the FFM was run in its prediction mode calculating the water cut and oil production from year 2005 to 2026 and therefore the SRM was developed on such data. This was due to the specific objectives of the project. But once the SRM's development was completed, it was checked in couple of occasions to see if it can correctly match the actual production from some of the horizontal wells' production history. The results were very promising.

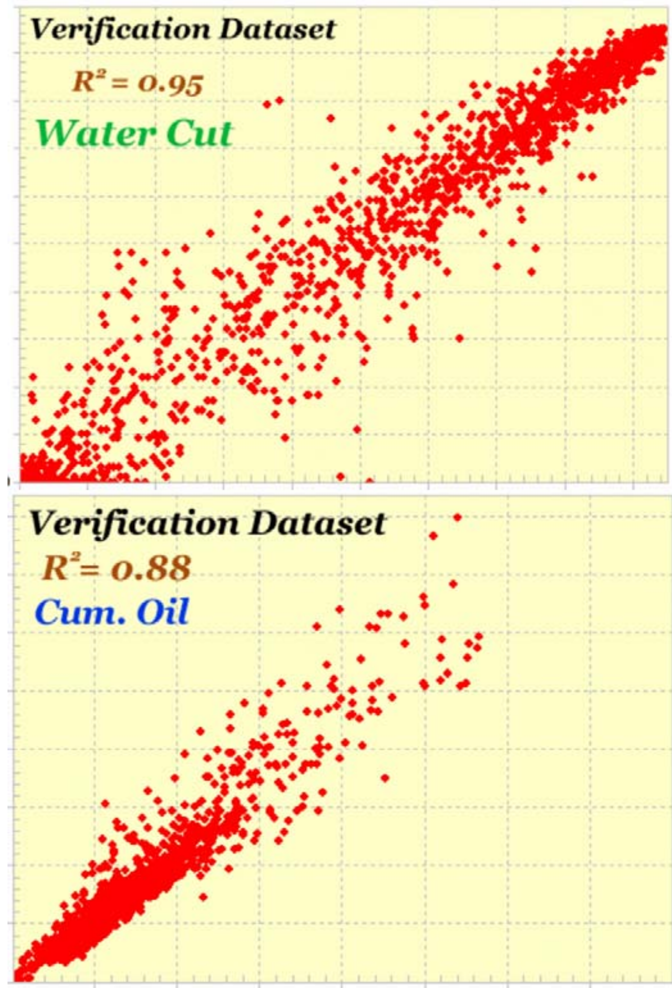

Figure 8. Validation of the Surrogate Reservoir Model using 40% of the data that was not used during its development. Here actual FFFM outputs are plotted against SRM's predictions.

Once the SRM is developed and validated it can be used to generate oil and water production profiles as well as instantaneous water cut profiles for any of the wells in real time. In this project one of the objectives was to study the effect of imposing liquid cap rate on the water cut and cumulative oil production for each well. Figure 9 shows three dimensional view of cumulative oil production and instantenuous water cut as a function of time and liquid cap rate that is imposed on the well. Quick visual inspection of wells such as those shown in Figure 9 can help in analyzing well behavior as a function of liquid cap rates and identifying wells that can benefit from relaxing such restrictions.

As part of this study we identified the wells that would benefit the most from relaxing rate cap restrictions using a candidate selection methodology that incorporated fuzzy cluster analysis technique.

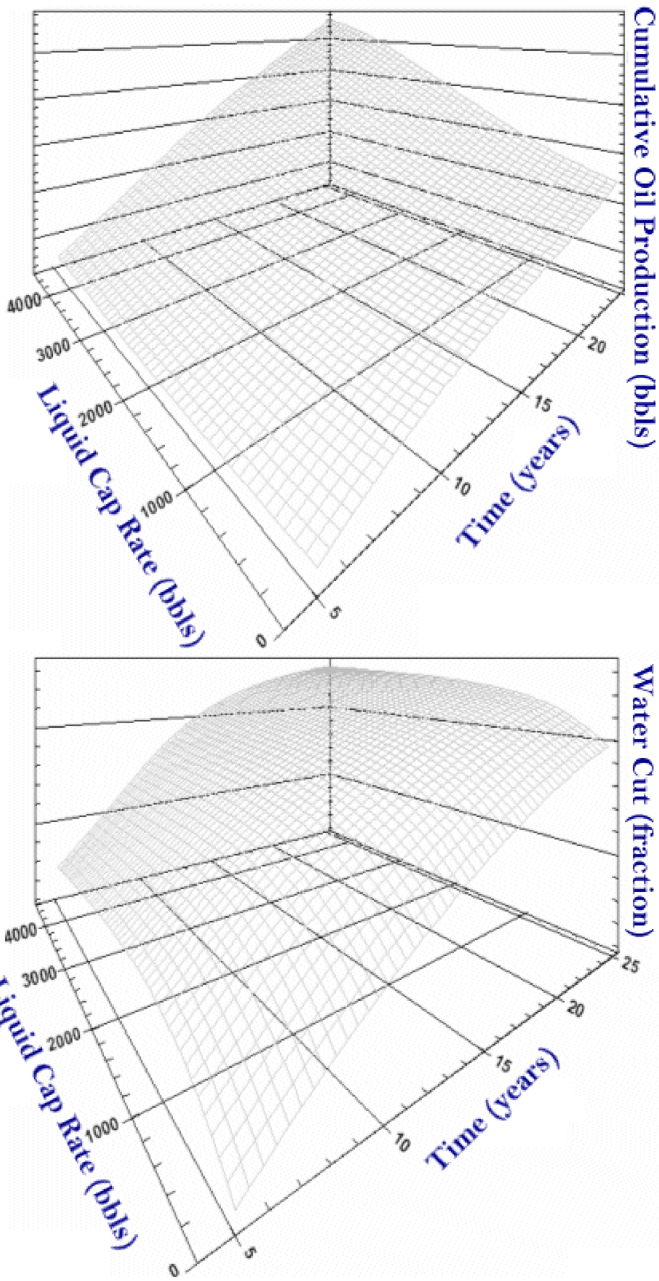

Figure 9. SRM's output for the behavior of one well in the field showing water cut and cumulative oil production as a function of time and the liquid cap rate imposed on the well.

Analysis of Uncertainty

Upon completing the development of the Surrogate Reservoir Model for this particular filed another objective of the project could now be addressed effectively. The objective was to analyze the uncertainties associated with many interpretations that go into developing a Full Field Model and quantifying their contribution to the FFM's output, i.e. cumulative oil and water production and instantenuous water cut.

It is well known that many paramters that go into an earth model and form the foundation of any reservoir simulation are far from being certain. Actually when new versions of FFMs are released it is usually the result of better information that has become available about the earth model and the dynamic data. The geological, geophysical and petrophysical interpretations, calculations and measurements that form the foundation of the earth model as paramters that go into the reservoir simulation model, each carry a certain amount of uncertainty. SRM along with Monte Carlo simulation can serve as an important technique to quantify these uncertainties and demonstrate their individual or collective impact on the model's outcome.

The procedure that was used in this study to analyze the contribution of the uncertainties associated with some of the parameters that are used in the FFM (essentially a Monte Carlo simulation approach with SRM as the objective function) is as follows:

1. Identify the parameters that you are going to analyze. It is recommended that you start with the parameters that have the most contribution to the process outcome. Result of KPI analysis as shown in Figure 6 is usually a good start.
2. For each of the parameters define a probability distribution function (pdf). The pdf can take the form of uniform, triangular, guassian, or descrete as appropriate.
3. Run the SRM thousands of times, each time randomly selecting a value from the defined pdf as input to the model and save the output.
4. Plot the the output of the previous step in the form of a histogram. This histogram is essentially the pdf of the output that you are trying to analyze.

Upon completion of the above steps, instead of a single value for the model output, let's say instantenuous water cut of a particular well at year 2010, you now have a probability distribution function that would show the minimum, the maximum and sometimes the most likely water cut for that year. Following is a demonstration of the above process.

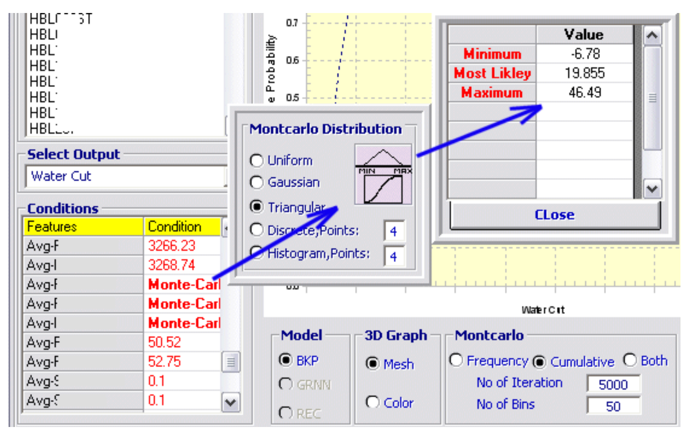

Figure 10. Assigning pdf to specific parameters in SRM.

In this example the uncertainties associated with capillary pressure values in the three layers above a particular horizontal well is going to be analyzed as shown in Figure 10.

Once the parameters that are going to be studied are identified, the appropriate pdf can be assigned to each. Then the number of times the SRM (the objective fungtion of the Monte Carlo simulation) should be run for the analysis is identified. This number is identified as 5000 at the bottom of Figure 11. It took less than 6 seconds to make the 5000 runs, and to plot the results as shown in Figure 11.

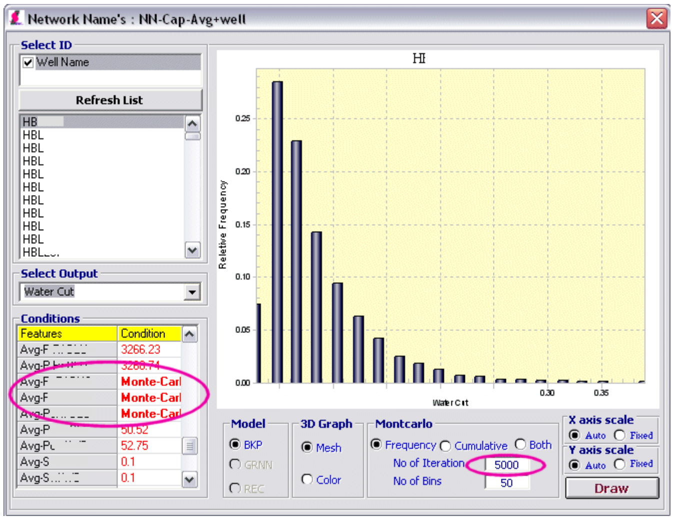

Figure 11. The resulting pdf for the instateneous water cut of a particular horizontal well.

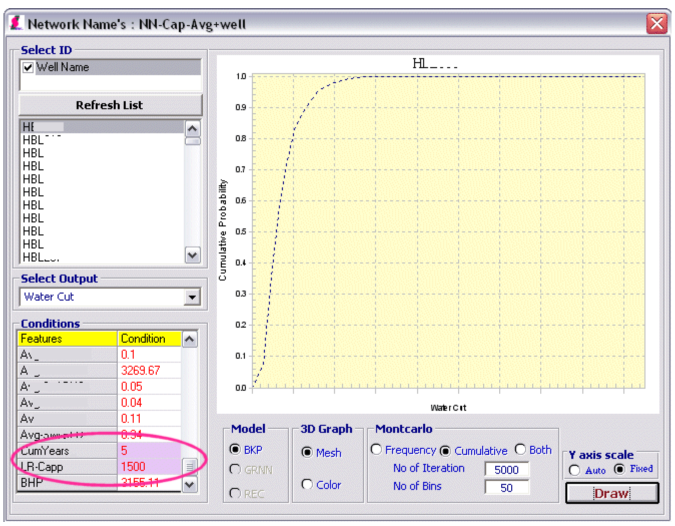

Figure 12. Cumulative pdf for the instateneous water cut of a particular horizontal well.

Figure 12 shows the cumulative pdf for the same problem as Figure 11. Also in this figure you can see that the analysis has been performed for year 5 (end of year 2010) at a liquid cap rate of 1500 barrels per day. Figure 11 shows that for this particular well the most likely water cut is about 5 percent with possibility of being as little as 2 percent and as much as 20 percent with much less probabilities.

Figure 13 shows the three dimensional output of SRM for the same well as a function of time and liquid cap rate with identifying the water cut to be 13.5 percent for year 5 at 1500 barrels per day liquid cap rate.

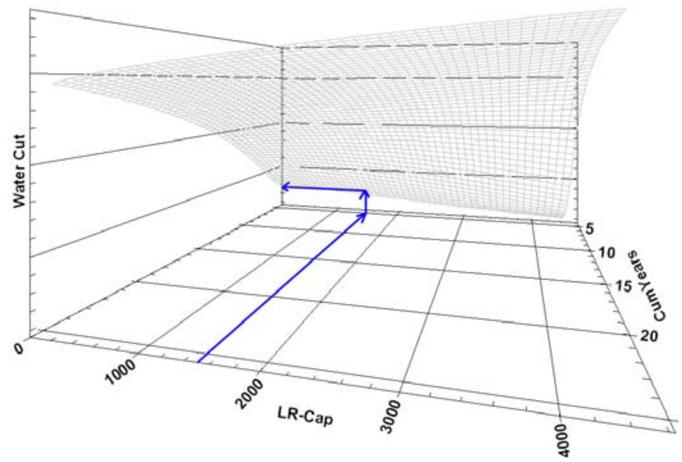

Figure 13. Water cut for the same well as Figures 11 and 12 as a function of time and liquid cap rate.

Figures 14 and 15 show the probability distribution function and three dimensional plots of cumulative oil production for the same well shown in Figures 11 through 13.

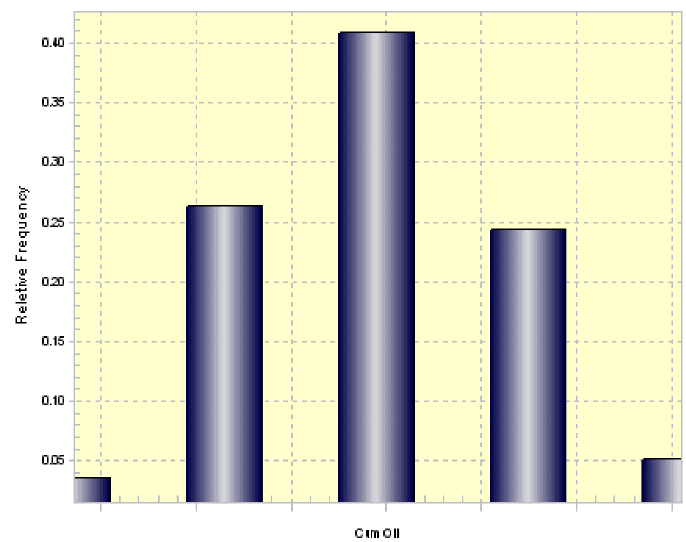

Figure 14. Probability distribution function for cumulative oil.

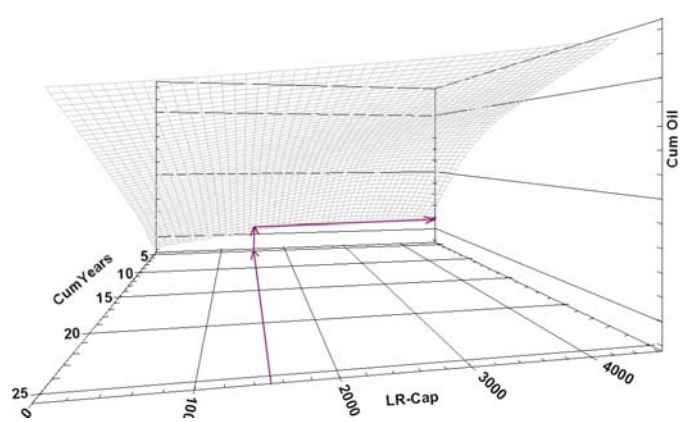

Figure 15. Cumulative oil as a function of cap rate and time.

Conclusions

In this paper, results of developing a Surrogate Reservoir Model (SRM) to accurately represent a Full Field Model (FFM) were presented. The essential steps that need to be taken in order to be able to develop such models were identified. These steps include careful representation of static and dynamic data during the data collection stage and performing Key Performance Indicator (KPI) analysis using Fuzzy Paatern Recognition (FPR) technology for dimensionality reduction.

Validation of the SRM using a significant portion of the data that has not been used during the development stage was presented. The resulting SRM was then used to perform uncertainty analysis via Monte Carlo simulation methods and the results were demonstrated.

It is the belief of the authors that SRM will play a significant role as the enabling technology for the smart fields since they are capable of bridging the gap between high frequency data streams coming from the field and much slower analytical and numerical techniques that are used for reservoir management.

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References

1. Heinemann, Gerken, and von Hantelmann, Using Local Grid Refinement in a Multiple-Application Reservoir Simulator, SPE 12255, SPE Reservoir Simulation Symposium, 15-18 November, San Francisco, California, 1983.
2. Ewing and Lazarov, Adaptive Local Grid Refinement, SPE 17806, SPE Rocky Mountain Regional Meeting, 11-13 May, Casper, Wyoming, 1988.
3. Mohaghegh, S., Popa, A. S. and Ameri, S.: "Intelligent Systems Can Design Optimum Fracturing Jobs", *SPE 57433*, *Proceedings*, 1999 SPE Eastern Regional Conference and Exhibition, October 21-22, Charleston, West Virginia.
4. Mohaghegh, et. al. Design Optimum Frac Jobs Using Virtual Intelligence Techniques. ***Computers and Geosciences Journal***, October 2000, Vol. 26, Issue 8, pp 927-939, Elsevier Science Publications, Amsterdam, Holland.
5. FracPro, Hydraulic Fracturing Simulator by Pinnacle Technologies. http://www.pinntech.com/subs/fracpropt.html
6. Queipo, Pintos, Rincón, Contreras, and Colmenares, SPE 63065, Surrogate Modeling–Based Optimization for the Integration of Static and Dynamic Data Into a Reservoir Description, 2000 SPE Annual Technical Conference and Exhibition held in Dallas, Texas, 1–4 October 2000.
7. Queipo, Goicochea, and Pintos, Surrogate Modeling-Based Optimization of SAGD Processes, SPE 69704, 2001 SPE International Thermal Operations and Heavy Oil Symposium held in Porlamar, Margarita Island, Venezuela, 12-14 March 2001.
8. Zerpa, Queipo, and Pnitos, An Optimization Methodology of Alkaline-Surfactant-Polymer Flooding Processes Using Field Scale Numerical Simulation and Multiple Surrogates, SPE 89387, 2004 SPE/DOE 14th Symposium on Improved Oil Recovery held in Tulsa, Oklahoma, U.S.A., 17-21 April 2004.
9. Naidu, Neural Network Surrogate Model for Multidisciplinary Design Optimization, Master Thesis, Department of Aerospace Engineering, India Institute of Technology, Bombay, India, July 2004.
10. A User's Guide to LHS: Sandia's Latin Hypercube Sampling Software, http://www.prod.sandia.gov/cgi-bin/techlib/access-control.pl/1998/980210.pdf
11. Design and Analysis of Experiment, by Douglas C. Montgomery, John Wiley & Sons, ISBN: 047148735X.
12. Zafari and Reynolds, Assessing the Uncertainty in Reservoir Description and Performance Prediction with the Ensemble Kalman Filter, SPE 95750, 2005 SPE Annual Technical Conference and Exhibition held in Dallas, Texas, 9–12 October 2005.
13. Zhang, Lu and Chen, Dynamic Reservoir Data Assimilation with an Efficient, Dimension –Reduced Kalman Filter, SPE 95277, 2005 SPE Annual Technical Conference and Exhibition held in Dallas, Texas, 9–12 October 2005.
14. Mohaghegh, Virtual Intelligence Applications in Petroleum Engineering: Part 1 – Artificial Neural Networks. *Journal of Petroleum Technology*, Distinguished Author Series, September 2000, pp 64-73.
15. Mohaghegh, Virtual Intelligence Applications in Petroleum Engineering: Part 2 – Evolutionary Computing. *Journal of Petroleum Technology*, Distinguished Author Series, October 2000, pp 40-46.
16. Mohaghegh, Virtual Intelligence Applications in Petroleum Engineering: Part 3 – Fuzzy Logic. *Journal of Petroleum Technology*, Distinguished Author Series, November 2000, pp 82-87.
17. ECLIPSE™, Reservoir Modeling and Simulation software by Geoquest, Schlumberger.
http://www.slb.com/content/services/software/reseng/eclipse_simulators/
18. Fuzzy Pattern Recognition is a module in IDEA™, the software application that was used during the development of SRM. IDEA™, Intelligent Systems modeling, Data Mingin and analysis software by Intelligent Solutions, Inc. http://www.intelligentsolutionsinc.com/products.htm