ADVANCES IN RESERVOIR SIMULATION & MODELING WITH ARTIFICIAL INTELLIGENCE & DATA MINING

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Engineers and geo-scientists are faced with complex, non-linear and dynamic problems as they attempt to increase recovery from hydrocarbon reservoirs. They use a variety of analytical and numerical solutions to model the intricate nature of fluid flow through porous media. Other disciplines such as military, manufacturing and medicine that are heavily dependent on science and technology to achieve their objectives have been successfully using the latest in data analytics, information technology and engineering to enhance their products and processes. Artificial Intelligence and Data Mining (AI&DM) represent the state-of-the-art in such advance technologies. Use of AI&DM in the exploration and production industry dates back to early 1990s, but it has not enjoyed wide acceptance and success until recently. Innovative applications of AI&DM in our industry has started to make a serious impact on many companies bottom-lines that had the vision to implement them in a variety of ways in their assets.

In this article two newly developed technologies are presented that integrate classic reservoir engineering with Artificial Intelligence and Data Mining. Surrogate Reservoir Models are developed to unleash the hidden and often undiscovered potentials of conventional reservoir simulation models by being utilized as a tool for exhaustive search of the solutions space, quantification of uncertainties and real-time reservoir management. Unlike conventional geo-statistical approaches that need hundreds of simulation runs, SRM development requires only a handful of runs and can reproduce accurate simulation results instantaneously. Top-Down, Intelligent Reservoir Models are an entirely new and novel way of reservoir modeling. Top-Down models are developed using an intuitive workflow of integrating well production history with well logs in order to form a cohesive model of reservoir dynamics. They are capable of identifying sweet spots in the reservoir as optimum infill locations by tracking hydrocarbon depletion and accounting for remaining reserves as a function of time. Top-Down models provide production forecast of existing wells and predict new wells performance.

SURROGATE RESERVOIR MODEL (SRM)

Surrogate Reservoir Model[1-4] has been developed in response to the need for real-time reservoir modeling and in order to make Real-Time Reservoir Management (RTRM) a reality. SRM is developed using the state-of-the-art in Artificial Intelligence & Data Mining (AI&DM). Artificial Intelligence & Data Mining is a collection of complementary analytical tools that attempt to mimic life when solving non-linear, complex and dynamic problems. AI&DM is consisted of, but is not limited to, analytical techniques such as Artificial Neural Networks[5], Genetic Optimization[6], and Fuzzy Logic[7].

Surrogate Reservoir Model (SRM) is an accurate replica of complex reservoir simulation model that may include tens or hundreds of wells and millions of grid blocks. SRM runs provide results such as wells' pressure and production profiles or pressure and saturation distribution throughout the reservoir, in real time. SRM is developed using a unique series of data generation, manipulation, compilation and management techniques. These techniques are designed to take the maximum advantage of characteristics of artificial neural networks complemented with fuzzy set theory. Upon completion of modeling process and validation, SRM can accurately replicate the results generated by highly sophisticated reservoir simulation models in response to changes made to the model input, in fractions of a second. The fact that thousands of SRM runs can be performed in seconds makes uncertainty analysis a practical task. This allows the uncertainty band associated with any decisions to be identified quickly. It takes only a handful of simulation runs to generate the required data to develop a SRM.

SRM has been successfully field-tested and peer-reviewed. In a recent study performed on a giant oil field in the Middle East, a SRM was developed to replicate the existing simulation model of the field that was developed using a commercial simulator. Consisting of approximately a million grid blocks, the computing time required for a single run of the existing simulation model is 10 hours on a cluster of 12 parallel CPUs. Upon development, calibration and validation of the SRM that could successfully and accurately replicate the results of the simulation model, tens of millions of SRM runs were performed in order to comprehensively explore the reservoir model's solution space so a successful field development strategy could be developed. The objective was to increase oil production from the field by relaxing the rate restriction that was imposed on wells. The key was to identify those wells that would not suffer from high water cuts once a rate relaxation program was put into place. The SRM had to take into account and quantify the uncertainties associated with the geological model while accomplishing the objectives of this project.

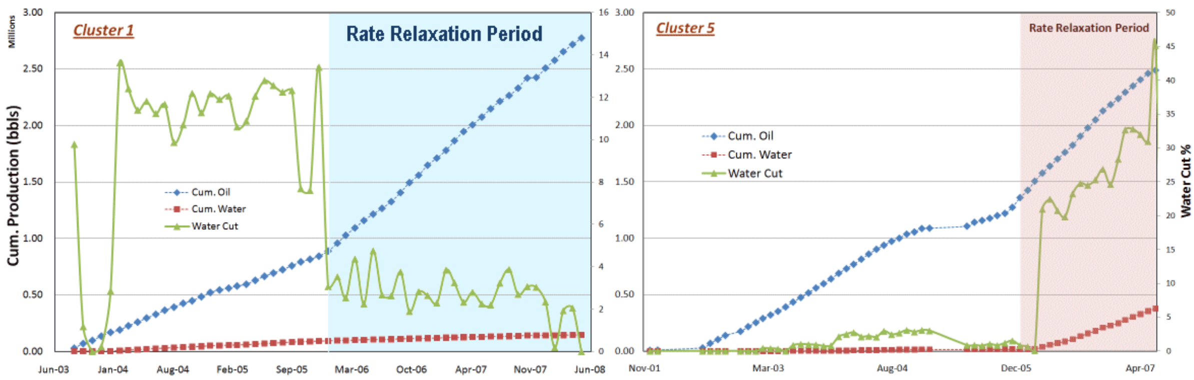

Figure 1. Results of lifting rate restriction on typical wells from clusters 1 and 5.

Upon completion of tens of millions of SRM runs (equivalent to tens of millions of simulation runs) the 165 wells in the field were divided into 5 clusters, based on the risk of rising water cuts. It was recommended that wells in clusters 1 and 2 be subjected to rate relaxation. Furthermore, it was predicted that these wells would produce small amount of water and large amount of incremental oil in the next 25 years. On the other hand, more than 100 wells placed in clusters 4 and 5 were identified as wells that will produce large amounts of water if the rate restrictions were lifted.

Upon completion of the study, rate restriction was lifted from 20 wells. These wells were selected from among all the clusters to provide a representative spatial distribution of the reservoir and examine the accuracy of the SRM predictions. After more than two and a half years of production the results were analyzed. As can clearly be seen from Figure 1 (similar results observed from all other wells in the corresponding clusters as summarized in Figure 2), wells in clusters 1 and 2 produced large amounts of incremental oil while the water production declined. The opposite effect was observed in wells that were classified in clusters 4 and 5, as predicted by the SRM. Figure 2 shows the maximum incremental water cut normalized for all wells in each of the clusters. It is clear from this figure that in accordance

with the SRM's predictions water cut decreased in wells classified in clusters 1 and 2 while increasing significantly in wells classified in clusters 4 and 5.
Results shown in the above study as well as other similar studies demonstrate the robustness of SRM technology. SRM can be used to develop replicas of sophisticated and large reservoir simulation models that can then be used in order to drive the main engine of Real Time Reservoir Management (RTRM).

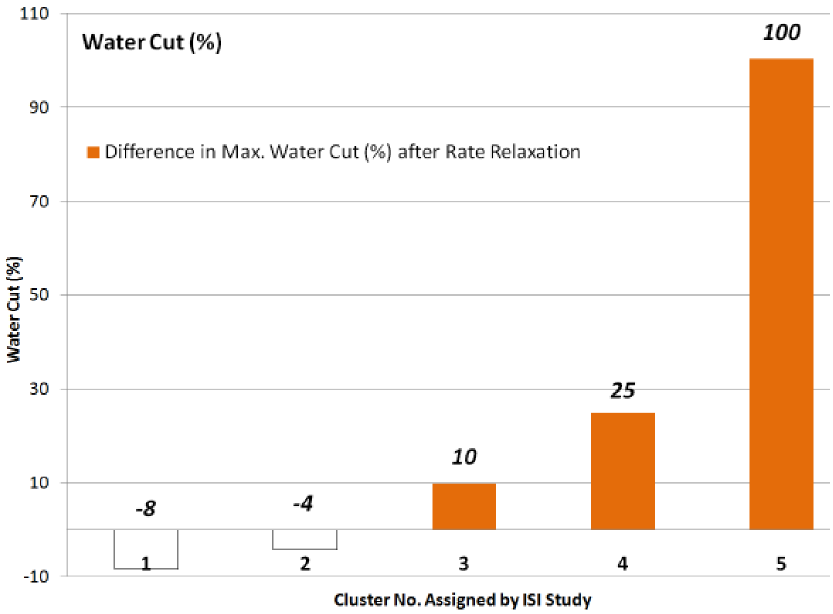

Figure 2. Percent increase in maximum water cut normalized for all wells in clusters 1 through 5.

TOP-DOWN, INTELLIGENT RESERVOIR MODELING

Traditional reservoir simulation and modeling is a bottom-up approach. It starts with building a geological model of the reservoir followed by adding engineering fluid flow principles to arrive at a dynamic reservoir model. The dynamic reservoir model is calibrated using the production history of multiple wells and the history matched model is used to strategize field development in order to improve recovery.

Top-Down Intelligent Reservoir Modeling approaches the reservoir simulation and modeling from an opposite angle by attempting to build a realization of the reservoir starting with well production behavior (history). The production history is augmented with core, log, well test and seismic data in order to increase the accuracy and fine tune the Top-Down model. The model is then calibrated (history matched) using the most recent wells as blind dataset. Although not intended as a substitute for the traditional reservoir simulation of large, complex fields, this novel approach can be used as an alternative (at a fraction of the cost and time) to traditional reservoir simulation in cases where performing traditional modeling is cost (and man-power) prohibitive. In cases where a conventional model of a reservoir already exists, Top-Down Intelligent Reservoir Modeling should be considered a complement to, rather than a competition for the traditional technique. It provides an independent look at the data coming from the reservoir/wells for optimum development strategy and recovery enhancement. Top-Down Intelligent Reservoir Modeling provides a unique perspective of the field and the reservoir using actual measurements. It provides qualitatively accurate reservoir characteristics that can play a key role in making important and strategic field development decisions.

AN ALTERNATIVE TO CONVENTIONAL MODELING

Top-Down Intelligent Reservoir Modeling starts with well-known reservoir engineering techniques such as Decline Curve Analysis, Type Curve Matching, History Matching using single well numerical reservoir simulation, Volumetric Reserve Estimation and calculation of Recovery Factors for all the wells (individually) in the field. Using statistical techniques multiple Production Indicators (3, 6, and 9 months cumulative production as well as 1, 3, 5, and 10 year cumulative oil, gas and water production and Gas Oil Ratio and Water Cut) are calculated. These analyses and statistics generate a large volume of data and information that are spatiotemporal snap shots of reservoir behavior. This large volume of data is processed using the state-of-the-art in artificial intelligence and data mining in order to generate a complete and cohesive model of the entire reservoir. This is accomplished by using a set of discrete modeling techniques to generate production related predictive models of well behavior, followed by intelligent models that integrate the discrete models into a cohesive picture and model of the reservoir as a whole, using a continuous fuzzy pattern recognition algorithm.

Top-Down Intelligent Reservoir Model is calibrated using the most recent set of wells that have been drilled in the field. The calibrated model is then used for field development strategies to improve and enhance hydrocarbon recovery.

DETAILS AND AN EXAMPLE OF TOP-DOWN MODELING

Top-Down Modeling is an elegant integration of state-of-the-art in AI&DM with classic reservoir engineering techniques and principles. It provides a unique perspective of the field and the reservoir using actual measurements. It provides qualitatively accurate reservoir characteristics that can play a key role in making important and strategic field development decisions.

Year	Number of Well Drilled
1986	4
1987	6
1988	15
1989	134
1990	99
1991	72
1992	13
1993	5
1994	0
1995	1
Total	**349**

Table 1. Number of wells starting production in each of the years.

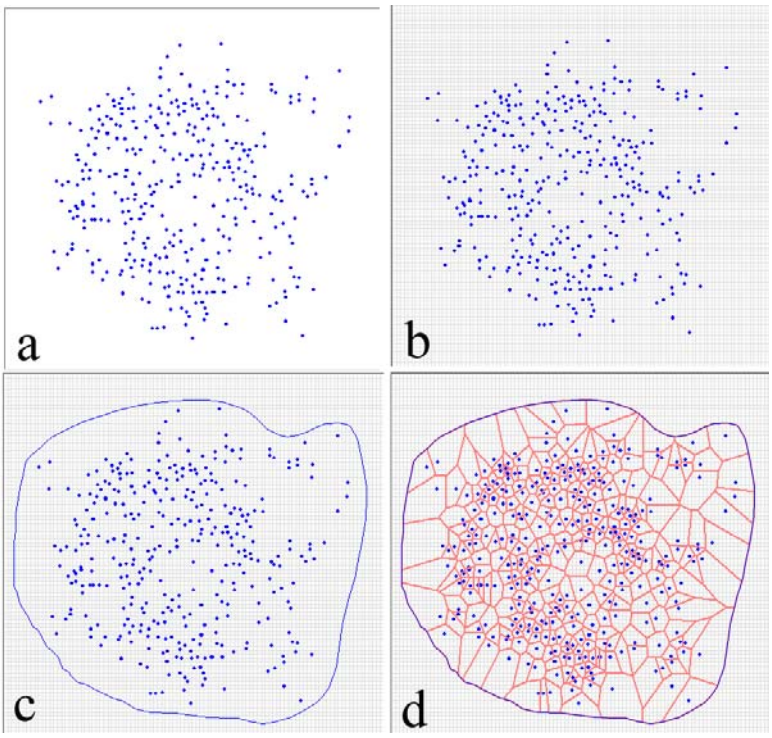

Figure 3. Generating the Voronoi cells for the wells in the Carthage field, Texas.

One of the most important advantages of Top-Down modeling is its ease of development. It is designed so that an engineer or a geologist with a Bachelor's degree will be able to comfortably develop a Top-Down model in a relatively short period of time with minimum amount of data. The disadvantage of Top-Down modeling is that it cannot be performed on "any" field. It is designed for fields that have at least 50 wells and about 5 to 7 years of production.

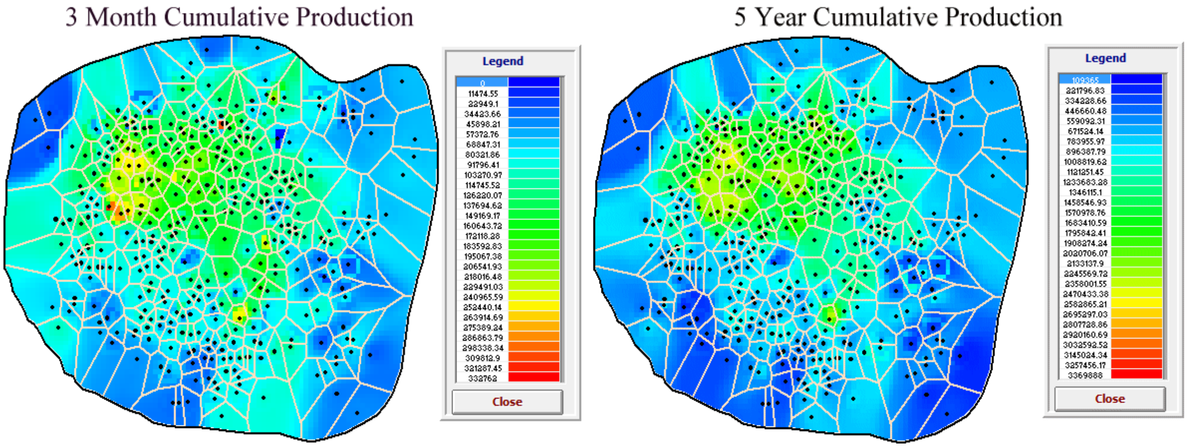

Figure 4. Results of discrete predictive modeling showing the distribution of first 3 months and 5 year cum. production for the entire field.

Location and monthly production rate data for all wells and well logs (not necessary for all wells) are the minimum data requirement for the Top-Down modeling. Figures 3, 4 and 5 present a short summary of the processes used to complete a Top-Down model. These figures are related to a Top-Down modeling study that was performed on part of Carthage field in Texas that included 349 wells. These wells were drilled from 1986 to 1995. Table 1 shows the number of wells that were drilled on any given year since 1986. Figure 3 shows the well locations, followed by identification of boundary and the Voronoi grids for all the wells in the analysis. Once the Decline Curve Analysis and other steps that were mentioned above were completed, the discrete modeling and fuzzy pattern recognition are performed. The distribution of first three months of production as well as the 5 year cumulative production are (results of discrete predictive modeling) shown in Figure 4.

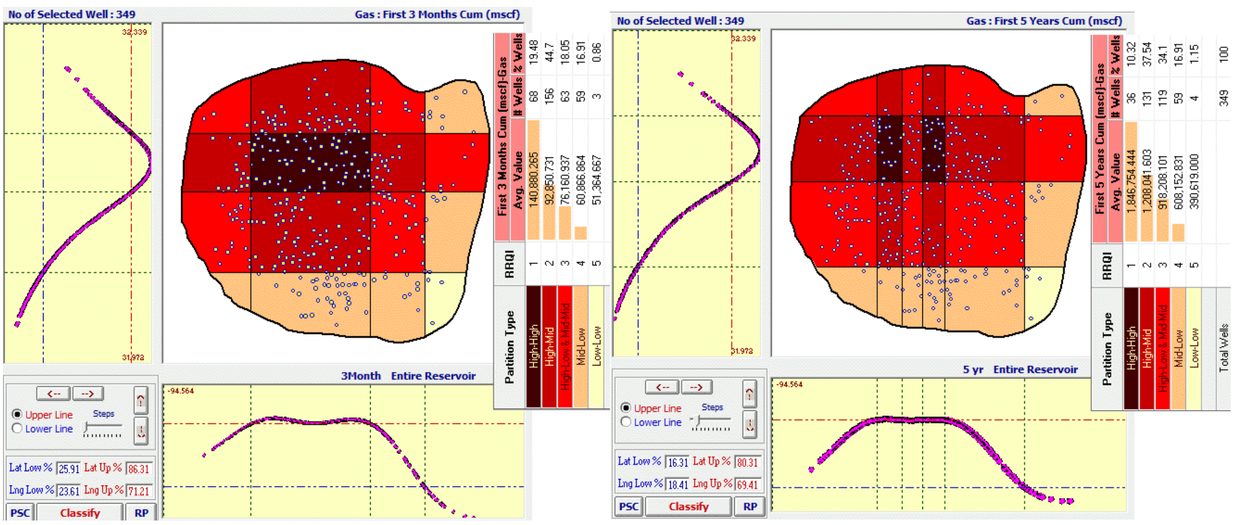

Figure 5. Results of Fuzzy Pattern Recognition showing the sweet spots in the field for the first 3 months (left) and 5 year cum. production (left).

Figure 5 shows the results of fuzzy pattern recognition. The sweet spots in the field are shown with the dark brown color. The Relative Reservoir Quality (RRQ) is indicated by the colors in this figure. Higher quality of the reservoir are indicated with darker color. Figure 5 shows the depletion in the reservoir as the sweet spot shrinks between 3 months and 5 years (from left to right). This provides an indication of depletion and a guide on where to drill the next wells in this field.

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