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Reservoir Simulation and Modeling Based on Pattern Recognition

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Abstract

In this paper a new class of reservoir models that are developed based on the pattern recognition technologies collectively known as Artificial Intelligence and Data Mining (AI&DM) is introduced. The workflows developed based on this new class of reservoir simulation and modeling tools break new ground in modeling fluid flow through porous media by providing a completely new and different angle on reservoir simulation and modeling. The philosophy behind this modeling approach and its major commonalities and differences with numerical and analytical models are explored and two different categories of such models are explained. Details of this technology are presented using examples of most recent applications to several prolific reservoirs in the Middle East and in the Gulf of Mexico.

AI-Based reservoir models can be developed for green or brown fields. Since these models are developed based on spatio-temporal databases that are specifically developed for this purpose, they require the existence of a basic numerical reservoir simulator for the green fields while can be developed entirely based on historical data for brown fields. The run-time of AI-Based reservoir models that provide complete field responses is measured in seconds rather than minutes and hours (even for a multi-million grid block reservoir). Therefore, providing means for fast track reservoir analysis and AI-assisted history matching are intrinsic characteristics of these models. AI-Based Reservoir Models can completely substitute numerical reservoir simulation models, work side by side but completely independent or be integrated with them in order to increase their productivity.

Advantages associated with AI-Based Reservoir Models are short development time, low development cost, fast track analysis and have the practical capability to quantify the uncertainties associated with the static model. AI-Based Reservoir Model includes a novel design tool for comprehensive analysis of the full field and design of field development strategies to meet operational targets. They have open data requirement architecture that can accommodate a wide variety of data from pressure tests to seismic.

Numerical Reservoir Simulation and Modeling vs. AI-Based Reservoir Modeling

Pattern recognition capabilities of Artificial Intelligence & Data Mining (AI&DM) can play many different roles in assisting engineers and geoscientists in building better and faster reservoir simulation models. The objective of this article is to introduce a set of comprehensive and complete workflows that have been developed based on the AI&DM for building full field reservoir simulation models. Two of these workflows that have recently been introduced will be covered in this article. In order to put these new AI-Based workflows in perspective and for the purposes of this article, let us summarize reservoir simulation and modeling as a process that ultimately models production from a field (of multiple wells) as a function of reservoir and fluid characteristics, operational constraints and other variables in the following formulation:

$$q = f\,(x_1, x_2, ..., x_n,\ \&\ y_1, y_2, ..., y_n,\ \&\ w_1, w_2, ..., w_n)$$

Where

$$q = production\ \ from\ the\ reservoir$$

$$x_1, x_2, ..., x_n = reservoir\ \&\ \ fluid\ \ characteristics$$

$$y_1, y_2, ..., y_n = operational\ constra\,\mathrm{int}\,s$$

$$w_1, w_2, ..., w_n = other\ \ parameters$$

$$f\,(\ ) = \ functional\ relationship$$

The above equation simply states that production from a field is modeled using a series of ***functional relationships*** between reservoir-fluid characteristics, operational constraints (drilling new wells, injecting water, shutting some wells, changing the surface facility capacity, …) and other variables such as well configurations, completion techniques, etc. This formulation is applicable for both numerical reservoir simulation and AI-based modeling. In both of these modeling techniques the intent is to model production as a function of reservoir-fluid characteristics, well characteristics and operational constraints. The major difference between these two techniques appears in the philosophy of the state of our knowledge of the phenomenon (fluid flow in porous media) and the assumptions made during the modeling process.

Role of Major Assumptions

In numerical simulation and modeling, the functional relationships used in the above equation consist of the law of conservation of mass, Darcy's law (Fick's law of diffusion in the cases that such formulation is required), thermodynamics and energy conservation (if we are modeling thermal recovery), etc. These functional relationships are believed to be true, deterministic and unchangeable. Therefore, if the production that results from numerical simulation and modeling does not match our observation (measurements) from the field, we conclude that the reservoir characteristics (the static model) may not be ideally measured and interpreted and therefore must be modified in order to achieve the match.

This is the conventional wisdom and has been the common practice during the past several decades. The validity and application of this technology is not disputed. However it should be pointed out that this functional formulation has evolved from simple relationships in the early days of reservoir simulation (single-phase, Darcy's law) to a much more complex set of relationships. These relationships enables modeling more complexities in the reservoir (multi-phase flow, dual porosity formulation, compositional formulation, coupling with geo-mechanics and surface facilities, etc.) and are bound to evolve even further as our knowledge of these physical phenomena deepens.

Therefore, during the history matching of a numerical reservoir simulation model, since the functional relationships are constant and unchangeable (i.e. our current understanding of the physical phenomena is good enough that we do not need modification no matter which reservoir we are modeling) the engineer concentrates on modification of reservoir characterization (such as permeability) in order to reach a reasonable match. Since the reservoir characterization is represented by a geo-cellular (static) model, developed by geoscientists, and is full of interpretations and uncertain values, we as engineers feel comfortable changing these numbers in order to get the match. Please note that this approach is not being criticized but merely explained in order to emphasize the differences between these technologies.

	Numerical Model	AI-Based Model
Reservoir Characteristics	***Uncertain:*** • Measurements • Interpretations (subject to modification during the history matching)	***Uncertain:*** • Measurements • Interpretations (subject to modification during the history matching)
Functional Relationships	***Certain:*** • Conservation of Mass • Darcy's Law (unchanged during the history matching)	***Uncertain:*** • Relationship between reservoir characteristics and production. (subject to modification during history matching)

Figure 1. Main difference between numerical reservoir simulation & modeling and AI-based reservoir modeling.

In AI-based reservoir modeling some of the assumptions that are made in the conventional numerical modeling are modified. Instead of holding the functional relationship constant, these relationships are allowed to change in addition to the possibility of modifying the reservoir characteristics. In other words, constant, deterministic and non-flexible functional relationships between production and reservoir characteristics are avoided. The functional relationship that generates the observed production from the reservoir using the set of measured reservoir characteristics is sought through the AI&DM-based pattern recognition technology. Of course reservoir characteristics can also be modified if one set of reservoir characteristics (measurements) is believed to be better than the one being used. Once a set of reservoir characteristics that geoscientists are reasonably comfortable with are identified, they are not modified during the history matching process. Instead, the functional relationships are modified until a match is attained.

Direct or Indirect Use of Physics

As engineers we have been trained to use first principle physics whenever we attempt to model any phenomenon. It is a fact that some physical phenomena are too complex to be modeled for one or both of the following reasons.

1. We may not know "all" the parameters that are involved in the makeup and the behavior of a phenomenon.
2. Even if we know "all" the parameters, the relationship between these parameters may be too complex to model.

As humans we control and operate highly complex machinery and navigate through sophisticated puzzles without building a physics-based model in our mind. How do we do it? We perform these complex actions by observation and pattern recognition. In AI-based reservoir simulation and modeling, we try to mimic this pattern recognition process. Instead of using physics in its first principle and explicit form, we use physics (our scientific understanding of the fluid flow through porous media) as inspiration for building a library of clever observations. In the case of AI-Based Reservoir Models, this library of clever observations is called a customized spatio-temporal database. The spatio-temporal database is used to developing (train) a predictive model by modifying the free parameters that represent the strength of interconnections between parameters. As the training process continues, the algorithm converges to a state where it can mimic the behavior of the hydrocarbon reservoir. In other words, instead of explicitly formulating the physics, we try to deduce the physics from the observations in an implicit fashion.

Data-Intensive Sciense, the Fourth Paradigm

History of science and technology can be divided into several eras (Hey, 2009). It all started with experimental science at the early age of science. Several hundred years ago the theoretical branch of science emerged and gave rise to theories such as newton's laws of motion, Kepler's laws of planetary motion and Maxwell's laws of electrodynamics, optics and electric circuits. The last several decades have been the age of computational science where fast computers have provided the means for simulation and modeling in areas such as computational fluid dynamics, meteorological and climatological, aerospace and hydrocarbon reservoir simulations, to name a few. According to Jim Gray[1], the legendary American computer scientist, we have now entered the new age of *escience* or *data-intensive science* where massive amounts of data can be collected from physical phenomena and or simulations and new models can be built based on these data.

Moving from each of the above ages of science to the next required a paradigm shift on how we observe, interact, model and attempt to control the phenomena around us. It is now time for another paradigm shift into the fourth paradigm that is the *data-intensive science*.

Steps Involved in developing AI-Based Reservoir Models

There are five major steps involved in completion of an AI-based reservoir modeling project. These steps are summarized below:

1. *Development of a spatio-temporal database.*

   AI-Based Reservoir Models are developed using data. Therefore, the first step in any AI-based reservoir modeling project must start with developing a representative spatio-temporal database. The extent at which this spatio-temporal database actually represent the fluid flow behavior of the reservoir that is being modeled, determines the potential degree of success in developing a successful model. As we will see in the following section, the nature and class of the AI-Based Reservoir Model is determined by the source of this database.

   The term spatio-temporal defines the essence of this database and is inspired from the physics that controls this phenomenon and is described by the diffusivity equation. The main objective of modeling a reservoir is to be able to know the value of pressure and saturation at any location in the reservoir and at any time. Therefore, data and information that can provide snap shots of changes in pressure as a function of space and time are of importance and such data needs to be collected, organized and processed.

   An extensive data mining and analysis process should be conducted at this step to fully understand the data that is housed in this database. The data compilation, curation, quality control and preprocessing is one of the most important and time consuming steps in developing

[1] Jim Gray: (1944-2007) Legendary American computer scientist received the Turing Award for seminal contributions to computer science.

an AI-Based Reservoir Model. “Curse of Dimensionality” is one of the issues that is associated with AI-Based Reservoir Modeling and must be handled eloquently during this step of the process. Proper handling of this important issue can make or break the entire modeling process.

2. *Simultaneous training and history matching of the reservoir model.*

   In numerical reservoir simulation and modeling the practice is to build a flow model based on the static model that is developed. The reservoir simulation mode that emerges as the result of this process is usually our base model. Production data (field measurements and observations) are then used to history match the base model, usually by modifying the reservoir characteristics that are provided in the static model.

   In AI-Based Reservoir Model we start with the static model and try to honor it and not modify it during our history matching process. Instead, we will analyze and quantify the uncertainties associated with this static model at a later stage in the development (step 4 that follows). The model building and history matching in AI-Based Reservoir Models are performed simultaneously during training the reservoir model to learn the fluid flow behavior in the specific reservoir being modeled. The spatio-temporal database developed in the previous step is the main source of information for building and history matching the AI-Based Reservoir Model.

   Issues that must be taken into consideration at this step of the modeling include the status of the reservoir (modeling a green field and a brown field are completely different), the purpose of the model (AI-Based Reservoir Models developed for history matching purposes and those developed for predictive analysis purposes) and the objective of the model (modeling pressure and saturation changes in the reservoir versus modeling injection and production behavior at the well or coupling both in one model). Each of the abovementioned issues determine the nature of the tools and the strategies that are used in developing a successful AI-Based Reservoir Model.

   It is of utmost importance to have a clear and robust strategy for validating the predictive capability of the developed AI-Based Reservoir Model. The model must be validated using completely blind data that has not been used, in any shape or form, during the development of the AI-Based Reservoir Model. Both training and calibration datasets that are used during the initial training and history matching of the model are considered non-blind. Some may argue that the calibration – a.k.a. testing dataset – is also blind; this argument has some merits but if used during the development of the AI-Based Reservoir Model can compromise validity and predictability of the model and therefore such practices are not recommended.

3. *Designing field development strategies*

   One of the unique features of the AI-Based Reservoir Modeling workflow is a field development design tool that assists engineers in making reservoir management decisions. This is done using fuzzy pattern recognition that has the capability of taking large amounts of data with little or no apparent trend and extract patterns that can lead to effective decision making. This design tool can show the depletion in the reservoir and remaining reserves as a function of time that can help engineers decide on well placement and/or remedial operations. Some details on how this tool can be used have been shown in several previous publications (Gomez 2009 – Kalantari 2009 – Kalantari 2010 – Mata 2007 – Mohaghegh 2009c).

4. *Sensitivity analysis and quantification of uncertainties*

   During the model development and history matching that was mentioned in Step2, it was pointed out that static model is not modified during the history matching process. Knowing that the static model includes inherent uncertainties, lack of such modifications may present a weakness of this technology. To rectify this, the AI-Based Reservoir Modeling workflow includes a comprehensive set of sensitivity and uncertainty analyses.

During this step of the process the developed and history matched model is thoroughly examined against a wide range of changes in reservoir characteristics and/or operational constraints. The changes in pressure or production rate at each well are examined against potential modification of any and all the parameters that have been involved in the modeling process. These sensitivity and uncertainty analyses include, single- and combinatorial-parameter sensitivity analyses, quantification of uncertainties using Monte Carlo simulation methods and finally development of type curves that can be performed either on well bases or for the entire field.

5. *Application of the model in predictive mode*

   Once the development, validation and analysis of the AI-Based Reservoir Model is completed, the model can be used in the predictive mode in order to respond to the “What If” questions that are raised by the reservoir management team.

Types of AI-Based Reservoir Models

There are many types of AI-Based Reservoir Models. They can be classified based on several categories. Classified can be based on the output they provide (grid-based model, well-based model, and fully-coupled model), based on the type of field they are being applied to (green fields vs. brown fields), or based on their functionality (models built for history matching purposes or models for predictive and field development purposes). But the most important of all classifications is the classification based on the source of data used for development.

AI-Based Reservoir Models are mainly classified based in the main source of the data used to develop the spatio-temporal database that forms the foundation of the model. If the source of the sptio-temporal database is a numerical reservoir simulation model, then the AI-Based Reservoir Model will be called a Surrogate Reservoir Model (SRM). If the source of the sptio-temporal database is actual field data (historical production data, well logs, cores, well test, seismic attributes, etc.) then the AI-Based Reservoir Model will be called a Top-Down, Intelligent Reservoir Model, or Top-Down Model (TDM) for short.

Surrogate Reservoir Models (SRM)

Surrogate Reservoir Model (SRM) is an accurate replica of the traditional numerical reservoir simulation model. It may be questioned that when a numerical reservoir simulation model exists why an AI-Based Reservoir Model would be necessary. Necessity of SRM has to do with the fact that massive potentials of the existing numerical reservoir simulation models go unrealized because it takes a long time to make a single run. Numerical models that are built to simulate complex reservoirs require considerable run-time even on cluster of parallel CPUs. Exhaustive and comprehensive evaluation of the solution space for designing field development strategies as well as quantification of uncertainties associated with the static model are the type of analyses that require large number of simulation runs in order to provide meaningful and usable results. When a numerical simulation model takes hours for a single run, performing such analyses become impractical and the engineers have to compromise by designing and running a much smaller number of runs in order to make decisions.

SRM has the capability of reproducing highly accurate well-based and grid-based simulation responses as a function of changes to all the involved input parameters (reservoir characteristics and operational constraints) in fraction of a second. This can be accomplished for reservoir simulation models that take hours or days to make a single run. SRM has been successfully tested and validated with several commercial and in-house (belonging to NOCs) reservoir simulators such as ECLIPSE™[2], IMEX™ and GEM™[3] and POWERS™[4] and replicating models with up to 6.5 million grid blocks. Among the major advantages of SRM over proxy models or response surfaces is the required number of simulation runs for their developments. While hundreds of simulation runs are required to build proxy models or response surfaces, building SRM requires only a small number of simulation runs (usually between 10 to 15 runs). This is due to a unique an innovative sampling of data for the generation of the required spatio-temporal database.

Surrogate Reservoir Models (SRM) – Case Studies

Several papers have been published on this topic (Mohaghegh, 2009b – Mohaghegh, 2010). In a recently published paper (Mohaghegh 2009a) the predictions made by an SRM were examined against more than two and a half years of production from the field. This SRM was developed for a giant oil field in the Middle East (brown field). It was demonstrated that all SRM predictions proved to be accurate. The SRM was developed based on a reservoir simulation model with about one million grid blocks that included 165 horizontal wells. Historically, oil production from this field had been capped at 1,500 barrel of liquid per day (BLPD) with a total field production that was capped at 250,000 barrels of oil per day (BOPD). Water was being injected in this field for both pressure maintenance and displacement of oil. The production at each well (and the entire field) was being controlled (capped) in order to avoid premature water breakthrough. Increase in water cut in some of the wells had started to worry the reservoir management team.

The objective of the project was to increase oil production in this field by identifying the wells that would benefit from relaxing the production rate from 1,500 BLPD to higher rates (up to 4,500 BLPD). The risk associated with this reservoir management decision was that while some wells would benefit from such action (rate relaxation) other wells would run the risk of high water cut that could eventually result in killing the well. The key was to know which wells should and should not be subject to rate relaxation. This became a search and optimization problem with the reservoir simulation model at the center of the optimization routine as the objective function. The solution space (the universe of all possible parameter being modified within their given range) of this hyper dimensional problem was so vast that a reasonable search for the optimum solution (which wells should be subject to rate relaxation) would require hundreds of thousands of simulation runs. With a single simulation run taking 10 hours on a cluster of 12 CPUs, reaching a reasonable solution became impractical.

An SRM that was able to accurately generate oil and water production rates as a function of time for all the 165 wells over the next 25 years was developed for this field. A single SRM run would take only a fraction of a second. The developed SRM was used to analyze the entire solutions space (all possible combinations of production scenarios) while quantifying the uncertainties associated with the static model that was used in the flow simulator. After hundreds of thousands of SRM runs the results were analyzed and recommendations on which wells should be subject of rate relaxation were made.

It is notable that in order to develop this SRM only 10 simulation runs were performed using the actual reservoir simulator. This is important since hundreds of simulation runs are required to develop the simplest response surfaces that would have limited applicability. Upon completion of the analysis with the SRM, wells in this field were divided into 5 clusters as shown in Figure 2. Wells in clusters 1 and 2 were identified as those that would benefit from rate relaxation and those in clusters 4 and 5 were identified as wells that should not be opened up to more production since SRM analyses had indicated high water production for these well if rates were relaxed.

[2] Schlumberger Information Service
[3] Computer Modeling Group
[4] Saudi Aramco, In-House Simulator

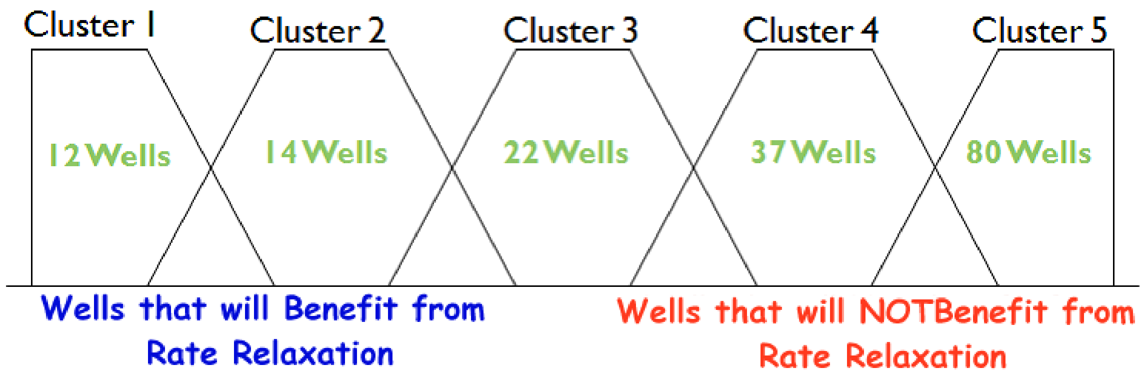

Figure 2. SRM analysis divided the wells in the field into clusters based on their potential response to rate relaxation.

Upon completion of this study rates were relaxed on 20 wells in this field. After more than two and a half years of production, wells that were classified in clusters 1 and 2 showed high incremental oil production while water production increased insignificantly, or remained the same, resulting in lower water cut. On the other hand all wells from cluster 4 and 5 that became subject to rate relaxation produced very large amounts of water increasing their water cut to dangerous levels. Results of oil and water production in several wells from some of the clusters are shown in Figures 3 to 5.

Figure 3 shows oil and water production as well as instantaneous water cut for two wells in cluster 5 before and after rate relaxation. Water cut in both wells is less than 5% (as low as 1%) in both wells before the rate relaxation. Water cut increases to 25% and 45%, respectively, in these wells a few months after the start of rate relaxation. Figure 4 shows oil and water production as well as instantaneous water cut for two wells in clusters 1 and 2, before and after rate relaxation. Water cut in the well from cluster 2 (left) is less than 2% before the rate relaxation and it does not go above 1% after rate relaxation. Water cut in the well from cluster 1 (right) is about 12% before the rate relaxation and it drops to an average of 3% after rate relaxation (decrease in water cut corresponds to large amount of oil production while water production stays constant or increases ever so slightly). All these results are exactly in-line with SRM predictions (see Figure 2). Figure 5 summarizes the results of all 20 wells that were subject of rate relaxation in the past 2.5 years. These results are normalized on a per-well per-cluster basis for better comparison. These figures show that the production from the field in the past two and a half years correspond to the predictions made by SRM.

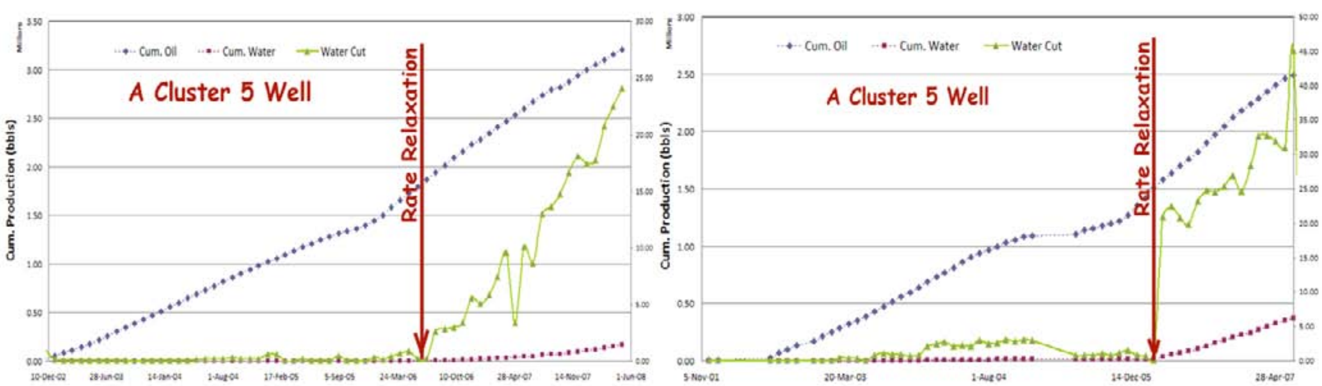

Figure 3. Examples of wells classified in Clusters 4 and 5. These wells showed high water cut after rate relaxation.

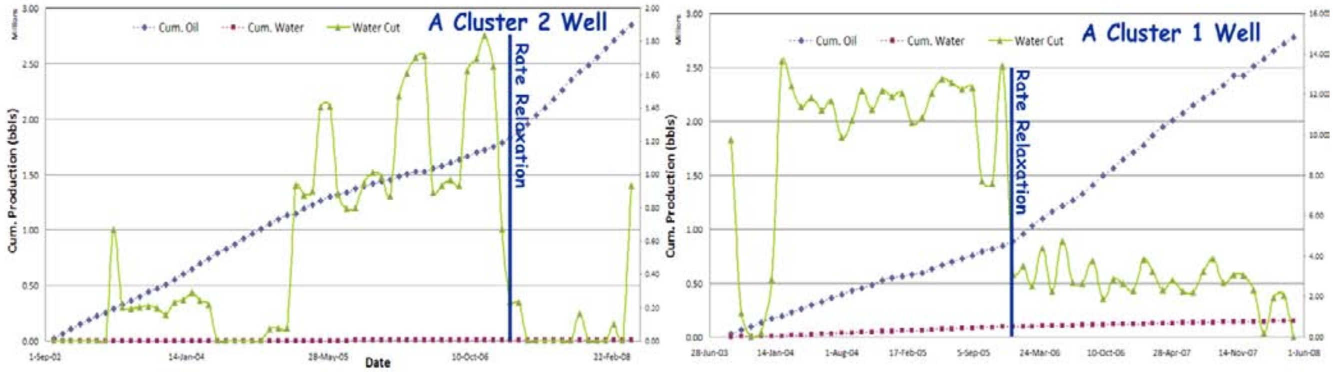

Figure 4. Examples of wells classified in Clusters 1 and 2. These wells showed low water cut after rate relaxation.

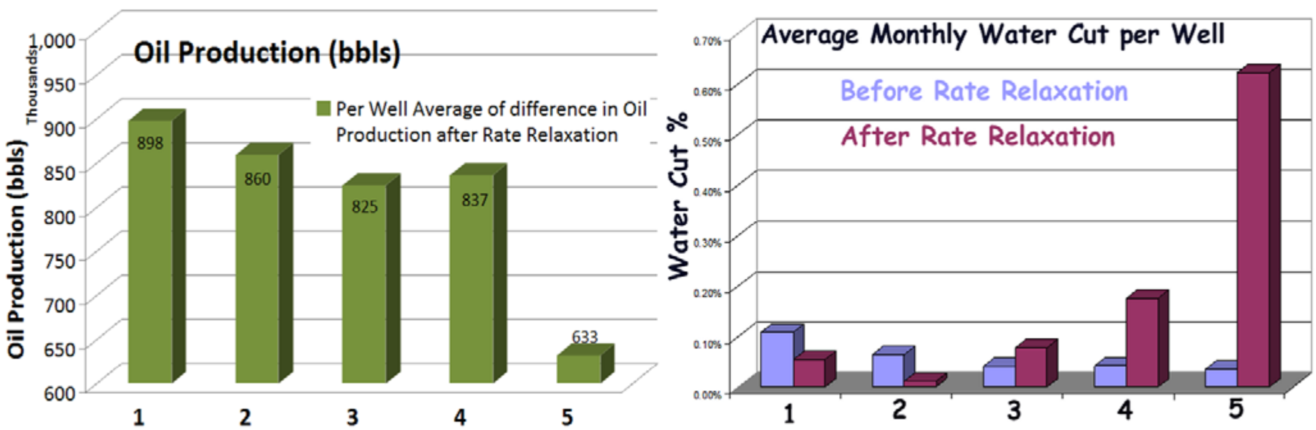

Figure 5. Incremental oil production and average monthly water cut due to rate relaxation for all five clusters.

It should be noted that results shown above demonstrate that the numerical reservoir simulator for this asset performed very well in modeling and consequently predicting the complex fluid flow behavior in this naturally fractured carbonate reservoir. On the other hand, without an SRM that allowed hundreds of thousands of simulation runs to be made in a short period of time, achieving such results from the numerical simulator would have been next to impossible. It can be concluded from this study (and other similar studies) that massive potentials associated with existing numerical reservoir simulation models goes unrealized because of their huge computational overhead. Using SRM will tap into this unrealized potential and can result in much higher return on operators' reservoir simulation and modeling investment. SRM can be looked at as an enabling reservoir management tool that makes comprehensive analysis of reservoir simulation models, possible. Furthermore, the near real-time speed of SRM runs provides means for practical quantification of uncertainties associated with the static model. Real-Time Reservoir Management as an enabling technology for the smart fields is another application of this technology.

In a different case study that will be published soon, SRM was able to match, with very high accuracy, the results of an in-house numerical simulation model (of a netional oil company) from a series of several green fields (both off shore and onshore) in the Middle East. These SRMs were developed using only nine simulation runs and then were validated with runs of completely blind (different operational constraints) simulation runs. The results were highly accurate SRMs in all three cases. Resutls of this study will be published upon permission from the NOC.

Top-Down Models (TDM)

If the spatio-temporal database that is used for the development of the AI-Based Reservoir Model is constructed from actual field data such as historical production and injection data, well logs, core analysis, well tests and seismic attributes, then the AI-Based Reservoir Model that results from this field-based historical database is called a Top-Down, Intelligent Reservoir Model or Top-Down Model (TDM) for short. The interesting aspect of the Top-Down Model is its complete dependence to the actual field data or minimal impact of interepreation. In TDM the physics of the fluid flow in the reservoir is not modeled using first principal physics, rather it is deduced from the actual field data and production history.

Of course during the development of the spatio-temporal database traditional reservoir engineering are extensively used in order to generate the type of data that would assist the training and history matching of the TDM. Reservoir engineering practices such as calculation of volumetric reserves (on a per well basis), decline curve analysis, well test interpretation, calculation of porosity and water saturation from density and resistivity logs, etc. are to populate the spatio-temporal database.

Top-Down Models (TDM) – Case Studies

Many papers have been published in recent years that demonstrate the applicability of Top-Down Modeling in building reservoir simulation models for many different types of reservoirs from tight gas formations, to shale plays to sandstone and finally naturally fractured prolific carbonate reservoirs of Gulf of Mexico and the Middle East (Grujic, 2010 – Zargari, 2010 – Khazaeni, 2010 – Kalantari, 2010 and Mohaghegh, 2010).

In a recent Top-Down Modeling study of a highly complex carbonate reservoir that included water injection for pressure maintenance and oil displacement and more than 300 injection and production wells, history matches were achieved for the entire asset as well as for the individual formations that included tens of producing wells. Figure 6 shows these matches where both field production history and the match from the Top-Down Model are shown.

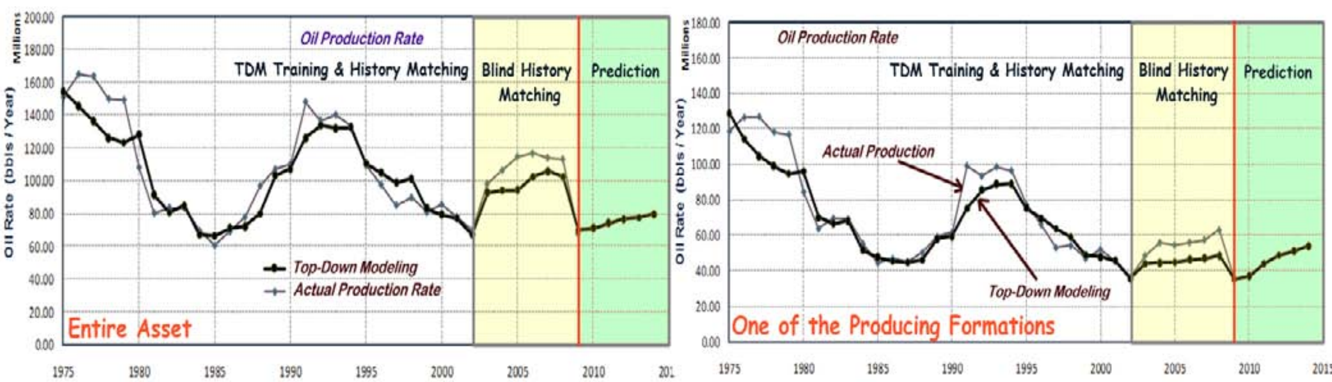

Figure 6. Model training, blind history matching and prediction for the entire asset and one of the producing formations.

Furthermore, individual wells that were completed (with multiple strings) in multiple formations and individual strings (vertical, deviated and lateral boreholes) were history matched. Examples of some of these modeling and history matching are shown in Figure 7. In these figures (Figures 6 and 7) the graph is divided into three segments. Production from 1975 to 2001 was used to train and simultaneously history-match the TDM while production from 2002 to 2009 was used to examine the quality of the history matched model. In other words production from 2002 to 2009 was used as blind history match. Production from 2010 to 2014 is TDM predictions.

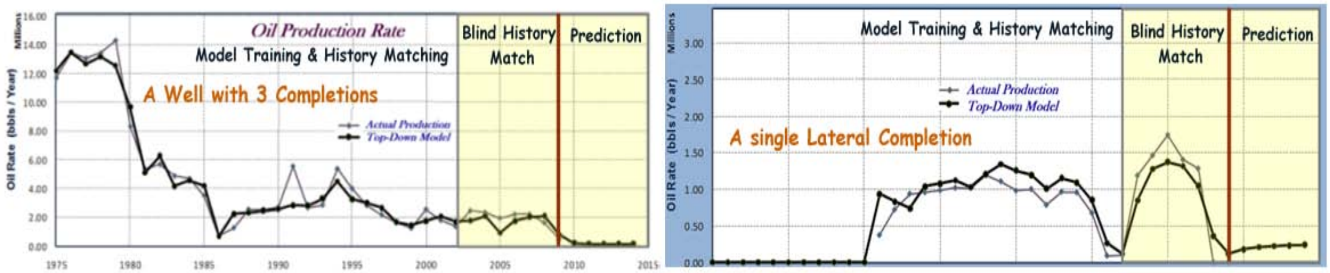

Figure 7. Model training, blind history matching and prediction for a well completed in multiple formations and for a single lateral completion.

Figure 8 shows the water saturation distribution in one of the producing formation as a function of time depicting the movement of injected water and oil saturations in this formation. More details and results from this study will soon be published.

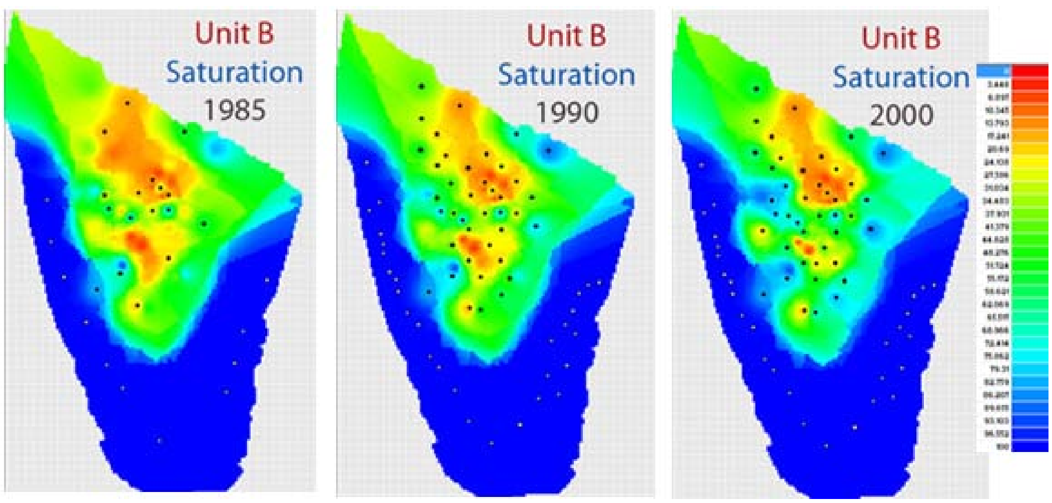

Figure 8. Water saturation distribution in one of the producing formations generated by the Top-Down Model.

Advantages and Disadvantages of AI-Based Reservoir Models

Advantages of AI-Based Reservoir Models include relatively short development time, since the complete development cycle of an AI-Based Reservoir Model is measured in weeks and not years. Needless to say, the complexity of the field being model may increase the development time to several months. Consequently, the resources that are required for the development of an AI-Based Reservoir Model will be much less than those required for a numerical reservoir simulation model. Another advantage of AI-Based Reservoir Models is their minimal computational overhead. An AI-Based Reservoir Model will run on a laptop (or even a handheld) computer (and if the need arises on a smart phone) providing results in seconds and minutes rather than hours and days. This high speed calculation allows for fast track analyses and decision making.

AI-Based Reservoir Models are organic in nature since they are data dependent. As more data becomes available, the model can be re-trained in order to learn from the new data and to enhance its performance. The field development design tool (that was not discussed in this article) provides a quick view of overall field performance (depletion, remaining reserves …) as a function of time and puts the overall performance of the reservoir in perspective for effective decision making.

Conclusions

AI-Based Reservoir Models use pattern recognition capabilities of Artificial Intelligence & Data Mining (AI&DM) in order to build relationships between fluid production, reservoir characteristics and operational constraints. This is indeed a new way of looking at a reservoir and its fluid flow behavior. This is a technology at its infancy. It requires input from major players including scientists, engineers, academicians, service companies, IOCs, NOCs and independents to grow and mature. This technology has the potential to contribute to the art and science of reservoir simulation and modeling and add to the existing set of tools that are currently used in our industry for reservoir management.

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