Abstract:

A novel approach to reservoir simulation and modeling applied to a mature giant oilfield in the Middle East is presented. This is a prolific brown field producing from multiple horizons with production data going back to mid-1970s. Periphery water injection in this filed started in mid-1980s. The field includes more than 200 active producers and injectors. The production wells are deviated or horizontal and have been completed in multiple formations.

Different types of field data (measurements) used in this empirical, full field reservoir simulation and modeling technology such as production and injection history, well configurations, well-head pressure, well logs, time-lapse saturation logs, and well tests. The well tests were used to estimates the static pressure of the reservoir as a function of space and time. Time-lapse saturation logs were available from large number of wells indicating the state of water saturation in multiple locations in the reservoir at different times.

The challenge was to simultaneously history match static reservoir pressure, time-lapse water saturation and production rates for all the wells in the field throughout the production and injection history of the asset. The full field model was built using machine learning technology to train and history match a Top-Down Model (TDM) using data from 1975 to 2001. The history matched TDM was deployed in prediction mode to forecast production from 2002 to 2010 and compared the results with the historical production from this period (Blind History Match). Finally future production
from the field (on a well by well bases), based on the Top-Down Model, was forecasted. This process was simultaneously and inter-dependently performed for production rate, water saturation and static reservoir pressure.

History matches on a well-by-well basis and for the entire asset is presented. The quality of the matches clearly demonstrates the value that can be added to any given mature asset using pattern recognition technologies to build empirical reservoir simulation models.

**TOP-DOWN MODELING (TDM) TECHNOLOGY**

Traditional numerical reservoir simulation is the industry standard for reservoir management. It is used in all phases of field development in the oil and gas industry. The routine of numerical simulation studies calls for integration of static and dynamic measurements into a reservoir model that has been formulated based on our current understanding of fluid flow in porous media and numerical solution of the formulation in the context of an interpreted geological model.

Numerical simulation is a bottom-up approach that starts with building a geological (geo-cellular or static) model of the reservoir. Using modeling and geo-statistical manipulation of the data the geo-cellular model is populated with the best available geological and petrophysical information. Engineering fluid flow principles are added and solved numerically to arrive at a dynamic reservoir model. The dynamic reservoir model is calibrated using the production history of multiple wells by modification of the multiple parameters involved in the geological model in a process called history matching and the final history matched model is used in predictive mode to strategize the field development in order to improve recovery.

Characteristics of the numerical reservoir simulation and modeling include:

- It takes a significant investment (time and money) to develop a geological (geo-cellular, static) model to serve as the foundation of the reservoir simulation model.
- Development and history matching of a reservoir simulation model is not a trivial process and requires modelers and geoscientists with significant amount of experience.
- It is an expensive and time consuming endeavor.
- A prolific asset is required in order to justify the significant initial investment that is required for a reservoir simulation model.

Top-Down Intelligent Reservoir Modeling (TDM)\(^1\) that is an innovative integration of reservoir engineering, reservoir modeling, statistical analysis and advanced data-driven analytics uses machine learning to serve as an alternative or a complement to the traditional numerical reservoir simulation and modeling. When compared to the numerical reservoir simulation and modeling, TDM takes quite a different and independent approach to full field reservoir simulation and modeling. The most important distinguishing characteristics of TDM that recognizes it from the numerical reservoir simulation are:

- It does not assume that we have all the information necessary to build a fully representative geological model of the asset, understanding all the underlying geological behavior, and
- It does not assume that we fully understand and are able to formulate all the complexities and intricacies of fluid flow through porous media for the asset being modeled.

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\(^1\) This technology was invented and introduced to the E&P industry by Intelligent Solutions, Inc. in 2008
The integration of the technologies that were named above, form the foundation of a comprehensive spatio-temporal database. This database represents an extensive set of snapshot of fluid flow in the formation in space and time. It is expected that all the characteristics that governs the complexity of fluid flow in the reservoir to be captured in this extensive spatio-temporal database. The spatio-temporal database is assimilated using the following data:

i. Well location (latitude, longitude, TV, MD)

ii. Well construction (Vertical/Slanted/Horizontal, Inclination, Azimuth, ...)

iii. Well logs (gamma ray, density, resistivity, sonic, ...)

iv. Formation evaluation (Formation Tops, Gross Thickness, N2G, Porosity, Saturation, ...)

v. Core analysis (Permeability, Relative Perm, Capillary Pressure, ...)

vi. Well tests

vii. Well interventions (workovers, stimulations, hydraulic fractures, ...)2

viii. Seismic

ix. Operational constraints (well head pressure, Shut-in durations, Artificial lift, ...)

x. Production and injection rates (oil, water, gas)

As it can be noted from the list above, TDM is far more than statistical analyses of production data in order to find simple correlation between wells. TDM is a comprehensive and integrated set of reservoir engineering, modeling, statistics, and data-driven analytics of all that is relevant in the production of fluids from an asset. It seeks to integrate the data gathered from all these sources into a complete database that would understand and honor the differences that exist in the scale and nature of the sources where the above data are gathered from. Furthermore, the database must be setup in such a manner that can represent the intricate details that are crucial to modeling and history matching production of hydrocarbon from an asset.

Upon completing the assimilation of the spatio-temporal database, which proves to be one of the most important steps in development of a Top-Down Model (TDM), the process of training and history matching of the TDM is performed simultaneously. It must be noted that a rigorous blind history matching is required in this step of the process to ensure the robustness of the Top-Down Model. The blind history match refers to a process through which certain part of the production history (usually the tail-end) is intentionally left out of the TDM development and history matching process and is used solely for validation purposes. Once the training and history matching step of the TDM is completed, the TDM is deployed in prediction mode and is asked to forecast the production from all the individual wells in the asset. The prediction from the TDM is compared with the production history that was left out of the modeling process in order to judge the validity (predictive capability) of the TDM.

Using the design tool that is part of the TDM process, field development strategies are planned and then using the history matched model (in predictive mode) the plans are tested to see if they fulfill the reservoir management objectives. This process is repeated, iteratively (by planning new wells to be drilled and predicting their performance), until the reservoir management objectives are met. Once the objective is accomplished, the plan is forwarded to operation for implementation.

The Top-Down Model is an evergreen model since it can easily be incorporated into a closed-loop process that can be updated and re-trained using new data as they become available. TDM workflow (part of which is shown in Figure1) includes the following steps:
1. Identifying the objectives of the project  
2. Understanding the reservoir and its history  
3. Data collection, management and quality control  
4. Assimilation of the spatio-temporal  
5. Data mining and pattern recognition  
6. Determination of the number of data-driven models required for the TDM  
7. Input-output selection for each of the data-driven models  
8. Training and history matching the data-driven models  
9. Validating the data-driven models  
10. Integration of the data-driven models into final TDM  
11. Field-wide Fuzzy Pattern Recognition  
12. Post-modeling analysis using the TDM  

Once the data is collected, quality controlled and assimilated into the said spatio-temporal dataset, it is processed using the state-of-the-art in artificial intelligence and data mining (neural modeling, genetic optimization and fuzzy pattern recognition) in order to generate a complete and cohesive model of fluid flow in 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 agents that integrate the discrete models into a cohesive model of the reservoir as a whole, using a continuous fuzzy pattern recognition algorithms.

![Figure 1. Reservoir management workflow using Top-Down Modeling](image-url)
The Top-Down, Intelligent Reservoir Model is calibrated using the most recent data from existing wells and/or a set of wells that have recently been drilled in the field. The calibrated model is then used for field development strategies to improve and enhance hydrocarbon recovery.

Prior applications of Top-Down Modeling to synthetic cases (Mata 2007, Gomez 2009) and actual assets, both conventional (Gaskari 2007, Mohaghegh 2009, Kalantari 2010, Khazaeni 2011, Mohaghegh 2011) and unconventional (Grujic 2010, Zargari 2010, Kalantari 2011, Esmaili 2012, Mohaghegh 2012) have been published extensively.

CASE STUDY; A MATURE, GIANT OILFIELD IN THE MIDDLE EAST

Top-Down, Intelligent Reservoir Modeling (a.k.a. TDM) was applied to giant mature oilfield in the United Arab Emirates. The oilfield is located in the Rub-Al-Khali basin on the eastern shelf of the Arabian platform. It is included in a geological setting characterized by thick sedimentary deposits, primarily carbonates, accumulated and deformed by intermittent tectonic movements that resulted in relatively gentle folding, faulting, and salt movement. The field is an ovate anticline with a north-south major axis about 22 miles long, producing from Lower Cretaceous buildups with estimated reserves of 20 billion barrels of oil (Al Sharhan 1993).

Figure 2. Map of the south-central portion of the asset used for the Top-Down Modeling.
The Top-Down Model was applied to the south-central portion of the field shown in Figure 2. This filed produces from five different formations called Units #1 through 5. Unit #1 being the shallowest of the five. The five units may or may not be present at all locations in the field since they may pinch out in locations and reappear in other locations. Many of the wells in this asset are completed in multiple units. There are wells that are completed only in one unit and wells that are completed in all the five units along with wells that are completed in any combinations of the units. The multiple completions usually include multiple laterals (also called strings) that are drilled completely in one of the multiple units that are present at the location where the well is placed.

<table>
<thead>
<tr>
<th>Units</th>
<th>Producers</th>
<th>Injectors</th>
<th>Active Producers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unit #1</td>
<td>43</td>
<td>31</td>
<td>31</td>
</tr>
<tr>
<td>Unit #2</td>
<td>65</td>
<td>41</td>
<td>36</td>
</tr>
<tr>
<td>Unit #3</td>
<td>39</td>
<td>31</td>
<td>13</td>
</tr>
<tr>
<td>Unit #4</td>
<td>71</td>
<td>46</td>
<td>36</td>
</tr>
<tr>
<td>Unit #5</td>
<td>46</td>
<td>25</td>
<td>31</td>
</tr>
<tr>
<td>Total</td>
<td>264</td>
<td>174</td>
<td>147</td>
</tr>
</tbody>
</table>

Figure 3. Number of wells used in the Top-Down modeling Study.

Figure 3 shows the number of producers and injectors completed in each of the unit. Even though many of the producers may not be active at the present time, during the development of the Top-Down Model all the wells that have been completed in the asset and contributed to the injection or the production at some time during the life of the asset are included in the model and history matched.

**Data Availability**

Being a prolific mature field with more than 35 years of production and injection history from more than 430 wells meant that a very large pool of data was available for this asset. The available data included detail production and injection history from every single well to well logs, well tests, conventional and special core analysis, Pulse Neutron Logs, seismic, etc. The mere size of this data set with its multiple scales (that may be considered as a good example for the recently coined phrase “Big Data”) while providing a wealth of potential information usually has the tendency to create a data tsunami that will overwhelm most reservoir modelers engaged in traditional numerical modeling.

The All 438 wells (264 producers and 174 injectors) were included in the model. Production data was available from 1975 and water injection data was available from its inception in 1980. Well construction data (vertical slanted and horizontal) and changes in perforations throughout the history of each well were included in the model.
Figure 4. Example of the Pulse Neutron Log (PNL) available for several wells at different points in time. For example, four PNL was available for this particular well.

Static data incorporated in the model was extracted from well logs and petro-physical calculations included formation tops and thicknesses (for each of the units), porosity and saturation. Permeability and relative permeability data were available from core analysis. Well tests that had been performed throughout the history of the field on multiple wells provided a view of changes in static reservoir pressure as a function of time and space. Furthermore, Pulse Neutron Logs that were run on multiple wells at different times in the history of this asset provided much needed information about the changes in water saturation throughout the reservoir.

Figure 4 shows four different Pulse Neutron Logs performed on a well from 1983 to 1989 showing the changes in water saturation at the well as a function time that reflects the impact of static reservoir characteristics as well as oil production and water injection in selected points (at certain well locations) throughout the reservoir as a function of time. Similar logs were available at multiple locations in the asset.
As far as the static reservoir characteristics are concerned, the available information may either reflect a specific point in the reservoir (i.e. the well) when for example well logs are being considered, and sometime they may be representative of a larger volume of the reservoir (including the well) such as a well test. Using an allocation algorithm that was developed by integration of Voronoi Graph Theory (Dickerson 2011) and Fuzzy Cluster Analysis (Höppner 1997), as shown in Figure 5, the reservoir is divided into polygons in order to accommodate this incompatibility of scales.

The data used for the development of the TDM in this project is organized into three categories such as Static Data, Dynamic Data, and Reservoir Response. Each of the categories are then further divided into several sub-categories. Following is list of the data that was available and used during the development of the TDM:

1. Static Data
   a. Well location and trajectory
      i. Latitude
      ii. Longitude
      iii. Inclination
iv. Azimuth
v. TVD

b. Reservoir Characteristics
   i. Well Logs
      • Gamma ray, Sonic, Density, Resistivity, ...
      • Formation Tops
      • Porosity, Saturation, ...
   ii. Cores
      • Permeability
      • Relative Permeability
      • Capillary Pressure
   iii. Fluid Characteristics
      • Viscosity
      • Density
      • Composition

c. Completion
   i. Open hole/Cased hole
   ii. Completed interval
   iii. Shot density

2. Dynamic Data
   a. Changes in completion intervals
   b. Workover and stimulation
   c. Duration of production/injection
   d. Wellhead/flowing bottomhole injection/production pressure

3. Reservoir Response
   a. Oil rate
   b. Water rate (Water cut)
   c. Gas rate (GOR)
   d. Static Reservoir Pressure
   e. Time-lapse water saturation
Although from a reservoir engineering point of view existence of static reservoir pressure and water saturation throughout the reservoir as a function of time and space is a blessing, they provide a serious challenge to the numerical reservoir simulation modelers, since simultaneous history matching of production from the wells along with static reservoir pressure and time-lapse water saturation markedly increases the complexity of the history matching process.

One of the main reasons for reaching out to a new and different reservoir simulation and modeling technology such as TDM in this particular asset was the massive challenge associated with preforming such a complex, simultaneous and multi-objective (production, static pressure and time-lapse saturation) history matching on more than 260 wells producing from five different units.

A cautionary note needs to be added at this point. As technologies such as data-driven solutions, data-driven analytics, predictive analytics, and data mining have started to enjoy certain amount of popularity among E&P professionals, misuse of these technologies have been emerging, mostly by well-intended individuals that either do not have a solid background, experience and understanding of the reservoir and production engineering, or by E&P professionals with limited understanding of data-driven analytics and machine learning.

Attempts to correlate production and injection in an asset without giving the required attention to the fundamentals of fluid flow in porous media, at best, provides superficial results that cannot be trusted to generate fundamentally sound and repeatable results. These attempts are usually made using the over-the-counter statistical packages that have not been custom-developed to handle such challenging tasks. These tools, at the very best and when used appropriately, can provide multiple visualization schemes and are equally useful in the oil and gas industry as they are in pharmaceutical, or any other industry, for that matter, since they lack the very important and vital component of domain relevance that can be appropriately used by the domain experts.

It has been authors’ experience that fundamental understanding of reservoir engineering, production engineering and reservoir modeling, as well as access to custom-made data-driven analytics and machine learning workflows are an absolute requirement for successful development of reservoir simulation models that are solely based on measured data.

**TOP-DOWN MODEL TRAINING & HISTORY MATCHING**

Once the assimilation of the spatio-temporal database is completed a series of pattern recognition and data mining exercises are performed. These data mining and pattern recognition exercises serve multiple purposes. They are a crucial step in understanding and learning the reservoir that is being modeled. They reveal the influence of different parameters in the production from the asset. They help the modeler in understanding the impact of reservoir characteristics versus the design parameters in the particular asset. Data mining and pattern recognition exercises shed light on all these and eventually help in identifying the best set of parameters that need to be used as input to the data-driven models that will be developed as part of the TDM.

For example for this cases study the project objectives determined the number of data-driven models that needed to be developed and used in sequence in order to form the final TDM. Figure 6 shows the flow diagram for the TDM in this study. In this flow diagram it is shown that “Data-Driven Static Pressure” model had to be developed first and its results (with other data in the spatio-temporal database) had to be used in order to develop the “Data-Driven Water Saturation” model. Result of “Data-Driven Static Pressure” and the Data-Driven Water Saturation” models along with other data in the spatio-temporal database were used to develop the “Data-Driven Production Rate” model.
The final TDM for this asset included three data-driven models that would run in sequence (as shown in Figure 6) in order to provide the required results for this asset. For example all the static inputs from the spatio-temporal database along with all the dynamic inputs from the spatio-temporal database at time “t” are needed (as well as the “Static Reservoir Pressure” at time “t-1”) to generate the “Static Reservoir Pressure” at time “t” for all the wells in the asset. Next, all identified static inputs along with dynamic input at time “t”, as well as recently calculated “Static Reservoir Pressure” at time “t” are required as input to the “Data-Driven Water Saturation” model (as well as the “Water Saturation” at time “t-1”) in order to calculate “Water Saturation” at time “t” for all the wells in the asset. Similarly, to calculate the production rates at each well at time “t”, all identified static inputs along with dynamic input from time “t” as well as recently calculated “Static Reservoir Pressure” and “Water Saturation” at time “t” (along with Production Rate from time “t-1”) are required to be used in the “Data-Driven Production Rate” model.

Figure 7. The timeline used for training, history matching, blind history matching and forecasting for the Top-Down Model.
Data from this asset was available from 1975 to 2010. Production, static pressure and water saturation data from 1975 to 2001 was used to train and history match the Top-Down Model while similar data from 2002 to 2009, although available, was not used during the training and history matching process. This segment of the historical data was put aside for use after the training and history matching is completed. This so called blind history match data was to be used as a blind validation dataset to measure the goodness of the TDM and identify the degree of confidence one can have on the forecasts that are made by the TDM. The Top-Down Model is then used to forecast production from the asset into the future. This development scheme is shown in Figure 7.

Figure 8. History match, blind history match, and forecasting for the Well #C-10 for Static Reservoir Pressure (above) Time-Lapse Water Saturation (middle) and Oil Production (bottom). For the oil production the cumulative production (right y axis) is shown using shaded areas. Red squares in all three plots indicate field measurements while lines indicated Top-Down Model results.
Results of training, history matching, blind history matching and forecasting of the TDM are shown in the following six figures (Figures 8-13). In these figures the results are shown for individual wells and their completions in a given geological formation. In these figures three graphs are shown. In all three graphs the x-axis is time (date) that extends from the initial production date (1975) to the forecasted time of 2015. The time in the x-axis is divided into three segments (recognized by different background colors) identifying the period of time used for training and history matching (1975-2001 – white background), the period of time used for blind history matching (2002-2009 – gray background) and finally period of time used for forecasting (2010-2015 – yellow background).

In each of the graphs the field measurements are shown using red squares while the results from the Top-Down Model is shown using lines and circles of different colors (based on the nature of the graph). In each of the figures a small schematic of the asset (on the corner of each graph) shows the relative location of the well being analyzed using a red boundary.

In these figures the top graph shows the Static Reservoir Pressure (at the given well) as a function of time. The middle graph shows the water saturation (measured using time-lapse Pulse Neutron Logs) as a function of time. The bottom graph shows the oil production as a function of time. The annual oil production is shown with lines and points (left y-axis in bbsl per year) and the cumulative oil production as shaded area (right y-axis in bbls).

The first four figures (Figures 8 through 11) are good examples of the quality of the TDM in simultaneously matching three important parameters in the hydrocarbon production process in this complex reservoir. Similar plots are generated and are available for every individual well in the asset that is completed in each of the units. These figures clearly demonstrate the quality of the TDM in honoring all the field measurements. The accuracy by which the TDM follows the trend of change in static reservoir pressure, water saturation and oil production, indicates that the data-driven models have captured the essence of fluid flow through this complex and naturally fractured carbonate reservoir. The quality of the match specifically during the blind history match period points to the robustness of this Top-Down Model.

Unlike some recently published studies that use only production and injection data in order to build a model (for example for water-flooding operations), inputs to the TDM (all three data-driven models) include well location and trajectory details, reservoir characteristics as well as operational constraints. In other words, in the TDM model, when the location of the well changes, it constitutes a change in the reservoir characteristics (as measured by well logs, cores and well tests) that will impact the static reservoir pressure, water saturation and production from the well (model outputs).

This resembles the type of reservoir simulation models that a reservoir engineer is used to seeing and dealing with. On the other hand, when data such as well location and trajectory, operational conditions and reservoir characteristics plays no role in predicting responses from a well in an asset, the model resembles a purely time-series modeling (location independence), an approach that does not lend itself to reservoir simulation and modeling.

It is, therefore, understandable why some reservoir engineers would have a hard time trusting the predictive capabilities of such models and accepting the technology that generates such results. In such cases these critics ask the famous question; “Does the Correlation Mean Causality?”

It is important to note that to capture the complexities of fluid flow in porous media using the Top-Down Modeling technology one must take into account many details. Some of the details and engineering complexities that must be incorporated into a reservoir model (and is honored and incorporated by the TDM) include, but are not limited to:

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2 To protect the confidentiality of the data, all the production values that are presented in the figures in this paper have been modified to arbitrary numbers.
a. Not all wells are drilled at the same time. The fact that in an oilfield wells are drilled in phases is one of the most important issues that must be taken into account. Although this may sound like a trivial fact to a non-reservoir engineer\(^3\), the consequences of not taking this important issue into account is far reaching.

A sound and robust Top-Down Model must take into account the interference between wells as they are put on production. This means that static and dynamic information of the offset wells must be taken into account while assembling the data for a given well. Since wells are put into production at different times, the offset wells are constantly changing as a function of time. A well that started as an important offset to a given well at the early time in the life of a well, may soon give its place to another offset well that have been drilled later but is closer to the well of interest.

b. There is a practical limit in measurements made in the field. Principles of fluid flow through porous media indicate that pressure change at any given point in the reservoir impacts all other wells throughout the reservoir, instantaneously. Although this is true from a theoretical point of view, there are physical and practical limits on how much of such impact can be measured. This is controlled by the distance from the source of pressure change (and is a function of permeability). This practical limit must be taken into account while assembling the spatio-temporal database.

c. Impact of reservoir behavior should be distinguished from the impact of manmade incidents. If there is no interference in the production from a given well, the reservoir should and will display a clean and non-noisy behavior at each well. The fact that most of the time the actual field measurements (oil production rates for example) are noisy and include multiple ups and downs has to do with human interventions (surface facility issues that cause fluctuation in back pressure, well shut-ins, etc.) These non-reservoir impacts need to be communicated with the data-driven model.

Figures 12 and 13 demonstrate the validity and robustness of the TDM developed for this asset. The two wells in these figures were drilled and put on production after the designated date for the training and history matching. These wells were completed in 2003 (Well #B-02) and in 2005 (Well #B-03) while the training and history matching of the Top-Down Model stopped at 2001. Therefore pressure, saturation and production data from these two wells are only available after the training and history matching of the TDM has been completed. In other words, TDM had never seen or been exposed to the data from these two wells (and several other wells in the asset that are in the same situations). This is called “Blind History Matching”. The data shown in these figures are obtained by deploying the TDM in the forecasting mode.

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\(^3\) Some operators have chosen to approach data-driven analytics in their operations by employing expertise of statisticians and machine learning experts, or by using generic, off-the-shelf statistical or machine learning tools. Most of the time such practices results in disappointments, or at best mediocre results. The main reason is the lack of domain expertise or even domain sensitivity. The experience of using E&P professionals and train them in the art and science of artificial intelligence, data mining, and data-driven analytics have proven to be a far more effective approach.
Figure 9. History match, blind history match, and forecasting for the Well #B-01 for Static Reservoir Pressure (above) Time-Lapse Water Saturation (middle) and Oil Production (bottom). For the oil production the cumulative production (right y axis) is shown using shaded areas. Red squares in all three plots indicate field measurements while lines indicated Top-Down Model results. Pressure values, water saturation values and production rates have been intentionally removed from all the figures.
Figure 10. History match, blind history match, and forecasting for the Well #C-30 for Static Reservoir Pressure (above) Time-Lapse Water Saturation (middle) and Oil Production (bottom). For the oil production the cumulative production (right y axis) is shown using shaded areas. Red squares in all three plots indicate field measurements while lines indicated Top-Down Model results.
Figure 11. History match, blind history match, and forecasting for the Well #H-50 for Static Reservoir Pressure (above) Time-Lapse Water Saturation (middle) and Oil Production (bottom). For the oil production the cumulative production (right y axis) is shown using shaded areas. Red squares in all three plots indicate field measurements while lines indicated Top-Down Model results.
d. Known physics of the fluid flow through porous media must be captured and reflected accurately in the Top-Down Model.

Figure 12: History match, blind history match, and forecasting for the Well #B-02 for Static Reservoir Pressure (above) Time-Lapse Water Saturation (middle) and Oil Production (bottom). For the oil production the cumulative production (right y axis) is shown using shaded areas. Red squares in all three plots indicate field measurements while lines indicated Top-Down Model results.
Figure 13. History match, blind history match, and forecasting for the Well #B-03 for Static Reservoir Pressure (above) Time-Lapse Water Saturation (middle) and Oil Production (bottom). For the oil production the cumulative production (right y axis) is shown using shaded areas. Red squares in all three plots indicate field measurements while lines indicated Top-Down Model results.
Figure 14. Comparison of Top-Down Model results with actual field measurements for the cumulative oil production versus time for the entire asset. Total number of active producers completed in each of the geologic formations are shown in the bar graph on the bottom as a function of time.

Figure 15. Comparison of Top-Down Model results with actual field measurements for the annual oil production versus time for the entire asset. Total number of active producers completed in each of the geologic formations are shown in the bar graph on the bottom as a function of time.
Once the history matching process is completed for all the wells in the asset, the production from both the field measurements as well as the results from the Top-Down Model are summed in order to calculate the oil production for the entire asset. Results of this exercise are shown in Figures 14 and 15. Figure 14 shows the cumulative oil production while Figure 15 shows the annual oil production as a function of time.

Figure 16. Map of water saturation as a function of time in Unit A. All measured values of water saturations throughout the history of the field is honored in this map. Honoring of the measured water saturation values at different time and space are shown in the history match results of middle graphs in Figures 8 through 13. Where and when field measurement values were not available Top-Down Modeling results have been substituted at the well locations and then geo-statistics have been used to generate complete map of the water saturation throughout the field.
**POST-MODELING ANALYSIS**

Once the Top-Down Model is trained, history matched and validated for accuracy (by performing blind history matching) the TDM can be used in order to plan future operations in the field. The TDM can be used in order to identify the best location for infill wells, using an innovative fuzzy pattern recognition technology that allows the fluid flow throughout the reservoir be tracked as a function of time\(^5\). The TDM can also be used to identify the most efficient mode of production that can be imposed on the producers. Optimize the water injection process, identifying how much water should be injected in which injection wells in order to maximize production with minimum amount injected water. Identify and map reservoir conductivity from the interaction between injection and production wells.

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\(^5\) This feature of the TDM is not being covered in this article and will be covered in a separate technical paper.
To briefly demonstrate one of the capabilities of the TDM in the post-modeling analysis phase, one of the many exercises that can be performed is shown here. In this post-modeling exercise one can identify the contribution of existing injection wells to the oil production. This is done by identifying the degree of contribution from each injection well to the producers. Then by performing an optimization routine, one is able to schedule optimum water injection to maximize oil production in the field, while minimizing the risk associated with high water cut in the producers that would eventually result in killing the well.

Figures 16 and 17 are examples of parts of such an exercise. This specific post-modeling analysis that is currently being performed for the Unit #1 in this asset6 will be completed and presented in a future technical paper. Figure 16 shows the map of water saturation in the field as a function of time developed based on total amount of water that was injected in Unit #1.

In Figure 17, similar maps are shown this time in a scenario that only 75% of the actual volume has been injected in each of the injection wells. In other words, by examining multiple scenarios as such, while the TDM is deployed in its forecasting mode, one can identify the optimum amount of water that need to be injected in this unit (in each individual well) without sacrificing oil production. Performance of this exercise in other units have shown very promising results, where millions of barrels of water could be saved (when compared with already scheduled water injection) with positive impact on oil production. In other words, TDM was able to show that oil production can be increased by selectively changing the amount of injection in multiple injection wells where the total injection would be less than what was originally scheduled.

CONCLUSIONS

Developing reliable reservoir simulation models for mature fields is a challenging prospect. The conventional wisdom suggests that increase in data availability must result in better understanding of the characteristics of the asset which in turn should facilitate building better, more accurate, more reliable and more robust reservoir simulation model for that asset. This is generally true, but the reality on the ground suggest that when it comes to mature fields, this conventional wisdom, sometimes, does not work in our favor. In other words, in some mature fields, as the asset ages and more and more information through data becomes available, it results in a tough challenge for the reservoir simulation and modeling efforts. This is due to the fact that as the reservoir engineers and modeler try to build a representative numerical model of the asset, they face a large number of measured data as reservoir response that they need to match simultaneously.

The asset that was modeled in this study is a good example. In this asset, not only the production from the wells needed to be matched, all the matched points needed to comply with measured static reservoir pressures and time-lapse water saturations throughout the history of the asset. Having so many anchors during numerical modeling will limit the number and the range of the parameters that can and need to be tuned in order to achieve a history match. Furthermore, as the number of wells increase, which is usually the case in mature fields, the match needs to achieve in a larger instances in space and time and therefore, the process will become even more challenging.

In such a data-rich environment, data-driven solutions are a natural substitution, or complement to the numerical reservoir simulation models. If the right workflow is adopted, the massive amount of available data, that may be argued to be the manifestation of “Big Data” in our industry, can result in an accurate, robust and interactive reservoir model that can be used effectively to drive future operations in the field. This study and its results are solid demonstration of the use of a custom designed, data-driven workflow for a data-rich mature field environment.

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6 Similar exercise was performed for Unit #3 based on a request from an IOC that is a major shareholder in this asset. This IOC has decided not to allow the publication of this exercise for Unit #3. Publication of similar exercise that is currently being performed for other units (including Unit #1) will not require the permission from this IOC and therefore will be published upon completion. Figure 17 is part of this new exercise on Unit #1.
REFERENCES


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