AI-Based Simulation: An Alternative to Numerical Simulation and Modeling

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Abstract: Numerical simulation and modeling has dominated the computational sciences for decades. From Computational Fluid Dynamics (CFD) to Numerical Reservoir Simulation (NRS) most of the computational modeling is performed by numerically solving a set of nonlinear partial differential equations. When historical or experimental data exists, it is used to calibrate the computational model. In this paper we propose a technology to use the historical and/or simulated to build data driven models. These data driven models that are developed using artificial intelligence and data mining technologies have many uses some of which are: when the physics of the phenomenon being modeled is poorly understood and when the numerical modeling is computationally expensive. In this paper we use modeling of petroleum reservoirs to introduce this new modeling technology based on pattern recognition capabilities of artificial intelligence and data mining.

Keywords: Numerical Modeling, Simulation, Artificial Intelligence, Data Mining, Reservoir Modeling, Reservoir Simulation.

1 Introduction

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.

2 Philosophy and Approach

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:

\[
q = f(x_1, x_2, \ldots, x_n, \& y_1, y_2, \ldots, y_n, \& w_1, w_2, \ldots, w_n)
\]

Where

\[
q = \text{production from the reservoir}
\]
\[ x_1, x_2, \ldots, x_n = \text{reservoir & fluid characteristics} \]

\[ y_1, y_2, \ldots, y_n = \text{operational constraints} \]

\[ w_1, w_2, \ldots, w_n = \text{other parameters} \]

\[ f() = \text{functional relationship} \]

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, composi-
tional formulation, coupling with geo-mechanics and surface facilities, etc.) and are bound to evolve even further as our knowledge of these physical phenomena deepens.

<table>
<thead>
<tr>
<th>Reservoir Characteristics</th>
<th>Numerical Model</th>
<th>AI-Based Model</th>
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<tbody>
<tr>
<td><strong>Uncertain:</strong></td>
<td>Measurements</td>
<td>Measurements</td>
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<td></td>
<td>Interpretations</td>
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<td>(subject to modification during the history matching)</td>
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<tr>
<td><strong>Certain:</strong></td>
<td>Conservation of Mass</td>
<td>Relationship between reservoir characteristics and production.</td>
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<td></td>
<td>Darcy's Law</td>
<td>(subject to modification during history matching)</td>
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<td>(unchanged during the history matching)</td>
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**Figure 1.** Main difference between numerical reservoir simulation & modeling and AI-based reservoir modeling.

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.

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.

We may not know “all” the parameters that are involved in the makeup and the behavior of a phenomenon.

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 Science, 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

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

3 Steps Involved

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

   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 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 quan-
tify 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.

Figure 2. Comparing the accuracy of the Field “R” SRM with the in-house numerical reservoir simulator for a run that was included during the training; Oil and gas production from all the wells in the field.
4 Types of AI-Bases 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 spatio-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 spatio-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™, IMEX™ and GEM™ and POWERS™ and replicating models with up to 6.5 mil-

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

**Figure 3.** Comparing the accuracy of the Field “R” SRM with the in-house numerical reservoir simulator for a run that was included during the training; Oil and gas production from one of the wells in the field.

**Surrogate Reservoir Models (SRM) – Case Study**

Several papers have been published on this topic (Mohaghegh 2009a - Mohaghegh, 2009b – Mohaghegh, 2010). In a recently published paper (Mohaghegh 2012) it was demonstrated that SRM can accurately reproduce the result of a large reservoir simulation model. In this case study application of Surrogate Reservoir Model (SRM) to an onshore green field in Saudi was presented. High computational cost and long processing time of reservoir simulation models limits our ability to perform comprehensive sensitivity analysis, quantify uncertainties associated with the geologic model or to evaluate a large set of scenarios for development of green fields. SRM accurate-
ly replicates the results of a numerical simulation model with very low computational cost and allows for extended study of reservoir behavior and potentials.

This study is about a reservoir simulation model that has been developed for a green field using Saudi Aramco’s in-house “Powers™” simulator. The geological model that serves as the foundation of the simulation model is developed using analogy that incorporates limited measured data augmented with information from similar fields producing from the same formations. The reservoir simulation model is consisted of 1.4 million active grid blocks including 40 vertical production wells and 22 vertical water injection wells.

![Figure 4](image)

Figure 4. Comparing the accuracy of the Field “R” SRM with the in-house numerical reservoir simulator for a run that was included during the training; Oil and gas production from one of the wells in the field.

For the development of the SRM a total of nine simulation runs were identified to be sufficient. Simulation runs were made, the static and dynamic data from the simulation runs were extracted to develop the necessary spatio-temporal dataset. Key Performance Indicators (KPI) that rank the influence of different reservoir characteristics
on the oil and gas production in the field were identified and ranked. SRM was trained and results of the simulation model were matched. The developed SRM was finally validated using a blind simulation run.

SRM for this reservoir was then used to perform sensitivity analysis as well as quantification of uncertainties associated with the geological model. These analyses that require millions of simulations runs, were performed using the SRM in minutes.

![Figure 5](image_url)

**Figure 5.** Comparing the accuracy of the Field “R” SRM with the in-house numerical reservoir simulator for a blind run; Oil and gas production from all the wells in the field.

Figures 2 through 4 show the comparison of the SRM with the in-house reservoir simulation model for two of the simulation runs that were included in the training of the SRM. In Figure 2 the comparison is made for total field production (both oil and gas). Figure 3 and 4 show the comparison for randomly selected wells in two of the
simulation runs that were included in the training of the SRM. It can be seen in all these figures that the SRM can reproduce the results of the in-house simulator with high accuracy.

The trained SRM is validated against a complete blind run of the reservoir simulation model. For this purpose a tenth run was made where the operational constraint was completely different (although within the range) from the runs that were made to build the spatio-temporal database for the training and matching of the SRM.

The operational constraints of the blind run are BHP of 1000 psi and maximum oil rate of 15,000 barrels. Figure 5 shows the comparison of the SRM with the blind run of the in-house reservoir simulation model. In Figure 5 the comparison is made for oil and gas production for the entire field (top two graphs) and for two randomly selected wells in blind run of the simulation model (the middle and bottom graphs).

It can be seen in all these figures that the SRM can reproduce the results of the in-house simulator with high accuracy, even with the operational constraints that it has never seen or been trained for. This shows the generalization and abstraction capability of the SRM. Using this capability sensitivity analysis, quantification of uncertainties and comprehensive exploration of the solution space for identification of optimum field development strategies become practical. All these analyses can be performed in record time.

Surrogate Reservoir Model (SRM) can be developed for both brown and green fields, as long as a numerical reservoir simulation model for a given asset exists. SRM can be built to replicate the results of the numerical reservoir simulation model with high accuracy while having the advantage to run at speeds that can be compared with the real-time (fractions of a second). This high speed and minimal computational footprint coupled with high accuracy (in replicating numerical reservoir simulation model results) make SRM an ideal tool for real-time reservoir management, design of master development plans as well as uncertainty assessment.

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 interpretation. 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). Here we will provide the summary of a Top-Down Modeling study performed on a Shale Gas reservoir.

Producing hydrocarbon from Shale plays has attracted much attention in the recent years. Advances in horizontal drilling and multi-stage hydraulic fracturing have made shale reservoirs a focal point for many operators. Our understanding of the complexity of the flow mechanism in the natural fracture and its coupling with the matrix and the induced fracture, impact of geomechanical parameters and optimum design of hydraulic fractures has not necessarily kept up with our interest in these prolific and hydrocarbon rich formations.

![Figure 6. Distribution of Shale in Kentucky.](image)

In this example we demonstrate using Top-Down Modeling to forecasting and analyzing oil and gas production in shale reservoirs. In this new approach instead of imposing our understanding of the flow mechanism and the production process on the reservoir model, we allow the production history, well log, and hydraulic fracturing data to force their will on our model and determine its behavior. In other words, by carefully listening to the data from wells and the reservoir we developed a data driven
model and history match the production process from Shale reservoirs. The history matched model is used to forecast future production from the field and to assist in planning field development strategies. We use the last several months of production history as blind data to validate the model that is developed.

![Figure 7](image1.png)

**Figure 7.** Formation Depth, Pay Thickness and Porosity distribution used in the TDM.

![Figure 8](image2.png)

**Figure 8.** Strategy used during the training and history matching of the Top-Down Model for the Lower Huron Shale.

While the details of the Top-Down modeling application to Lower Huron Shale can be found in the literature (Grujic 2010) a short summary is presented here. Thickness of the shale formations in Kentucky are shown in Figure 6. Depth, formation thickness and porosity distribution of the portion of the field that is the subject of Top-Down Modeling is shown in Figure 7.

The TDM for the Lower Huron is trained and history matched. During the TDM training and history matching part of the production history (usually the tail-end of the
production) is removed from the model building process and is used as blind test in order to check the validity of the reservoir model. The quality of the TDM is usually judged based on its capability to predict the part of the production history that has not been used during the reservoir model training.

*Figure 9.* Results of the TDM (monthly rate and cumulative production) as applied to the production from the entire field.

Figure 8 shows the strategy that was incorporated during the Top-Down Model training, history matching and blind history matching for the Lower Huron Shale. Production history was available for this field from 1982 to 2008. The Top-Down Model was trained and history matched with data from 1982 to 2004 and production history from 2005 to 2008 was left out to be used as validation of the model in the form of blind history matching.

Figure 9 shows the result of training and history matching of the Top-Down Model for Lower Huron shale when applied to the production history of the entire field (this study included a portion of a field with 75 wells). Top-Down Model is built (trained and history matched) on a well by well basis and in order to generate the plot in Figure 9, both production history and TDM results had to be combined for all the wells in the study. In this figure result of TDM is compared with the actual production history from the field in monthly production rate versus time and cumulative field production versus time. To demonstrate the results of TDM on single wells two examples are presented in Figure 10.
This figure shows the results of TDM model training and history matching (blind portion of history matching is shown in different color) for two wells, namely well KF1184 and KF1638. These figures demonstrate the predictive capability of TDM in Lower Huron shale.

Figure 10. Results of the Top-Down Modeling (monthly rate and cumulative production) as applied to the production history from wells KH1184 and KF1638.

5 Advantages and Disadvantages

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 (de-
pletion, remaining reserves …) as a function of time and puts the overall performance of the reservoir in perspective for effective decision making.

6 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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