INTELLIGENT SOLUTIONS, INC.

AI-BASED RESERVOIR MANAGEMENT

ANALTERNATIVE TO TRADITIONAL RESERVOIR MODELING

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This document introduces a new class of reservoir management tools that are developed by Intelligent Solutions, Inc. based on the pattern recognition technologies collectively known as Artificial Intelligence and Data Mining (AI&DM). This new technology breaks new ground in modeling of fluid flow through porous media by providing a completely novel and different angle on reservoir modeling workflow.

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

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 models. Two of these workflows that have recently been introduced are 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

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

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

$$y_1, y_2, ..., y_n = operational \ constraints$$

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

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

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 (tuned) in order to achieve a 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 (tuning) 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.

	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.*

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 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 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*.

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

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

Step One: 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 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.

Step Two: 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.

Step Three: 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 2009).

Step Four: 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.

Step Five: 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. Classification of AI-Based Reservoir Models can be based on the model output, based on the type of field the model is being applied to, based on the stage of recovery, or finally based on the functionality of the model.

When the AI-Based Reservoir Models are classified according to the model output they are classified into three types of AI-Based Reservoir Models:

1. Well-based model: These are AI-Based Reservoir Models that provide rate profiles (production rate versus time if flowing bottom-hole pressure is specified) or pressure profiles (pressure versus time if well rate is specified). The rate or pressure specification at the well can be either constant or variable (as a function of time).

2. Grid-based model: These are AI-Based Reservoir Models that provide pressure, saturation and mole fractions distribution throughout the reservoir as a function of time. Regardless of the size of the reservoir and the degree of heterogeneity of the static model, grid-based models can accurately generate time varying fluid behavior in the reservoir.

3. Fully coupled model: When the above two models (well-based and grid-based reservoir models) are coupled together, the AI-Based Reservoir Model is said to be fully coupled. In this cased the interaction between operational constraints and fluid flow behavior are modeled simultaneously.

When the AI-Based Reservoir Models are classified to reflect the type of the field that is being modeled they are classified into two types of AI-Based Reservoir Models:

1. Green Filed model: These are AI-Based Reservoir Models that are generated for fields with little or no production history. Obviously historical data for a green field is not available and therefore the techniques that are required to deal with such situations call for specific practices in model development. Models developed for green fields have significant capabilities for uncertainty analyses.

2. Brown Field model: These are AI-Based Reservoir Models that are generated for fields with significant amount of production history. Brown field models honor the historical production and provide tools for forward looking predictions on fluid flow behavior in the field.

When the AI-Based Reservoir Models are classified according to the stage of recovery they are classified into two types of AI-Based Reservoir Models:

1. Primary recovery: These are AI-Based Reservoir Models that are generated for fields during the primary recovery. In other words no water, gas (natural gas, nitrogen, CO_2 etc) or other fluids are being injected in the reservoir and the field is being produced based on its internal energy.

2. Enhanced recovery: These are AI-Based Reservoir Models that are generated for fields during the enhanced recovery. In these models water, gas (natural gas, nitrogen, CO_2 etc) or other fluids are being injected in the reservoir for pressure maintenance, displacement or other recovery enhancement schemes.

When the AI-Based Reservoir Models are classified to reflect the functionality of the model they are classified into two types of AI-Based Reservoir Models:

1. History matching models: These are AI-Based Reservoir Models that are built in order to be used for AI-Assisted history matching. Models built to be used for history matching can quickly be changed into models for reservoir management once the history matching process is completed.

2. Reservoir management models: These are AI-Based Reservoir Models that are generated for reservoir management purposes. These models display strong capabilities for fast track analysis of the reservoir, uncertainty analysis and production optimization and recovery enhancement.

But the most important of all classifications is the classification based on the source of data used for development. AI-Based Reservoir Models are fundamentally 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.

Please note that for a given project only one AI-Based Reservoir Model is constructed. Using the above classifications helps reservoir engineers, modelers and reservoir managers to decide the essence of the AI-Based Reservoir Model for a given project. For example for a given project you may decide on developing a well-based Surrogate Reservoir Model for a brown field during enhance recovery and for reservoir management purposes.

ADVANTAGES & 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.

The disadvantage of AI-Based Reservoir Models is that they need to be built based on either an existing model or an existing field. AI-Based Reservoir Models cannot be built independently for studying general purpose reservoir simulation and modeling. AI-Based Reservoir Models are indeed purpose and case specific custom models.

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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