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Application of Surrogate Reservoir Model (SRM) to an Onshore Green Field in Saudi Arabia; Case Study
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Abstract
Application of the Surrogate Reservoir Model (SRM) to an onshore green field in Saudi Arabia is the subject of this paper. SRM is a recently introduced technology that is used to tap into the unrealized potential of the reservoir simulation models. High computational cost and long processing time of reservoir simulation models limit our ability to perform comprehensive sensitivity analysis, quantify uncertainties and risks associated with the geologic and operational parameters or to evaluate a large set of scenarios for development of green fields. SRM accurately replicates the results of a numerical simulation model with very low computational cost and low turnaround period and allows for extended study of reservoir behavior and potentials. SRM represents the application of artificial intelligence and data mining to reservoir simulation and modeling.

In this paper, development and the results of the SRM for an onshore green field in Saudi Arabia is presented. A reservoir simulation model has been developed for this green field using Saudi Aramco’s in-house POWERSTM simulator. The geological model that serves as the foundation of the simulation model is developed using an analogy that incorporates limited measured data augmented with information from similar fields producing from the same formations. The reservoir simulation model consists of 1.4 million active grid blocks, including 40 vertical production wells and 22 vertical water injection wells.

Steps involved in developing the SRM are identifying the number of runs that are required for the development of the SRM, making the runs, extracting static and dynamic data from the simulation runs to develop the necessary spatio-temporal dataset, identifying the key performance indicators (KPIs) that rank the influence of different reservoir characteristics on the oil and gas production in the field, training and matching the results of the simulation model, and finally validating the performance of the SRM using a blind simulation run.

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

Introduction
Field “R” is an onshore field that produces from carbonate reservoirs in anticlinal traps consisting of an upward shoaling sequence of marine carbonate capped by anhydrite. The formation consists primarily of limestone and dolomites with reservoir heterogeneities characterized by the existence of high permeability streaks, faults and fractures. The review of logs suggests that reservoir characteristics can vary significantly over relative short distances.

Oil-water contact was interpreted for this reservoir. The API gravity of the oil varies from 24° to 32° in the oil bearing zones and the crude viscosity varies from 1.5 cp to 4 cp. The reservoir is initially undersaturated and is currently undeveloped.

Reservoir simulation model was constructed for this field primarily for field development planning purposes using the in-house massively parallel processing simulator. The model is 3-phase, 3-component (oil-water-gas), and single-porosity single-permeability; although no free gas in the reservoir is expected due to planned pressure maintenance by water injection. The simulation model for field “R” consists of 1.4 million active cells with an areal grid size of 250 m x 250 m. The model includes 40 vertical production wells and 22 vertical water injection wells and the model’s run time is approximately 12
minutes on a cluster of CPUs. Figures 1 and 2 show some of the reservoir characteristics of field “R.” Due to the limited number of wells that have been drilled in this field, considerable uncertainties exist in reservoir description as well as in the engineering data. Performing uncertainty/risk analysis is critical to realistically assess the potential of field development.

Fig. 1. Structural map of field “R” in Saudi Arabia.

Fig. 2. Permeability (in x direction), porosity and initial oil saturation of field “R” in Saudi Arabia.

**Surrogate Reservoir Models (SRMs)**

Classified as an AI-based Reservoir Model (Mohaghegh, 2011), the Surrogate Reservoir Model (SRM) is defined as an accurate replica of a reservoir simulation model that runs in real-time. Developed for the first time to replicate a mature field in the Middle East (Mohaghegh, 2006a, 2006b, 2006c and Mohaghegh, 2009), SRM can be applied to both mature and green
fields. SRMs are ensemble of multiple, interconnected neuro-fuzzy systems that are trained to adaptively learn the fluid flow behavior from a multi-well, multilayer reservoir simulation model, such that they can reproduce results similar to those of the reservoir simulation model (with high accuracy) in real-time.

It may be questioned that if a numerical reservoir simulation model exists, why a SRM would be needed. Necessity of SRM has to do with the fact that massive potential 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 running parallel on a cluster of CPUs. Exhaustive and comprehensive evaluation of the solution space for designing field development strategies as well as the quantification of uncertainties associated with the static model are the type of analyses that require a large number of simulation runs to provide meaningful and usable results. Even at 12 minutes per run, 10,000 simulation runs of field “R” that might be needed for reasonable uncertainty quantification would take about three months. Given the time it takes for a single numerical simulation run, performing comprehensive analyses that are required for reservoir management purposes become impractical and the engineers have to compromise by designing and running a much smaller number of runs to make timely decisions.

It will be demonstrated in this paper that SRM has the capability of reproducing highly accurate simulation responses as a function of changes to all the involved input parameters (reservoir characteristics and operational constraints) in a fraction of a second.

It should be also mentioned here that SRMs, as a new way of building replicas of the reservoir simulation model, are complex systems that cannot possibly be explained in detail in one technical paper. Our objective is to explain the details of developing SRM in multiple papers, each dedicated to several aspects of this new technology. As such, this paper will be dedicated to explaining a subset of features of SRMs.

**SRM vs. Response Surface and Other Reduced Order Models**

Advantages of the SRM over the response surface and other reduced order models are:

Response surface and other reduced order models that are developed using statistical approaches use predetermined functional forms that must be identified in advance. Then the results of hundreds of simulation runs are fitted to these predetermined functional forms hoping that the observed behavior from the reservoir simulation model follows a predetermined, well behaved functional form. During the training and matching of the SRM, no predetermined functional forms are identified. SRMs are developed using universal function approximation technology that will adapt and fit an infinite set of functional forms that may change from one set to another many times within the time and space domain that is the subject of our analysis.

Response surface and other reduced order models that are developed using hundreds of simulation runs (realizations) by SRM can be developed with only a handful of simulation runs. This is due to a unique and efficient use of the data generated by the simulation runs. The SRM developed for field “R” that is represented in this paper is developed using only nine simulation runs.

When a simulation run is completed there are two sets of information that can be extracted from it. First are pressure or production profiles at each well and the second is pressure and saturation changes throughout the reservoir that has resulted from the production/injection process. While the pressure and production profiles are presented at each individual well, the changes in pressure and saturation throughout the reservoir are identified at each grid block. Unlike response surface and reduced models that are only capable of reproducing a version of pressure and production at each well, SRM provides accurate replication of simulation results not only at each well but also at each grid block. By using well-based SRMs, one can reproduce rate and pressure profiles at each well in seconds, and while using grid-based SRMs one can reproduce pressure and saturation distribution at each grid block location at each time-step.

**Steps Involved in Developing the SRM**

Following are the major steps involved in completion of the SRM for the onshore green field in the Saudi Arabia.

**Designing Simulation Runs**

As mentioned in the previous section, a small number of simulation runs is sufficient for the development of the SRM. A total of nine simulation runs were designed for the development of the SRM for field “R.” Table 1 summarizes the operational constraints that were used for each of the nine simulation runs. In this Table it is shown that the bottom-hole pressure (BHP) and maximum liquid rate in each run were varied within the expected operational ranges. These operational constraints were imposed on all the producing wells in the field. While in five of the simulation runs, the BHP were kept constant for the entire 20 years of production, and in four of the simulation runs, the BHP was varied as a function of time.
The schemes for the variation of the BHP are shown in Fig. 3.

<table>
<thead>
<tr>
<th>Run Number</th>
<th>Bottom-Hole Pressure (psi) For all the wells in the field</th>
<th>Maximum Liquid Rate (bbls/d)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>500</td>
<td>10,000</td>
</tr>
<tr>
<td>2</td>
<td>500</td>
<td>15,000</td>
</tr>
<tr>
<td>3</td>
<td>1,000</td>
<td>10,000</td>
</tr>
<tr>
<td>4</td>
<td>1,500</td>
<td>10,000</td>
</tr>
<tr>
<td>5</td>
<td>1,500</td>
<td>15,000</td>
</tr>
<tr>
<td>6</td>
<td>1,500 - 1,000 - 500 (variable in steps)</td>
<td>10,000</td>
</tr>
<tr>
<td>7</td>
<td>1,500 - 1,000 - 500 (variable in steps)</td>
<td>15,000</td>
</tr>
<tr>
<td>8</td>
<td>1,500 - 500 (variable continuous)</td>
<td>10,000</td>
</tr>
<tr>
<td>9</td>
<td>1,500 - 500 (variable continuous)</td>
<td>15,000</td>
</tr>
</tbody>
</table>

Table 1. Nine simulation runs designed for the development of the SRM for field “R”

Fig. 3. Variable BHP constraints in steps and continuous use in the simulation runs.

**Making the Simulation Runs**

Once the necessary simulation runs were designed, the runs were made. At 12 minutes per simulation run, less than 2 hours of computational time was sufficient to generate the required data for the development of the field “R” SRM.

**Development of the Spatio-Temporal Database**

SRMs are developed using data extracted from simulation runs. Therefore, the first step in any SRM project starts with developing a representative spatio-temporal database. The extent at which this spatio-temporal database actually represents the fluid flow behavior of the reservoir that is being modeled, determines the potential degree of success in developing an accurate model.

The term spatio-temporal defines the essence of this database. It 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 collection, compilation, organization and processing must be performed with such needs in mind.

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 the SRM. “Curse of Dimensionality” is one of the issues that is associated with SRM 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.

The main ideas behind the development of the spatio-temporal database are:

Dynamic allocations of reservoir volume to each well, using the modified Voronoi Graph Theory, along with dynamic and operational based up-scaling of the geological model, accurate coupling of the information generated in step (a) with the time based production and injection activities, and association of each well with its corresponding offset wells (injectors and
producers both in space and time) are used to generate a cohesive record of an event that adequately represent the fluid flow in the reservoir.

The details of developing the spatio-temporal database including the development of the allocated polygons using the Voronoi Graph Theory as well as the dynamic and operational based up-scaling that uses a special tier system, along with the parameters that were included in the spatio-temporal database will be covered in a separate paper.

**Generating Key Performance Indicators**

One of the most important steps in the development of the SRM is the identification of key performance indicators (KPIs). The spatio-temporal database that was developed in the previous step includes a very large number of parameters that need to be analyzed and possibly included in the predictive model. It is a fact that not all of the parameters have an equal impact on the oil and gas production throughout the reservoir. Using a large number of input parameters in developing a predictive model will result in a system with serious tractability issues. Therefore, it is very important, and even vital to the success of the training, matching and validating of the SRM to be able to efficiently identify the KPIs of a given model.

![Fig. 4. Impact of the reservoir characteristics (at the well location) on the oil production.](image)
Results of the KPI analysis are summarized in Figs. 4 and 5. Keeping in mind that in the spatio-temporal database the reservoir characteristics for each of the wells along with its associated offset wells have been compiled, the KPI analysis can identify the impact of each of these parameters on the production from each well. In Fig. 4, all the reservoir properties that are associated with the well itself (not including the properties of its offset wells) are compared with one another. The length of each bar is indicative (comparatively) of the impact that each property has on the oil production. Also, as seen in this figure, it is clear that the initial oil saturation in the reservoir has the highest impact on the oil production followed by initial pressure. The three reservoir characteristics, porosity, permeability and formation thickness seem to have equal (but less than saturation and pressure) impact on the oil production followed by drainage area.

In Fig. 5, each of the reservoir characteristics has been evaluated independently and the corresponding reservoir property at the well location has been compared with the two closest offset wells.

Training and Matching the SRM

The process of building (training) the SRM and matching its performance with that of the reservoir simulation model, is performed simultaneously. During this process the SRM is trained to learn the reservoir model and the fluid flow behavior in the specific reservoir simulator being modeled. The spatio-temporal database developed in the previous step is the main source of information for building and matching the SRM. Please note that the SRM may be a collection of several models that are trained, matched, validated and finally used in concert to generate the desired results.

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 (SRMs 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 vs. 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 SRM.

It is of the utmost importance to have a clear and robust strategy for validating the predictive capability of the developed SRM. The model must be validated using completely blind simulation runs that have not been used, in any shape or form, during the development of the SRM. Nevertheless, it is important to select the blind runs such that they fall within the ranges (both static and dynamic) that were used during the training of the SRM.

Both training and calibration datasets that are used during the initial training and matching of the SRM are considered non-blind. Some may argue that the calibration – a.k.a. testing data set – is also blind; this argument has some merits but if used during the development of the SRM it may compromise the validity and predictability of the model, and therefore such practices are not recommended.
Fig. 6. SRM of field “R” during the training process. The graph on the left shows the performance of the SRM on the calibration dataset while the graph on the right shows the change in the error of the training data set. The error is calculated by subtracting the SRM calculated oil production from the oil production from the reservoir simulation model.

During the training and matching of the SRM for field “R,” data from the nine simulation runs that were organized in the spatio-temporal database was used. The training and calibration included 65% and 10% of the data in the spatio-temporal database, respectively. The calibration dataset is used as a blind data set to make sure that the SRM is not over-trained. Figure 6 is a snapshot of the training of the SRM.

The remaining 25% of randomly selected data (even during the training and matching process) was left out as a blind data set for validation of the SRM. Since this 25% is randomly selected from within the spatio-temporal database, it does not represent a cohesive simulation run from start to finish. Therefore, we do not consider this 25% of randomly selected data as a measure for the validation of the SRM. Nevertheless, if the SRM does not perform satisfactorily on this 25% of randomly selected data, then the chances of it performing well on a completely blind simulation run would be minimal.

Figure 7 shows the performance of the SRM on the 25% of randomly selected data from within the spatio-temporal database. It is clear from this figure that the SRM is displaying a strong performance in predicting the oil rate for a blind data set.

Figures 8 through 10 shows the comparison of the SRM with the in-house reservoir simulation model for two of the simulation runs that that were included in the training of the SRM. In Fig. 8 the comparison is made for total field production (both oil and gas). Figures 9 and 10 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 of these figures that the SRM can reproduce the results of the in-house simulator with high accuracy.
Fig. 7. Performance of field “R” SRM on the 25% of randomly selected blind data from the spatio-temporal database.

Fig. 8. Comparing the accuracy of 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.
Validating the SRM

The trained SRM is validated against a complete blind run of the reservoir simulation model. For this purpose a 10th 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 1,000 psi and maximum oil rate of 15,000 barrels. Figures 11 through 13 shows the comparison of the SRM with the blind run of the in-house reservoir simulation model. In Fig. 11 the comparison is made for oil and gas production for the entire field. In Figs. 12 and 13, the comparison for two randomly selected wells in a blind run of the simulation model are shown.

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.
Fig. 11. Comparing the accuracy of 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.

Fig. 12. Comparing the accuracy of field “R” SRM with the in-house numerical reservoir simulator for a blind run; oil and gas production from one of the wells in the field.

Fig. 13. Comparing the accuracy of field “R” SRM with the in-house numerical reservoir simulator for a blind run; oil and gas production from one of the wells in the field.
Sensitivity Analysis

As it was previously mentioned, due to limited number of wells that have been drilled in this field, considerable uncertainties exist in reservoir description as well as in the engineering data. One of the ways to address known uncertainties that is associated with the static model is to use SRM to perform sensitivity analysis.

The type of the sensitivity analysis that is presented in this section can be used effectively during the history matching process of the numerical reservoir simulation model. In the analyses that are presented here, type curves are developed to put in perspective the sensitivity of production to various parameters at different locations in the reservoir. For example, for each individual well, these type curves can show how sensitive the production is to any given variable (i.e., permeability) at many predetermined locations in the reservoir. Therefore, it will not be necessary to modify the permeability of the entire reservoir using a “permeability multiplier” to achieve history match at a certain location (well) in the reservoir. Knowing which parameter to modify and how much, to achieve a history match, can help modelers make localized “small” modifications to key parameters and avoid large-scale modifications of the static model.

![Fig. 14. Sensitivity analysis of field “R” using the SRM. Sensitivity of oil rate to BHP for all the wells in the field (in general and on average) as a function of different values of permeability in the Tier One grid blocks (grid blocks closest to the wellbore).](image)

The results of the sensitivity analysis are presented in the form of a type curve. Type curves can be generated using the SRM for the individual wells, groups of wells, or for the entire field in seconds. Figures 14 through 16 are examples of several type curves that have been developed for field “R” using the SRM.

Figure 14 shows the sensitivity of oil rate to BHP as a function of permeability in Tier One grid blocks in general for all the wells in field “R.” This type curve is a general type curve that shows the overall impact of permeability in Tier One grid blocks. Although it is useful for comparison to other tier blocks in the reservoir, it cannot be a big help on a well by well basis. For the purposes of achieving history match in any given well one should use type curves that are shown in Figs. 15 and 16.

Figures 15 and 16 demonstrate the sensitivity of oil rate to BHP as a function of permeability in Tier One grid blocks for four selected wells in different locations in the field. Figure 15 shows the sensitivity for Wells A and B that are located in the southern part of the reservoir while Fig. 16 shows the sensitivity for Well C in the central part of the reservoir and Well D in the northern part of the reservoir. Please note that these four wells portray four different behaviors. This is due to all other parameters that are involved in flow of fluid in the reservoir. The heterogeneous nature of the reservoir dictates this nonuniform response to modification to any given parameters.

When a permeability multiplier is used to modify the permeability for the entire field, to achieve a history match for a given
well, the sensitivity of different locations of the field to different parameter modifications are ignored. The difference in the response of the reservoir to modification of a given parameter is, in itself, an indication of the heterogeneity of the reservoir that needs to be honored and accounted for. We believe that using SRM in the way it is mentioned here is a better way of honoring overall reservoir heterogeneity and the work that has gone into developing the geological model in the first place.

Fig. 15. Sensitivity analysis of field “R” using the SRM. Sensitivity of the oil rate to BHP for Wells A and B in the field as a function of different values of permeability in the Tier One grid blocks (grid blocks closest to the wellbore).
Fig. 16. Sensitivity analysis of field “R” using the SRM. Sensitivity of oil rate to BHP for Wells C and D in the field as a function of different values of permeability in the Tier One grid blocks (grid blocks closest to the wellbore).
Quantification of Uncertainties Associated with the Geological Model

As previously mentioned, the limited number of wells that have been drilled in this field, result in considerable uncertainties in reservoir description. This is true with all green fields where the sample data from logs and core are so limited that analogy or general geological understanding of the field becomes the limits of our understanding of the reservoir heterogeneity. Although surface seismic may be available in many of the prolific green fields, deduction of reservoir parameters as needed for simulation and modeling is a stretch and many scientists are still working on feasible solutions. It is a universally agreed issue that uncertainties associated with the reservoir characteristics and therefore the static model that is used for the analysis of green fields poses a serious challenge to comprehensive modeling of these fields and therefore uncertainty analysis in such cases become an important step that needs to be taken into account.

On the other hand, as the number of grid blocks required to build a geologic model for the reservoir simulation models increase, so does the amount of time required for a single run. As previously mentioned, in the case of field “R” 1.4 million active cells are used to model this reservoir. Even with massively parallel, multi-cluster computational resources, it takes about 12 minutes to make a single run. This means that a reasonably simple uncertainty analysis that requires only 1,000 simulation runs will take more than eight days of computational time and the slightest mistake or modification that would require the runs to be repeated will take another eight days. A more comprehensive uncertainty analysis that would require extensive sampling of the geological model with about 10,000 runs would take about three months, even with such massive resources. On the other hand, an uncertainty analysis with a moderate 1,000 runs will only takes a few seconds with the SRM. Given the accuracy of the SRM that has already been demonstrated, this is a significant advancement in the analytical power of the existing reservoir simulation models.
Figures 17 through 19 shows the uncertainty analysis performed using field “R” SRM for three individual wells in this field. Each of these analyses was performed using 5,000 SRM runs and they took less than five seconds each. In these analyses, the total oil production during the first year was calculated using field “R” SRM when all the permeability values in the field were modified, sampling from the frequency distribution functions that were developed using all the available values in the simulation model. This represented a large range of permeability values. But the range in such analyses can be changed to represent any minimum and maximum values as well as any type of distribution function (i.e., triangular, uniform, Gaussian, etc.). Along with representing the probability distribution that is presented in Figs. 17, 18 and 19, P10, P50 and P90 for each of these wells are also identified.

Conclusions

Application of SRM to an onshore field (Field “R”) in Saudi Arabia was presented. The process and steps involved in the development of the SRM for field “R” was explained and discussed. It was shown that the SRM is trained and matched with the results from the in-house numerical simulation model and was validated using a blind simulation run. Furthermore, use of the SRM in performing sensitivity analysis and uncertainty analysis was demonstrated.

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.
Fig. 19. Uncertainty analysis of field “R” using the SRM. Uncertainty associated with permeability of the formation (all Tiers) for Well x3.

References


