Development of Surrogate Reservoir Model (SRM) for fast track analysis of a complex reservoir

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Abstract: Reservoir simulation is the industry standard for reservoir management that is used in all phases of field development. As the main source of information, prediction and decision-making, the Full Field Models (FFM)

is regularly updated to include the latest measurements and interpretations. A typical FFM consists of large number of grid blocks and usually takes hours for each run. This makes comprehensive analysis of the solution space and incorporation of the FFM in smart fields impractical. Surrogate Reservoir Models (SRMs) are introduced as a bridge to make Real-Time Reservoir Management possible. SRMs are replicas of FFM that can run in fractions of a second. They accurately mimic the capabilities of FFM and are used for automatic history matching, real-time optimisation, real-time decision-making and quantification of uncertainties. This paper presents the development of SRM using the state of the art Artificial Intelligence and Data Mining (AI&DM) techniques. An example application to giant oil field in the Middle East and the accuracy of SRM predictions are presented. SRM is used in order to identify the wells that are prime candidate for rate relaxation with the objective of higher oil production without an increase in water cut. After 30 months of production all SRM predictions were proved accurate.
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1 Background

Over the past several years, computer simulation has made major advances in terms of scope and complexity. Today they can reach the levels of accuracy, which make it possible to play realistic scenarios of complex mechanical and geophysical processes. The success of computer simulation techniques is due to the development of efficient algorithms and solution methods for general partial differential equations, the advancement of modern computational fluid dynamic and multi-physics simulation technologies, as well as due to the availability of increasingly capable hardware platforms, such as supercomputer facilities, and Beowulf clusters.

Reservoir simulation is now an industry standard. No serious alternative to the conventional reservoir simulation and modelling is in the horizon. It is a well-understood technology that usually works well in the hand of experienced reservoir engineers performing simulation and modelling that incorporates reasonably good geological, geophysical and petrophysical interpretations and measurements with the reasonably sophisticated simulators that are currently available in the market. The reservoir models that are built for an average size field with tens and sometimes hundreds of wells tend to include very large number of grid blocks. As the number of reservoir layers or the thickness of the formations increase the number of cells included in the model approaches several millions. Technologies such as Local Grid Refinements (Heinemann et al., 1983; Ewing and Lazarov, 1988) have been developed to dampen the geometric increase of the number of grid blocks required for detailed and focused simulation and modelling around the wellbore and locations in the reservoir where more detail is required, but the size of the models remains in the several millions of cells.

As the size of the reservoir models grow, the time required for each run increases. Schemes such as grid computing and parallel processing helps to a certain degree but cannot close the large gap that exists between simulation runs and real-time processing that is needed for exhaustive search of the solution space or quantification of uncertainties associated with the geologic (geocellular) model. On the other hand with the new push for smart fields (also known as i-Fields, Field of the Future, Digital oil Field, etc.) in our industry that is a natural growth of smart completion and smart wells, the need for being able to process information in real time becomes more pronounced. Surrogate Reservoir Models (SRMs) are the natural solution to this necessity since they run in real time (provide instantaneous results as the input to the simulation model is modified). In this paper, authors will introduce a detailed process for the development of SRMs.

First attempt in developing a surrogate model in the oil and gas industry was concentrated on developing a surrogate model for a hydraulic fracturing simulator. In 1999, a surrogate model (Mohaghegh et al., 1999; Mohaghegh et al., 2000) that was able to accurately mimic the capabilities, a hydraulic fracturing simulator called FracPro (Pinnacle Technologies, 2008), was developed. They used the surrogate model for real-time optimisation of hydraulic fracture design of tight formations. If we define surrogate modelling in the context of model development that can replicate results of complete reservoir, hydraulic fracturing, and/or other comprehensive numerical simulators, then authors were unable to find other serious efforts that can be sited in the literature. Other attempts for surrogate model developments can be found in the literature (Queipo et al., 2000, Queipo et al., 2001; Naidu, 2004; Zerpa, et al., 2004) that does not necessarily fit the definition that is presented in this paper.

The next attempt in developing surrogate models (being discussed in this paper) was on a major oil field in the Middle East. In this research and development effort, the target was a full field reservoir model that included close to a million grid blocks and more than 165 horizontal wells. During this study, a Surrogate Reservoir Mode that was able to successfully mimic the behaviour of the full field reservoir model was developed and validated. The SRM was then used for candidate well selection as well as quantification of uncertainties associated with the geologic model. The results were used for important decision-making on the future of the field and optimum operation of the horizontal wells. Please note that in this manuscript the terms Full Field Model (FFM), dynamic model and reservoir simulation model are used interchangeably.

2 Reservoir analysis using Surrogate Reservoir Model

When the quantification of uncertainties associated with the geologic model is one of the objectives, SRM can prove to be valuable asset. Since a single run of the FFM takes several minutes or hours, uncertainty analysis becomes a painful and time-consuming process. In order for the uncertainty analysis to be meaningful, the number of geologic realisations of the reservoir must be statistically significant. This is the reason behind the fact that most of the techniques used for quantification of uncertainties call for analysis of several (sometimes hundreds of) geological realisation of the reservoir. As the number of independent parameters involved in a problem increases, so does the number of realisations needed for statistical significance. It can be argued that each grid block in an FFM represents a set of several independent variables. Given the high number of grid blocks in even a moderate size FFM, one can imagine that the number of realisations needed in order to have a statistically significant dataset will be relatively large.

There have been many advances in statistics and geostatistics that contribute to decreasing the number of realisations required for such analysis while keeping the integrity of the analysis intact. Nevertheless, even after all the approximations and techniques such as Latin Hyper Cube (Wyss and Jorgensen, 1998) and Design of Experiment (Montgomery, 2005), the number of the simulation runs required for a reasonably accurate uncertainty analysis remains quite high.

SRM plays an important role in addressing problems such as those mentioned here. It provides the means for making hundreds and even thousands of simulation runs in matter of seconds. In the problem that is presented in this paper, we demonstrate a Monte Carlo simulation study for uncertainty analysis on several parameters that were making significant contribution in the outcome of the simulation model. The Monte Carlo simulation used the dynamic model of giant oil field in the Middle East as its objective function. The SRM that was built to represent this reservoir simulation model was validated using a significant number of blind data and had proven to be quite accurate. During the uncertainty analysis using Monte Carlo simulation, the SRMs (essentially the dynamic model) were run 5000 times in less than 10 seconds.

3 SRM in the context of smart fields

One of the major issues that must be addressed as we approach the smart field era is the bottleneck that currently exists between high-frequency data streams (coming from the field through permanent down-hole gauges) and the major reservoir management tools, specifically reservoir simulation models. While the data streams provide data at a time scale of seconds, the reservoir simulators or the FFMs run in time scales of several hours or even days. The problem intensifies when we realise that in many cases in order to make reservoir management decisions, several FFM runs have to be made.

Intelligence is the resultant of well-coordinated combination of hardware and software. Human intelligence, for example, is based on precisely coordinated combination of the brain (hardware) and the mind (software). In order to have an actual 'intelligent' or smart field both hardware and software is needed. Our industry is in dire need of enabling software solutions for the smart fields.

Many scientists around the world are currently working on this problem using different tools such as Kalman filters (Zafari and Reynolds, 2005; Zhang et al., 2005) and other techniques, we claim that in order to successfully address this complex issue Artificial Intelligence & Data Mining (AI&DM) must be a significant contributor to any serious effort. To realise the merit of this claim, one needs to observe that not a single industry (from aerospace to automotives and from manufacturing to household appliances) has been able to increase its products intelligence quotient without significant use of intelligent systems. In this manuscript, the term intelligent system or AI&DM is referred to a series of techniques that include but are not limited to artificial neural networks (Mohaghegh, 2000a), genetic optimisation (Mohaghegh, 2000b) and fuzzy logic (Mohaghegh, 2000c).

This paper presents an example of developing such application that is considered to be an enabling technology for the smart fields. Here we describe the steps that need to be taken in development of an SRM and present the results.

4 Reservoir management and the model

The total daily oil production from this giant oil field is capped at 250,000 barrels per day (the field is capable of producing more). Furthermore, each well is capped at 1500 barrels of liquid per day. Since water is being injected as part of a pressure maintenance programme, and since water cut has been a problem in some wells, the production cap is imposed in order to avoid bypassing oil and creating hard to produce oil banks that are left behind. On the other hand it was suspected that several wells in the field might be capable of producing more oil without the threat of high water cut and a carefully planned rate relaxation programme was desired and became the main objective of this project.

The FFM that was the target of this study is a reservoir simulation model built for this giant oil field in the Middle East. Figure 1 shows a cross section of the reservoir in order to demonstrate the complexity of this model. The FFM represented the formation that is identified by XXX in Figure 1.

Figure 1 The cross section of the reservoir that the FFM is based on (see online version for colours)

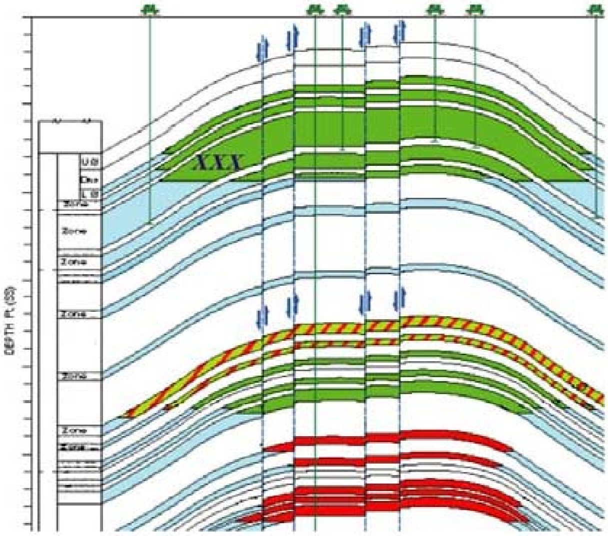
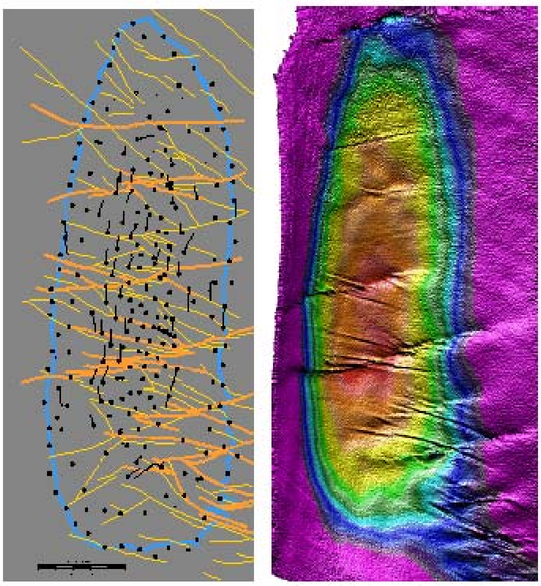


Figure 2 shows an approximate top view of the field with approximate locations of the horizontal wells. As it is shown in Figure 1, this reservoir is multi-layered. Most of the wells are completed in one particular layer and layers above and below the layer in which the wells are completed contribute to the production.

Figure 2 Top view of the reservoir with approximate location of more than 165 horizontal wells and location of major and minor faults (left) and top view of an structure map of the formation being studied (right) (see online version for colours)



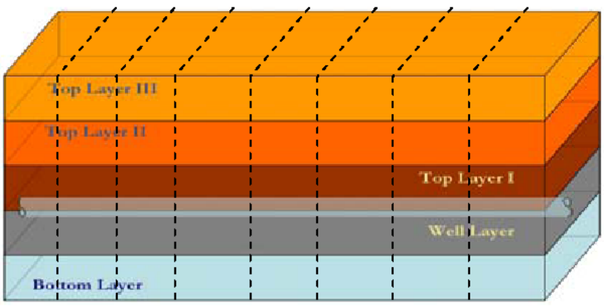
The operation in this field includes water injection into some of the layers for pressure maintenance and sweep purposes. Gas injection is also taking place in some areas of the field. The reservoir includes many major and minor faults (Figure 2) that have been detected by geoscientists and are part of the geological model that has been used to build the FFM. Several rock types have been identified in this reservoir and have played an important role in developing the geological and later the dynamic model. The dynamic model has been developed using ECLIPSE™ (Schlumberger, 2008) and includes about one million grid blocks. A single run of the version of the dynamic model used for this study took about 10 hours on a cluster of twelve 3.2 GHz Intel Xeon CPUs.

5 Curse of dimensionality

The first step in developing an SRM is to identify the FFM that it is going to represent. The FFM includes two sets of information that need to be represented in the SRM. These two sets of information are the static, geologic model and the dynamic flow characteristics.

There are essentially three major types of SRM. These are Grid-block-based SRM, Well-based SRM and Domain-based SRM. The type of SRM determines the SRM elemental volume and SRM blocks that are used for a specific project. Detail on the types of SRM will be discussed in a separate paper. To fulfil the objectives of this study, it was determined that a well-based SRM is required. Furthermore, only horizontal wells in this field were being studied. After carefully studying the characteristics of the reservoir and its multi-layered nature, it was decided to represent the reservoir characteristics around the wellbore using five representative layers. This is shown in Figure 3 where there is a bottom layer representing the simulation layers below the wellbore, the layer that includes the wellbore, and three distinct layers above the wellbore known as top layer I, that is immediately above the wellbore and layers II, and III that represent the rest of the layers in the reservoir.

Figure 3 Schematic diagram of the SRM elemental volume for a well-based SRM used in this study. The elemental volume includes 40 SRM blocks (see online version for colours)



Furthermore, each layer is divided into eight equal sections. The size of each section is a function of well's length and therefore may not be the same from well to well. List of parameters that have been identified to be used in the SRM development from the static model are shown in Tables 1 and 2. As it is shown in Figure 3, the model for the SRM includes five layers with eight segments per layer adding up to a total of 40 SRM blocks per SRM elemental volume. While data shown in Table 1 is collected on a 'per-SRM block' basis, data in Table 2 need to be collected on a per well (SRM elemental volume) basis.

Table 1 List of parameters used in the SRM development on a per segment basis (see online version for colours)

Parameters Used on a per segment basis	
Mid Depth	Thickness
Relative Rock Ttype	Porosity
Initial Water Saturations	Stylolite Intensity
Horizontal Permeability	Vertical Permeability
Sw @ Reference Point	So @ Reference Point
Capillary Pressure/Saturation Function	Pressure @ Reference Point

Now let's try to calculate the number of parameters contributed by the static model that should be used during the SRM development. There are 12 parameters in Table 1 and one value per SRM block is needed from this table. That would add up to 480 parameters. Plus there are 16 parameters identified in Table 2 and we need one value for each well (SRM elemental volume) from this table. This makes the total number of parameters from the static model to add up to 496. To this number of course, we have to add the dynamic parameters that will be identified and needed during the SRM development.

It goes without saying that 496 are too many parameters. Some may argue that SRMs are the same as reduced order models while other may confuse SRM as response surface. Authors are of the opinion that SRM are neither a reduced order model nor a response surface. This has to do with the fact that in constructing an SRM we take full advantage of discrete mathematics that have been used in development of reservoir simulators. We do this by dividing the reservoir into segments that are 'alike' (elemental volumes). Therefore, instead of reducing the order of the problem, we first reduce the problem size. Furthermore, response surfaces are developed solely based on model outputs and lack the engineering capabilities of a predictive model (as defined by the system theory), while SRMs are engineering tools that fully adhere to the requirements of the system theory (Ashby, 1956).

With 496 parameters we have too many parameters to develop an SRM. In intelligent systems, this is called the 'Curse of Dimensionality' and is common whenever complex phenomena are to be modelled accurately.

Table 2 List of parameters used in the SRM development on a per well basis (see online version for colours)

Parameters Used on a per well basis	
Latitude	Longitude
Deviation	Azimuth
Horizontal Well Length	Productivity Index
Distance to Free Water Level	Water Cut @ Reference Point
Flowing BHP @ Reference Point	Oil Prod. Rate @ Reference Point
Cum. Oil Prod. @ Reference Point	Cum. Water Prod. @ Reference Point
Distance to Nearest Producer	Distance to Nearest Injector
Distance to Major Fault	Distance to Minor Fault

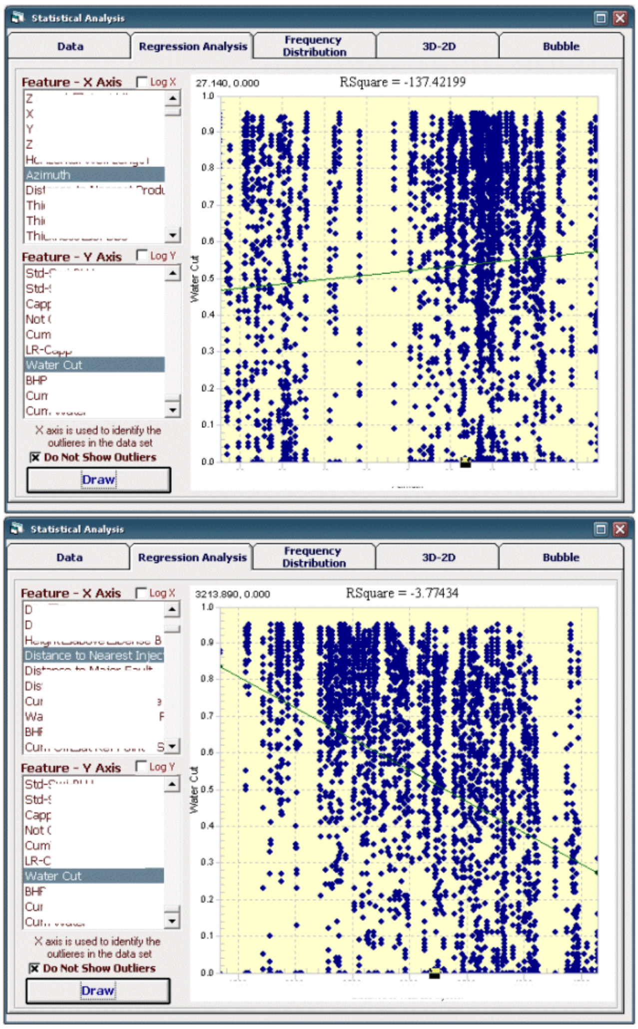
Figure 4 shows the actual behaviour of water cut as a function of two typical parameters that are being considered in this project, namely Azimuth and Distant to Nearest Injector. From this figure, it is clear that there are no '*apparent*' patterns that can be readily detected between water cut and Azimuth or between water cut and Distant to Nearest Injector.

Once the parameters that represent the static model are identified, the next step is the identification of the dynamic parameters that need to be considered. This is an important step in the development since it controls the number of simulation runs that has to be performed.

One of the key issues in SRM development is to realise that it is impractical to develop a global SRM. A global SRM is an SRM that is capable of replicating all the functionalities of a reservoir simulation model. Developing a global SRM is a trap that should be avoided. To be practical, one needs to identify the specific objectives of a project and then design and develop the appropriate SRM for that project. In other words, many SRMs with different capabilities can be developed to represent the same FFM.

For the purposes of this project, we needed to build an SRM capable of accurately predicting simultaneous water cut, cumulative oil production and cumulative water production for every horizontal well at any given time.

Figure 4 Behaviour of instantaneous water cut as a function of well Azimuth and Distance to the Nearest Injector for 165 horizontal wells at several different times (see online version for colours)



In order to satisfy these objectives, ten runs were designed and performed on the FFM. The ten runs included five runs with a predetermined cap on the total field production and five similar runs where no cap was imposed on the total production from the field. The five runs included are as follows:

1 imposing a nominal production cap of 1500 barrels of liquid per day on each well

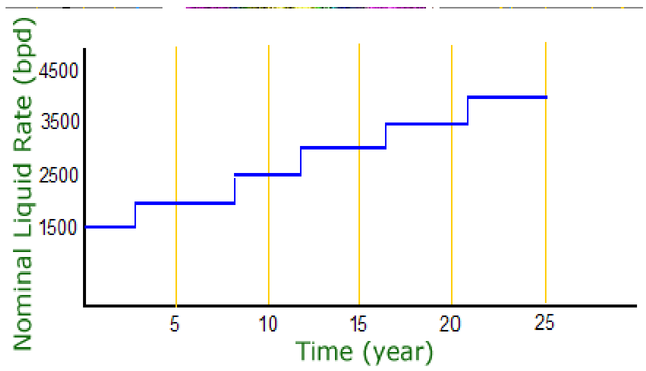
2 imposing a nominal production cap of 2500 barrels of liquid per day on each well

3 imposing a nominal production cap of 3500 barrels of liquid per day on each well

4 imposing a nominal production cap of 4500 barrels of liquid per day on each well

5 changing the imposed nominal production cap on each well according to Figure 5.

Figure 5 The Imposed production cap scheme on the FFM to generate dynamic data for the development of SRM (see online version for colours)



Once the total number of parameters (static and dynamic) that must be used in the development of the SRM was identified, the first order of business for the development of the SRM is reducing the dimensionality of the problem to a manageable and reasonable number. We do this by using Fuzzy Pattern Recognition (Mohaghegh, 2000c; Intelligent Solutions, Inc., 2008).

This technology can be used to identify the Key Performance Indicators (KPIs) in any process. The idea is that when we look at all the 165 horizontal wells in our field, given the specific flow characteristics of the field being studied, some of the parameters will have more significant contribution to the well behaviour than others.

The objective is to identify these key parameters and use ‘them’ during the development of the SRM. This task is much more complex than it may appear. Nevertheless, KPIs can be identified.

Figure 6 shows the top 23 parameters that were identified through the KPI procedure. Using the same feature, we were able to identify the overall contribution of each of the layers to the production from the horizontal wells. Figure 7 shows the contribution of each layer to the instantaneous water cut. In this figure, contribution of all the parameters was used in order to calculate the overall contribution of each layer to the production from the horizontal wells. It is interesting to note that the layer containing the wellbore has the lowest contribution to the production among the five layers. This seems to be counterintuitive since most of the time during the history matching process engineers tend to modify the parameters closest to the wellbore in order to achieve a match.

Figure 7 shows that in this particular multi-layer reservoir, by the time the fluids have made their way to the layer where the horizontal well is located, it is too late to modify any parameters to achieve a history match. This figure clearly shows that the top three layers control the water production in this reservoir and must be dealt with during the history matching procedure before the parameters in the well layer (where the wellbore is located) are modified.

Figure 6 KPIs identified for the SRM development (see online version for colours)

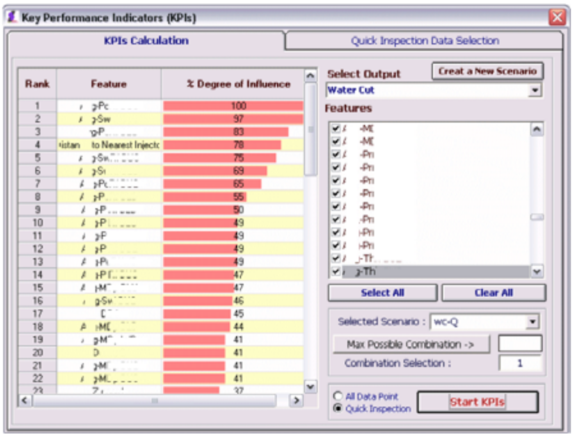
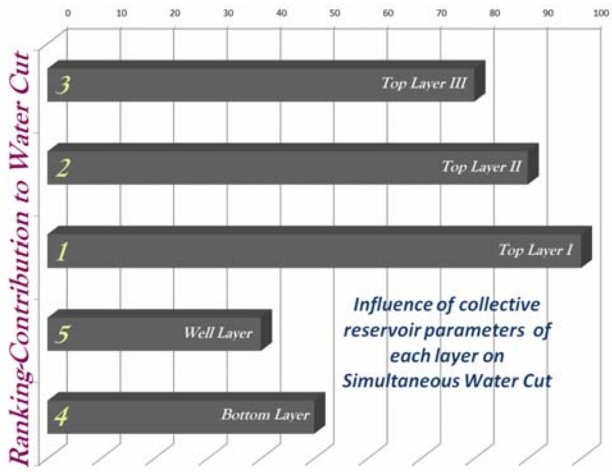


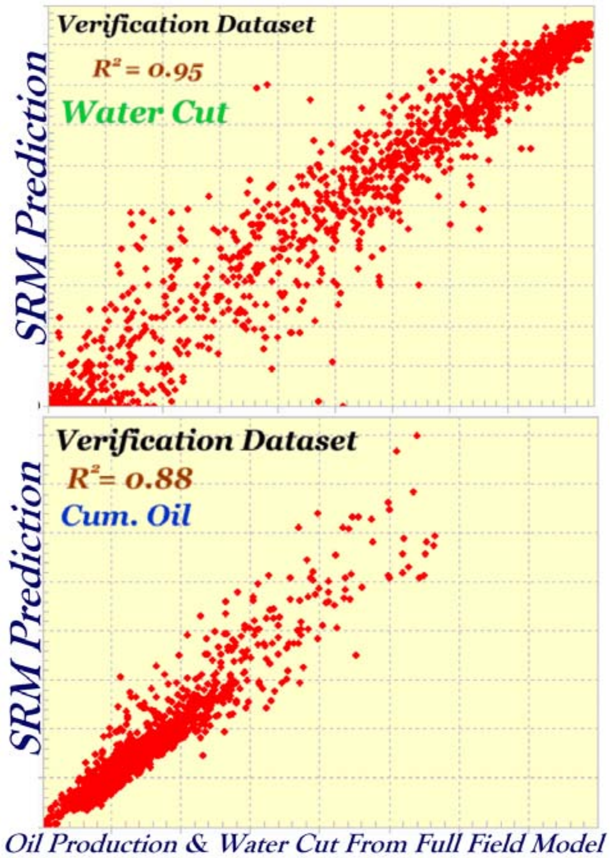
Figure 7 Contribution of each layer to the production from the horizontal wells (see online version for colours)



6 Validation of SRM

Once the SRM is developed it must be validated with data that has not been used during its development. For this project, 40% of the original data was set aside for the validation purposes. Once the SRM's development was completed its predictions were plotted against FFM's results for cumulative oil production and instantaneous water cut from many wells at different times. In both cases, the results were acceptable and therefore the analysis could continue. Figure 8 shows the validation plots for cumulative oil production and simultaneous water cut.

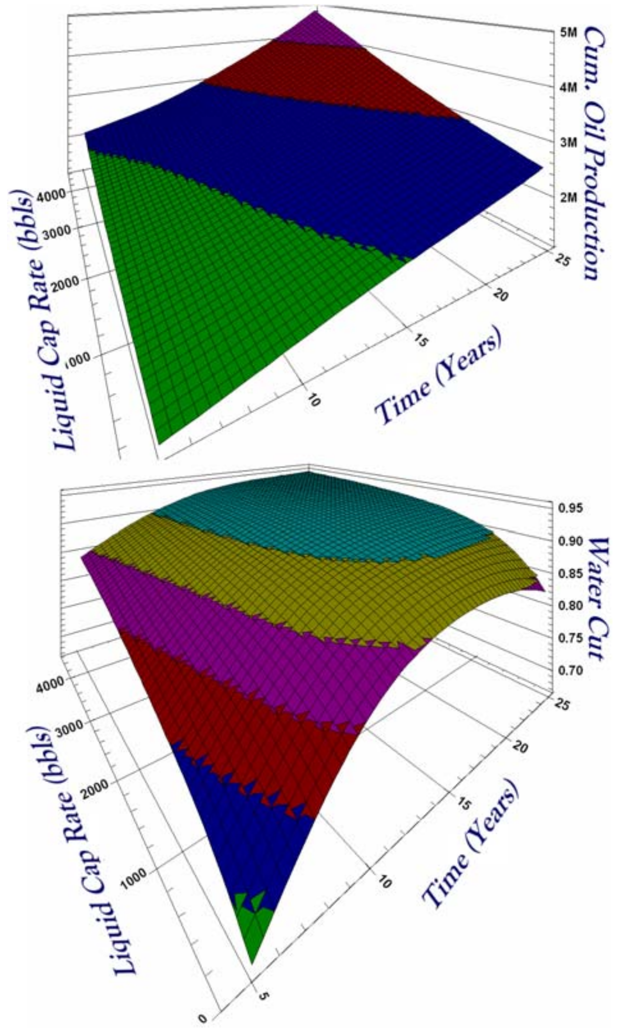
Figure 8 Validation of the SRM using 40% of the data that was not used during its development. Here actual FFM outputs are plotted against SRM's predictions (see online version for colours)



It should be noted that the FFM was run in its prediction mode calculating the water cut and oil production from year 2005 to 2030 and therefore the SRM was developed on such data. This was due to the specific objectives of the project. But once the development of the SRM was completed, it was checked in couple of occasions to see if it can correctly match the actual production from some of the horizontal wells' production history (in an 'extrapolation to the past' mode), i.e. productions from several years prior to 2005 and satisfactory results were achieved.

Once the SRM is developed and validated, it can be used to generate oil and water production profiles in the next 25 years for all the wells in the field as well as instantaneous water cut profiles in real time. In this project, one of the objectives was to study the effect of imposing different liquid cap rates on the water cut and cumulative oil production for each well. Figure 9 shows three-dimensional view of cumulative oil production and instantaneous water cut as a function of time and imposed liquid cap rate for a particular horizontal well. Quick visual inspection of wells response to different imposing liquid cap rate as a function of time (such as those shown in Figure 9) helped the team in analysing all the wells in the field in order to identify the wells that can benefit from relaxing such restrictions.

Figure 9 SRM's output for the behaviour of one well in the field showing water cut and cumulative oil production as a function of time and the liquid cap rate imposed on the well (see online version for colours)



7 Uncertainty analysis

Upon completing the development of the SRM for this particular field another objective of the project could now be addressed effectively. The objective was to analyse the uncertainties associated with many interpretations that go into developing an FFM and quantifying their contribution to the FFM's output, i.e. cumulative oil and water production and instantaneous water cut.

It is well known that many parameters that are used to construct a geological model and form the foundation of any reservoir simulation are far from being certain. Actually when new versions of FFMs are released it is usually the result of better information that has become available about the geological model and the dynamic data. The geological, geophysical and petrophysical interpretations, calculations and measurements that form the foundation of the earth model, as parameters that go into the reservoir simulation model, each carries a certain amount of uncertainty. SRM along with Monte Carlo simulation can serve as an important technique to quantify these uncertainties and demonstrate their individual or collective impact on the model's outcome.

The procedure that was used in this study to analyse the contribution of the uncertainties associated with the geological model is as follows (essentially a Monte Carlo simulation approach with SRM as the objective function):

1 Identify the parameters to be analysed. It is recommended to start with the parameters that have the most contribution to the process outcome. Result of KPI analysis as shown in Figure 6 is usually a good start.

2 For each of the parameters, define a Probability Distribution Function (pdf). The pdf can take the form of uniform, triangular, Gaussian or discrete as appropriate.

3 Run the SRM thousands of times, each time randomly selecting a value from the defined pdf as input to the model and save the output.

4 Plot the output of the previous step in the form of a histogram. This histogram is essentially the pdf of the output that is being analysed.

Upon completion of the above steps, instead of a single value for the model output, let's say instantaneous water cut of a particular well at year 2010, one now have a pdf that would show the minimum, the maximum and sometimes the most likely water cut for that year. Following is a demonstration of the above process.

In this example, the uncertainties associated with capillary pressure values in the three layers above a particular horizontal well is going to be analysed as shown in Figure 10. Once the parameters that are going to be studied are identified, the appropriate pdf can be assigned to each. Then the number of times the SRM (the objective function of the Monte Carlo simulation) should be run for the analysis is identified. This number is identified as 5000 at the bottom of Figure 11. It took less than 6 seconds to make the 5000 runs, and to plot the results as shown in Figure 11.

Figure 10 Assigning pdf to specific parameters in SRM (see online version for colours)

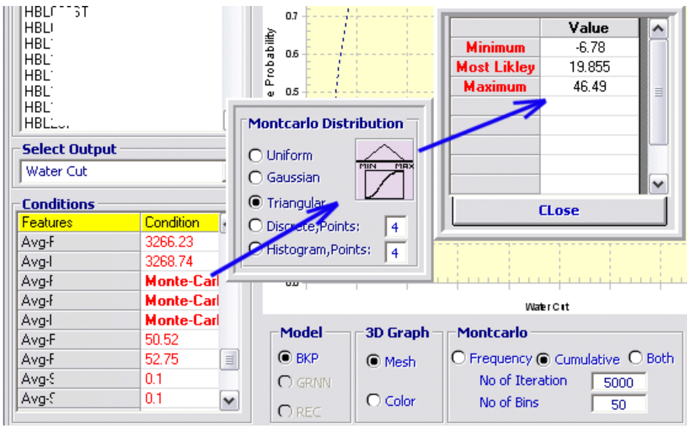


Figure 11 The resulting pdf for the instantaneous water cut of a particular horizontal well (see online version for colours)

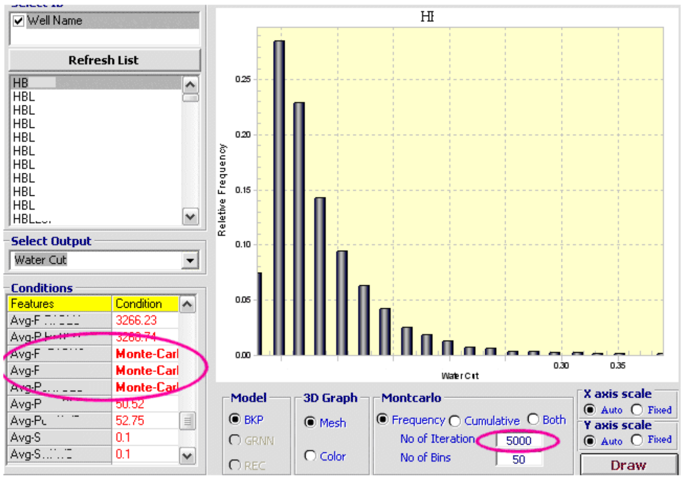


Figure 12 shows the cumulative pdf for the same problem. Also in this figure, one can see that the analysis has been performed for year 5 (end of year 2010) at a liquid cap rate of 1500 barrels per day. Figure 11 shows that for this particular well the most likely water cut is about 5% with possibility of being as little as 2% and as much as 20% with much less probabilities. Figure 13 shows the pdf of cumulative oil production for the same well shown in Figure 11.

Figure 12 Cumulative pdf for the instantaneous water cut of a particular horizontal well (see online version for colours)

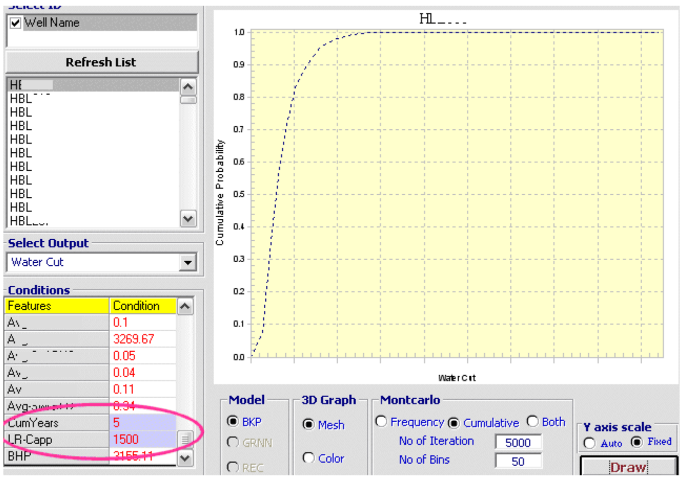
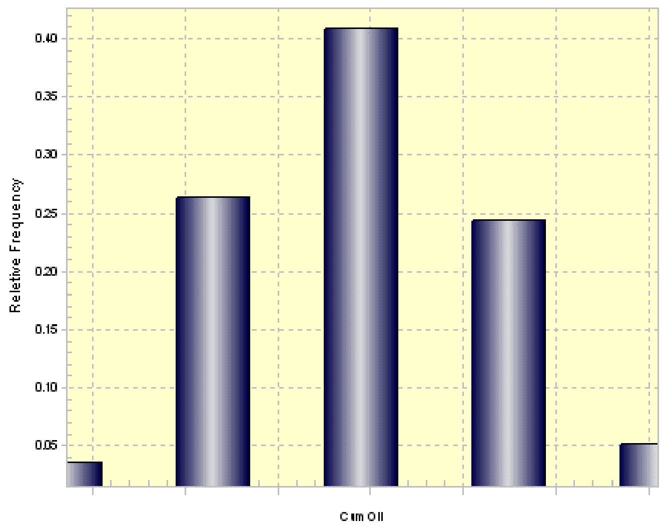


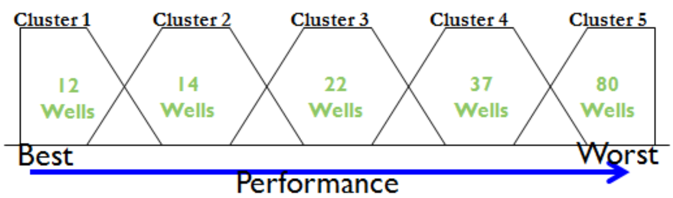
Figure 13 Pdf for cumulative oil (see online version for colours)



8 Results and discussions

Once all the wells were analysed and their cumulative oil production as well as water cut for the next 25 years were calculated (taking into account the uncertainties associated with the geologic model), as shown in Figures 9 through 13. The outcome of the analyses was tabulated all the wells ranked based on their performance (a combination of oil production and water cut in the next 25 years) and then classified using the fuzzy cluster algorithm as part of the same software application mentioned previously. Using this process wells that would benefit the most from rate relaxation were identified. Figure 14 shows the five fuzzy clusters that were identified at the conclusion of the project. As shown in this figure, 12 wells were identified as prime candidate for rate relaxation. It was concluded that these 12 wells have the potential of producing large amounts of oil in the next 25 years as the result of rate relaxation without any danger of high water cut. The 80 wells in Cluster 5 were identified as those that although would produce more oil, their water production may pose serious problems in the future. It was recommended that a thorough economic study be performed on these wells to determine whether the company would benefit from a rate relaxation of the wells in this cluster.

Figure 14 165 wells in the study were divided into five fuzzy clusters based on benefiting from rate relaxation (see online version for colours)



Wells that were classified in Cluster 2 were also recommended for rate relaxation. These wells would also benefit from increase in oil production without any serious threat from high water cut. Wells in Cluster 3 were showing mixed results and some more detail analyses may be required to sift through them in order to identify those with a better chance of good oil production and acceptable water cut. Wells in Cluster 4 showed serious increase in water cut once the rate was relaxed.

Upon completion of the study the operating company decided to relax rate restriction on 20 wells in two batches starting with ten wells in the January of 2006, followed by another ten wells in the February of 2007. To confirm the findings of the project and the effectiveness of the SRM, it was decided to relax the rate restriction on a variety of wells from all of the clusters. Figure 15 shows the distribution of the wells that were increased in production in the past two rounds of rate relaxation.

From the 20 wells that were subjected to rate relaxation four were from Cluster 1, two from Cluster 2, six from Cluster 3, four from Cluster 4 and four from Cluster 5. This distribution not only covered all the clusters, it also covered a reasonable geographic area. Results of the rate relaxation after 2 years of production (less than 2 years in some cases) are shown below.

Figure 15 Cluster distribution of the 20 wells that were subjected to rate relaxation (see online version for colours)

Number of Wells Bean-ed Up	ISI Clluster of Well	
4	1	20%
2	2	10%
6	3	30%
4	4	20%
4	5	20%
20		100%

To show the effect of rate relaxation on oil and water production, total production of each phase (oil and water) was normalised as shown in the following two equations:

$$\Delta Q_O = \frac{(Q_O)_{AF} - (Q_O)_{BF}}{N} \tag{1}$$

$$\Delta Q_W = \frac{(Q_W)_{AF} - (Q_W)_{BF}}{N} \tag{2}$$

where

ΔQ_P = normalised, post-rate relaxation, phase (oil or water) production difference

$(Q_P)_{AF}$ = total phase (oil or water) production for '*x*' number of months after rate relaxation

$(Q_P)_{BF}$ = total phase (oil or water) production for the same '*x*' number of months before rate relaxation

N = number of wells in a given cluster.

Figures 16 and 17 show the normalised, post-rate relaxation, oil production and water production differences for wells from all five clusters. Figure 16 shows a clear reducing trend in oil production from the wells in Cluster 1 (about 900,000 barrels increase in oil production) to wells in Cluster 5 (633,000 barrels increase in oil production), as predicted by the SRM analysis. This trend is even more pronounced when water production (Figure 17) and water cut (Figure 18) values are examined. Please note that increase in water production from wells (and not oil production) was the main concern of the operating company.

Figure 16 Normalised, post-rate relaxation, average per well oil production for wells from each cluster (see online version for colours)

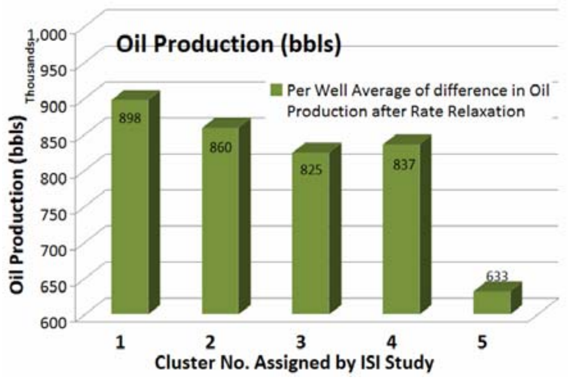


Figure 17 shows the normalised, post-rate relaxation, water production differences for wells from all five clusters. It is notable that water production actually decreases by an average of 4230 barrels per well in Cluster 1 wells and by an average of 3900 barrels per well in Cluster 2 wells, while it has increased by an average of 171,080 barrels per well in Cluster 5 wells. The trend in water production increase in Figure 17 is quite clear. Furthermore, Figure 18 shows the instantaneous water cut for different clusters. In this figure, the maximum water cut before and after the rate relaxation (for the same number of months) are subtracted in order to show the water cut trend in the wells as a function of the cluster they have been assigned to.

Wells in Clusters 1 and 2 show a decrease in maximum water cut, while wells in Clusters 3–5 show an increase in the maximum water cut. These findings (Figures 16 through 18) confirm the accuracy of the analyses performed by SRM.

Figure 17 Post-rate relaxation average per well water production for wells from each cluster (see online version for colours)

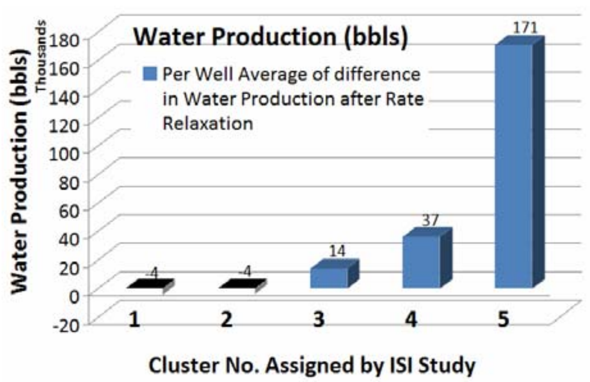
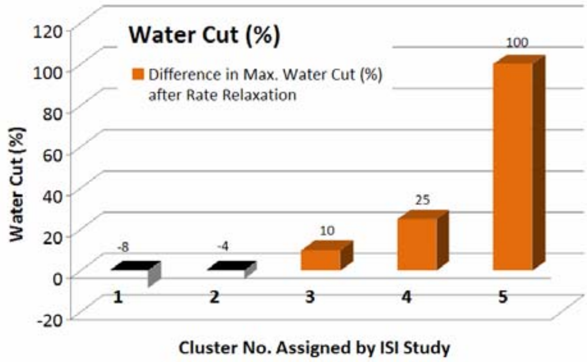


Figure 18 Maximum water cut difference for wells from each cluster (see online version for colours)



9 Conclusions

Details of developing an SRM to accurately represent an FFM for a giant oil field in the Middle East were presented. The steps involved in development of SRM include identification of project objective, representation of static and dynamic data, identification of KPIs and finally training of the SRM model.

The developed SRM was validated using a significant portion of the data that has not been used during the development stage. The resulting SRM was then used to perform uncertainty analysis via Monte Carlo simulation method. Furthermore, the SRM was used to classify the wells in the field into five distinct clusters as a function of their future oil and water production potentials. After the completion of the study, rate relaxation was performed on 20 wells in the field. Oil and water production in the 2 years after the rate relaxation demonstrated the accuracy of SRM analyses.

It is the belief of the authors that SRM will play a significant role as the enabling technology for the smart fields since they are capable of bridging the gap between high-frequency data streams coming from the field and much slower analytical and numerical techniques that are used for reservoir management.

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Nomenclature

ΔQ_P	Normalised, post-rate relaxation, phase (oil or water) production difference
$(Q_P)_{AF}$	Total phase (oil or water) production for '*x*' number of months after rate relaxation
$(Q_P)_{BF}$	Total phase (oil or water) production for '*x*' number of months before rate relaxation
N	Number of wells in a given cluster.