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Integration of a Risk-Management Tool and an Analytical Simulator for Assisted Decision Making in IOR

V. Alvarado, SPE, SDM LLC; E.-M. Reich and Y. Yi, IRIS Research; and K. Potsch, SPE, OMV A.G.

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Abstract

Risk management has become an integral part of the decision-making workflow in the oil and gas upstream business. As many oil fields reach a mature state, the need for rejuvenation and decline mitigation of assets set ground for Improved-Oil Recovery (IOR) opportunities. However, the associated decision-making process requires incorporating screening, reservoir simulation and financial evaluation, demanding complex multidisciplinary team efforts. It is important that any stage of the analysis, technical, strategic and economically sound decisions should be made.

On one hand, IOR screening, whether based on technical grounds or 'gut feeling' experience, or better yet on both criteria, leaves a number of possible IOR processes available for evaluation through simulation. Analytical simulation and applicability screening tools are often favored on early stages. However, their crude application could mislead the decision process if results are not carefully interpreted and combined with reservoir engineering expertise and additional evaluation criteria.

We propose to combine IOR screening strategies with spatial reservoir information to help to create appropriate sector models as starting point for more detailed evaluations. For this purpose, we couple an analytical simulator/IOR screening tool with a software tool that aids framing the IOR decision-making problem effectively, in the form of influence diagrams. From these diagrams, it is possible to create Tornado Diagrams, Decision Trees and Monte Carlo profiles that assist Reservoir Engineers with the task of properly and rationally framing the decision process, for example with regard to economic risk assessment and NPV analysis associated with IOR.

The coupling between both software solutions is proposed in a way that avoids the inflexible monolithic constructions. We illustrate advantages of the proposed approach through a speedy analysis of a publicly available case.

Introduction

We define here Improved Oil Recovery (IOR) operation to comprise the injection of energy and fluids typical of tertiary recovery as well as technologies that enable extension of field life via access to reserves, such as special well architectures. Some of the IOR methods become viable in the current scenario of high oil price. However, IOR projects involve higher complexity than traditional E&P operations, not only because of the typically high CAPEX and sometimes-high OPEX values, but also because of the number of options available, with the concomitant more complex decision-making process. On the other hand, improper choice of IOR processes for a given asset or a portfolio could lead to elevated risks. IOR projects generally follow a workflow that includes screening, preliminary evaluation, detailed appraisal simulation and economic evaluation to launch the project, as described by Goodyear and Gregory[1]. Figure 1 summarizes this workflow. In their paper, Goodyear and Gregory discuss important elements of risk assessment and management of IOR projects. Thompson and Goodyear[2] elaborate further on identification of IOR potential, within the framework of Risk Management. Their approach to using financial risk indicators such as the risk and reward chart that allows one to compare IOR projects with other Exploration & Production projects.

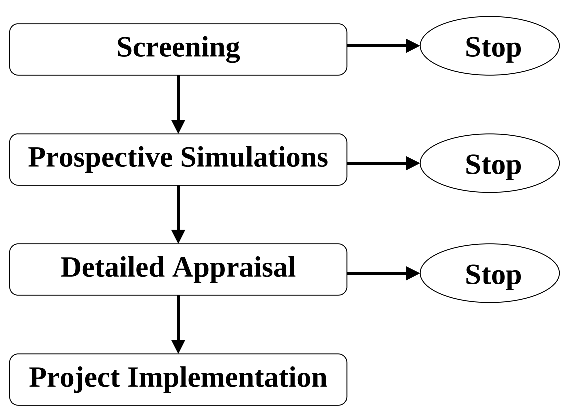

Figure 1. Workflow for IOR decision analysis. Stop flags are necessary to decide if an IOR process needs further investigating (adapted from Goodyear and Gregory[1]).

To manage risk, consistent and rational screening procedures are required as a first step in order to diminish the number of options for detailed evaluation. Generally, this step demands a small set of reservoir and fluid parameters, averaged over representative portions of the reservoir in question. One could argue that this is a feasibility analysis based on applicability limits. A number of options for screening are available, starting from comparison with applicability intervals in lookup tables[3] to more elaborate strategies such as Artificial Intelligence (AI) techniques[4]. In the case of the analytical simulator used here, Sword[5,6], fuzzy-logic has been coded for this process. Tables can also be obtained through data collation of field experiences, working in essence by mining analogue reservoir data in a database. This strategy has also been used successfully in a number of examples and is also available in the analytical simulator. Detailed discussion of this can be found in a number of references[4,7].

Once the screening step is completed, a small set of IOR methods are left as likely candidates. The next step is to determine performance, so that a measure such as additional recovery factor or production profile can be used to rank the remaining methods. Data mining[7] also helps to deal with this issue, but simulation is more commonly used for this purpose, either analytical or sector-model numerical simulation.

To go beyond preliminary economic evaluations, it is necessary to estimate project performance of a given IOR process, and not only prospective simulations. For this purpose, full-field reservoir models are usually developed and numerical reservoir simulation is used to determine process performance. However, mature or brown fields may lack enough reservoir characterization data as to build a detailed model or time represents a constraint for the evaluation. Expected performance may not be enough to justify further data gathering through reservoir re-characterization and review of legacy data. A strategy based on analytical simulation has been proposed to attend this simulation need[8,9]. To facilitate risk management and automate the evaluation process, we have exploited the ability of the analytical simulator to be linked with other Windows application through a COM interface[10,11].

We briefly describe the simulation strategy based on analytical models in the following section. Then, a relevant summary on tools for framing a decision-making process and carrying out risk analysis is presented, followed by an explanation of the linkage between decision-making and risk management software with the analytical simulator. Closing remarks are provided in the conclusions section.

Analytical Simulation

The proposed simulation strategy relies on using a number of sector models, each of which is representative of a reservoir section. Figure 2 illustrates the idea behind this. Each of the well patterns is representative of a distinct sector of the reservoir and its corresponding volume. The way the reservoir is split depends on the information available, but in most cases, interpreted faults from Geophysical surveys, description of depositional environments, net/gross maps and other characteristics of the reservoir and its fluids can be used for the purpose. The choice of sectors may depend on the particular type of IOR methods. In the case of chemical floods, clay content and water salinity may need to be considered.

The steps for the proposed procedure go as follows:

1. ***Definition of clear objectives***. As indicated by several authors[12,13], this step applies to any decision-making exercise. As Coopersmith et al.[13] explain, "Stating the decision problem is the first step to focusing a team's framing effort and shout not be overlooked; it is critical". This step guides the next steps, because here the problem is clearly framed and the important question is formulated. This is not necessarily the entry place for a team to declare the problem, since the givens have to be provided by decision makers before a team works on uncertainties and decisions already framed.
2. ***Data collation***. There are several sources of data that need be consulted, but some essential ones are pay continuity and stratification charazteristics, plus trap structure. Pay continuity can be used to penalize net thickness in analytical models as interwell spacing increases. This way, the recovery factor will be correctly estimated.
3. ***Screening of IOR methods***. This is the beginning of the flowchart in Figure 1. This step can be automated by using more local reservoir property values, instead of representative average values. However, this was not studied here, but it is being investigated.
4. ***Critical Project Parameters (CPP)***. Among the list of tools in decision-making analysis, it is the Tornado Diagram the one that is perhaps the most appropriate to assist this step. Automation of this step leads to speedy evaluations. No operational or local restrictions are included in this step.
5. ***Sectioning of the Reservoir***. One of the examples previously analyzed[9] illustrates this clearly. A distribution of CPP's on the reservoir map could serve for this purpose[8].
6. ***Local history match***. This step focused on fitting pilot area results, which usually are more intensively characterized. However, this is not a necessary step, although it allows diminishing some of the uncertainty. If the decision problem at hand does not accommodate or need this step, it can be skipped altogether.
7. ***Sensitivity analysis***. Once the intervals for uncertainty are more clearly defined and the project is evaluated on field-based cases, then a full-field sensitivity analysis can be carried. As previous step, this one is a function of how the decision-making problem is framed.
8. ***Decision analysis***. The results of the full-field analysis can be used to feed a decision-analysis tool such as an Influence Diagram or a Decision.Tree[12]. Monte Carlo simulations can be performed by sampling the parameter space of important uncertainties (once the CPP's have been obtained).

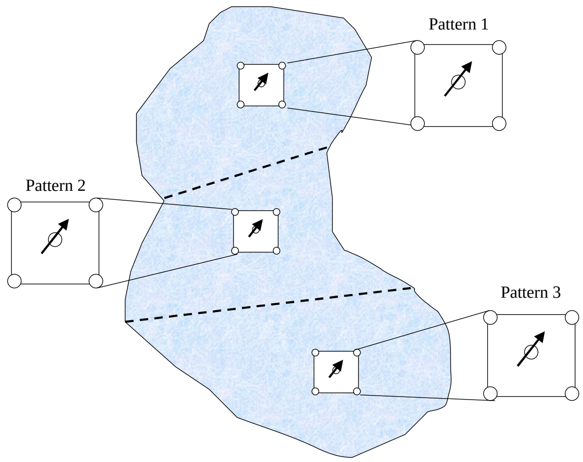

Figure 2. Sketch of a hypothetical reservoir map and representative well patterns for 3 reservoir sections.

It is step 8 the one that more clearly illustrates the need for automation of the data flow among different applications. While it should be apparent that an analytical simulator is well suited for a large number of different simulations, the evaluation of each scenario or case would become a tedious process. This in turn defeats the fast simulation time of the simulator. A possibility already implemented in the suite of the Department of Energy (DOE) Simulators is a direct economic evaluation or even a Monte Carlo simulation for Risk Analysis pruposes[14]. DOE analytical simulators represented great progress, but the lack of flexibility in this monolithic programming style does not allow to adequate the simulator to the frame of certain decision-making processes. This motivated a more flexible concatenation among different software tools. We will describe this scheme in the following section.

A word of caution in regards to the use of analytic solutions is necessary. In order to make sense of the decision-making analysis, the analytic solution should be physically meaningful to capture the recovery mechanisms. In this sense, for instance, compressibility effects are not captured by analytic solutions in Sword (except for a Cyclic Water Injection module). Well patterns are limited to either a set of one injector and one producer in a 2D section or a 5-spot model in 3D (an approximate extension by using a correlation). The reservoir is layer-cake type, with analytic solutions provided for either Dykstra-Parson (DP) or Vertical Equilibrium (VE) approximations. These two approximations can be used as limiting cases for either no vertical communication, and therefore no gravitational segregation, or complete vertical communication. Now, during execution of steps 4 and 6, validation runs should be carried out to choose the better approximation.

Figure 3 depicts the cumulative oil recovery (or recovery factor) as a function of time for a waterflooding (WF) case. The simulation was carried out for several values of the oil viscosity (1, 10 and 50 cp from top figure to the bottom one) and several IOR processes, although only WF results are presented. A total of 10 layers were defined for the model simulated, but a number of cases for up to 25 layers were evaluated. A Dykstra-Parson coefficient of V=0.1 was used to distribute the values of the horizontal permeability (the data were taken from a heavy-oil reservoir study). A Kv/Kh value of 0.5 was used, which is consistent with the known information of the unconsolidated sandy reservoir. UTCHEM 9.82, the University of Texas Chemical Simulator[15], was used to numerically simulate the waterflood in incompressible mode. An equivalent model was simulated using Sword for both DP and VE solutions. Notice that although both approximations seem adequate an oil viscosity value of 1 cp, it is the VE approximation the one that better predicts the recovery factor as well as production rate and water cut (not shown).

One more point to consider is that no injectivity restriction is being considered in rate-controlled analytical simulations. However, injector-to-procuder pressure-drop boundary conditions can be used out to estimate how realistic the rates are for given reservoir characteristics.

Finally, pay continuity should be used to adjust available net pay to be consistent with the interwell connectivity. A smooth decaying function, C(d), with d the interwell distance, can be defined on the basis of geologic information (sedimentary environment and prior experience in the field or analogue reservoirs).

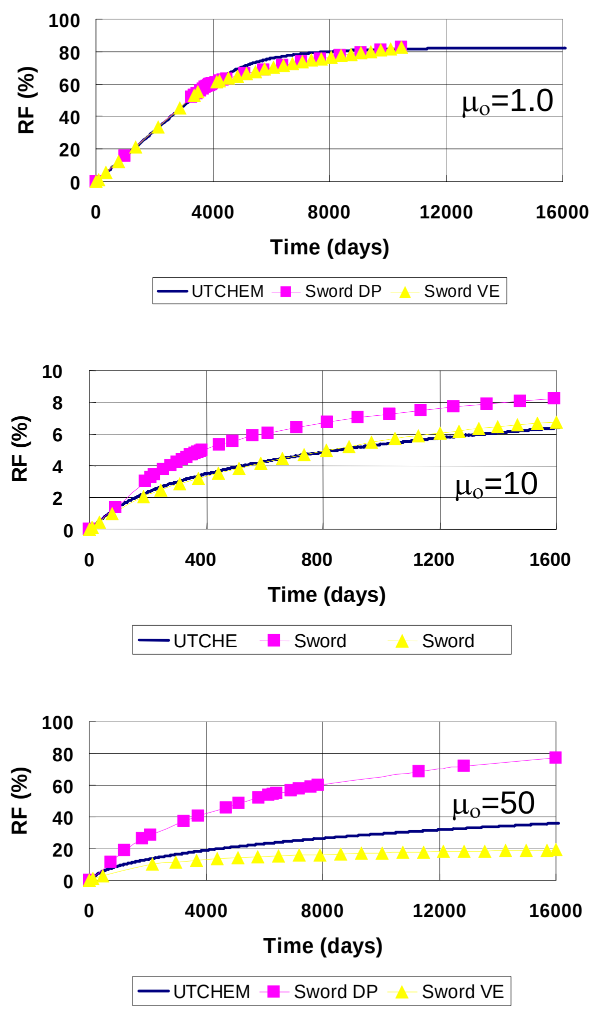

Figure 3. Recovery factor (cumulative oil recovery) as a function of time for a waterflood in a 5-spot pattern. Oil viscosity changes from 1cp (Top), 10 cp (middle) to 50cp (bottom).

Computer-assisted decision-making

In this section, we explain how we proceeded to link a decision and risk analysis tool and the analytical simulator. There are several software tools that allow users to assist decision-making. In this instance, we recurred to DPL, a program developed by Syncopation software. The choice was made becomes of the intimate link between DPL and Excel, as well as for the possibility of using Influence Diagrams and then directly generate all other results (decision trees, tornado diagrams, risk profiles, etc.) from the Influence Diagram.

Figure 4 depicts an influence diagram (top right pane) and the corresponding default decision tree (bottom pane). The influence diagram is comprised of value (rounded squares), uncertainty (ovals) and decision (squares) nodes and arcs to represent influences. The diagram is built from right to left, and the number of details of the model increases in the same direction. The basic decision model is represented with this construct. The rightmost node is the objective function, in this case represented by the Net Present Value (NPV). The simplest cash flow or economic model requires the Capital Expenditure (CAPEX) and the Operational Expenditure (OPEX), plus sales or positive cash flow. In practice, tax and royalties have to be taken into account, but the financial model of a particular project is of no importance for the discussion. As the diagram indicates, the essential contributor to positive cash flow is the hydrocarbon production profile as it is the main source of sales, which in turn is calculated from the reservoir simulation. Once important elements of the decision model have been incorporated, the model can be run to determine which of the options considered the most profitable (highest NPV) is. Values can be linked to an Excel workbook, so that the values are calculated in Excel.

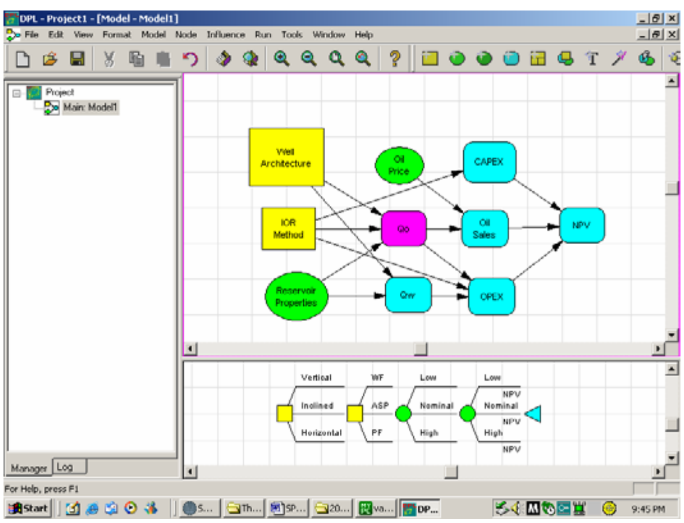

Figure 4. Snapshot of a DPL project. Upper right pane shows an influence diagram, while bottom pane contains the corresponding decision tree.

Figure 5 shows a datasheet for the analytical simulation. Each time some of the parameters need be changed to consider a new scenario, the simulation has to be run manually and the results have to be saved. One example of this is the evaluation of the impact of uncertainties on NPV, if that is the objective function, or recovery factor or some other quantity. Going back to the influence diagram in Figure 4, the uncertainties associated with the reservoir properties could be the values of the horizontal permeability for each layer, net pay value, end-point relative permeabilities among other parameters. However, the data do not need to be transcribed manually, because the simulator can be linked to Microsoft Windows applications such as Excel through COM interface. Calls of Visual Basic Script code (VBA) to Sword can transfer data to the simulator and recall results back to Excel, after execution of a given scenario. In principle, any number of calls can be easily programmed via VBA and a number of IOR methods can be evaluated, depending on the needs of the decision-making framework.

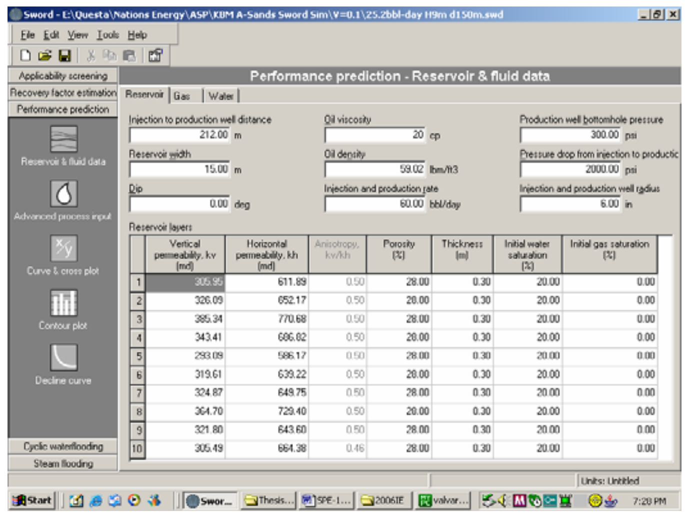

Figure 5. Snapshot of Sword datasheet for simulations. Gas and water data are provided in other datasheet (not shown).

What the last aforementioned connection through VBA calls implies is that because of the ability to intimately link influence diagrams with Excel, and likewise with Sword, then it turned out to be relatively easy to read out information from multiple simulations and several sector models to recreate a variety of decision problems using analytical results.

Figure 6 shows a possible scheme to develop a computer-assisted decision-making process that carries out automatic calls to the simulator. This would apply to a case for which an influence diagram was already prepared by an asset team. This linkage would require loading worksheets with each sector-model data set. However, the process can start directly from the workbook and the use the calculation links in worksheets to create the appropriate influence diagram. This option is already available in the software package tested here and is certainly operative in risk management tools running in Excel. Once the basic influence diagram is generated, one can work directly with the nodes. For instance, value nodes that define input variables can be changed to uncertainty nodes, whether continuous or discrete, so uncertainty propagation can be analyzed. This way, the process is steered from the Decision and Risk Management tool, which allows one to update the worksheets containing the models. The automated scheme can be further facilitated by using spreadsheet templates that contain the necessary VBA scripts.

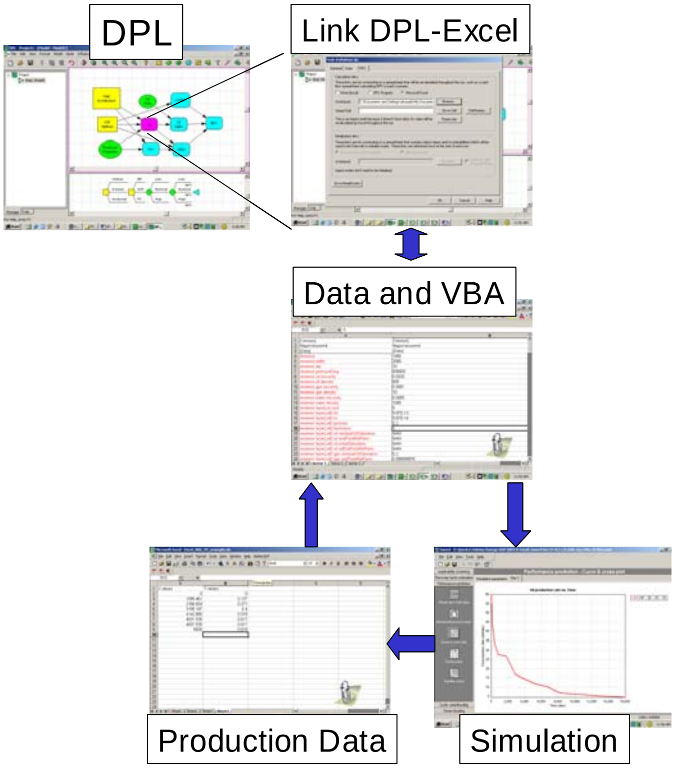

Figure 6. Automation diagram linking Influence diagrams to analytical simulator through VBA applications.

Conclusions

The ideas proposed and tested here allowed us to automate a simulation results processing for a variety of decision-making and risk analysis strategies through linkage between applications. The programming structure of the software tools used here facilitates tasks such as running a decision analysis or assisting risk analysis evaluations through VBA programming. Enough flexibility is built in for the scheme to adapt to a variety of decision and risk analysis problems in IOR

The full-field simulation scheme is not intended to replace numerical reservoir simulation, except in situations when time constraints or lack of data limit the development of the necessary reservoir model. This idea was originally conceived to deal with a portfolio of similar assets for which frequent reviewed can only be accomplished with fast simulation techniques.

We are currently developing a real-reservoir case to be presented elsewhere. The focus of the research is to apply the methodology to evaluation of chemical methods such as polymer, surfactant or alkaline-surfactant-polymer floods. An interesting development to pursue is the possibility to automate the creation of applicability maps based on screening criteria. This possibility is not currently available.

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