Transfer of Reservoir Uncertainty in SAGD Projects

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The transfer of the uncertainty in the reservoir and fluid properties as well as the uncertainty of operational parameters of a SAGD process, by means of proxy models as efficient substitutes of thermal reservoir simulation, is investigated in this work. Two different methodologies for the generation of simplified models are evaluated, including the application of Design of Experiment techniques along with Response Surface Methodology; and physical based proxy models from Butler's SAGD theory. The workflows of both methodologies together with results from examples of the uncertainty assessment of the SAGD performance are illustrated. Those results demonstrated the advantage of using physical based proxies over entirely empirical models.

Introduction

During any oil & gas field development process, investment decisions follow an information cycle that starts from acquisition, processing and interpretation of subsurface data, creating the information needed to construct mathematical models used, in turn, to assess the reservoir performance under some controllable assumptions, which necessarily involve investments (e.g. number of wells, type of well, etc.). Different field development scenarios are generated, and decision criteria are applied in order to select and implement the optimum production scheme. Once the wells are drilled and production starts, more information is available for feeding-back the cycle.

Mathematical models generated by numeric reservoir simulation plays a critical role during such information loop. Reservoir simulation is one of the most important tool engineers have to make and support decisions about field development. This fact has historically guided the R&D efforts on reservoir modeling towards improving the modeling of physical processes that could occur within an oil & gas reservoir. Thus, more precise numerical approximations with greater number of gridblocks and smaller time-steps are being used, pursuing a higher degree of detail in the physics representation of the recovery process.

Numeric reservoir simulators are then available for predicting the reservoir performance of very complex process as it is the case of the Steam Assisted Gravity Drainage (SAGD). The intrinsic temperature transient behavior of this thermal recovery process, especially at the steam front which has to travel through the cold reservoir; the compositional and multi-phase nature of the problem, since different fluid components might appear in aqueous, oleic or gaseous phases; along with the reservoir heterogeneity, make the numeric solution the best approach to accurately model the physics of the problem.

However, the paradigm of very detailed reservoir modeling fails when the transference of uncertainty from reservoir variables to any performance variable of a SAGD project is required. This is evident, for instance, when Monte Carlo Simulation is applied, using as transference function the thermal reservoir simulator. Since the complex numeric solution leads to high computational time, unfeasible times would be require to depict an unbiased description of the uncertainty of the given SAGD performance variable. Not modeling adequately the uncertainties during a SAGD development project increases the chance of making biased decisions and underestimate the risk.

A change in the paradigm of very detailed modeling has been suggested in the literature, see for example Bos, 2004, in which some precision in the physical modeling should be sacrificed in order to efficiently integrate the uncertainty modeling to the field development studies and thus, be able of improving the making decision process. The use of proxies or simplified models instead of highly complex and time-consuming reservoir simulators, it seems to be the key in order to efficiently integrate the uncertainty modeling into the SAGD development studies. The challenge, then, is to efficiently generate proxies, as precise as possible, to be used as efficient substitutes of the reservoir simulator to successfully incorporate the uncertainty analysis into the reservoir management process of SAGD projects. The precision mentioned before is related to the degree of representation of the physical reality. This reality might correspond to actual production information coming from a pilot project, for example or by the results from a more detailed reservoir numerical model.

The proxy-modeling methodology includes invariably a calibration process which supplements the lack of modeling precision by using some empirical factors that adjust the proxy performance to more truthful production information. Three different strategies of proxy-models generation has been identified in SAGD projects: 1) static measures of the goodness of reservoir fitted to a reservoir simulation response, see for example McLennan et al; 2) use of Design of Experiments (DOE) and Response Surface Methodology (RSM) to generate polynomials fitted to reservoir simulator responses, see for example Vanegas et al, 2006 and 2007; and 3) physical-based proxies which are also adjusted to SAGD simulation responses, Vanegas et al, 2008.

This work aims to illustrate the methodology of the latter two proxy-model generation strategies by examples of application to synthetic SAGD reservoir models.

Proxy-models generated by DOE

Experimental design techniques and response surface methodology are being, nowadays, widely used to build totally empirical models, without any physical basis, of reservoir simulators. In general, experimental design theory explains how to sample, over the operational region, the number of cases and levels of input factors used in the simulation work to achieve the most information at the lowest computational costs. On other hand, response surface methodology focuses on developing simple models using Linear Regression Analysis by finding the coefficients of a selected model through the minimization of the mean sum of square errors between the proposed model and the simulator outputs.

In a reservoir simulation study the factors are the input parameters of a numeric reservoir simulator that affect the response of any reservoir performance variable; and the levels are the values given to the input factors used to run the chosen set of reservoir simulation cases.

A structured workflow to apply DOE techniques to reservoir simulation studies has emerged along the time (Peng and Gupta 2004, White and Royer, 2003, Dejean and Blanc 1999) and is shown in Figure 1. The first stage is the pre-experimental planning, where expert knowledge is required to list the input variables, factor ranges and probability distributions. The construction of the empirical model usually requires an initial screening stage where the most influential variables and their effects over the simulation response are identified, thus, the number of variables is decreased and so the simulation effort needed to build the proxy. Experimental designs at two levels are required during the screening process, examples of those designs includes full and fractional factorial designs, see Barros, B., et al, 1995.

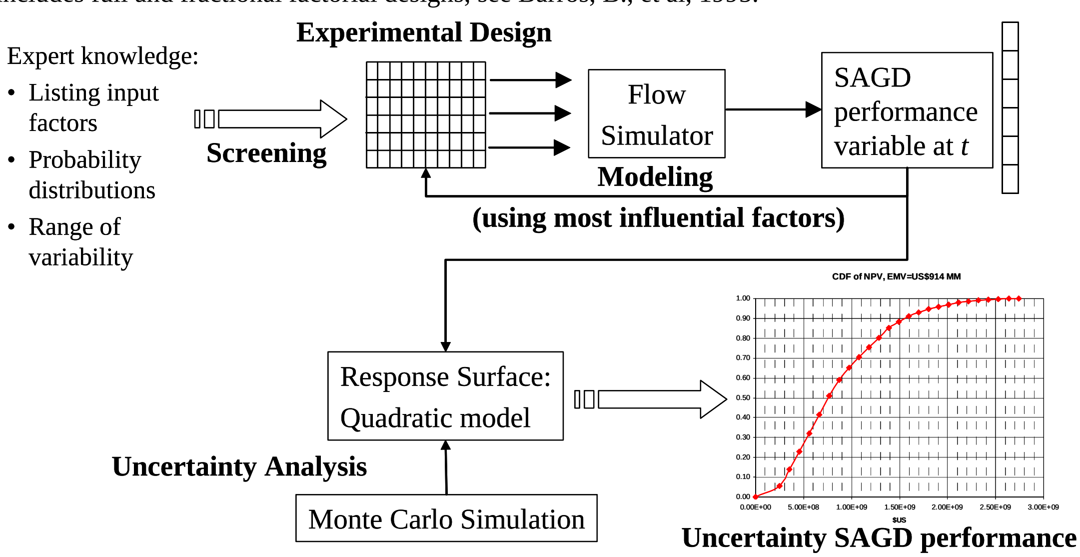


Figure 1. Design of Experiment Workflow

Once the most influential variables are selected, a new experimental design is built, this time using more than two levels, thus, the non-linearity of the response can be represented by quadratic or higher order terms within the response surface. Designs used in this stage are: D-optimal, Composite Designs, fractional factorial designs and Box-Behnken designs, details about those designs are found in Myers, H. and Montgomery, D.C.

In the model construction stage, multivariate linear regression theory is used in order to find the coefficients on a pre-selected model. Quadratic models have worked very well in most of the petroleum applications. Stepwise techniques are used to improve the quality of prediction by iteratively removing the non-significance terms. Statistics as prediction error sum of squares and coefficient of multiple determination are used to measure the quality of the model, (Dejean and Blanc, 1999).

Once the model is built and accepted as good predictor it can be used to determine the probability distribution curve of the SAGD performance variable using Monte Carlo Simulation. The input parameters are modeled as random variables described by given probability distribution functions, then random sampling from those functions along with the use of the regression model allows the estimation of the uncertainty of the SAGD performance.

This methodology is illustrated using a synthetic 2-D reservoir model of a single SAGD well pair, where the main purpose was to generate a proxy model to predict SAGD performance, in terms of maximum Net Present Value over 15 years of production. Simulations were performed using a two-dimensional model in a homogeneous and isotropic reservoir. This example is presented with all details in Vanegas, et al, 2006.

The reservoir/fluid parameters chosen for the preliminary screening are depicted in Table 1. This analysis was done using a two-level fractional factorial experiment design consisting of 32 simulation cases. In a two-level design, maximum and minimum values, codified as +1 and -1, respectively, are selected to represent the entire range of variability of each parameter. Details about the fractional designs can be found in Box, G.E., et al, 2005.

After running the simulation cases the effect of each input variable over the NPV of the SAGD project is calculated and plotted in the Pareto plot of Figure 2.

Table 1. Range of variability of variables used in the screening analysis, after Vanegas et al, 2006

Parameter	**Min. (-1)**	**Max. (1)**
Porosity (fraction)	0.25	0.35
Vertical permeability (md)	700.00	2,500.00
Ratio of vertical to horizontal permeability	2.00	3.00
Thickness (m)	20.00	40.00
Oil viscosity	60,000.00	2,000,000.00
Methane content (gas mole fraction)	2.00	15.00
Oil saturation (fraction)	0.65	0.85
Rock thermal conductivity (J/m C day)	450,000.00	750,000.00
Injector and producer spacing (m)	5.00	12.00
SAGD well pattern spacing (m)	50.00	150.00
Max. steam injection rate (m3/d)	200.00	600.00
Preheating period (days)	50.00	200.00
Operating pressure (KPa)	4,000.00	8,000.00

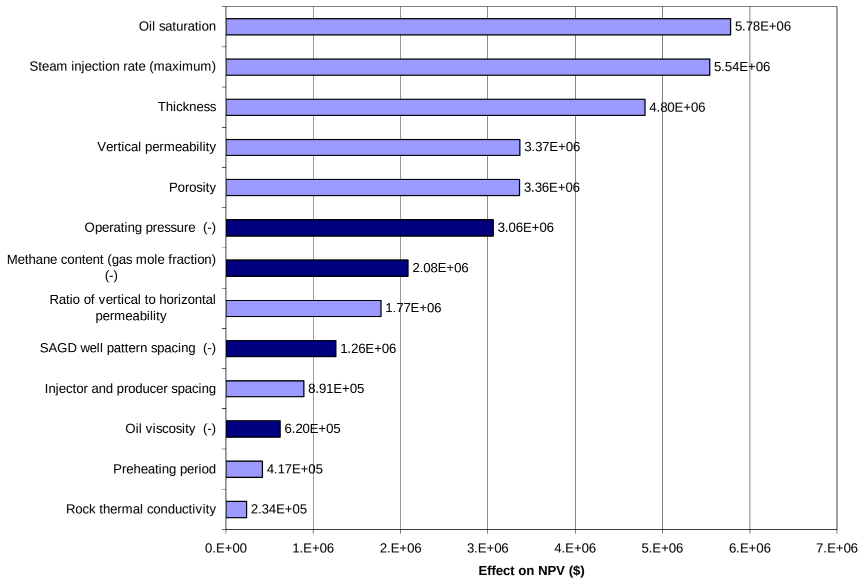


Figure 2. Pareto plot of effects, after Vanegas et al, 2006

According to Figure 2 the oil saturation is the most influential factor on the NPV of the SAGD project considered in this example. A change in the oil saturation from 0.65 to 0.85 causes an average increasing of $5.87 MM on the NPV. The most influential variables were identified as oil saturation, maximum steam rate, reservoir thickness, vertical permeability, porosity and operating pressure. Those factors were chosen by fitting the NPV output to a linear regression model. The parameters used to fit the best linear model would be the most influential, since their coefficients in the linear model also have the most statistical significance. The selected variables were then used to fit a quadratic model by sampling the operation region using a set of 77 simulation cases defined by a Central Composite Design (CCD). Details about the theory involving composite designs and response surface methodology appear in Myers, R.H., and Montgomery, D.C., 1995. The results of the 77 simulation cases were used to calculate the coefficients of a model that minimized the Prediction Sum of Squares (PRESS). The minimization of PRESS allows increasing the power of prediction of the model which can also be expressed in terms of the normalized Q^2 statistic. Another useful statistic is the R^2_{adj}, which is the adjusted coefficient of multiple determination. R^2_{adj} measures the percentage of variability observed on the response and explained by the regression; it is adjusted to be able of comparing the different possible models, since the simple R^2 statistic will increase when adding more terms to it, see Dejean, J. P., and G. Blanc, 1999. The chosen model consists of one constant term, six linear terms; 16 quadratic terms, among quadratic and two-factor interactions; and 11 three-factor interaction terms. The statistics of this model: R^2_{adj} =0.963 and Q^2=0.937, along with the comparison of the NPV predicted by the proxy and the observed from the simulator in Figure 3 shows the good performance of the proxy model.

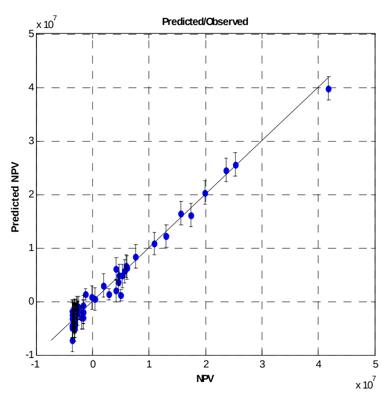


Figure 3. NPV predicted by proxy versus NPV observed using simulation, after Vanegas et al, 2006

Finally, the uncertainty in the NPV can be easily assessed using Monte Carlo simulation over the response surface model. In this example all random variables were assumed to follow triangular probability distribution functions except the operating variables: maximum steam rate and operating pressure which were modeled using uniform probability distributions. After 50,000 realizations of the random variables the cumulative distribution function of the NPV was calculated and it is depicted in Figure 4.

The simplicity in the proposed regression model makes it an appropriate tool to efficiently assess the uncertainty of the SAGD process, however the flexibility of this methodology is limited by some restrictions including: - the difficulty to include the variability of geologic variables along the reservoir into the response surface function; which is the fact one of most influential factors affecting the production performance of a SAGD project; - the limitation of the proxy model to extrapolate the input variability range of the independent variables; this is consequence of the lack of physical basis in which the response surface model is built; and - the inability to reproduce the time-dependent characteristic of the simulation response, which would allow to know the behavior of the SAGD performance uncertainty in time.

The previous restrictions in the application of DOE techniques motivated the exploration of analytical solutions of the SAGD process as proxies for the thermal reservoir simulator with the final objective of incorporate the uncertainty analysis in the reservoir management of SAGD projects.

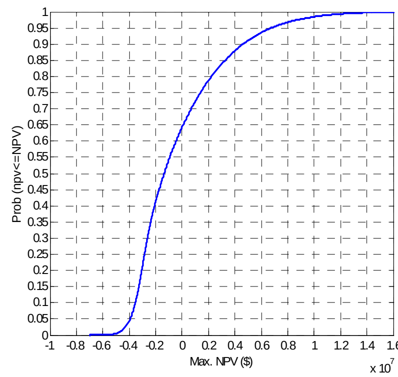


Figure 4. CDF of. NPV, after Vanegas et al, 2006

Physical based proxy

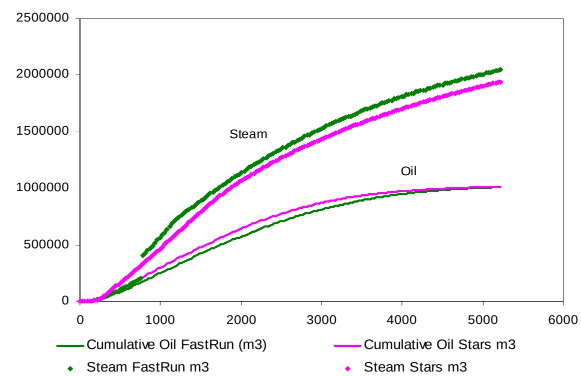
Analytical models of oil recovery processes as SAGD are based on ideal assumptions that simplified a lot the complexity of the physical process; however they are able to include the main mechanisms that drive the process by defining the relationship among the input variables that correctly describe the physical phenomenon. This is a great advantage over simplified models built based exclusively on the regression techniques showed in the previous section. The analytical solution of the SAGD process can be viewed as an adequate trade off between the physics representation of the very detailed and complex numeric reservoir simulators, and the simplicity of empirical models built using DOE and RSM techniques. This special characteristic makes it an excellent candidate to build efficient and very reliable proxies for the assessment of uncertainty of SAGD performance.

A proxy model methodology was developed based on the Butler's SAGD theory described in a 1987 paper and also with more detail in Rose's PhD thesis, 1993. The details of the modeling strategy for such proxy model appear in Vanegas et al, 2008.

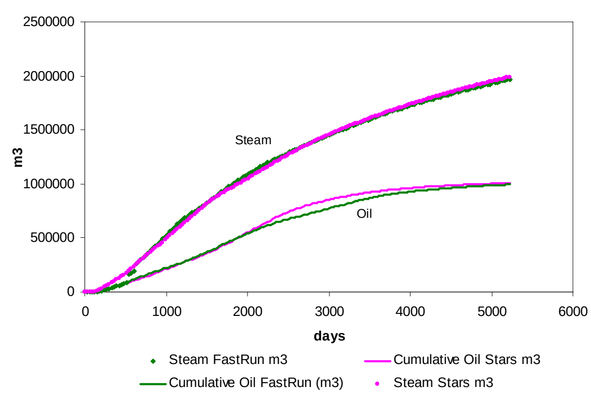
The physical based proxy-model proposed in this methodology allows the prediction of oil flow rate, cumulative oil production and cumulative steam injection time-profiles during both: the rising and spreading steam chamber periods for a confined SAGD well pair. Important modifications to the original Butler's model were implemented to suit it as surrogate model of the thermal reservoir simulator, including: - coupling the Butler's models for both stages of the SAGD process: the steam rising and steam spreading periods for a confined well pair; - calculation of the average relative permeability as a function of the instantaneous steam oil ratio for each time-step; - implementation of suitable correlations for the calculation of fluid properties as well as the option of using tabulated fluid properties; - the heterogeneity of the reservoir was explicitly contemplated by a convenient averaging of the reservoir properties along the interface, taking advantage of the time discretization as well as the discretization of the interface employed by the original Butler's model; - adjusting factors were implemented to fit the model to field measurements or flow simulation results; and – the stochastic calculation of SAGD production variables was implemented through Monte Carlo Simulation, allowing the use different geological realizations together with proper probability distribution functions attached to the other rock/fluid properties and operational parameters. This probabilistic SAGD performance tool was named with the acronym of FastRun: Forecasting Analytical SAGD model for Transference of Reservoir Uncertainty.

The good performance of the proxy model can be observed in Figure 5a and 5b. Figure 5a shows the cumulative oil production and cumulative steam injection results from FastRun, without applying any adjusting factor, compared to the solution coming from the thermal simulation of a single and homogeneous SAGD well pair. The good behavior of the proxy validates the physical assumptions used by the Butler's model as well as the modifications implemented on it.

On other hand, Figure 5b shows the comparison of the production results between FastRun and the reservoir simulator for a very heterogeneous SAGD well pair. In this case the proxy was adjusted to the simulation results by modified factors. As in the homogeneous case, the results coming from the fitted proxy are very close to the simulation results, encouraging the application of the proxy to the uncertainty analysis. A workflow for the application of FastRun as stochastic prediction tool is illustrated in Figure 6.



a) Homogeneous case, and no adjusting factors



b) Heterogeneous case, and fitted proxy

Figure 5. Comparison of production results between FastRun and flow simulation

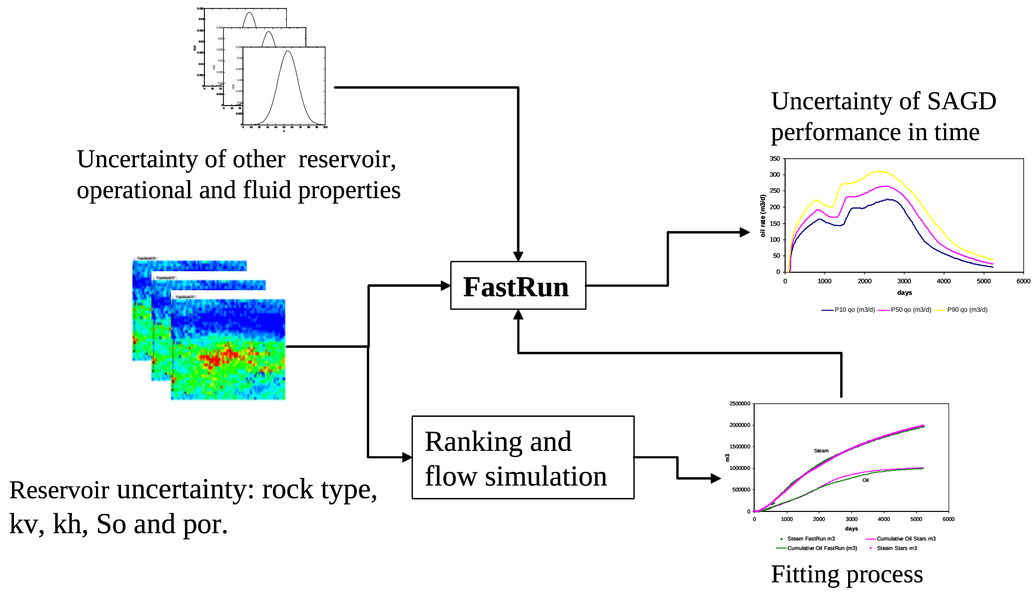


Figure 6. Workflow for the uncertainty assessment of SAGD performance using FastRun

The transfer of the uncertainty from the reservoir / fluid properties and operational parameters to the SAGD production variables using the physical based proxy requires an initial fitting process. This process aims to complement the modeling deficiencies of the analytical model by defining some empirical factors that adjust the proxy results to more truthful production information, which can be the output of a reservoir simulator or actual production data. A set of different and probable production possibilities is used to fit the proxy model, mainly over a range of reservoir realizations, in order to obtain a solution of wider applicability.

A previous selection of the geological realizations used to run the simulation cases during the fitting process is also required. This is done by ranking the different geological realizations that define the reservoir uncertainty model. Static measures like the Original Oil In Place (OOIP) or connectivity measures of geological objects can be used to select a set of geological realizations that covers the range variability of such ranking parameter. The results of the same prediction tool, FastRun, with no adjusting factors can also work as ranking parameter.

Once the selected simulation cases are run, their results are used within a simulated annealing type of optimization algorithm focusing the minimization of the mean square error of the cumulative oil production and cumulative steam injection.

The fitted proxy is then used as main “machine” during the stochastic calculation of the SAGD production variables. Besides the transference of the uncertainty in the spatial distribution of geological variables as rock type, vertical and horizontal permeability, oil saturation and porosity, the proxy allows the transference of uncertainties in the reservoir/fluid thermal properties, residual oil saturation, steam injection pressure, steam quality, oil API and start-up time defined from specific probability distribution functions, through the SAGD production variables.

This methodology was applied to a single SAGD well pair where the reservoir uncertainty model was defined by one hundred realizations of the geological variables along with a sample of fifty reservoir/fluid properties and operational parameters values per geological realization. Details of the reservoir description and the example itself appear in Vanegas, et al, 2008.

Figures 7, 8, 9 and 10 show the FastRun outputs, after running the 5,000 different cases, of the uncertainty in the oil rate, Cumulative Steam Oil Ratio (CSOR), cumulative oil production and cumulative steam injection, respectively. The uncertainty is represented by a band between the P10 and P90 curves as a function of time.

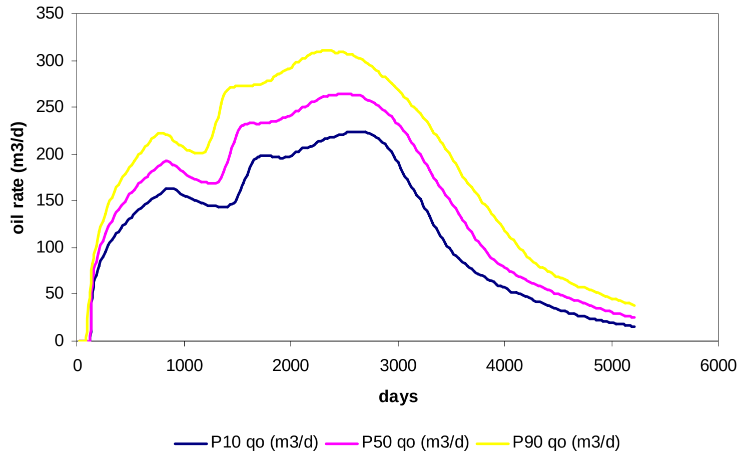


Figure 7. Uncertainty in the oil rate of a single SAGD well pair

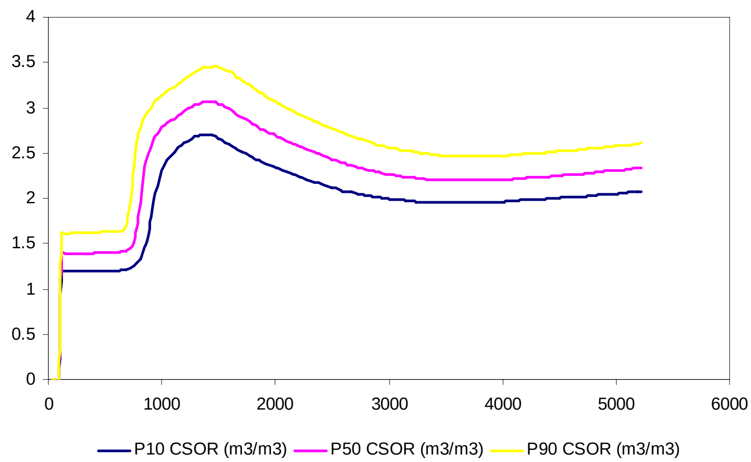


Figure 8. Uncertainty in the CSOR of a single SAGD well pair

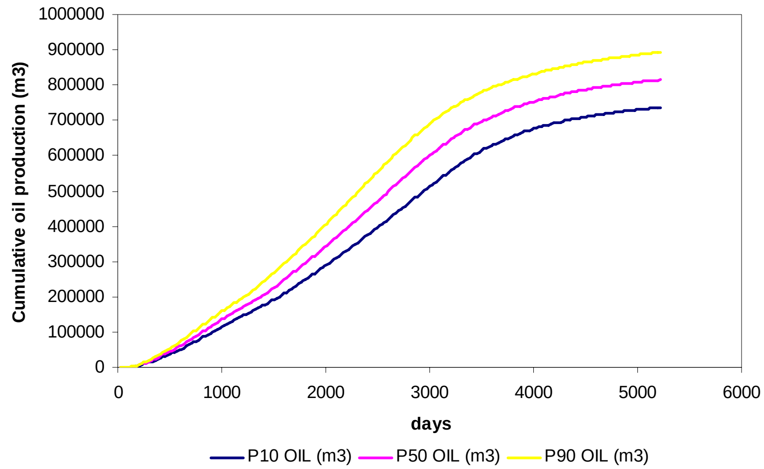


Figure 9. Uncertainty in the cumulative oil production of a single SAGD well pair

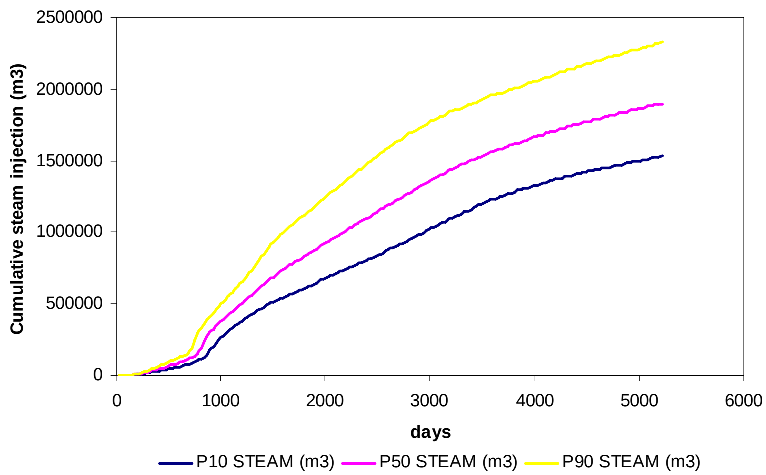


Figure 10. Uncertainty in the cumulative steam injection of a single SAGD well pair

The results showed in the previous plots permit the estimation of the uncertainty at any time during the expected production time of a SAGD well pair. This information, incorporated in the production management of any SAGD project, would help to make sounder and better decisions.

Conclusion

Two different approaches to transfer the uncertainty from reservoir / fluid and operational parameters to SAGD performance variables through fitted simulation proxies were investigated; namely: proxies generated using Design of Experiment (DOE) techniques along with Response Surface Methodology (RSM); and physical based proxies. Although, DOE & RSM techniques are useful to generate efficient simulator surrogates, they are not flexible enough to include the uncertainty of the spatial distribution of reservoir variables, as well as the time dependency of the SAGD performance variables. Those limitations are overcome using the proxy models based on the Butler's theory of the SAGD process. The physical based proxy, after a proper fitting process, permits an adequate balance of precision and efficiency, making it ideal to use it as surrogate of complex reservoir simulator during the assessment of the uncertainty of the SAGD performance.

The physical proxy also offered the possibility to estimate the uncertainty of SAGD production variables using 3-D reservoir models in large areas (multi well pair scenarios), which is an impossible task for conventional reservoir simulators.

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