Global Optimization and Uncertainty Assessment for History Matching the Valhall Field

A study was made of a global-optimization method to history match a complex reservoir model. Evolutionary algorithms (EAs) were applied, and methods for improving the convergence of the optimization cycle were used. Sensitivity parameters, correlations, and parameter trends were identified in a global search space, and an uncertainty assessment of the most recent history match was carried out with an experiment-design matrix.

Introduction

The focus of this study was to assess the Valhall field reservoir-simulation model by use of EAs and uncertainty assessments to improve the manual history match of the model. The Valhall field is complex with rock compaction as the main drive energy, which contributes to many challenges, including the reduction of porosity (ϕ) and permeability (k) with time and continued change of reservoir thickness caused by the compaction. The compaction can affect different parts of the reservoir differently. For example, the reduction in the pore volume can vary between regions, resulting in problems with the history-matching process in which changing a particular parameter can have opposite effects on wells or regions. **Fig. 1** shows the workflow used for uncertainty assessment.

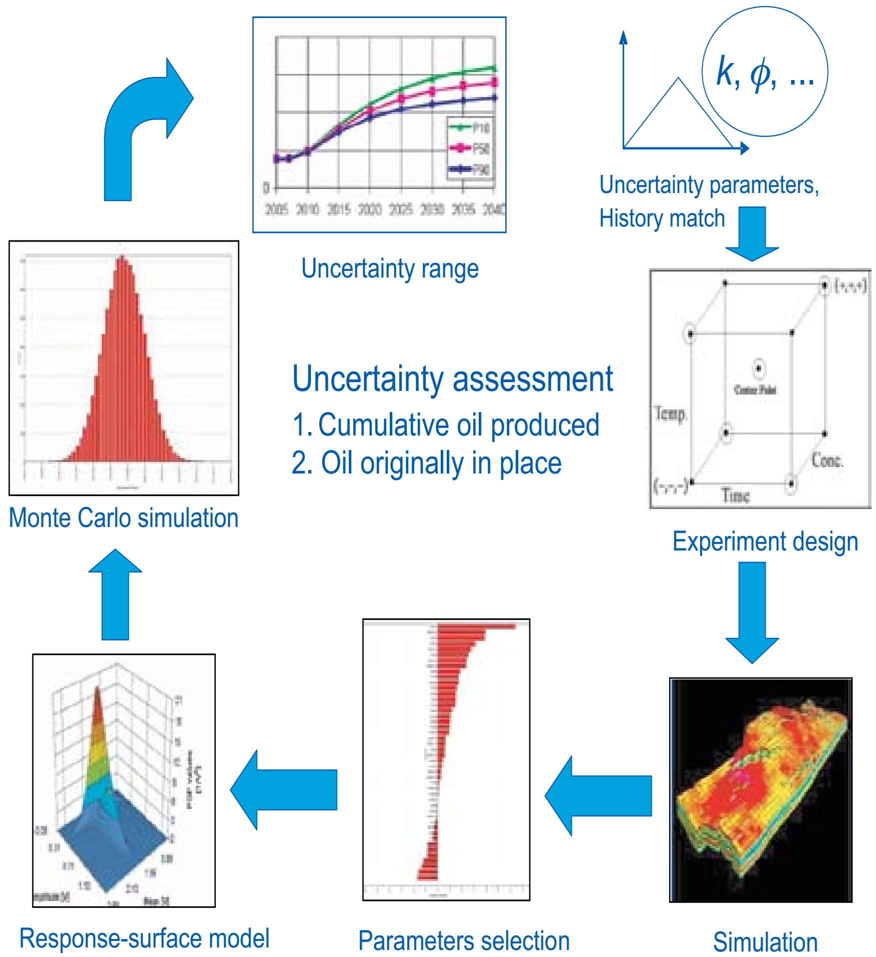

Fig. 1—Uncertainty-assessment workflow.

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The Valhall field is an oversaturated Upper Cretaceous chalk reservoir in the North Sea approximately 290 km offshore Norway in 69 m of water. Discovered in 1975, oil production began in 1982. Oil originally in place was estimated at 4.3×10^8 m^3. Total production at the time this paper was written was 7.9×10^7 m^3 of oil equivalent. The primary reservoir is the Tor formation, with a secondary reservoir in the Hod formation. The thickness of the Tor formation varies, abruptly ranging from 0 to 80 m. Approximately 50% of the drive to date has been from rock compaction, observed by porosity reduction in infill wells. The porosity is greater than 50% in some places; some fractured permeability exists, but matrix permeability is low (less than 10 md). The average solution-gas/oil ratio

(GOR) for the field is approximately 20 std m^3/m^3, with an increase in the field GOR after 20 years' depletion of only 35%. The main challenges experienced during drilling and production included chalk and solids production, well failures and stability problems, fracture closure during depletion, and a subsiding seafloor around the original production platform.

Reservoir Model

The model was history matched previously by BP. The model root grid consists of 44×84×12 (44,352) cells with a grid size of 150×150 m and with a local grid refinement having 32×40×6 (7,680) cells and a grid size of 75×75 m. The three-phase model has an overall production period of 23 years. Historical data available included water-, gas-, and oil-rate history from 11 January 1982 to 1 January 2003. The reservoir model has 100 production wells. The 12 simulation zones were grouped in 12 geological layers. Fifteen major regions were defined in Layers 1–6, representing the Tor zone, and one region was defined in Layers 7–12, representing the Hod formation. These regions are based on the fluid-in-place estimates.

Rock-compaction tables, determined from the porosity-dependent vertical-stress curves, were used in the reservoir model to simulate compaction. These tables were entered as pore-volume multipliers, which vary as a function of pressure. The Valhall fluid is modeled as a single type. However, bubble-point variations exist that cannot be explained by gravity or temperature effects. Fluid variation is incorporated by use of six equilibrium regions.

Design Parameters

Uncertainties in hydrocarbon pore volume are considerable, even with a large number of well penetrations. The compaction data are based on laboratory measurements. Scaleup and overburden effects may result in field compaction behavior that is different from that measured in the laboratory. With high compaction and relatively low permeability, uncoupled models may affect the reservoir-energy match. A large variation in productive thickness of the Tor across the field leads to a high probability that even small faults could break communication paths. Therefore, the uncertainty of the transmissibility across mapped faults or in areas with thin productive Tor formation was investigated. Model parameters include rock properties such as porosity, permeability, and vertical transmissibility. Horizontal-permeability and porosity multipliers were defined for each region. In addition, vertical-transmissibility multipliers describing the barrier between the Tor and Hod formations were defined.

Porosity. Porosity multipliers were used to improve the pressure match, which was modified on a regional basis. Fifteen porosity multipliers were introduced with an upper and lower range of ±50% of the reference values for each parameter.

Permeability. Permeability multipliers were used to improve the pressure match, also modified on a region basis. The oil-rate constraint of the model introduced the permeability as an uncertainty parameter because the increase in pressure resulting from the higher oil-rate demand by the simulator could be compensated for by a change in the permeability values.

Transmissibility. In the crestal area, a significant pressure differential was observed across the barrier between the Tor and Hod formations, which could indicate decreased vertical transmissibility. Fifteen transmissibility multipliers were introduced between Layers 6 and 7, ranging from 0 to 1. The 16 regions defined groups of wells with similar GOR characteristics and were surrounded by assemblies of faults. Because these regions had similar production properties, they were deemed suitable as history-matching regions. This grouping was implemented to ensure that the history-matching process would not have opposite effects on wells in the same region. One porosity multiplier in each of 15 regions, one horizontal-permeability multiplier in each of 16 regions, and 15 vertical-transmissibility multipliers, representing the transmissibility between the Tor and Hod formation of each region, were selected for the history match.

Objective Function

The objective function is a numerical description of the system to be optimized, which is the difference between the observed value and the measured or simulated value and defines the quality of the history match. Also, prior information can be available from cores, logs, well tests, and seismic data. These data can be added to the objective function, which is independent of the observed and simulated data.

The objective function is nonlinear, and the minimum is found with several regularization methods. The main purpose was to achieve a pressure match to define the energy match. To reduce the computing time, the history match was carried out during the first 10 years of production. The individual contributions to the objective function included well oil-production rate (WOPR), well water-production rate (WWPR), and well pressure data from the selected wells. Once a pressure match was achieved, further contributions to the objective function could be added to the objective definition. The objective function was prioritized by pressure data from selected wells. However, other parameters like WOPR and WWPR were monitored constantly during each optimization cycle.

One or two wells were selected for the history match, depending on the number of wells in each region and the history data recorded for that well. The standard deviation of the observed field values was the measurement error, which was used to normalize the objective function. The measurement errors of the equipment used to gather most of the data were not available; therefore, these values were assumed on the basis of field experience.

EAs

EAs imitate biological evolution by creating new individuals (matched reservoir models) that inherit parameters from their parents (recombination and mutation), by determining the individual fitness (calculation of the objective function), and by exhibiting survival of the fittest as new parents (selection of the best-matched objective value). EAs use parallel structure in generating parent-to-child sequences and are defined by an iterative sequence of mutation and selection. This feature is transferred to parallel structures of the optimization-cycle program, allowing parallel computing.

Uncertainty-design-parameter sets were defined, which are modified to improve the history match. This process describes an individual that is a reservoir model with a specific different combination of selected parameters. The user defines the beginning configuration, which usually is the original parameter combination of the base case (reservoir model to be history matched). The user also defines the upper and lower limits of the parameter set identifying the search space. This set of parameters is called the first parent of the population. This parent then is copied several times, depending on the strategy used, into following parents, which represent different models with a different parameter combination inherited from the original parent by mutation.

Mutation of a parameter can be achieved by multiplying initial parameters with normally distributed random numbers, and the degree of mutation is determined by the step size of a parameter. The first generation includes several simulation models with different combinations of parameters. These models are used to generate the next generation. The next generation, called the children, represents several new simulation models generated with the parameters of the first generation. The children are generated by random parent-parameter selection and mutation. The number of children also is defined by the strategy (user defined). Each reservoir model that is created (member of the population) is defined by an objective function, and a transition function describes the process of transforming one population into a subsequent population by applying the process of mutation and selection.

Experiment Design

One method used to conduct an uncertainty study is an experiment-design matrix, which is a method that allows the user to gain maximum information from a series of systematically conducted experiments. Several parameters are varied simultaneously according to a series of statistically correct predefined patterns. These experiment-design techniques normally are used to minimize the number of simulations required for uncertainty quantification. The user predefines the input parameters as uncertain parameters. The same parameters identified for the history match will be used as input parameters for the experiment-design matrix. Consequently, the experiment design is used to investigate the variety of production forecasts on the basis of several history matches. A design is a set of parameter-value combinations in which responses can be measured. For a two-level factorial design, each parameter is assigned an upper and lower limit in all possible combinations; therefore, 2^n experiments are needed (n is the number of parameters). Likewise, three-level designs assign each parameter an upper, lower, and reference value in all possible combinations for a factorial design (3^n experiments are needed). For other types of experiment design, the design assigns each parameter three levels in a combination on the basis of statistical methods. This type of experiment design results in a large number of experiments required for the uncertainty assessment; however, it improves the precision of estimates produced by the response-surface model.

To reduce the number of experiments required, a three-level normally distributed Latin hypercube design matrix with 100 experiments was used. This technique allows sampling to be more precise than Monte Carlo methods, in which the distributions of the input factors are represented in the spacing of the factor levels. The main reasons to use this design matrix are that this method has been found to be more accurate than random sampling and it ensures that the entire range of combinations and variations of parameters is tested. Stratified sampling is used to estimate the means, variances, and distribution functions of an output. The next step was to create a proxy model for the specified response variable. Monte Carlo simulations were used later on the results of the proxy model to develop risked oil predictions.

Tornado-Chart Analysis and Response-Surface Modeling

The experiment-design-matrix results were analyzed with a tornado chart that was based on the coefficients generated in the response-surface polynomial equation, which also was used to analyze the effect of each parameter on the response variable. Parameters with large coefficients have the largest effect on the response variable. The response surface is based on least-squares and statistical-testing methods to quantify the relationship between the input variables and the output response.

Monte Carlo Simulation

Distributions for each parameter were chosen to create and run a Monte Carlo simulation. The input data included the simulator proxies and probability-density function or distributions for each independent parameter. The probability-density functions were obtained from field experience and historical data. The parameter distributions were based on expert knowledge and field experience. A total of 100,000 simulations was run on the response-surface models for each response variable.

Conclusion

A history match was achieved with a global-optimization method (i.e., EA). This history match was based on a pressure match, and several results were produced. The match was accomplished by manipulating 46 uncertain design parameters, including porosity, permeability, and transmissibility in different regions. An overall objective-function reduction of 31.8% for the best-case scenario was accomplished. Applying correlation and Bayesian techniques enhanced the convergence of the optimization run. The search space also was investigated, and a global minimum was searched, confirmed by inserting new parameters not searched before to ensure that both global and local search space has been explored.

The prediction runs overpredicted cumulative-oil forecasts because well and production downtime were not taken into account. Also, predictions were extrapolated far into the future, which can introduce discrepancies and errors. The GOR match for the history-match period did not change for most of the wells included in the objective definition. The total field GOR was reduced because of an increase in the overall pressure match.

EAs are useful in history matching of complex compaction-drive reservoirs because of their ability to explore an extremely wide range of parameter combinations and produce many results that can reflect compaction effects. A valid oil-production-, field-oil-in-place-, and original-oil-in-place-uncertainty assessment was obtained for a rock-compaction-drive reservoir. Validity was established through history matching and statistical analysis. A methodology combining reservoir simulation, experiment design, linear regression, and Monte Carlo simulation was used. To preserve the history match, the history-matched model and the design parameters used for the history match were used to create the experiment design. Despite constraints imposed by the history match, an acceptable range of uncertainty was calculated. **JPT**