A. S. Cullick, Landmark Graphics Corporation, Austin, TX; David Heath, Landmark Graphics Corporation, Denver, CO; Keshav Narayanan, Landmark Graphics Corporation, Austin, TX

Optimizing Multiple-Field Scheduling and Production Strategy with Reduced Risk

Extended Abstract for 2004 AAPG Cancun Conference

Large, multiple-field Exploration & Production assets require long-term commitments of capital that are tied to decisions on facilities, wells, scheduling, and production strategy. The decisions often must be made when there are high uncertainties, leading to risks. We present a system which integrates finite-difference reservoir simulation, an economics model, and a Monte Carlo algorithm with a global optimization search algorithm to identify more optimal reservoir planning and management decision alternatives under conditions of uncertainty, such that the associated risks are managed. The optimization problem is posed with the business goals stated as a general objective function and includes all constraints (economic, reservoir, production, and statistical) that need to be honored.

A comprehensive example is presented for an E&P asset with multiple oil fields produced through a common surface network. The formulation of the example problem includes decision variables for the scheduling of reservoir units, the number of wells, and production rate capacities. It incorporates the nonlinear response of the objective to reservoir performance and surface pressure constraint through a flow simulator. The analysis is multi-period, evaluating the impact of predicted performance over time for each decision alternative. The individual reservoir units have uncertainties in hydrocarbon volumes, reservoir quality, reservoir deliverability, fluid quality, and development costs. Decision solutions for objective functions of net present value (NPV) that mitigate risks are presented.

Background

E&P planning and operation decisions incorporate information and alternatives across many disciplines. There might be uncertainty in any of the components of the E&P value chain. These uncertainties lead to uncertainties in outcomes, such as NPV, rate of return (IRR), cumulative oil production, gas plateau period, etc. If the uncertainty can have negative outcome, we refer to that potential as risk. Figure 1 is a schematic of a decision process and framework wherein multiple components contribute to a distribution of outcomes. In the schematic, the decision to build a Floating Production Storage Offloading vessel (FPSO) in 2004 with 20 wells has a smaller IRR than building a Tension Leg Platform (TLP) with 30 wells in 2006, but the FPSO has smaller risk. The choice of decision will depend in part on the decision maker's risk tolerance.

The components in the framework are objective, requirements, state parameters (with or without uncertainty), decision variables, and constraints. An objective is the statement of the goal, and requirements can be imposed. State parameters are those that cannot be controlled and many times they are uncertain. They can be below-ground or above-ground and can be categorical or continuous. Categorical or discrete parameters are also referred to as 'scenarios'. Decision variables are those that are controllable and are usually choices available to the decision-maker. Constraints are boundary conditions, which restrict values available for the decision variables. Figure 1 gives a few examples of parameters and decision variables.

Common decision-making processes include decision trees, stochastic simulation, optimization, and their combinations. With decision trees, the decision-maker elucidates all possible outcomes with a branch-and-node diagram and assigns probabilities to discrete uncertain events. With stochastic simulation, the decision-maker assigns probabilities to uncertain parameters and elucidates scenarios which are sampled in a random fashion. With optimization the decision maker states an objective, defines the decision variables and relationships between the variables, constraints on variables, and assigns probabilities to uncertain parameters. The optimizer generates a set of decision variables that best meet the objectives while honoring the set of requirements and constraints.

Example problem

We present a series of examples using a synthetic data set and pose a common E&P decision scenario: at the beginning of year 2002, a Company is considering how to develop a new asset area that has three separated reservoir units, Units 1, 2, and 3 as shown in Figure 2. Each unit could be produced with up to four wells, connecting into individual gathering centers (GC). The proposed tubing and surface network system connecting the wells to the gathering centers and to a flow station are shown in Figure 2. The Company wishes to determine the best way to invest in this asset based on some business metric, while being constrained by an existing pipeline which has capacity of 20 thousands of barrels per day (TBD) available over the next 10 years. The Company decides to seek to maximize net present value (NPV) from three decisions: (1) the year (2003 to 2012) to begin production for each of the three units; (2) the number of wells to be drilled for each unit (0 to 4); and (3) the oil processing capacity to construct for each (0 to 20 TBD). The company also wants to manage the potential risks. The number of possible decision combinations for the scheduling and the number of wells is 125,000 (10^3dates x 5^3 wells); in addition there are the three continuous GC rate capacity decision variables. Obviously, the Company can not elucidate all possibilities in a decision tree. In practice, the Company might just consider a small number of the decision alternatives, based on best judgment and experience, in combination with some probabilistic analysis to account for uncertainty.

The presentation looks at alternative decision analysis approaches. The first is a simple intuitive, case study, approach, assuming no system uncertainty. The second approach uses optimization, again with no uncertainty. The third approach uses optimization with management of risks driven by system uncertainties.

Optimization System

Figure 3 is a schematic of the optimization system. The optimization system consists of three main workflows, an outer optimization workflow, or outer-loop, an inner scenario and uncertainty management simulation workflow, or inner-loop, and a dispatcher for distributed computing. The executables in the outer-loop are the optimizer, algorithms for computing summary statistics for the objective function and requirements, and connections to data stores. The executables in the inner-loop consist of a Monte Carlo engine that resolves and manages uncertainty, production profile generation, and an economic calculation. Inputs for the inner-loop can include geologic reservoir models and well models. The optimizer is a global search algorithm based on tabu and scatter search techniques.

Results and Discussion

The presentation will go through several decision analysis scenarios in detail. Here, we highlight just one scenario: that is, when Unit 1 has the highest expected volume, but also has the largest uncertainty and the highest expected costs. Unit 2 is somewhat in the middle, and Unit 3 has the lowest development costs, but is expected to have the lowest volume and productivity as well. Figure 4 shows the histogram for the asset and each of the Units' NPV values, for a single decision alternative of schedule, well number, and processing capacity.

The optimizer searches for the best decision which maximizes the mean NPV while honoring a requirement on the risk, given as NPV standard deviation. Figure 5 plots the iterations of the optimizer with mean NPV versus the standard deviation. There is a cluster of circled solutions (red) which are those solutions with high NPV and which meet the risk requirement. Figure 7 compares optimization with a "guess" solution (engineering judgment). The presentation discusses risk mitigation strategies that can be assessed with the optimizer (Figure 6).

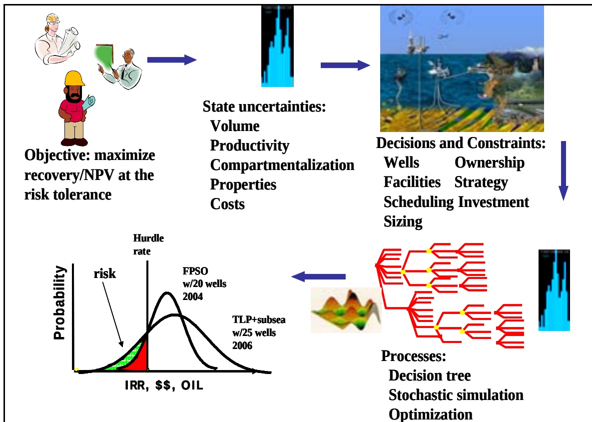

Figure 1: Decision processes with uncertainty to manage value and risk.

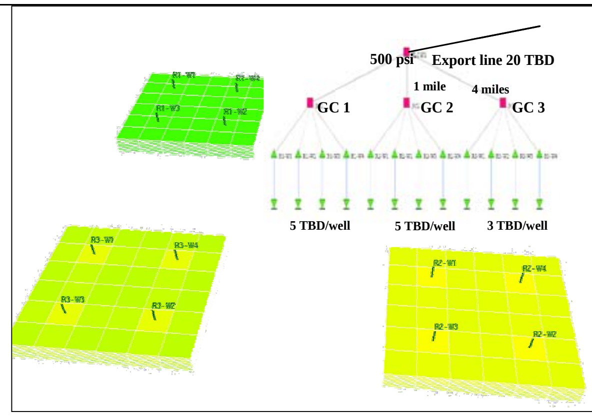

Figure 2: Synthetic data example with three separate producing reservoir units, gathering system configuration, and constraints.

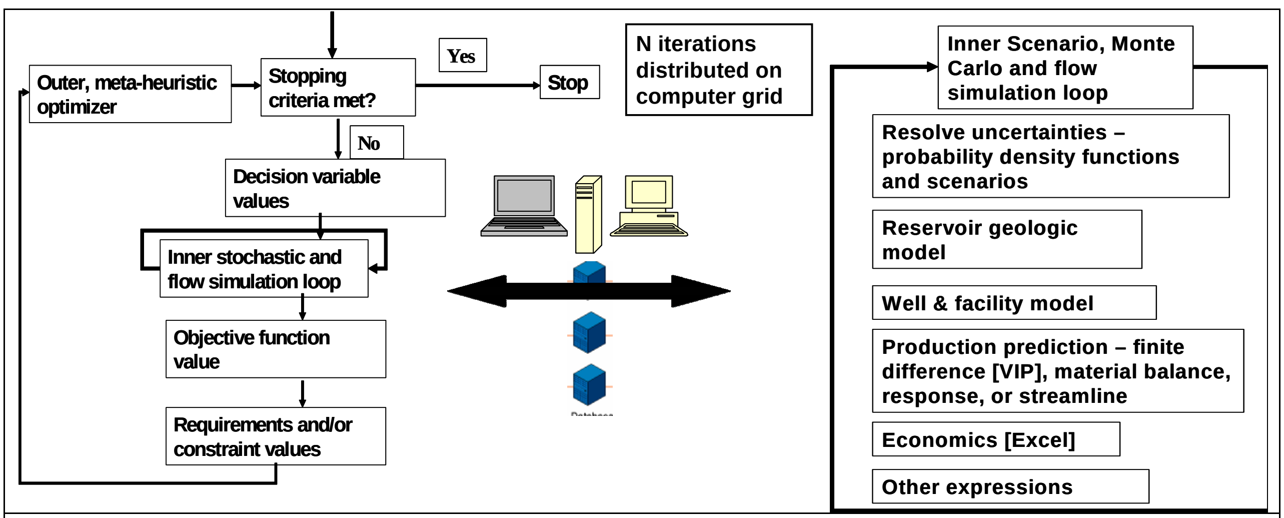

Figure 3: Schematic of outer-loop, inner-loop, and dispatcher.

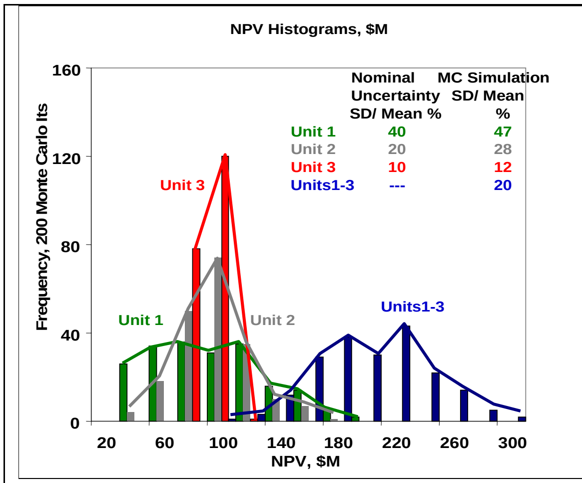

Figure 4: Monte Carlo simulations for net present value for a single set of decision variable values for Story 3.

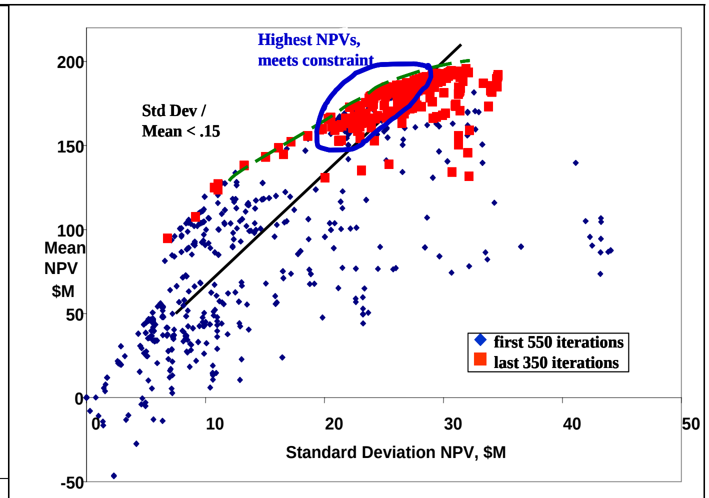

Figure 5: Mean net present value versus standard deviation for Story 3 with high Unit 1 uncertainty.

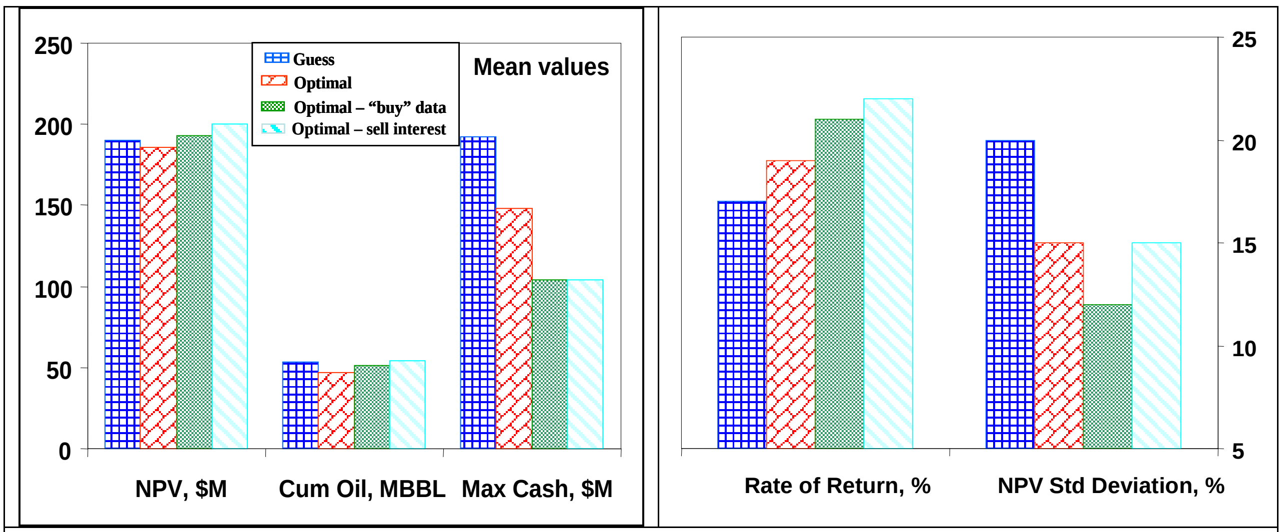

Figure 6: Oil production mean and economic means and standard deviation optimization results for Story 3 (Table 4 characteristics with property uncertainty