SPE 112258

Decision Support System for Economic Analysis of E&P Projects Under Uncertainties

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This paper was prepared for presentation at the 2008 SPE Intelligent Energy Conference and Exhibition held in Amsterdam, The Netherlands, 25–27 February 2008.

Abstract

This work presents the conception, modeling and development of an E&P projects economical analysis system under uncertainty that integrates the following modules:

- an optimization hybrid system for oilfields development based in evolutionary algorithms with distributed evaluation, proxies and use of quality maps to optimize the place and quantity of wells in a delimited petroleum field to maximizing the NPV of the alternative. Also, this system considers some technical constrains as the minimum wells distance and maximum wells trajectory.
- a model based on Genetic Algorithms and Monte Carlo simulation designed to find an optimal decision rule for some oil field development alternatives obtained from previous module, considering market uncertainty (oil price), that may help decision-making with regard to: developing a field immediately or waiting until more favorable market conditions.

In the economic analysis also is considered, for each alternative under evaluating, the option of investment in information taking in account interactions of different uncertainties types. This analysis considers the option of future production expansion by installing an additional well under reserve volume uncertainties in the in the area to be drained by the additional well.

Some computational intelligence techniques were applied in this system as: evolutionary algorithms, neural networks and fuzzy numbers; also, the system uses other techniques as Real Options and Monte Carlo Simulation to treat uncertainties.

The obtained outcomes show the benefits to have an integrated decision support system to the decision-making in the economic analysis of oilfields development.

Introduction

To analyze the option to develop some previously delimited petroleum field request investments which dimensions and benefits depend on the alternative being chosen. Some alternatives have different quantity and of the wells. The wells are vertical, horizontal or multilateral with several costs and benefits. The combination with other aspects as: platform type, recuperation method, production system, drills system, lifting, etc. becomes this problem more complex to optimize. Moreover, the alternatives of invest in information or just waiting for better market conditions will be considered. Also, it is necessary to consider the flexibility in the oilfield development, in order to incorporate a production increment (expansion option) by optional wells, depending on the market conditions and the reservoir behavior in the early months or years of production.

This is a typical complex and combinatorial optimization problem to need attend some constrains. Evolutionary optimization methods [1] are promissory in this kind of problem.

This problem searchs the alternative that maximizes the Net Present Value under uncertainties, this alternative must attend the technical constrains and consider technical and market uncertainties.

Decision Support System

Several methodologies are applied to reach the objectives of this work. The main approach is based in investment analysis under uncertainties, know as real options. This approach must be complemented with optimization methods, reservoir simulation, and stochastic processes.

The development of this work involves the definition and evaluation of the models to perform the economical analysis of oilfield development projects, as descreved following:

1. Optimization of the wells placement and quantity under certain conditions [2];
2. Optimization of the Decision Rule under market uncertainties [3];
3. Considering information investment and expansion option in the alternatives analisys [4].

The cycle of the whole system is the following:

The wells placement otimizator makes a broad search of the alternatives to develop an oilfield; this block provides a set of good alternatives, with several investments costs but a high NPV. The set of better alternatives obtained by the optimization module will be inputed to the model that analizes the alternatives under technical and market uncertainties, providing as response a decision rule about what alternative will be chosen in accord to the market and technical scenaries using Monte carlo simulation, stochastic process to simulate the market behaviour and fuzzy numbers to represent the technical uncertainties. In the other hand, after the explorarion phase of a discovered oilfield, it remains some technical uncertainties about the main oifield parameters. The decision to take is making more invest in information or making more development of the oilfield? Figure 1 shows the three modules composing the entire decision support system.

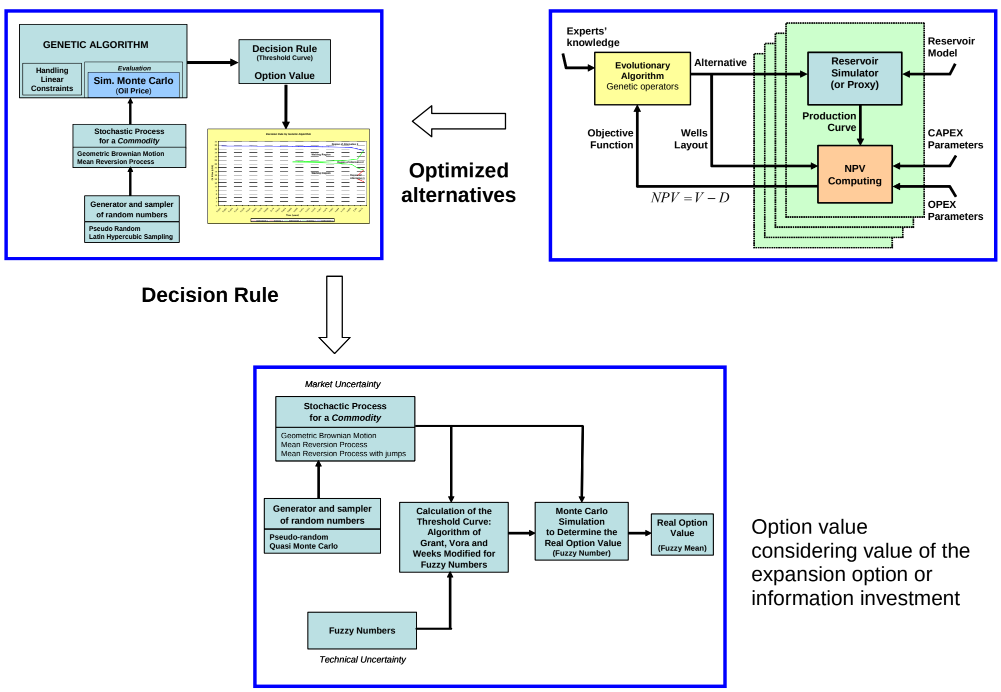

Figure 1—Support decision system

In the following sections the modules that compose the whole system are descrived.

Optimization of the wells placement and quantity under certain conditions

This block contains a system to optimize development alternatives. This problem consists on find the best alternative for the petroleum field development, in this case, to search the adequate number, positioning and type of wells to be drilled into petroleum field. The system modeled in this work consists in two main modules: the optimization module that contains the genetic algorithms and the objective function module composted by a reservoir simulator and the economical Net Present Value (NPV) [5] model (b). The iterative loop process is performed as following:

- the genetic algorithm generates a population where each individual of population is a proposal alternative to be evaluated by the NPV computing.
- to perform the evaluation for an individual, this is submitted to the reservoir simulator to obtain the oil, gas and water production curves. Once these curves are obtained by simulation, the NPV of the alternative is computed using some parameters related to capital expenditure (CAPEX), operational expenditure (OPEX) and other economical scenery parameters.
- to close the loop, the already calculated NPV returns to the optimization module, as the objective function for alternative.

Figure 2 shows the framework of the optimization system and the proposed iterative process.

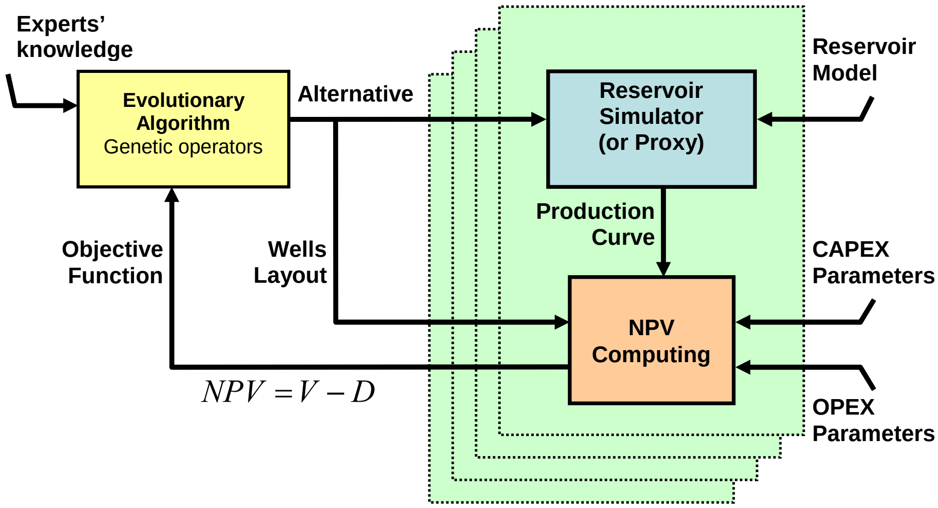

Figure 2—Framework of the Optimization System

A genetic algorithm approach implies the definition of the following issues:

- Chromosome representation;
- Genetic operators;
- Objective function.

The following subsections present more details about these definitions:

Chromosome representation

In this problem, an individual is represented by a variable length chromosome. The length variability is obtained using an activation mask [6] that enables or disables any gene of chromosome. Thus, an individual structure consists in dual layers of genes, with the lower layer describing the alternative as a list of wells (the normal chromosome), and the upper layer containing the activation mask flags.

Each gene of chromosome defines the wellhead position (*i*,*j*,*k*), the well direction (*dir*) and the well bore length (*dist*) [7].

Figure 3 illustrates the chromosome modeled to the optimization problem, where, a flag equal to "1" in activation mask indicates an active well and a flag equal to "0" indicates an inactive well.

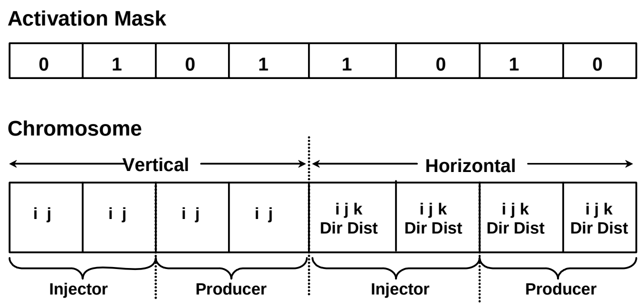

Figure 3—Chromosome representation [7].

Genetic Operators

This work uses the classical genetic operators [8]:

- Arithmetic crossover;
- Uniform Mutation;
- Non-uniform mutation;

In order to evolve the activation mask, the following operators were utilized:

- Addwell mutation [7]: turns to "1" any selected flag and
- Flipwell mutation [7]: toggle the selected flag.

Objective Function

As mentioned in section above, a chromosome or individual represents an alternative to be evaluated and this evaluation is performed as following:

1. Once obtained a new population of alternatives for any generation, each alternative is sent to the reservoir simulator;

2. Reservoir simulator provides oil, gas and water production from the received alternative;
3. Finally, the NPV for the alternative is computed using the production profile and some parameters (commodities, development and operational costs).

Reservoir Simulator

In this work, a commercial reservoir simulator [9] was used.

Linking the optimization algorithm and the reservoir simulator is made through files as following:

First, the optimization algorithm needs some information about the reservoir definition (grid size, grid type, cells dimensions, active cells), to set the genes domains, constrains and begin the optimization process. The requested information can read from .DAT and .INC files. These files contain all data and configurations used by simulator (grid size, grid type, cells dimensions, active cells, geologic parameters, initial conditions and even the well definitions).

Second, once started the genetic algorithm and the first population already generated, the population evaluation request the simulation of each individual of the population. Thus, the wells defined by an individual are recorded into .INC file using the reservoir simulator syntaxes for wells definition.

Next, the simulator is executed obtaining files that contain the simulation results. The daily rates of oil, gas and water production are extracted from the output files using a filtering application. These daily rates will be utilized to calculate the NPV of the alternative.

Net Present Value (NPV)

The calculated NPV is basically the difference between the expected value of cash flows from production process 10 minus the initial investment, as the Eq.(1) shows:

$$NPV = PV - D \tag{1}$$

where PV is the present value of the cash flows for the production and D is the development cost, i.e., the investments needed to start the exploitation.

The cash flow PV is calculated as the difference from the present value of the incomes PVR given by the oil and gas production minus the present value of the operational cost PVCop and the application of a taxes I, as the Eq(2) shows.

$$PV = \left(PVR - PVC_{op}\right)\left(1 - I\right) \tag{2}$$

The incomes $R(t)$ for each t, depends on the oil production $Q(t)$, the equivalent gas production $G(t)/1000$, and on the oil price $P_{oil}(t)$, as the Eq(3) shows.

$$R(t) = \left(Q(t) + G(t)/1000\right)P_{oil}(t) \tag{3}$$

The operational cost $C_{op}(t)$ is computed as the sum of the annual wells maintenance cost, fixed costs, variable costs, royalties, water handlin]g as the Eq.(4) shows.

$$C_{op}(t) = \left(mn_w + C_f + C_v\right)\frac{t}{360} + C_v Q(t) + R_y R(t) + C_w W(t) \tag{4}$$

The development cost D includes the drilled wells, conduction lines, platform and plant as the Eq.(5) shows.

$$D = \left(af_{hw} + r\right)n_w + b + \sum_{j=1}^{n_w} \left|p_j - P_{pl}\right| c_l \tag{5}$$

The horizontal well multiplication factor f_{hw} is computed as the Eq.(6) shows.

$$f_{hw} = \left(1 + \frac{n_{hw}}{n_w} f_h\right) \tag{6}$$

where n_{hw} is the quantity of horizontal wells in the alternative, n_w is the total wells quantity, and f_h is the cost factor for horizontal wells.

More details about this economic model can be revised in [2] and [7].

Constrains treatment

The optimization model modeled in this work considers some constrains as:

- Minimal distance between wells
- Horizontal wells maximum length
- Null blocks treatment

Taking advantages from the expert knowledge

The system development in this work is capable of using information obtained from expert knowledge or even from other decision support systems by applying two strategies:

- Initial seeds [2]
- Quality Maps [10] and Water Maps [2]

Using Proxies

A known drawback for using simulation is the amount of time requested to obtain responses of oil, gas, and water production. That is why the optimization system uses oil production curves approximations (proxies) and the simulations.

For this purpose, a learning process from production information provided by simulator is needed. As mentioned above, the simulator provides a cumulative oil curve from the alternative configuration. This curve is composed of several points (t_i, $O_{cum}(t_i)$) the number of this points can vary.

The approximation functions used in this work are Elman Neural Networks [11] and Hierarquical Neuro-Fuzzy with Binary Partition (NFHB) [12]. More details about the proxies modeling can be found in [2].

To determine if the proxy or the simulator will be used for any evaluation, the optimization system compares a uniform random realization u_i with a probability tax γ, as the Eq.(7) shows.

$$\begin{aligned} &\text{if } u_i \le \gamma \rightarrow \text{use the simulator} \\ &\text{if } u_i > \gamma \rightarrow \text{use the Proxy} \end{aligned} \tag{7}$$

The proxies using objectives to complement the intensive use of the reservoir simulator in effort to reducing the computational time needed to evaluate a GA population.

Using Distributed Processes

The dispended computational time to perform an optimization is one of the main drawbacks of the proposal system; in fact, any reservoir simulation can spend from a few seconds to several hours of execution time. For this purpose, the optimization system uses the global genetic algorithm [13] to exploit the computational force existing in several processors interconnected in a local network. The global genetic algorithm consists in a master processor contains the evolutionary algorithm (population, selection, reproduction) and several slave processors among the network performing the objective function (reservoir simulation or proxy, and the NPV compute). The global genetic algorithm uses the master-slave architecture of Figure 4.

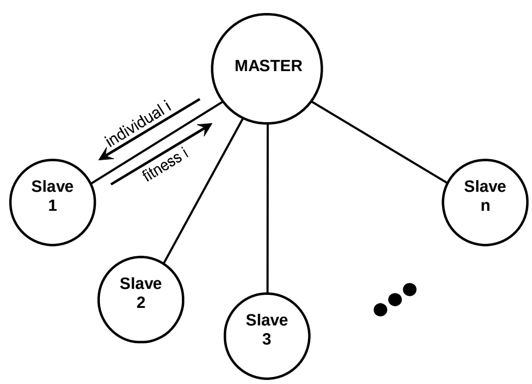

Figure 4—Master-slave architecture

To obtain the communication channels between master and slaves, the system uses CORBA (*Common Objects Request Broker Architecture*) [14][15] and, for the whole system implementation, C++ language is used.

Optimal decision rule by Monte Carlo and genetic algorithms

This module tries to obtain an optimal decision rule to invest in an oil reserve under market uncertainty (oil price). This decision rule is formed by a set of some mutually exclusive alternatives which describe some exercise regions through time, up to the expiration time of the concession. Each alternative presents a threshold curve, which is the critical value for optimal exercise of the real option; any value above it determines the optimal exercise of the real option. All the threshold curves together represent the decision rule that maximizes the value of these alternatives or investment options. Traditionally, to evaluate each alternative for investment in the oil field, an attempt to maximize the Net Present Value (*NPV*) [5][16] is performed, where the best alternative represents the one that provides the highest NPV.

In order to get a simple and adequate NPV equation, let v be the market value of one barrel of reserve (that is, v is the price of the barrel). If this reserve price v is directly related with the long-run oil prices, let be q the factor of proportionality [17], so that $v = q.P$.

For developed reserve transactions, as higher is the price per barrel of a specific reserve, as higher is the economic quality for that reserve. For a fixed reserve size and fixed oil price, as higher is the factor q as higher is the value of this reserve. So, let q be the economic quality of the reserve, defined as $q = \partial v / \partial P$. The q value depends of several reservoir characteristics: the permo-porosity properties of the reservoir-rock; the quality and properties of the oil and/or gas; reservoir inflow mechanism; operational cost; country taxes; cost of capital; etc [18]. In this case, the *NPV* equation for the business model may be written as Eq.(8)

$$NPV_t = qP_tB - D \tag{8}$$

where q is the economic quality of the reserve; P is the petroleum price; B is the estimated size of the reserve; D is the investment for development of the reserve.

For the fiscal regime of concessions (USA, UK, Brazil, and others), the linear equation for the NPV with the oil prices is a very good approximation [19] [20].

Modeling the uncertainty of Oil Prices

One stochastic process for modeling the oil prices is considered: Geometric Brownian Motion (GBM) and it is assumed the oil prices following a GBM, in the format of a risk-neutralized stochastic process, i.e., using a risk-neutral drift ($r - \delta$) instead the real drift α, as Eq.(9) shows.

$$dP = (r - \delta)Pdt + \sigma P dz \tag{9}$$

The GBM for simulating the future oil price $P(t)$, given the current price $P(t\text{-}1)$, is shown in the Eq.(10).

$$P(t) = P_{t-1} \exp\left[\left(r - \delta - 0.5\sigma^2\right)\Delta t + \sigma\varepsilon\sqrt{\Delta t}\right] \tag{10}$$

where r is the risk-free interest rate, δ is the oil field convenience yield rate, σ is the oil price volatility, Δt is the length of the time step, $\varepsilon\sqrt{\Delta t}$ is the Wiener increment, where ε is a normally distributed random variable $N(0,1)$.

The model that has been used is an extension of the one presented by Dixit [8], which was adapted to oil projects. For more details, see Dias [4] [18].

Monte Carlo Simulation and Sampling Variance Reduction

Monte Carlo Simulation (MCS) is the appropriate method for problems of higher dimension and/or stochastic parameters, often used to evaluate the expectation of a variable that is function of various stochastic variables, which is not analytically tractable. Therefore, samples are generated from some target probability distribution to create the diverse scenes to be evaluated. To reduce the error of the variable estimation provided by the simulation, the number of samples must be very large to achieve the desired precision. However, the bigger the number of samples, the greater the computational cost. The reduction of the error estimatives is also possible if the deviation standard is reduced.

Latin Hypercube Sampling (LHS) [21] [22] was suggested as a variance reduction technique, but can also be seen as a screening technique, in which the selection of sample values is highly controlled. Using LHS, an input sample is also generated based on the inverse transform method, given by Eq.(11):

$$P(t) = P_{t-1} \exp\left[\left(r - \delta - 0.5\sigma^2\right)\Delta t + \sigma\varepsilon\sqrt{\Delta t}\right] \tag{11}$$

where: $xh_{i,j}$ is a sample of LHS; i, j are the dimensions of LHS; n,k states of each dimension of LHS, U_i stands for an independent random uniform distribution on [0,1], i=1,…,n_j and $F^{-1}(U)$, $U \in (0,1)$, is the inverse transform for the particular input distribution. In this application, the approximation for the inverse of the cumulative Normal distribution is used.

The Optimal Decision Rule

The threshold curve, or optimal exercise curve of the option, represent the decision rule for the development of the field. With the simulated oil price $P(t)$ it is possible to estimate the value of developed of a reserve $V(t)$=$q.B.P(t)$. The threshold is the critical level that makes optimal the immediate investment to develop the oilfield. This threshold curve is the decision rule to exercise the option (exercise at or above the threshold), which maximizes the real options value. This optimal exercise curve is a function of the time. In this work, an approach of the threshold curve is obtained using a Genetic Algorithmic model.

Figure 5 shows the threshold curve and two paths of the oil price until the expiration of the option. One path reaches the threshold line at the point W (at t = 1.2 in this example), so the decision rule is to exercise the investment option at this time (the option is "*deep in the money*"), the option value at this moment is $F(1.2) = NPV = V - D = qPtB - D$. This value is a future value (t = 1.2 year). Thus, to calculate the present value, it must be multiplied by the discount factor e^{-rt}. The other path pass all the option period without reaching the threshold curve (point *Z*), in this case, the value of the option is zero (expires worthless).

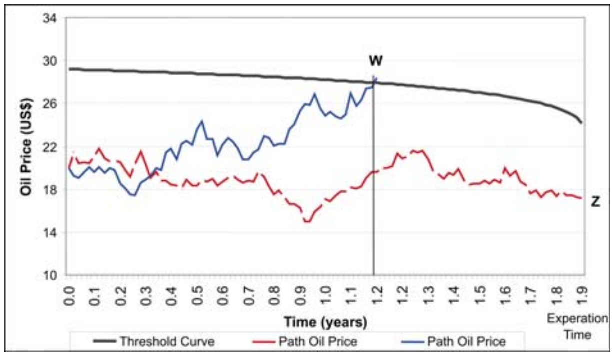

Figure 5—The Threshold curve and exercise of the real option simulated value

When the number of alternatives increases, the decision rule is formed by the intersection of the threshold curves of each alternative. In this case, the creation of waiting regions between the alternatives is possible [23].

Modeling of the Problem

This section describes the proposed model, which integrates the Monte Carlo simulation and the Real Options Theory into a Genetic Algorithm to obtain an optimal decision rule for three alternatives of investment in an oil reserve, considering that the price of oil is uncertain. In order to simulate the oil price, the following parameters are considered:

Expiration Time (T):	2 years;
Discretization Time (Δt):	7 days;
Interest rate free of risk (r):	8 % per year;
Convenience yield rate of the oil field (δ):	8 % per year;
Price volatility (σ):	25 % per year;
Initial oil price (P_0):	20 US$/bbl
Risk-adjusted discount rate (ρ):	0.12 % per year;
Estimated size of reserve (B):	400 MM barrels.

Three alternatives have been considered and present the following parameters:

Table 1—Parameters of the alternatives

	Alternative 1	Alternative 2	Alternative 3
Quality of reserve (q)	8 %	16 %	22 %
Investment for development (D)	400 MM US$	1000 MM US$	1700 MM US$

It is observed that it only makes sense to consider higher investment alternatives if an increase in the economic quality of the reserve is obtained, that is, the investment in more wells, for further drainage of the same reservoir, enhances the economic quality of the reserve being developed. In other words, such investment represents the means to extract oil more quickly. For this reason, this type of alternative worths more than the other one with few wells for draining the same reserve.

The problem of determining the optimal decision rule for these three alternatives considering the uncertainty of oil prices is difficult to compute because of its nonlinearity. As a result, the genetic algorithms represent a good choice for finding the optimal decision rule for the oil field development.

The threshold curve may be approximated by means of logarithmic functions in the form $a + b\ln(\tau)$ and a free point, situated near the expiration time of the option T, where $\tau = T - t$ and t is an instant of time [3] [4] [24]. A logarithmic function is chosen because it represents a good approximation to the threshold curve obtained by finite differences [4][24]. For several alternatives, there are several mutually exclusive threshold curves that determine the exercise regions. These exercise regions are delimited by the intersections between threshold curves. The possible existence of waiting regions [23] between the regions formed by the alternatives is also considered. The waiting regions are approximated by a logarithmic function a_W-b_W $\ln(\tau)$ and the free point. The coefficients value of the above functions (a, b, a_W, b_W) and the free points values are determined by the genetic algorithm. Thus, for the case of three alternatives, five regions may be formed (two waiting regions and three exercise regions, one for each alternative) [23].

Cromossome representation

Thus for the case of three alternatives, the chromosome is composed by 5 genes; each gene is formed by three alleles with real value that represent the threshold curve parameters of each alternative (variables a e b of logarithm curve and the free point) [3][4][24], as well as the parameters of waiting regions (the free point and variables a_w, b_w), as Figure 6 illustrates.

The threshold and waiting curves are subject to a set of constraints to guarantee the formation of the exercise regions and reducing the search space.

The domain restrictions are defined from the critical oil price in the expiration, so that in the expiration, the exercise of the option is attractive. The NPV of the alternative of lesser investment must be as minimum zero.

The free points are chosen in each alternative for the same instant, corresponding to steps of 0.1 year. The logarithmic curve begins at instant $0.1+\Delta t$, where Δt corresponds to the time interval. Therefore, the linear restrictions for each threshold and waiting curve are:

$$\begin{aligned} a + b\ln(0.1+\Delta t) &\geq \text{FreePoint} \\ a_W - b_W \ln(0.1+\Delta t) &\leq \text{FreePoint} \\ a + b\ln(0.1+\Delta t) &\geq 0 \\ a_W - b_W \ln(0.1+\Delta t) &\geq 0 \end{aligned}$$

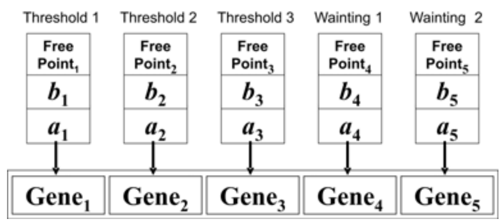

Figure 6—The Chromosome model

Evaluation of the Chromosome

The objective of the genetic algorithm is to maximize the Net Present Value of the real option (*NPV* of the oil reserve, Equation 1). The Monte Carlo simulation is employed using 10000 iterations and, for each iteration (i), the oil price is estimated for each 2-day interval (t) until expiration time (2 years), assuming the oil price behaviour as the Geometric Brownian Motion. The Latin Hypercube Sampling was used to provide the necessary random numbers for the stochastic process. Then, for each iteration, a "path" of the oil price, denoted $Path_i$, is formed.

The following describes the steps to evaluate each chromosome:

1. The evaluation of chromosome j (for j = 1,2,…population size) begins with the first iteration of the Monte Carlo simulation (i = 1).
2. From the parameters for the logarithmic function and free point contained in the chromosome (j), the decision rule is constructed for the three alternatives, defining the waiting and exercise regions.
3. One Path_i of the oil price is created and for each time interval(t) it is verified if the oil price reaches one of the exercise regions.
   - If the oil price reaches an exercise region, the option is exercised, the NPV (F_i) for this oil price is calculated, and then the algorithm goes on to the next iteration (step 1).
   - If Path i has been completed, i.e., it is at expiration, and none of the exercise regions has been reached, then the *NPV* is zero and the algorithm goes on to the next iteration (step 1).
4. Repeat steps 1, 2 and 3 for each iteration of the Monte Carlo simulation (i).
5. Once finished the Monte Carlo simulation, the evaluation value (fitness) for chromosome (j) is determined by the mean value of the NPVs (F_i) found for each iteration, as Eq.(12) shows.

$$F_j = \frac{\sum_{i=1}^{10000} F_i}{\text{Iterations number}} \qquad (12)$$

The best chromosome obtained by the genetic algorithm will be the one that maximizes the value F_j.

Considering information investment and expansion option in the alternatives analisys

This problem investigates an alternative for the development of an oil production strategy where there is the possibility to expand the production by means of adding an additional well in the future, depending on market conditions and technical information generated by the initial production of the field. The oil price is the market uncertainty, where it is assumed to follow one of two possible stochastic processes: Geometric Brownian Motion or Mean Reversion Process.

The technical uncertainty corresponds to the volume of the oil reserve to be drained in the area of the optional well. This technical uncertainty is denoted by B.

In this work it is assumed that three years are necessary to construct the additional well. After the end of construction, the well starts to produce oil; however, the technical sceneries of B are revealed after a year of production (i.e. in year t = 4). The option to invest in an additional well is limited to a five year period as Figure 7 shows, that is, the option to invest in an additional well initiates with the revelation of the technical sceneries and from this moment (year $t = 4$) the option can be exerted in any instant during the next 5 years. After this period, the option expires (in year $t = 9$). After the exercise of the option the well is able to produce oil for up to 30 years.

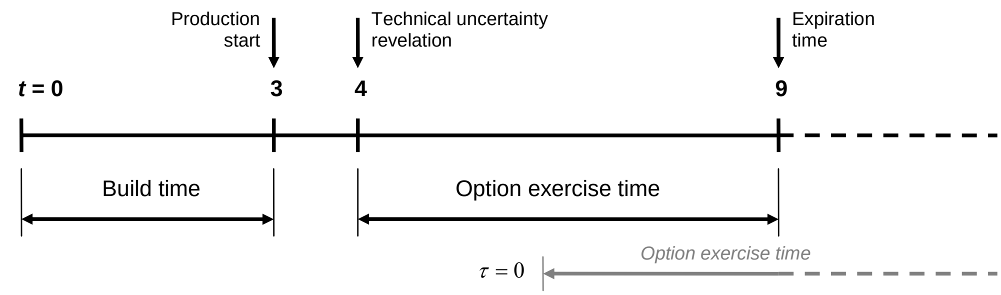

Figure 7—Option exercise time

To determine the option value a hybrid methodology is applied that joins the stochastic simulation with fuzzy numbers. In this methodology technical uncertainties are represented by fuzzy numbers, instead of the common triangular probability distributions used in traditional methods of option value evaluation.

The fuzzy number allows dealing with the technical uncertainty as a whole, avoiding the need to sample it, as it would be the case for the triangular probability distribution; this method greatly speeds up the process of the Monte Carlo simulation.

To determine the boundary of optimal exercise (or threshold curve), the algorithm of Grant, Vora and Weeks [25] was adapted to work with fuzzy numbers [26]. Constructed the threshold curve it to make simulations for the oil price from the initial price, the option value, will be the mean fuzzy [26][27] of all the values that reach or surpass the threshold curve in the simulation, brought to the present value.

After the threshold curve has been established, the behavior of the oil price is simulated from an initial price; the option value will be the mean fuzzy [26][27] of all the values that reach or surpass the threshold curve in the simulation, brought to the present value.

The evaluation of investment in information problem is described as following: let a discovered but not developed oil field containing uncertainties about the reserve size B and economic quality q, it exists the possibility of invest in information to reduce the risks and to reveal some reserve characteristics. The problem consists on evaluate what is the best information investment alternative considering the oil price following a stochastic diferencial equation. Let k alternatives of information investment. Let be $D(B_k)$ denotes the oil development cost. The NPV of the oil field refered to the alternative k is defined as Eq.(13):

$$VPL(P)_K = V(P)_K - D(B_K) = q_K \cdot P \cdot B_K - D(B_K) \tag{13}$$

where:

$V(P)$	reserve value
q_k	economic quality of the reserve for k alternative (stochastic)
B_k	reserfe size for k alternative (stochastic)
P	oil proce at t time (US$ bbl)
$D(B_k)$	oil field development cost for k alternative

Each k alternative has a cost for the revealed information denoted I_k that is expected to occur in $t = 0$, but the information is revealed only in t_k. The interval (t_0, t_k) is a waiting time for revealed informations and, at this period, the option can not be exerced.

For an oil price today and its evolution process, it is desired to determine how is the best alternative of investment k to be applied, considering the oilfield with a mature stage of development (T years). In this analysis, technical uncertainties as reserve size B and economic quality of reserve q are considered; and market uncertainties as the oil price are also considered asumming a Geometric Brownian Motion (GBM). To determine the option value, be applied two methodologies: Stochastic simulation that uses Monte Carlo simulation where the uncertainties are represented by triangular pdfs and a hybrid methodology with stochastic processes to oil price and fuzzy numbers rather than triangular pdfs to represent the technical uncertainties [26].

Aknoweledges

The authors would like their gratitude to Petrobras for financial support by ANEPI Project, and ICA Laboratory at PUC-Rio for infra-structural support.

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