공학석사 학위논문

An Economic Analysis Using Multi-objective Genetic Algorithm And Stochastic Process With Real Option

다목적 유전 알고리듬과 실물옵션 모델의 확률론적 접근에 의한 경제성 분석

2014 년 12 월

서울대학교 대학원

에너지시스템공학부

문 동 호

Abstract

An Economic Analysis Using Multi-objective Genetic Algorithm And Stochastic Process With Real Option

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Both the risk of a project and the flexibility of decision making are extremely crucial in analyzing the economic efficiency of reservoir development. Existing models cannot include operational, geological and market risks due to deterministic assumptions of future cash flow.

This study developed a model for analyzing economic efficiency stochastically using a multi-objective history matching process along with Real Option Valuation (ROV). The multi-objective genetic algorithm was introduced to generate history matching data in the reservoir. The well performance for a simulated reservoir was predicted by additional drilling sites at stages of development. ROV was employed to reflect the payback period and business risks simultaneously.

The asset value of the operating field can be improved up to 6-12%. Compared to the conventional models for analysis of economic efficiency, the proposed method can flexibly determine the time for additional drilling to manage the uncertainty of the project.

Keywords : economic analysis, real option valuation,

multi-objective history matching, well optimization

Student number: 2013-21013

Table of Contents

List of Tables

List of Figures

1. Introduction

Decisions have to be made at every level of reservoir development. The impact of development decisions on the success or failure of a project can be significant. Also, most of the time, a slightly better decision may lead to a considerable increase in the value of the project. Thus, decisions should be based on the most relevant and accurate economic evaluation's tools available. Defining economic evaluation problems clearly is as important in economic analysis as any other situation that requires a decision. The project evaluation of oil and gas under uncertainty is a key aspect of reservoir engineering and management. However, Discounted Cash Flow (DCF) model which is economic evaluations tool is the most popular to appraise potential investment. This model is relatively simple. It predicts a stream of cash flows, in and out, over the expected life of a project, then discounts them at a rate that reflects both the time value of money and the riskiness of those cash flows. such tools are most often computationally expensive. A DCF analysis provides clear, simple and fast. However, it also has limitations.

First, DCF analysis is static. It assumes that a project plan is frozen and unalterable and that management is passive and follows the original plan irrespective of changing circumstances. However, management tends to modify plans as circumstances change and uncertainties are resolved. Management interventions tend to add value to that calculated by DCF analysis. Second, DCF assumes future cash flows are predictable and deterministic. In practice, it is often difficult to estimate cash flows, and DCF can often incorrect value certain types of projects. For this reasons, flexibility in making development decisions tool is essential. Thus options need to change the capacity of facilities, the scale of a project, the timing of investment etc. and these options must be evaluated under technical and market uncertainties.

(ROV) has been introduced to recognize the flexibility to adapt to future decisions with uncertainty (Paddock et al., 1988; Dixit and Pindyck, 1994; Bailey et al., 2003). However, most of conventional researches for ROV have focused to price to market uncertainties, such as changes in oil and gas prices, interest rates etc. Lee et al. (2000) developed an option pricing model for development project. In exploration level Park et al. (2013) proposed compound real options incorporated with a stochastic approach for evaluating an uncertainty. However, technical uncertainties, such as operational conditions, subsurface uncertainty are also key aspect to design ROV model.

Singh et al. (2012) studied the ROV model to integrate geological uncertainty obtained by reservoir modeling within the ROV framework. However, decision making absences from this study, so practical option’s value is not considered. As a result, it appraises the project by NPV considering volatility effect. In other words, any flexible decision making is impossible for reservoir development.

This study focused on the solution of DCF model’s weakness, technical uncertainty and absence of decision making. The authors constructed the proposed ROV model in specific time and specific location to drill extra well problem. To solve the geological uncertainty provide the reservoir modeling by multi-objective genetic algorithm which suggested by Schulze-Riegert et al. (2007). After reservoir modeling, production performance will be predicted and evaluate the additional well optimization project with proposed model. In this study, the probability model will be proposed for flexibility decision making to drill addition well in various time and location influenced by market and technical uncertainties after performing sensitivity analysis for ROV parameters due to geological, operational and technical uncertainties.

2. Theoretical Backgrounds

2.1. Real options

2.1.1 Real options valuation

Real Options Valuation (ROV) is also an economic analysis technique, but more advanced than Discounted Cash Flow (DCF). DCF is an economic analysis technique to value a project using the concept of time value of asset. In this technique, future cash flows (*F(t)*) are determined and discounted to derive the Present Values (PV), and the sum of all PVs is the Net Present Value (NPV). NPV assumes all the risks in a project are completely accounted for by the rate of return (*r*), and it does not allow for uncertainty and changing circumstances. Eq. (2.1) is the general form of the NPV.

$$\mathrm{NPV} = \mathrm{Benefits} - \mathrm{Costs} = \frac{F(t)}{(1+r)^t} \tag{2.1}$$

In comparison, ROV is a process of valuing an asset with uncertainties and changing circumstances. As opposed to NPV, ROV incorporates market, geologic and operational and technical uncertainties. Simply put, ROV is an extension to Net Present Value (NPV)/Present Value (PV) analysis shown as Eq. (2.2)

$$\mathrm{NPV/PV} = \mathrm{Benefits} - \mathrm{Costs} \tag{2.2}$$

$$\mathrm{ROV} = \mathrm{Benefits}\ \mathrm{x}\ p(x) - \mathrm{Costs}\ \mathrm{x}\ p(y)$$

In Eq. (2.2), If the option has been exercised, *p(x)* represents the probability that subsequent benefits are also positive. On the other hand, *p(y)* represents the probability that the option will be positive. Here *x* and *y* are the variables through which these probabilities are quantified. It is evident from the above concept that a major difference between the DCF evaluation and the ROV evaluation is the introduction of uncertainty in current and future benefits through the probabilities *p(•)*.

The concept of ROV to application for the evaluate models for geologic and operational uncertainty. In order to assess why ROV may be more realistic and flexible in valuing assets compared to NPV, here are two reasons (Johnson, 2010) that may specifically apply to petroleum E&P industry:

1. When an investment is valued using NPV, it is assumed that production rates are fixed and there is no allowance for changes in future production rates that might occur due to changing circumstances. However, as opposed to NPV, the ROV concept allows for changing circumstances and in considering changes in future production rates.

2. The ability of ROV make use of more available information such as project volatility due to oil price fluctuations as well as geologic uncertainty, schedule uncertainty etc.

DCF is still the basis to appraise potential investments for most oil companies. It is easy and requires less information to appraise the valuation. It is believed (Coy, 1999) that ROV yields more realistic asset evaluation than DCF because the ROV model incorporates the variability and uncertainty in the model parameters. ROV may highlight extra value for projects, where DCF fails to see the hidden value, or may highlight low value of falsely bloated value projects by DCF (Bailey et al., 2003). The strength of ROV is based on the accuracy of the parameters used in its models and parameter selection is a vital part of ROV (Bailey et al., 2003).

2.1.2 Application for real options

Real options emerged from financial options when Myers (1977) applied option pricing theory to the valuation of non-financial investments. A financial option is the right but not the obligation to buy or sell a specified quantity of underlying asset at a fixed price at or before the expiration date of the option. There are two types of option: call and put options. A call option gives the right to buy an underlying asset for a specific price within or at a specified time. A put option gives the right to sell the underlying asset (Schwartz and Trigeorgis, 2004).

The variables used to value a financial option can be compared with their analogs in real options. An option to develop oil reserves, for example, is similar to a financial call option. Table 2.1 presents financial and real options compared each variables.

The NPV of the developed hydrocarbon reserves is the price of the underlying asset, *S*, in a financial option. The NPV of the expenditure needed to develop the reserves is like a financial option's exercise price, *X*. The time left on an exploration and production (E&P) lease is the time to expiration of a financial option, *T*. The risk-free rate of return, r_f is identical for both financial and real options. The project volatility in E&P project, including hydrocarbon price uncertainty, is analogous to the volatility of stock prices, σ. Finally, profits foregone because production has been delayed are like the lost dividends in the financial option, δ. As long as management holds an unexercised option to invest in a project, it foregoes the money that would have flowed from it had the project been producing revenue.

Table 2.1 Financial and real options compared (Bailey et al. 2003)

Financial call option	Variable	Real option to develop hydrocarbon reserves
Stock price	S	Net present value of developed hydrocarbon reserves
Exercise price	X	Present value of expenditure to develop reserves
Time to expiration	T	For example, time remaining on lease, time to first oil or gas
Risk-free interest rate	r_f	Risk-free interest rate
Volatility of stock price	σ	Volatility of cash flows from hydrocarbon reserves
Dividends foregone	δ	Revenue or profits foregone

2.1.3 Project volatility model

The analogies between real and financial options are not exact. Trying to force real options into a conventional financial-options framework may result in misleading outcomes. One key difference in the two options types is that the exercise price of a financial option is normally fixed. For a real option, this price is associated with development costs, and may be volatile, fluctuating with market conditions, service company prices and rig availability. In the E&P industry, volatility is usually a consolidated value comprising the uncertainty involved in many things, including oil prices and production rates. Determining volatility in real options can be difficult (Bailey et al., 2003).

The volatility of a particular property is a statistical measure of the dispersion of that property under given condition. There are two types of project volatility; historical volatility and implied volatility. Black-Scholes model is the representative approaches of the volatility calculation. Implied volatility is appropriate for stock market. Therefore, it usually uses in financial option. On the other hands, historical volatility is appropriate for project investment. So, in real option historical volatility is suitable.

There are several approaches of calculate historical volatility, Copeland and Antikarov (Copeland & Antikarov 2001) presented a method to estimate the historical volatility parameter in ROV from a project.

The detailed steps for calculating the project volatility by the Copeland and Antikarov method are outlined below:

$F(0)$ = Known cash flow in year 0

$F(t)$ = [Future incoming cash flow (revenue) – Opex]

= Uncertain cash flow in the t_{th} year, where t=1, 2,……, T

r = Continuously compounded discount rate (the rate used to discount future cash flows to their present values) r

$MV(n)$ = Market value of the project at time n (expectation over the future cash flows)

$PW(n)$ = Present worth of the project at time n (expectation over the future cash flows)

$k\ (n)$ = A random variable that represents the continuously compounded rate of return on the project between time n-1 and time n.

The present value at any time t is calculated by multiplying the future cash flow, , with the discount factor, $DV(t)$ i.e.

$$PV(t) = F(t) \text{ x } DV(t) \tag{2.3}$$

IN Eq. (2.3), for a fixed discount rate, r, discretely compounded over time, t and compounded discount rate:

$$DV(t) = \frac{1}{(1+r)^t} = e^{-rt} \tag{2.4}$$

Denoting the present value at time n of future cash flows as $MV(n)$:

$$MV(n) = \sum_{t=n+1}^{T} F(t)\, e^{-r(t-n)} \tag{2.5}$$

Adding the cash flow at time n, to Eq. (2.5) for the present worth $PW(n)$.

$$PW(n) = MV(n) + F(n) = \sum_{t=n}^{T} F(t)\, e^{-r(t-n)} = MV(n-1)\, e^{k(n)} \tag{2.6}$$

Substitution of the Eq. (2.6), and so,

$$k(n) = \ln \left[\frac{PW(n)}{MV(n-1)}\right] \tag{2.7}$$

Since the cash flows are uncertain, the corresponding *PW(n)* are actually random variables (outcomes from simulation). Finally, get a distribution for using equation (2.7) and the standard deviation of this distribution is the project volatility like Eq. (2.8).

$$\sigma(n) = \mathrm{std}(k(n)) \tag{2.8}$$

If the volatility of the project changes with time, this method can still be used to compute time varying volatility by computing distributions of k for different times and standard deviation of each k will generate volatility for each year.

2.1.4 Binomial-lattice option valuation

Basically, there are two types of options – European and American style options. The difference between these two types of options is the date of exercising the options. A European style option can be exercised only at the date of expiration of option, while American style option can be exercised anytime before the date of expiration of the option.

There are two types of models in ROV, the Black-Scholes model and binomial lattice option valuation (BLOV). The Black-Scholes model is a mathematical model of a financial market containing certain derivative investment instruments (Black & Scholes, 1973). From the model, one can deduce the Black–Scholes formula, which gives a theoretical estimate of the price of European-style options. On the other hands, BLOV allow valuation of both the European and American-type options. BLOV is a generalized numerical method for the valuation of options. In general, the BLOV model does not have closed-form solutions (Cox et al. 1979). And for this reason, the American option is implemented in the oil industry to take advantage of the availability of flexibility in timing. Although BLOV is computationally slower than the Black-Scholes model for ROV, it is more accurate for longer-period (Yound & Wiley, 2011) such as options in upstream petroleum industry projects which can last for several years.

BLOV uses two lattices, the lattice of the underlying asset and the valuation lattice. First, the lattice of the underlying asset is figured by moving forward from left to right towards the terminal nodes at the date of expiration. It shows how the future asset values could possibly evolve. The left most node usually contains the value of the NPV of the underlying asset. At each step the value of the underlying asset will increase or decrease by a factor of u or d ($u \geq 1,\ 0 < d \leq 1$), per time step of the lattice. So, if S_0 is the current price, then in the next time step the price will either go up or go down like, $S_{up} = S_0 u$ and $S_{down} = S_0 d$. The factors u and d, which determine the upward and downward movements at each node, are functions of the volatility of the underlying asset and the time step between each column of the lattice. They are given as Eq. 2.9:

$$u = e^{\partial\sqrt{\Delta t}} \text{ and } d = \frac{1}{u} = e^{-\partial\sqrt{\Delta t}} \tag{2.9}$$

The probability of the asset value going up is designated as u, which implies that the probability of the value going down is d. This is shown in the Figure 2.1. and Figure 2.2. Figure 2.2 is whole process for construction of a lattice underlying asset and probability of future assets.

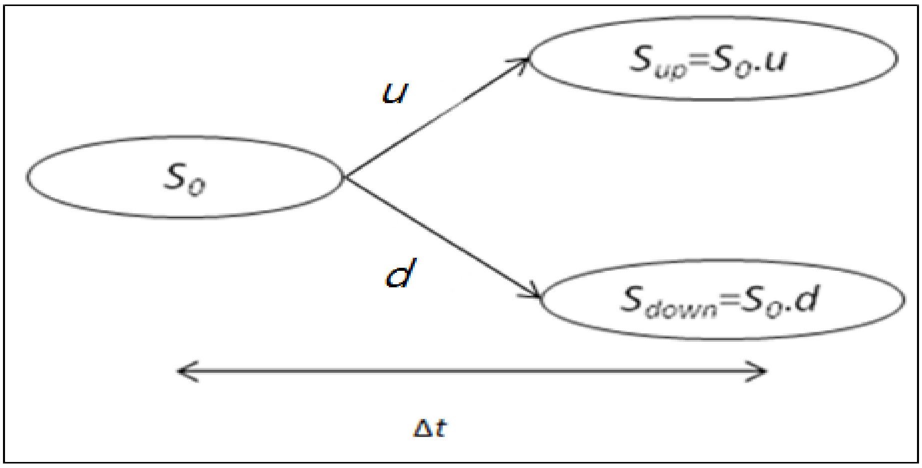


Figure 2.1 Lattice of the underlying asset.

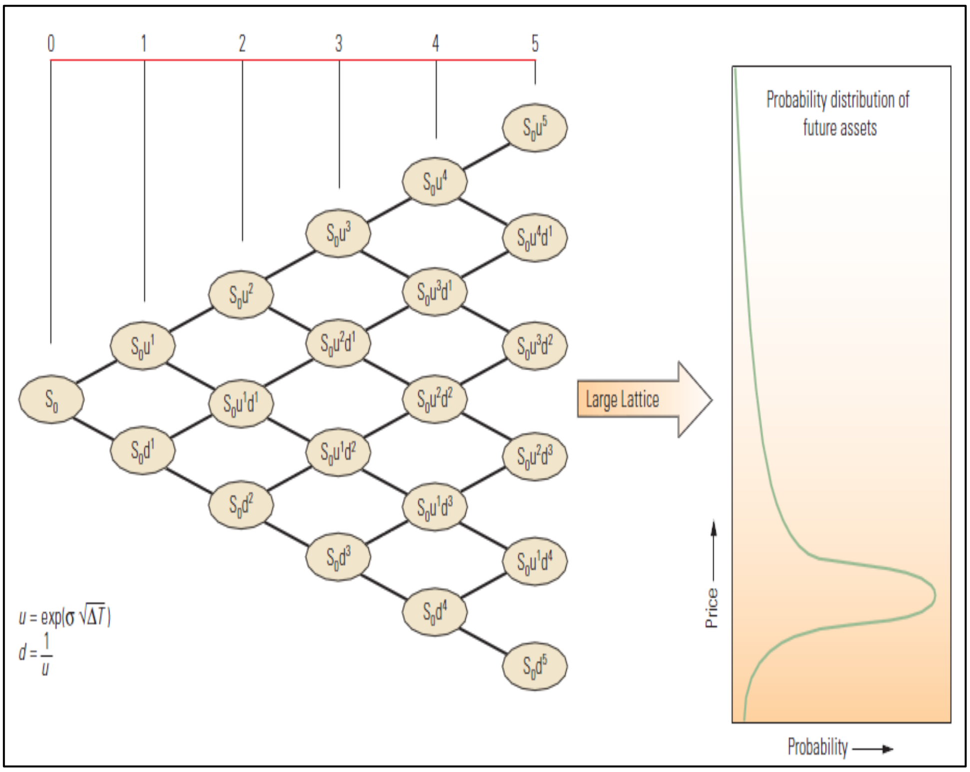


Figure 2.2 Probability distribution of future payoffs obtained from the values in the terminal nodes of the underlying lattice. (Bailey et al., 2003)

Next step is the valuation lattice. The option valuation lattice consists of equal number of nodes and branches as the lattice of the underlying asset. At each node in the terminal branch of the underlying lattice like, the nodes at the expiration date (*T*), the option value is calculated as MAX[(S_n – K),0], where K is the CAPEX for developing the asset and S_n is the asset value at the date of expiration. Now starting from these values in the terminal nodes, move backwards towards the first node of the lattice to obtain the value of the option at each node. And then value the asset' option at the date of interest using the parameters p, u and d. It calls back induction. The future payoffs in two adjacent nodes behind the node at the date of interest and calculate the expected value by weighting them with their respective probabilities. To infer the parameters of P, this solution based on Black-Scholes model and obtained by Cox et al. (Cox et al. 1979). Eq. 2.10 is the solution of p and Eq. 2.11 is the call option price in present time.

$$p = \frac{e^{r\Delta t} - d}{u - d} \tag{2.10}$$

$$C = [P \cdot A + (1 - P) \cdot B]\, e^{r\Delta t} \tag{2.11}$$

This process is shown in Figure 2.3.

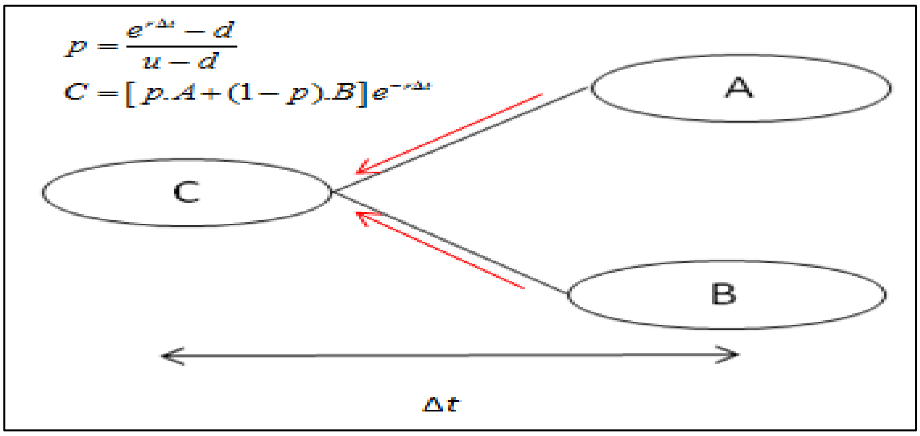


Figure 2.3 Calculation of option valuation lattice.

2.2. The Oil Price Model

The three types of oil price model used in modeling financial commodities are geometric Brownian motion (GMB) process, Mean Reverting (MR) process, and mean reversion with jumps (MRJ) process. However, mean reverting (MR) processes are the most widely used to model for oil price. Ornstein and Uhlenbeck (Ornstein & Uhlenbeck, 1930) is the most popular MR model.

Mean reverting processes incorporate the concept of demand and supply. Simply, MR model's concept is the producing a counter-balancing effect. There are three properties of this model. First, the price is said to follow MR process if price follows a log-normal diffusion. Second, price changes in MR models are not independent. Last, MR models have a long term equilibrium price and mean reversion rate.

The Ornstein-Uhlenbeck method is widely used for modelling a mean reverting process. Below formulae to be used based on Ornstein-Uhlenbeck model (Dias, 2004).

W_t = Brownian- Motion, also called Weiner process. $\rightarrow dW_t \sim N(0,\sqrt{dt})$

λ = Speed of mean reversion

μ = 'long run mean', to which the process tends to revert.

σ = Measure of the process volatility

T = Time

Δt = small time

P_t = Price of oil at time 't'

The process of fluctuation in oil price 'P' is modeled as Eq. 2.12

$$dP = \lambda\,(\mu - P)\,dt + \sigma\,dW_t \tag{2.12}$$

The exact formula of the Ornstein-Uhlenbeck mean reverting process which is obtained as a solution to the differential Eq. 2.13 that holds for any size of Δt is:

$$P_t = e^{-\lambda\Delta t}\,P_{t-1} + (1 - e^{-\lambda\Delta t})\mu + \sigma\sqrt{\frac{(1 - e^{-2\lambda\Delta t})}{2\lambda}}\,dW_t \tag{2.13}$$

To estimate the three parameters of MR model, historical data of oil price is necessarily. Then parameter estimation can be done using well known techniques for parameter estimation such as Least Square regressions, and Maximum Likelihood. Once we have historical data of oil prices, we can examine the distribution of annual changes in the natural logarithm of price, as oil prices are usually said to follow a log-normal distribution.

2.3. Multi-objective optimization

2.3.1 Pareto optimal front

In practice may real world problems have two or more competing objectives. When these objectives are conflicting with each other, there is no single best solution but a set of trade-off solutions otherwise known as the Pareto Optimal set. This set contains all the decision vectors that cannot be simultaneously improved i.e. by improving one objective function, another objective function value will worsen, Each of the solutions in the Pareto optimal set offer acceptable performance when all objectives are considered and therefore higher level information is required for decision makers to select a solution (Coello et al., 2002).

The Pareto optimal front shown in Figure 2.4 as the solid line displaying the best solutions found in P.

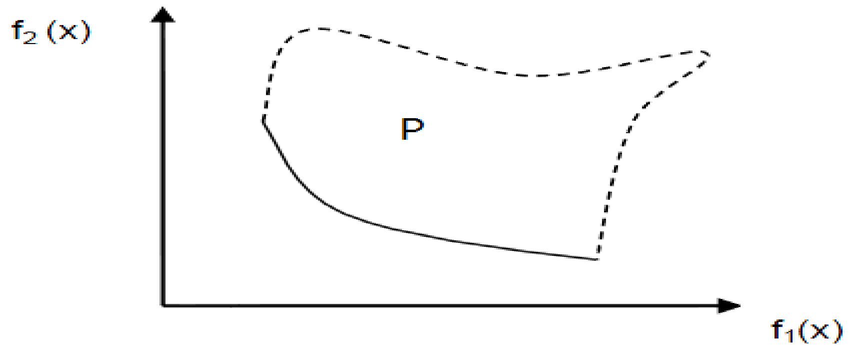


Figure 2.4 The Pareto front of an optimization with two objective functions.

2.3.2 Multi-objective genetic algorithm

There are an extensive range of genetic algorithms but often differ in their methods to support the inclusion of Pareto optimality. In this study Non-Dominated Sorting Genetic Algorithm II (Deb et al., 2000) is used multi-objective optimization for history matching.

NSGA-II is an algorithm establishing the dominance relationships between individuals and providing a fast sorting method of chromosomes. This algorithm uses a measure of crowding around individuals to ensure diversity in the population.

Figure 2.5a is an example of non-dominated sorting in the 2D objective space. The black circle means the best non-dominated solutions with the first rank. Solutions P and Q dominate other solutions expressed in gray squares with the i^{th} rank and empty white diamonds with the nth rank. Solutions P and Q are equivalent because they are not dominated each other for the given objectives f_1 and f_2. Solution P is superior to solution Q for the second objective f_2, while the latter is better than the former for the first objective f_1 (Min, 2013).

In brief, solutions with the i^{th} rank are dominated by other solutions with the first to the i-1^{th} rank, while superior to other solutions with more than the $i+1^{th}$ rank.

After the non-dominated, sorting crowding-distance sorting aims to preserve diversity of solutions.

Eq. (2.14) expresses how to calculate the crowding distance between two arbitrary solutions which lie in the same non-dominated front as shown in Figure 2.5b. If some of solutions in the same front are picked up for generating the next population, solutions with a larger crowding-distance value have more possibility to be selected than solutions with a smaller crowding-distance value. That is, less crowded solutions are preferred to preserve the diversity of population if they are in the same front (Min, 2013).

$$\sigma^j = \sum_{i=1}^{M} \frac{d_i^j}{f_i^{\max}} \tag{2.14}$$

where

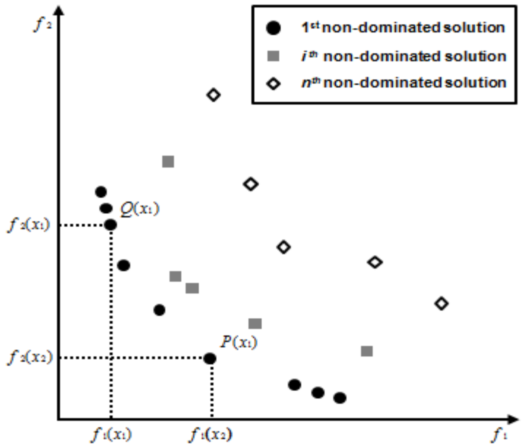
σ^j : *crowding distance of the j^{th} solution in the non-dominated front*

M : *the number of objective function*

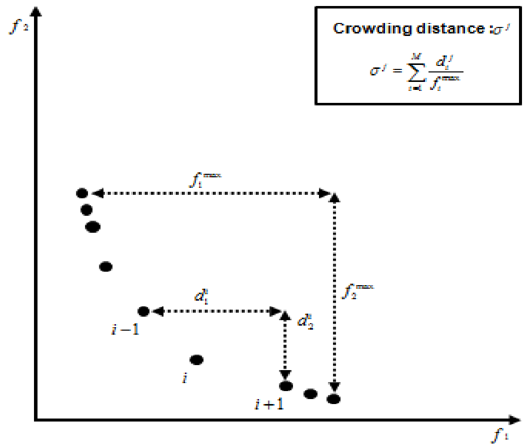
i : *objective function number*

d_i^j : *displacement between two neighbors with the j^{th} solution*

$f_i^{\max}$: *maximum distance in the direction of the i^{th} objective function.*



(a) Non-dominated sorting



(b) Crowding distance sorting

Figure 2.5 Conceptual diagram for the selection scheme in NSGA2: (a) non-dominated sorting and (b) crowding distance sorting (Min, 2013).

3. Incorporating reservoir uncertainty in ROV

The main purpose of this study is an economic analysis by multi-objective genetic algorithm and real option valuation (ROV) using switch option to acquire reliable reservoir’s asset histogram. Proposed model use NSGA-II algorithm to assess the production forecast of reservoir performance for multi-objective optimization and use ROV to economic forecast of drilling additional well.

An algorithm is presented to forecast reservoir uncertainty and its corresponding economic analysis which is ROV. Five steps are worked for incorporating flow rate uncertainty in the ROV calculation.

First, develop reservoir modeling by multi-objective algorithm. Second, these stochastic reservoir models are then input into the reservoir flow simulator to determine future hydrocarbon production rates. Third, determine future cash flows about these production rates. Next, these future cash flows are used to determine project volatility using an appropriate model for project volatility such as the method by Copeland and Antikarov (2001). Finally, future cash flows, capital expenses, project volatility, and rate of return are used in the BLOV model to determine the option value for investing in the project at a certain time in future.

The above steps to incorporate flow rate uncertainty in the ROV calculations are detailed in Figure. 3.1.

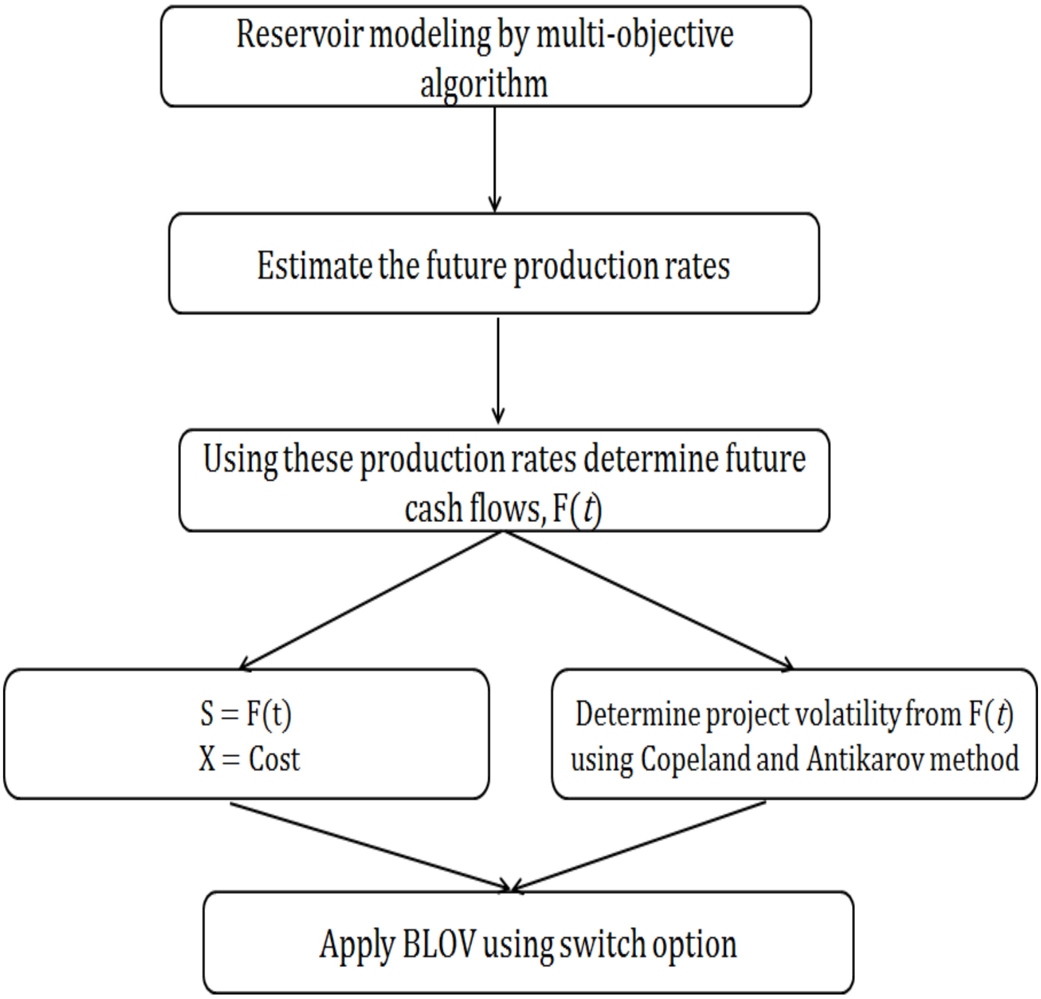


Figure 3.1 Algorithm for incorporating reservoir uncertainty in ROV

3.1. Frame work of well optimization scenario

Create the scenario for well optimization to the reservoir that initially has several production wells only. Basic information available about the reservoir characteristics such as permeability and production rates about few years is from these several production wells. Using this base information reservoir modeling will be proceeded by multi-objective algorithm and then, future production rates are shown of the reservoir. Having scenarios for drilling additional well which consider where and when of the reservoir enables us to calculate NPV and sensitivity analysis about economic parameters and take appropriate decisions regarding further development of the reservoir. Concretely, these scenario will be considered where (locations) and when (year) for extra well, over and above the existing producing wells.

This scenario may forecasted economic returns and gives a more correct estimate for the economic value of the field. Our objective is to evaluate reliable models of economic analysis to reservoir for additional drilling that using ROV. Figure 3.2 shows flow diagram of drilling additional scenario.

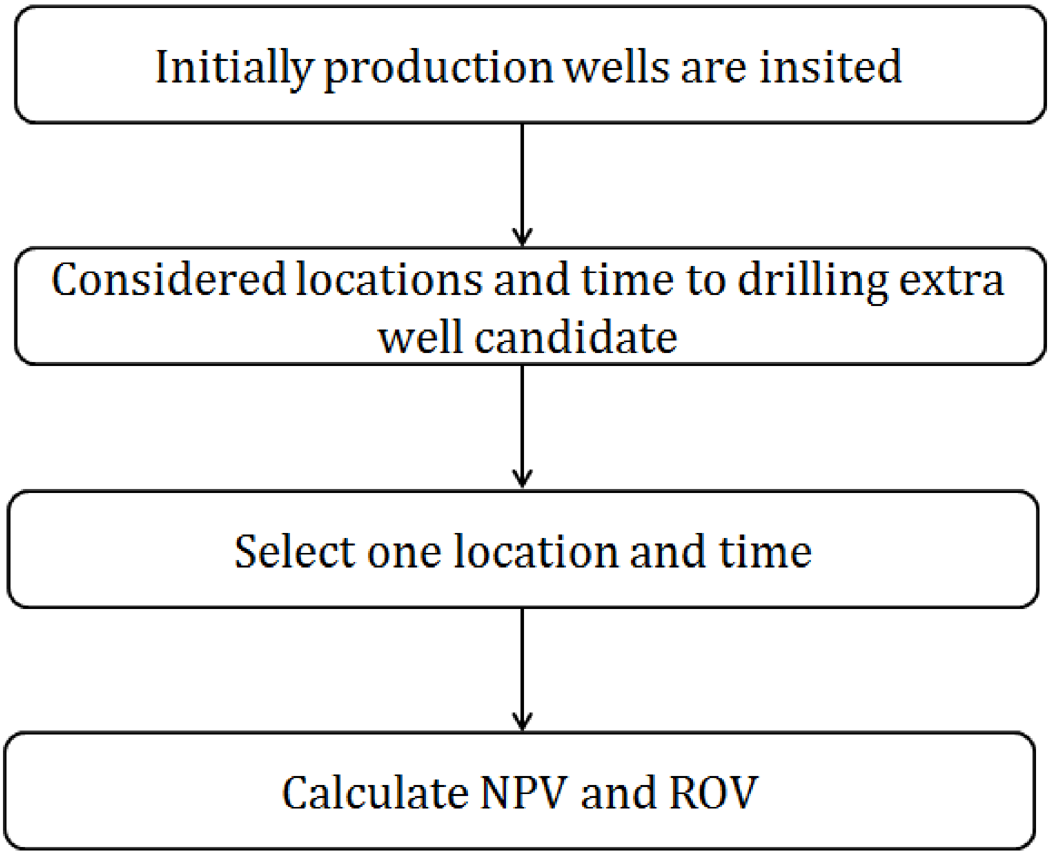


Figure 3.2 Flow diagram of well optimization scenario.

3.2. History matching by multi-objective genetic algorithm

For performance reservoir history matching multi-objective genetic algorithm is used. Figure 3.3 is flow diagram used in multi-objective genetic algorithm.

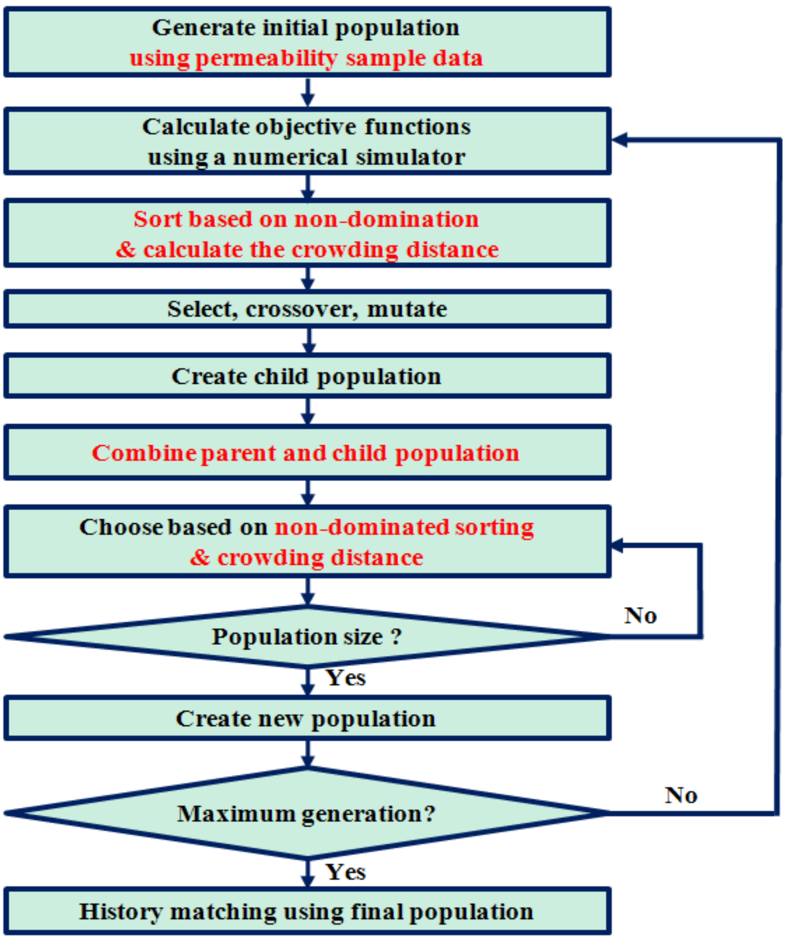


Figure 3.3 Flow diagram used in history matching (Han, 2010).

Uncertainty parameters are x-directional permeability k_x of each grid-block. Response parameters are calculated production data to be matched. In this study, history matching aim to economic analysis, three response parameters are calculated that field oil production rate, field gas production rate, field water production rate. An individual objective function f is a quantified data mismatch for each production data type. Multi-objective history matching aims to minimize the individual objective functions simultaneously. Seven different objective functions are drawn as depicted in Eqs. (3.1) through (3.3). All the individual objective functions are normalized with their corresponding statistical parameters. f_1 to f_3 are the simulated daily production rate at the three producers in 2 years.

$$f_1 = \sum_{i=1}^{n} \left(\frac{FOPR_i^{cal} - FOPR_i^{obs}}{\sigma_1^w} \right)^2 \tag{3.1}$$

$$f_2 = \sum_{i=1}^{n} \left(\frac{FGPR_i^{cal} - FGPR_i^{obs}}{\sigma_2^w} \right)^2 \tag{3.2}$$

$$f_3 = \sum_{i=1}^{n} \left(\frac{FWPR_i^{cal} - FWPR_i^{obs}}{\sigma_3^w} \right)^2 \tag{3.3}$$

where

i : *time step*

$FOPR$: *field oil production rate*

$FGPR$: *field gas production rate*

$FWPR$: *field water production rate*

obs : *observed data*

cal : *calculated data from reservoir simulation*

n : *number of observed data*

σ : *standard deviation of observed data*

w : *weight factor for the objective function*

NSGA-II algorithm is optimized through total 10 generation and 100 generations. Table 3.2 shown as GA parameters for history matching using NSGA-II algorithm.

Table 3.1 Summary of GA parameters

GA parameters	Value
Crossover probability	0.9
Polynomial order for crossover	10
Mutation probability	0.1
Polynomial order for mutation	20
Population size	10
Generation size	100

3.3. Construction switch option

Switch option can provide a hedge against the likelihood that another project will be more economic sometime in the future. For example, a company may decide to drill a well in a certain location. If the well is dry, then the company has lost the cost of drilling. The well location was an operational alternative, a decision that had to be made there and then. However, if there were another party guaranteeing some minimum return on the well, the company drilling the well would have a real option, because it could decide in the future whether to call on that guarantee, thereby minimizing any downside risk and maximizing any upside potential (Bailey et al., 2003).

Without drilling case (case 1) and drilling extra well case (case 2) are independent cases with different cash-flow NPVs and project volatilities. Propose model establishes the static NPV, excluding switching costs, and associated volatility of the two cases.

A switching option can be analyzed by constructing two lattices, one for each of the two underlying assets. The simplest case assumes these two lattices are completely correlated—each step up or down in one underlying lattice corresponds with the same step in the other. In this way, nodes in the two cases can be directly compared to construct a valuation lattice for the upgrade. The valuation lattice is obtained by subtracting the upgrade cost from the last column of the Case 2 lattice, comparing this to the last column of the Case 1 lattice, and selecting the larger value at each node. This reflects Operation's right to choose the better of the two cases in any eventuality. The option value is then computed by backward induction using the Case 1 risk-neutral probabilities, *p*. Changing the cost to upgrade affects the value of the upgrade option. In this case, the five-step lattice is set for switch option.

In lattices for drilling additional extra well case, case 1 and case 2 have different lattices of the underlying asset, but the lattice structure is the same, allowing a node-by-node comparison between them. Nodes in Case 2 do not considered, except for the final column, to indicate that no decision is made until the end of one year. The last column of the valuation lattice is constructed by comparing the value of Case 1 to equivalent node value of Case 2 minus the implementation cost. This also provides the decision to keep Case 1 or switch to Case 2. The other nodes of the valuation lattice are constructed by back-induction, using the risk-neutral probabilities from Case 1, the base case. The value of the project with the switch option will be calculated. Figure 3.4 shows switch option flow diagram.

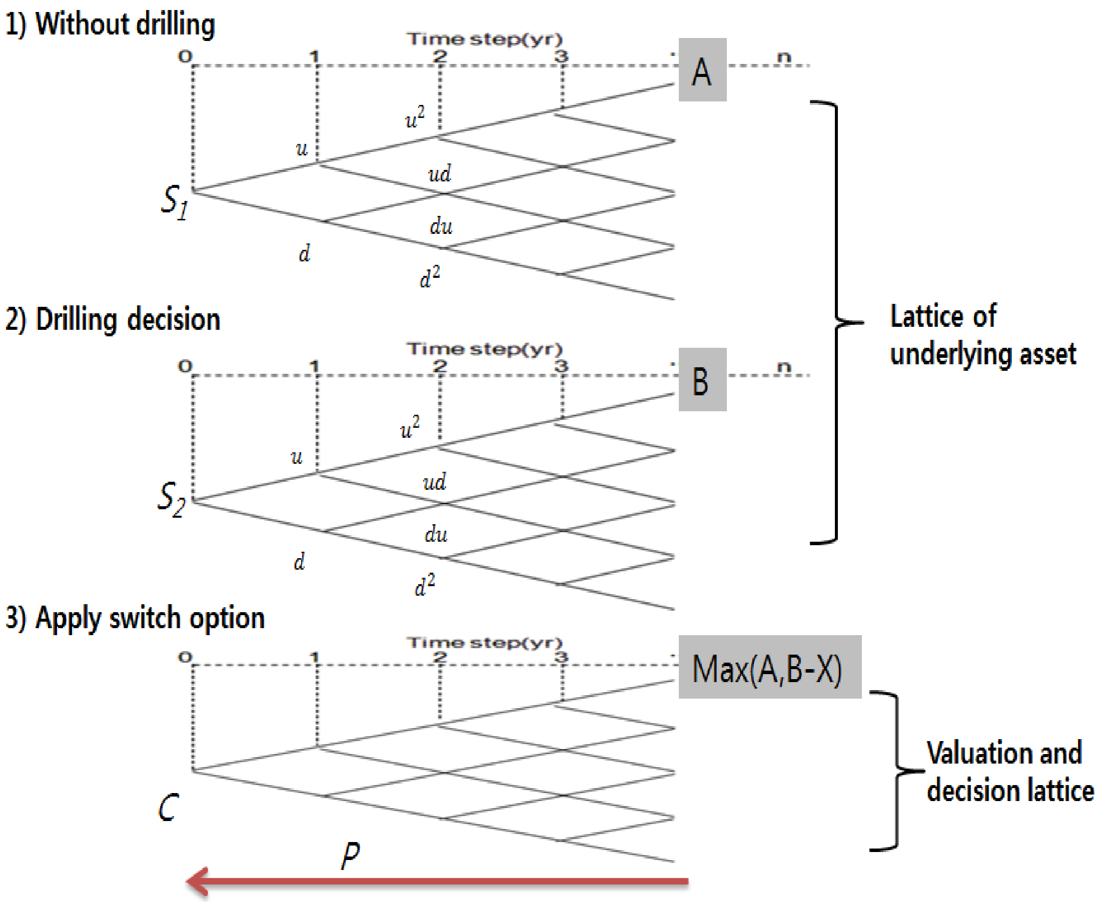


Figure 3.4 Flow diagram used in switch option.

4. Applications and Analysis

The proposed methodology for the uncertainty assessment of well placement optimization was applied to the PUNQ-S3 reservoir. Concretely, the proposed model which is incorporating reservoir uncertainty in ROV performed to the PUNQ-S3.

4.1. PUNQ-S3 and scenario summary

4.1.1 PUNQ-S3

The PUNQ-S3 model has been taken from a reservoir engineering study on a real field operated by Elf Exploitation (Floris et al., 2001). It was qualified as a small-size industrial reservoir engineering model. The data available for the PUNQ-S3 model included the porosities and permeabilities at well sites, and the synthetic production history of the first 2 years. The model contains 19×28×5 uniform grid blocks with an areal dimension of 180×180 m^2, among which 1761 blocks are active. Permeability varies from 10.0 to 500 md with an arithmetic mean of 220.0 md following a log-normal distribution as Figure 4.1.

Table 4.1 summarizes the reservoir properties of the field. The reservoir is under-saturated with dead oil of which viscosity is 3.0 cp. Initial reservoir pressure is 2,000 psia, and initial water saturation is 25%. Porosities are assumed 0.15 as constant.

Table 4.1 Reservoir properties of the reference field

Properties	Value	Unit
Reservoir size	19×28×5	m×m×m
$\Delta x = \Delta y = \Delta z$	180	m
Initial pressure	2,000	psi
Average porosity	0.15	fraction
Oil viscosity (dead oil)	3.0	cp
Rock compressibility	3.0E-05	psi^{-1}
Water compressibility	5.0E-07	psi^{-1}
Oil formation volume factor	1.01	rb/STB

4.1.2 Scenario

Two production wells, i.e., W1, W2, are set up along the reservoir as shown in Figure 4.1. Bottomhole pressure is 500.0 psia for two production wells. During field production, two weeks of each year are needed for each well to do a shut-in test to collect the corresponding pressure data. History matching is carried out from the startup date to 760 days.

For proposed model two cases performed two cases independently.

CASE 1: After history matching, production behavior is predicted up to 20 years. In without drilling case, an economic analysis using NPV conducted based on 760 days historical production data. The economic parameters used for the NPV calculations are given in Table 4.2.

CASE 2: In drilling extra well case, drilling location and time were considered in same time. Three location candidates and eight times when each year after history matching (3 – 10 year) are objectives for economic analysis using ROV. So, there are total 24 (3 x 8) scenarios for economic analysis. Figure 4.1 shows the drilling extra well candidate location. Each extra well drill to plan each year when 3 year to 8 year after produce 2 years. The economic parameters used for the ROV calculations are given in Table 4.3. Project volatility is calculated from each scenario.

After all the case performed switch option conducted using **CASE 1** and **CASE 2.** The total number of switch option performed was 24 (3 x 8).

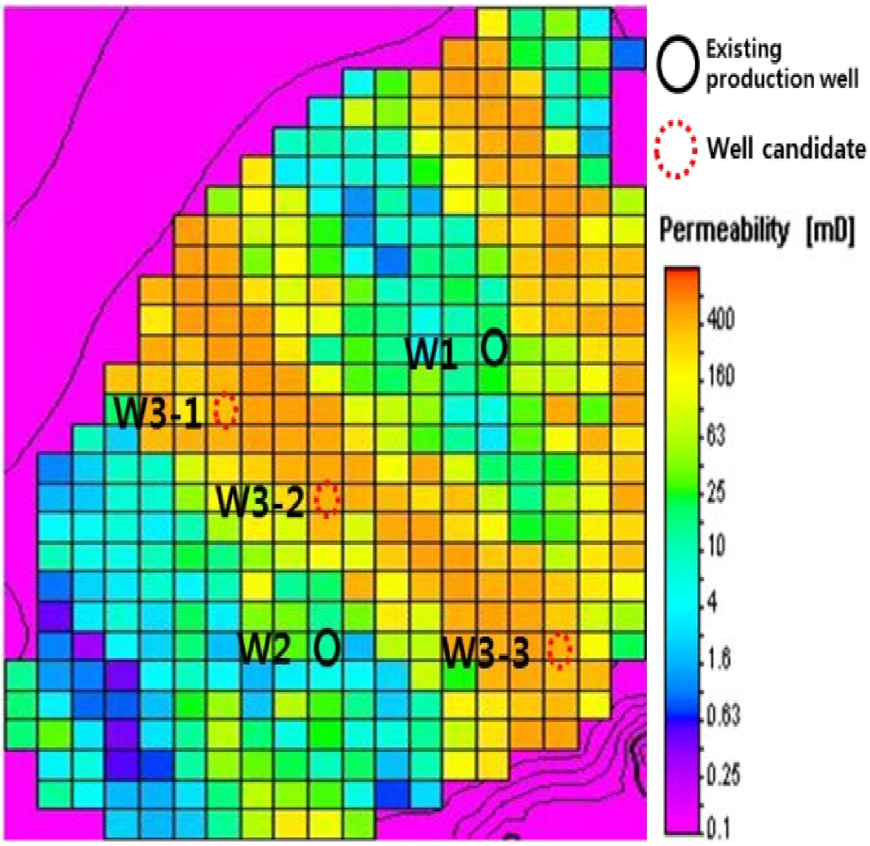


Figure 4.1 Permeability distribution and well location in the PUNQ-S3.

Table 4.2 Parameters for NPV calculation for the PUNQ-S3

Parameter			Value
Discount rate, dimensionless			0.1
Inflation rate, dimensionless			0.05
Oil price, $/stb			75 - 110
Gas price, $/Mscf			3 - 12
Price volatility, dimensionless			0.25
Risk-free interest rate, dimensionless			0.5
Reversion speed, dimensionless			0.125
Operation cost, $	Fixed cost, $/day		1,500
	Variable cost	Oil handling cost, $/stb	5
		Gas handling cost, $/Mscf	10
		Water handling cost, $/stb	3
Capital expenditure, $			500,000,000
Income tax, dimensionless			0.4
Infill well cost, $/well			25,000,000

Table 4.3 Parameters for ROV calculation for the PUNQ-S3

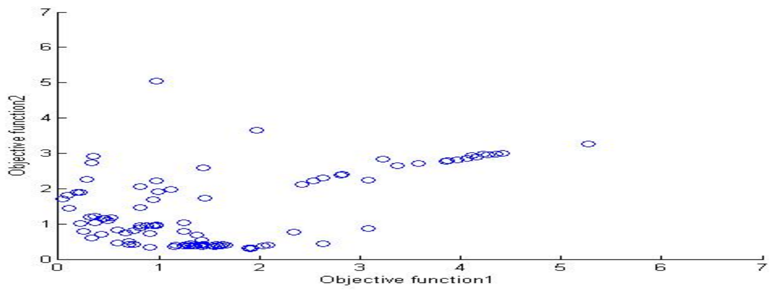
Parameter	Value
Drilling time, year	3 - 10
Time to expiration, days	760 - 4045
Exercise cost, $/well	25,000,000
Risk-free interest, dimensionless	0.5

4.2. Result of multi-objective history matching and prediction due to each scenario

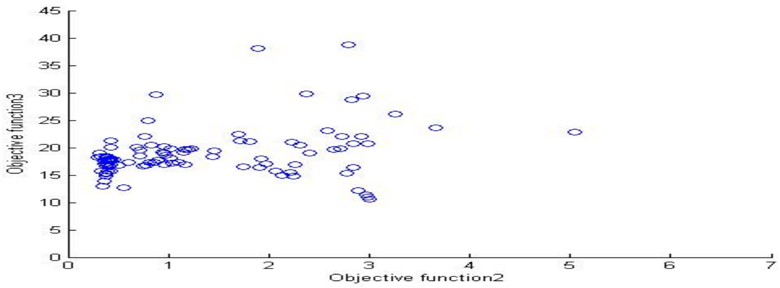
Figure 4.2 and Figure 4.4 presents the spread of last generation solutions obtained from the model with that of NSGA-II in three 2D and 3D objective spaces: $f_1(x)$: cumulative oil production of the field, $f_2(x)$: cumulative gas production of the field, $f_3(x)$, : cumulative water production of the field.

Total 47 optimal solutions is provided multi-objective history matching which non-dominated sorted by crowding distance. Figure 4.3 and figure 4.5 shows the spread of 47 optimal solutions.

47 optimal solutions used in prediction due to each scenario. Figure 4.6 shows the cumulative oil production that history-matched and prediction of the field for the without drilling. For comparison, three representative probability prediction (P10, P50, P90) which use single objective history-matched (SOGA) for prediction of production are performed. On the other hand, from figure 4.7 to figure 4.9 shows the cumulative oil production of the field for the each scenario which is history-matched by the model, NSGA-II and SOGA of prediction for 20 years. It is obvious that the history-matched and improve the production performance than the without drilling. The most optimized production of additional well drilling is the case that drilling W3-3 in 3^{th} year shown as figure 4.9 (a).



(a) $f_1(x)$ **vs.** $f_2(x)$



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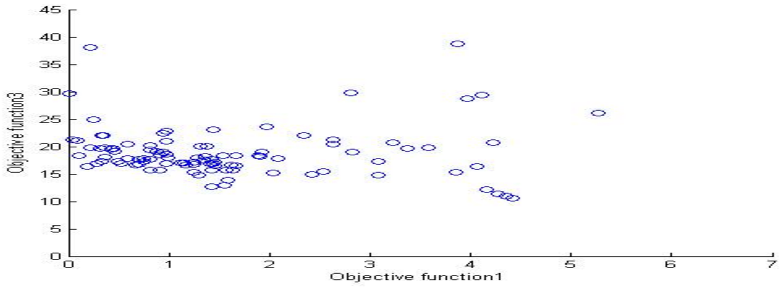
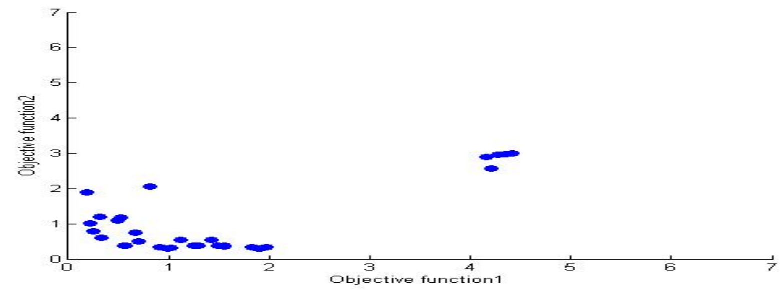
(b) $f_1(x)$ **vs.** $f_3(x)$

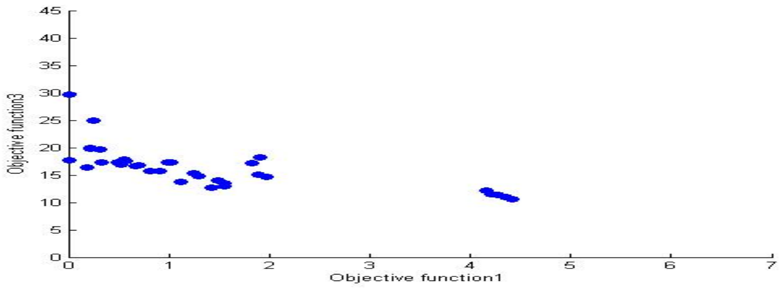


(c) $f_2(x)$ **vs.** $f_3(x)$

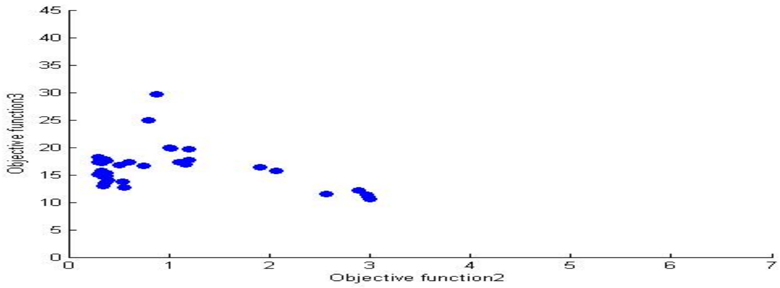
Figure 4.2 Distribution of last generation solutions in 2D of NSGA-II.



(a) $f_1(x)$ **vs.** $f_2(x)$



(b) $f_1(x)$ **vs.** $f_3(x)$



(c) $f_2(x)$ **vs.** $f_3(x)$

Figure 4.3 Distribution of 47 optimal solutions IN 2D of NSGA-II.

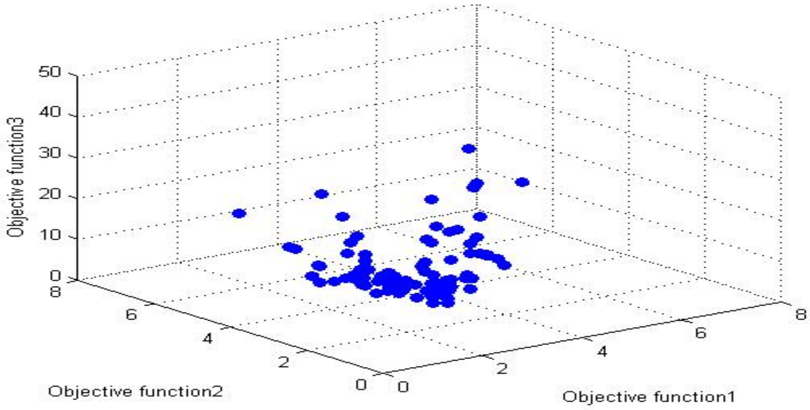


Figure 4.4 Distribution of last generation solutions in 3D of NSGA-II.

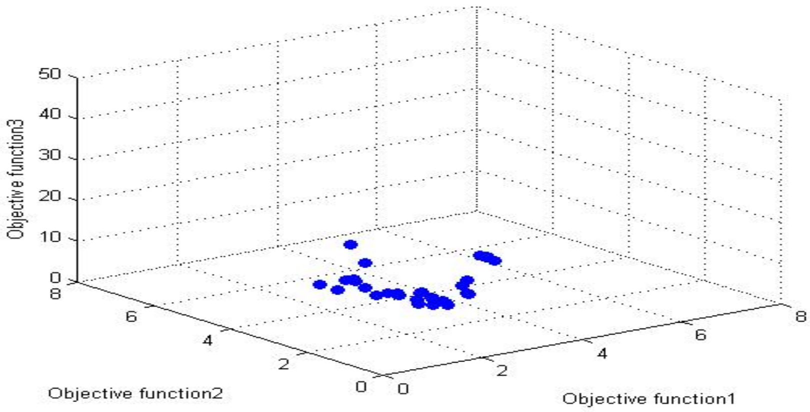


Figure 4.5 Distribution of 47 optimal solutions in 3D of NSGA-II.

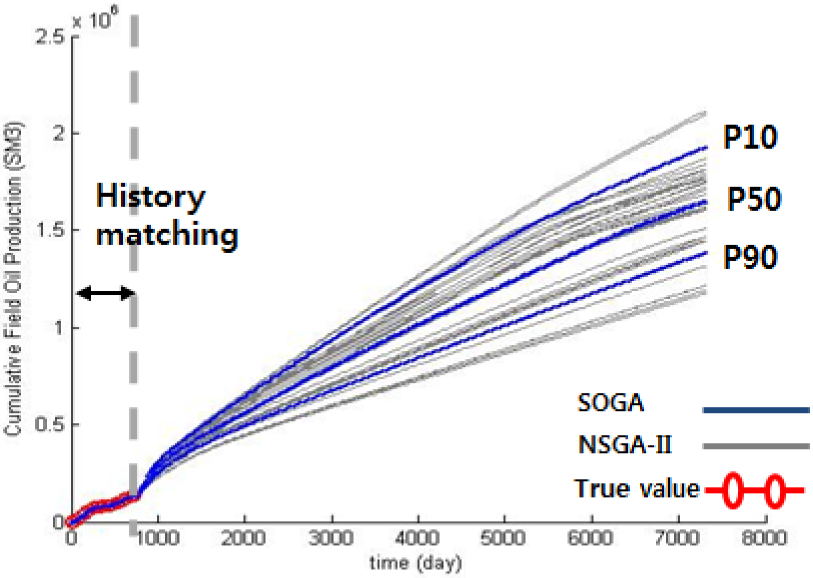
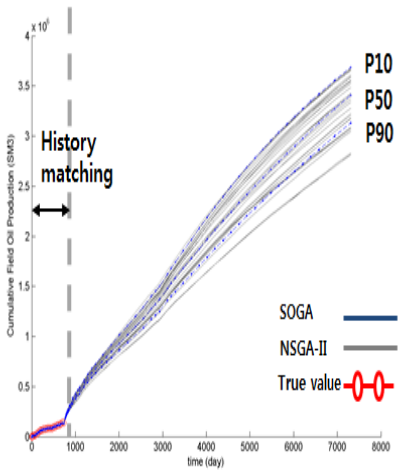
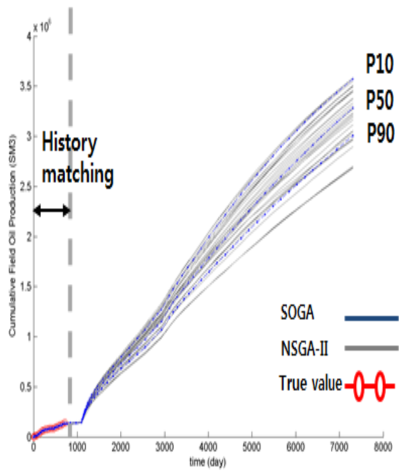


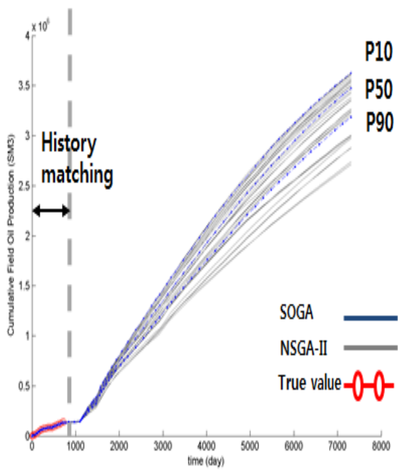
Figure 4.6 Prediction of field oil production after history matching by SOGA and NSGA-II for without drilling.



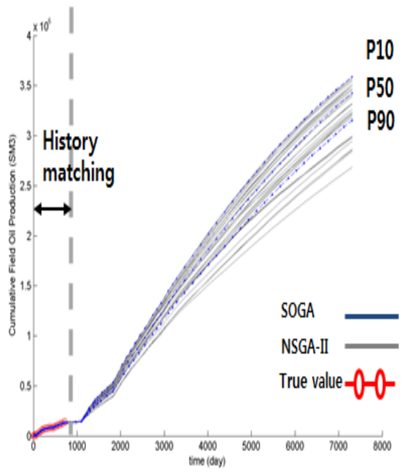
(a) Drilling W3-1 in 3rd year



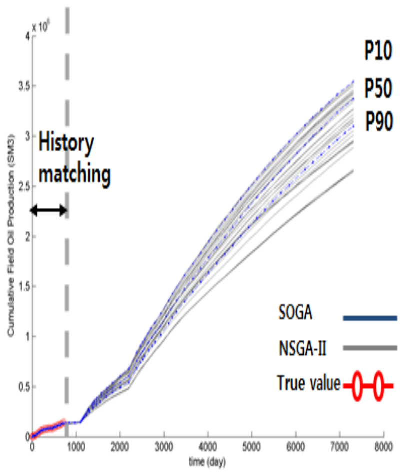
(b) Drilling W3-1 in 4th year



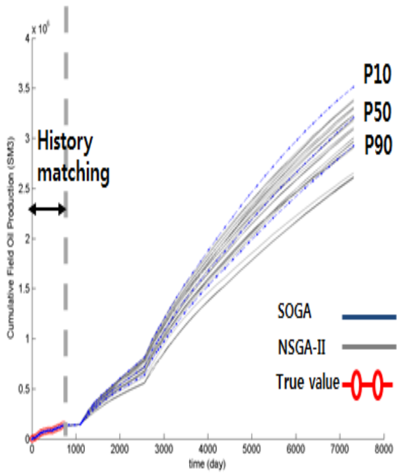
(c) Drilling W3-1 in 5th year



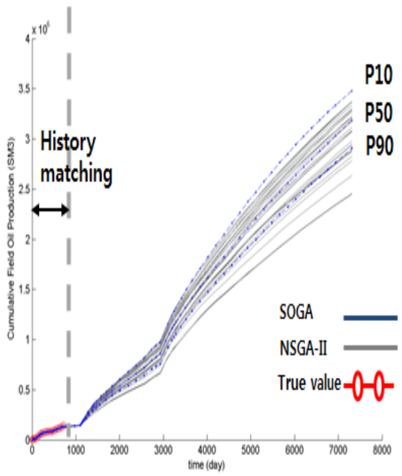
(d) Drilling W3-1 in 6th year



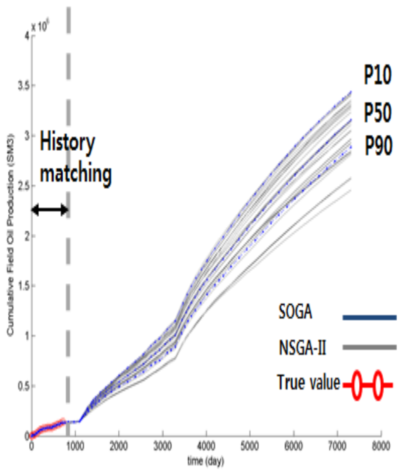
(e) Drilling W3-1 in 7th year



(f) Drilling W3-1 in 8$^{th\ t}$ year

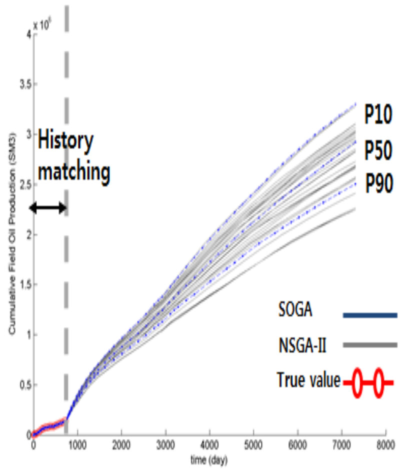


(g) Drilling W3-1 in 9th year

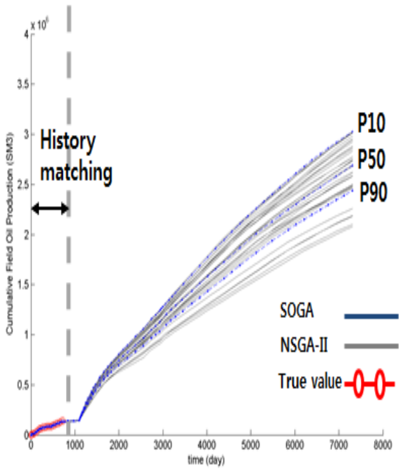


(h) Drilling W3-1 in 10th year

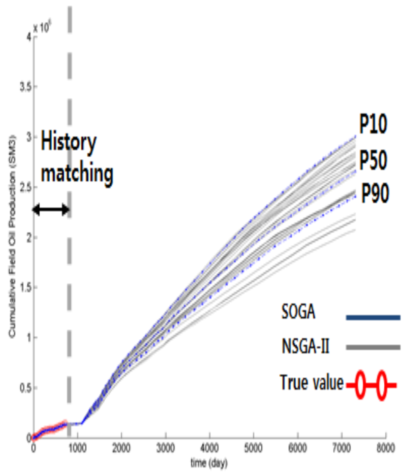
Figure 4.7 Prediction of field oil production after history matching by NSGA-II for drilling W3-1 due to time scenario.



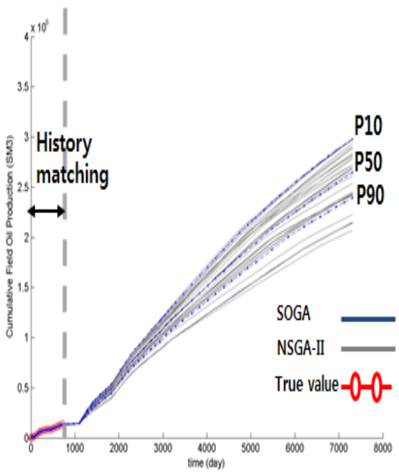
(a) Drilling W3-2 in 3rd year



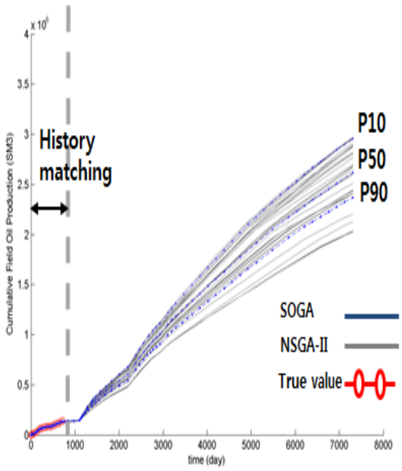
(b) Drilling W3-2 in 4th year



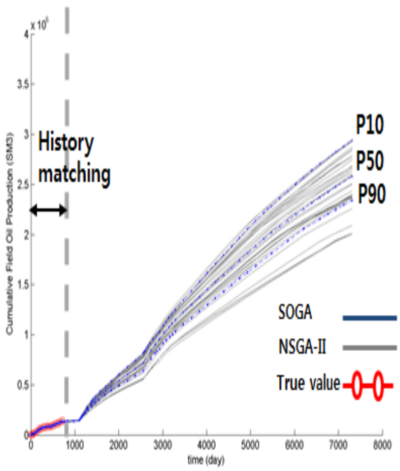
(c) Drilling W3-2 in 5th year



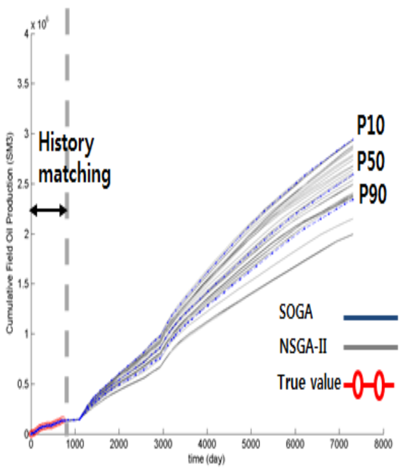
(d) Drilling W3-2 in 6th year



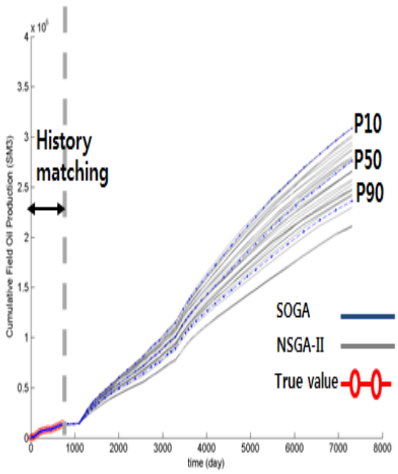
(e) Drilling W3-2 in 7th year



(f) Drilling W3-2 in 8th year

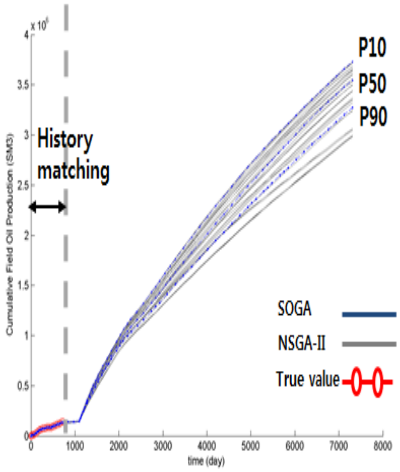


(g) Drilling W3-2 in 9th year

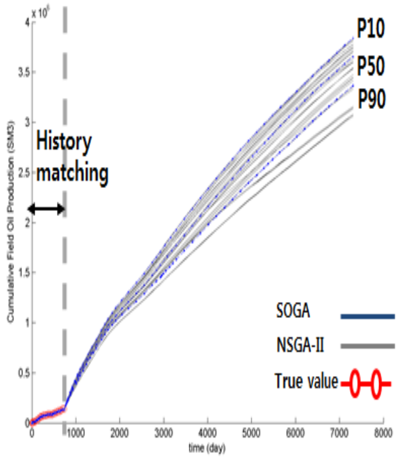


(h) Drilling W3-2 in 10th year

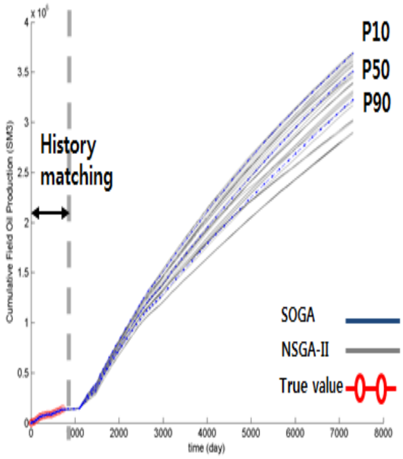
Figure 4.8 Prediction of field oil production after history matching by NSGA-II for drilling W3-2 due to time scenario.



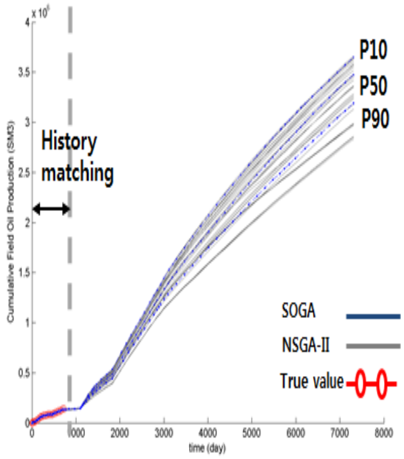
(a) Drilling W3-3 in 3rd year



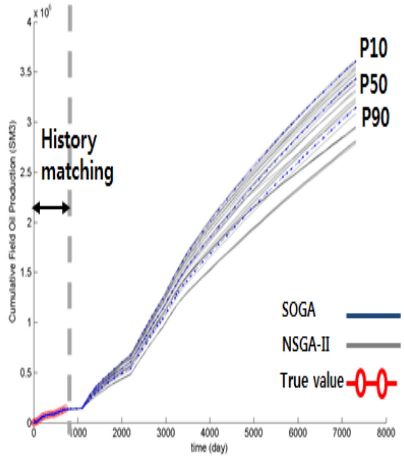
(b) Drilling W3-3 in 4th year



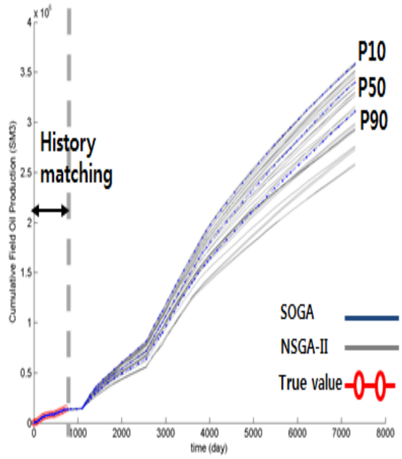
(c) Drilling W3-3 in 5th year



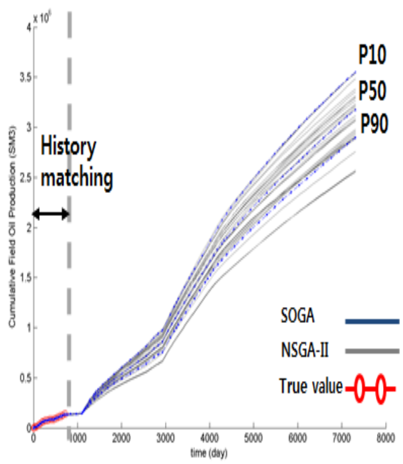
(d) Drilling W3-3 in 6th year



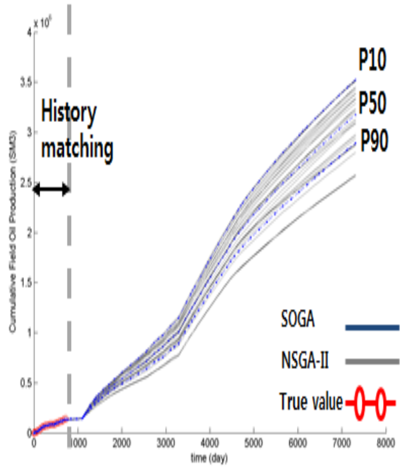
(e) Drilling W3-3 in 7^{th} year



(f) Drilling W3-3 in $8^{th\ t}$ year



(g) Drilling W3-3 in 9^{th} year



(h) Drilling W3-3 in 10^{th} year

Figure 4.9 Prediction of field oil production after history matching by NSGA-II for drilling W3-3 due to time scenario.

4.3. Decision making based on NPV

Decision making is based on NPV which are tree representative probability scenarios. A standard NPV model is calculated which used economic parameters, Table 4.2. To obtained NPV, MR model which is oil price model and cumulative production of oil, gas and water that prediction in chapter 4.2.

The following equation from Eq. 4.1 to Eq. 4.5 is used to obtain forecast of future cash flows and NPV for each scenarios. Eq. is the standard form which calculate NPV

$$PV = F(t) \times DV(t) \tag{4.1}$$

$$F(t) = (q(t) \times p) - COST \tag{4.2}$$

$$DV(t) = \frac{1}{(1+r)^t} = e^{-rt} \tag{4.3}$$

$$PV = F(t) \times DV(t) \tag{4.4}$$

$$NPV = \sum PV = \frac{F(t)}{(1+r)^t} \tag{4.5}$$

From table 4.4 to table 4.6 is the NPV for the each scenario. The low (P90), median (P50), high (P10) probability model predictions are shown. In standard method, decision making was conducted based on these tables. Drilling W3-3 in 3rd year is the best decision in NPV analysis. In P50 case, NPV of the project is $8,704 million sown as table 4.6 (a).

Table 4.4 NPV in the case of W3-1 due to time scenario.

Probability	NPV (M$)
P10	8,784
P50	8,596
P90	8,399

(a) Drilling W3-1 in 3rd year

Probability	NPV (M$)
P10	8,695
P50	8,497
P90	8,289

(b) Drilling W3-1 in 4th year

Probability	NPV (M$)
P10	8,597
P50	8,408
P90	8,296

(c) Drilling W3-1 in 5th year

Probability	NPV (M$)
P10	8,489
P50	8,297
P90	8,087

(d) Drilling W3-1 in 6th year

Probability	NPV (M$)
P10	8,396
P50	8,194
P90	8,012

(e) Drilling W3-1 in 7th year

Probability	NPV (M$)
P10	8,287
P50	8,063
P90	7,869

(f) Drilling W3-1 in 8th year

Probability	NPV (M$)
P10	8,195
P50	7,958
P90	7,754

(g) Drilling W3-1 in 9th year

Probability	NPV (M$)
P10	8,094
P50	7,845
P90	7,659

(h) Drilling W3-1 in 10th year

Table 4.5 NPV in the case of W3-2 due to time scenario.

Probability	NPV (M$)
P10	7,254
P50	7,046
P90	6,947

(a) Drilling W3-2 in 3rd year

Probability	NPV (M$)
P10	7,156
P50	6,954
P90	6,796

(b) Drilling W3-2 in 4th year

Probability	NPV (M$)
P10	7,069
P50	6,859
P90	6,687

(c) Drilling W3-2 in 5th year

Probability	NPV (M$)
P10	6,954
P50	6,746
P90	6,596

(d) Drilling W3-2 in 6th year

Probability	NPV (M$)
P10	6,849
P50	6,648
P90	6,496

(e) Drilling W3-2 in 7th year

Probability	NPV (M$)
P10	6,712
P50	6,596
P90	

(f) Drilling W3-2 in 8th year

Probability	NPV (M$)
P10	6,645
P50	6,498
P90	6,249

(g) Drilling W3-2 in 9th year

Probability	NPV (M$)
P10	6,596
P50	6,387
P90	6,199

(h) Drilling W3-2 in 10th year

Table 4.6 NPV in the case of W3-3 due to time scenario.

Probability	NPV (M$)
P10	8,895
P50	8,704
P90	8,595

(a) Drilling W3-3 in 3rd year

Probability	NPV
P10	8,799
P50	8,546
P90	8,365

(b) Drilling W3-3 in 4th year

Probability	NPV
P10	8.701
P50	8,595
P90	8,368

(c) Drilling W3-3 in 5th year

Probability	NPV
P10	8,622
P50	8,465
P90	8,295

(d) Drilling W3-3 in 6th year

Probability	NPV
P10	8,529
P50	8,305
P90	8,126

(e) Drilling W3-3 in 7th year

Probability	NPV
P10	8,415
P50	8,256
P90	8,096

(f) Drilling W3-3 in 8th year

Probability	NPV
P10	8,306
P50	8,146
P90	7,905

(g) Drilling W3-3 in 9th year

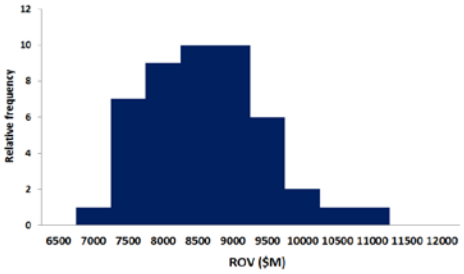
Probability	NPV
P10	8,219
P50	8,059
P90	7,876

(h) Drilling W3-3 in 10th year

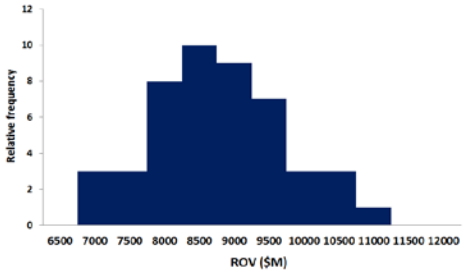
4.4. Decision making based on ROV

An economic analysis based on ROV presents histogram. Because it based on NSGA-II history matching used multi-objective genetic algorithm. ROV model is calculated which used economic parameters, Table 4.3. To obtained histogram of ROV, switch option was constructed and cumulative production of oil, gas and water that prediction in chapter 4.2 is used. From figure 4.9 to figure 4.11 show histogram of ROV due to each scenario. By presenting the results in histogram, it can be make decision flexibility.

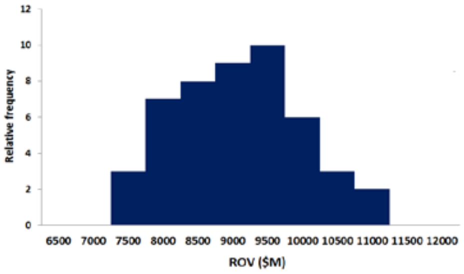
In proposed method, decision making was conducted based on these histograms. Drilling W3-1 in 5th year is the best decision in ROV analysis shown as figure 4.10 (a). In this case, ROV of the project, expected profit is $9,083 million. $ 379 million is the option premium for the option to switch that delay the drilling. By delaying the decision, project finds the unlocking values that higher revenue and efficient design solutions for the additional drilling.



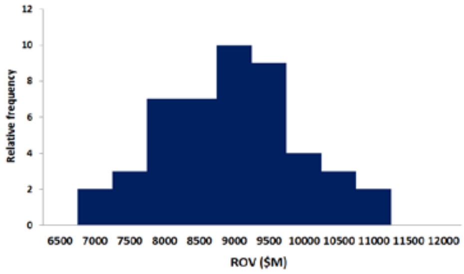
Expected profit: 8,617 M $
(a) Drilling W3-1 in 3rd year



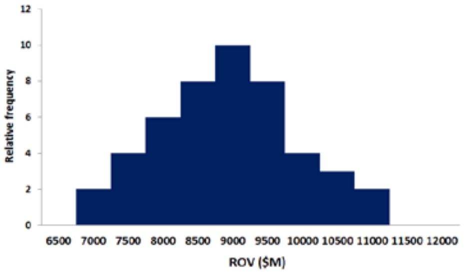
Expected profit: 8,777 M $
(b) Drilling W3-1 in 4th year



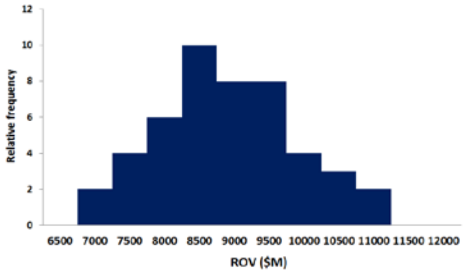
Expected profit: 9,083 M $
(c) Drilling W3-1 in 5th year



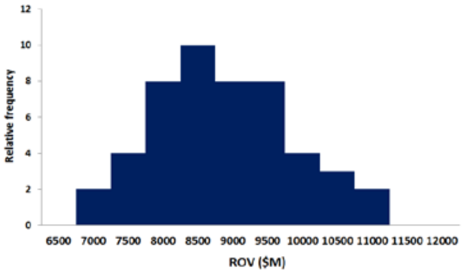
Expected profit: 8,957
(d) Drilling W3-1 in 6th year



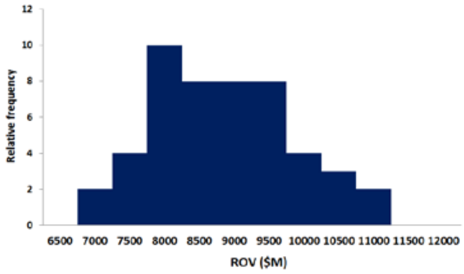
Expected profit: 8,926 M $
(e) Drilling W3-1 in 7th year



Expected profit: 8,904 M $
(f) Drilling W3-1 in 8th year

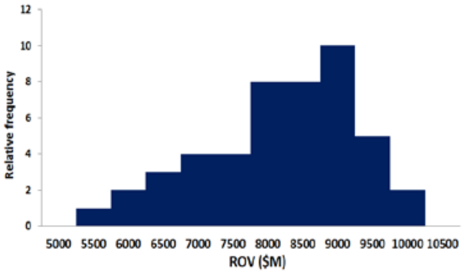


Expected profit: 8,867 M $
(g) Drilling W3-1 in 9th year

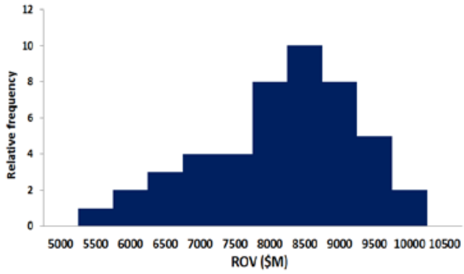


Expected profit: 8,847 M $
(h) Drilling W3-1 in 10th year

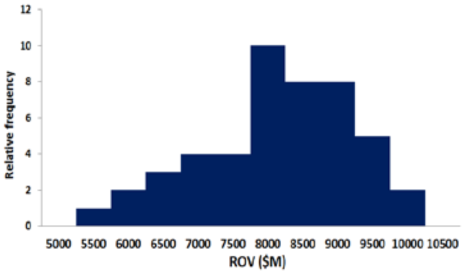
Figure 4.10 Histogram of ROV in the case of W3-1 due to time scenario.



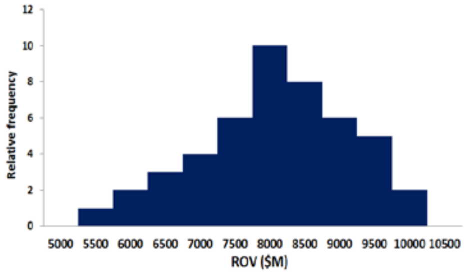
Expected profit: 7, 394
(a) Drilling W3-2 in 3rd year



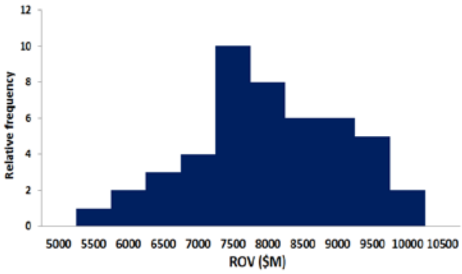
Expected profit: 7,372 M $
(b) Drilling W3-2 in 4th year



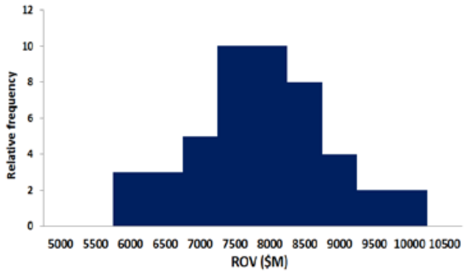
Expected profit: 7,351 M $
(c) Drilling W3-2 in 5th year



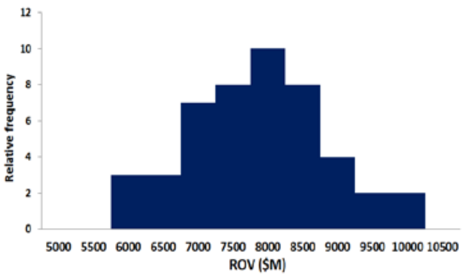
Expected profit: 7,287 M $
(d) Drilling W3-2 in 6th year



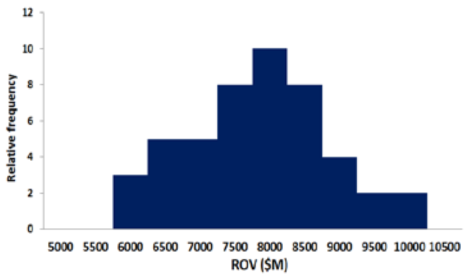
Expected profit: 7, 223 M $
(e) Drilling W3-2 in 7th year



Expected profit: 7,085 M $
(f) Drilling W3-2 in 8th year

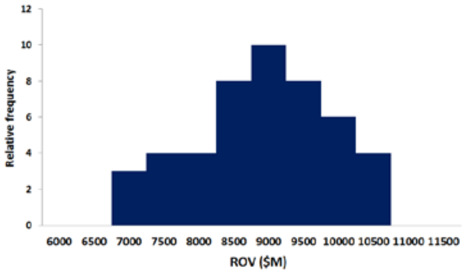


Expected profit: 7,064 M $
(g) Drilling W3-2 in 9th year

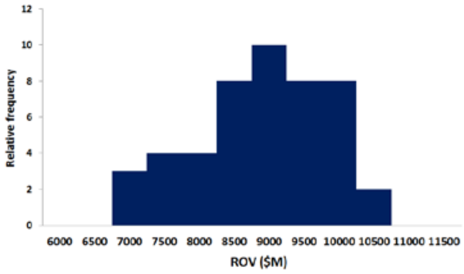


Expected profit: 6,766 M $
(h) Drilling W3-2 in 10th year

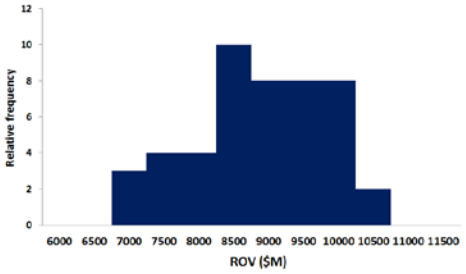
Figure 4.11 Histogram of ROV in the case of W3-2 due to time scenario.



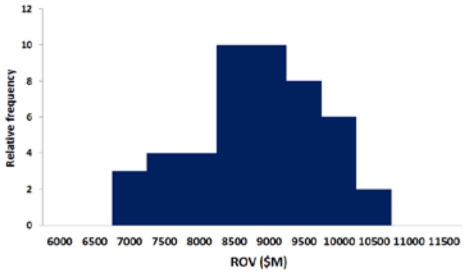
Expected profit: 8,951 M $
(a) Drilling W3-3 in 3rd year



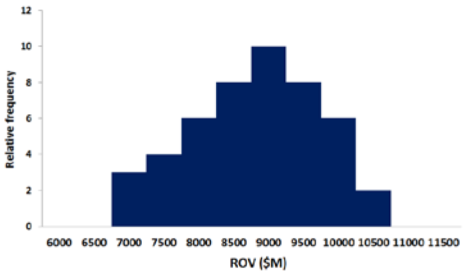
Expected profit: 8,894 M $
(b) Drilling W3-3 in 4th year



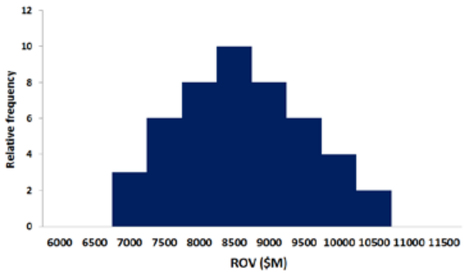
Expected profit: 8,872 M $
(c) Drilling W3-3 in 5th year



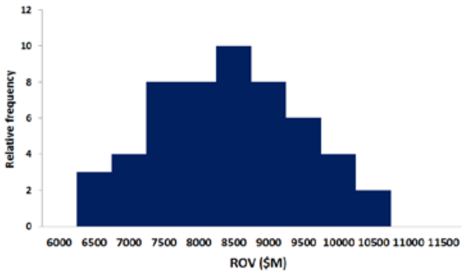
Expected profit: 8, 830 M $
(d) Drilling W3-3 in 6th year



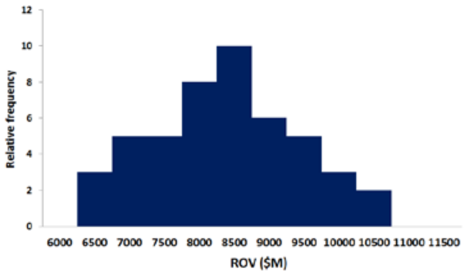
Expected profit: 8,809 M $
(e) Drilling W3-3 in 7th year



Expected profit: 8,617 M $
(f) Drilling W3-3 in 8th year



Expected profit: 8,057
(g) Drilling W3-3 in 9th year



Expected profit: 7,957 M $
(h) Drilling W3-3 in 10th year

Figure 4.12 Histogram of ROV in the case of W3-3 due to time scenario.

4.4. Sensitivity analysis and NPV vs. ROV

Two difference models which are NPV and ROV derived different conclusion. In NPV model that conventional economic analysis tool drilling W3-3 in 3rd year is the best scenario. NPV appraise the well optimization project to $ 8,704 million based on cumulative oil and gas production. However, proposed model based on ROV drilling W3-1 5th year is the best scenario. Proposed model appraise this project to $ 9,083 million. This model has unlocking value, $ 379 million called option premium. To find out this conclusion sensitivity analysis about economic parameters for each model was performed.

4.1.2 Sensitivity analysis

Figure 4.10 show the result of sensitivity analysis about NPV. In result of sensitivity analysis about NPV, cumulative oil production is the most sensitivity parameter. That's the reason why Drilling W3-3 in 3rd year provided the highest NPV. That scenario optimized production and predicted the highest cumulative oil production.

However, shown as figure 4.11 stock price, volatility and expiration date is the most sensitivity parameters about ROV in order. Even though, these three parameters, stock price, volatility, expiration date, are similar to implication in ROV model. Stock price is the NPV. It means volatility and expiration date implicates to ROV as NPV.

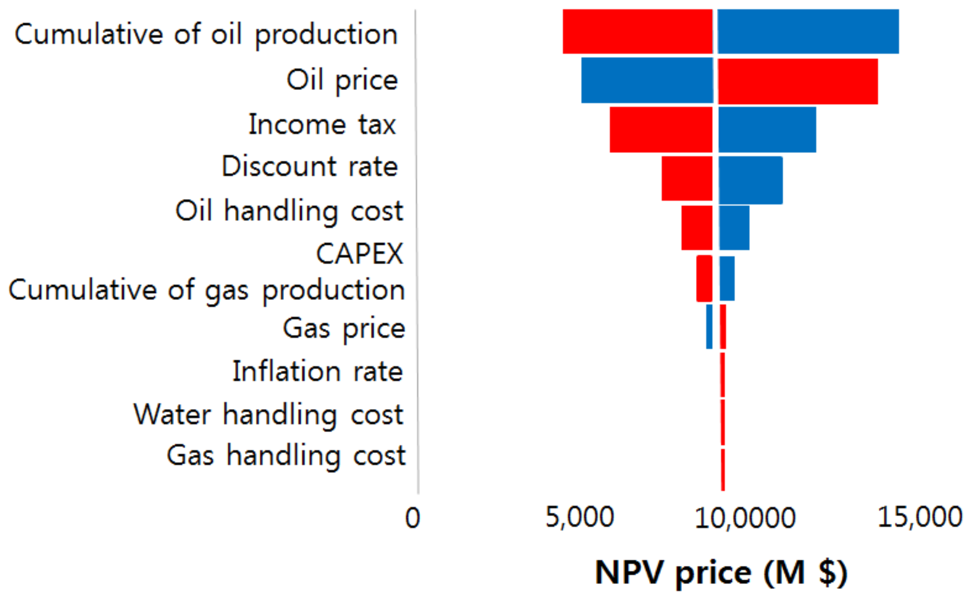


Figure 4.13 Sensitivity analysis of NPV

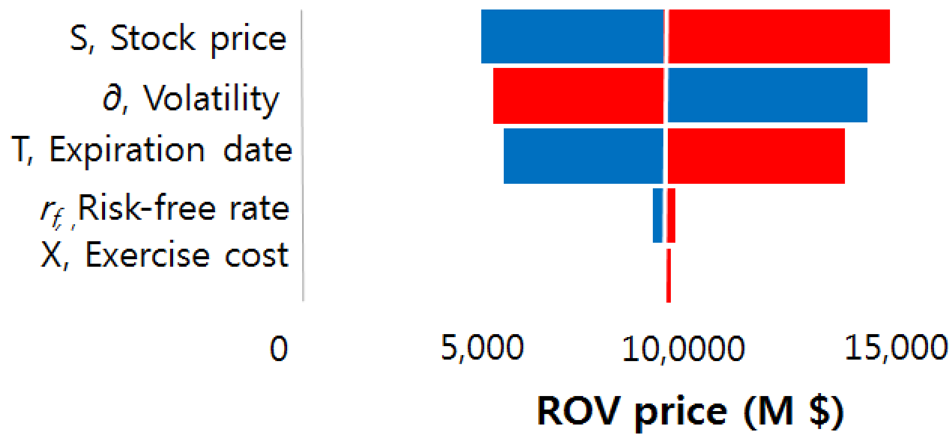


Figure 4.14 Sensitivity analysis of ROV

4.4.2 ROV vs. NPV

Above explained, ROV and NPV provided different conclusion. And result of sensitivity analysis, volatility and expiration date is the most implication parameters To ROV. Project volatility is related to geological uncertainty. When drill the specific site and time in reservoir project volatility changed. According to Eq. 2.9 – 2.11 expiration time, *T* parameters in ROV is used in *p*, risk-neutral probability. If time to expiration is higher, risk-neutral probability will be increase.

$$u = e^{\partial\sqrt{\Delta t}} \text{ and } d = \frac{1}{u} = e^{-\partial\sqrt{\Delta t}} \tag{2.9}$$

$$p = \frac{e^{r\Delta t} - d}{u - d} \tag{2.10}$$

$$C = [P \cdot \mathrm{A} + (1 - P) \cdot \mathrm{B}]\, e^{r\Delta t} \tag{2.11}$$

By drilling, volatility increases and by delaying the drilling, risk-neutral probability increase suddenly. Additional, according figure 4.11 higher volatility increases ROV and higher risk-neutral probability decreases ROV.

From figure 4.12 to figure 4.14 shows volatility and risk-neutral probability changes due to drilling each well. By delaying the drill W3-1 when 5th year project volatility is higher than risk-neutral probability. That is the reason why drilling W3-1in 5th year is the best scenario based on ROV.

In study of sensitivity analysis, NPV model do not consider geological uncertainties and operational uncertainties. However, ROV model can consider from project volatility and time to expiration. Even though, these parameters consider any uncertainties and find the unlocking value called option premium. ROV increases reservoir value from uncertainties. Based on proposed model, the best scenario to drill extra well is drilling W3-1in 5th year.

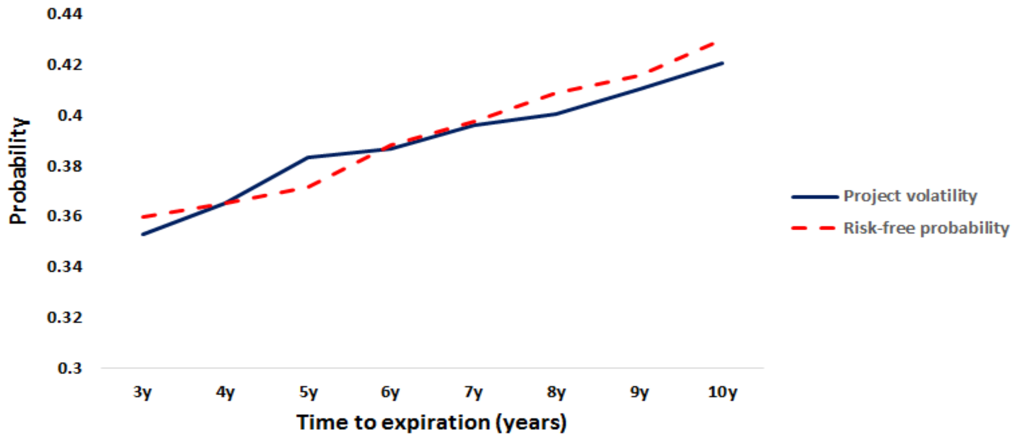


Figure 4.15 Volatility and Risk-neutral probability changes due to drilling year (W3-1).

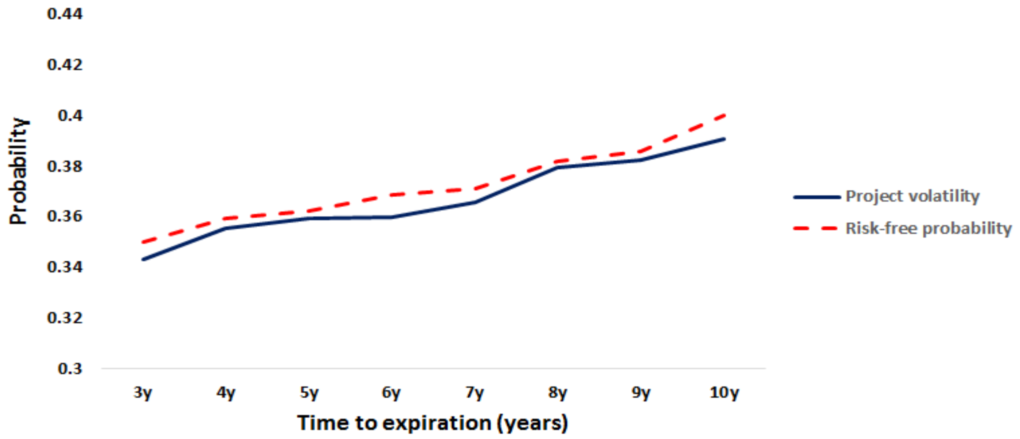


Figure 4.16 Volatility and Risk-neutral probability changes due to drilling year (W3-2).

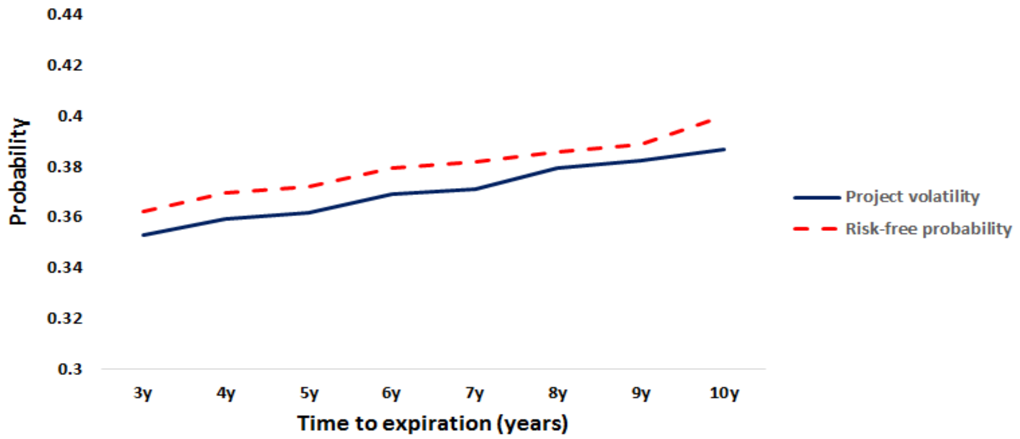


Figure 4.17 Volatility and Risk-neutral probability changes due to drilling year (W3-3).

5. Conclusion

Project evaluation under uncertainty is a key aspect of reservoir engineering and management. In multi-objective uncertainties such as market uncertainties and technical uncertainties, that confront major project. That is the reason why flexibility in making development decision is essential. This necessitates the use of ROV for development planning and decision making in upstream petroleum projects. The objective of this study is development economic model based on ROV. For proposed model, extension of ROV framework used binomial lattice, which is more accurate, practically for longer periods. And, for reliable histogram to management project multi-objective algorithm, NSGA-II is used. The following conclusion can presented based on the work in this study.

1. According to proposed economic analysis ROV uncovers hidden economic potential of hydrocarbon prospects that convention NPV analysis might not identify.

2. For comparison, evaluating reservoir developing used ROV with multi-objective history matching and NPV with single-objective history matching, proposed model presents the probabilistic and reliable range because multi-objective genetic algorithm used. When managing the reservoir develop project,

proposed model can help the flexible decision making.

3. Economic parameters are quantifiable by sensitivity analysis. So specific uncertainty may handle and manage. In the result of sensitivity analysis, geological uncertainties are related to project volatility. High volatility lead to high uncertainty and then, it may increase the value of the reservoir.

Proposed model improve flexibility for decision making by reducing uncertainty in economic evaluation. On the basis of in this study, explore the full potential of ROV in upstream petroleum industry projects can work. Proposed economic analysis is useful in reservoir development projects such as, EOR decision, surface facilities decision.

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요약(국문초록)

석유개발 사업에 대한 경제성 분석은 성공에 대한 Risk (불확실성), 의사결정의 유연성에 대한 고려가 대단히 중요하다. 일반적인 경제성 평가 모델들은 미래 현금흐름에 대한 결정론적 가정으로 인해 사업에 수반되는 여러 위험요소들과 그에 따른 변동성을 반영할 수 없다.

본 연구에서는 다목적 히스토리매칭과 Real Option Valuation (ROV)의 확률론적 접근을 이용하여 경제성평가 모델을 개발하였다. 사업의 불확실성과 자본회수기간을 반영하기 위해 ROV를 사용하였으며, 다목적 히스토리 매칭을 사용하여 자산가치를 확률론적으로 분석하였다. 제안한 기법은 가상 저류층에서 다목적 유전 알고리듬으로 추가 시추 위치와 시기에 따른 생산거동을 예측한 후, ROV를 결합하여 경제성 분석을 수행하였다.

제안한 모델을 통하여 자본회수기간과 사업의 불확실성을 동시에 정량적으로 산출하여 운영광구의 자산가치를 약 6-12% 향상할 수 있다. 또한, 이전의 경제성 평가 모델들과는 다르게 사업의 불확실성에 따라 추가 시추시기를 유연하게 결정함으로써 석유개발 사업의 위험성을 낮췄다.

주요어: 경제성 평가, 실물옵션, 다목적 히스토리매칭, 추가 시추

학 번: 2013-21013