Risk-Quantified Decision Making in Reservoir Management

by

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ABSTRACT

Limited understanding of the complex subsurface brings uncertainty and risk of production shortfalls in the oilfield development. Geostatistics provides tools to model the geological uncertainty that occurs in reservoir decision making. The common decision criterion under uncertainty is to find the strategy that maximizes the expected return. But the value of assets is influenced by investors' tendency to risk, which could lead to different responses in decision-making problems. Therefore, risk-quantified decision making becomes increasingly important in reservoir management.

Decision analysis tools such as minimizing expected loss and maximizing expected utility are suitable for many petroleum applications. They are often employed when investors are sensitive to risk. Since the specific utility function is difficult to quantify in practice, the mean-variance criterion and maximizing the risk-adjusted value are widely employed when there is no explicit utility function. These approaches employ variance as the measure of risk. The variance, however, is often considered inadequate to quantify risk as investors dislike the downside volatility and are less concerned about unusual windfalls. This research develops techniques to improve risk-quantified decision making in reservoir management. The main contributions of the thesis include: (1) The impact of preferences on decision analysis is demonstrated, and a workflow is proposed to establish the relationship between the preference measurements. The relationship is constructed by connecting the risk tolerance of utility functions and penalty factor of loss functions. (2) The downside-risk approach is introduced in reservoir decision making within the expected utility framework. The risk in this approach is reflected by the downside volatility and quantified by the lower partial variance, which is able to improve the reservoir decision making by explicitly analyzing risk. (3) Preferences are taken into account in value of information (VOI) analysis by integrating the utility theory into the simulation-regression approach. The consideration of different risk preferences leads to a more robust VOI analysis in spatial decision situations.

The proposed methodologies are applied to the design of production strategies. The impact of different preferences in the decision-making process is documented, and the limitations of current approaches are revealed. The ultimate goal of this research is to improve reservoir management in the presence of geological uncertainty by explicitly quantifying and managing risk.

Dedication

This thesis is dedicated to

My parents:

Wenjun, *Xiaomei*

and

My girlfriend:

Ying

Who give me endless support and love.

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First of all, I would like to sincerely thank my supervisor, Dr. Clayton V. Deutsch, for providing invaluable advice and constant guidance throughout my Ph.D. journey. His patience and encouragement inspire me to stay confident in life.

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List of Symbols

Symbol	Description
$\boldsymbol{D}$	An ensemble of alternatives
$\boldsymbol{g}$	An ensemble of geological models
$\boldsymbol{y}$	An ensemble of geophysical models
$Cov(\cdot)$	Covariance operator
$F(\cdot)$	Cumulative density function
$E(\cdot)$	Expected value operator
$L(\cdot)$	Loss function
LPM_α	Lower partial moment of order α
max	Maximim
min	Minimum
N	Number of realizations
P_o	Oil price
d_0	Optimal alternative
z_{opt}	Optimal estimate
λ	Penalty factor
$f(\cdot)$	Probability density function
T	Production life
V	Profit distribution
v_n	Profit value evaluated on realization n
X	Random variable
r	Risk tolerance
$\mathbb{S}$	Search space
σ	Standard deviation
d	The alternative

Symbol	**Description**
τ_+	The attitude toward to potential
τ_-	The attitude toward to risk
v_0	The benchmark value
r_d	The discount factor
$z^\star$	The estimate value
n	The index of realizations
$argmax$	The index of the maximum value
$argmin$	The index of the minimum value
$\hat{v}$	The regression value
z	The true value
C_w	Total cost to drill the wells
Q_o^t	Total volumes of oil at time t
$Q_t^{w,i}$	Total volumes of water injected at time t
$Q_t^{w,p}$	Total volumes of water produced at time t
UPM_α	Upper partial moment of order α
$U(\cdot)$	Utility function
P_w^i	Water injection cost
P_w^p	Water production cost

List of Abbreviations

Abbreviation	Description
2-D	Two-dimensional
3-D	Three-dimensional
4-D	Four-dimensional
ARA	Absolute risk aversion
CDF	Cumulative distribution function
COI	Cost of information
ES	Expected shortfall
EV	Expected value
FSD	First-order stochastic domiance
GSLIB	Geostatistical software library
LPM	Lower partial moment
M	Million
MAUT	Multi-dimensional scaling
MCS	Monte Carlo simulation
MDS	Multidimensional scaling
MLU	Mean-lower partial variance-upper partial variance
MPSO	Modified particle swarm optimization
MRST	MATLAB Reservoir simulation toolbox
MSE	Mean square error
NPV	Net present value
OOIP	Original oil in place
PDF	Probability distribution function
PLSR	Partial least square regression
PoV	Posterior value

Abbreviation	Description
Pr	Reliability of information
Prob	Probability
PSO	Particle swarm optimization
PV	Prior value
RAV	Risk-adjusted value
SAGD	Steam-assisted gravity drainage
SGS	Sequential Gaussian simulation
SNESIM	Single normal equation simulation program
SSD	Second-order stochastic domiance
STB	Stock tank barrel
TI	Tolerance interval
TSD	Third-order stochastic domiance
UPM	Upper partial moment
USGSIM	Ultimate sequential Gaussian simulation program
VNM	Von Neumann and Morgenstern
VOI	Value of information

Chapter 1

Introduction

The complex distribution of subsurface properties combined with limited data brings challenges to reservoir characterization. With the improvement of computer performance, reservoir characterization has evolved from a determined model to a model with uncertainty, and now into risk management (Ma and La Pointe, 2011; Mamudu et al., 2020; Santos et al., 2017c; Suslick and Schiozer, 2004). Risk analysis and decision making have become increasingly important in the optimization of reservoir management.

Decision analysis tools for the risk-sensitive position include minimizing expected loss and maximizing expected utility (Sivakumar et al., 2015; Xuena and Jinlan, 2011). The loss function and utility function are not directly related to each other, as the loss function is often used in parameter estimation while the utility function is commonly employed in the optimization of strategies (Deutsch, 2020; Vasylchuk and Deutsch, 2018). These functions aim to capture investors' preferences to alternate outcomes. Therefore, a better understanding of the influence of risk attitudes will improve reservoir decision making.

The main framework for risk-quantified decision making based on expected utility generally includes (Khosravanian and Aadnoy, 2016; Wood and Khosravanian, 2015): (1) quantification of uncertainty based on multiple realizations, (2) risk preference analysis through a utility function, and (3) making decisions based on the maximum expected utility. However, the utility function is difficult to quantify in practice (Gallardo and Deutsch, 2020), which leads to the application of the mean-variance criterion or the risk-adjusted value (Wang et al., 2020; Zhou et al., 2017). These approaches are often utilized in different contexts (selection or optimization), and both of them assess risk by variance (Markowitz, 1952). However, variance is an inappropriate measure of risk. Studies on the lower partial moments and semi-variance are proposed to improve the measure of risk (Kettunen and Salo, 2017; Mondal and Selvaraju, 2019). These risk measurements are based on downside volatility, which is more consistent with investors' behavior.

Additional information plays an important role in reservoir decision making. Value of information (VOI) analysis is a prior analysis that evaluates the quality of decision-relevant information (Hong et al., 2018; Waggoner, 2002). The relationship between uncertainty, decision making, and VOI analysis is shown in Figure 1.1. It indicates that decision making and VOI analysis are implemented under a situation with uncertainty, and the gathering of information could reduce uncertainty and enhance confidence in the decision making. It should also be noted that the VOI becomes worthwhile if the decision could be changed with additional information. That is, VOI attributes value to the potential of increasing profits by enabling decision-makers to better adjust their choices in the accommodation of potential uncertainties (Bratvold et al., 2009). VOI is usually expressed as the difference between expected return with information and expected return without information, which has the underlying assumption of risk neutrality (Chen et al., 2017; Eidsvik et al., 2015a; Santos et al., 2017b). In order to better understand the role of information in decision making, different risk preferences will be taken into consideration in VOI analysis.

This chapter introduces the challenges in reservoir decision making that motivate the research of this dissertation, as well as a description of the contributions and thesis outline. Section 1.1 discusses the limitations of current techniques, which provides the background for the problem setting of this research. Section 1.2 summarizes the research contributions and thesis statement. The outline of the thesis and a brief summary of each chapter are presented in Section 1.3.

1.1 Problem setting

Decision analysis is a critical task in the petroleum industry. The complex geological distribution of subsurface rock and fluid properties cannot be fully understood from limited data. There is inevitable uncertainty and this must be considered with different preferences of investors in the process of decision-making under uncertainty. A better understanding of risk preference is an important theme in decision analysis, but challenges remain in reservoir decision analysis under geological uncertainty. Among them, the following three aspects are the main challenges addressed in this research.

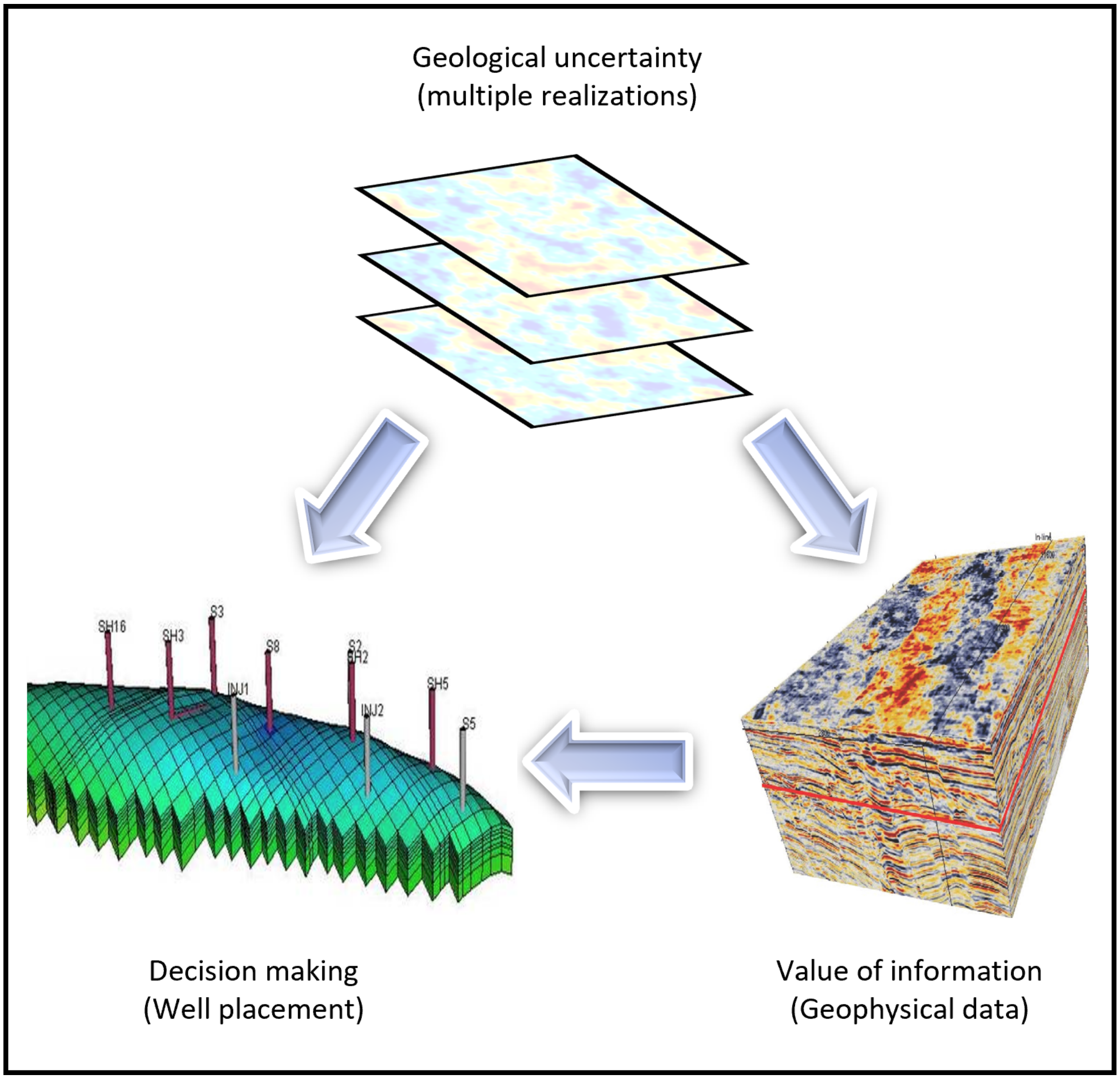


Figure 1.1: Relationship of geological uncertainty (multiple realizations), decision making (well placement), and VOI analysis (geophysical data) in reservoir management (De Barros and Deutsch, 2018; Moradi et al., 2010; Odoh et al., 2014).

(1) Preference measurements in the presence of geological uncertainty

The first challenge comes from the difference of preference measurements in the presence of geological uncertainty. Investors hold different attitudes in the decision-making process under uncertainty. Decision analysis tools for the non-risk-neutral position (risk-averse position and opportunity-seeking position) include minimizing expected loss and maximizing expected utility. In these decision analysis tools, preferences are measured by loss functions and utility functions. Loss functions are often used in parameter estimation, while utility functions are commonly employed in the optimization of strategies. Although these preference measurements are widely applied in the petroleum industry, there is little research on their relationship.

(2) Decision making explicitly considering risk

The second challenge comes from risk measurement in reservoir decision analysis. In many practical applications, variance or standard deviation of returns is utilized to assess risk, such as the mean-variance model and risk-adjusted value. These approaches are under the expected utility framework and widely applied in reservoir decision making. However, it is obvious that investors dislike the downside volatility more than upside potential. Variance or standard deviation penalizes upside potential disproportionately, which makes them inappropriate to measure risk. Semi-variance and lower partial moments are proposed as alternatives to improve risk measures. Therefore, in the context of reservoir decision making, it is necessary to develop a more robust decision model with appropriate risk quantification.

(3) Value of information analysis for different risk positions

Lastly, there are also some challenges involved in VOI analysis. VOI analysis is aimed to facilitate decision making by valuing future information. The decision-related information is worth collecting when its value exceeds the cost. VOI analysis is performed before collecting information, which makes it difficult to estimate the conditional value. Although many approaches have been developed to approximate the posterior value, such as the simulation-regression approach and double-loop Monte Carlo approach. But all of these approaches are implemented associated with expected return on the premise of risk neutrality, which disregards the influence of preferences on the VOI analysis.

1.2 Research contributions and thesis statement

In order to solve the above problems, this research consists of three parts: (1) construct the relationship between the penalty factor in loss functions and the risk tolerance in utility functions; (2) improve the decision model with an explicit consideration of risk in the context of decision-optimization; (3) evaluate the VOI with a consideration of different risk preferences. These objectives are expanded on below:

- The relationship between loss functions and utility functions will be constructed. More specifically, the connection between the penalty factor and risk tolerance in decision analysis is investigated. The purpose is to strengthen the understanding of preference measurements for reservoir decision making in the presence of geological uncertainty.

- A more robust risk measurement method will be introduced in reservoir decision-making to capture different risk positions. In this approach, the risk is clearly assessed by the downside volatility, and the decision criterion is based on maximizing the expected utility.

- VOI analysis will be conducted with preferences taken into account. It is implemented by integrating the utility theory into the simulation-regression approach. The impact of attitudes will be analyzed by performing a sensitivity analysis of different risk positions.

This research focuses on improving reservoir management by capturing preferences in the presence of geological uncertainty. It will be achieved by developing a workflow based on expected utility with an explicit consideration of risk. The proposed research provides (1) a new perspective for the place of loss functions and utility functions in petroleum applications; (2) an enhanced risk management in reservoir decision making; (3) a more robust way to perform VOI analysis in the decision-relevant context. This proposed workflow will provide more scientific and reasonable decision analysis for investors by capturing various attitudes toward risk, which has significance in managing oilfield production strategy.

Thesis statement

Understanding the impacts of risk preferences has great significance to reservoir management. Reservoir decision making and risk management in the presence of geological uncertainty will be enhanced by explicitly analyzing risk.

1.3 Thesis outline

This research focuses on improving reservoir decision making and risk management in the presence of geological uncertainty. It will be achieved by developing a workflow based on expected utility with an explicit consideration of risk. The outline of this thesis is organized as follows.

Chapter 2 reviews relevant literature on some concepts and techniques. A summary of the development of reservoir decision making is provided. The basic concepts of utility theory and risk management are also documented. Several current decision-making approaches with the incorporation of different risk positions are then presented. The limitations of these methods and their applications in the petroleum industry are discussed.

Chapter 3 addresses the relationship between different preference measurements in the presence of geological uncertainty. Loss functions and utility functions are utilized to measure the non-risk-neutral position in many petroleum applications. The main goal of this section is to investigate the relationship between the penalty factor of loss functions and the risk tolerance of utility functions.

Chapter 4 discusses the downside-risk approach in decision making. Since some controversies exist in the mean-variance criterion and risk-adjusted value about measuring the risk by variance. A workflow based on the downside-risk approach is developed to improve risk management. In this approach, investors only penalize downside volatility and use the lower partial variance to quantify risk. This is more consistent with investors' behavior.

Chapter 5 illustrates the workflow of VOI analysis for different risk preferences. The synthetic geophysical information is firstly generated through rock physics analysis. Then, the conditional expectation of the given information in the posterior value is approximated by the simulation-regression approach. Lastly, the sensitivity analysis of different risk attitudes is conducted to investigate their impacts on VOI.

Chapter 6 is the application of the downside-risk approach in the design of production strategies in the presence of geological uncertainty. The case study utilizes stochastic simulation to transfer geological uncertainty and then employs the downside-risk approach as decision-making criterion. A comparison between the mean-variance approach and the downside-risk approach is also provided.

Chapter 7 presents a case study to illustrate the impact of risk preferences on evaluating geophysical information. This case study is demonstrated in a spatial decision situation related to the production strategy selection, and it is implemented by integrating utility theory in the simulation-regression approach to incorporate different preferences.

Chapter 8 wraps up the thesis with conclusions and future work. The impacts of risk preference in reservoir management are summarized, and the benefits of using the risk-quantified decision making are evaluated. Lastly, the possible directions for future research are discussed to further improve reservoir management.

Chapter 2

Literature review

This chapter involved a series of topics related to decision analysis in reservoir management. It covers the utility theory, geological uncertainty, reservoir decision making, and value of information. The relevant literature is reviewed in the following sections.

2.1 Utility theory

In the past few decades, utility theory has had a profound impact on decision analysis. The concept of utility originated from the St. Petersburg game proposed by Nicolaus Bernoulli (Plous, 1993). It could reflect the investor's satisfaction over a set of alternatives, which is different from simple monetary value or wealth (Armstrong, 1948; Bernoulli, 1954; Eidsvik et al., 2015a; Weber, 2019).

2.1.1 Utility and preference

Risk preference is an attitude-related term toward the risk, which includes risk-averse, risk-neutral, and opportunity-seeking (Hillson and Murray Webster, 2017). The behavior to risk could be described by the curvature of the utility function in the decision theory (Fellner and Maciejovsky, 2007) (Figure 2.1): (1) For the risk-averse position, people tend to choose the decision that avoids low outcomes for the sake of safety, even it has a lower expected return. This implies the utility function has a concave shape with a diminishing marginal utility; (2) For the risk-neutral position, investors only pay attention to the expected return in the decision making without consideration of risk. This utility function has a linear shape with a constant marginal utility; (3) For the opportunity-seeking position, more interest is shown in the high reward outcomes even if associated with high risk. The utility function has a convex shape with an increasing marginal utility.

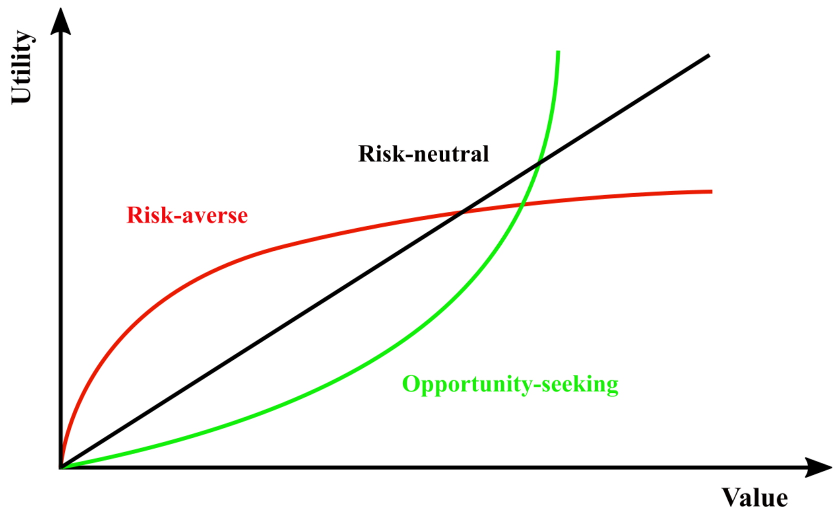


Figure 2.1: Utility function with different risk positions.

Since the real utility function is difficult to obtain in practice, many different types of utility functions $U(x)$ are employed in economics to reflect the investor's tendency for risk. The most commonly used utility functions are the exponential form, power form, log form, and quadratic form, all of them are able to reflect different risk positions (Cozzolino, 1977; Huang and Litzenberger, 1988). In addition, the absolute risk aversion (ARA) is widely utilized to quantitatively characterize the risk attitude under the given utility function (Arrow, 1971). It is defined as:

$$\mathrm{ARA} = -\frac{U^{(2)}(X)}{U^{(1)}(X)} \tag{2.1}$$

Where X is a random variable. $U^{(1)}(\cdot)$ and $U^{(2)}(\cdot)$ denote the first derivative and second derivative of the utility function, respectively. A larger value of ARA often indicates a more risk-averse consumer. For example, the exponential utility function, $U(X) = \frac{1-e^{-rX}}{r}$ and $r \neq 0$, has the absolute risk aversion $\mathrm{ARA} = r$. This r is also called risk tolerance, and it is the only parameter in the exponential utility function that determines risk preference.

2.1.2 Expected utility

The expected utility is a famous theory for decision making under uncertainty. This concept was first conceived by Dianiel Bernoulli, and a systematic framework of the expected utility theory (VNM expected utility theory) was built in 1947 by John von Neumann and Oskar Morgenstern. This theorem indicates that a rational decision is always associated with the maximum expected utility.

Four basic axioms are given in VNM expected utility theory to define a rational decision-maker (Morgenstern and Von Neumann, 1953). Assuming a decision-maker faced with three alternatives $\{A, B, C\}$. The relationship $A \succ B$ represents the A is strictly preferred than B; $A \succsim B$ indicates the A is preferred at least as much as B; $A \sim B$ means the A is indifferent to B. The basic axioms in the VNM expected utility theory is that (Akkaya, 2021; Keith and Ahner, 2021): (1) Completeness: it indicates investors have a well-defined preference. Either $A \succsim B$ or $B \succsim A$ or both. (2) Transitivity: it implies people make decisions consistently. If $A \succ B$ and $B \succ C$, then $A \succ C$. (3) Independence: if A is preferred to B, the combination of A and C is also preferred to the combination of B and C using the same probability p. If $A \succ B$, then $pA + (1-p)C \succ pB + (1-p)C$ for $\forall p \in [0, 1]$. (4) Continuity: if the investor prefers A to B and B to C, then there should be a combination of A and C in which the investor is indifferent between this mix and B. If $A \succ B$ and $B \succ C$, then $pA + (1-p)C \sim B$ for $\exists p \in [0, 1]$.

The approaches under the VNM expected utility framework are summarized into three categories based on Markowitz (2014): (1) Implicit utility function, like mean-variance criterion, is able to approximate the maximum expected utility in a risk-averse position; (2) Expected utility approximation, it approximates expected utility through a Taylor series expansion. The profit distribution might not be required in this non-parametric approach; (3) Explicit utility function, the utility function and the profit distribution should be specified in this method. The utility function widely used in the petroleum industry has an exponential form. The details of these approaches will be illustrated in Section 2.3.

The expected utility theory has gradually been applied in the oil industry, such as the selection of production strategy (Santos et al., 2017c; Wood and Khosravanian, 2015), optimization of well placement (Güyagüler and Horne, 2004), optimization of casing string placement (Khosravanian and Aadnoy, 2016), and exploration portfolio management (Moore et al., 2005). The reservoir decision making problems, taking production strategy selection as an example, with the expected utility framework could be expressed as:

$$d_0 = \underset{d \in \boldsymbol{D}}{\operatorname{argmax}}\, E\{U(V(\boldsymbol{g}, d)\} \tag{2.2}$$

Where $U(\cdot)$ and $V(\cdot)$ are the utility function and profit function, respectively. $\{\boldsymbol{g} = g_n; n = 1, 2, \ldots, N\}$ represents an ensemble of geological models from N realizations. $\boldsymbol{D}$ is a set of production strategies, and d_0 is the optimal production strategy.

2.1.3 Multi-attribute utility theory

There are many situations that our decisions are influenced by multiple factors, multi-attribute utility theory (MAUT) is useful in quantifying the relative attractiveness of multi-attribute alternatives (Allah Bukhsh et al., 2019; Gass and Harris, 1997). The construction of a multi-attribute utility function is based on decomposing the function into lower-order assessments (Andersen et al., 2018; Greco et al., 2016). Under the assumption of utility independence and preferential independence, the multi-attribute utility function could be expressed as the addition or multiplication of the one-attribute utility functions (Kaddoura et al., 2018; Keeney and Sicherman, 1976).

The MAUT has also been applied in the petroleum industry for project selection and investment management. Suslick and Furtado (2001) aimed to improve investment decisions in petroleum exploration from these three main targets: financial, environmental and technological gain. These attributes are combined in an additive or multiplicative multi-attribute utility model, and a high-dimensional sensitivity analysis is utilized to assess the weights in this multicriteria decision model. Lopes and de Almeida (2015) employed MAUT to evaluate projects which are in the development phase. Three aspects are taken into consideration: financial return, hydrocarbon production, and political risk. The one-attribute utility function is obtained from the questionnaire, and the multi-attribute utility function is constructed by the sum of these one-attribute utility functions. Santos et al. (2017a) also used the MAUT in the selection of production strategies. The objectives include maximizing oil recovery and maximizing net present value (NPV). The weights of each attribute are analyzed through sensitivity analysis, and the summation of all the weights should equal one.

2.2 Multiple realizations in the presence of geological uncertainty

The complete reservoir in the subsurface is difficult to accurately measure. The uncertainty in reservoir characterization comes from our incomplete understanding caused by limited data and geological variability at all scales. Therefore, understanding uncertainty is significant for improving reservoir management.

2.2.1 Uncertainty analysis

The exploration and development of oilfields are inherently risky. Investors often rely on the predicted economic return to make decisions under uncertain situations. Caers (2011) used Figure 2.2 to illustrate the elements involved in the modeling uncertainty in Earth Sciences problems. It mainly includes three aspects as follows:

- Uncertainty from data (green boxes)
- Uncertainty from parameters (orange boxes)
- Uncertainty from models (blue boxes)

These elements cover the uncertainty ranging from geological modelling and physical modelling to economic modelling. The source of the uncertainty could be mainly explained by the following aspects (Da Cruz, 2000; Gorbovskaia and Belozerov, 2016; Ma, 2010; Ma and La Pointe, 2011):

- Heterogeneous petrophysical properties and irregular reservoir geometry
- Complex fluids and recovery mechanism
- Incomplete information and limited data
- The fluctuation of future oil prices

In this research, the scope of uncertainty is restricted to the geological model due to the sparse sampling of the reservoir. Geostatistical techniques are employed to transfer this uncertainty with multiple realizations through stochastic simulation.

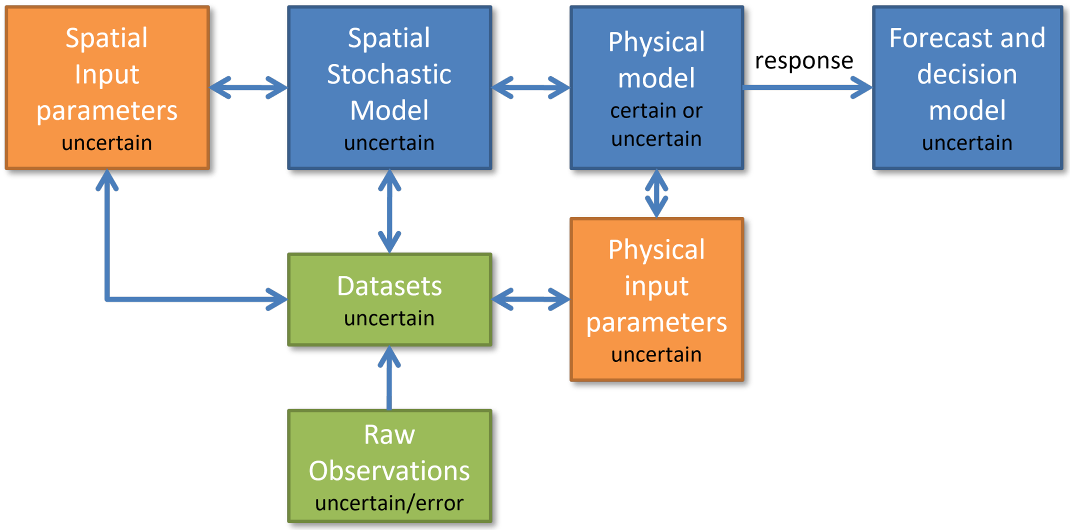


Figure 2.2: The elements for modeling uncertainty in the Earth Science problem (Caers, 2011).

Conventionally, the production strategy in hydrocarbon field development is designed based on a single reference case (Erbas and Christie, 2007; Nakajima and Schiozer, 2003). The reference case represents the deemed most appropriate model for predicting future reservoir performance. The deterministic model could be regarded as a useful start in the Earth Sciences problem, it is only one outcome of a large ensemble of possible geological scenarios. Making decisions based on one reference case disregards the geological uncertainty (Deutsch, 2018; Scheidt et al., 2018).

In statistics, a popular way to quantify uncertainty is based on standard deviation (Rachev et al., 2011). Standard deviation (σ) is a measure of dispersion from the variable relative to its expected value, which is defined in Equation 2.3. It gives us an understanding of the variability around the expected value of the distribution. This concept is not only used to measure the local uncertainty in the geostatistics (Caers, 2011; Ma and La Pointe, 2011), but also provides a quantified estimate of economic uncertainty in decision analysis (Gallardo and Deutsch, 2020).

$$\sigma = \sqrt{E\{(X - E\{X\})^2\}} \tag{2.3}$$

Many other techniques are also proposed to quantify uncertainty, such as bootstrap and precision. Bootstrap analysis is a statistical resampling technique developed by Efron (1982). It allows us to quantify uncertainty by constructing confidence intervals of estimate statistics. This approach is implemented by resampling the original data with replacement, and it is useful to evaluate the parameter uncertainty in many natural resource applications (Caers, 2011; Pyrcz and Deutsch, 2014; Selle and Hannah, 2010). Additionally, Precision is also able to measure uncertainty by characterizing the narrowness of a distribution (Harding, 2021; Wilde, 2010). A narrower distribution usually indicates less uncertainty. Consider a tolerance interval (TI) in Equation 2.4:

$$\mathrm{TI} = E\{X\} \times t \tag{2.4}$$

Where t is the tolerance value, which is usually 15% in the mining industry (Dohm, 2005). The precision (PRE) is the probability within the specified tolerance interval around the expected value, it could be expressed in Equation 2.5:

$$\mathrm{PRE}(t) = \mathrm{Prob}\{E\{X\} - \mathrm{TI}(t) \leq X \leq E\{X\} + \mathrm{TI}(t)\}\} \tag{2.5}$$

The uncertainty of interesting variables caused by the incomplete understanding could be characterized by the probability distribution. Despite many different ways are proposed to describe uncertainty, they are often related to the volatility of the distribution.

2.2.2 Monte Carlo simulation

Geostatistics provides tools to quantify uncertainty and support reservoir uncertainty analysis (De Barros and Deutsch, 2018; Deutsch, 2018). Monte Carlo simulation (MCS) is a well-established technique in statistics, it is widely used in geostatistics to characterize geological heterogeneity by generating multiple realizations that are equally probable. This technique relies on the random sampling of realizations from a specified probability distribution and the geological uncertainty is captured by the difference between the realizations. The workflow of Monte Carlo simulation in the uncertainty quantification and decision analysis involves these four steps (Deutsch, 2018): (1) formulate the transfer function, (2) simulate multiple realizations using the input variables, (3) compute the assembled response models, and (4) understand the uncertainty and facilitate decision analysis. This process is sketched in Figure 2.3.

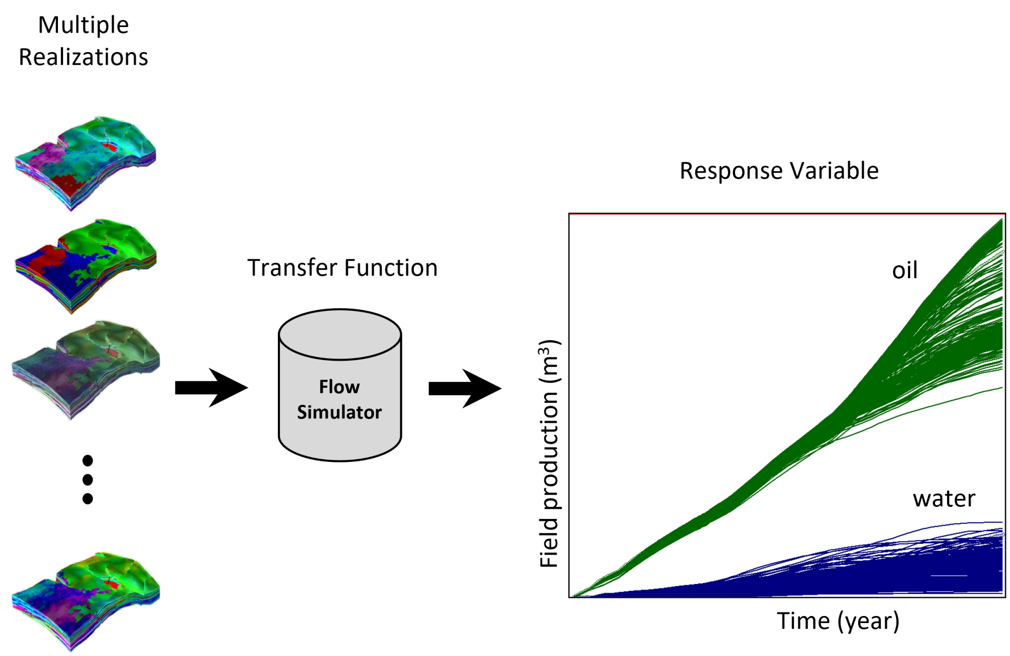


Figure 2.3: Reservoir modeling captures geological uncertainty using multiple realizations (De Barros, 2019).

Although MCS takes advantage of an ensemble of realizations to transfer uncertainty, a long-standing problem is that multiple realizations usually lead to increased computational costs, especially in well placement optimization. In order to improve the computational efficiency, a proxy model and realization reduction are commonly utilized in petroleum industry applications.

(1) Proxy model

A proxy model provides a cheap alternative to approximate the non-linear response of numerical simulation in subsurface modeling. It sacrifices some degree of accuracy to significantly improve computational efficiency, which is especially useful in optimizing problems considering multiple realizations. The main methods used to build a proxy model include the statistical method and physical-based method.

A statistical method, such as the surface response model or convolutional neural network (Fetel and Caumon, 2008; Kim et al., 2020), could be used to construct the proxy model. The observation data sets are trained to forecast the reservoir performance without relying on any physical process, so this data-driven proxy model does not necessarily preserve geological characteristics.

The physical-based proxy model reduces the computational cost by approximating the physical process in the reservoir simulation. Cardoso and Durlofsky (2010) proposed the reduced-order modeling to construct the proxy model, it is implemented by projecting the Newton solver in a low-dimensional space to improve the computation cost. Pouladi et al. (2017) applied the fast marching algorithm to build the proxy model in well placement optimization, which is able to approximate the bottom hole pressure. Gallardo and Deutsch (2019) introduced an approximate physics-discrete simulator to model the steam chamber in steam-assisted gravity drainage (SAGD). It is more computationally efficient than the full-physical thermal simulation.

(2) Realization reduction

Realization reduction aims to select a subset of representative realizations from the full set of models. It often includes two steps: realization ranking and realization selection. The realization ranking could be categorized as static and dynamic based on the properties of underlying realizations. The static ranking employs the calculation of connected reservoir volume or original oil in place (OOIP) as the measure. McLennan and Deutsch (2005) described the statistic measures for the static ranking in the heavy oil recovery process. The dynamic ranking of realizations is able to reflect the connective of the reservoir. The dynamic ranking is based on fluid flow to account for the production mechanism. For example, Sharifi et al. (2014) introduced time of flight in the implementation of dynamic ranking to reflect the connectivity of the reservoir.

After ranking the realizations, many approaches are proposed to select the representative realizations. The traditional method of selecting represent realizations is based on low, median, and high quantile values (P10, P50, and P90), but these three realizations are not sufficient to span the geological uncertainty. Scheidt and Caers (2010) applied multi-dimensional scaling (MDS) and clustering methods to select representative realizations. Rahim and Li (2015) proposed a mixed-integer linear optimization to minimize the Kantorovich distance of static properties for the representative realizations. Jesmani et al. (2020) aimed to cover all realizations in the well placement optimization by randomly selecting the representative realizations. Mahjour et al. (2021) compared the distance-based clustering and metaheuristic algorithm in the selection of representative models.

2.3 Reservoir decision making

Risk management and decision analysis are becoming essential in the optimization of production strategies. Many studies have documented the application of decision analysis in the petroleum industry under geological uncertainty (Bratvold and Begg, 2010; Eidsvik et al., 2015a; Shafiee et al., 2019). The following will outline some important concepts and main technologies in reservoir decision making.

2.3.1 Techniques with an explicit utility function

(1) Decision making with an exponential utility function

The expected utility is calculated by summing the weighted utility values, and the weights come from the probability distribution. In the practical applications of reservoir management with an explicit utility function, the expected utility in Equation 2.2 could be solved by using multiple realizations (Equation 2.6), and the utility function $U(\cdot)$ should be specified.

$$\underset{d \in \boldsymbol{D}}{\operatorname{argmax}}\, E\{U(V(\boldsymbol{g}, d)\} = \underset{d \in \boldsymbol{D}}{\operatorname{argmax}}\, \frac{1}{N} \sum_{n=1}^{N} U(V(g_n, d)) \tag{2.6}$$

Generally, the approaches used for constructing the utility function include questionnaires and interviews, like the 50-50 gamble (Berger, 2013) or certainty equivalent (Walls, 2005a). Since the interview opportunities are few and the interview process is complicated, it makes the investor's utility function difficult to obtain in practice. Therefore, a simplified utility function with an exponential form is proposed by Cozzolino (1977), and Walls (2005b) introduced it in the petroleum industry to investigate the impact of investors' risk position. The exponential utility function is given by:

$$U(X) = \begin{cases} \dfrac{1}{r}(1 - e^{-rX}) & r \neq 0 \\ X & r = 0 \end{cases} \tag{2.7}$$

The risk tolerance r is the only parameter to reflect the risk position in Equation 2.7. In order to investigate the impact of different risk positions, the sensitivity analysis is often performed by varying the coefficient r (Al Harthy, 2007; Güyagüler and Horne, 2004).

This exponential utility function is also popular in petroleum industry, Ozdogan and Horne (2006) applied this exponential form utility function in the assessment of well placement. Wood and Khosravanian (2015) employed the exponential utility function to support investment decisions in the upstream gas and oil industry.

2.3.2 Techniques with an implicit utility function

(1) Mean-variance criterion

The mean-variance criterion is a cornerstone of modern portfolio theory. It is widely applied in different disciplines for its simplicity (Rubinstein, 2002). In this criterion, the efficient frontier is established from the optimal alternatives based on maximizing expected return for a given level of variance, or minimizing variance for a specific level of expected return (Markowitz, 1952). The set of decisions on the efficient frontier could be considered optimal decisions that dominate other decisions in the bottom right (Figure 2.4). Taking alternatives A and B as an example to illustrate the mean-variance rule. A is preferred over B when they have the following relationship in Equation 2.8. It also requires that the equalities are not satisfied for both equations at the same time.

$$E_A(X) \geq E_B(X) \text{ and } \sigma_A^2(X) \leq \sigma_B^2(X) \tag{2.8}$$

Where $E(\cdot)$ and $\sigma(\cdot)$ denote the expectation operator and standard deviation operator, respectively. In the mean-variance criterion, variance or standard deviation is treated as the measure of risk, and the efficient frontier could approximate the maximizing of expected utility for risk-averse investors (Markowitz, 2014). Due to the convenience of implicit utility functions in the decision-making process, this mean-variance model has also been introduced in the petroleum industry for the decision selection problems (Gallardo and Deutsch, 2020; Wang et al., 2020). However, we need to be cautious when applying this model in practice, because this decision model has limited ability in the comparison of alternatives (Gallardo and Deutsch, 2020).

(2) Risk-adjusted value

Risk-adjusted value (RAV), also called certainty equivalent, is another important concept

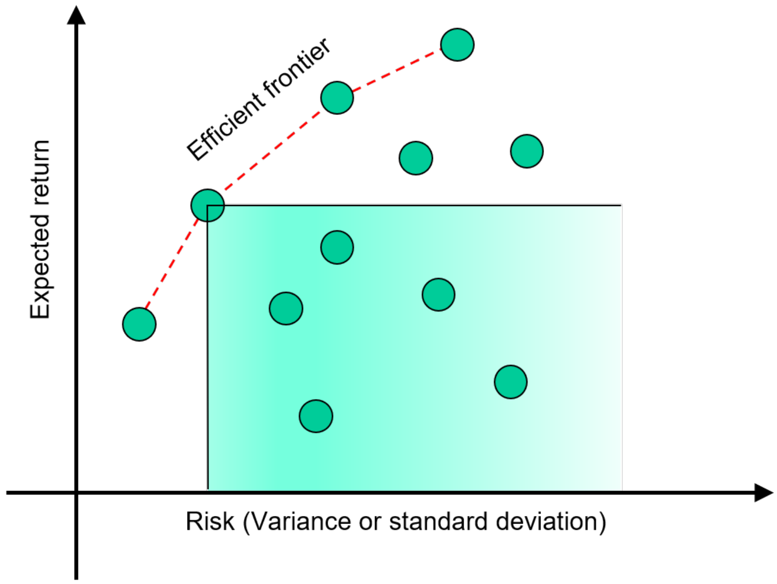


Figure 2.4: A sketch of the mean-variance model.

introduced from economics to the petroleum industry. It is the cash value that a firm attributes to a decision alternative involving uncertain outcomes (Walls, 2005a). A mathematical form of risk-adjusted value is expressed in Equation 2.9.

$$U(\mathrm{RAV}) = E(U(X)) \tag{2.9}$$

Where RAV is the risk-adjusted value, and $E(\cdot)$ represents the expectation operator. Since the utility function $U(\cdot)$ usually increases monotonically, it implies a decision based on maximizing the risk-adjusted value will lead to the same result as maximizing expected utility $E(U(X))$. Cozzolino (1977) proposed a simplified form of RAV (Equation 2.10). The maximum RAV is also consistent with the efficient frontier in mean-variance criterion.

$$\mathrm{RAV} = \mu - \frac{1}{2} r \sigma^2 \tag{2.10}$$

Where μ and σ are the expected value and the standard deviation of the profits, respectively. The advantage of risk-adjusted value is its intuitive expression of the value under the measure of utility. Although this value has monetary units, it also incorporates decision-makers' risk attitudes. Therefore, the maximizing of RAV is often employed in an optimization problem to capture different preferences, such as well placement optimization and pit-shell optimization (Acorn et al., 2020; Capolei et al., 2015; Jesmani et al., 2020; Moore et al., 2005).

(3) Stochastic dominance rule

The stochastic dominance rule is another approach that does not require a specific utility function (Levy, 2015). There are three main relationships in stochastic dominance rule: first-order stochastic dominance (FSD), second-order stochastic dominance (SSD), and third-order stochastic dominance (TSD). Assuming the cumulative distribution functions (CDF) of random variables X for decision A and B are $F_A(X)$ and $F_B(X)$ in the interval $[a, b]$, respectively. A first-order stochastically dominances B when they satisfy the condition in Equation 2.11. A sketch is utilized to illustrate this relationship, which is shown in Figure 2.5a. It shows that if $F_B(X)$ is not less than $F_A(X)$ for any given value $x \in [a, b]$, then A dominates B in the sense of FSD.

$$F_A(x) \leq F_B(x) \text{ for } \forall x \in [a, b] \tag{2.11}$$

The conditions for FSD are very strict, which leads to SSD and TSD. $G_A(X)$ and $G_B(X)$ are the areas enclosed by the CDFs, the horizontal axis ($y = 0$) and a changeable vertical axis ($x \in [a, b]$). Then, A second-order stochastically dominates B when they satisfy the condition in Equation 2.12. The SSD allows $F_A(X)$ and $F_B(X)$ to intersect each other, which could be reflected by Figure 2.5b.

$$G_A(x) \leq G_B(x) \text{ or } \int_a^x \Big(F_A(t) - F_B(t)\Big)\, dt \leq 0 \text{ for } \forall x \in [a, b] \tag{2.12}$$

Similarly, $\{H_A(X), H_B(X)\}$ is defined as the area enclosed by $\{G_A(X), G_B(X)\}$, the horizontal axis ($y = 0$), and an alternate vertical axis $x \in [a, b]$. $E_A(X)$ and $E_B(X)$ are assumed as the expected returns of A and B, respectively. Then, A third-order stochastically dominances B when they satisfy Equation 2.13. In addition, the relationship among these three dominance rules is FSD $\subseteq$ SSD $\subseteq$ TSD.

$$E_A(x) > E_B(x) \text{ and } H_A(x) \leq H_B(x) \text{ for } \forall x \in [a, b] \tag{2.13}$$

The stochastic dominance rule has been applied in the petroleum industry. For example, Lean et al. (2010) investigated the market efficiency of oil spot and futures price by stochastic dominance rule. Gallardo and Deutsch (2020) combined the mean-variance criterion and stochastic dominance to reduce the number of alternatives in well position selection. This rule was also introduced in the mining industry for optimizing pit shell and block caving drawpoints (Acorn et al., 2020; Ugarte Zarate et al., 2020).

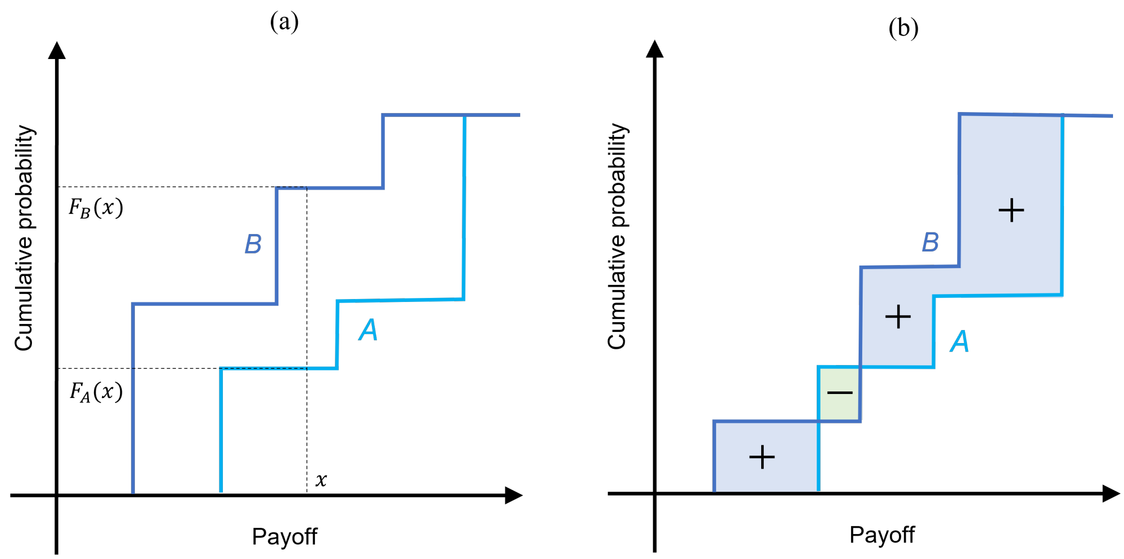


Figure 2.5: A sketch of stochastic dominance relationship between alternatives A and B. (a) The relationship for first-order stochastic dominance. (b) The relationship for second-order stochastic dominance. The area of $(-)$ indicates the $F_A(x)$ is greater than $F_B(x)$, while the area of $(+)$ denotes the $F_A(x)$ is smaller than $F_B(x)$.

2.3.3 Techniques with expected utility approximation

(1) Mean-variance approximation

The expected utility is often approximated by the Taylor series expansion (Fahrenwaldt and Sun, 2020; Garlappi and Skoulakis, 2011; Harvey et al., 2010). The Taylor series for expected utility $E\{U(X)\}$ at x_0 is expressed as:

$$E\{U(X)\} = U(x_0) + U^{(1)}(x_0)E\{(X - x_0)\} + \cdots + \frac{1}{n!}U^{(n)}(x_0)E\{(X - x_0)^n\} \quad (2.14)$$

Where $U^{(n)}(\cdot)$ is the n-th derivative of utility function $U(\cdot)$. When $n = 2$ and $x_0 = 0$, $E\{U(x)\}$ will be approximated by the first three terms of Equation 2.14.

$$E\{U(X)\} \approx U(0) + U^{(1)}(0)E\{X\} + \frac{1}{2!}U^{(2)}(0)E\{X^2\} \tag{2.15}$$

Where $U(0)$, $U^{(1)}(0)$, $U^{(2)}(0)$ are constants, $E\{X\}$ is the expected return. When $x_0 = EV$, the expected utility could be approximated by:

$$E\{U(X)\} \approx U(EV) + U^{(1)}(EV)E\{X - EV\} + \frac{1}{2!}U^{(2)}(EV)E\{(X - EV)^2\} \tag{2.16}$$

Where $U(EV)$, $U^{(1)}(EV)$, $U^{(2)}(EV)$ are constants, and $E\{X^2\} = Var\{X\} + E^2\{X\}$. The expected utility could be approximated by the mean and variance, which is also called the mean-variance approximation approach (Markowitz, 2014).

(2) Mean-semivariance approximation

Many studies have documented the alternatives to substitute variance in the expected utility framework (Ballestero, 2005; Klebaner et al., 2017). Estrada (2004) approximated the expected utility by applying Taylor series at the expected value from Equation 2.16. It could be expressed as the mean and semi-variance by replacing the variance with twice the semi-variance of profits (Equation 2.17).

$$E\{U(X)\} \approx U(EV) + U^{(2)}(EV) \times S_B^2 \tag{2.17}$$

Where $S_B^2 = E\{\min[(X - B), 0]^2\}$ denotes the semi-variance with a benchmark B. $U^{(2)}(\cdot)$ is the operation of the second derivative of $U(\cdot)$. Guo et al. (2012) employed the mean-variance model in the petroleum investment decisions. Santos et al. (2017c) utilized the relationship in Equation 2.17 to optimize production strategies. Sefair et al. (2017) proposed a linear scheme to solve the mean-semivariance project portfolio selection problem, this approach is illustrated in an upstream oil project selection.

In order to get higher precision, the skewness preference is also included in the approximation of expected utility by the Taylor series expansion (Brockett and Kahane, 1992; Chiu, 2010; Hassett et al., 1985). The skewness preference is captured by the third moment about the mean, which could be expressed as:

$$E\{U(X)\} \approx U(EV) + \frac{1}{2!}U^{(2)}(EV)E\{(X - EV)^2\} + \frac{1}{3!}U^{(3)}(EV)E\{(X - EV)^3\} \tag{2.18}$$

2.3.4 Techniques outside expected utility

(1) Decision making with a loss function

Loss functions are often used in parameter estimation, it assigns different penalties in the underestimation and overestimation to facilitate decision making (Agterberg and Bonha Carter, 2005; Schorfheide, 2000; Yousefzadeh, 2017). Journel (1984) introduced this concept in geostatistics to improve the estimation variance criterion. Da Cruz et al. (2004) utilized an asymmetric linear loss function in the quality map to facilitate the optimization of well placement. De Barros (2019) explained the loss function in reservoir management with the consideration of geological uncertainty. The loss function is also widely employed in the mining industry in recent years. Sivakumar et al. (2015) utilized the loss function to measure the benefit and risk in the evaluation of vendor selection. Vasylchuk and Deutsch (2018) provided a simple method to implement the minimum expected loss in the grade control. Vasylchuk and Deutsch (2019) applied the loss function in the optimization of surface mining. Consider an estimate $z^\star$ from the variable Z, the optimal estimate z_{opt} could be found by minimizing the expected loss in Equation 2.19.

$$z_{opt} = \underset{z^\star \in \mathbb{A}}{\operatorname{argmin}} \, E\{L(Z, z^\star)\} \tag{2.19}$$

Where $L(\cdot)$ is the loss function, $\mathbb{A}$ denotes the allowable interval for the estimate. In the resource modeling applications, the expected loss could be solved by a discrete sum over all the realizations of simulation in Equation 2.20 (Glacken, 1996).

$$E\{L(Z, z^\star)\} = \frac{1}{N} \sum_{n=1}^{N} f(z_n) L(z_n, z^\star) \tag{2.20}$$

A simple example in Figure 2.6 will be used to illustrate the workflow of minimizing the expected utility in parameter estimation. In this case study, the loss function has a linear form, which is given below:

$$L(z, z^\star) = \begin{cases} \lambda_1(z - z^\star) & z \geq z^\star \\ \lambda_2(z^\star - z) & z < z^\star \end{cases} \tag{2.21}$$

Where z is the true value, and $z^{\star}$ denotes the estimated value. The estimated error is defined as $z^{\star} - z$ in the loss function. $z^{\star} - z < 0$ represents underestimation and $z^{\star} - z > 0$ denotes overestimation. λ_1 and λ_2 are the penalties assigned for the underestimation and overestimation, respectively. Loss functions are classified as symmetric or asymmetric based on the penalty on each side. The symmetric loss function means the penalty is the same in the underestimation and overestimation ($\lambda_1 = \lambda_2$), while the asymmetric loss function unequally weights underestimation or underestimation ($\lambda_1 \neq \lambda_2$). It is supposed that $\lambda_1 = 0.5$ and $\lambda_2 = 0.1$ in this case study, a sketch of this linear loss function is shown in Figure 2.6a. The probability distribution for a categorical variable Z is displayed in Figure 2.6b. Three scenarios, $\{z^{\star} = 1, 5, 9\}$, of calculating the expected loss are given in Figure 2.6c, the expected loss is calculated by averaging all possible losses caused by the difference between the estimated value and the true value. The plot between expected loss and the estimate $z^{\star}$ is shown in Figure 2.6d, we can see the expected loss decreases and then increases with increasing z. The minimum expected loss is reached when z equals to 8, which is the optimal estimate.

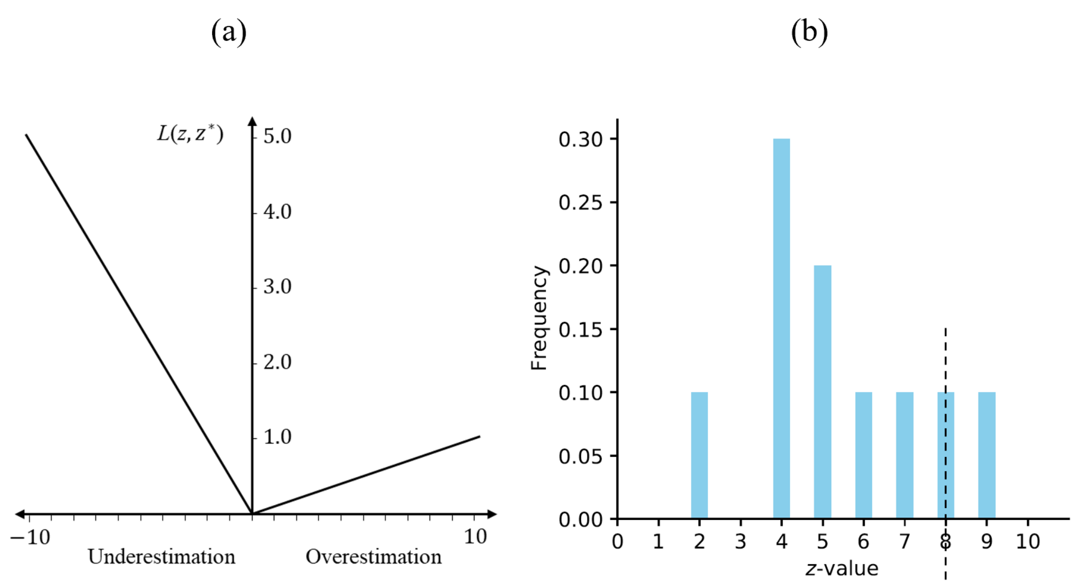
Additionally, Journel (1984) proved that for a linear loss function, the p-quantize of the distribution is the value that minimizes the expected loss. The p-quantile is calculated based on the weights on the overestimation and underestimation in the loss function.

$$p = \frac{\lambda_1}{\lambda_1 + \lambda_2} \tag{2.22}$$

The optimal estimate z_{opt} is the p-quantile value from the distribution of Z, which is shown in Equation 2.23.

$$z_{opt} = F_Z^{-1}(p) \tag{2.23}$$

Where $F^{-1}(\cdot)$ is the inverse cumulative distribution function. It indicates when $\lambda_1 = \lambda_2$ ($z_{opt} = 0.5$), the optimal value would be the median. When $\lambda_1 < \lambda_2$ ($z_{opt} < 0.5$), the optimal estimate would be less than the median. This can be explained that more penalties for overestimation would lead to a more conservative estimate. Similarly, when $\lambda_1 > \lambda_2$ ($z_{opt} > 0.5$), the optimal estimate would be greater than the median since underestimation is penalized more than overestimation.



(c)

$z^* = 1$	$z^* = 5$	$z^* = 9$
L(1-2)=0.5	L(5-2)=0.3	L(9-2)=0.7
L(1-4)=1.5	L(5-4)=0.1	L(9-4)=0.5
L(1-4)=1.5	L(5-4)=0.1	L(9-4)=0.5
L(1-4)=1.5	L(5-4)=0.1	L(9-4)=0.5
L(1-5)=2.0	L(5-5)=0.0	L(9-2)=0.4
L(1-5)=2.0	L(5-5)=0.0	L(9-2)=0.4
L(1-6)=2.5	L(5-6)=0.5	L(9-2)=0.3
L(1-7)=3.0	L(5-7)=1.0	L(9-2)=0.2
L(1-8)=3.5	L(5-8)=1.5	L(9-2)=0.1
L(1-9)=4.0	L(5-9)=2.0	L(9-9)=0.0
E(L)=2.2	E(L)=0.56	E(L)=0.36

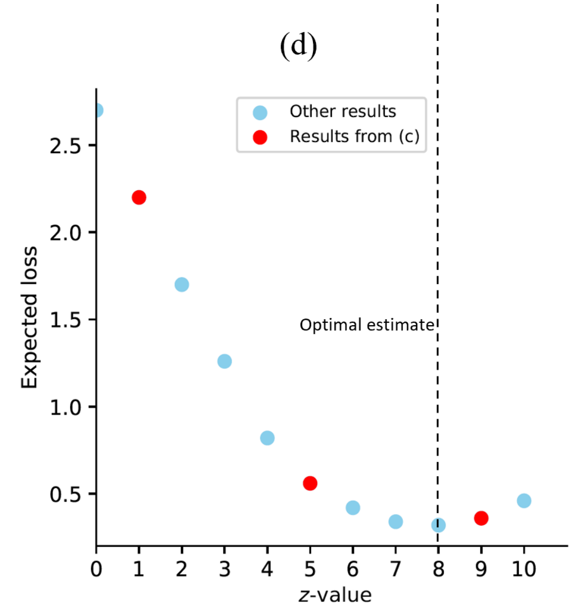


Figure 2.6: A case study to show the workflow of minimizing expected loss in the parameter estimation (Deutsch, 2010). (a) The asymmetric linear loss function. (b) The distribution of variable z. (c) The expected utility for three scenarios. (d) The optimal estimate with the minimum expected loss.

2.4 Value of information

The concept of value of information (VOI) analysis originates from business decisions (Schlaifer, 1959), and it was first introduced in the petroleum industry for the drilling decision (Grayson, 1960). The new information is able to change our previous understanding of the uncertainty with the increased knowledge of subsurface. VOI analysis should be implemented in the context of decision making, information does not have any value if the decision remains the same (Bratvold et al., 2009; Trainor Guitton et al., 2014). That is, the information would be considered valuable if it could change the decision, and it is worth collecting when the VOI exceeds the cost of information (Figure 2.7).

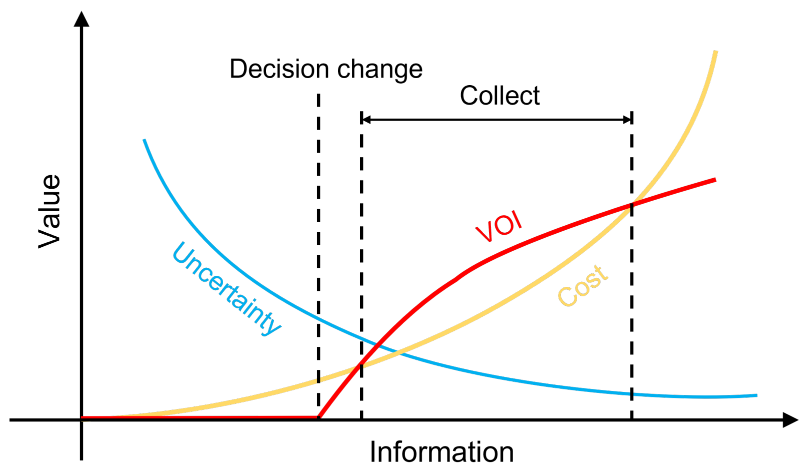


Figure 2.7: A sketch of the changes of uncertainty, cost and VOI along with the increasing information.

2.4.1 Classification of information

Information is often categorized based on its reliability and sampling method in the VOI analysis of Earth Science problems. Based on the reliability of information, they could be categorized as perfect information and imperfect information. The perfect information indicates the information has no noise and is directly related to the prospect outcome. The imperfect information indicates the information is measured with noise or without a direct relationship with the prospect outcome. Perfect or imperfect information is alternatively regarded as the reliability of information. They could be measured by the conditional probability in the posterior value. Perfect information has a conditional probability of 1, while the conditional probability of imperfect information is less than 1. Most information in Earth Science is imperfect, such as geophysical information. Trainor Guitton et al. (2011) proposed an approach to measure the reliability of geophysical information. It is based on simulating the synthetic information as a comparison. Trainor Guitton (2014) applied this approach to analyze VOI in the context of groundwater sustainability decisions.

Additionally, the information could also be categorized as partial information and total information based on their sampling method (Ketzenberg et al., 2006; Williams and Johnson, 2015). Partial information, like well data, is locally sampled, while total information, like geophysical information, is exhaustively sampled at every location. Total information is often used as secondary data in geological modeling, since it is able to provide information in the unsampled location in the partial information. In Table 2.1, Eidsvik et al. (2015a) summarized the characteristics of different types of information in the aspect of perfect or imperfect, and partial or total.

There are also some other criteria for information classification. According to the way of collecting information, it can be divided into sequential information and simultaneous information (Eidsvik et al., 2018; Hoffman et al., 2011; Morosov and Bratvold, 2021). According to the source of information, it can be divided into single-source information and multiple-source information (Avolio et al., 1991; Shaw, 1982). The appropriate information classification should be designed based on our research goals.

Table 2.1: The classification of information (Eidsvik et al., 2015a).

Category	Perfect	Imperfect
Total	Accurate observations are collected for all locations. This is rare, occurring when there is highly accurate data gathering with extensive coverage.	Noisy observations are gathered for all locations. A typical example is the collection of geophysical information with extensive coverage.
Partial	Accurate data are gathered at some locations. This information could be obtained, for instance, when the core samples are carefully analyzed.	Noisy observations are gathered at some locations. A typical example is the collection of well logging in the well drilling process.

2.4.2 VOI analysis in the Earth Sciences

Many uncertainties surround the future regarding cumulative oil production or net present value due to the limited information for drilling wells. This geo-spatial uncertainty related to the subsurface properties could affect the investor's behavior on the design of production strategy. The decision-related information is often collected to reduce uncertainty and improve decision-making. The value of information (VOI) is defined by the difference between posterior value (PoV) and prior value (PV). Under a risk-neutral position, the PoV and PV are, respectively, calculated from the expected value with information and the expected value without information.

$$\begin{aligned} \mathrm{VOI} &= \mathrm{PoV} - \mathrm{PV} \\ &= \begin{bmatrix} \text{Expected value with} \\ \text{additional information} \end{bmatrix} - \begin{bmatrix} \text{Expected value without} \\ \text{additional information} \end{bmatrix}. \end{aligned} \tag{2.24}$$

Two questions are often involved in VOI analysis. The first one is how accurate/reliable of the information (Trainor Guitton, 2010; Trainor Guitton et al., 2011). The measure of information reliability is often considered a challenge in VOI analysis . In most Earth Science problems, the information is not directly related to the decision-related properties, for example, the geophysical information is indirectly related to the geological properties, the uncertainty exists between the transfer of geophysical information to the geological properties. Data reliability has attracted many researchers in information analysis (Agmon and Ahituv, 1987; Trainor Guitton et al., 2011). Data reliability means the information is directly or indirectly related to the decision-related property. It could also simply be expressed as the conditional probability in Equation 2.25 (Eidsvik et al., 2015a; Trainor Guitton, 2010). Perfect information has a reliability of $\mathrm{Pr} = 1$, while imperfect information has a reliability of $\mathrm{Pr} < 1$. Although the information reliability in many engineering problems is accessible from the success rate of repetitive experiments, it is difficult to determine the reliability of the information in Earth Science problems. Bickel et al. (2008) incorporated seismic information into a decision making framework, and proposed a workflow to measure the reliability of 4-D seismic based on the rock physics analysis. Trainor Guitton et al. (2011) introduce a framework to measure the reliability of geophysical information (Pr) in the presence of geological uncertainty.

$$\mathrm{Pr} = \mathrm{Prob}\ \{\text{Interpretation from information} \mid \text{the truth geological scenario}\} \qquad (2.25)$$

The second question is about whether the information is worth its cost or not in VOI analysis (Eidsvik et al., 2015b; Heath et al., 2017; Kunst et al., 2020). This is because VOI analysis is performed before collecting it, which makes it difficult to calculate an accurate posterior value. Many different methods have been proposed to approximate the posterior value, such as Gaussian approximation, double-loop Monte Carlo, and simulation-regression approach, which will be described in detail in the next subsection. Generally, in order to determine whether the information is worth collecting, VOI analysis should be placed in the context of decision making. Information is worth collecting when the value of information is greater than the cost of information.

VOI analysis is considered by engineers in the petroleum industry. Cunningham and Begg (2008) employed VOI approach in the construction of learning well strategy in the offshore well program, it would facilitate the identification of the optimal well order in a sequential drilling project. Santos and Schiozer (2017) evaluated the value of additional injection well in the context of selecting production strategy, and the reliability of additional information is analyzed based on sensitivity analysis. Santos et al. (2017b) also investigated the drilling information in the aspect of the ability to reduce uncertainty, the ability to change decisions, and the ability to increase profit. These aspects are utilized as the standards to assess the value of this information. Hong et al. (2018) addressed the value of history matching in the framework of decision-based VOI analysis, this procedure was implemented in both static and dynamic models. Dutta et al. (2019b) applied this approach to analyze the value of 4-D seismic in a spatial decision situation. He et al. (2018) also applied the concept of VOI assessment in the context of whether to execute a pilot or not in the Brugge oilfield. These applications indicate that VOI analysis could be implemented in the context of reservoir decision making.

2.4.3 Posterior value estimation

The PoV is the value of an event occurring after taking additional information into account. Since VOI analysis is performed before actually collecting the data, which makes it difficult to calculate the conditional expectation in posterior value. Previous research documents the approaches to approximate the conditional expectation, such as Gaussian parameter model (Dutta et al., 2019a; Jalal and Alarid Escudero, 2018), double-loop Monte Carlo (Barros et al., 2015; Heath et al., 2018), and simulation-regression approach (Eidsvik et al., 2008; Strong et al., 2015). These approaches will be discussed below.

(1) Parameter model

The parameter model was introduced to estimate the PoV by Eidsvik et al. (2008), and Bhattacharjya et al. (2010) employed spatial statistical models in the assessment of the value of decision-related information. This approach based on the parameter model often depends on a strong assumption of Gaussian framework to analytically calculate the posterior value. Bhattacharjya et al. (2013) extended this approach in the multivariate model with an assumption in a multivariate Gaussian space. Under the Gaussian modeling assumption, the PoV of information $\boldsymbol{y}$ is expressed as:

$$\mathrm{PoV}(\boldsymbol{y}) = \mu_w F\left(\frac{\mu_w}{\sigma_w}\right) + \sigma_w f\left(\frac{\mu_w}{\sigma_w}\right) \tag{2.26}$$

Where $\mu_w = \sum_{i=1}^{n} \mu_i$ and $\sigma_w^2 = \sum_{i=1}^{n} \sum_{i=1}^{n} \sigma_{ij}$ denote the mean and variance of the profit distribution at the n spatial units, respectively. $f(\cdot)$ and $F(\cdot)$ refer to the probability density function and cumulative density function of a standard Gaussian distribution. This approach has been applied in many different disciplines. Rojnik and Naveršnik (2008) employed a parameter model with Gaussian process to analyze the value of health information. Eidsvik and Ellefmo (2013) applied this Gaussian model to approximate the value of boreholes in mineral exploration. Rezaie et al. (2014) applied the parameter model with closed skew-normal distributions to seismic amplitude information analysis. Although the parameter model approach is convenient and computationally efficient, it heavily relies on the assumption of the Gaussian framework.

(2) Double-loop Monte Carlo

The PoV is the expected outcome over all the best decisions from each possible scenario. In the risk-neutral position, PoV is expressed in Equation 2.27 (Dutta et al., 2019b). It indicates this process involves two nested expectations .

$$\mathrm{PoV}(\boldsymbol{y}) = E_{\boldsymbol{y}}\left\{\max_{d\in\boldsymbol{D}}\left\{E_{\boldsymbol{g}}\left\{V(\boldsymbol{g}, d) \mid \boldsymbol{y}\right\}\right\}\right\} \tag{2.27}$$

Where $E_{\boldsymbol{g}}$ and $E_{\boldsymbol{y}}$ are the nested expectations with the uncertainty from geological models $\boldsymbol{g}$ and information models $\boldsymbol{y}$, respectively. The expected value could be numerically solved via performing Monte Carlo simulation (Brennan et al., 2007). The double-loop Monte Carlo approach is based on two nested simulations to quantify PoV. Thus, the PoV could be written as:

$$\mathrm{PoV}(\boldsymbol{y}) = \frac{1}{N_2}\sum_{n_2=1}^{N_2}\max_{d\in\boldsymbol{D}}\left\{\frac{1}{N_1}\sum_{n_1=1}^{N_1}\left\{v(g_{n_1}, d) \mid y_{n_2}\right\}\right\} \tag{2.28}$$

Where N_1 and N_2 are the number of realizations in the first-loop simulation and second-loop simulation, respectively. It indicates a two-step procedure is involved in this approach, the first-loop Monte Carlo is performed to calculate the inner expression, which aims to capture the uncertainty from the geological model. The second-loop Monte Carlo is utilized to calculate the outer expression, it is used to reflect the uncertainty from the information (Dutta et al., 2019b). The selection of the sample size in the inner expression is crucial, this conditional expectation is often approximated based on the rejection sampling (Dutta et al., 2019b; Rothery et al., 2020).

The double-loop Monte Carlo is proposed by Barros et al. (2015), his workflow is based on a twin experiment to optimize the production strategy within a closed-loop reservoir management framework. Dutta et al. (2019b) applied the double-loop Monte Carlo to evaluate the value of time-lapse seismic data, and Hong et al. (2018) utilized this approach in the assessment of production data in the history matching. Although this approach does not have any simplifying assumptions involved, it has a significant constraint on computational demand for VOI assessment as it requires a large number of reservoir simulations.

(3) Simulation-regression approach

The idea of using regression to estimate the VOI originates from medical decision making, it aims to use a regression function to approximate the expectation in the inner loop of PoV (Strong et al., 2015; Tuffaha et al., 2016). Inspired by this idea, Eidsvik et al. (2017) proposed the simulation-regression approach in VOI analysis for subsurface energy resources applications. The simulation-regression approach is a computationally efficient approach in the estimation of posterior value. It is implemented based on constructing a regression relationship between the value outcomes and the possible information scenarios under multiple realizations (Eidsvik et al., 2017; Strong et al., 2014). That is, in the presence of geological uncertainty, the conditional expectation $E\{\, V(\boldsymbol{g}, d) \mid y_n \,\}$ could be approximated by the regression value $\hat{v}(y_n, d) = F_d(y_n)$, where $F_d(\cdot)$ is a regression function for alternative d. Thus, the PoV is expressed below:

$$
\begin{aligned}
\mathrm{PoV}(\boldsymbol{y}) =& \frac{1}{N} \sum_{n=1}^{N} \max_{d \in \boldsymbol{D}} \Big\{ E \Big\{ \, V(\boldsymbol{g}, d) \mid y_n \, \Big\} \Big\} \\
\approx& \frac{1}{N} \sum_{n=1}^{N} \max_{d \in \boldsymbol{D}} \hat{v}(y_n, d)
\end{aligned}
\tag{2.29}
$$

Using the simulation-regression approach in the VOI analysis has gradually attracted people's attention in the oil industry. Eidsvik et al. (2017) utilized the simulation-regression approach to evaluate the value of geophysical information in the presence of geological uncertainty. His research showed that, under the Multi-Gaussian framework, the simulation-regression approach produces similar results with the parameter model approach. Dutta et al. (2019a) presented the comparison between the simulation-regression approach and double-loop Monte Carlo. The result indicates the simulation-regression approach is computationally more efficient than the double-loop Monte Carlo method with similar accuracy. Dutta et al. (2019b) employed this approach in the evaluation of time-lapse seismic in the context of well placement. In the regression between high-dimensional geophysical data and profit values, partial least square regression is tested to have a higher efficiency than principal component regression. He et al. (2019) applied the simulation-regression approach to evaluate the value of production data in the production forecast. It simplified the process of production forecast by directly using the observed data without model calibration. Anyosa et al. (2021) combined the simulation-regression approach and statistical analysis to assess the value of seismic information. Different regression approaches are also evaluated in the VOI analysis under the decision context of CO_2 injection.

Chapter 3

Preference measurements in the presence of geological uncertainty

This chapter demonstrates the impact of preferences on decision analysis and a workflow is proposed to investigate the relationship between different preference measurements (loss function and utility function). The proposed workflow is illustrated using an exponential utility function and a quadratic utility function in decision making with uniformly distributed alternatives. The relationship between these preference measurements is constructed by connecting the penalty factor of loss functions and the risk tolerance of utility functions. Limitations are discussed at the end of the chapter.

3.1 Motivation

Risk preference plays an important role in the development of decision theory, it refers to investors' tendency or behavior in the presence of uncertainty. The development of decision theory in the energy industry ranges from the minimum expected loss to the maximum expected utility (Deutsch, 2020), they are utilized to incorporate investors' preferences in decision making. The utility function is a well-known tool to quantify risk attitude, and a rational decision is associated with the maximum expected utility, different risk positions could be quantitatively measured by the utility function. In addition, the loss function is also popular in capturing investors' attitudes. It incorporates different penalties in the underestimation and overestimation to facilitate decision-making (Goodfellow et al., 2016; Schorfheide, 2000). Investors are able to find the estimate most likely to produce the desired outcome by minimizing the expected loss.

Loss functions are often used in parameter estimation, such as mineral grade control in the classification of ore and waste (Vasylchuk and Deutsch, 2018; Verly, 2005). In contrast, utility functions are commonly employed in the optimization of strategies, such as the well placement optimization in the petroleum industry (Güyagüler and Horne, 2004; Ozdogan and Horne, 2006). These functions are often employed in different contexts, which brings difficulties to integrate these two frameworks. Although preference measurements, like loss function and utility function, provide approaches to manage risk in reservoir decision making, the underlying relationship between them is not clear.

This chapter aims to investigate the relationship between the loss function and utility function. This is conducted by using the exponential utility function and quadratic loss function. The relationship between risk position in utility function and the penalty factor of the loss function is constructed, which provides a new perspective for understanding the loss functions and utility function in decision making.

3.2 Preference measurements in decision making

In the past few decades, the utility function has had a profound impact on decision theory. It is an essential tool to measure the satisfaction of decision-makers and reflect people's preferences under risk (Eidsvik et al., 2015a; Zou et al., 2020). The framework of expected utility theory was first proposed by Dianiel Bernoulli and systematically organized by Von Neumann and Morgenstern in 1947. This theorem indicates that the rational decision is always associated with the maximum expected utility. The decision-making problems in the petroleum industry with expected utility could be formulated as follows (Vizcaino, 2019):

$$d_0 = \underset{d \in \boldsymbol{D}}{\operatorname{argmax}} E\{U(V(\boldsymbol{g}, d)\} \tag{3.1}$$

Where d_0 denotes the optimal alternative, and $V(\cdot)$ refers to the profit function. $\boldsymbol{D}$ is a set of alternatives, and $\boldsymbol{g}$ is an ensemble of geological models. The expected utility $E\{U\}$ could also be expressed as the summation of a series of utility values with equal weights (Equation 3.2). These weights come from a countable set of equal-probability N realizations generated from stochastic simulation. Taking three alternatives (A, B, C) as an example, the process of decision making using expected utility is shown in Figure 3.1.

$$\underset{d \in \boldsymbol{D}}{\operatorname{argmax}} E\left\{U\left(V(\boldsymbol{g}, d)\right)\right\} = \underset{d \in \boldsymbol{D}}{\operatorname{argmax}} \frac{1}{N} \sum_{n=1}^{N} U\left(v(g_n, d)\right) \tag{3.2}$$

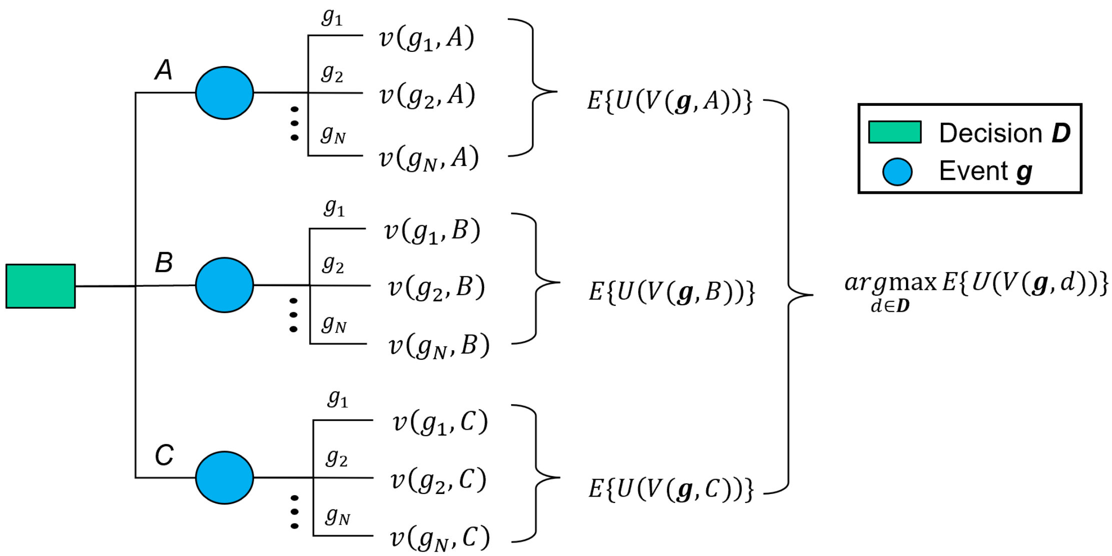


Figure 3.1: The workflow of reservoir decision making based on expected utility.

The other crucial concept in decision theory is the loss function, which is extensively utilized in parameter estimation (Chakraborty and Das, 2018; Meena et al., 2018). In subsurface resource management, the process of using a loss function to identify the optimal decision is expressed in Equation 3.3. That is, the desired decision with loss functions is calculated from a two-step optimization. The first round of optimization requires minimizing the expected loss to find the optimal estimates. After that, the other round of optimization is performed to maximize the optimal estimates over all the alternatives. This two-step optimization with loss function could be sketched in Figure 3.2.

$$d_0 = \underset{d \in \boldsymbol{D}}{\operatorname{argmax}} \left\{ \underset{Z^\star(d)}{\operatorname{argmin}} E \left\{ L \left(Z(\boldsymbol{g}, d), Z^\star(d) \right) \right\} \right\} \tag{3.3}$$

Where $L(\cdot)$ denotes the loss function. $Z(\cdot)$ and $Z^\star(\cdot)$ are the functions for true variable and estimate variable, respectively. For a given strategy d, the expected loss could also be expressed in Equation 3.4 for the mineral grade control (Deutsch, 2020; Vasylchuk and Deutsch, 2018). It is calculated from a discrete sum over all simulated realizations:

$$E \left\{ L(Z(\boldsymbol{g}, d), z^\star(d)) \right\} = \frac{1}{N} \sum_{n=1}^{N} L \left(z(g_n, d), z^\star(d) \right) \tag{3.4}$$

Where $z(\cdot)$ represents the value of mineral grade represented by multiple realizations, and $z^*(\cdot)$ is the single value of estimated grade. N is the number of realizations.

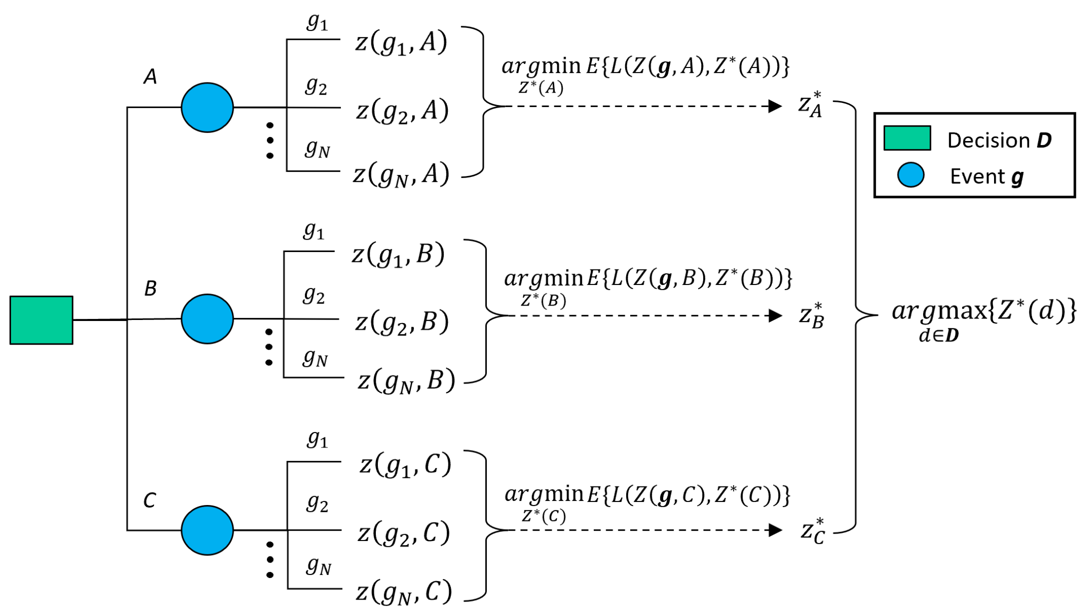


Figure 3.2: The workflow for reservoir decision making based on expected loss.

A simple example is utilized to illustrate the impact of different risk positions in decision making (Figure 3.3). Suppose a rational investor needs to make a decision between two alternatives, A and B. For decision A, it has an uncertain outcome, that is, 50% chance to obtain 10M and 50% chance to get 40M. While for decision B, the investor would receive a certain amount of money (25M). The investor aims to maximize the expected utility in the decision making, and the expected utility of each alternative under different risk positions is shown in Figure 3.4.

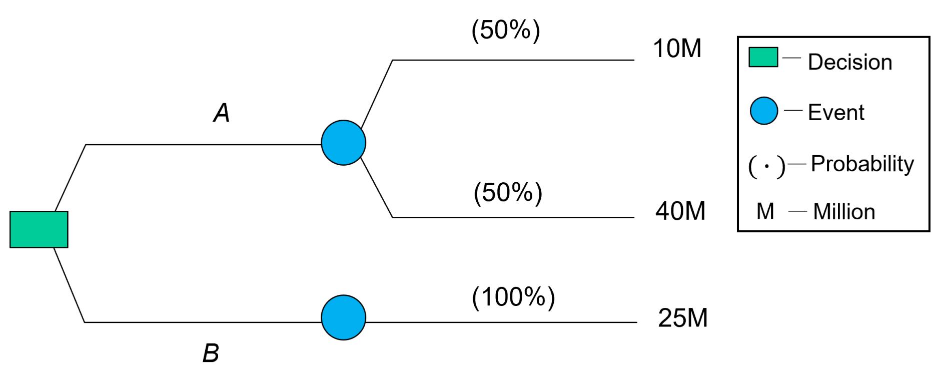


Figure 3.3: A simple decision tree for binary decision making.

(a) Investors holding risk-neutral positions have a linear utility function shown in Figure 3.4a. In this situation, maximizing expected utility is equivalent to maximizing expected value, and the risk-neutral investor prefers the alternative with a larger expected value. Since $E\{(V(A))\} = 0.5 \times 10 + 0.5 \times 40 = 25$M, and $E\{(V(B))\} = 1.0 \times 25 = 25$M, alternative A is as preferred as the alternative B for investors in a risk-neutral position.

(b) The risk-averse investors possess a concave utility function. In Figure 3.4b, it can be seen that $E\{U(V(A)\} = 0.5 \times U(10) + 0.5 \times U(40)$, and $E\{U(V(B)) = U(25)$. The alternative B is preferred over A in this risk position due to $E\{U(V(A)) < E\{U(V(B))\}$. This result indicates risk-averse investors, in this case, prefer the alternative with a safe outcome.

(c) The decision-maker in Figure 3.4c has an opportunity-seeking position. It shows that $E\{U(V(A))\} > E\{U(V(B))\}$ due to the concave shape of utility function. Thus, people would show more interest in alternative A than B in this risk position, which implies that opportunity-seeking investors, in this example, tend to choose the alternative with an uncertain outcome.

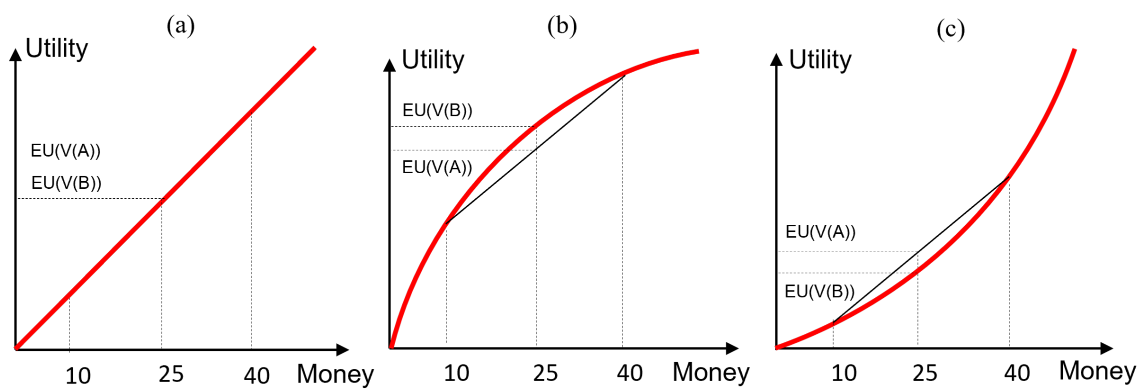


Figure 3.4: The expected utility of alternatives A and B under different risk positions. (a) The risk-neutral position. (b) The risk-averse position. (c) The opportunity-seeking position.

This example indicates that different risk positions are able to alter the decision making in practical applications. A better understanding of risk position is significant in reservoir decision making. The risk position is captured by the curvature of the utility function, and it is quantified by the risk tolerance (Santos et al., 2017c; Walls, 2005a). Therefore, the impact of risk preference on decision making could be explored by performing sensitivity analysis of the risk tolerance in the utility function.

Another example is used to illustrate the impact of loss functions in decision making. In this example, it is assumed the profit returns from alternatives A and B are normally distributed, and they have the same mean and different variance. The linear loss functions with different preferences are utilized to penalize the error between the estimated value and the true value. For a given penalty factor, the optimal estimate for alternative A and B are $z^{\star}_{opt}(A)$ and $z^{\star}_{opt}(B)$, respectively. They could be solved from the p-quantile value in Equation 2.22 (Journel, 1984). The final decision is changed under different penalty factors in the linear loss functions, three main scenarios are analyzed below:

(a) The first scenario is a symmetric linear loss function with an equal penalty on the overestimation and underestimation (Figure 3.5a). The optimal estimate equals the median, or expected value, as the alternatives are Gaussian distributed (Figure 3.6a). Thus, $z^{\star}_{opt}(A) = z^{\star}_{opt}(B)$, which indicates alternatives A and B are equivalent to the investors with this loss function.

(b) The second scenario is an asymmetric loss function with more penalty on the overestimation (Figure 3.5b). The optimal estimate is less than the median (or expected value) based on the quantile value. It can be observed from Figure 3.6b that the optimal value for alternative A is larger than that of B, $z^{\star}_{opt}(A) > z^{\star}_{opt}(B)$. Therefore, people would choose alternative A.

(c) The last scenario is an asymmetric loss function with more penalty on the underestimation (Figure 3.5c). The optimal estimate is larger than the median (or expected value), and the quantile value indicates the optimal value for alternative A is less than that of B, $z^{\star}_{opt}(A) < z^{\star}_{opt}(B)$, in Figure 3.6c. Thus, the decision-makers would favor alternative B.

The above case study implies different attitudes on the overestimation and underestimation are able to alter the outcome in decision analysis. In practical applications, especially in mineral grade control, investors' attitudes toward the estimated error are important in the decision-making process. Different attitudes are captured by the penalty factor in the loss function. Therefore, the impact of attitudes on the overestimation and underestimation in decision making could be investigated by performing sensitivity analysis on the penalty factor in the loss function.

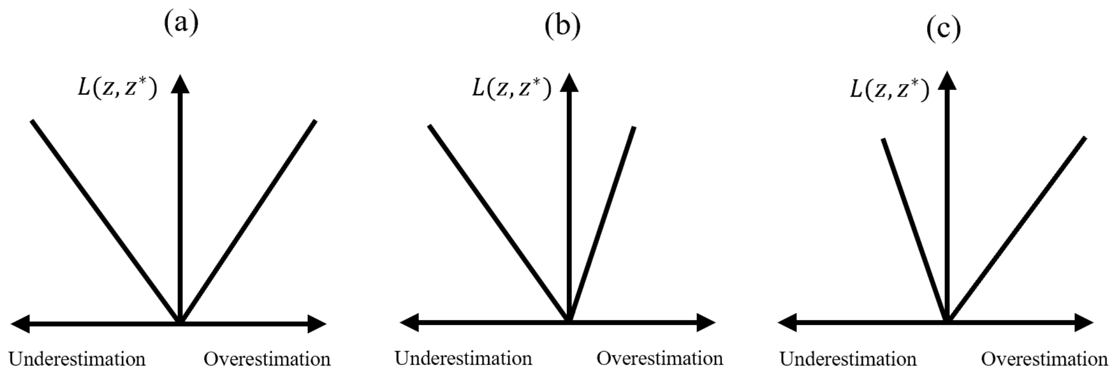


Figure 3.5: The linear loss function with different penalty factors. (a) The symmetric loss function with equal weights. (b) The asymmetric loss function with more weights on the overestimation. (c) The asymmetric loss function with more weights on the underestimation.

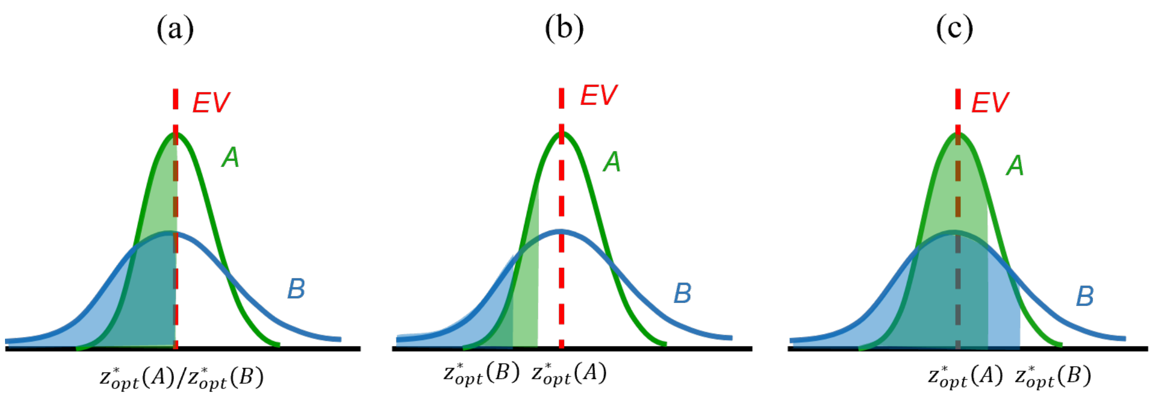


Figure 3.6: The optimal estimates of each alternative under different loss functions. (a) The optimal values under a symmetric linear loss function. (b) The optimal values under an asymmetric linear loss function with more penalty on the overestimation. (c) The optimal values under an asymmetric linear loss function with more penalty on the underestimation.

3.3 Loss function and utility function selection

Many different forms of loss functions have been proposed, such as linear loss function, quadratic loss function, indicator loss function, and so on (Chen, 2019; Kinyanjui and Korir, 2020; Sypherd et al., 2019). Therefore, selecting an appropriate form is the priority of applying loss functions in decision analysis. In this chapter, the quadratic loss function is employed to link with the utility function. This loss function is a commonly used form because it is similar to the mean square error in regression analysis. Consider a random variable Z and its estimation $z^\star$. The quadratic loss function is formulated in Equation 3.5, and it is shown in Figure 3.7.

$$L(z, z^\star) = \begin{cases} \lambda_1 (z^\star - z)^2 & z \geq z^\star \\ \lambda_2 (z^\star - z)^2 & z^\star > z \end{cases} \tag{3.5}$$

In the above equation, the loss is defined as the estimated error according to the difference between the estimated value $z^\star$ and true value z. The $z^\star - z < 0$ means the underestimation, while $z^\star - z > 0$ stands for the overestimation. λ_1 and λ_2 are penalty factors with positive values. The $\lambda = \frac{\lambda_1}{\lambda_2}$ could reflect the symmetry of the quadratic loss function. It is categorized as a symmetric loss function ($\lambda = 1$) and asymmetric loss function ($\lambda \neq 1$) based on the penalty for the overestimation and underestimation. Since the optimal estimate relates only to the λ, the quadratic loss function could be simplified to $\lambda_2 = 1$ and $\lambda_1 = \lambda$, and investors' attitudes are reflected by the penalty factor λ.

The symmetric quadratic loss function ($\lambda = 1$) has an interesting property. It indicates that the optimal estimate is determined by the distribution's expected value regardless of distribution shape. The proof of optimal estimate in symmetric quadratic loss function based on expected value (EV) could be found as follows:

$$\begin{aligned} \frac{dE\{L(Z, z^\star)\}}{dz^\star} &= \frac{dE\{(z^\star)^2 - 2Zz^\star + z^2\}}{dz^\star} \\ &= -2E\{Z\} + 2z^\star \\ &= -EV + z^\star \end{aligned} \tag{3.6}$$

Let $\frac{dE\{L(Z, z^\star)\}}{dz^\star} = 0$, the optimal estimate $z^\star_{opt} = EV$. The result indicates investors prefer the decision with a larger expected return in the context of a symmetric quadratic loss function, independent of the type of distribution.

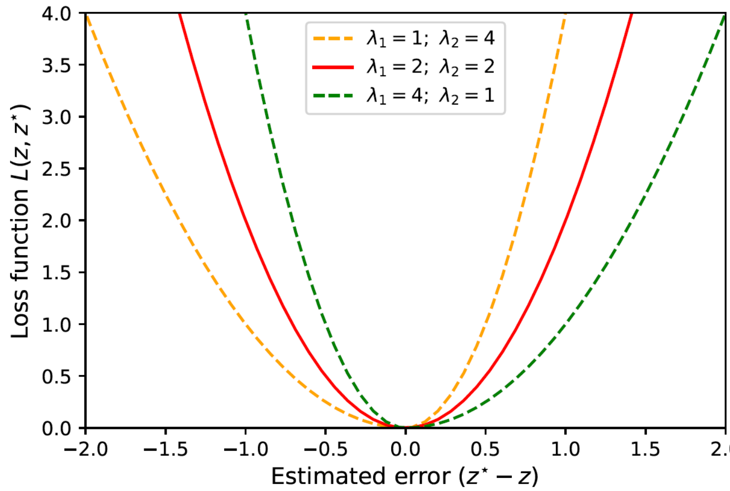


Figure 3.7: The quadratic loss function with different penalty factors.

Since the utility function for each investor is difficult to obtain in practice, various models of utility functions have been developed to investigate the impact of risk positions on decision making. The commonly utilized forms are quadratic utility function, exponential utility function, and the power utility function (Gerber and Pafum, 1998; Niromandfam et al., 2020). The exponential utility function is utilized in this chapter, which is suitable for the risk representation in the economic-related decision making, and has the characteristic of being monotonic increasing (Cozzolino, 1977). The exponential utility function has a form in Equation 3.7, it is also commonly used in the petroleum industry to incorporate risk attitudes (Suslick and Schiozer, 2004; Wood and Khosravanian, 2015).

$$U(v) = \begin{cases} \dfrac{1-\exp(-rv)}{r} & r \neq 0 \\ v & r = 0 \end{cases} \tag{3.7}$$

Where r and v are the risk tolerance and the monetary value, respectively. The risk tolerance r is the only parameter to reflect the risk position (Figure 3.8): (1) $r > 0$ stands for the risk aversion. Decision-makers prefer a safe decision with a certain outcome, even though it has a lower expected return. This utility function has a concave shape with a diminishing marginal utility; (2) $r = 0$ represents risk neutrality. Investors only pay attention to the expected return, and the risk is not under consideration. There is a linear relationship between utility and monetary value; and (3) $r < 0$ implies the opportunity-seeking position, which is associated with a convex shape of utility function. The alternative has a high potential of rewards in spite of the high risk.

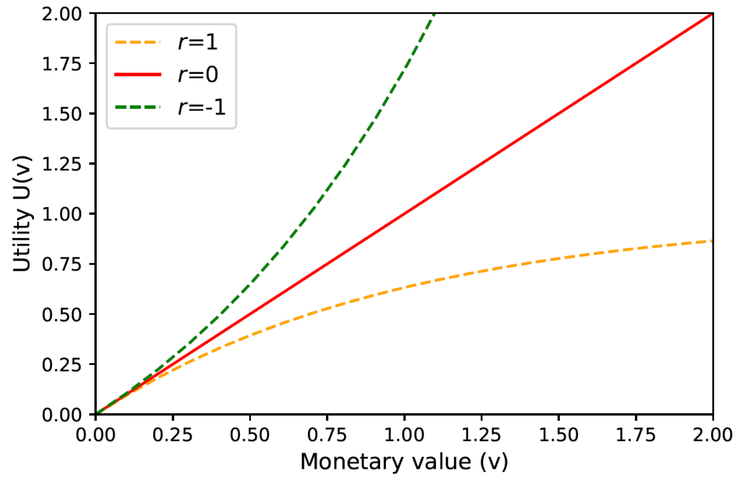


Figure 3.8: The exponential utility function with different risk tolerance.

Since the utility function for the risk-neutral position is linear, the expected utility for this risk position only depends on the expected return (Equation 3.8). That is, maximizing the expected utility is equivalent to maximizing the expected value in a risk-neutral position.

$$E\left\{U(V)\right\} = \int U(V)f(V)dV = \int Vf(V)dV = EV \quad \text{For} \quad r = 0 \tag{3.8}$$

Where V is the profit distribution and $f(\cdot)$ is the probability density function. Thus, the optimal estimate is equal to the expected return in quadratic loss function when $\lambda = 1$, and the expected utility also depends on the expected return in exponential utility function when $r = 0$. This property indicates the equivalence between the symmetric quadratic loss function and exponential utility function with a risk-neutral position, because they are both used in decision making based on the expected return.

3.4 Transitional parameters in preference measurements

This section aims to compute the transitional parameters in different preference measurements by analyzing the impact of preferences on decision making. In order to simplify the calculation, the alternatives, A and B, are assumed to have uniformly distributed returns $V(A)$ and $V(B)$, in the intervals of $[a, b]$ and $[c, d]$, respectively.

The loss function is an important measurement to evaluate the fitness of the estimate in the presence of uncertainty (Otchere et al., 2021; Xie et al., 2018). The optimal estimate is the value that minimizes the expected loss. The $z^{\star}_{opt}(A,\lambda)$ and $z^{\star}_{opt}(B,\lambda)$ are the optimal estimates of decision A and decision B with the penalty factor λ taken into account. According to Appendix A.1a, they are given by the following equations:

$$z^{\star}_{opt}(A,\lambda) = \frac{a+\sqrt{\lambda}b}{1+\sqrt{\lambda}} \quad \text{for} \quad \lambda \neq 1 \tag{3.9}$$

$$z^{\star}_{opt}(B,\lambda) = \frac{c+\sqrt{\lambda}d}{1+\sqrt{\lambda}} \quad \text{for} \quad \lambda \neq 1 \tag{3.10}$$

As the optimal estimate is affected by the penalty factor, we define the transitional penalty factor λ_T as the penalty factor when the optimal estimates in different decisions are the same (Figure 3.9). That is, the transitional penalty factor λ_T is the value when the optimal estimate from alternative A and B are the same (Equation 3.11), and it could also be numerically solved from Equation 3.15.

$$z^{\star}_{opt}(A,\lambda_T) = z^{\star}_{opt}(B,\lambda_T) \tag{3.11}$$

Additionally, rational investors aim to maximize the expected utility in decision making. For the risk-neutral position, the maximizing of expected utility is equivalent to the maximizing of expected value. While for the risk-sensitive investors with an exponential utility function (Appendix A.1b), the expected utility for decision A and B are expressed as follows:

$$E\left\{U(V(A),r)\right\} = \frac{1}{r} + \frac{\exp(-br)-\exp(-ar)}{r^2(b-a)} \quad \text{for} \quad r \neq 0 \tag{3.12}$$

$$E\left\{U(V(B),r)\right\} = \frac{1}{r} + \frac{\exp(-dr)-\exp(-cr)}{r^2(d-c)} \quad \text{for} \quad r \neq 0 \tag{3.13}$$

The expected utility is also affected by the risk tolerance, which might change the outcome in decision analysis (Figure 3.9b). In order to find the balance of two alternatives, the transitional risk tolerance r_T is defined as the value when the expected utility of decision A

is equal to it is in decision B (Equation 3.14). Since the difference between $E\{U(V(A), r)\}$ and $E\{U(V(B), r)\}$ is very small when the r becomes large in the exponential expected utility. Thus, the transitional risk tolerance r_T could be numerically solved by comparing the ratio of these two terms with one (Equation 3.16).

$$E\left\{U(V(A), r_T)\right\} = E\left\{U(V(B), r_T)\right\} \tag{3.14}$$

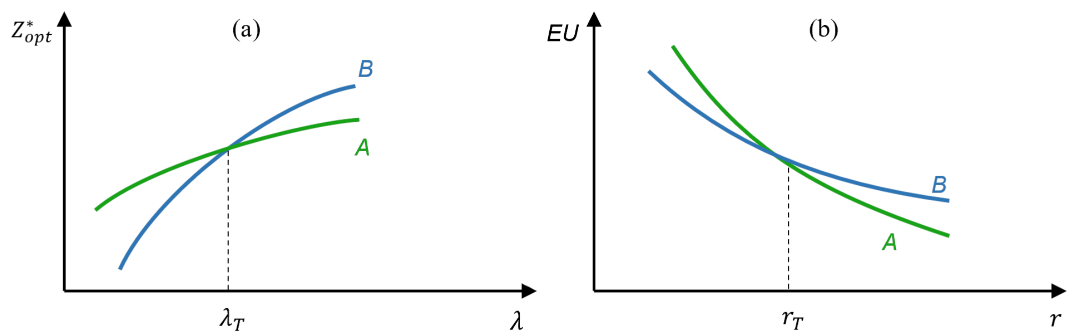


Figure 3.9: A sketch to illustrate the transitional parameters for different preference measurements. (a) The transitional penalty factor λ_T. (b) The transitional risk tolerance r_T.

Both the transitional penalty factor λ_T and transitional risk tolerance r_T are able to reflect the balance of two different decisions. That is, the decision-makers are indifferent to these two decisions in this situation. It also implies the equivalence of these transitional parameters under the same decision-making context. Therefore, we could investigate the relationship between loss function and utility function by comparing these transitional parameters. The numerically way to solve the transitional parameters is based on Equation 3.15 and Equation 3.16:

$$PF(\lambda) = \frac{a-c}{d-b} - \sqrt{\lambda} \quad \text{for} \quad \lambda \neq 1 \tag{3.15}$$

$$RT(r) = 1 - \frac{\Big(\exp(-br) - \exp(-ar)\Big)\,(d-c)}{\Big(\exp(-dr) - \exp(-cr)\Big)\,(b-a)} \quad \text{for} \quad r \neq 0 \tag{3.16}$$

Where $PF(\lambda)$ and $RT(r)$ are the functions for penalty factor and risk tolerance, respectively. The values of transitional parameters could be numerically solved by finding their intersection with the X-axis.

3.5 Link between loss function and utility function

The following flow chart is used to illustrate the workflow of investigating the relationship between different preference measures (Figure 3.10). There are three main aspects in this workflow: Firstly, the appropriate form of the loss function and utility function should be determined. In this chapter, the quadratic loss function and exponential utility function are used to illustrate the workflow. Second, the alternatives are compared under different decision criteria. When investors are indifferent to these two decisions, we can obtain the transitional penalty factor and transitional risk tolerance. These transitional parameters are comparable because they lead to the same decision. Lastly, this process could be simplified by adopting uniformly distributed alternatives, and the relationship of preference measurements will be constructed by repetitive experiments with different decisions.

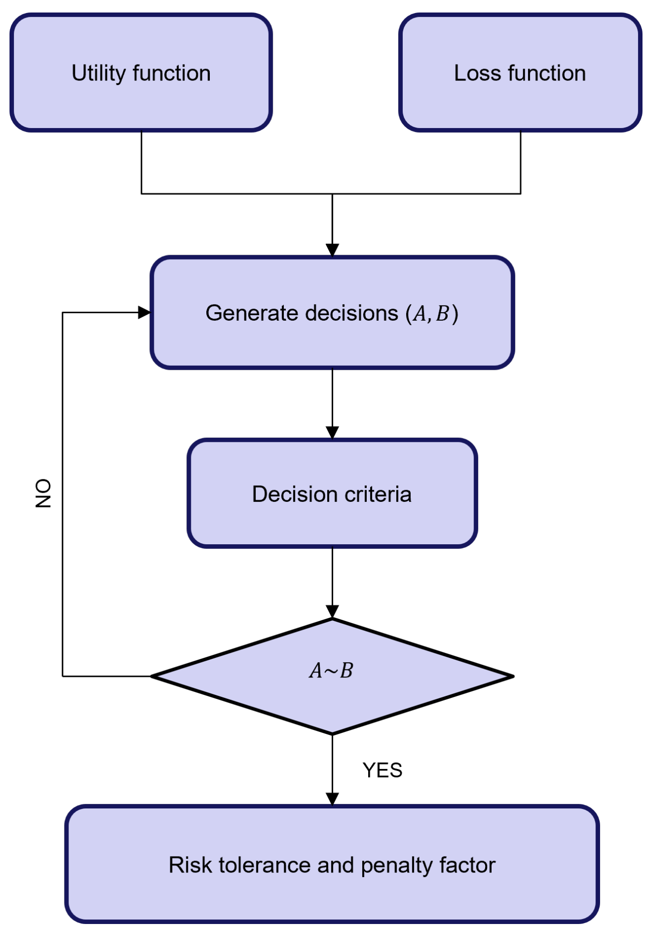


Figure 3.10: A sketch of workflow to connect the loss function and utility function.

The parameters in the loss function and utility function that reflect personal preference are penalty factor and risk tolerance, respectively. Thus, our target is to investigate the relationship of different preference measurements by connecting the penalty factor and risk tolerance. Since these parameters may change the outcome of decision making, there may be a situation where investors are indifferent to the decisions. In this situation, the parameters are named as transitional penalty factor and transitional risk tolerance. The transitional penalty factor λ_T and transitional risk tolerance r_T are solved from $PF(\lambda_T) = 0$ and $RT(r_T) = 0$, they are the intersections of $PF(\lambda)$ and $RT(r)$ with the X-axis. An example is used to illustrate the numerical solution of these transitional parameters. It is carried out for two alternatives uniformly distributed in the interval of $[2.0, 7.0]$ and $[3.0, 5.0]$, respectively. The result indicates $PF(\lambda)$ only has one intersection with the X-axis, while the $RT(r)$ has two intersections with the X-axis (Figure 3.11). Therefore, the transitional penalty factor λ_T is 0.24, and the transitional risk tolerance r_T is 0.62. The other intersection at zero in Figure 3.11b is invalid.

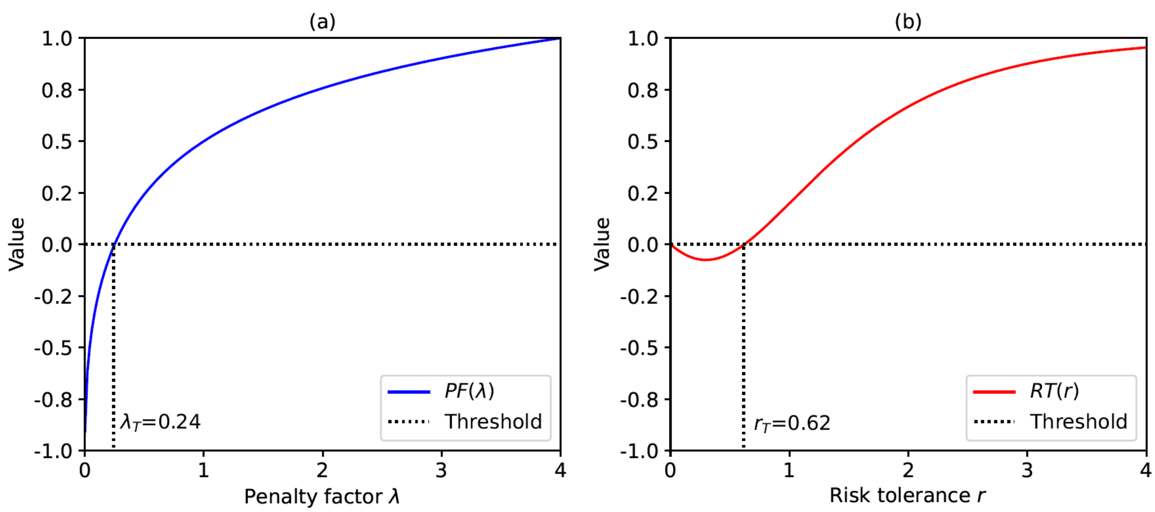


Figure 3.11: An example of numerically solving the transitional parameters from: (a) The quadratic loss function. (b) The exponential utility function.

The transitional parameters can be found only in the case of alternatives with overlapping distributions (Figure 3.12). These distributions are intersected with each other in a limited range, their intervals could be expressed by four different points c, a, b, d in Figure 3.12b. These points are sequentially generated: Firstly, randomly sample the point c within the interval of $[0.1, 1.0]$. Secondly, the spaces between every two adjacent points are randomly generated in the interval of $[0.1, 1.0]$, and lastly, the distributions are obtained by the accumulative sum of these random increments. 200 experiments are conducted by changing the distributions' intervals, the transitional penalty factor λ_T and corresponding transitional risk tolerance r_T are recorded to construct the cross plot (Figure 3.13). Since the transitional penalty factor λ_T has a large range, it is transformed to the logarithmic transitional penalty factor $\ln \lambda_T$ for an intuitive display.

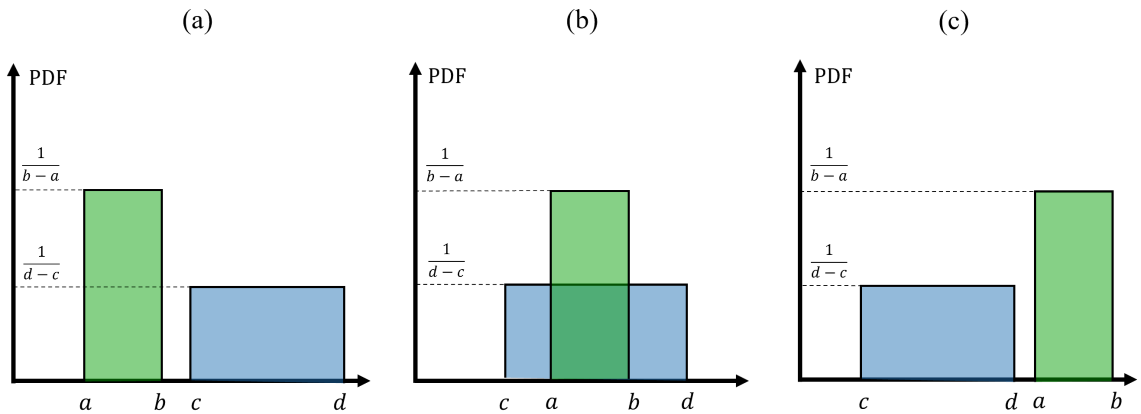


Figure 3.12: The position of two decisions (green and blue) with uniform distributions. (a) The decisions have separate distributions. (b) The decisions have overlapping distributions. (c) The decisions have separate distributions.

The relationship between the risk tolerance and penalty factor is summarized from observing the cross plot in Figure 3.13: (1) the dots in origin indicate the symmetric quadratic loss function is equivalent to the risk-neutral position in the exponential utility function, which is also consistent with the conclusion from Section 3.3; (2) the dots in the second quadrant represent the asymmetric quadratic loss function with more penalty on the underestimation. It is related to the risk-seeking position in the exponential utility function; and (3) the dots in the fourth quadrant imply the asymmetric quadratic loss function with more penalty on overestimation. It corresponds to the risk-averse position in the exponential utility function. In addition, the logarithmic of transitional penalty factor $ln\lambda_T$ has an approximate negative trend with the transitional risk tolerance r_T. That is, a smaller penalty factor is more likely to be related to a larger risk tolerance. Although this relationship is not quantitative, a workflow to integrate the loss function and utility function is established.

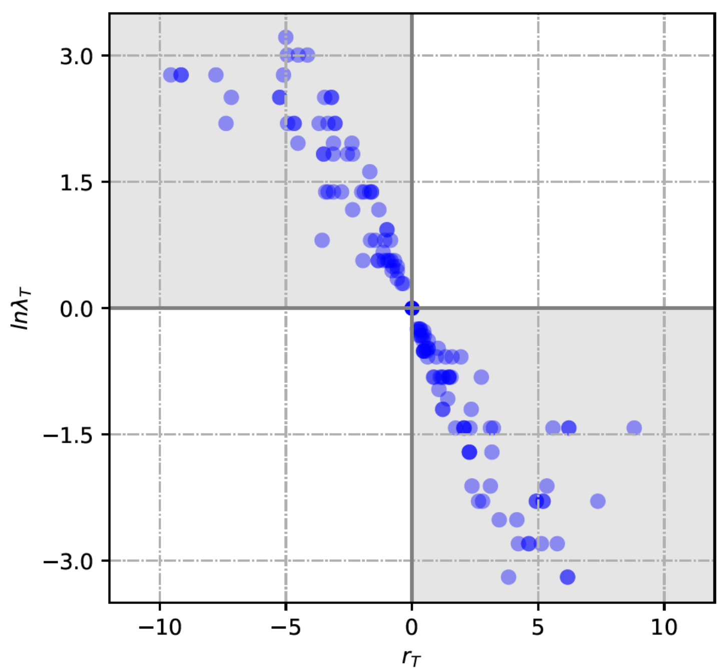


Figure 3.13: The cross plot between transitional penalty factor (logarithmic scale) and transitional risk tolerance (linear scale).

3.6 Conclusion

The relationship is constructed between the risk tolerance of utility function and the penalty factor of loss function. The result indicates that (1) the symmetric quadratic loss function produces the same result with the risk-neutral position in exponential utility function, as the decision criterion in these preference measurements is based on the expected return, (2) the asymmetric quadratic loss function with more penalty on underestimation corresponds to the risk-seeking position in exponential utility function, and (3) the asymmetric quadratic loss function with more penalty on overestimation corresponds to the risk-averse in the exponential utility function. In addition, the transitional penalty factor has an approximate inverse relationship with the transitional risk tolerance, the smaller penalty factor has a high probability of connecting with the larger risk tolerance.

There are also many limitations involved in the proposed workflow. For example: (1) The relationship between the penalty factor and risk tolerance is not quantitative. They only have an approximate inverse relationship. (2) Only the quadratic loss function and exponential utility function are considered in our example. There are many different loss functions and utility functions that are worth trying in the future. (3) All the alternatives are assumed to be uniformly distributed to simplify the calculation. Although this research has some limitations, a framework of integration of the loss function and utility function is established. The constructed framework still exhibits the possible potential between them, and provides a new understanding of preference measurements in practical applications.

Chapter 4

Decision making with an explicit consideration of risk

Decision analysis in the petroleum industry is challenging due to the inherent uncertainty from the limited understanding of the subsurface. In recent years, the expected utility theory has gained widespread attention in reservoir decision making. When there is no explicit utility function, the mean-variance criterion or maximizing risk-adjusted value is a convenient alternative under the expected utility framework. In these approaches, variance is used as the measure of risk. However, investors only dislike the downside volatility. To improve risk management in the oilfield in the presence of geological uncertainty, the lower partial moment is utilized as the risk assessment in this chapter. The main content is organized by the following four sections to illustrate the downside-risk approach in reservoir decision making: (1) discuss the motivation of this chapter; (2) summarize the difference between the mean-variance model and the mean-variance optimization, (3) review different risk measurement methods, and summarize the characteristics of these approaches; (4) introduce the downside-risk approach with an explicit consideration of risk, which is demonstrated in the mean-lower patial-variance-upper partial variance (MLU) model and MLU optimization, respectively.

4.1 Motivation

The expected utility theory is famous for decision making under conditions of uncertainty. This theorem indicates that a rational decision (d_0) is always associated with the maximum of expected utility (Markowitz, 2014). The decision-making problems in the petroleum industry, such as the production strategy selection from a set of countable alternatives ($\boldsymbol{D}$), could be formulated in Equation 4.1. It captures geological uncertainty by generating multiple geological models $\{\boldsymbol{g} = g_n; n = 1, 2, \ldots, N\}$ with equal probability. These geological models are used to construct the economic model (v) during the decision-making process.

$$d_0 = \underset{d \in \boldsymbol{D}}{\text{argmax:}}\ \frac{1}{N} \sum_{n=1}^{N} U\left(v(g_n, d)\right) \tag{4.1}$$

Variance is extensively utilized to measure the risk in reservoir decision making under the expected utility framework when there is no implicit utility function, such as mean-variance criterion (Markowitz, 2014) or risk-adjusted value (Cozzolino, 1977). The mean-variance criterion approximates expected utility for risk-averse investors, and variance or standard deviation is treated as the measure of risk (Figure 4.1). This criterion is used in the context of decision selection, and it has been applied in the petroleum industry for production strategies and investment selection (Al Harthy, 2007; Gallardo and Deutsch, 2020; Wang et al., 2020). The risk-adjusted value measures an investment's return with the risk taken into consideration by the risk tolerance (r). It is often used in the context of decision optimization to capture different preferences. The maximization of risk-adjusted value is mathematically equivalent to the efficient frontier in the mean-variance criterion (Equation 4.2). It has also been widely utilized in well placement with the mean-variance optimization to capture different risk attitudes (Capolei et al., 2015; Chang et al., 2015; Jesmani et al., 2020; Mohsin Siraj et al., 2017). Consider a production strategy d in the search space $\mathbb{S}$ with countless alternatives, the objective function in well placement is constructed by transferring the monetary distribution (V) from multiple geological models. The decision-optimization process using the risk-adjusted value could be formulated below:

$$d_0 = \underset{d \in \mathbb{S}}{\text{argmax:}}\ E\{V(\boldsymbol{g}, d)\} - r\sigma^2\{V(\boldsymbol{g}, d)\} \tag{4.2}$$

However, the variance is often considered inadequate to assess risk, as people are mainly concerned about the volatility below a certain level (Al Janabi, 2015; Deng et al., 2020; Grootveld and Hallerbach, 1999). Some unusually high outcomes are not of concern, yet they increase the variance significantly. Alternatives are developed to improve the assessment of risk, like semi-variance, downside risk or lower partial moment (Cumova and Nawrocki, 2014; Salah et al., 2018; Santos et al., 2017a,1; Sortino and Van Der Meer, 1991; Viole and Nawrocki, 2016). Thus, the need to improve the measure of risk in reservoir decision analysis motivates explicitly analyzing risk.

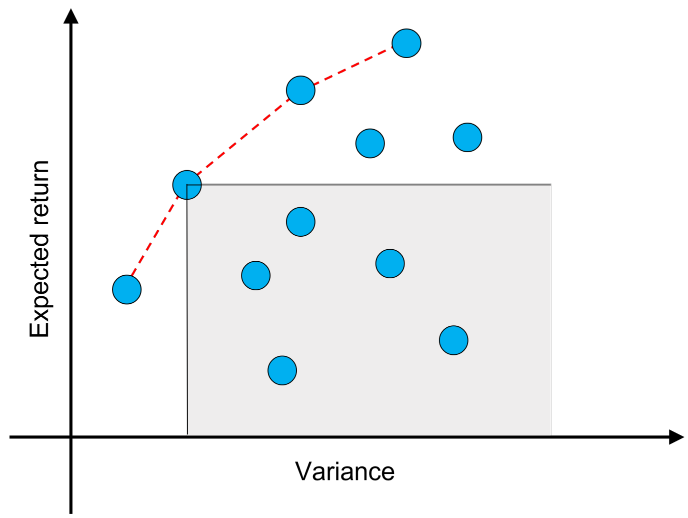


Figure 4.1: A sketch of the mean-variance model. The red dotted line is the efficient frontier, and the dots in the shadow area is dominated by the dot in the upper left corner.

4.2 Variance-based approach in decision making

The variance-based approach in decision making could be illustrated from two aspects: the mean-variance criterion (mean-variance model) and maximizing the risk-adjusted value (mean-variance optimization). These approaches employ variance as the measure of risk. In this section, a detailed comparison between the mean-variance model and mean-variance optimization will be given.

The advantage of mean-variance model is that the decision-making process only depends on statistical parameters (mean and variance). The optimal alternatives in the efficient frontier are dominant over other alternatives regardless of the risk attitude. It is convenient for those who do not have any theoretical background of utility theory in economics. This model, however, has two major limitations: (1) it is designed for situations with a countable number of alternatives, such as drilling order selection; and (2) there could be more than one optimal alternative on the efficient frontier, investors might not be able to identify a unique best alternative based on this model.

The mean-variance optimization is suitable for more practical applications, such as well placement optimization, where countless alternatives are involved in the decision-making process. This approach is able to capture different attitudes by the risk tolerance, but the specific value of risk tolerance is difficult to quantify in practice. Thus, sensitivity analysis is often performed on the risk tolerance to explore the impact of attitudes on decision-making. In this approach, there is only one optimal alternative, which means investors could identify the best alternative according to different preferences. The engineers also need the knowledge of utility theory in economics to better understand investor attitudes

A comparison between the mean-variance model and mean-variance optimization is shown in Table 4.1. It provides a summary of the mean-variance approaches with six aspects (number of alternatives, number of optimal alternatives, preferences, utility background, expected utility theory, and measure of risk). These approaches are consistent with the expected utility framework, and they use the variance to measure the risk in decision making.

Table 4.1: Comparison between the mean-variance model and mean-variance optimization.

	Mean-variance model	Mean-variance optimization
Alternative	Accountable	Not accountable/Accountable
Optimal alternative	One/More	One
Attitude	Not necessary	Necessary
Utility knowledge	Not necessary	Necessary
Expected utility	Consistent	Consistent
Measure of risk	Variance	Variance

4.3 Measure of risk

Risk originates from a situation involving uncertainty, and it is often associated with undesirable events going to happen. (Balzer, 1990; Hillson and Murray Webster, 2017; Ma and La Pointe, 2011; Rachev et al., 2011). This term is often utilized in decision theory (Knight, 2012; Sortino and Van Der Meer, 1991), which is significant to reservoir decision making in the presence of geological uncertainty. In this subsection, the major approaches of assessing risk in the context of economics are described.

The traditional way to manage the risk is based on the maximum shortfall. It employs the magnitude of the worst scenario to define the risk, which could be expressed as $\max\{v_0 - v, 0; v \in V\}$. Where v is the value from the profit distribution V, and v_0 is an appropriate risk benchmark. This benchmark is widely accepted as the minimum acceptable return, which is a predefined target in the decision-making process (Jin et al., 2006; Markowitz, 2010; Sortino et al., 2001). There have been many criticisms of this approach (Hauge et al., 2014; Huysmans et al., 2006). An obvious shortcoming of this measure of risk is that it does not consider the size of the shortfall. Meanwhile, it also ignores the probability distribution, which may make decision-makers too conservative (Klebaner et al., 2017).

The other traditional way to measure risk is based on the probability of shortfall (Balzer, 1990). It is defined as: $\mathrm{Prob}\{v < v_0; v \in V\}$. This approach only takes the probability into account, which ignores all the information in the profit distribution. Since the probability of shortfall and the maximum shortfall are incomplete in the risk measurement, some researchers employed the expected shortfall (or conditional value-at-risk) to define the risk, the mathematical form of expected shortfall (ES) could be expressed in Equation 4.3 (Acerbi et al., 2001; Sortino et al., 2001; Tasche, 2002). However, there are some concerns that downside risk is linearly measured in this approach. That is, investors have an underlying risk-neutral position in the front of downside risk (Sortino et al., 2001).

$$ES = E\left\{v_0 - V;\ \text{for all } v_0 - V > 0\right\} \tag{4.3}$$

Markowitz (1952) proposed the mean-variance criterion in decision analysis under the expected utility framework to capture different risk attitudes. However, there are some controversies in this criterion about measuring the risk by variance in Equation 4.4. Since it is obvious that investors only dislike the downside volatility, variance or standard deviation is often considered inadequate as they disproportionately penalize the upside potential. Additionally, a similar concept of risk-adjusted value is proposed by Cozzolino (1977), the maximization of risk-adjusted value is mathematically equivalent to the efficient frontier in the mean-variance criterion. It has also been widely utilized in the petroleum industry with the mean-variance optimization to capture different risk attitudes (Capolei et al., 2015; Chang et al., 2015; Jesmani et al., 2020; Mohsin Siraj et al., 2017).

$$\sigma^2(V) = E\{(V - E\{V\})^2\} \tag{4.4}$$

As people only dislike the volatility below a certain level, alternatives are developed to improve the risk assessment in the fields of economics and finance, such as semi-variance or lower partial moment (Fabozzi and Peterson, 2003; Salah et al., 2018; Santos et al., 2017c; Sortino and Van Der Meer, 1991). Markowitz (2014) commented the semi-variance could be an alternative of variance in the measure of risk, which is a particular form of lower partial moments. Viole and Nawrocki (2016) claimed the risk in investment could be quantified by the probability of investment return below a specified benchmark. Klebaner et al. (2017) and Ayub et al. (2011) used the lower partial moments to assess the downside volatility and quantify the risk. Assuming the profit distribution V has a cumulative probability distribution $F(V)$, the α-th lower partial moments with the truncated value v_0 is given by:

$$LPM_\alpha(V, v_0) = (-1)^\alpha \int_{-\infty}^{v_0} (V - v_0)^\alpha dF(V) \tag{4.5}$$

Many risk assessment approaches have been documented in this subsection. However, only the variance and lower partial moment are appropriate in decision analysis under the expected utility framework. That is, these risk measurements are able to capture different risk positions in the decision-making process.

4.4 Downside-risk approach in decision making

In many practical applications under the expected utility framework, variance is often treated as the measure of risk, such as the mean-variance model or risk-adjusted value. A simple example from Sortino et al. (2001) is used to illustrate the limitation of assessing risk by variance in decision analysis (Figure 4.2). The profit distribution of two alternatives, A and B, have the same mean and variance. The profit distribution of alternative A is right-skewed, while alternative B has the shape of a nearly normal distribution. If investors make decisions using the mean-variance criterion, these two alternatives would make no difference for investors in any risk position. However, it is obvious that most decision-makers would prefer the alternative A, as its profit distribution has a larger upside tail and smaller downside volatility. Thus, using variance as the measure of risk over-penalizes upside volatility, which is inconsistent with investors' behavior.

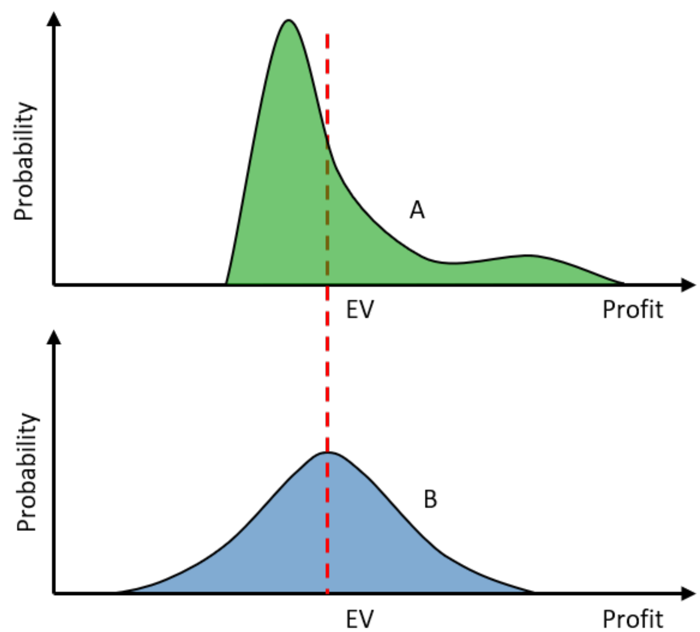


Figure 4.2: The profit distributions from two alternatives with the same expected value and variance.

A growing number of researches are focusing on the downside volatility to measure the risk in decision analysis. Dimitrakopoulos et al. (2007) introduced the concept of downside risk in the optimization of open-pit mine design. The standard deviation is regarded as the uncertainty, the downside risk and upside reward are separated by the minimum acceptable return. Cumova and Nawrocki (2014) combined the downside risk and upside potential in the expected utility framework, which was used to incorporate preferences on the risk and potential. Viole and Nawrocki (2016) employed the lower partial moment and upper partial moment to quantify the risk and potential, respectively. Figure 4.3 illustrates the concept of downside risk, upside potential, and other components in the profit distribution. It indicates that uncertainty is quantified by the variance, risk is assessed by the downside volatility, and potential is measured by the upside volatility. The risk and potential are truncated by a benchmark, which is a predefined target (Klebaner et al., 2017; Ling et al., 2020).

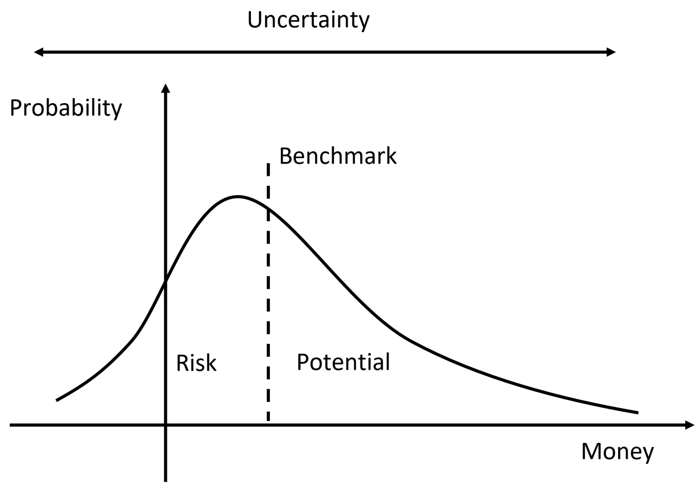


Figure 4.3: The illustration of risk and potential in a probability distribution.

In order to integrate the downside risk into the expected utility framework, Zakamouline and Koekebakker (2009) and Zakamouline (2014) proposed a generalized mean-variance approach, which decomposes the expected utility into the form of partial moments (Equation 4.6) by Taylor series expansion.

$$E\{U(V)\} = l_+ UPM_1(V, v_0) - \frac{r_+}{\beta} UPM_\beta(V, v_0) - \lambda_0 (l_- LPM_1(V, v_0) + \frac{r_-}{\alpha} LPM_\alpha(V, v_0)) \tag{4.6}$$

Where V refers to the profit with a monetary value, and v_0 denotes the benchmark (minimum acceptable return) for the lower partial moment of order α (LPM_α) and upper partial moment of order β (UPM_β). λ_0 is a positive value. l_+ and $l_-$are indicator functions that take values in $\{0, 1\}$. Santos et al. (2017a) applied this generalized mean-variance approach to separately incorporate the attitudes on risk and potential in the context of decision selection. The expected utility could be expressed in Equation 4.7 with an explicit analyzing risk, which is a particular case of Equation 4.6 when $\lambda_0 = 1$, $l_- = 1$, $l_+ = 1$, $\alpha = 2$ and $\beta = 2$. The detailed proof could be found in Appendix A.2.

$$E\{U(V)\} = E(V, v_0) - \frac{LPM_2(V, v_0)}{\tau_-} + \frac{UPM_2(V, v_0)}{\tau_+} \tag{4.7}$$

Where $E(V, v_0)$ refers to $E(V - v_0)$. $UPM_2(V, v_0) = \int_{v_0}^{+\infty} (V - v_0)^2 dF(V)$ denotes the upper partial variance and $LPM_2(V, v_0) = \int_{-\infty}^{v_0} (V - v_0)^2 dF(V)$ is the lower partial variance. $\tau_+ = \frac{-2}{r_+}$ represents the attitude to the upside potential (upside opportunity-seeking $0 < \tau_+ < \infty$, upside risk-neutral $\tau_+ \to \infty$), and $\tau_- = \frac{2}{r_-}$ is the attitude on the downside risk (downside risk-averse $0 < \tau_- < \infty$, downside risk-neutral $\tau_- \to \infty$).

The mean-variance criterion (mean-variance model) and maximizing risk-adjusted value (mean-variance optimization) are variance-based approaches. In order to improve the measure of risk in these approaches, the downside-risk approach would be demonstrated in the following two aspects: the mean-lower partial variance-upper partical variance (MLU) model and the MLU optimization.

4.4.1 MLU model in decision making

The mean-variance criterion is widely used for the decision selection problem, it is controversial due to the inappropriate measurement of variance by risk. Due to the alternatives with higher expected returns, lower risks, and higher potential are more attractive, in this research, a MLU model is developed according to Equation 4.7, which is a 3-D model composed of the mean, lower partial variance, and upper partial variance (Figure 4.4). This model is able to facilitate decision analysis by capturing the expected return, downside volatility (risk), and upside volatility (potential) of the profit distribution from each alternative. Taking alternatives A and B as an example to illustrate the rule in the MLU model. The alternative A is preferred over alternative B when they have a relationship in Equation 4.8. It also requires that the equalities of all equations are not satisfied at the same time. Similar to the mean-variance model, the efficient frontier of MLU model is constructed based on the set of optimal alternatives. This model is consistent with the expected utility framework, and also applicable in the context of decision selection.

$$\begin{cases} E(A) \geq E(B) \\ UPM_2(A) \geq UPM_2(B) \\ LPM_2(A) \leq LPM_2(B) \end{cases} \tag{4.8}$$

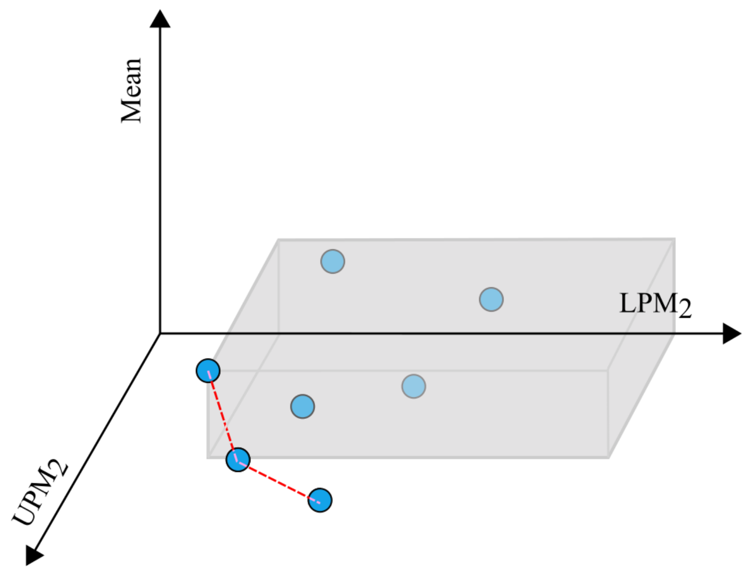


Figure 4.4: A sketch of the MLU model. The red dotted line is the efficient frontier, and the dot in the corner dominates other dots in the shadow box.

Two examples are utilized to compare the mean-variance model and the MLU model. In the first case (Figure 4.5a), based on the stochastic dominance rules, alternative B is preferred over alternative A. More specifically, alternative B dominates alternative A by the first-degree stochastic dominance, as the payoff from alternative B is larger than the payoff from alternative A at any quantile (Acorn et al., 2020; Whang, 2019). In the mean-variance model, only the expected return and variance from the profit distribution are taken into account in the decision-making process, the alternatives on the efficient frontier are regarded as the optimal decisions, which have (1) a larger mean and equal/smaller variance or (2) a smaller variance and equal/larger mean. Thus, we are unable to distinguish the better alternative based on the mean-variance criterion in this case, because alternative B has both a larger mean and variance than alternative A (Figure 4.5b). That is, alternatives A and B both are on the efficient frontier in the mean-variance model, which indicates their preference relationship is not certain. This case would also be applied in the MLU model for comparison. The results in Figure 4.5b depict alternative B has a larger mean and upside partial variance than alternative A, meanwhile, the lower partial variance of alternative B is smaller than that of alternative A. According to the character of optimal alternatives in the efficient frontier from the MLU model, the investors preferred alternative B over alternative A based on the analysis from the MLU model.

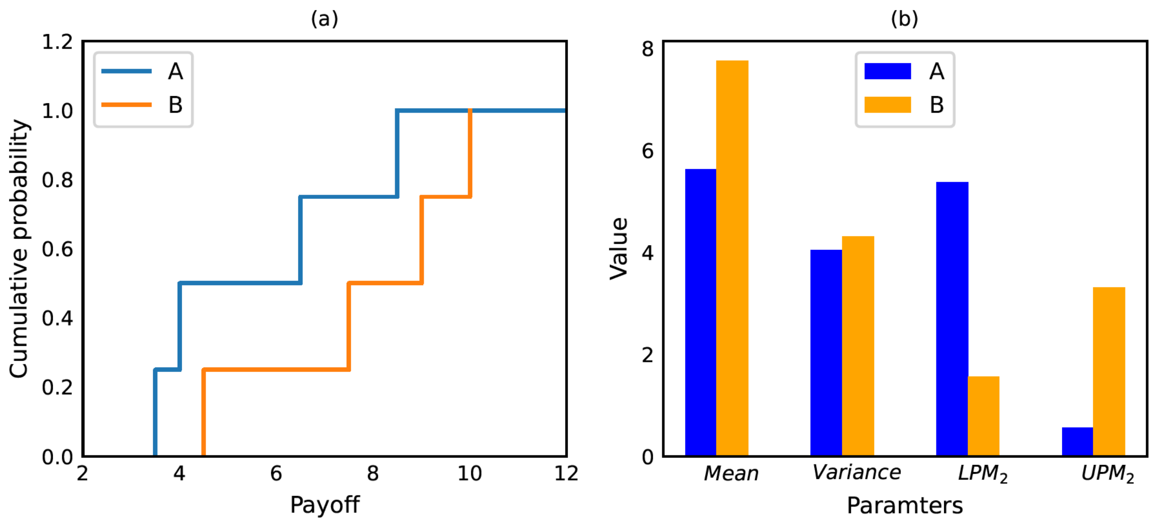


Figure 4.5: Comparison between mean-variance model and MLU model in the first case. (a) The cumulative distributions for alternatives. (b) The parameters involved in these decision models (minimum acceptable return is 7).

In the second case (Figure 4.6a), alternative B is also preferred over alternative A. Although the cumulative probability distributions of these alternatives are intersected with each other, the area under the cumulative probability distribution of A is larger than that of B for any payoff values, which indicates alternative B dominates alternative A by the second-degree stochastic dominance (Gallardo and Deutsch, 2020; Müller et al., 2017). The parameters involved in the mean-variance model and MLU model are shown in Figure 4.6b. The results show the mean and variance of alternative B are greater than that of alternative A, which indicates these strategies do not have a clear preference relationship in the mean-variance model. Meanwhile, the downside volatility of alternative B is smaller than that of alternative A, and the upside volatility of alternative B is larger than that of alternative A. Therefore, using the MLU model, alternative B could be identified as the preferred decision over alternative A. From these two examples, only the alternative B is identified as the optimal decision in the MLU model, which is consistent with the investors' behavior.

4.4.2 MLU optimization in decision making

The mean-variance model is only applicable in the situation when alternatives could be enumerated (Figure 4.1). In order to capture different risk attitudes in practical problems that are related to countless alternatives, maximizing the risk-adjusted value is often utilized

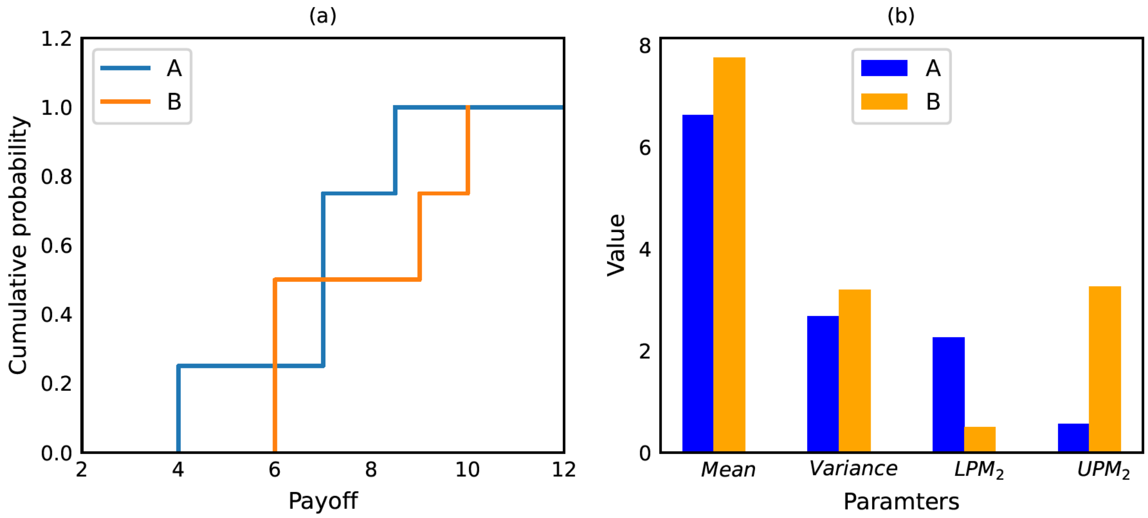


Figure 4.6: Comparison between mean-variance model and MLU model in the second case. (a) The cumulative distributions for alternatives. (b) The parameters involved in these decision models (minimum acceptable return is 7).

in the context of decision optimization (Equation 4.2). But variance is inappropriate to measure the risk in this approach. Thus, we will discuss the application of the downside-risk approach in decision optimization.

A typical application of decision optimization is the well placement in the petroleum industry, it is often associated with significant uncertainty and risk due to the limited understanding of the subsurface (Epelle and Gerogiorgis, 2020; Naderi and Khamehchi, 2017; Pouladi et al., 2020). In order to improve risk management in the well placement optimization in the presence of geological uncertainty, a workflow is proposed based on the MLU optimization. Four main steps are involved in this workflow: (1) transfer geological uncertainty by multiple realizations, (2) set up economic models from flow simulation, (3) capture preferences in the decision rule, and (4) perform decision optimization by explicitly analyzing risk. These steps are detailed described in the following.

(1) Transfer geological uncertainty by multiple realizations

The geological model consists of the structure model, lithofacies model, petrophysics model, and dynamic fluid model (Pyrcz and Deutsch, 2014; Yin et al., 2020). They are hierarchically modeled to characterize the reservoir (Figure 4.7). However, the subsurface resource is difficult to accurately measure caused by the limited data and variability at all scales. This incomplete understanding of the reservoir leads to large uncertainty in the geological modeling and a great challenge in well placement. The geostatistical community provides tools to quantify the geological uncertainty. It is conducted by generating multiple geological models (realizations) using stochastic simulation (Deutsch, 2018). These different geological models have an equal probability, and their difference is able to reflect the geological uncertainty.

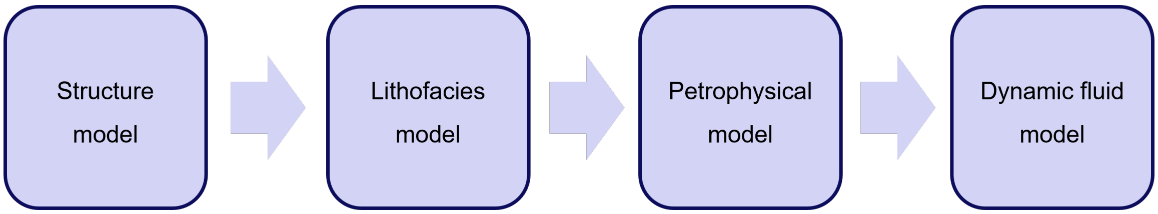


Figure 4.7: A sketch of the hierarchically geological model in reservoir characterization.

(2) Set up economic models by reservoir simulation

Net present value (NPV) is a common economic index to analyze the profitability of a project. It is obtained by performing reservoir flow simulation. The NPV of a given production strategy in a determined geological model is expressed below:

$$\text{NPV} = \sum_{t=1}^{T} \frac{R_t - E_t}{(1 + r_d)^t} - C_w \tag{4.9}$$

Where T is the total production time, and r_d refers to the discount factor. R_t and E_t represent the revenue and expense at time t during the operation. C_w denotes the total cost to drill the wells. In a two-phase (oil and water) flow model, R_t and E_t are given by:

$$R_t = p_o Q_t^o \tag{4.10}$$

$$E_t = p_w^p Q_t^{w,p} + p_w^i Q_t^{w,i} \tag{4.11}$$

Where Q_t^o is the total volumes of oil at the time t. P_o is the oil price. $Q_t^{w,p}$ and $Q_t^{w,i}$ are the total volumes of water produced and water injected at the time t. P_w^p and P_w^i are the water production cost and water injection cost. Investors usually have the target to maximize the economic value of the oil field, and the economic model is constructed by the NPV from reservoir simulation. In the risk-neutral position, the expected NPV is often adopted as the objective function to measure the reservoir potential in the presence of geological uncertainty (Onwunalu and Durlofsky, 2010; Zhao et al., 2020).

(3) Incorporate preferences in the decision criterion

Decision criterion in petroleum industry considers economic models converted from geological models based on limited well or seismic constraints. Since risk and potential coexist in the well placement under the geological uncertainty, the decision criterion of maximizing expected utility is adopted to capture different attitudes. For a given production strategy (d) in the presence of geological uncertainty, the lower partial variance and upper partial variance are expressed in Equation 4.12 and Equation 4.13, respectively.

$$LPM_2(V, v_0) = \frac{1}{N}\sum_{n=1}^{N}(\min[v(g_n, d) - v_0, 0])^2 \tag{4.12}$$

$$UPM_2(V, v_0) = \frac{1}{N}\sum_{n=1}^{N}(\max[v(g_n, d) - v_0, 0])^2 \tag{4.13}$$

The risk-quantified decision optimization in the well placement considers multiple realizations in an ensemble of stochastic models. These realizations are able to capture geological uncertainty, and the expected utility in Equation 4.7 could be expressed in Equation 4.14.

$$\begin{aligned} E\{U(V)\} =& \frac{1}{N}\sum_{n=1}^{N}\Big(v(g_n, d) - v_0\Big) - \frac{1}{\tau_-}(\frac{1}{N}\sum_{n=1}^{N}(\min[v(g_n, d) - v_0, 0])^2) \\ &+ \frac{1}{\tau_+}(\frac{1}{N}\sum_{n=1}^{N}(\max[v(g_n, d) - v_0, 0])^2) \end{aligned} \tag{4.14}$$

The above equation could be used as the objective function in the optimization algorithm to locate the optimal well plan. The lower partial variance and upper partial variance are utilized to measure the risk and potential, respectively. It indicates rational investors prefer the profit distribution with a larger expected value, higher volatility on the upside, and smaller volatility on the downside, which is consistent with investors' behavior.

(4) Perform decision optimization with an explicit consideration of risk

Many global optimization algorithms have been introduced in petroleum industry to facilitate the design of oilfield production strategies, which include particle swarm algorithm (Boah et al., 2019; Redoloza and Li, 2021), genetic algorithm (Emerick et al., 2009; Hamida et al., 2017; Naderi and Khamehchi, 2017), simultaneous perturbation stochastic approximation algorithm (Carpinelli et al., 2018; Pouladi et al., 2020) and so on. Generally, these algorithms can not guarantee to find the global optimal well position among countless alternatives, but their results are able to approximate the actual global solution (Liberti and Maculan, 2006; Migdalas et al., 2013). In this research, the expected utility is utilized as the objective function in these optimization algorithms, and well locations in the production strategy (d) are the design variables in well placement optimization. The optimization is used to select the optimal production strategy by maximizing the expected utility under certain constraints $\mathbb{S}$.

$$d_0 = \underset{d \in \mathbb{S}}{\text{argmax:}}\ E(V(\boldsymbol{g}, d), v_0) - \frac{LPM_2(V(\boldsymbol{g}, d), v_0)}{\tau_-} + \frac{UPM_2(V(\boldsymbol{g}, d), v_0)}{\tau_+} \tag{4.15}$$

The above objective function could be numerically solved by using multiple realizations in Equation 4.12. This MLU optimization employs lower partial variance to measure the risk, which is able to improve risk management in well placement optimization.

4.5 Conclusion

Variance is often utilized as the measure of risk in reservoir decision making, such as the mean-variance model and mean-variance optimization. However, there are many arguments about the measure of risk by variance. Thus, the difference between the mean-variance model and mean-variance optimization is explored. Their advantages and limitations are summarized to guide future applications. After that, different risk measurements are reviewed. These previous researches indicate that the lower partial moment is a more robust alternative for variance in the measure of risk in decision analysis under the expected utility framework. Lastly, the downside-risk approach is introduced in this chapter with an explicit consideration of risk. This approach is illustrated in MLU model and MLU optimization:

In the context of decision selection, a MLU model is developed based on the expected return, lower partial variance, and upper partial variance. The risk in this model is measured by the downward volatility below a benchmark, and it is quantified by the lower partial variance. Two synthetic examples are used to compare the MLU model and mean-variance model. The results imply that the MLU model has a better capability to identify the optimal decisions than the mean-variance model by explicitly assessing risk.

In the context of decision optimization, the workflow of MLU optimization is presented to improve the risk assessment in mean-variance optimization. Four main steps are involved in this workflow: (1) use multiple realizations to transfer geological uncertainty; (2) perform reservoir simulation to construct economic models; (3) make the decision criterion under the expected utility framework; and (4) employ the downside-risk approach in the optimization of well locations.

Chapter 5

Value of geophysical information analysis for different risk positions

Geophysical data is critical information to improve reservoir decision making in the presence of geological uncertainty. Since the gathering of geophysical information is often expensive, value of information (VOI) analysis is often performed to assess the benefits of geophysical information before collection. However, the traditional VOI analysis is associated with a risk-neutral position. That is, the posterior value and prior value are calculated based on the expected return disregarding different risk positions in the presence of geological uncertainty. This chapter proposes a workflow to capture different risk attitudes in the VOI analysis. It is implemented by combining the utility theory and the simulation-regression approach. A simplified case study is utilized to demonstrate the workflow of VOI analysis in the spatial decision situations, and the impact of risk preferences in VOI analysis is presented.

5.1 Motivation

Decision analysis is essential in the petroleum industry. Before making a critical decision, geophysical information is often collected to facilitate the decision making. The gathering of information is essential as it helps to reduce uncertainty and enhance confidence in decision making. The information has no value unless it potentially changes the decision, and it is worth collecting when the value of information exceeds the cost of information. The concept of VOI originates from business decisions (Schlaifer, 1959), and it was first introduced in the petroleum industry for the drilling decision (Grayson, 1960). VOI analysis is carried out under uncertainty where the information might be worthwhile if it could help to change the decision. This approach has been applied in the petroleum industry to evaluate the value of information, such as the measurement of seismic reliability in geophysics

(Eidsvik et al., 2008; Rezaie et al., 2014), the optimization of production strategy based on the information from additional wells (Trainor Guitton et al., 2014), and the assessment for the probability of leaking or sealing fault in the aquifer (Anyosa et al., 2021). The collected data provides information for guiding reservoir development, it reduces geological uncertainty by increased knowledge of the subsurface (Eidsvik et al., 2015b). VOI is commonly expressed as the difference between the expected return with additional information and the expected return without information if the decision-maker has a risk-neutral position (Bratvold et al., 2009).

$$\mathrm{VOI} = \begin{bmatrix} \text{Expected value with} \\ \text{additional information} \end{bmatrix} - \begin{bmatrix} \text{Expected value without} \\ \text{additional information} \end{bmatrix} \tag{5.1}$$

The future information is difficult to predict before collecting it, especially the conditional probability of outcomes given the possible information. Approaches are proposed to approximate the VOI, such as simulation-regression (Eidsvik et al., 2008; Strong et al., 2015), Gaussian approximation (Jalal and Alarid Escudero, 2018), and moment matching (Heath et al., 2018). However, all existing research into VOI analysis focuses on the risk-neutral position (Dutta et al., 2019a; Eidsvik et al., 2008). That is, the posterior value and prior value are calculated based on the expected return disregarding different risk positions in the decision-making process and VOI analysis. In this research, the utility theory is incorporated in the VOI analysis. The expected utility framework is a widely utilized theory to capture risk attitudes in the decision-making process, and utility function could measure the satisfaction of decision-makers. Thus, this research will apply the utility theory in the VOI analysis to investigate the influence of different risk positions. It mainly includes: Firstly, using multiple realizations to transfer geological uncertainty; Next, introducing the utility theory in the VOI analysis. Lastly, performing sensitivity analysis of different risk attitudes in the VOI analysis. An example is presented in the selection of production strategy with the consideration of reservoir spatial heterogeneity. The result indicates that investors' preferences will influence the gathering of geophysical information, a better understanding of risk preferences is able to enhance the VOI analysis.

5.2 VOI analysis in spatial decision situations

The gathering of geophysical data is often considered to facilitate decision making in the petroleum industry. The data could provide information for guiding the design of production strategies in reservoir development, and also reduce geological uncertainty by increased knowledge of the subsurface (Bratvold et al., 2009; Eidsvik et al., 2015a). The general form of VOI is given by:

$$\mathrm{VOI}(\boldsymbol{y}) = \mathrm{PoV}(\boldsymbol{y}) - \mathrm{PV} \tag{5.2}$$

Where $\mathrm{PoV}(\boldsymbol{y})$ is the posterior value with information $\boldsymbol{y}$, PV is the prior value without collecting information. It is supposed that risk-neutral investors need to make a decision from an ensemble of alternative $\boldsymbol{D}$ in presence of geological uncertainty. Before making the decision, it might be worth collecting geophysical information to facilitate the decision-making process. In this spatial decision situation, the PoV and PV are, respectively, expressed as follows (Dutta et al., 2019b; Eidsvik et al., 2017):

$$\mathrm{PV} = \max_{d \in \boldsymbol{D}} \left\{ \frac{1}{N} \sum_{n=1}^{N} v(g_n, d) \right\} \tag{5.3}$$

$$\mathrm{PoV}(\boldsymbol{y}) = \frac{1}{N} \sum_{n=1}^{N} \max_{d \in \boldsymbol{D}} \left\{ E\left\{ V(\boldsymbol{g}, d) | y_n \right\} \right\} \tag{5.4}$$

Where $\{\boldsymbol{g} = g_n; n = 1, 2, \ldots, N\}$ denotes an ensemble of geological models from N realizations, and y_n is the simulated impedance in n-th realization. $\{V(\boldsymbol{g}, d) = v(g_n, d); n = 1, 2, \ldots, N\}$ is a profit distribution, and $v(g_n, d)$ is the profit value from the alternative d and geological model g_n. It indicates that PV maximizes expected profit over all the alternatives, and the PoV is calculated by averaging the profit values from the optimal returns in each realization. Thus, the VOI in the risk-neutral position could be expressed as:

$$\mathrm{VOI}(\boldsymbol{y}) = \frac{1}{N} \sum_{n=1}^{N} \max_{d \in \boldsymbol{D}} \left\{ E\left\{ V(\boldsymbol{g}, d) | y_n \right\} \right\} - \max_{d \in \boldsymbol{D}} \left\{ \frac{1}{N} \sum_{n=1}^{N} v(g_n, d) \right\} \tag{5.5}$$

Many uncertainties surround the future regarding cumulative oil production and net present value due to the limited information from drilling wells. The geospatial uncertainty associated with subsurface properties could affect the investor's behavior in the design of production strategies. The decision-related information is often collected to reduce uncertainty and improve decision making. The main target in VOI analysis is to determine the value of purchasing information. It is challenging because in most cases, information is measured indirectly, making it difficult to calculate an accurate posterior value. Many different methods have been proposed to approximate the posterior value. The simulation-regression approach is the most recently proposed method that has been applied to geophysics. It will be described in detail in the next subsection. Moreover, VOI analysis is performed before collecting the information. This concept is easily confused with terminal analysis. Hong et al. (2018) explained the difference between VOI analysis and terminal analysis using Figure 5.1. It indicates that the main difference between these two concepts is whether the information analysis is before or after the information is collected.

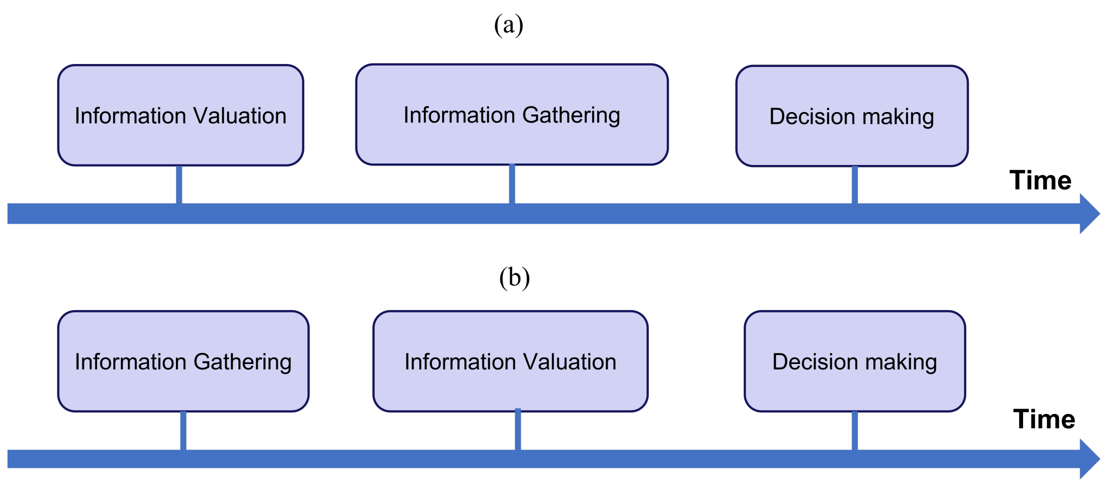


Figure 5.1: A sketch of an explanation of two different concepts in the information analysis. (a) The procedure of VOI analysis. (b) The procedure of terminal analysis (Hong et al., 2018).

VOI analysis has received increasing attention in the petroleum industry, especially in the field of geophysics (Eidsvik et al., 2008; Przybysz Jarnut et al., 2015; Trainor Guitton et al., 2014). Geophysical data provides important information for guiding oilfield exploration and development. However, the cost of seismic data acquisition is high. Therefore, it is becoming popular in the industry to use VOI analysis to help determine whether to acquire seismic data. Houck (2004) introduced VOI analysis based on probability modeling in geophysics to evaluate the economic impact of geological data quality. Bickel et al. (2008) analyzed the reliability of seismic in the West Texas 3-D land survey to create more value. Dutta et al. (2019b) utilized the simulation-regression approach to approximate the value of geophysical information in the context of well placement. These applications show that VOI analysis could be part of the decision-making process.

5.3 Methodology

In the evaluation of geophysical information, the decision-related information is usually the seismic attribute, such as impedance (Dutta et al., 2019b; Trainor Guitton et al., 2011). A workflow (Figure 5.2) is proposed to incorporate different risk attitudes in the VOI analysis in the presence of geological uncertainty. This workflow consists of five main steps: (1) quantify geological uncertainty by multiple stochastic realizations; (2) simulate the corresponding geophysical attributes (impedance models) by rock physics analysis; (3) perform reservoir simulation to construct the economic models; (4) capture risk preferences in the decision-making process and VOI analysis by integrating utility theory; (5) approximate the VOI using the simulation-regression approach. Some important concepts and methods involved in this workflow will be described below.

5.3.1 Simulation-regression approach

The main challenge in VOI analysis is the estimation of PoV, especially the conditional expectation of PoV. The simulation-regression approach was proposed by Eidsvik et al. (2017) in the geophysical area. This technique aims to approximate the conditional expectation in the PoV using the regression method. In the simulation-regression approach, the conditional expectation in PoV is approximated by two major steps (Dutta et al., 2019a): Firstly, simulating future geophysical models and possible prospect values, and then regressing the information and the profits. The detailed steps involved in the simulation-regression workflow under the risk-neutral position are as follows:

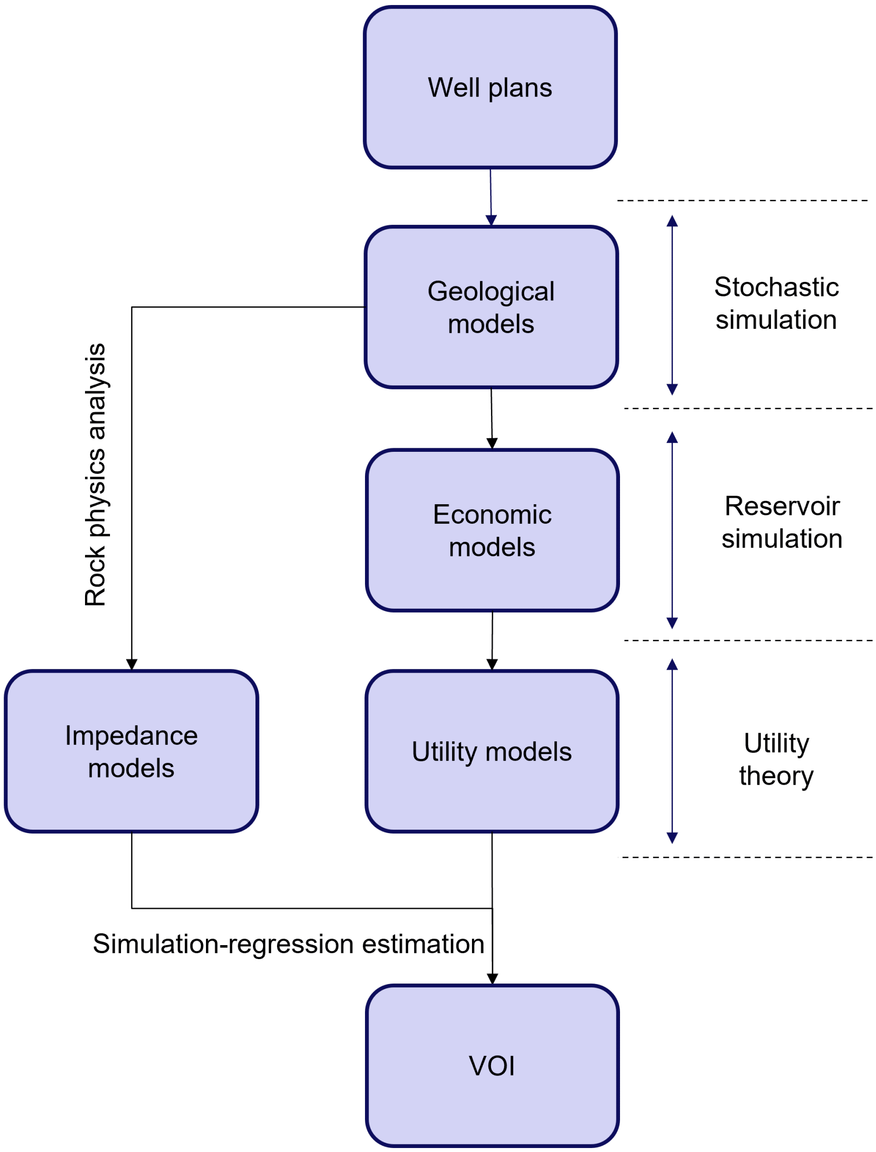


Figure 5.2: A sketch of VOI approximation considering risk preferences in the presence of geological uncertainty.

(a) Simulate an ensemble of geological models $\left\{\boldsymbol{g} = g_n; n = 1, 2, \ldots, N\right\}$ using N realizations to transfer geological uncertainty.

(b) Generate the synthetic impedance models $\left\{\boldsymbol{y} = y_n; n = 1, 2, \ldots, N\right\}$ by rock physics analysis.

(c) Perform reservoir simulation to obtain the profit values $v\left(g_n, d\right)$ from the alternative d and n-th geological model.

(c) Calculate the prior value (PV) based on maximizing the expected return over all the alternatives.

$$\mathrm{PV} = \max_{d \in \boldsymbol{D}} \left\{ \frac{1}{N} \sum_{n=1}^{N} v\left(g_n, d\right) \right\} \tag{5.6}$$

(d) Regress between the impedance and the profit values. The regression values $\hat{v}(y_n, d)$ are able to approximate the inner conditional expectation in PoV:

$$\hat{v}(y_n, d) \approx E\left\{ V\left(\boldsymbol{g}, d\right) \mid y_n \right\} \tag{5.7}$$

Substitute Equation 5.7 into Equation 5.4, the PoV could be approximated by the following equation.

$$\mathrm{PoV}(\boldsymbol{y}) \approx \frac{1}{N} \sum_{n=1}^{N} \max_{d \in \boldsymbol{D}} \hat{v}(y_n, d) \tag{5.8}$$

(e) Calculate the VOI from the difference between the PoV and PV.

$$\mathrm{VOI}(\boldsymbol{y}) \approx \frac{1}{N} \sum_{n=1}^{N} \max_{d \in \boldsymbol{D}} \hat{v}(y_n, d) - \max_{d \in \boldsymbol{D}} \left\{ \frac{1}{N} \sum_{n=1}^{N} v\left(g_n, d\right) \right\} \tag{5.9}$$

The simulation-regression approach provides a practical way to approximate VOI. The main idea of the simulation-regression approach is to approximate the conditional expectation in the PoV using the regression approach (Eidsvik et al., 2017). This idea was first proposed in medical decision-making to estimate the value of health data by Strong et al. (2014), the detailed proof could be found in Appendix A.3. Compared with other methods introduced in the literature review (Section 2.4), the simulation-regression approach is much more computationally efficient.

5.3.2 VOI analysis for different preferences

The traditional VOI analysis has the underlying assumption of a risk-neutral position. In order to capture different risk positions in the VOI analysis, the utility concept is integrated into the VOI analysis (Equation 5.10), which gives a more robust definition of VOI.

$$\text{VOI} = \left[\begin{array}{c} \text{Expected utility with} \\ \text{additional information} \end{array} \right] - \left[\begin{array}{c} \text{Expected utility without} \\ \text{additional information} \end{array} \right] \tag{5.10}$$

In this workflow, the profit values $v(g_n, d)$ are transferred to the utility values $v^u(g_n, d, r)$ using a utility function $U(\cdot)$ with a risk tolerance r, which could be given by:

$$v^u(g_n, d, r) = U(v(g_n, d), r) \tag{5.11}$$

The PV is calculated based on maximizing the expected utility over all the alternatives. Thus, the PV under the utility-scale is expressed below:

$$\text{PV} = \max_{d \in \boldsymbol{D}} \left\{ \frac{1}{N} \sum_{n=1}^{N} v^u \left(g_n, d, r \right) \right\} \tag{5.12}$$

The utility values and geophysical models are regressed to obtain the regression values $\hat{v}^u(y_n, d, r)$. It could approximate the conditional expected utility in the inner loop of PoV. Thus, the PoV under the utility-scale is approximated as:

$$\text{PoV}(\boldsymbol{y}) \approx \frac{1}{N} \sum_{n=1}^{N} \max_{d \in \boldsymbol{D}} \hat{v}^u \left(y_n, d, r \right) \tag{5.13}$$

Thus, Equation 5.9 could be transferred to Equation 5.14. It is able to estimate the VOI with preferences taken into account, the preferences are quantified by the risk tolerance r in utility functions.

$$\text{VOI}(\boldsymbol{y}) \approx \frac{1}{N} \sum_{n=1}^{N} \max_{d \in \boldsymbol{D}} \hat{v}^u(y_n, d, r) - \max_{d \in \boldsymbol{D}} \left\{ \frac{1}{N} \sum_{n=1}^{N} v^u \left(g_n, d, r \right) \right\} \tag{5.14}$$

The main idea of this approach is to replace traditional economic models with utility models. It integrates the utility theory into the simulation-regression method, which can capture different risk positions in VOI analysis.

5.3.3 Partial least squares regression

The geophysical data and economical values are related in a very high dimension. Partial least squares regression (PLSR) has been adopted in the assessment of high dimensional information (Dutta et al., 2019b; Nocita et al., 2014). It is an approach that integrates the advantages of principal components analysis and multivariate regression (Abdi, 2003). This technique is particularly appropriate for a very large set of independent variables, it aims to maximize the correlation between the projection of predictors and projection of responses (Rosipal and Krämer, 2005). The PLSR model could be expressed by:

$$X = EP^T + R_x \tag{5.15}$$

$$Y = FQ^T + R_y \tag{5.16}$$

Where X is a matrix of predictors, Y is a matrix of responses. E and F are the projections of X and Y. P and Q matrices correspond to the loadings. R_x and R_y, respectively, refer to the matrices of residuals for X and Y. PLSR aims to develop a regression model between E and F, that is, $\{F = EB + R\}$, where B is the coefficient matrix, and R is the residual matrix. The latent variables E and F are computed by Xw and Yc, where w and c are the weight vectors with a unit length. They are determined by maximizing the covariance between E and F in Equation 5.17.

$$\max\colon \text{Cov}\left(E, F\right) = \max\colon \text{Cov}\left(Xw, Yc\right) \tag{5.17}$$

This process could be sketched in Figure 5.3. It indicates the process of PLSR includes three main steps: Firstly, decompose the original predictors and responses, which should satisfy the maximum covariance between the decomposed latent variables, Secondly, perform least squares regression in a low-dimensional latent space. Lastly, the decomposed latent variables could transform into the original space using the loading matrixes. This PLSR approach would be employed in our research to approximate VOI under the simulation-regression approach.

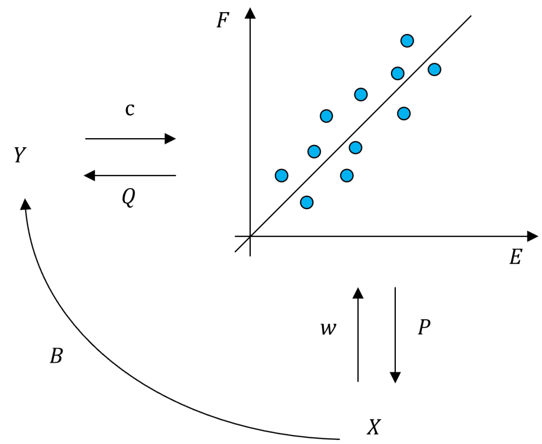


Figure 5.3: A sketch of particle least square regression (Yoshida et al., 2017).

5.4 Synthetic example

A simple case study is shown below to illustrate the workflow of calculating the VOI, and the impacts of risk preferences in the VOI analysis (Figure 5.4). In the context of deciding to drill ($d = 1$) or not drill ($d = 0$) a well with an uncertain outcome (wet $n = 1$ and dry $n = 0$). People are planning to collect geophysical information to facilitate this decision making in well drilling, the information ($\boldsymbol{y}$) only has two possible scenarios (positive polarity $y = 1$ or negative polarity $y = 0$). A simplified decision tree for this case study is shown in Figure 5.4, which includes all the given values in the VOI analysis. The geophysical information does not affect the outcome values under each decision scenario. The reason is that the subsurface reservoir exists without any uncertainty, the outcome values only rely on the different decisions rather than the information.

5.4.1 Workflow of VOI analysis in spatial decision situations

It is supposed that the investor has a risk-neutral position, the target of VOI analysis is to determine the amount of money that investors are willing to pay for the geophysical information. The prior value (PV) is the value without collecting the information, which could be calculated by maximizing the expected value over all the alternatives. The outcome of drilling the well: $E\{V(d = 1)\} = 3.2 \times 0.25 - 0.8 \times 0.75 = 0.2$M, and the outcome of giving up drilling: $E\{V(d = 0)\} = 1.0 \times 0.0 = 0.0$M. Thus, people would choose to drill

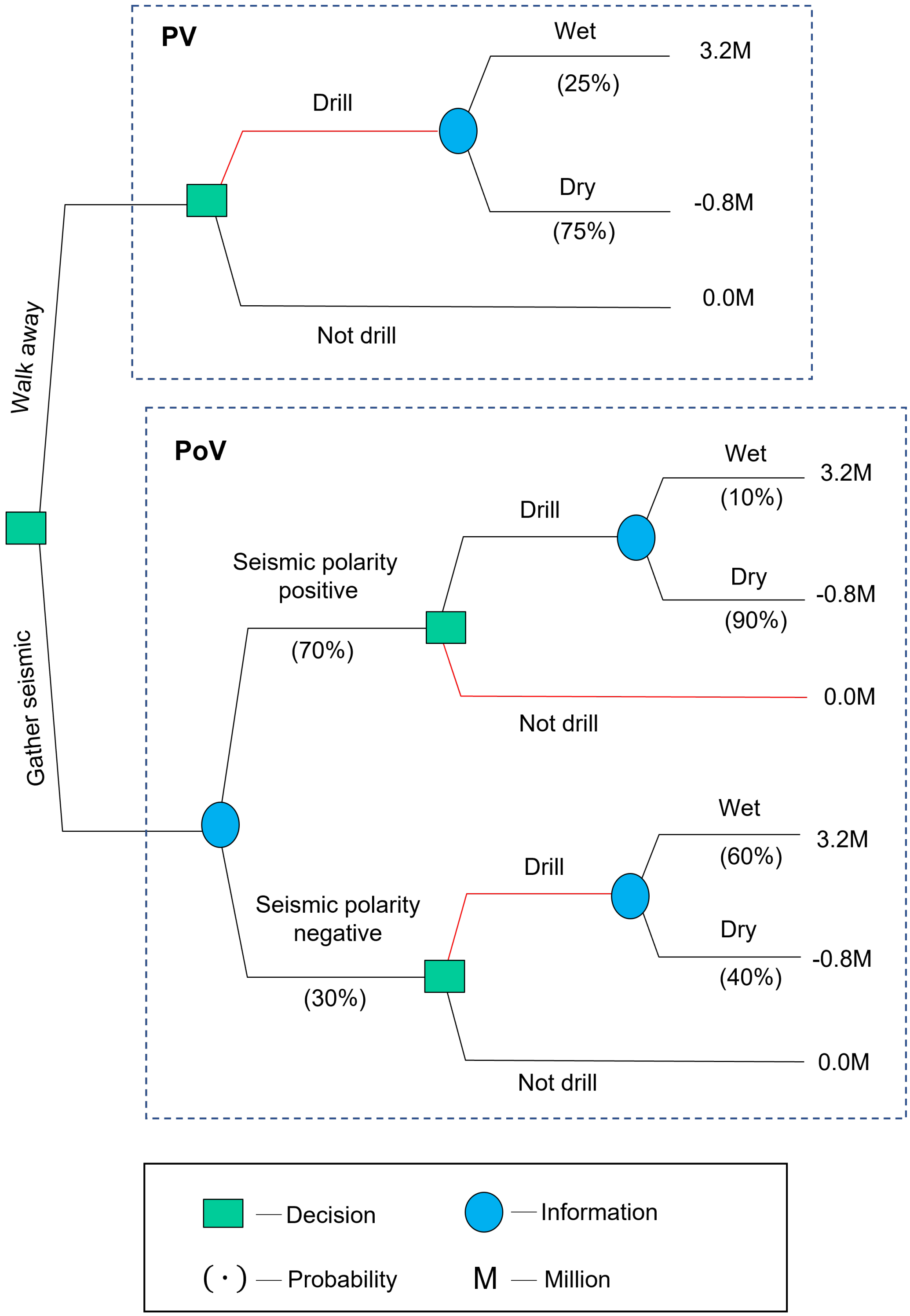


Figure 5.4: The simplified decision tree for VOI analysis (modified from Eidsvik et al. (2017)).

the well, and the PV is shown below:

$$
\begin{aligned}
\mathrm{PV} =& \max\left\{E\left\{V(d=1)\right\}, E\left\{V(d=0)\right\}\right\} \\
=& \max\{0.2, 0.0\} \\
=& 0.2\mathrm{M}
\end{aligned}
\tag{5.18}
$$

The posterior value (PoV) is the value with the consideration of information. The investors might make different decisions under each information scenario:

(a) If the seismic polarity is positive, $p(y=1)=0.7$. The outcome of drilling the well $E\{V(y=1, d=1)\} = 3.2 \times 0.1 - 0.8 \times 0.9 = -0.4$M, the outcome of giving up drilling the well: $E\{V(y=1, d=0)\} = 0.0$M. Thus, people would choose to walk away under in a situation of positive polarity, and the corresponding outcome $v(y=1)$ is:

$$
\begin{aligned}
v(y=1) =& \max\left\{E\left\{V(y=1, d=1)\right\}, E\left\{V(y=1, d=0)\right\}\right\} \\
=& \max\{-0.4, 0\} \\
=& 0.0\mathrm{M}
\end{aligned}
\tag{5.19}
$$

(b) If the seismic information has a negative polarity, $p(y=0)=0.3$. The outcome of drilling the well: $E\{V(y=0, d=1)\} = 3.2 \times 0.6 - 0.8 \times 0.4 = 1.6$M. The outcome of giving up drilling the well: $E\{V(y=0, d=0)\} = 0.0$M. Thus, people would choose to drill the well in a situation of negative polarity, and the corresponding outcome $v(y=0)$ is:

$$
\begin{aligned}
v(y=0) =& \max\left\{E\left\{V(y=0, d=1)\right\}, E\left\{V(y=0, d=0)\right\}\right\} \\
=& \max\{1.6, 0.0\} \\
=& 1.6\mathrm{M}
\end{aligned}
\tag{5.20}
$$

According to the investors' behavior in the possible information scenarios, the PoV is calculated by summing the conditional expectations over all the information scenarios.

$$\begin{aligned}\mathrm{PoV}(\boldsymbol{y}) =& p(y=1) \times v(y=1) + p(y=0) \times v(y=0) \\ =& 0.7 \times 0.0 + 0.3 \times 1.6 \\ =& 0.48\mathrm{M}\end{aligned} \tag{5.21}$$

The VOI is defined as the difference between the PoV and PV. Thus, the value of geophysical information in this case study is given by the following:

$$\mathrm{VOI}(\boldsymbol{y}) = \mathrm{PoV}(\boldsymbol{y}) - \mathrm{PV} = 0.28\mathrm{M} \tag{5.22}$$

The result of VOI should be compared with the cost of acquiring this information. It indicates that risk-neutral people will collect the seismic if the cost is below 0.28M.

5.4.2 Impacts of risk positions in VOI analysis

Most investors are sensitive to the risk in practical applications, in this example, the exponential utility function is utilized to capture investors' tendency to risk. Suppose the investors are risk-averse with a risk tolerance of $r = 0.5$, the monetary values could be transferred into utility values, including $u(d = 1, n = 1) = 1.6, u(d = 1, n = 0) = -0.98$, and $u(d = 0) = 0.0$. Therefore, based on the maximizing of expected utility in decision analysis, the PV is expressed in Equation 5.23. The result implies that people would not choose to drill the well when there is no additional information available.

$$\begin{aligned}\mathrm{PV} =& \max\left\{E\left\{U(d=1)\right\}, E\left\{U(d=0)\right\}\right\} \\ =& \max\{0.25 \times 1.6 - 0.75 \times 0.98, 0.0\} \\ =& 0.0\end{aligned} \tag{5.23}$$

In the calculation of PoV (Eqaution 5.13), investors will make different decisions under each possible information (positive polarity or negative polarity), which is summarized below:

(a) If the seismic polarity is positive, people would choose to give up drilling the wells.

$$
\begin{aligned}
u(y=1) =& \max\left\{E\left\{U(y=1,d=1)\right\}, E\left\{U(y=1,d=0)\right\}\right\} \\
=& \max\{1.6\times 0.1 - 0.98\times 0.9, 0.0\} \\
=& 0.0
\end{aligned}
\tag{5.24}
$$

(b) If the seismic polarity is negative, people would choose to drill the wells.

$$
\begin{aligned}
u(y=0) =& \max\left\{E\left\{U(y=0,d=1)\right\}, E\left\{U(y=0,d=0)\right\}\right\} \\
=& \max\{1.6\times 0.6 - 0.98\times 0.4, 0.0\} \\
=& 0.568
\end{aligned}
\tag{5.25}
$$

Based on the choices in each possible information scenario, the PoV for the investors in a risk-averse position ($r = 0.5$) is calculated as follows:

$$
\begin{aligned}
\mathrm{PoV}(\boldsymbol{y}) =& p(y=1)\times u(y=1) + p(y=0)\times u(y=0) \\
=& 0.7\times 0.0 + 0.3\times 0.568 \\
=& 0.17
\end{aligned}
\tag{5.26}
$$

The value of geophysical information for the risk-averse investors ($r = 0.5$) is expressed:

$$
\mathrm{VOI}(\boldsymbol{y}) = \mathrm{PoV}(\boldsymbol{y}) - \mathrm{PV} = 0.17 \tag{5.27}
$$

Thus, the geophysical data would be worth collecting when the utility of seismic is less than 0.17. It is supposed that the cost of collecting seismic is 0.2M, the risk-neutral investors would collect it (VOI > 0.2), while risk-averse people ($r = 0.5$) will give it away (VOI $< U(0.2)$). The result indicates that different attitudes would impact the value of geophysical information, which leads to the change of decisions related to collecting information.

5.5 Conclusion

VOI is an estimate of the value of decision-related information. In order to investigate the effect of risk preferences in the VOI analysis, a workflow to approximate VOI considering different risk preferences in the presence of geological uncertainty is proposed. This workflow employs an ensemble of realizations to capture geological uncertainty, and the utility theory is integrated into the simulation-regression approach to approximate VOI. This workflow would enhance the VOI analysis by considering different risk positions. Additionally, a simple example is utilized to demonstrate the workflow of VOI analysis in spatial decision situations, and the impact of different risk positions in VOI analysis is also presented. The result indicates that different attitudes in the VOI analysis might produce different decisions about gathering information. The robust VOI analysis should take risk preferences into account in spatial decision situations with uncertain outcomes.

Chapter 6

Application: reservoir decision making

Seeking the optimal production strategy is an essential step in hydrocarbon reservoir development. It is challenging as high risk is often involved due to the complex subsurface and limited information. Thus, the petroleum industry has become increasingly concerned with risk management when designing production strategies in the presence of geological uncertainty. This chapter is focused on the application of the downside-risk approach in the design of production strategy, which will be illustrated from two aspects: decision optimization (MLU optimization) and decision selection (MLU model). The downside-risk approach is applied in the context of well placement optimization and drilling order selection, respectively. The comparison between the downside-risk approach and mean-variance approach is demonstrated in these cases, and the impact of risk attitudes on decision analysis is also presented.

6.1 Introduction

Reservoir decision making is one of the most crucial tasks in the petroleum industry. It often involves high risk in the presence of geological uncertainty due to a limited understanding of the subsurface reservoir. In many petroleum applications, the decision criterion is based on a mean-variance criterion or maximizing risk-adjusted value. These approaches utilize variance to measure risk, and they are performed under the expected utility framework. However, variance is often considered inadequate to assess risk, as investors only dislike the downside volatility below a certain benchmark. The downside-risk approach has been documented in Chapter 4 from the aspects of decision optimization (MLU optimization) and decision selection (MLU model). In this approach, the lower partial variance is utilized to quantify risk by only penalizing the downside volatility, which is consistent with investors' behavior in decision making. In this chapter, the downside-risk approach is applied in the design of production strategies of a synthetic reservoir model with the consideration of spatial heterogeneity. It is illustrated in the context of well placement optimization (decision optimization) and drilling order selection (decision selection), respectively. The observation implies that the downside-risk approach outperforms the mean-variance approach because it is able to improve reservoir decision making by explicitly assessing risk.

6.2 Decision making in well placement optimization

This section will demonstrate the application of MLU optimization in decision making. It is illustrated in the context of well placement optimization, and the difference between the mean-variance optimization and MLU optimization is also discussed.

6.2.1 Background

Consider a 2-D channelized reservoir (1200m $\times$ 1200m) that has been produced for 2 years with 3 wells, including 2 injection wells ($I1, I2$) and 1 production well (P1) (Figure 6.1). It is planned to drill other 4 infill wells, including 3 production wells ($P2, P3, P4$) and 1 injection well (I4), to increase the oil production for the next 8 years. The well plan is to be optimized by maximizing the expected utility over the total producing life of 10 years.

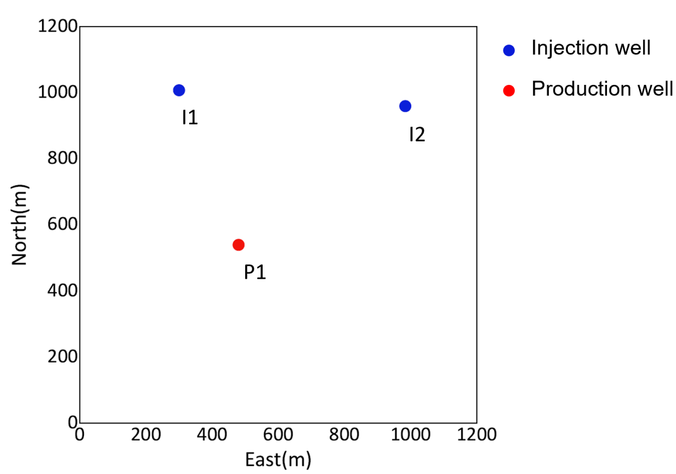


Figure 6.1: The location of predrilled exploration wells.

All of these exploration wells are drilled in the channelized sandstone, and the detailed information of these exploration wells is shown in Table 6.1. It is assumed the porosity in the channelized sandstone is between 15% to 30%, and permeability in this depositional environment is distributed between 30mD to 1000mD. In the floodplain mudstone, the porosity has a distribution between 10% to 14%, and permeability ranges from 1.5mD to 25mD. During development, the injection wells keep a constant rate control of $70\text{m}^3/\text{day}$, and the production well has a constant bottom hole pressure of 3.9×10^7Pa. All the infill wells are drilled at the same time in this example.

Table 6.1: Summary of the information from exploration wells.

	I1	I2	P1
Well type	Injection well	Injection well	Production well
Well constraint	$70\text{m}^3/\text{day}$	$70\text{m}^3/\text{day}$	$3.9 \times 10^7\text{Pa}$
Facies	Channel	Channel	Channel
Rock type	Sandstone	Sandstone	Sandstone
Porosity	24%	28%	18%
Permeability	80mD	316mD	32mD

Multiple equiprobable realizations are generated by stochastic simulation to characterize the geological uncertainty (Figure 6.2). An ensemble of 100 realizations of lithofacies is simulated using the SNESIM program with a multi-point geostatistical algorithm (Liu, 2006; Strebelle, 2002). The training image in reservoir modeling originates from the channelized depositional environment with two distinct facies, channel and floodplain. Next, the porosity and permeability are simulated conditioned to the facies using the sequential Gaussian simulation (SGS) by the GSLIB-style program USGSIM (Manchuk and Deutsch, 2012). These petrophysical properties have a correlation of 0.6 in this example. Finally, the initial water saturation is modelled using the petrophysical models based on the relationship from Leverett J-function (Leverett et al., 1942; Yin et al., 2020).

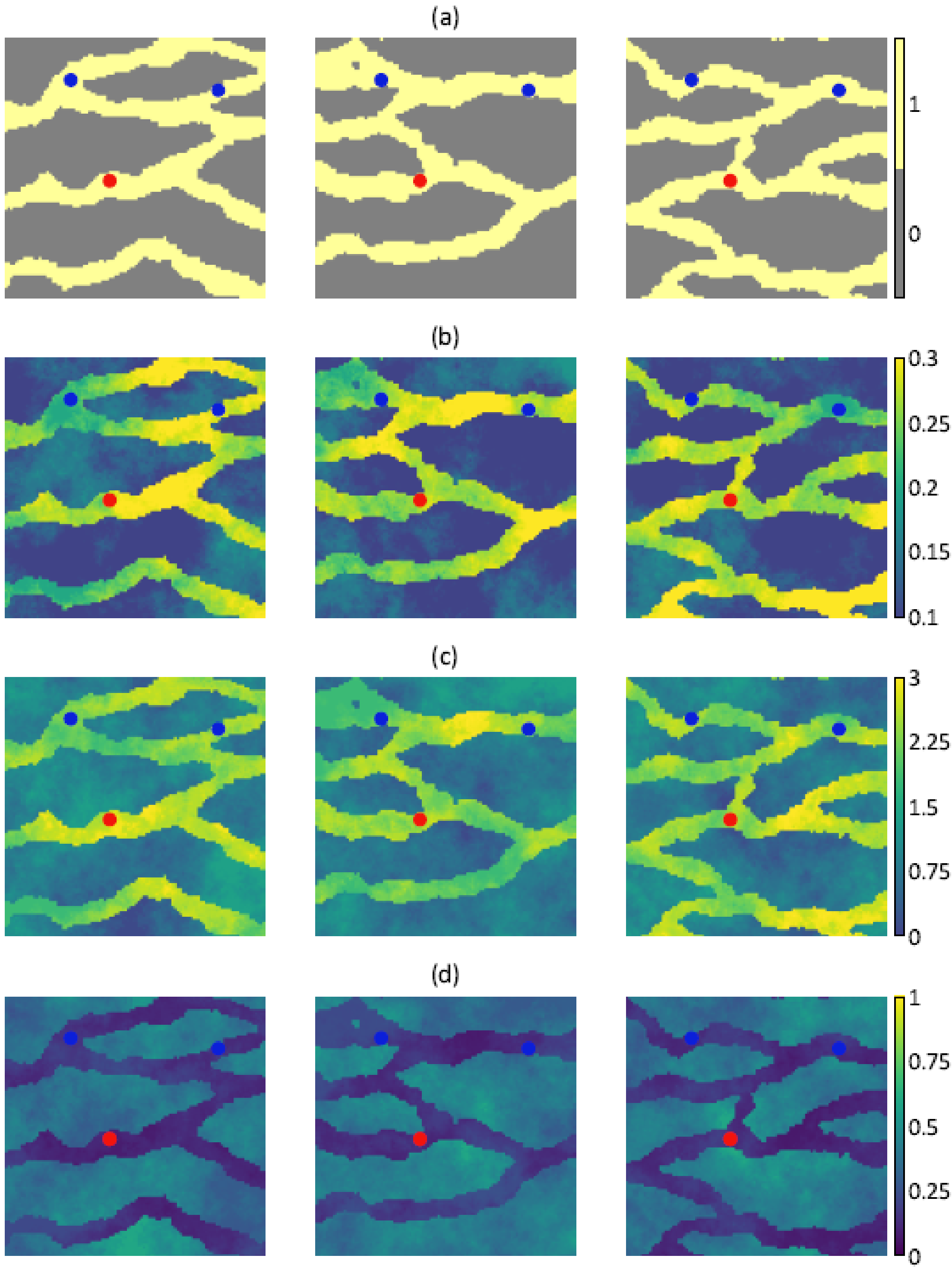


Figure 6.2: Three representative realizations of (a) Lithofacies (code 1 is channelized sand and code 2 is floodplain mud), (b) Porosity, (c) Permeability (millidarcy on a logarithmic scale), and (d) Water saturation. The blue dots are predrilled injection wells, and the red dot is the predrilled production well.

Ideally, all the realizations should be considered to capture the geological uncertainty. However, it is computationally expensive to optimize the production strategy over a large set of realizations by flow simulations (Nwachukwu et al., 2018; Shirangi and Durlofsky, 2016). In order to improve the computational efficiency, 20 representative realizations are selected based on the similarity of simulation models (Figure 6.3). It is conducted by applying multi-dimensional scaling (MDS) and distance-based clustering in the simulation models (Mahjour et al., 2020; Yousefzadeh et al., 2021).

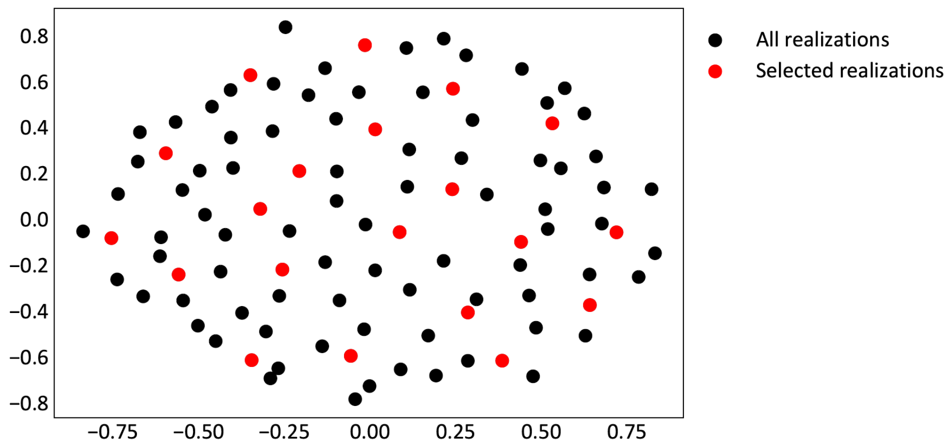


Figure 6.3: The result of realization reduction. The two axes are arbitrary coordinates from MDS.

6.2.2 Workflow

This case study illustrates the application of the downside-risk approach in well placement optimization. A schematic of the proposed workflow to manage risk in well placement optimization is shown in Figure 6.4. The workflow is outlined below:

(a) Determine the candidate wells $\{d = w_i; i = 1, 2, \ldots, 8\}$, where i is the index of wells. $\left\{w_i; i = 1, 2, 3, 4\right\}$ are constants to represent the locations of predrilled wells $\{\mathrm{P1}, \mathrm{I1}, \mathrm{I2}, \mathrm{I3}\}$, and $\{w_i; i = 5, 6, 7, 8\}$ are locations to be optimized for infill wells $\{\mathrm{P2}, \mathrm{P3}, \mathrm{P4}, \mathrm{I4}\}$.

(b) Employ multiple realizations ($\boldsymbol{g}$) to transfer the geological uncertainty. In order to improve computational efficiency in the well placement optimization, the selected representative realizations are utilized in this example.

(c) Set up the economic model $v(\cdot)$ for the well plan d under a determined geological model g_n. The economic model is composed of the revenue from oil production, the cost from water injection/production, and the cost from drilling the wells.

$$v(g_n, d) = \sum_{t=1}^{T} \frac{p_o Q_t^o(g_n, d) - \left(p_w^p Q_t^{w,p}(g_n, d) + p_w^i Q_t^{w,i}(g_n, d)\right)}{(1 + r_d)^t} - C_w \tag{6.1}$$

Where T - total production time (years), r_d - discount factor (%), C_w - total cost to drill the wells ($), Q_t^o - total volumes of oil at time t in units of stock tank barrel (STB), p_o - oil price ($/STB), $Q_t^{w,p}$ - total volumes of water produced at time t (STB), $Q_t^{w,i}$ - total volumes of water injected at time t (STB). p_w^p- water production cost ($/STB), and p_w^i-the water injection cost ($/STB).

(d) Transfer the profit distribution into expected utility. The profit distribution comes from the economic models of multiple realizations.

$$E\{U(V(\boldsymbol{g}, d)\} = E\{V(\boldsymbol{g}, d), v_0\} - \frac{LPM_2\{V(\boldsymbol{g}, d), v_0\}}{\tau_-} + \frac{UPM_2\{V(\boldsymbol{g}, d), v_0\}}{\tau_+} \tag{6.2}$$

Where $V(\boldsymbol{g}, d) = \{v(g_n, d); n = 1, 2, \ldots, N\}$ is the profit distribution over the N representative realizations for the well plan d. v_0 denotes the predefined benchmark.

(e) Optimize the well plan by maximizing the expected utility from Equation 6.2, which is called the MLU optimization.

$$d_0 = \underset{d \in \mathbb{S}}{\operatorname{argmax}} E\{U(V(\boldsymbol{g}, d))\} \tag{6.3}$$

Subject to:

$$\left\|w_i - w_j\right\| > w_0^{\min} \text{ and } i \neq \text{j} \tag{6.4}$$

Where d_0 is the optimal production strategy, and $\mathbb{S}$ is the study area. $w_0^{\min}$ denotes the minimum spacing between wells, which is 150m in this case study. $\|\cdot\|$ is the operator that computes the Euclidean distance.

(f) Perform sensitivity analysis to investigate the impact of attitudes, and make a comparison between the MLU optimization (Equations 6.2 and 6.3) and mean-variance optimization (Equation 4.2) in well placement.

Additionally, the risk tolerance τ_+/τ_-(MLU optimization) and r (mean-variance optimization) could reflect investors' acceptable level of risk in decision analysis with uncertain outcomes. The values of these parameters are related to the monetary units, and they could be obtained through questionnaires or interviews (Walls, 2005a). However, when there is no opportunity to conduct these surveys, the sensitivity analysis is often performed to investigate the impact of preferences in decision making. In this example, two particular sets of risk tolerance values are utilized to capture investors' different preferences in mean-variance optimization and MLU optimization.

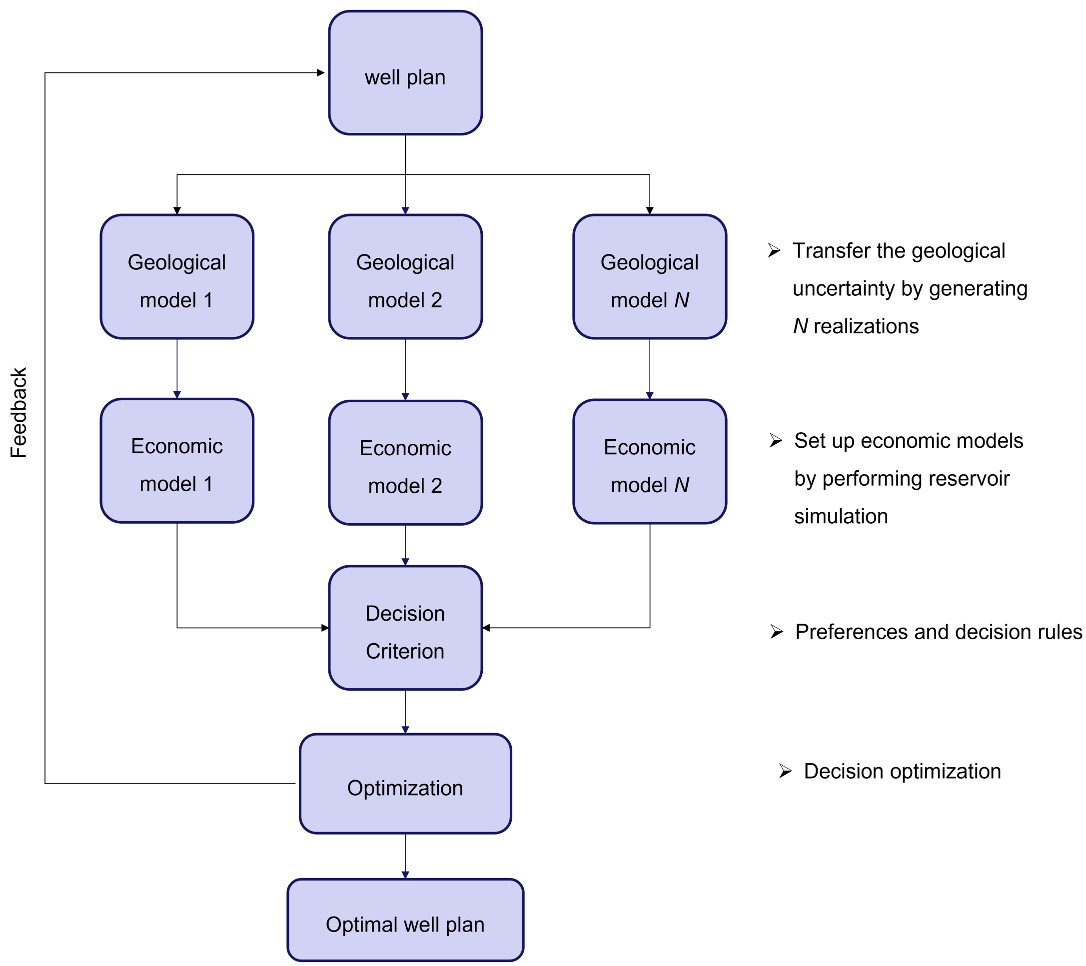


Figure 6.4: A sketch of the workflow for the MLU optimization in decision making.

6.2.3 Results

MATLAB Reservoir Simulation Toolbox (MRST) is utilized to perform the reservoir simulation, which is an open-source toolbox developed by SINTEF (Lie, 2019). The detailed economic parameters and simulation parameters are shown in Table 6.2 and Table 6.3, respectively. The particle swarm optimization (PSO) algorithm is employed in this example to identify the optimal well locations, which is a metaheuristic algorithm inspired by the social behavior of birds. This algorithm was developed by Eberhart and Kennedy (1995) and has been widely applied in well placement (Afshari et al., 2014; Harb et al., 2020; Nwankwor et al., 2013). The PSO algorithm is different from classic optimization approaches, like gradient descent, in that the objective function is not required to be differentiable. The modified particle swarm optimization (MPSO) algorithm is proposed by Tian and Shi (2018), it improves the PSO algorithm to achieve a balance between the exploration and exploitation (Ding et al., 2014). Using the same swarm population size (20) and a maximum number of iterations (120), the convergence plot based on the PSO algorithm and MPSO algorithm in the risk-neutral position is shown in Figure 6.5. The result indicates that the PSO algorithm has a premature convergence and is quickly trapped in the local optima. While the optimization based on the MPSO algorithm converges to a larger value, which implies this algorithm has a stronger ability to escape local optimum. Therefore, the MPSO algorithm will be employed for the following well placement optimization to investigate the impact of different risk attitudes.

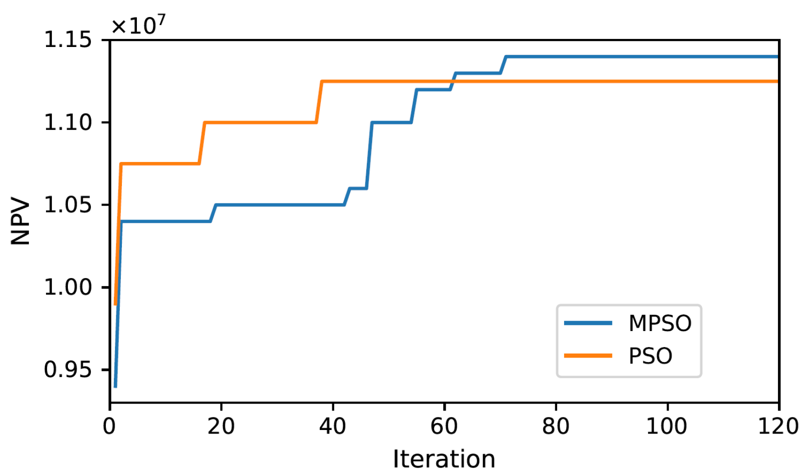


Figure 6.5: The convergence plot of PSO and MPSO in a risk-neutral position.

Table 6.2: Economic parameters in the well placement.

Parameter	Value
Oil price	$60\$/\mathrm{STB}$
Water price	$6.0\$/\mathrm{STB}$
Water injection cost	$7.0\$/\mathrm{STB}$
Discount factor	10%
Well drilling cost	$1 \times 10^6\$$

Table 6.3: General simulation information in the well placement.

Parameter	Value
Number of grids	$30 \times 30 \times 1$
Grid size	$40\mathrm{m} \times 40\mathrm{m} \times 40\mathrm{m}$
Phases	Water (W) and oil (O) phase
Fluid densities (WO)	$1000\mathrm{Kg/m^3}, 700\mathrm{Kg/m^3}$
Fluid viscosities (WO)	$1\mathrm{cp}, 5\mathrm{cp}$
Rock compressibility	$1 \times 10^{-13}\mathrm{Pa^{-1}}$
Initial reservoir pressure	$4 \times 10^7\mathrm{Pa}$
Injection well	$70\mathrm{m^3/day}$
Production well	$3.9 \times 10^7\mathrm{Pa}$
Production life	10 years

The optimization results of mean-variance optimization and MLU optimization are shown from Figure 6.6 to Figure 6.10. In these two approaches, the optimal production strategies are designed based on different preferences. It can be observed that the deployment of development wells is placed in a grid map of the average permeability models, and the profit value from each representative realization is displayed in the histogram. The result in the risk-neutral position (Figure 6.6) shows a larger expected profit $(1.14 \times 10^7\$)$ than the results in other risk positions. It indicates risk-neutral investors aim to design a production strategy with the largest expected return in these two approaches.

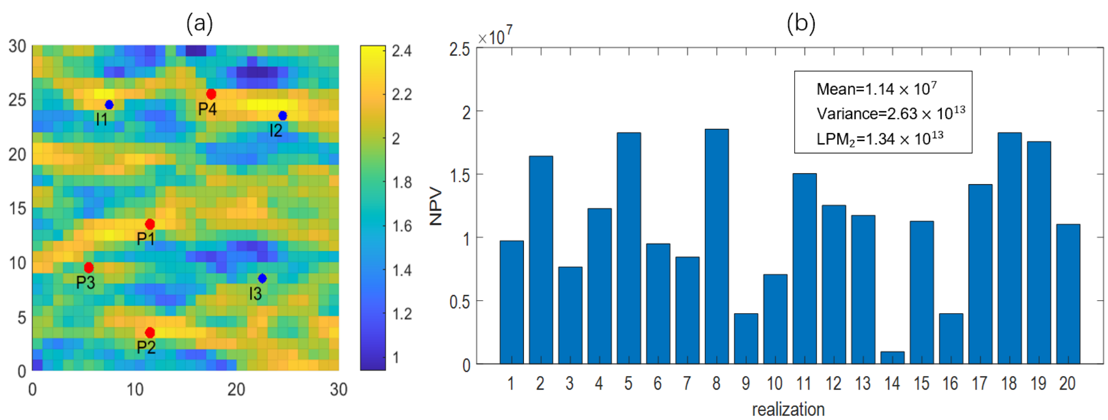


Figure 6.6: Results of a risk-neutral position. (a) The optimal well locations. (b) The profit distribution from representative realizations.

Figure 6.7 and Figure 6.8 display the optimal production strategy and profit distribution of the mean-variance optimization for different risk positions. The variance is treated as the measure of risk in this mean-variance approach. The production strategy under a risk-averse position $(r = 1 \times 10^{-7})$ indicates decision-makers might reduce the variance by decreasing the upside volatility. It has a smaller variance compared with other risk positions. For the opportunity-seeking position $(r = -1 \times 10^{-7})$, investors might seek some undesirable scenarios (negative NPV) to increase the variance. It often has a larger variance compared with other risk positions. Results from the mean-variance approach are inconsistent with investors' behavior, as people only dislike the downside risk. In practice, they would not pursue these negative values in an opportunity-seeking position, and the downside risk has not been significantly reduced in a risk-averse position using the mean-variance optimization.

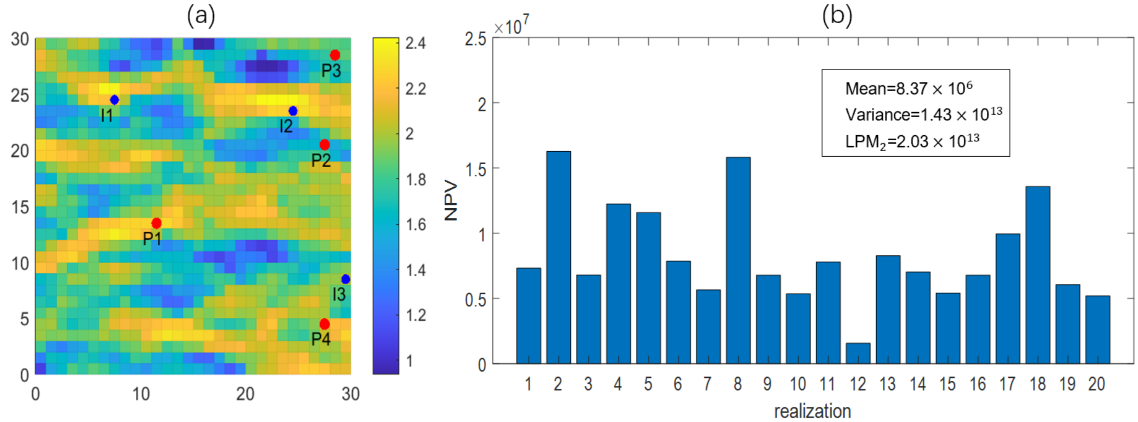


Figure 6.7: Results of a risk-averse position in the mean-variance optimization. (a) The optimal well locations. (b) The profit distribution from representative realizations.

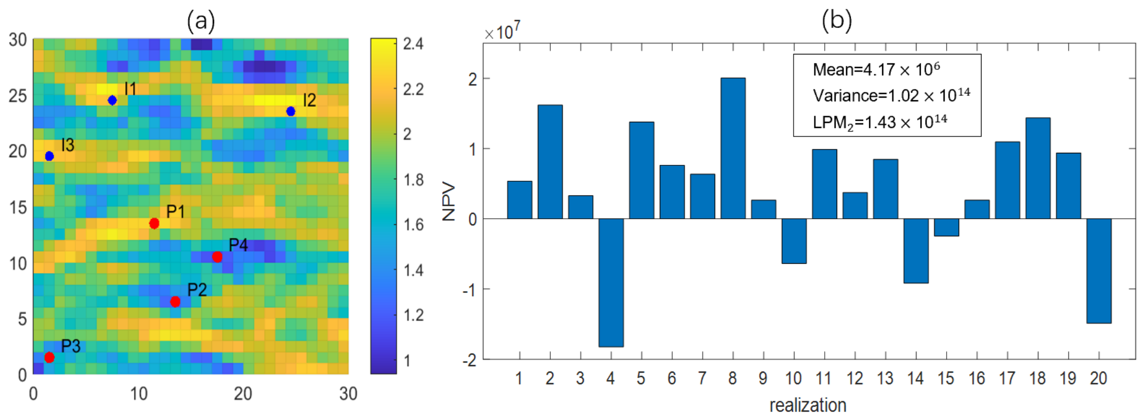


Figure 6.8: Results of an opportunity-seeking position in the mean-variance optimization. (a) The optimal well locations. (b) The profit distribution from representative realizations.

The optimal production strategies and profit distribution under the MLU optimization are shown in Figure 6.9 and Figure 6.10. The lower partial variance is employed as the measure of risk in this approach, and the red dotted line $(1.14 \times 10^7\$)$ is regarded as the benchmark for the downside risk and upside potential. It can be observed that, compared with the risk-neutral position, the lower partial variance is significantly reduced in the risk-averse position $(\tau_- = 1 \times 10^5, \tau_+ = 1 \times 10^8)$. In the opportunity-seeking position $(\tau_- = 1 \times 10^8, \tau_+ = 1 \times 10^5)$, the result indicates the upside volatility from this position is obviously larger than other risk positions, because investors are only interested in the upside potential. Therefore, this approach is more consistent with investors' behavior than the mean-variance optimization.

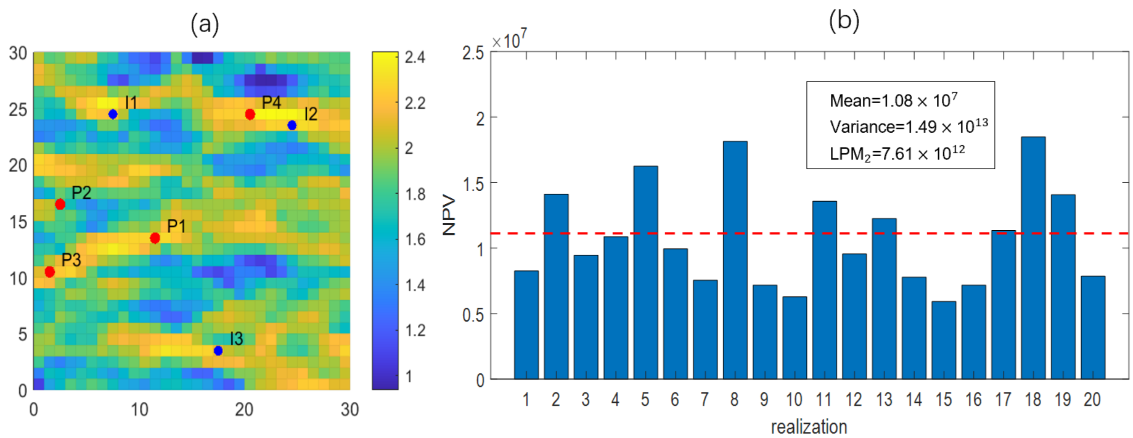


Figure 6.9: Result of a risk-averse position in the MLU optimization. (a) The optimal well locations. (b) The profit distribution from representative realizations.

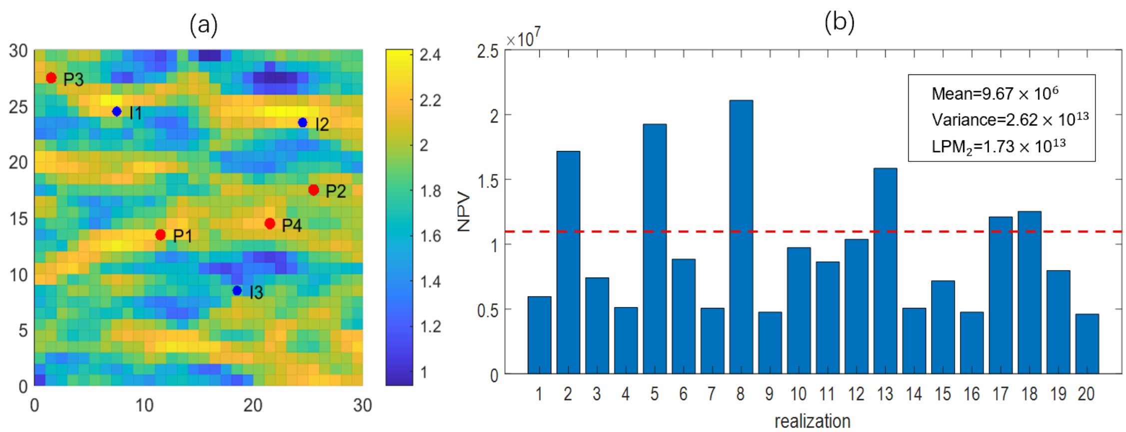


Figure 6.10: Results of an opportunity-seeking position in the MLU optimization. (a) The optimal well locations. (b) The profit distribution from representative realizations.

The result from Figure 6.6 indicates that the worst and the best scenario in a risk-neutral position are realization 14 and realization 8, respectively. In the presence of geological uncertainty, compared with the production strategy from a risk-neutral position (Figure 6.11a), investors who have a risk-averse position $(\tau_- = 1 \times 10^5, \tau_+ = 1 \times 10^8)$ would prefer the production strategy in Figure 6.11b. It can be seen that the production strategy under the risk-averse position would become more beneficial in realization 14, those investors want to maximize safety and improve some bad outcomes. Similarly, the production strategy in the best scenario (realization 8) under a risk-neutral position (Figure 6.11c) would be further improved by the decision-makers who have an opportunity-seeking position ($\tau_- = 1 \times 10^8, \tau_+ = 1 \times 10^5$) in Figure 6.11d, because opportunity-seeking investors would pay more attention to higher returns.

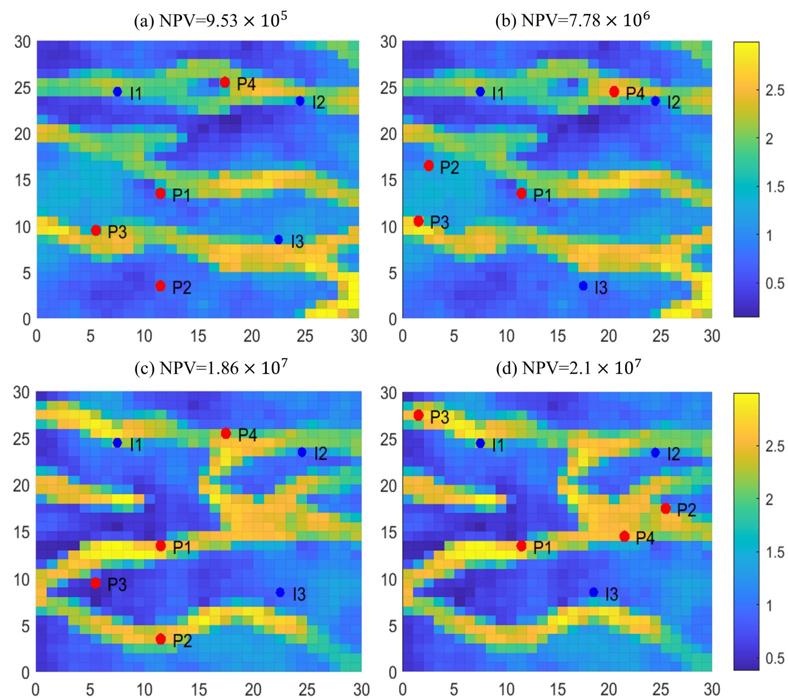


Figure 6.11: Production strategies from different preferences in a determined realization. (a) The risk-neutral position in realization 14. (b) The risk-averse position in realization 14. (c) The risk-neutral position in realization 8. (d) The opportunity-seeking position in realization 8. The grid maps are the permeability models on a logarithmic scale.

6.3 Decision making in drilling order selection

This section is used to illustrate the application of the MLU model in the production strategies selection. The difference between the MLU model and mean-variance model is also compared by applying them in the context of drilling order selection.

6.3.1 Background

Consider a 2-D reservoir model with two-phase (oil and water) flow in the background of channel sedimentation. The reservoir has been developed for two years with three wells, including two production wells and one water injection well. The production well has a constant bottom hole pressure of 3.9×10^7Pa, and the injection well has a constant volume of water of 70m^3/day. Now, it is planning to drill another four infill wells to increase the production, and the locations of these wells are shown in Figure 6.12. These four infill wells are drilled sequentially, with the interval between every two wells being six months. The target of this case study is to select the optimal drilling order from the total production life of 10 years.

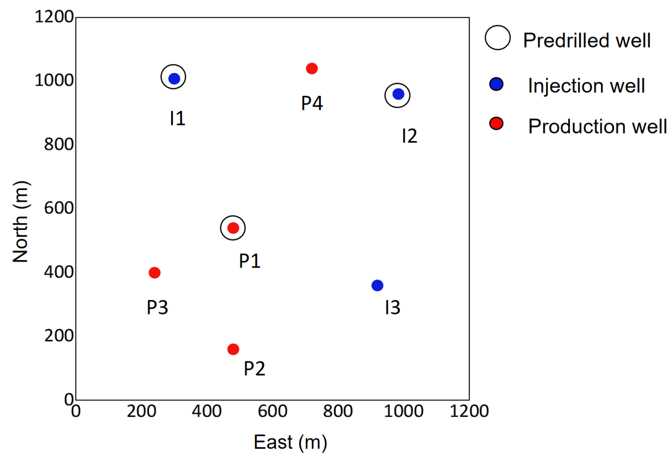


Figure 6.12: The well locations in the drilling order selection.

The drilling order for these four infill wells would involve a total of 24 options, as shown in Figure 6.13. In each strategy, the uncertainties associated with multiple geological conditions are transmitted through multiple equiprobable geological models, and these geological realizations are assumed to be matched with the production data. In order to determine the optimal drilling order from the 24 alternatives, the manager would consider the trade-offs between risks and rewards to make a decision.

Choice	Drilling order	Choice	Drilling order	Choice	Drilling order	Choice	Drilling order
d_1	P3→I3→P2→P4	d_7	P3→I3→P4→P2	d_{13}	P3→P4→I3→P2	d_{19}	P4→P3→I3→P2
d_2	P3→P2→I3→P4	d_8	P3→P2→P4→I3	d_{14}	P3→P4→P2→I3	d_{20}	P4→P3→P2→I3
d_3	I3→P3→P2→P4	d_9	I3→P3→P4→P2	d_{15}	I3→P4→P3→P2	d_{21}	P4→I3→P3→P2
d_4	I3→P2→P3→P4	d_{10}	I3→P2→P4→P3	d_{16}	I3→P4→P2→P3	d_{22}	P4→I3→P2→P3
d_5	P2→P3→I3→P4	d_{11}	P2→P3→P4→I3	d_{17}	P2→P4→P3→I3	d_{23}	P4→P2→P3→I3
d_6	P2→I3→P3→P4	d_{12}	P2→I3→P4→P3	d_{18}	P2→P4→I3→P3	d_{24}	P4→P2→I3→P3

Figure 6.13: A list of alternatives in the drilling order selection.

6.3.2 Workflow

This case study is utilized to illustrate the application of the MLU model in the drilling order selection. The main difference between the drilling order selection and well placement optimization is that we could enumerate all the alternatives. The workflow for decision selection based on MLU model is shown in Figure 6.14 and outlined in detail below:

(a) Enumerate all the alternatives $\boldsymbol{D}$. There are 24 alternatives for the design of well drilling order in this case study (Figure 6.13).

(b) Simulate an ensemble of realizations $\{\boldsymbol{g} = g_n; n = 1, 2, \ldots, N\}$ to transfer the geological uncertainty. Usually, the decision selection has a limited number of alternatives, which is much more computationally efficient than the decision optimization.

(c) Set up the economical models $\{v(g_n, d); n = 1, 2, \ldots, N; d \in \boldsymbol{D}\}$ using reservoir simulation from geological models.

(d) Construct the MLU model based on the mean, lower partial variance, and upper partial variance from the profit distributions of 24 alternatives. For a given drilling order d, these parameters are calculated below:

$$E\{V(\boldsymbol{g}, d)\} = \frac{1}{N} \sum_{n=1}^{N} v(g_n, d) \tag{6.5}$$

$$LPM_2\Big(V(\boldsymbol{g}, d), v_0\Big) = \frac{1}{N} \sum_{n=1}^{N} \Big(\min\Big[v(g_n, d) - v_0, 0\Big]\Big)^2 \tag{6.6}$$

$$UPM_2\Big(V(\boldsymbol{g}, d), v_0\Big) = \frac{1}{N} \sum_{n=1}^{N} \Big(\max\Big[v(g_n, d) - v_0, 0\Big]\Big)^2 \tag{6.7}$$

(e) Select the optimal decisions based on the efficient frontier in the MLU model.

(f) Compare the optimal alternatives from the efficient frontier of mean-variance model and MLU model.

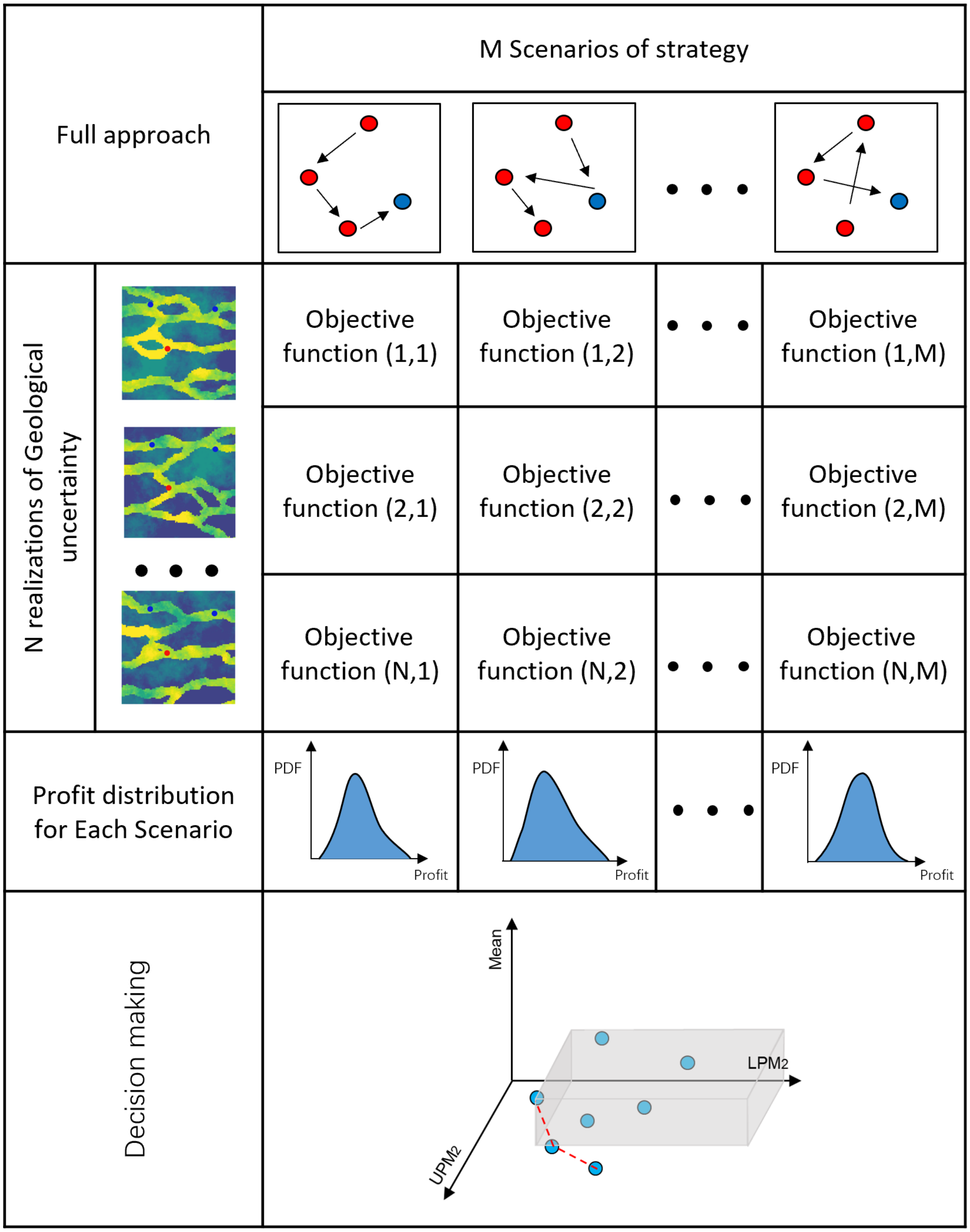


Figure 6.14: A sketch of workflow for the MLU model in decision making.

6.3.3 Results

Different drilling orders in various geological scenarios lead to the change of profit values. The profit distribution for each decision is available from the reservoir simulation of 100 realizations. Figure 6.15 provides a boxplot of profit distributions for the set of alternatives. The profit distributions from different alternatives overlap each other, and they are mainly distributed between $0.75 \times 10^7\$$ to $1.5 \times 10^7\$$. The red dotted line ($1.14 \times 10^7\$$) is regarded as the truncation between risk and potential, the profits from multiple realizations in all the alternatives are distributed around the given benchmark.

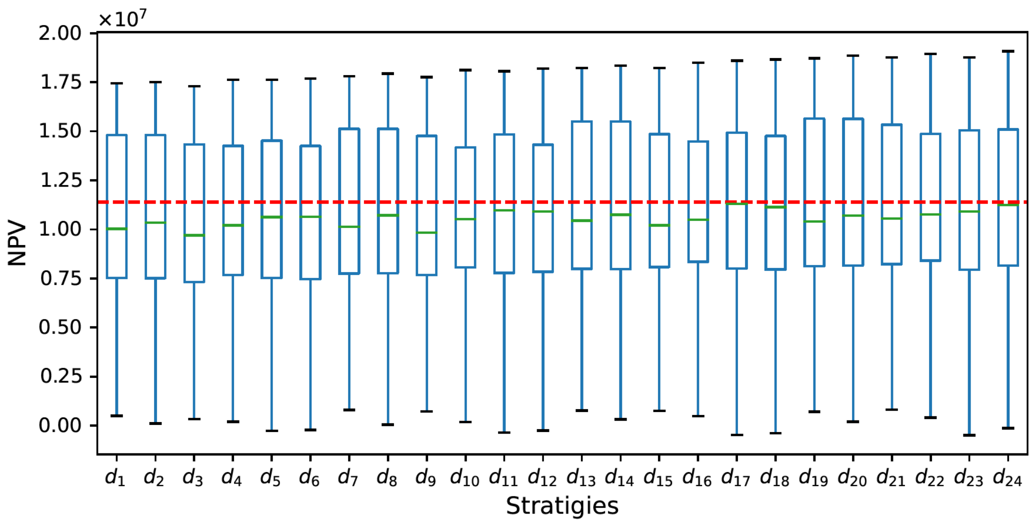


Figure 6.15: The boxplot of profit distributions from different drilling orders.

The expectations and variances from profit distributions involved in the different drilling orders are plotted in Figure 6.16. According to the mean-variance criterion, the optimal decisions on the efficient frontier often have a smaller variance or a larger expectation. It can be observed that the efficient frontier in the mean-variance model is made up of 8 alternatives: d_4, d_{10}, d_{16}, d_{22}, d_{24}, and d_{20} (Figure 6.16). However, the mean-variance model has limited ability for comparing alternatives according to previous theoretical examples. The MLU model is constructed in Figure 6.17 based on the mean, lower partial variance, and upper partial variance. The dots in this model represents the 24 alternatives for different drilling order, the optimal alternatives are in the efficient frontier based on the rules in the MLU model.

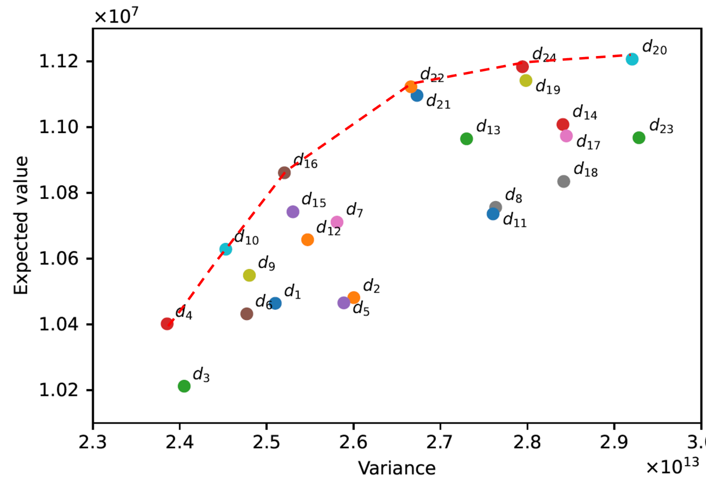


Figure 6.16: The efficient frontier in the mean-variance model.

However, it is difficult to determine the efficient frontier and optimal alternatives from a visual inspection of the MLU model (Figure 6.17). The MLU dominance matrix is designed to reflect the dominant relationship between every two decisions (Figure 6.18). The blue block indicates the alternative in the row is dominated by the other alternative in the column, and the grey block implies there is no dominance between the alternatives. It can be observed that all the blocks on the column of alternatives d_{20} and d_{24} are grey, which indicates these strategies are undominated by other alternatives. Since the optimal decisions on the efficient frontier should not be dominated by any other decisions, the alternatives d_{20} and d_{24} are identified as the optimal projects based on the rules of the MLU model.

There are six optimal alternatives identified from the efficient frontier of the mean-variance model: $d_4, d_{10}, d_{16}, d_{22}, d_{24}$, and d_{20}. But it can be seen from Figure 6.19 that d_4, d_{10}, d_{16} and d_{22} are worse than d_{24}. Because these alternatives have smaller expectations, larger downside volatility and smaller upside volatility than d_{24}. Therefore, some preference relationships are not identified in the mean-variance model. While in the MLU model, only d_{24} and d_{20} are both on the efficient frontier (Figure 6.17). Although d_{24} has a larger expected value and a larger upside volatility than the d_{20}, the lower partial variance of d_{24} is also larger than the d_{20}. Therefore, compared with the mean-variance model, the MLU model excludes some unreasonable choices, which enhances decision analysis in the presence of geological uncertainty.

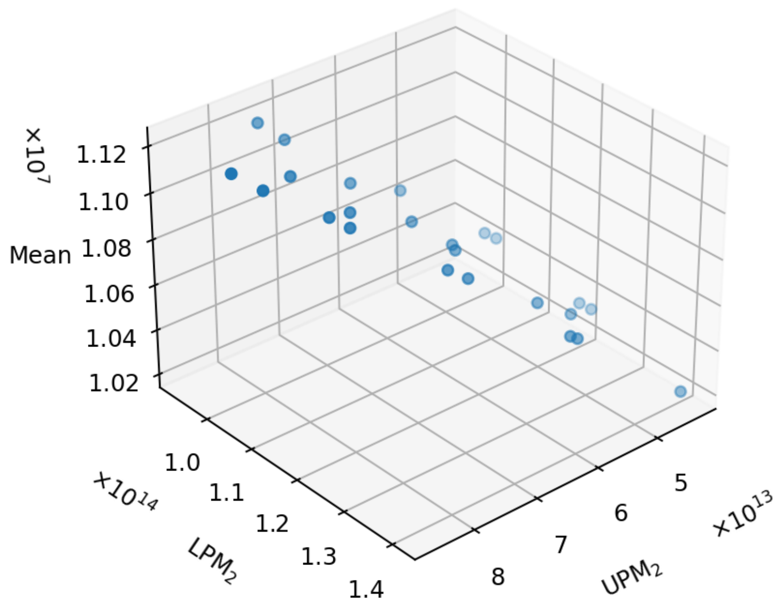


Figure 6.17: The MLU model of the drilling order selection.

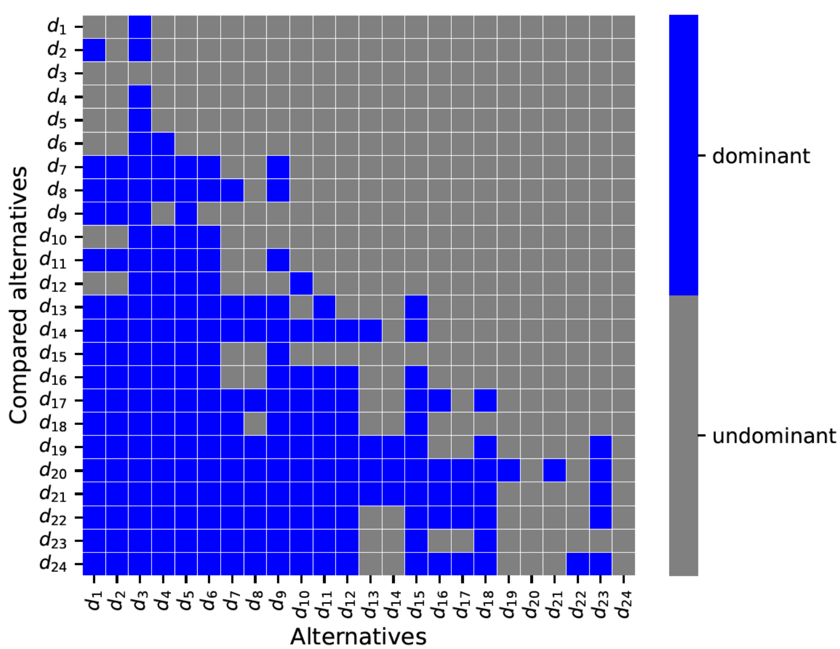


Figure 6.18: The MLU dominance matrix of the drilling order selection.

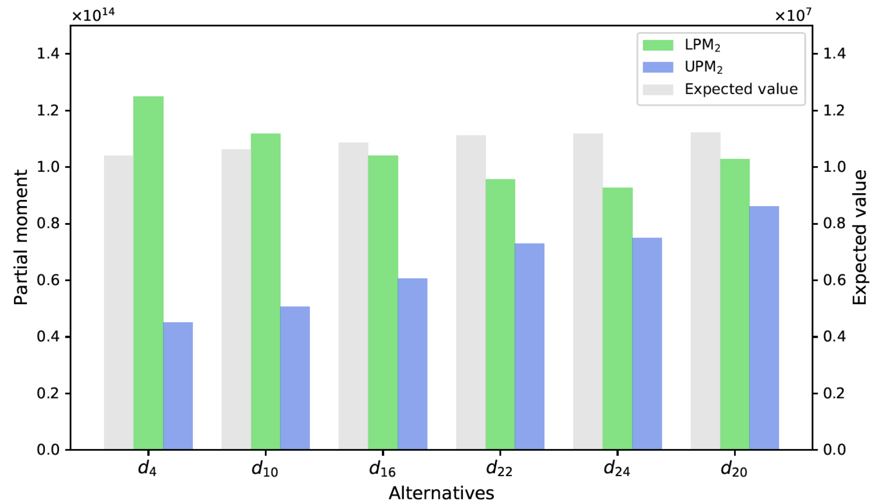


Figure 6.19: The parameters of optimal alternatives in the mean-variance model.

6.4 Conclusion

In this chapter, the downside-risk approach is applied to design production strategies in the context of decision optimization and decision selection. The first example is the well placement optimization with a consideration of spatial heterogeneity under geological uncertainty, the expected utility framework is utilized as the decision criterion to incorporate risk attitudes, and the measure of risk is based on the lower partial variance, which improves the well placement by explicitly assessing risk. The result indicates that the optimum well placement could be affected by different risk positions on the downside risk and upside potential. Investors with a risk-neutrality always prefer the production strategy with a larger expected profit, people with a risk-averse position are likely to choose the decision with a smaller lower partial variance, and investors who have an opportunity-seeking position might tend to the well locations with a larger upper partial variance. The mean-variance optimization and MLU optimization are also compared in this example. Since the investors only dislike the downside volatility, which indicates that the mean-variance optimization over-penalized the high values in the risk-averse position. Thus, the lower partial variance is more robust than the variance as a measure of risk. The MLU optimization is more consistent with investors' behaviors, and it is outperformed the mean-variance optimization in well placement optimization.

The second example is related to the drilling order selection. Since the mean-variance criterion is often utilized in the petroleum industry to select the production strategy in the presence of geological uncertainty, variance is considered inadequate to assess risk as people only dislike the volatility below a certain level. In Chapter 4, a high-dimensional MLU model is proposed to facilitate decision-making by an explicit risk. This model utilized the lower partial variance to qualify the measure of risk, and the set of optimal alternatives could be identified based on the efficient frontier. In this chapter, the MLU model is applied in the drilling order selection in the presence of geological uncertainty. The observation implies that both decision models do not always help us to find the best single alternatives. Compared with the mean-variance model, the MLU model is able to reduce the number of optimal alternatives by excluding some unfavorable alternatives. Therefore, the chance of obtaining better results is increased in the drilling order selection by employing the MLU model with an explicit consideration of risk.

Chapter 7

Application: value of geophysical information analysis

Geophysical information is valuable in the design of production strategies in oilfield development. Since the value of geophysical information is often analyzed in the underlying assumption of a risk-neutral position, a framework is proposed to capture different risk positions in the VOI analysis. It is implemented by integrating utility theory into the simulation-regression approach. This framework has been discussed in Chapter 5. In this chapter, we will focus on the application of the proposed workflow to some practical problems, and the impact of different preferences in VOI analysis is also discussed. It will be illustrated through a case study of evaluating geophysical information in the context of production strategies selection.

7.1 Introduction

Geophysical data provides important information to improve the understanding of the subsurface geological model. Before collecting geophysical information, VOI analysis is often performed to evaluate the worth of the information (Bratvold et al., 2009; Eidsvik et al., 2015b; Trainor Guitton et al., 2014). However, VOI is often calculated from the difference between the expected value of the posterior value (PoV) and the prior value (PV), which has the underlying assumption of a risk-neutral position. A practical workflow for effective integration of different preferences in the VOI analysis in the presence of geological uncertainty is demonstrated in Chapter 5. This workflow consists of five main steps: (1) employ multiple geological models to transfer geological uncertainty, (2) simulate the geophysical information from rock physics analysis, (3) construct economic models under the given production strategies, (4) convert economic models to utility models to capture preferences, and (5) approximate VOI for different risk positions by using the simulation-regression approach. The main goal of this workflow is to combine utility functions into the simulation-regression approach. The utility function quantitatively measures the satisfaction of decision-makers, it is a useful tool under the expected utility framework to capture risk attitudes in the decision-making process. The simulation-regression approach is proposed by Bratvold et al. (2009) to approximate the posterior value in the VOI analysis. In this chapter, a case study is presented to demonstrate the implementation of the proposed workflow. It is applied to evaluate the geophysical information in the context of production strategies selection. The impact of different risk positions in the VOI analysis will also be demonstrated in this case study.

7.2 Value of geophysical information

This section will demonstrate the application of VOI analysis for different risk positions. The impact of preferences will be discussed by evaluating the value of geophysical information in the context of production strategies selection.

7.2.1 Problem formulation

Consider a 2-D channelized reservoir that will be produced for 10 years. It has been under production for 2 years with one producer and two injectors (Figure 7.1). The three exploration wells in Figure 7.1a are drilled in the channel. The detailed information of these exploration wells is shown in Table 7.1. During the development of oilfield, the injection wells keep a constant rate control with $70\text{m}^3/\text{day}$, and the production well has a constant bottom hole pressure of $3.9 \times 10^7\text{Pa}$. In order to increase the oil production, four infill wells are planned to drill in the location shown in Figure 7.1b. It is supposed that all the infill wells are drilled at the same time in this example. However, there is great uncertainty involved in the subsurface, which leads to the two alternatives (D1, D2) in the oilfield development: (1) D1 refers to drilling the infill wells; (2) D2 represents the infill wells are not drilled. Before making the decision, investors are planning to collect the geophysical information to facilitate this decision making. Thus, the target of this example is to evaluate the value of geophysical information in the context of production strategy selection considering different risk positions.

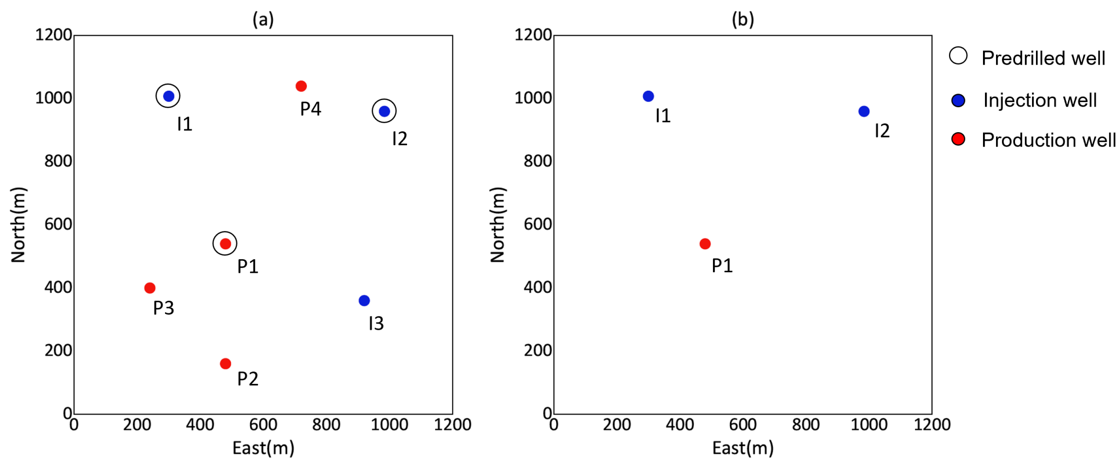


Figure 7.1: The locations of producers and injectors in different production strategies. (a) The alternative D1. (b) The alternative D2.

Table 7.1: The table summarizes the information from exploration wells.

	I1	I2	P1
Well location	(300m, 1008m)	(984m, 960m)	(480m, 540m)
Porosity	24%	28%	18%
Permeability	80mD	316mD	32mD
Lithofacies	Channelized sandstone	Channelized sandstone	Channelized sandstone

7.2.2 Data modeling

The data in VOI analysis mainly includes geological models, geophysical models, and economic models. They are modeled based on the observed data from limited wells, which would be described below:

Firstly, an ensemble of geological models is generated from stochastic simulation to capture the geological uncertainty (Figure 7.2). The multiple-point geostatistical algorithm is utilized to model the depositional facies spatial heterogeneity. The petrophysical models, porosity and permeability, are simulated within the constraint of depositional facies using the USGSIM program. This program allows enables the cosimulation of multiple variables within different rock types (Manchuk and Deutsch, 2012).

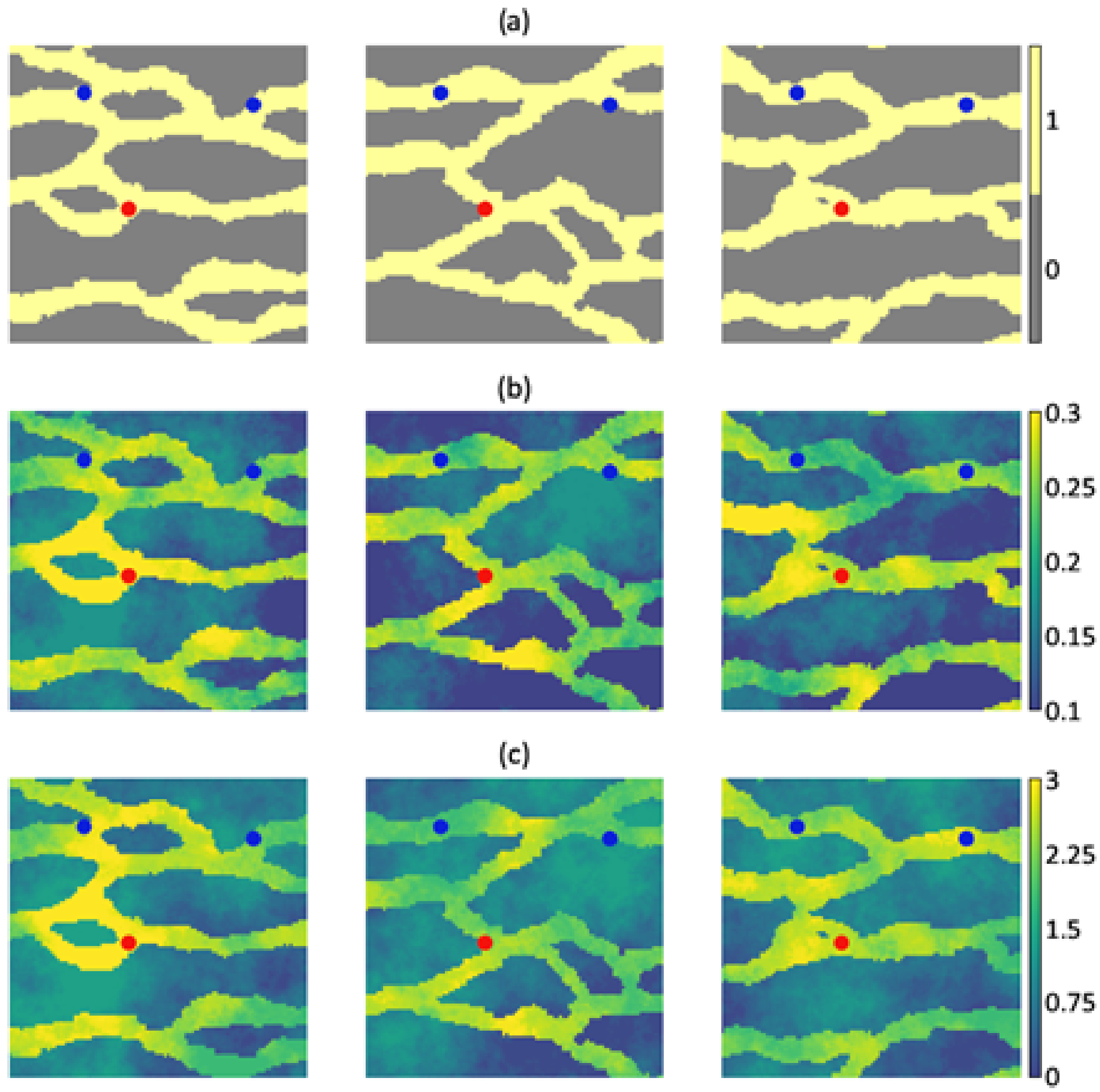


Figure 7.2: Three realizations each of: (a) Lithofacies (code 1 is channelized sand and code 2 is floodplain mud). (b) Porosity. (c) Permeability (millidarcy on a logarithmic scale).

Next, the possible seismic responses could be generated using the simulated geological models. The synthetic geophysical information is closely related to the reservoir properties, such as acoustic impedance. It often has a negative correlation with porosity and permeability (Mavko et al., 2020; Pyrcz and Deutsch, 2014). The synthetic impedance is generated using the program PEM_3D, which is based on Gassmann's theory to construct the petrophysical elastic model (Hadavand and Deutsch, 2015). The synthetic seismic attributes are upscaled to be consistent with the geophysical sampling interval, and then the upscaled seismic attributes are smoothed using the moving window average, as shown in Figure 7.3.

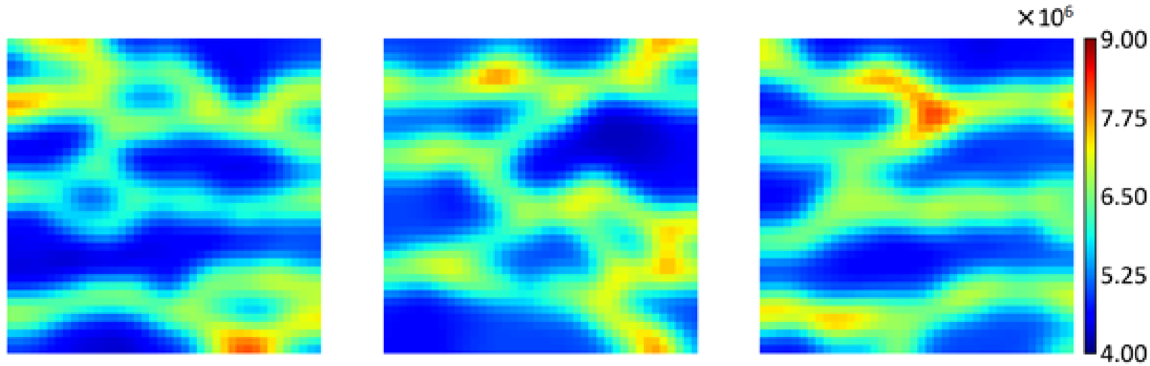


Figure 7.3: Three realizations of synthetic acoustic impedance.

The net present value (NPV) is calculated by conducting flow simulation to measure the performance of the reservoir. The prior NPV distributions of these two alternatives are shown in Figure 7.4, these distributions are calculated before collecting information, that is, these NPV distributions are generated without considering future information. It is obvious that alternative D1 has a larger expected NPV than alternative D2. Thus, investors with a risk-neutral position would select the alternative D1 if we do not collect the information.

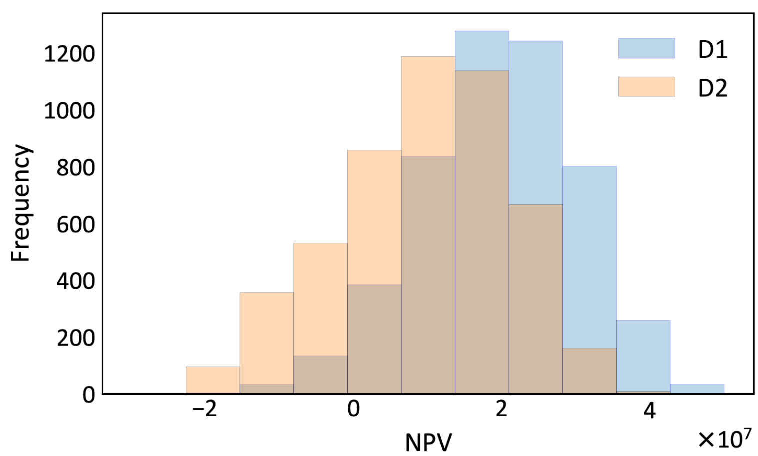


Figure 7.4: The prior distribution of these two alternatives.

Finally, all the monetary values are converted to a utility-scale using the exponential utility function. The decision-making process is based on maximizing the expected utility, and the VOI is also calculated under the utility-scale. The effect of risk attitudes on the VOI analysis also will be investigated by performing sensitivity analysis of risk tolerance in the following Subsection 7.2.4.

7.2.3 Partial least square regression

Partial least square regression (PLSR) is employed in the simulation-regression approach. PLSR is a multivariate regression approach aiming to maximize the correlation from decomposed matrixes from projections of predictor and projections of responses (Dutta et al., 2019b; Meacham Hensold et al., 2019; Tantishaiyakul et al., 2006). The quality of the PLSR model can be evaluated from the mean square error (MSE) by implementing k-fold cross-validation. It can be observed that as the number of principal components increases, MSE first decreases and then gradually increases. The number of principal components to minimize the MSE could be found in Figure 7.5. It indicates 9 principal components in the regression model could bring the minimum MSE in the alternative D1, and the optimum number of principal components is 12 in the alternative D2.

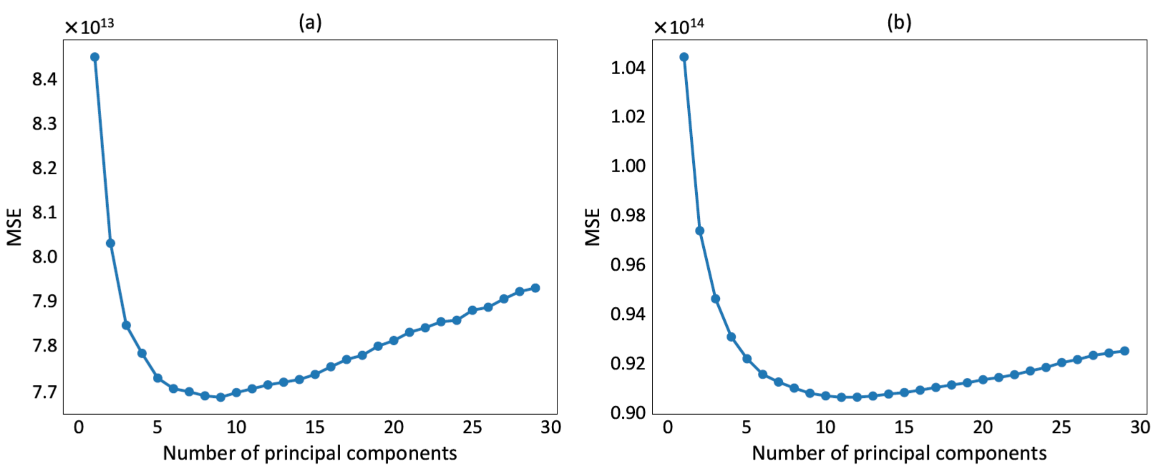


Figure 7.5: Relationship between MSE and number of principal components under a risk-neutral position. (a) The alternative D1. (b) The alternative D2.

The data set is split into training and test sets. The training set is used to fit regression models with the optimum number of principal components, and the test set is utilized to evaluate the performance of the regression models. The scatter plot in Figure 7.6 shows the relationship between observed values from the test sets and predicted values from PLSR regression. It can be seen that the dots distribute symmetrically around a 45-degree diagonal. After constructing these regression models, the conditional expectation in the PoV would be approximated using these regression values.

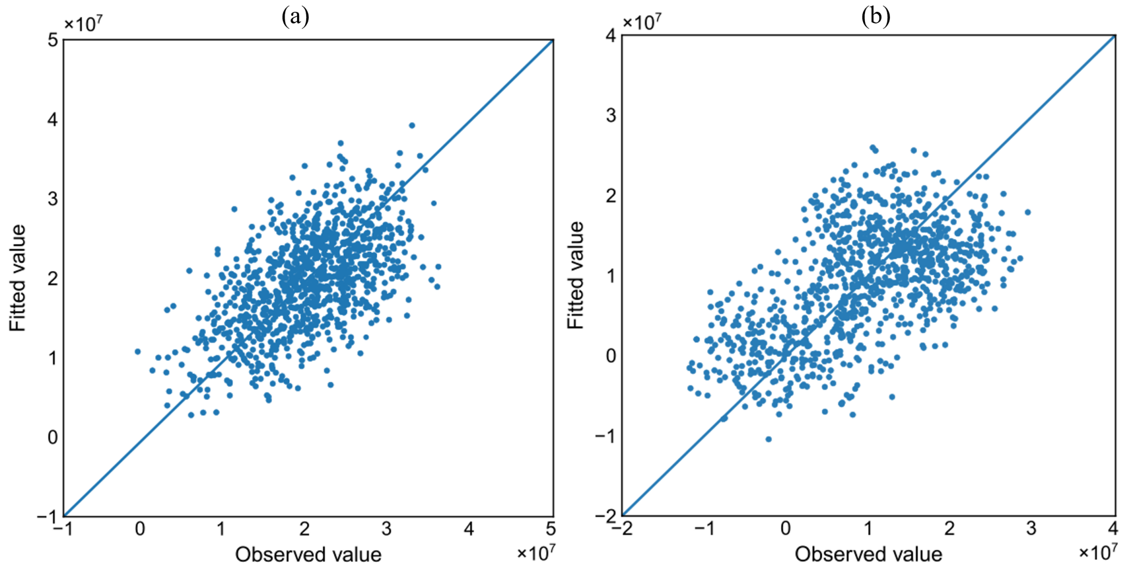


Figure 7.6: Scatter plot of fitted values vs observed values under the risk-neutral position for two different alternatives. (a) The alternative D1. (b) The alternative D2.

7.2.4 VOI analysis for different risk positions

The profit distributions are normalized between 0 to 1, and then transferred into the utility-scale (Figure 7.7). In the normalized space, the utility values are also scaled between 0 and 1, which is consistent with the range of the normalized monetary values. Since the number of realizations is limited, the uncertainty in the VOI analysis could be captured by the bootstrap analysis (Dutta et al., 2019b; Eidsvik et al., 2017). It can be observed that different risk positions will affect the investors' decision about the gathering of seismic. Assuming the cost of information (COI) is 3.6×10^{-3} (or 2.7×10^{5}\$), it is a normalized value that needs to be transferred into the utility-scale in different risk positions. The seismic would be worth collecting when $EU(\text{VOI}) > U(\text{COI})$.

The result in Figure 7.8 indicates that the decision about collecting or giving up gathering information would be impacted by the preferences on risk. Investors with the risk tolerance of $r = 0$ and $r = 1$ are not willing to collect the seismic, because the expected utility of VOI, $EU(\text{VOI})$, is less than the utility value of information cost $U(\text{COI})$. But when the risk tolerance $r = -1$, investors would prefer to collect the impedance information as it has a larger expected utility of VOI, that is, $EU(\text{VOI}) > U(\text{COI})$.

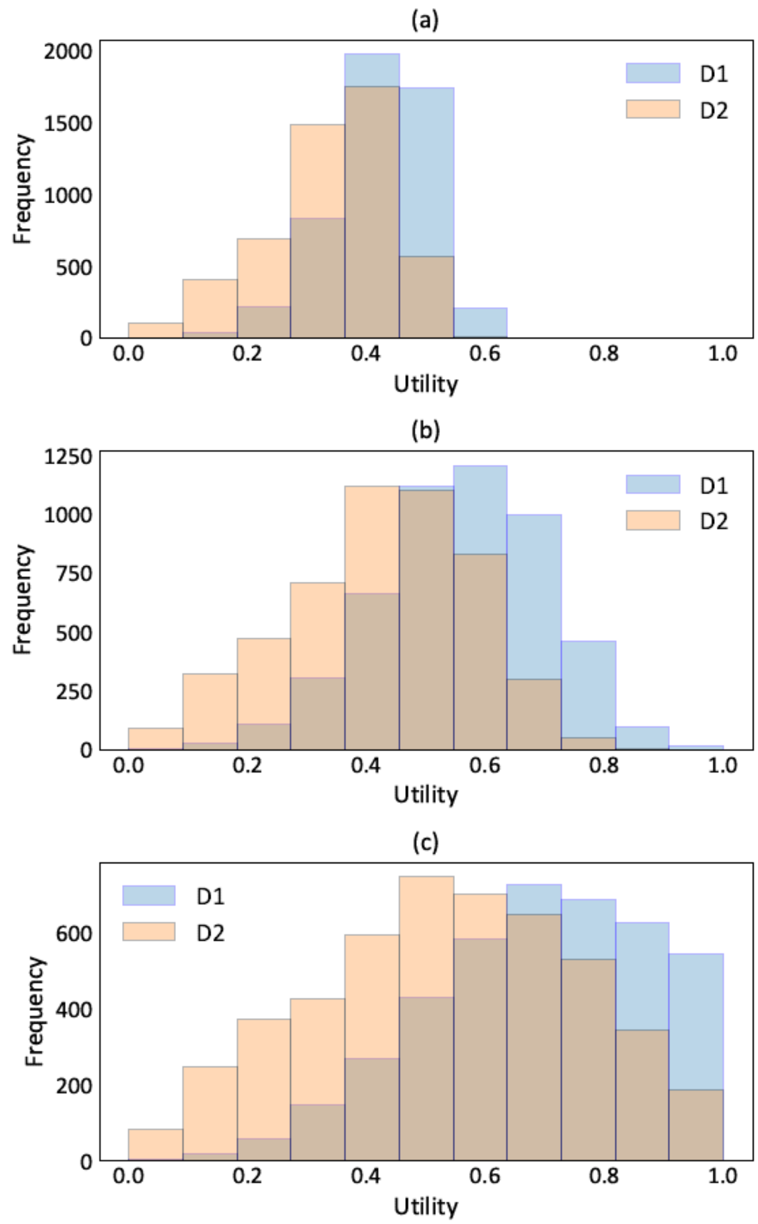


Figure 7.7: The utility distributions for alternatives over different risk positions. (a) The risk-averse position ($r = 1$). (b) The risk-neutral position ($r = 0$). (c) The opportunity-seeking position ($r = -1$).

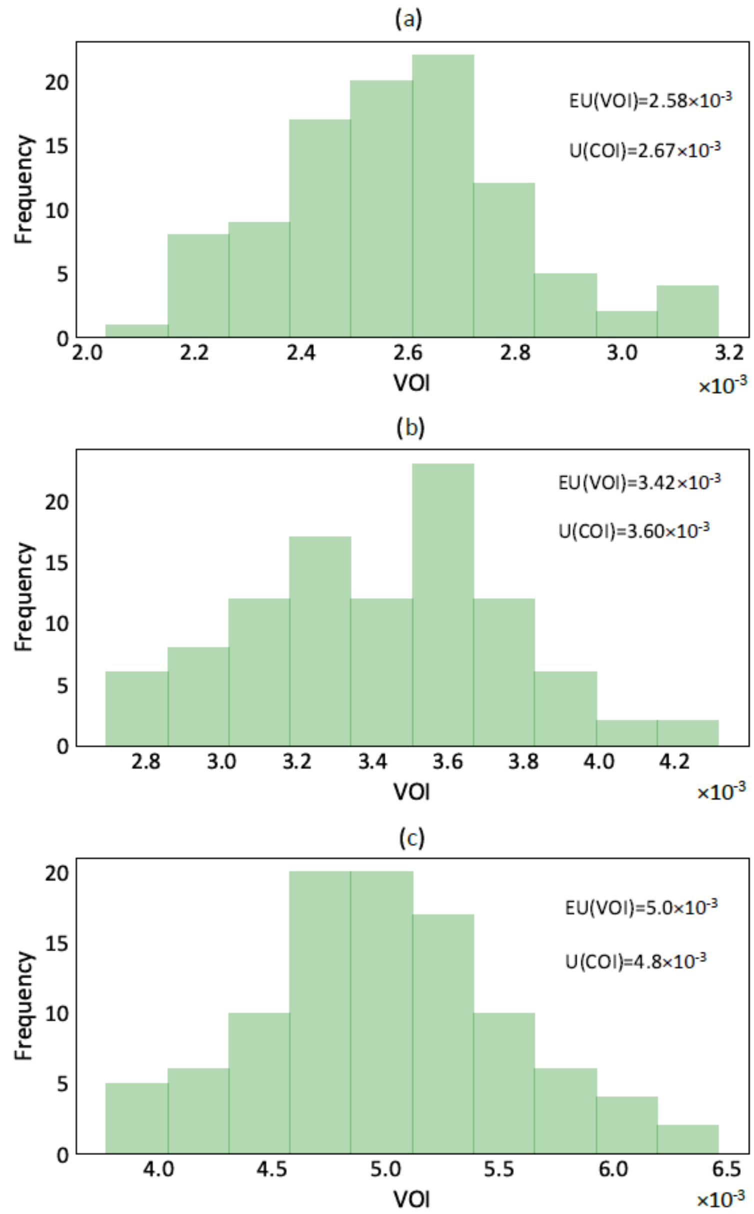


Figure 7.8: The VOI distributions for alternatives over different risk positions. (a) The risk-averse position ($r = 1$). (b) The risk-neutral position ($r = 0$). (c) The opportunity-seeking position ($r = -1$).

It can be observed from Figure 7.9a that with the increase of risk tolerance, both $U(\text{COI})$ and $EU(\text{VOI})$ become smaller. The result in Figure 7.9b indicates that investors who are not sensitive to the risk (r is close to zero) are not willing to collect the seismic, because the expected utility of VOI is less than the utility value of seismic cost. But investors who are sensitive to the risk (r is much greater or smaller than zero) prefer to collect the impedance information as it has a larger expected utility of VOI.

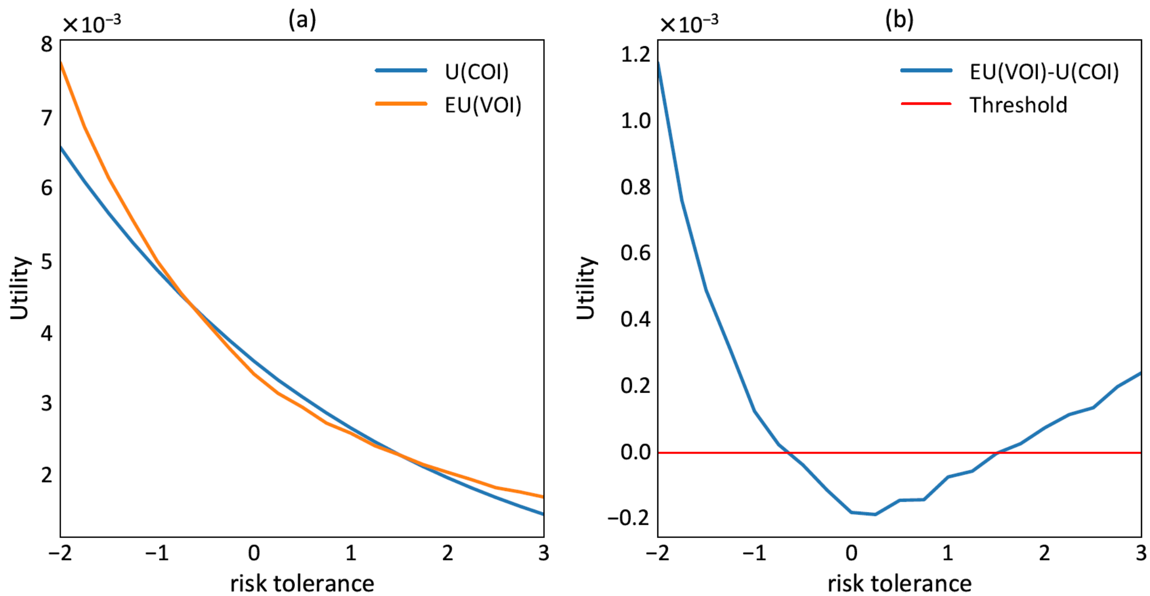


Figure 7.9: The result of VOI analysis for different risk positions. (a) The plot of $U(\text{COI})$ and $EU(\text{VOI})$. (b) The plot of difference between $EU(\text{VOI})$ and $U(\text{COI})$.

7.3 Conclusion

VOI analysis is an estimate of the additional value from decision-related information. To investigate the impact of risk appetite in VOI analysis, a workflow for approximating the VOI considering different risk positions in the presence of geological uncertainties is proposed in Chapter 5. This workflow integrates utility theory into the simulation-regression approach to approximate the VOI. The utility theory takes different risk attitudes into account in the decision analysis, and the simulation-regression approach is an efficient technique l to approximate the VOI. In this Chapter, the proposed workflow is applied in a 2-D channelized reservoir to evaluate geophysical information in the context of selecting optimal production strategies. The partial least square regression is employed in the simulation-regression approach to approximate the conditional expectation of the PoV. The impact of risk preferences is analyzed by performing sensitivity analysis to the risk tolerance, which provides useful insight for decision-makers in the VOI analysis. The result indicates that, in our example, investors who have a risk-neutral position are not willing to gather the information, while investors who are sensitive to the risk are more likely to collect the geophysical information. Thus, different risk appetites would affect the decision about gathering information in VOI analysis. It would be more robust for VOI analysis with the risk positions taken into account by integrating the utility theory in the simulation-regression approach.

Chapter 8

Concluding remarks

Reservoir management often involves high risk due to the lack of knowledge about the subsurface. Investors hold different risk preferences in reservoir decision making in the presence of geological uncertainty. Therefore, understanding the impact of risk preferences leads to improved reservoir management.

This thesis contributes to reservoir management by investigating the impact of risk preferences under the expected utility theory, and reservoir decision making in the presence of geological uncertainty is improved by using an explicit analysis of risk. These approaches are illustrated in the design of production strategies in a 2-D synthetic reservoir in Chapter 6 and Chapter 7. In this chapter, a summary of the main contributions of this thesis as well as the limitations of the methodologies and ideas for future work are provided.

8.1 Summary of contributions and limitations

Expected utility is a popular theory in decision analysis to reflect investors' preferences. However, current approaches often ignore the impact of risk preference in reservoir management. Within the expected utility framework, three primary contributions are made in this thesis: Firstly, the relationship between preference measurements is constructed in the presence of geological uncertainty. Secondly, the expected utility framework is introduced in reservoir decision making with an explicit consideration of risk. Lastly, the impact of preference is analyzed in VOI analysis under the spatial decision situation.

8.1.1 Preference measurements under geological uncertainty

Loss functions and utility functions are important tools in decision analysis as they could capture different preferences from investors. These subjective attitudes are reflected in the penalty factor in loss functions and risk tolerance in utility functions. The penalty factor assigns the weights penalizing underestimation and overestimation, and the risk tolerance measures the investors' preference in a risky activity. However, the loss function is often utilized in parameter estimation while the utility function is used in the optimization from a set of alternatives. Although both of these preference measurements are utilized in resource decision analysis, there is no clear understanding of their relationship.

To improve the understanding of preference measurements in the presence of geological uncertainty, a workflow is developed in Chapter 3 to establish the relationship between utility functions and loss functions. Their relationship is constructed based on risk tolerance and penalty factors. The decision based on loss functions aims to maximize the optimal estimates from minimizing the expected loss, while the decision criterion for the utility function is based on maximizing the expected utility. The corresponding risk tolerance and penalty factor could be connected when investors are indifferent to the alternatives.

There are some limitations involved in this workflow: (1) This approach is illustrated using the exponential utility function and quadratic loss function. There are many other forms of preference measurements that should be investigated. (2) In order to simplify the computation, all the profit distributions are assumed to be uniformly distributed, but in practice, the profit distributions could be more complex. (3) The relationship between risk tolerance and penalty factors is not exact. That is, they do not have a one-to-one relationship. Although limitations exist in this workflow, it provides a new perspective on the place of loss functions and utility functions in petroleum applications.

8.1.2 Decision making with an explicit consideration of risk

Variance is often utilized to measure risk for making decisions in the energy industry. It is utilized in the form of a mean-variance criterion or maximizing risk-adjusted value under the expected utility framework (Huang and Yang, 2020; Motta et al., 2000). But investors dislike the downside volatility less than a certain benchmark. Therefore, there is a need to improve the risk measurements in decision making. The approaches utilized to assess risk are summarized in Chapter 4. This summary indicates that only variance and lower partial moments are appropriate in the expected utility framework, and lower partial moment is more consistent with investors' behavior.

The downside-risk approach is introduced in Chapter 4. In this approach, the profit return is truncated to the downside risk and upside potential based on a benchmark. The lower partial variance quantifies the downside risk, and the upper partial variance measures the upside potential. This approach is discussed in the context of decision selection and decision optimization. In decision selection, the MLU model is developed based on the mean, lower partial variance and upper partial variance, which has a stronger ability to identify optimal alternatives than the mean-variance model. In the decision optimization, a workflow of MLU optimization in the presence of geological uncertainty is proposed to improve the measure of risk in the mean-variance optimization (maximizing the risk-adjusted value). Moreover, the difference between the MLU model and MLU optimization is discussed, the main advantage of MLU model is that preference is not taken into account in this model, while the MLU optimization has the primary advantage that this approach could be applied in a situation with countless alternatives.

In Chapter 5, the downside-risk approach is applied in the design of production strategies. The MLU optimization is compared with mean-variance optimization in the well placement optimization (decision optimization), the result indicates that the MLU optimization is more consistent with investors' behavior. Additionally, the MLU models are applied in drilling order selection (decision selection), and its result is compared with the mean-variance model (mean-variance criterion). The results reveal that the lower partial variance outperforms variance in the measure of risk, which improves reservoir decision making by explicitly analyzing risk.

8.1.3 Value of information for different risk positions

VOI analysis is used in the assessment of decision-related information before collecting it. This approach has been applied to geophysical information in the spatial decision situation, and the simulation-regression approach is employed to estimate the conditional expectation of the posterior value. VOI is often defined as the difference of expected value between posterior value and prior value, which is associated with an underlying risk-neutral position.

The main contribution of Chapter 6 is to give a more general definition of VOI analysis, it is defined by the difference of expected utility between the posterior value and prior value.

It is implemented by integrating the utility theory in the simulation-regression approach, which is able to capture different risk positions in VOI analysis. The detailed workflow of VOI analysis for different risk positions is introduced in Chapter 6. It consists of five steps: (1) multiple realizations to capture uncertainty, (2) model the geophysical information, (3) simulate the profit distribution under each alternative, (4) transfer the profit distribution into the utility space, and (5) perform simulation-regression in the utility distribution. A small example is utilized to illustrate the VOI analysis should be implemented under the decision-related context and the impact of different risk positions in VOI analysis.

In Chapter 7, the proposed workflow is applied to assess the value of geophysical information in the design of production strategies. It is used to explore the impact of risk positions on VOI analysis. The results indicate that different risk positions may alter the decision to gather information. That is, a better understanding of risk positions may lead to a more robust VOI analysis. This workflow also has some limitations: (1) A notable one is about the source of information. Only a single source of formation is considered in this research, but there are often multiple sources involved in practical applications. (2) Another limitation is related to the estimation of the posterior value. Although the simulation-regression approach has been used in many studies to estimate VOI, other methods could also be considered to approximate VOI.

8.2 Future work

Several areas may be considered to improve the risk-quantified decision making in reservoir management. Some ideas for future research are presented as:

(a) Preference measurements in multi-attribute decision making

As mentioned previously, there are limitations involved in the investigation of preference measurements. The established relationship in Chapter 3 is a special case using the exponential utility function and quadratic loss function with the uniformly distributed alternatives. Therefore, different types of functions should be utilized to construct a more general relationship, and more complex alternative distributions should also be taken into account. Additionally, the objective factors that affect decision making are only monetary values in this thesis, but in practice, there are many objective factors that could affect our decisions, such as the recovery factor (Virine and Murphy, 2007) and time horizons (Zhao et al., 2020). Thus, the multi-attribute utility theory could be adopted to quantify the impact of each factor in decision making (Martins et al., 2020), which is also an important topic to improve reservoir decision making.

(b) Computational efficiency in multiple realizations

It is computationally expensive to perform well placement optimization taking multiple realizations into account, especially when the number of realizations is very large. Numerous approaches have been developed to improve computational efficiency in robust optimization, such as surrogate models in reservoir simulation or advanced algorithms in representative realizations selection. In this research, the representative realization is selected just by using the static models based on the clustering method, which disregards the dynamic information. Some approaches are proposed to improve computation efficiency using dynamic information, for example, selecting the presentation realization based on time of flight (Pouladi et al., 2017), or constructing the surrogate modelling based on the model order reduction (Ghadiri et al., 2021). These promising approaches could improve the computation efficiency as well as accuracy in well placement optimization.

(c) Global optimization in decision making

In most situations, countless alternatives are involved in the decision-making process. Many global optimization algorithms have been developed to improve decision optimization. They are employed to find the minimum or maximum value from a given objective function. The MPSO algorithm is utilized in our research, which is better than the PSO algorithm in escaping from local optimum. However, limited by computational resources and the model complexity, global optimization algorithm does not ensure the global best solution in most cases (Floudas and Gounaris, 2009; Wang et al., 2012). There is a trade-off between the optimal solution and feasible solution. Therefore, a measure of the difference between the optimization solution and the global best is an important topic in the heterogeneity reservoir.

(d) VOI analysis with multiple sources

VOI analysis has been introduced in geophysics in recent years, it evaluates the value of geophysical information to facilitate decision making. In Chapter 5, a workflow is proposed to integrate utility functions in the simulation-regression approach, the proposed methodology highlights the importance of preferences in the VOI analysis. However, the source of information considered in our research only comes from one source (geophysical data). But in many practical applications, multiple sources of information are commonly used to facilitate decision making, such as geophysical data (Eidsvik et al., 2008; Przybysz Jarnut et al., 2015), production data (Hong et al., 2018), and well data (Hanea et al., 2019; Trainor Guitton et al., 2014). Therefore, it is significant to evaluate the value of information from multiple sources in future work.

(d) Application in more practical situations

The synthetic geological models are utilized in the examples of this research. Although realistic oilfield data is difficult to obtain, some public datasets are available for the purpose of research, such as the Brugge field (De Barros, 2019; Zhang et al., 2018) or the Norne field (Lorentzen et al., 2020). It could be more intuitive by applying the proposed approach in a practical situation. Additionally, in the real world, uncertainty may also come from economic factors, such as the fluctuation of oil prices and water prices. Thus, using the realistic oilfield data in the presence of economical uncertainty could also be a direction in future work.

The topics discussed above are some additional work to improve the methodologies and workflows developed in this thesis. Additional research should be applied to increase the robustness and reliability of risk management in reservoir decisions in the presence of geological uncertainty.

8.3 Final comments

Recall the thesis statement proposed in Chapter 1: *Understanding the impacts of risk preferences has great significance to reservoir management. Reservoir decision making and risk management in the presence of geological uncertainty will be enhanced by explicitly analyzing risk*.

In this thesis, risk preference is investigated in reservoir management under the expected utility framework. Guiding by this theory, a workflow based on the downside-risk approach is developed to improve risk management. In the downside-risk approach, the risk is reflected by the downside volatility and quantified by the lower partial variance, which is able to improve reservoir decision making by explicitly analyzing risk.

Since the VOI analysis is often implemented under the risk-neutral position, it could be improved by considering different risk positions. In this thesis, the preference is taken into account in the VOI analysis under the spatial decision situation, it is performed by integrating the utility theory in the simulation-regression approach. This approach provides a more robust VOI analysis by analyzing the impact of preferences.

Lastly, the contribution and the limitations of this research are summarized. Some additional work in the future is discussed, which is able to improve the risk-quantified decision making in reservoir management in the presence of geological uncertainty.

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Appendix A

Appendices

A.1 Preference measurements in decision making

(a) Quadratic loss function: As for the decision has a uniform distribution within the interval between a and b, the expected loss $E\{L(Z, z^\star)\}$ is expressed below:

$$\begin{aligned} E\Big\{L(Z, z^\star)\Big\} &= \int_a^{z^\star} (Z - z^\star)^2 \frac{1}{b-a} dZ + \int_{z^\star}^b \lambda (Z - z^\star)^2 \frac{1}{b-a} dZ \\ &= \frac{1}{3(b-a)} \Big((z^\star)^3 - a^3 + 3z^\star a^2 - 3(z^\star)^2 a\Big) \\ &+ \frac{\lambda}{3(b-a)} \Big(b^3 - (z^\star)^3 - 3z^\star b^2 + 3(z^\star)^2 b\Big) \end{aligned} \tag{A.1}$$

Using the first derivative test to find the extreme point of expected loss function. It is conducted by taking the derivative of $E\{L(Z, z^\star)\}$ with respect to $z^\star$ as follows:

$$\begin{aligned} \frac{dE\Big\{L(Z, z^*)\Big\}}{dz^\star} &= \frac{1}{b-a} \Big((z^\star)^2 + a^2 - 2az^\star\Big) + \frac{\lambda}{b-a} \Big(-(z^\star)^2 - b^2 + 2bz^\star\Big) \\ &= (1-\lambda)(z^\star)^2 + 2(b\lambda - a)z^\star + a^2 - \lambda b^2 \end{aligned} \tag{A.2}$$

The optimal estimate $z^\star_{opt}$ is valid in the interval $[a, b]$. Let $\frac{dE\{L(Z, z^\star)\}}{dz^\star} = 0$, the optimal estimate $z^\star_{opt}$ could be solved:

$$z^\star_{opt} = \frac{a + \sqrt{\lambda} b}{1 + \sqrt{\lambda}} \quad \text{for} \quad \lambda \neq 1 \tag{A.3}$$

(b) Exponential utility function: The expected utility for a decision with a uniform distribution X of interval between a and b is expressed in Equation A.4.

$$E\Big\{U(X)\Big\} = \int_a^b \frac{1 - \exp(-rX)}{r} \frac{1}{b-a} dX = \frac{1}{r} + \frac{\exp(-br) - \exp(-ar)}{r^2 (b-a)} \quad \text{for} \quad r \neq 0 \tag{A.4}$$

A.2 Downside-risk approach in decision making

Insights about the downside-risk approach are drawn from Equation 4.7. Appendix A.2 summarizes the derivation process of this equation from previous research (Cumova and Nawrocki, 2014; Santos et al., 2017a; Zakamouline and Koekebakker, 2009). It aims to give a more detailed illustration of the downside-risk approach in decision making under the expected utility framework. Consider a monetary distribution X, the expected utility $E\{U(X)\}$ is expressed as:

$$E\{U(X)\} = \int_{-\infty}^{\infty} U(X)dF(X) \tag{A.5}$$

Where $F(X)$ is the CDF. The expected utility is truncated by the reference point x_0, which is given by:

$$E\{U(X)\} = \int_{-\infty}^{x_0} U_{-}(X)dF(X) + \int_{x_0}^{\infty} U_{+}(X)dF(X) \tag{A.6}$$

Where U_- and U_+ are the utility function above and below the reference point, respectively. Applying the Taylor series expansions for $U_-(x)$ and $U_+(x)$ around x_0, which yields:

$$\begin{aligned} E\{U(X)\} = &\int_{-\infty}^{x_0} \left(\sum_{N=0}^{\infty} \frac{1}{N!} U_{-}^{\{N\}}(x_0)(X - x_0)^N \right) dF(X) \\ &+ \int_{x_0}^{\infty} \left(\sum_{N=0}^{\infty} \frac{1}{N!} U_{+}^{\{N\}}(x_0)(X - x_0)^N \right) dF(X) \end{aligned} \tag{A.7}$$

The lower partial moments and upper partial moments in the N-th order are defined as (Anthonisz, 2012; Gökgöz and Atmaca, 2017):

$$LPM_N(X, x_0) = (-1)^N \int_{-\infty}^{x_0} (X - x_0)^N dF(X) \tag{A.8}$$

$$UPM_N(X, x_0) = \int_{x_0}^{+\infty} (X - x_0)^N dF(X) \tag{A.9}$$

Substituting Equations A.8 and A.9 into Equation A.7. The expected utility could be expressed as:

$$
\begin{aligned}
E\{U(X)\} = U(x_0) + & \sum_{N=1}^{\infty} \frac{1}{N!} U_{-}^{\{N\}} (-1)^N LPM_N(X, x_0) \\
& + \sum_{N=1}^{\infty} \frac{1}{N!} U_{+}^{\{N\}}(x_0) UPM_N(X, x_0)
\end{aligned}
\tag{A.10}
$$

In order to capture different risk positions in the upside and downside, the truncated utility function with a threshold of x_0 is used, which is given by:

$$
U(x) = \begin{cases} (x - x_0) - \frac{r_+}{2}(x - x_0)^2 & x \geq x_0 \\ -(x_0 - x) + \frac{r_-}{2}(x_0 - x)^2 & x < x_0 \end{cases}
\tag{A.11}
$$

The utility function could be approximated by a quadratic form in a certain wide range of return by Tylor series expansion (Jia and Dyer, 1996; Markowitz, 1959). The expected utility in Equation A.10 is simplified into the partial moments form:

$$
\begin{aligned}
E\{U(x)\} = & UPM_1(X, x_0) - \frac{r_+}{2} UPM_2(X, x_0) \\
& - \left(LPM_1(X, x_0) + \frac{r_-}{2} LPM_2(X, x_0) \right)
\end{aligned}
\tag{A.12}
$$

The expected utility in Equation A.12 could be further simplified below:

$$
E\{U(X)\} = E(X - x_0) - \frac{r_+}{2} UPM_2(X, x_0) - \frac{r_-}{2} LPM_2(X, x_0) \tag{A.13}
$$

Where r_+ is the attitude for the upside volatility (upside risk-seeking $r_+ < 0$, and upside risk-neutral $r_+ = 0$), and r_- is the attitude for the downside fluctuation (downside risk-averse $r_- > 0$, and downside risk-neutral $r_- = 0$).

A.3 Regression to approximate conditional expectation

Many studies have documented the use of regression to approximate conditional expectations (Lin, 2018; Strong et al., 2015). According to these studies, Appendix A.3 is used to illustrate the principle of approximating conditional expectation by regression. Firstly, the dependent variable Y is split into the conditional expectation function $E\{Y|X\}$ and a mean-zero error term e. That is:

$$Y = E\{Y|X\} + e \tag{A.14}$$

Where $E\{e\} = 0$. Equation A.10 has a similar form with regression models (Strong et al., 2015). Taking the mean square error regression as an example, it aims to minimize the mean squared error (MSE) between the observed variable Y and regression model $m(x)$.The MSE of $E\{(Y - m(x))^2\}$ is given by:

$$\begin{aligned} E\{(Y - m(x))^2\} =& E\left\{(Y - E\{Y|X\} + E\{Y|X\} - m(x))^2\right\} \\ =& E\left\{(Y - E\{Y|X\})^2\right\} + E\left\{(E\{Y|X\} - m(x))^2\right\} \\ & - 2E\left\{(Y - E\{Y|X\})(E\{Y|X\} - m(x))\right\} \end{aligned} \tag{A.15}$$

Since $E\left\{Y - E\{Y|X\}\right\} = E\{e\} = 0$, and $E\left\{(Y - E\{Y|X\})^2\right\} = E\{e^2\}$ does not impact the optimization. Thus, the minimizing of MSE could be simplified:

$$\underset{m(x)}{\text{argmin:}}\ E\{(Y - m(x))^2\} \equiv \underset{m(x)}{\text{argmin:}} E\left\{(E\{Y|X\} - m(x))^2\right\} \tag{A.16}$$

When $m(x) = E\{Y|X\}$, the $E\{(Y - m(x))^2\}$ reaches to the minimum. Thus, regression $m(x)$ offers a way of approximating the conditional expectation $E\{Y|X\}$.