Applying real options theory to value flexibilities in groundwater remediation: an economic method to identify the optimal remediation strategy

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Danyang Zhang
aus Liaoning, China

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Dekan: Prof. Dr. Peter Grathwohl

1. Berichterstatter: Prof. Dr. Peter Grathwohl

2. Berichterstatter: Prof. Dr. Olaf Kolditz

Abstract

Remediation investment projects are commonly evaluated based on traditional NPV (net present value) method. The traditional NPV method, however, is often misleading because it does not take into account the uncertainty of the future and the flexibilities the manager has in terms of adjusting the remediation strategy on demand. Typical imbedded real options during remediation projects include deferring, stopping and switching: deferring means to watch and to investigate (such as done in monitored natural attenuation, MNA); stopping means that the site manager can stop the remediation once the given target is met; switching means to replace a technology in operation by another technology/option that may become more appropriate in the future. Since these contingent management options are not considered by traditional NPV method, remediation strategies offering ample scope of flexibilities can be easily undervalued and, thus, the decisions made based on the traditional NPV method can be wrong.

This study introduces a new approach for optimal remediation strategy making applying real options theory. MNA, pump-and-treat (P&T) and a permeable reactive barrier (PRB) are considered in this study as example technologies to demonstrate the approach. The remediation time frame is divided into a number of management periods, in which available options may be exercised. Introducing the concentration of the contaminant as the underlying asset, exercise of the options is triggered by the actual level of contamination compared to the given threshold levels. Uncertainty in concentration level is quantified with Monte Carlo simulations. The real options analysis provides the expected values of the alternative strategies. These strategies will be ranked based on their expected values. A hypothetical case is taken to demonstrate the approach and the sensitivity of the results to the changes of parameters is investigated. It is shown that this new approach is capable of identifying the optimal remediation strategy in terms of cost and effectiveness. It is an improvement compared with traditional economic decision-making techniques. The results suggest that real options theory is particularly appropriate to value remediation strategies with flexibility facing future uncertainties, thus having the potential to significantly improve remediation decision making. It is demonstrated that the optimal decision is very much depending on underlying conditions with respect to target and regulation levels, site conditions, economic assumptions, technologies' effectiveness and their uncertainties. Voluntarily postponing MNA and applying more active remedial technology instead is recommended for projects where high economic value of cleaned land calls for high effectiveness.

Zusammenfassung

Sanierungsprojekte werden im Allgemeinen nach der traditionellen Kapitalwertmethode bewertet. Diese berücksichtigt jedoch weder die Unsicherheiten bezüglich der Entwicklung von Eingangsgrößen in der Zukunft noch die Flexibilität, die Sanierungsstrategie in Laufe eines Projektes an die Nachfrage anzupassen, wie es beispielsweise durch Aufschub oder Stopp der Sanierung, oder durch das Wechseln der Sanierungsstrategie geschehen kann. Typisch für den Aufschub der Sanierung ist beispielsweise das Überwachen natürlicher Schadstoffminderungsprozesse (engl.: Monitored Natural Attenuation, MNA). Ein Sanierungsstopp ist gegeben, wenn der Projektleiter die Sanierungsmassnahmen einstellen kann, weil das vorgegebene Ziel erreicht ist. Wechseln der Sanierungsstrategie ist dann eine Möglichkeit, wenn die betriebene Technologie durch eine andere Technologie/ Option, die in Zukunft besser geeignet sein kann, zu ersetzen. Diese möglichen Management Optionen werden durch die traditionelle Kapitalwertmethode nicht berücksichtigt. Deshalb werden Sanierungsstrategien, welche viel Spielraum für Flexibilität bieten, leicht unterbewertet, was dazu führt, dass Entscheidungen, die auf der traditionellen Kapitalwertmethode beruhen, falsch sein können.

Diese Arbeit führt einen neuen Ansatz zur Entwicklung optimierter Sanierungsstrategien unter Anwendung der Real-Optionen-Theorie ein. Diese Studie prüft beispielhaft die Technologien MNA, pump-and-treat (P&T) und reaktive Wand (engl.: permeable reactive barrier, PRB) zur Demonstration des Ansatzes. Der Zeitraum der Sanierung wird in mehrere Managementperioden unterteilt, in denen die verfügbaren Optionen angewendet werden können. Die Konzentration des Schadstoffes wird als Grundlage betrachtet, so dass die Anwendung der Optionen durch den aktuellen Grad der Belastung, verglichen mit dem vorgegebenen Grenzwert bestimmt wird. Die Unsicherheit im Grad der Schadstoffkonzentration wird durch Monte Carlo Simulationen quantifiziert. Die Optionen-Analyse bestimmt den Erwartungswert der alternativen Strategien. Diese Strategien werden nach ihrem erwarteten Optionenwert geordnet. Zur Demonstration des Ansatzes wird ein hypothetischer Fall vorgeführt und die Sensitivität der Ergebnisse gegenüber Änderungen der Parameter untersucht. Es wird gezeigt, dass dieser neue Ansatz die optimale Sanierungsstrategie hinsichtlich der Kosten und Wirksamkeit identifizieren kann. Dies ist eine Verbesserung gegenüber den traditionellen ökonomischen Methoden zur Entscheidungsfindung. Die Ergebnisse weisen darauf hin, dass die Real-Optionen-Theorie sich besonders dazu eignet, Sanierungsstrategien mit Flexibilität gegenüber zukünftigen Unsicherheiten zu bewerten. Somit haben sie das Potential, die Entscheidungsfindung bei

Sanierungsprojekten signifikant zu verbessern. Es wird gezeigt, dass die optimale Entscheidung sehr stark von den Rahmenbedingungen in Bezug auf Sanierungszielwerte, Standort-Bedingungen, ökonomische Annahmen sowie von der Wirksamkeit der Technologien und ihren Unsicherheiten abhängt. Ein freiwilliger Verzicht oder ein freiwilliges Aufschieben von MNA zu Gunsten der Anwendung einer aktiven Sanierungstechnologien wird für Projekte empfohlen bei denen eine hoher Wert der sanierten Fläche eine hohe Wirksamkeit verlangen.

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List of abbreviations and symbols

Abbreviations

BM	Brownian motion
DCF	discounted cash flows
GA	Genetic Algorithm
GBM	geometric Brownian motion
METEORS	a multistage technicoeconomic model
MNA	monitored natural attenuation
NPV	net present value
OV	value of an option
pdf	probability density function
POC	point of compliance
P&T	pump and treat
PRB	permeable reactive barrier
Sc.	scenario
Std.	standard deviation
WACC	weighted average cost of captical

Symbols

B_{land}	benefit from selling the land
c	price of a European call option
CF_t	net cash flow at time t
C_i	cost of scenario i
C_0	concentration at time zero
C_{MNA}	level of the MNA threshold
$C_{MNA,up}$	upper limit of the MNA threshold
C_T	level of the stop threshold
$C_{T,up}$	upper limit of the stop threshold
$C(t)$	concentration at time t
D_t	length of each decision period
E	expected value
f	price of an option
k	conductvity
L_V*	switching land value when the optimal action for the first period changes
mAq	aquifer thickness
M	strategy chance to meet the target
M_i	chance to meet the target for scenario i
NP	number of periods
p	price of a European put option
pi	probability of scenario i
P_{RN}	risk-neutral probability
r	discount rate
S	stock price
$S_{optimal}$	value of the optimal strategy
Std_{MNA}	standard deviation of concentration distribution after a period of MNA
Std_{PRB}	standard deviation of concentration distribution after a period of PRB

$Std_{P\&T}$	standard deviation of concentration distribution after a period of P&T
t	the time when the cash flow occurs
T	total time of the project
V	value of the underlying asset
V_i	value of scenario i
V_{lc}	value of clean land
V_n	value of the strategy n
X	striking price of the underlying asset
y	total width of the contaminated area
σ	volatility of the stock price
λ	decay rate constant
λ_{MNA}	decay rate constant of MNA
$\lambda_{P\&T}$	decay rate constant of P&T
λ_{PRB}	decay rate constant of PRB

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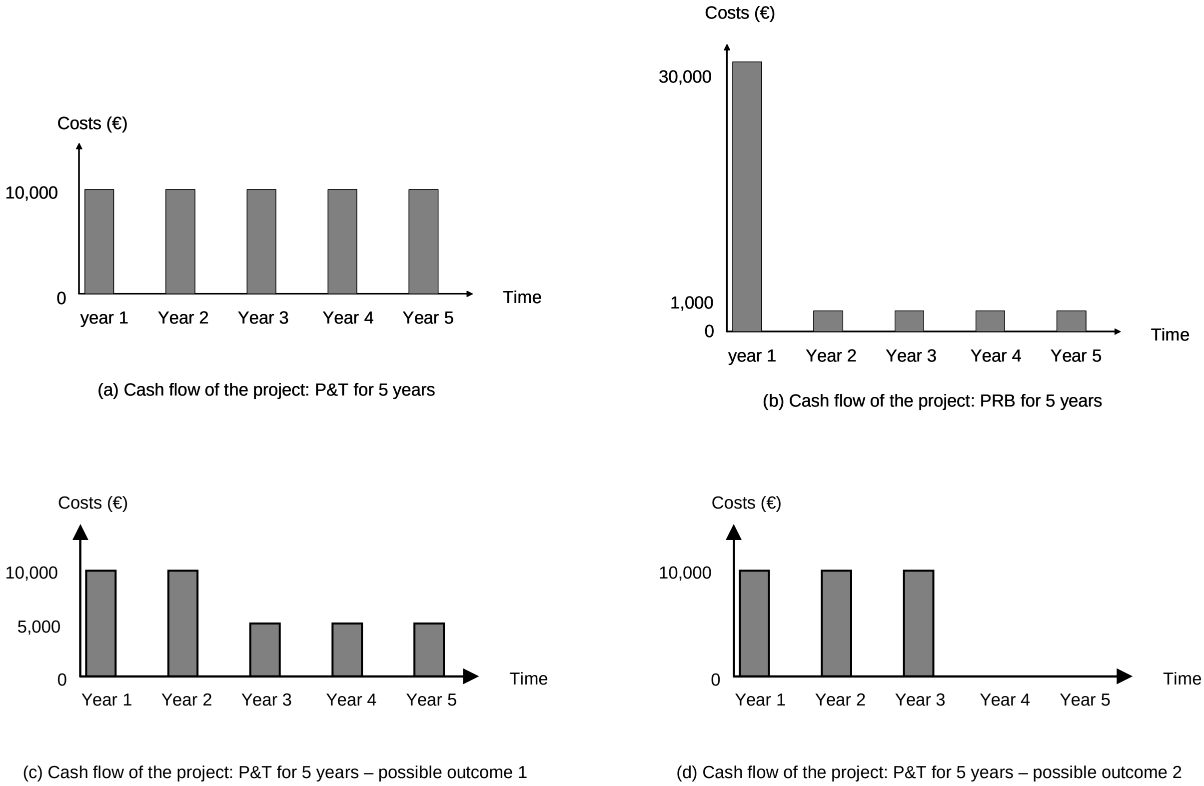
1. Introduction

1.1 Problem description

Remediation investment projects are commonly evaluated by the traditional NPV (net present value) method. This method, however, is often misleading because it does not take into account the uncertainty of the future and the flexibilities the manager has in terms of adjusting the remediation strategy on demand. It assumes a static decision-making process, where the decisions are made at the beginning without the management's ability to change over time. Decisions made based on this manner can easily undervalue remediation strategies offering ample scope of flexibilities, and thus, can not be optimal.

Figure 1-1 shows the deficiency of traditional method for remediation decision making by a greatly simplified example. When choosing the best remediation strategy, traditional approach will define the strategies first, supposing that they will not be changed. For example, two strategies are compared: strategy 1 is to implement P&T (pump and treat) for the entire decision time frame; strategy 2 is to implement PRB (permeable reactive barrier) for the entire decision time frame. The traditional method will value these two strategies based on the cash flows shown in Figure 1-1a and b. Assuming a discount rate of 5%, the NPV (in terms of cost) of the P&T strategy would be 45,460 ERU, whereas the NPV of the PRB strategy would amount to only 33,546 ERU (see chap. 2 for more details). However, it is not taken into account that one technology (here: P&T) might be more flexible than the other one (here: PRB) if the conditions at the site develop differently than expected. To give an example: What if the concentration after some years of P&T is low enough to switch to a cheaper option like MNA (monitored natural attenuation)? In this case, the cash flow will look like Figure 1-1c instead of a. A switch from P&T to cheaper MNA would reduce the cost of this strategy to 32,492 EUR, which is cheaper than the NPV of the PRB strategy. In another case, what if the remediation target is met after some years of P&T? The cash flow will look like Figure 1-1d instead of a. If after three years of P&T the remediation target could be met, strategy cost will become even lower (28,594 EUR).

Situations shown in Figure 1-1c and d are only two examples out of numerous cases which are not considered by traditional method. So the advantage of more flexible technologies such as P&T compared with less flexible technologies such as PRB is not taken into account by the traditional method.



(a) Cash flow of the project: P&T for 5 years

(b) Cash flow of the project: PRB for 5 years

(c) Cash flow of the project: P&T for 5 years – possible outcome 1

(d) Cash flow of the project: P&T for 5 years – possible outcome 2

Figure 1-1: Schematic illustration of the problem of implementing traditional method for remediation strategy making

Real options theory develops together with the criticism and dissatisfaction of the commonly used traditional NPV method. Real options method can be an alternative to the traditional way of valuing strategies. It considers multiple decision pathways as a consequence of management's flexibility to choose the optimal options along the decision path when uncertainty becomes resolved. It provides great insights into the value of flexibility facing future uncertainties. Since the real options theory has not yet been much extended to remediation strategy making, there are not ready made real options models which can be adapted. There are a lot of difficulties and obstacles, which have to be overcome.

Firstly, options in remediation projects are unlike financial options, which are legally defined contracts. Important features such as the underlying asset and so-called embedded options in remediation projects need to be defined before the analysis. This has to be done fulfilling the common spirit of real options valuation in general while reflecting the most critical features of remediation strategy making at the same time. The common spirit of real options valuation is that it is a technique for evaluating investments under conditions of uncertainty. The manager has the flexibility to exercise a certain option depending on the actual outcome of the underlying asset. So there must be uncertainties in the development of the underlying asset. The manager must have the flexibilities to decide what to do. The decisions will be made according to the underlying asset. These main elements have to be identified in remediation projects so that the real options theory can be applied.

Secondly, there is not much research done for valuing complicated path-dependent remediation options. Standard financial options valuation techniques such as Black-Scholes model or the binomial tree and standard real options valuation method in a common sense such as partial diferential equation method are not feasible for the given problem. Because the underlying asset in remediation projects can not be traded; it may not even be necessarily an economic term. And thus it is not possible to make a replicating portfolio as done in the classic way of real options valuation. (A replicating portfolio is a portfolio of assets whose changes in value match those of a target asset. For example, a portfolio replicating an option can be constructed with certain amounts of the stock underlying the option and bonds. This is the method used in the Black-Scholes model.) Moreover, not like a plain option in financial market, there are multiple options involved in the remediation decision making. In a plain European call option, the option holder has the right to buy a certain stock at a certain price on a certain date in the future. He will only exercise the option when the stock price turns out higher than the exercise price of the option. There is only one option (option to buy) and no further consequences. And it does not influence the development of the underlying stock price. In remediation decision making, there are multiple options involved and any decision made is going to influence the future uncertainty of the underlying and flexibility on that path. A new innovative option valuation approach is needed to deal with the specific problem in remediation strategy making.

Thirdly, the method developed is greatly simplified as one of the first attempts to solve remediation decision making problems by real options valuation. There is future research potential to extend the method to solve more sophisticated problems and to improve its applicability and accuracy.

1.2 Thesis objectives

The first objective of this thesis is to examine the shortcomings of the traditional way of remediation strategy making from a financial perspective to compare with the innovative real options method. The purpose is to indicate that even though the traditional way is widely taught and easy to implement, it is not proper for most of the investment projects in real world, including remediation investments. Extra insight should be given by the real options approach to provide better strategy recommendation.

Even though there are some methods which are applied to value real options, direct application of any classic method of real options valuation in remediation projects would end up with searching for proper questions to the given methods. The second objective of this thesis is to develop and illustrate a new approach that is specially designed for remediation real options valuation. This new approach will be applied to compare remediation strategies quantitatively in terms of their costs and effectiveness facing uncertainty with the help of the real options method. By means of a hypothetical case study it will be demonstrated how a strategy valuation based on real options may provide decision makers with practically improved and theoretically founded guidance for optimal long term remediation strategy making.

The third objective is to investigate the sensitivity of the results to changing parameters. Five categories of parameters are investigated: regulative, site-specific, economic, technology-related, and time parameters. Regulative parameters are related with the thresholds. These thresholds can change when sites are contaminated on different levels and when the regulations change. Site-specific parameters include aquifer thickness, conductivity and total width of the contaminated area. Site-specific parameters are highly dependent on the conditions of different contaminated sites. Economic parameters include land value, technology cost and discount rate. Technology-related parameters include effectiveness and uncertainties of technologies' effectiveness. Time parameters include total time frame of the project and number of decision periods in the project. It is intended to generalize the roles of these parameters in the optimal strategy making.

The fourth objective of this thesis is to identify the research potentials and opportunities in the future regarding the further development and application of this new approach for remediation strategy making. This study does not provide a final solution but a pioneer method with several simplifications. It uses abstracted descriptions of technology effects and costs, is based on several simplifying assumptions, and possesses some limitations with regard to its applicability. Hence there is a great potential to continue and improve the work started in this thesis. The inspiration for future research is also an important goal of this study.

1.3 Thesis outline

Traditional NPV method and real options theory

In this chapter, at first, the traditional NPV method, which is commonly used in investment valuation, and its shortcomings are presented. This method is applied to a simple example of remediation project to demonstrate its principles and limits. After that, the real options theory is introduced. Its origins from financial option pricing theory and some common methods of real options valuation are presented.

Previous real options applications for environmental projects

This chapter provides an overview of previous work on the application of real options theory to environmental projects. It first reviews some work on general environmental projects, concerning their methods and findings. In the second part special attention is paid to the application on remediation projects. A critical assessment of the previous studies of other researchers in this area is provided.

Real options valuation model for optimal remediation strategy making

This chapter describes how the real options valuation model is built up in this study step by step. Firstly, the main uncertainty involved in remediation projects is identified. Then the options that the decision maker has during the project life time are investigated. After that a decision tree to solve this problem is built. Then it is demonstrated how the strategies are valued and the optimal strategy is defined and recommended. Finally, it shows how the optimization algorithm solves the problem when the number of periods becomes big.

Application of the valuation model to a hypothetical case

In this chapter, the real options valuation model for optimal remediation strategy making is applied to a hypothetical case. After defining all the relevant assumptions concerning the regulative parameters, site parameters, economic parameters, technology parameters and time parameters, the strategies are evaluated with the model developed in this study. It is shown how the optimal strategy can be identified and the optimal remedial activity to start with can be recommended.

Parameter sensitivity analysis

This chapter describes the results of the sensitivity analysis. Using the previous case as a reference case, a comprehensive analysis of different types of parameters (regulative, site-specific, economic, technology-related, and time parameters) is conducted, in order to assess these parameters' influence on the outcome of valuation.

Future research

This chapter focuses on the future research potential. Further studies are needed for a more successful application of real options theory to the optimal strategy making for remediation projects. The possible directions of research needed are listed.

Conclusions and discussion

This chapter provides the main conclusions and the final discussion of this PhD thesis about the application of real options theory to optimal remediation strategy making.

2. Traditional NPV method and real options theory

2.1 Traditional NPV method and its shortcomings

Net present value (NPV) is used to calculate the present value of multiple future cash flows. The nominal net value of any future (past) monetary benefits and costs is discounted (accumulated) to its present value. There are two reasons for discounting: time value of money and risk. In other words, one Euro today is worth more than one Euro in the future; One Euro which is safe is worth more than one Euro which is risky. The common formula for NPV is as follows:

$$NPV = \sum_{t=0}^{T} \frac{CF_t}{(1+r)^t} \qquad \text{(Eq. 2-1)}$$

Where, t is the time when the cash flow occurs, T is the total time of the project, r is the discount rate, and CF_t is the net cash flow, which is the cash inflow minus the cash outflow at time t.

Even though the traditional NPV rule is relatively simple, widely taught and accepted, its assumptions neglect two main issues in decision making: 1, the fact that there are uncertainties in the project, which can not be easily predicted today. 2, the management's strategic flexibility to make the decisions as these uncertainties become known over time. Table 2-1 shows the main assumptions of NPV comparing with reality.

Table 2-1: Comparison of traditional NPV assumptions and the realities

Traditional NPV assumptions	Realities
Decisions are made now and never changed again.	Not all decisions are made today; some are open for the future when uncertainties become resolved. Decisions can be changed in the future.
Future scenarios are fixed according to the prediction today.	Future scenarios are uncertain; the development is usually stochastic and risky in nature.
Once the decision is made, the project will be passively managed.	A project is usually actively managed through the project's life.

In the introduction, two remediation strategies are compared by the traditional NPV method. The detailed calculation is shown below. Assume that P&T costs 10,000 EUR every year. PRB costs 30,000 EUR in the first year and 1,000 EUR every year after the first year. According to equation 2-1, the present value of the costs of these two strategies can be calculated as the following:

$$NPV_{P\&T} = \sum_{t=0}^{4} \frac{10{,}000}{(1+5\%)^t} = \frac{10{,}000}{(1+5\%)^0} + \frac{10{,}000}{(1+5\%)^1} + ... + \frac{10{,}000}{(1+5\%)^4} = 45{,}459.5$$

$$NPV_{PRB} = \sum_{t=0}^{4} \frac{30{,}000}{(1+5\%)^t} = \frac{1{,}000}{(1+5\%)^0} + \frac{1{,}000}{(1+5\%)^1} + ... + \frac{1{,}000}{(1+5\%)^4} = 33{,}546.0$$

As mentioned in the introduction, the decision made based on this method is not optimal. This is because of three reasons: 1. Flexible technologies, such as P&T are undervalued. 2. The active management is not given value. 3. Potential better strategies are not investigated. As a result, another valuation method which is more capable for the remediation strategy making is needed.

This is not to say that NPV should be abandoned in all kinds of investment decision making. NPV method was first developed to value bond and stocks held passively by the investors (Trigeorgis, 1996). Fisher's book "The Theory of Interest" in 1930 and Williams' book in 1938 "The Theory of Investment Value" were the first to express the DCF (discounted cash flows) method in modern economics. It is proper for investment projects with low uncertainty and passive management (Figure 2-1). An example for this kind of investment is government bond. The future cash flows are certain. And the bond holders are passive investors because there is little they can do to bonds to alter the cash flows. For investment projects with uncertainty and active management, which is the case for most of the investment projects including remediation projects, the traditional NPV method is not feasible because it becomes impossible to forecast exact future cash flows and companies are not passive investors. Facing uncertainty, companies have the flexibility to sell the asset, invest further, wait and do nothing, or abandon the project. The alternative valuation method for this kind of investments is the real options method. (See Figure 2-1)

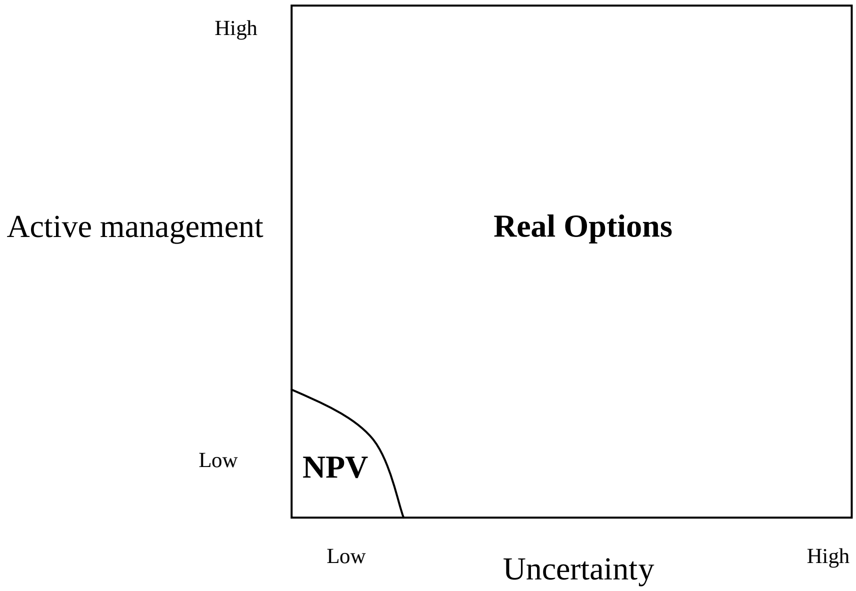


Figure 2-1: The difference between traditional NPV method and the real options method

2.2 Real options theory

The real options theory origins from the option pricing theory in financial market. So before introducing the real options theory, a brief introduction of financial options shall be given below.

2.2.1 Financial options and option valuation

The concept of options exists since ancient times. In ancient Greece, Thales used options to secure a low price for olive presses in advance of the harvest. In the early 1600s, trading in tulip options blossomed in Holland during the tulip mania. The planted tulip bulbs are only payable at the buying date if the harvested bulb exceeds a certain weight. (Brach, 2003) The common spirit in options is that it is a right but not an obligation to take a certain action. The action will only be realized if the actual situation meets a certain criterion. Above are some early examples of options. When stocks appeared in history, options on stocks also existed. But they were not traded on an exchange. Buyers and sellers had to find each other by themselves and prices are arbitrary. Options were difficult to deal with and were very illiquid at that time. The birth of modern options came with the work of Black and Scholes and Merton on option pricing in 1973, which could determine the fair market value of options. Within the same year, the Chicago Board of Trade opened the Chicago Board Options Exchange. Since then, modern financial options market came into existence. A financial option is defined as follows: An option provides the holder with the right, but not the obligation to buy or sell a specified quantity of an underlying asset at a predetermined price (called a strike price or an exercise price) at or before the expiration date of the option. A call option gives the holder the right to buy the underlying asset at or before a certain date for a certain price. A put option gives the holder the right to sell the underlying asset at or before a certain date for a certain price. The option which can be exercised at any time before the expiration date is called an American option. The option which can be only exercised at the expiration date is called a European option. (Detailed information please find in Hull (2005), Natenberg (1994), Kolb (2002), and Fontanills (2005).

Attempts to value derivatives such as options have a long history, the French mathematician Louis Bachelier showed one of the earliest attempts in his doctoral thesis, The Theory of Speculation (Bachelier, 1900). He tries to price options on French Government bonds. He used Brownian motion (BM) to model the fluctuation of stock prices on the market. He was on the right track. But BM allows stock price to be negative. However, it is under Bachelier's work that the geometric Brown motion later on became a basic model for a stock price process in the modern theory of finance. Samuelson (1965) considered perpetual American options (an option with an infinite expiration date is considered to be perpetual). He used geometric Brownian motion (GBM) to model the random behavior of stock. GBM limits the values strictly greater than zero compared with BM; it is a more reasonable description of stock price dynamics. In his model, the expected rate of return of the stock and the discount rate for the option is depending on the unique risk characteristics of the underlying stock and the option. Thus, this model is greatly arbitrary because of the arbitrary discount rate. Until then, no one could figure out consistently how much options should cost for people with different risk aversions which cause different discount rates. The breakthrough came with the work of Black and Scholes (1973) and Merton (1973). They also use GBM to model the development of the stock price. But their work is based on the no-arbitrage condition in a risk neutral world. No arbitrage requires that the market is complete and there are sufficient amount of active investors with complete information who will notice any possible mispricing, put a lot of pressure on it, and quickly eliminate it. As a result, there are no arbitrage opportunities. In a risk neutral world the investor requires no excess return for taking risks, and the expected return on all securities is the risk-free rate. In their model all cash flows are discounted at the risk free rate. In 1997, Scholes and Merton won the Nobel Prize in economics for this seminal work (Black had died in 1995), which made derivatives very popular financial instruments and lead to the rapid growth of financial market in the last decades. The Black and Scholes model is still the most widely used option pricing model used by traders today.

In order to derive the formula, Black and Scholes construct a risk-free portfolio consisting of a certain amount of options and a certain amount of stocks. Assuming no arbitrage, this portfolio earns the risk free interest rate. The derivation of the differential equation is out of the scope of this thesis. Interested readers can have a look at classic finance text books for details (Hull, 2005). The differential equation is:

$$\frac{\partial f}{\partial t} + rS\frac{\partial f}{\partial S} + \frac{1}{2}\sigma^2 S^2 \frac{\partial^2 f}{\partial S^2} = rf \qquad \text{(Eq. 2-2)}$$

f is the price of an option (it can be both a call option and a put option), *t* Is the time, *r* is the risk free rate, *S* is the stock price, σ is the volatility of the stock price. Depending on different boundary conditions, formulas for different option types can be derived. In case of a European call option on a non-dividend paying stock, the price of the option at time zero is:

$$c = S_0 N(d_1) - Xe^{-rT} N(d_2) \qquad \text{(Eq. 2-3)}$$

In case of a put option, it is:

$$p = Xe^{-r(T-t)} N(-d_2) - SN(-d_1) \qquad \text{(Eq. 2-4)}$$

Where

$$d_1 = \frac{\ln(S_0 / X) + (r + \sigma^2 / 2)T}{\sigma\sqrt{T}} \qquad \text{(Eq. 2-5)}$$

$$d_2 = \frac{\ln(S_0 / X) + (r - \sigma^2 / 2)T}{\sigma\sqrt{T}} = d_1 - \sigma\sqrt{T} \qquad \text{(Eq. 2-6)}$$

c is the price of call option, p is the price of put option, X is the striking price of the underlying asset, T is the time to maturity, and N(x) is the cumulative probability function of a standardized normally distributed variable x. Using other boundary conditions, formulas for other types of options can be derived.

Some option values may be solved through closed-form analytical solutions such as the Black-Scholes formula, but some can not. In case there is no analytical solution, numerical methods must be used. Simulation, binomial lattice and finite difference method are three commonly used methods.

Boyle (1977) proposed a Monte Carlo simulation approach for European option valuation. Simulation models simulate thousands of possible paths of the value evolution of the underlying asset from time zero to the expiration date. Decisions can be made according to the outcomes. The expected value is discounted by the risk free rate back to time zero to obtain the option value. It is very useful for valuing options where the payoff is dependent on the path of the underlying asset or where there are multiple underlying variables. The binomial technique was originally developed by Cox, Ross and Rubinstein (1979). The life of the option is divided into a number of small time intervals of length Δt. They assumed that in each time interval, the value of the underlying asset V either moves up to uV or down to dV. The binomial tree showing the development of the underlying asset can be drawn. The option value at each final node can be calculated. It is max [(S-X), 0] for a call option, and max [(X-S), 0] for a put option. (S is the value of the underlying asset, X is the exercise price.) With the risk-neutral probability $P_{RN} = (R-d)/(u-d), (R=e^{r\Delta t}, u = e^{\sigma\sqrt{\Delta t}}, d = 1/u)$ the value of an option is $OV = (P_{RN} *OV_u + (1- P_{RN})*OV_d)*e^{-rt}$. The expected option value at each time step can be calculated backwards. The value for the very beginning node in the binomial tree is the value of the option value in question. The finite difference method was first proposed by Schwartz (1977). The partial differential equation which represents the option value is replaced by a set of difference equations by discretising all state variables. The first and second derivatives are replaced by a finite difference approximation. The continuous differential equation is approximated with a discrete difference equation. Option value is calculated by solving the difference equation. There are two state variables, stock price and time to maturity. Time is discretized into M intervals and price into N intervals. This can be shown in an M by N grid. Knowing the stock price at maturity, the option value at maturity is max [(S-X), 0] for a call option, and max [(X-S), 0] for a put option. The other boundary conditions are: when the stock price is zero, option value is K for a put option, 0 for a call option; when the stock price is N, option value is 0 for a put option, (N-X) for a call option (N>X). The option value is calculated backwards from the maturity time to time zero. For a detailed description of these three methods, see Hull (2005).

2.2.2 From financial options to real options

As implied by the name, real options evaluate real physical assets, instead of financial assets. They have some similarities with financial options. An important feature for both of them is flexibility. A real option is commonly defined as any decision that creates the right, but not the obligation, to pursue a subsequent decision. The highlight is that business decisions are flexible in the context of strategic capital investment decision making. It is very often related with strategic planning.

Real options theory develops together with the criticism and dissatisfaction of the traditional way of capital budgeting, the commonly used NPV method. In the traditional approach, the future cash flows of an investment are calculated and discounted to the present. If this present value minus the cost is greater than zero, it is said that the NPV is positive and the investment decision is a “go”; otherwise not. (For remediation projects, NPV can be negative.) It assumes that either the investment is reversible, or, if the investment is irreversible, it is a now or never problem. It implies that the cash flows are fixed and the manager acts passively. These assumptions are not true for most of the investments in the world. As mentioned by Brennan and Schwartz (1985), the major deficiency of this approach is the neglect of the stochastic nature of cash flows and the capability of managers to respond. This method can easily undervalue projects with imbedded options, because the value of flexibility is considered to be zero. Thus the traditional NPV method, which is applied very often due to its simplicity, must be recognized to provide wrong results in many cases. Realising the limitation of the traditional NPV method and the value of flexibility, there are some extensions of the traditional method, such as scenario analysis and expected value analysis. These methods model the future development as several different outcomes to find the expected return. They are an improvement compared with traditional NPV method. Still, there is no management reaction involved. So the value of flexibility is still not reflected.

In the 1970s Arrow and Fisher (1974) and Henry (1974) introduced the term of “quasi-option value” in environmental economics. Their setting is that the future cost of the current irreversible environmental damage is uncertain. In their framework, the option value represents the value of the information that becomes available when uncertainty is resolved over time. At the same time with the breakthrough of Black-Scholes option pricing model (Black and Scholes, 1973, Merton, 1973) in finance, the techniques for pricing real options has been developed independently in the investment research. The term “real options” was coined by Stewart Myers in 1977, referring to the application of option pricing theory to the valuation of real physical investments with learning and flexibility. Today, the term of real options has been broadened. It is not restricted to the application of option pricing theory from finance. Real options approach became a systematic and integrated approach using financial theory, economic analysis, management science, decision sciences, statistics and econometric modelling in valuing real physical assets in a dynamic and uncertain business environment. Typical real options include deferring (to wait before taking an action until more is known or the timing is expected to be more favorable), expanding or contracting (to increase or decrease the scale of a operation in response to the actual situation), switching (to alter the mix of inputs or outputs of a production process) and abandoning (to discontinue an operation and liquidate the assets).

The first applications of real options theory were to natural resource investments. After that, it was applied in other areas such as research and development, development of new technologies, company valuation and so on. Brennan & Schwartz (1985) demonstrated how to apply real options theory to value natural resource projects and to derive optimal decisions. McDonald & Siegel (1986) stress the option value of postponing an irreversible investment. Dixit & Pindyck (1994) provided conceptual real options frameworks for capital budgeting decisions. The application of real options theory to remediation projects is an idea still in its infancy. Some applications in environmental projects including remediation projects will be discussed in Chapter 3.

2.2.3 Methods of valuing real options

The methods for valuing real options are contingent claims (the same method introduced in session 2.2.1, this term is given by Dixit and Pindyck (1994) when dealing with real options), dynamic programming and integrated decision tree & Monte Carlo based method. Different kinds of real options can be solved differently by different methods. Each of these methods has its specific features which limit them to certain kinds of problems.

2.2.3.1 Contingent claims approach based on "no arbitrage" assumption

Since we are treating investment opportunities as options instead of static cash flows, it is a straightforward idea to apply directly option pricing theory from finance. This is the method introduced in session 2.2.1. Either there is an analytic solution as in the Black-Scholes model or it needs to be solved numerically, the basic assumption is the no arbitrage condition in a risk neutral world. Dixit and Pindyck (1994) refer to this approach with the general term "contingent claims". The basic idea is the construction of a replicating portfolio of existing assets for the real option in question. Discount rate is not subjectively set. All values are discounted at the risk free rate. It has been recommended by Brennan and Schwartz (1985), Trigeorgis and Mason (1987), Copeland, Koller and Murrin (1994) and Trigeorgis (1999). Amram and Kulatilake (1999) have the most extensive exposition of this approach. They assume that capital markets are complete. All corporate investments have equivalents in the capital markets and can be effectively hedged through a traded tracking portfolio. The calculated value is the “no arbitrage” value of the investment.

The contingent claims approach employs the standard replicating portfolio way of thinking for financial option pricing, as in the Black-Scholes model (Black and Scholes, 1973, Merton, 1973). The basic idea is to derive a partial differential equation reflecting the value of a risk free option-stock portfolio, with gradual changes in its composition approaching the maturity of the option. The key to the problem is the solution to certain partial differential equations. Brennan and Schwartz (1985) demonstrated how to use this approach to value natural resource projects and to derive optimal decisions as one of the first applications of real options. With the concern of remediation projects, Lentz and Tse (1995) used the option pricing approach to value real estate contaminated with hazardous materials.

One important drawback of contingent claims approach for real options valuation is that the “no arbitrage” condition may not hold in some cases in real options. Dixit and Pindyck (1994) stated that “Specifically, capital markets must be sufficiently “complete” so that, at least in principle, one could find an asset or construct a dynamic portfolio of assets…the price of which is perfectly correlated with V. … However, there may be cases in which this assumption will not hold.” (V is the real option value in question) For these cases in real options, “no arbitrage” is usually hard to prove valid. The principle of no arbitrage does not require every individual in the market be fully rational, but it does require that sufficiently many motivated decision makers with access to sufficient resources notice any possible mispricing, put a lot of pressure on it, and quickly eliminate the mispricing. And thus, there is no risk-free net profit. This is much too rigid for a lot of real asset markets. Another objection to contingent claims is that a risk free portfolio can not be constructed because these real assets based on which the real options are valued are not even traded. So, even though getting inspiration from the option pricing theory in financial market, contingent claims approach is not a proper way for a lot of real options based on real assets.

2.2.3.2 Dynamic programming

Dixit and Pindyck (1994) propose the use of dynamic programming in those cases where “no arbitrage” is not a reasonable assumption. Dynamic programming is an approach developed by Bellman and others in the 1950’s. It is used extensively in management science. It formulates the problem in terms of a Hamilton-Jacobi-Bellman equation and solves backwards with respect to time for the value of the asset. The word “programming” has no connection to computer programming. It comes from the term “mathematical programming”, a synonym for optimization. The “dynamic programming” mentioned in this chapter is the method presented by Dixit and Pindyck (1994) about how to value in continuous time the option of waiting. The idea is that the whole sequence of decisions is split into two parts: the immediate choice and the remaining choice; the optimal decision can be found by working backwards. A partial differential equation can be derived and the solution to it is the option value. By solving the equation, the optimal timing to exercise the option can also be indicated. When the differential equation cannot be solved analytically, it needs numerical methods as in contingent claims analysis. Attention should be paid to the discount rate used in contingent claims and dynamic programming. No arbitrage assumption in a risk neutral world is the condition for applying risk free discount rate in contingent claims approach. When the assumption does not hold, dynamic programming is applied; a discount rate other than risk free rate has to be set subjectively. Insley (2002) used dynamic programming and finite difference approach to estimate the optimal timing of the option to harvest a forest. For remediation projects, the market for land after remediation is far from complete, no-arbitrage condition does not hold. Thus dynamic programming instead of contingent claims should be applied. As remediation projects are concerned, Conrad and Lopez (2002) developed an option-pricing model to rank investments that might improve water quality. They suppose that the development of the concentration of the pollutant over time is a Brownian motion. They consider the damage based on the concentration of the pollutant as an underlying asset, the costs as exercise price (see also chap. 3).

One disadvantage of dynamic programming is the subjective assessment of the discount rate. Another disadvantage of this method is that it is only valuing one option: the option of deferring. When there are several options involved, it can not handle the problem.

2.2.3.3 Integrated decision tree & Monte Carlo based real options analysis

Decision tree analysis is very often used to assist decision makers choose among various decision options in time when these options will lead to uncertain consequences. The problem is demonstrated over time in a hierarchical structure of nodes. Figure 2-2 shows an example of a decision tree for a three-stage decision problem. The squares are decision nodes. They represent the decisions made based on the actual situation among all possible decision options. The circles are probability nodes. They represent the probabilities of the sequences after taking a decision. A utility function is set by the decision maker. The expected value of the utility function is calculated for different combination of decision nodes bases on the probabilities. The result of the decision tree analysis is the best combination of all the decisions maximizing the utility function. It has a lot of advantages which make it a proper tool to identify and structure real options. First, it has the strength in addressing sequential decisions. Second, it is very flexible in capturing the underlying and the decisions. Last but not least, it is not a black box; it is easy to explain to the management. A lot of economic models which deal with real options valuation are based on the underlying principles of decision tree analysis. Some examples are given in the next chapter.

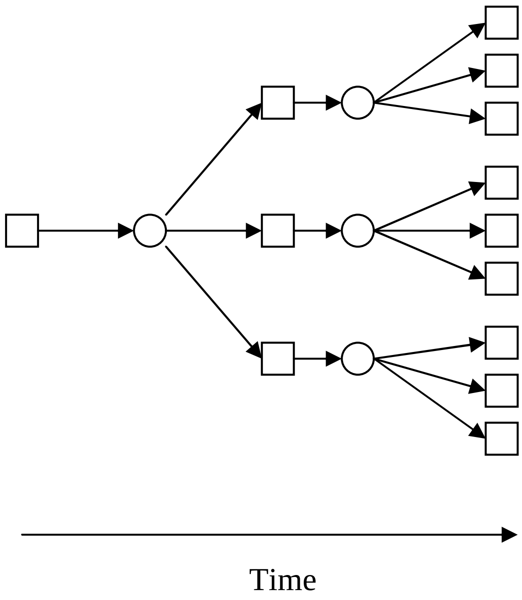


Figure 2-2: Typical structure of a decision tree

The Monte Carlo simulation was originally developed to address the issue of uncertainty. Basically it generates an ensemble of realizations of the output based on random sampling of probability distributions of the input variable. With increasing number of realizations, the results become more reliable. In capital budgeting facing uncertainty, it became a very useful tool. The use of Monte Carlo simulation to value financial options was introduced by Boyle in 1977. For valuing real options, Monte Carlo simulation is also a very practical tool, which can be combined with other techniques such as a decision tree as a parameter determining technique.

As discussed previously, contingent claims approach is not proper for most real options problems because of the rigid “no arbitrage” assumption. Dynamic programming approach is not proper for projects with multiple options. The integrated decision tree & Monte Carlo simulation based technique provides a new inspiration for real option valuation. It is a practical tool because of the flexibility to deal with different kinds of management flexibilities facing various types of uncertainty sources. It does not require complete market nor complete information. There can be more than one options involved in the valuation. The uncertainty does not have to be a typical process used in contingent claims and dynamic programming such as GMB. This integrated approach involves building a tree representing all alternatives, all possible situations and the rational response options of the management. Expected cash flows are calculated based on the probabilities, which are calculated based on the Monte Carlo realizations simulating the future uncertainties. The discount rate is chosen usually using the weighted average cost of capital (WACC). The optimal strategy and its associated value are determined based on a backwards calculation. It is a very straightforward way to demonstrate the sources of uncertainties and the future decisions. Amram and Kulatilaka (2000) showed how to use this method, using pharmaceutical R&D as an example.

This method shares a disadvantage with the dynamic programming approach; it applies a fixed subjective discount rate to the analysis. However, this method is proper to illustrate the idea of real options and approximate the value of flexibility. More research is needed for the justification of discount rate proper for remediation projects, which accurately represent the risks involved in the projects. However, the discount rate discussion is out of the scope of this thesis.

3. Previous real options analysis for environmental projects

3.1 Applications to general environmental projects

As mentioned in the previous chapter, economists have extended the financial options theory to real options theory to value real assets in the real world. They are aware of the value of flexibilities and active management facing future uncertainty. For environmental projects, like the other investments projects, there are usually a lot of flexible options to choose when a decision has to be made. The management is not passive investors. They are able to make rational decisions facing the actual situation. Most of these decisions have irreversible consequences. These characteristics of environmental projects are especially proper for real options valuation.

"Quasi-option value" was introduced by Arrow and Fisher (1974), and Henry (1974). In both studies, the analysis of the land development under uncertainty was conducted in a two-period model. The decision maker has to choose between preservation and development. They show that for the "development" plan, "the expected value of benefits under uncertainty is seen to be less than the value of benefits under certainty" (Arrow and Fisher, 1974). The value of this difference is called quasi-option value. This is the extra value for preserving an option under uncertainty. Ignoring this value, irreversible "development" plan would be overvalued. They showed that flexibility has value in environmental decision making. Making an irreversible decision eliminates this option value of preservation.

Greenley et al. (1981) developed a procedure for measuring the option value of water quality and applied it to a case study in the South Platte River Basin, Colorado, US. The objective of the study was "to test empirically the application of the Henry framework in the measurement of benefits of water quality improvement." Utilising the model of Henry (1974) they compare the benefit from a large expansion in mining development and the option value of postponing the decision and preserve the water quality. Similarly, they also compare the benefit from the current water based recreation use and the option value of non-use preservation values. They "provide an empirical test of Weisbrod's (1964) proposal that option value and other preservation values should be added to the aggregate consumer surplus of recreation activities to determine the total benefit of environmental amenities to society" (Greenley et al. 1981).

Lentz & Tse (1995) used the option pricing approach to value real estate contaminated with hazardous materials. They assumed that the property owner has the option to remove the hazardous materials and further more redevelop the property. They followed the contingent claims method presented by Dixit and Pindyck, assuming the property cash flows and the redevelopment cost to be stochastic processes. The differential equation was derived and closed-form solutions are provided. The criteria to determine the value maximizing strategy were developed. The option value of real estate and the optimal removal and optimal redevelopment point are identified.

Conrad (1997) applied the real option approach for the decision problem of whether or not to cut an old-growth forest. It is assumed that the value of the old-growth forest is a known constant; the amenity value is a GBM process. The partial differential equation for the option value is derived and analytic solution is provided. The critical amenity value can be identified to decide when to cut the forest.

Forsyth (2000), building on Conrad (1997), used option pricing theory to decide whether or not to preserve a wilderness area. She followed the dynamic programming method demonstrated by Dixit and Pindyck, assuming the amenity value of the wilderness area follows a stochastic process. A numerical method (finite difference) was used to solve the differential equation. Critical levels for amenity value necessary to justify preserving a wilderness area were calculated. She demonstrated the importance of the assumed stochastic process to the results by showing the dramatic effect on the critical value by changing the stochastic process from GBM to a logistic growth process. Since the movements of a lot of underlying assets of real options are not like stock price, which can be described by GBM, the assumed process should be carefully chosen.

Conrad & Lopez (2002) presented an option-pricing model to rank investments that might improve water quality. They applied the framework demonstrated by Dixit and Pindyck to value investment options for the provision of safe drinking water for New York City. It was assumed that the pollutant concentration is stochastically increasing over time, and that the pollution causes damage if pollutant concentration exceeds a given threshold. Two options, the implementation of a watershed management plan to improve water quality, and the filtration of water were considered. Differential equations were derived and solved analytically for the critical barriers (concentration or damage), which would trigger the implementation of a particular project. They concluded that "the option-pricing approach provides the theoretically correct way to rank projects that might improve water quality. It provides a logical framework for integrating stochastic models of water quality with economic measures of cost and damange" (Conrad & Lopez, 2002)

Bosetti et al. (2004) applied an optimal adaptive development strategy option valuation model to consider development possibilities of land that has been degraded through previous economic activities. They built up a discrete-time, stochastic model and applied it to Ginostra, a town on Stromboli island in Italy. Three options are considered: 1. preservation, 2. remediation, 3. development. Expected present values are calculated for different strategies. The optimal adaptive development strategy is determined and the option value is calculated.

3.2 Applications to remediation projects

The real options involved in a remediation project are mainly the remedial activities that should be implemented and their timing. These activities include: 1. wait and do nothing, 2. choose a certain technology and remediate, and 3. stop if the remediation target is met. The underlying parameter in these decision makings is not economic terms. It is the contaminant concentration. The contaminant concentration decides whether the remediation has to start right away or it is allowed to wait; it decides which technologies are allowed to be implemented; it also decides if the target is met or not. Some integrated decision supporting tools involving real options were investigated by some researchers to assist remediation decision making.

Bage & Samson (2002) developed a multistage technicoeconomic model (METEORS) to select the optional strategy for the remediation of a contaminated site and to determine the strategy value. They extended the traditional cost-benefit analysis (mentioned as traditional NPV method in this thesis) by considering irreversibility of remediation technologies, technology effectiveness, and uncertainty of contamination development. Benefit is generated from selling or development of the site and costs are generated by the remedial activities and information acquisition. Two technologies were considered: bioventing and biopile. They considered the implementation of an ex situ technology bioplile requiring irreversible excavation (once the material is excavated, the option of in situ remediation is permanently eliminated); while it is considered reversible to implement an in situ technology bioventing which preserves the option to switch to a different technology (either in situ or ex situ). In their multistage model, there are three alternatives at the beginning of each new stage: select a technology, acquiring new information and then select a technology, and do nothing. Three site situations are considered in the model (heavily contaminated, moderately contaminated and weakly contaminated). It is assumed that the effectiveness of the technology decides the probability of attaining a given situation from an initial site situation. Through consideration of all possible site situations and their probabilities of occurrence due to different combination of technology choices, the expected value of the site remediation strategy can be expressed as a weighted mean of the values of the remediation applied to each of the situations (value means benefit minus cost). The technical and economic evaluation of a remediation strategy is integrated into this single expected value. These values for different strategies are compared and an optimal strategy is the one with the highest strategy value.

Wang and McTernan (2002) developed an environmental decision analysis model to identify optimum remediation approaches for contaminated aquifer systems. They combined stochastic hydrology, risk assessment, simulation modeling, cost analysis into the decision making process for a Superfund site in the southern United States. Monte Carlo simulation of transport modeling was employed to define the outcomes of contaminant excursions. Bayesian modeling was used to define the worth of additional data. These modeling were combined with a decision tree to identify optimum remediation configurations. Sensitivity analysis was performed to investigate the effect of decision parameters (capital, operational and maintenance costs). Two technologies were considered: 1. bioremediation and 2. pump and treat. The time required to remediate the site was set to be 10 years, which is the same for all remedial action alternatives. Their research questions are: is remediation necessary? when should the remediation start, and what remediation technique should be employed? A geostatistical approach called conditional simulation was used to determine the size, location and concentration distribution of the plume. Three states of nature were used based on the concentration of contaminant within the groundwater reaching the POC (point of compliance). The probabilities for these states of nature generated by the groundwater models using Monte Carlo simulation were used in the decision tree analysis to calculate the expected cost. The costs considered are the costs due to the remedial activity and the cost of failure (failure is defined as exceeding a certain level of the contaminant concentration). It is a cost minimizing decision model. The optimal strategy is the one with the lowest cost.

The work of Bage & Samson (2003) describes an application of the model METEORS presented in Bage & Samson (2002) to a hypothetical site. The same two technologies, three alternatives at the beginning of each stage, and three site situations as stated in the 2002 paper are considered in the application. Two stages are involved in the project. The biopile treatment effectiveness index was fixed to 100%, meaning that it is guaranteed to produce a final site situation that is weakly contaminated. The bioventing treatment effectiveness was set to be less than 100%, which are given for different original levels of contamination. They built up a decision tree showing all choices with different paths and the probabilities of occurrence. Expected strategies values are calculated (calculation method described in 2002 paper) and the strategy with the highest strategy value is the optimal. They commented that for more complex simulations (more available technologies, more stages or more possible situations), the implementation of the model becomes more difficult. When the amount of possible strategies becomes large, strategy value calculation and the optimal strategy identification will need the assistance from computer programming

Bage & Samson (2004) presented another application of METEORS to a real diesel-contaminated site. The same two technologies, three alternatives, three site situations as stated in 2002 paper are considered. The effectiveness of bioplile is fixed to 100%. An effectiveness index for bioventing was developed to quantify the probability of reaching a given state from a given situation. Eight parameters (associated with site and contaminant) were weighted using a two by two comparison methods to calculate the effectiveness of bioventing. Different time constraints were tested which could restrict the set of available technologies. Different time restrictions have been tried using the model, varying from one to five years (stages), along with one simulation without time restriction. “The output of the model is a remediation strategy that guides, year after year, the selection of the most optimal technology considering the evolution of the remediation.”

3.3 Discussion

The previous research work on the application of the real options methodology in environmental decision making, in particular for optimal remediation strategy making, provide inspiration, concepts, and methods that could be followed in this thesis. Connections to this thesis: 1. The remediation technologies and their timing as real options. 2. The future contaminant concentration as the underlying asset. 3. The decision tree as a tool to analyze the problem. 4. Monte Carlo simulation as a tool to capture uncertainty of the future contaminant concentration. 5. Cost and benefit sources and 6. Expected value calculation method. But there are also shortcomings that had to be fixed in order to develop a suitable valuation framework for remediation strategies.

The research of Bage and Samson from 2002 to 2004 provides an interesting framework for a proactive way of thinking for the remediation strategy making. But there are some limitations to their work. First of all, there is no regulation restrictions on the two technologies considered in their model. The decision maker can choose either one of them. In realisty, some technologies might have a stricter threshold to be allowed to implement than others. These thresholds are like the exercise prices in financial options. This is a very important aspect for real options valuation. It reflects the value of active management facing uncertainty making the decision “what to do if something happens”. This is not an issue in the Bage and Samson’s work. Secondly, it is not mentioned in their work how many stages are there when there is no time restriction. Interpreting from their effectiveness of technologies assumptions, it may not exceed the number of years that generate so many strategies that the computer program can not handle. So how to solve the problem when the number of strategy is too many to solve remains a question. Thirdly, in their work, the optimal strategy is set guiding the remedial activity stage after stage at the current knowledge and not changed again in the future. But it has to be realized that the optimal strategy is only expected to be optimal at the time when the analysis is done. When the next stage comes, the situation and knowledge may change, the strategy made based on the old expectation may be outdated. last but not least, the uncertainty associated with the technology effectiveness is not considered in Bage and Samson's work. In their papers, the probability to achieve a certain site situation after implementing a certain technology for a certain initial site situation is set without uncertainties. This problem is dealt with better in Wang and McTernan's work.

Wang and McTernan's work provide inspiration on how to describe the uncertainty of the contaminant concentration with Monte Carlo simulation. But there are some limitations to their work which have to be overcome. First of all, in their work, they only valued the option of postponing the investment. The flexibilities provided by technologies to be switched are not given value. When an action is decided to be taken, one technology is chosen and implemented for ten years. There is no switching between technologies even though it is possible. Secondly, Sensitivity analysis is only performed for two costs parameters, capital and operational costs. Other important parameters such as technology effectiveness and regulative parameters were not investigated.

To overcome the shortcomings of the previous researches, this thesis tries to implement the following points: 1. Thresholds for different technologies. 2. Optimization when the number of strategies becomes too big. 3. Sensitivity analysis for more parameters. 4. The idea of doing the analysis at the beginning of each stage.

4. Real options valuation model for optimal remediation strategies

In practice the majority of site remediation projects are evaluated through cost – benefit analysis based on the traditional NPV method. The fact is that site remediation decision making can be very complex facing various sources of uncertainties and flexibilities imbedded in the strategies. As previously discussed, the traditional way can not assist the decision making properly. For optimal remediation strategy making, where more than one options are involved and the uncertainty is path dependent, direct application of financial option pricing and dynamic programming are not feasible; decision tree based analysis combined with Monte Carlo simulation will be applied in this thesis. The purpose is to develop an integrated approach using financial theory, economic analysis, decision science, statistics, hydrology and simulation modeling to assist optimal decision making for remediation projects. This approach can take into account the risks a remediation project may face and the value that proactive management may bring.

4.1 State of the environment under uncertainty

In financial option valuation, the uncertain underlying asset is the stock price. The decision of exercising an option is depending on the stochastic development of stock price. In remediation projects, the underlying asset which is uncertain is no longer an economic term. Uncertainty mainly stems from the inability to accurately predict the effectiveness of the remediation technology in terms of improving the environmental quality at the site. In this study, Monte Carlo simulation is used to represent the uncertainty concerning the further development of environmental quality. For simplicity, quality is described by means of a single value of contaminant concentration in groundwater. In each point of time, depending on the previous path of combination of technologies, a stochastic model simulates the distribution of the concentration outcomes uniquely.

Monte Carlo simulation approximates the probability of certain outcomes by running multiple trial runs using random variables. Each of these runs is called a realization. It is a stochastic technique based on the use of random numbers and probability statistics. It is especially useful when a system is too complex for an analytical solution. With the help of Monte Carlo simulation, a complex system can be sampled in a number of random configurations, which are used to describe the system as a whole. With a higher number of random runs, the statistics of the ensemble of realizations approaches a better description of the system. It is a proper tool for this study to simulate the possible outcomes of future contaminant concentration.

To describe the state of the environment, a simple contaminant degradation equation as follows is used.

$$C(t) = C_0 * e^{-\lambda * t} \qquad \text{(Eq. 4-1)}$$

C(t) is the concentration at time t, C_0 is the concentration at time zero, λ is decay rate constant. The values of λ may be assumed different for individual technologies. This simple degradation formula can be replaced by any other appropriate model, e.g. an analytical or numerical contaminant transport model.

To describe the uncertainty, a random part is added to the formula. MATLAB function randn() is used to generate arrays of random normally distributed numbers with mean of zero and variance of one. Equation 4-2 can generate n random normally distributed numbers with mean $C_0 * e^{-\lambda * t}$, and standard deviation of Std. It is used to simulate the future outcomes of the contaminant concentration after a certain technology is implemented.

$$C(t) = C_0 * e^{-\lambda * t} + Std * randn(1, n) \qquad \text{(Eq. 4-2)}$$

4.2 Options and option thresholds

Options

Flexibility exists due to the ability of the manager to make a decision on technologies to apply depending on the actual situation he or she will face in future. Typical imbedded real options of remediation projects include deferring, stopping and switching: deferring means to watch and to investigate (= MNA); stopping means that the site manager can stop the remediation once the given target is met; switching means to replace a technology in operation by another technology/option that may become more appropriate in the future because of an altered distribution of the contamination (switching e.g. from pump-and-treat, P&T, to monitored natural attenuation, MNA). In this model, we consider four options: “P&T”, “PRB”, “MNA” and “Stop”. P&T and PRB are more active techniques than MNA, but also more expensive. P&T and MNA are more flexible to be switched to other technologies compared with PRB.

Option thresholds

Different technologies have different threshold conditions which allow them to be implemented. Normally this is regulated by the authority. For example, there are more restricted criteria for MNA to be applied than P&T and PRB. MNA is said to be a gentle option to manage contaminated land and groundwater and may not be applied if pollution levels are above a certain value. This certain value is the threshold value for MNA. When the concentration is above this value, P&T or PRB has to be implemented. P&T and PRB are more effective techniques compared with MNA. They have much higher costs than MNA. It is supposed that P&T and PRB will be switched to MNA as soon as the concentration is lower than the MNA threshold. The option “Stop” will be only possible if the concentration value representing the environmental state is at or below the target level of remediation, which serves here as threshold value. So each option has their thresholds which control the exercise of this option. Some options can share the same threshold. These thresholds are defined by concentration of the contaminant. Of course, within the range allowed by regulations, the thresholds can be changed by the management to search for a potential better strategy. This will be discussed in the later part which investigates individual parameters.

4.3 Decision tree

Decision tree analysis is a tool which can be used in situations where optimal decisions depend on uncertain events and the decisions made under these events. A tree structured graph illustrating future uncertainties, future decisions and their possible consequences is composed. A decision tree for remediation projects can look e.g. as shown in Figure 4-1. It is shown in this tree all the possible decisions and their uncertain consequences - the different levels of possible future contaminant concentrations. The decisions according to these future concentrations are also shown in the tree, which are decided by the threshold values. By calculating the expected strategy value, the optimal strategy with the highest strategy value can be chosen among all possible strategies. In the following part, the main elements in the decision tree for a typical remediation project will be elaborated.

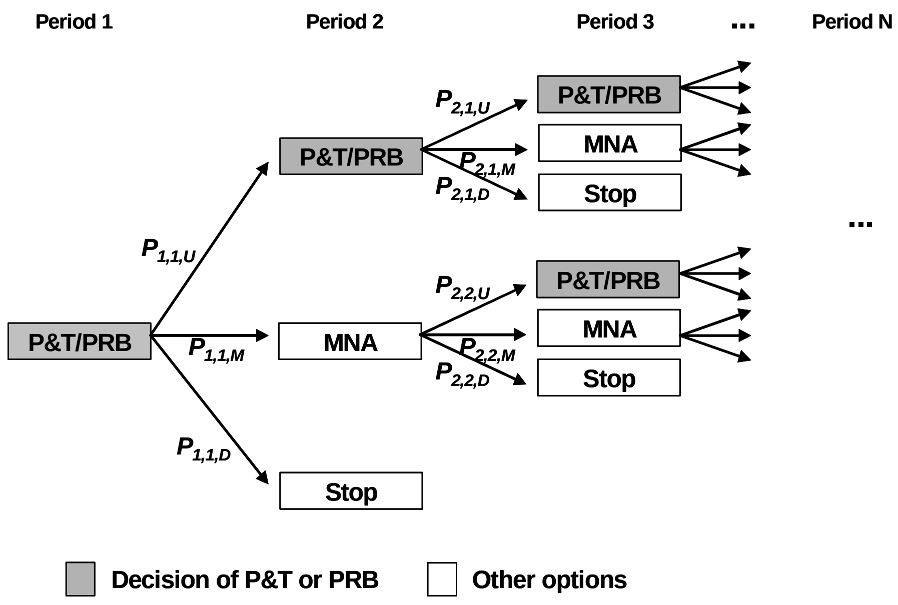


Figure 4-1: A decision tree for remediation projects

Length of the entire decision framework

This is the length of the total planning time. It can vary from project to project. Some remediation projects are long term, they can take decades. Some are short term, they can take only several years. The length of the entire decision framework does not have a big influence on the structure of the decision tree. But it can have very big influence on the total cost, benefit and the optimal strategy chosen in the end. First, generally speaking, with a longer decision framework, the total cost is higher for the same technology mainly due to the operational cost. The benefit is higher because it is more likely to meet the target. Second, the effect is different for different technologies depending on the cash flow structure. It has more impact on technology with more evenly distributed cash outflows such as P&T. For PRB, the cost is very high at the beginning of the project whereas operational cost is rather low compared with P&T. A longer total frame of the project will have less effect on costs of PRB than P&T. Compared with PRB, a longer decision framework increases the total cost of P&T more tremendously (under reasonable discount rate). And thus, with similar expected benefit, technologies such as P&T have a lower chance to be favored compared with the situation in a shorter decision framework. For a technology with low operational cost, the effect of the length of decision framework is lower, and thus, there is a higher chance for these technologies to be favored compared with a shorter decision framework. Third, with the same target level, a shorter length of the decision framework may favor a more active strategy.

Periods

A decision period is the time period between the point of time when a decision is made and the end of this chosen activity. Except for stop, the next decision has to be made again at the end of each decision period. The number of decision periods (NP) is depending on the length of the entire decision framework (T), and the length of each decision period (D_t). NP = T / D_t. With the same length of the entire decision framework, the more periods there are, the more accurate the decision making can be. This is because the length of each decision period is shorter. Thus, the decision maker can react to the actual situation more actively in a shorter time. This can result in better strategy making compared to the same project with less decision periods. It also provides a more accurate strategy value calculation. Of course, because of reality reasons, the length of each decision period should be within a reasonable range.

Decision points

The squares shown in Figure 4-1 are the decision points. The gray squares represent the choice of a technology between P&T and PRB. These are the decisions which have to be made when the concentration is above MNA threshold. With different combinations of these two technologies through the entire tree, the remediation plan for the site can change. So these points are very critical for the decision making. The white squares in Figure 4-1 represent the other options. These options are “MNA” and “Stop”. These decisions are within certain limits because the decision is made only according to the thresholds. Whether MNA will have to be applied in the next management period or the remedial activity can be stopped depends on the actual contaminant concentration and the threshold value set. So if the concentration turns out to be lower than the stop threshold (C_T), the remedial activity will be stopped. If the concentration turns out to be below the MNA threshold (C_{MNA}), and above C_T, MNA will be implemented.

Extension of the decision tree

As shown in Figure 4-1. The decision tree always develops in the same pattern. As long as the branch does not stop, it will always divide into three branches. When the period number is big, it is neither possible nor necessary to draw the whole decision tree to demonstrate the problem. But we can still solve the problem with the help of computer and programming algorithms.

4.4 Strategy and strategy valuation

Strategy

A strategy is defined as a decision map with all the decisions specified at the decision points for P&T and PRB in the decision tree. Each combination of the decision points for P&T and PRB (see Figure 4-1) makes one strategy. When the number of periods is *NP*, there are as many as $2^{2^{NP-1}}$ possible strategies in one decision tree. Figure 4-2 is an example of one strategy out of 16 strategies in total for a three-period project. Figure 4-2 is a decision tree for one strategy. It is used as an example in the later part to demonstrate how a strategy is valued. A strategy map captures the remedial decisions period after period through the entire decision frame. But this is the expectation at the present point of time. At the end of this decision period, the situation is likely to be different than what we expect at the present day. Our knowledge of the site and technologies will change. Then a new round of analysis has to be done all over again. So special attention should be paid to the very first decision point, which indicates what should be implemented for the first decision period.

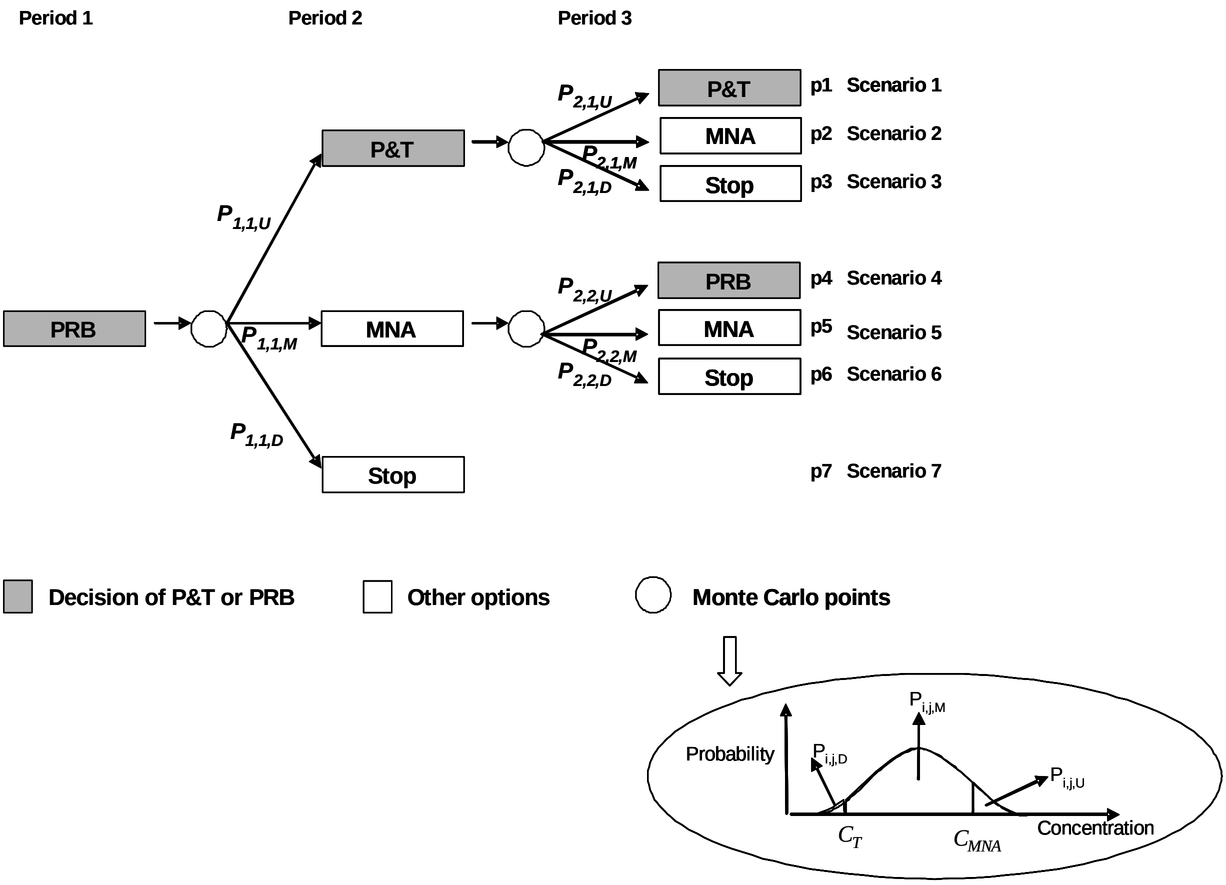


Figure 4-2: One strategy example for a three-period remediation project

Scenario and scenario probability

A scenario is one path through the decision tree for a certain strategy, from the very beginning till the end. A strategy is composed of a set of scenarios. The strategy example illustrated in Figure 4-2, contains e.g. seven scenarios. Each scenario has different scenario probabilities. Each of them is cumulated from the beginning of the tree to the end. For example, $p1=P_{1,1,U}*P_{2,1,U}$. All scenario probabilities add up together equals to one. So p1+p2+…+p7=1. With time passes by, when we are at the end of the entire decision frame, only one scenario will be realized. But at the point of time at the beginning of the decision frame, it is uncertain which scenario will become true in the future. So the strategy value is an expected value calculated to make the decision, based on our best knowledge of the site and technologies today. It is not necessarily exactly the number which turns out in the end.

Monte Carlo points and probability branches

Probability branches show that after a remedial activity takes place, there can be uncertain outcomes in the future with different probabilities. These probabilities are based on the result of Monte Carlo simulations. The circles in Figure 4-2 are the Monte Carlo simulation points. After each remediation activity is chosen, random uncertain concentration outcomes are generated by Monte Carlo simulation as discussed in 4.1. These realizations are grouped into three categories according to the thresholds. If the concentration is below C_T, the remedial activity will be stopped. If the concentration is between C_T and C_{MNA}, MNA will be implemented in the next period. If the concentration is above C_{MNA}, P&T or PRB has to be implemented in the next period. The number of realizations in one category divided by the total number of realizations equals the probability of this category.

Strategy value calculation and optimal strategy selection

Once a remediation project is started, the manager has the option to switch between certain technologies and switch to the option "Stop" once the target is met. The uncertainty in the future concentration of the contaminant is described by a stochastic process. This is similar to the underlying asset in financial options. Monte Carlo simulation is used to simulate the outcome probability density function (pdf) of concentration at the end of each management period after a certain option has been exercised. At the end of each decision period, a decision will be made on which technology to use if remediation has to be continued. The value of flexibility to choose among different options (technologies) should be taken into account when remediation strategies are set-up. It is similar to a compound option in the financial market. On each decision point, a decision is made and the right for the next option is bought.

The decision tree shown in Figure 4-3 illustrates the problem for a three-period project. Suppose that at the beginning of the remediation the current concentration is C_0, which is above C_{MNA}. Since the concentration is not low enough to apply MNA, a decision has to be made on the technology to be used in the first period. After this first period, there is a certain probability $P_{1,1,D}$ that the concentration will be below C_T. In this case, the remediation can be stopped. At probability $P_{1,1,M}$, the concentration will be above C_T but below C_{MNA}, then MNA will be applied in the next period. With probability $P_{1,1,U}$, the concentration will turn out to be above C_{MNA}, and then the site manager has to choose between P&T and PRB again. That is, he or she has to decide whether to continue the operation of the technology used in the first management period or to switch to an alternative. If the remediation is not stopped after the first period, then at the end of the second period decisions have to be made again in the same manner as at the end of the first period. For a project with more than three periods, the decision tree will expend in this pattern. It is obvious that, in this example, MNA and Stop options depend totally on the actual concentration compared with the thresholds. It is the decision between P&T and PRB that is critical to the whole problem.

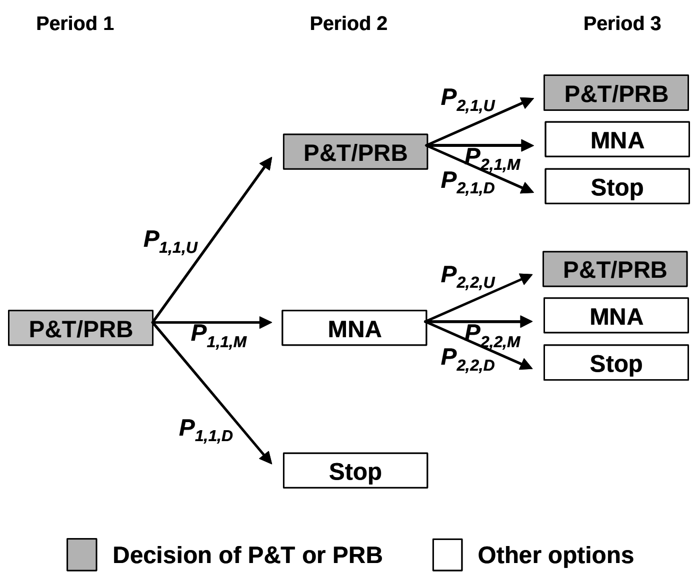


Figure 4-3: Decision tree for a three-period remediation project

Figure 4-2 shows one example strategy out of 16 possible strategies. If 1 is used to indicate P&T and 0 is used to indicate PRB, the strategy in Figure 4-2 can be indicated as string 0110. Each digit indicates a decision point on a certain position of the decision tree, the order is from left to right, from top to bottom. As discussed previously, it is the decision between P&T and PRB that is critical to the whole problem, every strategy can be characterized by a single string representing the combination of P&T and PRB decisions. For the whole decision problem, it is the first digit of the string which is the most important. It tells the decision maker which technology to choose for the first decision period under the current conditions.

The optimal strategy is the one with the highest expected option value (Equation 4-3). This (net) expected value will be calculated for all possible strategies (in this three period case, optimization is not needed). The expected value of a strategy is the weighted average value of all scenarios. The weights are expressed by probabilities of the scenarios (see Equation 4-4). Each scenario probability depends on the probabilities in the previous parts of the path, for example, P1 = $P_{1,1,U}$ * $P_{2,1,U}$. (See Figure 4-4.) These probabilities in the previous parts of the path are calculated from the pdfs of contaminant concentration resulting from a Monte Carlo simulation. This simulation can be based on any model that is seen to be an appropriate means to make the required prediction under uncertainty. In the example presented here a simple decay model is used, whereas the value of the rate constant is based on the respective option chosen in the previous management period. The three probabilities $P_{i,j,U}$, $P_{i,j,M}$ and $P_{i,j,D}$ are calculated from the entire pdf according to the threshold concentrations. (i is the index for longitudinal positions of the Monte Carlo points on the tree, j is the index for latitudinal positions of the Monte Carlo points on the tree. See Figure 4-2.) The mean of each of the three parts of the pdf is taken as the new starting concentration for the next management period. The scenario value is the present value of the expected land value minus the present value of the cumulative cost. (Equation 4-5) The expected land value is the clean land value times the chance to meet the target in this scenario (Equation 4-6). The present value of the scenario cost is the cumulative present value of all costs that occur in this scenario.

The weighted average of all the scenarios' chances to meet the target (M_i) is the chance to meet the target of this strategy (M). The weights are the scenario probabilities. (Equation 4-7) For scenarios which do not end up with the stop option in Figure 4-2 (scenarios 1, 2, 4 and 5), Monte Carlo simulation is performed to calculate the chances of meeting the target after the third period for these scenarios, as shown in Figure 4-4. The chance to meet the target of the strategy is not totally shown in Figure 4-2. There are chances that the target will be met for scenarios 1, 2, 4 and 5, as shown in Figure 4-4. It should be kept in mind that the total chance to meet the target is higher than the sum of scenario probabilities of scenarios 3, 6 and 7.

$$S_{optimal} = Max(E(V_1), E(V_2), ..., E(V_n)) \qquad \text{(Eq. 4-3)}$$

$$E(V_n) = \sum_i pi \ \ * V_i \qquad \text{(Eq. 4-4)}$$

$$V_i = E(B_{land}) - E(C_i) \qquad \text{(Eq. 4-5)}$$

$$E(B_{land}) = M_i * V_{lc} \qquad \text{(Eq. 4-6)}$$

$$E(M) = \sum_i pi * M_i \qquad \text{(Eq. 4-7)}$$

The parameters and variables are defined as follows:

$S_{optimal}$	value of the optimal strategy
E	expected value
V_n	value of the strategy n
pi	probability of scenario i
V_i	value of scenario i
B_{land}	benefit from selling the land
C_i	cost of scenario i
V_{lc}	value of clean land
M_i	chance to meet the target for scenario i
M	strategy chance to meet the target

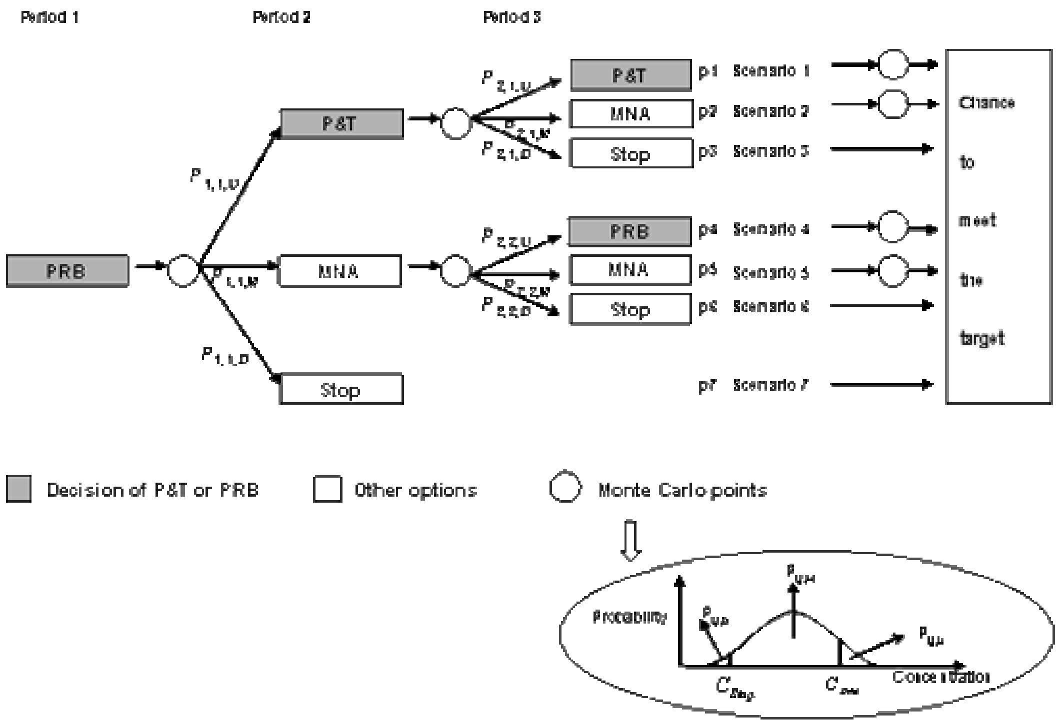


Figure 4-4: Scheme of individual strategy valuation

To find the best strategy, all possible strategies are investigated. Due to the uncertainty of the Monte Carlo simulation, the value of each strategy can vary from time to time slightly.

This is why the optimal strategy can change when some strategies have very similar strategy values. To catch all possible candidates, the investigation is done for ten times. Each time an optimal strategy is chosen. After ten times, ten candidate optimal strategies are listed (in a three-period case). Most of them are exactly the same. There are one or two other strings chosen. With increasing number of runs, no new candidate strings are found. It shows that ten runs are enough to capture all possible candidate optimal strategies for a three-period project. In case that they are not the same, each of them are run for 100 times to calculate their strategy value. The mean and standard deviation of each candidate's strategy value are calculated. Based on this, the decision maker can decide which one is the best depending on their requirement of the mean and the standard deviation. In this case, it is supposed that the decision maker wants to maximize the mean strategy value while minimize the standard deviation. Suppose the decision maker provides the criterion as: when strategy value is positive, Max (mean/Std.); when strategy value is negative, Min (|mean|*Std.).

Except for the uncertainty of Monte Carlo simulation, more than one candidate strategies can also be caused by the characteristics of the strategy itself. For example, when the probability of reaching a certain decision point is zero, it doesn't matter what to choose on this point any more. In this situation, there will be strategies which are actually the same in pairs. For example (see Figure 4-3), if $P_{2,1,U}$ is zero, the decision between P&T and PRB in the next period has no importance. That means the third digit of the strategy string does not matter. Then, strategies in pairs, for example, strategy 0110 and strategy 0100 are the same.

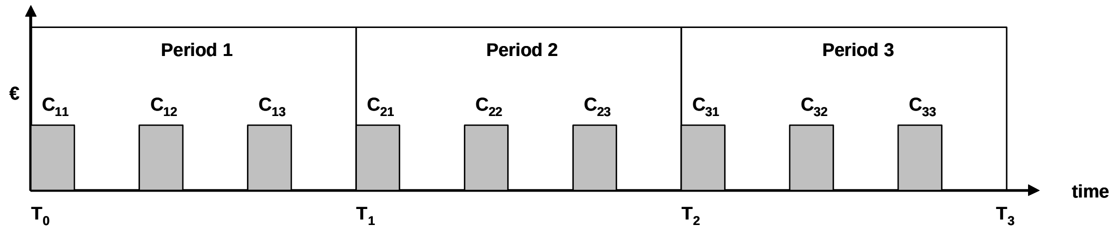
It is important to keep in mind that it is the first decision point that is concerned. The whole analysis is done to decide what to do for the first period! It is an optimal choice based on the best knowledge of the decision maker at this moment. It is not a strategy which will guide in the later periods regardless of the new knowledge and the outcomes of the uncertainties. At the end of each period, the analysis will be done again according to the actual situation and the best knowledge at that time.

As shown in the valuation, both costs and strategy effectiveness are taken into account. The strategy effectiveness is represented by the chance to meet the target. A higher chance to meet the target will generate more benefit. Lower cost will increase the total strategy value. According to the conceptual framework set in this thesis, the strategy having the maximum total expected strategy value is the optimal one. It should be noted that additional criteria, targets or rules (e.g. to meet a minimum threshold value of the chance to meet given demand for good environment) are not considered.

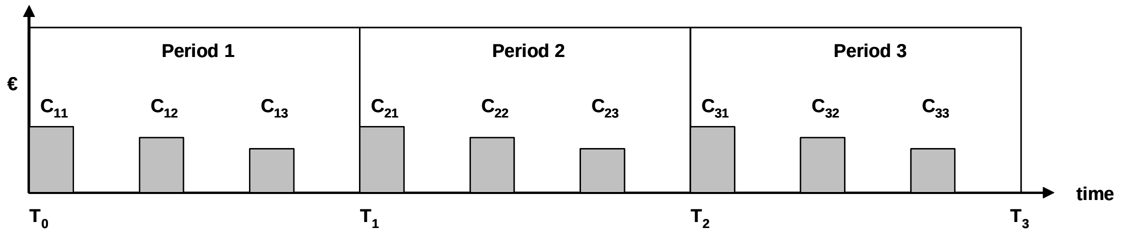
Discounting

For projects with long time frame, discounting is a very important issue for the valuation. The further in the future does a cash flow happen, the more it is discounted. So with a higher discount rate, the future cash flows play a less important role in the valuation. In this model, all values are in terms of present value, which means that they are all discounted. The discounting is done step by step. First the cash flows are discounted back to the beginning of each period. Then the sum of cash flows of each period is discounted back to time zero and then summed up. In this study, it is supposed that the land will be sold as soon as the target is met. The sooner the land can be sold, the less will the benefit from sales revenue be discounted, and the larger the net strategy value will be. We take a three-period project as an example (Figure 4-5a). Suppose that it is a nine year project. There are three periods in this project. There are three years in each period. Suppose that the cash flow in each year is $C_{11} = C_{12} = \ldots = C_{33} = 5000$ EUR. The discount rate is 5%.

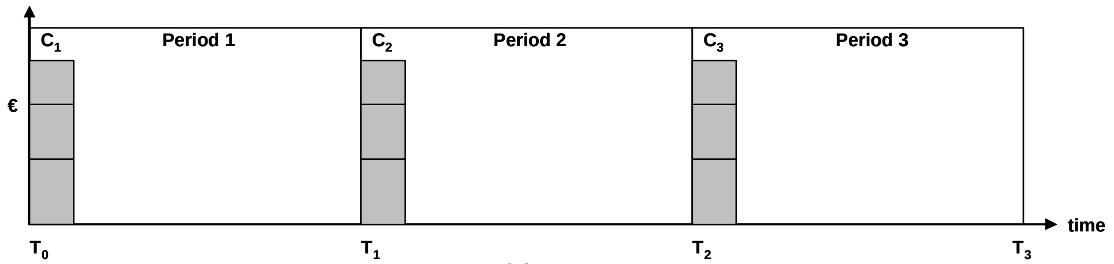
The discounting steps are demonstrated in Figure 4-5b-e. Step 1, the cash flows are discounted back to the beginning of each period. Step 2, they are summed up within each period as the cumulative cash flow of each period. Step 3, the cumulative cash flows are discounted back to time zero. Step 4, the period cumulative present values are summed up as the present value of all the cash flows. This is the present value of all the cash flows.



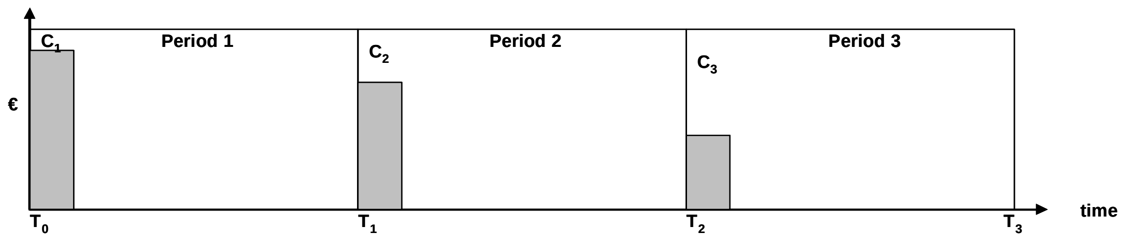
(a) Project cash flows



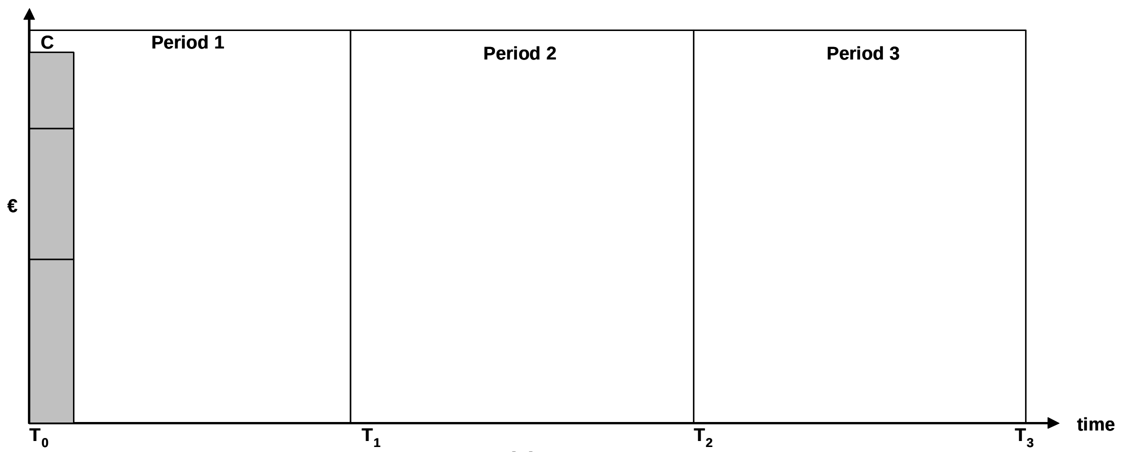
(b) Step 1



(c) Step 2



(d) Step 3



(e) Step 4

Figure 4-5: Discounting method applied to the strategy valuation

4.5 Steps to build up the model

To sum up, there are six steps in the framework:

Step 1: Identify the uncertainties and options

Step 2: Build up a decision tree demonstrating all possible outcomes and decision reactions in actual situations

Step 3: Expected strategy values are calculated

Step 4: Optimal strategy is identified based on certain criteria; the decision for the first decision stage is recommended

Step 5: Sensitivity analysis

Step 6: At the beginning of the next decision stage, the analysis is done in the same way based on the new knowledge and new situation at that time

4.6 Optimization algorithm for projects with more than four periods

As mentioned before, when the number of periods is NP, there are as many as $2^{2^{NP-1}}$ possible strategies to be valued. When NP is bigger than 4, it takes very long time to go through all possible strategies or even impossible to go through all strategies with present calculation capacities. In this situation, an optimization algorithm can be used to select the optimal strategy. In this study, a Genetic Algorithm (GA) is used for the optimization. The implementation is adapted from the codes provided by Houchk, Joines and Kay (1996)[1].

GA is a stochastic search method which operates on a population of solutions. Under GA, a population of representations (called chromosomes) of candidate solutions (called individuals) evolves towards better solutions. It creates a population of chromosomes then applies crossover and mutation to the individuals in the population to generate new individuals. Individuals are ranked by comparison to a particular fitness function. The chromosomes in the first population are generated randomly covering the entire range of possible solutions. The population size depends on the nature of the problem. A proportion of existing population is selected to breed a new generation. Better solutions (with better fitness values) are more likely to be selected. The average fitness of the next generation will increase since only the best organisms from the first generation are selected for breeding the next generation. The generational process terminates when a termination condition has been reached, e.g. a fixed number of generations has been reached. The discussion about GA is out of the scope of this thesis. See Goldberg (1989) for more details about GA.

[1] Website: http://www.ise.ncsu.edu/mirage/GAToolBox/gaot/

Under GA, individuals are represented as binary strings of 0s and 1s. In the remediation strategy optimization problem investigated in this thesis, the critical decision is between P&T and PRB when the concentration turns out to be higher than the MNA threshold. When 0 represents PRB and 1 represents P&T, putting all decision points between P&T and PRB in a string, every strategy can be represented by a single and unique string. For example, when NP = 5, there are 16 decision points for P&T and PRB in the decision tree. One strategy can be represented by string 1001010000011110.

In the remediation strategy optimization problem, the fitness function is set to be the strategy value. It is calculated for each solution according to the method introduced in the previous chapter. The purpose is to find the string with the highest strategy value possible. The population size of each generation is 50. First, 50 random strings of 0s and 1s are generated and evaluated. Then by applying crossover and mutation to the best individuals, the next generation of individuals is generated. The number of generations is 10. One optimization run terminates when this number is reached. Ten runs of optimization are done and the best string is the one with the highest fitness value. This number of generation is considered to be enough because the results of optimization runs are identical in the first digit of the string, which indicates the decision in the first period. Bigger number of generations does not provide different result for the first digit of the optimal string.

5. Application of the real options valuation model

5.1 Overview

This chapter applies the real option valuation method to a hypothetical case and investigates the sensitivity of the results to the changes of parameters. Through the hypothetical case of a three-period project, it is shown how optimal strategy can be made for remediation projects with uncertainties in the future concentration development and management flexibilities when the uncertainties resolves by time. Input parameters set for this case include regulative parameters, site parameters, economic parameters, technology parameters and time parameters. The valuation is done according to the framework built up in the previous chapter. Conclusions and strategy recommendations are given. Then this case will be used as a reference case for the sensitivity analysis. The input parameters are changed and the impacts of these parameters on the optimal strategy making are investigated. The purpose is to shed light on the optimal strategy making for sites with different characteristics, projects with different time scope, and for situations when regulation and market price for land are changed, and when technology costs and effectiveness are different.

5.2 Reference case

5.2.1 Assumptions

The total planning time frame is T = 30 years, the number of decision periods is NP = 3. This means that the decision will be made every ten years. The current concentration is set to be 1, serving as a (dimensionless) reference value. The threshold concentrations are set to $C_{MNA} = 0.15$, $C_T = 0.01$. That means, the groundwater quality has to be improved by a factor of 100 compared to the current situation in order to be considered “clean”. The price of “clean land” is expected to be 400 €/m^2, assuming a site area of 2.5 hectare. Decay rate constants are set to $\lambda_{P\&T} = 0.21$, $\lambda_{PRB} = 0.12$, $\lambda_{MNA} = 0.02$. 10,000 realizations are made as demonstrated in Equation 4-2 for each Monte Carlo simulation point with the same standard deviation for all technologies ($Std_{P\&T} = Std_{PRB} = Std_{MNA} = 0.07$). We distinguish 4 types of costs: installation cost, reactivation cost, operational cost and stopping cost. Estimates for different options were calculated according to Kübert (2002), Bürger et al. (2003) and Bayer et al. (2005) for the following set of site parameters: depth to the groundwater table is 2 m, thickness of the aquifer is 5 m, the conductivity is 0.0005 m/s, the hydraulic gradient is 0.001, total width of the contaminated area is 100 m. Parameters for technologies are: two pumping wells (P&T),

unit drilling and well construction cost is 2000 €/m, equipment cost for P&T is 15,000 €, unit cost of reactive material for water treatment is 600 €/m^3 (same for both P&T and PRB), site preparation and mobilization costs for P&T and PRB is 30,000 €, material cost for funnel installation is 250 €/m^2, MNA requires 10 monitoring wells at drilling cost of 200 €/m, and MNA sampling cost is 250 € for each sample. The sampling rate is set to be twice a year. Cost for regular checks and controls of the operating system is 2000 €/year. Estimated costs are shown in Table 5-1. The discount rate is set to be 3%.

Table 5-1: Cost assumptions for different technologies in the reference case

Cost type	P&T	PRB	MNA
Installation cost (€)	85,005	311,250	20,000
Reactivation cost (€)	17,005	77,817	6,000
Operational cost per year (€)	17,873	2,100	7,000
Stopping cost (€)	6,800	3,113	2,000

5.2.2 Results

5.2.2.1 Optimal strategy

After enumerating all possible strategies, the optimal strategy is identified, which is 1111 as shown in Figure 5-1. The strategy recommendations are: (I) Apply P&T whenever the concentration exceeds C_{MNA}. (II) Apply MNA whenever the concentration is below C_{MNA}, but the target is not met. (III) Stop the remediation and sell the land whenever the target is met. Due to the random element in Monte Carlo simulation, the strategy value calculated for the same strategy varies for each run. The mean values of the strategy value, strategy cost, strategy benefit and chance to meet the target for 100 runs are shown. The results are: strategy value = 2,170,600 EUR, chance to meet the target = 48.78%, expected benefit = 2,521,200 EUR, expected cost = 350,520 EUR. The most important indication from this analysis is that P&T should be implemented in the first decision period.

In Figure 5-2a, the bars show the scenario probabilities and the stars show the scenario values. Scenario 1 has a very low probability compared with the other scenarios. This means that, under the current assumptions, especially the current concentration and the effectiveness of P&T, after two periods of P&T, it is not likely to end up with concentration levels calling for a continuation of P&T in the third period. Scenarios 3, 6 and 7 all end up with "Stop" option after the second period or even in the first period, respectively. This means that the target is met and the land can be sold. It should be kept in mind that there are also chances that, after the third period, scenarios 1, 2, 4 and 5 will meet the target and the land will be sold.

Figure 5-2b shows the cumulative cost, benefit and strategy value. The benefit occurs more in the later periods because the target is more likely to be met when the time is longer. It is also shown that the slope of cumulative benefit is decreasing with time. One reason is that the concentration reduction is not linear to the changing of time (see Eq. 4-1). As a result, the increasing of benefit is not linear. With strategy benefit being the main influencing factor, the slope of strategy value has the same characteristic. The second reason is that the discounting effect reduces the value further in future. In this case, the strategy benefit is very high compared with the strategy costs. The development of the strategy value is mainly driven by the benefit. Figure 5-2c shows the frequency of the values calculated for strategy 1111 for 100 times.

After going through all the strategies ten times, there are two candidate strings for the best strategy, which are 1111 and 1101. They are actually the same. The reason can be found when the scenarios which are associated with these digits are investigated (see Figure 5-1). These scenarios are scenarios 1, 2, 3 and 4. As shown in Figure 5-2a, the probability of scenario 1 (p1) is very low. It is almost zero. At the same time the probabilities of scenarios 2, 3 and 4 are higher. The reason why p1 is almost zero can not be $P_{1,1,U}$ is almost zero. Because if $P_{1,1,U}$ is almost zero p2 and p3 will be also low, which is not true. So the only reason is $P_{2,1,U}$ is almost zero. This indicates that the third digit of the string does not matter because it is almost impossible that this decision will need to be made. As s result, 1111 and 1101 are identical.

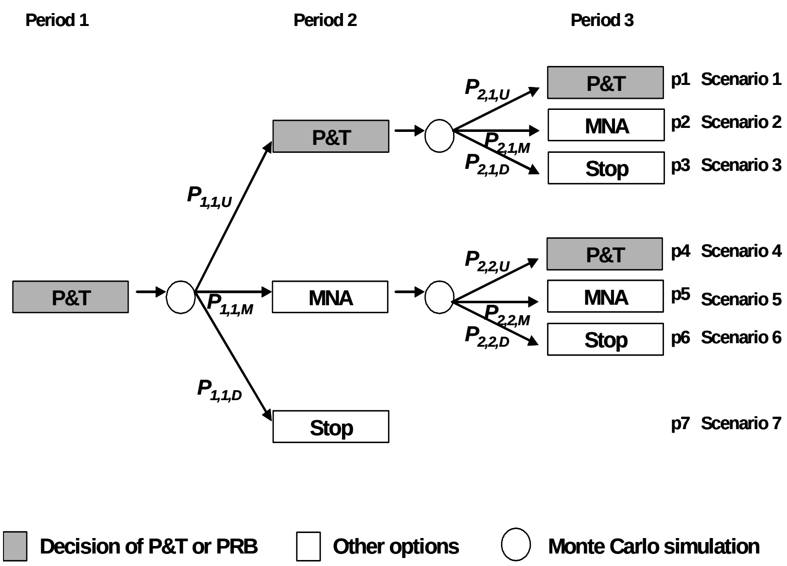
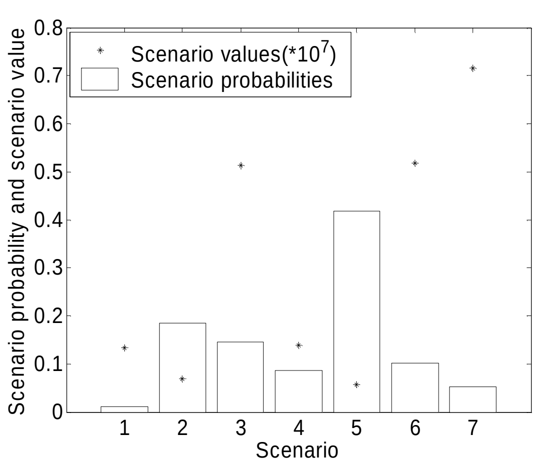
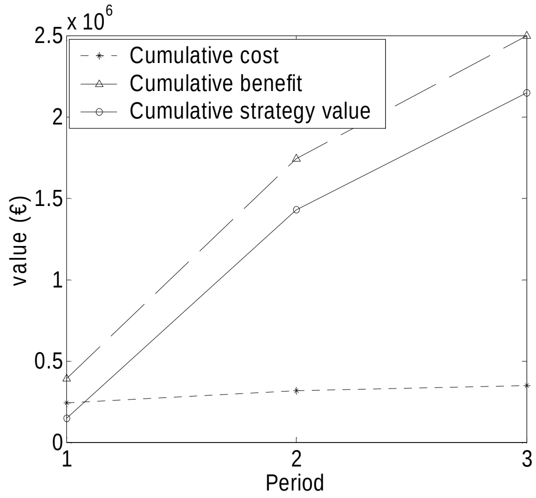


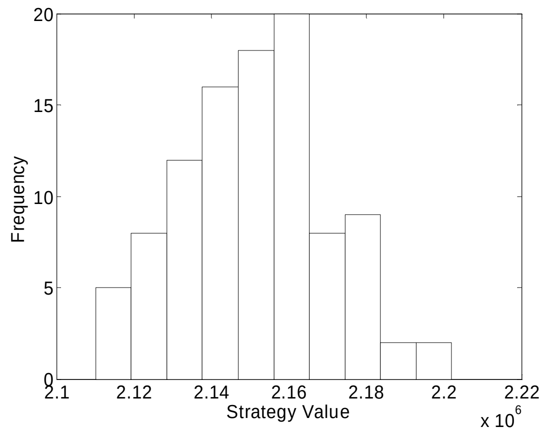
Figure 5-1: Decision tree for the optimal strategy 1111 for the reference case



(a) Scenario probabilities and values



(b) Cumulative cost, benefit and value



Reference case parameters:

$C_0 = 1$; $C_T = 0.01$; $C_{MNA} = 0.15$

mAq = 5 m, k = 0.0005 m/s; y = 100 m

$V_{lc} = 10^7$ €, r = 3%.

$\lambda_{P\&T} = 0.21$; $\lambda_{PRB} = 0.12$; $\lambda_{MNA} = 0.02$

$Std_{PT} = Std_{PRB} = Std_{MNA} = 0.07$

30-year plan; 3 periods

(c) Frequency of strategy values (100 runs)

Figure 5-2: Results of the optimal strategy 1111 for the reference case

5.2.2.2 Alternative strategies

To gain more insight of the result for the optimal strategy, two alternative strategies are compared with the optimal strategy. One is "Apply PRB as long as the concentration is above C_{MNA}" (strategy 0000 shown in Figure 5-3). This strategy is typically considered as an alternative to P&T and is very often used in practice. As will be shown, it is a more expensive strategy with lower chance to meet the target compared with the optimal strategy. So it is worse in both perspectives of cost and effectiveness. The other one is "Commence with PRB in the first period, but apply (switch to) P&T if the concentration is above C_{MNA}" (strategy 0111 shown in Figure 5-5). The purpose of analyzing this strategy is to show that managerial reasons (in this study, it refers to the switching to MNA as soon as the concentration is lower than C_{MNA}) can have big influence on the decision making.

Strategy 0000

The results of this strategy are: strategy value = 1,053,700 EUR, chance to meet the target = 30.91%, expected cost of 376,510 EUR, expected benefit = 1,430,300 EUR. This strategy is ranked worse because it has a lower strategy value due to a higher expected cost and lower expected benefit compared with the optimal strategy.

1. The expected cost of the comparative strategy 0000 is higher than the cost of the optimal strategy. This is because of the high installation cost of PRB. Under the current settings, strategy 1111 has cost advantage.

2. The lower benefit is because of the lower chance to meet the target compared to the optimal strategy. Figure 5-4a shows the scenario probabilities and the scenario values. Compared with the optimal strategy (shown in Figure 5-2a), the outcomes of the comparative strategy concentrate very much within the first three scenarios. This is due to the assumption that P&T has a higher effectiveness than PRB. So after the first period of PRB there is a larger likelihood to switch to go to the first branch in the second period. This will lead to scenarios 1, 2 and 3.

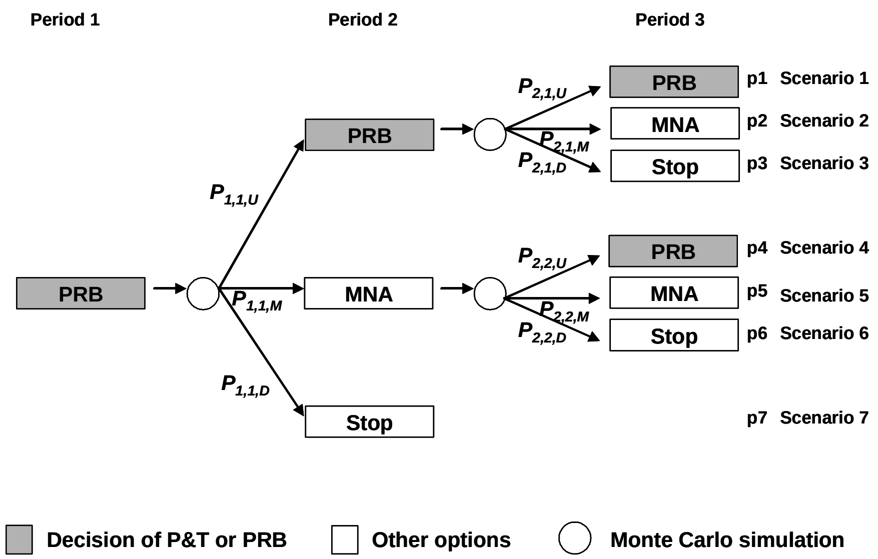
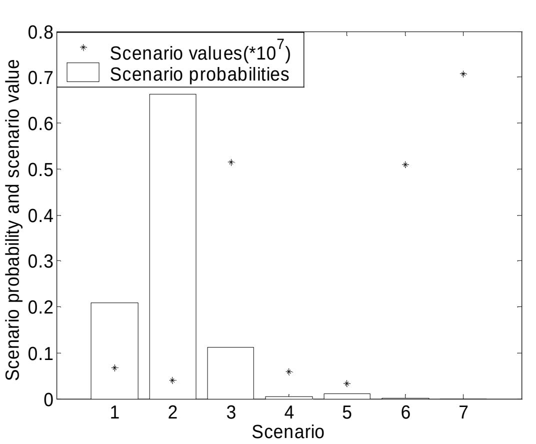
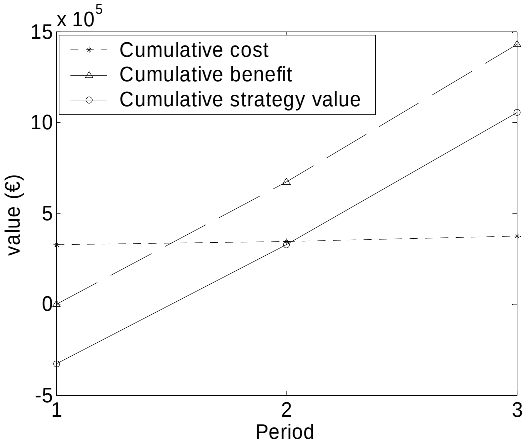


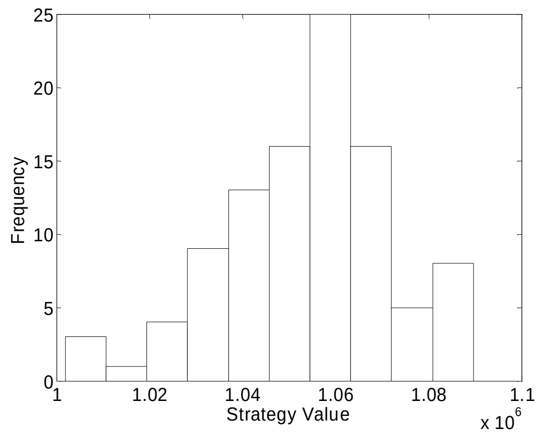
Figure 5-3: Decision tree for the alternative strategy 0000 for the reference case



(a) Scenario probabilities and values



(b) Cumulative cost, benefit and value



(c) Frequency of strategy values (100 runs)

Figure 5-4: Results of alternative strategy 0000 for the reference case

Strategy 0111

The results of the optimal strategy 1111 and strategy 0111 are compared in Table 5-2. As shown, opposite to strategy 0000, strategy 0111 has a higher chance to meet the target than strategy 1111.

Table 5-2: Comparison of the strategy valuation results of strategy 1111 and strategy 0111

Strategy	Strategy value (€)	Cost (€)	Benefit (€)	Chance to meet the target
1111 (optimal)	**2,170,600**	**350,520**	**2,521,200**	**48.78%**
0111 (comparative)	2,0793,00	539,720	2,619,000	52.34%

Starting with PRB, its results also concentrate very much in the first three scenarios for the same reason as strategy 0000 discussed before. But it applies the more effective technology P&T in the second period if the concentration should be above C_{MNA} after the first period. As a result, the effectiveness of strategy 0111 is clearly better than those of strategy

0000. This can be seen in the high probability of scenario 3 (it ends up with stop, i.e. M_3 = 100%) compared with strategy 1111 and strategy 0000.

The optimal strategy starts with the more effective technique P&T. The result is that its results do not concentrate so much in the first three scenarios as the strategies starting with PRB. This is the reason for the low probability of scenario 3. As shown in Figure 5-2a, the probabilities of scenarios 4, 5, 6 and 7 are higher than the comparative strategies. This indicates that after the first period of P&T, it is more likely to switch to the cheaper but considerably less effective technology MNA or to stop after the first period. The higher probability values of scenarios 6 and 7 for strategy 1111 are favorable since both scenarios feature a "Stop" option thus intensively contributing to the value of the respective strategy.

As discussed above, looking at the "stop scenarios" (scenarios 3, 6 and 7) shown in Figure 5-2a and Figure 5-6a, strategy 0111 has higher probability of scenario 3, while strategy 1111 has higher probability in scenarios 6 and 7. But the probability of scenarios 6 and 7 of strategy 1111 can not compare with the high probability of scenario 3 of strategy 0111. The total probability of stop scenarios (scenarios 3, 6, and 7) for strategy 0111 is higher than strategy 1111. This can be better seen from the comparison of Table 5-3 and Table 5-4 (Sc.: scenario). The comparison demonstrates the contribution of individual scenarios to the strategy benefit.

Table 5-3: Scenario benefits of the optimal strategy 1111 in the reference case

	Sc. 1	Sc. 2	Sc. 3	Sc. 4	Sc. 5	Sc. 6	Sc. 7	Sum
Expected scenario chance to meet the target	0.50%	5.20%	13.98%	3.90%	9.03%	10.49%	5.68%	48.78%
Scenario benefit (€)	2,0328	21,1416	76,7431	158,562	366,929	575,703	420,785	2,521,200

Table 5-4: Scenario benefits of comparative strategy 0111 in the reference case

	Sc. 1	Sc. 2	Sc. 3	Sc. 4	Sc. 5	Sc. 6	Sc. 7	Sum
Expected scenario chance to meet the target	2.47%	14.96%	34.36%	0.20%	0.19%	0.16%	0%	52.34%
Scenario benefit (€)	100,423	608,228	1,885,717	8,131	7,725	8,781	0	2,619,000

Strategy 0111 has a lower strategy value. This is because its cost is much higher than strategy 1111 due to the high installation cost of PRB and the switching cost from PRB to P&T. After all, it has a lower strategy value. As a result, strategy 1111 is ranked better due to its cost advantage. It indicates that when benefits are similar, which means one strategy does not have an absolute advantage in benefit, the cost will play a critical role. Both benefit and cost are important for the composition of the strategy value.

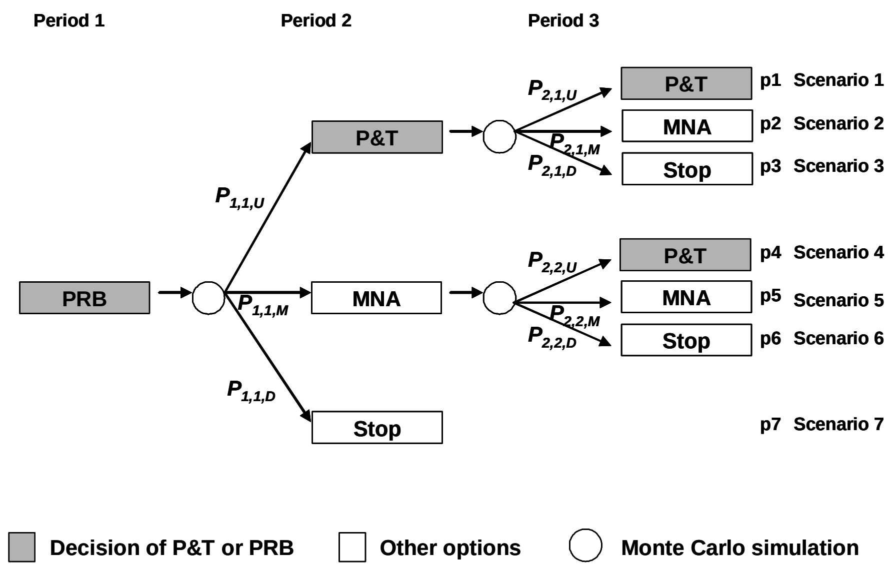
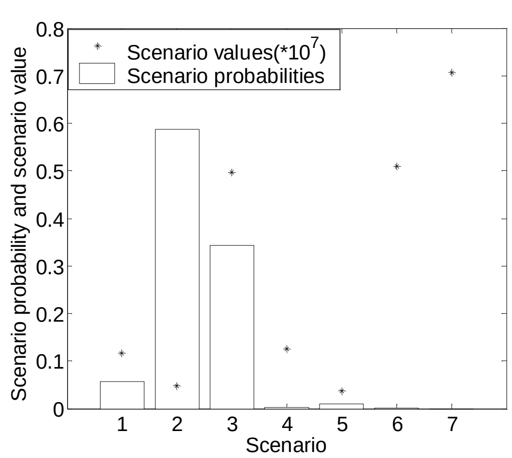
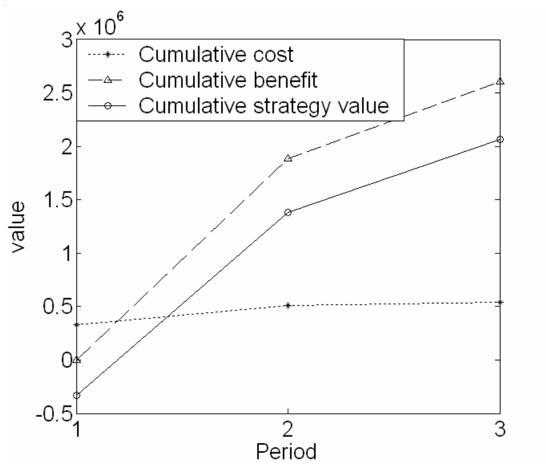


Figure 5-5: Decision tree for alternative strategy 0111 for the reference case



(a) Scenario probabilities and values



(b) Cumulative cost, benefit and value

Figure 5-6: Results of alternative strategy 0111 for the reference case

5.2.2.3 Conclusions from the reference case

Comparing the optimal strategy and the comparative strategies, under the assumptions applied to create a reference case, it can be concluded that:

1. The recommendation would be to apply P&T during the first decision period.

2. The strategy value is more driven by the expected benefit than the expected cost. Strategies with higher effectiveness have a clear advantage. This finding might be less

pronounced or inapplicable for other relationships between assumed land value and level of given cost parameters.

3. PRB, due to relatively high installation cost, is disadvantageous compared to P&T. Possible advantages because of low operational cost do not influence the result in this reference case. However, when assumptions change, this advantage may show effect.

5. Due to different technology effectiveness, the strategies considered here have different scenario probability distribution pattern. The strategy with higher probabilities of scenarios end up with “Stop” option is likely to have a higher benefit.

Furthermore, the results give some first indications that the outcome of an optimal strategy search largely depends on the given situation as specified by the set of input parameters. With different assumptions about the parameters, the results can be different. The optimal strategy can change. This will be investigated in the sensitivity analysis in the next section.

5.3 Parameter sensitivity analysis

This section investigates the sensitivity of the results to the changes of parameters. It shows the influences of different parameters on the strategy making. The reference case discussed above will be used as a benchmark. Parameters are divided into 5 groups: regulative parameters, site parameters, economic parameters, technology parameters and time parameters.

5.3.1 Regulative parameters

Regulative parameters refer to the determinative thresholds according to which the remedial activity can be switched or stopped. Suppose the current concentration is C_0, the threshold levels are set to be relative values compared with the current concentration. Normally, these parameters are set according to target values fixed in the regulation or negotiations with responsible authority. For example, the thresholds for stopping (the target level, C_T) and switching to MNA (C_{MNA}) are like this. When the concentration is below C_T, the remedial activity can be stopped. When the concentration is below C_{MNA}, but above $C_{T,}$ MNA will be applied. Otherwise more intensive remedial activities such as P&T and PRB have to be applied. In the following, the assumptions and parameter values of C_{MNA} and C_T are systematically varied compared to the reference case, and the implications of these variations to the result of the strategy valuations are discussed.

The cases created through new parameter settings are divided into three groups (all setting changes are constant for all periods):

1. Both C_T and C_{MNA} are lower: compared with the reference case, this group refers either to cases of more severely contaminated sites or to situations where planned land use is more sensitive and calls for more strict targets. This means it is more difficult to stop and to switch to MNA. C_T and C_{MNA} are lowered in steps of 10% compared with the previous case;

2. Both C_T and C_{MNA} are higher: these are less severely contaminated sites compared with the reference case. C_T and C_{MNA} are both higher. And thus it is easier to stop or to switch to MNA. Here, C_T and C_{MNA} are stepwise increased by 10%;

3. C_{MNA} is voluntarily lowered: in these cases, the regulative thresholds are the same as the reference case. C_{MNA} is voluntarily adjusted within the range allowed by the regulation to search for better strategies. In other words, MNA is not applied for a certain concentration range even though the regulation allows to. Different cases are considered, lowering C_{MNA} in steps of 10% compared with the previous case. The results are shown in Table 5-5. All values are the averages of 100 runs. All parameters not mentioned in the table are the same as the reference case. The first digit of the best string shows the optimal decision for the first period. 1 represents P&T, 0 represents PRB. As shown, candidate strings are different from each other in each case. The reasons have been discussed in section 4.4, and will be further discussed in section 5.3.2.1.

Table 5-5: Sensitivity analysis results for regulative parameters

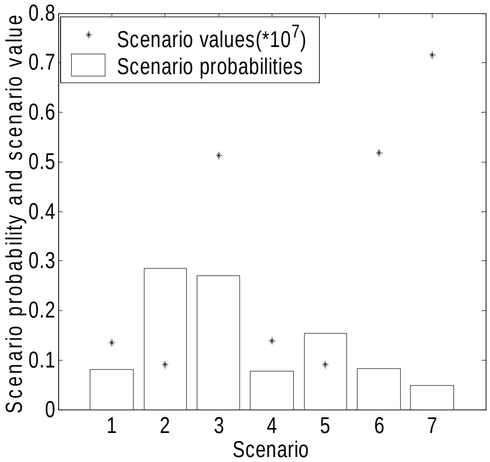
		Parameters	Candidate strings	Best string	Strategy value (€)	Cost (€)	Benefit (€)	Chance to meet the target
Reference		**$C_0 = 1$ $C_T = 0.01$ $C_{MNA} = 0.15$**	**1111 1101**	**1111**	**2,170,600**	**350,520**	**2,521,200**	**48.78%**
Both C_T and C_{MNA} are lower	**Case 5.3.1-1**	$C_0 = 1$ $C_T = 0.009$ $C_{MNA} = 0.135$	1111 1101	1101	2,347,200	357,650	2,704,900	52.31%
	Case 5.3.1-2	$C_0 = 1$ $C_T = 0.0081$ $C_{MNA} = 0.1215$	1111 1101 1110	1111	2,528,100	360,080	2,888,200	55.95%
	Case 5.3.1-3	$C_0 = 1$ $C_T = 0.0073$ $C_{MNA} = 0.1094$	1111 1101 1110	1111	2,667,000	364,350	3,031,300	58.74%
	Case 5.3.1-4	$C_0 = 1$ $C_T = 0.0066$ $C_{MNA} = 0.0984$	1111	1111	2,776,700	368,290	3,147,100	61.04%
Both C_T and C_{MNA} are higher	**Case 5.3.1-5**	$C_0 = 1$ $C_T = 0.011$ $C_{MNA} = 0.165$	0111 0110	0110	2,042,100	537,400	2,579,500	51.34%
	Case 5.3.1-6	$C_0 = 1$ $C_T = 0.0121$ $C_{MNA} = 0.1815$	0111 0110	0111	2,007,500	535,110	2,542,600	50.50%
	Case 5.3.1-7	$C_0 = 1$ $C_T = 0.0133$ $C_{MNA} = 0.1997$	0101 0100 0110 0111	0111	1,951,200	531,370	2,482,500	49.26%
	case 5.3.1-8	$C_0 = 1$ $C_T = 0.0146$ $C_{MNA} = 0.2196$	0111 0101 0110	0111	1,856,600	525,860	2,382,500	47.29%
C_{MNA} is voluntarily lowered	**Case 5.3.1-9**	$C_0 = 1$ $C_T = 0.01$ $C_{MNA} = 0.135$	1111 1101	1111	2,400,000	355,130	2,755,200	53.27%
	Case 5.3.1-10	$C_0 = 1$ $C_T = 0.01$ $C_{MNA} = 0.1215$	1111 1101	1111	2,598,000	359,480	2,957,500	57.13%
	Case 5.3.1-11	$C_0 = 1$ $C_T = 0.01$ $C_{MNA} = 0.1094$	1111	1111	2,763,400	363,560	3,127,000	60.38%
	Case 5.3.1-12	$C_0 = 1$ $C_T = 0.01$ $C_{MNA} = 0$	1111 1110	1111	3,480,700	396,850	3,877,500	75.46%

5.3.1.1 Both C_T and C_{MNA} are lower

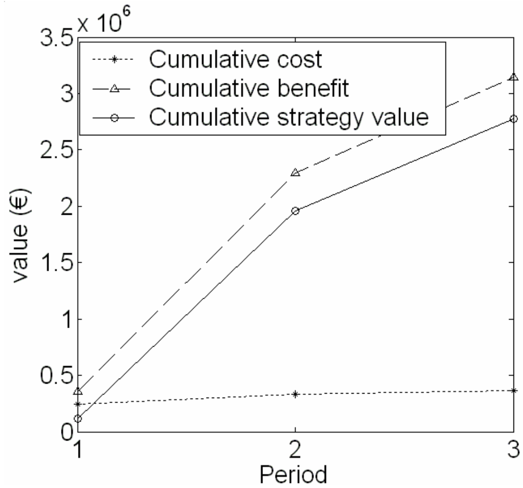
1. In this case, the decision of what to do in the first period does not change compared with the reference case. P&T should be applied for the first period.

2. The cost increases with lower threshold levels. This is because the more expensive techniques can not be switched to a cheaper technique so easily. This can be seen from Figure 5-2a and Figure 5-7a. Compared with the reference case, the probabilities of the first three scenarios in case 5.3.1-4 are higher. This is because of the more severe contamination or a

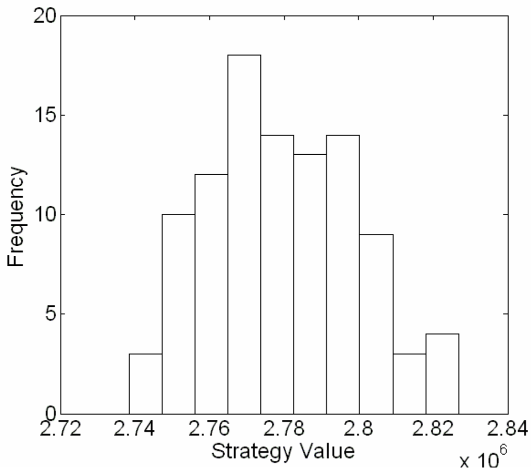
stricter target level. After the first period of P&T, it is more likely to apply intensive remedial activities in the second period. It is less likely to switch to a cheaper technology MNA or to stop. As a result, the strategy is more expensive.



(a) Scenario probabilities and values



(b) Cumulative cost, benefit and value



(c) Frequency of strategy values (100 runs)

Regulative parameters

Case 5.3.1-4
Parameter changed compared to reference case:

$C_T = 0.0066$
$C_{MNA} = 0.0984$

Figure 5-7: Results of optimal strategy 1111 for case 5.3.1-4

3. The benefit from selling the land increases when threshold levels are lower. Lower threshold levels represent either a more severely contaminated site or a stricter regulation due to e.g. a more sensitive land-use, which makes it more difficult to switch to MNA. This means more intensive techniques such as P&T and PRB have to be applied. The result is that the chance to meet the target is higher. This can be seen when comparing Figure 5-2a and Figure 5-7a. The scenarios in which the remedial activity can be stopped after the second period (or earlier) and the land can be sold are scenarios 3, 6 and 7. With the probabilities of scenarios 6 and 7 being similar, the probability of scenario 3 increases from the reference case to case

5.3.1-4. This is ultimately the reason for the increasing benefit with decreasing threshold levels C_{MNA} and C_T. This surprising result of an increasing effectiveness of the remediation with lower (i.e. stricter) targets is caused by managerial reasons, namely by applying the rule “switching to MNA as soon as it is possible ($C \leq C_{MNA}$)”. The implication for management is that MNA should not be applied too early if effectiveness is very important. This will be further discussed in section 5.3.1.3 when C_{MNA} is voluntarily lowered.

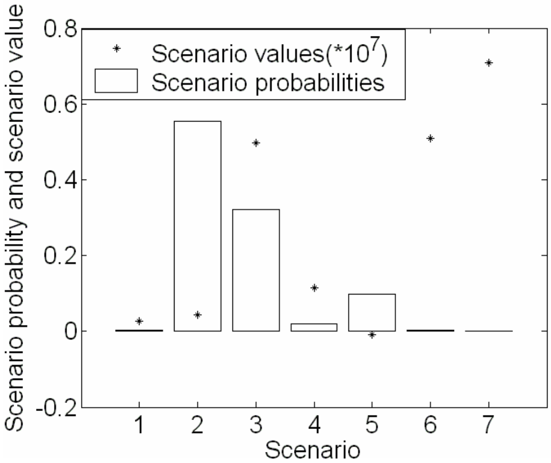
4. The strategy value (benefit minus cost) increases compared to the reference case with decreasing threshold levels. This is shown clearly comparing Figure 5-2b and Figure 5-7b. In the cases considered here, the effectiveness (as represented by the chance to meet the target) i.e. the benefit of a strategy is obviously dominating the result. Remediation cost plays a minor role. The relative influence of benefit and cost is closely related to the assumed land value, which was evidently set relatively high. So even though the cost increases with decreasing threshold levels, the strategy value still increases because of the more significant increase of the strategy benefit. Figure 5-2c and Figure 5-7c show the distributions of the strategy values of both cases. The role of the land value will be investigated in detail further below (see section 5.3.3.1).

5. The same strategy represented by one string has different implications (i.e. outcomes) when settings change. This is because different scenario probability distributions depend on the given threshold levels. The latter plays a very important role in the likelihood of scenario realization in reality. Whether better strategy can be identified by changing threshold levels within allowed range will be discussed in section 5.3.1.3.

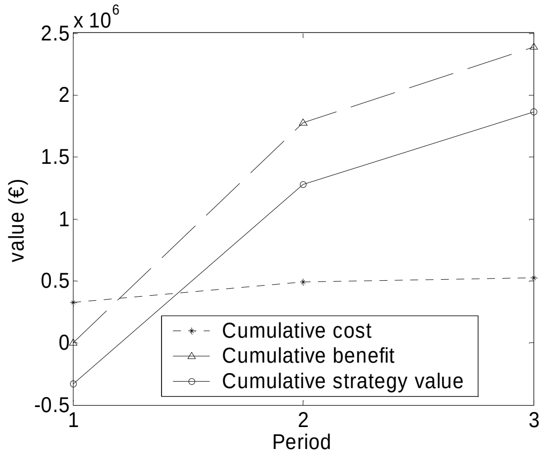
5.3.1.2 Both C_T and C_{MNA} are higher

1. When the site is less severely contaminated or planned land use is rather insensitive and allows for a higher remediation target, the recommended decision of what to do in the first period changes compared with the reference case. Strategy 0111 is optimal, and PRB should be applied in the first period.

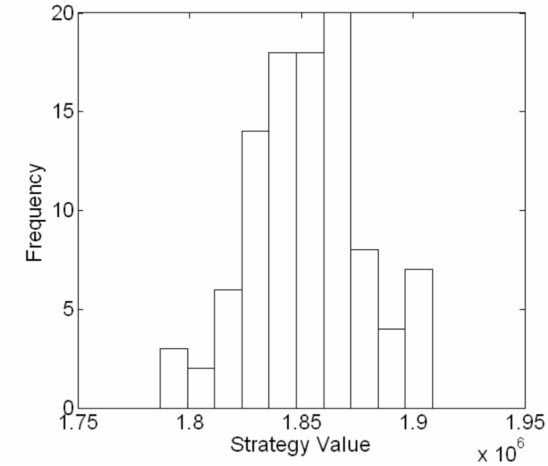
The evaluation results of the ‘former’ optimal strategy 1111 for the new parameter settings (cases 5.3.1-5 to 5.3.1-8) reveals that its strategy value is distinctly lower than the value of strategy 0111. This is mainly due to the lower chance to meet the target (32.52%): The results for strategy 1111 are: strategy cost = 333,230 EUR, strategy benefit = 1,715,900 EUR, strategy value = 1,382,700 EUR.



(a) Scenario probabilities and values



(b) Cumulative cost, benefit and value



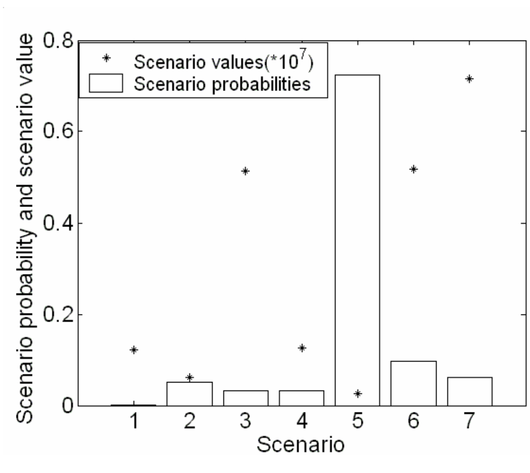
(c) Frequency of strategy values (100 runs)

Regulative parameters

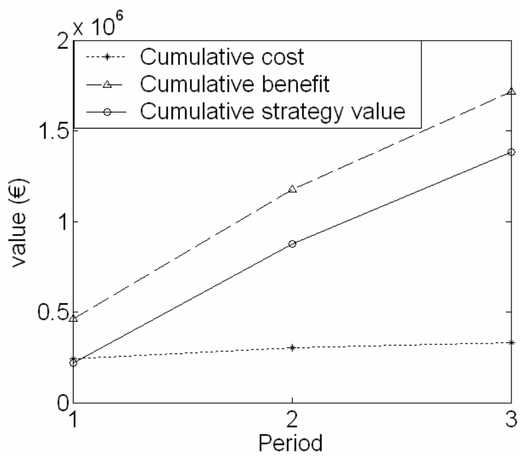
Case 5.3.1-8
Parameter changed compared to reference case:

$C_T = 0.0146$
$C_{MNA} = 0.2196$

Figure 5-8: Results of optimal strategy 0111 for case 5.3.1-8



(a) Scenario probabilities and values



(b) Cumulative cost, benefit and value

Figure 5-9: Results of comparative strategy 1111 for case 5.3.1-8

The reason why strategy 0111 is more effective than strategy 1111 has been discussed in previously in section 5.2.2.2. In case 5.3.1-8 settings, when the site is less contaminated, it is the same reason. Applying P&T in the first period, strategy 1111 is more likely to switch to MNA after the first period. As a consequence, strategy 1111 will be less effective over the entire planning period of 30 years than strategy 0111 (switch to MNA is less likely due to less effective technique PRB in first period). The effect can be shown in the higher probability of the first three scenarios for strategy 0111 compared with strategy 1111 (see Figure 5-8a and Figure 5-9a). In the reference case, even though strategy 1111 has a lower strategy benefit, it still has a higher strategy value due to the lower cost. But in the case 5.3.1-8 settings, the lower cost advantage of strategy 1111 can not compensate the much lower benefit. As a result, strategy 0111 is ranked better because of the higher benefit (see Figure 5-8b and Figure 5-9b). The frequency of the strategy values of these two strategies are shown in Figure 5-8c and Figure 5-9c.

The results show the complex relation between variables. Strategy value is decided by cost and benefit. The slight change in parameter settings can change the proportion of the cost and benefit in the strategy value. And thus, changes the result. With different scenario probability distribution, the expected cost and benefit can change. For example, the same strategy 0111 is not optimal under the reference case settings. But under case 5.3.1-8 settings, 0111 becomes the optimal strategy due to changes in expected cost and benefit caused by the slight change in regulative parameters. The interplay of different parameters and variables and the relation between these parameters and variables decide the valuation result. These variables include various aspects involved in remediation decision making besides regulative parameters: site parameters, economic parameters such as land value and costs, technology effectiveness and effectiveness' uncertainties, and time parameters. These parameters will be investigated in the discussion from section 5.3.2 to section 5.3.5.

2. For strategies starting with the same technology, when the threshold levels are higher, the strategy cost, the strategy benefit, the strategy value and the chance to meet the target all decrease. The reasoning is the opposite to point 2 to point 4 of section 5.3.1.1. Therefore it is not repeated here.

5.3.1.3 C_{MNA} is voluntarily lowered

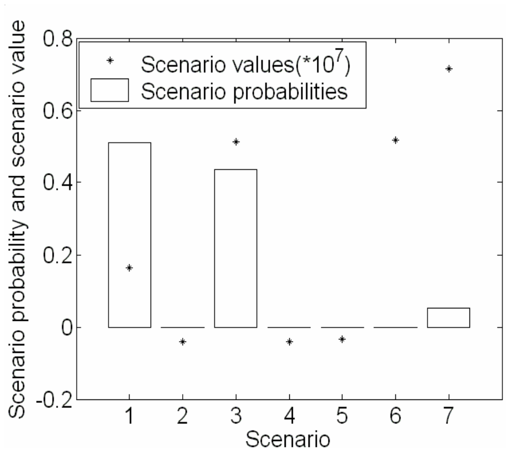
The upper limits of the thresholds levels, $C_{T,up}$ and $C_{MNA,up}$ are set by the regulation i.e. they both can not be increased without permission. Since $C_{T,up}$ demarcates the environmental status "clean", it is obvious that it will not be lowered voluntarily: $C_T = C_{T,up}$. The decision maker's flexibility that remains is to lower the threshold level for switching to MNA: $C_{MNA} < C_{MNA,up}$. The effect of doing so is not straightforward. The results are discussed below.

1. When C_{MNA} is voluntarily lowered, the optimal strategy is the same as the reference case, which indicates that P&T should be applied for the first period.

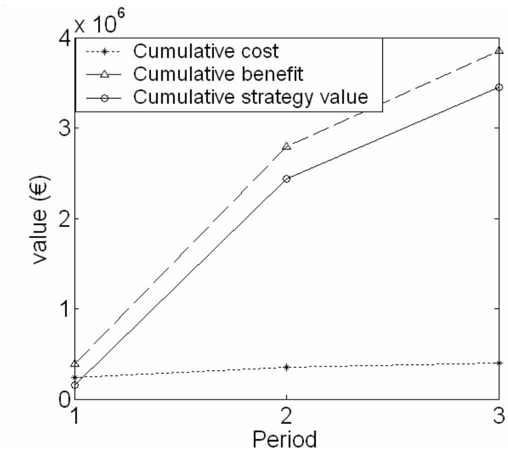
2. When C_{MNA} is voluntarily lowered, the strategy cost, the strategy benefit, the strategy value and the chance to meet the target all increase. The cost increases because switching to MNA requires lower concentration values that can be achieved only by prolongation of the operation time of active remediation. At the same time, the chance of meeting the target is increased, which yields an increased strategy benefit. Since the strategy benefit increases more significantly than the cost, the strategy value increases.

3. An extreme example is case 5.3.1-12, where MNA is not applied at all. Shown in Figure 5-10a, the probabilities of scenarios 2, 4, 5 and 6 are zeros because MNA is not applied (see Figure 5-1 for the tree structure). It has high stopping scenario probabilities after the second period compared with the reference case (scenarios 3, 6 and 7 in Figure 5-2a). Even though the cost increases, the strategy value still increases because of the much higher benefit (compare Figure 5-2b and Figure 5-10b). Figure 5-10c shows the frequency of the strategy value of the optimal strategy in case 5.3.1-12 for 100 runs.

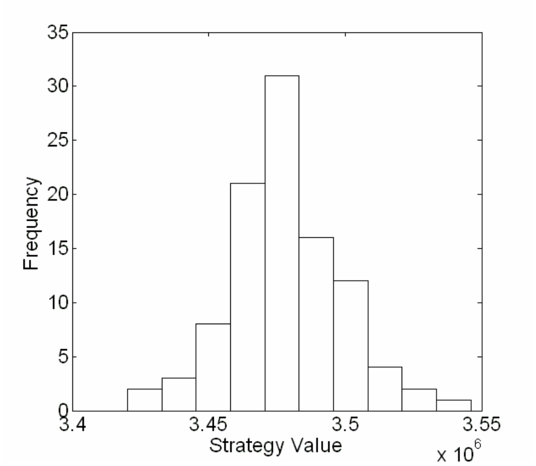
A comparative strategy 0111 is taken under the case 5.3.1-12 settings. In the previous comparisons, it is concluded that strategy 0111 is more effective because strategy 1111 switches to MNA too early. It may be taken wrong as a universal conclusion for all situations that strategy 0111 is more effective than strategy 1111. It is important to point out that this is not true any more in the settings in case 5.3.1-12, when MNA is not applied any more. The results of strategy 0111 and strategy 1111 under case 5.3.1-12 settings are compared in Table 5-6. As can be seen, strategy 1111 is more effective than strategy 0111. (See Figure 5-10 and Figure 5-11 for detailed information about these two strategies under case 5.3.1-12 settings.) In this case, strategy 1111 has higher strategy value because of higher benefit and lower cost compared with the comparative strategy 0111.



(a) Scenario probabilities and values



(b) Cumulative cost, benefit and value



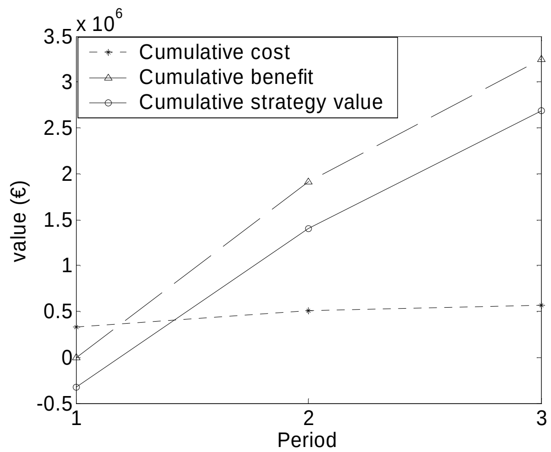
(c) Frequency of strategy values (100 runs)

Regulative parameters

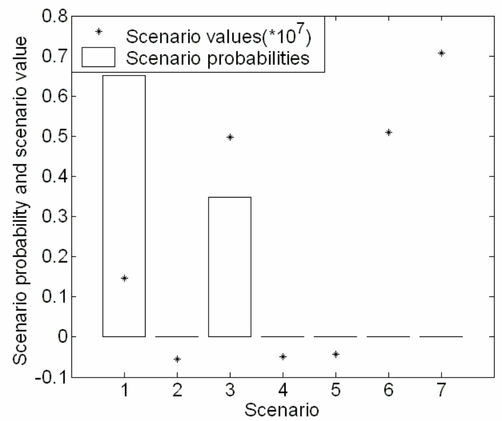
Case 5.3.1-12
Parameter changed compared to reference case:

$C_{MNA} = 0$

Figure 5-10: Results of optimal strategy 1111 for case 5.3.1-12



(a) Scenario probabilities and values



(b) Cumulative cost, benefit and value

Figure 5-11: Results of comparative strategy 0111 for case 5.3.1-12

Table 5-6: Results of strategy 1111 and 0111 using case 5.3.1-12 parameters

Strategy	Strategy value (€)	Cost (€)	Benefit (€)	Chance to meet the target
1111 (optimal)	3,480,700	396,850	3,877,500	75.46%
0111 (comparative)	2,695,400	565,970	3,261,400	67.97%

5.3.1.4 Conclusion

1. The regulative parameters have significant influence on strategy cost, strategy benefit (due to the influence on strategy effectiveness), and after all, strategy value.

2. Under the condition of high land value, effectiveness is a more dominant factor compared with cost.

3. When the threshold levels are lower, the more effective technology, P&T, is preferable for the first period. When the threshold levels are higher, PRB is preferable for the first period.

4. The same strategy represented by one string may mean quite different actions over time depending on scenario probabilities. The scenario probability distribution depends on the given threshold levels. Therefore, the threshold levels play a very important role in the optimal remedial activity identification.

5. Voluntarily lowering C_{MNA} is investigated in this case for all periods. It does not change the optimal remedial action for the first period. But it does increase the estimated strategy value by changing cost and the strategy effectiveness. As discussed previously, by changing the scenario probability distribution, it can change the actual realized remedial activities over time. When effectiveness is the main criterion in the decision making, MNA should not be applied too early even though the threshold is met.

5.3.2 Site parameters

Site parameters include aquifer thickness (mAq), conductivity (k) and total width of the contaminated area (y). In the following part, the effect of changing assumptions about these parameters to the result will be examined. The results are shown in Table 5-7. If not mentioned, the parameters are the same as the reference case.

Table 5-7: Sensitivity analysis results for site parameters

		Parameters	Candidate strings	Best string	Strategy value (€)	Cost (€)	Benefit (€)	Chance to meet the target
Reference		**mAq = 5 m k = 0.0005 m/s y = 100**	**1111 1101**	**1111**	**2,170,600**	**350,520**	**2,521,200**	**48.78%**
Aquifer thickness	**Case 5.3.2-1**	mAq = 2 m	1111 1101 0110	1101	2,263,500	242,730	2,506,200	48.47%
	Case 5.3.2-2	mAq = 10 m	1101 1111	1101	1,978,000	533,470	2,511,500	48.57%
Conductivity	**Case 5.3.2-3**	k = 0.0001 m/s	1111 1101	1101	2,300,000	207,400	2,507,400	48.48%
	Case 5.3.2-4	k = 0.0009 m/s	1111 0111 1101	1111	2,022,800	495,580	2,518,400	48.71%
	Case 5.3.2-5	k = 0.0015 m/s	0110 0111	0111	1,872,600	750,150	2,622,700	52.41%
	Case 5.3.2-6	k = 0.0030 m/s	0101 0110 0111	0111	1,550,300	1,065,600	2,615,900	52.28%
Total width of contaminated area	**Case 5.3.2-7**	y = 50 m	1111 0111 0110	1111	2,258,900	259,840	2,518,700	48.73%
	Case 5.3.2-8	y = 20 m	0110 0111 0101 0100	0110	2,386,500	230,530	2,617,000	52.30%
	Case 5.3.2-9	y = 10 m	0111 0110 0100	0111	2,423,500	191,950	2,615,400	52.27%
	Case 5.3.2-10	y = 200 m	1111 1101	1111	1,985,100	531,960	2,517,000	48.72%

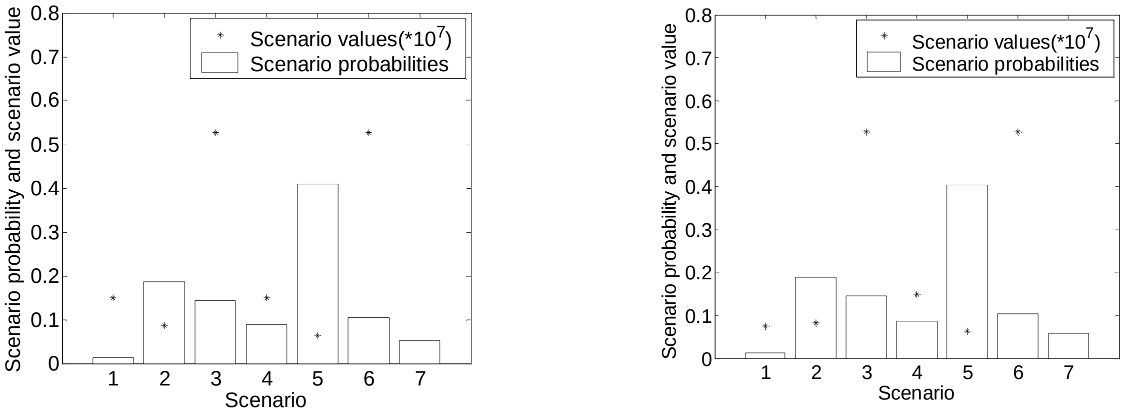
5.3.2.1 Aquifer thickness

1. When the aquifer thickness changes, the optimal remedial action for the first period does not change. P&T should be applied.

2. When the aquifer thickness reduces (case 5.3.2-1), the strategy cost reduces. This is because the remedial activity needs less material, energy and labor. Because of the same reason, when the aquifer thickness increases, the strategy cost increases (case 5.3.2-2). The changes in aquifer thickness do not influence the strategy effectiveness so much. As a result, the benefit does not change significantly. So the strategy value is changed mainly due to the changing costs.

3. Candidate strings are different from each other in each case. The two reasons for it have been discussed in section 4.4: similar strategy values and identical strings. Case 5.3.2-1 is taken here as an example to demonstrate these two reasons. Strategy 1111 and 1101 are identical strings. This can be seen in Figure 5-12. The probability of scenario 1 is almost zero. As discussed in section 4.4, the third digit of the string does not matter. As a result, 1111 and 1101 are identical. Strategy 0110 is listed as a candidate string because of the other reason. It

has similar strategy value as strategy 1101 (1111). The results for strategy 0110 are: strategy value = 2,250,400 EUR, strategy cost = 364,050 EUR, strategy benefit = 2,614,500 EUR, chance to meet the target = 52.24%. This strategy has higher benefit due to the higher chance to meet the target. It is a more expensive strategy due to the high installation cost and switching cost. After all, Strategy 0110 has a similar strategy value with the optimal strategy. As a result, strategy 0110 is also listed as a candidate string. As discussed in section 4.4, it is supposed that the decision maker provides the criterion as: when strategy value is positive, Max (mean/Std.); when strategy value is negative, Min (|mean|*Std.). According to these criteria, the optimal strategy is chosen. The same criteria are applied in this study when multiple candidate strings appear.



(a) Strategy 1111 (a) Strategy 1101

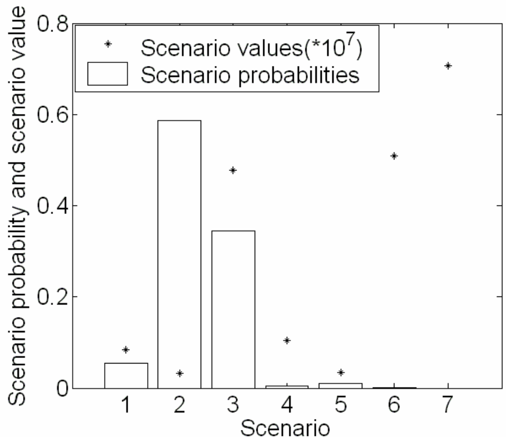
Figure 5-12: Scenario probabilities and values for strategy 1111 and 1101 in case 5.3.2-1

5.3.2.2 Conductivity

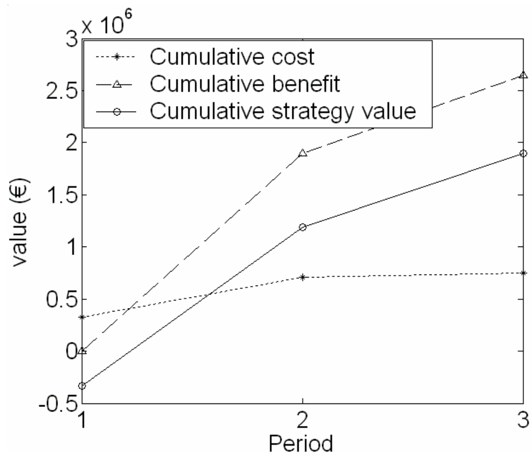
1. The change of conductivity can change the optimal remedial action for the first period when it is increased to a certain level. In case 5.3.2-5 and case 5.3.2-6, the optimal decision for the first period would be to apply PRB. The comparison of strategy 1111 and strategy 0111 is shown in Table 5-8. The detailed information about these two strategies using case 5.3.2-5 parameters is shown in Figure 5-13 and Figure 5-14. The reason why strategy 0111 is more effective has been discussed in chapter 5.2.2.2. Therefore it is not repeated here. Comparing the costs in Table 5-2 and Table 5-8 reveals that, with a higher conductivity, the low cost advantage of strategy 1111 is no longer significant using case 5.3.2-5 parameters compared with the reference case. As a result, with a slightly higher cost and much higher benefit, the strategy 0111 has a much higher strategy value compared with strategy 1111, as shown in Figure 5-13b and Figure 5-14b.

Table 5-8: Comparison of results of strategy 1111 and 0111 in the reference case, case 5.3.2-3, case 5.3.2-4, case 5.3.2-5 and case 5.3.2-6

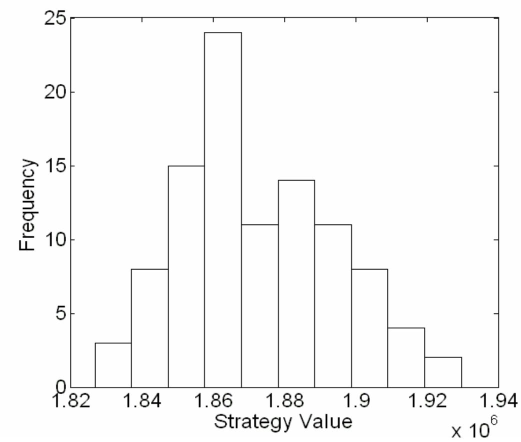
	Strategy	Reference case	Case 5.3.2-3	Case 5.3.2-4	Case 5.3.2-5	Case 5.3.2-6
Strategy cost (€)	1111	350,520	207,400	495,580	714,370	1,257,200
	0111	539,720	455,570	623,870	750,150	1,065,600
Strategy benefit (€)	1111	2,521,200	2,507,400	2,518,400	2,512,900	2,519,000
	0111	2,619,000	2,618,100	2,618,500	2,622,700	2,615,900
Strategy value (€)	1111	2,170,600	2,300,000	2,022,800	1,798,600	1,261,700
	0111	2,079,300	2,162,600	1,994,600	1,872,600	1,550,300



(a) Scenario probabilities and values



(b) Cumulative cost, benefit and value



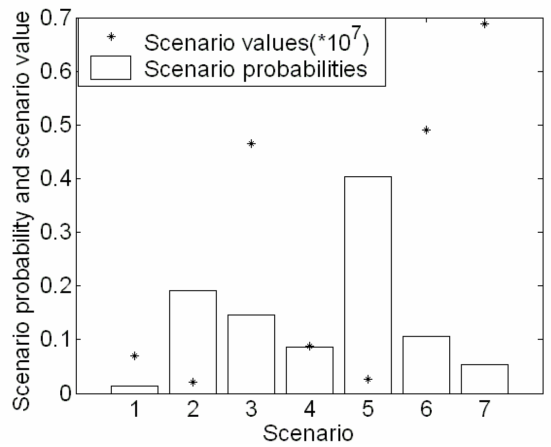
(c) Frequency of strategy values (100 runs)

Site parameters

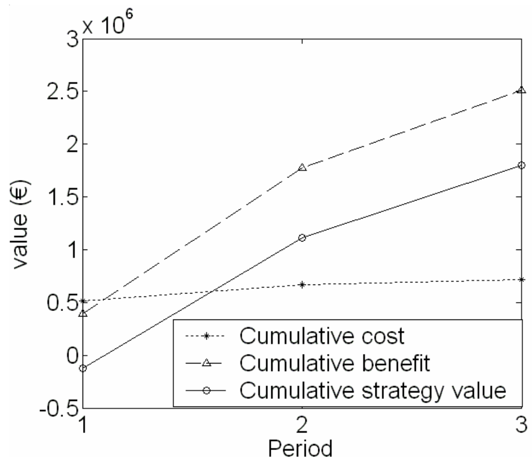
Case 5.3.2-5
Parameter changed compared to reference case:

k = 0.0015 m/s

Figure 5-13: Results of optimal strategy 0111 for case 5.3.2-5



(a) Scenario probabilities and values



(b) Cumulative cost, benefit and value

Figure 5-14: Results of comparative strategy 1111 for case 5.3.2-5

2. Conductivity influences mainly the cost, not the strategy effectiveness and thus, not the benefit. When the conductivity is lower, the cost is lower. This is true for both P&T and PRB. It is because when the conductivity is lower, P&T needs a lower pumping rate. The lower pumping rate causes less cost. For PRB, lower conductivity means that the barrier needs less filling material. With the same reasoning, a higher conductivity causes higher cost. The influence is different for these two technologies. As shown in Table 5-8, the effect of changing cost due to changing conductivity on P&T is bigger than PRB. Therefore, the influence on the cost of strategy 1111 is bigger than strategy 0111. This is also the reason why optimal strategy switches. By influencing the cost, conductivity influences the strategy value, while the influence on strategy benefit is not significant. After all, when the conductivity increases, the strategy value decreases; when the conductivity decreases, the strategy value increases.

5.3.2.3 Total width of the contaminated area

1. The change of total width of the contaminated area can change the optimal remedial action for the first period when it is reduced to a certain level. In case 5.3.2-8 and case 5.3.2-9 strategy 0110 is optimal. A comparison with strategy 1111 is shown in Table 5-9. As can be seen, the reason is the same as discussed in session 5.3.2.2: the cost advantage of strategy 1111 is no longer significant enough to overcome the disadvantage of lower effectiveness.

2. If one looks at the strategies starting with the same technology for the first period, total width of the contaminated area influences mainly the cost, not the benefit. The benefit is changing slightly because of little deviations in the probability distribution of C (Eq. 4-2) produced by Monte Carlo simulation from one run to the next. When the total width of the

contaminated area is shorter, the cost is lower. A longer total width of the contaminated area causes higher cost. By influencing the cost, conductivity influences the strategy value, while the influence on strategy benefit is not significant. After all, when the total width of the contaminated area increases, the strategy value decreases; when the total width of the contaminated area decreases, the strategy value increases.

Table 5-9: Comparison of results of strategy 1111 and 0110 using case 5.3.2-8 parameters

Strategy	Strategy value (€)	Cost (€)	Benefit (€)	Chance to meet the target
0110 (optimal)	2,386,500	230,530	2,617,000	52.30%
1111 (comparative)	2,312,000	205,450	2,517,400	48.71%

5.3.2.4 Conclusion

1. The site parameters mainly have influence on costs. They do not have significant influence on the strategy effectiveness. As a result, they do not influence the benefit so much.

2. A thicker aquifer, higher conductivity and longer total width of contaminated area will cause higher costs and thus lower strategy value; a thinner aquifer, lower conductivity and shorter total width of the contaminated area will cause lower costs, and thus higher strategy value.

3. P&T cost is more sensitive to conductivity and total width of the contaminated area than PRB. As a result, when these two parameters change, P&T can loose the low cost advantage in the reference case.

4. When the conductivity is very high or the total width of the contaminated area is short, PRB is preferred for the first decision period; when the conductivity is low or the total width of the contaminated area is long, P&T is preferred for the first decision period.

5.3.3 Economic parameters

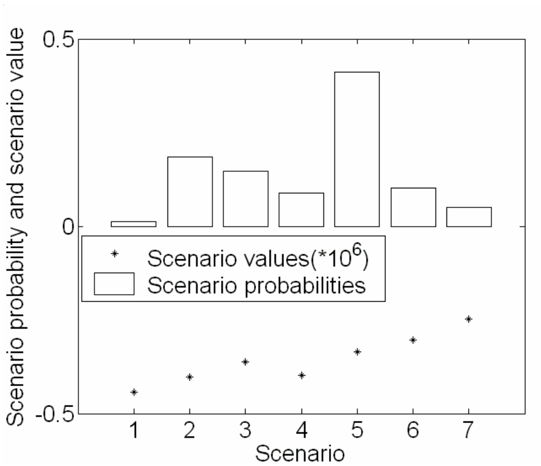
Economic parameters include: land value, technology costs and discount rate. Land value (V_{lc}) is the value of the land as if it was clean. It equals the land price multiplied by the land area. Recall that the strategy benefit is solely realized by selling the land whereas the benefit equals to V_{lc} multiplied by M (chance to meet the target). Technology cost is the cost associated with a certain technology. It includes installation cost, reactivation cost, operational cost and stopping cost. The role of technology cost is analyzed by multiplying a cost factor (e.g. + 30% or -30%) to all costs. The interest (or discount) rate (r) has a very big influence on the future cash flows. Future cash flows are less important with a larger the discount rate. The results of the study with respect to economic parameters are shown in Table 5-10. All parameter values not mentioned in the table are the same as the reference case.

Table 5-10: Sensitivity analysis results for economic parameters

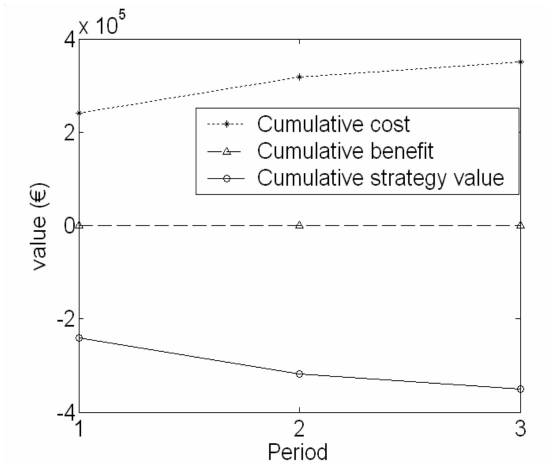
		Parameters	Candidate strings	Best string	Strategy value (€)	Cost (€)	Benefit (€)	Chance to meet the target
Reference		**$V_{lc} = 10^7$ € Costs (Table 5-1) r = 3%**	**1111 1101**	**1111**	**2,170,600**	**350,520**	**2,521,200**	**48.78%**
Land value	**Case 5.3.3-1**	$V_{lc}=2*10^7$ €	0110 0101 0111 1101 1111	0111	4,695,200	539,760	5,234,900	52.33%
	Case 5.3.3-2	$V_{lc}=10^5$ €	1111	1111	-325,350	350,530	251,840	48.71%
	Case 5.3.3-3	$V_{lc}=0$	1111	1111	-350,500	350,300	0	48.72%
Technology cost	**Case 5.3.3-4**	PRB costs increase 30%	1101 1111	1111	2,168,300	350,560	2,518,800	48.74%
	Case 5.3.3-5	PRB costs reduce 30%	0110 0111 1101 1111	0110	2,173,000	440,660	2,613,600	52.23%
	Case 5.3.3-6	P&T costs increase 30%	1101 0111 1111	1111	2,078,000	438,180	2,516,200	48.68%
	Case 5.3.3-7	P&T costs increase 80%	1111 0111 0110 1101	1111	1,933,900	584,210	2,518,100	48.73%
	Case 5.3.3-8	P&T costs increase 90%	0111 1111 0110 0101 1101	0110	1,913,500	703,440	2,617,000	52.29%
	Case 5.3.3-9	P&T costs reduce 30%	1101 1111	1111	2,257,500	262,860	2,520,400	48.75%
Discount rate	**Case 5.3.3-10**	r = 0%	0110 0111	0111	4,569,500	659,560	5,229,000	52.29%
	Case 5.3.3-11	r = 2%	1101 0110 1111	1101	2,735,000	378,740	3,113,700	48.53%
	Case 5.3.3-12	r = 6%	1111 1101	1111	1,062,000	290,270	1,352,300	48.70%

5.3.3.1 Land value

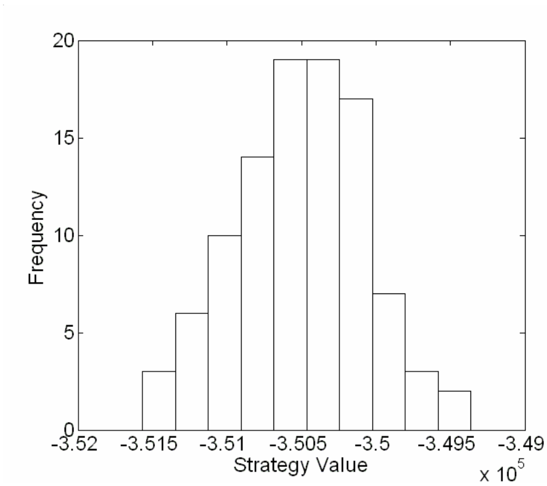
As discussed previously, land value (V_{lc}) is the source of strategy benefit, which represents strategy effectiveness. Thus, when land value increases, effectiveness plays a more important role than strategy cost. This can be seen from the switching of optimal action for the first period when V_{lc} is increased to $2*10^7$ EUR in case 5.3.3-1. As discussed in section 5.2.2.2, strategy 0111 is a more effective strategy with higher cost than strategy 1111. In case 5.3.3-1, 0111 becomes the optimal strategy because of the higher effectiveness. The switching point of the land value (L_V*) when the optimal action for the first period changes is $V_{lc} = 2*10^7$ €. When the land value decreases, the optimal strategy does not change.



(a) Scenario probabilities and values



(b) Cumulative cost, benefit and value



(c) Frequency of strategy values (100 runs)

Economic parameters

Case 5.3.3-3
Parameter changed compared to reference case:

$V_{lc} = 0$

Figure 5-15: Results of optimal strategy 1111 for case 5.3.3-3

An extreme example is case 5.3.3-3. When the land is not sold even though the remediation is finished, the land value is set to be zero. In this case, there is only cost without benefit for the project. Detailed information about case 5.3.3-3 is shown in Figure 5-15. Because the land value is zero, in Figure 5-15a, the scenario values are actually the scenario costs. In Figure 5-15b, it is shown that the cumulative benefit is always zero. The strategy value is the same amount of the strategy cost. Figure 5-15c shows the frequency of the strategy value for 100 runs.

Changing discount rate and total time frame under zero land value assumption

When V_{lc} is zero, benefit is not an influencing factor any more. As a result, cost is the only criterion for the strategy valuation. The cheapest strategy is the optimal. Discount rate and the total time frame play very important roles in this situation because the cost is very sensitive to them. This is due to the different cash flow structures of different technologies.

The sensitivity of the results to changing discount rate and total time frame is shown in Table 5-11. If not mentioned, the parameters are set to be the same as the reference case.

PRB has a very high installation cost at the beginning and rather low operational cost afterwards. P&T has lower installation cost at the beginning, but relatively high operational cost thereafter. As discussed previously, discount rate has a bigger effect on the operational cost of P&T compared with PRB. When discount rate is 1% (case 5.3.3-13), the cheapest strategy is 0000. In this situation, the advantage of low operational cost makes PRB preferable. But when the discount rate increases to 3% (case 5.3.3-14), strategy 1111 becomes the cheapest strategy. Both costs of strategy 0000 and 1111 are lower because of the discounting. But the effect on strategy 1111 is bigger than strategy 0000. With a bigger discount rate, the high operational cost disadvantage of P&T becomes smaller. As a result, strategy 1111 becomes the optimal in case 5.3.3-14.

Except for low discount rate, the low operational cost advantage of PRB can also show effect when the time frame is very long. When the time frame is increased to 70 years (case 5.3.3-15), strategy 0000 becomes cheaper than strategy 1111.

If discount rate is reduced and total time frame is increased at the same time, the effect is more significant. This can be seen from case 5.3.3-16. It takes shorter time than case 5.3.3-15 to show the low operational cost advantage of PRB.

Table 5-11: Results for optimal strategies and comparative strategies with changing discount rate and total time frame when land value is zero

Zero land value		Parameters	Strategy	Cost (€)	Chance to meet the target
Discount rate	Case 5.3.3-13	r = 1%	Optimal strategy 0000 Comparative strategy 1111	402,260 408,900	30.93% 48.67%
	Case 5.3.3-14	r = 3%	Optimal strategy 1111 Comparative strategy 0000	350,520 376,510	48.78% 30.91%
Total time frame	Case 5.3.3-15	70 years	Optimal strategy 0000	410,590	65.50%
			Comparative strategy 1111	437,060	79.38%
Total time frame & Discount rate	Case 5.3.3-16	60 years r = 2%	Optimal strategy 0000 Comparative strategy 1111	445,880 457,430	58.14% 76.30%

5.3.3.2 Technology cost

1. When the technology costs are changed, the optimal action for the first period can change. This is shown in case 5.3.3-5, when the costs of PRB are reduced by 30%, PRB should be applied for the first period. As discussed before, under the reference case settings, strategy 0111 (same as 0110) is more effective than strategy 1111, strategy 1111 has a higher strategy value due to the cost advantage (shown in Table 5-2). In case 5.3.3-5 settings, when PRB cost is reduced the cost advantage of strategy 1111 can no longer overcome the benefit

disadvantage. Strategy 0110 becomes the optimal strategy. The same effect can be seen when P&T costs are increased. But to achieve the same effect, P&T costs have to be increased by 90%. This is again because of the discounting effect due to the cash flow structure of P&T. If discount rate is reduced to 1%, 0111 becomes the optimal strategy when P&T costs are increased by 25%. The comparison of strategy 0110 and 1111 with r = 1% and P&T costs increase 25% is shown in Table 5-12.

2. For the same strategy (for example, strategy 1111 in the reference case and case 5.3.3-6), when the technology cost decreases, the strategy cost reduces, the strategy value increases. When the cost increases, the effect is the opposite.

Table 5-12: Comparison of strategies when r = 1%, P&T costs increase by 25% (mean of 100 runs, other parameters are the same as the reference case)

r=0%	Strategy value (€)	Cost (€)	Benefit (€)	Chance to meet the target
0110 (optimal)	3,472,300	672,370	4,144,700	52.32%
1111 (comparative)	3,408,600	490,250	3,898,900	48.79%

5.3.3.3 Discount rate

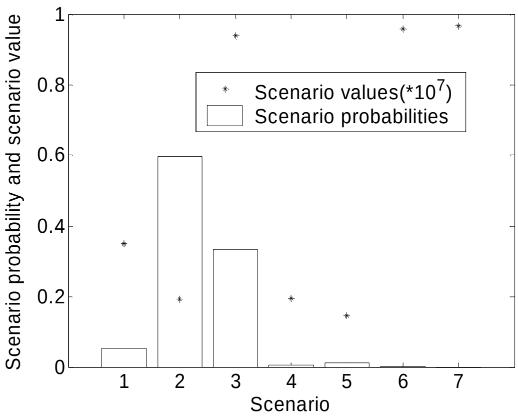
1. The net present values of cost, benefit and strategy value decrease with increasing discount rate. This is why the cost, benefit and strategy value all increase when the discount rate decreases as shown in Table 5-10.

2. Discount rate has different levels of influence on different cash flows. It has a bigger effect on future cash flows. A bigger discount rate makes the future cash flows less important. A smaller discount rate makes the future cash flows more important. As mentioned, under the condition of high land value, the technology effectiveness plays a very important role. This is reflected on the strategy benefit. Since benefit occurs in the further future compared with the cost, discount rate has a bigger impact on benefit than cost (see also point 3. further below). With a smaller discount rate, the future benefit is more important. In other words, with a smaller discount rate, the strategy effectiveness is more important. This is shown very clearly if we compare strategy 1111 and strategy 0111 under the condition of the reference case parameters (r = 3%) and case 5.3.3-10 parameters (r = 0%). The comparison is shown comparing Table 5-2 and Table 5-13. In both cases, strategy 0111 is more effective than strategy 1111, which is shown by the chance to meet the target. In the reference case, strategy 1111 is optimal because of the cost advantage. As discussed before, when r is decreased, the influence of effectiveness is increased. As a result, the cost advantage of strategy 1111 can no

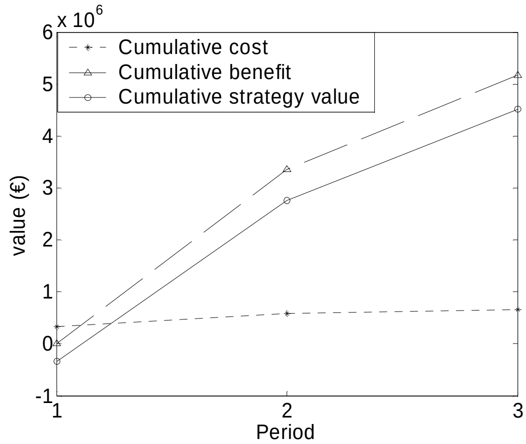
longer overcome the benefit disadvantage. Strategy 0111 becomes the optimal strategy. Detailed information about the optimal strategy under case 5.3.3-10 settings is shown in Figure 5-16.

Table 5-13: Comparison of strategies using case 5.3.3-10 parameters (mean of 100 runs)

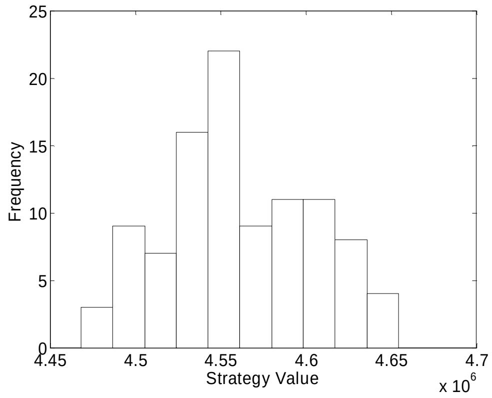
r = 0%	Strategy value (€)	Cost (€)	Benefit (€)	Chance to meet the target
0111 (optimal)	4,569,500	659,560	5,229,000	52.29%
1111 (comparative)	4,425,800	445,830	4,871,600	48.72%



(a) Scenario probabilities and values



(b) Cumulative cost, benefit and value



(c) Frequency of strategy values (100 runs)

Economic parameters

Case 5.3.3-10
Parameter changed compared to reference case:

r=0

Figure 5-16: Results of optimal strategy 0111 for case 5.3.3-10

3. For P&T and PRB, the effect of discount rate is different. P&T has less installation cost and more operational cost than PRB. PRB has a very intensive cost at the beginning but not so intensive cost afterwards. So P&T cost is more evenly distributed in time while P&B cost is very much distributed at the beginning. As a result, the cost of P&T is more sensitive to the discount rate than PRB. This can be seen comparing the strategy costs in Table 5-2 and

Table 5-13. When interest rate is reduced from 3% to 0% the cost of strategy 0111 increases less than those of strategy 1111 (strategy 0111 by 22.2%, strategy 1111 by 27.2%).

5.3.3.4 Conclusion

1. The land value is the source of benefit, which represent the strategy effectiveness. Higher land lave increases the importance of strategy effectiveness in the optimal strategy selection.

2. Cost plays an important role in the strategy valuation. When land value is very low, cost becomes a more important criterion for optimal strategy selection. When land value is zero, cost is the only criterion. The cheapest strategy is the optimal. If the decision maker wants to add the effectiveness as a criterion, a minimum chance to meet the target can be set.

3. Discount rate can change the relative importance of a factor to the valuation compared with other factors. A higher discount rate decreases the importance of effectiveness and thus relatively increases the importance of cost. A lower discount rate has the opposite effect.

4. Discount rate can change the cost and benefit structure of a strategy. All values are reduced after being discounted, including the cost, benefit and the strategy value. It has a higher effect on the cash flows which occur in the further future. It has more effect on the benefit compared with the cost. It also has more effect on the cost of P&T than PRB. PRB becomes preferable when discount rate is lower.

5. Changing of the project time frame can influence the optimal strategy making. The low operational cost advantage of PRB is more obvious in longer time frame. When time frame is long enough, PRB becomes the optimal action. This will be further discussed in section 5.3.5.1.

5.3.4 Technology parameters

Technology parameters refer to the effectiveness and uncertainties of the effectiveness. In this study, the effectiveness is represented by the decay rate constant. It is different for different technologies. For example, P&T is typically expected to be more effective than PRB (due to the effect of active pumping as opposed to pure passive treatment with PRB). The assumptions made in the reference case are accordingly: the decay rate constant of P&T ($\lambda_{P\&T}$) is higher than the one of PRB (λ_{PRB}). Within the reasonable range, the rates are changed, and the effects on the results are examined below. A second issue analyzed here is the uncertainty attributed to the technologies' effectiveness. In this study, this uncertainty is represented by stochastic representation of the development of contaminant concentration C over time (see eq. 4-2), resulting in a normally distributed probability density function of C, the standard deviation (Std.) of which is an input parameter that can assume any reasonable value. In the reference case, the standard deviations of the outcomes after a period of P&T, PRB and MNA are set to be the same, which is 0.07. In the following, it will be discussed how a change in standard deviation of different technologies will effect the results of the strategy evaluation.

5.3.4.1 Effectiveness of technologies

The effectiveness of technologies can not be estimated exactly in virtually all cases. This can over estimate or under estimate the effectiveness. Moreover, because of the development of technologies, the effectiveness can improve. As a result, the investigation of technology effectiveness is done by both increasing and decreasing the decay rate constant (λ). The decay rate constant defining the effectiveness of technologies are changed in two ways: 1. either $\lambda_{P\&T}$ or λ_{PRB} is changed, while keeping the other one the same as the reference case (the first two groups in Table 5-14); 2. $\lambda_{P\&T}$ and λ_{PRB} are changed at the same time (the last two groups in Table 5-14). It is assumed that PRB can not be more effective than P&T. The results are shown in Table 5-14. If not mentioned in the table, the parameter values are the same as the reference case.

Table 5-14: Sensitivity analysis results for effectiveness of technologies

		Parameters	Candidate strings	Best string	Strategy value (€)	Cost (€)	Benefit (€)	Chance to meet the target
Reference		**$\lambda_{P\&T} = 0.21$ $\lambda_{PRB} = 0.12$**	**1111 1101**	**1111**	**2,170,600**	**350,520**	**2,521,200**	**48.78%**
Changing effectiveness of P&T	**case 5.3.4-1**	Reduce $\lambda_{P\&T}$ by 25% $\lambda_{P\&T} = 0.16$	1111 1110 1101	1111	1,831,500	381,480	2,213,000	45.04%
	case 5.3.4-2	Reduce $\lambda_{P\&T}$ to 0.12 (same as λ_{PRB})	0000 0001 0011	0000	1,055,100	376,510	1,431,700	30.95%
	case 5.3.4-3	Increase $\lambda_{P\&T}$ by 25% $\lambda_{P\&T} = 0.26$	1111 1101	1111	2,850,400	326,270	3,176,700	55.84%
Changing effectiveness of PRB	**case 5.3.4-4**	Reduce λ_{PRB} by 25% $\lambda_{PRB} = 0.09$	1111 1101	1101	2,153,800	351,690	2,505,500	48.41%
	case 5.3.4-5	Increase λ_{PRB} by 25% $\lambda_{PRB} = 0.15$	1111 1101	1101	2,163,300	351,660	2,514,900	48.63%
	case 5.3.4-6	In crease λ_{PRB} to 0.21 (same as $\lambda_{P\&T}$)	1111 1110 1000 1100 1101	1111	2,163,000	357,920	2,520,900	48.78%
P&T and PRB are both less effective	**case 5.3.4-7**	Reduce both $\lambda_{P\&T}$ and λ_{PRB} by 25% $\lambda_{P\&T} = 0.16$ $\lambda_{PRB} = 0.09$	1111 1101	1111	1,827,500	381,470	2,209,000	44.96%
P&T and PRB are both more effectvie	**case 5.3.4-8**	Increase both $\lambda_{P\&T}$ and λ_{PRB} by 25% $\lambda_{P\&T} = 0.26$ $\lambda_{PRB} = 0.15$	1111 1101	1111	2,851,100	326,200	3,177,300	55.81%

5.3.4.1.1 Changing effectiveness of P&T

1. When $\lambda_{P\&T}$ is reduced to the level of λ_{PRB} (case 5.3.4-2), the optimal action for the first period becomes PRB. Two strategies 1111 and 0111 are compared below with the optimal strategy 0000 under case 5.3.4-2 settings. The results are shown in Table 5-15.

Because of the same effectiveness, the chances to meet the target for all strategies are similar. Again, small variations are caused by the uncertainty in Monte Carlo simulation. As a result, cost becomes the main criterion for the optimal strategy selection. Strategy 0111 is the most expensive strategy among the three due to the switching cost from PRB to P&T. Strategy 0000 is the cheapest one due to the low operational cost. Please note that relative economic advantages or disadvantages of either technology are governed by assumptions underlying the cost calculation. When installation cost of PRB is more expensive or when operational cost of P&T is reduced, strategy 0000 will get relatively more expensive compared with the other strategies which involve P&T and may therefore be not optimal under altered conditions. The time frame of remediation may also influence the outcome, e.g. when time frame is very short, P&T will be relatively cheaper than PRB, thus impairing the relative value of strategy 0000.

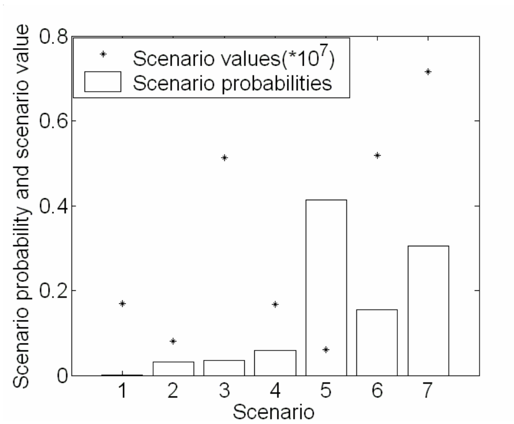
Table 5-15: Comparison of strategies using case 5.3.4-2 parameters (mean of 100 runs)

Strategy	Strategy value (€)	Cost (€)	Benefit (€)	Chance to meet the target
0000 (optimal)	1,055,100	376,510	1,431,700	30.95%
1111	1,024,400	404,990	1,429,400	30.90%
0111	875,760	554,890	1,430,700	30.92%

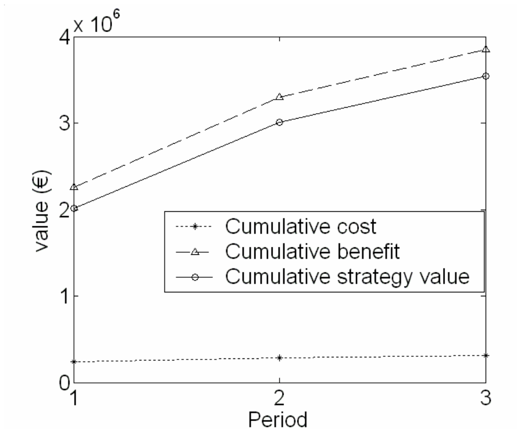
2. Increasing $\lambda_{P\&T}$ does not change the optimal action of the first period. P&T should be applied. Cost is reduced compared with the reference case. This is because when the technology is more effective, there is a bigger probability to switch the more intensive technique to MNA or to stop. In the case of MNA, the cost is much cheaper. In the case of stop, there will be no further costs. This can be seen very clearly if we compare Figure 5-17a and Figure 5-2a. The results of reference case concentrate more in scenarios 1, 2 and 3 compared with case 5.3.4-3. These scenarios are the ones which have to continue P&T after the first period of P&T. In other words, there is a much higher probability for case 5.3.4-3 to switch to MNA or to stop after the first period of P&T compared with the reference case. The opposite trend can be concluded when $\lambda_{P\&T}$ is reduced.

When $\lambda_{P\&T}$ is higher (case 5.3.4-3), expected benefit of strategy 1111 increases. This is because of the increase of the chance to meet the target. The total value of strategy 1111 also increases, due to the increase of benefit and the decrease of cost. (Compare Figure 5-17b and Figure 5-2b.)

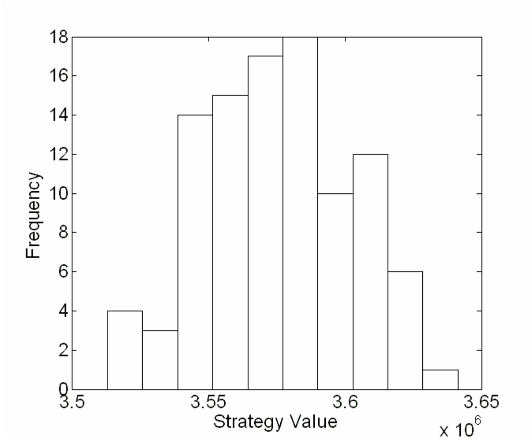
The chance to meet the target increases at higher lambda because overall higher effectiveness is dominating i.e. surmounts the role of the increased likelihood of switching to MNA.



(a) Scenario probabilities and values



(b) Cumulative cost, benefit and value



(c) Frequency of strategy values (100 runs)

Technology parameters

Case 5.3.4-3
Parameter changed compared to reference case:

$\lambda_{P\&T} = 0.26$

Figure 5-17: Results of optimal strategy 1111 for case 5.3.4-3

5.3.4.1.2 Changing effectiveness of PRB

When λ_{PRB} is changed, the results are not influenced very much. The optimal remedial activity for the first period is still P&T. As discussed in the previous section, when $\lambda_{P\&T}$ is reduced to the same level of λ_{PRB} (case 5.3.4-2: $\lambda_{P\&T} = \lambda_{PRB} = 0.12$), strategy 0000 is optimal. This is not the case when λ_{PRB} is increased to the same level of $\lambda_{P\&T}$ (case 5.3.4-6: $\lambda_{P\&T} = \lambda_{PRB} = 0.21$). To have a closer look to this apparent inconsistency, strategy 1111 shall be compared with strategy 0000 and 0111 under case 5.3.4-6 settings (see Table 5-16). Both in case 5.3.4-2 and 5.3.4-6, as $\lambda_{P\&T} = \lambda_{PRB}$ and strategies have hence a similar effectiveness, the expected benefits are similar. Cost is the main criterion for the optimal strategy selection. The difference is that under case 5.3.4-6 settings, increasing the effectiveness of PRB to the same level as P&T does not make strategy 0000 optimal. Strategy 1111 becomes the cheapest one. The costs of strategy 1111 and 0000 are listed with different λ in Table 5-17, under the condition of $\lambda_{P\&T} = \lambda_{PRB} = \lambda$. As shown, when λ increases, strategy 1111 becomes cheaper while strategy 0000 becomes more expensive. With higher technology effectiveness, there is a higher likelihood for both strategies to switch to MNA. As shown in Table 5-1, the operational cost of MNA is higher than PRB, but cheaper than P&T. So switching from PRB to MNA will increase the cost while switching from P&T to MNA will reduce the cost. As a result, in case 5.3.4-2 strategy 0000 is cheaper, while in case 5.3.4-6 strategy 1111 is cheaper.

Table 5-16: Comparison of strategies using case 5.3.4-6 parameters (mean of 100 runs)

Strategy	Strategy value (€)	Cost (€)	Benefit (€)	Chance to meet the target
1111 (optimal)	2,163,000	357,920	2,520,900	48.78%
0000	2,119,900	397,880	2,517,800	48.71%
0111	2,059,100	460,080	2,519,200	48.75%

Table 5-17: Comparison of strategy costs for strategy 1111 and strategy 0000 with the same λ

$\lambda_{P\&T} = \lambda_{PRB} = \lambda$	Strategy costs	
	1111	**0000**
$\lambda = 0.12$	404,990	376,510
$\lambda = 0.15$	387,640	380,980
$\lambda = 0.18$	368,770	390,910
$\lambda = 0.21$	357,920	397,880

5.3.4.1.3 Changing effectiveness of both P&T and PRB

1. Increasing or decreasing $\lambda_{P\&T}$ and λ_{PRB} at the same time does not change the optimal action for the first period. P&T is still the optimal.

2. When $\lambda_{P\&T}$ and λ_{PRB} increase, the strategy value increases. This is because of the increasing benefit due to the increasing chance to meet the target, and the decreasing of cost. Increasing chance to meet the target is caused by higher effectiveness of technology. Decreasing cost is because there is a higher probability to switch to a cheaper technology and to stop. When the $\lambda_{P\&T}$ and λ_{PRB} are decreased, the effect is the opposite.

5.3.4.2 Uncertainty of technologies' effectiveness

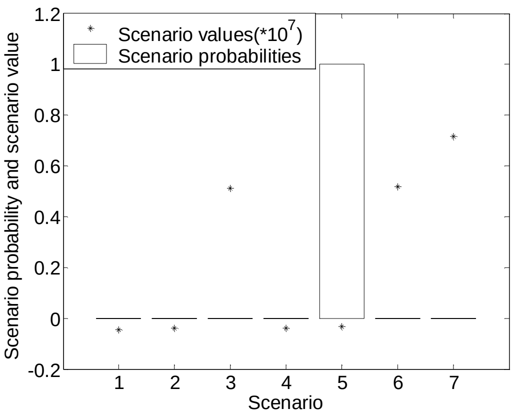
In reality, the levels of uncertainties associated with technologies' effectiveness are believed to be different for individual technologies. The effectiveness of widely used technologies like e.g. P&T and PRB can be predicted (estimated) with more certainty than the effectiveness of MNA. Moreover, the knowledge of technologies' effectiveness may improve over time due to increasing experience. As a result, probability density function of concentration can change. To examine these effects, the settings are changed in two ways: 1. Std. of effectiveness is changed for all technologies. 2. Std. of effectiveness is changed for individual technologies only. The results are shown in Table 5-18. Unless otherwise mentioned, the parameters are the same as the reference case.

Table 5-18: Sensitivity analysis results for uncertainty of technologies' effectiveness

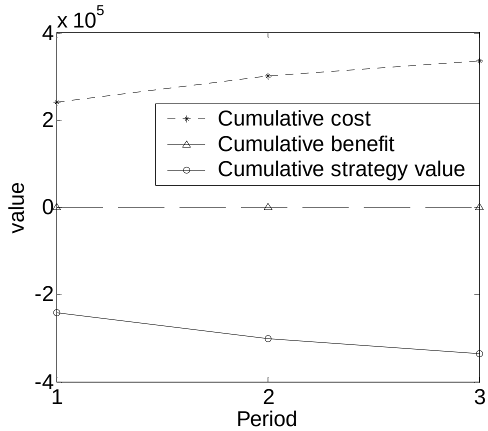
		Parameters	Candidate strings	Best string	Strategy value (€)	Cost (€)	Benefit (€)	Chance to meet the target
Reference		**$Std_{P\&T}$ = 0.07** **Std_{PRB} = 0.07** **Std_{MNA} = 0.07**	**1111** **1101**	**1111**	**2,170,600**	**350,520**	**2,521,200**	**48.78%**
Deterministc case	**Case 5.3.4-9**	$Std_{P\&T}$ = 0 Std_{PRB} = 0 Std_{MNA} = 0	1111	1111	-335,730	335,730	0	0.00%
All Std.s are smaller	**Case 5.3.4-10**	$Std_{P\&T}$ = 0.03 Std_{PRB} = 0.03 Std_{MNA} = 0.03	0111 0110 0101	0110	1,046,600	545,840	1,592,500	32.68%
All Std.s are bigger	**Case 5.3.4-11**	$Std_{P\&T}$ = 0.1 Std_{PRB} = 0.1 Std_{MNA} = 0.1	1111 1101	1111	3,043,000	347,150	3,390,100	62.19%
	Case 5.3.4-12	$Std_{P\&T}$ = 0.3 Std_{PRB} = 0.3 Std_{MNA} = 0.3	1111	1111	4,514,300	335,460	4,849,700	80.12%
Changing Std of MNA	**Case 5.3.4-13**	Std_{MNA} = 0.02	0111 0110 0101	0111	1,464,000	539,580	2,003,600	37.28%
	Case 5.3.4-14	Std_{MNA} = 0.3	1111 1101	1111	3,064,100	355,380	3,419,500	65.88%
Changing Std of P&T	**Case 5.3.4-15**	$Std_{P\&T}$ = 0.02	0110 0101 0100 0111	0100	1,291,500	547,970	1,839,500	42.22%
	Case 5.3.4-16	$Std_{P\&T}$ = 0.3	1111 1110	1111	4,193,300	333,620	4,527,000	73.54%
Changing Std of PRB	**Case 5.3.4-17**	Std_{PRB} = 0.02	1111 1101	1101	2,141,700	351,740	2,493,400	48.15%
	Case 5.3.4-18	Std_{PRB} = 0.3	0001 0000	0001	3,019,800	362,940	3,382,800	60.39%

5.3.4.2.1 Deterministic case: All standard deviations equal zero

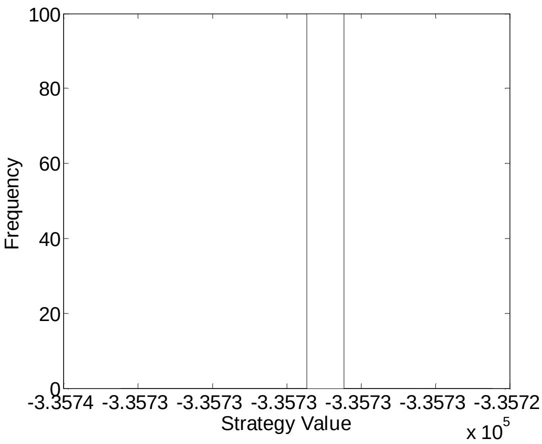
1. An extreme case is when Std. = 0 (case 5.3.4-9). This is called a deterministic case. As shown, the optimal action for the first period does not change. Seen from Figure 5-18a, strategy 1111 has only one scenario, scenario 5. Scenario 5 shows that after the first period of P&T, it will be switched to MNA. Then MNA will continue to be applied for the third period. This decision path is according to the assumption that decision maker will switch to MNA whenever it is possible. This may not be the case when the decision maker delays the application of MNA for a more effective remediation as discussed in section 5.3.1.3. In case 5.3.4-9, there is no benefit from selling the land (see Figure 5-18b). Since the Std. is zero, there is no uncertainty in the result. This is shown clearly in Figure 5-18c. When the Std. is zero, under the current settings for C_0, C_T, C_{MNA} and λ, there is no strategy which has the chance to meet the target. There is no benefit in any cases. To choose the optimal strategy, cost is the only criterion. The cheapest strategy is the optimal. In this case, it is strategy 1111.



(a) Scenario probabilities and values



(b) Cumulative cost, benefit and value



(c) Frequency of strategy values (100 runs)

Technology parameters

Case 5.3.4-9
Parameter changed compared to reference case:

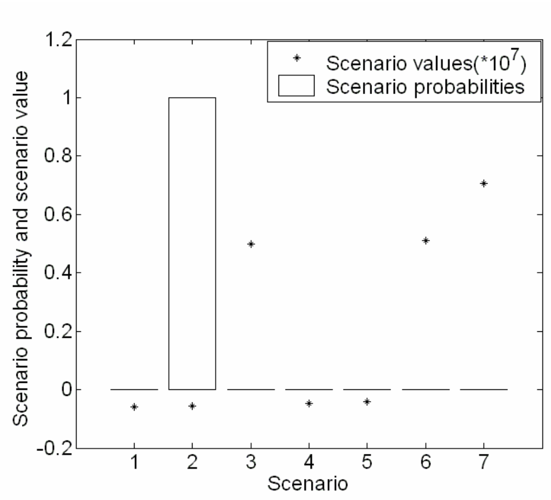
$Std_{P\&T} = 0$
$Std_{PRB} = 0$
$Std_{MNA} = 0$

Figure 5-18: Results of optimal strategy 1111 for case 5.3.4-9

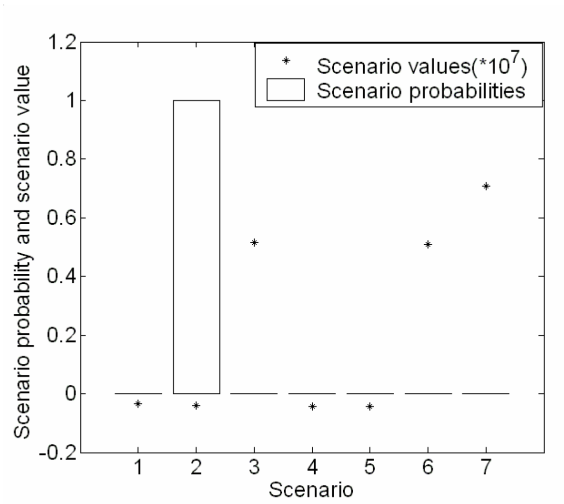
The results for strategy 0111 and 0000 are compared with the optimal strategy in Table 5-19. As shown, all strategies have zero chance to meet the target. Therefore, there is no benefit. The cheapest strategy is 1111. The scenario probabilities of strategy 0111 and 0000 are shown in Figure 5-19. These two strategies both have only scenario 2. Action path of strategy 0111: after the first period of PRB, it is switched to P&T. After the second period of P&T, it will be switched to MNA for the third period. Action path of strategy 0000: after two periods of PRB, it will be switched to MNA for the third period.

Table 5-19: Comparison of results of strategy 1111, strategy 0111 and strategy 0000 using case 5.3.4-9 parameters

	1111	0111	0000
Cost	335,730	553,430	387,980
Chance to meet the target	0%	0%	0%



Strategy 0111

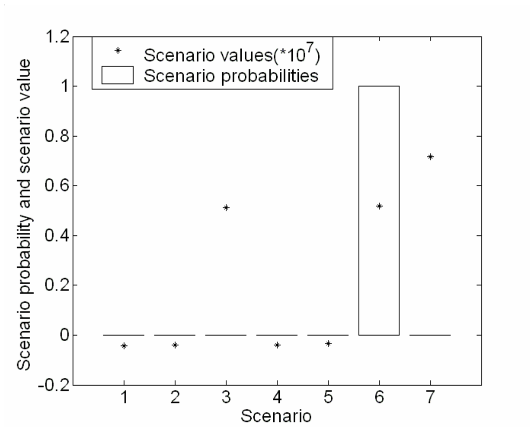


Strategy 0000

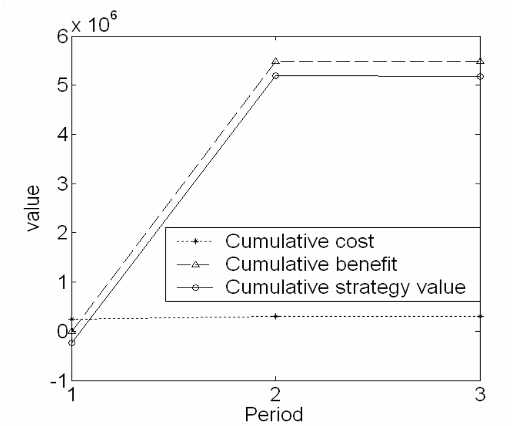
Figure 5-19: Scenario probabilities of strategy 0111 and strategy 0000 using case 5.3.4-9 parameters

2. The deterministic case's chance to meet the target will remain zero for a more severely contaminated site or a stricter target level compared with case 5.3.4-9 (when C_T is lower). In case of less severely contaminated site or a less strict target level compared with case 5.3.4-9 (when C_T is higher), the chance to meet the target can be one. When C_T is increased to 0.11, strategy 1111 ends up with "Stop" after the second periods (scenario 6). The case with C_T = 0.11 (other parameters are the same as case 5.3.4-9) is taken as another deterministic case to investigate the sensitivity of the results to uncertainty of technologies' effectiveness. Again, the strategy has only one scenario, which is scenario 6 (see Figure 5-

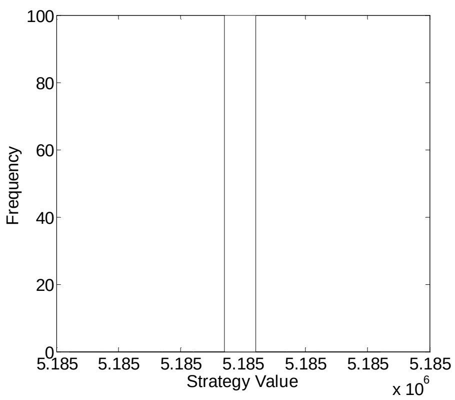
20a). That means the strategy start with P&T for the first period, and switch to MNA for the second period. After the second period, the target will be met. The cumulative strategy value, cost and benefit are shown in Figure 5-20b. Because of zero Std., there is no uncertainty of the strategy value (see Figure 5-20c). The comparison of strategy 0111, 1111 and 0000 under these settings is shown in Table 5-20. All strategies have a chance to meet the target of 100% and thus the same benefit. As a result, the cheapest strategy is the best. Under the current settings, strategy 1111 is the optimal one. The sensitivity analysis results for uncertainty of technologies' effectiveness when C_T = 0.11 are shown in Table 5-21.



(a) Scenario probabilities and values



(b) Cumulative cost, benefit and value



(c) Frequency of strategy values (100 runs)

Figure 5-20: Results of optimal strategy 1111 for case 5.3.4-9 when C_T = 0.11

Table 5-20: Comparison of strategy 0111, strategy 1111 and strategy 0000 (C_T = 0.11, other parameters same as case 5.3.4-9 settings)

Strategy	Strategy value	Cost (€)	Benefit (€)	Chance to meet the target
0111	4,975,600	512,490	5,488,100	100%
1111	5,185,000	303,140	5,488,100	100%
0000	5,143,100	345,020	5,488,100	100%

Table 5-21: Sensitivity analysis results for uncertainty of technologies' effectiveness (C_T = 0.11)

		Parameters	Candidate strings	Best string	Strategy value (€)	Cost (€)	Benefit (€)	Chance to meet the target
Deterministc case		**$Std_{P\&T}$ = 0** **Std_{PRB} = 0** **Std_{MNA} = 0** **C_T = 0.11**	**1111**	**1111**	**5,185,000**	**303,140**	**5,488,100**	**100.00%**
Reference case with C_T = 0.11		**$Std_{P\&T}$ = 0.07** **Std_{PRB} = 0.07** **Std_{MNA} = 0.07** **C_T = 0.11**	**1101** **1111**	**1111**	**5,623,900**	**308,470**	**5,932,400**	**95.74%**
All Std.s are smaller	**Case 5.3.4-19**	$Std_{P\&T}$ = 0.03 Std_{PRB} = 0.03 Std_{MNA} = 0.03 C_T = 0.11	1100 1111 1101 1110	1100	5,222,100	306,430	5,528,600	92.47%
All Std.s are bigger	**Case 5.3.4-20**	$Std_{P\&T}$ = 0.3 Std_{PRB} = 0.3 Std_{MNA} = 0.3 C_T = 0.11	1111 1110	1111	5,408,100	320,140	5,728,200	90.74%
Changing Std of MNA	**Case 5.3.4-21**	Std_{MNA} = 0.02 C_T = 0.11	1111 1110 1100	1110	5,647,100	304,830	5,952,000	95.78%
	Case 5.3.4-22	Std_{MNA} = 0.3 C_T = 0.11	1111 1101	1111	5,638,200	310,960	5,949,200	96.24%
Changing Std of P&T	**Case 5.3.4-23**	$Std_{P\&T}$ = 0.02 C_T = 0.11	1101 1111	1101	4,987,500	313,290	5,300,800	93.45%
	Case 5.3.4-24	$Std_{P\&T}$ = 0.3 C_T = 0.11	1111 1110	1110	5,419,800	320,810	5,740,600	91.03%
Changing Std of PRB	**Case 5.3.4-25**	Std_{PRB} = 0.02 C_T = 0.11	1000 1010	1000	5,711,800	347,700	6,059,500	97.62%
	Case 5.3.4-26	Std_{PRB} = 0.3 C_T = 0.11	1111 1101	1111	5,624,100	308,500	5,932,600	95.75%

5.3.4.2.2 Analysis with small standard deviations

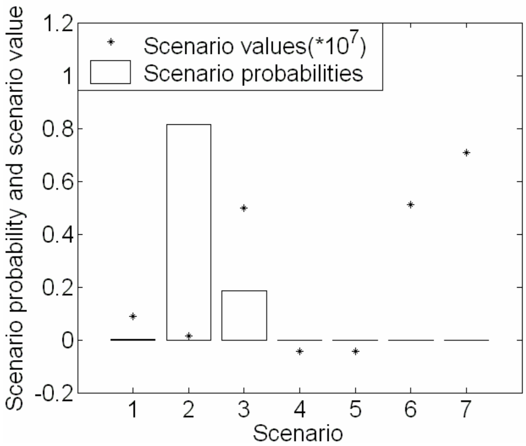
1. When all Std.s of the technologies' effectiveness are set to be 0.03 (see Table 5-18: case 5.3.4-10) the optimal remedial action for the first period changes: PRB should be applied for the first period.

To analyze the reasons, the performance of strategy 1111 under the condition of case 5.3.4-10 is compared with the optimal strategy 0110 in case 5.3.4-10. The results are shown in Table 5-22. It can be seen that strategy 0110 is clearly more effective than strategy 1111, and has therefore a much higher strategy value even though it is more expensive. Detailed information about these two strategies is shown in Figure 5-21 and Figure 5-22.

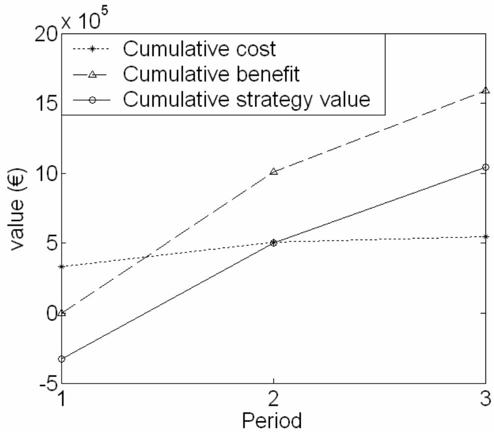
In contrast, under the condition in case 5.3.4-19 with all Std.s also being 0.03, the optimal action for the first period does not change. Under this condition, the results for strategy 0110 are: strategy value = 4,954,600 EUR, strategy benefit = 5,467,400 EUR, strategy cost = 512,800 EUR, chance to meet the target = 99.75%. Compared with the optimal strategy 1100, strategy 0110 is more effective and more expensive. Under case 5.3.4-19 settings, the effectiveness advantage does not overcome the cost disadvantage. As a result, strategy 1100 is the optimal. It can be argued that uncertainty about the technologies' effectiveness, if represented by normally distributed rates and the value of the distributions Std.s, can have different effect on the strategy making depending on the result of the underlying deterministic case. If the latter yields a 0% chance to meet the target, the optimal remedial action is more likely subject to a change at small Std.s than in the case where the underlying deterministic case has a 100% chance to meet the target.

Table 5-22: Comparison of strategies using case 5.3.4-10 parameters (mean of 100 runs)

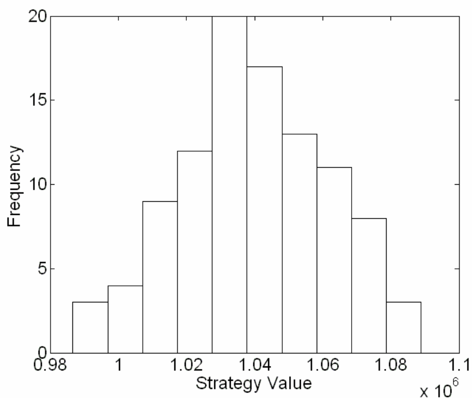
Strategy	Strategy value	Cost (€)	Benefit (€)	Chance to meet the target
0110 (optimal)	**1,046,600**	**545,840**	**1,592,500**	**32.68%**
1111 (comparative)	222,790	346,310	569,100	11.62%



(a) Scenario probabilities and values



(b) Cumulative cost, benefit and value



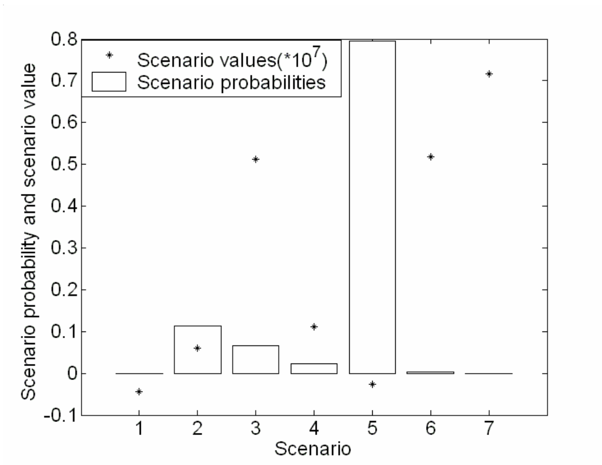
(c) Frequency of strategy values (100 runs)

Technology parameters

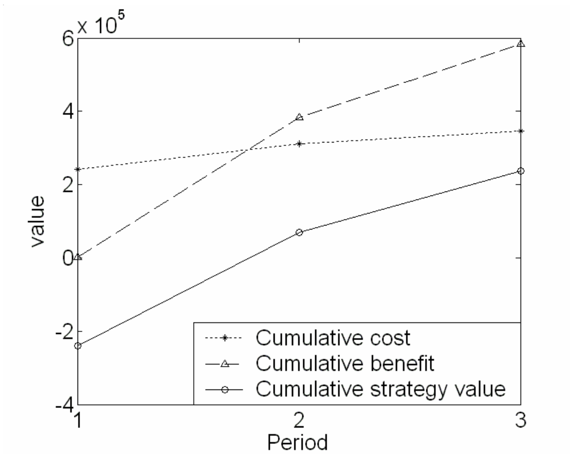
Case 5.3.4-10
Parameter changed compared to reference case:

$Std_{P\&T}$=0.03
Std_{PRB}=0.03

Figure 5-21: Results of optimal strategy 0110 for case 5.3.4-10



(a) Scenario probabilities and values



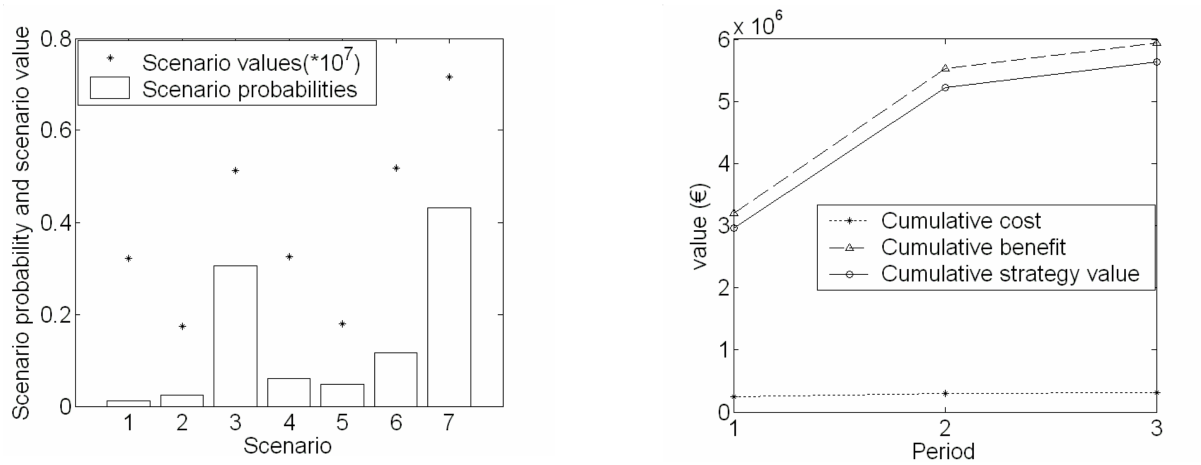
(b) Cumulative cost, benefit and value

Figure 5-22: Results of comparative strategy 1111 for Case 5.3.4-10

2. The distribution of scenario probabilities for strategy 1111 develop from a single scenario distribution for the case with Std. = 0 (Figure 5-18a) into a distribution of scenarios for cases with Std. = 0.03, and reference case Std. = 0.07 (Figures 5-22a and Figure 5-2a). In this way, technology uncertainty is influencing the evaluation significantly by changing the outcome probability density function (pdf) of concentration.

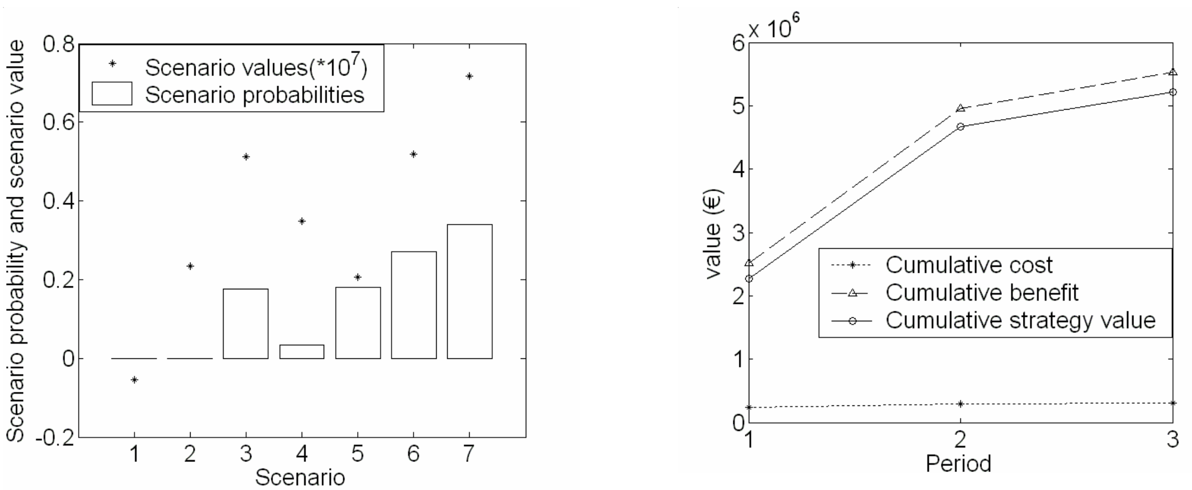
3. As shown in Table 5-18 and Table 5-21, with Std = 0.03, in case 5.3.4-10 and 5.3.4-19, the chance to meet the target is smaller compared with the their reference cases respectively. It can be seen in Figure 5-21a that with smaller Std.s the outcomes concentrate in scenarios 2 and 3. Compared with Figure 5-2a, it is clear that the stopping scenario probabilities (scenarios 3, 6 and 7) are much lower in case 5.3.4-10.

Figure 5-23 shows the results of the reference case with altered C_T (0.11 instead of 0.01). All other parameters are the same as in the reference case. Figure 5-24 shows the result of case 5.3.4-19. The smaller Std.s increase very much the probabilities of scenarios 5 and 6. The other scenarios are reduced. The reduction of scenarios 3 and 7 yields a reduction in the final chance to meet the target.



(a) Scenario probabilities and values (b) Cumulative cost, benefit and value

Figure 5-23: Results of optimal strategy 1111 for the reference case with C_T = 0.11



(a) Scenario probabilities and values (b) Cumulative cost, benefit and value

Figure 5-24: Results of optimal strategy 1100 for case 5.3.4-19

5.3.4.2.3 Analysis with big standard deviations

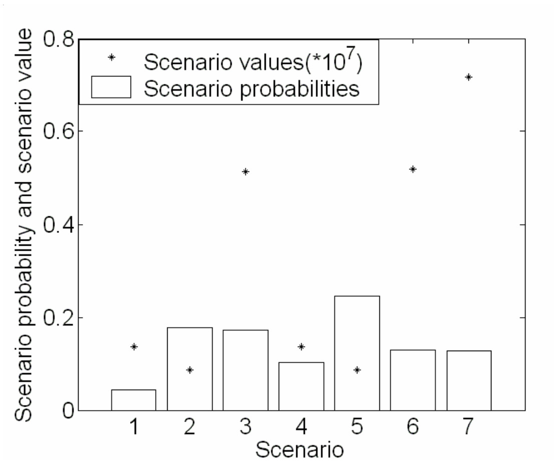
1. When all Std.s are bigger, the optimal remedial action for the first period does not change. This can be seen in Table 5-18 and Table 5-21.

2. With bigger Std.s, the distribution of scenario probabilities concentrates more and more in scenarios 1, 3 and 7. This trend can be seen clearly if we compare Figure 5-2a, Figure 5-25a and Figure 5-26a. This is because after the first period of P&T, with a higher standard deviation, the results distribute more widely. The result of bigger Std.s is that it is more likely to develop into the first ($P_{1,1,U}$) or the last branch ($P_{1,1,D}$) after the first period of P&T (see Table 5-23). These branches lead to scenarios 1, 2, 3 and 7. (See Figure 5-1 for the tree

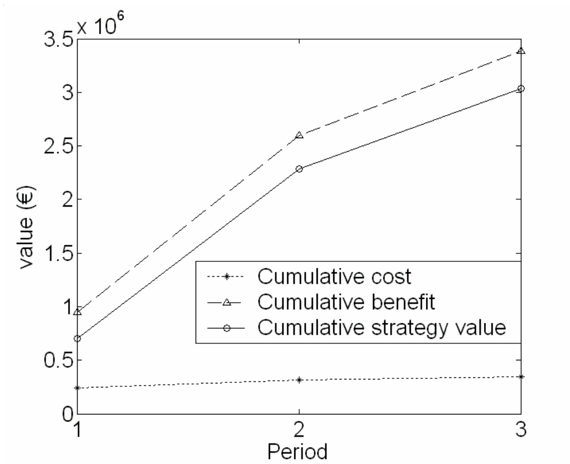
structure.) The trend of the result is that it increases the proportion of outcomes which end up in extreme directions, either very good, or very bad. The same reason applies for the outcomes after the second period of P&T (see Table 5-23). Branches $P_{2,1,U}$ and $P_{2,1,D}$ lead to scenarios 1 and 3. In this case, the probability of scenario 2 is lowered. After all, with a higher Std., the probabilities of scenarios 1, 3 and 7 increase. Probabilities of scenarios 4, 5 and 6 are lowered because of the lower $P_{1,1,M}$. Scenario 5 is further lowered by the lower $P_{2,2,M}$. The same trend can be observed for the investigated cases at $C_T = 0.11$ (compare Figure 5-20a and Figure 5-23a).

Table 5-23: Comparison of probability branches for the reference case, case 5.3.4-11 and case 5.3.4-12

	After the first period			After the second period					
Probability branches	$P_{1,1,U}$	$P_{1,1,M}$	$P_{1,1,D}$	$P_{2,1,U}$	$P_{2,1,M}$	$P_{2,1,D}$	$P_{2,2,U}$	$P_{2,2,M}$	$P_{2,2,D}$
Reference case	33.52%	61.21%	5.27%	3.52%	54.27%	42.21%	14.15%	69.01%	16.84%
Case 5.3.4-11	39.30%	47.67%	13.03%	11.20%	45.90%	42.90%	21.56%	51.14%	27.29%
Case 5.3.4-12	46.48%	18.54%	34.98%	36.60%	19.02%	44.41%	38.57%	18.88%	42.56%

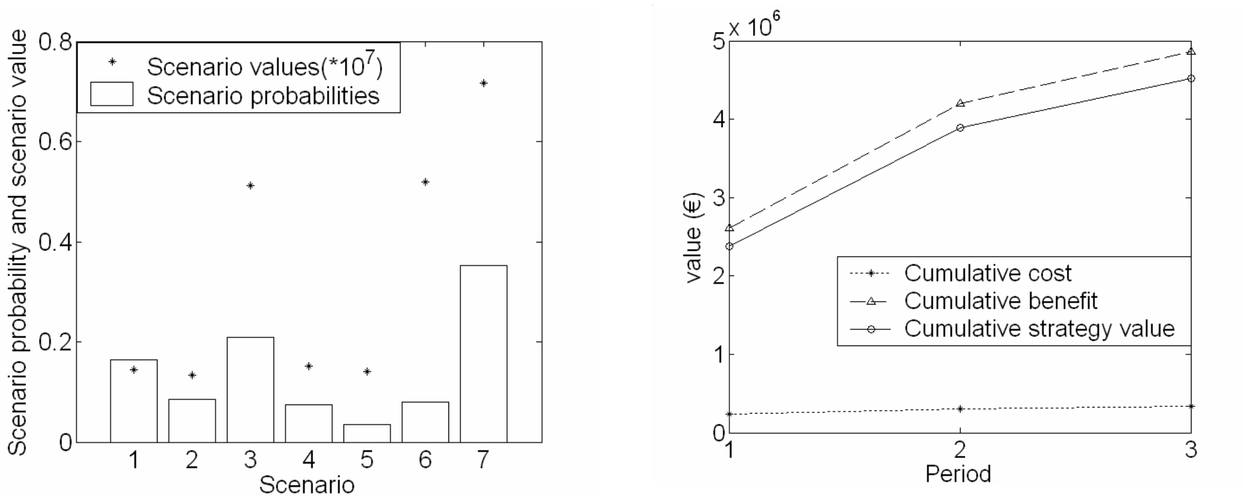


(a) Scenario probabilities and values



(b) Cumulative cost, benefit and value

Figure 5-25: Results of optimal strategy 1111 for case 5.3.4-11



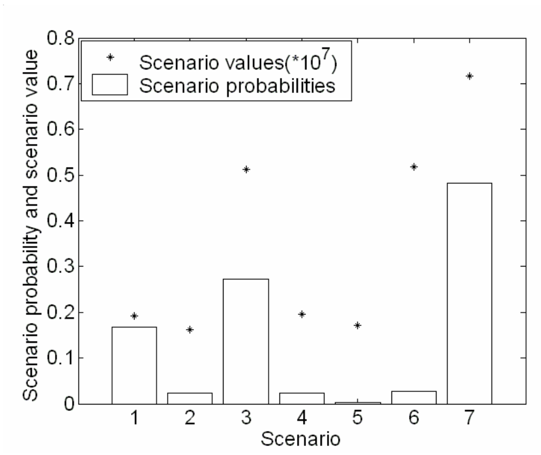
(a) Scenario probabilities and values

(b) Cumulative cost, benefit and value

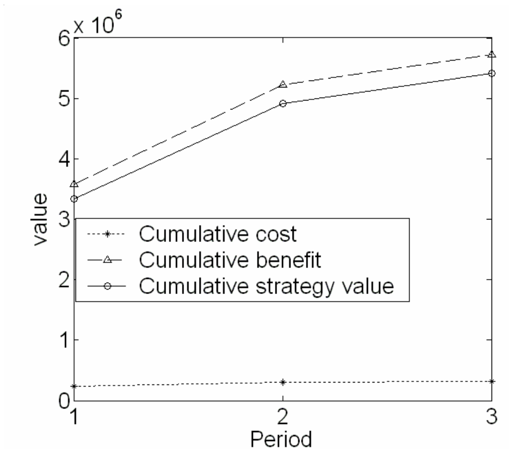
Figure 5-26: Results of optimal strategy 1111 for case 5.3.4-12

3. At C_T = 0.01, when the deterministic case's chance to meet the target is zero, the strategy chance to meet the target (and hence the strategy value) increases with higher Std.s. This is due to the increasing probability of scenarios 3 and 7 (they end up with stop after the second period). As a result, the strategy benefit is higher. With the similar cost, the strategy value is influenced by the strategy benefit, and therefore, it increases. But at C_T = 0.11, when the deterministic case's chance to meet the target is one, the strategy chance to meet the target decreases with higher Std.s (Case 5.3.4-20). Comparing Figure 5-20a and Figure 5-27a, it can be seen that higher Std.s increase the probability of scenario 1 and reduce the probabilities of scenarios 4, 5 and 6. The reduction of scenario 6 (stop scenario) in this case is the reason for the lower chance to meet the target.

4. Normally, a higher chance to meet the target indicates a higher benefit. But when chance to meet the target decreases from the deterministic case at C_T = 0.11 (100%) to case 5.3.4-20 (90.74%), the strategy benefit increases. And thus, the strategy value is higher. This is due to the higher scenario probability of scenario 3 (compare Figure 5-20a and Figure 5-27a). Scenario 3 indicates that the target is met and the land is sold after the first period, while in the deterministic case the land is sold after the second period. This means that in case 5.3.4-20, the benefit occurs earlier compared with the deterministic case. It can be seen if Figure 5-20b and Figure 5-27b are compared. As discussed previously, the later cash flow will be more discounted. The earlier selling of the land makes the benefit increase because of the discounting effect. As a result, the strategy value increases although the chance to meet the target is lower.



(a) Scenario probabilities and values



(b) Cumulative cost, benefit and value

Figure 5-27: Results of optimal strategy 1111 for case 5.3.4-20

5.3.4.2.4 Changing standard deviation of MNA

1. At C_T = 0.01 (chance to meet the target is zero for deterministic case):

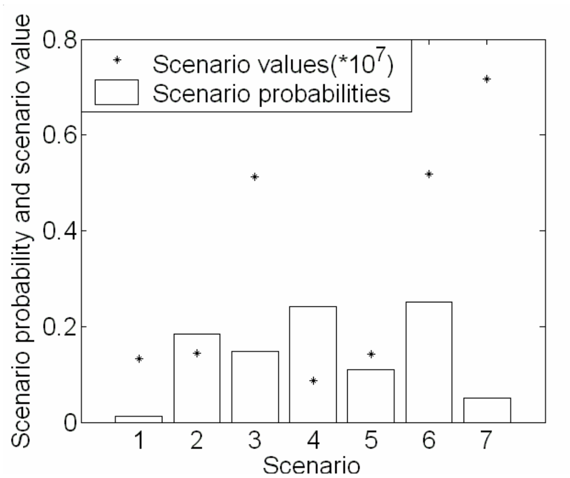
When Std_{MNA} decreases, PRB becomes the optimal action for the first period (case 5.3.4-13). Comparison with strategy 1111 (Table 5-24) reveals that strategy 1111 has a lower effectiveness than strategy 0111 for the same reason as was discussed several times before: too early switching to MNA of strategy 1111 results in a lower chance to meet the target. This is particularly true if the assumed standard deviation of the effectiveness of MNA is smaller than in the reference case. In this case, the effectiveness disadvantage of strategy 1111 is so big that the cost advantage can not overcome it. As a result, strategy 0111 becomes the optimal strategy.

Table 5-24: Comparison of strategies using case 5.3.4-13 parameters (mean of 100 runs)

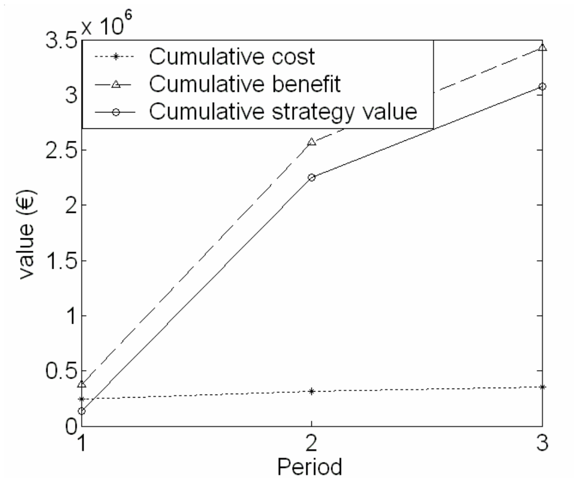
Strategy	Strategy value (€)	Cost (€)	Benefit (€)	Chance to meet the target
0111 (optimal)	**1,464,000**	**539,580**	**2,003,600**	**37.28%**
1111 (comparative)	897,920	348,640	1,246,600	21.12%

When Std_{MNA} is increasesd (case 5.3.4-14), the optimal action for the first period does not change: P&T should be applied. Detailed information is shown in Figure 5-28. The probabilities of scenarios 4 and 6 are increased compared with the reference case (Figure 5-2a). The probability of scenario 5 decreases. This is because of the high MNA standard deviation. It makes the result more spread into the upper or lower classes after applying MNA for a period.

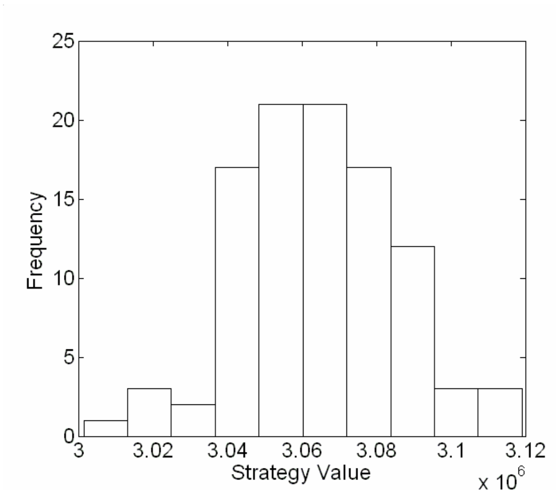
When Std_{MNA} increases, the strategy value increases. This is because the stopping possibility after MNA is higher due to the higher standard deviation. Therefore, scenario 6 (see Figure 5-1, it is the scenario to stop after the second period of MNA) has a higher probability in case 5.3.4-14 (Std_{MNA} = 0.3, Figure 5-28a) than in the reference case (Std_{MNA} = 0.07, Figure 5-2a). As a result, the chance to meet the target of the strategy is higher, which makes the strategy benefit higher.



(a) Scenario probabilities and value



(b) Cumulative cost, benefit and value



(c) Frequency of strategy values (100 runs)

Technology parameters

Case 5.3.4-14
Parameter changed compared to reference case:

Std_{MNA}=0.3

Figure 5-28: Results of optimal strategy 1111 for case 5.3.4-14

2. At C_T = 0.11 (chance to meet the target is one for deterministic case):

When Std_{MNA} is changed, the results do change only slightly. As shown in Figure 5-23a, the outcomes of the reference case with C_T = 0.11 concentrate very much in scenarios 3 and 7. Since the scenarios associated with MNA are scenarios 4, 5 and 6. The probabilities of these scenarios are very low. As a result, the influence of changing Std_{MNA} on the result is not significant.

5.3.4.2.5 Changing standard deviation of P&T

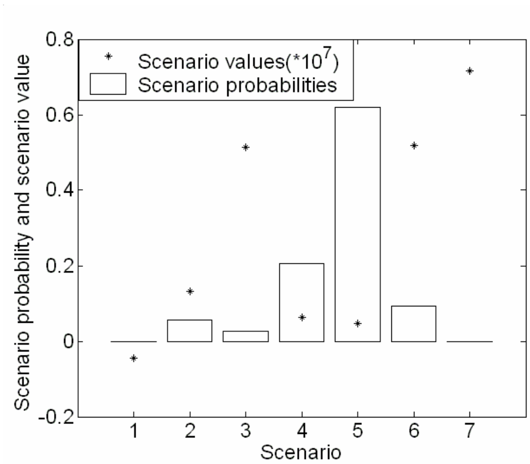
1. At $C_T = 0.01$ (chance to meet the target is zero for deterministic case):

When $Std_{P\&T}$ decreases, the chance to meet the target is smaller compared to the reference case. Benefit and the strategy value decrease as well. In case 5.3.4-15, the optimal action for the first period is changed into PRB (strategy 0100). Compared to strategy 1111, strategy 0100 is much more effective (Table 5-25). Figure 5-29 shows detailed information about strategy 1111. At smaller $Std_{P\&T}$ the results converge towards the deterministic case (scenario 5).

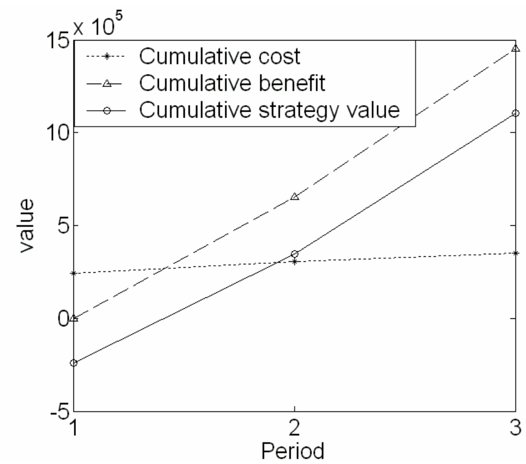
When $Std_{P\&T}$ increases, the effect is the opposite of what is described above. When $Std_{P\&T}$ increases, the optimal action for the first period does not change. P&T should be applied for the first period.

Table 5-25: Comparison of strategies using case 5.3.4-15 parameters (mean of 100 runs)

Strategy	Strategy value (€)	Cost (€)	Benefit (€)	Chance to meet the target
0100 (optimal)	**1,291,500**	**547,970**	**1,839,500**	**42.22%**
1111 (comparative)	1,131,900	349,910	1,481,900	32.13%



(a) Scenario probabilities and value



(b) Cumulative cost, benefit and value

Figure 5-29: Results of comparative strategy 1111 for case 5.3.4-15

2. At $C_T = 0.11$ (chance to meet the target is one for deterministic case):

When $Std_{P\&T}$ decreases from 0.07 to 0.02 (case 5.3.4-23) and when $Std_{P\&T}$ increases from 0.07 to 0.3 (case 5.3.4-24), the chance to meet the target reduces in both cases. The scenario probabilities and values of the optimal strategies for case 5.3.4-23 and case 5.3.4-24 are shown in Figure 5-30 and Figure 5-31. In case 5.3.4-23, compare with the reference case in Figure 5-23a, the probabilities of scenarios 4, 5 and 6 are increased. The reduction of scenarios 3 and 7 causes the reduction in chance to meet the target compared with the reference case. In case 5.3.4-24, seen from Figure 5-31, scenario probability of scenario 1 is increased while scenarios 4, 5 and 6 are reduced. The significant reduction of scenario 6 causes the reduction in chance to meet the target.

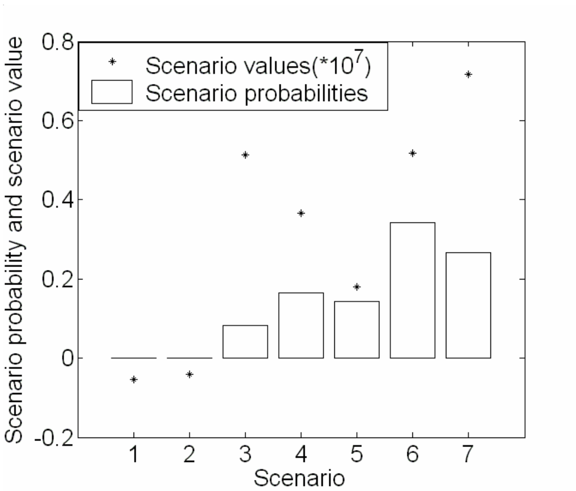


Figure 5-30: Results of optimal strategy 1101 for case 5.3.4-23

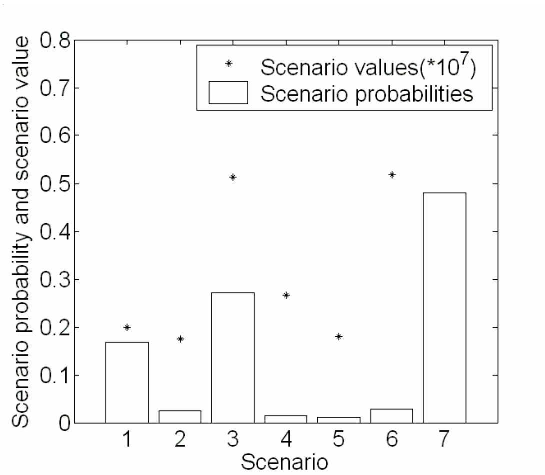
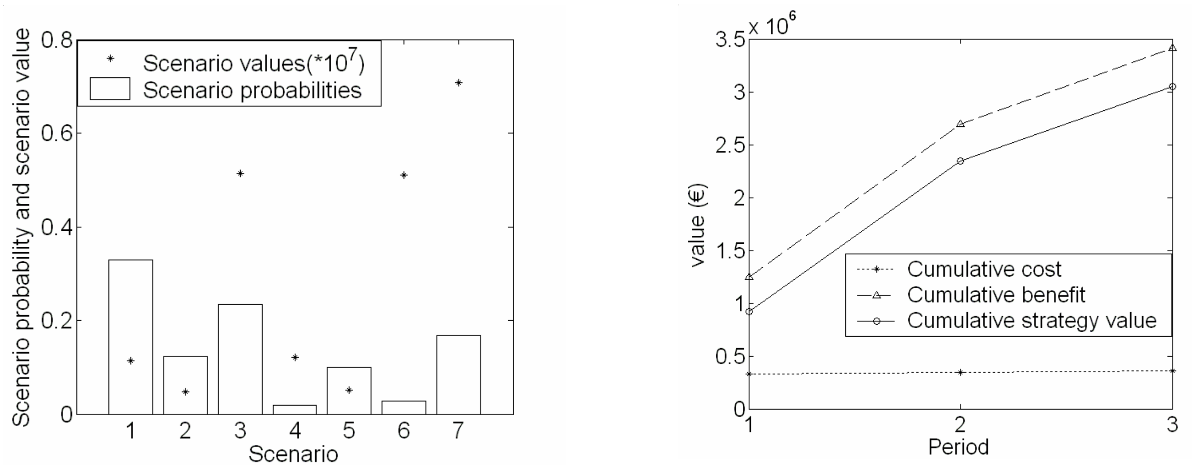


Figure 5-31: Results of optimal strategy 1110 for case 5.3.4-24

5.3.4.2.6 Changing standard deviation of PRB

1. At $C_T = 0.01$ (chance to meet the target is zero for deterministic case):

When Std_{PRB} decreases, the optimal action for the first period does not change. P&T should be applied for the first period. Strategy benefit and strategy value decrease. When Std_{PRB} increases, the optimal action for the first period becomes PRB. The strategy benefit and strategy value increase. The results of strategy 0001 in case 5.3.4-18 are shown in Figure 5-32. As shown, due to the increasing of Std_{PRB} scenario probabilities of scenarios 1, 3 and 7 increase (compared with the reference case shown in Figure 5-2). And thus, the chance to meet the target is increased.



(a) Scenario probabilities and value (b) Cumulative cost, benefit and value

Figure 5-32: Results of optimal strategy 0001 for case 5.3.4-18

2. At $C_T = 0.11$ (chance to meet the target is one for deterministic case):

When Std_{PRB} decreases, the chance to meet the target is higher. In the optimal strategy, the decrease of Std_{PRB} has the effect of converging to the deterministic case. As a result, the chance to meet the target is higher. When Std_{PRB} increases, the optimal strategy is 1111. Std_{PRB} does not have effect on the result.

5.3.4.2.7 Conclusion

Uncertainty about technologies' effectiveness has an effect on the strategy evaluation and decision making. It directly governs the uncertainty in the description of the situation after a particular management period, as is quantified by means of a probability density function (pdf) of concentration. Scenario probabilities change correspondingly. Higher uncertainty with respect to e.g. the effectiveness of P&T and PRB increases the probabilities of scenarios 1, 3 and 7 and reduces the probabilities of scenarios 2, 4, 5 and 6. Scenarios 3, 6 and 7 are stopping scenarios, which influence the strategy chance to meet the target. Changes in uncertainty of technology effectiveness cause complicated trade-off of probabilities between these scenarios. The effect is very different depending on the specific cases considered i.e. assumptions made with respect to other settings.

5.3.5 Time parameters

Parameters investigated below comprise (a) the total time frame of the project and (b) the number of management periods distinguished to describe the process of flexible decision making over time. Both projects with longer and shorter time frames compared to the reference case are considered in the following discussion. The effect of the number of management periods is examined by introducing 4, 5, 6, and 10 periods (reference case: 3 periods). Given the same total time frame, the length of each decision period becomes shorter with increasing number of periods. This means that the decision maker can react to the actual situation in a shorter time in a more flexible manner. The results are shown in Table 5-26. (The results for NP = 10 are shown in Table 5-29.) Unless otherwise mentioned in the table, the parameter values are the same as the reference case.

Table 5-26: Sensitivity analysis results for time parameters

		Parameters	Candidate strings	Best string	Strategy value (€)	Cost (€)	Benefit (€)	Chance to meet the target
Reference		**30 years 3 periods**	**1111 1101**	**1111**	**2,170,600**	**350,520**	**2,521,200**	**48.78%**
Total time frame	**Case 5.3.5-1**	10years	1111 1110	1111	1,183,800	240,560	3,589,400	4.84%
	Case 5.3.5-2	20years	1111 1110	1111	2,063,800	318,600	2,382,400	38.73%
	Case 5.3.5-3	40 years	1101 1111	1101	2,645,900	366,770	3,012,600	60.75%
	Case 5.3.5-4	60 years	1000 1111 1101 1110	1000	2,891,800	411,150	3,303,000	75.98%
Number of Periods	**Case 5.3.5-5**	4 periods	11111111 11110111 11111101	11111111	2,741,500	348,460	3,090,000	56.84%
	Case 5.3.5-6	5 periods	a*	a**	2,895,300	342,640	3,237,900	58.44%
	Case 5.3.5-7	6 periods	b*	b**	2,914,300	340,650	3,254,900	59.29%

Note:

a*: 1111110111111001
1110110111110101
1111111111111010
1111111101110001
1111111111111111
1111111111110111
1111111111111001
1110111110010001
1111111001111011
1111110111011111

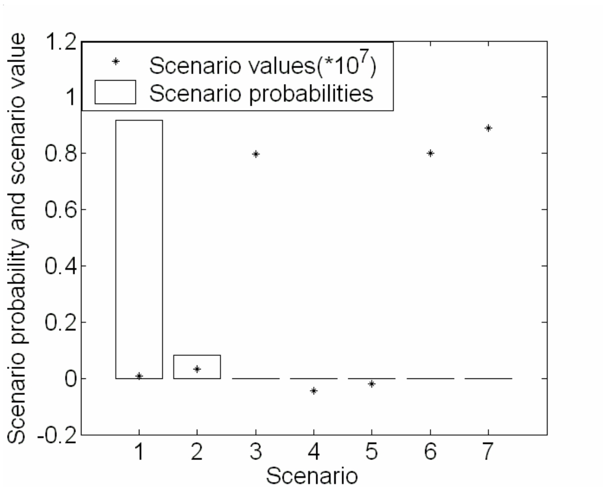
a: 1111111111111010**

b*: 1111111111111010111111100011111
11111100111100010101011101110001
1111110111111010101011111101011
1111111101110000111111101100101
1111110011110110011111100011000
1110110111110110111111101101010
1111111111111011111111100100001
1111110111111001111111111100100
1111110011111011111011101011100
1111110011111111111111101111110

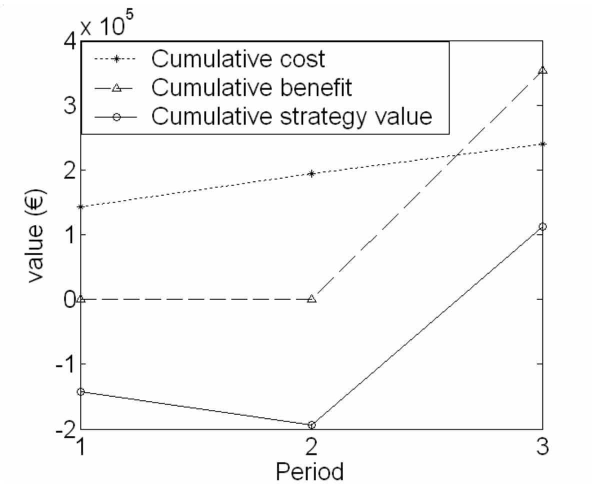
b: 1111110011110110011111100011000**

5.3.5.1 Total time frame

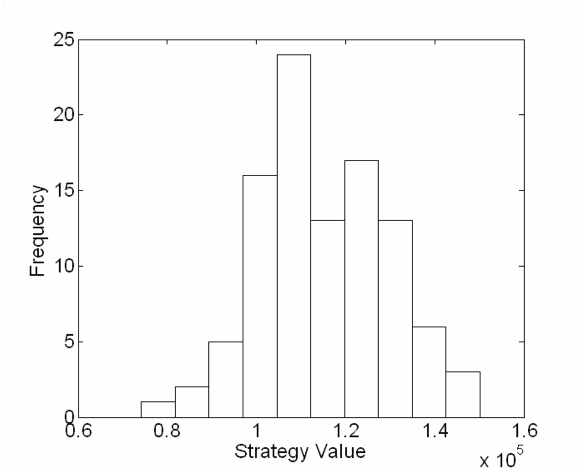
1. With a shorter time frame (case 5.3.5-1 and case 5.3.5-2), the chance to meet the target is lower. As a result, the benefit is remarkably lower (see Figure 5-33b). The cost is lower because the reduction of operational cost. Since the decreased benefit is dominating the evaluation, the strategy value is distinctly reduced compared to the reference case. The shorter time of treatment is the reason for lower effectiveness. Correspondingly, the results concentrate almost all in the first two scenarios (Figure 5-33a). Both strategy benefit and total value are lower than the reference case.



(a) Scenario probabilities and value



(b) Cumulative cost, benefit and value



(c) Frequency of strategy values (100 runs)

Time parameters

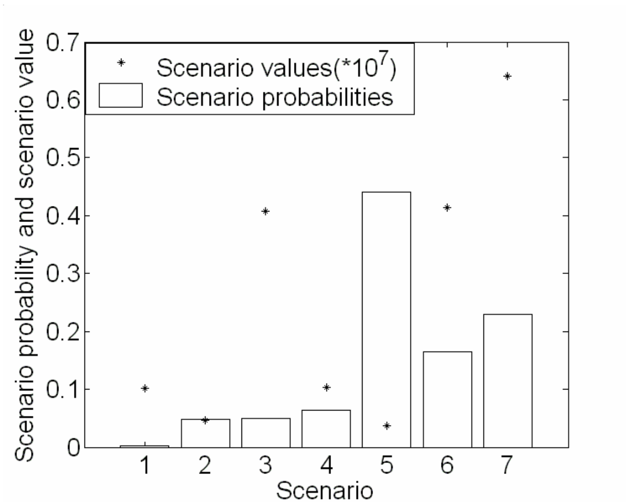
Case 5.3.5-1
Parameter changed compared to reference case:

T = 10 years

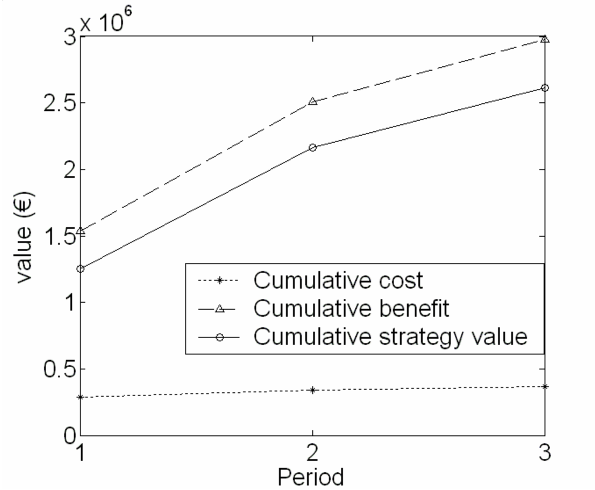
Figure 5-33: Results of optimal strategy 1111 for case 5.3.5-1

2. With longer time frame (case 5.3.5-3 and case 5.3.5-4), both the cost and the benefit (the chance to meet the target) increases. As shown in Figure 5-34a, the probabilities of the stop scenarios, scenarios 6 and 7, are higher because of longer time of remediation compared with the reference case (see Figure 5-2a). As a result, the strategy value increases due to the increasing strategy benefit (Figure 5-34b and Figure 5-34c).

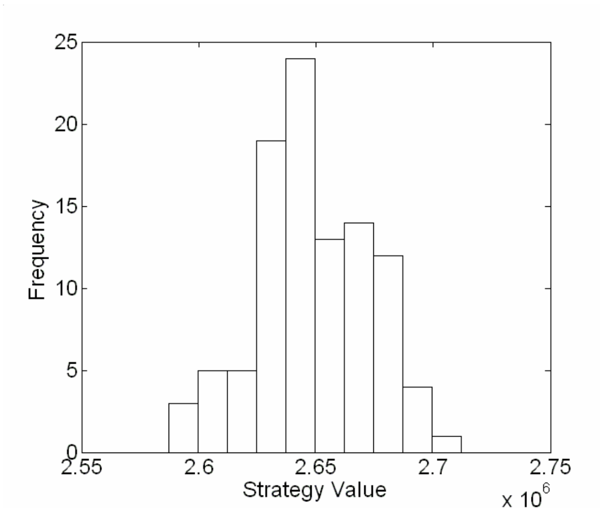
3. PRB becomes more favorable when the time frame is longer. More 0s appear in the candidate strings when the total time frame is longer. When T = 70 years, or when other conditions change, such as discount rate, PRB can even become the optimal action for the first period (see section 5.3.3.1, Table 5-11).



(a) Scenario probabilities and value



(b) Cumulative cost, benefit and value



(c) Frequency of strategy values (100 runs)

Time parameters

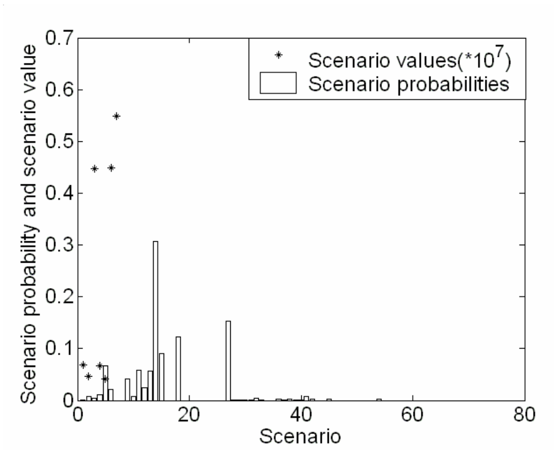
Case 5.3.5-3
Parameter changed compared to reference case:

T = 40 years

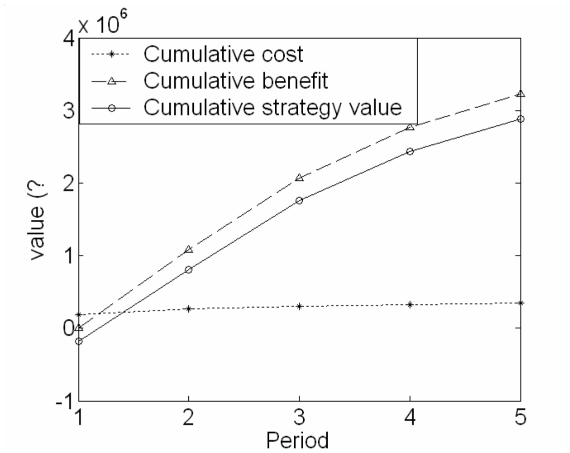
Figure 5-34: Results of optimal strategy 1101 for case 5.3.5-3

5.3.5.2 Number of periods

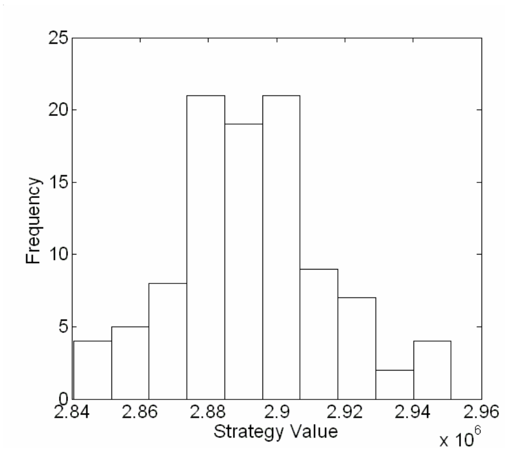
1. When the number of periods increases, the number of scenarios increases significantly. Figure 5-35a shows the scenarios when there are five decision periods. With the same total time frame, when the number of periods is increased, the length of each decision period is shorter. This means that the decision maker can react to the actual situation in a shorter time in a more flexible manner. For example, the remedial activity can be switched to a cheaper technology or to stop when the target is met in a shorter time period. Therefore, the management flexibilities are more accurately reflected in the analysis compared with less decision periods for the same project.



(a) Scenario probabilities and value



(b) Cumulative cost, benefit and value



(c) Frequency of strategy values (100 runs)

Time parameters

Case 5.3.5-6
Parameter changed compared to reference case:

NP = 5

Figure 5-35: Results of optimal strategy 1111 for case 5.3.5-6

2. With a higher number of periods, the strategy value increases. This is due to decreasing of the expected cumulative cost and the increasing of the expected cumulative benefit.

To see more clearly the effect of increasing period numbers on one certain strategy, strategy “P&T whenever the concentration is above C_{MNA}” (strategy 1...1) is examined. The period number will be increased to 10 for the same strategy. The results of strategy value, cost, benefit and chance to meet the target are shown in Table 5-27. The cumulative strategy values are shown in Figure 5-36.

As shown in Figure 5-36, when the number of periods is large, e.g. 10 periods, the cumulative value is reduced in the earlier periods, while the cumulative value is increased in the later periods. At the beginning of the remediation projects, there is almost only cost without benefit. This is because the benefit will occur later when the target is met. When each decision period is very short, this trend can be seen very clear. The starting positions (vertical) of three curves are different. The starting position of the curve for three periods is higher because there is already a chance to meet the target in the first period (the first ten years). As a result, the strategy value is positive in the first decision period. In the curve for ten periods, there is no chance to meet the target in the first two periods (the first six years). As a result, the strategy value remains negative in the first two periods. In the ten periods curve, the cumulative strategy value even reduces in the second period. This is due to the increase of the operational cost. The cumulative strategy value is increased in the later periods when the number of periods is bigger. The shorter the decision period is, the sooner can the land be sold. Therefore the benefit will be less discounted. As a result, the benefit increases. After all, the expected strategy value increases.

Table 5-27: Strategy "Apply P&T whenever the concentration is above C_{MNA}" (strategy 1…1) with different number of periods

Periods	NP=3	NP=6	NP=10
Strategy value	2,170,600	2,914,000	3,478,700
Cost	350,520	340,700	338,090
Benefit	2,521,200	3,254,700	3,816,800
Chance to meet the target	48.78%	59.29%	67.87%

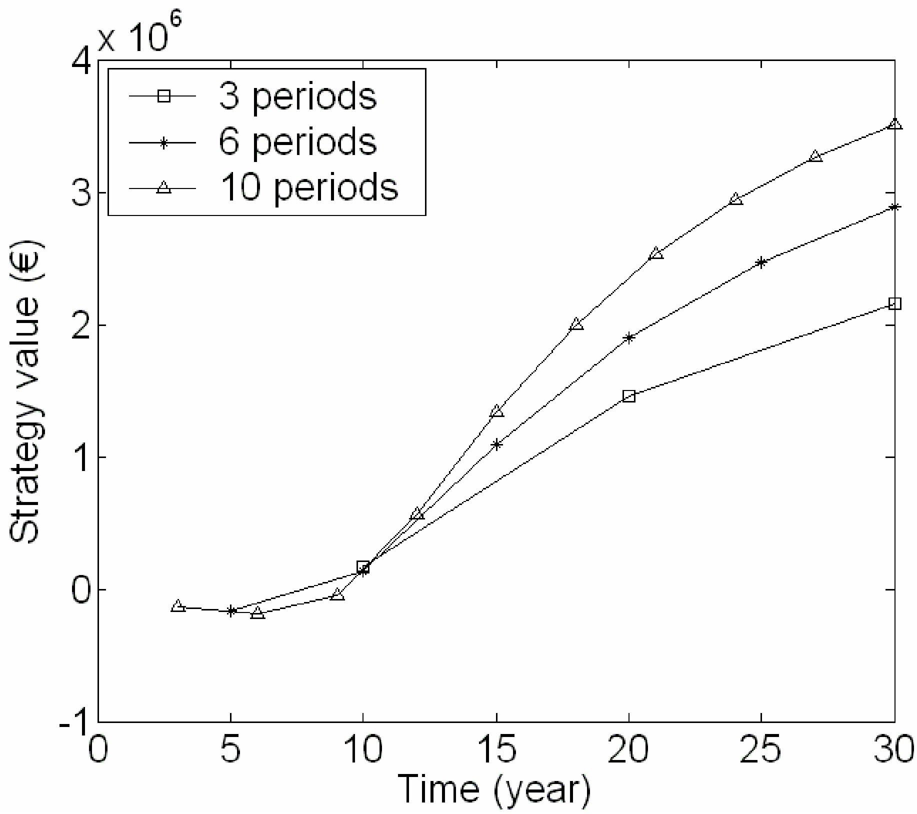


Figure 5-36: Strategy values of strategy "P&T whenever the concentration is above C_{MNA}" (strategy 1...1) for different number of management periods using the reference case parameters

3. When NP <= 4, optimization is not needed. It is possible to go through all possible strings and identify the optimal string with “Brute Force”. The case with NP = 4 (case 5.3.5-5) is tested with both “Brute Force” and “Optimization”. The results from ten optimization runs are shown in Table 5-28. As shown, there are three candidate strings selected after ten optimization runs, which are identical with the candidate strings selected by “Brute Force” (see Table 5-26). The strategy value, strategy cost, strategy benefit and chance to meet the target of the optimal strategy chosen by the optimization are shown in Table 5-28 (mean of one hundred valuations). When NP > 4, optimization is applied to perform the valuation. As discussed in section 4.6, ten optimization runs are done and the best string is the one with the highest strategy value. The results for NP = 5, 6 (case 5.3.5-6 and case 5.3.5-7) are shown in Table 5-26. The optimization results (ten runs) for NP = 10 are listed in Table 5-29. There are 512 digits in each string. Only the first twenty digits are shown in Table 5-29. The candidate strings are different from each other. But the first digit is always identical. And thus, the optimal remedial activity indicated for the first decision periods is identical.

Table 5-28: Optimization results for the reference case with NP = 4

Parameters	Candidate strings	Best string	Strategy value (€)	Cost (€)	Benefit (€)	Chance to meet the target
4 periods	11111111 11110111 11111101	11111111	2,746,000	348,480	3,094,500	56.93%

Table 5-29: Optimization results for the reference case with NP = 10

Parameters	Candidate strings (each string has 512 digits, first 20 are shown)	Best string (512 digits, first 20 shown)	Strategy value (€)	Cost (€)	Benefit (€)	Chance to meet the target
10 periods	11101100111010111111... 11111111111001111111... 11101010111111001111... 11111101111110101101... 11111101111101001111... 11101101111100110111... 11101111111011111111... 11111001110011011111... 11101111110110101111... 11101100111111001111...	11101111111011111111...	3,362,900	344,040	3,706,900	65.39%

6. Future research

As presented in the previous chapters, the research conducted on the application of real options theory to remediation projects provides a proactive and dynamic way of optimal strategy making compared with the traditional practice. Meanwhile, the research has raised some new questions that require further investigation which will improve the implementation of this new approach. The areas of future research needed are discussed below.

- A more appropriate model to describe the development of the environmental situation over time needs to be implemented. In this thesis, a simple decay model is used to describe the development of the contaminant concentration with and without the effect of technical measures. This simple model can be replaced by a more accurate and more sophisticated model, which can better predict the development of the contaminant concentration and, even more important, can reflect uncertainty stemming from incomplete knowledge of site conditions more realistically than the hypothetical parameter distributions employed in this thesis.
- More accurate descriptions of the effectiveness and uncertainties of the technologies are needed. Quantitative description of the technologies' effect needs to be more detailed. In this thesis, the assumptions are rather simple. The effectiveness and uncertainty are supposed not to change after the same technology is implemented for a period. Future research can focus on the changing effectiveness and uncertainties of the technologies in different point of time.
- A continuous reduction in uncertainty due to improved knowledge from ongoing monitoring and additional site investigations are also not taken into account here. The role of gaining knowledge for optimal strategy making should therefore be incorporated in future research.
- Future research is needed to improve the model into a more adaptive one. In this thesis, there are only three technologies considered. And there are certain rules for the technologies to switch between each other. When there are more technologies and different ways of switching between them, the model developed can not function any more. There is a need to increase the flexibility of the model in terms of a general applicability to a wide range of remediation projects. More research is needed for a different and more powerful algorithm to perform the valuation in two ways: strategy valuation and strategy optimization.

- Attention should be paid to the discount rate taken for the analysis. As discussed in the previous chapters, the discount rate has a very big impact on the strategy valuation. In this thesis, the discount rate is taken as given. More research is needed about the discount rate itself. Research is needed to consider: Which economic model should be used to calculate the discount rate? Is there uncertainty about discount rate? If there is, how to take it into account in the valuation?
- Further research is needed for the uncertainty of the costs. In this thesis, the uncertainties of the costs are not very much investigated. There is some discussion on it in the sensitivity analysis. But still, the costs of technologies are set to be the same during the time when the technologies are implemented. More research is needed on how to build the cost uncertainty into the model and take it into account in the strategy valuation. To achieve this, the uncertainties of the costs have to be investigated.
- In this thesis, the valuation using the real options method is only shown for hypothetical cases. Using a combination of the strategy valuation model and the flow and contaminant transport model (see 1st item in the list) will allow applications to real site problems that are required to further promote the real options approach. This kind of application will possibly raise further questions, entailing additional research topics not listed here.

7. Conclusions

This thesis presents a new approach for optimal remediation strategy making applying real options theory. The goal was to improve the traditional way of strategy making from a static and passive way into a dynamic and proactive way. By doing this, the value of management flexibility can be taken into account facing future uncertainty.

It is demonstrated that the traditional NPV method for remediation strategy making does not take into account the future uncertainties and the flexibilities of management. As a result, the strategies with various imbedded options are undervalued. The optimal strategy chosen based on the traditional method is thus not really optimal. A new approach which can overcome these shortcomings of the traditional way of strategy making is needed.

The herein presented real options framework is oriented from the findings of the option pricing theory in finance. Combining the decision tree analysis and Monte Carlo simulation, all possible strategies providing different options are valued. The future uncertainty of the contaminant concentration and the reaction of the decision maker to the actual situation are all taken into account in the valuation. The uncertain contaminant concentration is seen as the underlying asset. The flexible choices of the decision maker are seen as options. The different thresholds allowing different technologies to be implemented are considered as exercise prices. By calculating the expected strategy values, the strategies are ranked. The optimal strategy is the one with the highest expected strategy value.

The sensitivities of the results to the changes of the parameters are investigated. It is shown that when land value of the site is very high, the effectiveness is a more important factor than the cost. When the land value is low, the cost is the dominating factor in the optimal strategy making. Moreover, voluntarily postponing the application of MNA can improve the effectiveness of the strategy. Furthermore, PRB is more preferable when the total time frame of the project is very long. The sensitivity analysis also indicates that increasing the number of periods can increase the strategy value and more accurately capture the management flexibility.

After all, in this study, it is shown that the herein presented real options framework is capable of supporting remediation strategy making. The remediation strategy that is optimal in terms of cost and effectiveness can be identified to guide the remediation action through the entire decision period. It is an improvement compared with traditional economic decision-making techniques for remediation projects because it takes into account both the uncertainty in contaminant concentration development in time and inherent management flexibilities. Real options change remedial planning from a passive and static pattern into an active and dynamic pattern. But the model presented here is greatly simplified. The application shown in the thesis illustrates the concept rather than specifically comparing the technical options considered. For an in-depth analysis, there are great future research potentials. Among others, the incorporation of site-specific conditions including the implementation of a groundwater flow and transport model (instead of the simple decay model used here) seems to be the most relevant research topic in near future.

8. Reference

Alvarez, L.H.R. and Stenbacka, R., 2003. Optimal risk adoption: a real options approach. Economic Theory, Vol.23, Issue 1, pp. 123-147.

Amram, M. and Kulatilaka, N., 1999. Real Options: Managing Strategic Investment in an Uncertain World. Harvard Business School Press, USA.

Amram, M. and Kulatilaka, N., 2000. Strategy and Shareholder Value Creation: The Real Options Frontier. Journal of Applied Corporate Finance, Vol. 15, No. 2, pp. 15-28.

Arrow, K.J. and Fisher, A.C., 1974. Environmental Preservation, Uncertainty, and Irreversibility. The Quarterly Journal of Economics, Vol. 88, Issue 2, pp. 312-19.

Bachelier, L., 1900. Théorie de la spéculation, Annales Scientifiques de l'École Normale Supérieure Vol. 3, Issue 17, pp. 21–86

Bage, G. F. and Samson, R., 2002. A technicoecomomic approach for the selection of a site remediation strategy - part A: theory. Environmental Management, 30, No. 6, pp. 807-815.

Bage, G. F. and Samson, R., 2003. A technicoecomomic approach for the selection of a site remediation strategy - part B: model application. Environmental Management, 31, No. 1, pp. 69-78.

Bage, G.F., Samson, R. and Sinclair-Desgagne, B., 2004. A proactive approach can make site remediation less expensive. Environmental Management, 34, No. 4, pp. 449-460.

Bayer, P., Finkel, M. & G. Teutsch, 2005. Cost-optimal Contaminant Plume Management with a Combination of Pump-and-treat and Physical Barrier Systems. –Ground Water Monitoring and Remediation, 25, No. 2, Spring 2005, pp. 96-106.

Batabyal, A.A. and Yoo, S.J., 2005. Indivisibility and divisibility in land development over time and under uncertainty. Journal of Environmental Management, Vol. 76, Issue 2, pp. 185-190.

Bellman, R., 1952. On the Theory of Dynamic Programming. Proceedings of the National Academy of Sciences, 1952

Bellman, R., 1957. Dynamic Programming. Princeton University Press, Princeton, NJ.

Black, F. and Scholes, M., 1973. The Pricing of Options and Corporate Liabilities. Journal of Political Economy 81, pp. 637-659.

Bosetti, V., Conrad, J.M., Messina, E., 2004. The value of Flexibility: Preservation, Remediation, or Development for Ginostra?. Environmental and Resource Economics, 29, pp. 219-229.

Boyle, P., 1977. Options: A Monte Carlo Approach. Journal of Financial Economics, 4, pp. 323-328.

Brach, M.A., 2003. Real Options in practice. John Wiley & Sons, Inc.

Brennan, M. J., and Schwartz, E. S., 1976. The Pricing of Equity-linked Life Insurance Policies with and Asset Value Guarantee. Journal of Financial Economics, Vol.3, pp.195-214.

Brennan, M. J., and Schwartz, E. S., 1977. The Valuation of American Put Options. Journal of Finance, Vol.32, pp. 449-62.

Brennan, M. J., and Schwartz, E. S., 1985. Evaluating Natural Resource Investments. Journal of Business, 58, 2, pp. 135-157.

Bürger, C., Finkel, M., Teutsch, G., 2003. Reaktionswandsysteme und „Pump-and-Treat“ – Ein Kostenvergleich. Grundwasser – Zeitschrift der Fachsektion Hydrogeologie 3/2003, pp. 169-180.

Bürger, C. M., Bayer, P, and Finkel, M., 2007. Algorithmic funnel-and-gate system design optimization. Water Resources Research, Vol. 43.

Committee on Valuing Ground Water and National Research Council, 1997. Valuing Ground Water - Economic Concepts and Approaches. National Academies Press.

Conrad, J.M., 1980. Quasi-Option Value and the Expected Value of Information. The Quarterly Journal of Economics, Vol. 94, Issue 4, pp. 813-20.

Conrad, J.M., 1997. Analysis on the option value of old-growth forest. Econogical Economics, Vol. 22, pp. 97-102.

Conrad, J.M. and Lopez, A., 2002. Stochastic water quality: Timing and option value of treatment. Water Resources Research, 38, 2-1 – 2-7.

Copeland, T., Koller, T. and Murrin, J., 1994. Valuation: Measuring and Managing the Value of Companies (Wiley Frontiers in Finance). John Wiley & Sons Inc.

Cox, J.S. and Ross, S., 1976. The Valuation of Options for Alternative Stochastic Processes. Journal of Financial Economics, Vol.3 (March 1976), pp.145-166.

Cox, J.S., Ross, S., and Rubinstein, M., 1979. Option Pricing: A simplified Approach. Journal of Financial Economics, 7, pp. 229-264.

Damodaran, A., 1996. Investment Valuation: Tools and Techniques for Determining the Value of Any Asset. New York: John Wiley & Sons.

Datar, V. and Mathews, S.H., 2004. European Real Options: An Intuitive Algorithm for the Black-Scholes Formula. Journal of Applied Finance. Vol. 14, No. 1. Spring/Summer 2004 (http://papers.ssrn.com/sol3/papers.cfm?abstract_id=560982 last viewed 01.11.2008)

Dixit, A. and Pindyck, R. S., 1994. Investment under Uncertainty. Princeton, New Jersey: Princeton University Press.

Espinoza, R.D. and Luccioni, L., 2007. An Approximate solution for Perpetual American Option with Time to Build: the Value of Environmental Remediation Investment Projects. International Journal of Business, Vol. 12, No. 3. (http://realoptions.org/papers2005/Espinoza_An%20Approximate%20Solution%20for%20Perpetual%20American%20Option.pdf last viewed 01.11.2008)

Farrow, S., 2004. Using Risk Assessment, Benefit-Cost Analysis, and Real Options to Implement a Precautionary Principle. Risk Analysis. Vol. 24, No. 3, pp. 727-735.

Fisher, A.C., 2000. Investment under uncertainty and option value in environmental economics. Resource and Energy Economics. Vol. 22, pp. 197-204.

Fisher, I., 1930. The theory of interest. New York: The Macmillan Co.

Fontanills, G.A., 2005. The Options Course Second Edition: High Profit & Low Stress Trading Methods. Wiley; 2nd edition.

Forsyth, M., 1997. The Economics of Site Investigation for Groundwater Protection: Sequential Decision Making under Uncertainty. Journal of Environmental Economics and Management. Vol. 34, Issue 1. pp. 1-31.

Forsyth, M., 2000. On estimating the option value of preserving a wilderness area. Canadian Journal of Economics. Vol. 33, No. 2, pp. 413-434.

Goldberg, D. E., 1989. Genetic Algorithms in Search, Optimization, and Machine Learning. Addison-Wesley.

Greden, L. and Glicksman, L, 2005. A real options model for valuing flexible space. Journal of Corporate Real Estate, 2005, Vol. 7, Issue 1, pp. 34-48.

Greenley, D. A., Walsh, R. G. and Young, R. A., 1981. Option Value: Empirical Evidence from a Case Study of Recreation and Water Quality. The Quarterly Journal of Economics, 96, (4), pp. 657-673.

Houcha, C., Joines, J., and Kay, M., 1996. The Genetic Algorithm Optimization Toolbox (GAOT) for Matlab 5. [Online] (Updated 12th June, 1998) Available at http://www.ise.ncsu.edu/mirage/GAToolBox/gaot/ [Accessed 26th April, 2009]

Henry, C., 1974. Option values in the economics of irreplaceable assets. Review of Economic Studies. Vol. 41, pp. 89-104.

Henry, C., 1974. Investment decision under uncertainty: the irreversible effect. American Economic Review, Vol. 64, pp.1006-12.

Hull, J.C., 2005. Options, Futures, and Other Derivatives. Prentice Hall; 6th edition.

Insley, M., 2002. A Real Options Approach to the Valuation of a Forestry Investment. Journal of Environmental Economics and Management. Vol. 44, Issue 3, pp. 471-492.

Insley, M. and Rollins, K., 2005. On Solving the Multirotational Timber Harvesting Problem with Stochastic Prices: A Linear Complementarity Formulation. American Journal of Agricultural Economics. Vol. 87, Issue 3, pp. 735-755.

Janney, J.J. and Dess, G.G, 2004. Can real options analysis improve decision making? Promises and pitfalls. Academy of Management Executive, vol. 18(4), pp. 60-75.

Kirkwood, C.W., 1996. Strategic Decision Making. Wadsworth Publ. Co., Belmont, CA.

Kolb, R.W., 2002. Futures, Options, and Swaps. Blackwell Publishers.

Kübert, M., 2002. Möglichkeiten zur Analyse der Kosten für die Erkundung von Schadstoffahnen im Grundwasser im Hinblick auf die Nutzung und Kontrolle natürlicher Rückhalte- und Abbauprozesse. Diploma Theses, Center of Applied Geosciences, University of Tübingen.

Lentz, H. and Tse, K. S. M., 1995. An Option Pricing Approach to the Valuation of Real Estate Contaminated with Hazardous Materials. Journal of Real Estate Finance and Economics, 10, pp.121-144.

Majd, S. and Pindyck, R.S., 1987. Time to Build, Option Value, and Investment Decisions. Journal of Financial Economics, Vol. 18, pp. 7-27.

McDonald, R. L. and Siegel, D., 1986. The Value of Waiting to Invest. Quarterly Journal of Economics, Vol. 101, No. 4, pp. 707-727.

McKnight, U.S. and Finkel, M., 2008. Model-based preliminary assessment of mega-site management options: a new approach to improve tiered decision-making. Groundwater Quality: Securing Groundwater Quality in Urban and Industrial Environment, (Proc. 6th

International Groundwater Quality Conference held in Fremantle, Western Australia, December 2007), IAHS Publ. 324, 2008, pp. 499-506.

Merton, R.C., 1973. The Theory of Rational Option Pricing. Bell Journal of Economics and Management Science 4, No. 1, pp. 141-183.

Milne, A. and Whalley, A. E., 2000. Time to build, option value and investment decisions': a comment. Journal of Financial Economics, 2000, Vol. 56, Issue 2, pp. 325-332.

Morio, M., Finkel, M., et al., 2008. Improving mega-site revitalisation strategies by trading off benefits from future land use and clean-up costs. Groundwater Quality: Securing Groundwater Quality in Urban and Industrial Environment, (Proc. 6th International Groundwater Quality Conference held in Fremantle, Western Australia, December 2007), IAHS Publ. 324, 2008, pp. 555-562.

Mun, J., 2005. Real Options Analysis: Tools and Techniques for Valuing Strategic Investments and Decisions. Wiley; 2nd edition.

Myers, S., 1977. Determinants of Corporate Borrowing. Journal of Financial Economics. Vol. 5, pp. 147-175.

Natenberg, S., 1994. Option Volatility & Pricing: Advanced Trading Strategies and Techniques. McGraw-Hill; 2nd edition.

Paddock, J. L., Siegel, D.R. and Smith, J.L., 1988. Option Valuation of Claims on Real Assets: the Case of Offshore Petroleum Leases. Quarterly Journal of Economics, Vol. 103, pp. 479-508.

Paleologos, E.K. and Lerche, I., 2002. Option Coverage Techniques for Environmental Projects. Journal of Management in Engineering, Vol. 18, No. 1, January 2002, pp. 3-6.

Pandele, M., Finkel, M., et al., 2008. Strategic Groundwater Management facing Time-Variant Boundary Conditions. Groundwater Quality: Securing Groundwater Quality in Urban and Industrial Environment, (Proc. 6th International Groundwater Quality Conference held in Fremantle, Western Australia, December 2007), IAHS Publ. 324, 2008, pp. 531-538.

Rendleman, R.J., and Barter, B. J., 1979. Two State Option Pricing. Journal of Finance, 34, pp. 1092-1110.

Rokke, T.W.S., 2004. Valuing Real Options in Strategic Investments. First Edition, Difo-Druck GmbH, Bamberg.

Samuelson, Paul A.,1965. Rational theory of warrant pricing. Industrial Management Reviews, Vol. 6, pp. 13-31.

Saphores, J.-D.M, 2004. Environmental Uncertainty and the Timing of Environmental Policy. Natural Resource Modeling, Vol. 17, No. 2, pp. 163-190.

Schädler, S., Morio, M. and Finkel, M., 2008. Land use related cost estimates for contaminated site development: consequences of uncertainty to planning and investment decisions. Groundwater Quality: Securing Groundwater Quality in Urban and Industrial Environment, (Proc. 6th International Groundwater Quality Conference held in Fremantle, Western Australia, December 2007), IAHS Publ. 324, 2008, pp. 539-546.

Schwartz, E.S., 1977. The Valuation of Warrants: Implementing a New Approach. Journal of Financial Economics, Vol. 4, pp. 79-94.

Schwartz, E.S. and Trigeorgis, L., 2004. Real Options and Investment under Uncertainty: Classical Readings and Recent Contributions. Cambridge, Mass: MIT Press, Sharpe, W.F., 1978. Investments. Englewood Cliffs, N.J.: Prentice-Hall.

Trigeorgis, L. and Mason, S.P., 1987. Valuing Managerial Flexibility, Midland Corporate Finance Journal, Vol. 5, Number 1, 1987, pp. 14-21.

Trigeorgis, L., 1996. Real Options: Managerial Flexibility and Strategy in Resource Allocation. MIT Press.

Trigeorgis, L., 1999. Real options: A Primer in James Alleman and Eli Noam, The New Investment Theory of Real Options and its Implication for Telecommunications Economics, James Alleman and Eli Noam, eds., Kluwer Academic Publishers, Boston, 1999, pp. 3-33.

Tzouramani, I. and Mattas, K., 2004. Employing real options methodology in agricultural investments: the case of greenhouse construction. Applied Economics Letters. Vol. 11, Issue 6, pp. 355-359.

Van den Bergh, J.C.J.M., 2008. Optimal Diversity: Increasing Returns versus Recombinant Innovation. Journal of Economic Behavior & Organization. Vol. 68, Issue 3-4, pp. 565-580.

Van Putten, A.B. and MacMillan, I.C., 2004. Making Real Options Really work. Harvard Business Review, Vol. December, pp. 134-41

Wang, T.A. and McTernan, W.F., 2002. The development and application of a multilevel decision analysis model for the remediation of contaminated groundwater under uncertainty. Journal of Environmental Management. Vol. 64, pp. 221-235.

Weisbrod B.A., 1964. Collective-consumption services of individual-consumption goods. Quaterly Journal of Economics, Vol. 78, Issue 3, pp 471-477.

Williams, J.B., 1938. Theory of Investment Value. Augustus M Kelley Pubs.

9. Appendix

9.1 Program structures

9.1.1 Program for projects with NP <= 4

- BestString gives the optimal string. It calls three functions (bruteForce, fitSVLimitation10 and OneStringFigure).
- bruteForce calls one function (fitSVLimitation10). It runs through all possible strings and find one candidate optimal string.
- fitSVLimitation10 gives the value of a given string.
- OneStringFigure is based on fitSVLimitation10. The only difference is that it plots the outputs as figures. It will not be listed in appendix 10.2.

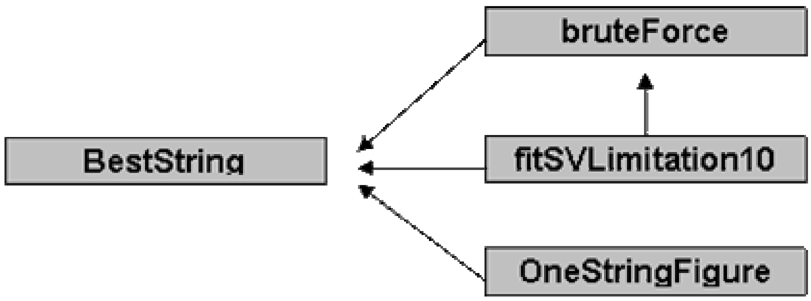


Figure 9-1: Relations between functions when NP<=4

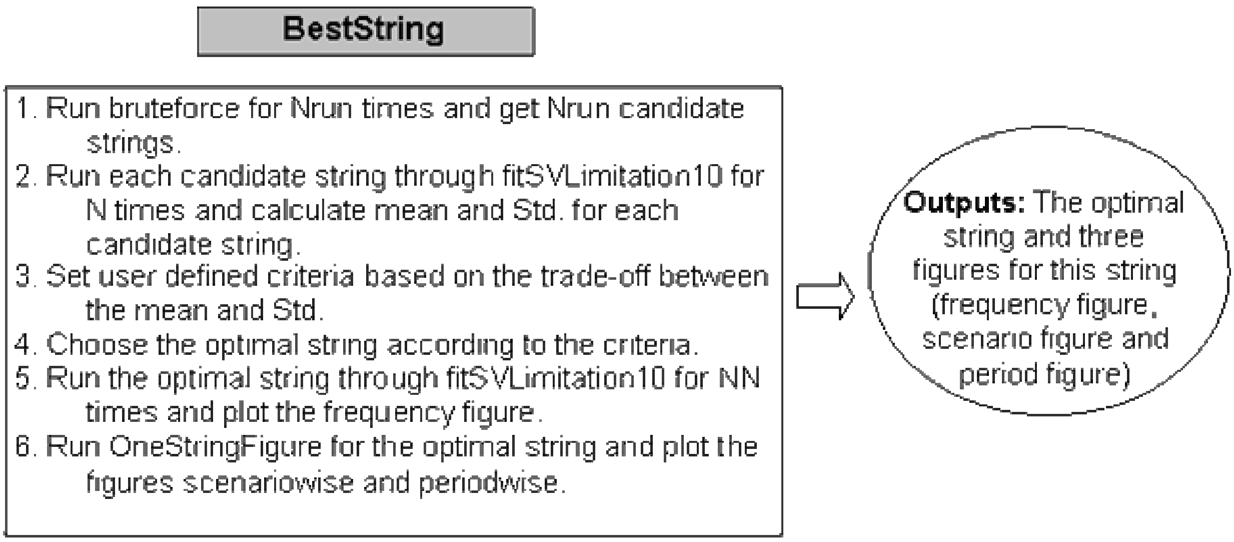


Figure 9-2: Optimal string selection and figures generation

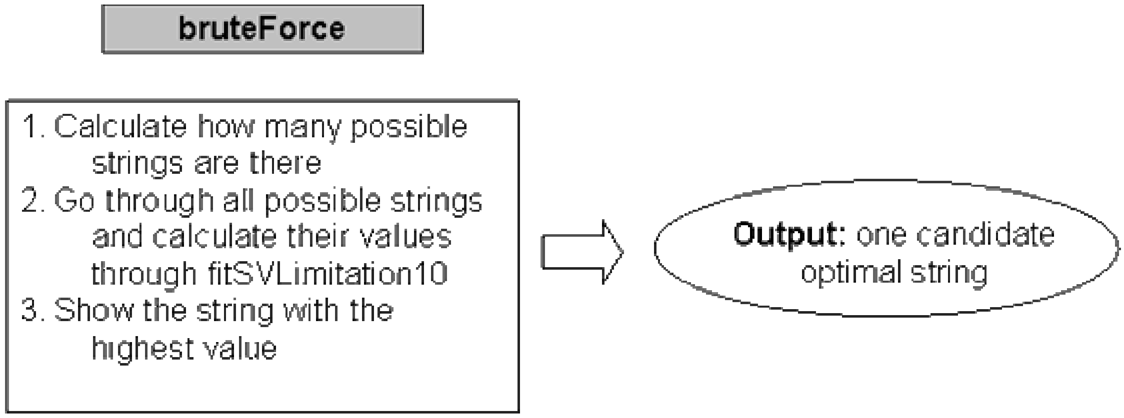


Figure 9-3: Function bruteForce - going through all possible strings

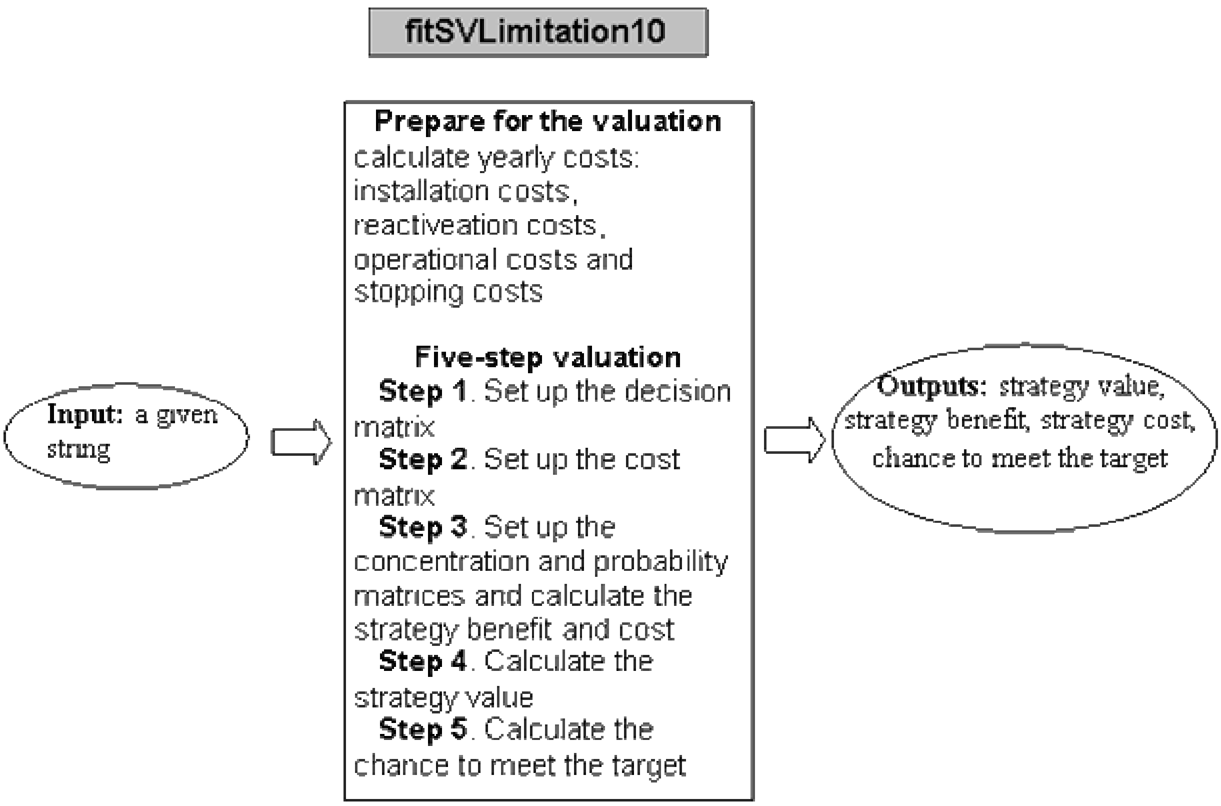


Figure 9-4: Function fitSVLimitation10 - single string valuation

9.1.2 Programs for projects with NP > 4

As discussed in section 4.6, GA is a stochastic search method which operates on a population of solutions. To use this method for the real options valuation in this study, two drivers are written by Claudius Bürger.

One driver program is called myGAOpt. It defines the parameters for the valuation such as length of the project, NP and costs. It also defines number of optimization runs, population size of each run and the number of fitness function evaluations per run. It calls GA which is written by Houchk, Joines and Kay. The output of myGAOpt is the results of ten optimization runs.

The other driver is called EMOFIT. It converts strategies into representing binary strings. It is called by GA. It calls FitSVLimitation9_gl.

A fitness function is calculated by FitSVLimitation9_gl to value each strategy. FitSVLimitation9_gl is adapted from fitSVLimitation10 (code is provided in the next section). It is called by EMOFit and returns a fitness value to EMOFit.

FitSVLimitation9_gl is almost the same as fitSVLimitation10. So it is not repeated. The codes for GA written by Houchk, Joines and Kay are not listed in the appendix.[2]

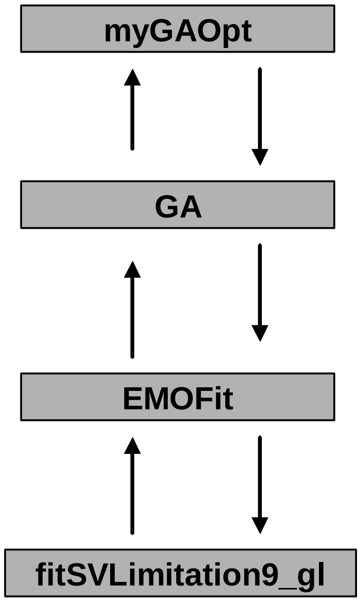


Figure 10-5: Relations between functions when NP > 4 (optimization)

[2] These codes can be found on website: http://www.ise.ncsu.edu/mirage/GAToolBox/gaot/ (last viewed on 26.04.09)

9.2 MATLAB codes

9.2.1 The optimal string identification

```
function bestS=BestString     %% file name: BestString.m

%% This function gives the optimal string. It runs bruteForce for Nrun times and
%% finds the Nrun listed best strings (some are the same). Then it runs each
%% candidate string through fitSVLimitation10 (file name: fitOneStringInfo.m) for N
%% times, then finds out the mean and STD of the results of each string. The best
%% string is the one chosen according to the criteria given by the user.
%% In the end, the frequency of the optimal string for NN time will be shown. The
%% scenario and period figures will also be shown.

%%% Set the parameters %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

global LDP %% length of the total decision period
global NP  %% number of periods
global r   %% discount rate

%%future uncertainties of the concentration
global StdPT   %% standard deviation of the concentration after a period of P&T
global StdPRB  %% standard deviation of the concentration after a period of PRB
global StdMNA  %% standard deviation of the concentration after a period of MNA

%%effectiveness of the technologies
global Dpt   %% decay rate constant of P&T
global Dmna  %% decay rate constant of MNA
global Dprb  %% decay rate constant of PRB

%%tresholds
global ConStop  %% threshold to stop, the target level
global ConMna   %% threshold to switch to MNA

%%land price
global PP %% land price euros/m^2

LDP=30;
NP=3;
r=0.03;
StdPT=0.07;
StdPRB=0.07;
StdMNA=0.07;
Dpt=0.21;
Dmna=0.02;
Dprb=0.12;
currentconc=1; %current concentration (=100% - reference value)
ConStop=0.01*currentconc;
ConMna=0.15*currentconc;
PP=400;
Nrun=10;  %% number of time that bruteForce will be run
N=100;     %% number of runs of each candidate string to calculate the Mean and Std.
NN=100;   %% number of runs for the frequency figure

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
result=[];
SSSS=[];
cost=[];
string=[];

%% run bruteForce Nrun times and get the candidate strings
for i=1:Nrun
    result(i,:)=bruteForce ;
end
result;
value=result(:,1)';
S=result(:,2:end)
```

```
%%%%% run each candidate string for N times and calculate the mean and Std.
%%%%% and find the optimal string according to the criteria set by the user

HH=[];
for j=1:Nrun
    for i=1:N;
HH(j,i)=fitOneStringInfo(S(j,:));
    end
end
HH;

m=[];
for j=1:Nrun;
m(j,:)=[mean(HH(j,:)),std(HH(j,:))];
end
m

qq=mean(m(:,1));

%% user defined criteria
if qq>=0
    md=zeros(Nrun,1);
    for j=1:Nrun
        md(j,1)=m(j,1)/m(j,2);
    end
    max(md);%% when the strategy value is possitive, try to find the biggest ratio
%% of value/Std;
    [a,b]=find(md==max(md));
elseif qq<0
    md=zeros(Nrun,1);
    for j=1:Nrun
        md(j,1)=(-m(j,1))*m(j,2);
    end
    min(md);%%when the strategy value is negative, try to find the smallest
%% (-m(j,1))*m(j,2);
    [a,b]=find(md==min(md));
end
a
bestS=S(a,:)  %% this is the optimal string


%%%%%%%%%%%%%%%%% generate the frequency figure for the optimal string
gg=[];
for i=1:NN
 [fitness,InflowTotal,SstrategyCost,Pm]=fitOneStringInfo(bestS);
gg=[gg;[fitness,InflowTotal,SstrategyCost,Pm]];
end

figure(111)
COLORMAP(white)
hist(gg(:,1))
xlabel('Strategy Value')
  ylabel('Frequency')
  hAll = findall(gcf);
for idx = 1 : length(hAll)
  try
    set(hAll(idx),'fontsize',18);
  catch
  end
end

gg=mean(gg);
Svalue=gg(1,1)   %% strategy value of the optimal string
Sbenefit=gg(1,2)  %% strategy benefit of the optimal string
Scost=gg(1,3)     %% strategy cost of the optimal string
SprobMeet=gg(1,4) %% chance to meet the target of the optimal string

OneStringFigure(bestS)  %% generate the scenario and period figures of the optimal
%% string
```

9.2.2 Going through all possible strings

```
function result=bruteForce   %% file name: bruteForce.m

%% This function runs through all possible strings and finds out the best string.


%%% Set the parameters %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

global LDP %% length of the total decision period
global NP  %% number of periods
global r   %% discount rate

%%future uncertainties of the concentration
global StdPT   %% standard deviation of the concentration after a period of P&T
global StdPRB  %% standard deviation of the concentration after a period of PRB
global StdMNA  %% standard deviation of the concentration after a period of MNA

%%effectiveness of the technologies
global Dpt   %% decay rate constant of P&T
global Dmna  %% decay rate constant of MNA
global Dprb  %% decay rate constant of PRB

%%tresholds
global ConStop  %% threshold to stop, the target level
global ConMna   %% threshold to switch to MNA

%%land price
global PP %% land price euros/m^2

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

results = [];
SS=[];

%% calculate how many decision points are there %%%%%%%%%%%%%%%%%%%

%% generate a matrix with 9s (when NP is fixed, the size of the matrix is known)

ND=9*ones(3^(NP-1),NP);

%% add MNA decisions %%
    for i=1:NP
        for j=2:3:(3^(i-1))
            ND(j,i)=2;
        end
    end
%% add stop decisions %%
for i=1:NP
        for j=3:3:(3^(i-1))
            ND(j,i)=3;
        end
end
%% adjust for Stop decisions (once stoped, next decision will be stop)
 for i=1:(NP-1)
        for j=1:(3^(i-1))
        if ND(j,i)==3
            ND((3*j-2),(i+1))=3;
            ND((3*j-1),(i+1))=3;
            ND((3*j),(i+1))=3;
        end
        end
 end
%% count how many decisions are there to make
    g=0;
    for i=1:NP
         for j=1:3:(3^(i-1))
             if ND(j,i)~=3
             g=g+1;
```

```
            end
        end
    end
   g; %% this is the number of decisions

%% go through all possible strings %%%%%%%%%%%%%%%%%%%%%%%%%%%

for i = 1:2^g %% there are 2^g possible strings
    % get binary number
    binN = dec2bin(i-1);
    % make it a string
    binStr = num2str(binN);
    % get length of bin string
    binLen = length(binStr);
    % create leading zeros
    S = [];
    for j = 1:binLen
        S = [S,str2num(binStr(1,j))];
    end

    if g-binLen ~= 0
      zeroVec = zeros(1,g-binLen);
      S = [zeroVec,S];
    end

    [fitness]=fitOneStringInfo(S);

     results = [results;fitness'];

     SS= [SS;S];

end
results;
SS;

MaxBenef = max(results(:,1)); %% the string with the highest strategy value is the
%% optimal


II=find(results == MaxBenef);
SSS=SS(II,:);
result=[MaxBenef SSS]; %% show the optimal strategy value and the optimal string
```

9.2.3 Calculating the strategy value, strategy benefit, strategy cost and chance to meet the target for any given string

```
function [fitness,InflowTotal,SstrategyCost,Pm]=fitSVLimitation10(S)
%% file name: fitOneStringInfo.m

%%% This function gives detailed results of a given string.

%%% Set the parameters %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

global LDP %% length of the total decision period
global NP  %% number of periods
global r   %% discount rate

%%future uncertainties of the concentration
global StdPT   %% standard deviation of the concentration after a period of P&T
global StdPRB  %% standard deviation of the concentration after a period of PRB
global StdMNA  %% standard deviation of the concentration after a period of MNA

%%effectiveness of the technologies
global Dpt   %% decay rate constant of P&T
global Dmna  %% decay rate constant of MNA
global Dprb  %% decay rate constant of PRB
```

```
%%tresholds
global ConStop  %% threshold to stop, the target level
global ConMna   %% threshold to switch to MNA

%%land price
global PP %% land price euros/m^2

Ns=10000; % number of realizations for each single Monte Carlo simulation point

currentconc=1; % current concentration (=100% - reference value)

kprb=250; %% per m^2
PT=2000;  %% per m

Repla=100; %%replacement cost per year

%%%%%% P&T=1  PRB=0  MNA=2 stop=3 %%%%%%%%%%%%%%%%%%%%%%%
LEP=LDP/NP; %% length of each decision period

aa=25000; %% Site area
Vland=aa*PP; %% value of land as if clean.

%%% Site parameters %%%%%%%%%%%%%%%%%%%%%%%%%%
mfl=2;  %% depth to the ground water table
mAq=5; %% thickness of the aquafier
eta=0.7; %% efficiency of the pump
k=0.0005; %% m/s
i=0.001; %% hydraulic gradient
y=100; %% unit: m Wtotal of the contaminated area
Q=2*y*k*mAq*i; %% p&T rate [m3/s]
W=1.5*y; %% the total funnel length
H=mfl+mAq+3;
KEN=0.20;
KAW=1; %% m^3

%%%%%%%%%%% installation costs %%%%%%%%%%%%%%%

Nwell=2; %number of wells
DeIn=10; %% meters, same for PT and PRB
equip=15000;   %% --> pump, treatment container(s), piping, ...
FiV = 0.7*Q*10/0.45; %% GW flow rate through all gates (70% of Q)
%% * contact time in reactor material (10 h)
%% / porosity of reactor material (45%)
Kfim = 600; %% (kfim = unit costs filling material, e.g. 600 EUR per m3)
FiC = FiV*Kfim; %% filling costs

SiC = 30000; % site installation costs (preparation & mobilization)

MNA=200;   %%per meter (MNA)
NMNAwell=10; %%number of wells (MNA)
freqMNA = 2 ; % 2 times a year (MNA)
cMNAsample = 250;  % 250 Euro per sample (analysis + transport + personnel) (MNA)

PTinwof=SiC+PT*Nwell*DeIn+equip;
PRBinwof=SiC+W*(0.5+mfl+mAq)*kprb;

%%%%Installation costs
PTin=SiC+PT*Nwell*DeIn+equip+FiC;
PRBin=SiC+W*(0.5+mfl+mAq)*kprb+FiC;
MNAin=MNA*DeIn*NMNAwell;

%%%%%reactivation costs (treated as similar to reinstallation) %%%%%%%%

ptre=0.20*PTinwof+FiC;
prbre=0.25*PRBinwof+FiC;
mnare=0.30*MNAin;

%%%%%operation costs (per year) %%%%%%%%%%%%%%%%%%%%%
control = 2000;  %% Check & control operating system
```

```
elww = 3600*Q*H/eta*KEN+365*KAW*Q*60*60*24;  %% electricity and water
%%Q/(60*60*24) per day, insdead of per second
anacost = NMNAwell*freqMNA*cMNAsample; % cost for analyses

PTop=control+elww+Repla; %% operational cost of P&T per year
PRBop=control+Repla ; %% operational cost of PRB per year
MNAop=control+anacost; %% operational cost of MNA per year

%%% first year of installation for each period: costs include installation cost,
%% operational cost for this year

PTIN=PTin+PTop;
PRBIN=PRBin+PRBop;
MNAIN=MNAin+MNAop;

%% first year of reactive (reactivation cost + operation cost)
PTre=ptre+PTop ;
PRBre=prbre+PRBop;
MNAre=mnare+MNAop;

%%%%% operation costs (whole period except for the first year, discounted back to
%% the value as the first year of the period)
PTope=0;
PRBope=0;
MNAope=0;

c=1:(floor(LEP)-1);
ptope=PTop*exp(-r*c);
PTope=sum(ptope)+(LEP-floor(LEP))*PTop*exp(-r*floor(LEP)); %% when the length of LEP
%% is not a integer, it is taken into account by the second term

prbope=PRBop*exp(-r*c);
PRBope=sum(prbope)+(LEP-floor(LEP))*PRBop*exp(-r*floor(LEP));

mnaope=MNAop*exp(-r*c);
MNAope=sum(mnaope)+(LEP-floor(LEP))*MNAop*exp(-r*floor(LEP));


%%%stopping costs %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
PTst=0.08*PTinwof;
PRBst=0.01*PRBinwof;
MNAst=0.10*MNAin;

%% strategy valuation by 5 steps %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%% Step 1, set up the decisions Matrix %%%%%%%%%%%%%%%%%%%%%

%% generate a matrix with 9s (when NP is fixed, the size of the matrix is known)

ND=9*ones(3^(NP-1),NP);

%% add MNA decisions %%
    for i=1:NP
        for j=2:3:(3^(i-1))
            ND(j,i)=2;
        end
    end

%% add stop decisions %%
for i=1:NP
        for j=3:3:(3^(i-1))
            ND(j,i)=3;
        end
end

%% adjust for Stop decisions (once stoped, next decision will be stop)
 for i=1:(NP-1)
        for j=1:(3^(i-1))
        if ND(j,i)==3
            ND((3*j-2),(i+1))=3;
```

```
            ND((3*j-1),(i+1))=3;
            ND((3*j),(i+1))=3;
        end
        end
 end

%% put the given decision string into the matrix for P&T PRB decisions%%%
h=0;
    for i=1:NP
         for j=1:3:(3^(i-1))
             if ND(j,i)~=3
             h=h+1;
             ND(j,i)=S(1,h);
             end
         end
    end
    ND ;

%% Step 2. set up the costs matrix %%%%%%%%%%%%%%%%%%%%%%%

NC=zeros(3^(NP-1),NP); %%the size is the same as the dicision matrix
%% acording to the decisions in the decision matrix, set the costs (all set as if
%% they are the first installed)
                for i=1:NP
                    for j=1:(3^(i-1))
                        if ND(j,i)==0
                            NC(j,i)=PRBIN+PRBope;
                        elseif ND(j,i)==1
                            NC(j,i)=PTIN+PTope;
                        elseif ND(j,i)==2
                            NC(j,i)=MNAIN+MNAope;
                        elseif ND(j,i)==3
                                    NC(j,i)=0; %%% stopping costs are different, it
%% will be adjusted later on
                        else ND(j,i)=ND(j,i);
                        end
                      end
                 end
                NC;
%% adjust for the reactivation costs (once a technology is installed, all the
%% following non-very-first first application will be reactivation)
for i=1:(NP-1)
        for j=1:(3^(i-1))
            if ND(j,i)==0
                for i=(i+1):NP
                    for j=1:(3^(i-1))
                        if ND(j,i)==0
                            NC(j,i)=PRBre+PRBope;
                        end
                    end
                end
            elseif ND(j,i)==1
                for i=(i+1):NP
                    for j=1:(3^(i-1))
                        if ND(j,i)==1
                            NC(j,i)=PTre+PTope;
                        end
                    end
                end
            elseif ND(j,i)==2
                for i=(i+1):NP
                    for j=1:(3^(i-1))
                        if ND(j,i)==2
                            NC(j,i)=MNAre+MNAope;
                        end
                    end
                end
            end
        end
end
```

```
  NC;
%% adjust for different operational costs for different technologies
    for i=1:(NP-1)
        for j=1:(3^(i-1))
        if ND(j,i)==0 && ND((3*j-2),(i+1))==0
            NC((3*j-2),(i+1))=PRBop+PRBope;
        elseif ND(j,i)==1 && ND((3*j-2),(i+1))==1
            NC((3*j-2),(i+1))=PTop+PTope;
        elseif ND(j,i)==2 && ND((3*j-1),(i+1))==2
            NC((3*j-1),(i+1))=MNAop+MNAope;
        end
        end
    end
  NC;
 NCstr=NC;

 %% adjust for the stopping cost (land value not included)
 for i=2:NP
        for j=3:3:(3^(i-1))
        if ND(j,i)==3 && ND(j/3,(i-1))==0
            NCstr(j,i)=PRBst;
        elseif ND(j,i)==3 && ND(j/3,(i-1))==1
            NCstr(j,i)=PTst;
        elseif ND(j,i)==3 && ND(j/3,(i-1))==2
            NCstr(j,i)=MNAst;
        end
        end
 end

%% adjust for the stopping cost and the value of the clean land
for i=2:NP
        for j=3:3:(3^(i-1))
        if ND(j,i)==3 && ND(j/3,(i-1))==0
            NC(j,i)=PRBst-Vland;
        elseif ND(j,i)==3 && ND(j/3,(i-1))==1
            NC(j,i)=PTst-Vland;
        elseif ND(j,i)==3 && ND(j/3,(i-1))==2
            NC(j,i)=MNAst-Vland;
        end
        end
end
  NC;

  %%%%%%%%%%%%% discount NC %%%%%%%%%%%%%%%%%
  for i=1:NP
        for j=1:(3^(i-1))
            NC(j,i)=NC(j,i)*exp(-r*LEP*(i-1));
        end
  end
  NC;

  %%%%%%%%%%%%% discount NCstr  %%%%%%%%%%%%
  for i=1:NP
        for j=1:(3^(i-1))
            NCstr(j,i)=NCstr(j,i)*exp(-r*LEP*(i-1));
        end
  end
  NCstr;

  %%% prepare for calculating the expected cost for each period
  NCs=NCstr;

  %% Calculating the strategy cost %%%%%%%%%%%%%%%%%%%
  %% cumulative costs for each scenario %%
        for i=2:NP
            for j=1:(3^(i-1))
                if rem(j,3)==1
                NCstr(j,i)=NCstr((j+2)/3,(i-1))+NCstr(j,i);
                elseif rem(j,3)==2
```

```
                NCstr(j,i)=NCstr((j+1)/3,(i-1))+NCstr(j,i);
                else
                NCstr(j,i)=NCstr(j/3,(i-1))+NCstr(j,i);
                end
            end
        end
  NCstr;

%cumulative values for each scenario%%
        for i=2:NP
            for j=1:(3^(i-1))
                if rem(j,3)==1
                NC(j,i)=NC((j+2)/3,(i-1))+NC(j,i);
                elseif rem(j,3)==2
                NC(j,i)=NC((j+1)/3,(i-1))+NC(j,i);
                else
                NC(j,i)=NC(j/3,(i-1))+NC(j,i);
                end
            end
        end
    NC; %%the costs of all the scenarios are the last column in the matrix

%%%%%%%Step 3.set up the concentration and probability matrix, and calculate the
%% strategy benefit  and cost


NCon=9*ones(3^NP,(NP+1));
NCon(1,1)=currentconc;

Npro=9*ones(3^NP,(NP+1));
Npro(1,1)=1;

        for i=1:NP
            for j=1:(3^(i-1))
                %%%Monte Carlo simulation%%%%%%%%%%%%%%%%%%%%%%%%
                    if ND(j,i)==1
                        Con=(NCon(j,i)*exp(-Dpt*LEP))+StdPT*randn(1,Ns);
                    elseif ND(j,i)==0
                        Con=(NCon(j,i)*exp(-Dprb*LEP))+StdPRB*randn(1,Ns);
                    elseif ND(j,i)==2
                           Con=(NCon(j,i)*exp(-Dmna*LEP))+StdMNA*randn(1,Ns);
                    elseif ND(j,i)==3
                        Con=-5000+0.07*randn(1,Ns); %take  a huge negative number so
%% that the probability will be inherited mainly by the last branch of the next
%% three. When it is stop, the concentration is not relevant anyways
                    end

                    d1=0; %counter
                    d2=0; %counter
                    d3=0; %counter

                    for k=1:Ns
                        if Con(k)<ConStop
                              d3=d3+1;
                              p3=d3/Ns; %the probability of stop for the next period
                        elseif Con(k)<=ConMna
                               d2=d2+1;
                               p2=d2/Ns; %the probability of MNA for the next period
                        else
                              d1=d1+1;
                              p1=d1/Ns; %the probability of P&T/PRB for the next
%% period
                         end
                    end

                     Gstop=Con(find(Con<ConStop ));
                     Gmna=Con(find(Con>=ConStop & Con<=ConMna));
                     Gptprb=Con(find(Con>ConMna ));

                     if(length(Gptprb)~=0)
```

```
                        ACptprb=mean(Gptprb);%% the new current concentration for
%% the next period
                        NCon((3*j-2),i+1)=ACptprb;
                     else p1=0;
                         NCon((3*j-2),i+1)=-9;%% to show that this is an empty group
                     end;

                     if(length(Gmna)~=0)
                        ACmna=mean(Gmna);
                       NCon((3*j-1),i+1)=ACmna;
                     else p2=0;
                         NCon((3*j-1),i+1)=-9;
                     end;

                     if(length(Gstop)~=0)
                        ACstop=0;
                       NCon((3*j),i+1)=ACstop;
                     else p3=0;
                         NCon((3*j),i+1)=-9;
                     end;

                    Npro((3*j-2),i+1)=p1*Npro(j,i);
                    Npro((3*j-1),i+1)=p2*Npro(j,i);
                    Npro((3*j),i+1)=p3*Npro(j,i);
                    %% once a group is empty, the p according to this group
                    %% will be zero. And because the probability will be
                    %% multiplied by the probability of the next branches, the
                    %% next pranches will all be zero

            end
        end
      %%% until here we get all the probabilities
      NCon;
      Npro;

      %%% calculate the expected cost for each period
     NCs;
      for i=1:NP
         for j=1:(3^(i-1))
             NCs(j,i)=NCs(j,i)*Npro(j,i);
         end
      end
      NCs;
      excost=[];
      excost=sum(NCs);

      %%% calculate the period landvalue inflow
Inflow=zeros(3^(NP+1),NP+1);
    for i=2:NP+1
        for j=3:3:(3^(i-1))
        Inflow(j,i)=Vland*exp(-r*LEP*(i-1))*Npro(j,i);
    end
end
Inflow;
%% when it is stop, all the following branches can not generate land value
%% any more
for i=1:NP
        for j=1:(3^(i-1))
            if ND(j,i)==3
                Inflow((3*j-2),(i+1))=0;
                Inflow((3*j-1),(i+1))=0;
                Inflow((3*j),(i+1))=0;
            end
        end
end
Inflow;
Inflow=sum(Inflow);
InflowTotal=sum(Inflow);
```

```
  %%%%%%%%%%  cumulative cost and cumulative benefit
  for uu=1:NP-1
      excost(1,uu+1)=excost(1,uu)+excost(1,uu+1);
  end
  for uu=1:NP
      Inflow(1,uu+1)=Inflow(1,uu)+Inflow(1,uu+1);
  end
  excost;
  Inflow;

%%calculate the strategy cost
  cc=zeros(3^(NP-1),1);
    for j=1:3^(NP-1)
        cc(j,1)=NCstr(j,NP)*Npro(j,NP);
        SstrategyCost=sum(cc);
    end
cc;
SstrategyCost;

%%% adjust for the benefit to get after the last period for each scenario
      NCC=NC;
       i=NP;
            for j=1:(3^(i-1))
              if ND(j,i)~=3
                  if Npro(j,i)~=0
                  NCC(j,i)=NCC(j,i)-Vland*(Npro(3*j,i+1)/Npro(j,i))*exp(-r*LEP*NP);
                  end
              end
            end
            NCC; %% the last colum contains the final scenario values

%% Comments for Step 3: The cases when it stops and when the group is empty are the
%% ones deserve more attention. Once it stops, the concentration is no longer
%% relevant as long as the probability is carried on. Once the group is empty, all
%% the following probabilities later on will be zero.

%% Step 4. Calculating the strategy value %%%%%%%%%%%%%%%%%%%%%%%
cc=zeros(3^(NP-1),1);
    for j=1:3^(NP-1)
        cc(j,1)=NCC(j,NP)*Npro(j,NP);
        Scost=sum(cc);
    end
cc;
Scost;
u=sum(Npro(:,NP+1)); %% this should be 1

%%  Step 5. Chance to meet the target %%%%%%%%%%%%%%%%%%%%%%%%%

%% generate the matrix containing only the chances which will not meet the target
for i=1:(NP+1)
            for j=1:(3^(i-1))
                if NCon(j,i)<=ConStop
                    Npro(j,i)=0;
                end
            end
end
NproN=Npro; %%the matrix of not meeting the target chances

%%chance to meeting the target
       Pm=1-sum(NproN(1:3^(NP),(NP+1)));

  strategyValue=InflowTotal-SstrategyCost;
  fitness=strategyValue;
```

9.2.4 Driver for GA: myGAOpt

```
function myGAOpt   %% file name: myGAOptDY.m

global LDP
global NP
%%discount rate
global r
%%future uncertainties of the concentration
global StdPT
global StdPRB
global StdMNA
%%effectiveness of the technologies
global Dpt
global Dmna
global Dprb
%%tresholds to switch
global ConStop
global ConMna
%%land price
global PP

LDP=30;
r=0.03;
StdPT=0.07; %Standard deviation of the concentration (same for all)
StdPRB=0.07;
StdMNA=0.07;

Dpt=0.21; % degradation rate constant for P&T (approx. 50% in 5 years)
Dmna=0.02;  % degradation rate constant for MNA
Dprb=0.12;  % degradation rate constant for PRB
currentconc=1; %current concentration (=100% - reference value)
ConStop=0.01*currentconc; %% we can stop when the concentration is bellow this level
ConMna=0.15*currentconc;  %%bellow this concentration and above ConStop,  MNA
                %above this concentration, P&T or PRB
PP=400;  %% land price per m2
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%

NN=100;

NP=4;%%%%%%%%%%%%%%%%%%%number of periods%%%

% set up the decisions Matrix%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%generate a matrix with 9s (when NP is fixed, the size of the matrix is
%%known)

ND=9*ones(3^(NP-1),NP);

%%add MNA decisions%%
    for i=1:NP
        for j=2:3:(3^(i-1))
            ND(j,i)=2;
        end
    end
%%add stop decisions %%
for i=1:NP
        for j=3:3:(3^(i-1))
            ND(j,i)=3;
        end
end
%%adjust for Stop decisions (once stoped, next decision will be stop)
for i=1:(NP-1)
        for j=1:(3^(i-1))
        if ND(j,i)==3
            ND((3*j-2),(i+1))=3;
            ND((3*j-1),(i+1))=3;
            ND((3*j),(i+1))=3;
```

```
        end
        end
 end
%%count how many decisions are there to make
    g=0;
    for i=1:NP
         for j=1:3:(3^(i-1))
             if ND(j,i)~=3
             g=g+1;
             end
         end
    end
   g

precis = 1;

strfun = 'EMOFit';
filehead = 'Optim';
filetail = '.mat';
runs = 10; %%%number of runs (this will generate runs best strings)
funEval = 500;  % number of fitness function evaluations per run

pcross = 0.5;  %uniform crossover probability
PopSize = 50;  % increase if optimal values are too different for each optimization
%run
pmut = 1/PopSize; %mutation rate

NoOfGen=floor(funEval/PopSize)

bounds = [0;(2^g)-1]'

first = true;
save First.mat first

for run = 1:runs

    fitn = [];
    Popp = [];
    save GaFit.mat fitn Popp
       filename = [filehead,num2str(run),filetail];

       [iniPop]=initializega(PopSize,bounds,strfun,[],[precis 0]);
    % iniPop(:,1:end-1)

       [x,endPop,bPop,traceInfo] = ga(bounds,strfun,[],iniPop,[precis 0
1],'maxGenTerm',NoOfGen,'tournSelect',[4],...
        'myuniformXover',[pcross],'binaryMutation',[pmut]);

    save(filename,'x','endPop','bPop','traceInfo')

    load GaFit.mat fitn Popp

    save(['Sup',filename],'Popp','fitn')
    dec2bin(x)

end
```

9.2.5 Driver for GA: EMOFit

```
function [sepp,fit]=EMOFit(x,jodel)%%loads the additional parameters, conversions,
%% file name: EMOFit.m

global NP
global Ns
global g
```

```
probThresh = 0.700000;

%load theRealData.mat SSS fittt probb retVal

% get binary number
    binN = dec2bin(x);
    % make it a string
    binStr = num2str(binN);
    % get length of bin string
    binLen = length(binStr);
    % create leading zeros
    S = [];
    for j = 1:binLen

        S = [S,str2num(binStr(1,j))];

    end
    if g-binLen ~= 0
      zeroVec = zeros(1,g-binLen);
      S = [zeroVec,S];
    end

    [fitness]=fitSVLimitation9_gl(S);

       %fittt = [fittt; fitness(1)];
       %probb = [probb; fitness(2)];


    %retVal = [retVal,fit];
    fit = fitness;
    %save theRealData.mat SSS fittt probb retVal
    sepp = x;
```