The use of Real Options and Multi-Objective Optimisation in Flood Risk Management

Submitted by

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I certify that all material in this thesis which is not my own work has been identified and that no material has previously been submitted and approved for the award of a degree by this or any other university.

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Abstract

The development of suitable long term flood risk intervention strategies is a challenge. Climate change alone is a significant complication but in addition complexities exist trying to identify the most appropriate set of interventions, the area with the highest economical benefit and the most opportune time for implementation. All of these elements pose difficulties to decision makers. Recently, there has been a shift in the current practice for appraising potential strategies and consideration is now being given to ensure flexible, adaptive strategies to account for the uncertain climatic conditions. Real Options in particular is becoming an acknowledged approach to account for the future uncertainties inherent in a flood risk investment decision.

Real Options facilitates adaptive strategies as it enables the value of flexibility to be explicitly included within the decision making process. Opportunities are provided for the decision maker to modify and update investments when knowledge of the future state comes to light. In this thesis the use of Real Options in flood risk management is investigated as a method to account for the uncertainties of climate change.

In addition to Real Options, this thesis also explores the use of optimisation techniques to aid the decision making process when identifying the most appropriate long term intervention strategies. Methods are required which can search for the most optimal solutions whilst accounting for a range of performance metrics. Single and multi-objective genetic algorithms are therefore investigated in this thesis.

The Real Options concepts are combined with a multi-objective optimisation algorithm to create a decision support methodology which is capable of searching for the most appropriate long term economical yet robust intervention strategies which are flexible to future change. A state of the art flood risk analysis model is employed to evaluate the risk associated to each strategy.

The methodology is applied to a section of the Thames Estuary as a case study to demonstrate the techniques above. The results show the inclusion of flexibility is advantageous while the outputs provide decision makers with supplementary knowledge which previously has not been considered.

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List of Abbreviations

BCR	Benefit Cost Ratio
CBA	Cost Benefit Analysis
CCA	Contingent Claims Analysis
DCF	Discounted Cash Flow
DEFRA	Department for Environment, Food and Rural Affairs
DTM	Digital Terrain Model
EAD	Expected Annual Damage
GA	Genetic Algorithm
GCM	Global Climate Model
GIS	Geographic Information System
MAUT	Multi-Attribute Utility Theory
MCDA	Multi-Criteria Decision Analysis
MOGA	Multi-Objective Genetic Algorithm
NDS GA	Non Dominated Sorting Genetic Algorithm
NPGA	Niched Pareto Genetic Algorithm
NPV	Net Present Value
NSGA	Non-dominated Sorting Genetic Algorithm
PAES	Pareto Archived Evolution Strategy
PDE	Partial Differential Equations
RASP	Risk Analysis for System Planning
RDM	Robust Decision Making
RP	Return Period
RFSM	Rapid Flood Spreading Model
SPEA	Strength Pareto Evolutionary Algorithm
SPRC	Source-Pathway-Receptor-Consequence model
VaR	Value at Risk
VEGA	Vector Evaluated Genetic Algorithm
UKCP09	UK Climate Projections 2009

Chapter 1 Introduction

1.1 General

Flooding is considered to be one of the worst types of natural disasters in the world. The most common sources of flooding include river and flooding, coastal flooding, surface water flooding and ground water flooding. Each of which can have devastating consequences such as damage to properties, disruption to transport and public services, injuries and even fatalities. The most recent floods such as the UK widespread summer floods of 2007 and the Cumbria floods of 2009 resulted in serious consequences showing the threat of flooding is still very present, and in fact has the potential to get worse. There are many factors which can contribute to an increase in the risk of flooding such as the future impacts of climate change, socio-economic change, the physical environment and the ageing infrastructure of current flood protection. In addition, with the uncertainty present in many of these factors the challenge to flood risk management becomes very complex. Flood risk management therefore faces many difficulties in the effort to reduce flood risk and maintain or improve the existing level of protection.

A key area of flood risk management is the development of long term, sustainable and economically efficient flood risk management intervention strategies which can account for the future uncertainties of climate change. The development of these strategies is complex due to the evolving nature of flood risk and in particular the growing threat from climate change. The complexities are further compounded by the large portfolio of possible intervention measures to choose from, the large range of performance measures to consider and the set of criteria and many stakeholders to satisfy. In addition, the flood risk community are acknowledging the need to build in adaptability and flexibility within flood risk intervention plans to ensure that flood defences implemented today will provide sufficient protection for future generations and not be a burden to future flood protection schemes.

This thesis therefore looks to advance the development of long term flood risk intervention strategies, address the requirements and complexities that are currently present and aid the decision making process. To do this, this thesis investigates two

concepts which independently have the potential to improve different aspects of the current approach when developing and selecting flood risk strategies. This thesis also looks to combine these concepts to create a decision support methodology which can address the problems simultaneously.

The first of these concepts is Real Options. A Real Option is the right but not the obligation to undertake an investment decision. Similar to financial options, Real Options account for uncertainty in the valuation of an irreversible investment by providing decision makers with opportunities such as delaying, expanding, contracting and abandoning when more knowledge of the future uncertainty comes to light. Essentially a Real Option can provide flexibility and account for future uncertainty in the decision making process when irreversible investments such as the implementation of a flood defence are considered. These concepts would be very suitable in flood risk management, the need to account for climate change uncertainty and capture flexibility within flood defence plans is becoming a necessity.

The second approach considered in this thesis is the use of optimisation techniques. Optimisation algorithms are automated searching methods which search for the optimal solution according to a given objective. With the large portfolio of possible combinations of intervention measures, an automated process to determine the better performing strategies would be advantageous. Furthermore, multi-objective optimisation can simultaneously optimise according to a range of competing criteria. This would enhance the decision making process in flood risk management, a range of different objectives can be considered resulting in an optimal trade-off of potential solutions.

With the advantages that both these methods can potentially bring to flood risk management, this thesis will look to create a decision support methodology which utilises both the Real Options concepts and optimisation techniques.

1.2 Objectives

The main objective of this thesis is to develop a new methodology to aid the decision making process during the development of long term flood risk intervention strategies. More specifically, the detailed objectives are as follows:

- To develop a decision support framework for the development of long term flood risk management.

- To develop an evaluation methodology that analyses potential intervention strategies according to a range of possible performance measures. The evaluation methodology should account explicitly for future climate change uncertainties by utilising the information provided by UKCP09.
- To incorporate flexibility and adaptability within the development of long term intervention strategies by introducing the concepts of Real Options and Real Options Analysis into flood risk management.
- To develop an optimisation based methodology to aid selection of the most appropriate long term intervention strategy for the least cost flood risk management.
- To further develop the above methodology by accounting for multiple performance criteria within the appraisal process without applying prior weightings or prioritising preferences, thus improving the information provided to decision makers on different optimal solutions.
- To improve the computational efficiency of a flood risk analysis model used to evaluate optional intervention strategies with the aim to enable the repetitive use of this model during the optimisation process.
- To incorporate the Real Options concepts, optimisation techniques, a flood risk analysis tool and a costing model to produce a decision support methodology which is able to develop long term sustainable, flexible and adaptive intervention strategies.
- To test, verify and demonstrate the developed decision support methodology on a real life case study.

1.3 Structure of Thesis

This thesis contains eight chapters including this introductory chapter. The next chapter (Chapter 2) provides a literature review on the topics that are relevant to this thesis. Chapters 3, 4, 5 and 6 present methodologies which build upon an existing risk analysis model to incorporate Real Options and optimisation techniques and ultimately create the decision support methodology. Chapter 7 provides a real life application of the decision support tool on the Thames Estuary in London. Finally Chapter 8 provides a summary and draws conclusions on the work presented in this thesis. Suggestions for future work are also given. A more detailed outline of this thesis is given below.

In Chapter 2 a review of existing flood risk management approaches is provided, looking at the traditional and most current methods to analyse flood risk as well as the appraisal process for the selection of flood risk plans. The current problems that face flood risk management are discussed in detail focusing specifically on the challenges of developing appropriate long term intervention strategies. This is followed by a review of the current methods for decision making under uncertainty. Specific focus is given to Real Options as a method to provide flexibility in uncertain environments. The review explores the different Real Options available, the valuation of Real Options and practical applications. Finally, a literature review on optimisation methods is given. In particular, single and multi-objective evolutionary optimisation methods are investigated and their application in flood risk management is discussed.

In Chapter 3 an existing flood risk analysis model is described which will form the foundations of the decision support methodology developed in this thesis to analyse potential flood risk intervention strategies. In order to couple the risk analysis model with optimisation techniques in a later chapter, a series of modifications are suggested and verified to improve the computational efficiency.

In Chapter 4 an evaluation process is described which analyses potential intervention strategies according to the benefits, in terms of flood risk reduction, and the costs of implementation. The main stages of the evaluation process are detailed, looking specifically at its connection with the risk analysis tool and an automated costing model. The Chapter also considers climate change uncertainty and describes how the evaluation process accounts for the uncertainty using UKCP09 data. The evaluation process is then advanced further by the inclusion of Real Options.

In Chapter 5 two different optimisation techniques are investigated and coupled with the evaluation process in Chapter 4. Firstly, a single objective flood risk optimisation problem is formulated which is to be solved using a single objective Genetic Algorithm (GA). The GA process is detailed giving a description of how it can be used for this flood risk problem. The advantages and disadvantages of this approach are also discussed. Secondly, a multi-objective optimisation problem is formulated and the Non-dominated Sorting Genetic Algorithm II (NSGAII) is employed to improve upon the weaknesses from the single objective GA and solve the new multi-objective problem. An additional criterion, a loss of life surrogate is also introduced.

In Chapter 6 the uncertainties of climate change are given further consideration by increasing the range of possible future scenarios that are considered during the evaluation process. The methodologies presented so far in this thesis are then brought together to produce a decision support methodology which optimises maximum expected utility given a range of uncertainty. Chapter 6 finishes by advancing the decision support methodology further to consider intervention strategies as decision trees whilst incorporating the Real Options concepts. The process for this is explained and the advantages discussed.

In Chapter 7 a case study on a section of the Thames Estuary is undertaken applying the concepts and methodologies presented in this thesis. Firstly a comparison of the traditional Net Present Value (NPV) approach with the new Real Options approach is undertaken. A single objective optimisation follows describing the additional benefits of optimisation in flood risk management. A multi-objective optimisation then takes place for three different cases: a case which considers one future projection analysed over two objectives, a case which considers multiple future projections analysed over two objectives and finally multiple projections analysed over three objectives. Comparisons between these are given. The Chapter concludes with an application of the Real Options based optimisation methodology.

In Chapter 8 a summary is made and relevant conclusions are drawn. This is then followed by suggestions for future work.

Chapter 2 Literature Review

2.1 Introduction

This thesis is exploring the integration and use of Real Options and optimisation techniques within flood risk management decision making. It is therefore necessary to put current flood risk management practise and issues into context and have an understanding of Real Options and optimisation techniques. A literature review is required which

- Investigates current methods for flood risk analysis
- Highlights some of the issues and challenges present in flood risk management
- Details methods available for decision making under uncertainty
- Explores the concepts of Real Options and its applicability to flood risk management
- Investigates optimisation techniques, specifically single and multi-objective GAs and their applicability to flood risk management

Therefore in this Chapter a literature review is presented which explores flood risk management, decision making under uncertainty with a focus on Real Options, and optimisation techniques. Section 2.2 focuses particularly on flood risk management with Section 2.2.2 reviewing the traditional and current flood risk analysis methods and Section 2.2.3 addressing the complications of developing long term flood risk management plans. The review provides details on the complexities surrounding flood risk management with reference to climate change adaptation and current appraisal methods.

Section 2.3 reviews the available methods for decision making under uncertainty. Special attention is given to Real Options in Section 2.3.3 due to its relevance in this thesis. Section 2.3.4 concludes by reviewing the application of Real Options and in particular its application in flood risk management.

The final Section (2.4) introduces the benefits optimisation methods can provide to flood risk management, specifically evolutionary algorithms. Section 2.4.2 focuses specifically on single objective GAs followed by section 2.4.3 which focuses on multi-

objective GAs. Both these sections include a review of their current application with reference to flood risk management.

2.2 Flood Risk Management

2.2.1 Introduction

The risk from flooding in England and Wales is considerable with approximately 5.2 million people living in an area with the potential to flood (Environment Agency, 2009a). With the continuing development on floodplains and the growing threat from climate change, this risk is set to increase. The recent floods in the UK such as the summer floods of 2007 and the Cumbria floods of 2009 highlight the serious hazards posed by flooding and the importance of flood risk management. It is predicted that sea levels will rise over the coming decades and the frequency and severity of rainstorms will progressively increase (IPCC, 2007) putting pressure on flood risk management to adapt to the changing climate.

Flood risk management has seen a shift over the past decades from flood protection to a more risk based approach to adjust to the evolving nature of flood risk (Sayers et al., 2002) however it is recognised that additional changes will be necessary to effectively reduce flood risk further (Ashley et al., 2007, Merz et al., 2010). Section 2.2.2 explores the traditional and current methods used in flood risk analysis, looking into detail at the different processes available but also the future of flood risk management in the light of climate change adaptation.

Flood risk analysis can identify areas of high risk but identifying the most appropriate intervention measures can be very complex. The evaluation of potential intervention strategies is very important and highlights the significance of having an adequate option appraisal scheme in place. Section 2.2.3 looks at the complexities involved when developing flood risk strategies, the importance of climate change adaptation and the current best practise for appraising these options.

2.2.2 Flood Risk Analysis

Flooding has been, and will be a continual issue that causes severe problems around the world. Traditionally, methods to prevent flooding involved designing a flood defence system to ensure protection against a predefined safety level regardless of the economic value that the defences were protecting (Messner and Meyer, 2006). This approach does not take into account the benefits of flood protection and as a consequence construction

of defence systems could prove to be more costly than the return in benefits. This approach could also be seen to act as a barrier to developing long term flood risk strategies (Sayers et al., 2002). Recent developments in flood risk management show the importance of addressing all factors involved in flood risk, from the probability of a flood occurring to the resulting damage and its associated uncertainties (Apel et al., 2004).

Over the years many methods and tools have been established to evaluate flood risk and generate appropriate intervention measures to reduce damage. One of the important processes in flood risk analysis is determining the characteristics of a flood event. Consideration of the dynamic nature of flood propagation, with particular regard to inundation depth, velocity and flood duration enables a more accurate estimation of the expected damages (Hamer and Mocke, 2002).

A range of tools to establish this information is available. Hydraulic models can be employed to obtain the route of flood water over a floodplain from breached and overtopped defences and in many cases the depth, velocity and duration. One and two dimensional numerical models are an accepted approach to stimulate flood inundation with an extensive range of examples in the literature. For example Werner (2001) applies a 1D flow model to a floodplain reach along the River Saar in Germany, Djordevic et al (2005) develop a sewer network model (SIPSON) for urban flooding, Patro et al (2009) uses a 1D hydrodynamic model to simulate river flows in India and Abderrezzak et al (2009) employ a 2D numerical model to model flash flood propagation in urban areas. A raster based model, LISFLOOD-FP, has been developed for predicting fluvial flood inundation (Bates and De Roo, 2000) and coastal inundation (Bates et al., 2005). In addition various 1D and 2D models have been developed including HEC-RAS (USACE, 1995), MIKE 11 (DHI, 1995), SOBEK-1D (Delft Hydraulics Software, 1995) and TELEMAC-2D (Laboratoire National d'Hydraulique of Electricité de France, 1994).

Both 1D and 2D models have their advantages and disadvantages when computing overland flows. One dimensional models for instance are computationally efficient, require less data and perform well when simulating flood propagation in straight streets. The shortfall however lies in the lack of accuracy when representing hydraulic processes which are 2D and 3D in nature (Abderrezzak et al., 2009). 2D models on the other hand, excel in their ability to accurately model the flood inundation and their

sophisticated representation of the hydraulic processes allows essential information such as flow depth and velocity. As a result, 2D models require large amounts of data and are computationally intensive to run (Bates and De Roo, 2000). Methods which couple one and two dimensional models have been applied to simulate flood extent to capitalize on the advantages presented in both 1D and 2D models. See for example Laguzzi et al (2001), Horritt and Bates (2002), Lin et al (2006), Chen et al (2007) and Leandro et al (2009).

The accuracy of numerical models can be greatly enhanced by using high-quality digital terrain models (DTM) to portray the topography of the floodplain. Remotely sensed data such as LIDAR (Light Detection and Ranging) and SAR (airborne synthetic aperture radar) can support flood modelling by improving the accuracy of the DTM's (Horritt et al., 2001, Neelz et al., 2006, Sole et al., 2008). Another possibility to model flood inundation consists of using GIS (Geographic Information System) to produce flood maps of the study area. GIS can also be integrated with 1D and 2D models and DTM's to more accurately identify potential hazards (Brivio et al., 2002, Mark et al., 2004, Stanchev et al., 2009).

With the characteristics of a flood event determined, another important aspect of flood risk analysis is to estimate the damages. Estimation of damages as a consequence of a flooding event is generally determined by assembling information on the flood parameters such as depth, duration and velocity combined with information on the elements at risk be it a residential property, a person or an ecological system for example (Messner and Meyer, 2006). The elements at risk of being harmed by a flooding event can be expressed in monetary and non-monetary units and can have either an immediate effect or generate consequences at a later stage. For this reason flood damage is considered to be divided into two categories, direct and indirect and further classified into tangible and intangible (Penning-Rowsell et al., 2005b).

The majority of work estimating flood risk focuses on direct damages, using depth-damage or stage-damage functions as the most widely accepted method (Smith, 1994, Merz et al., 2004). Depth damage functions provide an economical damage associated to a building given an inundation depth (Dutta et al., 2003) and occasionally given duration and velocity (Middelmann, 2009). Penning-Rowsell et al (2005b) provide detailed methodologies to estimate damages and provide information on depth damage data. Damage is a function of the type of building and its size as well as the purpose of

non-residential properties (Johnson et al., 2007). Dutta et al (2003) use depth-damage functions integrated into a mathematical model to estimate flood damage in Japan while Merz and Thieken (2009) use depth damage curves alongside the Flood Loss Estimation Model (FLEMO) to estimate damage under uncertainty.

Consideration of indirect damages has also arisen taking into account factors such as loss of life (Penning-Rowsell et al., 2005a, Jonkman and Vrijling, 2008) and indirect monetary damage (Penning-Rowsell and Green, 2000, Bockarjova et al., 2007). Jonkman et al (2008) develop a model to evaluate the damage associated to all categories of flood damage.

The majority of the methods described so far are deterministic in nature, in that they evaluate flood damage for a given flooding scenario. For instance a specific sea level rise scenario serves as the boundary conditions for an inundation model, the resulting flood extent can then be compared to the present day or converted into estimated damages using the information on the elements at risk. Due to the uncertainty inherent in future scenarios, probabilistic methods have been researched to determine flood risk across multiple flooding states subject to uncertainty. Risk, R, can then be computed as an integral over a range of hydraulic loading events, multiplying each loading event by its resulting consequence such that:

$$R = \int f(L)C(L)dl \qquad (2.1)$$

Where *f(L)* is the probability of a loading event occurring and *C(L)* is the consequence as a function of the load *L*.

USACE (1996) assign probabilities to the range of flooding scenarios and consider damages that would be a consequence of a full range of probability weighted flood events. Apel et al (2004) and Apel et al (2006) present a dynamic probabilistic model system to assess flood risks and associated uncertainties by creating layers of uncertainty. The layers of uncertainty consist of aleatory and epistemic uncertainty. Vrijling (2001) on the other hand concentrates on failure probabilities of the defence system during a flood event to evaluate the probability of flooding. Hall et al (2003b) and Gouldby et al (2008) evaluate the risk of flooding by assessing the probability of failure for a defence system whilst giving consideration to a wide range of flooding

scenarios with varying severity. The approach described by Gouldby et al (2008) is used throughout this thesis and is explained in more detail in Chapter 3.

These risk based approaches form the basis for decision making in flood risk management. With the estimation of flood risk, potential intervention measures can be analysed which reduce this risk. The future of flood risk management is calling for holistic approaches which integrate these risk based approaches with measures for reducing effects of flooding, such as implementing warning systems and flood proofing properties (Merz et al., 2010) not just the consideration of structural defences. The FLOODsite project considers and develops methods to support integrated flood risk management (Samuels et al., 2009). In order to successfully implement an integrated flood management plan, all aspects of flood management need to be addressed including policy, regulation, decision making and the technical approaches (Ashley et al., 2007). It is therefore important with the consideration of the above aspects to develop long term flood risk strategies whilst also taking into account the uncertain future climate to manage flood risk successfully. The next section in this review explores the uncertainties within flood risk calculations before going on to explore the development long term strategies.

2.2.3 Uncertainty in Flood Risk Calculations

Uncertainties arise at every stage of the decision making process in flood risk management, therefore it is important to understand the sources and significance of uncertainty. This section explores the nature and form of the uncertainties present in flood risk calculations.

As in the main stages described in Section 2.2.1 for flood risk analysis and the risk analysis model described in Chapter 3 there are a number of assumptions that have been made to arrive at a value of risk. The assumptions that are made contribute a degree of uncertainty at each stage. Therefore the risk value depends on how the uncertainties are considered and handled. The main sources of uncertainty through this process include (Hall et al., 2009b):

- The representation of the sources of flooding
- The calculation and modelling process of damage
- The consideration of future climate change projections
- The costs
- The discount rate

The uncertainties above can be broadly categorised into two main different types of uncertainty, aleatoric and epistemic uncertainty. Aleatoric uncertainty describes the natural variability in a given process, often referred to as inherent uncertainty where observations can be described by probabilistic models (Apel et al 2004). Epistemic uncertainty is the uncertainty due to the lack of knowledge about a phenomenon of interest (Hall 2003).

Considering the first of the above sources of uncertainty (how the sources of flooding are considered in the risk process i.e. hydraulic loads such as river flows, waves and storm surges), the natural events are considered to be aleatoric. The uncertainties from temporal variations such as these natural forces cannot be reduced as it is not known when an event of a given size will occur (Neuhold et al., 2009).

It is however possible to handle this uncertainty within the flood risk calculations. Probability distributions are fitted to existing data and numerical models to provide estimates of the likelihood of occurrence. These probability distributions can then be used to estimate the likelihood of extreme hydraulic loads occurring. There is however epistemic uncertainty inherent in this process, where the uncertainty is often referred to as statistical uncertainty. There is uncertainty in the statistical models used to fit the distributions as well as uncertainty related to fitting a distribution to a set of data rather than the full population. Unlike aleatoric uncertainties, epistemic uncertainties can be reduced through the improvement of knowledge in a given area. For example, as datasets improve with a large size and variability of the data sample, better distributions can be created and a better understanding of the correct statistical model to fit will become apparent (HR Wallingford 2002b).

Another source of uncertainty also considered to be epistemic is the modelling process and calculation of the damages where there exists a range of uncertainties (Hall et al., 2009b).

For example, there is uncertainty in the knowledge of how defences will respond to a specific loading event. Risk models such as (Hall et al 2003b and Gouldby et al 2008) use fragility curves to determine the probability of a defence failing. However information such as the current condition of the defence or knowledge on the defence's behaviour is imperfect. This uncertainty can be represented using upper and lower bounds and thus producing upper and lower bound risk estimates.

There is also uncertainty in the numerical models used which describe physical processes. Physical processes are complex and decision makers require quantitative methods to represent these processes in order to base management decisions. In doing so, simplified assumptions are often used to construct models of an environmental system. The representation is therefore not fully accurate of the process being modelled and is subject to uncertainty (Beven, 2009). During the calculation of the damages, for example, the models used to propagate flood water across a floodplain make assumptions on how this water moves and transfers over the area.

Parameters and boundary conditions are also used in numerical models to calibrate and run simulations. Identifying the most appropriate values is difficult and best approximations are often used, again increasing the uncertainty within numerical models (Knight et al 2010).

Another source of uncertainty in the above list is the representation of future changes in the climate. Given the unknown behaviour of environmental parameters, uncertainty is handled through the consideration of scenarios. Developing long term strategies and assessing their performance over a range of future scenarios contains much uncertainty (HR Wallingford 2002b).

The next section in this review explores the complexities of developing long term strategies in flood risk management.

2.2.4 Developing Long Term Flood Risk Strategies

The choice of flood risk intervention measures today will impact the choices and actions of future generations, highlighting the importance of long term flood risk strategies (Evans et al., 2004a, Evans et al., 2004b). Developing long term strategies is however very complex. The complexity of the decisions primarily relates to the evolving nature of flood risk with particular regard to global climate change and socio economic development scenarios. A set of interventions may perform well against a range of criteria under one future scenario, but poorly under others. There are also numerous combinations of intervention measures available, deciding on the optimum strategy and the timing of implementing them can be complicated. Additionally long term strategies are needed to provide continuous protection from the constantly deteriorating and aging infrastructure. A particular problem on the Thames Estuary in the UK is that the majority of the defences will come to the end of their design lives at similar times,

highlighting the importance of developing long term strategies sooner rather than later (Lavery and Donovan, 2005).

Furthermore, with the shift in flood risk management, it is recognised that long term strategies must not just focus on structural defences but consider flood resilience and measures to reduce the effects of flooding (Merz et al., 2010) as well as complying with emerging policy agendas (Ashley et al., 2007). In the European Union, new environmental legislation such as the Water Framework Directive (European Parliament, 2000) and the Environmental Impact Assessment Directive need to be adhered to.

Traditionally, approaches to long term planning involved creating a portfolio of fixed intervention options and evaluating them over a range of different socio-economic and climatic futures (Evans et al., 2004a, Evans et al., 2004b). Although the need for long term flood risk intervention strategies to account for the future uncertainties whilst reducing the risk had been acknowledged, the importance of climate change adaptation has now become a prominent element (Environment Agency, 2009e).

Climate change adaptation has had much interest (Smit and Pilifosova, 2001, Adger et al., 2005, Hallegatte, 2009) and has been explored in water resources (Dessai and Hulme, 2007, Lempert and Groves, 2010), the forest sector (Ohlson et al., 2005) and flood risk (DEFRA and HM Treasury, 2009). In these examples, adaptive strategies are called for. Adaptive strategies are considered to be sequential decisions in which an initial action is taken; subsequent actions are then determined by new information obtained at a later point in time (Smit and Pilifosova, 2001, Hallegatte, 2009, Lempert and Groves, 2010). This ensures they are robust to the uncertain climatic conditions and incorporate a level of flexibility to adapt in the future.

In the literature robustness and flexibility are identified as key components in climate change adaptation. The necessity of flexibility (Evans et al., 2006, Wilby et al., 2008, Merz et al., 2010) and robustness (Lempert and Schlesinger, 2000, Hall and Solomatine, 2008) to account for the uncertainties of climate change are widely accepted. The definition for robustness has many variations, see for example (Rosenhead, 1990, Lempert and Schlesinger, 2000, Hall and Harvey, 2009, Bruijn et al., 2008). In summary, a robust option performs reasonably well regardless of the future outcome and can account for the uncertainties by evaluating strategies over a range of potential

future conditions. Developing robust strategies can often result in a large initial cost and is therefore not always the most economical approach (Ranger et al., 2010b). Although robust strategies account for future uncertainty, it is fixed over the planning horizon and any irreversible investment that is no longer suitable for the changing climate will become a sunk cost (Gersonius et al., 2010).

The ability to incorporate flexibility in decision making to adapt to future uncertainties also merits consideration in developing long term strategies. Making decisions on irreversible investments under uncertainty will benefit from flexibility to adapt when new information becomes available in the future (Ingham et al., 2007). The higher the uncertainty, for instance in areas such as flood risk management where the future climatic conditions are extremely uncertain, the value of flexibility will be even more important (Dixit and Pindyck, 1994).

A strategic flood risk management approach has been adopted by the UK Governments Department for Environment, Food and Rural Affairs (DEFRA) to adapt to and overcome the underlying difficulties inherent in long term planning by introducing flexibility (DEFRA, 2009). A 'managed adaptive' approach is employed to track any changes in risk over time and manage these changes through multiple interventions, promoting the incorporation of flexibility within an intervention strategy. Within this approach, various methods to manage the uncertainty are suggested, such as the use of Real Options, however there is no formal framework or valuation method in place to do so. Other methods have been proposed which address adaptive decision making and option planning for flood risk under an uncertain future climate (Ingham et al., 2007, Hall and Harvey, 2009, Gersonius et al., 2010, Ranger et al., 2010a).

The impact of the uncertainties resulting from climate change on future flood risk have been widely investigated, looking at the effects on flooding itself (Bates et al., 2008, Wilby et al., 2008) but also at developing appropriate intervention strategies across multiple future scenarios (Hall et al., 2003a, Evans et al., 2006, McGahey and Sayers, 2008). Developing long term adaptive strategies which are robust and flexible often requires decisions to be made under severe or deep uncertainty. There are many methods and tools available to aid decision making under uncertainty, which are explored further in Section 2.3. In addition to climate change, there are many other uncertainties present in flood risk management decisions which are described in Hall

and Solomatine (2008). Hutter and Schanze (2008) provide recommendations to handle these uncertainties in long term planning.

The development of long term strategies requires suitable methods of appraisal. Klein and Tol (1997) state that the most relevant evaluation methods for climate change adaptation are Cost Benefit Analysis (CBA), cost effectiveness analysis (Smith, 1996), multi-criteria analysis (Levy, 2005, Meyer et al., 2009) and risk benefit analysis. Currently in England and Wales the traditional guidance and appraisal methods for flood risk intervention options such as The Green Book (HM Treasury, 2003) and the FCDPAG3 guidance documents (DEFRA, 1999, DEFRA, 2006) suggest the use of CBA and specifically the NPV to evaluate and determine the most cost effective options. In the Netherlands, CBA is also strongly advocated (Jonkman et al., 2004, Kind, 2008), likewise in the US (USACE, 1996, FEMA, 2009).

Under the NPV rule, the strategy or investment with the highest NPV is the most favourable solution. The use of the Discounted Cash Flow (DCF) methods like NPV received large amounts of negative criticism when applied to projects or appraisal options being evaluated over a single projection into the future but are in fact subject to large amounts of uncertainty (Dixit and Pindyck, 1994, Copeland and Antikarov, 2001, Schwartz and Trigeorgis, 2004). The main assumption with these methods assumes the project or investment will follow the exact path defined at the outset through to the end of the project's life. In a highly uncertain environment such as flood risk management this assumption is inadequate. The projected future climate will undoubtedly change over the project life and therefore an optimal intervention strategy for a 100 year period today may well be suboptimal when new knowledge on future change becomes available. It is therefore important to account for future uncertainty during the appraisal of potential intervention strategies.

Another difficulty arising in flood risk management is the selection of the most appropriate or most optimum intervention strategy. Risk based analysis models such as those described in Section 2.2.2 are capable of quantifying the benefits associated with potential intervention options. They do not however necessarily facilitate the selection of the best, most optimum solutions. In themselves, they are not able to answer questions such as what are the best intervention options and when would be the best time to implement them. Methods are required which can address these questions and

identify the most suitable intervention options whilst searching through a large portfolio of plausible intervention measures.

2.2.5 Flood Risk Management Summary

In this review so far, Section 2.2.2 highlights the work that has been undertaken to develop and improve flood risk analysis methods with risk based approaches providing a strong basis for decision making. However, from Section 2.2.3 it can be seen that decision making in flood risk management is becoming very challenging. It is evident from the literature that the current systems in place for flood risk management decision making do not favour the search for adaptable and flexible intervention strategies. The need for climate change adaptation has been explicitly acknowledged but as yet there is no formal framework or methodologies in place to do so. It is evident that flood risk management requires a holistic, integrated approach. In addition, there is a large portfolio of available intervention measures, each of which can be implemented in many different sequences through time. Determining the most appropriate combination of mitigation activities is therefore another challenge faced by flood risk management decision makers.

This thesis therefore aims to improve the development of long term flood risk management planning by accounting for climate change uncertainty with flexible and adaptive approaches whilst also addressing three prominent questions: what type of intervention measure is most appropriate, when should it be implemented and where would it be most beneficial. The remainder of this literature review investigates Real Options to provide flexibility and adaptability to flood risk management and optimisation techniques to search for the most appropriate combination of intervention measures.

2.3 Decision Making Under Uncertainty

2.3.1 Introduction

Section 2.2.3 of this literature review highlights the need for decision making methods under uncertainty when developing long term flood risk management strategies. There are many methods available to aid the decision making process and Section 2.3.2 aims to give an overview of the techniques available. The following sections concentrate on one method in particular, Real Options, specifically addressing what a Real Option is,

its approach for incorporating flexibility and accounting for uncertainties and how it is applicable to flood risk management.

2.3.2 Methods for Decision Making Under Uncertainty

Classical decision theory is categorised into three differing levels of decision making according to Knight (1921). The first of which is certainty, also known as deterministic, where there is only one future state of nature. The second is risk, whereby there are multiple states of nature and the uncertainty can be quantified by probability distributions. The last is uncertainty, often referred to as strict or severe uncertainty (Sniedovich, 2007, Hine and Hall, 2010), deep uncertainty (Ranger et al., 2010a) or Knightian uncertainty (Knight, 1921, Ben-Haim, 2005). This final case refers to situations whereby our knowledge of the parameter under consideration is insufficient and its future state is completely unknown. In this case, the uncertainty cannot be quantified using probability distributions over the multiple future states of nature.

There is only one normative way of making a decision in the case of risk which is to apply probability distributions to the multiple states of nature (Lindley 2000). The expected utility can then be computed for an option as the sum of its probability-weighted outcomes where one would look to maximise expected utility across alternative options. The application of maximising expected utility allows the decision maker to incorporate attitudes to risk and preferences over the distribution of outcomes in the way adaptation options are evaluated. This is done through a utility function which takes outcomes (i.e. members of a pre-specified outcome space) as inputs and maps them into real numbers, in order to represent preferences over the outcomes. Outcomes that map to high utility levels would be preferred to those that map to low utility levels (Ranger et al, 2010b).

Unlike the case of decision making under risk where there is only one normative approach, for severe uncertainty there are various decision making methods. Two fundamental principles include Wald's Maximin (Wald, 1945) and Laplace's principle of insufficient reason, also referred to as The Principle of Indifference (Keynes, 1921). Wald's Maximin is essentially assuming a worst case scenario and is therefore more conservative compared to that of Laplace's principle. There have also been derivatives of these approaches including the Minimax Regret (Savage, 1951, Eldar et al., 2004).

As Laplace's principle applies a probability distribution to the uncertain state, the decision making problem is essentially being converted from a case of severe uncertainty to a case of risk. There is however a difficulty with Laplace's principle in that the state space must be constructed so as to be amenable to a uniform probability distribution. For example, the principle could not be applied if the state space is equal to the real number line (Sniedovich 2007). Additionally, Laplace's principle is sensitive to the description of chance events and can be altered by the introduction of irrelevant possibilities. In other words, if alternative ways of categorising the states of nature are introduced, the probability of the consequence can change (Gajdos et al., 2004).

Another method for decision making under uncertainty is robustness analysis. Robust decision making often utilises the Maximin or Minimax regret rule to quantify robustness (Ranger et al., 2010b). These rules assume the worst case scenario will occur. If a solution is robust against the worst case scenario it should perform reasonably well regardless of the outcome. Lempert and Groves (2010) focus on Robust Decision Making (RDM), emphasising the need to consider uncertainty as multiple views of the future and evaluating potential solutions using a robustness criterion rather than an optimality criterion.

Info Gap decision theory (Ben-Haim, 2001) is another method which focuses on a robustness criterion. In this approach, a best estimate of the unknown future is chosen; a decision option is evaluated against this point and against various levels of conditions departing from this point to determine its robustness. This approach has been applied to various problems including conservation (Regan et al., 2005) and flood risk management (Hall and Harvey, 2009) but the overall approach has had criticism from Sniedovich (2007) who questions how a best estimate can be determined when the future state is severely uncertain.

Info Gap decision theory and RDM (Lempert and Groves, 2010) are both robust satisficing methods whereby the aim is to ensure all constraints are satisfied. Robust optimisation is another field of decision making which rather than satisfying constraints concentrates on robustness with respect to objective functions. Like the satisficing RDM method, uncertainty is represented as various future scenarios, but instead aims to find an optimal solution that is not overly sensitive to any specific realisation of uncertainty (Bai et al., 1997). Beyer and Sendhoff (2007) provide an overview of different approaches used for robust optimisation. Lempert and Groves (2010) and

Hallegatte (2009) maintain that robust satisficing is preferable to robust optimising, thus avoiding a single best solution when a set of plausible solutions can be available. It is of note that optimisation does not necessarily result in a single best solution but can produce a set of trade-off solutions when certain techniques are used, see for example (Fonseca and Fleming, 1995, Coello, 1999). It is also argued that any satisficing problem can be written as an optimising problem (Sniedovich, 2008).

Multi-attribute utility theory (MAUT) and multi-criteria decision analysis (MCDA) (Dyer et al., 1992) are well known established methods with a growing literature. There is a wide range of methods available for MAUT and MCDA but the general principle is the same. Solutions are evaluated against several criteria and are either assigned scores according to their performance to produce an overall aggregated score or the criteria are weighted into one criterion or utility function with the goal to maximise utility. These methods are more applicable for multiple decision criteria rather than accounting for uncertainty (Ranger et al., 2010b), Dorini et al (2011) however provide a method to handle uncertainty using MCDA.

These multi-criteria decision making methods under risk can assign probabilities to the multiple states of nature and receive a consequence for each objective. This then leaves the trade-off problem in determining which option to go with. Under uncertainty, as well as the trade-off problem, problems arise in determining the consequences for each objective given the unknown state of nature (Keeney, 1982).

Decision tree analysis (Keeney, 1982) has the ability to account for uncertainty and proves to be a useful tool for decision making. Representing graphically the decisions and possible outcomes enables decision makers to translate complex problems into a comprehensible model. Each branch of a decision tree is an alternative course of action or decision and can branch off to represent multiple future time steps to account for uncertainty.

Real Options often utilises decision tree analysis to enable evaluation of potential solutions (Dixit and Pindyck, 1994, Copeland and Antikarov, 2001) and is becoming a recognized approach for decision making to account for future uncertainty. Essentially a Real Option is a mechanism for evaluating flexibility by allowing decision makers to make changes to an investment when new information arises in the future. It is defined as the right but not the obligation to undertake an action such as *expanding*, *deferring*,

contracting or *abandoning* at a predetermined cost before a predetermined point in time (Copeland and Antikarov, 2001). The next section of the literature review explores the background of Real Options, the various methodologies to value flexibility and its application to a variety of investment problems, in particular flood risk management.

2.3.3 Real Options

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

The concept of financial options is analogous to Real Options but in contrast Real Options refer to tangible assets such as land, buildings and facilities rather than financial instruments such as stocks and shares. A comparison of Real Options and financial options is made in Figure 2.1.

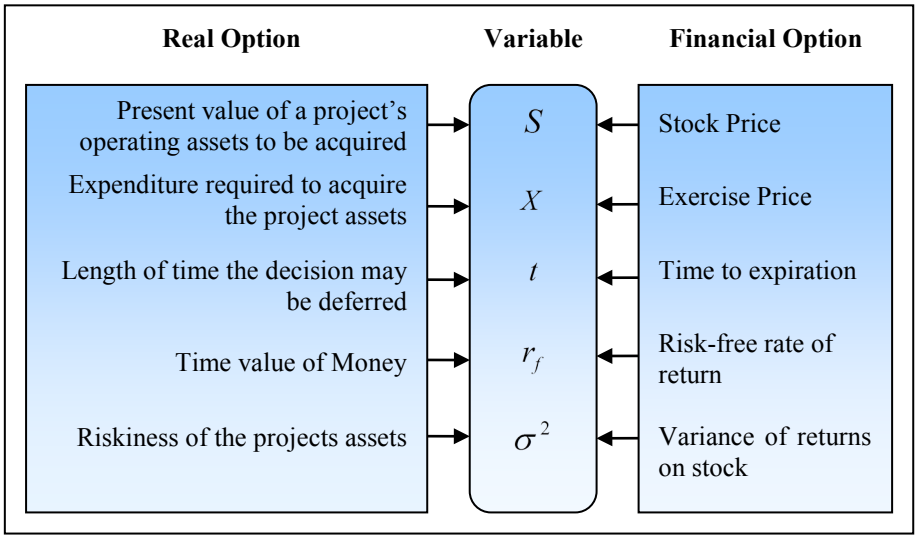


Figure 2.1 Relationship between Real and Financial Options

Many different Real Options exist to incorporate flexibility and account for future uncertainty. Schwartz and Trigeorgis (2004) classify Real Options into seven of the

most common categories. A brief description of each of the Real Options is provided below:

a) Option to defer. This provides the decision maker the opportunity to postpone an investment for a number of years until future uncertainties are identified. McDonald and Siegel (1986) produce a model to value the option to wait and consequently the optimal time to make the investment. When applied to a case study the importance of waiting was recognised. Capozza and Li (1996) extended this method to evaluate land redevelopment decisions.

b) Time to build option. Also known as staging the investment, where a series of options are undertaken at different points in time. This provides the option to abandon if uncertainties grow unfavourable or expand otherwise (Yeo and Qiu, 2003). Majd and Pindyck (1987) discuss a model using the time to build option for an irreversible investment which has an option to delay at each stage of the project. The optimal choice at each period is either to invest at the maximum rate or wait for an improvement in external conditions.

c) Option to alter operating scale. This provides options to expand or contract an investment depending on the future outcomes of uncertainty. The options to shut down and restart are also available. Trigeorgis and Mason (1987) use Contingent Claims Analysis (CCA) to value the option to expand or contract. Yuan (2009) formulate an expansion strategy on n European options. In any time period of the investment, expansion can be applied to the option until the expiration date. The option value is found by evaluating the profit increase that may be possible by expansion in the future. The value determines whether it is optimal to expand now, later or never.

d) Option to abandon. If uncertainty conditions decline severely, it can be more favourable to abandon the investment on a permanent basis. The assets and resources can be resold or reused elsewhere to reduce loss. Myers and Majd (1990) use Partial Differential Equations (PDE) to value the abandonment option. The results show that the optimal time to abandon is when the salvage value of the assets is greater than the project value.

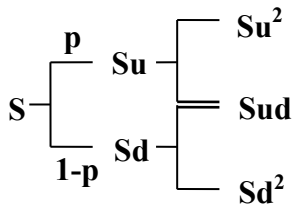
e) Option to switch. If there is a dramatic change in prices or demand, the output of the investment can be altered midway. Alternatively the output can remain the

same but the inputs can differ. Kulatilaka and Trigeorgis (1994) devise a general framework which enables management to switch between alternative technologies. If switching requires no cost, flexibility is simply the value of the rigid project plus the sums of the values to switch in the future. However if there is a cost, the creation of compound interactions discredits this and the value of the flexible project must be determined simultaneously with the optimal operating policy.

f) Growth options. Undertaking an early investment such as R&D or a lease on undeveloped land can present future opportunities for growth. These sets of interrelated options are known as compound options. Kulatilaka and Perotti (1998) analyse the strategic interaction of investments that induce cost advantage over rivals. They show that higher uncertainty may increase the company's incentive to invest when there is imperfect competition.

g) Multiple interacting options. Often investments involve undertaking numerous options. It can be beneficial to combine these options as the combined value of the options may differ from the sum of separate options when they interact (Copeland and Antikarov, 2001)

The Nobel Prize winning Black-Scholes formula is widely used to value financial options (Black and Scholes, 1973, Merton, 1973) and although it was developed for this use, alongside the work of Cox et al (1979), it became the fundamental mathematics behind Real Options. The simple binomial discrete-time option pricing formula by Cox et al (1979) expanded upon the work done by Black, Scholes and Merton. In its simplest form the method follows the concept that in any time period the asset can move to one of two possible prices with a given probability (see Figure 2.2).



S	Current stock price
Su	Increase in stock price (move up)
Sd	Decrease in stock price (move down)
p	Probability of moving up
1-p	Probability of moving down

Figure 2.2 Binomial Option pricing diagram

The valuation of the option uses dynamic programming, by recursively calculating the option price at each node of the binomial lattice, then moving from right to left discounting the values to the present time period.

While these methods value financial instruments, analogies have been made between financial and Real Options to justify the use of these methods for valuing Real Options. In spite of this, differences remain which question the compatibility of these methods to value real investments. A fundamental variation lies in the fact that Real Options are irreversible decisions unlike financial options which are publicly tradable (Dixit and Pindyck, 1994). Copeland and Antikarov (2001) consider the Black-Scholes formula for valuing Real Options inappropriate because the original assumptions are deemed too simplistic and unsuitable for valuing complex Real Options. Yeo and Qiu (2003) outline further differences between the two, showing even more so the incompatibility of using financial option valuation to value Real Options.

Wang and de Neufville (2004) explain that Real Options can be broadly classified into two categories, Real Options "in" systems and Real Options "on" systems. Real Options "on" systems are Real Options which focus on the external factors of a system. These options will benefit most from financial valuation tools (Rivey, 2007). Real Options "in" systems, on the other hand, incorporate flexibility into the structural design of the system and valuing this flexibility using financial tools is less suitable.

Methods to value flexibility in real investments were being identified throughout the field. de Neufville et al (2005) valued flexibility by using a value-at-risk (VaR) approach for Real Options valuation where VaR is defined as the probability of the maximum possible loss. Flexibility is calculated as the difference between the most realistic projected NPV and the expected NPV across different uncertain future scenarios. Other methods include CCA (Trigeorgis and Mason, 1987), CCA coupled with dynamic programming (Dixit and Pindyck, 1994), PDEs (McDonald and Siegel, 1986), NPV combined with the Black-Scholes formula (Luehrman, 1998), binomial (Copeland and Antikarov, 2001) and trinomial (Zhao and Tseng, 2003) decision trees and binomial decision lattices (Copeland and Tufano, 2004).

Traditional techniques used for valuing real investments such as DCF were considered to be inadequate (discussed in Section 2.2.3). It was recognised that the DCF approaches and specifically NPV should not be dismissed but used as a fundamental

building block in the analysis process. DCF assumes a now or never investment, neglecting the added value of flexibility and ignoring the uncertainties of the future (Dixit and Pindyck, 1994). Real Option evaluation can be considered a special case of NPV by capturing the future uncertainties and embedding flexibility into the option (Copeland and Antikarov, 2001).

2.3.4 Application for Real Options

The application of Real Options has been widely used over the years for various R&D problems and investment decisions. For example valuing oil properties and developments (Smith and McCardle, 1996, Lazo et al., 2003), design of maritime security systems (Zhang et al., 2009), optimal capacity for hydropower projects (Kjaerland, 2007, Bockman et al., 2008), renewable electrics R&D (Davis and Owens, 2003), dam investments (Michailidis and Mattas, 2007), development of land (Capozza and Li, 1996, Cunningham, 2006), construction of a car park garage (de Neufville et al., 2005, Zhao and Tseng, 2003), designing satellite fleets (Hassan et al., 2005) and evaluating mine plans (Dimitrakopoulos and Sabour, 2007).

The benefits of Real Options are beginning to be recognised in flood risk management. Dobes (2008) identifies the role Real Options can play in the adaptation to climate change, providing examples relating to the construction of airport runways and flood defences. In the UK, the UK Treasury issued an update to the “Green Book” (HM Treasury and DEFRA, 2009) which proposes Real Options as an appropriate approach for assessing climate change adaptation strategies. In DEFRA documentation (DEFRA, 2009) the use of Real Options is recommended in addition to traditional approaches to value flexibility in order to consider adaptive strategies. Gersonius et al. (2010) applied Real Options to the process of option planning in urban drainage systems to incorporate flexibility for adaptation to climate change whilst reducing future flood risk.

2.3.5 Decision Making under Uncertainty Summary

In Section 2.3.2 a range of methods for decision making under uncertainty are provided. These are very relevant in flood risk management, where it is often the case that decisions are required under severe uncertainty. Having methods to account for the uncertainty can improve the decision making process. From the literature in Section 2.3.3 and current applications in Section 2.3.4, it can be seen that the use of Real Options is very advantageous for investments facing uncertain futures and projects which require flexible and adaptive approaches. Real Options provide the flexibility

within decision making and furthermore the Real Options "in" systems approach enables flexibility to be inherently designed into irreversible investments and infrastructure whilst providing the additional value of flexibility within the NPV calculations, ensuring more suitable appraisal methods. It can be seen that Real Options can address some of the issues facing flood risk management, this is evident by the growing interest in this field. However the use of Real Options has only been suggested, there is limited application and methodological guidance on its use in this area. In this thesis Real Options analysis will be used in the context of flood risk management decision making to address the need for adaptable and flexible options, it will also aim to provide a methodology for the use of Real Options in this area.

2.4 Optimisation in Flood Risk Management

2.4.1 Introduction

Optimisation refers to finding the best possible solution to a problem given a set of limitations or constraints. Optimisation methods and techniques are used to solve complex problems by searching for the optimal solution. Through the exploration of various combinations of decision variables within the search space, an optimal solution consistent to the problem objectives can be established.

As can be seen from Section 2.2, flood risk problems are very complex. With such a large portfolio of intervention measures, it becomes a challenge to generate strategies which are economically efficient, sustainable and robust to uncertainty but also satisfy the many stakeholders involved in such decisions. As flood risk problems vary in complexity with numerous constraints, non-linearity, time varying objective functions and large dimensionality (Kingston et al., 2007) finding optimal solutions is very challenging. Traditional optimisation methods such as gradient based methods (Juels and Wattenberg, 1995), enumerative methods (Bellman, 1954), Random Search (Beasley et al., 1993) and Simulated Annealing (Kirkpatrick, 1983) are designed to solve optimisation problems that have a single optimal solution, have continuous, differentiable objective functions, and have linear and recursive properties. If the optimisation problem consists of an extensive range of conditions, these traditional methods will not be robust enough (Coello et al., 2002). That is usually the case with the long-term flood risk management optimisation problems which are typically large, complex, non-linear, discrete and multi-modal optimisation problems (Kingston et al., 2007)

Evolutionary Algorithms have grown in popularity for solving such complex problems. In the next section of the literature review (Section 2.4.2) single objective GAs are discussed in detail. The following Section (2.4.3) reviews the literature of multi-objective evolutionary algorithms specifically looking at water and flood related literature.

2.4.2 Single Objective Optimisation

There is a range of single objective evolutionary based optimisation techniques including GA's (Goldberg, 1989), Shuffled Complex Evolution (Duan et al., 1993), Ant Colony Optimisation (Dorigo et al., 1996) and Particle Swarm Optimisation (Kennedy and Eberhart, 1995). Although these techniques differ in their methodology, they share many similarities obtained from their evolutionary based nature. For example these methods are able to deal with a population of solutions simultaneously rather than just a single point in the search space. They are able to evolve and improve upon previous solutions whilst covering large areas of the search space (Kingston et al., 2007).

A popular technique is the GA. A GA is a stochastic search technique based on Darwin's theory of natural selection and survival of the fittest. A population evolves over time by sharing information amongst the fittest members. The algorithm is initiated by randomly generating a population of chromosomes. These chromosomes are made up of genes with each gene representing a decision variable. The fitness or performance of these chromosomes is determined, with the 'fitter' or better chromosomes having a higher likelihood of being selected for the next generation. Throughout each generation, genetic operators such as crossover and mutation are applied to the chromosomes to generate new generations of solutions to further explore the search space of potential solutions. The process is repeated until a convergence criterion has been met or a solution optimal to the objective function has been found (Goldberg, 1989).

The fundamental principles of a GA originated from Holland (1975) with various literature detailing the basic methodology, see for example (Goldberg, 1989, Deb, 1998). Specific details within the GA can vary including the different methods available for selection, crossover and mutation. There are four common selection processes including tournament selection, proportionate selection ranking selection and steady state selection (Goldberg and Deb, 1991). Different crossover or recombination methods include one point, two point, uniform and averaging (Deb, 1998). These methods typically crossover two different chromosomes at a certain location to produce

two new offspring, compared with mutation which involves altering the chromosome or a specific gene. Crossover has a much higher probability of occurring compared with mutation. Various mutation methods include random replacement and creep/adjacency.

There are many strengths attributed to GAs, for instance their ability to explore large, complex or poorly understood search spaces or the effectiveness with which they can find good solutions from a high dimensional problem. GAs are considered to be robust search algorithms and can handle any type of objective function, unlike traditional approaches.

Given these strengths, difficulties do exist. One difficulty lies in the lack of constraint handling within GAs (Michalewicz and Janikow, 1991). To account for this, it is possible to assign penalty functions to any candidate solution which violates the constraints reducing the value of the fitness function. Smith and Coit (1995) provide a range of different penalty functions which can be implemented. Another approach would be to modify the genetic operators to make the problem non-constrained.

Another weakness of the GA is that it is liable to prematurely converge (Andre et al., 2001). This most commonly occurs if a local optimum is found at the beginning of the search and gets immersed in the selection and crossover processes at each stage blocking the search from finding a global optimum. A number of ways to prevent premature convergence includes increasing mutation probability, increasing population size and increasing the number of non-random chromosomes in the initial population (Kapelan, 2010).

GA's are widely used in the water sector. For example for designing water quality monitoring networks (Park et al., 2006), least-cost design of water distribution networks (Savic and Walters, 1997, Kapelan et al., 2004), irrigation planning and management (Kuo and Liu, 2003), sampling design for water distribution systems (Kapelan et al., 2005) and reservoir flood control (Chang, 2008).

Within flood risk management looking specifically at the development of suitable flood risk management strategies, Gersonius et al (2010) use a GA to search for optimum flood risk contingency plans with the objective to minimise net present value of life cycle costs.

2.4.3 Multi-Objective Optimisation

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

The Pareto optimal set is also referred to as the Pareto optimal front shown in Figure 2.3 as the solid line. F contains all the solutions for the multi-objective problem with the solid line displaying the best solutions found in F.

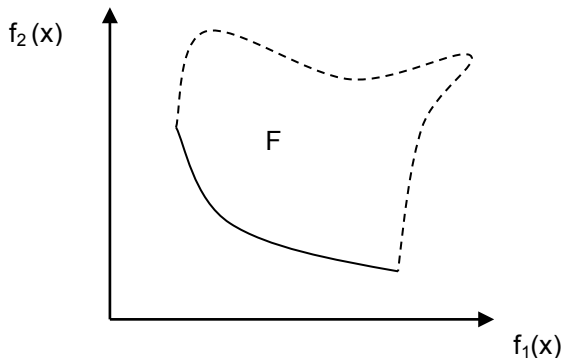


Figure 2.3 The Pareto Front of an optimisation problem with two objective functions

There are many methods available to deal with multiple conflicting criteria, some of which do not use the notion of Pareto Optimum. Table 2.1 describes the main approaches which do not employ the Pareto based approach.

Some of the methods explained in Table 2.1 combine multiple objectives into one or apply preferences to certain objectives. Applying weights and aggregating factors into a single objective loses a large amount of available information which can be of benefit to decision makers. Without this information insight into the problem and characteristics of the solutions are lost. Additionally combining multiple objectives into one utility function or applying preferences requires extensive knowledge of the objectives and can result in sub optimum solutions if incorrect weights are applied a priori of the optimisation process (Coello, 1999).

The next set of methods described in this review simultaneously optimises conflicting criteria and are based upon the notions of Pareto Optimality. Goldberg (1989) introduced Pareto based fitness assignment into evolutionary algorithms where all non-dominated solutions in the population are assigned an equal probability of reproduction. This concept of Pareto ranking identifies all the non-dominated solutions and assigns a ranking of 1. These are artificially removed and the next set of non-dominated solutions is ascertained. These are assigned rank 2. This process is repeated each time increasing the rank by 1 until all solutions are suitably ranked.

Table 2.1 Multi-Objective methods which do not employ Pareto based approaches

Name	Method	Strengths	Weaknesses	Application
Lexicographic ordering	Rank objectives in order of importance	Simple, computationally efficient	Favours specific objectives	Dauer and Kruger (1980) for water resource planning
Constraints method	Turns all but one objective into a constraint	Simple	Time consuming, difficult to code many objectives	Ranjithan et al (2001) coupled this method with evolutionary algorithms
Min-Max approach	Optimises the worst performing objective function	Not sensitive to Pareto curve, can find solutions that are convex or not	Requires prior knowledge of the problem	Coello and Christiansen (2000) use it for multi-objective problems in structures
Weighted Sum Approach	Assigns weighting coefficients to each objective and aggregates into single objective	Simple, computationally efficient	No method on how to distribute weights correctly	Liu et al (1998) aggregate weights for optimal structural design
Vector Evaluated Genetic Algorithm (VEGA)	Modified GA with differing selection process	Produce numerous solutions from one run	If search space is non-convex, unable to create Pareto optimal solutions	Zitzler and Thiele (1998) use VEGA to solve the knapsack problem and compare against other multi-objective approaches

Srinivas and Deb (1994) utilized the Pareto ranking concept (Goldberg, 1989) for the Non-dominated Sorting Genetic Algorithm (NSGA). The NSGA varies from a GA in the selection process but crossover and mutation remain the same. During selection the Pareto ranking method is performed as well as a sharing method. Sharing is used to allow multiple optimal points to co-exist in the population. Srinivas and Deb (1994)

carried out a comparison of the NSGA against VEGA. It was shown that the NSGA can maintain stability and uniform reproductive potential across non-dominated individuals whereas VEGA cannot.

Fonseca and Fleming (1993) introduced the Multi Objective Genetic Algorithm (MOGA) which employs a slightly different adaptation of Pareto ranking for its fitness assignment. Each individual solutions rank is defined by the amount of individuals in the current population that dominate it. Figure 2.4 displays the equation to calculate the rank.

Rank (xi, t) = 1 + pi (t)

Where xi = an individual solution

t = generation

pi (t) = number of individuals that dominate xi

Figure 2.4 A form of the Pareto ranking calculation used in MOGA

Horn et al (1994) introduced the Niched Pareto Genetic Algorithm (NPGA). In this method tournament selection is used with two alterations, the first being Pareto dominance and the second being fitness sharing. The idea is that two individuals are chosen at random and compared against a subset of the population. If one individual is dominated by the subset and the other is not, then the non-dominated individual is selected. If either both are dominated, or both are non-dominated, fitness sharing is employed.

Veldhuizen (1999) carried out a comparison of the NSGA, MOGA and NPGA. It was found that MOGA was far superior to the other two and the NSGA was proven to be the most ineffective. Deb et al (2000) deduced that the NSGA's shortfalls included high computational complexity, lack of elitism and a need for a sharing parameter. However strengths have also been identified including its ability to handle any number of objectives and its sharing method on the individual solutions to ensure a better distribution of individuals (Coello, 1999). Zitzler and Thiele (1998) undertook a comparison of four different optimisation techniques namely the NSGA, NPGA, VEGA and the weighted sum method on the Knapsack problem. In contrast to Veldhuizen (1999), the NSGA outperformed all other techniques followed by VEGA. The reason

for this is attributed to the NSGA's ability to cover a large range of the Pareto front. The NPGA did not achieve any outstanding results and a comparison with MOGA did not take place.

Srinivas and Deb (1994) note that the ranking method used in MOGA is likely to produce a large selection pressure which could cause premature convergence. This has been avoided by the use of a Niche formation method to distribute the population over the Pareto optimal area. Another shortfall arises in MOGA due to the use of the sharing method on the objective functions not the individuals. Having diversity amongst the individuals is important to decision makers. MOGA's strengths consist of its simplicity and ease to implement (Coello, 1999).

Coello (1999) discusses the strengths of the NPGA. As the method does not apply Pareto ranking to the entire population, the method tends to be very fast. It also generates reasonable Pareto fronts which can be kept for many generations. The downsides to this method incorporate requirements for a sharing factor and a sensible choice of tournament size.

Zitzler and Thiele (1999) presented the Strength Pareto Evolutionary Algorithm (SPEA) to overcome the shortfalls of the previous evolutionary algorithms. This method was the first to establish elitism as a needed concept. Elitism helps to retain the non-dominated individuals. SPEA uses an archive called the external non-dominated set which contains non-dominated solutions from previous populations. Non-dominated individuals are placed in the archive at each generation and assigned a strength value. All individuals in the current population have their fitness calculated based on the strength value of the external non-dominated solutions. This can ensure closeness to the Pareto front and an even distribution of individuals. Zitzler and Thiele (1999) found that SPEA could successfully guide the search towards the Pareto front. When analysed against the Knapsack problem, it extensively outperformed the NSGA, NPGA, VEGA and the weighted sum approach.

Knowles and Corne (2000) introduced the Pareto Archived Evolution Strategy (PAES). This method uses an archive to keep and update non-dominated solutions and be a benchmark for new generations. To maintain diversity a crowding procedure is used to divide objective space. Each solution is placed in a grid location based on values of its objectives to determine the number of solutions in each location. PAES was tested

against several other techniques including the NPGA and a version of the non-dominated sorting genetic algorithm (NDS GA) over a range of different test problems. The results showed that PAES worst performance was still superior to all the other techniques.

Deb et al (2000) modified the NSGA to produce the NSGA-II. The NSGA-II is an adaptation of NSGA with the shortfalls removed. Deb et al (2000) compared the NSGA-II against the PAES on five difficult test problems. The NSGA-II outperformed PAES and was able to better distribute its population along the Pareto front.

Many of these multi-objective evolutionary algorithms have been applied in the water sector. For example sampling design of water distribution systems using MOGA (Kapelan et al., 2003), rehabilitation of water distribution systems using a modified NSGAII (rNSGAII) (Kapelan et al., 2006), reservoir management (Reddy and Kumar, 2006) and evacuation planning using the NSGAII (Saadatseresht et al., 2009).

2.4.4 Optimisation in Flood Risk Management Summary

In the literature so far, a wide range of differing multi-objective optimisation GA's have been identified but there has not been an application of evolutionary multi-objective optimisation techniques for flood risk management decision making despite the available benefits. Having the capability to optimise simultaneously the many conflicting criteria within flood risk management and provide insight into the problem characteristics will be a great asset for flood risk management decision making. Furthermore these optimisation approaches can identify the better performing intervention strategies providing optimal combinations of intervention measures, answering questions such as: what types of interventions would be most appropriate, where would they be most beneficial and when should they be implemented. In this thesis the incorporation of optimisation techniques and specifically a multi-objective GA is integrated with a flood risk model to improve decision making and provide additional information to decision makers regarding the different criteria available.

2.5 Summary

In this Chapter, a literature review relevant to flood risk management, decision making under uncertainty with focus on Real Options and optimisation techniques is presented.

From the literature in Section 2.2, a review of traditional and current flood risk analysis methods were provided. The literature indicates that to date, risk based analysis tools

are the most advanced and progressive method to evaluate areas at risk to flooding and will form the foundations to future holistic approaches. It is therefore appropriate in this thesis to use a risk based analysis model to form the basis for the work presented.

With the aim to address issues facing flood risk management and improve the methodologies available for decision making, Section 2.2.3 reviewed the literature and current position of flood risk management to identify keys areas to be addressed. One of the most prominent matters established from Section 2.2.3 which faces flood risk management is the future uncertainty of climate change. The need to develop economical yet flexible and adaptive flood risk plans which will effectively reduce flood risk in present and future climatic conditions is very apparent. It is evident from the literature that the current systems in place for flood risk management decision making do not favour the search for adaptable and flexible intervention strategies. The need for climate change adaptation has been explicitly acknowledged but as yet there is no formal framework or methodologies in place to do so. The methodologies presented in this thesis will therefore aim to address the need for adaptable flood risk intervention strategies which account for future uncertainty.

To do this, Section 2.3 investigated decision making methods under uncertainty (Section 2.3.2) and specifically Real Options as a method to provide flexibility and adaptability (Section 2.3.3). In summary a Real Option allows a decision maker to make changes to an investment when new information arises in the future. Opportunities such as *delaying* the investment, *abandoning, switching, expanding, contracting* and having multiple options interacting together are potential choices for decision makers (Copeland and Antikarov, 2001). Applying these concepts encourages more flexibility to be built into a system or investment than in normal current practice and by appropriately valuing this flexibility, the benefits can be greatly enhanced when future uncertainty is present.

The return on investment decisions relating to flood risk management are subject to significant uncertainty. For example, the future impacts of climate change on the drivers of flood risk are highly complex, involving consideration of the potential impacts of mitigation policies and the subsequent physical response of the climate system. The Real Options philosophy seeks to identify opportunities for incorporating flexibility into the decision making process to mitigate the potential impact of these uncertainties, making this an ideal candidate for flood risk management. The advantages of Real

Options are very apparent and it is clear that the requirements of flood risk management such as the need for flexibility and to account for uncertainty can be provided by Real Options. There is however limited application and methodological guidance on its use in this area. This thesis therefore explores the integration of the concepts of Real Options and the value of flexibility within flood risk management to aid the development of adaptable flood risk strategies but to also promote the use of Real Options in this area.

In the literature review, Section 2.2.3 highlighted another problem facing flood risk management when identifying suitable flood risk management plans. It was found that decisions are compounded by multiple criteria, time bounded constraints and numerous stakeholders each with differing preferences. Furthermore with a large portfolio of structural and non-structural intervention measures to choose from as well as deciding upon the most appropriate time and location to implement them, the development of intervention strategies becomes very complicated. To improve flood risk management further, the selection of the most appropriate combination of intervention strategies according to a range of evaluation criteria is another important issue to consider and is therefore addressed in this thesis.

Section 2.4 explored optimisation methods and their applicability to flood risk management to aid the search for the most appropriate intervention strategies. From the introduction in Section 2.4.1, traditional optimisation methods were found to be inappropriate for the complexities within flood risk. The literature based on single objective GA's were reviewed in Section 2.4.2 and multi-objective GA's were explored in 2.4.3. The benefits of single and multi-objective GA's to search for the most appropriate solutions can be seen and have both been applied in various water related problems. Furthermore, multi-objective optimisation provides the ability to handle many differing criteria. There had not however been an application of multi-objective optimisation techniques for flood risk management decision making despite the available benefits. Having the capability to optimise simultaneously the many conflicting criteria within flood risk management and provide insight into the problem characteristics will be a great asset for flood risk management decision making. Multi-objective optimisation algorithms have the potential to improve upon the decision making process and aid decision makers to develop and select the most appropriate flood risk management strategies. This thesis will investigate the integration of multi-

objective optimisation within flood risk management as a method to search for the most appropriate intervention strategies. The methodologies presented throughout this thesis including the concepts of Real Options and multi-objective optimisation will be integrated within a flood risk analysis model. The next Chapter of this thesis presents a state of the art methodology for flood risk analysis.

Chapter 3 Flood Risk Assessment

3.1 Introduction

Flood risk analysis and assessment plays a vital role in flood risk management decision making, providing the economic evaluation of the benefits for risk mitigation measures. A flood risk analysis model, Risk Assessment for System Planning (RASP) (HR Wallingford, 2002a) was developed to support flood risk management and assess the performance and risks associated with systems of defences. In particular, RASP focuses on the probability of flooding at a particular location within a floodplain taking account of the protection afforded by defences.

In this thesis RASP is used to evaluate potential flood risk mitigation measures and assess the risk associated to intervention strategies. Throughout this thesis RASP provides the fundamental basis for the methodologies presented and therefore a clear understanding of RASP is required. Section 3.2 provides a summary, discussing in particular the methodology and concepts behind RASP. For a full detailed description see (Hall et al., 2003b, HR Wallingford, 2004b, Gouldby et al., 2008).

With the intention to couple RASP with optimisation techniques, it can be expected that numerous simulations of the model will be required. With this in mind, Section 3.3 investigates two measures that can be taken to improve the computational efficiency of the risk analysis model whilst preserving the prediction accuracy. Section 3.3 also explores the applicability of these changes to the planned methodologies in this thesis whilst validating whether these changes can be used.

3.2 RASP Methodology

The fundamental concept behind the RASP methodology is the system based approach of the Source-Pathway-Receptor-Consequence (SPRC) model (Sayers et al., 2002), see Figure 3.1. The SPRC model represents systems and processes, by considering the risks associated with the source, pathway and receptor, an overall risk or consequence can be established. Within RASP, the source is considered to be the loading conditions (e.g. fluvial levels and coastal tides and waves), the pathway refers to the connection between the source and the receptor (e.g. the flood defences or the floodplain leading to a

housing development or area at risk) and the receptor in the context of RASP denotes the properties or land which is damaged in the event of a flood.

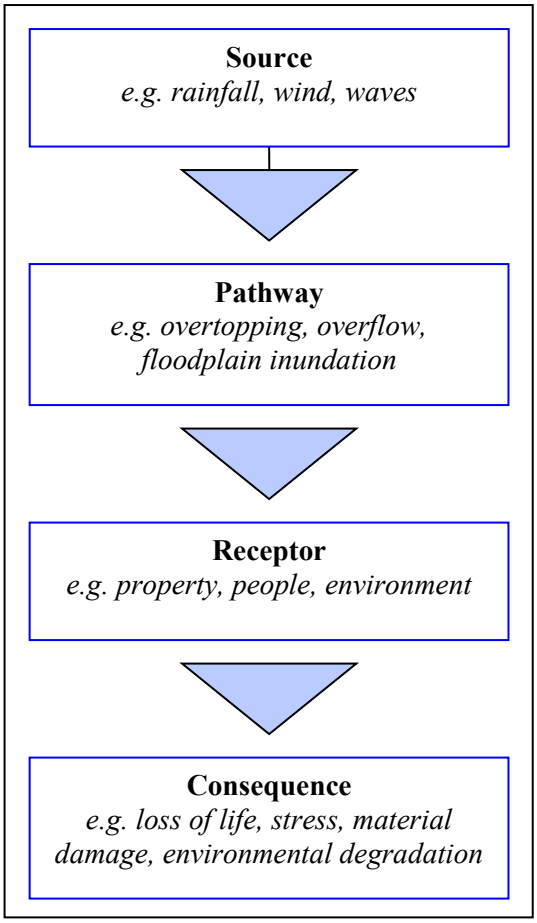


Figure 3.1 SPRC model (Gouldby et al., 2005)

Systems risk analysis depicts the flood area of interest into naturally formed flood systems. These are continuous areas of the floodplain which are defined by natural borders such as rivers, coasts and high ground. The flood systems are discretised into impact zones and further again into impact cells, see Figure 3.2. Each of these cells is susceptible to flooding from the rivers or coasts. The flood systems are protected from flooding by n discrete defences ($d_1, d_2, \ldots, d_n$). Within RASP, defences are classified according to type, material and further classified according to the level of protection (e.g. wide, narrow, front protection, rear protection etc). Each defence is independent from each other and consequently their response to a flood event will differ.

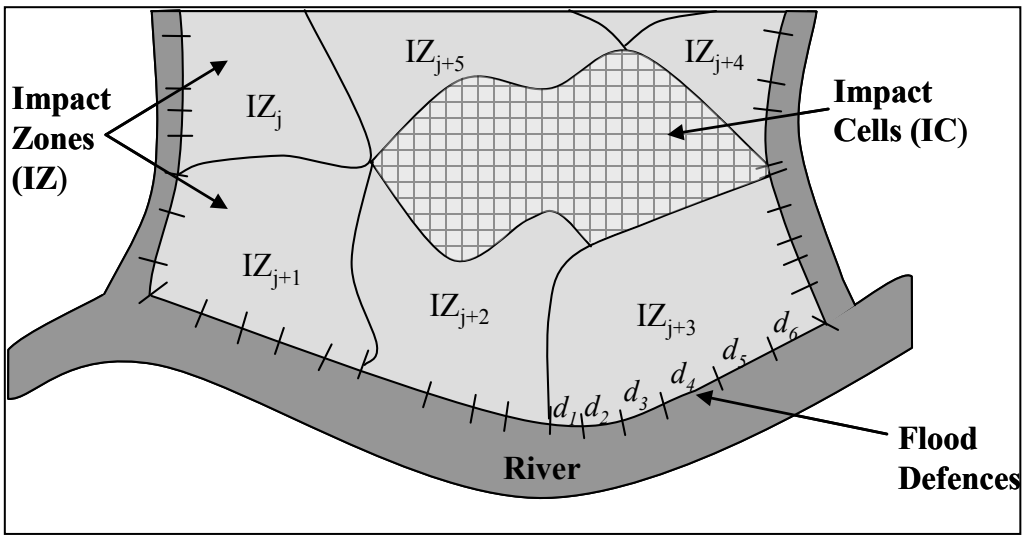


Figure 3.2 Conceptual illustration of the modelled flood system in RASP (Gouldby et al., 2008)

Defence failure from either breaching or overtopping is defined as a continuous random variable conditional on load and is represented by fragility curves (Platt, 1995, Simm et al., 2009, Schultz et al., 2010). A fragility curve is a plot of the probability of failure against load; a generic fragility curve can be seen in Figure 3.3. Uncertainty bounds are defined within the fragility curve to account for some of the uncertainties present in the model such as the accuracy of the loading conditions and other input parameters (HR Wallingford, 2004a). In practice, the loading levels, *l*, are associated with flood Return Periods (RPs) (Gouldby et al., 2008).

The continuous line of defence sections forms a defence system. During a flooding event, a defence can exist in two possible states failed ($d_{i,}$) or not failed ($\overline{d_i}$). The defence system state, *D*, for a given load represents each individual defence state, there exists 2^n possible combinations of failed and not failed defences in *D*. The conditional probability of any particular defence system state, for example a system state containing *k* failed defences and *n-k* not failed defences, for a given load is obtained through the multiplication rule:

$$P_{D|L}(d,l) = P[D = d|L = l] = \prod_{i=1}^{k} p(d_i|l) \prod_{i=k+1}^{n} [1 - p(\overline{d}_i|l)] \tag{3.1}$$

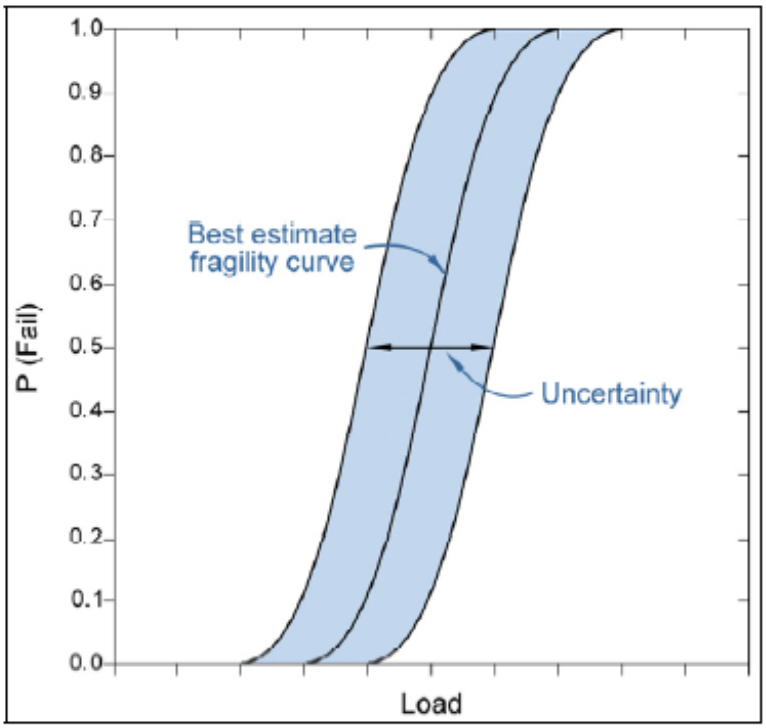


Figure 3.3 A generic fragility curve with uncertainty bounds (HR Wallingford, 2004b)

RASP utilises Monte Carlo simulations to generate a set of *M* different defence system states for a given load. The defence system state dictates the volume of flood water to propagate into the floodplain and in turn the flood depth. The defence system states generated from the Monte Carlo simulations along with the hydraulic loads form the boundary conditions for a hydraulic flood spreading model, which is used to simulate the *M* flood events to obtain the flood depth. A Rapid Flood Spreading Model (RFSM) (Lhomme et al., 2008, Krupka et al., 2007) is a computationally efficient simplified hydraulic model used within RASP for this purpose. RFSM takes the flood volumes which are discharged from breached or overtopped defences and spreads the water over the floodplain to obtain a flood depth grid.

RFSM is able to perform the spreading computation with runtimes several order of magnitudes smaller than more traditional inundation models such as those mentioned in Section 2.2.2. This is achieved by two means: (i) a representation of the topography that allows the use of large computational elements (sub-element topography approach), hence reducing the total number of elements; (ii) a simplified spreading algorithm based on a volume filling technique. The consequence is that there are some limitations to this model. For example, RFSM calculates the final depth over the floodplain rather than the

maximum depth because it does not consider the time evolution when predicting the spreading of water. Additionally the water velocity cannot be calculated. This can be a handicap, as firstly, a flood consequence is often considered to be not only a function of the depth but of the velocity as well, and secondly, the consequences of the flood can often be caused by the peak flow rather than the water ponding at the end of the event. An improved version, RFSM-EDA (RFSM – Explicit Diffusion wave with Acceleration term), has been developed to remove the above limitations but can still achieve a high computational efficiency. RFSM-EDA uses the same topography representation as RFSM but includes a more advanced hydraulic engine. In the future RFSM-EDA could possibly be used within models such as RASP to improve probabilistic flood risk modelling (Jamieson et al., 2012).

RFSM is able to generate estimations of water depth and flood extent using much less computational resources than that required by alternative 2D models (either simplified or full shallow water). Comparisons between RFSM and a full shallow water inundation model, TUFLOW, were undertaken on a few study areas, and RFSM was shown to perform well with appropriate accuracy (Lhomme et al., 2008). Additionally, RFSM tracks the distribution of flood volumes across the floodplain, this allows to identify the defences that contributed flood volumes to any location in the floodplain. With the calculation of damages based on flood depth, it is then possible to attribute these damages back to the flood defences. This is useful within risk analysis modelling to identify the defences likely to generate the most damage and the highest priority for maintenance or improvement. For the purposes of this work and within the risk analysis of the RASP system, RFSM is deemed suitable.

When modelling a flood event, RFSM inputs the water discharged over or through the defences into impact zones adjacent to the defences and then propagates the water to neighbouring impact zones. Impact zones are created by a pre-processing tool which analyses the floodplain topography, the ground elevation inside each impact zone is recorded as a volume-level table. Figure 3.4 illustrates two neighbouring impact zones. The volume of water fills the first impact zone up to the first communication point. The communication point is the point on the boundary with the lowest ground elevation between two neighbouring impact zones. Any excess volume is calculated and spilled into the neighbouring impact zone. This process is repeated and the excess is reduced at

each iteration, until the excess is nil creating a flood depth grid which can be used to calculate damages.

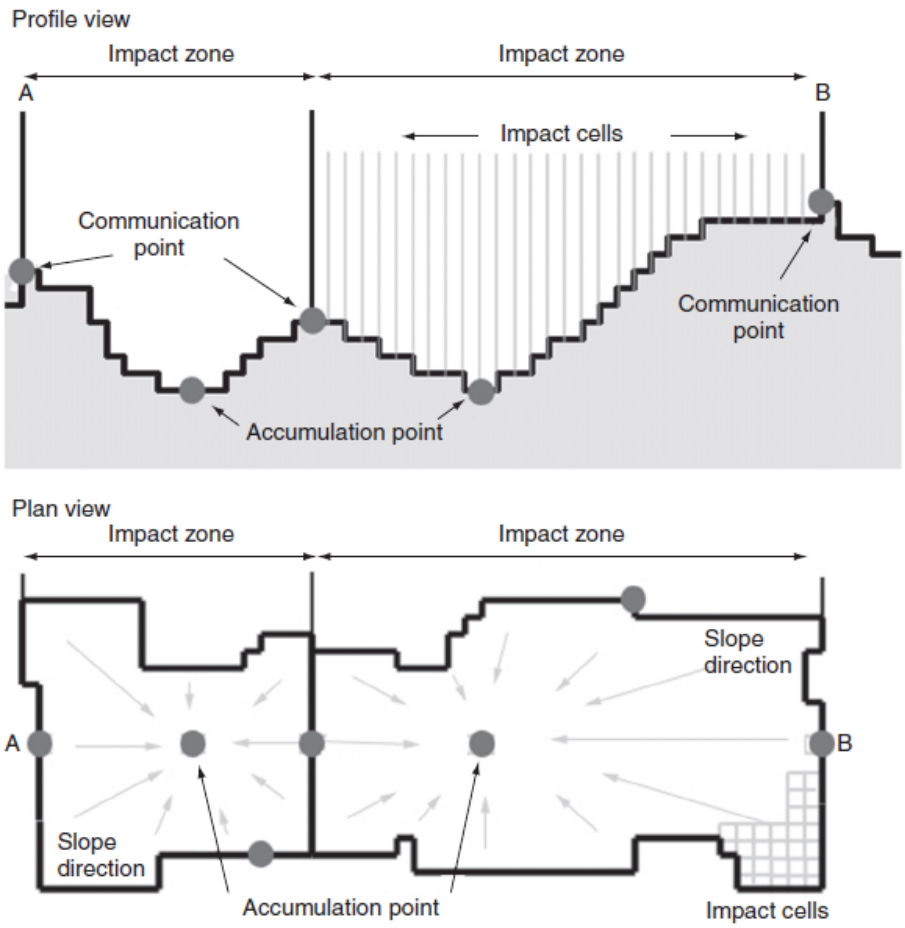


Figure 3.4 Principles and key features of the impact zones in RFSM (Gouldby et al., 2008)

The output of RFSM, the flood depth grid, is passed back into RASP and the conditional event probability of exceeding any particular flood depth y for a given impact zone is calculated as

$$p(Y > y | l) \approx \frac{a_l}{m_l} \tag{3.2}$$

where a_l is the number of system states that result in a flood depth greater than y under a loading event l and m_l is the total number of defence system states evaluated by RFSM for that loading event.

The unconditional annual probability of exceeding y can be obtained by discretising the continuous loading distributions for each defence section into q levels of l, ($l_1, l_2, \ldots, l_q$), giving

$$p(Y > y) \approx \sum_{i=2}^{q-1} \left[\left[p\left(L \geq \frac{l_i + l_{i+1}}{2} \right) - p\left(L \geq \frac{l_i + l_{i-1}}{2} \right) \right] \frac{a_{l_i}}{m_{l_i}} \right] \tag{3.3}$$

RASP is linked to the National Receptor Database (Environment Agency, 2009g) containing information on the number and type of properties in the floodplains. With this information it is possible to estimate the economic consequence owing to property damage. For each sampled defence system state, the flood depth is obtained from the hydraulic model and a resulting flood event economic damage is calculated by using relevant depth-damage curves (Penning-Rowsell et al., 2005b), see Figure 3.5.

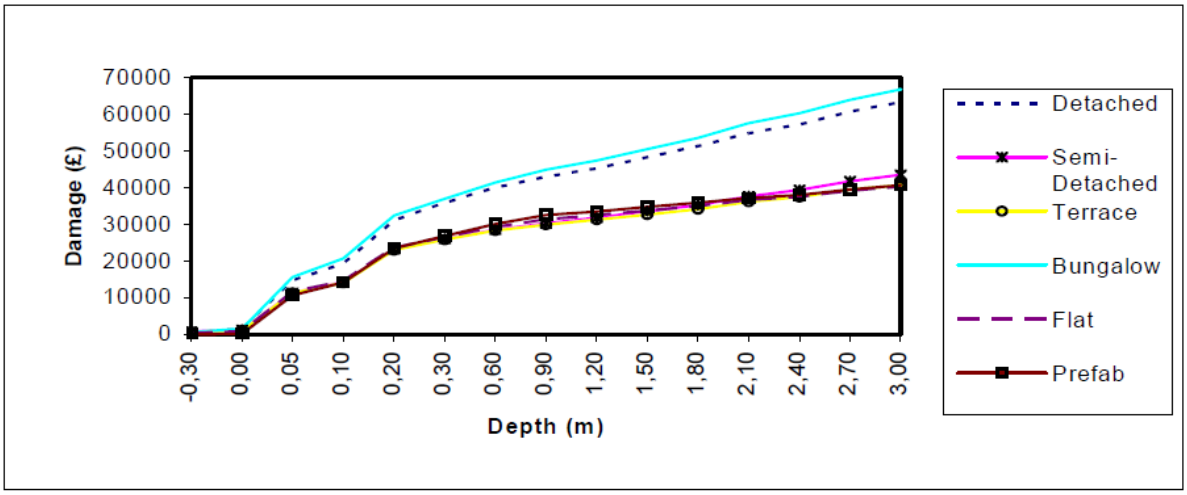


Figure 3.5 Depth damage functions for different residential house types (Penning-Rowsell et al., 2003)

The mean economic consequence, c, conditional on the loading event for a specific impact cell is given by

$$\bar{c}_l \approx \frac{1}{m_l} \sum_{j=1}^{m_l} c_j \tag{3.4}$$

The impact cell risk, R, expressed as Expected Annual Damage (EAD), can be calculated using the same load discretisation procedure from equation (3.3) giving

$$R \approx \sum_{i=2}^{q-1}\left[\left[p\left(L \geq \frac{l_i + l_{i+1}}{2}\right) - p\left(L \geq \frac{l_i + l_{i-1}}{2}\right)\right]\overline{c}_{l_i}\right] \tag{3.5}$$

The total risk for the floodplain area is the sum of the associated risk to each impact cell.

Figure 3.9 displays a simplified flow chart of the main stages of RASP described above.

3.3 RASP Modifications

In this thesis there is a requirement to run many realisations of RASP. RASP is used to evaluate the risk associated to potential flood risk intervention strategies (see Chapter 4) where a strategy consists of various intervention measures to be applied to a flood area at different time steps into the future. For the case study in Chapter 7, the current computational time for one RASP run takes approximately 44 seconds. The evaluation of an intervention strategy requires RASP to be run at each time step with additional runs required if there is consideration of different climate change scenarios. For example in Section 7.3, to evaluate a long term intervention strategy which consists of three 30 year time steps, evaluated over 3 different climate change scenarios will require 9 runs of the RASP model. Without any modifications to RASP, this would take 6 minutes and 36 seconds to run. As can be seen, the computational burden to consider and compare multiple intervention strategies becomes very large very quickly. The following two sections discuss two different modifications to the RASP methodology to reduce the computational time. Firstly simplifying the process to calculate the defence system states by replacing Monte Carlo sampling with expected values of volume is discussed in Section 3.3.1 and Section 3.3.2 analyses the number of RPs used within RASP and assesses whether this number can be reduced without compromising the final outcome.

3.3.1 Simplified RASP

The current computational efficiency of RASP is mainly influenced by the calculation of the defence system state. As explained in Section 3.2, Monte Carlo sampling is used to simulate many different combinations of failed and not failed defences. For each defence system, its state is obtained by generating n random numbers from a uniform distribution ranging between 0 and 1 and assigning them to the corresponding defence section. Using the fragility curves, if the random number for a particular defence section is greater than the probability of failure given the load, then that defence in the defence

system will denote fail, otherwise it will denote a non-failure. A hydraulic model is then employed to calculate the flood depth associated to each of these defence system states.

This process to simulate flooding associated with many thousands of defence system states is time consuming. Rather than sampling all of these defence system states it is possible to substitute the Monte-Carlo simulation, and associated flood volume calculations with a simpler estimate of the expected volume. This simplified method would use expected values of flood volume to produce a conceptual "mean" system state. Each defence conditional on the load has an associated volume if breached, $\bar{v}$, and a volume if overtopped, v. Multiplying these values by the probabilities of the defence breaching, $\bar{d}$, and overtopping, d, ascertained from the fragility curves, an expected volume $E(\bar{v}_l)$ conditional on load can be obtained:

$$E(\bar{v}_l) = \sum_{j=1}^{n} p(d_j)v_j + p(\bar{d}_j)\bar{v}_j \tag{3.6}$$

This one "mean" system state for the specific load is run with the hydraulic flood spreading model to obtain the economic damage, such that:

$$\bar{c}_l = f(E(\bar{v}_l)) \tag{3.7}$$

Where f *is* a function of the expected volume at each defence and $\bar{c}$ is the mean economic damage for a given load l. The resulting economic damage from equation (3.7) is then substituted into equation (3.5) and used to estimate the risk:

$$R = \sum_{i=2}^{q-1}\left[\left[p\left(L \geq \frac{l_i + l_{i+1}}{2}\right) - p\left(L \geq \frac{l_i + l_{i-1}}{2}\right)\right] f(E(\bar{v}_l))\right] \tag{3.8}$$

This approximation enables a significant improvement to the computational efficiency of the risk model. Rather than running a large number of flood simulations (approximately 2000) for every loading level, only one simulation is required. The approximation influences the accuracy of the performance metric calculation. This is, however, not an issue for the purposes of optimisation, if the change in accuracy is relative across solutions and the risk model maintains the relative order of better performing intervention strategies.

In order to be able to verify the use of RASP with the modification suggested, a comparison of both versions is required. The first version calculates defence system states using Monte Carlo sampling and is referred to as full RASP, the second version replaces Monte Carlo sampling with expected values of volume and is referred to as simplified RASP. In this thesis, RASP will be used to evaluate potential intervention strategies and assess the associated risk. The overall aim is to find the best performing strategy, in this case the strategy with the lowest risk. For comparison purposes, it would be appropriate to evaluate a set of intervention strategies using both the simplified RASP and the full RASP and compare the output. From the output, it would be expected that the simplified RASP produces similar EAD results to the full RASP but more importantly the order of strategies according to performance is maintained. In other words, the change in EAD is relative. Coupling the simplified RASP with evolutionary optimisation techniques should still produce the same results under the full version of RASP.

The comparison uses the model of the section of the Thames Estuary described in Chapter 7. With this model an initial set of 500 flood risk intervention measures were randomly generated (i.e. changes to the configuration of the defence system, raising the crest level, for example) were made. The risk associated with each of the intervention measures was then evaluated using both the full and simplified risk models. Figure 3.6 displays a graph of the full and simplified results plotted against each other for the 500 flood risk intervention measures. As can be seen there is very little difference in EAD between the two models.

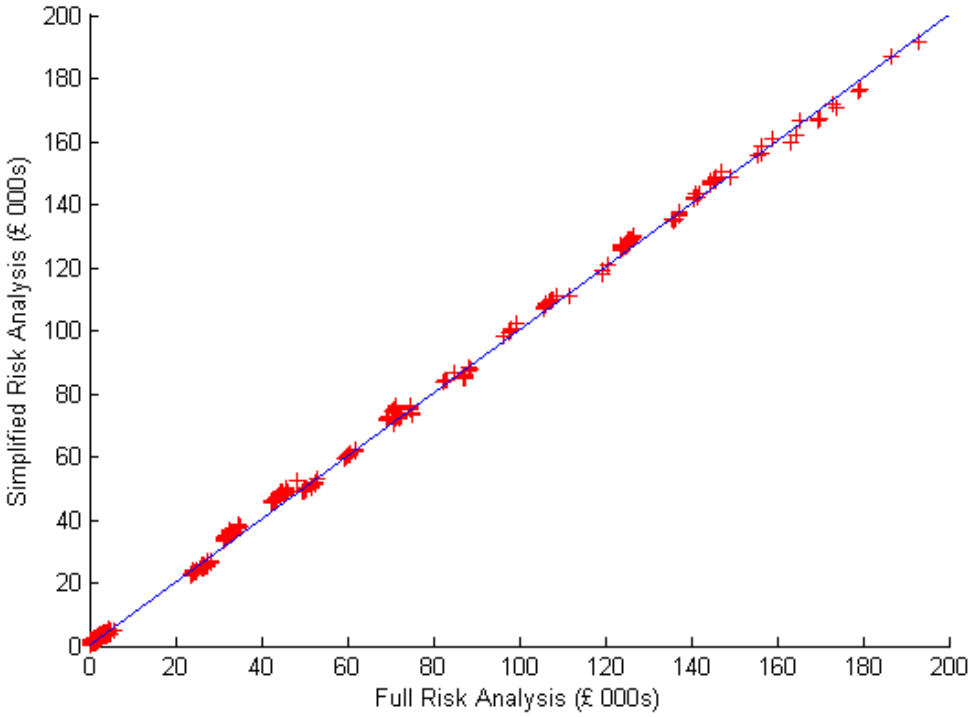


Figure 3.6 The full and simplified risk analysis results for a set of 500 intervention measures

A sample of the results obtained are also shown in Table 3.1 where a comparison is undertaken to assess how the use of optimisation will be impacted by a change in risk model. The bottom triangle in blue displays the EAD for the first 15 intervention measures analysed using the full risk analysis model. A cross evaluation matrix of each intervention measure is shown to compare all possible combinations of interventions, identifying the better performing measures (i.e. the measures with lower EAD values). For each individual rank comparison, the better performing intervention measure is written in the matrix. The cross evaluation matrix for the full risk analysis shows that intervention measure 9 performs the best with no other intervention obtaining a lower EAD. Likewise, intervention 4 has the worst performance, it was not able to outperform any other intervention measure.

The same intervention measures were also evaluated using the simplified risk model and again compared in a cross evaluation matrix. The results obtained for the first 15 under the simplified risk model are shown in the top triangle in yellow in Table 3.1. If the simplified risk model is a suitable replacement to the full version then the order of better performing interventions should be approximately equal. As in the comparison of

the full risk model, the simplified risk model identified intervention measure 9 to have the highest performance and intervention measure 4 to have the lowest.

Table 3.1 Rank comparison between the full and simplified risk analysis model when evaluating a set of intervention strategies, table entries are the winning strategy (i.e. less EAD)

EAD (£)		36,400	148,300	142,600	148,900	60,700	70,700	26,000	3,900	2,000	73,100	128,800	2,200	46,900	71,100	60,800	Simplified risk analysis	
Strategy		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15		
33,700	1	1	1	1	1	1	1	7	8	9	1	1	12	1	1	1	1	36,400
145,800	2	1	2	3	2	5	6	7	8	9	10	11	12	13	14	15	2	148,300
141,300	3	1	3	3	3	5	6	7	8	9	10	11	12	13	14	15	3	142,600
149,000	4	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	4	148,900
60,400	5	1	5	5	5	5	5	7	8	9	5	5	12	13	5	5	5	60,700
70,700	6	1	6	6	6	5	6	7	8	9	6	6	12	13	6	15	6	70,700
26,500	7	7	7	7	7	7	7	7	8	9	7	7	12	7	7	7	7	26,000
4,700	8	8	8	8	8	8	8	8	8	9	8	8	12	8	8	8	8	3,900
1,200	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	2,000
72,200	10	1	10	10	10	5	6	7	8	9	10	10	12	13	14	15	10	73,100
125,900	11	1	11	11	11	5	6	7	8	9	10	11	12	13	14	15	11	128,800
1,900	12	12	12	12	12	12	12	12	12	9	12	12	12	12	12	12	12	2,200
43,300	13	1	13	13	13	13	13	7	8	9	13	13	12	13	13	13	13	46,900
70,800	14	1	14	14	14	5	14	7	8	9	14	14	12	13	14	15	14	71,100
60,100	15	1	15	15	15	15	15	7	8	9	15	15	12	13	15	15	15	60,800
Full risk analysis		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Strategy	
		33,700	145,800	141,300	149,000	60,400	70,700	26,500	4,700	1,200	72,200	125,900	1,900	43,300	70,800	60,100	EAD (£)	

From Table 3.1 it is evident that a similar identification of better performing systems is found in both triangles and thus across both versions of the risk analysis model, with only two cases which did not correspond. From the full results of all 500 intervention measures, 97.82% of the interventions follow the same recognition of performance for both versions of RASP thus suggesting the simplified version can replace the full version in this instance for the optimisation process. This is further verified by Figure 3.6 where the results produced by both models are very similar. This test was repeated for 5 different sets of 500 randomly generated intervention measures to verify the results (see Table 3.2).

Each test verifies that for the case study in Chapter 7 the simplified risk analysis model is a reasonable approximation for the full version and can be used for the purposes of optimisation without compromising results for the case study below. Across all 5 tests the average percentage of systems following the same performance is 97.97%. Furthermore, a computational reduction in speed of approximately 22 seconds for an individual run is achieved using this modification. This is approximately half the original time taken. It is therefore envisaged that this modification to RASP will be able

to improve the overall run time of the methodologies presented in the following Chapters of this thesis by approximately half.

Table 3.2 Percentage of interventions which achieve the same rank ordering when evaluated against the full and simplified risk analysis tool

Test Number	**Number of interventions following same pattern for full RASP and simplified RASP (%)**
Test 1	97.82
Test 2	98.26
Test 3	97.77
Test 4	97.88
Test 5	98.13
Average	97.97

3.3.2 Reducing the Number of Flood Events

Another significant element contributing to the computational efficiency of RASP is the number of loading conditions or RPs used in the model to simulate flood events. The number of loading scenarios is limited; inclusion of all possible scenarios is prohibitively expensive in terms of computational time. As the performance of a defence structure is partly controlled by the magnitude of the load acting on the structure and the structures response to the load, the failure rate will be determined given different loading conditions. It is therefore important to consider numerous different loads. The resolution at which the probability space associated with the hydraulic loading conditions is discretised (ie the number of RPs) affects the model run time, and can significantly influence the results, (Ward et al., 2011). To further reduce the runtime for the purposes of optimisation analysis, the number of loading levels was also reviewed. Reducing the number of RPs will affect the probability of defence failure and consequently impact the EAD. If the number of RPs, however, can be minimised without significantly influencing the EAD output, the computational time can be greatly improved. This section investigates the optimal number of RPs in terms of computational time whilst reducing the impact on the output.

For the case study in Chapter 7, 40 RPs on average are used within the model, typically ranging from a 1 year to a 10,000 year event. The simplified version of RASP was run with a range of different RPs and compared against the associated flood damage to a floodplain when evaluating an intervention strategy to see if a reduction in the number

of RPs is acceptable. The number of different loads used with their associated RPs can be seen in Table 3.3.

Table 3.3 Flood events belonging to each set of return periods

40RPs	30RPs	20RPs	10RPs	9RPs	8RPs	7RPs	6RPs
1	1	1	1	1	1	1	1
2	5	5	100	100	100	100	100
5	10	10	300	300	300	300	300
10	30	50	500	600	600	1000	1000
20	50	90	600	1000	1000	3000	3000
30	70	130	1000	1500	3000	6000	10000
40	90	170	1500	3000	6000	10000	
50	110	200	3000	6000	10000		
60	130	300	6000	10000			
70	150	400	10000				
80	170	500					
90	190	600					
100	200	800					
110	250	1000					
120	300	1500					
130	350	3000					
140	400	4500					
150	450	6000					
160	500	8000					
170	600	10000					
180	700						
190	800						
200	900						
250	1000						
300	1500						
350	3000						
400	4500						
450	6000						
500	8000						
600	10000						
700							
800							
900							
1000							
1500							
3000							
4500							
6000							
8000							
10000							

For this specific case study, plotting the sets with 40, 30 and 20 RPs against the flood damage obtained shows very little, if no difference at all (see Figure 3.6). The difference in these sets of RPs is a reduction in the number of smaller flood events which do not have a large impact on the flood damage. Replacing the set of 40RPs with 20RPs will therefore have a very minimal impact on the flood damage as can be seen from the difference in EAD in Table 3.4. In addition an improvement of 4 seconds in computational time can be seen. This will improve the computational time when running many realisations of RASP. The use of 20RPs over 40 is therefore more advantageous as the computational speed has improved without significantly impacting the resulting EAD. To see if the number of RPs can be reduced further, smaller sets of RPs are investigated and are compared against the set of 20RPs.

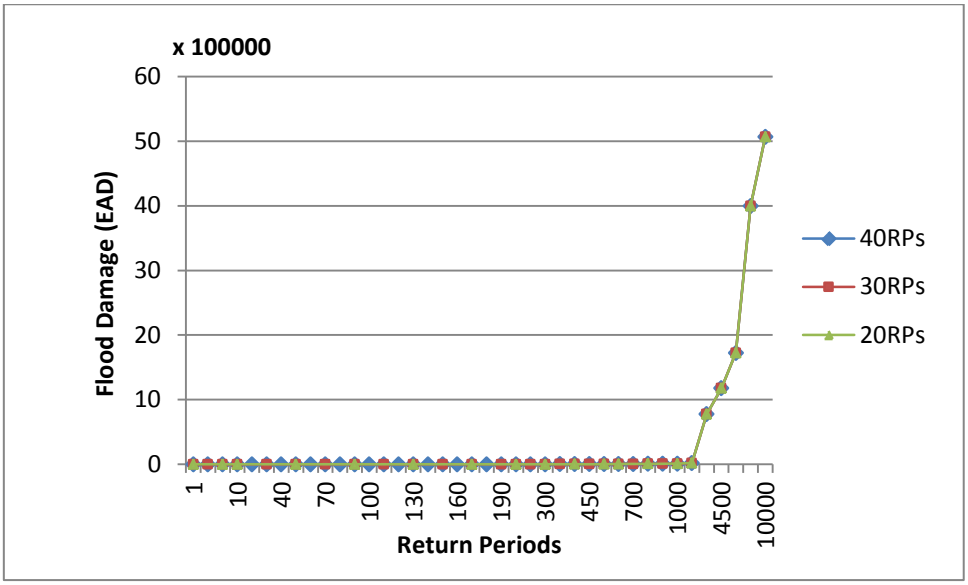


Figure 3.7 Flood damage against RP for the sets of 40, 30 and 20 RPs

Removing additional RPs from the set of 20 will require larger flood events to be eliminated. Sets of 6 to 10 RPs are investigated and the flood events considered within these sets can again be seen in Table 3.3. As the number of larger RP's is reduced a difference in flood damage is more noticeable and a larger difference in EAD is seen. Figure 3.7 compares the 20, 10 and 9 RP sets.

Looking at Figure 3.7 the flood damage obtained from the sets of 9 and 10 RPs follow the same outline when comparing the flood damage. There is however a slight difference between the 9 and 10 RP sets compared to the 20 RPs. This is further verified by the results in Table 3.4 whereby there has been a modest change in EAD between the

20RP set and the 9 and 10 RP set. It can now be seen that as the number of flood events is reduced, the output in risk begins to decrease in accuracy too. At this level there is still only a minimal change in the output and with a further reduction in computational time the reduction in the number of flood events is still advantageous.

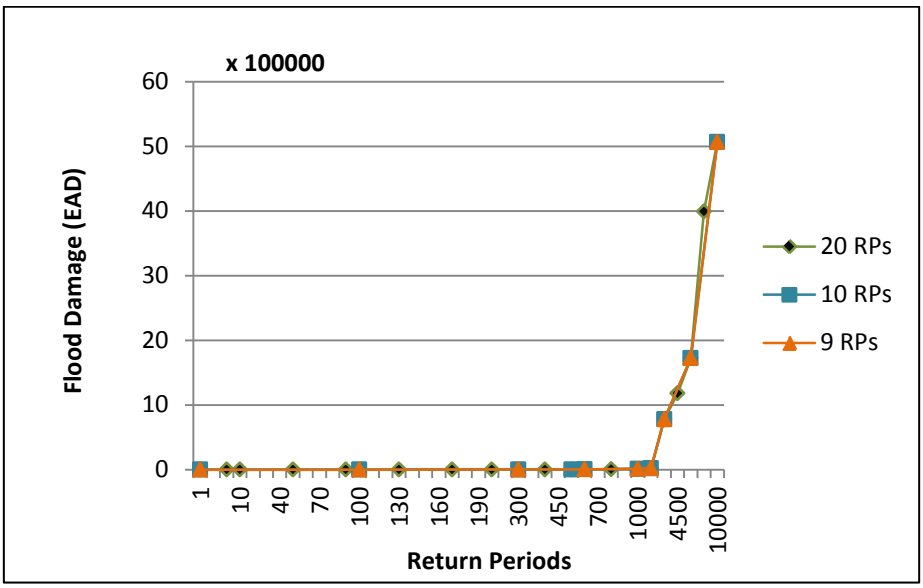


Figure 3.8 Flood damage against RP for the sets of 20, 10 and 9 RPs

Figure 3.8 compares the sets of 6, 7, 8 and 9 RPs. The sets of 7 and 8 RPs follow the same outline when plotting the associated flood damage. Compared to the set of 9 RPs, there is again a slight difference in flood damage. This difference however is most significant when compared against the set of 6 RPs. Furthermore the difference in EAD between the sets of 7 to 9 RPs is minimal but a considerable difference is obtained with 6 RPs. With the significant change in EAD between 6 and 7 RPs and no improvement in computational time the use of the set of 6 RPs is unfavourable. There is a minimal difference in EAD between 7 and 8 RPs and with a computational improvement of a second; the use of 7 RPs would be beneficial. This extra second in computational time will have a large impact on the overall run time of many RASP realisations. Comparing the set of 7 RPs to the original set of 40 RPs, the step change in EAD between these is smaller than the difference between the sets of 6 and 7. Furthermore, the computational efficiency for this specific case study has advanced by 6 seconds per RASP run, achieving a much needed improvement in the computational time of many RASP runs.

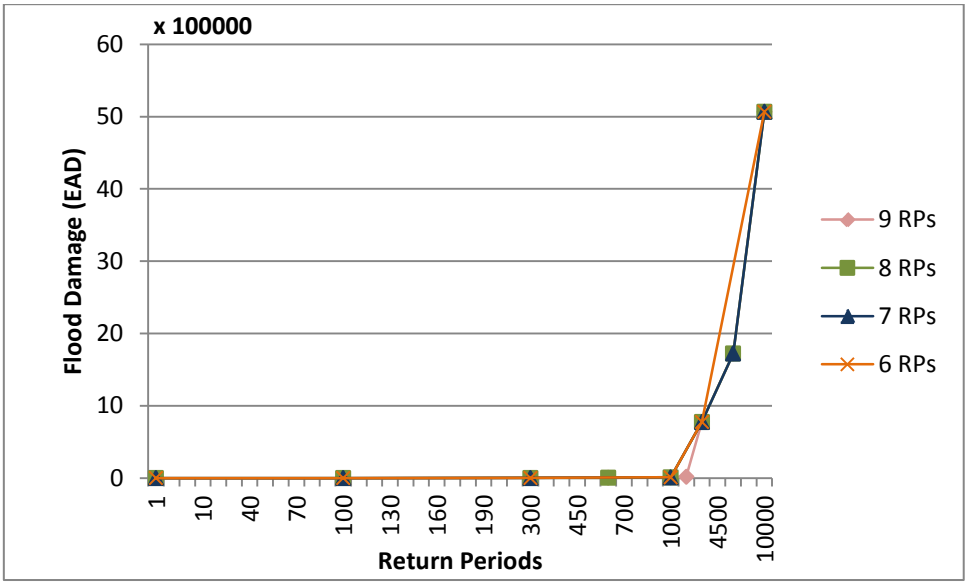


Figure 3.9 Flood damage against RP for the sets of 9, 8, 7 and 6 RPs

Table 3.4 Comparison of EAD and length of time taken to run RASP with differing numbers of return periods.

Number of RPs	RASP output EAD (£'s)	Time taken (sec)
40	1,959	22
30	1,960	20
20	1,965	18
10	2,602	17
9	2,605	17
8	3,008	17
7	3,023	16
6	4,273	16

As stated at the beginning of this section, it is important to consider numerous different loading conditions to better assess the performance of the defences and the overall risk to a floodplain. The more flood events considered however, the longer it takes to evaluate the risk. With the aim to reduce the computational time of RASP, minimising the number of loading conditions is a feasible way to do this. In this section, different numbers of loading conditions have been investigated on the case study in Chapter 7 to improve the computational time as much as possible before a significant change in the output is realised. It was found that the use of 7 different loading conditions provides a

reasonable output from the model but most importantly delivers an improvement in speed of 6 seconds.

Figure 3.9 displays a simplified flow chart of RASP highlighting the modifications suggested in sections 3.3.1 and 3.3.2.

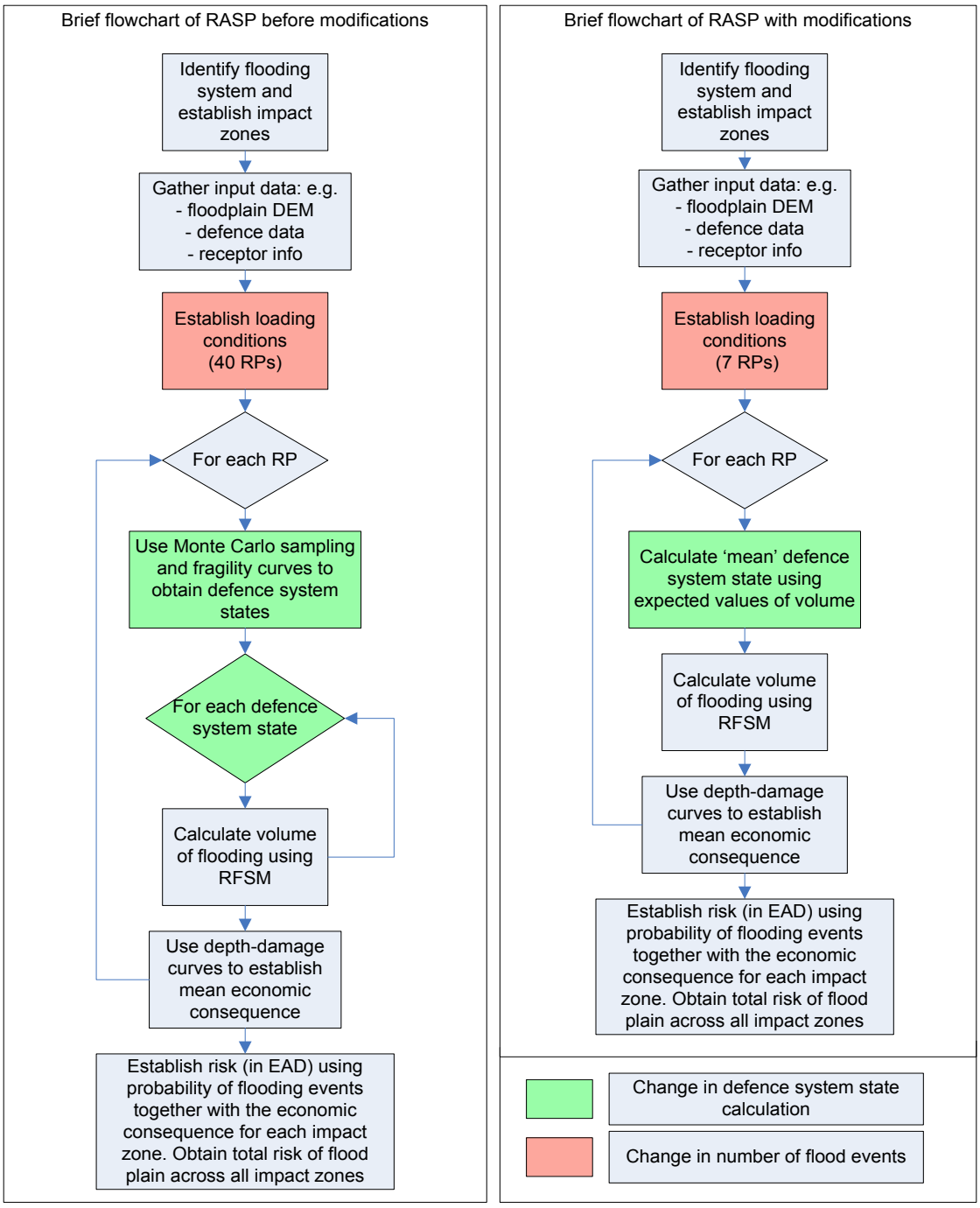


Figure 3.10 A simplified flowchart of the RASP methodology compared against the proposed changes

3.4 Summary

This chapter focuses on the risk analysis tool, RASP. After the introduction, Section 3.2 begins with an explanation of the methodologies behind RASP and describes the main processes. In summary RASP evaluates the risk associated to a floodplain area considering a range of flooding events and the probability of failure for the defences protecting the area of interest. The following Chapters in this thesis explore the development of potential flood risk intervention strategies and RASP plays a key role evaluating the associated risks. It is therefore important to understand the concepts behind RASP as it will form the basis for the remainder of the work presented.

There will be a requirement for many simulations of RASP. The evaluation of a single strategy may require multiple runs of RASP to represent future points in time and various climate change scenarios. To then compare multiple intervention strategies, the number of RASP runs increases rapidly. Looking at the case study in Chapter 7, a single realisation takes 44 seconds (computational resources used in this work are described in Section 6.6) which is infeasible to evaluate and compare thousands of strategies. Therefore Section 3.3 addresses two methods which can reduce the computational time. Firstly, Section 3.3.1, investigates an approach to replace the computationally expensive Monte Carlo sampling of defence system states with a much quicker expected volumes approach. This change, although produced a slight difference in the EAD output, kept the change in EAD relative between intervention strategies. For the purpose of comparing intervention strategies, the better performing strategies will always be selected regardless of the approach used and can therefore validate the change in the defence system state calculation. The improvement of 22 seconds is very beneficial for the intentions of this thesis. When the better performing strategies have been identified, a more accurate EAD can be obtained for these strategies using the Monte Carlo approach if necessary. For the remainder of this thesis, unless stated otherwise, the expected volumes approach will be used within RASP instead of Monte Carlo sampling.

Although, for this particular case, the reduction in time from 44 to 22 seconds was a significant step, an additional reduction in time would be advantageous given the expectation to run many realisations of RASP. Section 3.3.2 investigated a second method to further improve the computational efficiency. Specifically, a sensitivity analysis on the number of flood events considered in RASP was undertaken for the case study in Chapter 7. The performance of a defence is partially determined by the load

acting on it. To better assess the performance of the defences and the overall risk to a floodplain, it is preferable to consider numerous flood events. The more flood events considered however, the longer it takes to evaluate the risk. With the aim to reduce the computational time of RASP, minimising the number of loading conditions was investigated. A differing number of loading conditions were considered, assessing the impact these had on the RASP outputs and the time taken to run. It was found that the use of 7 different loading conditions provides a reasonable output from the model but most importantly delivers an improvement in speed of 6 seconds for the case study in Chapter 7.

Applying both of the suggested changes from Sections 3.3.1 and 3.3.2, the time taken is reduced from 44 seconds to 16. This improvement has a significant impact on the computational time and enables RASP to be at the centre of the methodologies presented in the following chapters. The next Chapter provides a methodology to evaluate potential flood risk intervention strategies and addresses the inclusion of flexibility and adaptability within a flood risk strategy.

Chapter 4 Flood Risk Intervention Strategies

4.1 Introduction

Chapter 3 described the methodology behind a state of the art flood risk analysis tool, RASP, which provides the fundamental basis for the methodologies presented in Chapters 4, 5 and 6. In Chapters 4, 5 and 6 the issues discussed in the literature review (Chapter 2) are addressed. One of the primary objectives in this thesis stemming from the conclusions of the literature review is how to answer three prominent questions in flood risk management, namely

- What types of intervention measures would be most beneficial?
- Where will these intervention measures be most appropriate?
- When should these measures be implemented?

To answer these questions an evaluation process is required to allow a quantitative assessment of the differing intervention strategies, enabling the ineffective interventions to be screened out whilst identifying the better performing strategies. This Chapter, therefore, presents a methodology to evaluate different intervention strategies. The evaluation process needs to take in to account the most critical performance criterion, the expected economical benefits (i.e. reduction in flood risk damage) and the expected costs. Another important aspect of the evaluation process is to account for future climate change uncertainty identifying robust strategies and allowing adaptation to climate change. This requires the development of the strategies themselves to inherently capture a level of flexibility as well as the evaluation process to recognise it. This aspect again stems from the conclusions of the literature review and the need to consistently reduce flood risk given the uncertainties of climate change and enable strategies to adapt when more information about the future is known.

Given this, the next section, Section 4.2 specifically explores the evaluation of different intervention strategies providing a technical analysis to estimate the associated benefits and costs. Section 4.3 then addresses how climate change uncertainty can be accounted for and explores the development of robust strategies and its importance. Section 4.4 extends the methodology further incorporating Real Options into flood risk

management. The Chapter concludes with a summary of the methodology presented in Section 4.5.

4.2 Evaluating Intervention Strategies

A key component of decision making in flood risk management is recognising and quantifying the impact different strategies will have on a flood area and how these strategies perform according to a set of criteria. Identifying this information is necessary for decision makers to determine the most appropriate strategy. Two criteria in particular are regularly considered for the evaluation of intervention strategies, these being the economic benefits and costs of implementing a strategy. This section therefore presents a methodology to evaluate intervention strategies according to these criteria. This is an important stage for the thesis as the following Chapters will build upon the evaluation process adding additional functionality to improve the decision making process.

4.2.1 Intervention Strategies

Intervention strategies form an important aspect of flood risk management, enabling the management of whole flooding systems. Throughout this thesis, a flood risk intervention strategy is considered to be a plan of mitigation activities consisting of different combinations of intervention measures occurring at different points in time. There is a large portfolio of different intervention measures available including structural and non-structural activities. Structural measures, X_s, include raising the crest level of defences and increasing the capacity of the defence for future expansion. Non-structural measures, X_f, include flood proofing properties on the floodplain and issuing flood warnings. Defence maintenance, X_m, is also another option available for inclusion in intervention strategies.

4.2.2 Risk Reduction

In this thesis, the damage in terms of risk reduction of an intervention strategy is obtained using the risk analysis tool, RASP (Gouldby et al., 2008). As explained in Chapter 3, RASP calculates the present day risk associated to a flood area taking into account the protection afforded by defences. It is possible to calculate the risk associated to an intervention strategy by modifying the data within the model to express each of the intervention measures. For example intervention measures can be applied in the model by modifying the fragility curves, defence characteristics or depth damage curves (see Table 4.1). Calculation of the flood risk associated with an intervention at a

future point in time can be achieved by expressing the future state in the model. For example a future climate change state can be represented by modifying the extreme value distributions of hydraulic loads. Specific climate variables which are expected to change over time can be individually represented. Taking sea level rise for example, the associated water level for each flood event can be modified to represent this increase. Socio-economic development also evolves over time and the change in the state can be represented in the model by modifying the depth damage curves. Calculating the flood risk also takes into account the condition of the flood defences, over time these deteriorate and this must be recognised in the model. The deterioration of defences can be accounted for by modifying the condition grade of the defence.

Table 4.1 Intervention options and how they are reflected in RASP

Intervention Measures	Represented in RASP
Raise crest level	Crest level height – defence characteristics
Increase capacity of defence for expansion through base widening	Defence class – defence characteristics
Maintenance	Condition grade – fragility curves
Set back properties	Floodplain features
Flood proof properties	Depth damage curves
Flood warning	Depth damage curves

With the risks obtained for the different intervention measures it is possible to calculate the associated benefit. Let the risk, R, of a given intervention strategy be a function of the intervention measures, the extreme flood events, l, and the performance of the defence infrastructure X_p such that $R = f(X_s, X_m, X_f, l, X_p)$. The standard approach to assess the benefit is determined as the difference in risk between the 'do nothing' option and the intervention measure. The 'do nothing' option reflects the decision to not make any investments at any point in time. These are summed up over the planning horizon to obtain the overall benefit in EAD of an intervention strategy and then discounted back to the present day, as follows:

$$Benefit = \sum_{t=1}^{T} \frac{f(X_s, X_m, X_f, l, X_p)_t - f(l, X_p)_t}{(1+r)^t} \tag{4.1}$$

where r is the discount rate, T is the total number of years in the planning horizon and t is the yearly index.

4.2.3 Costs

The costs associated to each intervention strategy are calculated using the costing methodology developed under FRMRC2 WP4.5 (Hames, 2010), with the basis of the cost model drawing extensively from the Cost Estimation Model given by Phillips (2008). The methodology adopted identifies costs for each of the different defence classes categorised in RASP as formulated for the National Flood Risk Assessment (HR Wallingford, 2002a). Similar to RASP, the costing model is based on a systems approach, the SPRC model, such that the cost model is given as:

$$C_D = C_S + C_P + C_R \tag{4.2}$$

where C_D is the total cost at a given time step, C_S , C_P and C_R are the costs associated to the source, pathway and receptor respectively. Figure 4.1 shows the main stages involved in the cost calculation.

The costs associated with the pathway take into account the mobilisation, M, and operating, O_D, costs, the quantity of work required, Q_j, and the costs of materials, R_j, such that:

$$C_P = M + O_D + \sum_{j=1}^{m} Q_j R_j \tag{4.3}$$

where m is the number of maintenance and construction items.

The quantity of work required is expressed using the characteristics of the defence such that:

$$Q_j = V_D L \; f(D_x, O, C) \tag{4.4}$$

where V_D is the defence dimensions, L is the length of defence that requires attention, D_x is the severity of the defects which is a function of the condition grade of the defence, O is the intervention measure being applied and C is the RASP defence class. Figure 4.2 displays the main stages in the calculation of the work required for a given defence type.

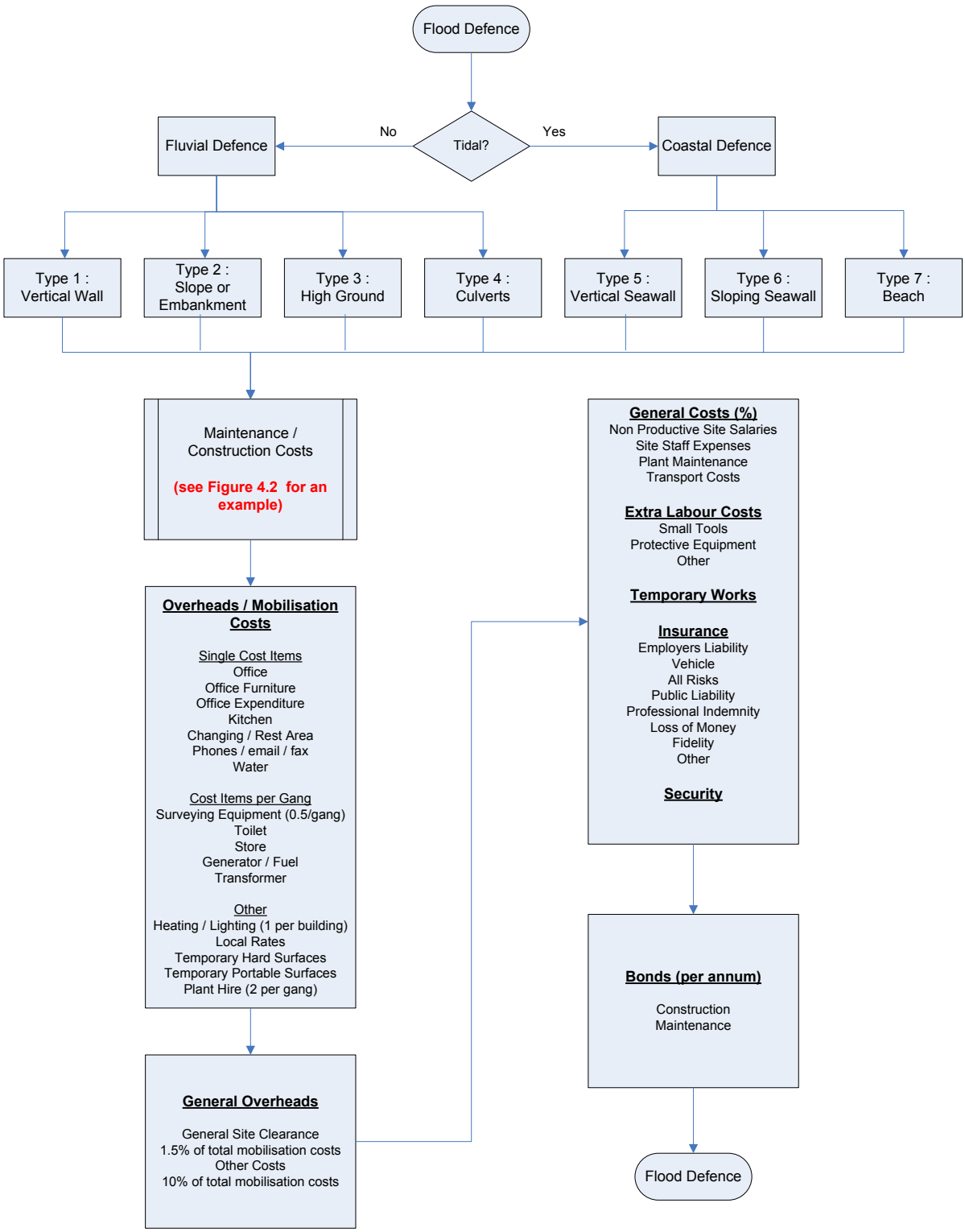


Figure 4.1 Component of the automated costing methodology

The total overhead and mobilisation costs are based on a combination of prices published by Langdon (2010) and expressed as:

$$M + O_D = \sum_{j=1}^{m} z_j (TU_j + M_j) + A \tag{4.5}$$

where z_j is the unit number of each mobilisation activity, T is the number of weeks on site, U_j is the unit cost of overheads for mobilisation activity, M_j is the mobilisation and demobilisation for each activity, A is the site access costs and m is again the number of maintenance and construction items.

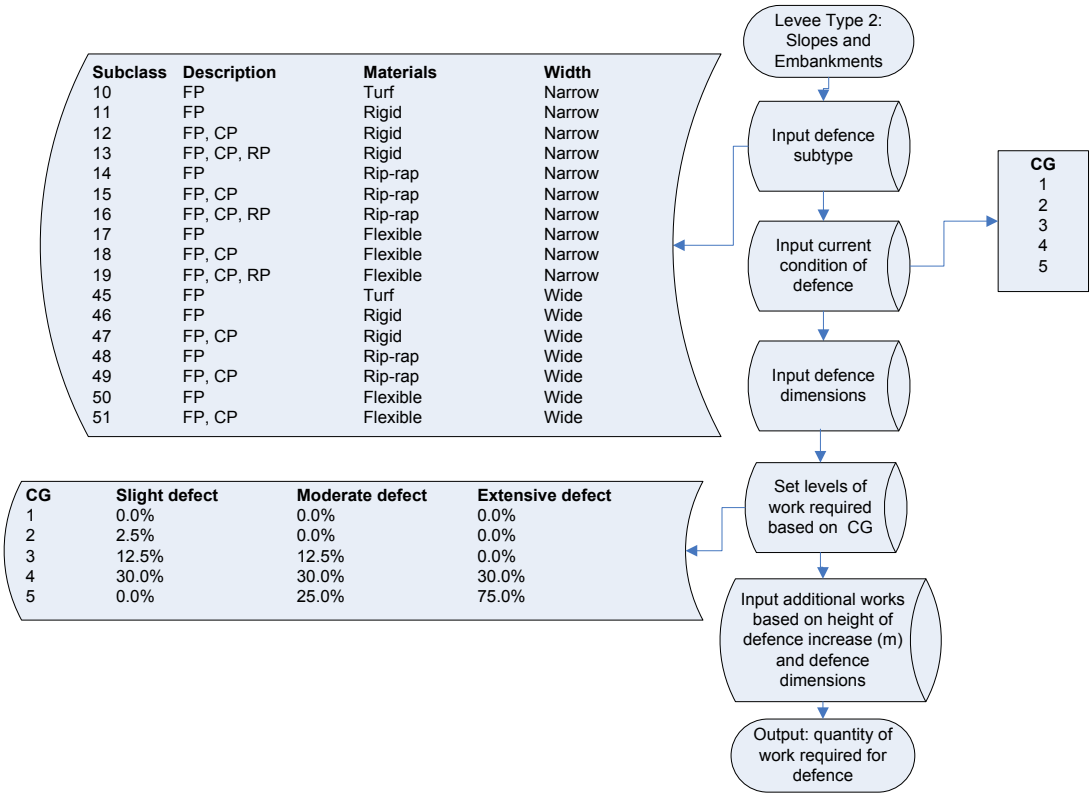


Figure 4.2 Flowchart to calculate the quantity of work required in the cost model for a type 2 defence as defined in the risk analysis model

Non-structural responses seek to minimise the impact of flooding on receptors in the floodplain. Activities such as flood proofing properties and issuing flood warnings represent the costs of C_R. Maintenance costs within the model support four levels of maintenance including do nothing, low, medium and high each of which correspond to a rate of deterioration. The deterioration rates used with in this model are obtained from (Environment Agency, 2009d) where by deterioration curves were derived for each RASP defence type and show the expected time in years that defences will deteriorate to different condition grades. The deterioration rates in these curves are based on the experiences of a range of practitioners, asset managers and consulting engineers, with

regard to deterioration of flood defence assets in both coastal and fluvial environments. Deterioration curves were produced to give a best-estimate deterioration with upper and lower bands to account for the uncertainty. In this thesis, the uncertainty bands are used to represent different levels of maintenance to demonstrate the potential of putting in more or less effort to see a reduction or increase in deterioration and thus the associated benefits and costs of employing different maintenance regimes. The costs of maintenance for each of the RASP classes are based on (Environment Agency, 2009c) and are scaled up and down to represent the uncertainty bands and in this case the high or low maintenance. A 'do nothing' rate is also provided showing the fastest deterioration, this rate has no associated cost. Table 4.2 provides examples of the best estimate deterioration rates and the time taken to deteriorate between condition grades for different defence types.

Table 4.2 The deterioration rates showing the time taken in years for different defence types to deteriorate through the condition grades (Environment Agency, 2009d)

Defence Type	Condition grade				
	1	**2**	**3**	**4**	**5**
Sheet pile fluvial vertical wall	0	20	80	120	140
Sheet pile coastal vertical wall	0	8	30	53	60
Gabions fluvial vertical wall	0	5	10	22	28
Rip-rap fluvial embankment	0	15	30	130	150
Rigid fluvial embankment	0	15	30	100	120

Condition grades represent the deterioration within the risk analysis model explained in Chapter 3 and influence the risk attributed to different defences. There are 5 condition grades, with 1 representing a defence in very good condition and 5 being very poor condition, the higher the condition grade the higher the risk will be. Overtime the defences will deteriorate, modelled in the risk analysis tool by the increasing condition grades, until the defence is no longer providing sufficient protection. The implementation of structural interventions will improve the defences performance and will result in a change in condition grade back to 1 or 2. This will reset the condition grade within the defence characteristics database within the risk model and the defences will then begin deteriorating at the rate of the newly set condition grade (see Table 4.2).

The cost, C_D, is calculated at each time step and is a function of the intervention measures such that $C_D = g(X_s, X_m, X_f)$. These are summed up across the planning horizon and discounted back to the present day, as follows:

$$Cost = \sum_{t=1}^{T} \frac{g(X_s, X_m, X_f)_t}{(1+r)^t} \tag{4.6}$$

to give a total cost, *Cost,* for the full intervention strategy, where r is the discount rate, T is the total number of years in the planning horizon and t is the index of years. Table 4.3 provides cost outputs when using the methodology to obtain costs for different defence types and characteristics.

Table 4.3 Example of the outputs obtained from the cost model for given defence characteristics and intervention options

Defence Type	Defence length	Defence height	Condition grade	Intervention option	Cost (£)
Sheet pile fluvial vertical wall	150m	1m	1	Raise crest level by 1m	137,700
Sheet pile coastal vertical wall	100m	2m	5	Refurbish	186,200
Brick and Masonry fluvial vertical wall	125m	2.4m	1	Raise crest level by 2.4m	273,900
Rip-rap fluvial embankment	100m	1m	2	Widen base	61,000
Turf fluvial embankment	130m	2m	1	Raise crest level by 2m	101,100

4.2.4 Intervention Strategy Evaluation Process

With the calculation of the benefits in terms of flood risk reduction and the costs presented in Section 4.2.2 and 4.2.3 respectively, a process is now required which in an automated manner evaluates a full intervention strategy. Figure 4.3 illustrates a flow chart of the full evaluation process of an intervention strategy for this thesis. The process begins by generating an intervention strategy and assessing the strategy to ensure it conforms to a set of constraints to prevent unrealistic and infeasible strategies being evaluated. The constraints include limitations on defence height and width increases and continuity across time steps. Then for each time step the benefits and costs are calculated as explained in Sections 4.2.2 and 4.2.3. At each time step or future point in time it is important to recognise and represent any changes in the state. For example, over time the defences will begin to deteriorate, the load on the defences may increase as well as an increase in socio economic developments. These changes need to be represented within RASP at each time step of the planning horizon.

The calculation of the total benefits requires the risk for the 'do nothing' or baseline case. Figure 4.3 provides a flow chart for the evaluation of the base line. With the total benefits and costs calculated, the NPV and the Benefit Cost Ratio (BCR) can be obtained to assess the performance of the strategy. The NPV and BCR provide equally acceptable criteria for showing whether an individual project is worthwhile.

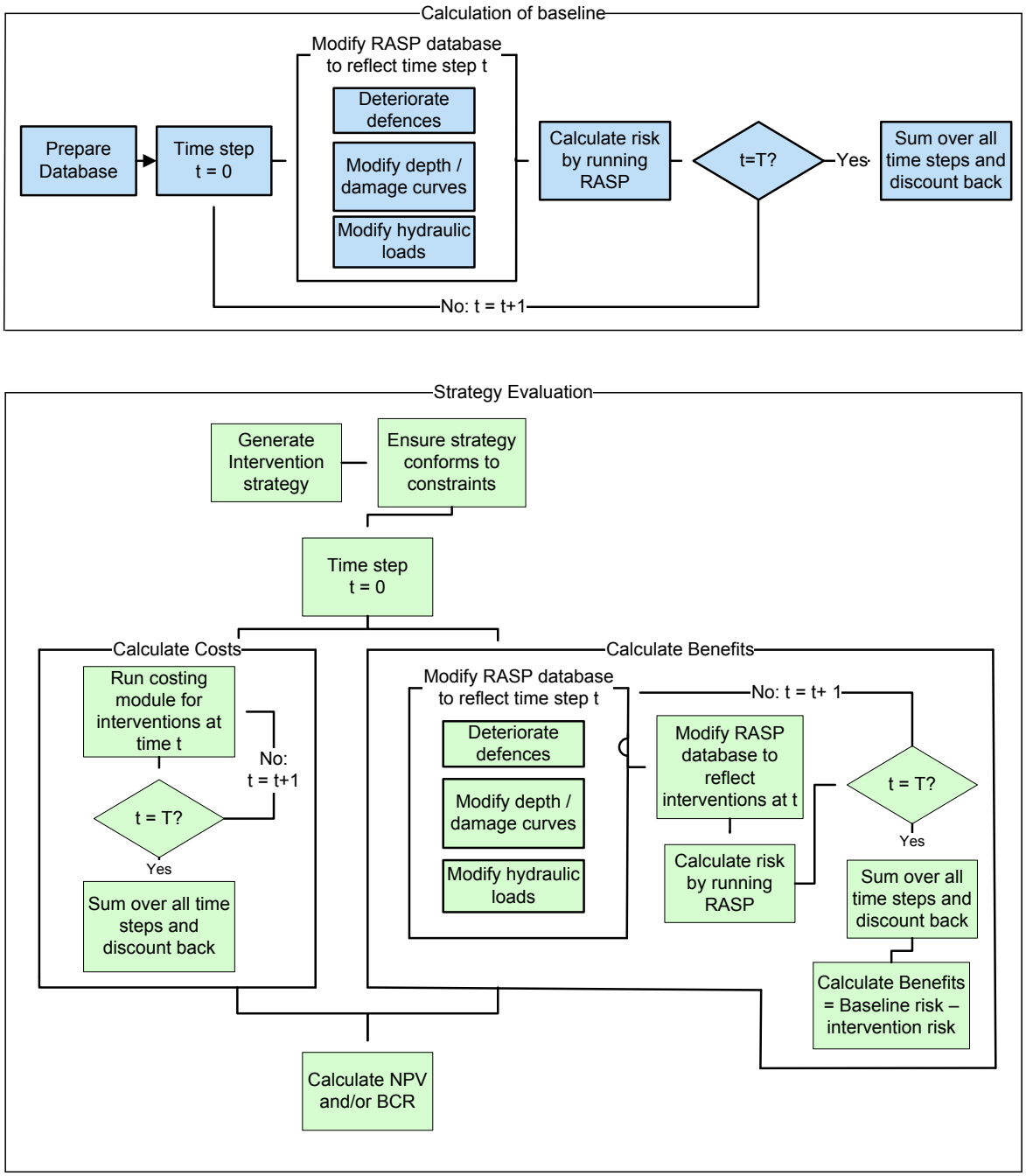


Figure 4.3 Flowchart for the 'do nothing' baseline case (top) and a flowchart for the evaluation process of a flood risk intervention strategy (bottom)

They are both able to show when, for a given discount rate, the project benefits exceed costs. However, both methods evaluate investments differently and are able to provide differing information. The NPV for example looks to maximise wealth, and thus highlights the options which provide the largest potential contribution to welfare. BCR on the other hand looks to maximise limited resources by finding an investment which obtains proportionally the most benefit for the least cost. For this reason both the NPV and BCR are considered in the analysis undertaken in the methodology.

In both stages of the calculation of the benefits and costs, a discount rate is applied to calculate the present day value of the strategy. A recommended standard declining discount rate is provided in the Green book (HM Treasury, 2003) to be used to appraise policies and projects (Table 4.4). However the choice of discount rate has been at the centre of debate and primarily depends on the pure time preference rate. A high pure time discount rate of the future favours avoiding the costs of mitigating against the impacts of climate change now. For the purposes of climate change adaptation, the Stern Review (Stern, 2006) identifies a requirement that a low pure time discount rate is necessary to prevent future generations from being valued less than the present generation. The discount rate can have a significant impact on what appears to be the optimum intervention strategy and therefore consideration must be given to the rate used. In Section 7.3 a sensitivity analysis of the discount rate is undertaken.

Table 4.4 The declining long term discount rate (HM Treasury, 2003)

Period of years	0-30	31-75	76-125	126-200	201-300	301+
Discount rate	3.5%	3.0%	2.5%	2.0%	1.5%	1.0%

4.3 Accounting for Uncertainties

As seen from Section 2.2.3, there are a large range of uncertainties present in flood risk calculations. Looking specifically at the Thames Estuary, which is the area of interest for the case studies in Chapter 7, there are a large number of uncertain variables to be considered when undertaking flood risk analysis. Hall et al (2009b) have summarised these uncertainties. For example, considering the hydraulic loading levels, there is uncertainty in the water levels at the outer boundary of the estuary, in the discharge at upstream fluvial boundary of estuary, in the water levels at the assets in the estuary and in the shape of the tide or storm surge. The sources of uncertainty for these variables can mainly be attributed to statistical and model uncertainty. Similarly there is

uncertainty when considering defences such as in the crest level of the defences, the probability of the defences breaching, the location and width of the breach as well as the rate of beach growth and also uncertainty in the probability of failure to close the barriers and gates on the Thames Estuary. The sources of these uncertainties are epistemic, with the uncertainties attributed to sources such as accuracy in measurements, limited information on the defences and lack of knowledge on the breaching processes. Hall et al (2009b) also describe the uncertainties in the Thames Estuary with regard to the modelled flood area. For example, there is uncertainty in the DTM, the flood plain roughness and the knowledge on the location and type of properties in the flood area.

This thesis looks to develop and apply methodologies which can account for future uncertainties during the development of long term strategies. Given the large number of uncertainties, this thesis focuses on the uncertainty in the hydraulic load, more specifically the sea level rise uncertainty due to climate change. Sea level rise influences the flood risk and performance of assets and is therefore a suitable variable to assess these methodologies on. There are a range of uncertainties in future sea level rise projections. Relative sea level in the UK changes for two reasons; the volume of the oceans is changing and there is land movement due to isostatic rebound following the end of the last ice age (Murphy et al., 2009). There is uncertainty associated with both of these factors. Whilst there is a degree of uncertainty associated with land movement, the rate of movement can be estimated fairly accurately (Milne et al., 2006). The main uncertainty therefore lies with sea level changes resulting from the changing volume of the oceans. In the present day, assuming a stationary climate, the volume of the oceans is relatively constant. However in the future with projected increases in temperature the volume of the oceans may increase due to thermal expansion and sea ice melt.

Future projections of sea level rise are derived from global climate models (GCMs). A GCM simulates the fundamental physics of the atmosphere, ocean and land surface. The projections from GCMs have a degree of uncertainty due to the emissions scenarios used to drive the model, the natural variability within a model and the structure and parameters used to construct a given model (Hawkins and Sutton, 2011). In a GCM, sea level changes occur solely as a result of the thermal expansion of the water, factors such as ice melt and land movement are then factored in to provide an absolute change in sea level (Murphy et al., 2009).

The strategies evaluated in the manner described in Section 4.2.4 are fixed over the planning horizon and are only evaluated against one potential future outcome. In this thesis, this is considered to be deterministic when only one future is in consideration. Given the uncertainties of the future impacts of climate change, consideration of one potential future is inadequate. An optimum strategy today may well be suboptimum in the future if the climatic conditions deviate from the single projection analysed. Rather than designing a strategy which is optimal for a given future state, it is preferable to design a flexible strategy which can account for, i.e. can adapt to, potential changes in future conditions.

An important input into flood risk intervention strategies is therefore an adequate understanding of the variability that the assets and intervention measures face (e.g. the climate conditions that can be expected over the life of the asset). This is commonly done by designing infrastructure to be able to withstand any possible change throughout the lifetime of the asset. Ingham et al (2006) call this 'headroom' in water investment planning whereby a margin is added on to the expected demand to allow for all possible future uncertainties. In flood risk management, the height of the defence includes a 'freeboard' allowance as a safety margin to account for uncertainties (Environment Agency, 2009b).

Understanding the impact from environmental and socio economic conditions on proposed or existing assets enables decision makers to better plan for the future. It is therefore very important to consider multiple future scenarios when developing long term flood risk intervention strategies. In this thesis, the future states are represented using the UKCP09 probabilistic scenarios (Murphy et al., 2009) and socio economic development scenarios (Evans et al., 2004). Specifically UKCP09 provide data on a range of climate variables for three emission scenarios, high, medium and low. Figure 4.4 displays the predicted sea level rise for the three UKCP09 high, medium and low emission scenarios.

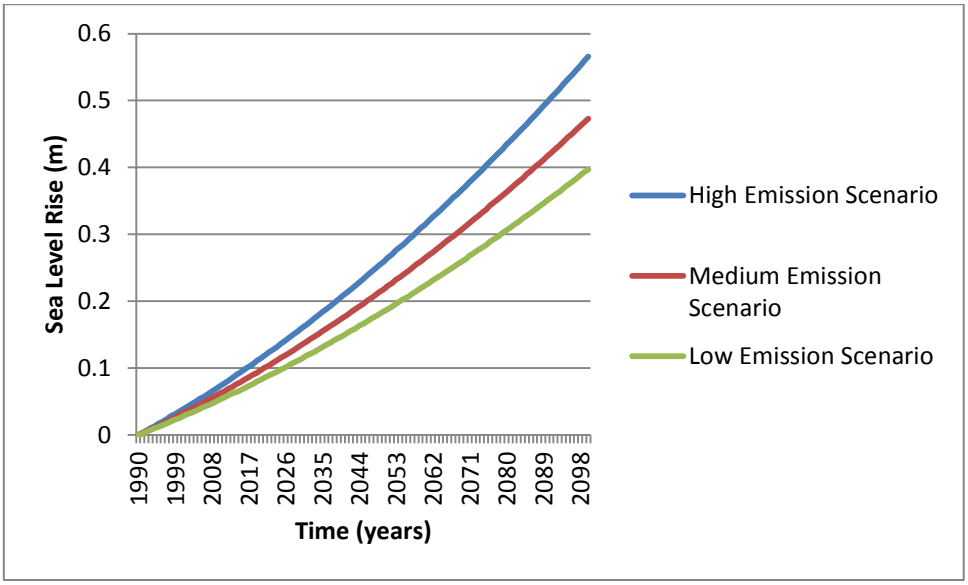


Figure 4.4 Estimated sea level rise for the three UKCP09 emission scenarios

No information is provided on the likelihood associated with the emission scenarios. Therefore to analyse the performance of the intervention options over the range of scenarios, when no information on likelihood is available, a range of decision making methods under severe uncertainty can be applied. Section 2.3.2 describes some of the methods available. These approaches require assumptions about the likelihood of scenarios and therefore depend on the user's attitude to risk. Until probabilistic information is provided on the likelihood of emission scenarios, the decision making methods under severe uncertainty will allow strategies to be evaluated against a range of potential scenarios and account for future uncertainty.

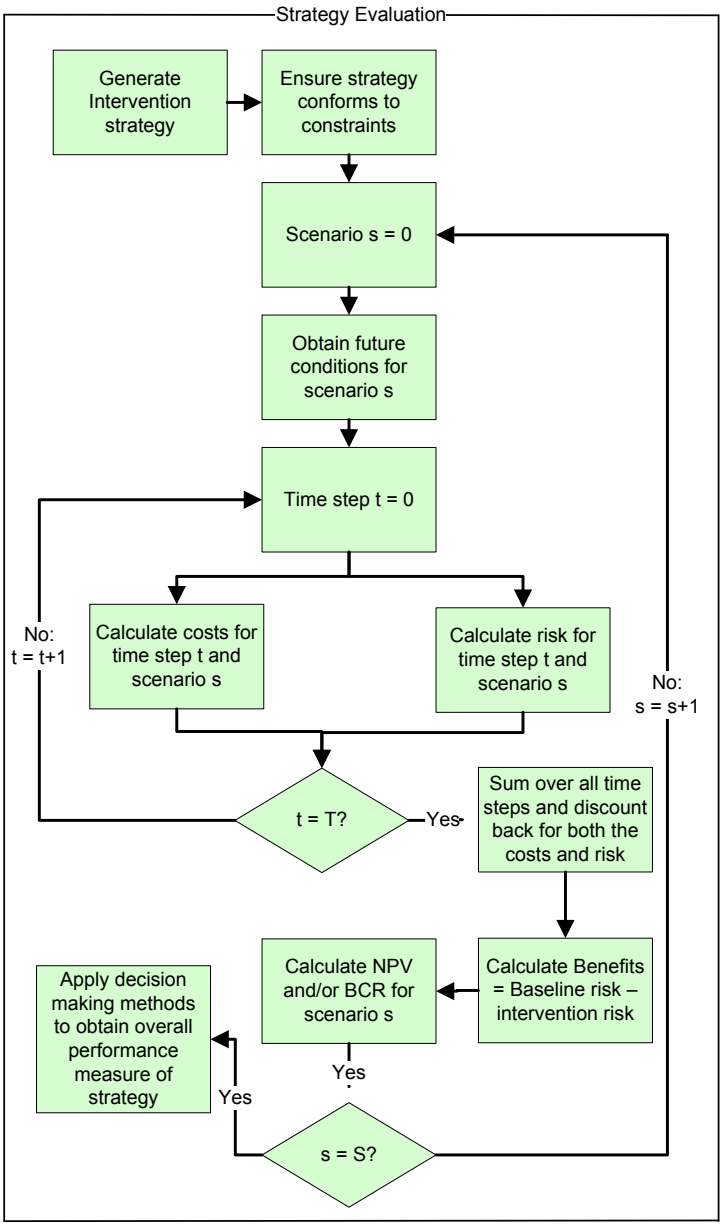


Figure 4.5 Flowchart of the strategy evaluation process when considering a range of future scenarios

Figure 4.5 displays a revised flowchart of the evaluation process in Section 4.2.4 to include the evaluation of an intervention strategy over a range of future scenarios. In this process, the future states need to be represented in the RASP model. As in Section 4.2.2, future climate change scenarios can be represented by modifying the extreme value distributions of hydraulic loads and socio-economic development scenarios are represented by modifying the depth damage curves. These changes occur as in the previous flow chart when calculating the benefits.

4.4 Real Options in Flood Risk Management

The procedure described in Figure 4.5 evaluates strategies over a range of future climate projections. The selected strategy is assumed to reduce flood risk and provide sufficient protection over the life of the strategy regardless of the change in future conditions. This is advantageous compared to considering just one scenario which does not account for climate change uncertainty. These strategies are however still fixed over the planning horizon and although they account for climate change variability they are based on particular assumptions about future change. The magnitude of future change is essentially unknown (Rayner, 2010). Rates of change may be faster or slower than the rates assumed and therefore the planned time steps when interventions are required will change. Building flexibility into the strategy and enabling an adaptive approach can avoid this. Adaptation accounts for future uncertainty and enables decisions to be made based on actual rates of change, leading to robust and flexible strategies.

The Real Options philosophy seeks to identify opportunities for incorporating flexibility into the decision making process to mitigate the potential impact of future uncertainties and in turn creates opportunities for adaptation. For example, where it is beyond doubt that a flood defence has come to the end of its useful life and requires major refurbishment there are a range of possible decisions. Assuming a worst case climate change scenario and constructing a flood defence based on this assumption is likely to be sub-optimum as it requires significant up-front expenditure and may well constitute an over-design should the worst case scenario not be realised. Constructing a defence that is inherently flexible and capable of future modification is one approach for implementing a Real Option within a flood risk system. A wide defence that is constructed in a way that enables its crest to be raised in the future, should there be a requirement, is an example of a Real Option. The option to raise a defence or not is purchased at the outset. The decision whether to exercise the option is delayed to a future date when more information regarding future climate change impacts, for example, is known (see Figure 4.6).

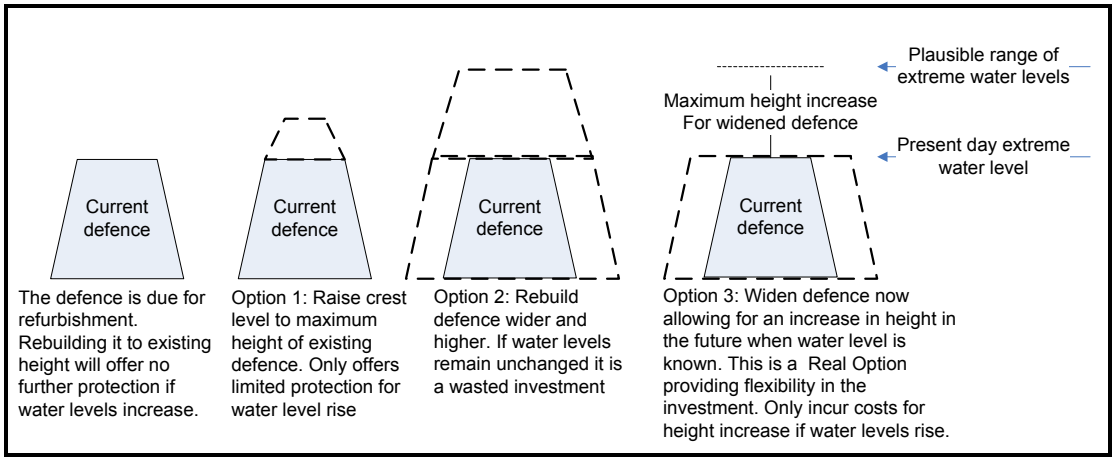


Figure 4.6 Description of a flood risk management Real Option

There may however, be uncertainty regarding whether to refurbish a defence, set-back a defence or continue with maintenance activities, the cost of which may rise as the structure approaches the end of its design life. Delaying the decision to refurbish and continue with the maintenance is another example of implementing Real Options based concepts. Flexibility is maintained and the decision to refurbish or setback is delayed until more information is known. The cost of the option is the increase in maintenance costs as the structure deteriorates. The value of the option lies in the decision to delay major investments until future uncertainties are reduced.

In coastal and estuarine environments, managed retreat is increasingly likely and habitat loss and creation issues are an additional consideration. The purchase of land in the lee of the existing defence system can be considered as a Real Option. Future developments in the area can be restricted and decisions delayed regarding the relative extents of setback and habitat creation until future uncertainties that influence these decisions can be reduced.

The value of Real Options is in their ability to adapt to future climate change scenarios. To appraise the performance of Real Options it is therefore necessary to take an appropriate account of future uncertainties, in particular relating to climate change. The evaluation procedure explained in Section 4.3 accounts for the future uncertainties. Within the evaluation process explained in Sections 4.2 and 4.3 the concepts of Real Options can therefore be incorporated into the analysis of the strategy with the additional value of flexibility included. In this thesis, the use of Real Options resembles Real Options "in" systems where flexibility is embedded within the design of the infrastructure system. de Neufville et al (2005) provides an approach to value flexibility

for a Real Options "in" systems project and the approach adopted in this thesis follows a similar procedure. Assuming future uncertainty is present, flexibility is evaluated as the difference between an option with embedded flexibility and an option defined in a standard deterministic way. Essentially, the value of a strategy is equal to the NPV plus the value of flexibility. If there is no uncertainty considered, the value of an intervention strategy is simply the NPV. The incorporation of flexibility can only be justified in an uncertain future, if the future state is known the standard deterministic approach will be favourable.

The flood risk intervention strategies will be designed to naturally incorporate this flexibility and inherently capture the Real Option concepts. These strategies provide the opportunity to adapt and implement options such as delaying, expanding, contracting and abandoning. Rather than having intervention strategies fixed over the planning horizon, the strategies will be able to adapt when knowledge of the uncertain future becomes available. Section 7.3 provides an example of the application of Real Options in flood risk management. A comparison of traditional NPV approaches against the proposed Real Options approaches has been undertaken. In this comparison the advantages of Real Options is apparent. The ability to adapt in the future to account for the unknown changing climate is a powerful element for long term planning in flood risk management.

Chapter 6 further discusses the incorporation of Real Options into flood risk management, considering the representation of an intervention strategy as a decision tree with multiple paths into the future, with the use of threshold values to determine the better path to take. The methodology presented in Chapter 6 further demonstrates the value of flexibility and aids the visualisation of the possible adaptation options available to decision makers.

4.5 Summary

In this Chapter, Section 4.2 describes an evaluation process to enable the assessment of flood risk management intervention strategies. The evaluation process specifically evaluates an intervention strategy according to the benefits through flood risk reduction and the costs of implementation. Section 4.3 expands upon the evaluation process to evaluate the strategies according to a range of future climate change scenarios. The importance of accounting for climate change uncertainty during the decision making process was a conclusion of the literature review (Chapter 2) but the need for adaptation

was also highlighted. Section 4.4 advances the evaluation process further by integrating the concepts of Real Options into the evaluation process to incorporate flexibility and provide opportunities for adaptation and robustness.

The outcome of this Chapter therefore provides an evaluation process to assess flexible and adaptive flood risk strategies which account for the future uncertainties of climate change. With an appropriate evaluation process in place, it is still a challenge to decide upon an optimal combination of measures. There is a large portfolio of intervention measures available for the development of an intervention strategy, each of which can occur at future points in time. Evaluating every combination of intervention measures is impractical and only considering a select few can result in many, potentially better, strategies being ignored. The next Chapter investigates the inclusion of evolutionary algorithms to advance the evaluation process allowing for the optimisation of intervention strategies.

Chapter 5 Optimisation in Flood Risk Management

5.1 Introduction

It is widely recognised that flooding cannot be prevented and risk management approaches are often employed to minimise the likelihood of, and consequences associated with, extreme floods. To effectively manage flood risk it is necessary to have an evaluation process in place to quantify the current risk and then assess a range of potential mitigation options. Chapter 4 provides an evaluation process for the assessment of potential intervention plans; the next step of this thesis therefore needs to focus on assessing a range of potential mitigation options and identifying the most appropriate. Automated search algorithms provide methods which seek to find the better performing solutions and would be ideal candidates for this.

The purpose of this chapter is therefore to explore the integration of automated search techniques in flood risk management, considering specifically evolutionary optimisation algorithms. Section 5.2 begins by discussing the motivation for which evolutionary algorithms are required in flood risk management and discusses the concerns of optimising mitigation options. Section 5.3 focuses specifically on incorporating a single objective GA while Section 5.4 introduces multi-objective optimisation.

5.2 Optimising Flood Risk Options

Mitigation measures can vary and may include standard maintenance activities of existing infrastructure, defence construction or refurbishment and flood proofing properties. The option appraisal process aims to identify those that perform the best. The evaluation process explained in Chapter 4 is capable of quantifying the risk reduction and costs associated with different intervention strategies, it does not necessarily facilitate the selection of the most optimum ones. It is not able to answer questions like, which intervention strategy is the best and when do they need to be implemented? This shortcoming arises as a result of the potentially vast decision space that requires consideration. In any given floodplain system it is not unusual to have in excess of 100 different defence sections, as well as mechanical infrastructure (e.g. pumps, gates and barriers). So, in principle, it is necessary to consider, for each element of the system, a number of different options: maintenance expenditure (this could be

increased or decreased), refurbishment or complete replacement. Furthermore, mitigation measures are not restricted to the major infrastructure. Flood proofing of properties on the floodplain can also be a viable risk reduction measure and consideration of how many and which properties to fit also require assessment, in combination with the infrastructure measures.

Current approaches applied in practice, typically use expert judgement based selection methods to reduce the options to a manageable number. These are then trialled at different times within the appraisal period. Given the complexity of the problem and its subjective nature, this process is fallible. Advances in the scientific computational field have seen the development of a wide range of automated searching routines that offer a more robust solution to this problem (see Section 2.4). A formal optimisation method has the capability to identify the optimum combination of mitigation activities and is explored in Section 5.3.

More recently, it is becoming increasingly apparent that it is also necessary to consider a wider range of performance metrics when considering flood protection infrastructure in addition to risk reduction and costs. More specifically, environment impacts, business disruption costs, loss of life and amenity value, are all potentially important indicators of the value of flood risk mitigation measures to society and there is an increasing demand for these performance metrics to be formally considered as part of the appraisal process. Section 5.4 introduces multi-objective optimisation to facilitate the consideration of numerous criteria simultaneously.

Optimisation has the potential to solve several difficulties facing flood risk decision making and looks to be influential in the improvement of flood risk management. Hall and Solomatine (2008) however suggest the quest for optimisation of flood defence systems should be pursued with caution. During the development of long term flood risk mitigation plans, the selection of an intervention strategy occurs under severe uncertainty. In situations of severe uncertainty, there is a question as to whether it is preferable to seek an outcome which is optimal or whether it is wiser to make a decision that delivers a satisfactory outcome under a wide range of possible outcomes. Hallegate (2009) and Lempert and Groves (2010) also raise concerns regarding the use of optimisation to adapt to climate change uncertainty and recommend the search for a robust strategy instead. Ben-Haim (2005) promotes “robust satisficing” where “satisfice” refers to achieving an acceptable outcome rather than achieving the best

possible. There is however no reason as to why the optimisation process cannot search for the best robust or most flexible solution in an uncertain environment. The optimisation of flood defence systems does not need to assume the environmental conditions do not change over time producing an outcome that is not robust or flexible to a range of future scenarios. Robust optimisation provides techniques to find the best possible outcome over a range of future scenarios (Beyer and Sendhoff, 2007). In addition Voortman and Vrijling (2003) propose methods to account for climate change uncertainty during the optimisation of flood defence systems using a risk based optimisation. Hall et al (2009a) apply optimisation techniques and in particular a GA to improve the search for portfolios of flood risk management options. In their paper it is recommended that their approach is further explored to identify options that are as far as possible robust to the future uncertainties. It is suggested their work on robust options and dealing with uncertainty (Hall and Solomatine, 2008, Hine and Hall, 2010) can be integrated with optimisation to do so.

In this thesis, robust strategies can be optimised using the evaluation process in Chapter 4. The analysis takes into consideration the need for flexible and adaptive strategies which account for climate change uncertainty. The strategies are evaluated over a range of potential future scenarios and a better performing strategy according to all scenarios can be selected. Optimising using an evaluation process such as this will identify the better robust strategies. Optimisation techniques can therefore optimise for solutions which satisfy a set of criteria and account for future uncertainty. With this in mind, it would be much more advantageous to select one of the optimum, better performing strategies rather than a lesser, dominated strategy. Rather than accepting any strategy which satisfies a set of criteria, wouldn't it be preferable to select the *best* strategy which satisfies the set of criteria?

Various studies have been undertaken to optimise flood risk management plans (see for example Voortman et al (2002) and Lund (2002)). Hall and Solomatine (2008) suggest the search for an optimum solution could however exploit the features and resources of the system, often making economic efficiency a priority over safety. Voortman at al (2002) optimise for a flood defence system aiming to minimise the construction costs of the mitigation activities provided the system fulfils a pre-defined requirement on failure probability. This can be seen to make cost efficiency a priority as flood defence systems are chosen based on the minimisation of investment costs. Even though a constraint is

put in place to ensure a particular safety level is reached, the approach used does not look to further improve safety but instead to reduce construction costs.

This however does not need to be the case. The use of multi-objective optimisation does not optimise for one single optimum solution but instead a trade-off of optimum solutions ensuring each solution is assessed according to a range of criteria. Consequently, results are provided which are optimum according to each criteria, it is then up to the decision maker to select the most appropriate strategy, whether that is to fully maximise risk reduction or to minimise the costs or to find a suitable medium. In addition other criteria can be considered to improve the decision making process. Using this approach, predefined safety levels are not required as the process will look to maximise safety. With the information provided from multi-objective optimisation the decision maker can control the priority of different criteria and ensure safety is not disregarded.

5.3 Single Objective Optimisation

In this section, a single objective optimisation technique is investigated as a method to search for the most optimum combination of intervention measures. Section 5.3.1 formulates the specific single objective optimisation problem while Section 5.3.2 focuses on the inclusion of a single objective GA in flood risk management to solve the problem described. Sections 5.3.3, 5.3.4 and 5.3.5 detail the different components of the GA and how they have been used in this thesis to address the problem specified.

5.3.1 Problem Formulation

The problem description involves the identification of better performing combinations of intervention measures according to a given objective. The mathematical formulation of the problem is to find a chromosome or vector $X^* = (x_1^*, x_2^*, ..., x_n^*)$ which optimises $f(x)$ such that:

$$f(x) = \max NPV \tag{5.1}$$

or

$$f(x) = \max BCR \tag{5.2}$$

where *NPV* and *BCR* are described in equations (5.3) and (5.4) respectively and the vector X^* represents a combination of possible intervention measures (see Section 5.3.3 for more details).

$$NPV = \sum_{t=1}^{T} \frac{Benefit_t - Cost_t}{(1+r)^t} \tag{5.3}$$

$$BCR = \sum_{t=1}^{T} \frac{Benefit_t}{(1+r)^t} \Bigg/ \sum_{t=1}^{T} \frac{Cost_t}{(1+r)^t} \tag{5.4}$$

where $Benefit_t$ is the benefits (reduction in EAD) at time t as defined in equation (4.1), $Cost_t$ is the costs at time t as defined in equation (4.6), r is the discount rate and T is the total number of years considered in the solution.

For an economical investment, the output of the optimisation of equation (5.1) must have $f(x) \geq 0$, while for the optimisation of equation (5.2), $f(x) \geq 1$. A set of constraints must also be applied to ensure the investment is reasonable and realistic. For example, constraints are placed on the range of values the intervention measures can take and the timing of implementation (e.g. limits on the height of a defence are given to avoid unrealistic interventions). Constraints are also placed on the frequency of defence interventions, it would not be feasible to increase the height of a defence twice in the space of 5 years for example. The next section (Section 5.3.2) describes a single objective GA to solve the above problem.

5.3.2 GA

As discussed in Section 2.4.2, one of the many strengths attributed to a GA is their ability to efficiently explore large search spaces. This attribute becomes very useful in flood risk management; the search space of possible intervention strategies can potentially be very large given the portfolio of intervention measures and the possible timings for implementation.

A single objective GA searches for the most optimum solution according to one criterion by using evolutionary techniques on the search space to locate the global optima. The GA is based on Darwin's theory of natural selection and survival of the fittest, closely resembling the evolutionary process which takes place in human genetics. Feasible solutions in the search space are represented in the GA as chromosomes, with each chromosome built from a set of genes which describe the main

features of the solution. Similarly to human genetics where genes determine traits such as eye colour or hair colour, genes in the GA determine the decision variables which form the building blocks of a solution.

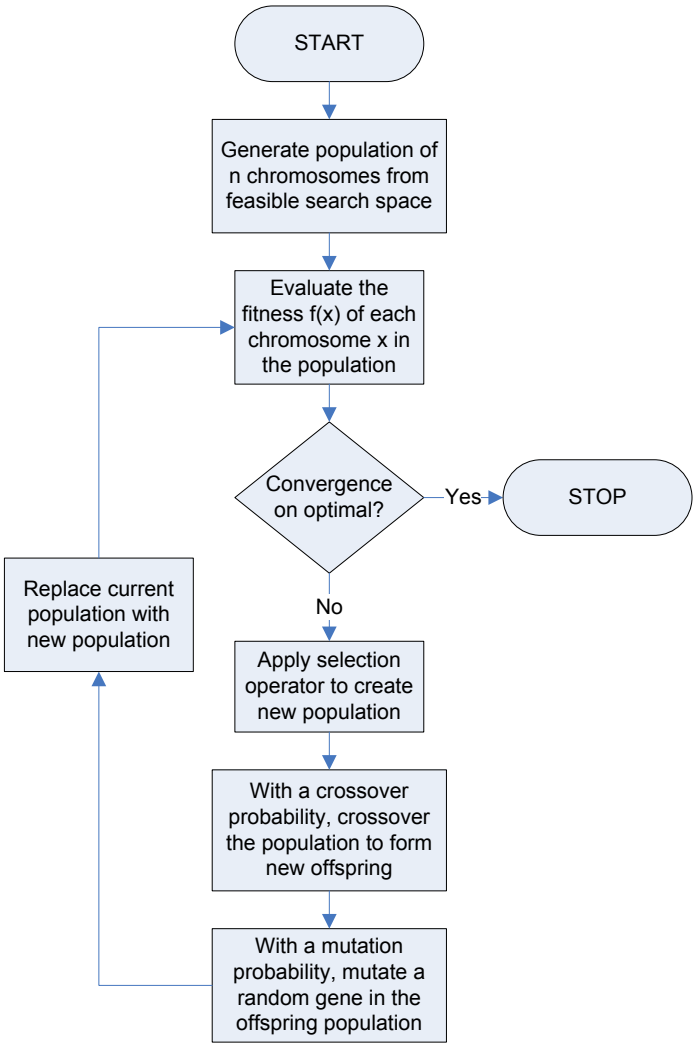


Figure 5.1 A flowchart of the GA process

The GA begins by generating a set or population of chromosomes from the search space, known as the parent population. Each individual chromosome from the population is evaluated according to an objective function assigning a fitness value to each chromosome. From the parent population a new population is created called the child population. This is made up from the better performing solutions of the parent population identified from the fitness values as well as modified chromosomes using genetic operators such as crossover and mutation. The process is then repeated, the chromosomes from the child population are evaluated becoming the parent population from which the next set will be based on. The GA process relies on subsequent

generations to continually improve and converge upon a global optimum. The main stages of the GA are described in Figure 5.1.

In this thesis, the requirement of the GA is to identify the better performing combinations of intervention measures, determining a solution which describes the most appropriate intervention measures to implement, when and where according to a specific performance measure; the maximum NPV or BCR. The next sections describe in detail the main stages of the GA when addressing this problem. The solution or chromosome structure is discussed in Section 5.3.3 followed by a description of the fitness evaluation and objective function in Section 5.3.4. Section 5.3.5 focuses on the genetic operators and the specific methods used in this thesis.

5.3.3 Intervention Strategy Coding

The chromosomes represent potential intervention strategies. As in Chapter 4, an intervention strategy is a combination of intervention measures occurring at different sequences through time for a given flood area. Chromosomes are formed from a sequence of genes where each gene characterises an intervention measure at a given time for a specific location (a flood defence or flood zone). There is a range of intervention measures considered in a gene. For each of the defences in the flood area, a combination of structural interventions, X_s, (raising the crest level of defences and increasing the defences capacity for future expansion) and flood defence maintenance, X_m, are considered. The vector form of a chromosome X^* is a sequence of genes which have varying combinations of intervention measures for a given location and time such that $X^* = (x_1^*, x_2^*, ..., x_n^*)$ where n equals the total number of genes in the chromosome. The intervention measures in the gene can represent a variety of different possible options which are described in Table 5.1. Table 5.1 also expresses how the intervention measures are represented in the GA.

In the approach adopted in this thesis, a gene which characterises structural or maintenance interventions can either apply the intervention to a single defence in the flood area or to a group of defences. The advantages of grouping flood defences are two-fold. Firstly, it is often more realistic and economically efficient to apply intervention measures to a group of defences rather than individually and secondly, grouping defences will improve the optimisation problem as there will be fewer decision variables to consider.

Table 5.1 The different intervention measures available and how they are represented in the GA

Intervention measure	Options for measure	Represented within GA
Raising the crest level of a defence	Discretised height increases: 0m, 0.33m, 0.66m, 1m, …	Hard coded integers: 0,1,2,3,…
Increasing the defences capacity for expansion through widening the base	Discretised width increases: 0m, 0.5m, 1m, 1.5m, 2m,…	Hard coded integers: 0,1,2,3,4,…
Defence maintenance	No maintenance, low, medium or high	Hard coded integers: 0, 1, 2 or 3

As in Figure 5.1, the GA begins by generating an initial set of chromosomes. These are randomly generated, with each gene randomly assigned a value from a predefined range of a specific intervention measure (see Table 5.1). The chromosomes are evaluated according to an objective function to obtain its fitness. This is explained in Section 5.3.4.

5.3.4 Fitness Evaluation

Each chromosome is evaluated according to an objective function, assigning a performance measure or fitness to the intervention strategy. In the single objective GA, an appropriate objective function would be a form of cost-benefit analysis to combine the risk reduction in terms of damage with the costs of implementing the strategy (for example using the NPV or BCR as defined in equations 5.3 and 5.4 respectively).

Chapter 4 describes an evaluation process which analyses an intervention strategy according to the benefits and costs to obtain either of these performance measures, assigning a fitness to each strategy. This evaluation process is therefore integrated into the GA algorithm to analyse each solution and provide the fitness values.

5.3.5 GA Operators

If convergence upon an intervention strategy has occurred or a stopping criterion has been met, the GA stops and the optimum solution is selected from the current population. Otherwise, GA operators are applied to generate the next population of solutions. The first GA operator to be applied is selection. The selection procedure determines which strategies will be going through to the next generation, with the better

performing strategies assigned a higher probability of going through. In this thesis, binary tournament selection is used whereby two chromosomes are picked at random, the better performing strategy will survive into the next generation. This process is repeated until the new population is full.

The newly selected chromosomes then have the opportunity to undergo crossover and mutation. These operators are controlled by a probability of occurrence, with crossover more likely than mutation. Crossover and mutation are applied to generate different chromosomes and prevent convergence on a local optimum. The crossover operator typically performs an exchange of genes between two chromosomes from a particular location on the chromosome. The crossover method used in this thesis is single point crossover whereby a randomly chosen location on two selected chromosomes exchanges genes from that point onwards (see Figure 5.2). Crossover has a fairly high probability of occurrence with recommendations of 0.7 – 1.0 (Goldberg, 1989, Deb, 1998).

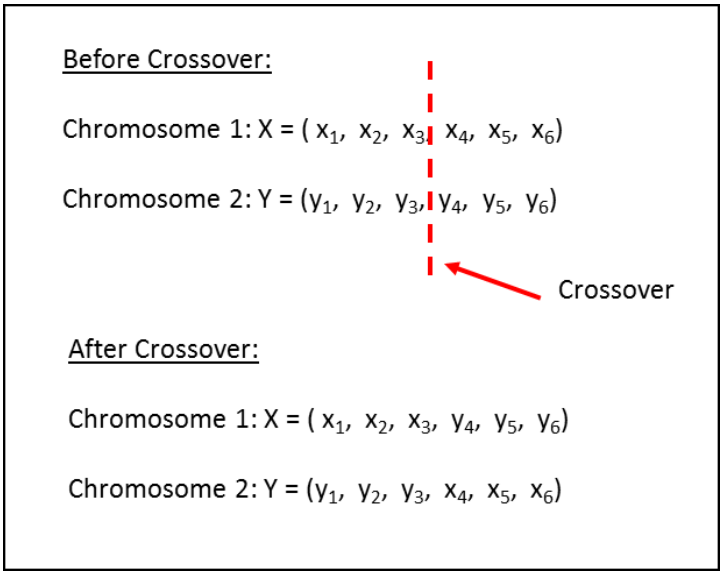


Figure 5.2 Applying single point crossover to two chromosomes

After crossover, mutation is possible. Mutation randomly mutates the value of a gene in a chromosome. Mutation occurs less frequently than crossover as a high occurrence can have a disruptive effect on the search. A suggested probability of occurrence ranges from 0.02 – 0.06 (Deb, 1998). The mutation operator in this thesis follows a random replacement procedure whereby a gene is chosen at random and the value is modified within the bounds of the decision variable range (see Figure 5.3).

The single objective GA has been applied and tested on an area of the Thames Estuary (Section 7.4) to show the advantages the GA brings to flood risk management when deciding on the most optimum solutions.

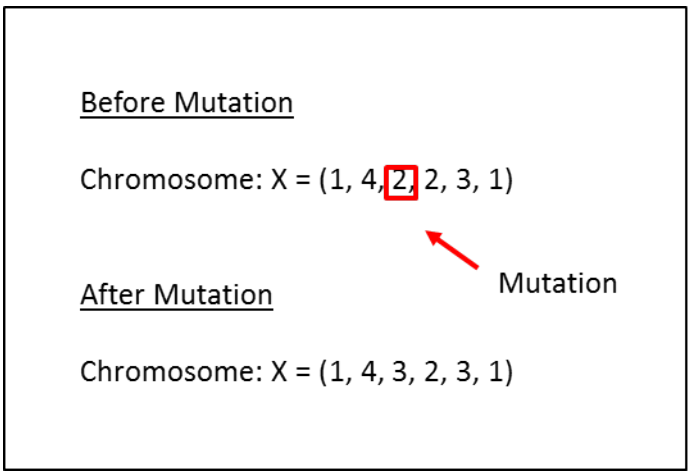


Figure 5.3 Mutation to a randomly chosen gene on a chromosome

5.4 Multi-objective Optimisation

In practice many real world problems have two or more competing objectives. When these objectives are conflicting with each other, there is no single best solution but a set of trade-off solutions. Accounting for multiple objectives can however be problematic and is often resolved by assigning weights to the objectives to produce a single criterion giving an output directly comparable to all other solutions. Setting preferences prior to optimisation and ultimately making the problem single objective, requires many simulations to produce a set of trade-off solutions. This can be very time consuming. In flood risk management, it is common practice to consider objectives economically. Loss of life and environmental impacts are therefore rarely considered in flood damage and vulnerability analysis because of the difficulties and often controversy involved in converting these factors into monetary terms (Messner and Meyer, 2006). Decisions are consequently based on the economic benefits and costs and are generally combined to produce a NPV. Additionally combining multiple objectives into one utility function requires extensive knowledge of the objectives and can result in sub optimum solutions if incorrect weights are applied a priori of the optimisation process (Coello, 1999).

Evolutionary multi-objective optimisation techniques optimise all conflicting objectives simultaneously whilst keeping them in their native metric. For example, loss of life can be expressed as number of people and optimised against the cost of an intervention

which is expressed in monetary terms. The aim of evolutionary multi-objective optimisation is not to identify the single best solution but to provide a set of trade-off solutions. This set of solutions is known as the Pareto optimal set (Fonseca and Fleming, 1998).

Evolutionary multi-objective algorithms present a major advantage in that weights and preferences of the objectives do not need to be set a priori (Coello et al., 2002). This allows all possible solutions to be considered and provides decision makers with a full range of information without eliminating potential solutions before the optimisation process has even started. With these Pareto optimal solutions, decision makers are presented with insight into the problem itself and furthermore, favourable solutions which are often overlooked under classical approaches are now available for consideration.

With the advantages that multi-objective optimisation can provide Section 5.4.1 sets out another problem to be solved in flood risk management whereby the objectives; benefits and costs, are evaluated individually rather than combined into a single objective. The opportunity to add another objective, a loss of life surrogate is also taken.

5.4.1 Problem Formulation

As in Section 5.3.1 the problem description involves the identification of better performing combinations of intervention measures but unlike the single objective optimisation problem, rather than optimising for a single criterion the problem now being solved optimises according to a set of criteria. There are three criteria considered in the multi-objective optimisation problem: the benefits in terms of risk reduction, the costs and a loss of life surrogate model. The benefits and costs are obtained from equations (4.1) and (4.6) respectively while the loss of life surrogate model is explained in Section 5.4.3, with the loss of life surrogate defined by equation (5.9).

The formulation of the problem is to find an intervention strategy or vector $X^* = (x_1^*, x_2^*, ..., x_n^*)$ which optimises $f(x) = [f_1(x), f_2(x), f_3(x)]$ such that:

$$f_1(x) = \max(Benefit) \tag{5.5}$$

$$f_2(x) = \min(Cost) \tag{5.6}$$

$$f_3(x) = \max(Life) \tag{5.7}$$

The final output of the optimisation process is a Pareto front of optimal intervention solutions. These solutions are compromises or trade-offs between the three objectives and it is up to the decision maker to determine which solution would be most appropriate. The information provided from the Pareto front significantly enhances the decision making process compared to the output form a single objective optimisation.

In this thesis, the NSGAII (Deb et al., 2000) is utilised to solve this multi-objective optimisation problem in flood risk management. The methodology is based on the GA procedure but with modifications to handle the selection and ranking of solutions when evaluated according to multiple criteria. Section 5.4.2 explains the NSGAII in more detail and describes how it is specifically used in this thesis.

5.4.2 NSGAII

The NSGAII is an evolutionary multi-objective optimisation technique which is based on the process involved in a GA and builds upon the foundations of the NSGA developed by Srinivas and Deb (1994). Like the GA, the NSGAII is also based on Darwin's theory of natural selection and survival of the fittest. The main stages of the NSGAII are described in the algorithm in Figure 5.4. As can be seen from a comparison between Figure 5.1 and Figure 5.4 the single objective GA and the multi-objective NSGAII share many similarities in the overall process. Similarities such as the generation and structure of the chromosomes (as explained in Section 5.3.3) as well as the crossover and mutation operators (in Section 5.3.5) are all unchanged.

There are also some differences between the NSGAII and the single objective GA. Solutions are evaluated simultaneously according to multiple criteria; this alters the mechanisms required for the fitness and selection processes. Unlike the fitness calculations for the single objective GA, the NSGAII has additional layers of classification for each individual solution. Before the selection operator occurs the solutions are ranked according to non-domination and assigned a crowding distance to determine its fitness.

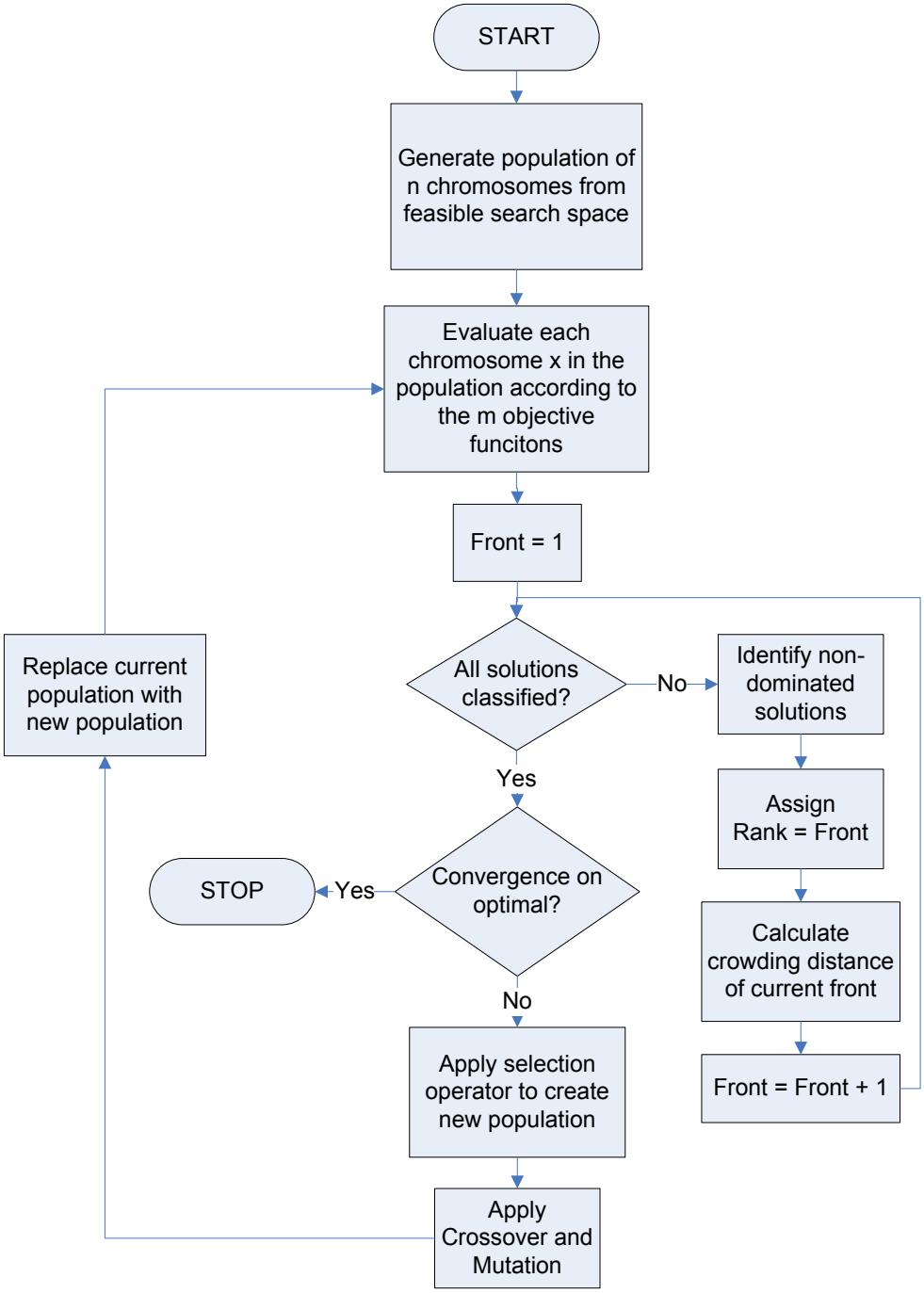


Figure 5.4 Algorithm describing the main stages of the NSGAII

5.4.3 Fitness Evaluation

As in the single GA, the evaluation process explained in Chapter 4 is utilised to analyse each intervention solution. However, rather than calculating a single performance measure such as the NPV or BCR, intervention strategies are assigned multiple performance measures e.g. the benefits and costs are treated independently. In addition, intervention strategies are also evaluated according to a third criterion, a surrogate for loss of life.

There are a range of factors that influence loss of life. Jonkman and Vrijling (2008) studied historical flood events and previous analysis to provide a list of the main determinants of loss of life which are major factors despite the differences in temporal and geographical location of a flood. The main factors are summarised as:

- Unexpected flooding without substantial warning
- Whether there is shelter available
- Collapse of buildings
- Water depth
- Rapid rise of water
- High flow velocities
- Age (with children and elderly being more vulnerable

Whilst there are complete models for life loss (Lumbroso et al., 2008, Aboelata and Bowles, 2010) a simplified approach is used here for demonstration purposes. The simple surrogate for loss of life calculates the annual probability of exceeding a flood depth y in a given impact zone and multiplies this by the number of people in that zone. This is summed across all impact zones in the floodplain to give:

$$Lifeloss = \sum_{i=1}^{k} P(Y > y) * N_i \tag{5.8}$$

where N is the estimated number of people in an impact zone, k is the total number of impact zones in the floodplain and i represents the impact zone index. In this thesis, the loss of life objective function looks to maximise the number of people no longer at risk and therefore represents the loss of life objective as follows:

$$Life = TotalLife - Lifeloss \tag{5.9}$$

where *Life* represents the number of people no longer at risk, *TotalLife* equals the total number of people on the floodplain which were at risk before the intervention strategy was implemented and *Lifeloss* represents the number of people still at risk after the intervention strategy has been implemented.

Each solution is assessed on how it performs according to each of the three criteria. The better performing strategies or the Pareto optimal strategies are said to be Pareto optimal if no other solution can improve some criterion without causing a simultaneous deterioration in at least one other criterion. To identify the better performing solutions, each solution in the population is ranked (see Figure 5.5).

The ranking procedure identifies the solutions which are not dominated by any other solution. A solution $\vec{u} = (u_1,...,u_k)$ is said to dominate a solution $\vec{v} = (v_1,...,v_k)$ if and only if u is partially less than v, i.e. $\forall i \in \{1,...,k\}, u_i \leq v_i \wedge \exists i \in \{1,...,k\} : u_i < v_i$ (Coello et al., 2002). From the full set of solutions in the population, the first set of non-dominated solutions is identified and these solutions are assigned the best rank, rank one. This set of solutions is then removed from contention so the next set of non-dominated solutions can be identified and assigned rank two. This process is repeated until all solutions have been assigned a rank. Within each assigned rank, the solutions are further assigned a crowding distance to determine within a rank which solutions have a higher fitness. The crowding distance is calculated as the average distance according to each objective that a solution sits between its nearest neighbours (see Figure 5.5). The larger the distance the better the solution is considered to be. The solutions which fall on the edge of the front are automatically assigned a high crowding distance. The crowding distance reduces the density of solutions around certain points and guides the selection process at various stages of the algorithm towards a uniformly spread out Pareto optimal front.

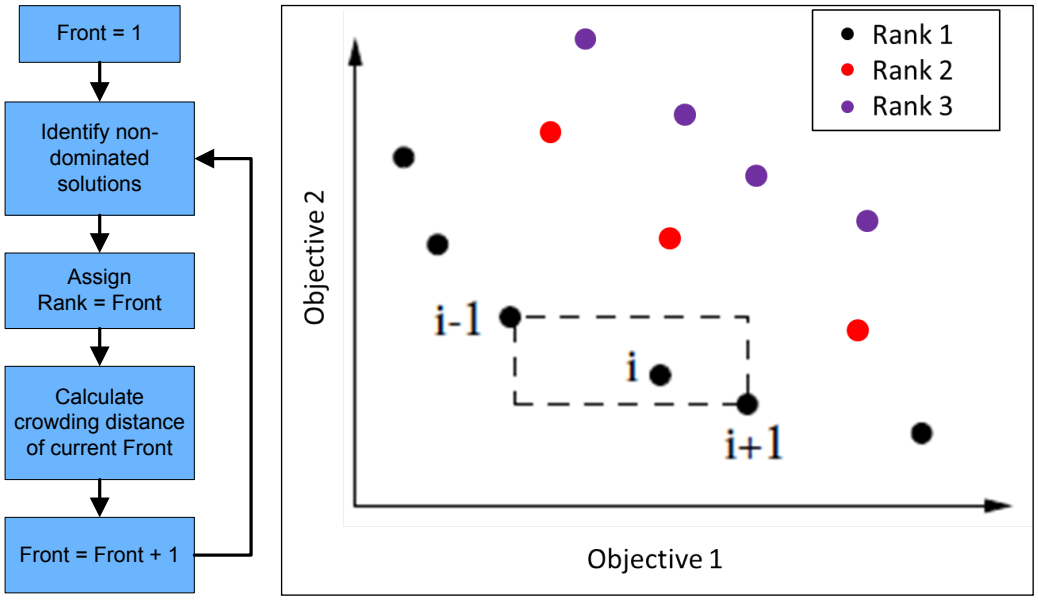


Figure 5.5 Algorithm for assigning fitness to solutions (left) and example diagram of ranked solutions with identified fronts and crowding distance calculation of solution *i* (right)

As in the GA process in Section 5.3.2, the selection operator used for the NSGAII in this thesis is binary tournament whereby two solutions are picked at random and compared. The better performing strategy is placed into the next generation and the process is repeated until a full population has been obtained. In the NSGAII, the

selection operator compares two solutions according to the rank, the lower the assigned rank the better. If the solutions are from the same rank, solutions are then compared according to the crowding distance which in this case, the higher the crowding distance the better. After the completion of the selection operator and with the solutions chosen for the next generation, crossover and mutation are applied in the same manner as in Section 5.3.5.

The multi-objective optimisation methodology is applied and tested on an area of the Thames Estuary (Section 7.5) investigating the advantages of considering multiple criteria in the decision making process and discusses methods to choose between the solutions available.

5.5 Summary

In this Chapter, Section 5.2 discusses the need for optimisation techniques and the advantages evolutionary optimisation methods can bring to flood risk management. It is found that the use of evolutionary algorithms have the ability to address two specific areas: determine the better, most appropriate intervention strategies given a large portfolio of mitigation activities and to do this whilst simultaneously considering a range of criteria. Combining these techniques with the evaluation process in Chapter 4 enables optimum intervention strategies to be identified which take account of climate change uncertainty. Furthermore, with the production of a Pareto front resulting from a multi-objective optimisation provides the decision maker with a range of potential solutions without weighting any criteria in advance.

Section 5.3 specifically formulates and solves the flood risk management problem as a single objective optimisation problem. This problem is then solved using a standard, single objective GA method. This section explains the methodology behind the GA and describes the approach adopted in this thesis to enable its use for a specific flood risk management problem.

Section 5.4 formulates and solves the flood risk management problem as a multi-objective optimisation problem and then explores the use of a multi-objective optimisation algorithm and highlights the advantages this can bring over the single objective GA. The differences between the multi-objective algorithm, the NSGAII, and the single objective GA are explained and again the approach used to solve a given flood risk management problem is described. In Section 5.4 a third objective was

introduced, a loss of life surrogate, in addition to the benefits in terms of risk reduction and costs. With the third objective, it is possible to investigate the effects a non-monetary criterion has on the most commonly used benefits and costs.

The inclusion of the evolutionary optimisation algorithms in flood risk management, introduces a new decision support methodology that can be used to develop optimum flood risk strategies and is summarised in the diagram in Figure 5.6.

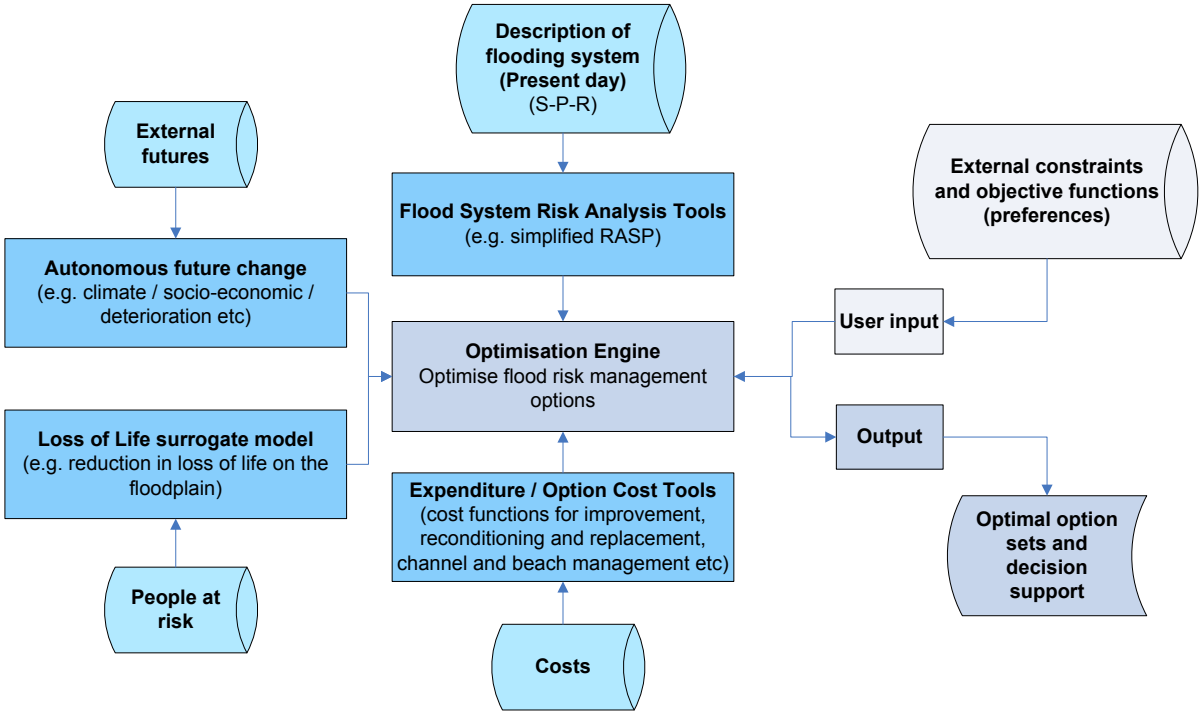


Figure 5.6 Diagram representing the decision support methodology which optimises flood risk intervention strategies according to multiple criteria

The methodology presented in this Chapter addresses two main issues stemming from the conclusions of the literature review and can help answer questions such as what intervention measures would be most appropriate, where should they be implemented and when would be the most advantageous time. The methodology also aids the decision making process providing much more insight into the characteristics of the problems and provides a range of optimal solutions for the decision maker to choose from.

The decision support methodology in Figure 5.6 is advanced further in the next Chapter. The next Chapter gives additional consideration to the future climate change uncertainties involved in the optimisation process, looking at an optimisation model to maximise expected utility and a model to incorporate flexibility by representing intervention strategies as Real Option decision trees. The use of multi-objective optimisation is clearly advantageous to help identify optimum solutions according to a range of criteria and is incorporated within the new decision support methodology described.

Chapter 6 Optimising Strategies under Uncertainty

6.1 Introduction

So far in this thesis, Chapter 3 introduces a risk analysis model, RASP, to evaluate the risk of flooding associated to different intervention measures. Modifications are provided to reduce the computational run time to enable many thousands of model realisations to be run efficiently. Chapter 4 describes a methodology to evaluate intervention strategies according to the benefits in terms of risk reduction and the costs of implementation. Measures to account for climate change variability and the inclusion of flexibility and adaptability are also discussed. Chapter 5 introduces automated evolutionary search algorithms to identify the better performing intervention strategies according to a range of criteria and to improve the decision making process. In addition to the benefits and costs, a loss of life surrogate is also considered in the evaluation process.

Chapter 6 aims to integrate the outcomes and methodologies presented in the preceding Chapters, Chapters 3, 4 and 5 to create an overall decision support methodology which identifies optimum, flexible and adaptive long term flood risk intervention strategies whilst satisfying a range of criteria to aid the decision making process.

One of the principal components of the decision support methodology is the inclusion of a range of climate change scenarios to account for uncertainty over time and to ensure the selected strategy will be robust or can adapt to any change in future climate impacts. The methodology presented so far is however limited in that it can only consider three possible climate change scenarios. In order to give consideration to a larger range of possible climate change futures in the evaluation process, Section 6.2 explores a method to sample different sea level rise outcomes. With the consideration of additional climate change scenarios, Section 6.3 investigates how the number of RASP runs can be reduced.

Section 6.4 assembles the processes from Sections 6.2 and 6.3 with the risk analysis model in Chapter 3, the evaluation process in Chapter 4 and the optimisation algorithms in Chapter 5 to develop a methodology which optimises for Pareto optimal strategies which maximise expected utility. Section 6.5 further evolves this process to include the

Real Options concepts represented as decision trees to improve the methodology and promote flexible and adaptive strategies. The optimisation of intervention strategies as decision trees is also discussed. Finally Section 6.6 provides an overview of the full decision support methodology combining the processes explored throughout this thesis.

6.2 Sea Level Rise Scenarios

As explained in Chapter 4, the evaluation process of an intervention strategy supports the UKCP09 high, medium and low emission scenarios to account for climate change variability. The approach adopted in Chapter 4 however only considers 3 future sea level rise (i.e. climate change) projections. It is more robust to consider a larger range of potential projections to avoid misrepresenting the full climate change distribution and ignoring many potential future outcomes. For this reason, this section focuses on increasing the number of projections the intervention strategies are evaluated against.

Looking specifically at the information provided by UKCP09, the data provided within the three high, medium and low scenarios include yearly predicted sea level increases from 1990 to 2100 for the 5th, 50th and 95th percentiles. Figure 6.1 shows the sea level increase of each of these percentiles for the medium emission scenario.

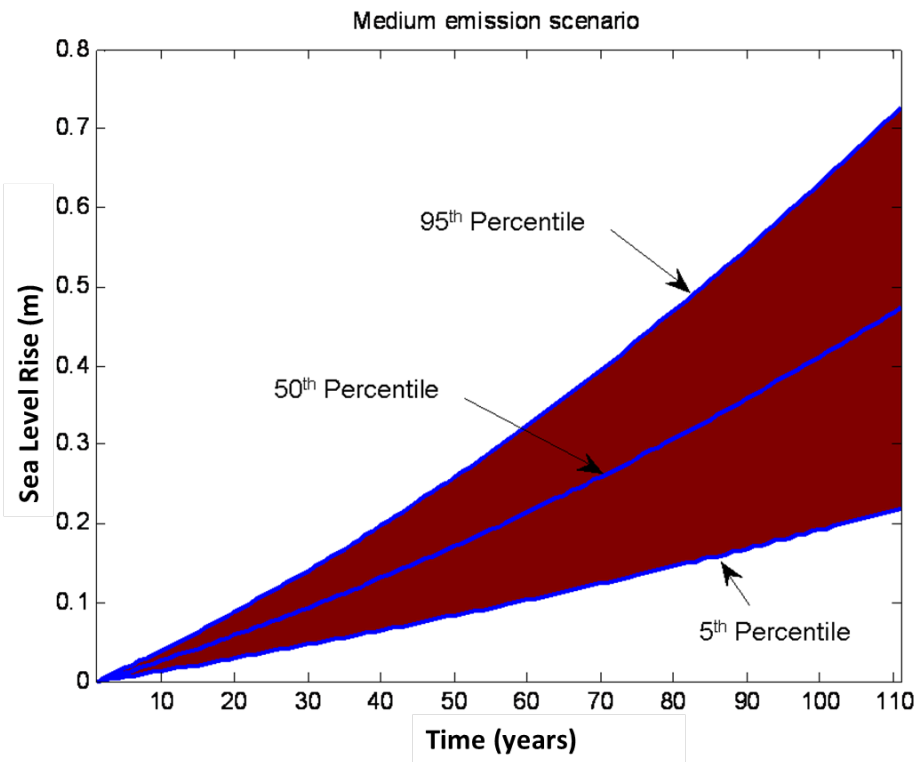


Figure 6.1 The predicted sea level rise for each year between 1990-2100 for the 5th, 50th and 95th percentile of the medium emission scenario

The 5th and 95th percentiles are at equidistance from the mean showing evenly distributed data. Given this, a normal distribution would be suitable to represent realistic sea level rise values for that scenario. The mean, μ, and the 5th and 95th percentiles, Q5 and Q95 respectively, can be obtained from Figure 6.1. With this σ can be calculated:

$$\sigma = \frac{(Q95 - \mu)}{\Phi^{-1}(0.95)} \tag{6.1}$$

For example Figure 6.2 shows the distribution of sea level rise data for the year 2030.

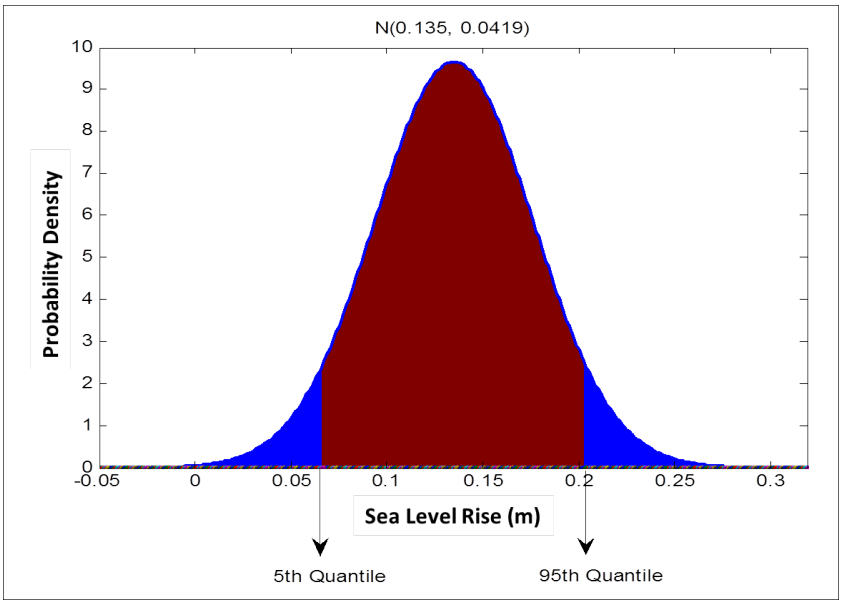


Figure 6.2 Normal distribution of sea level rise values for the medium emission scenario at the year 2030 with μ = 0.135m and σ = 0.0419m

It is then possible to sample from this distribution to produce a range of future scenarios to evaluate the intervention strategies against. To achieve a better representation of the potential future outcomes, all three UKCP09 emission scenarios should be considered. There is however no probabilistic information to suggest how all three emission scenarios can be sampled from. One method would be to produce normal distributions for each of the three low, medium and high scenarios and with a probability of 1/3 sample from the distributions. Depending upon where the distributions overlap, sampling from each with equal weighting can misinterpret the future projections i.e. looking at Figure 6.3, if the scenarios were to fall as in this example, there is a probability of a third that a sea level rise value will occur from one of the scenario lines but a very small if not zero probability that a sea level rise value will occur in between the scenarios. This does not seem very realistic.

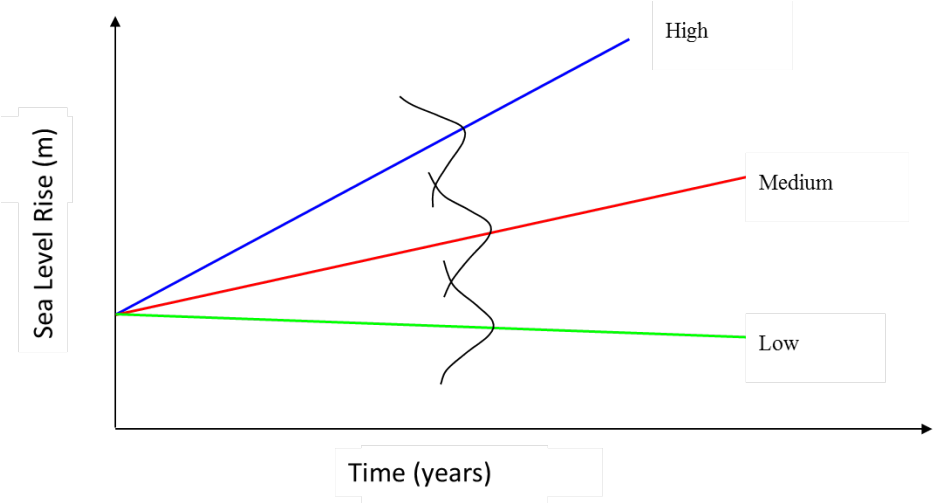


Figure 6.3 Illustration of a possible outcome of normal distributions from sampling over the high, medium and low UKCP09 emission scenarios

Therefore it is important to investigate how the three normal distributions each representing a high, medium and low scenario respectively compare. Figure 6.4 displays the three normal distributions on the same graph and it can be seen that there are no significant gaps between the peaks. This means the problem situation explained above will not occur and sampling from all three normal distributions will not disregard conceivable values.

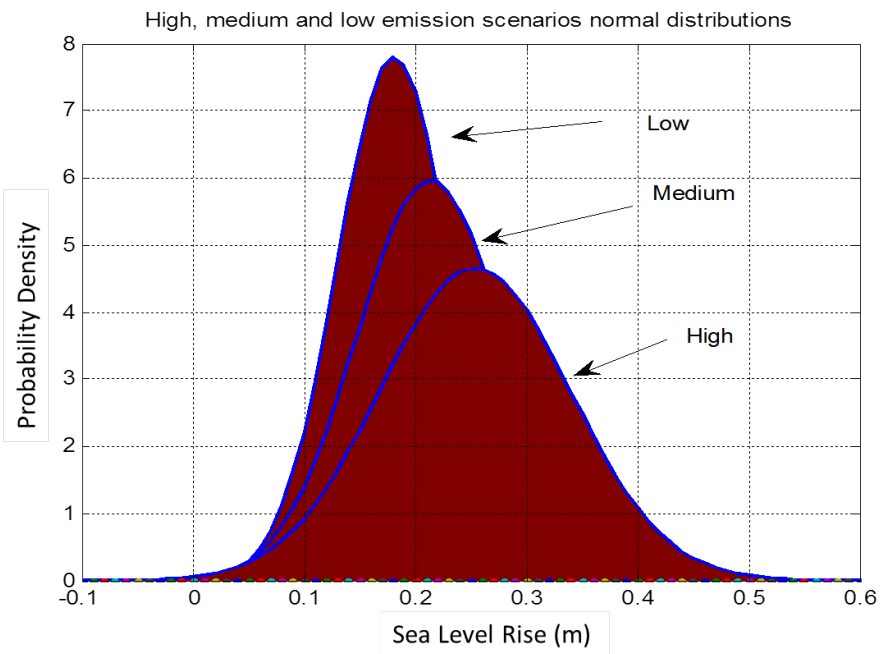


Figure 6.4 Normal distributions from the low, medium and high emission scenarios overlain on the same graph

Another potential problem with sampling from these normal distributions is that each distribution is specific to a time step. If there are no dependencies to previous time steps then the sampled future scenarios could be very erratic and unrealistic. For example, at time step one a sea level rise value of 0.8m could be sampled followed by a value of 0.2m for time step two. If at time step three the sampled value then increases back up to a value of 0.6m, a very unlikely realisation of the future is generated. Therefore sampling for multiple time steps must be dependent on the previous time step. This can be done by ensuring that for each projected future realisation, after the initial sea level rise value has been sampled, all future sampling for that future realisation occurs from the same emission scenario and the same percentile. For example, for a given future projection, if the first sea level rise value was randomly sampled from the medium emission scenario at the 80th percentile, the next sea level rise value must be sampled from the distribution of the second time step from the medium emission scenario at the 80th percentile. This process would produce a range of sea level projections each dependent on the previous time step (see Figure 6.5).

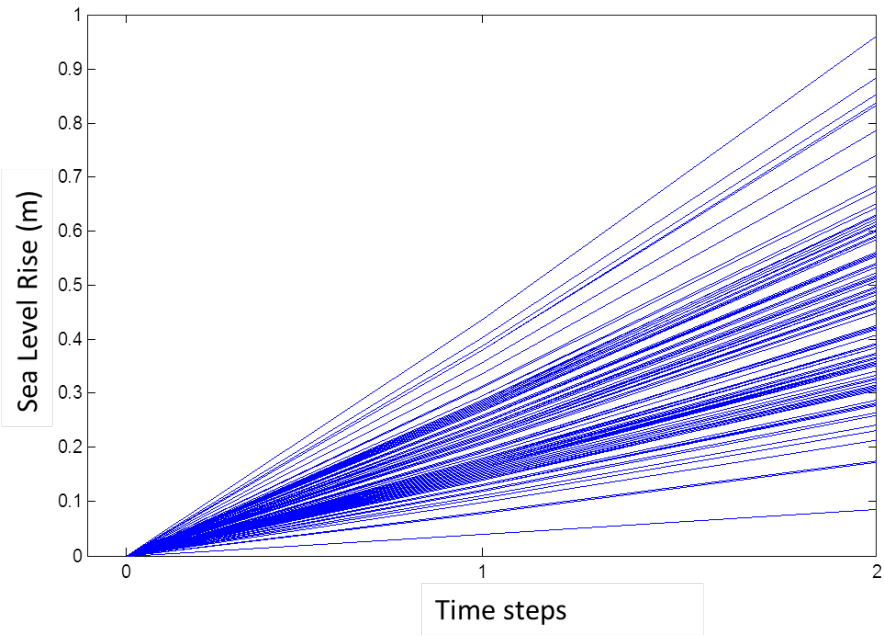


Figure 6.5 100 sea level rise projections dependent across time steps sampled from the high, medium and low emission scenarios with equal weighting

6.3 EAD vs. Sea Level Relationship

With the sampling approach described above in Section 6.2, it is now possible to sample a large range of future sea level rise scenarios and use these to evaluate intervention

strategies against in order to determine more robust and flexible solutions. However an increase in the number of sea level rise samples will result in an increase in the number of RASP runs required, consequently the less computationally efficient the methodology will become. The computational efficiency of the strategy evaluation process plays an important factor when coupled with optimisation algorithms. This section therefore investigates whether the number of RASP runs can be reduced whilst still being able to increase the number of sea level rise scenarios.

In order to reduce the number of RASP runs, a methodology is needed which can provide accurate EAD values for a given future scenario. One approach would be to establish a link between sea level rise and the outputs from RASP, if a relationship exists; the associated EAD can be calculated using this relationship. To test whether a relationship exists, the following steps were undertaken:

- Create a normal distribution of sea level rise for a given year
- Randomly sample 100 sea level rise values from the above distribution
- Set the model flood system in RASP to represent an intervention measure (i.e. raise all the defences in the flood system by 1m)
- Calculate the EAD of the flood system for each sampled sea level rise value
- Plot sea level rise against EAD to establish whether a relationship exists

These steps were undertaken for a range of different emission scenarios, different years and different intervention measures. The results in Figure 6.6 are based on the modelled flood system representing an area of the Thames Estuary (see Section 7.3) which was modified to represent a 1m height increase to all defences. 100 sea level rise values were sampled from a medium emission scenario at the year 2050 and evaluated against the modelled flood system. The resulting EAD obtained from RASP for each sea level rise value is plotted in Figure 6.6 (the squares). An exponential relationship between sea level rise and EAD is identifiable and this trend was found in all other combinations of test parameters used.

An exponential curve, $y = Ae^{bx}$, (the line in Figure 6.6) was plotted to compare against the results obtained from RASP. The constants A and b for the exponential curve were calculated using the EAD obtained from the highest and lowest sea level rise values only, using simultaneous equations. As it can be seen from Figure 6.6, the comparison of the EAD values obtained from RASP compared with the exponential curve follow a

very close fit. This was consistently found when repeating this test for different intervention measures and different sample sets (not shown in the thesis to save space).

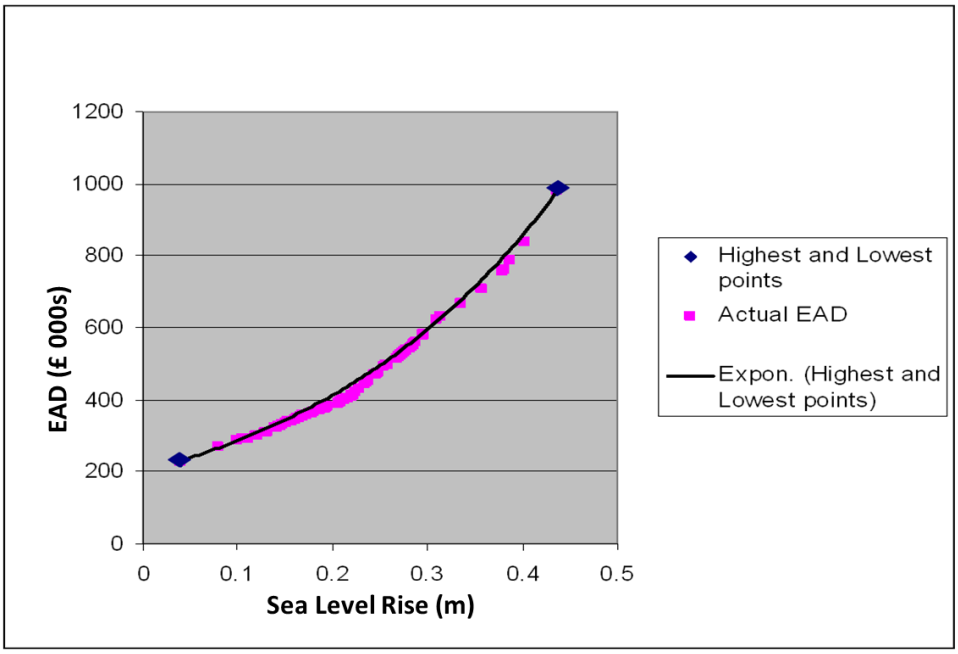


Figure 6.6 100 sea level rise samples plotted against the EAD obtained from RASP (square points) with an exponential curve (black line) fitted according to the lowest and highest sea level rise values (represented as diamonds)

Given this consistent relationship, only analysing the highest and lowest sea level rise samples from the full sample set using RASP is practical. The EAD for the remaining sea level rise samples can then be obtained from the exponential curve created by the two highest and lowest samples. The close relationship ensures the results are not compromised and a much larger range of possible climate change scenarios can be considered to account for the uncertainty without a significant increase in computational time.

6.4 Optimisation of Expected Utility Maximisation

With the sampling methodology in Section 6.2 and the EAD relationship with sea level rise in Section 6.3, it is now possible to account for a large number of potential climate change scenarios. Evaluating intervention strategies over a large range of scenarios and utilising the optimisation procedure explained in Chapter 5, an optimisation model which optimises for maximum expected utility can be created. The optimisation model can optimise for a set of robust strategies which perform well over the full range of climate change scenarios according to a set of multiple objectives as in Section 5.4.

Figure 6.7 displays an overview of the maximisation of expected utility optimisation model and the main stages it undertakes.

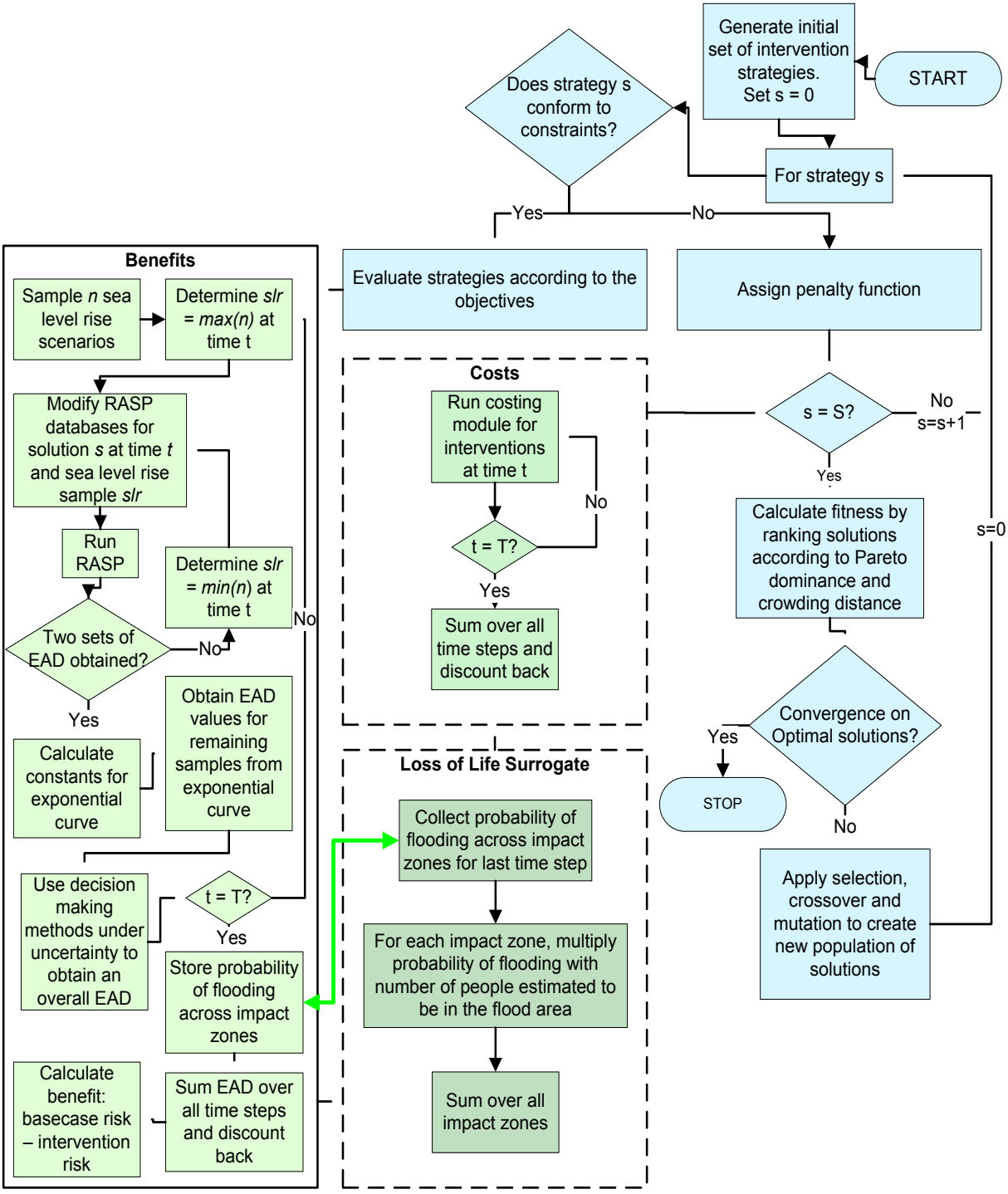


Figure 6.7 A flowchart describing the main stages of the optimisation model which maximises expected utility

The combination of objectives in Figure 6.7, the benefits, costs and loss of life are optional. Any combination of objectives can be chosen, it does not necessarily require

all three objectives to be solved for. Section 7.5.3 and 7.5.4 apply this optimisation model on the area of the Thames Estuary investigating first the trade-off between flood risk reduction and costs and secondly including an additional objective, loss of life.

6.5 Real Options based Optimisation

In addition to the optimisation model which looks to optimise maximum expected utility, with the components described in the previous Chapters it is also possible to utilise these to form a Real Options optimisation model. Rather than considering an intervention strategy as one single fixed path into the future (i.e. fixed set of interventions over the planning horizon), it is possible to represent the intervention strategy as a decision tree with multiple possible paths into the future (see Figure 6.8).

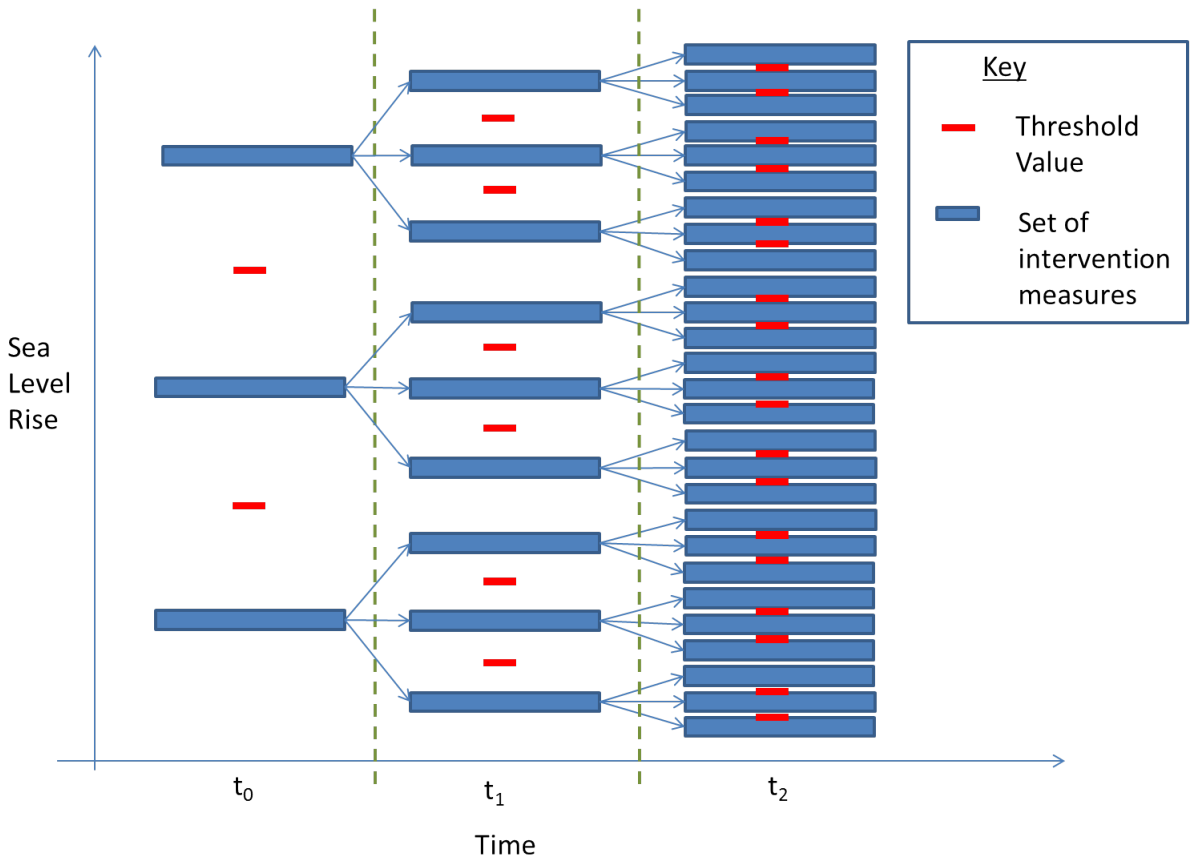


Figure 6.8 An intervention strategy as a decision tree with multiple paths into the future

The structure of the decision tree intervention strategy consists of optional paths at each time step of the planning horizon, where each path or decision node corresponds to a set of intervention measures (see Section 4.2.1 for a list of the possible intervention measures). The intervention measures coded as a decision tree inherently capture the Real Options concepts and the associated value of flexibility providing opportunities to

delay, contract, expand and even abandon investment decisions, depending on how the uncertain future actually unfolds.

The uncertainties relating to climate change are accounted for by evaluating each intervention strategy over a range of future sea level scenarios sampled from the approach explained in Section 6.2. Given a future scenario, the decision path taken is determined according to a threshold value. At each time step, if the sea level rise of a given scenario is greater than the threshold, the higher path is taken, if less, the lower path is taken. The total flood risk reduction and cost of each strategy is averaged over the paths analysed to give a total averaged flood risk reduction and cost.

The decision variables within the optimisation process not only include the intervention measures but also the threshold values as well. Optimising for the threshold values and the intervention measures to take at each time step, the model is able to inform the decision maker of the optimal path to take dependent upon the sea level rise.

As discussed in Section 4.4, the Real Options concepts promote the consideration of flexibility and adaptability within an investment. Representing a flood risk intervention strategy as a decision tree with multiple paths into the future allows Real Options to be exercised at each decision stage inherently capturing flexibility within the strategy. Each path is optimal for a given climate change output, in this case sea level rise. When more knowledge of the sea level increase comes to light the most appropriate Real Option or decision path can be selected. Furthermore, future decisions can be planned based on previous stages.

Given the severe uncertainty facing flood risk management, the requirement for flexibility and the opportunity to adapt when more knowledge is available is important. The use of decision trees as in Figure 6.8 which can inherently capture the Real Options concepts is therefore very appropriate. Through this methodology, the capability to evaluate flexibility and thus allow decision makers to consider adaptive options is provided. Furthermore, coupling the decision tree approach with optimisation will aid decision makers in determining the most optimal set of intervention strategies which are flexible, adaptive and therefore robust to the future uncertainties of climate change.

To represent intervention strategies as Real Option decision trees within flood risk management many of the main stages from the optimisation framework which maximises expected utility can be utilised and the overall outline of the process

involved can remain the same. For example, the new methodology will still generate different options and optimise to find the better performing strategies, evolving the population over time. It is necessary however to make some modifications to the components to support the Real Options decision tree. Sections 6.5.1, 6.5.2 and 6.5.3 discuss the modifications to the framework to incorporate the changes required, providing details on the evaluation of the decision trees and the approach adopted in this thesis to optimise for decision tree intervention strategies.

6.5.1 Problem Formulation

Similar to the problem formulated in Section 5.4.1, the overall aim of the Real Options based approach is to optimise to determine the better performing long term flood risk intervention strategies. The differences lie in the structure of the intervention strategies, with the aim in this case to incorporate flexibility inherently within the strategy using multiple decision paths. The problem description using the Real Options decision tree optimisation model is therefore to find a vector $X^* = (x_1^*, x_2^*, ..., x_n^*, T_{h_1}, ..., T_{h_w})$ which optimises $f(x) = [f_1(x), f_2(x), f_3(x)]$ where $f_1(x)$, $f_2(x)$ and $f_3(x)$ are defined by equations 5.5, 5.6 and 5.7 respectively, T_h represents the threshold values which determine the path through the decision tree and w represents the number of thresholds required. The vector of decision variables will contain an increase in options due to the numerous possible paths and the inclusion of the thresholds; this is described in more detail in Section 6.5.2.

The final output of the optimisation process is a Pareto front of optimal intervention solutions represented as decision trees with thresholds determining the optimal route through the decision tree given a particular sea level rise. The evaluation of an intervention strategy in this format is explained in Section 6.5.3.

6.5.2 Solution Coding

The chromosome representation differs from that described in Section 5.3.3 as the solution now considers multiple decision paths and threshold values. As in Section 5.3.3 a chromosome represents an intervention strategy which is made up of genes to correspond to the options being implemented. The vector form of a chromosome X^* is a sequence of genes which have varying combinations of intervention measures for a given location, time and decision path as well as threshold values for path selection such that $X^* = (x_1^*, x_2^*, ..., x_g^*)$ where g equals the total number of genes in the chromosome.

Figure 6.9 provides an example of how a chromosome is coded as a decision tree. The chromosome in this example represents a solution with two time steps and at the second time there are two optional paths. The threshold value is also included to determine which path to take at that time step. G represents the number of defence groups considered, two intervention options are available for consideration including structural measures and defence maintenance. As in the solution coding of an intervention strategy with a single path into the future, the intervention measures in the gene can represent a variety of different possible options which are described in Table 5.1.

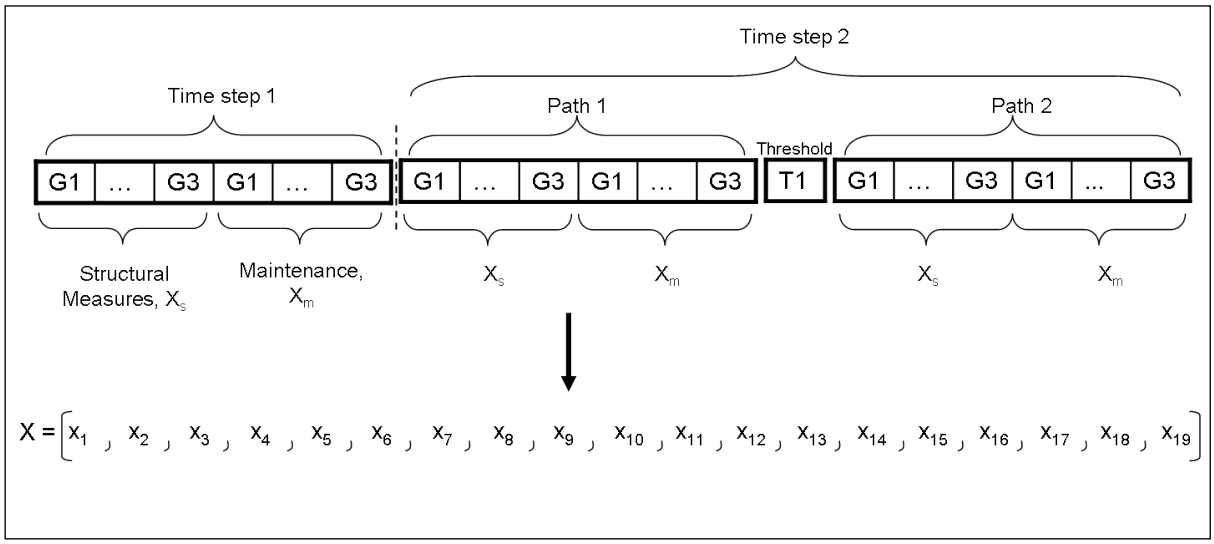


Figure 6.9 An example of a decision tree coded chromosome

Constraints are placed on the selection of genes for different paths and time steps. Firstly, the options for a given time step must be incremental on the previous time step (to ensure solution adaptability) and secondly, interventions considered for different paths in a time step must show a decreasing amount of options from top to bottom of the tree, i.e. the top path must have a greater or equal number of interventions occurring than the optional path below (again, to ensure adaptability of the solution obtained).

In addition to the genes representing intervention measures, there are also genes within the chromosome to correspond to threshold values. A threshold value is required for every decision on the selection of a path and represents a possible sea level rise value at that time step. The threshold values are sampled from normal distributions of sea level rise values from UKCP09 for each time step.

6.5.3 Fitness Evaluation

The fitness of a Real Options decision tree intervention strategy is calculated similar to the multi-objective optimisation problem discussed in section 5.4.3 where the benefits, costs and loss of life are all considered individually rather than combining each criterion into a single objective. With the values obtained for each of the three objectives, the NSGAII Pareto ranking method is then used as well as the crowding distance calculation to provide an overall fitness score for a given strategy.

The calculation of the three objectives differ slightly from the calculations used in the maximum expected utility optimisation model. The objectives now need to calculate the benefit (flood risk reduction), cost and loss of life of a strategy over a decision tree with multiple possible paths rather than a fixed single path. In the new approach, for each sea level rise sample, the route through the decision tree is determined according to the threshold values and sea level rise estimates of the sample at each time step. The benefit, cost and loss of life are evaluated for this path and sea level sample according to the benefits defined in equation (4.1), the costs defined in equation (4.6) and the loss of life surrogate in equation (5.9).

With a flood risk reduction, cost and loss of life value assigned to each sea level rise sample and its associated path, an overall average can be obtained for the full decision tree strategy by simply averaging over all the objective function values associated with each sample (see Figure 6.10). With an overall value for the flood risk reduction, cost and loss of life objectives, the NSGAII can rank the solutions according to these objectives and provide a fitness value for the solution. Other decision making methods under uncertainty can be utilised here to obtain the overall values for each criteria, for example rather than calculating an average, the worst case scenario can be used.

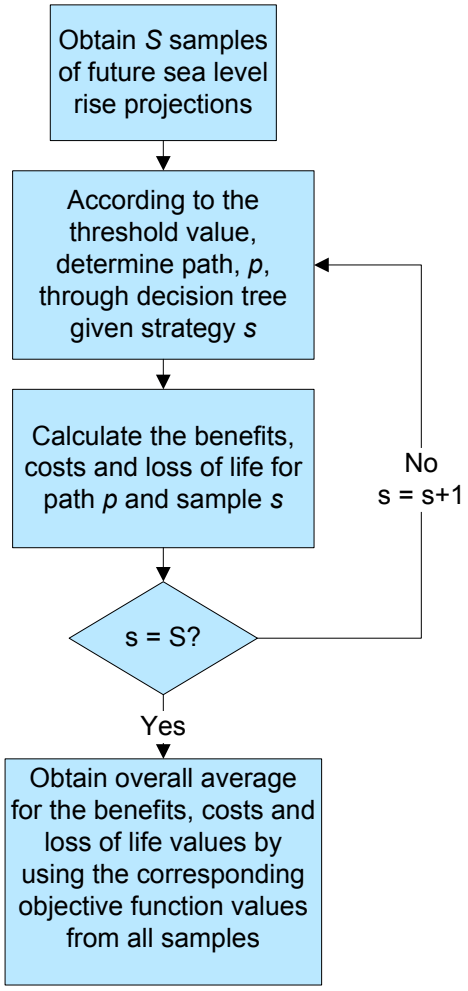


Figure 6.10 Flowchart describing main stages of the fitness calculation process for a decision tree evaluation

6.6 Computational Resources

The methodology presented in this thesis was written in C# to test and verify the concepts. SQL databases were used to store the information on the flood risk area and used to link the data to the risk analysis model. Initial simulations of the risk analysis model in Chapter 3 were undertaken on a standard spec windows laptop with a 1.8 GHz CPU and 1.5 GB RAM. With the inclusion of optimisation methods into the methodology and therefore the requirement to run thousands of simulations of the risk model, distributed computing resources were used. A parallel processing software, Condor, was used to evaluate a generation of different intervention strategies in parallel. The main application ran on a standard spec windows laptop with Condor queuing, executing and returning jobs automatically across idle network computers, again of standard spec. Cloud computing was also used, where a high CPU windows virtual

image with a SQL instance was created to run the methodology. The high CPU machine was able to run evaluations in parallel across its multiple cores.

6.7 Summary

In this Chapter, consideration is given to the climate change uncertainties present in flood risk management. Section 6.2 describes a methodology to generate a large range of potential future sea level rise projections which can be used to assess how intervention strategies perform under these possible futures. Evaluating intervention strategies over a large range of sea level rise samples increases the computational time due to the additional RASP runs required. Section 6.3 addresses this by providing a method to minimise the number of RASP realisations taking advantage of the relationship between sea level rise and the RASP output in EAD. Combining these methodologies with the approaches presented in Chapters 3, 4 and 5, a maximum expected utility optimisation model can be created, as explained in Section 6.4. This optimisation model is able to optimise for an intervention strategy which performs well over a wide range of possible futures and is optimal according to a range of multiple objectives. Section 6.5 takes this model further my incorporating flexibility inherently within the intervention strategy by structuring the strategy as a decision tree. The problem to be solved for this approach is formulated in Section 6.5.1 while Sections 6.5.2 and 6.5.3 detail the main stages which occur within the Real Options decision tree model and also how they differ from the optimisation model which looks at expected utility maximisation.

This Chapter essentially provides a decision support methodology which aids the development of long term flood risk management intervention strategies which are flexible, can adapt to a changing climate but are also optimal according to a range of criteria. It provides decision makers with the opportunity to value flexibility within the creation of potential options allowing for adaptability. The next stage of this thesis is to test the methodologies and the newly developed decision support system on various case studies. Chapter 7 investigates the use of Real Options, single and multi-objective optimisation techniques, the expected utility optimisation model and the Real Options based optimisation model on an area of the Thames Estuary in London.

Chapter 7 Case Study: Thames Estuary

7.1 Introduction

In this chapter, the methodologies presented throughout this thesis are tested and verified on an area closely resembling the Thamesmead flood area on the Thames Estuary. Section 7.2 introduces the specific area of interest and provides a background to the Thames Estuary. Section 7.3 undertakes tests comparing Real Options against the traditional NPV approach. Section 7.4 investigates the use of single objective optimisation and then compares the results to the manually chosen strategies from Section 7.3. Section 7.5 introduces multi-objective optimisation considering two and three objective applications to single and multiple future scenarios. Finally Section 7.6 tests the decision tree Real Options approach for multiple objectives and compares the solutions to those obtained in Section 7.5. The results are summarised in Section 7.7.

7.2 Introduction to the Thames Estuary

The Thames Estuary in London (Figure 7.1) is an area that is susceptible to flooding. A large scale flood event could have a devastating impact as it accommodates over a million residents and workers, 500,000 homes and 40,000 non-residential properties (Environment Agency, 2009a). In addition to the number of people who live and work on the floodplains, the floodplains are also home to institutional and business centres, heritage sites, numerous schools, hospitals, power stations and major transport links. The assets and number of people at risk in the tidal Thames floodplain include (Environment Agency, 2009b):

- 350 sq km land area
- 55 sq km designated habitat sites
- 1.25 million residents (plus commuters tourists and other visitors)
- Over 500,000 homes
- 40,000 commercial and industrial properties
- £200 billion current property value
- Key Government buildings
- 400 schools
- 16 hospitals

- 8 Power stations
- More than 1000 electricity substations
- 4 World Heritage sites
- Art Galleries and historic buildings
- 167km of railway
- 35 Tube stations
- 51 Railway stations (25 mainline, 25 DLR, 1 International)
- Over 300km of roads

The threat of flooding on the Thames Estuary occurs from a number of different sources, including high sea levels and surges propagating from the North Sea into the Estuary and extreme fluvial flows along the Thames and its tributaries. A surge tide entering the Thames estuary can increase the water levels by over 1m and can be a major flood threat especially if this coincides with the 'spring' tide when normal tide levels are higher (Environment Agency, 2009b). The floodplains at threat from flooding are highlighted in Figure 7.1.

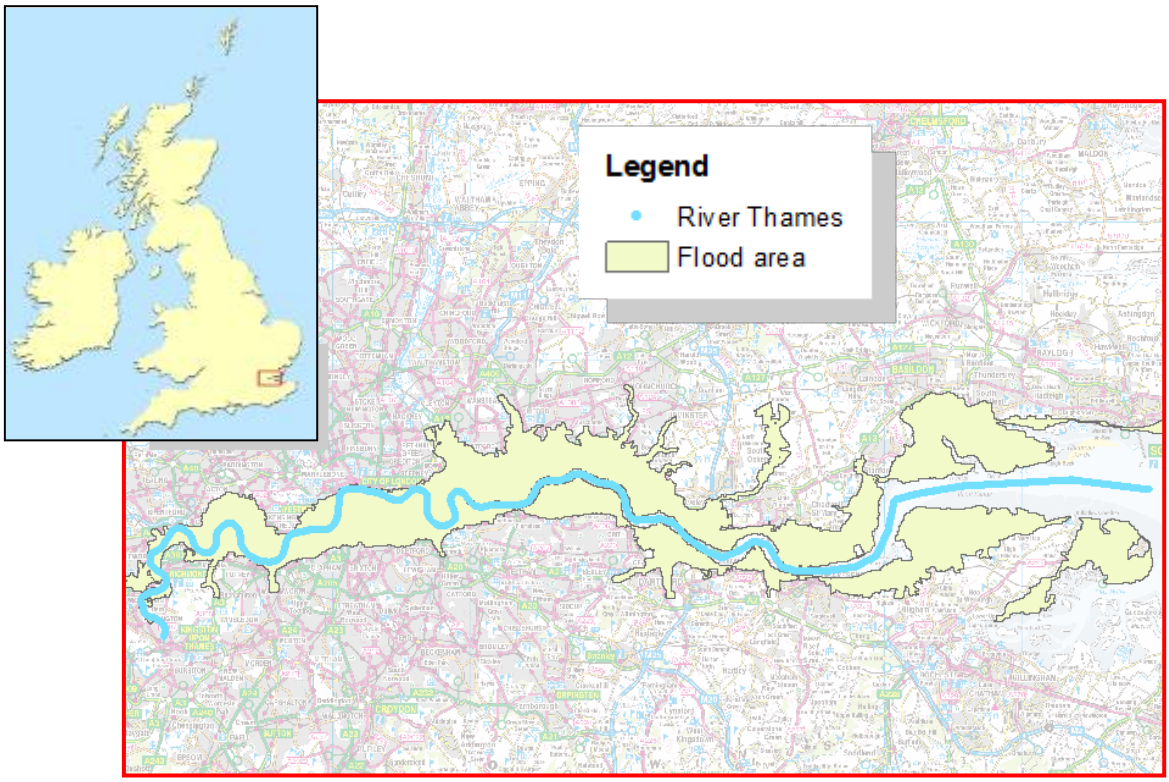


Figure 7.1 Location and map of the Thames Estuary in London, UK

Protection against flooding is provided by a range of fixed defences and actively operated barriers and flood gates. The Thames tidal flood defence system is made up of the Thames Barrier and eight other major flood barriers. It also includes 36 industrial flood gates, more than 400 smaller moveable structures and over 330km of walls and embankments (Environment Agency, 2009b). The majority of the defences were designed to protect against a 1-in-1000 year flood however, at the present day these flood defences are gradually deteriorating. In the longer term, with the potential impacts of climate change, the need to consider a range of intervention measures is evident. It is however recognised in the planning for the future of the Thames Estuary that the decisions made today can impact the ability to adapt in the future. It is important to ensure that the flood management system put in place does not become a burden for future generations but is adaptable to any changes faced (Environment Agency, 2009b). For example, if it is likely that there will be a requirement to raise, move or adapt flood defences, it is necessary to ensure that space is provided now to allow for these changes in the future. With this, the Thames Estuary is a very suitable case study to investigate the use of the Real Options concepts and optimisation methods provided in this thesis for flood risk management.

For computational reasons, the case studies presented in this Chapter do not focus on the full Thames Estuary. Instead, application of the methodologies presented in this thesis focus on a specific flood area, an area resembling the Thamesmead area of the Estuary (see Figure 7.2). This area contains 79 defences which have been classified into 5 groups according to defence characteristics (e.g. Defence Type and Condition Grade) and location. The 5 groups consist of a range of defence types including brick and masonry and sheet pile vertical walls, and rip-rap and rigid embankments. Figure 7.2 displays the floodplain of interest in the Thamesmead area protected by the 5 groups of defences and indicates the present day risk in EAD at each of the impact zones in the flood area.

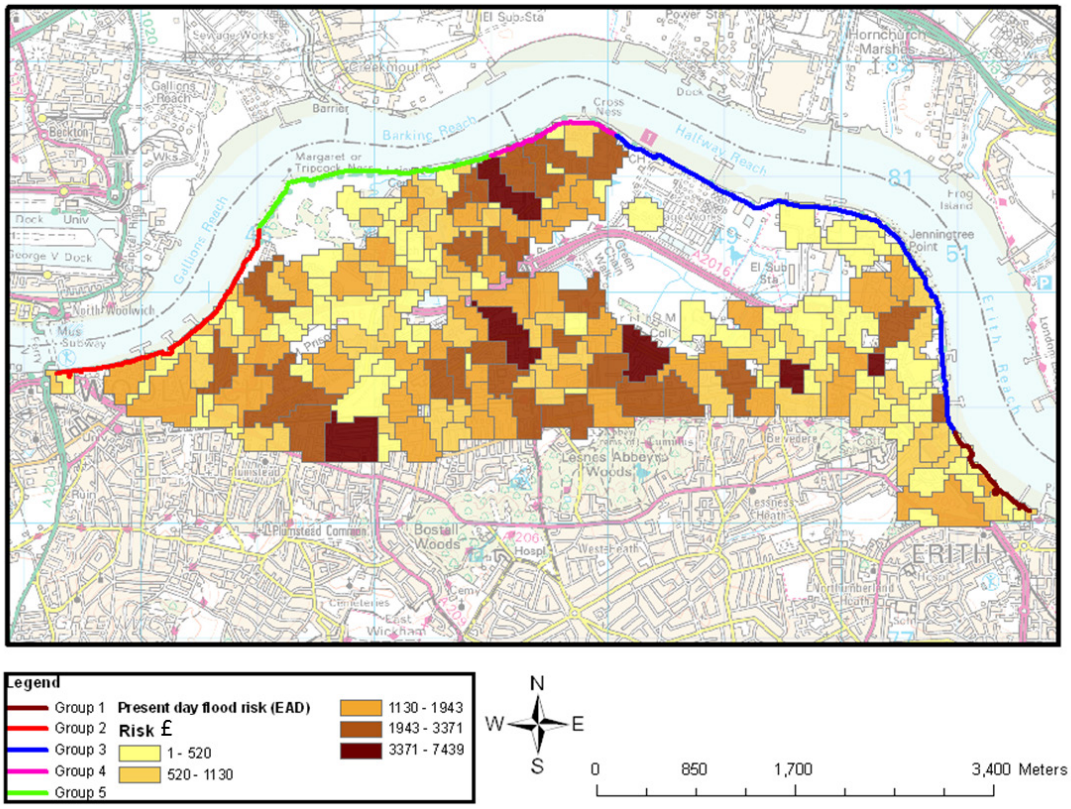


Figure 7.2 The present day flood risk to the flood area of interest with the 5 groups of defences protecting the floodplain

7.3 Case 1 – Comparison of Real Options against a traditional approach

In this case study, a comparison of the Real Options approach against a traditional approach is undertaken. It is assumed from the outset that all the defences in the Thamesmead area of the Thames Estuary are beyond economical repair and refurbishment is required. Four intervention strategies have been proposed to improve the current state of the defences but also to reduce flood risk over the next 90 years, these are summarised in Figure 7.3. The first of the four strategies, strategy A, is based on the Real Options concepts and naturally incorporates a level of flexibility to account for climate change uncertainty. Strategies B and D represent traditional approaches where the strategy is fixed over the planning horizon, i.e. when the capital type work is defined upfront. These strategies are based on a projected deterministic sea level rise for the full duration of the planning horizon. Finally, strategy C applies flexibility within the planning stages but does not purchase the flexibility upfront, i.e. flexibility is not inherently designed within the strategy, rather the flexibility is included within the decision to implement a given intervention measure. Figure 7.3 details the specific

interventions being applied for each strategy and the timing of implementation. In all strategies two intervention measures are considered, raising the crest level and increasing the defence's capacity for expansion if required.

Strategy A is represented as a decision tree with multiple, optional paths into the future. At the first time step, during refurbishment, the structure undergoes significant modifications, the crest level remains at the current level, the modified structure does however, incorporate the capacity to increase the level of protection (i.e. raise the crest level) in an efficient manner in the future. By expanding the footprint of the structure flexibility can be incorporated. This provides the opportunity to increase the height of the defence at a future point in time if a change in the climate requires, for example the sea level rises. At 2040, the defences are raised, with the increase determined by a given climate change scenario. For this strategy, there are three possible paths to take on the decision tree at 2040. If a high increase in sea level rise occurs (represented here by the high emission scenario) the top path is taken. Similarly, if a low sea level rise is seen (represented here by the low emission scenario), the bottom path is taken. If the sea level rise is in between, the middle path is taken (represented here by the medium emission scenario). This allows for flexibility in the strategy, determining the better mitigation activity according to the future outcome. For reasons of simplicity, the structure of the decision tree considered here differs from the structure in Section 6.5 and Section 7.5. Threshold values have not been included to determine the path to take as the evaluation only considers three defined scenarios which each have a preset path. The concept however remains the same and the demonstration of flexibility inherently designed into the strategy is still illustrated.

Strategy B raises the crest level at 2010 during refurbishment, making an assumption about the height increase before the future uncertainty is known. If the current structure cannot support the raise in crest level the footprint of the structure will also be modified (e.g. the width will be increased). In this case study, three strategies to represent B are used. Strategy B_l assumes a low emission scenario will occur and therefore predefines the crest level increase to support this future outcome. Strategy B_m assumes a medium emission scenario will occur, widening and raising the defences to reflect the medium emission scenarios sea level rise and finally strategy B_h assumes a high emission scenario will occur and therefore widens and raises the crest level to reflect this emission scenario.

Strategy C applies major refurbishment but maintains the current geometry and level of protection at the present day (2010) with the aim to bring the defences back to working condition. At 2040 the defences are then raised and widened with the width and height increases determined by the sea level rise scenario at that time step. Essentially, the strategy delays any structural changes until the future outcome is known.

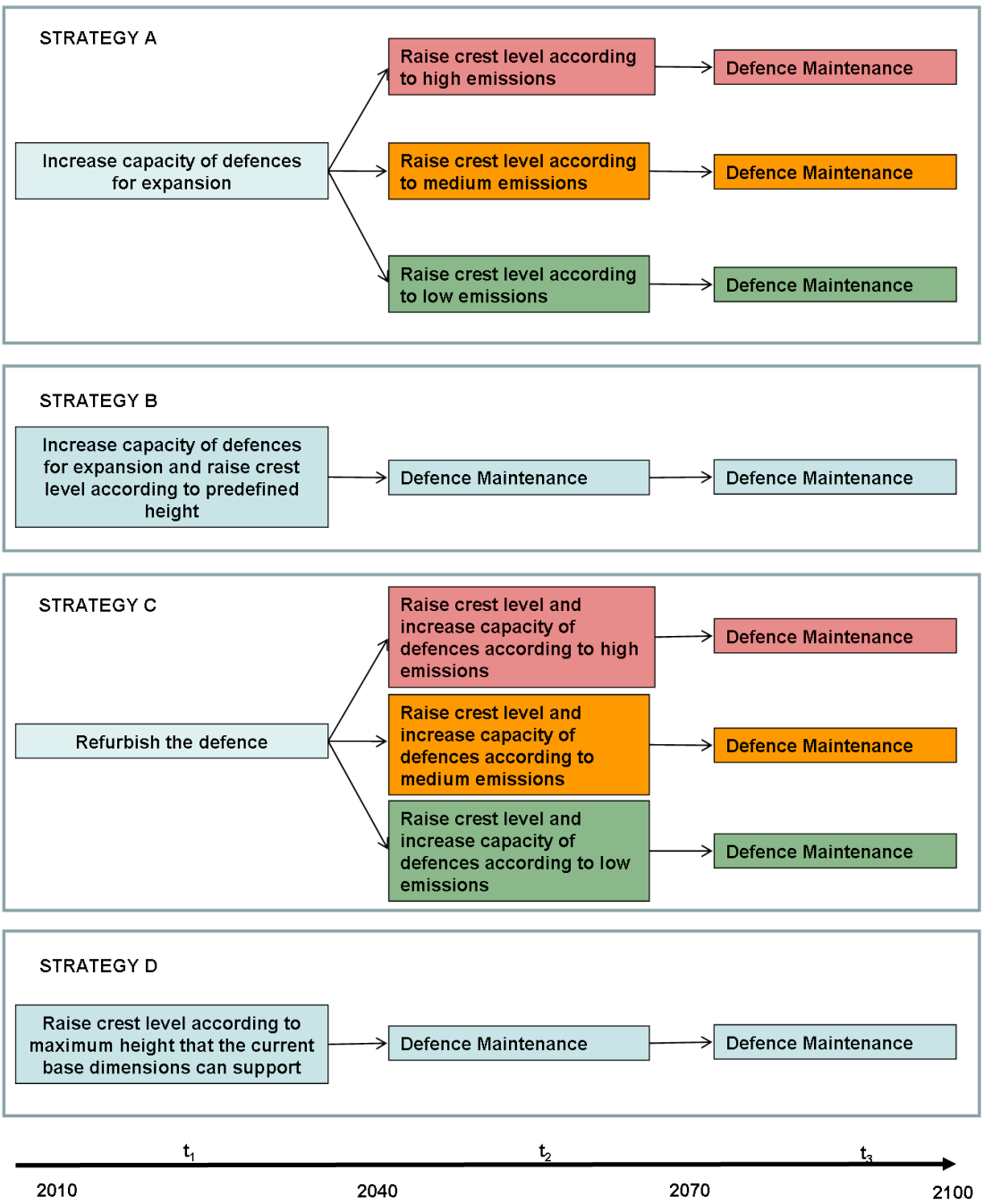


Figure 7.3 Diagram of the intervention strategies applied to the flood area and the associated timeline

Finally strategy D only raises the crest level of the defences at the present day (2010), up to a maximum height supported by the existing base. No flexibility is incorporated to enable further increase in the level of protection made.

In all strategies, the intervention measures are only considered for two epochs, at 2010-2040 and 2040-2070, to demonstrate the concepts and principles of Real options analysis. In practice, however, the Real Options approach does not constrain the number of epochs or intervention measures, and additional epochs and intervention measures can be incorporated (see Section 7.6).

The strategies in this example are compared in terms of flood risk reduction (benefits) and costs using the evaluation process explained in Chapter 4. A 'do nothing' option has also been implemented where no active interventions occur throughout the life time of the strategy. The strategies are analysed according to three different discount rates to investigate the sensitivity this has on the intervention strategy. The three discount rates used include the declining discount rate in the Green Book (HM Treasury, 2003), a more conservative rate of 1.4% based on the Stern review (see Section 4.2.4) and a higher rate of 5%.

Each strategy including the 'do nothing' option are analysed over a range of emission scenarios to represent the climate change uncertainty. This is characterised here by considering how each strategy performs over the low, medium and high emissions scenarios from UKCP09 (Murphy et al., 2009). In strategies A, B and C the height increase to be applied for a given emission scenario is equal to the predicted sea level rise of that scenario for the 50th percentile in 90 years time (the end of the strategies life).

Figure 7.4 displays the risk profile for Strategy A, B_l, B_m, B_h, C and D averaged against each of the three climate change emission scenarios. Strategy B, in all three cases, reduces the risk considerably from the outset as the crest levels of the defences are raised and the footprint of the structure increased during refurbishment regardless of the future scenario. The risk does however begin to increase towards the end of the planning horizon which is most noticeable for B_l as the defences are not protected in this situation. The lowest risk for B is obtained under strategy B_h as the defences are built for a larger impact on sea level rise.

The risk profile of strategy A and C do not see such an immediate improvement in EAD. For strategy A, the present day interventions involve widening the base during refurbishment, this reduces the risk compared to the 'do nothing' option as the condition of the defences have been improved. The full benefits are not obtained until the defences are increased at 2040. The height increase is determined by the scenario being evaluated (e.g. high, medium or low) and are therefore suitable for the given future outcome that occurs. The increase to the defence foundations has provided the opportunity to adapt the defences accordingly when more about the future is known. Strategy C follows the same risk profile as Strategy A, as the defences are maintained at the beginning improving the condition of the defences. At 2040 the height and width increases are undertaken according to the sea level rise at that time and are therefore obtaining the same risk reduction as A.

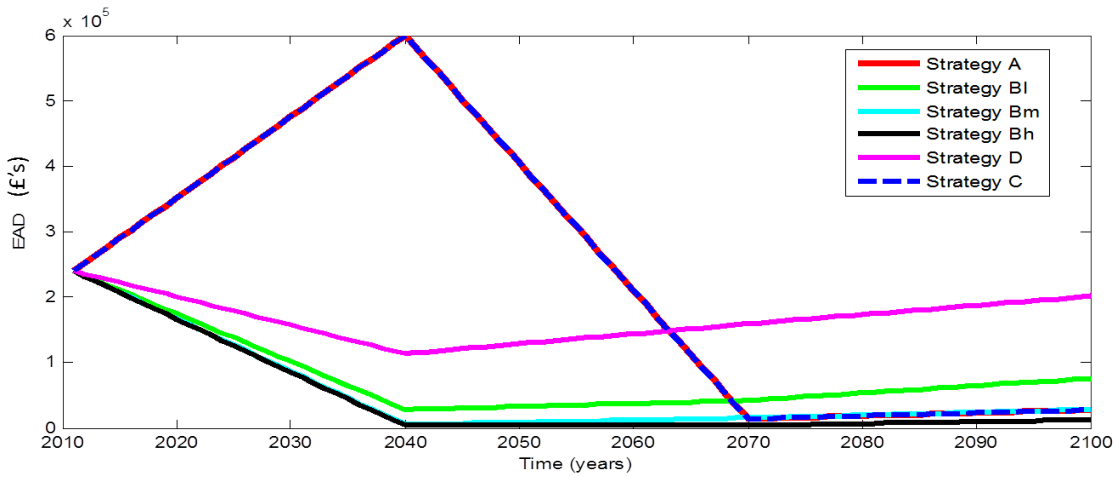


Figure 7.4 Risk profile of Strategy A averaged over all three scenarios compared to Strategy B evaluated individually over the three scenarios

Looking at strategy D, this strategy does not increase the capacity of the defence to allow for further expansion. In the first time step, a height increase is applied which is determined by the maximum amount that the current base dimensions can support. The maximum height varies between the individual defences according to their dimensions. The calculation to determine this height is based on an assumption that the base can support a height up to 1/3 of the bases length. With this approach, strategy D provides an initial reduction in risk but as the future unfolds, the defence cannot provide sufficient protection from the increases in sea level rise and the risk therefore increases significantly (see Figure 7.4). Without increasing the capacity of the defence, a

sufficient height increase cannot be implemented which maintains a level of protection against any increase in sea level rise, the options are limited for this strategy.

Table 7.1 Summary of the performance information of the intervention strategies under an uncertain future using the Green Book declining discount rate

Strategy	Scenario	Benefit (£M)	Cost (£M)	NPV (£M)	BCR
A	Low	61.41	20.87	40.54	2.94
	Medium	62.05	21.00	41.05	2.95
	High	65.94	21.16	44.78	3.12
	Average	63.13	21.01	42.12	3.00
B_l	Low	67.50	27.71	39.79	2.44
	Medium	67.36	27.71	39.65	2.43
	High	66.89	27.71	39.18	2.41
	Average	67.25	27.71	39.54	2.43
B_m	Low	69.11	28.02	41.09	2.47
	Medium	69.09	28.02	41.07	2.47
	High	68.80	28.02	40.78	2.46
	Average	69.00	28.02	40.98	2.46
B_h	Low	74.29	28.37	45.92	2.62
	Medium	74.28	28.37	45.91	2.62
	High	74.23	28.37	45.86	2.62
	Average	74.27	28.37	45.90	2.62
C	Low	61.41	31.81	29.60	1.93
	Medium	62.05	31.96	30.09	1.94
	High	65.94	32.13	33.81	2.05
	Average	63.13	31.97	31.16	1.97
D	Low	65.96	27.15	38.81	2.43
	Medium	66.80	27.15	39.65	2.46
	High	70.83	27.15	43.68	2.61
	Average	67.86	27.15	40.71	2.50

Table 7.1 displays the benefits, costs, NPV and BCR for each of the intervention strategies across the different future scenarios when using the Green book discount rate.

From this table it is possible to compare each of the four strategies in terms of the economic measures.

Firstly comparing strategy A with strategy B, strategy A is flexible and allows the strategy to evolve and adapt as knowledge of the future outcome becomes available. Strategy B instead makes an assumption about which future scenario will occur then widens and raises the height of the defences at the present day to protect against this assumed future scenario. Looking at the benefits attributed to strategy A, it can be seen that these increase as the sea level increases (e.g. for a low emission scenario the benefit achieved equals £61.41m which increases to £65.94m for a high scenario). Comparing this to Strategy B_l the benefits for each scenario decrease as the sea level rises (e.g. from Table 7.1 the benefit reduces from £67.50m for a low scenario to £66.89m for a high scenario). This is because in strategy B_l an assumption is made from the outset that a low emission scenario will occur and thus provides protection to account for the predicted low sea level rise scenario only. If a medium or high scenario in fact occurs, sufficient protection will not be provided and the benefits will decrease (the risk will increase). This will in turn lower the average NPV. Strategy A on the other hand has the ability to ensure an appropriate height increase has been implemented given the future outcome. For example, if a low scenario occurs, a minimal height increase can be implemented reducing the necessary expenditure, whereas if a high scenario occurs, a large height increase can be implemented giving additional benefits from an increasing sea level.

The NPV for strategy A averaged across all scenarios is equal to £42.12m compared with strategy B_l averaged over all three scenarios as £39.54m. This gives a 6.13% improvement for strategy A over B favouring the flexible approach.

Looking now at strategy B_m, this strategy assumes from the outset that a medium emission scenario occurs and therefore provides protection given the predicted sea level rise under this scenario. Similar to B_l, this is again a fixed predefined strategy and is not adaptable for a change in the assumed future outcome. Therefore this strategy can leave the defences with insufficient protection if the high scenario in fact occurs as seen through the reduction in benefits from a medium scenario at £69.09m to a high scenario at £68.80m. In addition, it can also incur a larger cost than necessary if the emission scenario is not as severe as first predicted (i.e. the low emission scenario occurs). Adequate protection for a low scenario in this instance costs £27.71m however

assuming a medium scenario requires an expenditure of £28.02m. Under a low scenario, the traditional strategy will however achieve a high benefit compared to that of the Real Options solution as it is protected for a higher increase in sea level rise. The extra costs required to undertake the larger intervention options will lower the overall NPV and in this case resulted in the Real Options solution being more favourable (the averaged NPV across all three climate change scenarios equals £40.98m for B_m, which is again lower than Strategy A).

Finally, analysing strategy B_h, this strategy assumes the high emission scenario will occur and thus provides the highest increase to the defences. Essentially this strategy protects against the worst case scenario. Under any emission scenario a high benefit can be obtained as seen in Table 7.2. However, this strategy also incurs large costs to implement the high interventions which can be unnecessary if the scenario is not as severe as initially expected (e.g. if the low and medium scenarios occur). In comparison to Strategy A the average cost over the three climate change scenarios for B_h is 25.02% higher. Given this, the average NPV is however higher than strategy A at £45.90m due to the initial benefits gained from implementing the interventions at the present day across all scenarios. As can be seen later on in this Chapter, the discount rate plays a large role in the calculation of the NPV and different outcomes are possible under different discount rates (for example see Table 7.3 where the opposite can be found). In this example, although the NPV favours strategy B_h, the BCR favours strategy A.

Given the uncertainty present in the outcome of the future climate and its impact, determining an appropriate height increase for the defences in advance which will provide adequate protection, regardless of the future outcome, whilst being economically efficient, is ambitious. However, the flexibility in delaying the decision to determine which height increase is most appropriate is not enough, as can be seen through the comparison of strategies A and C. Both strategies delay the decision to increase the height of the defence until more is known about the future sea level rise and in doing so obtain the same EAD reduction (see Table 7.1). However the cost to achieve this is significantly different, with strategy C having a 34.28% higher cost incurred. This difference between the two strategies is due to how the flexibility is used. Strategy A spends more money upfront to inherently capture flexibility within the design of the defence, it has taken the opportunity to increase the capacity of the defence during refurbishment. Although this requires more money to be spent upfront, the flexibility

achieved returns a better investment in the long term. Essentially, strategy A has purchased an 'insurance policy'. Strategy C does not buy this 'insurance policy' and only spends the money to refurbish the defences. As the future unfolds and further interventions are required, the additional money to modify the defence and increase the width is much larger because the defence does not have the flexibility inherently designed. Thus showing the advantages of the Real Options concepts and the opportunity to spend more upfront to increase the design flexibility. Purchasing an 'insurance policy' upfront to design and increase flexibility within the flood defences enables an economically efficient investment which provides protection from an uncertain future.

If the future outcome is known in advance, there is no value in having flexibility. There is no need to spend additional money upfront to account for an uncertain future when it is known how the future will unfold. However, for flood risk management it is not known how the future will unfold. Climate change is uncertain and as shown from Table 7.1, if the future outcome is unknown it is often more favourable to take a flexible approach and adapt accordingly or delay the irreversible investment until more is known about the future uncertainties. This has been shown through the comparison of strategy A with inherent flexibility compared to strategies B, C and D. The average NPV for strategy A is higher than strategies C and D as well as the low and medium scenarios of B. Furthermore, in all emission scenarios strategy A has a higher BCR of 3.00. If the future scenario changes from the assumed course the inclusion of flexibility becomes of high value. Therefore, having the means to value and consider this flexibility is advantageous for flood risk management.

From this case study it can be seen that the Real Options approach can be beneficial in the development of flood risk intervention strategies. It provides the opportunity to evaluate and value flexibility within an investment decision, which in a highly uncertain environment such as flood risk management can be advantageous. It has been demonstrated that the introduction of Real Options in flood risk management can enhance the methods to appraise investment decisions to account for future uncertainties and thus consider adaptive options. It is however important to note that a strategy which captures the Real Options concepts is not always necessarily the best option to take (for example, when comparing the NPV of B_h and A in Table 7.1). Whether this is the case or not, this case study has shown that Real Options gives decision makers a

means to value flexibility. Having the opportunity to consider flexible, adaptive strategies as well as more traditional strategies will further ensure the most appropriate options will be discovered.

The effects of using different discount rates are now investigated in this case study to see the impact it has on the decision making process. The analysis below is undertaken for a lower discount rate of 1.4% and a higher rate of 5% compared to the declining discount rate recommended in the Green book used above (which uses a range of values between 3.5% and 2.5% over the 90 year period considered here). It was found that the value of Real Options compared to that of a fixed non-flexible approach is dependent on the choice of discount rate used and that the choice of discount rate can heavily influence the performance of an intervention strategy. Table 7.2 displays the benefits, costs, NPV and BCR of each of the four intervention strategies using a rate of 1.4% and similarly Table 7.3 for a rate of 5%. Under the Green book discount rate it was found that the averaged NPV of strategy A outperformed two of the three evaluations of strategy B as well as C and D, but under the rate of 1.4%, the opposite was found showing B and D to outperform A. Whereas, under a rate of 5%, strategy A outperformed all other strategies significantly. This analysis highlights the importance of the discount rate and the impact it can have on the decision making process, the discount rates have significantly changed the values for the benefits. For example the averaged benefit for strategy A now equals £136.01m under a 1.4% rate or £26.23m for a 5% rate compared to £63.13m under the Green book rate. The biggest impact that has occurred for the decision making process is the change in the costs, more specifically, the cost to undertake strategy A. Under the Green book discount rate, the cost for strategy A was 24.18% lower than B_1, now for the 1.4% rate strategy A is 1.3% higher than B_1. This change has occurred because the lower discount rate of 1.4% favours making the changes now rather than paying for large costs at a future point in time (see Section 4.2.4 for a discussion on this). The opposite is found for a higher rate favouring a delay in the implementation of intervention options as can be seen through the difference in costs between the Green book rate and a rate of 5%. The cost for strategy A was 24.18% lower than B_1 whereas using the 5% rate it is now 70.37% lower. These changes cause a large impact to the overall NPV and result in changes to the overall decision.

Table 7.2 Summary of the performance information of the intervention strategies under an uncertain future using a conservative discount rate of 1.4%

Strategy	Scenario	Benefit (£ M)	Cost (£M)	NPV (£M)	BCR
A	Low	131.71	29.61	102.10	4.45
	Medium	133.42	29.82	103.60	4.47
	High	142.89	30.09	112.80	4.75
	Average	136.01	29.84	106.17	4.56
B_l	Low	141.61	29.45	112.16	4.81
	Medium	141.35	29.45	111.90	4.80
	High	140.31	29.45	110.86	4.76
	Average	141.09	29.45	111.64	4.79
B_m	Low	144.90	29.77	115.13	4.87
	Medium	144.84	29.77	115.07	4.87
	High	144.18	29.77	114.41	4.84
	Average	144.64	29.77	114.87	4.86
B_h	Low	156.50	30.14	126.36	5.19
	Medium	156.49	30.14	126.35	5.19
	High	156.34	30.14	126.20	5.19
	Average	156.44	30.14	126.30	5.19
C	Low	131.44	41.75	89.69	3.15
	Medium	133.20	42.00	91.20	3.17
	High	142.53	42.28	100.25	3.37
	Average	135.73	42.01	93.72	3.23
D	Low	138.50	28.87	109.63	4.80
	Medium	140.27	28.87	111.40	4.86
	High	149.50	28.87	120.63	5.18
	Average	142.76	28.87	113.89	4.94

Table 7.3 Summary of the performance information of the intervention strategies under an uncertain future using a higher discount rate of 5%

Strategy	Scenario	Benefit (£M)	Cost (£M)	NPV (£M)	BCR
A	Low	25.81	16.78	9.03	1.54
	Medium	25.91	16.87	9.04	1.54
	High	26.96	17.00	9.96	1.59
	Average	26.23	16.88	9.35	1.55
B_l	Low	29.81	26.93	2.88	1.11
	Medium	29.73	26.93	2.80	1.10
	High	29.56	26.93	2.63	1.10
	Average	29.70	26.93	2.77	1.10
B_m	Low	30.55	26.93	3.62	1.13
	Medium	30.54	26.93	3.61	1.13
	High	30.45	26.93	3.52	1.13
	Average	30.52	26.93	3.59	1.13
B_h	Low	32.43	26.93	5.50	1.20
	Medium	32.42	26.93	5.49	1.20
	High	32.41	26.93	5.48	1.20
	Average	32.42	26.93	5.49	1.20
C	Low	25.69	27.00	-1.31	0.95
	Medium	25.82	27.11	-1.29	0.95
	High	26.81	27.24	-0.43	0.98
	Average	26.11	27.12	-1.01	0.96
D	Low	29.06	26.09	2.97	1.11
	Medium	29.43	26.09	3.34	1.13
	High	30.78	26.09	4.69	1.18
	Average	29.76	26.09	3.67	1.14

The sensitivity analysis undertaken on the discount rate has demonstrated the importance of the discount rate and the impact it can have on the decision making process. For the remainder of this thesis, the Green book's declining discount rate will be used as this is the suggested rate for appraising investments set out by the UK

government. This sensitivity analysis has however highlighted the discount rate to be an important variable in the appraisal process.

7.4 Case 2 – Single Objective Optimisation

In this case study the single objective optimisation problem defined in Section 5.3.1 is investigated where the aim is to determine the most optimal intervention strategy according to the objective: maximise NPV (i.e. the present value of benefits minus costs). The case study is again based on the Thamesmead area of the Thames Estuary and the selected settings used in case study 1 (Section 7.3) remain the same for this case study. i.e. the defences are divided into the 5 groups, the strategies life time is again 90 years and the intervention options which were used in case study 1 (raising the crest level and widening the base) are available. This time however rather than manually selecting intervention options, the GA will determine the best combination of intervention measures.

The single objective optimisation process will run under a deterministic case where it is assumed there is no future uncertainty with regard to climate change. In this instance the solution generated by the GA will be comparable to the manually selected strategy, Strategy B, from Section 7.3. In this deterministic case, it is assumed from the outset that the worst case scenario, the high emission scenario, will occur. Therefore for a direct comparison, the optimised solutions will be compared to the manually selected strategy B_h from Section 7.3.

The optimisation of solutions will evaluate strategies according to the sea level rise impacts predicted for the high emission scenario and looks to determine the most optimal combination of height and width increases to protect against this scenario. The available height increase options that the decision variables can represent include the original increases discussed in Table 5.1 and three additional values based on the options in Section 7.3. Table 7.4 lists the possible height increase options that each defence group can undertake at each time step and how it is translated into the GA.

The GA parameters used within this case study include a crossover and mutation rate of 0.7 and 0.03 respectively with a population size of 200 optimised over 100 generations. The crossover and mutation rates used here both fall within the recommended rates suggested by Deb (1998) however a sensitivity analysis on these parameters is undertaken in Section 7.5.2. The population size and number of generations have been

selected according to the size of the problem being solved. Throughout the case studies below, it is expected that the values for population size and number of generations will increase as the problem expands and becomes more complex. A sensitivity analysis of the population size and number of generations is also provided below in Section 7.5.2.

Table 7.4 List of decision variables available for increasing the height of a defence

Decision variable code in the GA	Height Increase	Description
0	0.00m	Original height option (see Table 5.1)
1	0.30m	Predicted sea level rise increase for the low emission scenario at the 90th year
2	0.33m	Original height option (see Table 5.1)
3	0.36m	Predicted sea level rise increase for the medium emission scenario at the 90th year
4	0.44m	Predicted sea level rise increase for the high emission scenario at the 90th year
5	0.66m	Original height option (see Table 5.1)
6	1.00m	Original height option (see Table 5.1)
7	1.33m	Original height option (see Table 5.1)

Under these GA parameters, the optimisation problem was run three times (a relatively small number chosen due to high computational cost) and each time convergence was shown to the same optimal solution (see Table 7.5). For each test run in Table 7.5 a different random seed was used. As the GA is a stochastic search method the initial population (which are randomly generated from the search space) impacts where the initial search occurs. The initial population could lead the search to a local optimal instead of a global optimal. Altering the random seed for each test will ensure a different initial population and as the same optimum solution was found given different initial populations, convergence is verified.

Comparing the optimal strategy selected by the GA and the manually selected traditional strategy from Section 7.3 (see Table 7.6) it can be seen that the GA has chosen a strategy with a significantly larger NPV. Using the GA's ability to search through a large portfolio of possible intervention options and identify the better performing solutions, the GA is able to pinpoint the defences which require the most

attention and therefore concentrate the intervention options in the most needed areas. The optimal solution chosen by the GA has slightly increased the benefits to the flood area but more noticeably for a considerably lower cost compared with that of the manually chosen option. Identifying the areas which require the most attention prioritises the interventions to be applied, reducing the cost and therefore improving the NPV and BCR.

Table 7.5 Multiple runs of optimisation problem with differing seed (i.e. initial GA populations)

Test run	Seed	Benefit £ 000,000	Cost £ 000,000	NPV £ 000,000	BCR
1	81381	74.91	3.1	71.81	24.16
2	62125	74.91	3.1	71.81	24.16
3	17849	74.91	3.1	71.81	24.16

As the low cost suggests, the interventions suggested by the GA are minimal compared to that of the manually chosen strategy. The manually chosen strategy increases all defences in each of the 5 groups by 0.44m during the first time step. In comparison, the optimised strategy selects a specific intervention which only raises the crest level of the defences in group one at the first time step. The height increase selected is the largest available increase of 1.33m. The GA has identified the defence group which would have the largest impact on the reduction in risk and focuses the interventions in this area. By focusing the interventions, the costs are significantly reduced.

Table 7.6 Comparison of the manually chosen strategy in section 7.2 and the optimised strategy from the GA

Strategy	Benefit (£ M)	Costs (£M)	NPV (£M)	BCR
Manual	74.23	28.37	45.86	2.62
Optimal	74.91	3.10	71.81	24.16

The use of optimisation techniques for decision makers can therefore be advantageous in choosing an optimal investment according to NPV. Areas in the floodplain which are most in need of flood risk intervention measures are highlighted which enables the investment to be focused in priority areas. The information is obtained in an automatic manner which is much more time efficient compared to a manual selection approach.

The manual approach also has the disadvantage that potentially better performing solutions are often missed and not considered due to the large portfolio of available intervention options.

Potentially better solutions in terms of risk reduction have however, been dismissed by the optimisation process as the lower cost options have improved the NPV. Table 7.7 describes two additional strategies which were disregarded by the optimisation process in favour of strategies with lower costs. These solutions have a higher benefit than the optimum solution but due to the higher costs incurred from an increase in intervention measures applied, the overall NPV is less. As Hall and Solomatine (2008) discussed, the use of optimisation should be pursued with caution for the reason that economic efficiency is prioritised over safety. As can be seen from the results in the single objective optimisation (see Table 7.6 and Table 7.7), optimising for the maximum NPV does not necessarily put safety first but rather ensures an economical investment. In flood risk management where there are many considerations for decision makers, it is important to consider the most appropriate objective function. With the most appropriate objective function considered, optimisation would no longer need to be pursued with caution.

Table 7.7 Two strategies which were dismissed by the optimisation process

Strategy	Benefit £M	Costs £M	NPV £M	BCR	Intervention measures
1	75.07	4.10	70.97	18.31	Increase group 1 at time steps 1 and 3. Increase group 2 at time step 1.
2	75.27	6.58	68.69	11.44	Apply a range of crest level increases to groups 1, 2, 3, and 4 across all time steps

The output of a single objective optimisation is an optimum solution with regard to the set objective. Decision makers are not provided with a range of potential solutions or additional information on how well the optimum solution performs in relation to other solutions. It is possible to run many simulations of a single objective optimisation,

setting different objectives and preferences each time to obtain a range of optimum solutions. This is however time consuming and inefficient.

The use of multi-objective optimisation can instead provide decision makers with a range of Pareto Optimal solutions which have been optimised in accordance with multiple criteria simultaneously during one simulation. The decision maker has full access to a trade-off of optimum solutions in terms of individual benefits and costs and therefore an informed decision can be made as to which solution is most appropriate given the specific problem at hand. Section 7.5 investigates the use of multi-objective optimisation in flood risk management.

7.5 Case 3 – Multi-objective Optimisation

This section explores the application of multi-objective optimisation to aid flood risk management decision making (see Section 5.4 for details on the multi-objective optimisation process and problem formulation). Firstly, Section 7.5.1 applies the multi-objective optimisation methodology assuming a deterministic future to the area of the Thames Estuary described in Section 7.2. In this instance two objectives are considered, flood risk reduction and costs. A sensitivity analysis of the GA parameters is then undertaken in Section 7.5.2. Section 7.5.3 assumes future uncertainty is present and applies the multi-objective optimisation model from Section 6.4 to determine optimal strategies of expected utility maximisation under uncertain conditions. The case study finishes with an application of the multi-objective optimisation process considering the additional criterion, loss of life, in Section 7.5.4.

7.5.1 Case with One Future Projection - Deterministic

The analysis in Section 7.4 highlighted some of the potential weaknesses present in the single objective optimisation. For example, only a single solution is offered to the decision maker, this does not provide sufficient information. Furthermore, the single solution presented is not always the most suitable solution and could consequently misguide the decision maker. This case study looks to solve these issues by using multi-objective optimisation. Similarly to Section 7.4, it is again assumed that there is only one future projection and that a high emission scenario will occur. Making this deterministic in that only one future scenario is considered. The optimisation process looks to identify a range of Pareto Optimal intervention strategies given this one future outcome.

The decision variables which are considered within the intervention strategies include raising the crest level of the defences (see Table 7.4), increasing the capacity of the defences for future expansion and the level of maintenance applied. Widening the base can take a range of width increases while maintenance follows four possible options including 'do nothing', low, medium and high (see Table 5.1). The intervention strategies developed are long term strategies recommending a flood risk plan for the next 100 years with intervention measures considered at every 50 year time step. The GA parameters set for this case study again use a crossover and mutation rate of 0.7 and 0.03 respectively. Due to the increase in complexity of the optimisation problem being solved and the increase in the number of decision variables, a larger population size of 400 and a larger number of generations at 200 are used.

With the parameters and decision variables set, the problem formulated in Section 5.4.1 is solved for two objectives, flood risk reduction and costs. Figure 7.5 shows the progression of the Pareto Optimal front as the generations are advanced by the evolutionary algorithm. Each point on the graph represents a flood risk intervention strategy with the triangles representing solutions on the Pareto front and the circular points representing the remaining solutions. As the optimisation process progresses through the generations, the improvement of the Pareto front can be seen and eventually convergence to the optimal set is achieved.

Figure 7.6 displays the final Pareto front obtained from the 200th generation showing the trade-off between flood risk reduction and costs. In Figure 7.6, a solution cannot be improved according to one objective without causing a negative effect on the other objective. For example improving flood risk reduction will result in an increase in the costs. To determine the better performing strategy or the most preferred from the Pareto front, decision making methods can be used. Decisions can also be determined according to specific target levels that must be met for each criterion. For example, a specific flood risk reduction level that must be reached or if there is a constraint on the total expenditure allowed. Preferences and weightings can also be implemented to reduce the number of options available.

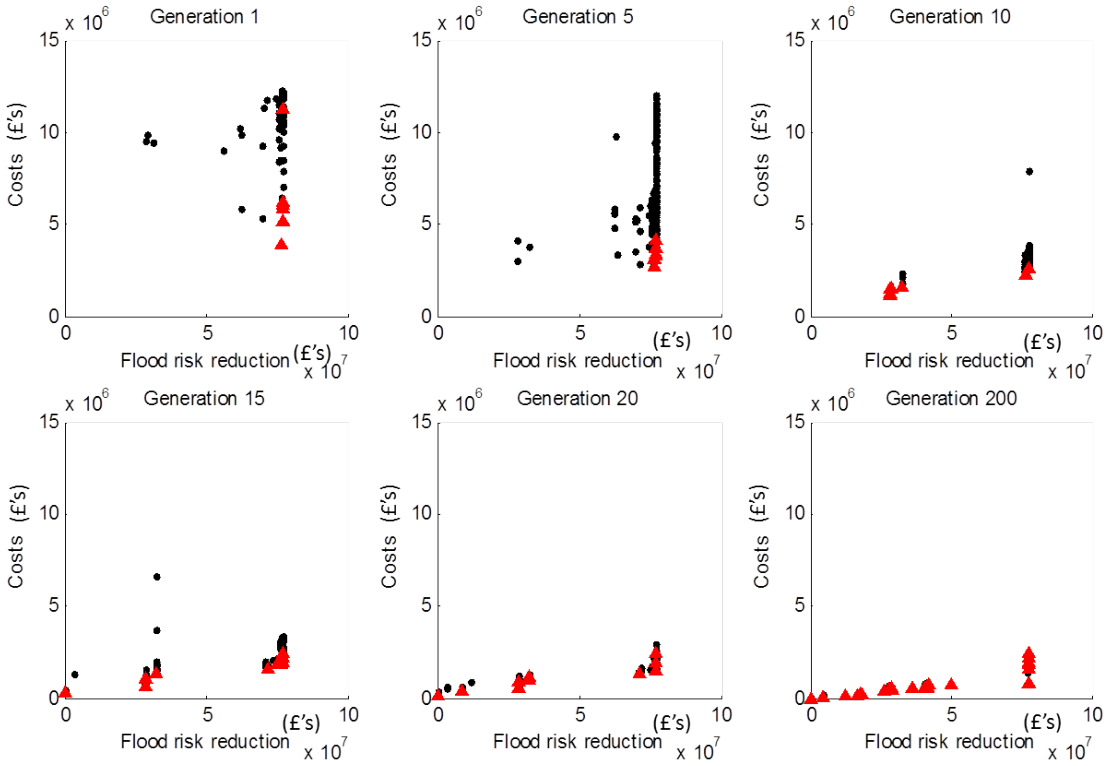


Figure 7.5 The development and progression of the Pareto Front (triangles) across the generations

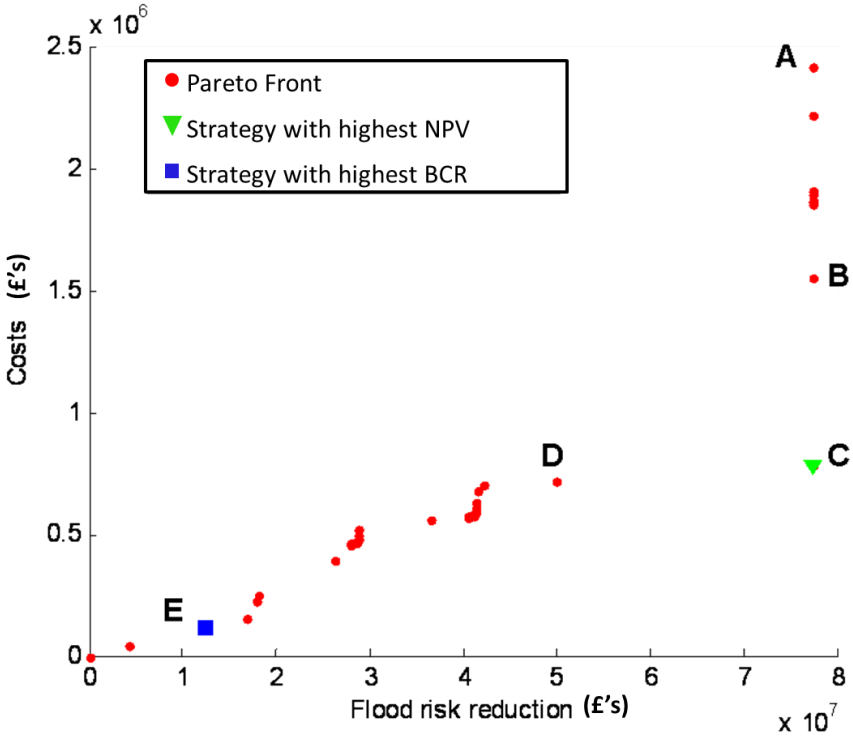


Figure 7.6 Pareto Front of the final generation of a deterministic optimisation of the benefits and costs

A common performance measure, as shown in the single objective optimisation, is the NPV (or BCR). Figure 7.6 highlights the strategies in the Pareto Front which have the highest NPV (triangle) and the highest BCR (square) for illustrative purposes. These solutions would have been selected under a single objective optimisation depending on the objective chosen. However, a more informative decision making process would involve the comparison and selection of the most appropriate intervention strategies using their respective positioning on the Pareto Front. The information provided to decision makers from the outputs of a multi-objective optimisation compared to a single objective output has already greatly improved. Rather than one single optimum solution, a full range of optimum solutions have been provided. The decision maker can visualise how solutions such as the highest NPV or BCR compare in relation to other optimal solutions.

Table 7.8 displays a summary of 5 optimal strategies from the Pareto front including the strategies with the highest NPV and BCR which have been highlighted in Figure 7.6. Comparing strategies C and D, it can be seen that for a minimal increase in cost, the benefits in terms of flood risk reduction can be significantly improved, favouring strategy C. Similarly, comparing strategy B and C, the increase in benefits for strategy B does not outweigh the considerable increase in costs.

The suggested intervention measures for these five solutions vary (see Table 7.8). Solution E for example, applies the minimum number of intervention options, only applying a low maintenance regime. For an increase in cost and a large increase in flood risk reduction, strategy D suggests applying a medium level of maintenance instead of a low level. To achieve the next increase in flood risk reduction, structural interventions are required. Solutions A, B and C suggest either a low or medium maintenance over the 100 years as well as a height increase to at least one group of defences in at least one of the time steps. In all three solutions, the defences in group 1 are increased by 1.33m. Group 1 defences protect a highly developed area in a vulnerable location to storm surges, and by increasing the height of these defences enables a large amount of the risk to be reduced. Solution C only raises this group of defences whereas strategy A has a much higher expenditure and raises 4 of the 5 groups of defences. As well as group 1, groups 2 and 4 are also raised in the first time step and like group 1 protect a highly developed area, however, the areas protected by groups 2 and 4 are not in such a

vulnerable location. By improving these defences the risk can be reduced but only minimally compared to group 1.

Strategy A also raises the defences of group 3 but this intervention is delayed until the second time step. The defences in group 3 do not protect a high risk area and the defences here are therefore not such a priority. The additional benefit to raise an additional three groups of defences is not that significant. The cost however is minimal compared to the amount of EAD reduction obtained. The EAD reduction for strategies A, B and C is significantly larger than D and E principally because the majority of flood risk is attributed to the defences in group 1, by increasing the height of these defences a large proportion of the damage can be prevented. The optimisation algorithm is able to identify the least cost options which gain a large benefit and essentially not undertake unnecessary intervention options which do not return a good investment.

Table 7.8 Summary of the benefits, costs, NPV, BCR and intervention measures of select strategies from the Pareto front highlighted in Figure 7.6

Strategy	Benefit (£M)	Cost (£M)	NPV (£M)	BCR	Intervention Measures
A	77.31	2.41	74.89	32.08	Time Step 1 Raise G1 by 1.33m, G2 by 1.00m and G4 by 0.33m Time Step 2 Raise G3 by 0.66m Medium Maintenance to G3 and 4
B	77.29	1.55	75.74	49.86	Time Step 1 Raise G1 by 1.33m, apply medium maintenance to G3 Time Step 2 Apply medium maintenance to G3
C	77.28	0.79	76.49	97.82	Time Step 1 Low maintenance to G1,3 and 4 Time Step 2 Raise G1 by 1.33m Low maintenance to G3
D	49.87	0.72	49.15	69.26	Time Step 1 Medium maintenance to G1, 3 and 4 Time Step 2 Medium Maintenance to G3
E	12.53	0.11	12.42	113.91	Time step 1 Low maintenance to G1, 3 and 4

It is important to provide decision makers with all the necessary information to ensure that the selected option is chosen with knowledge of all relevant information, as shown in Figure 7.6. The decision making process may result in the selection of a strategy with the highest NPV or BCR but it is still important to understand how this strategy fits in and compares to other potential solutions and ensure the best strategy is selected given the problem at hand. Multi-objective optimisation methods provide a means to present additional information to decision makers and offer additional insight into the problem, its characteristics and potential solutions, all of which is not typically available. The remaining cases in Section 7.5 continue using multi-objective optimisation but expand upon the problem being solved by considering multiple future scenarios (Section 7.5.3) and additional criteria (Section 7.5.4). Firstly, a sensitivity analysis is undertaken on the GA parameters in Section 7.5.2, looking at the crossover and mutation rates as well as the population size and number of generations.

7.5.2 Sensitivity Analysis of GA parameters

In the optimisation case studies done so far, a crossover rate of 0.7 and a mutation rate of 0.03 has been used. These values fall within the recommended range set by Deb (1998). To ensure these values are suitable, a simple sensitivity analysis is undertaken, comparing a selection of crossover and mutation rate combinations under the same optimisation problem conditions (see Table 7.9).

Table 7.9 The crossover and mutation rate combinations used in the sensitivity analysis for suitable GA parameter selection

Test	Crossover Rate	Mutation Rate
1	0.7	0.03
2	0.9	0.03
3	0.7	0.06
4	0.9	0.06

Test 1 in Table 7.9 represents the results of the case study in section 7.5.1 while Tests 2 to 4 optimise the same problem as Test 1 but vary the crossover and mutation rates. Figure 7.7 displays the Pareto Fronts of each of these tests. It can be seen that the Pareto fronts for each test have found are similar. The Pareto fronts of tests 2 and 4, the tests with the higher crossover rate, appear to have a better spread of optimal solutions on the Pareto Front. However, the time taken to achieve these fronts took 40% longer than the time taken to achieve the fronts with a lower crossover rate. Furthermore, tests 1 and 3

found additional solutions which would dominate the solutions in tests 2 and 4 if they were obtained for those optimisation runs, suggesting full convergence had not been reached. Given this, a lower crossover rate of 0.7 would be more suitable in these case studies.

With a lower crossover rate chosen, a comparison of the different mutation rates is required. The higher mutation rate found a solution with higher benefits while the lower mutation rate found a solution with the highest NPV. Both rates had identified the no cost option and were found to take approximately the same time to complete the optimisation run. The difference between these rates is minimal for this case study and so the crossover rate of 0.7 and mutation rate of 0.03 will continue to be used.

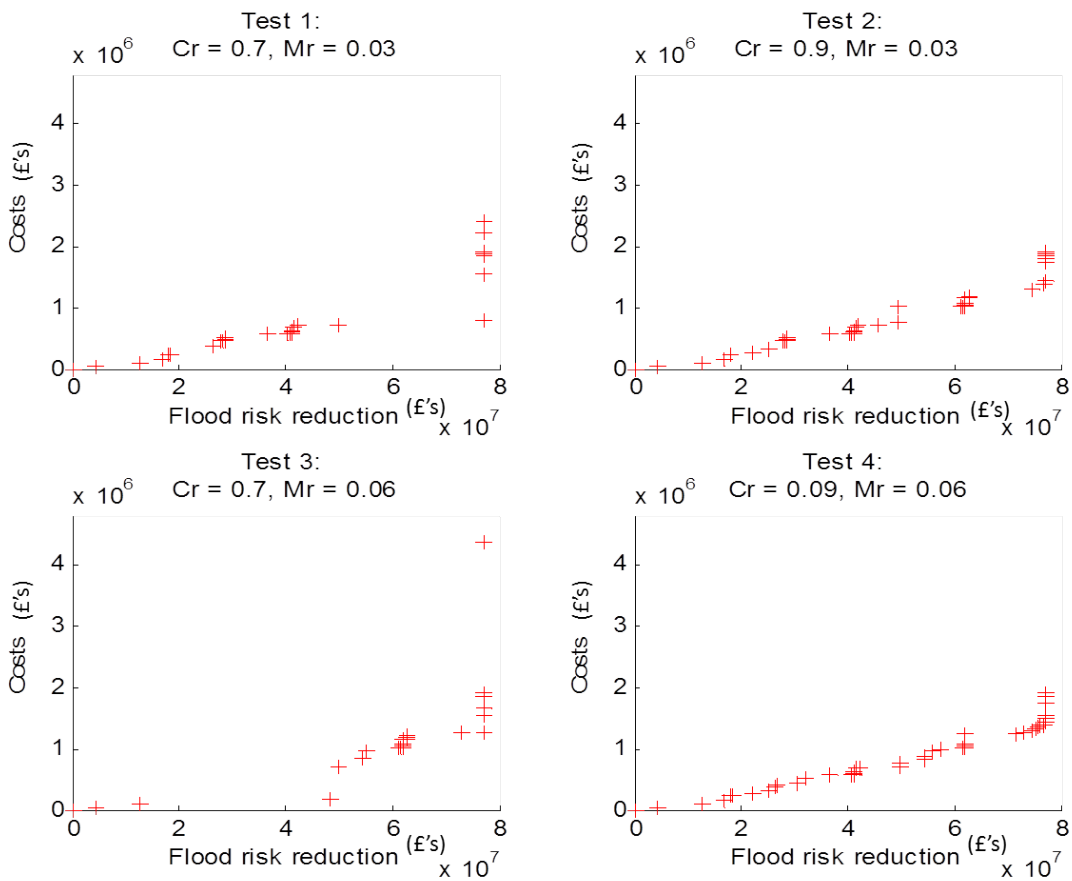


Figure 7.7 Comparison of the Pareto Fronts at the 200th generation for each crossover and mutation rate combination. (top left) Test 1 with crossover = 0.7 and mutation = 0.03 (top right) Test 2 with crossover = 0.9 and mutation = 0.03 (bottom left) Test 3 with crossover rate = 0.7 and mutation rate = 0.06 (bottom right) Test 4 with crossover rate = 0.9 and mutation rate = 0.06

As well as the crossover and mutation rates, other important parameters include the population size and the number of generations. In the multi-objective optimisation case

a population size of 400 as well as 200 generations are used. A sensitivity analysis is undertaken to analyse whether this is appropriate.

The sensitivity analysis makes a comparison between five sets of population size and total number of generations to assess whether the selected values are appropriate (see Table 7.10). Test 4 utilises the results from the deterministic case in Section 7.5.1 while tests 1, 2, 3 and 5 are run for the same problem but with varying combinations of parameter values.

Table 7.10 The number of generations and population size combinations used in the sensitivity analysis for suitable GA parameter selection

Test	Population Size	Number of Generations
1	100	100
2	100	200
3	400	100
4	400	200
5	600	250

The results from the five sets of parameters are shown in Figure 7.8 displaying each of the Pareto fronts. Looking first at tests 1 and 2 where a population size of 100 was used, it can be seen that the associated Pareto fronts have not converged to the global optimum solutions but instead to a local optima. Running the solutions for longer (for 100 generations and 200 generations) there has been no improvement on the Pareto front. The use of a population size of 100 is clearly too small and does not appropriately cover the search space. Tests 3 and 4 therefore use a much larger population size of 400. The Pareto fronts for these tests dominate all solutions from tests 1 and 2 further verifying the population size of 100 is too small. Optimal solutions have been identified along the front such as the least cost option, the 'do nothing' option. A population size of 400 is therefore much more suitable. The difference between the total number of generations from 100 to 200 has this time had more impact than compared to tests 1 and 2. The solutions found after the 200th generation dominate many of the solutions from the 100th generation. The solutions after the 100th generation are also clumped into three main areas whereas the Pareto front from the 200th generation provides a better spread. Finally, comparing test 4 to test 5 which considers a larger population size of 600 and a larger number of generations equalling 250 there is not a large difference between them. Many of the solutions found under test 5 were also found using a

population size of 400 and a generation size of 200. Test 5 does however provide a better spread of solutions along the Pareto front, most noticeably against the flood risk reduction axis after £50m. It can however be seen that test 4 found a solution which dominates these solutions in test 5 explaining why test 4 does not look as well spread. Given the not so large differences between tests 4 and 5, it is more suitable to use the population size of 400 and a generation of 200. This is because convergence can still be achieved when using a smaller number of generations of 200 and a smaller population size of 400. Reducing these parameters as much as possible without losing accuracy of the results improves the computational efficiency of the optimisation process.

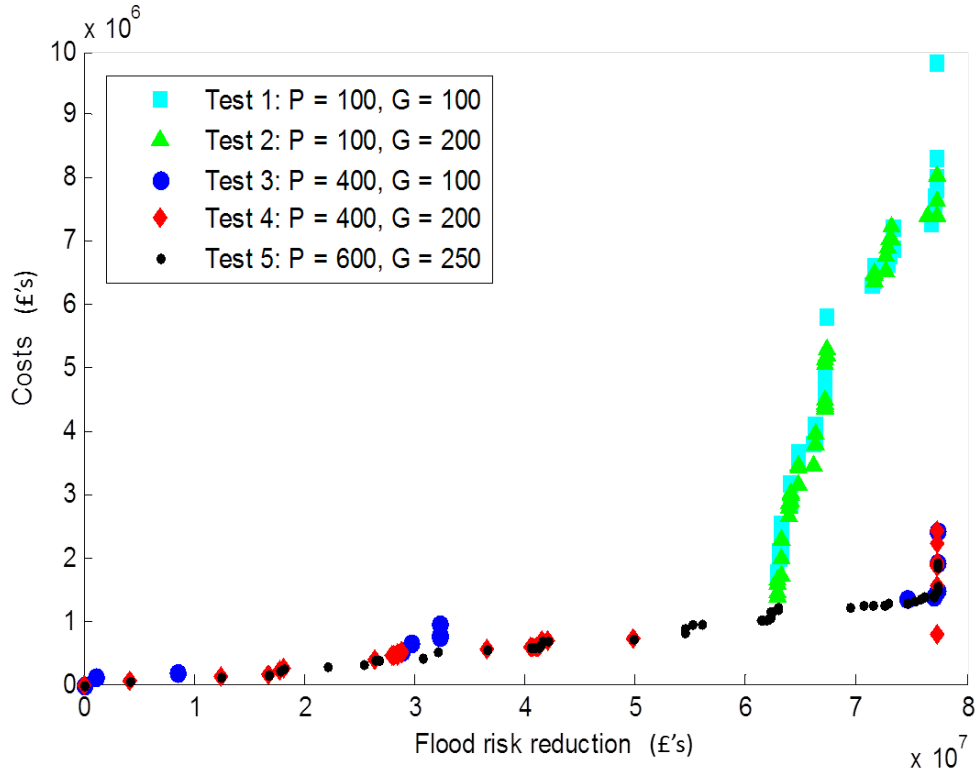


Figure 7.8 The Pareto Fronts for each of the five different combinations of population and generation parameters.

7.5.3 Optimisation of Expected Utility

In Section 7.5.1 multi-objective optimisation was used to determine the Pareto Optimal intervention strategies given one single future scenario. In this case study, it is now assumed the future is uncertain and there is no single possible future outcome. The optimisation model explained in Section 6.4 is used to optimise intervention strategies given an uncertain future to determine the optimal strategies with the maximum expected utility according to two objectives, flood risk reduction and costs. The

sampling method in Section 6.2 is used to obtain 1000 future sea level rise projections to evaluate each intervention strategy against. The intervention measures considered include raising the crest level, increasing the capacity of the defences for expansion through widening the base and the level of maintenance (see Table 5.1). A crossover rate of 0.7 and a mutation rate of 0.03 is used as well as a population size of 400 with the number of generations equalling 200. All strategies are discounted back to the present day using the Green Books declining discount rate.

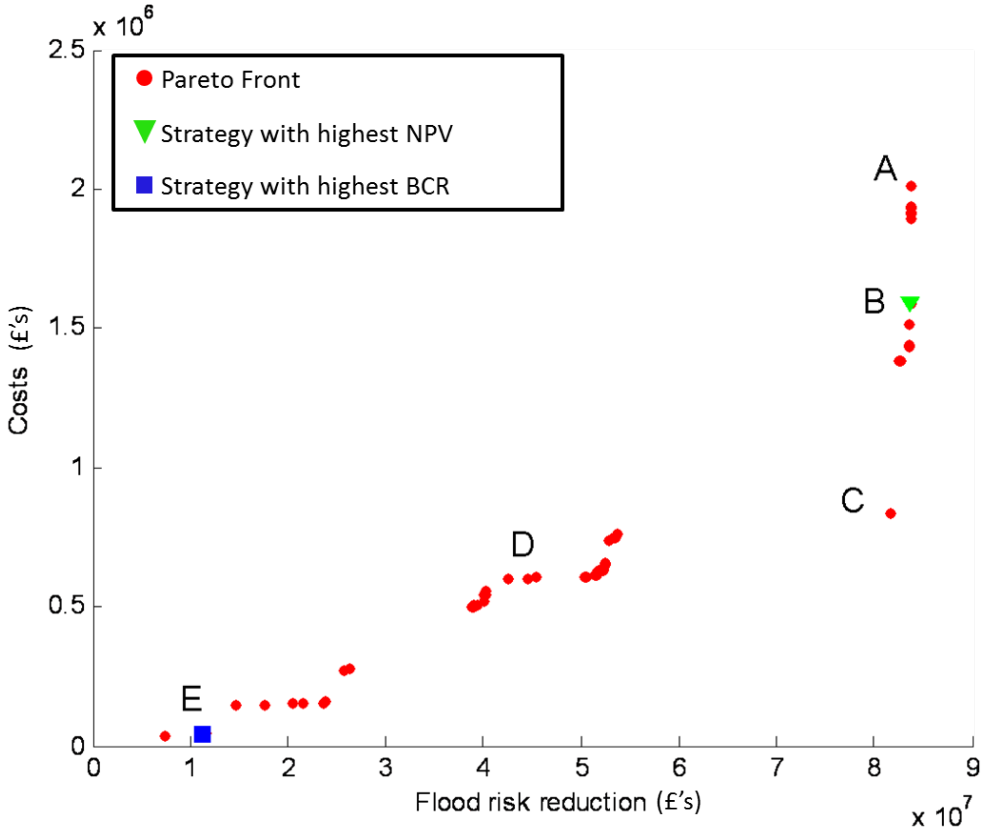


Figure 7.9 The Pareto Front for the 200th generation for optimisation under uncertainty of the benefits and costs

Figure 7.9 displays the Pareto front for the 200th generation of this optimisation. Each point on the graph represents an optimal intervention strategy. The strategies with the highest NPV and BCR have been individually identified as the triangular point and the square respectively as well as three other solutions for comparison purposes. Each optimal strategy is robust to a range of 1000 future sea level rise scenarios. Table 7.11 provides details on the five specific strategies highlighted in the Pareto Front.

Table 7.11 A summary of the solutions identified in Figure 7.9 detailing the benefits, costs, NPV, BCR and intervention options

Strategy	Benefit £M	Cost £M	NPV £M	BCR £M	Intervention measures
A	83.59	2.01	81.58	41.59	Time step 1 Widen and raise G1 by 1.33m, widen base of G4 Time step 2 Raise g1 by 0.30m, raise G4 by 0.36m
B	83.58	1.59	81.99	52.57	Time step 1 Raise G1 by 1.33m Time step 2 Apply medium maintenance to G3, raise and widen G4 by 0.30m
C	81.53	0.84	80.69	97.06	Time step 1 Apply medium maintenance to G3, raise and widen G4 by 0.30m Time step 2 Raise G1 by 0.36m, raise G4 by 0.33m, raise G2 by 0.33m
D	44.50	0.61	43.89	72.95	Time step 1 Apply medium maintenance to G3 Time step 2 Raise and widen G4 by 0.33m
E	11.34	0.004	11.3	283.5	Time step 1 Do nothing Time step 2 Raise and widen G4 by 0.36m

The majority of intervention measures suggested by each of the five long term strategies in Table 7.11 focus mainly on defence groups 1 and 4 and occasionally groups 2 and 3. The highest benefits are obtained when the crest levels of the defences in groups 1 and 4 are raised. Figure 7.10 displays the flood depth realisation from a 100 year flood event on the case study area. The majority of the flood water has accumulated behind defence groups 1, 3 and 4. The defences in groups 1 and 4 protect highly developed areas and the flood risk is therefore considerably higher here. The GA has recognised these locations of high risk and by focusing the substantial interventions to groups 1 and 4 the overall risk can be reduced and thus achieve a high benefit. The majority of land protected by group 3 is not as well developed (see Figure 7.2) and therefore has a lower

risk. As this area is not such a priority but does have a high flood depth associated, the GA suggests maintaining these defences rather than implementing more significant mitigation measures. The defences in Group 2 protect a highly developed area and during a 100 year flood event, the flood water overflows in this location too, verifying the selection of raising defences in group 2 for one of the strategies. As can be seen from Figure 7.10 there is a minimal flood depth accumulating by group 5. In addition this area does not accommodate a well developed area so has minimal risk. This verifies the exclusion of these defences from the majority of strategies suggested by the GA.

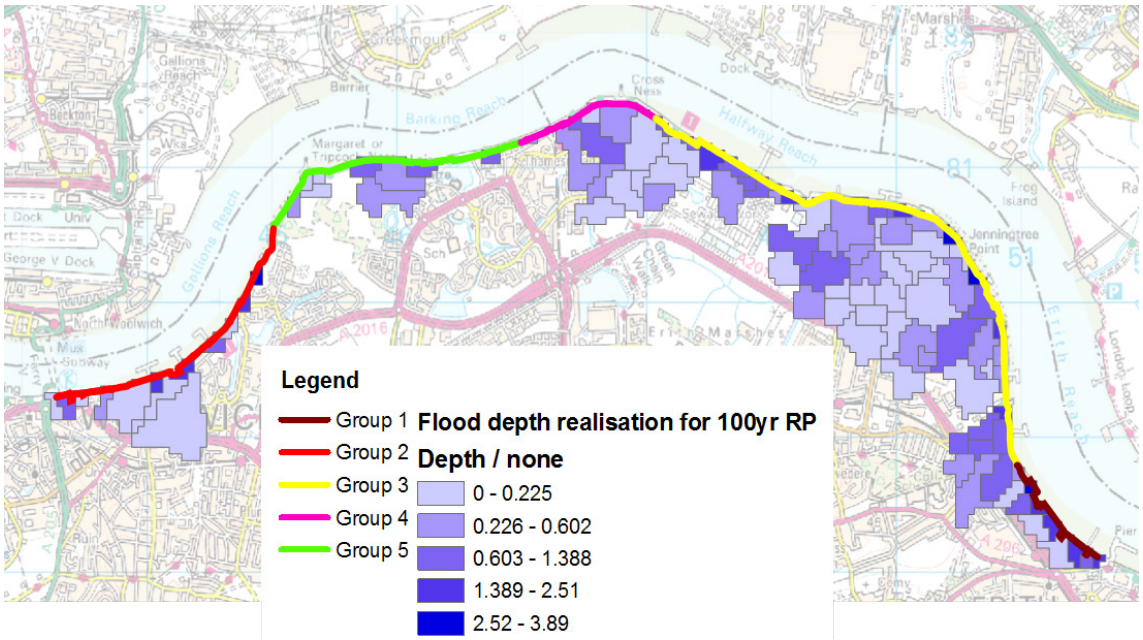


Figure 7.10 Flood depth realisation for a 100 yr RP of the Thamesmead area of the Thames Estuary

The Pareto front in Figure 7.9 was generated using a large range of future sea level rise scenarios. By considering the future climate change uncertainty, robust strategies can be developed which perform well over a range of future sea level rises. Given the severe uncertainty present in the future impacts of climate change on flood risk management, it is important to ensure that flood defences and flood management plans have been designed to perform well regardless of the future outcome. It is not advisable to develop strategies based on one future outcome; strategies which are optimal for a given scenario could perform badly under another. The optimisation model which maximises expected utility allows decision makers to consider a wide range of possible future outcomes which will be more effective in this current climate than only considering scenario, as above. Figure 7.11 displays the range of 1000 samples analysed in the case with multiple futures compared to the worst case scenario for the case with a single

future projection (dotted line). As can be seen from this figure, there are a large range of potential future projections which have not been accounted for in the deterministic case. Not taking the large range of samples into account can result in decisions that implement poor strategies if the resulting outcome deviates from the expected scenario. It is also illustrated that the deterministic case is no longer the 'worst case' scenario. The deterministic sea level rise was generated from the single, 50th percentile of the high emission scenario and considered the worst case when compared to the 50th percentile of the low and medium emission scenarios in the case 1 example. By sampling from each of the three emission scenarios using normal distributions to represent the range of plausible projections, samples with higher sea level rises than the deterministic sea level rise value have been generated. To fully assess the difference between the deterministic case with the case which maximises expected utility a comparison of the two optimal Pareto fronts has been undertaken.

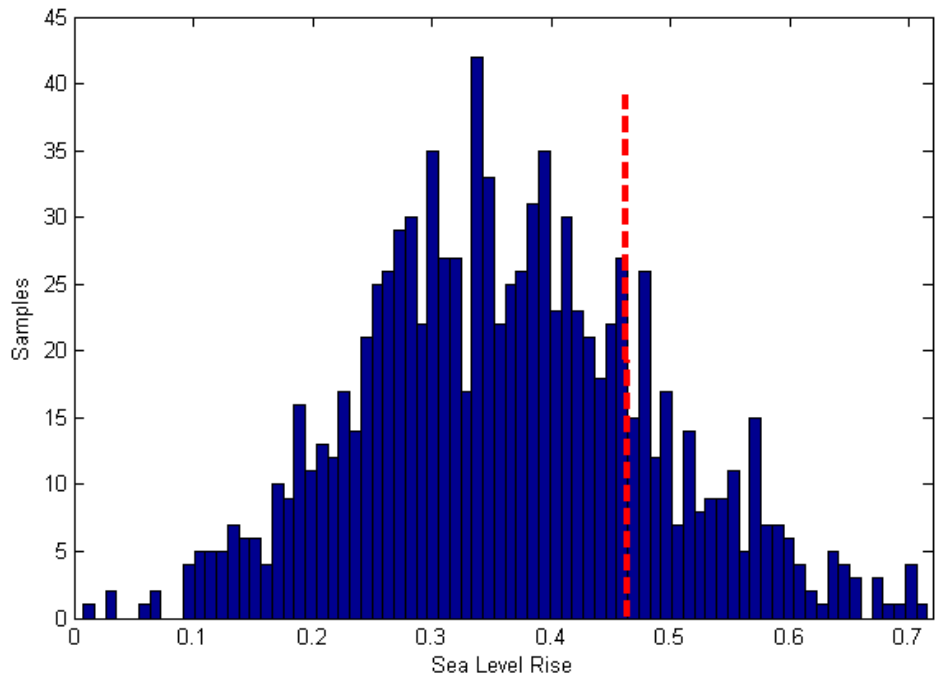


Figure 7.11 The range of sea level rise samples used for the evaluation of multiple future projections (in blue), the scenario evaluated against one future projection (red dashed line)

In order to compare the fronts like with like, the final generation from the deterministic evaluation (in Section 7.5.1) has been re-evaluated over the 1000 samples used in the maximisation of expected utility case. This enables the comparison of the performance of the maximum expected utility and deterministic solutions over the range of possible

future climate change scenarios. This re-evaluation will impact the flood risk reduction of the deterministic solutions as the EAD will now be averaged over 1000 future projections rather than one. The costs however, remain the same as the unit cost of an intervention measure does not change given a different future projection. The change in average EAD will impact the Pareto front causing a shift in the flood risk reduction and can result in a change in the Pareto optimal solutions. For example, the solution with the highest NPV under the evaluation of one sea level rise projection is no longer in the Pareto front when averaged over 1000 samples. Similarly strategies previously not considered Pareto optimal are now available for consideration in the trade-off curve. The updated deterministic Pareto front can be seen in Figure 7.12.

Table 7.12 The flood risk reduction for the deterministic case evaluated over one future scenario compared with the flood risk reduction evaluated over 1000 future scenarios for five strategies in Figure 7.12. Also includes the costs , NPV, BCR for the five strategies

Strategy	**Benefit £ M** (1 future projection)	**Benefit £ M** (averaged over 1000 samples)	**Cost £M**	**NPV £ M** (averaged over 1000 samples)	**BCR** (averaged over 1000 samples)
A	77.29	77.02	1.55	75.47	49.69
B_d	76.93	76.58	1.38	75.20	55.49
C	49.87	47.76	0.72	47.04	66.33
D_d	17.86	17.36	0.23	17.13	75.48
E	12.53	12.55	0.11	12.44	114.09

Five solutions from the deterministic front are detailed in Table 7.12 and Table 7.13 showing the change in EAD reductions from evaluating the strategies over one and 1000 possible futures. In the majority of solutions, the benefits have decreased when evaluating them over the 1000 scenarios. This is because the solutions have been optimised to protect against the deterministic sea level rise (the dotted line in Figure 7.11), however during the evaluation of 1000 futures there are a range of samples which exceed this sea level rise. The strategies would not provide protection for these samples and in these cases would lower the average flood risk reduction. With the deterministic

front evaluated over the same range of climate change projections as the maximum expected utility case, the two fronts can be compared.

Table 7.13 Intervention measures for the five intervention strategies in Figure 7.12

Strategy	Intervention Measures
A	Time Step 1: Raise G1 by 1.33m, apply medium maintenance to G3
	Time Step 2: Apply medium maintenance to G3
B_d	Time step 1: Raise G1 by 1m
	Time step 2: Do noting
C	Time Step 1: Medium maintenance to G1, 3 and 4
	Time Step 2: Medium Maintenance to G3
D_d	Time Step 1: Medium maintenance to G1, 3 and 4
	Time Step 2: Medium Maintenance to G3
E	Time step 1: Apply low maintenance to G1 and 4
	Time step 2: Apply low maintenance to G1 and 4

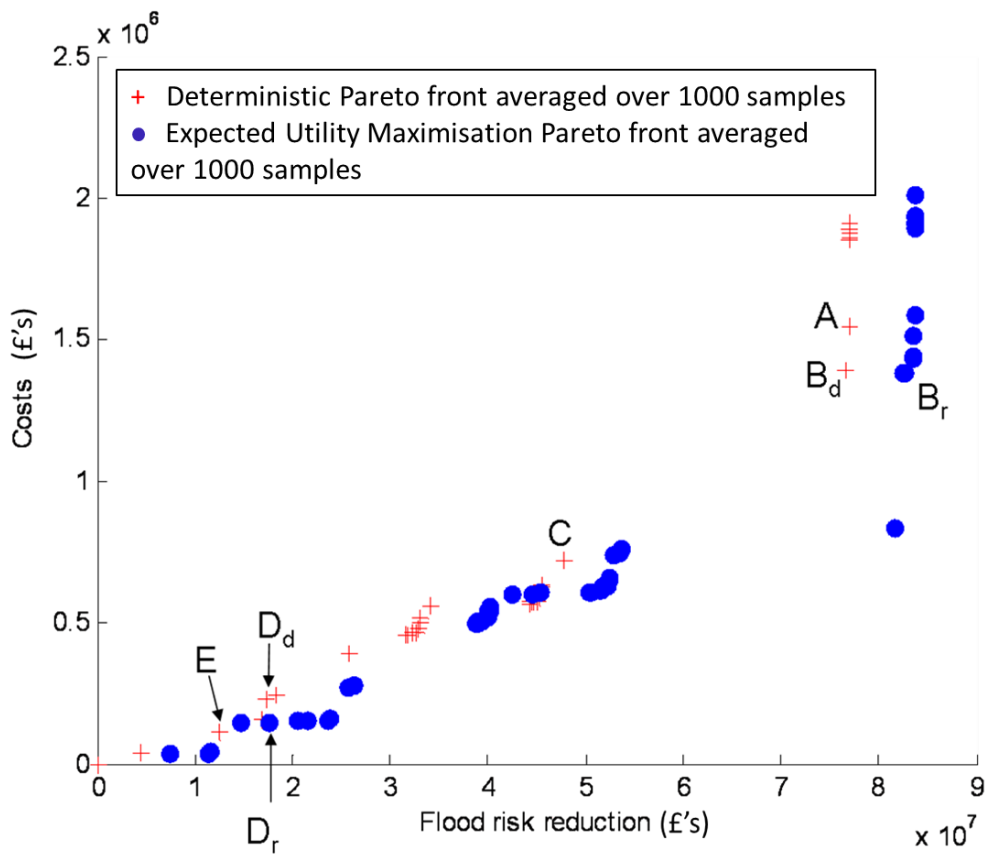


Figure 7.12 Comparison of the deterministic and maximum expected utility optimisation Pareto fronts

Figure 7.12 displays the two Pareto fronts for the deterministic case averaged over 1000 samples represented by crosses and the maximisation of expected utility case averaged over 1000 samples represented by circles. The comparison of these two fronts show the Pareto front of expected utility maximisation dominating the deterministic solutions as the majority of solutions in the expected utility case can obtain higher benefits for the same costs as the solutions from the deterministic case. For example comparing solutions B_r and B_d, these solutions have similar costs, differing by only 0.72%, but the maximum expected utility solution obtains a comparatively higher flood risk reduction by 7.21%. Similarly comparing solutions D_r and D_d, these solutions achieve equivalent benefits but the maximum expected utility solution achieves this at a 34.78% lower cost (see Table 7.14).

Table 7.14 A comparison between two solutions from the deterministic front and the maximum expected utility front from Figure 7.12 when averaged over 1000 future scenarios

Strategy	Benefits £ M	Costs £ M	NPV £ M	BCR	Intervention measures
B_d	76.58	1.38	75.20	55.49	Time step 1 Raise G1 by 1m
B_r	82.53	1.39	81.14	59.37	Time step 1 Raise G1 by 1m Time step 2 Raise and widen G4 by 0.30m
% difference	7.21	0.72	7.32	6.54	
D_d	17.36	0.23	17.13	75.48	Time step 1 and 2 Apply low maintenance to G1 and 4
D_r	17.44	0.15	17.29	116.26	Time step 2 Widen and raise G4 by 0.36m
% difference	0.46	-53.33	0.93	35.08	

The maximum expected utility case is able to dominate the deterministic case because of the consideration of a much larger range of future projections during the optimisation process thus enabling the strategies to perform well over any future outcome rather than restricting the solution to only perform well given one scenario. By optimising the strategies to perform well under one future outcome, during the consideration of additional scenarios the performance of the strategy can be reduced. This has been the case with the deterministic solutions in this example.

Considering a range of future scenarios with the optimisation process provides a trade-off of strategies which are optimal according to the benefit and cost objectives but are also robust to the uncertainties of climate change. Decision makers can identify different solutions which perform well over a range of scenarios and assess the associated benefits and costs to help the decision making process and as can be seen from this example, improve the economical investment compared to a deterministic approach. The optimisation model which maximises expected utility can therefore bring many advantages to decision makers in flood risk management. The next section investigates the use of this optimisation model with an additional criterion to see the effect this has on the selection process.

7.5.4 Additional Optimisation Criteria

The analysis presented so far focuses on the economic performance of an intervention strategy in terms of EAD reduction and costs. This section presents results when using a third objective, the loss of life as explained in Section 5.4.3 where in this example, the loss of life surrogate model is looking to maximise the total number of people no longer at risk. Similar to the above optimisation case, this case study again looks to optimise under uncertainty. 1000 sea level rise projections will be sampled from the three UKCP09 low, medium and high scenarios to evaluate the strategies against. The strategies consist of two 50 year time steps with the opportunity to implement three intervention measures: raising the crest level, widening the base and defence maintenance. As above, a crossover rate of 0.7, a mutation rate of 0.03, a population size of 400 and 200 generations are used.

Figure 7.13 displays the Pareto Front of the final generation for each pair of objectives with each point on the graph representing a potential flood risk intervention strategy. Considering the benefits in terms of flood risk reduction and costs, the typical trend sees an increase in costs to obtain an increase in benefits. Similarly, to improve the loss of

life value a high cost is required. Comparing loss of life against benefits, it can be seen that the higher the benefits the higher the number of lives no longer at risk.

Five solutions have been selected from the Pareto front to see how the different objectives impact the decision making process. Strategy A has been highlighted as it performs the best with regard to flood risk reduction. It also performs reasonably well under the loss of life objective but has by far the highest cost (see Table 7.15). The intervention measures suggested for this strategy (Table 7.16) apply a large number of height and width increases across both time steps. This number of interventions across a 100 year time step does not seem unreasonable and given the discount rate it will be less money to apply further interventions in the second time step. It therefore suggests at the present day to only make the necessary width and height increases needed to protect against flooding for the first 50 years. Any additional interventions required to protect against flooding during the second epoch are made at the next time step when the costs will be less due to the discount rate. Making all the interventions now would be extremely costly. Given this, this option is still the most expensive and although this solution performs well according to two objectives, its under performance on the third objective could restrict its selection. Strategy B outperforms all solutions with regard to the loss of life criterion and also performs well according to flood risk reduction, but again the cost to achieve this is fairly high. The lowest cost can be obtained by selecting Strategy E; this however will result in low performance with regard to the remaining two objectives. This strategy only applies interventions to group 4. This is a high risk area but it has not identified all of the priority groups (including groups 1 and 2) hence such a low flood risk reduction. Strategies C and D have identified that as well as improving group 4, a high EAD reduction is obtained through raising groups 1 and 2. This is because the flood risk areas these groups are protecting are highly developed areas and particularly for group 1 it is in a vulnerable location.

Strategies C and D find a compromise on the three objectives (see Table 7.15). Strategy D for example has a fairly low cost and a reasonable loss of life value but the flood risk reduction could be improved. Strategy C on the other hand obtains a high benefit but does not require a large cost to do so. The loss of life value is also reasonable. If there are no priorities or preferences on the criteria strategy C would provide a sensible trade-off. If the decision maker did need to apply preferences to the criteria, the Pareto front

enables a simple process to visualise the most appropriate solutions and see its impact on the other criteria.

Across all strategies in Table 7.16, the optimisation process has assigned a minimal number of interventions to groups 3 and 5. As explained in the previous case studies (see Section 7.5.3), these groups of defences are situated in a less developed area and do not require as many interventions as the other groups and therefore verifying the choices by the optimisation algorithm.

Table 7.15 Summary of the benefits, costs and loss of life values for the strategies highlighted in Figure 7.13

Strategy	Benefits £M	Cost £M	Loss of Life surrogate (1,000)
A	81.59	9.90	2.60
B	81.58	5.22	2.61
C	81.02	1.97	2.53
D	55.57	1.18	2.52
E	38.51	0.65	2.38

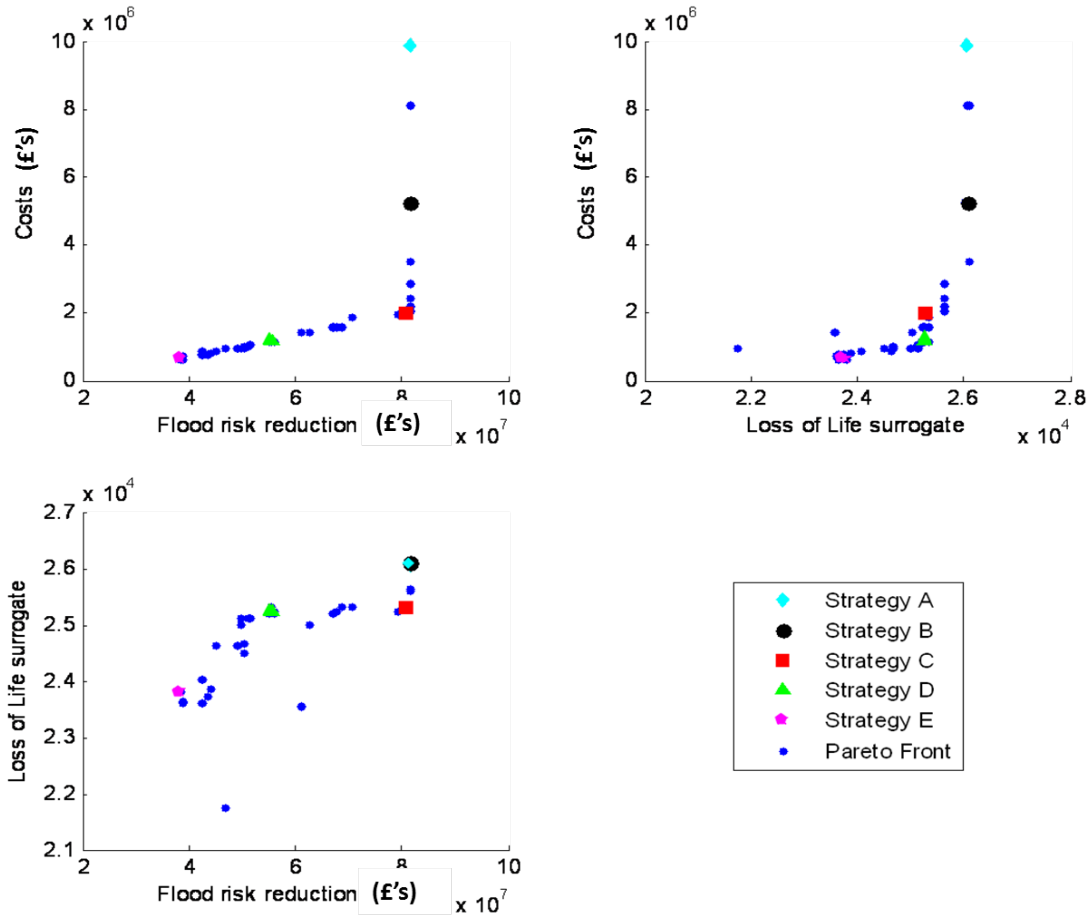


Figure 7.13 The Pareto Front for each pairwise objective for the Thames Estuary when considering a trade-off between three objectives

When considering an additional criterion, the decision making process becomes more complicated. It is not as simple as to select a strategy with performs well under the benefits and costs as this may not perform well given the third criterion. In most cases there will be a trade-off or a compromise that needs to be taken, multi-objective optimisation and its outputs enables the decision maker to make a fully informed decision under these conditions. Preferences and priorities may need to be applied to determine the most appropriate solution but it is much more favourable to do this after the search has taken place. Applying weightings to criteria in advance can limit the available solutions and decision makers can therefore miss potentially better solutions. This example has shown the benefits that multi-objective optimisation can bring to flood risk management and the advantages to the decision making process.

Table 7.16 Summary of the intervention measures implemented for each strategy highlighted in Figure 7.13

Strategy	Time step	Raise Crest Level (m) (to defence groups 1 -5)					Widen base (m) (to defence groups 1 -5)					Maintenance (M = medium, H = high)				
		1	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
A	1	1.33	0.46	0.46	0.30	0.00	1.0	3.0	0.0	2.0	1.0	0	0	0	H	M
	2	0.66	0.00	0.66	0.36	0.00	1.5	2.0	0.0	3.0	1.0	0	0	0	0	M
B	1	1.33	0.00	0.00	0.46	0.00	1.0	3.0	0.0	2.0	1.0	0	0	0	H	M
	2	0.66	0.00	0.66	0.33	0.00	1.5	1.0	0.0	1.5	1.0	0	0	0	0	0
C	1	0.66	0.00	0.00	0.00	0.36	0.0	0.0	0.0	0.5	1.0	0	0	0	0	0
	2	0.00	0.30	0.00	0.36	0.00	0.0	1.0	0.0	3.0	1.0	0	0	0	0	0
D	1	0.00	0.00	0.00	0.46	0.00	0.0	0.0	0.0	0.5	2.5	0	0	0	0	0
	2	0.33	0.36	0.00	0.36	0.00	1.5	2.0	0.0	3.0	1.0	0	0	0	0	0
E	1	0.00	0.00	0.00	0.36	0.00	0.0	0.0	0.0	0.5	1.0	0	0	0	0	0
	2	0.00	0.00	0.00	0.36	0.00	0.0	2.0	0.0	1.0	1.0	0	0	0	0	0

7.6 Case 4 - Real Options based Optimisation

In this case study, the Real Options optimisation model is used (see Section 6.5) to optimise for long term flexible and adaptive strategies. The previous optimisation case studies in this Chapter investigate the use of single and multi-objective optimisation on deterministic cases and cases with uncertainty. The deterministic cases only consider one possible future scenario making the optimisation process search for an optimal

solution without considering the future uncertainties of climate change. In flood risk management where the uncertainties of climate change will have a large impact on the decisions made, it is not plausible to ignore other possible scenarios. The optimisation under uncertainty therefore considers many possible future scenarios to ensure robust strategies are developed which are capable of providing protection irrespective of how the future unfolds. However in both these cases, the intervention strategies are considered to be fixed over the planning horizon and provide no opportunities to adapt in the future if a better more optimal solution presents itself. The Real Options optimisation model, therefore, allows the inclusion of flexibility to be evaluated and thus provides opportunities for adaptation. The intervention strategies include a level of flexibility which are represented as decision trees with optional decision paths. The decision trees created here have been designed in a simplistic manner primarily driven by the need to save computational time. Therefore only two time steps of 50 years are considered. The first time step does not have optional paths as the decision for the immediate future is made now. At the second time step, there are two optional paths allowing for enough flexibility in the solutions to demonstrate the advantages of Real Options.

The optimisation process optimises a population of 400 intervention strategies at each generation over 200 generations. As in Section 7.5 the intervention measures considered include raising and widening the foundations of the defences as well as applying defence maintenance. A crossover and mutation rate of 0.7 and 0.03 respectively is used obtained using the sensitivity analysis in Section 7.5.2. The Green book standard declining discount rate is used to return the strategies back to their present day value. As in Section 7.5.2, the two objective functions, maximising the flood risk reduction and minimising the costs are considered.

Figure 7.14 displays the progression of the Pareto front over the 200 generations as the solutions converge upon the optimal front. The triangular points represent the Pareto front at each stage over time while the circular points represent the remaining dominated solutions. The solutions can be seen to evolve and improve to a set of optimum solutions by the 200th generation.

The Pareto front from the 200th generation is displayed in Figure 7.15 represented by circular points. Four intervention strategies on the Pareto front have been identified, solutions A to D, including the solution with the highest NPV (triangular point) and the

highest BCR (square point). Table 7.17 displays the benefits, costs, NPV and BCR for these strategies while Figure 7.16 displays the structure of each of the four solutions and the intervention measures for each path.

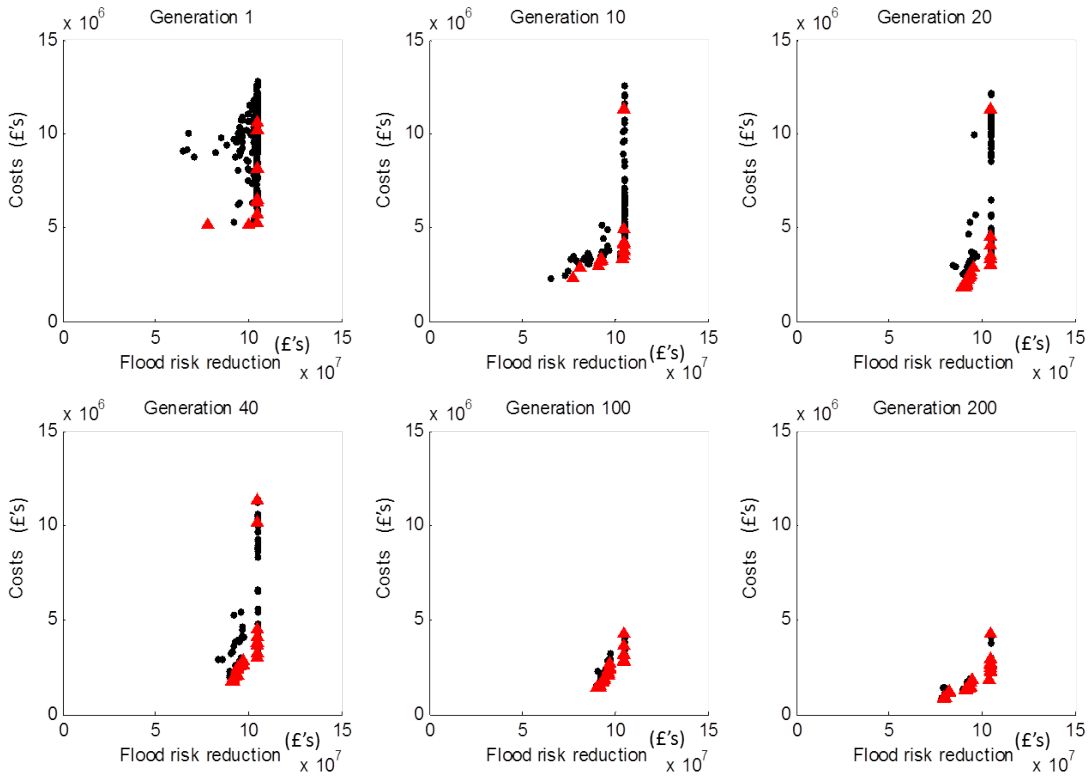


Figure 7.14 The progression of the Pareto Front for a Real Options optimisation on the Thames Estuary case study

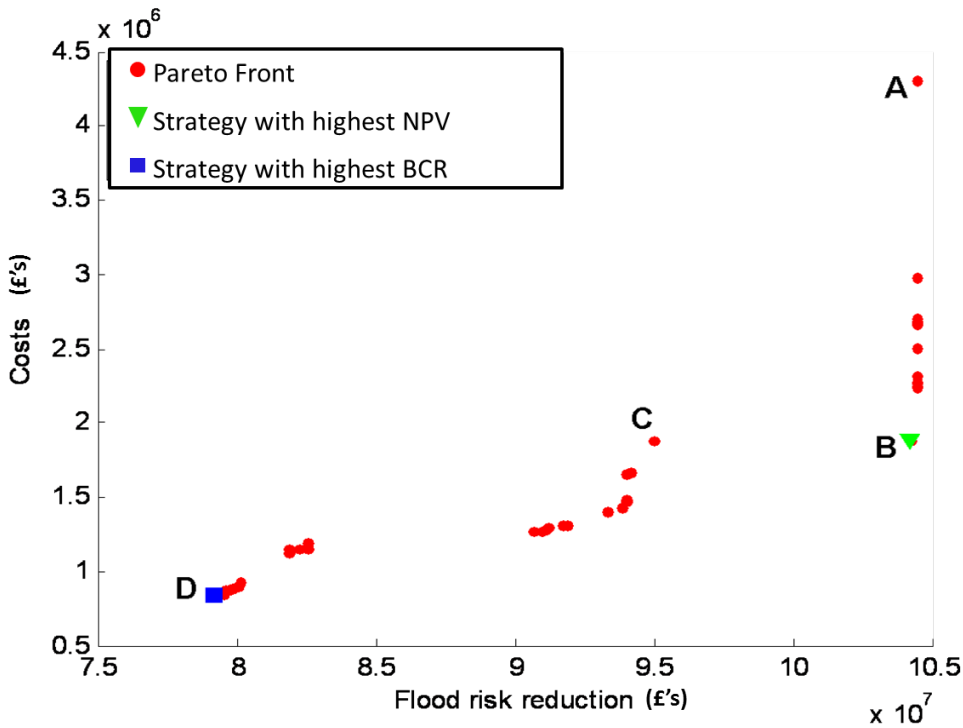


Figure 7.15 Pareto Front from the final generation of the Real Options optimisation run

Taking solution B, this is the solution which obtains the highest NPV. At the present day, solution B suggests widening the base to three groups of defences as well as raising two of these groups. By widening the base at the present day, this provides the opportunity to raise the crest levels further in the future if the impacts of climate change are higher than expected thus supporting the options in the top path. If there is little or no change to the increase in the climate change impacts the bottom path can be selected which recommends a 'do nothing' option where it does not undertake unnecessary interventions and thus spend unnecessarily. The optimised threshold value for this strategy recommends taking the top path if the sea level rise increases by the end of the planning horizon beyond 0.37m, otherwise the bottom path is optimal. 60.9% of the 1,000 sea level rise samples were directed to the top path while only 29.1% took the bottom. For solutions C and D, it is also recommended that if the sea level rises above 0.37m it is optimal to take the top path, otherwise take the bottom. In all three solutions, the bottom path does not suggest applying many intervention measures and in the case of solution B, a do nothing option is advised.

Table 7.17 The benefits, costs, NPV and BCR of the solutions highlighted in Figure 7.15

Strategy	Benefit £M	Cost £M	NPV £M	BCR
A	104.45	4.31	100.14	24.23
B	104.22	1.88	102.34	55.44
C	94.97	1.87	93.10	50.79
D	79.23	0.84	78.39	94.32

Strategy A on the other hand suggests taking the top path if the sea level rise increase goes beyond 0.52m, otherwise take the bottom path. Solution B achieves a very similar return in benefits compared to solution A but for a significantly lower cost which improves the overall NPV. The difference in cost can be attributed to the way the flexibility is used, similar to the comparison of solutions A and C in case study 1. Strategy A here does not purchase the 'insurance policy' for the second time step. If the sea level rise is beyond the threshold, a greater capacity for crest level raising needs to be introduced. This requires additional costs. Although the option is flexible in that a decision is delayed until more is known about the future impacts of climate change, the costs in the way this flexibility is used is less favourable. Solutions B and C instead purchase this 'insurance policy' to enable flexibility to be inherently built into the defences. B is then able to achieve similar benefits to A but for a reduction in costs of 56.38% and thus showing B to be more favourable. This difference in the use of flexibility can be described using the definitions of Real-In-Options and Real-On-Options by De Neufville (2003). Real-In-Options modifies the system by inherently designing flexibility into the infrastructure. Real-On-Options treats the infrastructure system as a black box and instead applies the flexibility to the decision making process related to the investment. In this case study, strategy A applies Real-On-Options, using a delay in the investment. Flexibility is not built into the design of the defences as the defences infrastructure needs to be modified in the second time step if the top path is taken. Strategy C applies Real-In-Options by building flexibility into the design of the system. In the second time step, the defence can be easily adapted to account for an increase in sea level rise

Comparing solution B to C, solution B has a minimal increase in cost but a significantly higher benefit is achieved thus making solution B again seem more favourable. This can

be attributed to the fact that Strategy B raises Group 1 at the first time step whilst widening it and thus gaining a large amount of benefit from the outset. Strategy C does not raise the crest level at the present day so does not realise the benefits until the second time step when both paths will suggest raising the defences in group 1. Solution D is the least expensive option but also returns the smallest flood risk reduction. The two paths in the second time step of solution D are fairly similar to that of solutions B and C but differs in the number of interventions implemented in the first time step. Solution D delays the decision to raise the crest level until the second time step and thus only suggests widening the base at this point. In doing so solution D looks to avoid spending more money at the present day by delaying the interventions. For example, group 1, which has shown to be influential in flood risk reduction (see Section 7.5.3) has no interventions applied to it at the first time step and delays widening or raising until the second time step resulting in less expenditure but solution D in return does not receive such a large flood risk reduction as other strategies.

The optimisation algorithm suggests a range of different optimum solutions varying by the costs and flood risk reduction objectives enabling the decision maker to see a list of options to base a decision on the most appropriate option for them.

Strategy A

G1	G2	G3	G4	G5
1.33	0.00	0.00	1.33	0.33
0.5	1.0	0.5	3.0	0.5
0	L	0	L	L

G1	G2	G3	G4	G5
1.33	0.00	0.33	0.46	0.36
0.5	2.5	0.5	2.5	3.0
M	0	0	0	M

Threshold Value:
0.52m

G1	G2	G3	G4	G5
1.00	0.36	0.00	0.00	0.30
0.0	0.0	0.0	0.0	0.0
0	L	0	0	L

2010 T_1 2060 T_2 2100

Strategy B

G1	G2	G3	G4	G5
1.33	0.00	0.00	0.00	0.33
1.5	0.0	0.0	3.0	0.5
0	0	0	0	0

G1	G2	G3	G4	G5
1.33	0.00	0.00	0.00	0.46
0.5	0.0	0.0	0.0	0.0
M	0	0	0	0

Threshold Value:
0.37m

G1	G2	G3	G4	G5
0.00	0.00	0.00	0.00	0.00
0.0	0.0	0.0	0.0	0.0
0	0	0	0	0

2010 T_1 2060 T_2 2100

Strategy C

G1	G2	G3	G4	G5
0.00	0.00	0.00	0.33	0.00
1.0	0.5	0.0	3.0	0.5
0	0	L	0	0

G1	G2	G3	G4	G5
1.33	0.00	0.00	0.00	0.46
0.0	0.0	0.0	0.0	0.0
M	0	0	0	0

Threshold Value:
0.37m

G1	G2	G3	G4	G5
0.46	0.00	0.00	0.00	0.00
0.0	0.0	0.0	0.0	0.0
0	0	0	0	0

2010 T_1 2060 T_2 2100

Strategy D

G1	G2	G3	G4	G5
0.00	0.00	0.00	0.00	0.00
0.0	0.0	0.0	3.0	0.5
0	0	0	0	0

G1	G2	G3	G4	G5
1.33	0.00	0.00	0.00	0.46
0.5	0.0	0.0	0.0	0.0
L	0	0	0	0

Threshold Value:
0.37m

G1	G2	G3	G4	G5
0.30	0.00	0.00	0.00	0.00
0.0	0.0	0.0	0.0	0.0
0	0	0	0	0

Figure 7.16 Summary of the intervention strategies identified in Figure 7.15. Each strategy is a decision tree with two optional paths at the second time step (T_2) with the percentage of samples evaluated at each path written. The first row of each block represents the group (G) where the

interventions are being implemented, the second row represents height increases in metres, the third row represents width increases in metres and the final row represents the defence maintenance (0 = no maintenance, L = low, M = medium, H = high)

Using the Real Options decision tree structure it is not possible to reach zero costs as even if the present day and bottom path suggest a do nothing option, there will always be another path with the opportunity to take a different course of action. This inclusion of flexibility and the option to adapt the strategy therefore increases the cost of the investment compared to strategies without flexibility. Even with the increase in cost, the incorporation of flexibility can still improve the overall investment decision. As can be seen when comparing the Real Options solutions with the deterministic and maximum expected utility solutions (see Sections 7.5.1 and 7.5.3).

The selection of intervention measures throughout the strategies in this case study are again similar to the selection of interventions in the previous sections. For example group 1 defences have been chosen regularly for increasing the height of the defence as this defence protects highly developed areas. These selections are a reflection on the location and type of area they are protecting as explained in detail in the previous case studies (see for example Section 7.5.3).

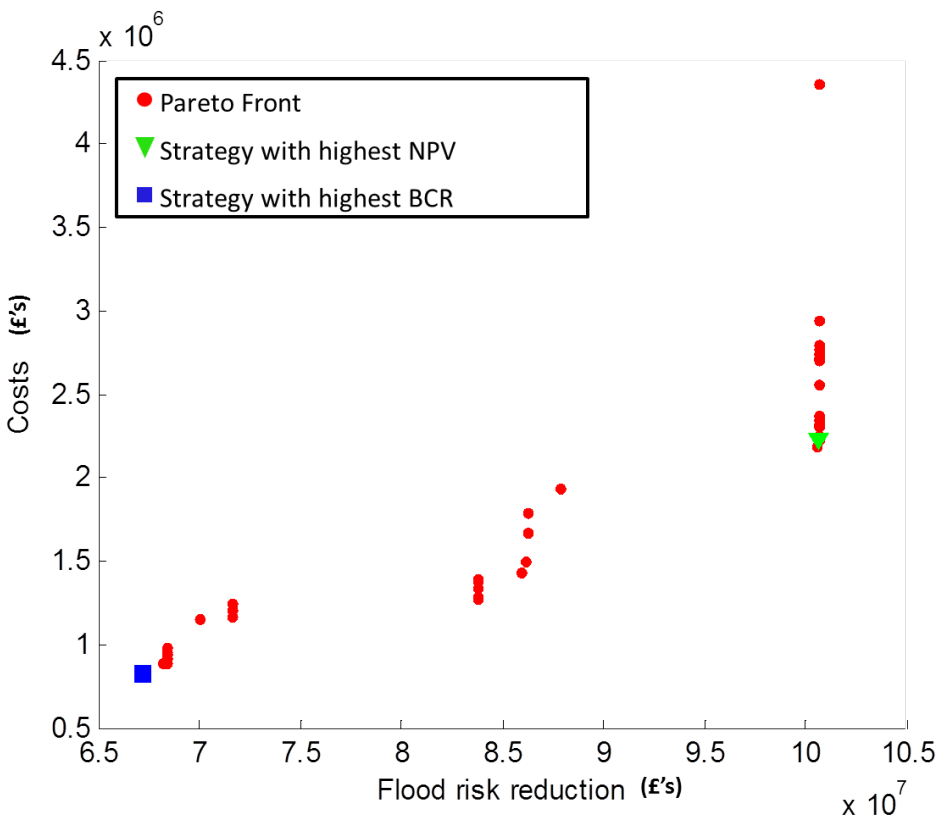


Figure 7.17 The Pareto front of the final generation re-evaluated over 1000 climate change samples

In order to compare the Real Options solutions with the deterministic and maximum expected utility, the final generation of the Real Options optimisation was rerun to evaluate the benefits and costs under the same 1000 future climate change scenarios used in the maximum expected utility and deterministic comparison (see Section 7.5.3). Similar to the re-evaluation of the deterministic front, the benefits of each Real Option solution will be altered impacting the final Pareto front. In addition the costs for each solution will also change because a differing number of samples will take the top and bottom paths once evaluated over a new range of samples. Figure 7.17 displays the new Pareto front after the re-evaluation.

With this re-evaluation of the final generation, Figure 7.18 displays the Pareto fronts of the Real Options optimisation compared to the deterministic optimisation. The deterministic Pareto front was optimised according to the 50th percentile of the high emissions scenario from UKCP09 and then re-evaluated over 1000 sea level rise samples from normal distributions of the high, medium and low emission scenarios (see Section 7.5.3).

From Figure 7.18, it can be seen that the inclusion of flexibility within the intervention strategies has increased the overall cost of the solutions. This inclusion of flexibility does however provide the opportunity to significantly increase the benefits in terms of flood risk reduction resulting in a considerable improvement to the overall investment. For example, the Real Options optimisation overall has been able to obtain solutions with significantly higher benefits than the deterministic approach. This is partly due to the additional optional paths in the Real Options solutions. Each path can be optimised to a smaller range of climate change samples and therefore better provide protection. Additionally, the deterministic solutions were optimised according to one climate change scenario and therefore when analysing the solutions over a range of samples, it is likely that these solutions will not fair so well under different samples and thus bring in less benefits. The solution with the highest benefit under the Real Options case reaches £100.70m compared to £77.03m from the deterministic case. However as these solutions fall on different parts of the Pareto front, it is harder to compare the improvement to the overall investment. Through the comparison of two solutions which fall on similar areas of the Pareto front, it is possible to compare and more easily make direct conclusions. For example solutions A_d and A_{RO} both have similar costs associated to their strategies with A_{RO} incurring a 13.25% higher cost than A_d. But in

return A_{RO} receives a 28.93% higher benefit. This improves the overall NPV by 29.12%. The intervention options for A_d apply a medium maintenance to group 1 and 3 across both time steps. It does not raise or widen any of the defences. A_{RO} instead widens the base of G1 and G4 in the first time step and is then able to raise the crest level along the top path if the sea level rise is above 0.30m, otherwise suggests spending less money and only apply maintenance to group 1 if the sea level is less than 0.30m.

Similarly comparing solutions B_d and B_{RO}, these solutions differ in costs by 0.71% but the Real Options solution, B_{RO}, returns a larger benefit by 8.63% and again improves the NPV, this time by 8.76% (see Table 7.18). B_d only raises and widens the defences in group 1 by 1m. B_{RO} is able to widen the base of the defences in Group 1 and 4 in the first time step, then in the second time step decides on the height of the crest level increase according to the climate change scenario. If the sea level increases beyond 0.56m, it is suggested the defences are raised by 1m in group 1 and apply maintenance to group 4 where as if it doesn't go beyond this threshold, a raise of 0.66m to group 1 is suggested. Having the flexibility within the strategy enables a more effective investment to be planned.

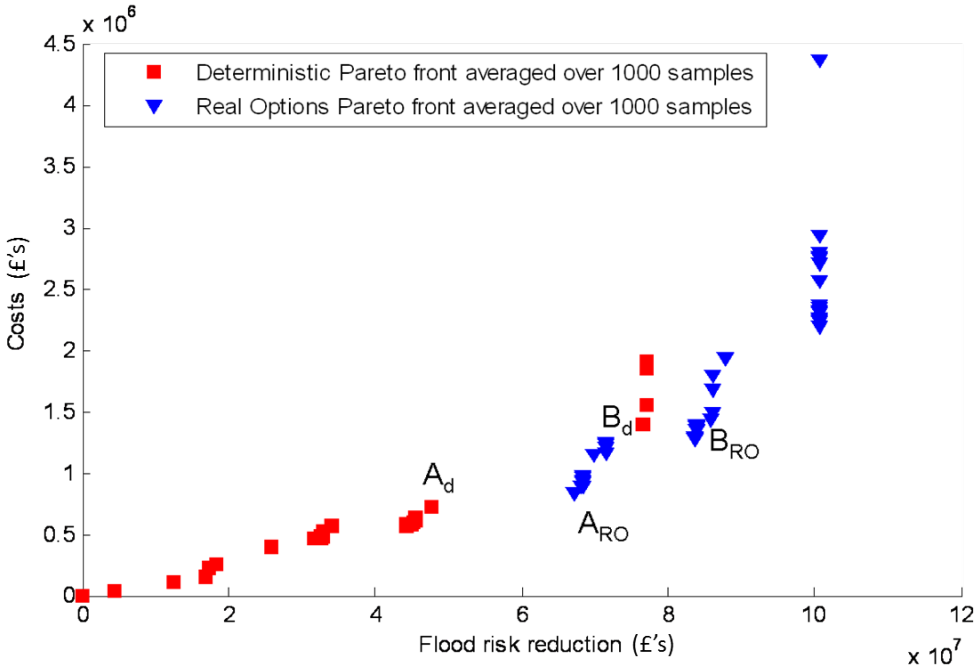


Figure 7.18 The Pareto front of the Real Options optimisation and deterministic optimisation for the Thames Estuary case study

From these two examples it can be seen with similar costs, the Real Options solutions will return higher benefits and thus dominate the deterministic options. This is because

the Real Options solutions have been designed to account for the future uncertainties of climate change by developing alternative, customised strategies appropriate for specific scenarios thus covering, in a flexible manner, a large range of possible future scenarios. The deterministic solutions on the other hand were designed to protect against one scenario only and without allowing for any flexibility in the intervention strategy. Therefore in the face of uncertainty where many different scenarios could potentially occur, the deterministic solutions may not be sufficient. These are therefore not as favourable and have been shown to be dominated by solutions which account for the future uncertainties of climate change as in the maximum expected utility comparison in Section 7.5.3 and the Real Options case here.

Table 7.18 A comparison of two solutions from the Real Options Pareto front and Deterministic Pareto front when evaluated over the same 1000 climate change scenarios as highlighted in Figure 7.18

Strategy	Benefit £M	Cost £M	NPV £M	BCR
A_d	47.76	0.72	47.04	66.33
A_{RO}	67.20	0.83	66.37	80.96
% difference	28.93	13.25	29.12	18.07
B_d	76.58	1.38	75.20	55.49
B_{RO}	83.81	1.40	82.41	59.86
% difference	8.63	1.43	8.75	7.97

The Real Options Pareto front does not extend as far towards zero as the deterministic front. This is partly because a ‘do nothing’ option is feasible for one path on a decision tree Real Option solution but a higher path will always be considered too resulting in options beginning at a higher benefit and cost. Therefore, it is not possible for a Real Options decision tree strategy to have zero costs and zero EAD reduction. However the Real Options front could be closer to zero than the results shown in Figure 7.18. It is likely in this case that the optimisation has struggled to reach low cost and low benefit solutions given the large number of decision variables. Running the Real Options optimisation for longer will improve the front further but the computational expense to do this is too demanding. Despite this limitation, the Real Options solutions obtained for

the current front have still been shown to dominate the deterministic solutions and thus show the advantages of Real Options and the value in evaluating flexibility.

Figure 7.19 now shows a similar picture when comparing the Real Options Pareto front with the front of expected utility maximisation from Section 7.5.3 with three solutions from each front highlighted for comparison purposes. Comparing firstly solutions A_r with A_{RO}, these solutions have similar costs, differing by 1.20% but the maximum expected utility solution has a higher benefit by 21.32% (see Table 7.19). This solution, solution A_r, is the only solution which dominates some of the Real Options front as it is able to obtain a high benefit for a fairly minimal cost. The remaining Real Options front then dominates the rest of the maximum expected utility front. For example, comparing solutions B_r and B_{RO} these solutions have similar benefits of £83.50m and £83.80m respectively but the Real Options solution is able to obtain this benefit for a 18.75% lower cost. Comparatively, two solutions with similar costs, C_r and C_{RO}, C_r is more costly by 0.52% but the Real Options solution C_{RO} increases the flood risk reduction by 4.86%.

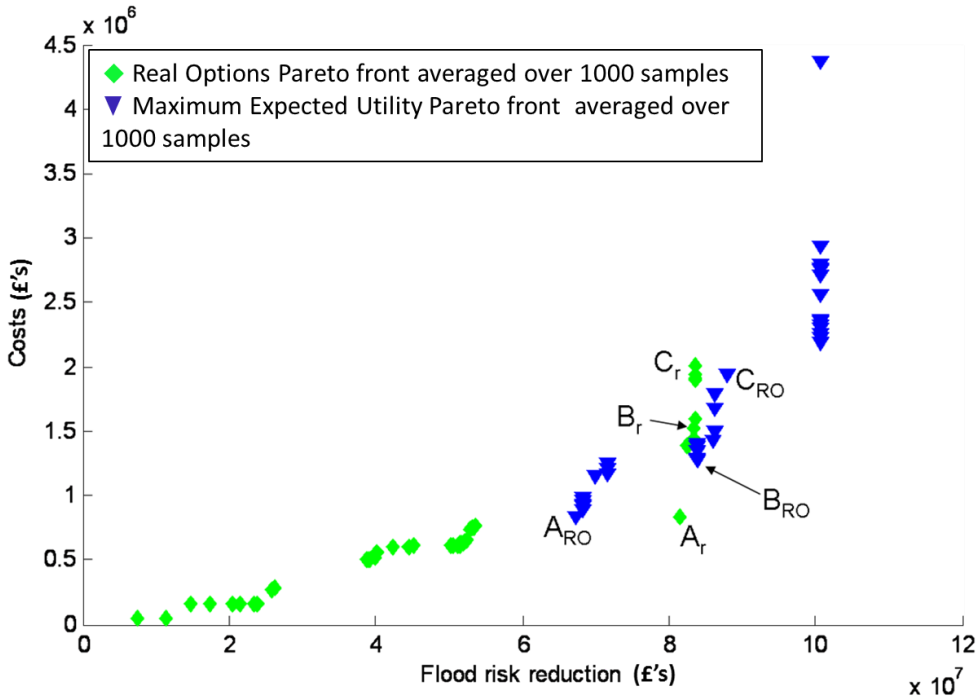


Figure 7.19 The Pareto fronts of the Real Options optimisation and maximum expected utility optimisation for comparison

Both the Real Options and maximum expected utility solutions account for future climate change uncertainty and strategies have been developed to ensure they will

perform well regardless of the future outcome. The introduction of the Real Options decision tree methodology in flood risk management to value flexibility brings advantages to the decision making process. The built in flexibility of the Real Options solution has in many instances enabled more dominated solutions to be presented, producing strategies which are adaptive. This is important during the development of long term intervention strategies. It has also been shown that the Real Options solutions do not always perform the best. As shown above, it is not necessarily the case that decision makers should immediately invest in a strategy with Real Options. However, from this case study, it is being demonstrated that the consideration of flexibility and having the means to evaluate flexibility can enhance the decision making process. In some instances, intervention strategies inherently capturing flexibility could outperform all other options, in other situations this may not be the case. Given this, the consideration of flexibility cannot be overlooked during the development of long term strategies. The methodology presented in this thesis introduces the opportunity to consider and value flexibility within investment decisions and can be used in conjunction with other appraisal methods to improve the decision making process.

Table 7.19 A comparison of two solutions from the Real Options Pareto front and maximum expected utility Pareto front as highlighted in Figure 7.19 when evaluated over the same 1000 climate change scenarios

Strategy	Benefit £M	Cost £M	NPV £M	BCR
A_r	81.53	0.84	80.69	97.06
A_{RO}	67.20	0.83	66.37	80.96
% difference	-21.32	-1.20	-21.58	-19.89
B_r	83.50	1.52	81.98	54.93
B_{RO}	83.80	1.28	82.52	65.47
% difference	0.36	-18.75	0.65	16.10
C_r	83.58	1.94	81.64	43.08
C_{RO}	87.85	1.93	85.92	45.52
% difference	4.86	-0.52	4.98	5.36

7.7 Summary

This Chapter applies the methodologies presented in this thesis on an area of the Thames Estuary. The specific area of interest is described in Section 7.2. Section 7.3 begins by comparing the Real Options approach to a more traditional approach for analysing intervention strategies. Four manually selected strategies were analysed, highlighting the differences between the Real Options process and the more traditional approach. It was shown, that when uncertainty is present, the value of flexibility incorporated into long term intervention strategies using the Real Options approach is beneficial. If the future is uncertain, it can be advantageous to inherently capture flexibility within the design of the strategy and provide the opportunity to adapt if required. Having the capability to evaluate flexibility appropriately enables decision makers to consider additional strategies which previously would have been overlooked.

The next case study in Section 7.4 investigates the use of the single objective optimisation methodology to search for the most appropriate long term flood risk intervention strategy. The optimum solution (the highest NPV) when compared to the manually selected strategy from the previous example was found to be more favourable. The automated process enables a thorough, extensive search for the most appropriate intervention strategy which is not possible during a manual selection.

Section 7.5 follows by applying multi-objective optimisation to search for the most appropriate long term strategies. Three different cases were explored. The first considered a deterministic optimisation where uncertainty is not considered and the objectives flood risk reduction and costs are kept separate to produce a Pareto front of options. Secondly, the uncertainty was considered using the optimisation methodology which maximised expected utility accounting for climate change uncertainty to optimise for the two objectives. Finally, three objectives were considered with the additional objective loss of life used within the optimisation model. The use of multi-objective optimisation provided many benefits and the output aids the decision making process in flood risk management. It was also found that the use of the expected utility optimisation methodology is advantageous in flood risk management when compared to an approach which only considers one future scenario. In flood risk management where the future is so uncertain, accounting for the uncertainties of climate change is vital. A sensitivity analysis of the GA parameters was also provided to justify the values used.

The final Section, Section 7.6, applied the Real Options based optimisation methodology on the area of the Thames Estuary. The intervention strategies inherently captured flexibility within the design of the strategies by representing the strategies as decision trees rather than single fixed paths over the planning horizon. In the example provided the value of flexibility was shown to improve the investment decisions, illustrating the benefits to flood risk management when considering flexibility and adaptability, especially when compared to a deterministic approach. In this example, it is more advantageous to allow opportunities to adapt at future points in time rather than deciding on the full course of action at the outset. The methodology presented in this thesis provides the means to evaluate and value flexibility in an investment decision. Given the benefits that can be obtained through the inclusion of flexibility as shown above, flexibility clearly should not be disregarded. It was also shown that strategies with flexibility are not necessarily the most favourable solutions. Having the capability to value flexibility and thus compare adaptive and non-adaptive intervention strategies allows decision makers to select the most appropriate investment decision for their given situation. The methodology presented has shown to enable the most appropriate long term strategies to be identified according to a range of competing objectives and provide many advantages to the decision making process in flood risk management.

Chapter 8 Summary and Conclusions

8.1 Introduction

In this Chapter, Section 8.2 provides an overview of the thesis with Section 8.2.1 giving a summary of the work presented and Section 8.2.2 listing the main contributions. Section 8.3 draws conclusions from the work while Section 8.4 completes the Chapter with recommendations for further work.

8.2 Summary

8.2.1 Thesis Summary

The main aim of this thesis is to explore the use of Real Options and optimisation techniques in flood risk management to improve upon the decision making process when developing long term flood risk intervention strategies. A decision support methodology was developed which builds upon the Real Options and optimisation concepts as well as additional components to create optimum long term robust and flexible intervention strategies.

The decision support methodology created in this thesis can be broken down into building blocks, with the first essential component discussed in Chapter 3, the risk analysis model, RASP. RASP is used to evaluate potential intervention strategies and quantify the risk associated to different intervention measures occurring at different points in time. With the intention to couple the risk analysis tool with optimisation methods at a later stage, modifications were suggested and verified to improve the computational efficiency.

The next building block of the decision support methodology requires a process which can analyse (i.e. quantify) the overall performance of a given intervention strategy in an automated fashion. This is developed and described in Chapter 4. The risk analysis tool from Chapter 3 is incorporated with a costing methodology, enabling performance indicators to be expressed. The evaluation process, accounts for the uncertainties relating to climate change by analysing the intervention strategies over a range of plausible future climate change projections and incorporates the concepts of Real

Options and Real Options analysis to inherently capture flexibility within the design of the intervention strategy.

With a process in place to evaluate long term robust and flexible flood risk intervention strategies, the next building block is an optimisation process to identify the better performing intervention strategies (Chapter 5). Both single and multi-objective optimisation algorithms are incorporated. An additional objective function is also included, a loss of life surrogate, within the evaluation process in order to provide a range of criteria during the multi-objective optimisation.

Finally in Chapter 6, the building blocks are combined together with an improved method to account for climate change uncertainty to produce an optimisation model which maximises expected utility. This model optimises for long term intervention strategies of expected utility maximisation according to single or multiple objectives. In this Chapter a second model is also produced which again uses the building blocks from the previous Chapters but instead looks to optimise flexible and robust intervention strategies. A methodology is described which treats intervention strategies as decision trees with multiple paths into the future rather than fixed strategies over the planning horizon.

Both these models and the various building blocks are tested and verified on a real life case study, the Thames Estuary in Chapter 7.

8.2.2 Summary of the Present Work Contributions

The main contributions of the work presented in this thesis are as follows:

- A new, Real Options concepts and Real Options Analysis based methodology, for representing and evaluating long-term intervention strategies in linear defence engineering systems under future climate change uncertainties. The intervention strategies considered are represented using threshold based decision trees enabling to explicitly represent optional future intervention paths.
- A new, single and multi-objective optimisation based methodology which makes use of the above Real Options concepts and analysis to identify, in an automated fashion, flexible/adaptable long term flood risk intervention strategies that account for future climate change uncertainty over the analysed planning horizon.

- A new, single and multi-objective expected utility optimisation methodology which searches for the most robust long term intervention strategies over a range of sea level rise samples from the UKCP09 low, medium and high emission scenarios according to a range of multiple objectives.
- A new, single and multi-objective, optimisation based methodology to optimise long term flood risk intervention strategies whilst trading-off the cost of interventions against the flood risk (expressed both as expected annual damage and as a potential loss of life) over one future scenario. The new methodology allows the identification of optimal dynamic intervention strategies over the analysed planning horizon.
- A model simplification to an existing flood risk analysis tool, RASP, which replaces the Monte Carlo sampling process with an expected values of volume approach to calculate the defence system states when coupled with optimisation techniques.
- A methodology to reduce the number of RASP runs over a large range of potential future scenarios, speeding up the EAD calculation.

8.3 Conclusions

The main conclusions from the work undertaken in this thesis are as follows:

- In flood risk management where climate change is very uncertain it is important to consider and account for the uncertainties during the development of long term flood risk intervention strategies. If only one future projection is considered it is likely that the strategy developed is sub-optimum if there is any change in the projected outcome. The use of the NPV during the appraisal of intervention options is also inadequate if evaluating options over one single future in an uncertain environment. When subject to large amounts of uncertainty, it is unlikely that the projected future outcome will remain the same resulting in an unsuitable appraisal of the intervention strategy. Again confirming the importance of considering and accounting for climate change uncertainty.
- The use of Real Options and Real Options Analysis is suitable for flood risk management to account for climate change uncertainty and incorporate flexibility to adapt in the future if required. The use of Real Options inherently captures the flexibility within the design of an irreversible investment, such as a

flood defence, and values this flexibility within the appraisal process to ensure an appropriate performance measure is assigned to the investment.

- Representing intervention strategies as decision trees which inherently capture the Real Options concepts lend themselves to easily adapt to any change in the future outcome. This approach enables decision makers to visualise the possible options and see the impact a chosen path will have given a potential future scenario. The incorporation of flexibility can significantly improve the economical investment and as can be seen from the case study in Section 7.6, provide additional benefits.
- The consideration of flexibility and adaptability is very important for the development of long term strategies but it is not always the most optimum solution. In some cases, the additional flexibility comes at a price and in that instance would not be worth accepting. This is not to say that flexibility should be ignored, it should be considered in the development of intervention strategies to assess if additional benefits can be achieved. Consequently, adaptive strategies should be developed in conjunction with more traditional interventions, providing decision makers with more information to base their decisions on. By considering both, the most appropriate solution can be chosen for the particular problem at hand and therefore obtain the greatest benefits.
- The use of evolutionary optimisation techniques within flood risk management can improve the decision making process. The evolutionary algorithms are able to search through complex, non-linear, often discrete and multimodal search spaces involving a large portfolio of possible intervention measures and identify the better performing options. A manual search is not only time consuming but can often result in high performance solutions going unseen.
- Multi-objective evolutionary algorithms can also provide many advantages to the decision making process as a range of competing criteria can be optimised simultaneously resulting in a trade-off of optimal solutions. This presents decision makers with a range of Pareto Optimal solutions, i.e. the full trade-off between competing objectives, thus providing decision makers with all the necessary information to make an informed decision given the problem at hand.
- The decision support methodology developed in this thesis which combines the Real Options concepts and the evolutionary optimisation algorithms is a useful tool in flood risk management to aid the development of optimal long term

flexible and robust intervention strategies. It can help to answer questions such as what types of intervention measures would be most appropriate, when should they be implemented and where given the future uncertainties of climate change.

8.4 Recommendations for Further Work

The recommendations for further work on the topics presented in this thesis are as follows:

- Expand on the current decision variables by incorporating additional intervention options and mitigation activities within the development of long term strategies by including options specific to a given river. For example, if evaluating the full Thames, include possible operational modifications to the Thames Barrier as a decision variable. The options are currently generic to all problems and locations, specifying options specific to a given area or problem will be more realistic and accurate.
- Consideration of additional evaluation criteria in addition to the objectives stated in this thesis. Possible objectives for consideration could include environmental damage, carbon footprint and impact or costs from disruption to businesses and public services. Further investigation on the impact that these different criteria have on the decision making process would be recommended.
- Explore the different decision making methods under uncertainty. In this thesis, an equal likelihood approach has been adopted to deal with the range of climate change scenarios. It would be of interest to undertake a sensitivity analysis on different approaches such as Wald's Maximin or Minimax Regret and analyse the impact these have on the optimal solutions in the Pareto Front and thus the decision making process.
- Expand the model runs for the Real Options optimisation process considering additional time steps and number of optional paths and assess whether the additional flexibility from the increased optional paths is advantageous.
- Explore the possibility of using alternative optimisation methods and/or different surrogate models and similar concepts with the main aim to reduce the computational time required for optimisation.
- Apply the expected utility optimisation and Real Options optimisation models to different case studies but also consider applying the models to different problems. This thesis has focused on the use of Real Options and optimisation

being applied to linear flood defence systems. The approach could however be applied to urban drainage problems or water distribution systems.

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