Adaptive and flexible approaches for water resources planning under uncertainty

Thesis submitted to University College London for the degree of Doctor of Philosophy

by

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Declaration

I, Kevis Pachos, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Signed: ____

Date: ____

Abstract

Planning for water supply infrastructure includes identifying interventions that cost-effectively secure an acceptably reliable water supply. In investigating a range of feasible interventions, water planners are challenged by two main factors. First, uncertainty is inherent in the predictions of future demands and supplies due for example to hydrological variability and climate change. This makes fixed investment plans brittle as they are likely to fail if future conditions turn out to be different than assumed. Therefore, adaptability to changing future conditions is increasingly viewed as a valuable strategy of water planning. However, there is a lack of approaches that explicitly seek to enhance the adaptivity of water resource system developments. Second, water resource system development typically affects multiple societal groups with at times competing interests. The diversity of objectives in water resource systems mean that considering trade-offs between competing objectives implied by the highest performing interventions is useful. Nonetheless, few multi-objective applications have aimed at adaptive scheduling of interventions in long-term water resource planning.

This thesis introduces two novel decision-making approaches that address these two challenges in turn. Both approaches apply principles of real option analysis via two different formulations (1) a multistage stochastic mathematical programme and (2) a multi-objective evolutionary algorithm coupled to a river basin simulation. In both cases, a generalised scenario tree construction algorithm is used to efficiently approximate the probabilistic uncertainty. The tree consists of possible investment paths with multiple decision stages to allow for frequent and regular modifications to the investment strategies. Novel decision-relevant metrics of adaptivity and flexibility are introduced, evolving their definition in the context of water resources planning.

The approaches are applied to London's urban water resources planning problem. Results from this thesis demonstrate that there is value in adopting adaptive and flexible plans suggesting that flexibility in activating, delaying and replacing engineering projects should be considered in water supply intervention scheduling. To evaluate the implementation of Real Option Analysis (ROA), the use of two

metrics is proposed: the Value of the Stochastic Solution (VSS) and the Expected Value of Perfect Information (EVPI) that quantify the value of adopting adaptive and flexible plans respectively. The investment decisions results are a mixture of 'long-term' and 'contingency schemes' that are optimally chosen considering different futures. The VSS shows that by considering uncertainty, adaptive investment decisions avoid £100 million NPV cost, 15% of the total NPV. The EVPI demonstrates that optimal delay and early decisions have £50 million NPV, 6% of total NPV.

Additionally, a comparison study of alternative optimisation approaches to water supply capacity expansion problem demonstrate that there is benefit in waiting to allow for improvements around supply uncertainty in the case of London's urban water resources planning problem. The results from the case study suggest that the proposed adaptive planning approach achieves substantial improvement in performance compared to alternative optimisation approaches with fixed plans saving more than £377 million, reducing NPV cost by 35%.

Using a multi-objective multi-stage real-options formulation of the water planning problem, the trade-offs between a long-term water management plan's resilience and its financial costs under supply and demand uncertainty are explored. The set of trade-off solutions consist of different investment plans that are adaptive to demand growth, approximated by a scenario tree, while robust to the effects of climate change supply uncertainty, represented by an ensemble of supply (hydrological) scenarios. Results show that, by being adaptive to demand uncertainty, the total NPV of the most resilient plans is lowered by 58.7%. The value in delaying investments by waiting for more accurate supply and demand estimates is 28.9% of total NPV.

It should be noted that the results from the case study are indicative and should not be considered prescriptively as they are based in a simplified representation of London's water supply system and should be further tested with the more detailed simulation model employed by the water utility which includes the latest proposed option designs, includes requirements to supply neighbouring water utilities, and considers more objectives.

Impact Statement

This work contributes to the advancement of adaptive water resources planning by proposing new decision-making approaches that explicitly enable adaptivity to future uncertainty. The research impact of this study is twofold.

First, this study has economic and societal impact. The results of this study may ultimately be used by water utilities to support the development of their long-term investment plans. The proposed approaches respond to decision-makers' needs in terms of understanding how alternative investments impact on associated objectives. Therefore, given the large socioeconomic and environmental impacts of investments in new supply or demand interventions, this study is a contribution towards reducing undesirable impacts.

Second, this study has academic impact since it presents significant advances in the development, understanding and application of adaptive water resources planning approaches. This work goes beyond the state-of-the-art methods and has resulted in one published journal paper with another two under review.

Publications

The work presented in Chapters 3 to 5 has appeared or has been submitted to the following peer-reviewed journals:

1. Erfani, T., **Pachos, K.** and Harou, J., 2018. Real-options water supply planning: Multistage scenario trees for adaptive and flexible capacity expansion under probabilistic climate change uncertainty, *Water Resources Research*.
2. **Pachos, K.**, Erfani, T. and Harou, J., 2019. Comparison of alternative approaches in water supply capacity expansion under uncertainty, *Water Resources Research*. (under review).
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Abbreviations

ALC	**A**ctive **L**eakage **C**ontrol
BRS	**B**eckton **R**euse **S**cheme
BRSn	**B**eckton **R**euse **S**cheme **n**on reverse osmosis
CP	**C**onstruction **P**eriod
DAPP	**D**ynamic **A**daptive **P**olicy **P**athways
DL	**D**esign **L**ife
DRS	**D**eephams **R**euse **S**cheme
DRSn	**D**eephams **R**euse **S**cheme **n**on reverse osmosis
EA	**E**volutionary **A**lgorithm
EBSD	**E**conomics of **B**alancing **S**upply and **D**emand
EFF	**E**nhanced **Ef**ficiency
EVPI	**E**xpected **V**alue of **P**erfect **I**nformation
ESD	**E**stuary **S**outh **D**esalination
EXP	**Exp**anded capacity of modular option
LRD	**L**ong **R**each **D**esalination
LTR	**L**ead **T**ime **R**isk
MAINS	**Mains** repair campaign
ME	**M**utually **E**xclusive
MET	**Met**ering
MILP	**M**ixed **I**nteger **L**inear **P**rogramming
MOEA	**M**ulti **O**bjective **E**volutionary **A**lgorithm
NPV	**N**et **P**resent **V**alue
OCT	**O**xford **C**anal **T**ransfer

PDF	**P**robability **D**ensity **F**unction
PDP	**P**lanning **D**ecision **P**eriod
PE	**P**robability of failure under **E**xtreme conditions
PS	**P**robability of failure under **S**evere conditions
RE	**Re**lease or reduction to average annual demand in ML/d
RDM	**R**obust **D**ecision **M**aking
RO	**R**obust **O**ptimisation
ROA	**R**eal **O**ptions **A**nalysis
RST	**R**iver **S**evern **T**ransfer
SLARS	**S**outh **L**ondon **A**rtificial **R**echarge **S**cheme
SRE	**S**urplus **R**equired to avoid a drought under **E**xtreme conditions
SRS	**S**urplus **R**equired to avoid a drought under **S**evere conditions
TWUL	**T**hames **W**ater **U**tilities **L**imited
UnC-D	**U**nused **C**apacity for **D**eterministic optimisation
UnC-RO	**U**nused **C**apacity for **RO**bust optimisation
UnC-ROA	**U**nused **C**apacity for **R**eal **O**ption **A**nalysis
UnC-TS	**U**nused **C**apacity for **T**wo **S**taged optimisation
UTR	**U**upper **T**hames **R**eservoir
UTRm	**U**upper **T**hames **R**eservoir **m**odular
VSS	**V**alue of **S**tochastic **S**olution
WRMP	**W**ater **R**esources **M**anagement **P**lan
WRZ	**W**ater **R**esource **Z**one
YR	**Y**ield **R**isk

Chapter 1

Introduction

1.1 Background and motivation

Planning for the future of water resources is facing unprecedented challenges due to rising concern about the impact of climate change, socioeconomic growth and increased urbanisation (Milly et al., 2008; Brekke et al., 2009; Fant et al., 2016). The performance of a water resource service is largely dependent on the uncertain nature of the long-term water supply and demand. Forecasted growth of water demands and amplified hydrologic variability increase the risks of water supply failures (Kundzewicz et al., 2007). This complex management problem motivates the need for innovative water resource management techniques for strategic long-term planning in order to deliver reliable water to customers.

Water agencies around the world are tasked with designing appropriate water supply plans capable of maintaining supply-demand balance. A water resource management plan contains a set of supply augmentation or demand reduction interventions scheduled to be delivered over a time horizon. Despite cost minimisation being usually an important objective in water resource planning, wider objectives should be considered, often including economic, environmental and social impacts. Therefore water planners need to address many competing interests when designing a river basin or infrastructure development plan.

Climate change is likely to cause a reduction in water supply (Barnett et al., 2005) while demand for water will vary with population growth, urbanisation, climate, people's standards of living, land use as well as technological changes (Taylor et al., 2013; Wada et al., 2013). The existing water infrastructures potentially cannot cope with future pressures to accommodate changes in surface and groundwater availability or population increases which may be greater than previously anticipated. This poses a challenge to asset managers who are required to make crucial investment decisions in the present accounting for the needs of a future which is largely unknown.

In the context of uncertainty, the definition of adaptivity involves quantifying the cost of ignoring uncertainty that can be avoided by adaptive plans to changing future conditions. The definition of flexibility involves quantifying the value of information in planning under uncertainty, that is, how valuable it is to know the future before making a decision.

To support water planners and managers in this complex process of identifying and evaluating plans under uncertainty, a variety of modelling approaches have been developed. Common water resource planning decision-making tools can be classified as either of the following:

- aggregated method where supply and demand are described as single values or probability functions for each year of the forecast (UKWIR, 2012). That is, the aggregated method requires that the water supply problem be simplified, comparing a single value of annual supply with an annual demand. This allows the problem to be solved with the use of mathematical programming optimisation models. The planning framework is termed Economics of Balancing Supply and Demand (EBSD) and has been used by the water industry since 2002 in England.

- system simulation method where a model of the resource system is used to evaluate metrics around performance indicators such as resilience and investment costs. Simulation models of water resource systems allow to account for non-linearities, such as “if-then” style rules which is not possible in linear programming applications (Maier et al., 2014) where important non-linear interactions are ignored (Matrosov et al., 2013).

This thesis evaluates and address the key issues of alternative methods used in water resources planning and proposes new approaches that allow for integration of flexibility and adaptivity into water investment plans as a way to address uncertainty arising from changes in climate, technological, socio-economic and political situations. By deriving flexibility and adaptivity metrics, the methods presented in this thesis quantify the value of adopting adaptive and flexible plans. These metrics are used to give a definition to flexibility and adaptivity. As the awareness of large uncertainties increases, especially those associated with climate change, the importance of flexibility (i.e. the ability to switch or change a decision depending on what outcomes materialise) in informing water investment planning is increasingly recognised (Groves et al., 2014; Haasnoot et al., 2013; Hino and Hall, 2017; Jeuland and Whittington, 2014; Kwakkel et al., 2015; Zeff et al., 2016). Despite the recognised benefits of adaptive planning, in practice many water resource planners still use conventional non-adaptive optimisation methods. For instance, in 2019, the benchmark least-cost approach used by water utilities in England for deriving their water resources management plans produce a single set of interventions as a programme of investment (UKWIR, 2016). The application of adaptive methods on real systems is considered state-of-the-art.

Water investment decisions that do not capture the value of flexibility increase the likelihood that plans perform poorly and are maladaptive to changing conditions. In response to this limitation, this thesis introduces two adaptive and flexible approaches to water management decision-making. In the first proposed approach, a decision-making framework of the aggregated method type is developed to introduce flexible and adaptivity to least-cost capacity expansion scheduling via multistage stochastic mathematical programming. In the second approach, a system simulation method coupled with Evolutionary Algorithm (EA) is used to identify flexible and adaptive water management plans considering multiple objectives. The methods proposed in this thesis go significantly beyond the existing practice, by proposing a number of alternative schedules and branches, along with a reference metric that allow asset planners decide which interventions should be activated under the which conditions at any given time of the long-term planning horizon, for both aggregated and system simulation methods.

As presented in detail in Chapter 2, sophisticated methods for decision-making under uncertainty are being developed and example methodologies include Real Options Analysis (ROA), Dynamic Adaptive Policy Pathways (DAPP) and Robust Decision Making (RDM). The approaches introduced in this thesis use principles of ROA as this allowed to illustrate how the evolution of different futures may trigger different options selection in a multi-stage framework. ROA was found to be relevant when asset managers in water utilities have concerns about the level of uncertainty in supply-demand forecasts and focus on choosing short-term actions that can anticipate responding to the resolution of uncertainty.

1.2 Scope and aims of research

The aim of this research project is to introduce new methods for water resources decision-making under uncertainty with the ability to value flexibility and adaptivity and to explore how the proposed approaches can be used to identify flexible sequences of water supply portfolio investments to close the uncertain future supply deficit. In particular, building on two water resource planning decision-making tools commonly used by water companies for investment appraisal, this thesis expands an aggregate supply demand modelling method and system simulation based planning method to enable adaptation to new conditions.

In order to achieve this aim, the following objectives were identified:

(i) Propose a methodology to approximate the stochastic supply and demand representing an ensemble of plausible futures in order to facilitate adaptive and flexible decision making to changing future conditions;

(ii) Develop new methodologies that explicitly allow for any possible value in postponing investments until more is learnt about whether they are needed;

(iii) Evaluate the strengths and weaknesses of alternative strategic planning and investment appraisal methodologies for water management and illustrate with specific case studies to aid justification of recommendations.

The proposed planning methods are validated by applying them to a real-world case study, the London urban water supply system which is managed by Thames Water Utilities Limited (TWUL). The London supply area has a significant supply-demand deficit throughout the planning period which requires investment to maintain security of supply (UKWIR, 2016). TWUL have identified a need to deliver a new large water resource option around the mid to late 2020s to secure reliable water supply to their customers. There are four different large water resource types of options available: wastewater reuse, desalination, a new large reservoir in the Upper Thames catchment and a Severn-Thames Transfer. Due to the wide range of different supply and demand scenarios, it is impossible to predict the exact timing and magnitude of the supply deficit. This uncertainty makes the selection of the most valuable option a challenging task.

The conditions for implementing flexible and adaptive plans exist: (i) The economic regulator of the natural monopoly water utilities requires they produce long-term supply demand plans (25 years or more) to justify short-term investment actions (next 5 or 10 years). That is, asset planners must select short-term interventions for the next Asset Management Period (AMP) and be able to demonstrate how they fit within a strategic long-term plan. A flexible position is possible and allows asset managers to review the plan in the distinct decision points (every 5 years) and respond by taking advantage of the observed changes to the main uncertainty drivers (e.g., water supply, demand, capital and operational cost of options); (ii) Some new large water resource schemes can be built in phases, that is, they can be expanded at a future stage if required by paying a relevant expansion cost. The flexibility to build resources in incremental stages allows for improved supply estimates before committing to larger schemes.

1.3 Thesis outline

Chapter 2 discusses the literature review on the methods used in decision-making under uncertainty with an emphasis on their application to water resource system planning practices. In this chapter, traditional followed by advanced decision-making approaches are presented and their suitability in addressing the inherent uncertainty and multi-criteria nature of the water resource planning problem is described.

Chapter 3 introduces a quantitative approach for extending a least-cost scheduling approach for water infrastructure planning used currently at a national scale in England to explicitly enable flexibility and adaptivity given future supply uncertainty. This is established by applying the ROA concept using scenario trees over a predefined planning horizon with distinct decision points to allow rebalancing of the supply-demand system at intermediate stages. This chapter offers a computationally efficient framework to generate a compact scenario tree to approximate the stochastic supply representing an ensemble of plausible futures.

Chapter 4 performs a comparison of the ROA approach presented in Chapter 3 with alternative techniques that consider uncertainty through the use of multiple scenarios to examine the impact on the performances of the proposed plans by each approach in terms of efficient use of network capacity and levels of investment.

Although the aggregate multi-scenario optimisation approaches in Chapter 3 and in Chapter 4 identified plans that can handle future supply demand uncertainty, the default single objective is that of least cost. Constraints are used to represent some objectives, for example the objective of keeping supply above demand. However, alternative objectives cannot be included directly in the optimisation approaches. To overcome this limitation, Chapter 5 introduces a system simulation method in which multiple planning objectives can be considered, including system resilience metrics as well as costs. The output of this approach is the set of portfolios that best satisfy the chosen objectives. This high performing set of adaptive plans, which can be referred as Pareto-optimal, contains the set of interventions where any further increase in performance in one metric will simultaneously decrease performance in one or more other. Each adaptive plan on the trade-off surface represents a unique combination of supply augmentation and demand reduction interventions where early investments are selected to enable flexibility in selecting later interventions as information on future supply-demand balance is gradually revealed.

Finally, Chapter 6 gives the main conclusions of this study and identifies future research directions.

The chapters of this thesis are developed to be largely self-contained because they are published as individual journal articles. Because of this, there is some repetition in introductions and background material.

Chapter 2

Literature review

2.1 Introduction

This chapter provides a review of the current literature regarding decision-making approaches under uncertainty and their application in water resources planning. The chapter is organised as follows: Section 2.2 discusses the types of uncertainty found in water infrastructure investment decision-making. Section 2.3 provides an overview of the traditional decision-making approaches in investment appraisal and their limitations while Section 2.4 discusses how advanced decision-making approaches are used to more efficiently reduce the impact of uncertainty. Finally, Section 2.5 presents stochastic optimisation tools used to solve water resource management problems and discusses the ones used in the formulations of the adaptive and flexible approaches introduced in this thesis.

2.2 Water resource planning under uncertainty

Investing in the right amount of new water supply infrastructure at the right time is the way to cost-effectively meet future water demands. However, developing plans that do not under or over-invest is difficult as future conditions such as climate change impacts or population growth are uncertain. Several decision-making approaches exist that schedule the implementation of interventions to maintain the supply-demand balance with consideration of uncertainties associated with future conditions.

The benefits and limitations of these decision-making approaches for investment appraisal are described below focusing on their applicability in the context of water demand and climate change uncertainty. Before reviewing the analytical approaches, it is important to first recognise the types of uncertainty that need to be addressed.

2.2.1 Types of uncertainty

Uncertainty refers to the limited available knowledge about certain future events. Accounting for uncertainty is crucial when planning refurbishment or expansion of a water resource network as the actual outcomes of an investment may differ from that which was expected when the decision was taken. Different types of uncertainties can be found in the literature according to the degree that the unknown future conditions can be managed.

The first distinction between risk and uncertainty was introduced by Knight in 1921 (Watkins and Knight, 1922). According to Knight, risk indicates the foreseeable and thus manageable part of what is unknown. The incalculable and uncontrollable part of what is unknown, consist the uncertain. Decision-making under risk and decision-making under uncertainty have been linked to whether or not probabilities can be used to account for future predictions. Uncertainties that cannot be treated probabilistically, known as Knightian uncertainties, include situations where experts cannot agree upon the probabilities and thus the statistical distributions of future conditions are unknown or cannot be trusted.

Uncertainty around the effects of climate change is considered to be of this type as until now there has not been a methodology to assess them. Although climate change is expected to have an impact on water supplies, there is still significant uncertainty in the timing, magnitude, and the sometimes even the direction of change (Walsh et al., 2014). Since climate change is a new process for which we have no historical equivalent, probabilities cannot be calculated based on the past. These types of uncertainties are the most difficult to handle and are referred to as deep uncertainty (Lempert, 2003) or severe uncertainty (Ben-Haim, 2006). Such uncertainty is characterised as a condition where decision makers cannot agree upon a model that effectively describes cause and effect or its key parameters (Walker et al., 2013). This leads to a situation where it is not possible to say with confidence whether one future state of the world is more plausible than another.

Another type of uncertainty that can be found in the literature is called *dynamic uncertainty* where uncertainty is assumed to resolve to a degree with the passage of time due to increasing knowledge on the impacts of the uncertain parameter such as climate change (Dittrich et al., 2016). According to Ford et al. (2002), project planners can use flexible strategies to exploit project value that is hidden in dynamic uncertainty. Flexible approaches, as explained in more detail in Section 2.4, allow for learning over time enabling plans to be cost-effectively adjusted as additional information becomes available.

2.3 Traditional decision-making approaches

Cost-benefit analysis and least-cost optimisation are widely used decision-making approaches in policy analysis when appraising projects. In this section, traditional decision-making approaches to appraise investment are described and the difficulties of applying these methods in the context of climate uncertainty are explained.

2.3.1 Cost-benefit analysis and net present value

Cost-benefit analysis attempts to maximise the benefits for society based on potential Pareto efficiency. It assesses whether it is worthwhile to implement a project by comparing all its monetised costs and benefits expressed over a defined time span to obtain its Net Present Value (NPV) as in Equation 2.1

$$NPV(i, N) = \sum_{T=0}^{N} \frac{R_t}{(1+r)^t} \tag{2.1}$$

where N is the total number of periods, r the discount rate, t is time and R_t is the net benefits (benefits minus cost) at time t.

The benefits and costs over time are discounted to present values, and a NPV is calculated by subtracting the net costs from the net benefits. A project should generally proceed when the NPV is positive as this indicates that the investment is economically desirable (Boardman et al., 2006). Provided that reliable data on costs and benefits are available, cost-benefit analysis can be carried out with limited technical resources and the results are accessible to a non-technical audience.

Cost-benefit analysis has been tested and successfully applied to many projects and policies (application examples include (Willenbockel, 2011) and (Kull et al., 2013)). However, water resource planners face considerable challenges when applying such decision-making approaches in an area of uncertainty such as climate change adaptation. The main reason is that the benefits of adaptation are hard to define, as these require knowledge about expected impacts of climate change and responses to them, which are hard to predict (Dessai and Sluijs, 2007). Moreover, analysing alternatives using NPV analysis take static perspectives of projects and alternatives producing strategies with fixed combinations of conditions and decisions (Ford et al., 2002).

Several studies in various domains have demonstrated that there are potential benefits of waiting for uncertainty to (partially) resolve before making important development decisions. As discussed in more detail in section 2.4.3, examples of such flexible applications can be found in automobile systems (Ward et al., 1995), car parking problems (De Neufville et al., 2006), risk management in petroleum development investments (Chorn and Shokhor, 2006a), renewable energy policy evaluation (Lee and Shih, 2010), multi-energy generation system expansion planning (Ceseña et al., 2016) to name a few. Hence, the application of Cost-benefit analysis and NPV in its basic formulation may be undervaluing projects as it does not exploit the potential benefits of flexible planning.

2.3.2 Deterministic mathematical programming

Deterministic approaches for balancing annual supply and demand have existed in the water industry for more than half a century and still form the basis of the existing Water Resources Management Plan (WRMP) framework (Padula et al., 2013a) required by the English statutory process. The main strength of the approach relies on its simplicity which makes it easy to explain facilitating the communication among stakeholders on getting the plans reviewed and agreed (Hall et al., 2012). Ability to communicate results is crucial as plans are produced in consultation with government regulators and are subject to public consultation which requires the results to be readily understood.

Mathematical programs minimise or maximise an objective which is a function of the decisions (Bazaraa et al., 1990). Decisions are represented by variables of different types. In water resources management, utilisation is modelled using non-negative continuous variables while binary variables are used to represent activation of options. Possible decisions are constrained by minimum requirements (e.g. demand has to exceed supply), limit in resources (capacity of options) etc. Objectives and constraints are functions of the variables as well as problem parameters, including capital and operational costs, supply demand forecasts and capacities of options. In deterministic mathematical programming models, all problem parameters are assumed to take fixed, known values. These values are estimated via forecasting methods.

The deterministic approach is formulated as Mixed Integer Linear Programming (MILP) optimisation problem as follows:

$$min\ z = \sum_{t,i} \frac{p}{(1+r)^t}[C_i(dS_{t,i} - dS_{t-1,i}) \tag{2.2}$$

$$+ F_i \times dS_i + V_i \times S_{t,i}]$$

$$s.t. \sum_i S_{t,i} + eS_{i,t} \geq \ D_t + h_t \ \ \forall t \tag{2.3}$$

$$S_{t,i} \leq dS_{t,i} \times cS_{t,i} \ \ \forall t, i \tag{2.4}$$

$$dS_{t,i} \leq dS_{t+1,i} \ \ \forall t, i \tag{2.5}$$

$$S_{t,i} \geq 0 \tag{2.6}$$

$$dS_{t,i} \in 0, 1. \tag{2.7}$$

The binary variable $dS_{t,i}$ denotes the activation of an optional supply source and the real variables $S_{i,t}$ and $eS_{i,t}$ indicate the extent of annual use of optional and existing supply sources respectively. The single objective is the minimisation of discounted capital, fixed (F_i) and variable (V_i) costs (equation 2.2) subject to constraints. The mass balance constraint 2.3 ensures that demand for water is met in every year of the planning period. A buffer h_t is added to demand D_t to account for the uncertainty around supply and demand (see section 2.3.2.1 for how this amount is calculated). Constraint 2.4 ensures that utilisation of supply options is up to its capacity while constraint 2.5 keeps an option on after its activation.

Applications of deterministic approaches in the water industry include a regional study in South East of England (Critchley and Marshallsay, 2013; Padula et al., 2013a) identifying and sharing water investment opportunities for the water companies operating in the region. While deterministic methods can be used as informative tools for decision-making, since water resource and infrastructure development have major financial environmental and social impacts, crucial investment decisions which have to be made in the present need to account for the needs of a future which is largely unknown. Therefore, deterministic modelling that assumes the known future results in sub-optimal plans and water supply deficits if future is less favourable than assumed (Chung et al., 2009).

2.3.2.1 Incorporating uncertainty in the deterministic approach

The planning framework known as Economics of Balancing Supply and Demand (EBSD) which has been used by the water industry since 2002 in England (UKWIR, 2012) uses deterministic modelling to identify a least-cost sequence of options that meet deficits under a given scenario. However, given a broad range of plausible future supply-demand conditions, a deterministic solution may not be optimal or feasible. To cater for specified uncertainties around supply and demand, a safety factor called 'headroom', h, is added to demand (Environment Agency, 2008). The calculation of 'headroom' aggregates nine supply-related and four demand-related sources of uncertainty (listed in table 2.1) into an annual estimate for each Water Resource Zone (WRZ) (UKWIR, 2002b). Hence, 'headroom' in a WRZ is defined as the difference between water available for use (which is deployable output plus bulk supply imports, minus bulk supply exports and minus reductions made for outage allowance and operational losses) and demand.

The Probability density function (PDF) for uncertainty in supply, $f_S(q)$, and demand, $f_D(q)$ (where q is a water supply or demand for water expressed in terms of ML/d) are calculated as the sums of all their different components of uncertainty. These are computed using Monte Carlo simulation which is a sampling technique in which a simulation process is repeated multiple times, at each time randomly selecting a particular instance of the unknown headroom component. Monte Carlo

Table 2.1: Sources of uncertainty in water supply/demand as modified by UKWIR (2002)

Supply side uncertainties
Vulnerable surface water licences data
Vulnerable groundwater
Time-limited licences climate change on demand
Bulk imports
Gradual pollution of sources (causing a reduction in abstraction)
Accuracy of supply-side data
Single source dominance
Uncertainty of impact of climate change on source yields
Uncertain output from new resource developments
Demand side uncertainties
Accuracy of subcomponent
Demand forecast variation
Uncertainty of impact of licences
Uncertain outcome from demand management measures

is a widely used technique in the probabilistic analysis of engineering systems with numerous applications, including the work of (Prudhomme et al., 2003) who use Monte Carlo simulation to calculate the uncertain impact of climate change in the flood regime in Northern England and Scotland.

The PDF of the combined headroom uncertainty, $f(h)$, which is the difference between the distribution of supply and the distribution of demand, is computed as the convolution of the two PDFs:

$$f(h) = \int_0^{q_m} f_s(q-h) f_d(q) dq \tag{2.8}$$

where q_m is the upper bound on the support for the distribution functions $f_S(q)$ and $f_D(q)$. The distributions of supply and demand are standardised by their mean values m_S and m_D, respectively. Hence, the headroom uncertainty pdf $f_u(h)$ is given by:

$$f_u(h) = f(h - \mu_s + \mu_d) \tag{2.9}$$

The water company in its WRMP should provide a deterministic quantity $h_T(P)$ called 'target headroom'. It is back-calculated from equation 2.9, by identifying an acceptable probability implying the 'Level of Risk', P, at which the distribution $f(h)$ may become negative:

$$h_T(P) = -F_u^{-(P)} \tag{2.10}$$

where $-F_u^{-(P)}$ is the inverse cumulative distribution function of $f_u(h)$ (equation 2.9) at probability P. The headroom calculation is repeated for every year of the planning period to identify how and when a range of management options is expected to yield a surplus or deficit compared with the target headroom.

While target headroom adds a probabilistic element to deterministic modelling, the approach is not explicitly risk-based and also not suitable for appraisal of adaptive management strategies (Hall et al., 2012). Headroom uncertainty cannot be directly interpreted in terms of the frequency of droughts. Conversely, a risk-based approach would make explicit the probabilities of a range of plausible future outcomes.

2.4 Advanced decision-making approaches

Since climate change uncertainties cannot be reduced by gathering further information (Walker et al., 2013; Werners et al., 2013), more advanced planning approaches are required to efficiently to reduce the impact of uncertainty (Abunnasr et al., 2015; Berke and Lyles, 2013; Quay, 2010). Multiple tools have been developed that are designed to be less sensitive to future uncertainties. This is achieved by considering multiple scenarios instead of optimising for one specific scenario, selecting strategies that provide benefits across a number of potential futures. This way, optimisation is obtained across a wide range of scenarios using different mechanisms to capture the uncertainty on future conditions.

Decision-making approaches that use multiple plausible futures have focused on two goals: achieving insensitivity (i.e. robustness) to changing conditions as well as making adaptive intervention strategies that respond to uncertainty over time (Maier et al., 2016). Pro-actively accounting for uncertainty can create plans that remain relevant longer by allowing for corrective actions and avoiding maladaptive outcomes (Walker et al., 2013). These tools have been applied largely in major infrastructure projects in multiple settings including water supply management, flood risk management, energy production, transportation development (Kwakkel, Walker and Haasnoot, 2016; Lawrence et al., 2013; Lourenço et al., 2014) and are reviewed in more detail below.

2.4.1 Robust decision making

RDM is an attempt to identify plans that perform well under a wide range of plausible future conditions (Lempert et al., 2006). That is, investment plans should aim to be insensitive to the most significant uncertainties (Lempert et al., 2006; Ray and Brown, 2015; Hall et al., 2012; Huskova et al., 2016). One commonly used definition of a robust system is one that performs satisfactorily well compared to other alternatives over a wide range of plausible future conditions rather than optimally under one (Lempert et al., 2006). To account for deep uncertainty, decision-making methods that seek robustness generally use a wide range of scenarios to produce plans that perform well across a variety of futures. Hence, the investment plan derived from this approach is insensitive to the most significant uncertainties (Lempert et al., 2006; Ray and Brown, 2015). Choosing plans that are optimal under certain conditions is often sacrificed to improve robustness i.e. a plan that is robust to many future scenarios will likely not be optimal in any (Lempert and Collins, 2007). Therefore, robust plans trade optimality with the ability to perform acceptably well in a wide range of future scenarios. Robust strategies that seek to ensure satisfactory performance over a wide range of futures are attractive to risk-averse decision makers as the risk of poor performance is reduced.

Many classes of optimisation problems, including linear programs, conic-quadratic programs and mixed-integer linear programs, allow for robust formulations. Robust optimisation problems optimises a deterministic objective and at the same time satisfies a constraint set for every possibly realisation of the uncertain parameters. In other words, it seeks to identify a solution under the worst-case scenario, where the worst case is evaluated with respect to all possible scenarios (Georghiou et al., 2011). A robust general formulation of a mixed-integer linear program is as follows:

$$min\ z = \sum_{t,i} \frac{1}{(1+r)^t}[C_i(dS_{t,i} - dS_{t-1,i}) \tag{2.11}$$

$$+ F_i \times dS_{t,i} + V_i \times S_{t,i}]$$

$$s.t. \sum_i S_{t,i} + eS_{t,i} \geq D_t^w \quad \forall t, w \tag{2.12}$$

$$S_{t,i} \leq dS_{t,i} \times cS_{t,i} \quad \forall t, i \tag{2.13}$$

$$dS_{t,i} \leq dS_{t+1,i} \quad \forall t, i \in Ir \tag{2.14}$$

$$S_{t,i} \geq 0 \tag{2.15}$$

$$dS_{t,i} \in 0, 1. \tag{2.16}$$

The binary variable dS_i denotes the selection of a scheme and the real variables $S_{i,t}$ and $eS_{t,i}$ indicate the extent of use of optional and existing schemes respectively. C_i, F_i and V_i denote the undiscounted capital cost, undiscounted fixed operational cost and undiscounted variable operational cost of intervention i, D_t^w is demand in time t in scenario w, $cS_{t,i}$ is the maximum capacity of intervention i in time t.

The single objective is the minimisation of discounted capital, fixed and variable costs (equation 2.11) subject to constraints. To make the solution robust even under the worst-case scenario, the mass balance constraint 2.12 is met in every plausible future scenario w. Constraint 2.13 ensures that utilisation of schemes is up to its capacity while constraint 2.14 keeps a scheme on after its activation.

In water resource systems planning, RDM was originally introduced by (Matalas and Fiering, 1977) as a decision-making tool for situations with poorly-characterised uncertainty and since then has been increasingly explored in the literature. RDM has been applied in a range of water resource planning contexts, such as England (Matrosov et al., 2013), in Australia (Mortazavi-Naeini et al., 2015), and Southern California (Tingstad et al., 2013).

While robust methodologies take into account a wide range of possible future conditions (i.e. mild to dire), the statistics used to quantify the performance of the system over the range of possible scenarios may result in over investment (Herman et al., 2015). That is, the main weakness of robust approaches is that it could be too conservative resulting to unnecessary extra capacity (Shapiro, 2012). In addition, different metrics to define robustness within an optimisation problem results in alternative robust decision methods that often reaches different results (Mortazavi-Naeini et al., 2015).

The RDM process determines the least vulnerable strategy without guidance on how to address the identified vulnerabilities in the re-design of a strategy. The lack of explicit guidance on how to address vulnerabilities might create the impression that RDM results in static strategies (Walker et al., 2013). A more thorough review of the RDM literature suggests that RDM can be used to identify adaptive strategies in response to how the future unfolds (Bloom, 2014; Groves et al., 2014). A signpost and trigger system is used to enable adaptive planning, where a strategy is modified in a pre-specified way in response to a pre-specified trigger. However, robust methods are still relatively novel in the academic and policy agenda for adaptation while the specification of these triggers need further clarification (Kwakkel, Haasnoot and Walker, 2016).

2.4.2 Dynamic adaptive policy pathways

Adaptive approaches are based on considering the uncertain future and responding to future conditions by adjusting intervention schedules as the future manifests (Maestu and Gómez, 2012). Adaptability enables a system to change pro-actively to environments, markets, regulations, and technology (De Neufville and Scholtes, 2011a). DAPP (Haasnoot et al., 2013) and ROA are amongst the decision-making processes that differently identify adaptive strategies under uncertain future (Ray and Brown, 2015). While DAPP appears in the literature to be implemented in situations with absence of information on likelihood of the multiple plausible futures (Haasnoot et al., 2013; Kwakkel et al., 2015; Kwakkel, Haasnoot and Walker, 2016), ROA typically makes use of probability information (Dixit and Pindyck, 1994; Ray and Brown, 2015) to treat future uncertainty.

DAPP is an amalgamation of two approaches, Adaptive Policy Making and Adaptation Pathways. The former is a structured approach for designing dynamic robust plans (Walker et al., 2001; Dessai and Sluijs, 2007; Kwakkel et al., 2010) and the latter approach uses adaptation tipping points to specify the conditions under which a given plan will fail as it no longer meets the specified objectives (Kwadijk et al., 2010). DAPP includes transient scenarios representing multiple uncertainties used to analyse the vulnerabilities and opportunities of policy actions and how they develop gradually over time. Alternative types of actions are then identified to address these potential vulnerabilities and opportunities, specifying a dynamic adaptive plan (Hamarat et al., 2014; Kwakkel et al., 2015; Herman et al., 2015).

In a water resource management context, adaptation tipping points could be a certain climate change trigger indicating that the current plan must change as new actions are needed to ensure water supply security. The challenge of this approach for water resource management applications is to identify good triggers for water management due to high natural variability as well as a monitoring framework for short time period of measurements (Diermanse et al., 2010).

Applications of integrated DAPP approach in long-term water management include the work of (Haasnoot et al., 2013) in the Rhine Delta in the Netherlands producing adaptive plans that are able to deal with unforeseen conditions due to uncertainties in future climate change as well as other social, political, technological and economic uncertainties. In an extension of this work, (Kwakkel et al., 2015) use a multi-objective evolutionary algorithm for robust optimisation to identify the most promising pathways under climate change uncertainties. A simple rule-based system is used to govern the activation of the next action on a pathway. Every five years, the results of the system in terms of causalities and economic damages are evaluated and classified into no event, small event, large event, and extreme event. A new action is activated if, in the previous five years, an event of the pre-specified level occurs.

The DAPP formulation using robust optimisation is as follows:

$$min\ F(l_{p,r}) = (f_{cost}, f_{casualties}, f_{damage}) \tag{2.17}$$

$$s.t. c_{damage} : \widetilde{y}_{damage} \leq Max_{FlodDamages} \tag{2.18}$$

$$c_{casualties} : \widetilde{y}_{casualties} \leq Max_{casualties}. \tag{2.19}$$

$$l_{p,r} = [p_1, p_2, p_3, r_1, r_2] \forall p \in P; \forall r \in R \tag{2.20}$$

where $l_{p,r}$ denotes a policy pathway, p_m is a policy action, P is the set of policy actions, r_n is a rule, R is the set of rules

$$f_i(y_i) = \widetilde{y}_i(IQR(y_i) + 1) \tag{2.21}$$

$$i \in [costs, casualties, damages]$$

y_i is the set of outcomes for outcome i across a set of scenarios, $\widetilde{y}$ is the median value for y_i, and IQR is the interquartile range for y_i. Hence, each of the three outcomes of interest (costs, casualties, and damages) is defined as the median value multiplied by the interquartile distance plus one to simultaneously minimise the median outcome as well as the dispersion around the median. The minimisation problem is subject to two constraints: constraint 2.18 ensures that the sum total of flood damage over the planning horizon does not exceed $Max_{FlodDamages}$; constraint 2.19 ensures the median value for the sum total of casualties over 100 years does not exceed the $Max_{casualties}$.

2.4.3 Real options analysis

Real options analysis is a probabilistic decision process with the ability to value the flexibility and adaptability in future decision-making when irreversibility and uncertainty are key characteristics of the decision problem (Dixit and Pindyck, 1994). While it can be used as part of the evaluation and design of DAPP (Buurman and Babovic, 2016), it is mainly used to enable planners to examine the implications of future uncertainties. Within ROA, flexibility is valued since it allows delaying commitment to large costly and irreversible decisions while either exercising different interventions or incrementally implementing interventions with high regret cost and long construction times until more information is available. Adaptation is enabled because ROA provides an optimal sequence of future investment decisions that respond to changes in uncertainty over time.

ROA originates from financial economics (Cox et al., 1979; Dixit and Pindyck, 1994; Merton, 1973) and extends the principles of cost–benefit analysis (see Section 2.3.1) to allow for learning based on an uncertain underlying parameter. Cost–benefit analysis and the NPV rule is not adequate in that they cannot properly capture management's flexibility to adapt and revise later decisions in response to new information (Trigeorgis, 1993).

Traditional ROA methods are based on financial theory, such as the Black-Scholes equation (Black and Scholes, 1973) or expected value decision tree analysis (Dixit and Pindyck, 1994). Black and Scholes (1973) and Merton (1973) defined and solved the financial option valuing problem. Inspired by them, Myers (1977) who first identified many corporate economic assets as call or put 'real' options, suggested the concept of a ROA. The next section provides a review of the commonly used option-pricing methods found in the literature.

2.4.3.1 Review of option-pricing theory

In financial options analysis, there are multiple methodologies and approaches used to calculate an option's value. Options, in finance, give an investor the right, but not the obligation, to buy or sell a security according to predetermined terms during some period. Stock option contracts can be of two categories: calls and puts. A call option gives the holder the right to purchase stock at a fixed exercise price at or before a specific date. A put option gives the holder the right to sell stock at a fixed exercise price at or before a specific date. Call and put options contracts are written on all sorts of assets and variables (such as bonds, interest rates, exchange rates, and commodities) and can be used to make a leveraged bet on future returns.

The Black-Scholes option-pricing model, developed in the early 1970s, is considered a classic result in the Finance industry. Black and Scholes (1973) demonstrated that an option over a stock has an economic value depending on the market price of the stock x and t the time elapsed since the option was written, by introducing the following equations:

Let $V(x,t)$ be the value at time t value of some option contract defined over an asset with current value x. $V(x,t)$ satisfies the Black-Scholes Partial Differential Equation (PDE) on the domain $D = (x,t)|x > 0, 0 < t < T$, subject to the terminal boundary condition $V(x,t) = f(x)$:

$$\frac{\partial V}{\partial t} + (r - y) \times x \times \frac{\partial V}{\partial x} + \frac{1}{2} \times \sigma^2 \times x^2 \times \frac{\partial^2 V}{\partial x^2} - r \times V = 0 \tag{2.22}$$

The parameters (r, y, σ, t) represent the risk free interest rate, the dividend yield, the volatility of the asset and the time to option maturity respectively. A European call of strike K has payoff $f(x) = max(x - K, 0)$ and satisfies $V(0, t) = 0$, namely the option value is zero if the asset becomes worthless. The solution subject to the relevant boundary conditions for a European call is:

$$C(x, K, r, y, \sigma, t) = x \times e^{-y \times t} \times N(d_1) - K \times e^{-r \times t} \times N(d_2) \tag{2.23}$$

where

$$[d_1, d_2] = \frac{1}{\sigma \times \sqrt{t}} \times [\ln{(\frac{x}{K})} + (r - y \pm \frac{1}{2} \times \sigma^2) \times t] \tag{2.24}$$

Several analytical methods exist for option-pricing, most remarkably Monte Carlo simulation (Boyle, 1977) and the binomial method developed by Cox et al. (1979). The binomial method use discrete time dynamics as opposed to the Black-Scholes model which applies continuous time dynamics. The stock price is assumed to follow a multiplicative binomial process over discrete periods. The time period between today and expiry of the option is sliced into many small time periods, marked by nodes.

Figure 2.1 shows a two-step binomial model, as adapted from Cox et al. (1979). Over the first period of time in the two-step model, the asset price may move either up to S_u with probability p or down to S_d with probability $1 - p$. Over the second period, if the price moved up to S_u in the first period then the price may move to either S_{uu} or S_{ud}. However, if the price moved down in the first period to S_d then in the second period it may move to either S_{du} or S_{dd}.

The notation used is (S_0, p, u, d) for the stock price today, the probability of a

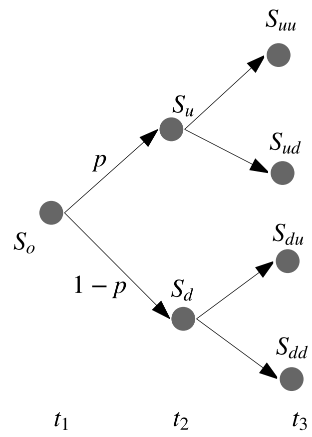

Figure 2.1: A two-step binomial model.

price rise, the factor by which the price rises and the factor by which the price falls respectively. This way, a tree of potential future asset prices is calculated. The tree contains potential future asset prices for each time period from today through to expiry. It is worth noting that as the Binomial Lattice is geared with smaller and smaller time increments, the option price will converge to the Black-Scholes value.

2.4.3.2 Real options in physical systems

Wang and De Neufville (2005b) identify two categories of ROA: Real Options 'on' systems and Real Options 'in' systems. Real Options 'on' systems focus on the external factors of a system and benefit from the use of financial valuation tools. These systems are mostly concerned with the valuation of investment opportunities. Some well-known cases of Real Options 'on' projects are on valuation of oil fields and pharmaceutical research projects where the key question is to value such projects and decide if investing in the project is financially sensible.

Contrarily, Real Options 'in' projects are the latest extension of real options theory into physical systems design are mostly concerned with design of flexibility (De Neufville and Scholtes, 2011a). A simple example of a Real Option 'in' a system is a spare tire on a car: it gives the driver the 'right, but not the obligation' to change a tire at any time, but this right will only rationally be used when the car has a flat.

Real options 'in' projects are of special interest to the study of engineering systems due to their features. As characterised by Roos et al. (2004), large-scale engineering projects last a long time meaning they need to be designed with the demands of a distant future in mind. They often exhibit economies of scale, which motivates particularly large construction. Yet have highly uncertain future requirements, since forecasts of the distant future are typically wrong. Under this context, there is a need of creating designs that can be easily adjusted over time to meet the actual needs as they develop. Real options can help engineers address the intrinsic uncertainties facing large-scale engineering systems allow them to manage the uncertainties pro-actively (De Neufville and Scholtes, 2011a).

The value of Real Options when used in large engineering projects can be found in a number of studies. Zhao and Tseng (2003) showed a successful application of flexibility in a car park design. The flexibility was embedded at the beginning of a car park construction, which provided options for future expansion. The extra construction cost can be viewed as an option in which a premium has to be paid first and the option can be exercised later. Trinomial lattice and stochastic dynamic programming were used to model the demand and optimal expansion process. The flexibility value was calculated by comparison on the expected profit between a baseline design and flexible design.

De Neufville et al. (2006) presented a multi-stage stochastic model for decision-making in highway development, operation, expansion, and rehabilitation. The model used real options as flexibility sources in both development and operation phases of a highway and Monte Carlo simulation to account for the evolution of uncertainties. This approach achieves decision-making optimality by maximising the expected profit.

Applications of ROA can also be found in communications satellite constellations (De Weck et al., 2004a), petroleum investments (Chorn and Shokhor, 2006b), mining operations (Cardin et al., 2008; Zhang and Kleit, 2016), energy generation system expansion (Martinez Cesena et al., 2015) and aircraft acquisition (Hu and Zhang, 2015) to name a few. These successful applications in other fields demonstrate that flexibility has value for uncertain future circumstances and should be implemented in system design. However, its use in water resource infrastructure expansion is still in its infancy and there is a gap in the literature, which requires further investigation.

2.4.3.3 Real options in water resources planning

There are three necessary conditions for real options analysis to be of value: there must be uncertainty, there must be learning meaning that the state of uncertainty must change over time and lastly there must be flexibility to act on the new information that becomes available (NERA, 2012). All three conditions are present in a water resources management context. Major uncertainties exist with respect to future rainfall levels as well as water demand. ROA relies on the assumption that uncertainty is dynamic i.e. uncertainty is assumed to resolve to a degree with the passage of time due to increasing knowledge on uncertain parameters such as climate change impacts (Dittrich et al., 2016). Hence, learning is achieved simply by allowing the passage of time which allow for better water supply and demand estimates. Flexibility exists in that construction of options can be deferred or accelerated according to how the future unfolds. Also, large interventions can be modular meaning that they can be built in phases. Given that there is sufficient flexibility, uncertainty and learning, ROA can bring benefits into forming long-term WRMP plans (NERA, 2012).

ROA is implemented through different techniques. These include decision trees, lattices, and Monte Carlo analysis (Trigeorgis, 1996; Lander and Pinches, 1998; Chow and Regan, 2011; De Neufville and Scholtes, 2011b) as well as multi-stage stochastic optimisation programs (Zhao et al., 2004; De Weck et al., 2004b; Wang and De Neufville, 2005a,b). Combination of staged decision-making (Hobbs, 1997;

Kracman et al., 2006; Ray et al., 2011; Kang and Lansey, 2012b; Beh et al., 2014; Cai et al., 2015; Vieira and Cunha, 2016) and ROA (Jeuland and Whittington, 2014; Steinschneider and Brown, 2012; Woodward et al., 2014a) can be found in the water and flood management literature. The number of decision stages in these multi-stage problems defines the frequency that intervention strategies can be modified in the planning horizon. For example, Ray et al. (2011)'s long-term water supply planning under climate change uncertainties extends 75 years into the future and the decision stages are made in years 2035, 2060, and 2085. In another work, Woodward et al. (2014a)'s model stages flood risk interventions every 50-year time step over a 100 year time horizon. There has been significant effort by using different decomposition methods (Escudero, 2009; Rockafellar and Wets, 1991; Mulvey and Ruszczyński, 1995), and/or uncertainty reduction and clustering techniques (Gröwe-Kuska et al., 2003; Dupačová et al., 2003; Gülpınar et al., 2004; Latorre et al., 2007; Heitsch and Römisch, 2005; Šutienė et al., 2010; Housh et al., 2013) to represent long term future uncertainty in stages using a scenario tree. Nevertheless, applying ROA in water resource planning is still challenging for three reasons. First, ROA is sensitive to the structure of the scenario tree so the parameterisation of its design must be defensible. This includes deciding the number of nodes over the planning horizon and choosing the branching between states. Secondly, the probability assignment to scenario branches and nodes affects the optimised investment decisions. This can become intractable for a relatively complex problem. Lastly, as the number of scenarios used grows, the problem becomes more complex, often without increasing the quality of the solution (Lander and Pinches, 1998; Wang and De Neufville, 2005a). To account for the above, a generalised uncertainty sampling and optimised scenario tree construction approach for multi-stage investment planning is proposed in Chapter 3.

2.5 Stochastic optimisation methods

Stochastic programs are mathematical programs where some of the problem parameters incorporated into the objective or constraints are uncertain. Uncertain problem parameters are modelled as random variables with known probability distributions. Stochastic programming problems can be used in both static and dynamic model constructions. Static models, or single-stage, are used when decision is taken only once in time. In contrast, dynamic models can be formulated as recourse problems where decisions are taken subsequently allowing for corrective actions. Applications of stochastic programming is wide and can be found in power scheduling (Nürnberg and Römisch, 2002), transportation problems (Barbarosoglu and Arda, 2004; Liu et al., 2009) and production planning (Fleten and Kristoffersen, 2008).

Recourse stochastic programming methods are a prevalent way to implement ROA in infrastructure investment planning (Zhao et al., 2004). ROA encourages staged decision-making with the intention to delay expensive and irreversible investment options until more information is available. Stochastic programming models allow for flexibility to be exercised through corrective decisions which can be postponed until more accurate data is available (Birge and Louveaux, 2011). This can be used to identify flexible water supply portfolios of infrastructure options which are adaptable to future changes. The next sections present a summary of the most commonly used stochastic optimisation approaches together with their formulations.

2.5.1 Chance constraints

A chance-constrained problem is a stochastic programming optimisation problem that uses random variables to find a decision which ensures that a set of constraints will hold with a minimum given probability i.e. they seek to safeguard a solution obtained against undesirable outcomes. The decision is to be made *here and now* and the models do not account for any corrective actions.

The general formulation of a chance (probabilistic) constraint, as introduced by Charnes et al. (1958), has the following form:

$$Prob\{G(x,\xi) > t\} \leq \alpha \tag{2.25}$$

where $G(x,\xi)$ is a real valued function of the decision vector x and random data vector ξ, and $\tau \in \mathbb{R}$ and $\alpha \in (0,1)$ are chosen constants.

In a simple water mass balance problem, there are only two possible options increasing water capacity by x_1, x_2 respectively. The size of each option (i.e. option capacity) is a variable. If ξ_1 is the uncertain water demand, the supply-demand balance will be met if and only if $x_1 + x_2 \geq \xi_1$. Since demand ξ_1 is a random variable, the fulfilment of this inequality can be guaranteed only on a probability level α.

If $c(x_1, x_2)$ is the building cost function of the two supply options, then the stochastic programming problem is:

$$min\ c(x_1, x_2) \tag{2.26}$$

$$s.t. prob\{x_1 + x_2 - \xi_1 > 0\} \geq \alpha \tag{2.27}$$

$$0 \leq x_1 \leq V_1 \tag{2.28}$$

$$0 \leq x_2 \leq V_2. \tag{2.29}$$

where V_1, V_2 are upper bounds of the option capacities. The total cost is minimised in equation 2.26 ensuring that the probability of supply deficit being greater than zero remains less than α (constraint 2.27).

This class of static stochastic programming models, where decision is taken only once in time, were introduced by (Charnes et al., 1958) dating back to 1958. Despite being around for a long time, chance constraints have not found wide applicability as computing the optimal solution for chance-constrained problems is extremely difficult (Erdoğan and Iyengar, 2006). Evaluating $ProbG(x, \xi) > t$ involves a multidimensional integral that becomes difficult to handle as the number of parameters grows, both numerically and from the modelling point of view (Shapiro, 2008).

2.5.2 Two-stage stochastic program

The other type of stochastic programming models is dynamic in that decisions are taken subsequently in such a way that between two subsequent decisions an observation of a random variable occurs. One of the basic recourse models is the two-stage recourse problem.

According to Dantzig (1955), the decision variables in a standard two-stage stochastic programme are divided into first stage and second stage sets. The first stage decision variables are made before the realisation of uncertainty. In the second stage where more information becomes available after the realisation of uncertainty, decisions are adjusted to the outcome using the second stage variables.

Based on Dantzig (1955), two-stage stochastic programming problem can be formulated as

$$min\ z = \sum_{t,i} \frac{1}{(1+r)^t}[C_i(dS_{t,i} - dS_{t-1,i}) \tag{2.30}$$

$$+ F_i \times dS_{t,i} + V_i \times S_{t,i} + \sum_w p^w B_t^w]$$

$$s.t. \sum_i S_{t,i} + ES_{t,i} + B_t^w \geq D_t^w \quad \forall t, w \tag{2.31}$$

$$S_{t,i} \leq dS_{t,i} cS_{t,i} \quad \forall t, i \tag{2.32}$$

$$dS_{t,i} \leq dS_{t+1,i} \quad \forall t, i \in Ir \tag{2.33}$$

$$S_{t,i} \geq 0 \tag{2.34}$$

$$B_t^w \geq 0 \tag{2.35}$$

$$dS_{t,i} \in 0, 1. \tag{2.36}$$

The objective of the two-stage stochastic programme (equation 2.30) is to minimise the sum of the first stage costs and the expected value of the random second stage costs where recourse (second-stage) decisions are made after observing the random output. The first stage decision variables are the binary supply intervention activation $dS_{t,i}$ variable and the utilisation variable $S_{t,i}$ denoting the amount of water supplied from an intervention. They correspond to investment and operation decisions over the planning horizon.

The second stage wait-and-see recourse action variable B_t^w is linked to the expected deficit costs and is delayed until more information is available as scenarios unfold. The consequences of potential supply shortage due to variations in water availability are being penalised by a user defined scarcity cost B_t^w. The scarcity cost variable is scenario-dependent and must be replicated for each scenario w.

Constraint 2.32 sets the available supply and constraint 2.33 forces an intervention once activated to remain active at later stages. Intervention activation constraints are non-anticipative stating that the first-stage decision should not depend on the scenario which will prevail in the second stage. In this case, $dS_{t,i}$ does not depend on each scenario w and is effectively determined before any information regarding the uncertain data has been obtained. On the other hand, B_t^w, the second-stage variable, is determined after observations regarding scenario w have been obtained. In essence, the goal of a two-stage model is to identify a first-stage solution that is well positioned against all possible observations of scenarios w.

2.5.3 Multi-stage stochastic program

Multi-stage stochastic programming problems are an extension of two-stage programming models capable to deal with problems where decisions should be made sequentially at certain periods of time based on information available at each time period.

Multi-stage stochastic programming models are a sequential decision-making method where corrective decisions can be made at several stages as more data becomes available. After the realisation of uncertainty (i.e., after a probabilistic event), an additional corrective (or recourse) decision is made defining which action should be taken in response to each random outcome. The decision at the next decision point considers the effects of further uncertainty to minimise the cost of each stage subject to the model constraints (Birge et al., 1996).

Multistage stochastic programmes are generally challenging to solve because of the exponential growth in decisions trees when multiple actions are possible and multiple uncertain events should be considered. Significant progress has been made recently to improve performance (Dyer and Stougie, 2006). This includes decomposition methods to define smaller and thus more efficient to solve equivalent subproblems (Escudero, 2009; Rockafellar and Wets, 1991; Mulvey and Ruszczyński, 1995), scenario-reduction techniques to optimally reduce the number of scenarios and hence to construct a computationally tractable scenario tree (Gröwe-Kuska et al., 2003; Dupačová et al., 2003; Gülpınar et al., 2004; Latorre et al., 2007; Heitsch and Römisch, 2005; Šutienė et al., 2010) and decision clustering to achieve a good approximation of the multi-stage stochastic solution while keeping the scenario tree intact (Housh et al., 2013). The proposed flexible and adaptive approach introduced in Chapter 3 uses principles of ROA applied to least-cost capacity expansion scheduling via multistage stochastic mathematical programming.

2.5.4 Multi objective evolutionary algorithms coupled with simulation

The interaction of multiple objectives in the context of investment planning has been long discussed in various active research fields (Brill Jr et al., 1982) including water resources engineering (Maass et al., 1962). Optimisation tools such as mathematical programming have for decades been used to solve water resource system capacity expansion problems (Loucks et al., 1981). Despite their success, they have been know to have difficulty in their potential to incorporate multiple objectives and to represent water system non-linearities without requiring simplification of performance measures (Woodruff et al., 2013).

To better capture stakeholder values, water resources management can be strengthened by multi-criteria approaches which help reconcile multiple and often competing water interests. Performance measures of interest, when evaluating water intervention options include ones that describe economic, social and environmental impacts as well as water supply security metrics such as reliability and resilience. The development of multi-objective optimisation approaches, identifying plans that represent the optimal ('best achievable') trade-offs between objectives (Kollat and Reed, 2007a), has made this approach practicable for real system design problems (Matrosov et al., 2015).

Multi-objective evolutionary algorithms (MOEAs) imitate the process of natural evolution and have found a wide range of applications in water resources planning under uncertainty (Reed et al., 2013; Maier et al., 2014). Evolutionary algorithms are heuristic search algorithms that mimic the biological process of natural selection to produce an approximation of the Pareto optimal solution space. The search is an iterative process that begins with randomly generated initial population of solutions whose performance is then evaluated. Better performing solutions survive into the next generation. The algorithms use the evolutionary principles of selection to promote survival and reproduction of better solutions in preference to less optimal solutions. The genetic operations of crossover and mutation are then applied to introduce variation into the surviving population to promote fitness of solutions. A detailed review of evolutionary algorithms can be found in Coello et al. (2007).

MOEAs link with simulation models of real water resource systems, allowing to account for non-linearities, such as “if-then” style rules, which is not possible in mathematical programming applications (Maier et al., 2014) where non-linear interactions are ignored or simplified (Matrosov et al., 2013). Water resource system simulators are able to incorporate non-linearities and explicitly calculate system performance using multiple criteria without the need to translate non- commensurable metrics into a single monetary metric. In combined multi-objective evolutionary optimisation and simulation, a water resource simulator acts as the objective function whose solution is the performance output of the model. MOEA coupled with simulation is used as the optimisation method of the proposed multi-objective multi-stage approach introduced in Chapter 5.

Chapter 3

Real-options water supply planning: Multistage scenario trees for adaptive and flexible capacity expansion under probabilistic climate change uncertainty

3.1 Introduction

Water utilities aim to maintain an efficient and reliable water supply service by optimally combining the scheduling of supply augmentation projects and demand reduction policies (Mortazavi-Naeini et al., 2014). Water planners investigate a range of feasible interventions including both the supply-side (e.g., wastewater reuse, desalination, reservoirs) and demand-side interventions (e.g., demand reduction, leakage reduction). In its simplest form, the capacity expansion problem refers to finding the optimum timing and scale of predefined projects. Deterministic supply-demand optimisation aims to meet service levels commitments under historically dire conditions and identifies a fixed least-cost schedule of system upgrades (Padula et al., 2013a). However, fixed investment plans are brittle, i.e., if future conditions turn out to be different than assumed, the plan is likely to fail (Chung et al., 2009). The antidote to brittleness is robustness (defined as a decision that performs acceptably well over a range of conditions) and flexibility (defined as the ability to switch a decision depending on outcomes that materialize) (Maier et al., 2016). Methods that use an ensemble of plausible scenarios to seek robustness and flexibility are discussed below.

Robust decision-making is an attempt to identify plans that perform well under a wide range of plausible future conditions (Lempert et al., 2006). That is, investment plans should aim to be insensitive to the most significant uncertainties (Lempert et al., 2006; Ray and Brown, 2015; Huskova et al., 2016). Adaptive approaches are based on considering the uncertain future and responding to future conditions by adjusting intervention schedules as the future manifests (Maestu and Gómez, 2012). Adaptivity enables a system to change pro-actively to environments, markets, regulations, and technology (De Neufville and Scholtes, 2011a). Dynamic Adaptive Policy Pathways (DAPP) and Real Options Analysis (ROA) are amongst the decision-making processes that differently identify adaptive strategies under uncertain future (Ray and Brown, 2015). While DAPP appears in the literature to be implemented in situations with absence of information on likelihood of the multiple plausible futures (Haasnoot et al., 2013; Kwakkel et al., 2015; Kwakkel, Haasnoot and Walker, 2016), ROA typically makes use of probability information (Dixit and Pindyck, 1994; Ray and Brown, 2015) to treat future uncertainty.

The decision-making process presented in this chapter aims to explicitly seek adaptivity and flexibility in least-cost supply-demand infrastructure investment planning. The value of adaptivity and flexibility is estimated under conditions of probabilistic uncertainty where probabilities are assigned to future states of supply. This is different to decision-making under deep uncertainty approaches (Lempert et al., 2006) where key criteria for evaluating alternative decisions such as robustness, adaptivity and trading off conflicting objectives are addressed without requiring probabilities (Lempert et al., 2006; Kasprzyk et al., 2012).

To account for the above, this chapter proposes a generalized uncertainty sampling and optimised scenario tree construction approach for multi-stage investment planning. A scenario tree is optimally built with multiple decision stages to allow for frequent and regular modifications to the investment strategies. The decision tree presented in this chapter uses a range of supply scenarios to represent uncertainties of future climate change effects from mild to dire. The range of possible climate change futures was defined by the UKCP09 weather generator, that provides probabilistic projections of precipitation, temperature and other variables for the UK using perturbed physics ensemble simulations (Murphy, Sexton, Jenkins, Boorman, Booth, Brown, Clark, Collins, Harris, Kendon et al., 2009). The analysis has used UKCP09 data assuming that the impacts are for a medium emissions scenario, as reported in Thames Water (2014). The scenario tree is incorporated into a multi-stage stochastic optimisation formulation that applies ROA for enabling flexible and adaptive water resource investment decisions. Frequent corrective decisions allow the model to compensate for insufficient or excessive investment made in initial decision stages. The recommendations of the proposed method depend on the probabilities assigned to the supply scenarios; errors in those probabilities will lead to errors in the model's recommendations. To measure the adaptivity and flexibility enabled by the ROA implementation, two metrics are used and discussed. The model is applied to a water supply infrastructure planning problem in England over 50 years with a 5-year decision-making time-step.

The proposed approach is described in Section 3.2 and the results of its application to Thames Water's London supply zone are presented and discussed in Section 3.3 and Section 3.4. Two metrics to evaluate the implementation of ROA are proposed in Section 3.4.3. Sensitivity of results to the use of different scenario trees and the characteristics of the uncertainty set used to create the trees are in Section

3.4.4. Section 3.4.5 discusses the limitation of the proposed method and Section 3.5 concludes the chapter.

3.2 Adaptive and flexible formulation for ROA implementation

Two steps are taken in formulating a multi-stage stochastic program for ROA implementation. In the first step, a scenario tree (see definition in section 3.2.1) is generated to approximate the stochastic supply representing an ensemble of plausible futures. In the second step, a multi-stage mathematical programming formulation is solved on the scenario tree to obtain the future plan under plausible future scenarios. The section concludes with an illustration of a utility that practices real options investment decision-making provided by the proposed formulation (section 3.2.4).

3.2.1 Scenario tree approximation

A discrete time horizon T is considered in which decisions are made at each stage $t \in T$. To facilitate adaptive decision-making to changing future condition, and to represent the multistage planning for flexible decision-making, a set of paths is built to represent the evolution of an uncertain future. The paths, or trajectories, correspond to a particular state of the uncertain parameter in time. These paths are approximated using a tree structure which is refer to as a *scenario tree*. The scenario tree, schematized in Figure 3.1 (a), is built by creating the root node at time stage 1 associated with the first stage deterministic decision. The successor nodes to the root depict the possible outcomes of the next decision point at time index 2. This process is repeated until the end of the planning horizon resulting in a tree structure. A single *scenario* is then defined as a unique path from the root node to the terminal node defined by a leaf showing one realization of the future. The probability of scenario occurrence is defined by multiplying all state transition probabilities of the scenario path starting from root leading to the leaf. The scenario tree is an approximation of the stochastic process and is suitable for multi-period decision-making as until a given point on the tree, the past is shared amongst a set of scenarios while a future event is yet to manifest. In Figure 3.1 (a), an example scenario tree structure is presented. Tree nodes F and G share a common point C and all decisions that come before it. Non-anticipativity enforces that investment decisions at time t only utilise any information that is available up to this stage. Hence, this dictates that all decisions made for scenario 2 and 3 should be the same on node A and C. The path indicates that the possible outcomes from C in the next stage is transition to either F with probability p_5 or G with probability p_6, subject to $p_5 + p_6 = 1$. The number of leaf nodes corresponds to the number of distinct scenarios and their probabilities are calculated as the multiplication of associated transition probabilities starting from root leading to the leaf node. For instance, the probability for supply scenario s_3 to occur, from root to the end of the planning horizon is $p_2 \times p_6 \times p_{11}$.

Manually generating the above scenario tree and deciding on the number of nodes, leafs, and probability information on each node for practical purposes requires complex calculation and sufficient judgment (Lander and Pinches, 1998). This is especially a major deterrent to ROA implementation in complex decision problems as scenario trees can quickly grow large. To account for this, the scenario tree is automatically constructed by implementing the fast-forward iterative greedy algorithm which aims to minimise a so-called probability distance between the uncertainty sets (Gröwe-Kuska et al., 2003). The algorithm optimally creates a most informative scenario tree based on the original stochastic process by successively bundling the tree nodes into separate sets to be later represented by a new node while maintaining the probability information of the constructed uncertain process as close as possible to the original stochastic process. By bundling similar scenarios and reducing the number of nodes this not only produces a valuable and smaller computationally accessible multi-stage decision model but also reduces the

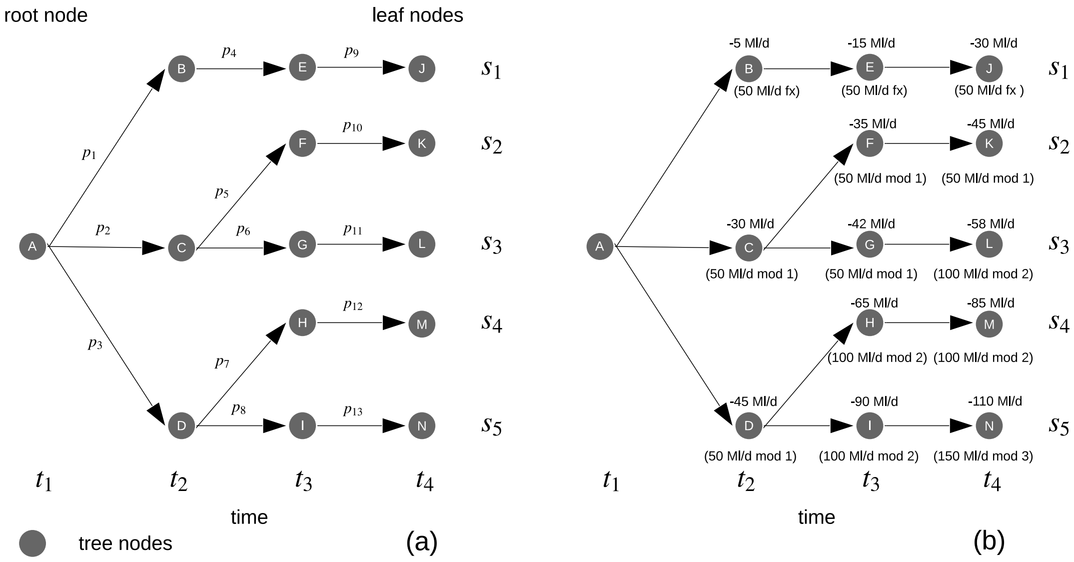

Figure 3.1: (a) A simple scenario tree structure with 14 nodes represented with letters A-N. s_i are the scenarios and p_i are the transition probabilities for each outcome branch; for each pair of branches the sum of the probabilities adds to 1. A path is defined from root node to leaf node at the end of the planning horizon. (b) An illustration of a simple water resource problem solved with the proposed real options formulation. The supply-demand gap and the activated intervention are provided above and below each tree node respectively.

burden of manually representing the uncertainty through scenario tree generation for multi-stage stochastic ROA implementation.

The next section gives details of the construction algorithm where the quality of the constructed tree is controlled by a metric that calculates the percentage of information lost known as 'relative probability distance' (Heitsch and Römisch, 2011). The lower the metric value is, the less information is lost and hence the more accurate the constructed tree becomes. This is set to 5% in this study as this is assumed to be an acceptable loss of information based on the work of Gröwe-Kuska et al. (2003). The tolerance indicates the relative probability distance between the constructed tree and the original stochastic process and consequently determines the number of scenarios preserved in the scenario tree.

3.2.2 Details for scenario tree construction algorithm

The scenario tree construction uses the supply scenarios of the original stochastic process (as defined in section 3.2) to build a tree with probabilistic weights assigned to each nodes used in the optimisation model. The tree construction is an optimisation method based on Kantorovich transport functional (developed by Gröwe-Kuska et al. (2003)) as follows, where

ξ, $\widetilde{\xi}$ is n-dimensional stochastic processes, ξ^i, $\widetilde{\xi^j}$ is scenarios (sample path of ξ), p_i,q_j is scenario probabilities, probability distribution of the processes ξ and $\widetilde{\xi}$ respectively, S is number of scenarios in the initial scenario set, J is index set of deleted scenarios, cJ is cardinality of the index set J; i.e., the number of deleted scenarios, $s = S$ - cJ is number of preserved scenarios, ε is tolerance for the relative probability distance, $c_t(\xi^i, \xi^j)$ is distance between scenario ξ^i,ξ^j.

Let P be the set of original scenarios, which contains the set of scenarios that will be deleted as well as the ones that will be preserved. Scenario set Q based on the scenarios having minimal Kantorovich D_K distance to P is computed in equation 3.1,

$$D_K(P, Q) = \sum_{i \in J} p_i \min_{j \notin J} c_T(\xi^i, \xi^j). \tag{3.1}$$

The probability q_j of the preserved scenarios is given by the rule,

$$q_j := p_j + \sum_{i \in J(j)} p_i, \tag{3.2}$$

where

$$J(j) := \{i \in J : j = j(i)\}, j(i) \in \arg\min_{j \notin J} c_T(\xi^i, \xi^j), \quad \forall i \in J.$$

That is, Kantorovich transport functional make sure that the scenario sample is the best possible approximation of the stochastic process. By bundling similar scenarios and reducing the number of nodes, this produces a smaller, computationally accessible multi-stage scenario tree that is the solution of the following optimal problem,

$$\min\{\sum_{i \in J} p_i \min_{j \in J} c_T(\xi^i, \xi^j) : J \subset \{1, ..., S\}, cJ = S - s\}, \tag{3.3}$$

where s = S - cJ is the number of preserved scenarios. The maximal reduction strategy is deduced to determine a reduced probability distribution Q of ξ such that the maximum number of scenarios are deleted subject to,

$$D_K(P, Q) < \varepsilon. \tag{3.4}$$

3.2.3 Staged mathematical model

With a scenario tree constructed, a mathematical program is formulated to represent the staged decision process for obtaining an optimal decision for each node of the scenario tree. This provides adaptive optimal solutions which propose actions to be implemented at each decision-making time interval and for each estimate of the uncertain future. A binary decision variable dS is introduced, representing the activation of an intervention at each node of the tree where the decision at each stage only depends on the information available up to that point. The following formulation defines the staged mathematical program for sequential capacity investment decision-making over time. Let N be the set of nodes on a scenario tree and N_t be the set of nodes belonging to stage t. For a node $n \in N$, $n-1$ and $n+1$ denote respectively, the predecessor and successor nodes on the scenario and with p_n the probability that node n is realised. For a node $n \in N$ and scenario $s \in \Omega$,

Ω_n is the set of nodes belong to scenario s.

$$min\ z = \sum_{n \in N_t, i \in I} \frac{p_n}{(1+r)^t}[cC_i \times (dS_{n,i} - dS_{n-1,i}) + fC_i \times dS_{n,i} + vC_i \times S_{n,i}], \tag{3.5}$$

$s.t.$

$$\sum_{i \in I} S_{n,i} + eS_n \geq \sum_{t \in T} D_t, \quad \forall n \in N_t, \tag{3.6}$$

$$S_{n,i} \leq aS_{l,t,i}, \quad \forall t \in T, n \in N_t, i \in I, l \in \Omega_n, \tag{3.7}$$

$$aS_{l,t+\lambda_i,i} \leq dS_{n,i} \times cS_i, \quad \forall t \in T, n \in N_t, i \in I, l \in \Omega_n, \tag{3.8}$$

$$aS_{l,t,i} = 0, \quad \forall i \in I, t \in T \wedge t \leq \lambda_i, n \in N_t, l \in \Omega_n, \tag{3.9}$$

$$dS_{n,i} \leq dS_{n+1,i}, \quad \forall n \in N, i \in I, \tag{3.10}$$

$$\sum_{i \in I_m} dS_{n,i}, \leq 1 \quad \forall n \in N, \tag{3.11}$$

$$dS_{n,i} \leq dS_{n-1,j}, \quad \forall n \in N, i \in I_d, j \in I_p, \tag{3.12}$$

$$S_{n,i} \geq 0, \quad \forall n \in N_t, i \in I, \tag{3.13}$$

$$dS_{n,i} \in \{0, 1\}, \quad \forall n \in N_t, i \in I, \tag{3.14}$$

where n is a node, t denotes time (stages), i is an intervention, p_n is the probability that node n is realised, r is the discount rate, $eS_{n,i}$ denotes levels of existing supply from intervention i, cC_i is the undiscounted capital cost of intervention i, cF_i is the undiscounted fixed operational cost of intervention i, cV_i is the undiscounted variable operational cost of intervention i, D_t is demand in time t, $cS_{n,i}$ is the maximum capacity of intervention i in node n, λ_i is the construction time period for intervention i, $dS_{n,i}$ is the activation of intervention i for node n, $S_{n,i}$ is the supply from intervention i for node n, $aS_{n,t,i}$ is the associate supply on the intervention i to supply on node n in time t.

The optimisation model minimises the expected cost of investments discounted back to the present. Constraint 3.6 makes sure the supply balances the demand in each node of the tree. Constraints 3.7 - 3.9 allow an intervention to be utilised up to its capacity considering its construction period, λ_i, before its activation;

constraint 3.7 sets an earliest year for the yield, constraint 3.8 sets the available supply to associate with construction period and constraint 3.9 prevents yield from being used during the construction period. Constraint 3.10 forces an intervention once activated to remain active at later nodes of the tree. Activation of two interventions that are mutually exclusive is avoided by introducing constraint 3.11 over the set of mutually exclusive interventions, I_m. Constraint 3.12 ensures that modular interventions can be further expanded as long as the previous phase has been completed. I_d denotes the set of dependent interventions and I_p denotes the set of pre-requisite interventions. The proposed problem structure follows a *node* based formulation related to the multi-stage stochastic program. Intervention activation constraints, due to path-dependency are non-anticipative. For instance, although scenario s_i and s_j end up in different terminal nodes, they can be passing through the same node in time t. In that case, the intervention activation decision variables at time stage t in scenario s_i equals that of other scenario s_j. This means that the multistage stochastic program will determine an optimal decision for each node of the scenario tree, given the information up to time stage t. Given that there are multiple succeeding nodes, the optimal decisions will not exploit hindsight, but they should anticipate future events. The mathematical model above allows non-anticipativity to be incorporated implicitly through its scenario tree formulation. Constraint 3.14 makes sure that an intervention can only be activated at most once in any scenario. The problem was modeled in GAMS (General Algebraic Modeling System Rosenthal (2012)), which is commercial tool for general optimization purposes that has been used in previous water resource planning studies Padula et al. (2013b) and solved with CPLEX.

3.2.4 Real options principles: a synthetic example

Figure 3.1 (b) illustrates a simplified manually constructed scenario tree for the purpose of demonstrating the ROA implementation. A utility is considered that wants to cost-effectively balance future supply-demand by investing in a new reservoir with three possible capacities (50, 100 or 150 ML/d). The 50 ML/d reservoir can be built with a fixed or modular capacity. As shown in Table 3.1, if the utility builds a 50 ML/d fixed capacity reservoir with 1,000 £m cost, they cannot expand it later. Alternatively if they pay a higher initial capex cost (1,100 £m) for a modular 50 ML/d reservoir design, they are able to expand later to 100 ML/d or further to 150 ML/d by paying the relevant expansion cost (Table 3.1). The 100 £m premium is an upfront cost the utility pays to reserve the right for expansion in later stages if required. This premium allows the utility to delay investment for the sake of acquiring information. The mathematical formulation in Section 3.2.3 finds the minimum discounted expected investment cost of capacity expansion over a four-stage planning horizon. The supply-demand gap is shown in each node of the tree. In t_2 node B, a fixed reservoir of 50 ML/d capacity is activated (50 ML/d fx) since its capacity is sufficient to balance the supply-demand gap till the end of the planning horizon. In t_2 node C, however, a 50 ML/d modular capacity is the most cost effective intervention that gives the ability to respond to uncertain supply-demand level in the future. If s_2 happens, it avoids further investment till the end of planning horizon, while under s_3, it requires the planner to expand capacity by an extra 50 ML/d at t_4 to balance the larger supply-demand gap. In t_2 node D, the 50 ML/d modular reservoir is again picked by the mathematical model, incrementally increasing capacity by an extra 50Ml/d and 100 ML/d under s_4 and s_5, respectively, till the end of planning horizon. This example shows how the ROA implementation is used to assess under different future scenarios the suitability of paying a premium to postpone capacity expansion.

TABLE 3.1: Cost, capacity and design of a reservoir for the illustrative example

Intervention	Capex/Expansion (£millions)	Capacity	Modularity
50 ML/d fx	1,000	50 ML/d	No ability to expand
100 ML/d fx	1,200	100 ML/d	No ability to expand
150 ML/d fx	1,400	150 ML/d	No ability to expand
50 ML/d mod 1	1,100	50 ML/d	Ability to expand to 100 ML/d
100 ML/d mod 2	140	100 ML/d	Ability to expand to 150 ML/d
150 ML/d mod 3	160	150 ML/d	No ability to expand

3.3 Application to infrastructure investment planning

England offers an interesting context to apply adaptive and flexible multi-stage investment planning because every 5 years, the economic regulator requires the water utilities to produce a plan demonstrating that the supply-demand balance is satisfied throughout their operating area over a long-term planning period. A plan is an optimal combination of new supply and demand management interventions, scheduled to meet estimated water supply zone demand plus an uncertainty allowance at least cost and is periodically updated. That is, company asset planners must select short-term (5 years) interventions for the next planning decision period and be able to demonstrate how they fit within a strategic long-term plan (25 years or more). Current water capacity expansion scheduling approaches used by water companies in England are based on deterministic annual supply-demand balance (Padula et al., 2013a). However, present investment decisions need to account for significant uncertainty.

Climate change projections for the United Kingdom in 2009 (UKCP09) is usually used to define the climate states in relevant studies of water asset planning in England (Murphy, Sexton, Jenkins, Booth, Brown, Clark, Collins, Harris, Kendon, Betts et al., 2009). Borgomeo et al. (2014, 2016) use daily time series of precipitation and temperature derived from the UKCP09 projections coupled with a transient stochastic weather generator produced by Glenis et al. (2015). They use a rainfall runoff model to generate daily flow time series to simulate the Thames water resource system. The output from each simulation is a record of the annual frequency of water shortages of different levels of severity (Borgomeo et al., 2016). The baseline supply uncertainty presented in this chapter has several sources of uncertainty including vulnerable surface and groundwater licenses, the impact of climate change on source yields, the gradual pollution of sources causing a reduction in abstraction as well as accuracy of supply side data which depends on the nature of the intervention (pumping, aquifer, etc) (Thames Water, 2014). Supply uncertainty is calculated using the UKCP09 for the current annual supply-demand planning framework, termed Economics of Balancing Supply and Demand (EBSD) (Padula et al., 2013a), where annual central estimates of supply are compared to central estimates of demand (see Thames Water (2014) for details). Multi-model ensembles of General Circulation Models (GCMs) can be used by water planners to derive probability distributions of climate change impacts (Dessai and Hulme, 2007; Fowler et al., 2007). The resulting scenarios define the domain of plausible outcomes under climate change.

The term 'deployable output' is used which is the volume of water that can be supplied from a water company's sources (surface water, groundwater, etc.) or bulk supply, constrained by environment, licensing, hydrological or hydrogeological factors, water quality and works capacity. In England, deployable output is estimated using prescribed methodologies as outlined in Water Resources Planning Tools (UKWIR, 2012), commonly through system simulation of long historical or plausible future hydrological time-series.

The proposed multi-stage modelling is applied to the London urban water supply area which is located in the Thames basin, south-east England. This basin has been classified as water stressed and is facing high population growth (Environment Agency, 2013) making it a suitable case study to investigate the use of the proposed flexible approach as without investment security of supply cannot be achieved. Water supply is managed by Thames Water, a privately owned water utility, serving 15 million customers across London and the Thames Valley. Financial costs include the net present value of capital expenditures incurred when selecting an intervention and operational expenditures, using a discount rate of 4.5% (Thames Water, 2014).

In this case study, a scenario tree is constructed to approximate the continuous distribution of the underlying London water supply (the annual yield or deployable output) provided by London's water utility (Thames Water). The supply's Cumulative Distribution Function (CDF) is used and the CDF is evenly partitioned into 100 regions. Each region's highest percentile value is picked up as the sample point. The probability of a scenario occurring is equal to the probability that supply falls within that region (supply range of each scenario interval is defined by the upper and lower percentile values). For instance, the scenario interval for scenario 2 is defined by (X_1, X_2) and its probability P(S_2) is calculated by,

$$P(S_2) = P(X_1 < X \leq X_2) = P(X \leq X_2) - P(X \leq X_1). \tag{3.15}$$

Given the evenly partitioned CDF using the percentile values, the probability of occurrence of each scenario is 1%. This is shown in Figure 3.2. This set is used to efficiently construct the scenario tree where the probability of each node and the threshold value for branching from one node to the other is calculated optimally. By applying the scenario reduction technique, the new probability of a preserved scenario will be equal to the sum of its former probability and of all probabilities of deleted scenarios that it represents (as per equation 3.2). The constructed optimal scenario tree is used for multi-stage stochastic programming model for ROA implementation where the values of the preserved scenarios are used to calculate the supply-demand gap thresholds that indicate which interventions should be activated under the given conditions.

Uncertainty around demand growth rate is not considered and it is assumed that the demand for water is expected to increase at a known rate. Figure 3.3 shows the

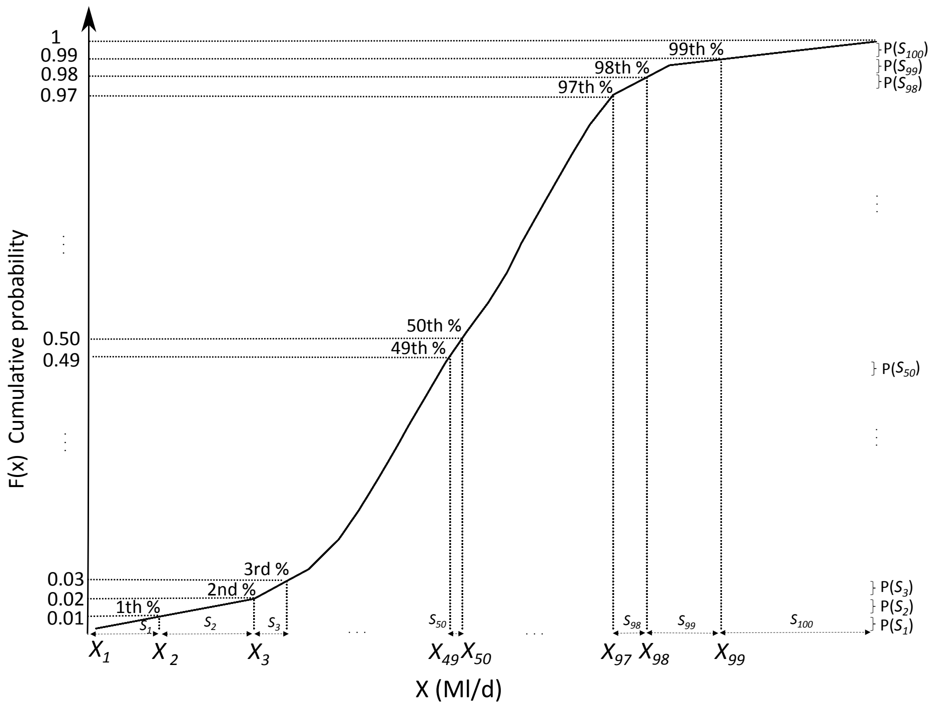

Figure 3.2: Definition of the scenario interval.

supply uncertainty range for London as well as the deterministic demand values. The problem is structured so as to allow asset managers to review the plan in the distinct decision points (every 5 years) and respond through selecting additional interventions or expanding existing ones, by taking advantage of the observed changes to the main uncertainty drivers (e.g., water supply, demand, capital and operational cost of intervention). Deployable outputs are assumed to remain constant during the five-year planning decision periods. Large water resource schemes can be built in phases. The flexibility to build resources in incremental stages allows for improved supply estimates before committing to larger schemes. Final plans are submitted in the year before the first planning decision period covered and in practice, the proposed approach would allow planners to decide on their investment plans depending on the supply-demand gap a year ahead of the 5-year period end. Although the plans should demonstrate security of supply over the entire fifty-year planning period, the main focus of asset managers is to decide which interventions should be implemented in the short-term i.e. the optimal investment portfolios for planning decision period 2020-2024.

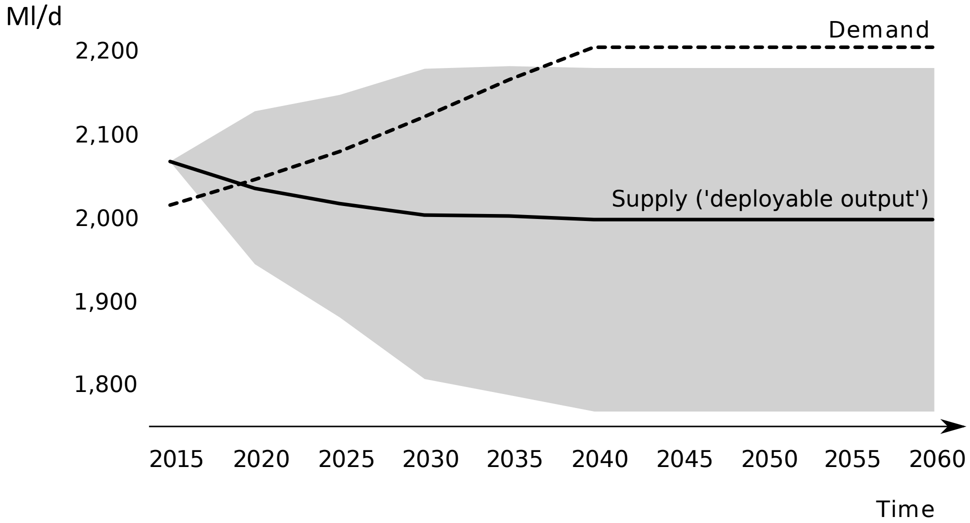

Figure 3.3: London deterministic demand and supply side uncertainty for five-yearly predicted levels during the planning period.

The scenario tree to approximate the stochastic London water supply-demand balance (due to supply uncertainty) is optimally produced as described in Section 3.2.1 using the uncertainty over the deployable outputs. The input data on supply and demand was provided by Thames Water. Each of the 100 unique paths denotes a plausible supply scenario (a set of deployable output values for each source). Each path starts from the unique root node at the first period and is linked to a supply scenario at each distinct time period (see Figure 3.4). The fifty-year planning period was divided in five-year time steps forming ten discrete time periods t. Asset managers can rebalance their infrastructure portfolios at the beginning of each planning decision period. Submission of final Water Resource Management Plans occurs one year before the plan is due to come into action following a consultation period. At each time step, the scenario tree branches into nodes that belong to the next period.

As seen in the simplified scenario tree in Figure 3.1 (a), in t_2 node C has a decision which leads to nodes F and G in next period representing different levels of supply-demand balance. The branching continues up to the nodes of the final

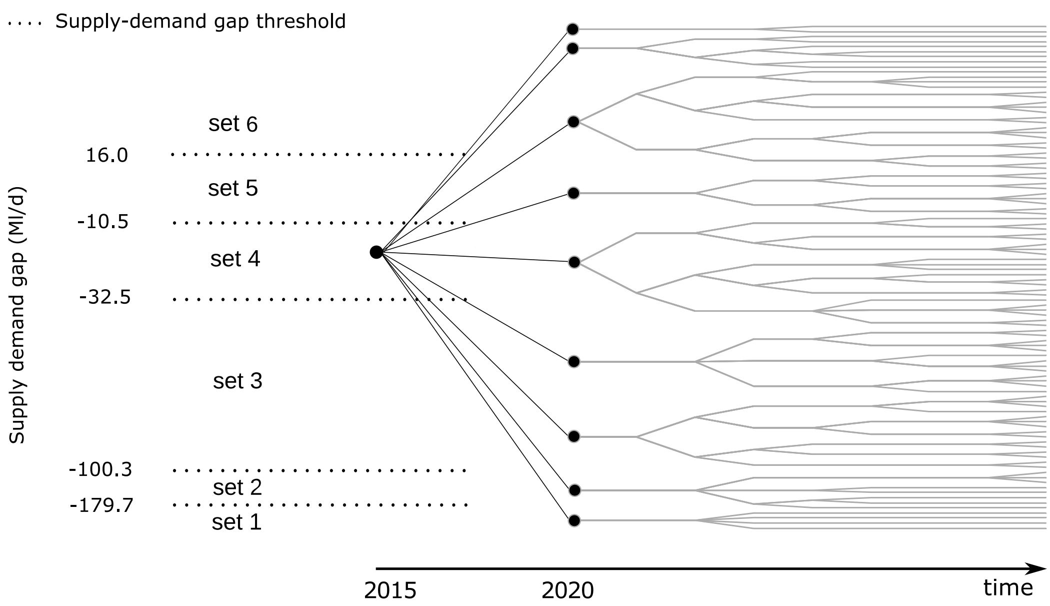

FIGURE 3.4: Clustering of solutions optimised for the 9 nodes in planning decision period 2020-2024 into six sets of interventions

period whose number corresponds to the number of supply scenarios. See Table 3.2 for the number of nodes used at each time step. It is noted that the scenario tree approximation method is independent from the staged mathematical model presented earlier and allows consideration of other sources of uncertainty through the use of joint probability distributions of random variables. This can be achieved if the uncertainty set is more than one dimensional, for instance, if it has both supply and demand distributions. The joint probability density function of supply-demand gap which represents the stochastic component is used to derive the scenario tree. Section 3.2.2 gives details of deriving the scenario tree when the uncertainty has more than one dimension.

In the appraisal process, 47 alternative supply interventions are considered listed in Table A.1 in Appendix A. Some interventions have been developed as long-term water resource interventions and are expected to be operated at high utilisation given their capacity (for instance intervention i28), while others are being considered by Thames Water as contingency interventions (for instance intervention i21), expected to be operated at low utilisation to avoid excessive operational costs. The type and capacity ranges of the interventions are given in Table 3.3 and are

TABLE 3.2: Number of nodes in each time step of scenario tree representing a planning decision period (PDP)

PDP	First year	Period	Nodes
PDP15	2015	2015-2019	1
PDP20	2020	2020-2024	9
PDP25	2025	2025-2029	11
PDP30	2030	2030-2034	15
PDP35	2035	2035-2039	30
PDP40	2040	2040-2044	40
PDP45	2045	2045-2049	50
PDP50	2050	2050-2054	60
PDP55	2055	2055-2059	60
PDP60	2060	2060-2064	100

TABLE 3.3: List of available London water resource supply intervention types considered in the appraisal process. The 47 interventions considered in the London case study are mapped to their type. Option information used in this chapter may not be consistent with the most recent data available (TWUL, 2018).

Resource Type	**Capacity range in ML/d**	**Construction period range in years**	**Premium for modular design**	**Intervention code**
Aquifer Recharge	2 - 8	2 - 3	-	i1 - i4
Desalination	50 - 150	4 - 7	8%	i5 - i12
Effluent Reuse	50 - 150	3 - 6	16%	i13 - i35
Groundwater	1.5 - 9	1 - 3	-	i36, i37
Reservoir	75 - 150	8 - 12	12%	i38 - i45
Transfer	158 - 242	7	-	i46, i47

provided by Thames Water. Large interventions of 50 ML/d or greater (such as effluent reuse schemes, desalination plants and reservoirs) can also be built with a modular capacity that allows expanding later on. This ability for future expansion comes at a price. For each type of intervention, the premium for modular capacity is expressed as a percentage. The percentage value expresses how much larger the initial capital investment cost of the intervention with modular capacity is compared to the fixed (unexpandable) one.

3.4 Results and discussion

3.4.1 Solving the water resource planning problem at multiple stages over time

Figure 3.4 shows the nine supply scenarios in planning decision period 2020-2024, at t_2 magnified from the scenario tree. The solutions in 2020 are clustered into six sets of optimal interventions, by identifying the common sets of interventions across the 9 nodes. Decision paths are formed using supply-demand gap threshold values. Each threshold value designates which set of interventions is optimal for the given forecasted deficit and leads to different amounts of water capacity increase for the planning decision period 2020-2024. The added water supply capacity is optimal for each scenario if it occurs. The scenario tree within the ROA incorporates uncertainty about how the evolution of different futures may trigger the selection of different interventions and hence examines the implications of future uncertainty. In this long-term water resource planning problem, sequential decisions are made at multiple stages over time. Early stage decisions are based on long term supply-demand forecasts whose accuracy decreases over time. The multistage optimisation model formulation allows adjusting earlier stage decisions in later stages. This way the model compensates for the impact of earlier decisions made under supply-demand forecast inaccuracy.

In the London case study, the scenario tree is made based on the state of the world as known in 2015; from that vantage point the future is described via six supply scenarios for 2020. In this case-study, if the planner in 2015 considers that the supply-demand balance in 2020 is most likely, based on their best forecasted estimate, to be between 10.5 ML/d and -32.5 ML/d, then set 4 is the best intervention response (Figure 3.4). This short-term set of investment interventions is optimally obtained using a scenario tree that considers the longer term future and hence the interventions associated with this set of interventions delineate the best response to uncertainty. The proposed approach is significant because least-cost scheduling

TABLE 3.4: Six alternative sets of interventions (S1 - S6) for planning decision period 2020-2024, new capacity in planning decision period 2020-2024 (ML/d), planned capacity (ML/d) and percentage of supply-demand scenarios where each set of interventions is activated

Interventions	S1	S2	S3	S4	S5	S6
i1	2					
i2	8					
i3	6					
i4	5			5		
i21	150			150	150	
i25		60				
i28	150	150	150			
i37	9			9		
PDP 2020-2024 capacity	180	210	150	14	0	0
Planned capacity	330	210	150	164	150	0
Scenarios	2%	7%	29%	22%	13%	27%

of water supply infrastructure is required of English water utilities, and there is wise-spread support at the policy level for improving it to consider flexibility and adaptivity.

Table 3.4 shows that forty percent of the 100 supply scenarios were directed to the top two paths (set 5, set 6) where no extra capacity is needed in planning decision period 2020-2024. However, in set 5, an intervention is planned to be delivered in planning decision period 2025-2029 to meet the future demand for water beyond the five-year period.

The remaining sixty percent are directed into paths where London water capacity is increased by selecting alternative interventions. When supply deficit is greater than 10.5 ML/d, intervention i28 is always selected with increasing utilisation, the amount of water supplied from an intervention, as levels of existing supply decrease. Figure 3.5 shows the utilisation of interventions i28 of 150 ML/d capacity and intervention i4 of 5Ml/d capacity indicating that small schemes are selected to postpone the activation of large schemes in case water supply in 2020 is no greater than 2,036.4 ML/d.

In set 4, intervention i28 is replaced by i21 in planning decision period 2020-2024

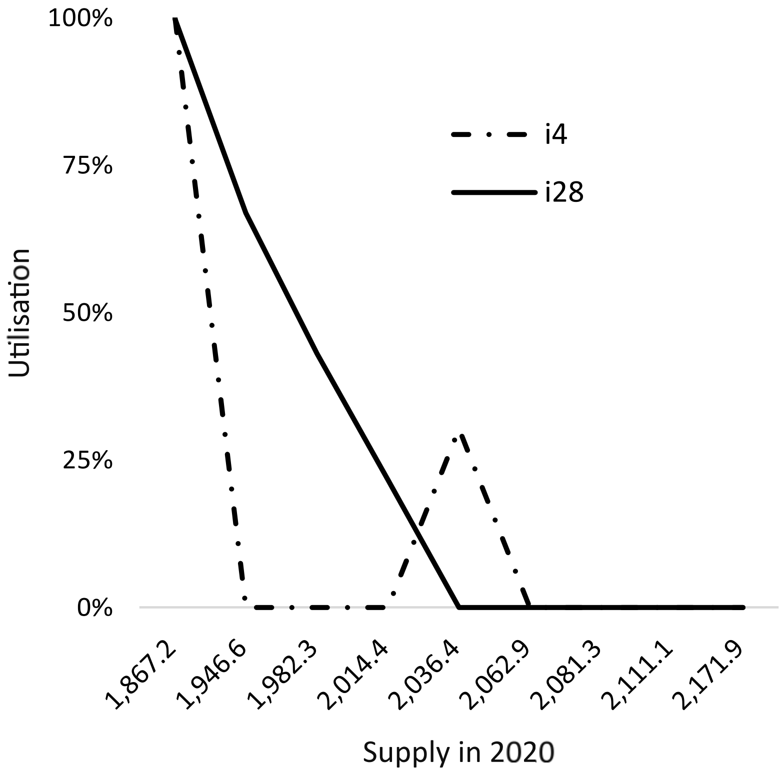

FIGURE 3.5: Utilisation of interventions based on levels of existing supply in planning decision period 2020-2024.

as an alternative intervention of type Effluent Reuse with 150 ML/d (see Table 3.4). The two interventions have equal capacity but contrasting intentional usage in terms of the amount of water produced. Intervention i21 has a relatively lower cost to build and a higher cost to operate and is considered to be a provisional contingency scheme. Contingency schemes are not expected to have a high capacity utilisation, resulting in an excess capacity due to their higher operational cost compared to the average cost of taking the water from alternative water sources. Due to their higher operational cost, these schemes can be substituted if less expensive interventions are available in the future.

Conversely, intervention i28 is an irreversible long-term intervention (once built, it is used for the rest of the modelled time-horizon) with an expected high utilisation rate given its relatively higher construction costs but lower operational costs. This indicates that the selection of schemes is decided on the basis of the estimated required water utilisation under different future uncertainty. In doing so, overspending on capital is avoided. When the lower operational costs outweigh the savings in the capital expenditure due to higher utilisation then the long-term intervention i28 is selected. Decision on 'long-term' intervention i28 is however delayed on the three paths that begin with set 4, set 5 and set 6 of investment interventions in 2020. Instead, the modelling suggests to replace this with activation of the contingency intervention i21 in set 4 and set 5, and no interventions activation in set 6. Interventions i1, i2 and i3 are only selected in the path that begins with set 1 in 2020, as these contingency schemes are only required when the supply-demand balance is expected to be less than -179.7 ML/d.

A key strength of ROA is the opportunity it provides for exploiting learning over time. For example, Figure 3.6 shows that if the estimated supply-demand gap is greater than 16.0 ML/d, there is no need to make an investment in the current planning decision period. This flexibility is valuable because by not selecting an intervention now and deferring it to the next planning period, asset managers avoid the costs of building an intervention until it is needed later.

The results, shown as a coloured bar chart in Figure 3.7, depict the frequency of activation of interventions in nodes at each time step on a scale from 0% (white) to 100% (black). A high percentage of activation denotes that the selection of this intervention is robust across a number of supply-demand scenarios. For instance, as shown in Table 3.4 in the S1 set of interventions, i1, i2 and i3 are all contingency interventions of small capacities which get activated at t_2 in the most extreme scenarios that correspond to 2% of all scenarios in t_2 . As shown in Figure 3.4, these extreme scenarios where S1 is selected at t2, pass through one node. Since, interventions i1, i2, i3 are selected only in S1, they have an activation frequency of 11% (1 out of 9 nodes) in Figure 3.7 in t_2. By the end of the planning period, unlike interventions i2 and i3, i1 has an increased activation frequency. This implies that contingency interventions i2 and i3 are only selected in extreme scenarios while activation of i1 is more robust across a number of supply-demand scenarios i.e. intervention i1 will also be activated in less extreme scenarios.

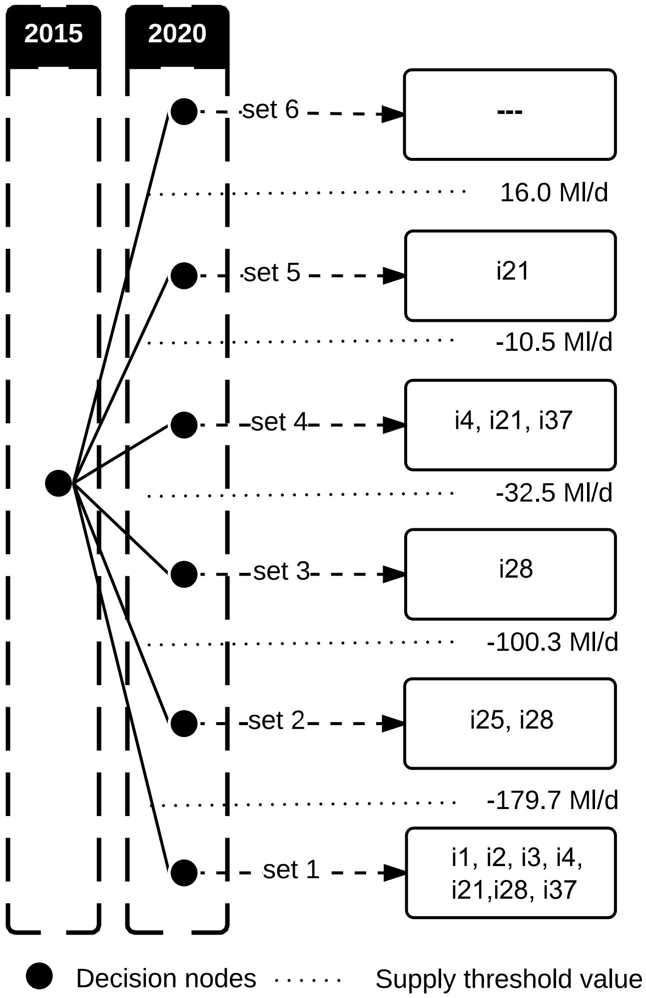

FIGURE 3.6: Set of interventions in planning decision period 2020-2024 for each decision path using supply threshold values.

3.4.2 Computational insight on the metrics used to evaluate the implementation of ROA

The calculations of the two metrics, namely Expected Value of Perfect Information (EVPI) and Value of Stochastic Solution (VSS), in multi-stage problems are explained below. These metrics were developed for the case of two-stage problems (Birge and Louveaux, 1997), and have been extended to multistage problems (Escudero et al., 2007).

For the minimisation model the following inequalities are satisfied,

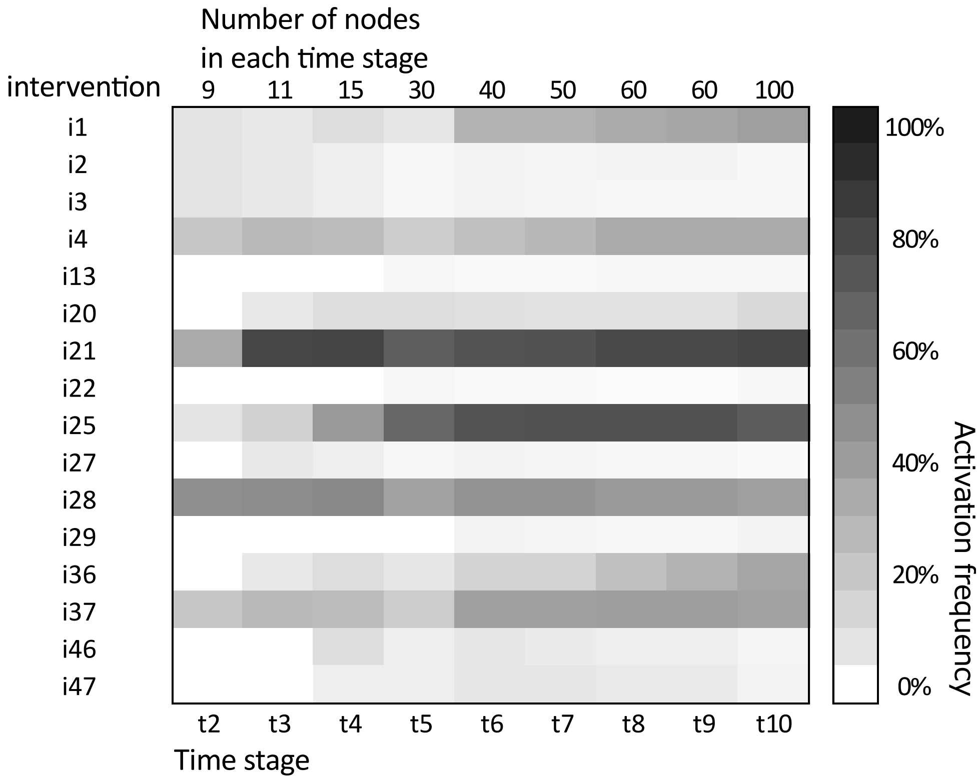

FIGURE 3.7: Frequency of activation of interventions in supply scenarios (nodes) at each time step.

$$WS \leq AP \leq EV, \tag{3.16}$$

where WS denotes the expected value of the objective function obtained by replacing all random variables by their expected values; WS is known in the literature as the wait-and-see resolution value. AP denotes the optimal solution value to the adaptive multi-stage stochastic problem presented in this chapter. EV denotes the expected result of expected value problem and measures how the optimal solution of the expected value problem performs allowing the other stages decisions to be chosen optimally as functions of different scenarios.

From equation 3.16, EVPI and VSS are calculated as follows,

$$EVPI = AP - WS, \tag{3.17}$$

$$VSS = EV - AP. \tag{3.18}$$

To calculate the EVPI, non-anticipativity constraints are relaxed at each time step so that decisions are made with perfect information about the future. From Equation 3.17, the difference $AP - WS$ displays the value of perfect information. From Equation 3.18, the difference $EV - AP$, known as the VSS, indicates the benefit of finding different solutions for each scenario by solving the stochastic program than to assume lack of uncertainty.

In the work of (Escudero et al., 2007) those parameters are generalised to the multistage case explained below. Let the expected result in t of using the expected value solution, denoted by EV_t for t = 2, . . . , T , be the optimal value of the AP model, where the decision variables until stage $t-1$, $(x_1, \ . \ . \ . \ , x_{t-1})$, are fixed at the optimal values obtained in the solution of the average scenario model.

For any multistage stochastic program, the following relations hold:

$$EV_{t+1} \leq EV_t \quad \forall t = 1, ..., T-1,$$

$$0 \leq VSS_t \leq VSS_{t+1} \quad \forall t = 1, ..., T-1.$$

VSS is defined in t, denoted by VSS_t, as

$$VSS_t = AP - EV_t \quad \forall t \in T.$$

3.4.3 Metrics for flexibility and adaptivity assessment

Two metrics used in stochastic programming problems (Birge and Louveaux, 1997; Escudero et al., 2007) are introduced, namely, Value of the Stochastic Solution (VSS) and Expected Value of Perfect Information (EVPI), to measure the adaptivity and flexibility of the decisions suggested by the ROA formulation. VSS is calculated by replacing the uncertain variables with their expected values and measuring the performance of this expected value problem to future uncertainty.

EVPI is estimated by comparing the solution of the ROA-based approach with the optimal solution for the wait-and-see problem with perfect information. The next section gives mathematical detail on the calculations of VSS and EVPI.

In the context of this example, VSS indicates the difference of implementing ROA via a multi-stage stochastic program that explicitly allows adaptation to different future conditions via a distribution of uncertain future supply instead of using the average supply values in each stage. VSS quantifies the cost of not recognising the uncertainty and hence ignoring the adaptivity advantage ROA provides. For the London case study, VSS is £113,206,815 discounted over the 50 years planning period. VSS estimates the value of adaptivity by quantifying the cost of ignoring uncertainty by Thames Water that can be avoided by adaptive plans to changing future conditions. For the London case study, the VSS result is significant when it is compared to the total investment NPV cost of £737,648,067. That is, VSS corresponds to 15.4% of the total NPV cost. This relatively high VSS value is an indication that supply uncertainty is an important factor in London's supply-demand problem where adaptive solution to changing future can mitigate its consequences.

EVPI measures the value of information in planning under uncertainty. EVPI estimates how important, in the context of uncertainty, evolution of information over time is and therefore it indicates the value of a wait-and-see decision; how valuable it is to know the future before making a decision. In the context of ROA implementation, EVPI is a measure of valuing flexibility of delaying irreversible investment commitments and taking early provisional actions until new information is available. For the London case study, EVPI is £44,092,250 discounted over the 50 years planning period which is 6% of the total NPV cost. EVPI estimates that the value of waiting to gain more information corresponds to 6% of total NPV. Even this small percentage reflects a significant value for the implementation of large irreversible long-term interventions given their large socioeconomic and environmental impacts.

3.4.4 Sensitivity to scenario tree

It is relevant to explore the sensitivity of results to the use of different scenario trees as well as the characteristics of the uncertainty set used to create the trees. Two types of sensitivity analysis have been performed. First, the consequences of generating and using alternative scenario trees in the analysis is investigated. The London case study was run using thirty different and randomly generated scenario trees from the stochastic London supply distribution making sure that each tree has the same uncertainty source data but has a different structure, i.e., different number of nodes at each time step as well as different branching structure. Then, a second type of sensitivity analysis is performed, to investigate the consequences of using random subsets of the full set of scenarios. Each tree was generated using a different subset of supply scenarios randomly sampled from the full set of 100 scenarios.

The results of both types of sensitivity analysis, shown as a bar chart in Figure 3.8 and Figure 3.9 respectively, depict the activation frequency of the interventions in planning decision period 2020-2024. It can be appreciated from both types of sensitivity analysis that most interventions suggested by the multi-stage optimisation planning have a high frequency of selection (more than 75%) indicating the quality of the interventions' activation recommendation regardless of whether a different scenario tree (first type of sensitivity analysis) or different subsets of the

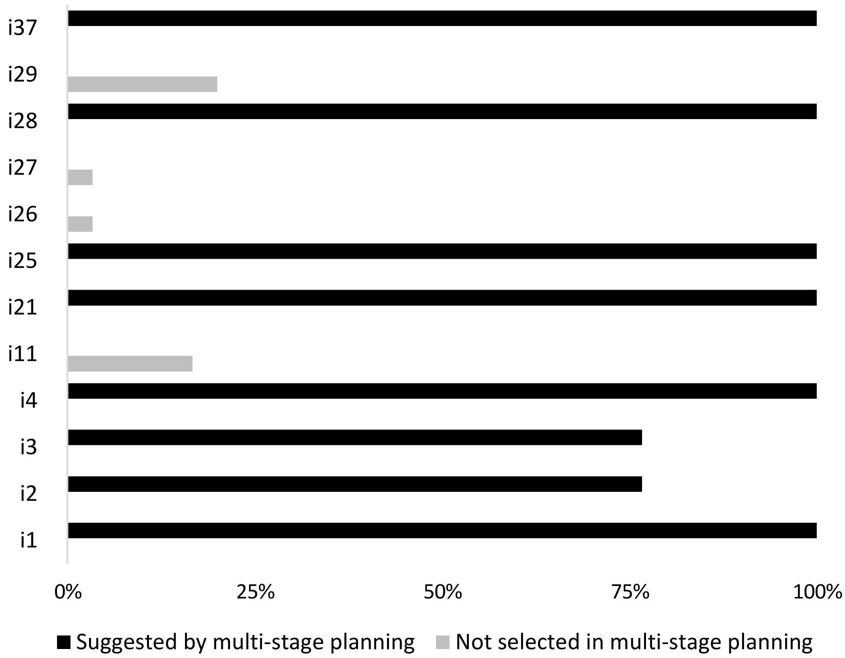

FIGURE 3.8: Activation frequency of interventions in planning decision period 2020-2024 using 30 scenario trees.

full set of scenarios were used (second type of sensitivity analysis). Other types of sensitivity analysis could include understanding the impact of using different relative tolerances by varying the relative distance between the constructed tree and the original stochastic process.

3.4.5 Limitations of the approach

The proposed approach is an extension of least-cost supply-demand planning (Padula et al., 2013a) aiming to optimise for flexibility and adaptivity in addition to cost when investing in infrastructure under supply uncertainty. Planning resources via the yield or 'deployable output' concept implies simplifying the problem by comparing a single value of annual regional supply with an annual demand. Although the use of regional annual supply and demand balancing is conceptually simple, these aggregate quantities are difficult to validate (Hall et al., 2012). Unlike simulation-based optimisation approaches that have become routine for analysing water policies (Brown et al., 2015), the proposed optimisation model does not rely

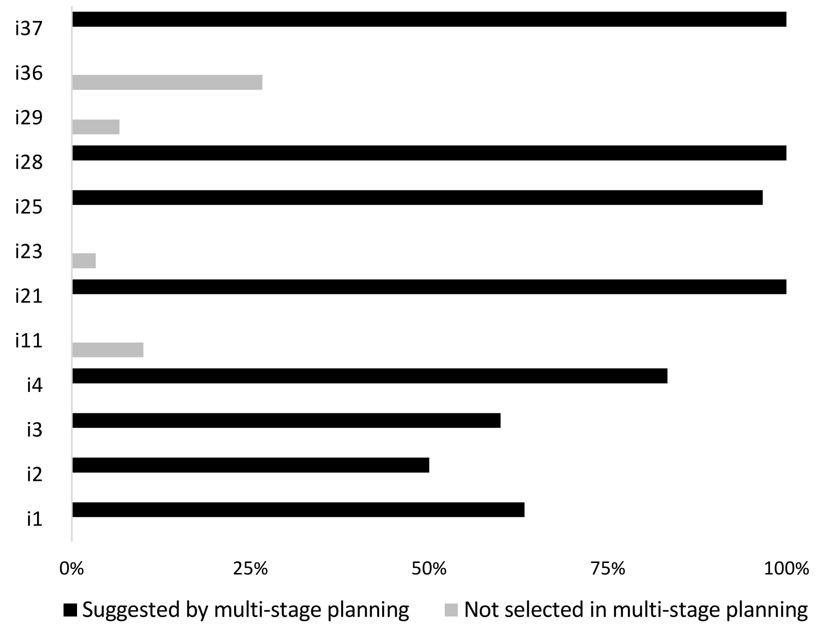

FIGURE 3.9: Activation frequency of interventions in planning decision period 2020-2024 using 30 subsets of the full set of scenarios.

on simulating alternative observable outcomes, such as the frequency with which customers are predicted to experience water shortages.

The analysis uses supply uncertainty data from the UKCP09 weather generator that addresses GCM uncertainties. Although the GCM-based climate projections are obtained from the most credible climate change information available, concerns in the assignment and use of probabilities to these future climate change scenarios have been raised (Maier et al., 2016). These climate models use numerous assumptions about how the future will unfold (Taner et al., 2017) which impact results. For instance, climate projections are contingent on greenhouse gas (GHG) emissions scenarios and future reductions in atmospheric aerosols (Stouffer et al., 2017) which are unknown. Such assumptions impact the probability distributions in climate model outputs which in turn will impact the supply probabilities and the findings of the analysis in the proposed approach (Dessai and Sluijs, 2007).

Another limitation of least-cost supply-demand planning is that plans are optimised using a single least cost objective, requiring all aspects of system performance to be monetized, leading to potentially imbalanced decisions (Matrosov et al., 2015). Using a single objective might prevent the finding of good solutions (Kasprzyk et al., 2015).

3.5 Conclusion

This chapter described how a least cost scheduling approach for water infrastructure investment planning, used currently at national scale in England, can be extended to explicitly enable flexibility and adaptivity given future supply uncertainty. The ROA concept using scenario trees over a predefined planning horizon with distinct decision points has been applied to allow rebalancing of the supply-demand system at intermediate stages. A compact scenario tree is generated to approximate the stochastic supply representing an ensemble of plausible futures. At each time step of the planning horizon, an optimal set of interventions is identified in each node of the scenario tree according to plausible source yield scenarios. Supply-demand gap threshold values are used to determine which path to follow in order to minimise the net present value cost of investments. The staged decision process provides the planner with adaptive solutions that their implementation can be delayed and replaced as information on future supply-demand balance is gradually revealed.

The proposed flexible and adaptive approach is applied to London's water supply planning problem. In the appraisal process, 47 interventions of different capacities (ranging from 1.5 ML/d to 150 ML/d) and alternative types (e.g. wastewater reuse, desalination, reservoirs) are considered. The 50-year planning period using 100 equally probable supply scenarios identified six optimal sets of investment interventions for the planning decision period 2020-2024. Depending on the forecasted short-term supply-demand balance, the planned capacity expansion ranges from 0 ML/d (no intervention) to 330 ML/d (as a result of activation of 7 interventions). The results show that the large forecasted gap between supply and demand in London is being bridged through 'long-term' (maintained after selection) interventions and through 'contingency schemes' when the gap is smaller.

The results demonstrate the benefits of ROA to enable adaptive and flexible decision-making in water resource planning. These are quantified using the VSS and EVPI metrics showing that, respectively, ignoring adaptive planning costs 15.4% of the total NPV and flexible decision-making has a value of 6% of the total NPV of London's water supply system. The introduction of the novel decision-relevant metrics of adaptivity and flexibility evolved their definition in the context of adaptive water resources planning. Sensitivity of results to the use of different scenario trees as well as the characteristics of the uncertainty set used to create the trees are assessed. They point towards high quality intervention activation selections by the proposed model.

Chapter 4

Application and comparison of alternative approaches to capacity expansion planning problem

4.1 Introduction

Least cost capacity expansion has been widely applied in water resource management problems to determine the interventions and their commitment time over a planning horizon. The objective is to minimise the total investment and the operating costs associated with the selected set of interventions while meeting the water demand. Capacity expansion models can be deterministic assuming one version of the future or stochastic where different future uncertainties around supply and/or demand (due to climate change and demographic change for instance) are considered.

Without the consideration of uncertainty, the solutions proposed by the capacity expansion models could result in water deficit or redundant capacity (Chung et al., 2009).

Deterministic water resources planning approaches that consider a single future are not suitable to address the uncertainty challenges. Stochastic models can address uncertainty in alternative ways, by seeking robustness (i.e. insensitivity to changes in future conditions) as well as adaptivity (i.e. ability to respond to future conditions). Robust approaches seek plans that perform satisfactorily well across a broad range of plausible climate conditions (Wilby and Dessai, 2010). Notable work of Lempert (2003); Lempert et al. (2006); Matrosov et al. (2013); Taner et al. (2017); Borgomeo et al. (2018) are in this category. Flexible approaches allow for learning over time enabling plans to cost-effectively adapt as more accurate information becomes available. The work of Haasnoot et al. (2013); Charlton and Arnell (2011); Paton et al. (2014); Woodward et al. (2014b); Beh et al. (2015a); Maier et al. (2016) are examples of this category.

Comparison of optimisation algorithms in the water resources field have demonstrated that for a given problem, a particular implementation of an approach can be found to outperform others (Kollat and Reed, 2006; Reed and Kollat, 2013). As a certain approach can be found to perform better on a certain problem compared to others, it is the characteristics of the problem being solved that determine when an approach may perform better than others (Maier et al., 2014).

In order to be able to compare the performance of different least cost capacity expansion approaches, appropriate performance assessment metrics need to be used. Despite cost minimisation being the single objective, water planners also seek to avoid inefficient use of infrastructure investment (Rosenberg et al., 2008). An important measure of economic efficiency is the rate of the unused capacity in urban water supply facilities (Lee, 2010).

This chapter compares the performances of four least cost planning approaches namely deterministic, two-stage, Robust Optimisation (RO) and Real Options Analysis (ROA) (as introduced in Chapter 3) on the basis of cost and unused capacity. With the exception of the deterministic, all other approaches consider multiple future scenarios to account for supply uncertainty. Although all four approaches aim to minimise costs, they address uncertainty in different ways, seeking either robustness or flexibility.

The results obtained by the conventional deterministic least cost scheduling and the three multi-scenario techniques are compared and validated, demonstrating the effectiveness of each approach. The next section describes the problem formulation of the alternative optimisation approaches. Section 4.3 presents the case study application of the four alternative approaches in solving the London's urban water resources planning problem and in Section 4.4 a discussion of the case study's results is presented. Finally, Section 4.5 concludes the chapter.

4.2 Methods

4.2.1 Problem formulation

The water resource management problem solved by each of the four least cost planning approaches is formulated using an aggregated method. In the aggregated problem formulation, supply capacity and demand are described as single values of probability functions for each year of the forecast to enable mathematical programming approaches to identify optimal scheduling of interventions. The supply demand forecasts correspond to an aggregated Water Resource Zone (WRZ), a sufficiently interconnected supply area where all residents face the same likelihood of supply shortfalls and within which, resources can be managed as a coherent unit.

The solution to the problem describes which actions should be taken at each decision point over the pre-specified planning period. Figure 4.1 (a) shows an example of a single path structure over a planning period consisting of four time steps while Figure 4.1 (b) shows the structure of a simple scenario tree, where scenarios represent multiple future paths over the same planning period. In both cases, at each decision node, the optimisation approach activates a set of interventions to solve

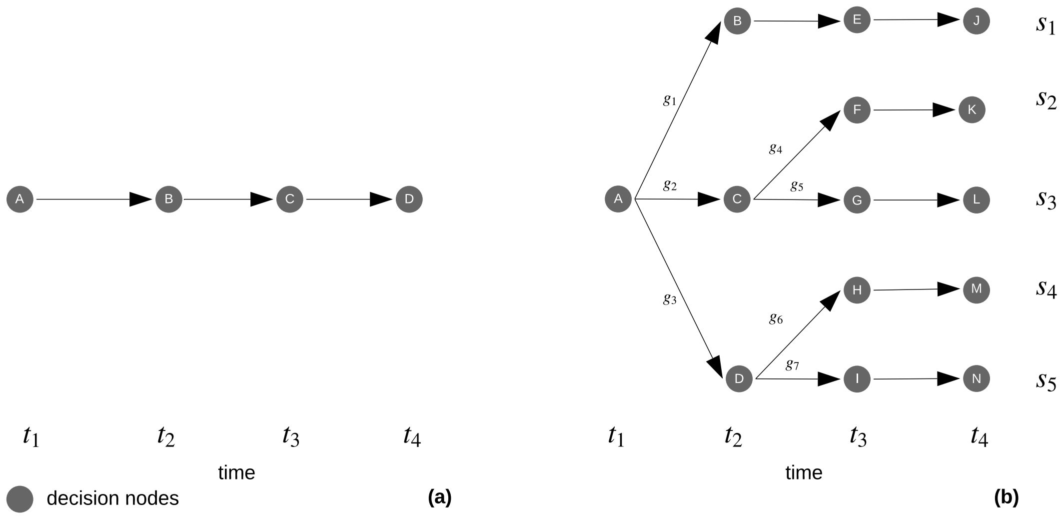

FIGURE 4.1: (a) A single path structure with 4 decision nodes (represented with letters A-D) defining a planning period consisting of four time steps. (b) A simple scenario tree structure with 14 decision nodes (represented with letters A-N) defining a planning period consisting of four time steps. The parameters s_i are the scenarios and g_i are the supply-demand gap values that show which path to follow.

the water resources planning problem. Fixed planning approaches solve the single path structure to produce a fixed schedule i.e. a single optimised investment plan consisting of a set of interventions where the optimal timing of each element of the plan is suggested. Flexible planning approaches solve instead a scenario tree to obtain an adaptive strategy i.e. a number of alternative branches and optimised plans under plausible future scenarios along with a reference supply demand gap metric that indicates the conditions under which a particular plan is the most suitable.

In this section, the optimisation formulations of the fixed planning approaches (deterministic, RO, two-stage) and the flexible ROA planning approach (multi-stage stochastic) used in the comparison study are presented.

4.2.2 Deterministic approach

The deterministic approach is formulated as mixed integer linear programming optimisation problem (Birge et al., 1996) as follows:

$$min\ z = \sum_{t,i} \frac{p}{(1+r)^t} [C_i(dS_{t,i} - dS_{t-1,i}) \tag{4.1}$$

$$+ F_i \times dS_i + V_i \times S_i]$$

$$s.t. \sum_i S_{t,i} + eS_{i,t} \geq \ D_t + h_t \ \ \forall t \tag{4.2}$$

$$S_{t,i} \leq dS_{t,i} \times cS_{t,i} \ \ \forall t, i \tag{4.3}$$

$$dS_{t,i} \leq dS_{t+1,i} \ \ \forall t, i \tag{4.4}$$

$$S_{t,i} \geq 0 \tag{4.5}$$

$$dS_{t,i} \in 0, 1. \tag{4.6}$$

The binary variable $dS_{t,i}$ denotes the activation of an optional supply source and the real variables $S_{i,t}$ and $eS_{i,t}$ indicate the extent of annual use of optional and existing supply sources respectively. The single objective is the minimization of discounted capital, fixed and variable costs (equation 4.1) subject to constraints. The mass balance constraint 4.2 ensures that demand for water is met in every year of the planning period. A buffer h_t is added to demand D_t to account for the uncertainty around supply and demand. Constraint 4.3 ensures that utilisation of supply interventions is up to its capacity while constraint 4.4 keeps an interventions on after its activation.

4.2.3 Robust optimisation approach

The RO formulation of the problem is as follows (Shapiro et al., 2009):

$$min\ z = \sum_{t,i} \frac{1}{(1+r)^t} [C_i(dS_{t,i} - dS_{t-1,i}) \tag{4.7}$$

$$+ F_i \times dS_{t,i} + V_i \times S_{t,i}]$$

$$s.t. \sum_i S_{t,i} + ES_{t,i} \geq D_t^w \quad \forall t, w \tag{4.8}$$

$$S_{t,i} \leq dS_{t,i} \times cS_{t,i} \quad \forall t, i \tag{4.9}$$

$$dS_{t,i} \leq dS_{t+1,i} \quad \forall t, i \in Ir \tag{4.10}$$

$$S_{t,i} \geq 0 \tag{4.11}$$

$$dS_{t,i} \in 0, 1. \tag{4.12}$$

The binary variable dS_i denotes the activation of an optional supply source and the real variables $S_{i,t}$ and $eS_{i,t}$ indicate the extent of annual use of optional and existing supply sources respectively. The single objective is the minimisation of discounted capital, fixed and variable costs (equation 4.7) subject to constraints. To make the solution robust even under the worst-case scenario, the mass balance constraint 4.8 requires that demand for water is met in every plausible future scenario w. Constraint 4.9 ensures that utilisation of supply interventions is up to its capacity while constraint 4.10 keeps an intervention on after its activation.

4.2.4 Two-stage stochastic approach

The two-stage stochastic programming problem is formulated as (Shapiro and Homem-de Mello, 1998):

$$min\ z = \sum_{t,i} \frac{1}{(1+r)^t}[C_i(dS_{t,i} - dS_{t-1,i}) \tag{4.13}$$

$$+ F_i \times dS_{t,i} + V_i \times S_{t,i} + \sum_{w} p^w B_t^w]$$

$$s.t. \sum_{i} S_{t,i} + ES_{t,i} + B_t^w \geq D_t^w \quad \forall t, w \tag{4.14}$$

$$S_{t,i} \leq dS_{t,i} cS_{t,i} \quad \forall t, i \tag{4.15}$$

$$dS_{t,i} \leq dS_{t+1,i} \quad \forall t, i \in Ir \tag{4.16}$$

$$S_{t,i} \geq 0 \tag{4.17}$$

$$B_t^w \geq 0 \tag{4.18}$$

$$dS_{t,i} \in 0, 1. \tag{4.19}$$

The objective of the two-stage stochastic programme (equation 4.13) is to minimise the sum of the first stage costs and the expected value of the random second stage costs where recourse decisions are made after observing the random output. The first stage decision variables are the binary supply intervention activation $dS_{t,i}$ variable and the utilisation variable $S_{t,i}$ denoting the amount of water supplied from an intervention. They correspond to investment and operation decisions over the planning horizon.

The second stage wait-and-see recourse action variable B_t^w is linked to the expected deficit costs and is delayed until more information is available as scenarios unfold. The consequences of potential supply shortage due to variations in water availability are being penalised by a user defined scarcity cost B_t^w. The scarcity cost variable is scenario-dependent and must be replicated for each scenario w.

Constraint 4.15 sets the available supply and constraint 4.16 forces an intervention once activated to remain active at later stages. Intervention activation constraints are non-anticipative stating that the first-stage decision should not depend on the scenario which will prevail in the second stage. In this case, $dS_{t,i}$ does not depend on each scenario w and is effectively determined before any information regarding the uncertain data has been obtained. On the other hand, B_t^w, the second-stage variable, is determined after observations regarding scenario w have been obtained. In essence, the goal of a two-stage model is to identify a first-stage solution that is well positioned against all possible observations of scenarios w.

4.2.5 Multi-stage stochastic approach

The formulation of the ROA approach as a multi-stage stochastic mathematical programme is as follows (Heitsch and Römisch, 2009):

Let N be the set of nodes on a scenario tree and N_t be the set of nodes belonging to stage t. For a node $n \in N$, $n-1$ and $n+1$ denote the predecessor and successor nodes respectively on the scenario and with p_n the probability that node n is realised. For a node $n \in N$ and scenario $s \in \Omega$, Ω_n is the set of nodes belong to scenario s.

$$min\ z = \sum_{n \in N_t, i \in I} \frac{p_n}{(1+r)^t} [cC_i \times (dS_{n,i} - dS_{n-1,i}) + fC_i \times dS_{n,i} + vC_i \times S_{n,i}], \tag{4.20}$$

$s.t.$

$$\sum_{i \in I} S_{n,i} + eS_n \geq \sum_{t \in T} D_t, \qquad \forall n \in N_t, \tag{4.21}$$

$$S_{n,i} \leq aS_{l,t,i}, \qquad \forall t \in T, n \in N_t, i \in I, l \in \Omega_n, \tag{4.22}$$

$$aS_{l,t+\lambda_i,i} \leq dS_{n,i} \times cS_i, \qquad \forall t \in T, n \in N_t, i \in I, l \in \Omega_n, \tag{4.23}$$

$$aS_{l,t,i} = 0, \qquad \forall i \in I, t \in T \wedge t \leq \lambda_i, n \in N_t, l \in \Omega_n, \tag{4.24}$$

$$dS_{n,i} \leq dS_{n+1,i}, \qquad \forall n \in N, i \in I, \tag{4.25}$$

where n is a node, t denotes time (stages), i is an intervention, p_n is the probability that node n is realised, r is the discount rate, $eS_{n,i}$ denotes levels of existing supply from intervention i, cC_i is the undiscounted capital cost of intervention i, cF_i is the undiscounted fixed operational cost of intervention i, cV_i is the undiscounted variable operational cost of intervention i, D_t is demand in time t, $cS_{n,i}$ is the maximum capacity of intervention i in node n, λ_i is the construction time period for intervention i, $dS_{n,i}$ is the activation of intervention i for node n, $S_{n,i}$ is the supply from intervention i for node n, $aS_{n,t,i}$ is the associate supply on the intervention i to supply on node n in time t.

The optimisation model minimises the expected cost of investments discounted back to the present. Constraint 4.21 makes sure the supply balances the demand in each node of the tree. Constraints 4.22 - 4.24 allow an intervention to be utilised up to its capacity considering its construction period, λ_i, before its activation; constraint 4.22 sets an earliest year for the yield, constraint 4.23 sets the available supply to associate with construction period and constraint 4.24 prevents yield from being used during the construction period. Constraint 4.25 forces an intervention once activated to remain active at later nodes of the tree.

The two-stage stochastic programme gives a solution, which works as a results of recourse to the uncertainty defined by the scenarios. That is to say, two-stage stochastic programming does not seek a solution on each scenario node and hence its solution does not provide adaptivity on each stage despite considering the recourse to the set of uncertain future. Conversely, in the multi-stage stochastic program, a recourse decision is made at the beginning of each time period allowing for flexibility to be exercised.

4.3 Case study

4.3.1 London urban water supply system

The four alternative optimisation approaches are applied to solve the London urban water supply demand problem. The London urban supply system is located in the Thames River Basin, an urbanised basin with a population of around 12 million resulting in a density four times higher than that of the rest of England. Water supply in the basin is managed by private water utilities at a WRZ level, defined as a zone with a forecasted supply demand position where water users experience the same risk of supply failure. The London WRZ has the most challenging supply demand balance in Thames Valley and is managed by Thames Water Utilities. In this zone, there is a significant supply-demand deficit throughout the planning period which requires investment to maintain security of supply (UKWIR, 2016). The deficit is predominantly driven by reductions in raw water availability due to the impacts of climate change in combination to population growth (Thames Water, 2018).

Every five years Thames Water Utilities is required to produce a water resources management plan, a strategic long-term plan where the company sets out how they intend to maintain the balance between supply and demand for water for their customers. To reflect that, the 50-year planning period was divided in 5-year time steps forming 10 discrete time periods t. In its 2019 water resources management plan (Thames Water, 2018), Thames Water used a least economic cost deterministic optimisation model as a baseline approach (in combination with extended approaches that included simulation models) to identify the preferred plan capable of maintaining the aggregated supply-demand balance. The alternative approaches of identifying a least cost plan by considering multiple supply scenarios are compared against the deterministic formulation which is equivalent to the baseline existing practice and in compliance with the national water planning regulations in the UK (UKWIR, 2016).

A feasible set of interventions is used as an input to the optimisation modelling, subsets of which define the alternative proposed portfolios of investment. The list of interventions considered in the London case study and their estimated costs and capacities are shown in Table A.1 in Appendix A. Financial costs include the capital expenditures incurred to build each intervention as well as operational expenditures. The NPV is calculated using a discount rate of 4.5% (Thames Water, 2018) in accordance with the HM Treasury 'Green Book' (Treasury, 2003) discount rates.

Interventions are irreversibly created with a significant possibility of regret potentially leading to costly unused capacities. Modular interventions offer the option to build them in phases, expanding their capacity at a future stage if required. The modular interventions entail a higher initial construction cost compared to non-modular counterparts. For instance, interventions i19 and i22 in Table A.1 in Appendix A correspond to the same effluent reuse investment option, of equal capacity. However, the capital cost of intervention i22 is higher compared to i19 showing the premium required for having an expandable capacity. The ROA approach, can evaluate if the benefit of having the option to expand the capacity in the future outweighs the additional upfront cost of building interventions in phases as decisions are made in multiple stages (a synthetic example of a modular intervention demonstrating this ROA principle can be found in Erfani, Pachos and Harou (2018)). The 'fixed plan' approaches are not relevant in this case since investment decisions are made at the beginning of the planning period and are fixed and not reviewed at each decision point.

4.3.2 Modelling for comparison

Figure 4.2 shows the flowchart of the two-step methodology for performing the comparison between the different programme appraisal optimisation techniques. In the first step, a 50-year plan is obtained by each approach where a set of interventions is activated at each 5 year time interval. Except for the deterministic approach that considers a single deterministic future for supply and demand, the alternative supply demand balance models (Two-stage, RO and ROA) are run under 100 individual supply scenarios, derived from the supply uncertainty distribution for London as shown in Figure 3.3, and a single (most likely) demand scenario. In step 2, the relevant interventions selected in the first five years (obtained in step 1) are fixed i.e. the set of interventions activated in step 1 remain activated in step 2. This is achieved through an additional constraint that forces the binary decision variables for the selection of a subset of interventions (I_f) in t_1 to be 1 (equation 4.26). All the supply demand balance models are then run under the same multiple individual supply scenarios and the single demand scenario. The reported NPV cost and average unused capacity over the 50-year planning period of each run is averaged across the 100 plans for calculating the two metrics for comparison. Since the ROA approach produces a number of alternative optimised plans for each plausible future scenario (branch), the average cost and unused capacity is calculated based on the cost for each plan and the percentage of scenarios that go through that branch (equations 4.27 and 4.28).

$$dS_{t_1,i} = 1 \quad \forall i \in I_f \tag{4.26}$$

$$\overline{Cost} = \sum_{b \in B} Cost_b \times w_b \tag{4.27}$$

$$\overline{UnC} = \sum_{b \in B} UnC_b \times w_b \tag{4.28}$$

where b is a set of interventions (plan) selected for a particular branch as suggested by the Real Options approach and w is the percentage of scenarios that go through that branch.

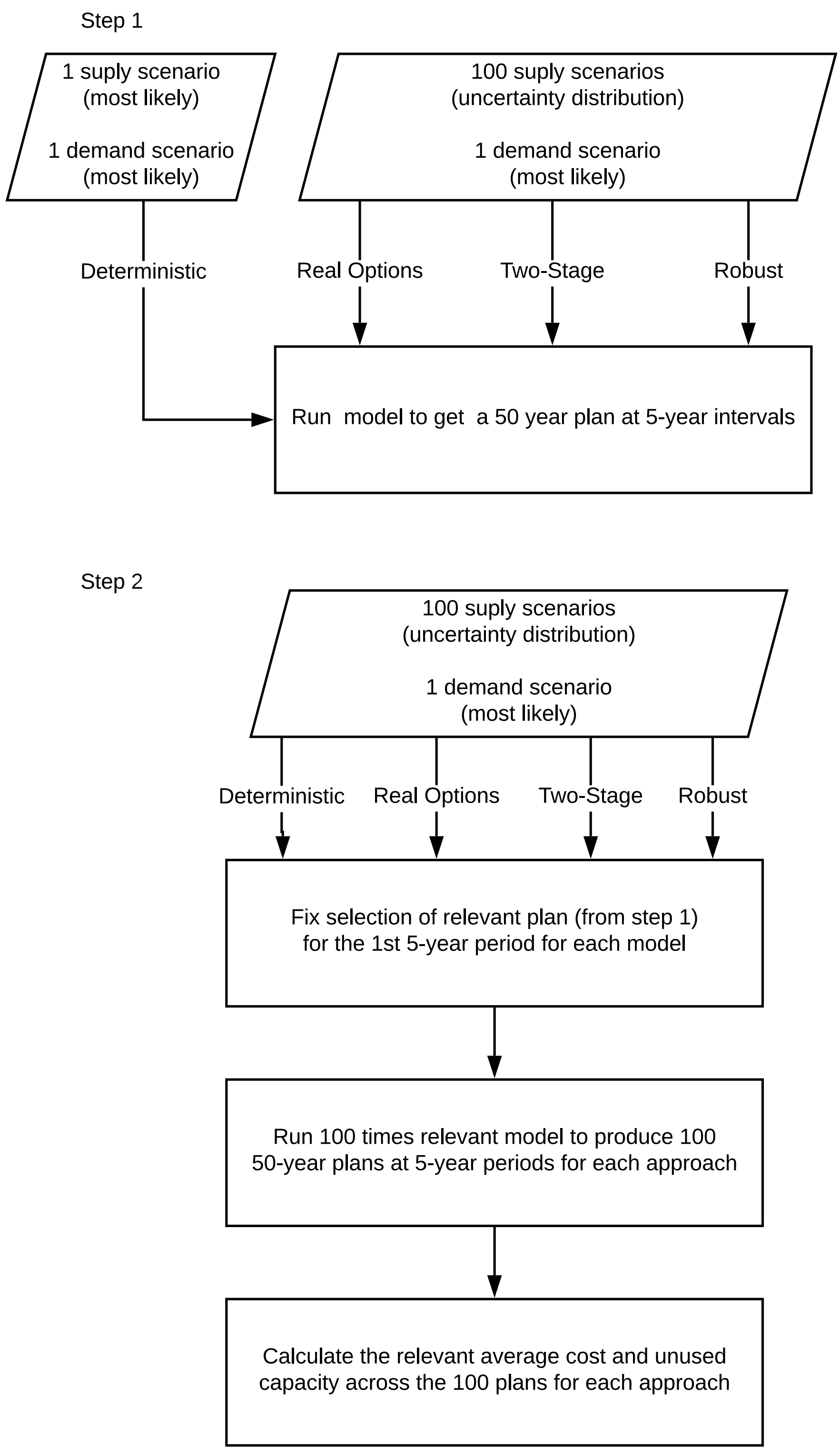

FIGURE 4.2: Flowchart of methodolody to compare cost and unused capacity between alternative optimisation approaches.

4.3.3 Water security

It is relevant for planners to consider potential water security issues of the future water supply system. Two types of droughts are identified for the London case study which are possible under future climate change scenarios, severe and extreme. Table 4.1 shows the values for the frequency of occurrence of severe and extreme conditions as well as the surplus capacity required to avoid imposing Level 4 restrictions (that include rota cuts and standpipes) during each type of drought (Thames Water, 2018). Imposing such restrictions is believed to have detrimental consequences for London and the national economy (Thames Water, 2018). The probability of Level 4 failure under severe and extreme conditions is defined as (Thames Water, 2018):

$$nS_t = \begin{cases} 1, & \text{if } SC_t \leq SRS \\ 0, & \text{otherwise} \end{cases} \quad \forall t \tag{4.29}$$

$$nE_t = \begin{cases} 1, & \text{if } SC_t \leq SRE \\ 0, & \text{otherwise} \end{cases} \quad \forall t \tag{4.30}$$

$$PS = \sum_t \frac{nS_t}{FS}, \tag{4.31}$$

$$PE = \sum_t \frac{nE_t}{FE}, \tag{4.32}$$

Water security (WS) is then calculated as:

$$WS = 1 - (PS + PE) \tag{4.33}$$

TABLE 4.1: Levels of drought (severe and extreme), frequency and surplus required to meet demand.

Drought	**Frequency**	**Surplus required**
Severe	200	70
Extreme	500	140

where PS and PE are the probability of failure under severe and extreme conditions respectively, t is a year of the planning period, SC_t is the surplus capacity in year t, SRS and SRE denote the surplus required to avoid a drought under severe and extreme conditions and FS and FE denote their frequency of occurrence. Lower PS and PE values indicate a higher water security under severe and extreme drought respectively.

4.4 Results and discussion

4.4.1 Comparing the performance of alternative optimisation approaches

A comparison of the proposed investment portfolios of four different optimisation approaches is conducted for the London case study. All strategies seek to define the optimal investment plan to solve the forecasted supply-demand gap. The traditional deterministic, two-stage and RO strategies propose a fixed portfolio (schedule) across the planning horizon without the flexibility to review the plan at discrete decision points. Conversely, the ROA, explicitly values and rewards flexibility unlike the fixed planning approaches, by choosing initial portfolios that can adapt to several branches of the tree that manifest only later. This flexibility allows planners to respond in a timely manner to supply changes, by delaying interventions until the future supply levels are known. Therefore regret is minimised if future reveals differently.

Table 4.2: Three alternative sets of interventions for Planning Decision Period 2020–2024 (ML/d), new capacity in Planning Decision Period 2020–2024 (ML/d) and planned capacity (ML/d) for deterministic, two-stage and robust methods.

Interventions	**Deterministic**	**Two-stage**	**Robust**
i1	2	2	
i2		8	
i3		6	6
i4		5	
i11			15
i21	150	150	150
i25	60		
i28		150	150
i36	2		
i37	9	9	9
DPD 2020–2024 cap	73	180	180
Planned cap	223	330	330

Table 4.2 shows the activation of interventions for the fixed plan approaches in Planning Decision Period (PDP) 2020–2024, which produce a single optimised investment plan. The short-term plans suggested by the two-stage and RO approaches lead to equal volumes of capacity increase for the planning decision period 2020–2024, as a result of activation of six (i1, i2, i3, i4, i28, i37) and four (i3, i11, i28, i37) interventions respectively. In both plans, intervention i21 is planned to be delivered in planning decision period 2025–2029 to meet the future demand for water beyond the 5-year period, resulting also in equal planned capacity.

Instead of a single investment plan, ROA produces an adaptive strategy. Table 4.3 shows the activation of interventions for each of the six paths as defined by plausible future scenarios (sets of interventions S1-S6). A path is selected if the forecasted supply demand gap is less than its corresponding threshold value. The results in Table 4.2 indicate that capacity in London is planned to increase by 330 ML/d in both RO and two-stage approaches. Compared to the ROA, this is equal to the capacity added in the path selected when the supply-demand gap is forecasted to be less than the most severe threshold (S1 in Table 4.3) which corresponds to only 2% of the 100 supply scenarios. Such approaches plan for the worst-case scenario potentially building excessive water capacity in the network.

Table 4.3: Six alternative sets of interventions (S1 - S6) as suggested by the Real Options approach for planning decision period 2020–2024, new capacity in planning decision period 2020–2024 (ML/d), planned capacity (ML/d) and percentage of supply-demand scenarios where each set of interventions is activated

Interventions	S1	S2	S3	S4	S5	S6
i1	2					
i2	8					
i3	6					
i4	5			5		
i21	150			150	150	
i25		60				
i28	150	150	150			
i37	9			9		
PDP 2020–2024 capacity	180	210	150	14	0	0
Planned capacity	330	210	150	164	150	0
Scenarios	2%	7%	29%	22%	13%	27%

Figure 4.3 shows the overlap between the selection of activated interventions suggested by deterministic, two-stage, RO and ROA. In order to make the Venn diagram interpretable in comparing the results of the alternative methods, the activated interventions across all sets (S1-S6 in Table 4.3) of the ROA are displayed rather than for each individual set. From this figure, it can be noted that the interventions suggested by ROA were to a large extent suggested also by Two-stage. In contrast, both deterministic and RO methods suggested the activation of 'unique' interventions (i36 and i11 respectively) that were not shared with the other approaches. The diagram in Figure 4.3 also shows that interventions i21 and i37 are activated in all four methods while i3 and i28 are selected in all three multi-scenario methods that consider uncertainty (Two-stage, RO, ROA). The high frequency of selection of these interventions across alternative methods implies that their activation is insensitive to supply uncertainty.

The deterministic approach does not account for supply uncertainty and, as expected, a deficit is shown in the London zone (see Table 4.4). The benefit of the responsiveness of the ROA is shown in Figure 4.4. The average unused capacity across the 50 year planning period of the interventions activated in the two-stage

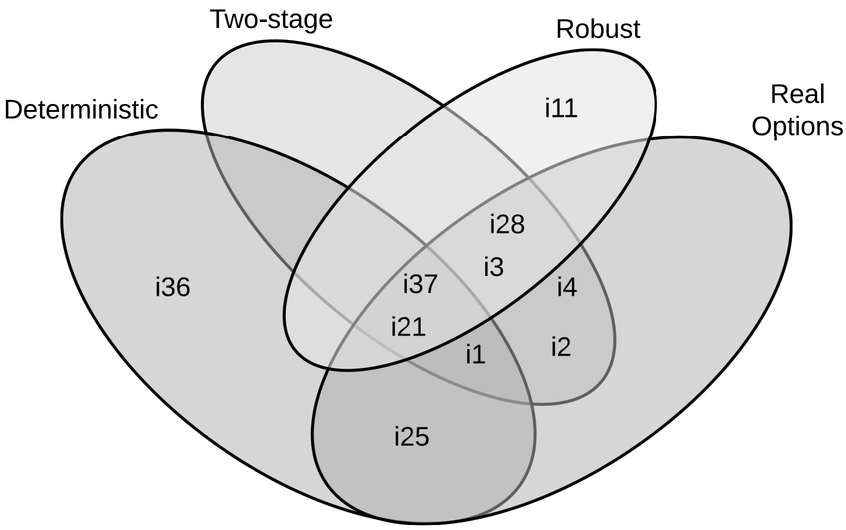

Figure 4.3: Overlap among the selection of interventions as suggested by alternative optimisation approaches for the planning decision period 2020–2024. The activated interventions across all six investment paths (S1 - S6 from Table 4.3)) are shown as suggested by the Real Options approach. See Table A.1 in Appendix A for a full definition of these interventions.

Table 4.4: Summary of costs, average unused capacity (UnC) and average deficit (Def) across the 100 scenarios for the alternative optimisation approaches, based on the interventions selected in each 50-year plan.

Method	Cost(£m)	UnC(ML/d)	Def(ML/d)
Deterministic	854.8	833	45.8
Real Options	721.8	415	-
Two-stage	1,098.9	1,565	-
Robust	1,103.5	1,558	-

and RO approaches is 1,565 ML/d and 1,558 ML/d respectively across the planning period while the ROA achieves a largely reduced average unused capacity of 415 ML/d. The difference in levels of utilisation can be attributed to the ability of the ROA to allow for adaptation lowering the risk of unnecessary investment by delaying any decisions to invest until necessary as information becomes available.

The benefit of the ROA is also reflected in the investment cost. The two-stage and RO strategies obtain the highest NPV cost which is significantly higher compared to the ROA differing by 35% (Table 4.4). The considerable increase in cost of these methods is due to the fixed intervention strategies they propose that tend to overinvest in large redundant capacity to be built into the water resource system in order to ensure that supply is secure under any possible future supply scenario.

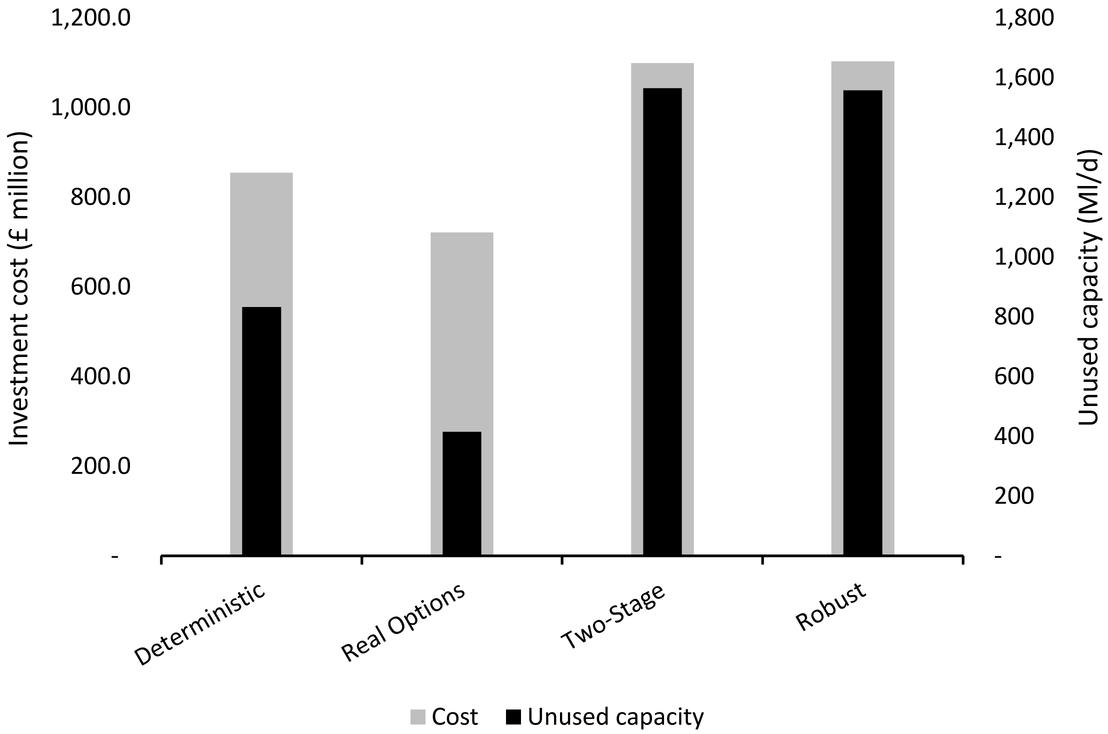

FIGURE 4.4: Comparison of cost and unused capacity between alternative optimisation approaches based on interventions selected over the entire 50-year planning period.

The average values over the 100 scenarios is derived to quantify the benefit of adaptation, for both cost and unused capacity. Average values (instead of maximum) are used to investigate the impact of optimising plans over multiple paths.

In practice, water infrastructure planners could avoid planning for the worst case scenario by waiting until improved uncertainty estimates become available with time. Flexible plans allow for such staged decision-making by periodically reviewing and adjusting plans to actual climate change impacts in water supply since submission of final Water Resource Management Plans occurs one year before the plan is due to come into action. The comparison of the London case study results validate that ROA dominates the alternative approaches both in terms of cost and unused capacity. Following the results, it is evident that there is benefit in waiting to allow for improvements around supply uncertainty in the case of London's urban water resources planning problem.

Table 4.5: Water security scores for each optimization approach calculated based on the probability of Level 4 failure under severe (PS) and extreme (PE) droughts. A water security score value closer to one indicates that a plan is more to a severe or extreme drought.

Approach	PS	PE	PS+PE	**Water security**
Deterministic	0.005	0.018	0.023	0.977
Robust	0.000	0.010	0.010	0.990
Two-stage	0.000	0.010	0.010	0.990
Real Options	0.030	0.018	0.048	0.952

4.4.2 Water security assessment

The water security assessment in this section evaluates and compares how reliable each plan, as proposed by the four optimisation approaches, is to different types of droughts (as defined in 4.3.3) that might occur under climate change.

Figure 4.5 shows the surplus (or unused) capacity values of each of the four plans throughout the 50-year planning period. The dotted lines indicate the surplus required to avoid drought under severe and extreme conditions. Capacity surplus in the two-stage and RO plans are projected to be higher than the surplus required for severe droughts during the planning period and therefore PS is zero (as defined in equation 4.31). In year 2040, capacity surplus is projected to be less than the surplus required for extreme droughts and PE is calculated to be 0.01 (as seen in Table 4.5). The large quantities of unused capacity in the plans suggested by two-stage and RO approaches provide a safety buffer which increases the level of water security that the company is able to provide under severe and extreme droughts, calculated to be 0.99 (as per equation 4.33).

Conversely, ROA aims to delay commitment to large interventions that build redundant capacity either by exercising different interventions or through incremental implementation. The plan suggested by the ROA approach operates with an unused capacity that is below the surplus required to avoid extreme conditions during the entire planning period. By 2040 the unused capacity is also below the surplus required to avoid severe conditions. This results in lower water security compared to two-stage and RO approaches, with a probability of failure under

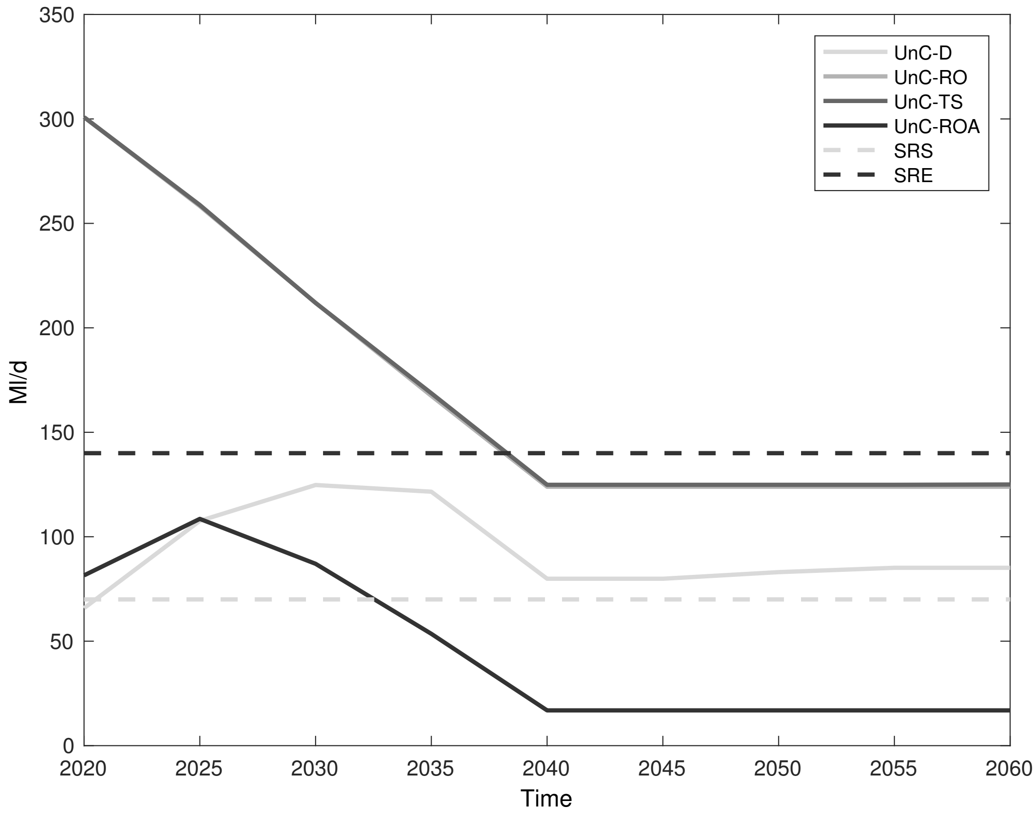

Figure 4.5: Levels of average unused capacity across scenarios for deterministic (UnC-D), robust optimisation (UnC-RO), two-stage (UnC-TS) and real options (UnC-ROA) approaches and surplus required to avoid drought under severe (SRS) and extreme (SRE) conditions.

severe and extreme conditions of 0.952 (as shown in Table 4.5). This suggests that there is a trade-off between cost and risk of drought under severe and extreme conditions, as defined by the water security metric. Based on this information, a water manager may decide if the risk is tolerable or whether further management actions are required to increase water security. Tolerable risk thresholds may change over time depending on which future risks materialise (Yohe et al., 2010).

The deterministic plan operates with an average unused capacity that throughout the planning period is always between the threshold for severe and extreme conditions, except for year 2020 where it is below both thresholds. However, from Table 4.4 it is noted that the deterministic plan would result in deficit under some scenarios as this approach does not account for supply uncertainty.

TABLE 4.6: Scores (on a 0-4 scale) for risk around lead time and supply contribution for each intervention selected across the four methods. LTR: Lead time risk, YR: Yield Risk

Code	Resource Type	Intervention Name	LTR	YR
i1	Aquifer Recharge	AR - HARS (Hornsey)	0.06	2.50
i2	Aquifer Recharge	AR Kidbrooke 8Mld (SLARS)	0.05	2.55
i3	Aquifer Recharge	AR Merton 6Mld (SLARS)	0.08	3.16
i4	Aquifer Recharge	AR SLARS - Streatham DOav 5Mld	0.06	3.70
i11	Desalination	Long Reach	1.44	0.24
i21	Effluent reuse	Beckton RO 150 ML/d	1.28	0.24
i25	Effluent reuse	Deephams RO 60 ML/d	0.9	0.24
i28	Effluent reuse	Mogden RO 150 ML/d Sunbury	1.28	0.24
i36	Groundwater	Addington	1.24	4.00
i37	Groundwater	Southfleet/Greenhithe (disagg)	0.8	4.00

4.4.3 Deliverability assessment

There is uncertainty associated with the lead times required for implementing water infrastructure investments and the final yield of supply sources i.e. the amount of water that can be deployed from an intervention once it has been delivered. In Table 4.6 the scores express the relative risks on a scale from 0 (low) - 4 (high) relating to risk of time delay or final yield upon construction. These are shown for the interventions selected across all optimisation methods and are used to evaluate the deliverability effects within the programme appraisal process. The input data for the deliverability assessment was provided by Thames Water.

It can be seen that large interventions such as desalination plants and effluent reuse schemes have a relative higher uncertainty around the time required for completion of construction while interventions that rely on groundwater abstraction display a higher relative risk around the volume of water they can provide. The short-term (i.e. interventions selected in the next 5 years) Deliverability Risk (DR) of a plan is evaluated according to which interventions are selected in the PDP 2020–2024. The DR of each plan is calculated as per equation 4.34 (Thames Water, 2018):

$$DR = \sum_{t,i,s}^{t=1} dS_{t,i,s} \times (LT_i + Y_i), \quad \forall i, s \tag{4.34}$$

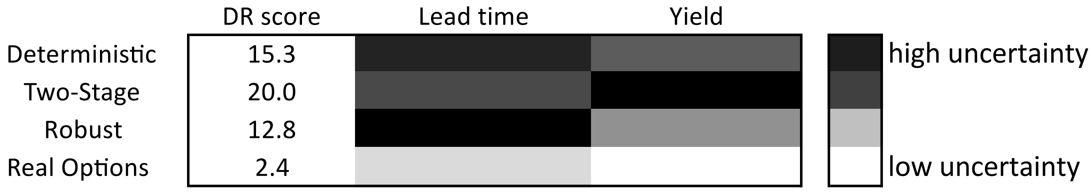

FIGURE 4.6: Deliverability risk (DR) assessment showing the confidence that the programme suggested by each approach will deliver on time the volume of water that it is expected to.

where the binary variable $dS_{t,i,s}$ denotes the activation of an optional supply source i in time t in scenario s, LT_i and Y_i is the lead time risk and yield risk of intervention i respectively.

Figure 4.6 shows the short-term deliverability assessment of each plan as suggested by the four optimisation methods. The ROA plan has the lowest DR score (2.4) indicating that there is greater confidence that the programme suggested by ROA will deliver on time the volume of water that it is expected to. The low deliverability risk compared to the alternative approaches can be attributed to the ability of the ROA to produce multiple strategies that reduce unnecessary investment. Unlike the investment plans proposed by the 'fixed plan' approaches which do not change across the scenarios, ROA produces a set of six alternative investment plans that is selected according to which scenario s occurs. For instance, as shown in Table 4.3, the empty set of interventions S6 that suggests a 'do nothing' strategy is activated in 27% of scenarios. By not activating any interventions, the DR value corresponding to the scenarios s of S6 is zero (as defined in equation 4.34).

The fixed plans suggested by the RO, deterministic and two-stage approaches have higher DR scores (12.8, 15.3 and 20 respectively). As suggested by the colour bar chart, while for the two-stage plan the deliverability risk can be attributed predominantly due to the possibility of reduced final yield, the deliverability risk of the RO plan is primarily due to the possibility of delay in the delivery of the new resource options. This shows the impact that a different set of interventions for the short-term period has on water planners' confidence that water will be delivered on time and in the volume that is expected to.

4.4.4 Limitations of comparison

Despite cost effectiveness being an important factor, stakeholders are increasingly asking for strategic planning approaches that consider wider benefits. Although alternative metrics such as water security and deliverability are reported post-optimisation, the optimisation formulation does not necessarily identify the solutions with highest water security or deliverability. Therefore, not including these metrics as an objective in the optimisation problem could be considered a limitation.

This is possible in simulation approaches that use a water resource network model to estimate network performance (such as surface water storage, water use, energy use, and operating costs) at each user-defined time-step. Water security, in this case, can then be represented by reliability (frequency of failures metric) and resilience (duration-failure) metrics that can be explicitly minimised to form part of the information used for the solution decision. A system simulation formulation, as shown in Chapter 5, reduces the need for problem simplification (Maier et al., 2014) as system performance can be calculated using multiple criteria without the need to translate non-commensurable metrics into a single monetary and is therefore widely used in multi-objective water resources problems (Reed et al., 2013). By defining water security or reliability as an objective in multi-objective evolutionary algorithm coupled with simulation, it is possible to explicitly optimise for those values.

4.5 Conclusions

This chapter presents a comparative analysis of four alternative optimisation techniques in water resource capacity expansion. Although all approaches seek to minimise investment costs, future climate change uncertainty is addressed differently. More specifically, the deterministic method is formulated based on a single forecasted future realisation without accounting for uncertainty. Conversely, Two-stage, RO and ROA consider multiple scenarios to address uncertainty by seeking robustness and flexibility.

The comparison study is demonstrated using the London water supply system. As expected, the deterministic plan that does not account for uncertainty would result in deficit under dry climate scenarios. This limitation of the deterministic method was overcome by the multi-scenario approaches that identified plans that can handle future supply uncertainty, avoiding a water deficit over the 50-year planning period in all 100 supply scenarios considered.

In contrast to deterministic, RO and two-stage approaches that produce fixed plans, ROA can optimise plans over multiple paths defined by plausible future scenarios and produce an adaptive strategy where decisions are made sequentially over time. The ability to review the plans make ROA well suited to explore the implications of modular interventions.

The performances of the proposed plans were compared in terms of required investment costs and unused capacity. The differences between the performances of the approaches applied to the London case study are evident. It was shown that adaptive plans performed better both in terms of cost (saving more than £377 million by reducing NPV cost by 35%) and unused capacity (avoiding more than 720 ML/d of unused capacity) compared to fixed plans proposed by two-stage and RO approaches. Two-stage and RO strategies perform poorly compared to ROA due to the fixed investment plans they suggest which do not allow for adaptation, building excessive capacity to the network. This demonstrates the benefit that the adaptive planning can bring to the water resource management decision-making process. Unlike Chapter 3, where the cost of not recognising uncertainty and the value of information were quantified, the comparison study in this chapter showed how the adaptive approach performs compared to alternative methods that consider uncertainty. To perform the comparison, additional evaluation metrics were used in order to explore the implications of adaptive planning.

To compare the performance of the proposed plans beyond cost and unused capacity, two alternative performance metrics were derived and evaluated. The water security metric evaluates the ability of a proposed investment program to maintain supply during two types of drought. It was shown that the level of water security under severe and extreme conditions for the fixed plans proposed by two-stage and RO approaches was calculated to be 0.99 while the adaptive plans achieved a lower 0.9522. The deliverability metric estimates the risk that a programme will deliver sufficient water on time for the short-term planning period. The effects of different courses of actions, as suggested by each approach, are compared using the two metrics. The results of the water security assessment suggest that there is a trade-off between cost and risk of drought under severe and extreme conditions. The ROA aims to lower excess investment producing plans that are less reliable to severe and extreme droughts compared to two-stage and RO approaches. The deliverability assessment indicates that ROA, by optimising plans over multiple paths, increase the confidence that the expected volume of water will be delivered on time. In comparing the performances of the single objective optimisation approaches, water security and deliverability metrics are reported post-optimisation. Chapter 5, demonstrates how in multi-objective approach, such a reliability metric can be defined as an objective that is explicitly optimised. As explained in the next chapter, simulating the water resource network model allows for the definition of a different reliability metric compared to the one used in this comparison study.

Chapter 5

Trade-off informed adaptive water resources planning under uncertainty

5.1 Introduction

Planning future interventions in water resource systems faces unprecedented challenges due to rising concerns about climate change, socioeconomic growth and increased urbanisation (Milly et al., 2008; Brekke et al., 2009; Fant et al., 2016). The performance of future water resource system services are impacted by the uncertain nature of long-term supply and demand. Unpredictable changes in water demands and future hydrological flows and their potentially amplified hydrologic variability increases the risks of future water supply failures (Arnell et al., 2013; Hegerl et al., 2018) and the sophistication required to prevent them (Salas et al., 2018). Equally, both service providers (utilities, river basin organisations, etc.) and their customers and stakeholders have grown in sophistication, increasingly demanding their interests be considered in the decision-making process (Carr et al., 2012; van Bruggen et al., 2019). This complex planning problem motivates the need for water resources planning approaches that enable strategic long-term decision-making.

Certain needs of water planning have increasingly become clear: the desire to replace simplified aggregated least-cost capacity expansion approaches (Padula et al., 2013b) and consider multiple objectives (Hitch, 1960; Banzhaf, 2009; Reed et al., 2013; Paton et al., 2014; Kasprzyk et al., 2013) to achieve multi-dimensional efficiency (i.e. the ability to appropriately trade-off the benefits implied by the best solutions). Also, in the face of different types of uncertainties with different levels of predictability, robustness (i.e. the ability to perform satisfactorily over a range of future conditions) and adaptivity (i.e. the ability to perform effectively under uncertainty) have become core objectives of water planning (Dessai and Hulme, 2007; Charlton and Arnell, 2011; Castelletti et al., 2010; Reed et al., 2013; Wise et al., 2014; Maier et al., 2014; Kwakkel et al., 2015; Herman and Giuliani, 2018). These are addressed in turn.

To better capture stakeholder values, water resources management can be strengthened by multi-criteria approaches which help reconcile multiple and often competing water interests. Performance measures of interest when evaluating water intervention options include ones that describe economic, social and environmental impacts as well as water supply security metrics such as reliability and resilience.

A water supply development plan, for example of a water utility, will typically propose a set of supply augmentation and/or demand reduction (water conservation) interventions over a planning time horizon. The ‘capacity expansion’ problem is a classic one of water resources engineering (Yakowitz, 1982; Luss, 1982; Padula et al., 2013b). Plans optimised to a single scenario are likely to have sub-optimal performance in other scenarios (Ben-Haim, 2006; Huskova et al., 2016) so in robustness approaches (Lempert, 2003; Lempert et al., 2006) multiple plausible futures are simulated concurrently to evaluate plans (Kang and Lansey, 2012a). Because many designs are possible, optimisation helps automate the search for efficient and robust water supply portfolios for capacity expansion (Kasprzyk et al., 2013;

Mortazavi-Naeini et al., 2014; Huskova et al., 2016) and determine the optimal scheduling of water supply interventions (Beh et al., 2015b).

Insensitivity (robustness) to future conditions can be achieved either through a static approach, that seeks to produce a fixed plan that performs well under a range of plausible futures or through an adaptive approach where multiple strategies, each optimal for different trajectories or 'pathways' (Haasnoot et al., 2013), are developed to dynamically address uncertainty over time, allowing for modifications to investment strategies as new information about uncertain conditions becomes available (Charlton and Arnell, 2011; Paton et al., 2014; Woodward et al., 2014b; Beh et al., 2015a; Maier et al., 2016). Most previous work in the timing of water resource interventions has been static, with limited ability to adapt to evolving uncertainty.

Uncertainty about future conditions such as supply and demand can be represented in the search process probabilistically or via scenarios. Probabilities can be used if stationarity around the stochastic processes such as hydrological variability and demand growth is assumed (Milly et al., 2015; Borgomeo et al., 2018). Much of the work in the area of non-probabilistic water resource analysis focused on developing robust designs under an ensemble of plausible supply conditions (Lempert et al., 2006). In this case, uncertainty is represented as a set of alternative future states of the world (Mahmoud et al., 2009) where relative likelihoods are not considered, at least initially. Examples include identifying long-term adaptation measures, such as water supply infrastructure sequencing, where robustness is considered either post-optimisation (Kasprzyk et al., 2013; Mortazavi-Naeini et al., 2014; Beh et al., 2015a) or explicitly as an objective within a multi-objective optimisation framework (Mortazavi-Naeini et al., 2015; Beh et al., 2017).

In other studies the likelihood of different future states is explicitly weighted via probabilities. For instance, Basupi and Kapelan (2013) seek optimal decision making under future demand uncertainty. Marques et al. (2015) use a multi-objective optimisation model for the design of water distribution network using

Real Options Analysis (ROA) concepts where scenarios that form the paths of a decision tree are assigned different probabilities. Woodward et al. (2014b) assign probabilities to the range of flooding scenarios where climate change uncertainty is significant to develop long-term flood risk strategies using ROA and multi-objective optimisation. In urban water management studies, probabilistic risk of exceeding the target frequency of water use restrictions has been used to evaluate the possible cost–benefit trade-offs associated with adaptation (Borgomeo et al., 2016).

Few applications have aimed at adaptive scheduling of interventions in long-term water resource planning. Such adaptive strategies could be implemented either using a rule-based system that seeks to optimise the rules that dictate the activation of the next action on a pathway (Haasnoot et al., 2012; Ranger et al., 2013; Kwakkel et al., 2015), or a time-based system where plans are reviewed periodically, allowing adaptation at fixed time intervals over the planning horizon (Marques et al., 2015; Beh et al., 2015a; Erfani, Pachos and Harou, 2018). Limitations of Erfani, Pachos and Harou (2018) are that plans are optimised using a single least cost objective and that simulation is not performed and therefore tangible outcomes cannot be assessed and evaluated (Padula et al., 2013b; Brown et al., 2015).

The proposed approach is a multi-objective multi-stage optimisation formulation that flexibly activates, delays, and replaces interventions to adapt to the future uncertain gap between supply and demand. The proposed Real Options Analysis (ROA) method finds threshold values of demand given an ensemble of plausible equally likely hydrological flow scenarios, above which it is optimal to invest in a certain combinations of investment options. A scenario tree is optimally built that uses a range of demand scenarios to represent future uncertainties with multiple decision stages to allow for frequent and regular modifications to the investment strategies. Strategies are identified to satisfy different levels of demand as projected through the use of the scenario tree, over a long-term planning period (50 years). The candidate sets of investment options are evaluated against multiple transient hydrological scenarios, ensuring plans are robust to a wide range of hydrological scenarios. Two objectives are used to explore the trade-off between financial and resilience indicators under level of service constraints which consider the frequency of failures in the simulated futures. The approach is applied to a real-world case study of planning London's water resource and supply system.

The next section describes the two steps of the proposed approach, the scenario tree construction and the adaptive optimisation formulation. Section 5.3 presents the case study application to Thames Water's London supply zone and in section 5.4 the case study's results are discussed. Section 5.5 concludes the chapter.

5.2 Adaptive and flexible multi-objective formulation

5.2.1 A hybrid approach to representing supply and demand uncertainty

The proposed method simulates alternative plans under a range of scenarios as structured by a decision tree. Water demand uncertainty is represented probabilistically in the decision-tree, and water supply uncertainty is considered by using an ensemble flow scenarios, typically considered equally likely.

These river basin simulations are coupled to a Multi-Objective Evolutionary Algorithm (MOEA) to automate the identification of adaptive long-term water resources plans while considering multiple objectives. In the first step, a decision tree using probabilistic demand information is generated whose branches represent possible demand values between decision stages, defining an ensemble of plausible future water demand scenarios for the entire planning period (see section 5.2.2 for details on how the tree is generated). The tree allows for implementation of ROA optimisation as the option to invest is reserved for future stages (Erfani, Pachos and Harou, 2018). In the second step, linked simulation and multi-objective optimisation identify adaptive Pareto-optimal investment plans whose intervention implementation is based on demand thresholds at specified planning intervals at each decision stage under plausible demand uncertainty defined by the demand scenarios.

MOEAs are heuristic global search algorithms that emulate the process of natural evolution and are known for their ability to optimise over multiple objectives (Coello et al., 2007; Nicklow et al., 2009). When more than one objective is considered, MOEAs produce a set of solutions that cannot be further improved in one objective without simultaneously reducing performance in one or more other objectives (Coello et al., 2007). The term ‘Pareto-approximate’ is actually the correct one to reflect the fact that an approximation to the “true” Pareto optimal set is seeked as in complex ‘real-world’ problems this remains unknowable (Herman et al., 2014).

5.2.2 Scenario tree approximation of demand uncertainty

The first stage of the approach involves generating a scenario tree that defines future demand scenarios and their probabilities over a planning horizon. A discrete time horizon T is considered in which decisions in relation to which interventions should be implemented are made at a number of decision points $t \in T$, spaced at regular time intervals (e.g., 5 years). The demand scenario tree is extracted out of the uncertain demand space as shown in Figure 5.1. The tree is generated automatically rather than manually using a fast-forward iterative greedy algorithm that aims to minimise a so-called probability distance between the uncertainty sets (Gröwe-Kuska et al., 2003). The algorithm optimally creates a scenario tree based on the original uncertainty space by successively bundling tree nodes into a single node while maintaining the probability of the original distribution. A scenario is defined as the unique path from the root node to one of the terminal nodes of the tree. The probability of a scenario occurrence is calculated as the multiplication

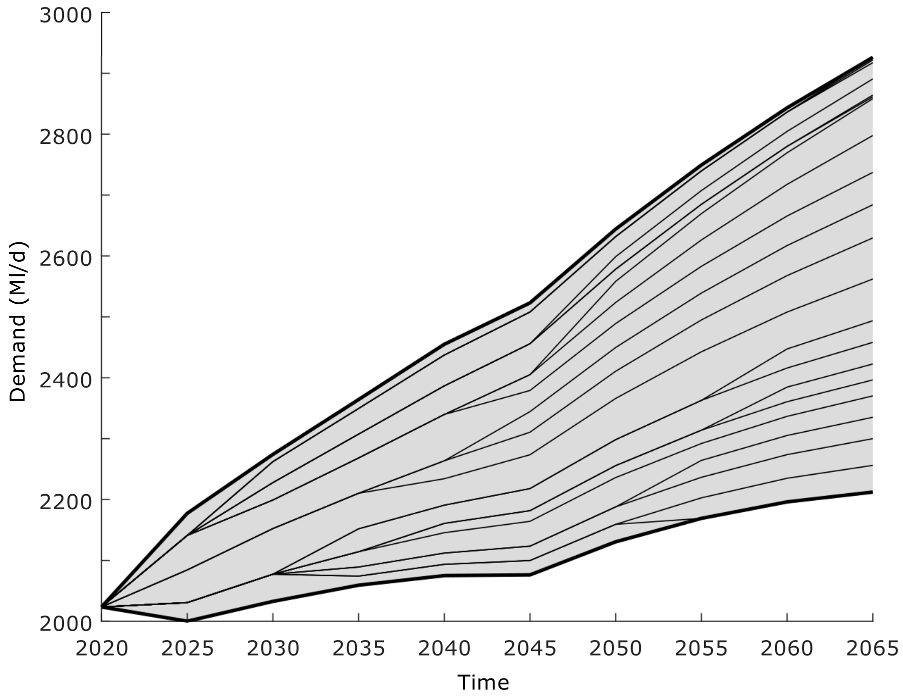

FIGURE 5.1: Original demand uncertainty approximated using a scenario tree.

of associated transition probabilities starting from the root leading to the terminal node. A more detailed description of the construction algorithm and its benefits can be found in Section 3.2.1 of Chapter 3.

The scenario tree is particularly appropriate for cases where planning is performed regularly over discrete time intervals, as is often the case in regulated water supply systems. Scenarios are grouped into sets that share common past decisions up until a certain point, before they diverge into subsequent branches as the future manifests. An example of a demand scenario tree for a 21-scenario problem is shown in Figure 5.2 (it is also drawn out in Figure 5.1). The decision in t_1 is the same for all scenarios as the future at that point is not yet known (Mulvey and Ruszczyński, 1995). According to the tree, at t_2, demand uncertainty is represented by three decision nodes. Solving the tree will require that the three possible investment decisions be the same within some subgroups of scenarios which are indistinguishable based on the information available up to that point. It can be seen that the subgroups of scenarios S_1 - S_9, S_{10} - S_{12} and S_{13} - S_{21} share common investment decisions at t_2. This is enforced by non-anticipativity constraints that

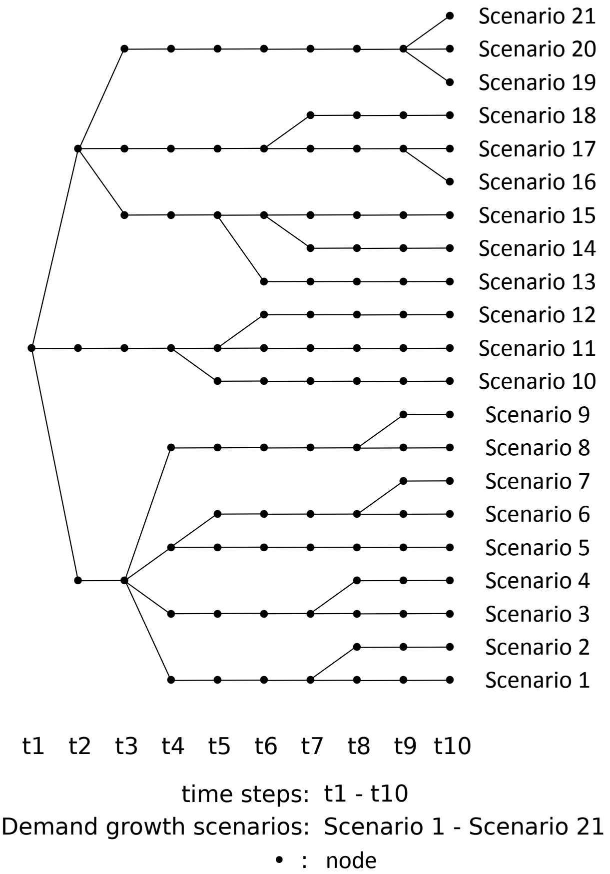

Figure 5.2: Scenario tree extracted from demand uncertainty.

ensure investment decisions at time t only utilise any information that is available up to this stage. The proposed methodology exploits the tree structure to provide flexibility in allowing initial water resource investment decisions to adapt to future changes in water demand (Erfani, Pachos and Harou, 2018). This staged decision process enables the virtual planners (implied by this model-based approach) to modify or delay investment plans as information on future demand is gradually revealed.

5.2.3 Simulation based optimisation

Once the decision tree is defined, a MOEA is used to identify adaptive investment decisions at each stage of the tree. Figure 5.3 shows a flowchart of the proposed approach considering multiple demand scenarios and realisations of future flow time-series. In step 1 the MOEA generates an initial random population of candidate adaptive plans. Each adaptive plan consists of a set of activated interventions at each node of the decision tree subject to the decision tree structure. This implies all scenarios that contain the same node in stage t must share common investment decisions in stage t. In step 2, this information is passed to a water resource system simulator in addition to other input variables such as inflows, network composition, operating rules, etc. The water resource system simulator predicts flow and storage at system nodes (reservoirs, junctions, abstractions, aquifers, treatment and desalination plants, etc.) and links (rivers, pipes, water transfers) using a weekly time step over a simulated time horizon. In this study, the computationally efficient Interactive River Aquifer Simulation (IRAS-2010) model is used which has been shown to emulate a model maintained by the Environment Agency regulator (Matrosov et al., 2011).

Supply uncertainty is considered through repeated runs of the tree over an ensemble of equally probable future flow scenarios; (Section 5.3.2 gives more details on the supply scenarios used in this study). That is, simulation is performed for each demand scenario of the tree over multiple future flow scenarios, each representing a unique climate scenario. To maintain hydrological consistency of a supply scenario, the same scenario is used in one simulation from start to finish (see Section 5.3.2 for more details).

Each simulation outputs performance metrics that are then weighted across all considered scenarios and passed to the MOEA as objective values (step 3). Until a user-defined stopping criteria is satisfied (explained in Section 5.3.3), the algorithm generates a new population (a set of portfolios of alternative water infrastructure and demand management interventions) at each node in the tree by performing crossover and mutation operations (step 4). As the MOEA algorithm converges a trade-off of Pareto-approximate (or non-dominated) adaptive plans is revealed (step 5).

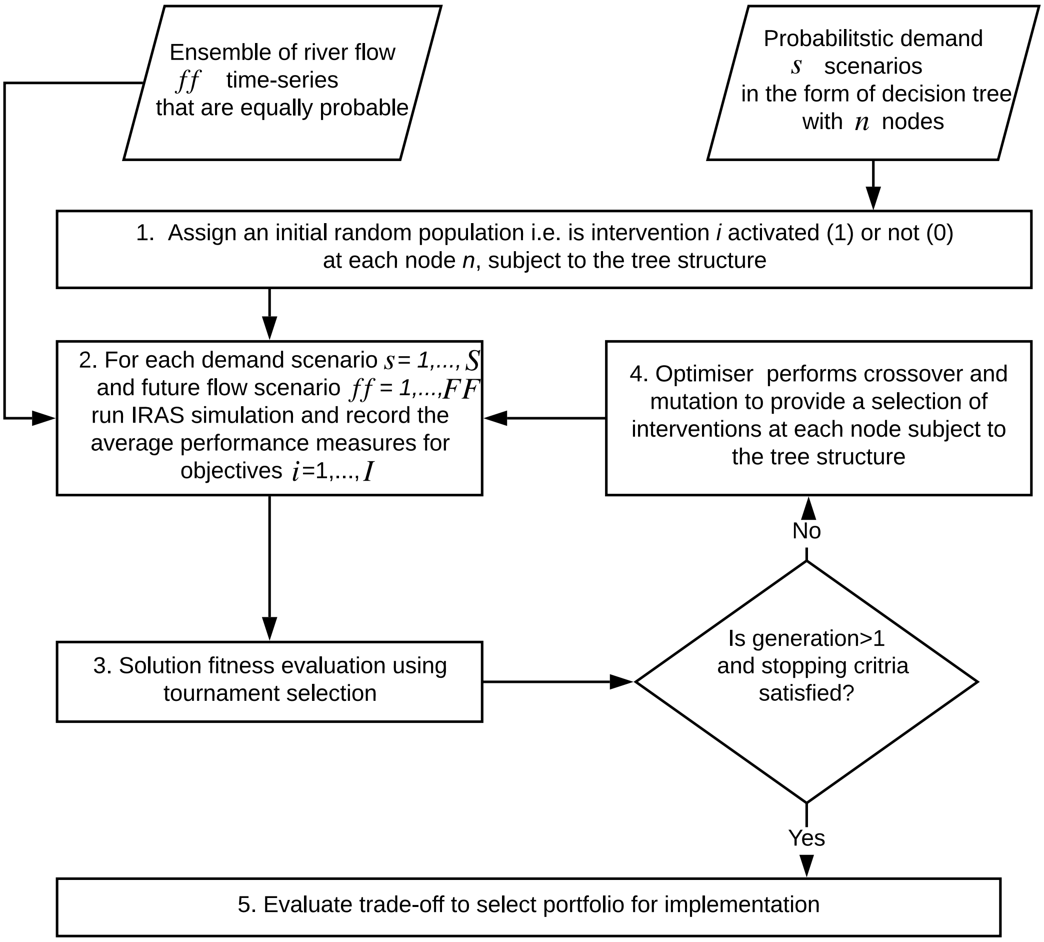

Figure 5.3: Methodology flow chart for optimising the decision tree using Genetic Algorithm and simulation.

5.2.4 Formulation

The problem formulation is described as the following multiobjective optimisation problem:

$$Optimise\ F(x) = (f_{Cost}, \overline{f}_{Res}), \tag{5.1}$$

$$s.t.$$

$$c_k \leq MFF_k, \quad \forall k \in K, \tag{5.2}$$

$$\sum_{i \in ME} dS_{n,i} \leq 1, \quad \forall n \in N_t, \tag{5.3}$$

$$dS_{n,i} \in \{0, 1\}, \quad \forall n \in N_t, i \in I, \tag{5.4}$$

where x is a vector representing a set of supply and demand interventions node, $dS_{n,i}$ is a binary variable denoting if intervention i in portfolio x is selected (1) or not (0) in node n on the decision tree, c_k is a constraint associated with Level of Service (LoS) k setting an acceptable maximum frequency of imposing the associated water-use restrictions on customers, MFF_k is the value of maximum failure frequency allowed for LoS k, and ME represents the set of mutually exclusive interventions.

The first objective (Equation 5.2) minimises the total capital and operational cost of implementing new supply and demand interventions in a portfolio. The cost is annualised and discounted with discount rate r over the planning time horizon and weighted by the probability p_n of the future scenarios (Equation 5.5)

$$f_{Cost} = \sum_{n \in N_t, i \in I} \frac{p_n}{(1+r)^t} \times \frac{tC_i}{DL_i} \times dS_{n,i}. \tag{5.5}$$

where tC_i is the total discounted cost (capital and operational) of implementing intervention i in node n at time stage t, p_n is the probability that node n is realised and DL_i is the design life of intervention i. The costs are normalised to each intervention's expected design life by dividing the investment cost of each intervention by its expected lifetime. The use of total investment cost per year allows for equal comparison between interventions that have unequal design lives. The second objective is to maximise system resilience which is defined by how quickly the system recovers from a failure (Moy et al., 1986). The average discounted maximum duration of the failure across all scenarios is then minimised (Equation 5.6)

$$\overline{f}_{Res} = (1+r)^{-t} \sum_{s \in S, n \in N_t} \max(D_{s,n}). \tag{5.6}$$

where $D_{s,n}$ is the duration of failure in scenario s in node n. A definition of a failure is problem dependent; the failure is defined in the case study section below.

5.3 Case study

5.3.1 Background

The proposed multistage multi-objective optimisation is applied to the London urban water supply area, which is located in the Thames basin of southeast England. The water supply is managed by Thames Water, a privately owned water utility serving 15 million customers across London and the Thames Valley. The region is characterised by a high population density compared to the rest of England, and facing a projected 25% increase in population by 2040 (Thames Water, 2014; Environment Agency, 2013). However, the actual population growth is uncertain making it a suitable case study to investigate the use of the proposed approach. Furthermore, water utilities and regulators in England and Wales are recently considering a move from a traditional single-objective least cost optimisation approach (UKWIR, 2012; Padula et al., 2013b) to identifying a "best value" plan that balances multiple performance criteria and seeks adaptivity (Thames Water, 2018). Hence, the proposed approach could be of particular interest to water utility planners in the UK and beyond.

This study considers 11 new supply and 4 new demand management interventions for the London water resource system shown in Table 5.1. Each option has characteristics related to its ability to provide water, construction period, design life and mutual exclusivity. Unlike aggregated supply-demand modelling approaches where interventions' contributions to supply expansion or demand reduction is a single number in the optimisation (Padula et al., 2013b; Erfani, Pachos and Harou, 2018), in this approach supply interventions and their operating rules are simulated over time whilst demand management options reduce aggregate annual demand.

Table 5.1: Supply and demand management interventions considered in the London case study. RE: release or reduction to average annual demand in ML/d, EXP: release in ML/d for expanded capacity of modular reservoir, CP: construction period in years, DL: design life in years, ME: mutual exclusivity.

Intervention	Code	RE/EXP	CP	DL	ME
Supply interventions					
Supply Option 1	SP1	267	10	80	SP2, SP1m
Supply Option 1 modular	SP1m	176/267	10	80	SP2, SP1
Supply Option 2	SP2	300	12	60	SP1, SP1m
Supply Option 3	SP3	26	5	60	-
Supply Option 4	SP4	60	6	60	SP5
Supply Option 5	SP5	60	6	60	SP4
Supply Option 6	SP6	150	6	60	SP7
Supply Option 7	SP7	150	6	60	SP6
Supply Option 8	SP8	17	12	60	-
Supply Option 9	SP9	15	4	25	-
Supply Option 10	SP10	150	6	25	-
Demand interventions					
Demand Management 1	DM1	50	0	25	-
Demand Management 2	DM2	165.1	0	60	-
Demand Management 3	DM3	11.6	0	25	-
Demand Management 4	DM4	88.7	0	60	-

Release from supply options during droughts occurs, when London's aggregate reservoir failure reaches a failure state according to the seasonal Lower Thames Control Diagram (LTCD) (refer to Matrosov et al. (2011)). Release from reservoir and groundwater options, which are modelled as having limited storage, is subject to available storage while desalination and reuse options release water indefinitely as long as the system remains in failure. The storage capacity of modular supply interventions can be expanded at a future stage by paying a relevant expansion cost. For instance, supply option 1 an be built with a fixed (SP1) or modular (SP1m) storage capacity, listed in Table 5.1 as two separate interventions that are mutually exclusive, i.e., at most one of the two interventions can be selected. For the modular option, the utility has to pay a premium upfront to reserve the right for further expansion (see Section 3.2.4 for a synthetic example of a reservoir option demonstrating this ROA principle).

A failure associated with the resilience objective (Equation 5.6) occurs when the London Aggregate Storage level drops below a certain threshold (LTCD level 3) and a non-essential water use ban is imposed. The aim of the objective is to minimise the duration of the imposed water use ban. The minimum level of service is set to 90% constraining the LTCD level 3 failure occurrence to not exceed one in 10 years on average (Constraint 5.2). The financial costs are net present values (NPV) of capital and operational expenditures incurred by implementing new interventions and using them given a discount rate, taken here to be 4.5% (Thames Water, 2018). The results of this study are indicative and should not be considered prescriptively as Thames Water's most recent plan Thames Water (2018) uses a more detailed simulation model, includes the latest proposed option designs, includes requirements to supply neighbouring water utilities, and considers more objectives.

5.3.2 Considering uncertainty in climate projections

To adequately illustrate water resource systems' behaviour during the eventual increased future droughts that may occur due to climate change, future supply uncertainty is represented by a consistent set of transient climate change forced daily river flow and monthly groundwater levels for the UK (Prudhomme et al., 2013) and are available from the National River Flow Archive (NRFA) online database. The scenarios represent equally probable hydrological flows and are derived from the set of transient climate projections obtained from the Met Office Hadley Centre Regional Climate Model (HadRM3-PPE) by dynamically downscaling the global climate model. The dataset consists of an ensemble of 11 equally probable flow time-series for the Thames basin between 1950 and 2098 (Prudhomme et al., 2013). In this study, a 50-year segment of the full time-series (2020 - 2070) is used to assess the performance of the water supply resource system on a weekly time-step.

The 11 members of the hydrology ensemble are independent and therefore time-series associated with one ensemble member can only be compared with the same ensemble member time series for a different time slice (Prudhomme et al., 2013). That is, each future flow scenario represents a unique climate scenario and therefore once a simulation begins under one scenario, that same scenario must be used until the end of the planning period. For this reason, each branch in the decision tree represents a possible water demand level while future climate change impacts on supply are considered by optimising the demand decision tree over the ensemble of 11 future flow scenarios. This way, the hydrological consistency of each supply scenario is maintained while results are robust to supply uncertainty in that they are capable of withstanding different climate change projections.

Both supply and demand uncertainty are considered through iteratively optimising a demand decision tree over an ensemble of future flow scenarios. For instance, in the first optimisation run, the mathematical programming formulation in Section

5.2 is solved on the demand scenario tree as depicted in Figure 5.2 using hydrological data of the future flow scenario 1. In the second run, the demand tree is solved using the future flow scenario 2 etc.

5.3.3 Computational experiment

The Epsilon-Dominance Non-dominated Sorting Genetic Algorithm II (e-NSGAII) (Kollat and Reed, 2006) that has been shown to effectively solve complex many-objective optimisation problems (Reed et al., 2013) is used. The algorithm employs epsilon-dominance archiving of high-performing solutions allowing the user to specify the required significant precision for each objective value. The ϵ value represents the minimum magnitude of change in the objectives that the user is interested to control the resolution of the solution set (Laumanns et al., 2002), with higher ϵ values resulting in a coarser resolution of the full Pareto front.

The multi-objective optimisation is run ten times each starting from a unique population using different random seed value to best approximate the Pareto front. Previous studies have used similar number of seeds to reduce the computational burden while ensuring that the influence of random number generation on the results is insignificant (Huskova et al., 2016). The initial population size was set to 512 and the algorithm operator parameters were chosen according to previous study recommendations (Kollat and Reed, 2007b; Matrosov et al., 2015). Each optimisation was run for 25,000 function evaluations or until a convergence metric was satisfied. Table 5.2 summarises the algorithm parameters including the objective ϵ values used for the case study. The ϵ values were selected to capture the minimum level of precision desired in differentiating between the performance of one portfolio alternative and another in each objective (1000 and 0.1 for cost and resilience respectively).

TABLE 5.2: Algorithm parameters and objective ϵ values for the London case study

Algorithm parameters	Values
Initial population size	512
Population scaling factor (for injection)	0.25
Number of generations per run	50
Probability of crossover p_c	1.0
Probability of mutation p_m	0.5
Distribution index for SBX crossover	15
Distribution index for polynomial mutation	20
Objectives	Epsilon
$f_{(Cost)}$	1,000 k£
$f_{(Resilience)}$	0.1 weeks

To determine each run's convergence a variance-based metric (Sinha et al., 2014; Erfani, Mokhtar and Erfani, 2018) η is used which is defined by,

$$\eta = \frac{\sigma^2_{V_i c}}{\sigma^2_{V_i o}} \tag{5.7}$$

where $\sigma^2_{V_i c}$ and $\sigma^2_{V_i o}$ denotes the variances of objective i (cost, resilience) in the current (c) and initial (o) population, respectively. A value of η close to zero indicates that the optimisation has converged. The search is terminated using two user-specified criteria: the algorithm terminates when $\eta \leq \eta_{stop}$ ensuring that the run has satisfactorily converged or when the maximum number of function evaluations has been reached. The latter one is used as an upper bound for the number of iterations necessary to ensure the convergence, stopping the algorithm with an acceptable solution close to the optimal solution.

5.4 Results and discussion

5.4.1 Solving the multi-objective water resource planning problem

Figure 5.4 (a) shows the Pareto-approximate adaptive plans (as defined in Section 5.2.3) produced by non-dominated sorting of the ten runs using different random seeds. Each point represents a unique Pareto-approximate adaptive plan proposing a set of investment options for each decision node of the scenario tree over the 50-year planning period. The investment cost is lower for adaptive plans with lower resilience implying that a higher acceptable level of resilience requires more investment. For example, Adaptive Plan 1 exhibits the lowest costs while Adaptive Plan 2 displays a balance between the two conflicting objectives. More risk-averse decision makers that desire high resilience may select Adaptive Plan 3 where financial performance (low cost) is traded in to obtain higher resilience. However, the cost to achieve a certain level of risk aversion could be considered excessive and requires consideration. For instance by comparing Adaptive Plans 2 and 3, as shown in Figure 5.4, a 0.22 reduction in weeks of non-essential use ban results in a £150 million increase in cost. Figure 5.4 (b) and (c) show the convergence behaviour of the MOEA algorithm, displaying the average objective values at each iteration and their variance respectively. As shown, the value of η (defined in section 5.3.3) drops sharply over the initial generations and convergence is achieved for both objectives in less than 50 generations. While cost converged smoothly after only 30 generations, resilience requires almost 50 generations.

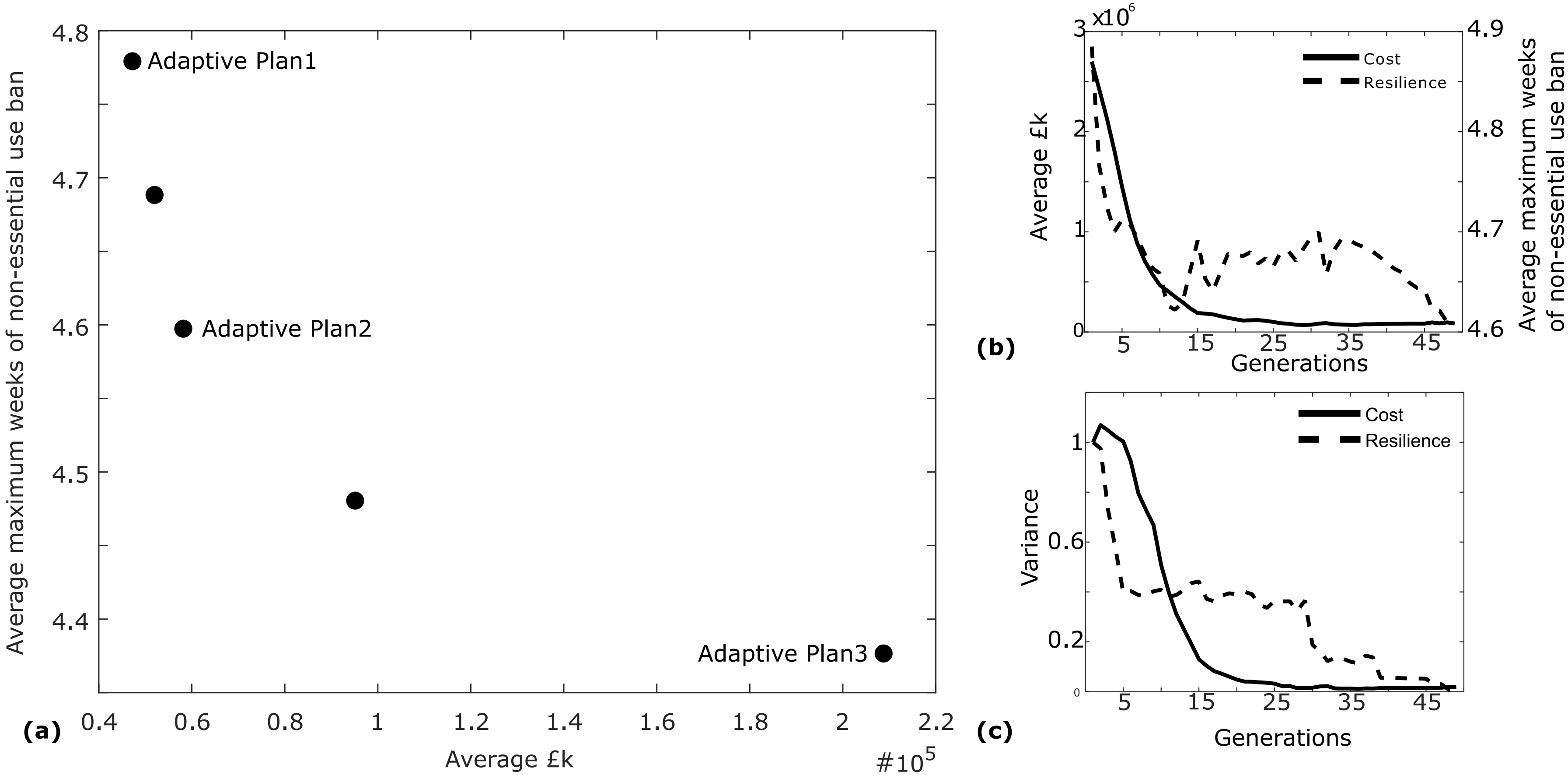

FIGURE 5.4: (a) Plot of the epsilon-nondominated Pareto optimal set. Each Adaptive Plan corresponds to a 50-year plan. The objective function values for cost and resilience reduction are shown. The direction of preference (minimisation) is downward. The ϵ value for resilience allows to generate 5 adaptive plans. (b) Average cost and resilience values at each iteration (c) Variance-based stopping criterion check, η, over generations. The algorithm terminates when $\eta \leq \eta_{stop}$.

The planning formulation maximises level 3 resilience (by minimising the length of level 3 failures). Level 3 failures are themselves constrained not to occur more frequently than once every 10 years.

For illustrative purposes, the extremities of the Pareto front as shown in Figure 5.4 (a) (Adaptive Plan 1 and Adaptive Plan 3) and a balanced adaptive plan towards the centre (Adaptive Plan 2) are chosen to reflect different preferences of decision makers. The investment trajectories for the three selected adaptive plans of the Pareto front are shown in Figure 5.5. The tree consists of 21 possible investment trajectories for each adaptive plan based on the demand scenarios depicted in Figure 5.2. Decisions to invest in or delay a set of interventions are made at the beginning of each time interval t. The decision points are spaced at 5-year time intervals and therefore an activated intervention, depending on its construction period, comes online either at the same or in a future time period.

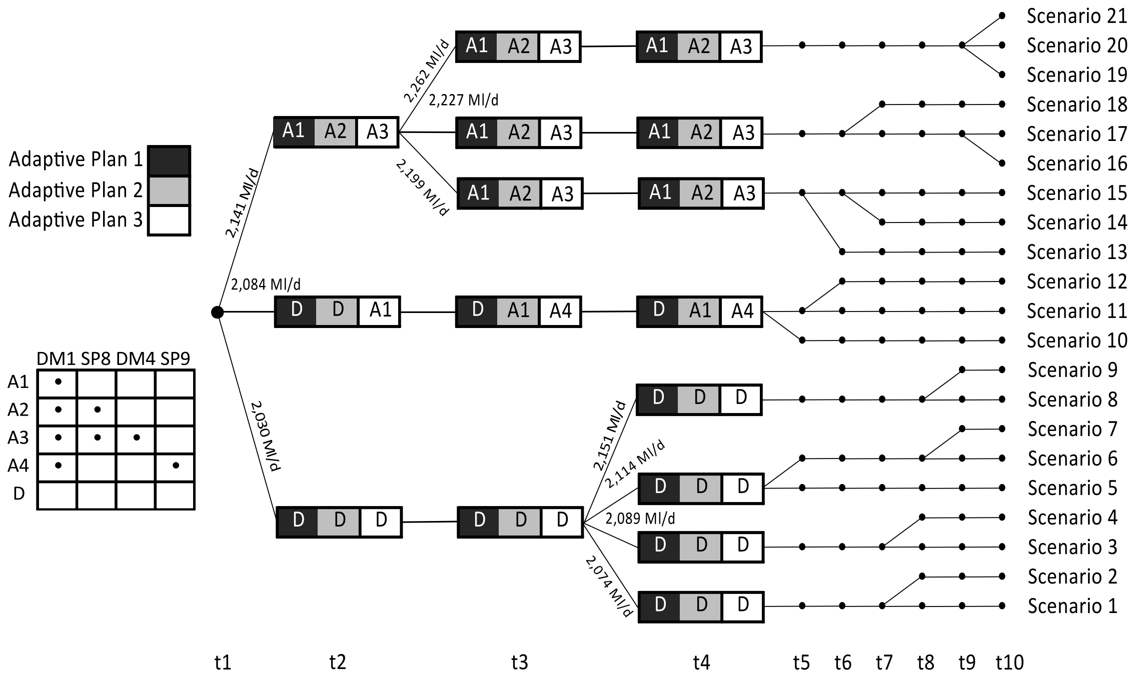

FIGURE 5.5: Resulting investment trajectories for three selected optimal Adaptive Plans for the short-term period (next 15 years). At each stage, a decision to activate a portfolio of supply demand interventions (A1-A4) or delay investment (D) is made. Each portfolio consists of a combination of interventions and is Pareto optimal if a demand scenario occurs. The demand threshold values in Ml/d on each arc show which path to follow out of the 21 demand scenarios (Scenario 1 - Scenario 21). Results do not incorporate all data from TWUL's latest plan.

Figure 5.5 details the short-term (t_1 - t_4, i.e. decisions made in 2020, 2025 and 2030) investment decisions of the three adaptive plans (represented by black, grey and white boxes), showing whether a portfolio that consists of a combination of interventions is activated (A1-A4) or delayed (D) at the beginning of each 5-year time interval under different demand scenarios differentiated by demand thresholds.

The term 'adaptive plan' is introduced in this chapter to describe a plan that can adapt to evolving uncertainty over time, given a particular preference of the decision maker on the cost-resilience trade-off. That is, two adaptive plans can have the same set of interventions activated in a given time step, but can evolve differently through the planning period, based on the preferred cost-resilience performance.

Each adaptive plan consists of a set of activated interventions at each node of the decision tree subject to the decision tree structure

The potential supply-side and demand-side water resource options that can be activated at each node of the tree are detailed in Table 5.1. Demand threshold values displayed on each branch indicate which path is optimal for a given demand at each interval. For instance, if the planner considers that demand for water in 2025 is most likely to be less than 2,030 ML/d (low demand growth), then the lower path is the best intervention response. If demand is between 2,030 ML/d and 2,084 ML/d (moderate demand growth) then the middle path is optimal, whilst if demand is 2,084 ML/d or greater (high demand growth) then the upper path should be selected.

The most pressing concern of water planners is short-term investment decisions, i.e., what to do now. However, these near-term decisions must be compatible with future investments and the resulting investment trajectories of which they are a part must demonstrate long-term water supply security under different future scenarios. Initial investment trajectories resulting from differing near-term decisions can follow a range of future branches based on future decisions. The decision determining which subsequent branch a planner should follow can be taken as new information on demand growth becomes available. This results in adaptive investment planning where initial investment decisions can be postponed and adjusted according to future possible demand conditions.

The decision tree approach results in ”wait-and-see” strategies which seek to delay the implementation of interventions until they are required and as more information about the future becomes known. The ability to defer investments enables planners to reduce overall intervention costs. For example, as seen in Figure 5.5, for all 3 adaptive plans, the decision in 2025 (t_2) to invest (increase supply or reduce demand) is postponed until later stages if demand is expected to be low. Only if demand in 2025 is expected to be moderate or high should planners invest in actions (infrastructure or demand management).

Each adaptive plan has alternative sets of interventions scheduled for implementation. For instance, as shown in Figure 5.5 in the moderate demand scenario the expensive Adaptive Plan 3 activates portfolio A1 while investments in Adaptive Plans 1 and 2 are delayed. In the high demand scenario, the cheapest Adaptive Plan 1 activates the intervention corresponding to portfolio A1 while in Adaptive Plans 2 and 3 the set of interventions in portfolios A2 and A3 are activated respectively. At the next decision stage (t_3), a delay in investment for the lower path is recommended. In the middle path, portfolio A1 is activated in Adaptive Plan 2 while in Adaptive Plan 3, the previously activated portfolio A1 from t_2 is expanded to portfolio A4. In the upper path, the previously selected interventions remain active without further investment. In practical applications, at the next decision stage (i.e., 5 years later) the optimisation should be performed again with the newly available demand scenarios that could be different compared to the original ones (Creaco et al., 2013).

To gain more insight on how the Pareto-approximate adaptive plans differ, in Figure 5.6 the short-term (t_1 - t_4) investment decisions for two demand interventions, Demand Management 1 (DM1) and Demand Management 4 (DM4) is plotted. It can be seen that if demand in t_2 is high (top path), DM1 is activated in t_2 in all 3 adaptive plans showing that the selection of this intervention is robust across adaptive plans that represent different trade-offs between the two objectives. Conversely, at the top path, DM4 is only activated in the more expensive Adaptive Plan 3 with higher resilience in t_2.

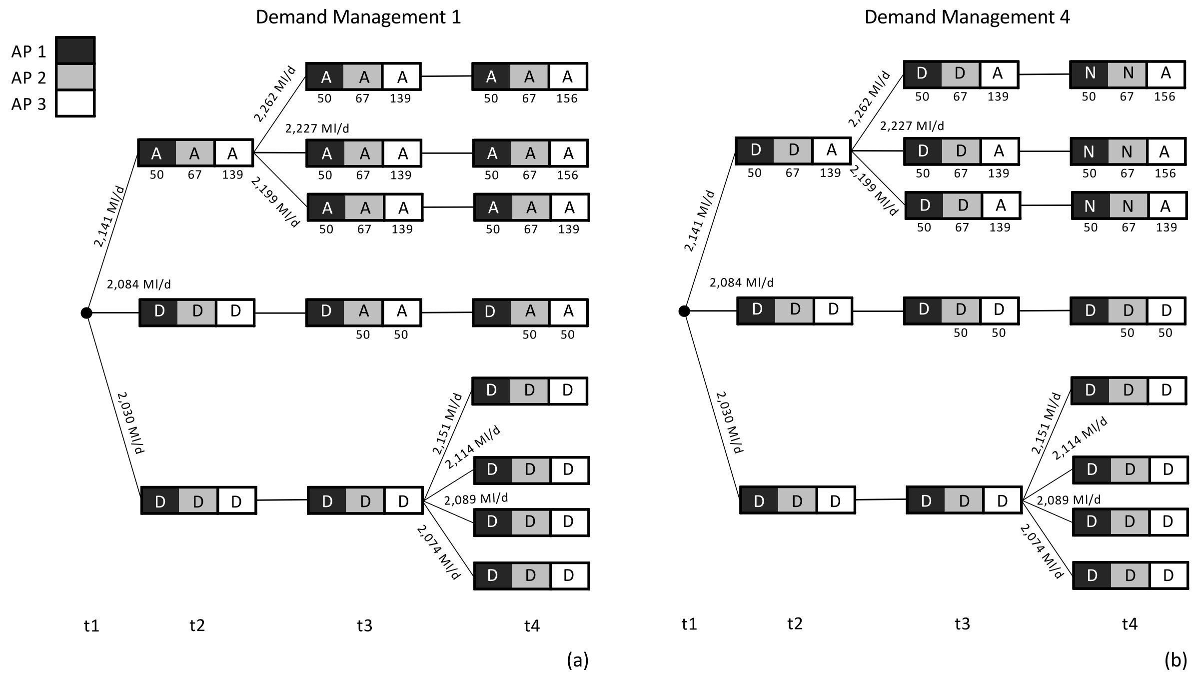

FIGURE 5.6: Investment trajectories for interventions Demand Management 1 (DM1) and (b) Demand Management 4 (DM4) for three selected optimal Adaptive Plans for the short-term period (next 15 years). At each stage, a decision to activate (A) or delay (D) a set of supply demand interventions is made. The demand threshold values in Ml/d on each arc show which path to follow.

If demand growth in t_2 is moderate (middle path), DM1 in not activated in the more cost-efficient Adaptive Plan 1 while in Adaptive Plans 2 and 3 DM1 is activated in t_3 andt_2 respectively. In the middle demand path, DM4 is not activated in any adaptive plan until the end of the short-term planning period.

If demand in t_2 is low (bottom path) then none of the two demand interventions are activated until the end of the short-term planning period. Leakage reduction is selected in all adaptive plans above a certain demand growth and implemented early on in the planning period while MET is present only in more costly adaptive plans with higher resilience. This effect can be attributed to the short lead time but large costs of leakage reduction and metering. In those scenarios, the pressing need to increase supply or reduce demand forces adaptive plans to adopt these interventions.

As later in the planning period more interventions become available, water supply interventions are preferred. As shown in Figure 5.5, in the moderate demand scenario, by t_3, the demand intervention implemented in the first decision stage is no longer adequate to meet a certain level of system resilience. This is the case of Adaptive Plan 3 that seeks high resilience, where a sypply option (SP9) is implemented by expanding portfolio A1 to portfolio A4.

Figure 5.7 depicts the activation frequency of the interventions across the 21 demand scenarios in each time step for the long-term planning problem. The combination of interventions in each adaptive plan, the time of their implementation as well as its activation frequency across the scenarios is plotted. Demand Management 1 (DM1) has the highest frequency of activation and is activated early on in all three adaptive plans. This suggests this demand intervention is robust across the cost-resilience trade-off as well as supply demand uncertainty. Supply option 2 (SP2) is activated in all three adaptive plans towards the end of the planning period. This shows a large supply scheme is not needed until later (t_7 given the data used). In Adaptive Plans 1 and 2 less interventions are selected compared to the more expensive and more resilient Adaptive Plan 3. DM1 and SP2 are selected across all adaptive plans showing that demand management should be put in place early and a large supply scheme towards the end of the planning period.

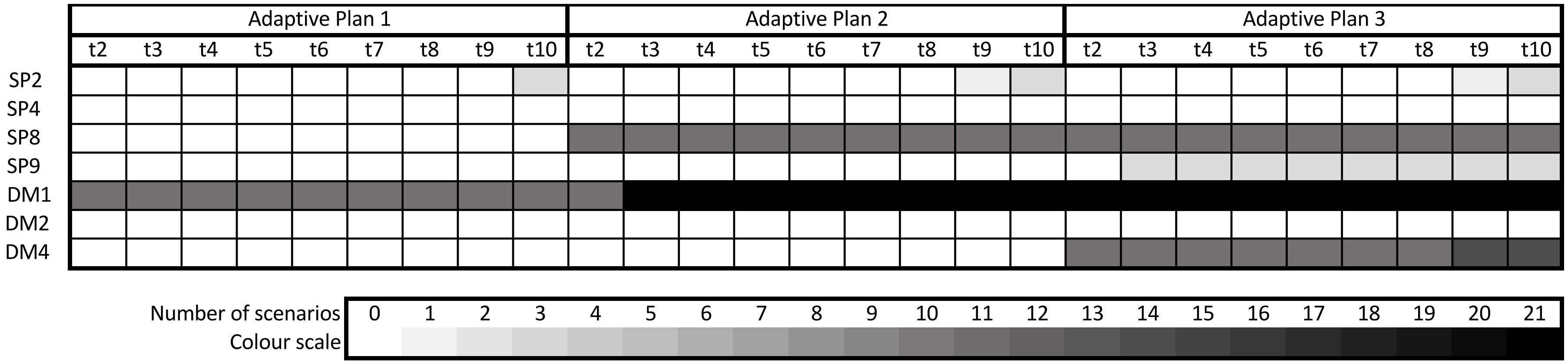

FIGURE 5.7: Activation frequency of interventions across the 21 demand scenarios for the long-term plan. Activated interventions include supply option 2 (SP2), supply option 4 (SP4), supply option 8 (SP8), supply option 9 (SP9), Demand Management 1 (DM1), Demand Management 2 (DM2), Demand Management 4 (DM4). Results do not incorporate all data from TWUL's latest plan.

5.4.2 Metrics for flexibility and adaptivity assessment

Two metrics used in stochastic programming problems (Birge and Louveaux, 1997; Escudero et al., 2007), namely Value of the Stochastic Solution (VSS) and Expected Value of Perfect Information (EVPI), are translated into decision-relevant metrics of adaptivity and flexibility in water planning decisions. To examine the implications on adaptivity and flexibility across the cost-resilience trade-off, the same three adaptive plans (i.e. Adaptive Plans 1, 2 and 3) are compared from the previous section. Each adaptive plan corresponds to a 50-year adaptive investment plan. By calculating the VSS and EVPI values, the three adaptive plans on the Pareto front are compared in terms of their ability to adapt to changing conditions and the value gained from delaying irreversible investment commitments respectively. This follows Erfani, Pachos and Harou (2018) who use the VSS and EVPI metrics to quantify the benefits of adaptivity and flexibility for a single objective multistage stochastic mathematical programming approach to water resource planning.

VSS is calculated for each adaptive plan by replacing the decision variables (i.e. activation of intervention in each planning interval) with expected values and comparing the cost requirements between the two. By fixing the first stage interventions and solving for all the scenarios, the MOEA will generate a new set of Pareto adaptive plans. EVPI is estimated by computing the cost difference between the expected value with perfect information and the expected value with current information for each Pareto adaptive plan. In order to allow for the cost comparison for VSS and EVPI calculations, adaptive plans that have the same level of system resilience r are selected. Section 5.4.3 gives mathematical detail on the calculations of VSS and EVPI for the multi-stage formulation.

The VSS and EVPI for the three individual adaptive plans, expressed as a percentage of the total cost of each adaptive plan, are shown in Figure 5.8. In the context of this case study, VSS illustrates the difference of using the multi-stage approach applied here which explicitly allows for adaptation to different future demand

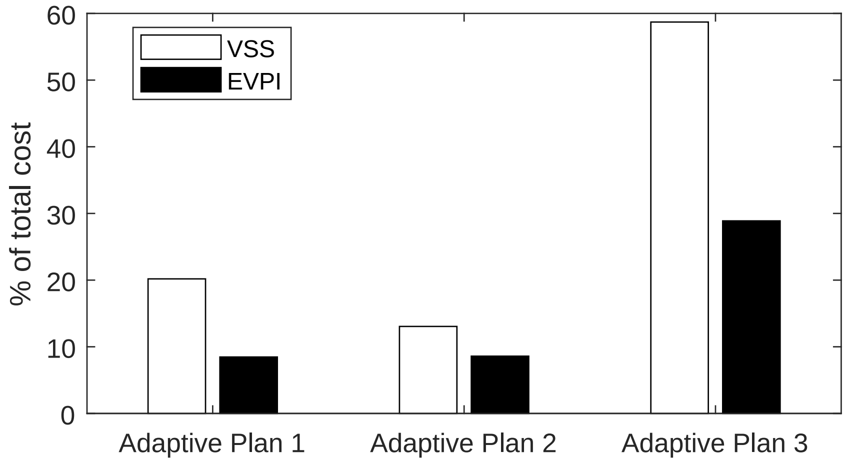

FIGURE 5.8: VSS and EVPI values as percentage of the total cost for three selected optimal Adaptive Plans.

conditions instead of considering the average demand values in each stage. VSS quantifies the cost of not recognising the uncertainty and therefore ignoring the adaptivity advantage. For the London case study, VSS, expressed as a percentage of the total cost, is higher for the most resilient Adaptive Plan 3 (58,7%) compared to Adaptive Plan 1 (20.2%) and Adaptive Plan 2 (13.1%). This indicates that, for high resilience plans especially, an adaptive approach has considerable financial value.

EVPI measures the value of information for planning under uncertainty and gives an upper bound on the value of undertaking further research in order to eliminate the uncertainty surrounding the decision about which set of interventions is optimal. In the context of this case study, EVPI indicates how much it is worth to invest in better demand forecasting. Again, the higher EVPI for Adaptive Plan 3 (28.9%) compared to Adaptive Plan 1 (8.5%) and Adaptive Plan 2 (8.6%) shows that for the more resilient and costly adaptive plan, there is high value in investing in demand forecasts.

5.4.3 Computational insight on the metrics used to evaluate the multi-staged MOEA

The calculations of the expected value of perfect information (EVPI) and the value of the stochastic solution (VSS), in multi-stage problems are explained below. These two metrics were developed for the case of two-stage problems (Birge and Louveaux, 1997), and have been extended to multistage problems (Escudero et al., 2007). Their values in a multi-stage framework with two objectives are calculated, for each Pareto approximate solution individually (see Section 3.4.2 for details on the calculations of EVPI and VSS in multi-staged problems).

VSS and EVPI are calculated using the cost values of the solutions that correspond to a given level of system resilience r. VSS is calculated by solving the "mean-value" problem resulting in a Pareto set of first stage solutions. EVPI is determined by computing the cost difference between the expected value with perfect information and the expected value with current information.

This sequence of non-negative values represents the cost of ignoring uncertainty and not providing adaptive solution to future condition until stage t in the decision making of multistage models. VSS and EVPI in multistage problems are then calculated as,

$$VSS = \sum_{t \in T} VSS_t, \tag{5.8}$$

and,

$$EVPI = \sum_{t \in T} EVPI_t. \tag{5.9}$$

5.5 Conclusions

This chapter proposed a multi-objective multi-stage approach for identifying adaptive water investment plans under probabilistic demand uncertainty and given multiple plausible supply futures. A multi-objective evolutionary algorithm was used to optimise future interventions for each node of a decision tree built to represent probabilistic demand uncertainty optimised over multiple equally probable hydrological flow scenarios. The obtained Pareto-approximate investment plans are adaptive and robust to the effects of supply demand balance uncertainty. Demand growth threshold values inform decision makers which investment trajectory would be best to follow to optimise cost and resilience of the water supply system. The plans are adaptive in that commitments being made in the short-term allow for a multiple choice of future commitments based on how the future demand growth unfolds.

The approach was applied to the London's (UK) water supply system. Given a scenario tree made of 21 future demand scenarios, 11 transient hydrological flow scenarios and two conflicting stakeholders' objectives, the cost of new interventions and the resilience of the system were optimised under level of service constraints. The possible new investments considered included 11 supply interventions (of type reservoir, transfer, waste water reuse, desalination) and 4 demand interventions (of type active leakage control, mains repair, efficiency, metering).

Resilience considers the average maximum number of weeks of non-essential ban use. The results showed that a small increase in system resilience, requires a high increase in costs. To operate with a resilience value of 4.77 weeks requires £47 million of investment while to operate with resilience of 4.37 weeks requires £208 million. To illustrate the benefits of the adaptive multi-objective multi-stage approach, three Pareto-approximate adaptive plans were selected and compared. Depending on which decision path is chosen, according to the forecasted short-term demand growth, an adaptive plan is selected based on the user's preference on the cost-resilience performance. Each adaptive plan suggests whether interventions should be delayed or activated.

Investments are postponed for the future when demand in 2025 is expected to be below 2,084 ML/d. If demand in 2025 is higher than 2,084 and below 2,141 ML/d then the user has the option to delay investment or implement demand management 1 (DM1) based on their preferred cost-resilience performance. If demand in 2025 is higher than 2,141 ML/d, new interventions need to be implemented to maintain desired levels of service. All three selected optimal adaptive plans implement demand management 1 (DM1) at the top path of the tree showing that, under higher demand conditions, the selection of this intervention is robust across adaptive plans that represent different trade-offs between cost and resilience.

The flexibility and adaptivity assessment of the three adaptive plans, quantified by their VSS and EVPI values, show that considering supply demand uncertainty in London's supply-demand problem is important. Resource managers can lessen the consequences resulting from uncertain levels of future supply-demand gap through adaptive planning and improved demand forecasts. For more costly adaptive plans that provide higher system resilience, this becomes more critical. VSS shows that for the most resilient adaptive plans, adaptive investment decisions to demand uncertainty reduce NPV by 58.7% EVPI estimates that for the most resilient adaptive plan the value of delaying investments by waiting to gain more accurate information is 28.9% of total NPV.

The multi-objective multi-stage optimisation in this study required running the simulation model for 25,000 function evaluations with each function evaluation run over 21 demand and 11 hydrological scenarios for each of the 10 random seeds, requiring a total of 57.75 million simulation model runs. Following Huskova et al. (2016), and to limit the number of function evaluations necessary for the optimisation to converge, each intervention had a fixed capacity (Table 5.1). Alternative capacities for the same interventions could be added as new interventions if just a few sizes are being considered. Fully optimising the capacity of interventions across their entire range could result in more adaptive plans but is left for future work.

Chapter 6

Conclusions

6.1 Summary and conclusions

Uncertainty in future supply and demand conditions motivates novel decision-making approaches that inform water managers which alternative combinations of interventions would be best to choose given stakeholder priorities. Most previous work in the scheduling of water resource interventions has focused in static approaches as part of which a single, fixed investment strategy is developed with limited ability to adapt to evolving uncertainty. This thesis has argued that adaptive water resources planning approaches that endeavour to develop multiple flexible investment strategies are useful in the face of a highly uncertain future. The flexible strategies are assigned to different plausible future paths and can respond to increased knowledge about future conditions by adjusting intervention schedules over the planning period.

This work contributes to the advancement of adaptive water resources planning by proposing new decision-making approaches that explicitly enable adaptivity to future uncertainty through the use of ROA concepts and scenario trees. The thesis started off by demonstrating in Chapter 3 how a least-cost scheduling approach for water infrastructure investment planning, used currently at national scale in

England, can be extended to enable adaptivity given future supply uncertainty. The stochastic supply is approximated by a compact scenario tree representing an ensemble of plausible futures. Chapter 3 shows how the proposed approach allows the planner to rebalance the supply-demand system at distinct decision points defined by the scenario tree, resulting in adaptive solutions whose implementation can be delayed and replaced as information on future supply-demand balance is gradually revealed.

To evaluate the implementation of ROA, two metrics are introduced: the Value of the Stochastic Solution (VSS) and the Expected Value of Perfect Information (EVPI) that quantify the value of adopting adaptive and flexible plans respectively. The analysis showed that by considering uncertainty, adaptive investment decisions avoid £100 million NPV cost, which corresponds to 15% of the total NPV. The EVPI demonstrates that optimal delay and early decisions have £50 million NPV, 6% of total NPV.

In Chapter 4 the proposed adaptive approach of Chapter 3 as well as alternative 'fixed plan' optimisation approaches are applied to a real-world utility to solve the water supply capacity expansion problem to perform a comparison. The performances of the proposed plans were compared in terms of required investment costs and unused capacity which demonstrated the benefit that the adaptive planning can bring to the water resource management decision-making process. The results from the case study suggest that the proposed adaptive planning approach managed to reduce NPV cost by 35%, compared to alternative optimisation approaches that produced fixed plans, saving more than £377 million. To compare the performance of the proposed plans beyond cost, two alternative performance metrics, water security and deliverability were derived and evaluated. The results of the water security assessment suggest that there is a trade-off between cost and risk of drought under severe and extreme conditions. The deliverability assessment indicates flexible approaches that optimise plans over multiple paths, increase the confidence that the expected volume of water will be delivered on time.

Although alternative metrics are reported post-optimisation these are not included as an objective in the optimisation problem. Limitations of the least cost approaches used in the comparison study in Chapter 4 can be considered that plans are optimised using a single objective and therefore tangible outcomes cannot be assessed and evaluated without translating non-commensurable metrics into a single monetary. To address these limitations, Chapter 5 presents a multi-objective multi-stage approach for identifying adaptive water investment plans under probabilistic demand uncertainty and given multiple plausible supply futures. Two objectives are used to explore the trade-off between financial and resilience indicators. The obtained Pareto-approximate long-term investment plans are adaptive and robust to the effects of supply demand balance uncertainty. Furthermore, Chapter 5 demonstrates that by considering supply demand uncertainty in London's supply-demand problem, water planners can lessen the consequences resulting from future uncertainty through adaptive planning and improved demand forecasts. The flexibility and adaptivity assessment of the alternative adaptive plans show that for more costly adaptive plans that provide higher system resilience, this becomes more critical. The results indicate that, in the case of the most resilient plans, by being adaptive to demand uncertainty, total NPV is lowered by 58.7% The value in delaying investments by waiting for more accurate supply and demand estimates is 28.9% of total NPV. The methods presented in this thesis quantify the value of adopting adaptive and flexible plans by deriving flexibility and adaptivity metrics which are used to give a definition to flexibility and adaptivity in the context of water resources management.

In this thesis, the methods presented were applied to London's urban water supply system. The results of this study are indicative and should not be considered prescriptively as they are based on a simplified representation of Thames Water's system. Thames Water's most recent plan (Thames Water, 2018) includes the latest proposed option designs, includes requirements to supply neighbouring water utilities, and considers more objectives.

Chapter 4 shows that it is important to recognise the limitations of 'fixed plan' optimisation approaches demonstrated by the favourable performance of the adaptive plans compared with those fixed at the beginning of the planning horizon. This thesis argues for aiming to explicitly seek adaptivity and flexibility in water investment planning through the use of decision trees that reflect different scenarios that may occur during the planning horizon. Due to computational complexity in accounting for all possible scenarios that represent future uncertainty in real-world applications, uncertainty is approximated by a decision tree involving a smaller number of scenarios through the use of a reduction technique (developed by Gröwe-Kuska et al. (2003)).

The decision trees display the most appropriate set of intervention measures at several planning horizon time steps depending on how the future unfolds. Investment decisions have to be made for each time interval of the decision tree resulting in multiple investment trajectories. Threshold values are optimised to determine which intervention trajectory is best to follow, given a future projection. The use of ROA principles enables the flexibility within the decision trees to be valued and thus account for the future uncertainties of demand growth and climate change. While future supply demand forecasts are expected to change, the methods presented in this thesis seek to inform present investment decisions, which therefore have to be based on present forecasts. In practical applications, at the next decision stage (i.e., 5 years later) the optimisation should be performed again with the newly available demand scenarios that could be different compared to the original ones (Creaco et al., 2013).

The optimisation objectives in Chapter 5 are explicitly based on the physical performance of the system since performance metrics such as supply reliability and resilience are calculated through a simulation. However, the interaction between the water management actions and their influence on hydrological variables was not explored. An integrated modelling approach could be used to address this two-way feedbacks between hydrological and human processes. Socio-hydrological models have already been applied in the context of flood risk management, exploring the interplay between the impact of human interventions on drought and flood events and human responses to hydrological extremes (Di Baldassarre et al., 2015, 2017). In a water resource management context, examples include addressing reservoir effects, i.e., when increasing water supply leads to higher water demands which eventually reduce the reservoir's initial water supply improvement (Di Baldassarre et al., 2018).

6.2 Limitations and future research

This thesis has mainly focused on the development of new water management planning methods that explicitly seek adaptivity and flexibility when investigating the implementation of a range of feasible interventions. The limitations of the proposed methods, related to their modelling formulation and applicability, provide guidance for future research with regards to methodological extensions and demonstration of their wide applicability in terms of problem scope.

The proposed methods are applied in the context of urban supply capacity expansion using a single case study, London's urban water supply system. Applying the proposed methods to alternative planning problems may reveal other observations not found in this study. Future work will include tailoring and applying the methods presented in this work to other water resources problem domains such as water distribution system design and flood management. Furthermore, alternative and more complex real-life case studies could be used considering a wider range of intervention measures as well as scenarios of future conditions not discussed in this work that would result in different decision tree structures.

The methodologies presented in this thesis can effectively identify adaptable solutions for long-term planning under uncertain future changes. However, the problem formulation (e.g. objectives, constraints, and decision variables) is assumed to remain constant throughout the long-term period. Given the many and evolving competing water interests and stakeholder objectives, this is unlikely to be the case. Consequently, future research could explore the incorporation of methods that enable the problem formulation to be changed over the planning period (Maier et al., 2014; Piscopo et al., 2015).

Although flexibility and adaptability are reported post-optimisation by calculating the VSS and EVPI values, the optimisation formulations of the proposed methods do not necessarily identify the most flexible and adaptive solutions. Therefore, not including these as objectives in the optimisation problem could be considered a limitation. Future work might therefore explore the implications of including flexibility and adaptability objectives in the optimisation formulation. However, that would move towards providing decision makers with a single solution rather than a set of optimal paths (Beh et al., 2015a).

Future work could also address challenges posed by conflicting economic, social and environmental objectives. Environmental performance, in the case of London's water supply problem, can be defined as a measure of how well the ecological flow of the Thames is maintained (Matrosov et al., 2015). The proposed multi-objective adaptive model introduced in Chapter 5 could be extended to consider such an environmental objective. That would allow alternative system designs to be evaluated considering performance measures that maximise environmental metrics while minimising economic costs.

In an extension of this work, the impact of modularity in the selection of interventions could be explored. Modular designs of large infrastructure projects exhibit built-in options, that can be implemented later if required. Based on a real options approach, the methods introduced here quantify the value in allowing flexibility in the implementation of large infrastructure projects. While modularity enables flexibility into the design of water resource infrastructures, it does not come for free as the costs of modularising go up as the number of modules increases (Baldwin and Clark, 2000). The proposed methods could be used to understand the impact of different levels of modularity in the selection of interventions. Insights gleaned from this sensitivity analysis may be useful in formulating design capabilities by suggesting appropriate number of increments of large modular interventions.

Appendix A

Details for the interventions considered in the London case studies

This appendix presents the alternative supply interventions considered in the case studies of Chapter 3 and Chapter 4. The 47 inteventions are listed in Table A.1.

TABLE A.1: List of available water resource interventions to supply London considered in the appraisal process. EY: Estimated yield (capacity) in Ml/day. CAP: Capital costs in £m, OP: Operational costs in £m

Code	**Resource Type**	**Scheme Name**	**EY**	**CAP**	**OP**
i1	Aquifer Recharge	HARS (Hornsey)	2	4.1	0.3
i2	Aquifer Recharge	Kidbrooke 8Mld (SLARS)	8	51.9	2.3
i3	Aquifer Recharge	Merton 6Mld (SLARS)	6	22.9	1.4
i4	Aquifer Recharge	SLARS - Streatham 5Mld	5	18.3	1.1
i5	Desalination	Estuary South 50 ML/d	50	435.2	7.9
i6	Desalination	Estuary South 100 ML/d	100	548.2	14.1
i7	Desalination	Estuary South 150 ML/d	150	644.8	20.0
i8	Desalination	Estuary South 50 ML/d ph 1	50	471.2	7.5

Table A.1 continued from previous page

i9	Desalination	Estuary South 100 ML/d ph 2	50	142.1	6.5
i10	Desalination	Estuary South 150 ML/d ph 3	50	142.1	6.5
i11	Desalination	Long Reach	15	81.6	3.2
i12	Desalination	Estuary North 150 ML/d	150	505.5	17.0
i13	Effluent reuse	Abbey Mills ROS 50 ML/d	50	238.4	6.6
i14	Effluent reuse	Abbey Mills ROS 100 ML/d	100	320.1	10.6
i15	Effluent reuse	Abbey Mills ROS 150 ML/d	150	423.3	15.6
i16	Effluent reuse	Abbey Mills ph 1 50 ML/d	50	309.4	5.8
i17	Effluent reuse	Abbey Mills ph 2 upgrade to 100 ML/d	50	93.3	5.1
i18	Effluent reuse	Abbey Mills ph 3 upgrade to 150 ML/d	50	93.3	5.1
i19	Effluent reuse	Beckton 50 ML/d	50	204.5	2.0
i20	Effluent reuse	Beckton 100 ML/d	100	260.9	3.6
i21	Effluent reuse	Beckton 150 ML/d	150	323.6	5.3
i22	Effluent reuse	Beckton ph 1 50 ML/d	50	236.5	2.0
i23	Effluent reuse	Beckton ph 2 upgrade to 100 ML/d	50	71.3	1.8
i24	Effluent reuse	Beckton ph 3 upgrade to 150 ML/d	50	71.3	1.8
i25	Effluent reuse	Deephams 60 ML/d	60	124.4	3.4
i26	Effluent reuse	Hogsmill 15 ML/d	15	75.7	3.3
i27	Effluent reuse	Hogsmill 35 ML/d	35	110.4	4.6
i28	Effluent reuse	Mogden 150 ML/d Sunbury	150	360.1	13.5
i29	Effluent reuse	Mogden ML/d Sunbury ph 1	50	263.2	5.1
i30	Effluent reuse	Mogden ML/d Sunbury ph 2	50	79.4	4.4
i31	Effluent reuse	Mogden ML/d Sunbury ph 3	50	79.4	4.4
i32	Effluent reuse	Mogden (Staines) 150 ML/d	150	566.0	19.0

Table A.1 continued from previous page

i33	Effluent reuse	Mogden 50 ML/d Stains ph 1	50	413.7	7.1
i34	Effluent reuse	Mogden 100 ML/d Stains ph 2	50	124.8	6.1
i35	Effluent reuse	Mogden 150 ML/d Stains ph 3	50	124.8	6.1
i36	Groundwater	Addington	1.5	2.7	0.3
i37	Groundwater	Southfleet/Greenhithe	9	20.0	1.1
i38	Reservoir	Abingdon 100 ML/d	100	1,206.0	3.8
i39	Reservoir	Abingdon 125 ML/d	125	1,431.2	6.5
i40	Reservoir	Abingdon 150 ML/d	150	1,450.0	4.3
i41	Reservoir	Abingdon 50 ML/d ph 1	50	1,009.2	1.6
i42	Reservoir	Abingdon 100 ML/d ph 2	50	336.4	1.3
i43	Reservoir	Abingdon 150 ML/d ph 3	50	336.4	1.3
i44	Reservoir	Abingdon 75+75 ML/d ph 1	75	1,216.7	3.0
i45	Reservoir	Abingdon 75+75 ML/d ph 2	75	1,216.7	5.5
i46	Transfer	Vyrnwy (158 ML/d)	158	271.9	17.9
i47	Transfer	Vyrnwy (242 ML/d)	242	413.4	23.1

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