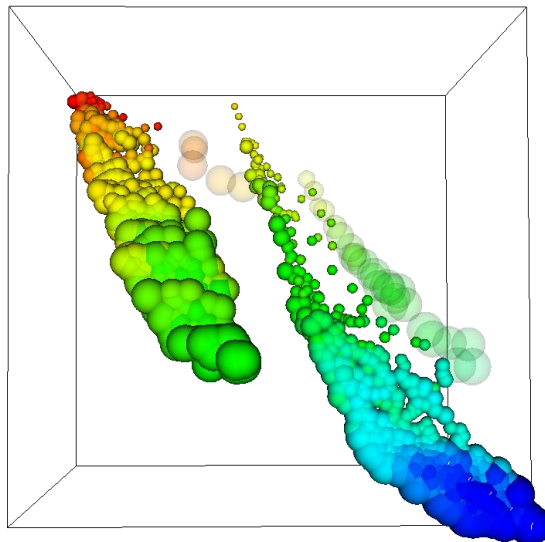


CIVIL, ENVIRONMENTAL AND GEOMATIC ENGINEERING
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Planning for robust water supply system investments under global change

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



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Declaration

I, *Ivana Huskova*, 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.

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Abstract

Climate change, population growth, institutional changes and the uncertainties inherent in these pose a major challenge to planning and management of water supply systems. Using historical river flow records to predict the behaviour of water resource systems into the future is no longer sufficient since the hydrologic record can no longer be assumed to represent future conditions. Planning under uncertainty approaches must allow considering future uncertainties in the water supply as well as demand and the institutions that manage water and its uses. Furthermore, water systems are complex and must meet multiple demands of a range of stakeholders whose objectives often conflict. Understanding these conflicts requires exploring many alternative plans to identify balanced solutions in light of important system trade-offs. The thesis focuses on improving the water resource planning process in the UK and to reflect trends in current water planning policy developments in the UK and worldwide. The challenge of long-term human-natural resource system planning is to identify high value portfolios of human interventions whilst considering the two main challenges: future deep uncertainty and multiple concurrent societal goals. This identification process is severely complicated by the exponentially large number of alternative combinations of schemes available to manage future resources. This research project demonstrates how simulating systems under multiple plausible realizations of the future coupled with ‘many-objective’ optimization can provide decision makers with robust solutions. Visual analytics is used to interact with results and demonstrate the benefits of this approach compared to traditional planning practices. Results presented here aim to aid water resources planners to orient investment strategies to meet key requirements and aspirations. These include but are not limited to maintaining the supply-demand balance and customer satisfaction in future, promoting sustainable use of resources, protecting the natural environmental, etc. The thesis aims to communicate to planners the increase in understanding of how such aspirations can be balanced taking into account uncertainties of future conditions using the proposed approaches.

Impact statement

This project demonstrates how a more sophisticated planning approach may be incorporated in the current practice. The planning approach proposed here was discussed throughout the research with Thames Water Utilities Ltd. (TWUL) to ensure its methods and objectives align with the aspirations of the UK's water industry. A project implementing the proposed approach into TWUL's upcoming Water Resource Management Plan along with the traditional methods is currently being undertaken as well as being applied in various forms in other industry projects (e.g., Water Resources of East Anglia, WRE, and Water Resources of South-East England, WRSE). The proposed approach and its findings were also presented at multiple national and international conferences such as the British Hydrological Society (BHS), American Geophysical Union (AGU) and European Geophysical Union (EGU) conferences, workshops and meetings with English water industry regulators and companies. The findings were acknowledged by the academic community - earlier study based on Chapter 3 was published in the Journal of Hydrology and the study presented in Chapter 4 was published in the Global Environmental Change journal.

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ALC	Active Leakage Control
AOGCM	Atmospheric-Ocean General Circulation Model
BRS	Beckton Reuse Scheme
CT	Columbus Transfer
DCE	Department of Climate and Energy
DRS	Deephams Reuse Scheme
EA	Environment Agency
Eff	Efficiency
ϵ -NSGAI	Epsilon-dominance Non-dominated Sorting Genetic Algorithm
ESD	Estuary South Desalination
FFs	Future Flows scenarios
GCM	Global Climate Model
IRAS-2010	Interactive River-Aquifer Simulation 2010 model
LAS	London Aggregate Storage
LoS	Levels of Service
LRD	Long Reach Desalination
LTCD	Lower Thames Control Diagram
Mains	Pipe repair campaign, i.e., mains replacement
Meters	Metering
MOEA	Multi-objective evolutionary algorithm
MORDM	Many-objective Robust Decision Making
NLARS	North London Artificial Recharge Scheme
NRFA	National River Flow Archive
nonRO	Non-Reverse Osmosis

NT	Northern Transfer
OCT	Oxford Canal Transfer
RDM	Robust Decision Making
RO	Reverse Osmosis
RST	River Severn Transfer
SLARS	South London Artificial Recharge Scheme
Tariffs	Seasonal tariffs
TWUL	Thames Water Utilities Ltd.
UTR	Upper Thames Reservoir
WRMP	Water Resources Management Plan
WRPG	Water Resources Planning Guidelines
WRZ	Water Resource Zone

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1. Chapter 1 - Introduction

1.1. Background

Water resource systems consist of both natural (e.g. rivers, lakes, aquifers, etc.) and engineered elements (e.g. reservoirs, canals, pumping stations, etc.). The interactions between these elements are complex and must be managed by public or private bodies to ensure the sustainable use of water resources, especially in densely populated areas. Water supply infrastructure in many major cities globally relies on aging assets designed and constructed over a century ago (Boyko et al., 2012). Refurbishment of existing infrastructure and capacity expansion is needed to cope with future pressures. Planning for such systems is a complex task involving identification of the problem, data collection, modelling, analysis of alternative solutions and implementation of a chosen plan (Jewell, 1986). Simulation models help analysts and decision makers understand and predict the behaviour of the system whilst optimization models aid in finding a solution to the identified problem. The two general types of models are described in more detail in section 1.2. This thesis focuses on the optimization and analysis of alternative solutions processes of the water resource systems planning.

Urban water supply planners have commonly employed narrowly defined, least-cost decision frameworks to guide capacity expansion subject to maintaining required service levels (e.g., Hsu et al., 2008; Padula et al., 2013). Planning that does not capture key concerns or preferences across major stakeholder groups explicitly increases the likelihood that policies are viewed as performing poorly (McConnell, 2010) and maladaptive. The optimality assumptions implicit to least-cost approaches assume a central planner for whom expected aggregated costs fully describe their preferences amongst water supply alternatives. One vision of optimality inevitably forces a decision maker to prior judgments without the knowledge of the decision's wider implications (Cohon and Marks, 1975). In real planning contexts, an increasingly diverse range of stakeholder perspectives must be addressed with major public investments and plans (Vogel and Henstra, 2015); this is particularly the case with decisions involving natural resources management (Jackson et al., 2012; Orr et al., 2007; Voinov and Bousquet, 2010). The emphasis is no longer only on one vision of optimality (e.g. least-cost) but on converging on a plan that addresses major concerns and acceptably allocates benefits between the major stakeholder groups and economic sectors (Loucks et al., 2005). Generating multiple alternative solutions that are good with respect to multiple

objectives but differ from each other enables explicit examination of the alternatives and gaining insight and knowledge about the system (Brill et al., 1982). Methods that clarify the trade-offs across the various benefits and impacts of portfolios of different supplies and water conservation actions have garnered a more significant role in recent published work (Arena et al., 2010; Beh et al., 2015; Herman et al., 2014; Kasprzyk et al., 2009; Matrosov et al., 2015; Mortazavi et al., 2012; Zeff et al., 2014).

Furthermore, many urban water systems across the globe face future stresses such as reduced or shifted water availability due to climate change, increased water demands, more demanding regulatory regimes and heightened service expectations (Ferguson et al., 2013; Hallegatte, 2009; Pahl-Wostl, 2009). Water resource systems are particularly sensitive to these changes and decision makers should consider these when assessing the suitability and effectiveness of their alternative future plans. Planners employed a single “most probable” future condition when designing their future system expansion in the past (Loucks and Van Beek, 2005). The likelihoods of future system stresses are however often deeply uncertain (Knight, 1921), i.e., it is difficult or impossible to quantify the probabilities of their occurrence. A system performing optimally under a single scenario of future conditions may perform poorly or even fail if future conditions diverge from the predictions of the single scenario. The uncertainty in future conditions motivates novel approaches that help discover which combinations of interventions would work well under a wide range of plausible futures, not only in a single anticipated scenario. Employing decision making under uncertainty methods (described in sections 1.3.2 and 1.3.3) is becoming a necessity for water resource systems planning.

1.2. Water resource systems modelling

1.2.1. Simulation modelling

Water resource simulation models have been used by researchers, engineers and decision makers, typically in an iterative or repetitive fashion, to aid the management and planning of their system since the 1950s (Maass, 1962). These models try to answer the “what if?” question (Harou et al., 2009) and predict the behaviour of a system. By changing input parameters the decision makers can explore how the system reacts to different situations thus assess the effectiveness of management policies and plans and inform decisions. Simulation can use decision variables as an input into the model and provide an answer about how a system’s performance would change by predicting the

distribution of flow and storages and associated metrics of economic, engineering and environmental performance. This corresponds to one of the main functions of water resource system analysis – evaluating the consequences of a certain pre-specified engineered system design.

The performance of a water resource system design may be assessed by a variety of performance metrics. The traditional engineering performance of a system is described by ‘reliability’ and ‘resilience’ of the system. The most widely used definitions of the two metrics are those proposed by Hashimoto et al (1982), where the reliability of a system is a probability that the system will be in a satisfactory state, i.e. the percentage of the modelling time horizon during which the system remained reliable. Resilience describes how quickly a system is able to recover from a failure if it occurs, i.e. it reflects the duration of a failure.

Kiritskiy and Menkel (1952) proposed three separate metrics of reliability later discussed by Klemes (1969): occurrence, temporal, and volumetric reliability. The occurrence reliability is represented by the ratio of the number of time steps in which the system was in satisfactory state to the total number of time steps in the modelling time horizon. The temporal reliability represents the ration of the total time spent in satisfactory state to the total modelled time horizon. As the number of time steps over which the temporal reliability is assessed approaches infinity the temporal reliability approaches Hashimoto’s definition of reliability. The volumetric reliability is defined as the ration of the volume of water supplied to the demand that meets the demand requirements to the total demanded volume which resembles the SI metric. Kundzewicz and Kindler (1995) argue that the volumetric reliability is often highly correlated with the temporal reliability.

Another two measures of reliability as defined by Hsu et al. (2008) are Shortage Index (SI) and Stability Degree (SD). SI serves as an indicator of a relative deficit whilst the SD turns the SI index into percentage reflecting how well a demand was satisfied.

Farhangi et al. (2012) use the SI, volumetric and temporal reliability measures to compare the performance of simulation and optimization models when applied to a single and three-reservoir system in Karoon basin in Iran. They show that considering different reliability metrics generates different solutions resulting in different conclusions about model suitability.

Shamir and Howard (1981) argue that when a system must be expanded to meet rising demands a reliability metric should be used to assess how well this rising demand is met by considered alternative designs. Similar to Farhangi et al. their work highlights that the reliability assessment depends on which definition of reliability is used and recommend to use reliability metric in terms of shortfalls relative to the desired demand, similar to the SI and volumetric reliability definitions.

Butler et al. (2017) use a reliability definition as “the degree to which the system minimizes level of service failure frequency over its design life when subject to standard loading”. To

assess such a metric of reliability, the chosen level of service measures and corresponding acceptable limits must be specified. This definition resembles the occurrence reliability definition and reflects the UK water companies’ approach to maintain reliable service. It is used in this project as reliability constraints in the problem formulation that constrain the frequency of imposing demand restrictions on a water company’s customers to a desired maximum frequency.

The Hashimoto’s definitions of reliability and resilience were employed in this study for reliability and resilience performance metrics to minimize both the frequency and duration of unsatisfactory low reservoir storage levels.

1.2.2. Simulation models

Simulation models can be divided into two main categories: rule-based models that model the actual system operating procedures incorporating user defined operating rules and policies, and optimization driven models that use optimization engine to allocate the flow of water throughout the system (Matrosov et al., 2011). The former use procedural programming instructions through “if then else” statements and iterative loops. The behaviour of the system is predictable based on the input data and pre-defined operating rules. These models are generally challenging to build but are able to represent realistic behaviour of the system (Matrosov et al., 2011). An example of rule-based simulation model includes e.g. Aquator (Oxford Scientific Software, 2008), and IRAS-2010 (Matrosov et al., 2011). Aquator is a commercial water resources model used by some UK water resources planners. It is user oriented with graphical user interface (GUI) and can be customised with VBA code. It however requires a license to use and its processing speed and runtime is too high to be considered for this project. The IRAS-2010 is a fast, generalised water resource system simulation model. The software is written in Fortran and is open-source allowing users to add new features or add

customised operating rules. Its ability to represent complex operating rules such as complex conjunctive surface-groundwater interactions is limited. More description of IRAS-2010 is provided in section 2.1.1.

Optimization driven models choose their own operating rules each time step depending on what is optimal based on an objective function, which can be a penalty function or economic benefit or cost, etc. These models are easier to build but can have difficulties representing complex operating. Such models include WATHNET (Kuczera, 1992), WRIMS (formerly CalSim) (Draper et al., 2004), and WEAP (SEI, 2016). The WATHNET model uses a network linear program (NetLP) to simulate the operation which searches for the minimum cost solution for distributing water through a network. It is relatively fast but requires extensive user input in input script format and only a simplified water system network representation. Its custom coding ability is also very limited. The WRIMS model utilizes a mixed-integer linear program to determine reservoir releases and water allocations at each time step. Instead of operating policies the user defines relative priorities for water allocation and storage. However, the weighted approach requires careful consideration to achieve desired outcomes and its runtimes are relatively slow. The WEAP model consists of a conceptual rainfall-runoff sub-model connected to an optimization sub-model that applies a mixed-integer linear programming routine to maximize demand satisfaction based on the water demand prioritization, supply preferences and environmental requirements, mass balances, etc. to allocate water. It features a GUI and provides a possibility to extend its functionality with user-defined variables and functions (in VBScript, JavaScript, Perl, or Python). Its main weaknesses in relation to the purpose of this study are license costs, slow runtime and the ability to represent only a simple linear operating rules.

Some simulation models can be used in either rule-based mode or optimization-driven mode such as RiverWare (Zagona et al., 2001) and Source (eWater, 2012; Welsh et al., 2013). The RiverWare model is based on Object Oriented Programming (OOP) paradigm. Users can create water resource system networks from pre-specified network objects such as reservoirs, stream gauges, canals, etc. using GUI. The rule-based simulation mode uses operating rules that need to be expressed in the RiverWare specific language, RiverWare Policy Language (RPL), by using a built-in syntax-directed editor. The optimization mode uses a pre-emptive goal programming algorithm and mixed-integer linear programming (MIP) to optimize user defined objectives according to their priorities. The MIP solver is used automatically to linearize any non-

linear variable at each time step. Its slow runtime, license requirement and limited custom coding make it unsuitable for this project’s purposes. The Source model includes a GUI for building and modifying the water resource network. The rule-based mode is able to model complex rules and processes and runs faster than the other mode but does not search for the most efficient solution. The latter uses the NetLP linear program to find minimum cost solution of allocating water through a network of links but can have longer run times for complex networks, smaller time steps or longer travel times than the rule-based mode. It also requires a license to run.

Table 1-1 summarizes the comparison of the mentioned models. The functionalities are listed in the order of preference for this project, i.e. the fast runtime being the most important due to the need to run many simulations during a single optimization run, and the flexible time-step being the least important. A model scored 1 against each functionality if it possessed the desired functionality, 0.5 if it had only partial functionality, and 0 if it did not have such functionality at all. The final scores show that the IRAS-2010 model provides the best application “fit” for this research project and was therefore selected for the simulation purposes.

Table 1-1. Comparison of the simulation models considered for this study.

Functionality	Fast runtime	Free licence	Custom coding (open source)	Complex operating rules	Flexible time-step	Final score
Software						
Rule-based						
Aquator	×	×	✓	✓	×	2
IRAS-2010	✓	✓	✓	<i>Limited</i>	✓	4.5
Optimization-driven						
WATHNET	✓	<i>Unclear</i>	<i>Limited</i>	<i>Limited</i>	✓	3.5
WRIMS	×	<i>XA solver needed</i>	<i>Limited</i>	×	✓	2.5
WEAP	×	×	✓	×	✓	2
Both modes available						
RiverWare	×	×	<i>Limited</i>	✓	✓	2.5
Source	×	×	✓	✓	✓	3

1.2.3. Optimization modelling

Optimization models seek to answer the question “What is the best possible course of action that I may follow?” (ReVelle, 2004), i.e., seeking the preferred action/arrangement among all possible ones. These models require a mathematical

problem formulation consisting of objective function(s) as a function(s) of design decision variables. Decision variables represent design choices such as the capacity or operational release rules of a reservoir in water resource management and planning problems. The feasibility of a design can be subject to equality and/or inequality constraints limiting the design possibilities. The constraints are used as restrictions on decision variable values (e.g., the possible range of capacities) or performance metrics of a system such as minimum river flow requirements that need to be satisfied.

Optimization problems can be single or multi/many-objective based on how many performance criteria are considered and how they are optimized for. A single objective (SO) problem consists of a single objective function and is defined as follows:

$$\text{Min } f(x)$$

$$\text{subject to } g_i(x) \leq 0 \quad \forall i \in \{1, \dots, m\}$$

$$h_j(x) = 0 \quad \forall j \in \{1, \dots, n\}$$

$$x \in \Omega$$

(Coello Coello, 2007)

1-1

where $x = [x_1, \dots, x_p]^T$ is a decision vector consisting of decision variables, Ω is a decision space, $f(x)$ is a scalar, and $g_i(x) \leq 0$ with $h_j(x) = 0$ are constraints that must be satisfied.

The objective function $f(x)$ can also consist of several objectives linearly combined into a single objective by weighting each accordingly (w_i):

$$\text{Min } f(x) = (w_1 f_1(x) + w_2 f_2(x) + \dots + w_n f_n(x))$$

1-2

This aggregation allows for traditional single objective optimization methods to be applied and has been widely used by water planners in the past as e.g. a single cost-benefit ratio. For instance, Cui and Kuczera (2003) minimize the aggregated capital cost and failure penalty of a proposed reservoir; Tu et al (2008) aggregate three performance objectives, satisfaction of low flow requirements and shortage indices for public and agricultural demands, to optimize reservoir operating rules; Padula et al (2013) minimize the capital and operating costs of the water supply infrastructure capacity expansion problem for South East England. However, if a monetary metric such as cost

is aggregated with non-monetary metrics such as environmental and social impacts, the latter must be monetized, which is not always available or even possible, or scaled based on decision makers preferences prior to the optimization. Decision makers very often seek only those solutions that reflect their prior knowledge about the problem, potentially missing out new alternative solutions. This decision bias has been identified by Gettys and Fisher (1979) as “cognitive hysteresis”. Optimizing conflicting objectives simultaneously may hide potentially relevant information about how these objectives interact with each other and which of their combinations lead to which outcomes. Hogarth (Hogarth, 1981) identifies this form of short-sightedness as “cognitive myopia”.

Many-objective optimization considers 4 or more objectives (Fleming et al., 2005; Reed et al., 2013) while multi-objective optimization involves only 2 or 3 objectives (Kang and Lansey, 2013; Kapelan et al., 2005; Mortazavi et al., 2012). Both allow for explicit optimization of each considered metric and instead of a single optimal solution provide a set of Pareto optimal solutions. A solution is Pareto optimal if and only if there exists no other feasible solution which, assuming minimization, would decrease some criterion without causing a simultaneous increase in at least one other criterion (Coello Coello, 2007). The decision makers are then able to perform a trade-off analysis to select a solution from the multi or many-objective space. Figure 1-1 illustrates the Pareto optimality: although solution A performs better in objective f_2 , solution B performs better in objective f_1 . There is a trade-off between objectives f_1 and f_2 ; decision makers must assess how much they are willing to sacrifice the performance of one objective in order to improve the performance of the other. The curve of solutions in Figure 1-1 is termed Pareto front or trade-off curve and all solutions on the Pareto front are non-dominated.

A solution is non-dominated, i.e., Pareto optimal, when there is no other solution that would perform better in all considered metric. Considering a minimization problem, vector u dominates vector v if and only if u is partially less than v (Coello Coello, 2007):

$$\forall i \in \{1, \dots, k\}: u_i \leq v_i \wedge \exists i \in \{1, \dots, k\}: u_i < v_i$$

1-3

The concept of dominance is illustrated by the blue boxes in Figure 1-1. Solution A is said to dominate the entire region depicted by the box which lower left-hand corner

starts with solution A. Any point inside this box exhibits worse performance in both objectives than solution A. Solution A is non-dominated as there exists no other feasible solution that would perform better in both objectives simultaneously.

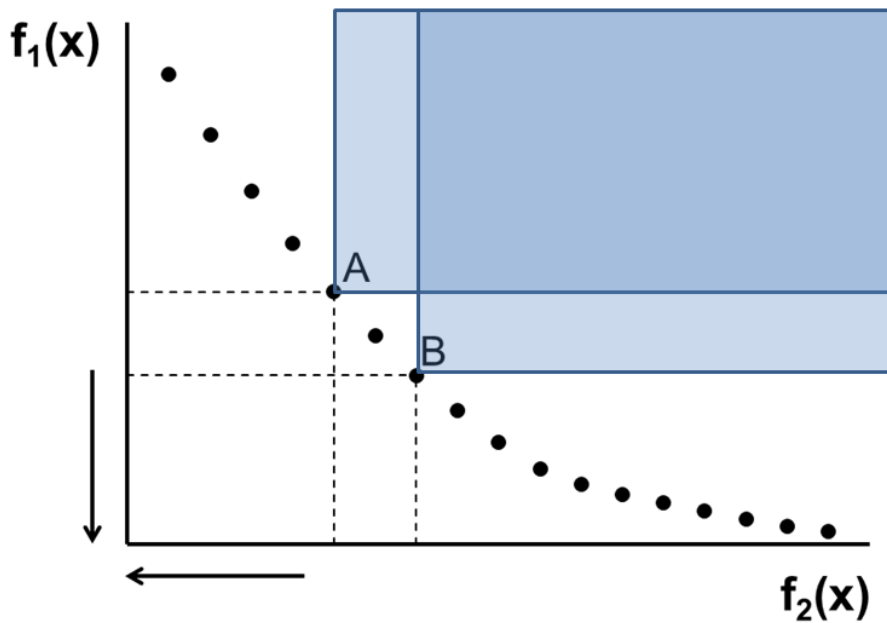


Figure 1-1. Pareto optimal front example of a two objective problem showing a trade-off between objectives f_1 and f_2 . The blue boxes illustrate a concept of dominance, e.g., solution A dominates the region depicted by the box which lower left-hand corner starts with point A. The direction of best performance is shown by arrows.

The general formulation of a many-objective problem is as follows:

$$\text{Min } F(x) = (f_1(x), f_2(x), \dots, f_k(x))$$

$$\text{subject to } g_i(x) \leq 0 \quad \forall i \in \{1, \dots, m\}$$

$$h_j(x) = 0 \quad \forall j \in \{1, \dots, n\}$$

$$x \in \Omega$$

(Coello Coello, 2007)

1-4

where $F(x)$ is a vector of individual objective functions $f_k(x)$.

1.2.3.1. Mathematical programming

Mathematical programming methods have long been used in water resource planning research and practice (Loucks and van Beek, 2006; Mays, 2005; ReVelle, 2004). These include linear and non-linear programming and dynamic programming, amongst many. Linear optimization models are very efficient in finding solutions to linear problems but when applied to complex water resource systems they require approximations and simplifications of the system's representation and problem objectives (Loucks and van

Beek, 2006). Mixed integer linear programming (MILP) reduces the need for continuous decision variables simplification. Decision variables in MILP can take a binary integer values representing a yes or no decision, i.e. if an option should be built or not (Mays, 2005). Padula et al. (2013) apply MILP to identify a least-cost plan for regional capacity expansion problem in South East England.

Dynamic programming (DP) (Bellman, 1952) divides the optimization problem into smaller sub-problems and solves each individually before identifying the overall optimum solution to the original problem. It works well with multi-stage decision problems but suffers from the ‘curse of dimensionality’ (Loucks and van Beek, 2006) as the number of optimization problems to be solved increases exponentially with the number of state variables. Braga et al. (Braga et al., 1985) applied DP for a proposed reservoir system planning in Sao Paulo, Brazil.

The limitations of these methods include the difficulty of representing the non-linearity of simulations and their potential to mask important performance trade-offs for real systems (Woodruff et al., 2013). Water systems often use non-linear rules and are likely subject to non-linear cost and benefit functions. Their complexity may mean that aggregation and simplification of performance measures are often required when using classical optimization methods. Stochastic dynamic programming (SDP) (Yakowitz, 1982; Yeh, 1985) has been developed to incorporate stochastic variables into DP. Stedinger et al. (Stedinger et al., 1984) apply SDP for optimizing reservoir operating rules for a single dam in the river Nile basin. Nevertheless, SDP might not be suitable for solving large ‘real-world’ water system problems (Castelletti et al., 2010) that are highly complex exhibiting non-linear, non-convex, high-dimensionality, i.e. requiring a large number of variables, characteristics and require considerations of multiple conflicting objectives. Multi-objective evolutionary algorithms (MOEAs) have been developed to effectively address these issues. MOEAs can help to overcome cognitive biases by discovering new solutions to new problems (Fogel, 1997). They are flexible and adaptive heuristic global search methods that simulate the process of natural evolution. The search is an iterative process that begins with a 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 lieu of 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.

MOEAs can handle large decision spaces and generate trade-offs (Coello Coello, 2007; Deb, 2001). By providing a set of alternative optimal solutions MOEAs allow for trade-off analysis to be incorporated into decision making process. When dealing with complex ‘real-world’ problems the “true” Pareto optimal set is unknown; a close approximation of the Pareto optimal set is therefore generally sought (Herman et al., 2014). For simplicity this is referred to as Pareto optimal in the following text. The suitability of applying MOEAs to real-world water resource management and planning problems when linked to non-linear simulation models has been widely recognized (Maier et al., 2014; Nicklow et al., 2010; Reed et al., 2013). MOEA approach was therefore chosen as the optimization method for this research project.

1.2.3.2. Robust optimization

Robust optimization (Mulvey et al., 1995) was developed to incorporate uncertainty and risk aversion directly into the optimization (Ben-Tal et al., 2009; Ben-Tal and Nemirovski, 2002; Bertsimas et al., 2011; Bertsimas and Sim, 2004; Watkins and McKinney, 1997). The focus of the optimization shifts from “optimality” to robustness. A robust solution performs satisfactorily well over a range of plausible future conditions rather than optimally under one. The metrics used to assess robustness of alternative solutions differ. In general, the robustness metrics can be divided into two groups: regret and satisficing measures (Herman et al., 2015). Regret reflects monetary or non-monetary cost of choosing incorrectly (Lempert and Collins, 2007a) or an incorrect choice of decision alternative (Savage, 1951). The former can be assessed as the deviation of a solution’s performance from its expected, i.e. average, performance across multiple future conditions (e.g., Kasprzyk et al., 2013) while the latter as the deviation of a solution’s performance from the desired performance under baseline conditions (e.g., Herman et al., 2015; Kwakkel et al., 2012). Satisficing reflects meeting specified performance requirements or reasonable performance (Simon, 1959). This is usually achieved by using a domain criterion (Schneller and Sphicas, 1983; Starr, 1962), which specifies the fraction of all considered future states where the solution performs satisfactorily (e.g., Beh et al., 2015; Herman et al., 2014; Moody and Brown, 2013).

Ray et al (Ray et al., 2013) argue that standard deviation and the spread of performance values across all scenarios are equally penalizing deviations above or below the expected value and can be used interchangeably. Another metric used in robust

optimization is a minimax criterion that minimizes the maximum risk or the worst-case performance. Giuliani et al. (2014) optimize operating policies of Conowingo Dam on the Lower Susquehanna River, USA, using the minimax approach, where the worst-case objective values are considered. Mortazavi et al. (Mortazavi-Naeini et al., 2015) compare the minimax robustness criterion with minimizing the spread of objective values across all considered scenarios in multi-objective robust optimization combined with stochastic simulation to optimize Lower Hunter urban bulk water supply infrastructure and drought contingency measures in New South Wales, Australia, considering 10,000 synthetic hydrologic scenarios and 2 demand scenarios. The two approaches provide significantly different results and conclusions on which alternative designs may be considered robust. Kwakkel et al. (Kwakkel et al., 2014) combine objective values with robustness measure such that the median objective value multiplied by its interquartile distance is optimized. All of these metrics assess robustness differently and would provide different advice on robust decisions; it is important to understand what exactly decision makers strive to achieve. Designing appropriate problem formulation should therefore directly involve the decision makers' opinions for each individual problem. Robust optimization approach was employed in this project with a combination of performance metric assessments discussed directly with involved decision makers.

1.3. Water resource systems planning

Planning into the future involves management of risk that may arise from various sources of uncertainty. Deterministic models are no longer adequate to represent future conditions where most of the data and parameters are unknown or uncertain (Pallottino et al., 2005). Uncertainty inherent to water resources maybe caused by natural variability in external conditions or a fundamental lack of knowledge or understanding, i.e., ambiguity (Simonovic, 2009). There are three sources of ambiguity: model uncertainty, arising from approximation and simplification of the modelled system, parameter uncertainty such as measurement and systematic errors, and decision uncertainty, which arises from the diversity of perspectives on the socio-economic and environmental value of water resources (Walker et al., 2003). Water resource planning problems are a classic example of a “wicked” problem (Liebman, 1976; Reed and Kasprzyk, 2009; Rittel and Webber, 1973).

Instead of defining “optimality” under historical or narrowly defined conditions, planners have been seeking “robustness” for planning under uncertainty (Ben-Haim,

2000; Haasnoot et al., 2013; Herman et al., 2015; Lempert et al., 2003). A robust system is one that performs well or satisfactorily well over a broad range of plausible future conditions rather than optimally under one. This provides low regret solutions achieving sufficient benefits no matter what future unfolds and which stakeholder assesses its success (Lempert et al., 2003).

Robustness is increasingly incorporated as a goal in many-objective water systems planning studies (Giuliani et al., 2014; Hamarat et al., 2014; Herman et al., 2014; Kasprzyk et al., 2013; Kasprzyk et al., 2012). Planning approaches seeking robustness have also been investigated in the UK's water resource planning context (Borgomeo et al., 2014; Matrosov et al., 2013a; Matrosov et al., 2013b) but none of those have incorporated robustness into many-objective optimization.

Several planning methods have been developed to consider uncertainty and seek robustness in water resources planning. These include Decision Scaling, Info-Gap Decision Theory (Info-Gap), Robust Decision Making (RDM) and Risk-based analysis, which are all described in the following subsections. .

These approaches cater mainly for static robustness of a plan against plausible future states (Dessai and Hulme, 2007; Hallegatte et al., 2012) which does not consider plans that are able to change over time. In contrast, dynamic robustness explicitly values the flexibility of a system (Walker et al., 2013). Most planning problems need to deal with future uncertainties that cannot be reduced by gathering more information and are not statistical in nature (Haasnoot et al., 2011). A plan that can adapt to changing conditions is well suited to problems facing deep uncertainty (Walker et al., 2013). Flexibility provides the right but no obligation to take an action (Cardin and de Neufville, 2008); flexible systems thus allow the interventions to be introduced when and where they are needed and overcome the development of unnecessary capacity (de Neufville et al., 2006). Planning approaches incorporating the dynamic robustness include Real options analysis and recently developed Dynamic Adaptive Policy Pathways, which are also discussed in following subsections.

The matrix in Figure 1-2 divides the planning approaches based on what solution they seek (optimal, robust, or flexible) and what modelling method they primarily use (simulation, optimization, or simulation together with optimization).

		<i>Primary solution aim</i>		
		Optimal	Robust	Flexible
<i>Primary modelling method</i>	Simulation		Decision Scaling Info-Gap RDM	
	Simulation-optimization		Risk-based analysis	Adaptation Pathways Real options
	Optimization	Capacity expansion		

Figure 1-2. Matrix of water resources planning approaches based primary modelling method and solution aim.

1.3.1. Planning approaches seeking optimal solutions

1.3.1.1. Capacity expansion

Increasing water demand and reduced or altered water supply result in a need to expand the water system supply capacity to maintain the supply-demand balance. When planning for future water supply system expansion decision makers have to decide where, when and by how much to increase the capacity of their supply system as the demand increases. Often there are many possible combinations of supply and demand management interventions to consider. Planners often do not possess enough time and computational resources to evaluate all possible combinations (portfolios) of interventions and their schedules using detailed simulation models. Optimization methods are therefore more often used to identify the preferred plan (Loucks and van Beek, 2006). A classical objective function minimizes the net present value of the total cost of the expansion often including monetized non-monetary metrics such as environmental and social impacts. The problem is often constrained to satisfy minimum desired service levels such as “filling in” the supply-demand gap as it occurs. Figure 1-3 illustrates the capacity expansion as the supply-demand gap arises which is shown as deficit by the black line. The coloured blocks show the increased capacity in ML/d obtained by implementing additional interventions.

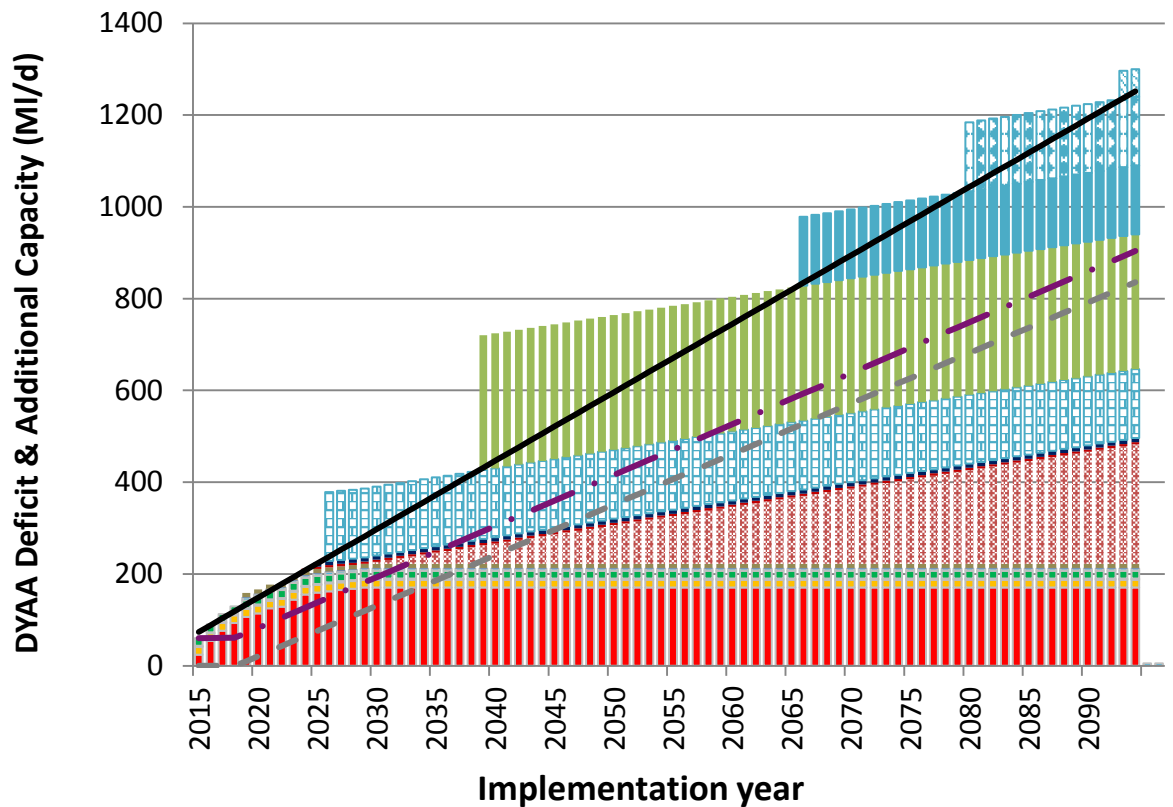


Figure 1-3. Bridging the supply-demand gap (deficit) shown by the black line by capacity expansion (coloured blocks). The plot is used only for illustration purposes (courtesy of Anna Wallen).

1.3.2. Planning approaches seeking robust solutions

The simulation-based planning approaches seeking robust solutions (Decision Scaling, Info-Gap, RDM) incorporate a sensitivity analysis in one form or another to better inform the decision-making process. Sensitivity analysis allows assessing how sensitive the output of a mathematical model is to different sources of uncertainty in its input (Saltelli et al., 2008). This aids the understanding of the model behaviour and from the water resources planning perspective understanding of how certain decisions or external conditions affect the behaviour of a system. There are several approaches to perform sensitivity analysis that may be divided into local and global analyses. In the local sensitivity analysis variables or parameters are varied one at a time by a small amount around some fixed point (Wainwright et al., 2014). In the global sensitivity analysis (e.g., Sobol sensitivity analysis (Sobol, 2001), Method of Morris (Morris, 1991)) variables or parameters are varied simultaneously over their entire plausible range and the effects on the output of both individual variables and parameters and interactions between them are assessed (Wainwright et al., 2014). The Decision Scaling and RDM are an example of a global sensitivity analysis whilst the Info-Gap applies local sensitivity analysis.

1.3.2.1. Decision Scaling

Decision Scaling method proposed by Brown et al. (2012) extends the scenario-neutral approach proposed by Prudhomme et al. (2010) which is based on global sensitivity analysis of catchment responses to plausible climate changes. The study used 17 Global Climate Model (GCM) scenarios with 4 greenhouse gas emissions scenarios to estimate changes in precipitation and temperature and their time series. These were used in a hydrological model for flood sensitivity testing. A climate response function was then created to simulate future flood risk in the UK as a function of climate change. This function characterizes a system's response to climate and is subsequently used to visualize and assess the impacts of climate change projections. By using the sensitivity of a given catchment information, climate model projections that would result in adverse effects such as violating certain operational thresholds can be identified. Prudhomme et al. (2010) suggest that the likelihood of such projections could then be derived.

Decision Scaling advocates a “bottom-up” approach where a system is first assessed to identify the most important thresholds in terms of decision-relevant risks. Climate projections are then used to identify climate conditions where the decision thresholds are crossed and to estimate probabilities associated with such conditions. This method shifts the focus from what the future climate might be to more specific question of if the climate that favours decision plan A is more or less likely than the climate that favours decision plan B (Brown et al., 2012). The decision alternatives are usually assumed to be identified a priori.

The Decision Scaling approach consists of three general stages as described by Brown et al (2012). The first stage begins with decision analysis where climate hazards, performance indicators and their thresholds, which when crossed indicate that adaptive action is needed, are identified. The second stage involves risk discovery, i.e., identification of climate states that cause risk. This includes sensitivity analysis to identify “risky” climate conditions, development of a climate response function and dividing the climate space according to optimal solutions. The benefit here is that the range of considered climate states is not limited by any probability distribution. The final stage proceeds with estimating “climate informed” probabilities of climate states and considering the residual risk (Brown and Baorang, 2011).

Brown et al (2012) demonstrate the approach on the Quabbin-Wachusett reservoir system supplying Boston, Massachusetts. A climate response model is constructed that

allows reservoir reliability to be estimated from a large ensemble of possible future conditions without being computationally expensive. The model predicts reservoir reliability as a function of mean climate statistics (precipitation and temperature as demonstrated in Vogel et al. (2001). Turner et al. (2014b) use this approach to assess Melbourne’s bulk water supply system performance in Australia using a reliability and vulnerability thresholds. Ghile et al. (2014) evaluate water supply infrastructure investments in the Upper and Middle Niger River basin using multiple performance metrics.

Decision Scaling is able to identify system vulnerabilities that “top down” approaches may struggle to discover (Turner et al., 2014b) and has demonstrated the importance of robustness indicators considering climate uncertainty (Moody and Brown, 2013).

1.3.2.2. Ingo-Gap Decision Theory

Proposed by Ben-Haim (2006), Info-Gap Decision Theory (Info-gap) is a non-probabilistic method used to evaluate robustness of decisions under ‘severe’ uncertainty (comparable to deep uncertainty) given the minimum performance requirements. Conditions of severe uncertainty lead to an ‘information gap’ between what is known and what needs to be known in order to make a sound decision (Ben-Haim, 2004). Info-gap compares the performance of candidate intervention plans under a wide range of plausible futures (robustness) and their potential rewards (opportuneness) under favourable conditions (Hall et al., 2012a). The method focuses on identifying the uncertainty horizon (i.e., the amount of uncertainty) that can be withstood before the system fails; it proceeds outwards from an initial “best-estimate”, i.e., the expected future conditions which must be known or estimated, until it identifies thresholds causing poor performance (Matrosov et al., 2013b). Info-gap can thus be seen as a technique using local sensitivity analysis centred at a particular reference strategy or intervention plan (Herman et al., 2014).

The uncertainty in Info-gap is characterized by a group of nested sets illustrated in Figure 1-4 where the parameter \tilde{u} represents the best estimate of future uncertain parameter u . The deviation between these two parameters is scaled by h which then represents the horizon of uncertainty α (Matrosov et al., 2013b). Each considered intervention plan is simulated against each horizon. This provides a range of performances or rewards for each plan in each uncertainty horizon where the minimum level of performance refers to robustness while the maximum level to opportuneness (Ben-Haim, 2006). The robustness measure reflects the maximum horizon of

uncertainty that can be tolerated by the plan whilst ensuring satisfactory performance above a predefined performance threshold. The opportuneness refers to the minimum level of uncertainty needed to obtain performance “windfall” or favourable performance (Ben-Haim, 2006). These measures are then usually plotted as functions of the horizon of uncertainty and performance levels which allows for direct comparison between the considered intervention plans.

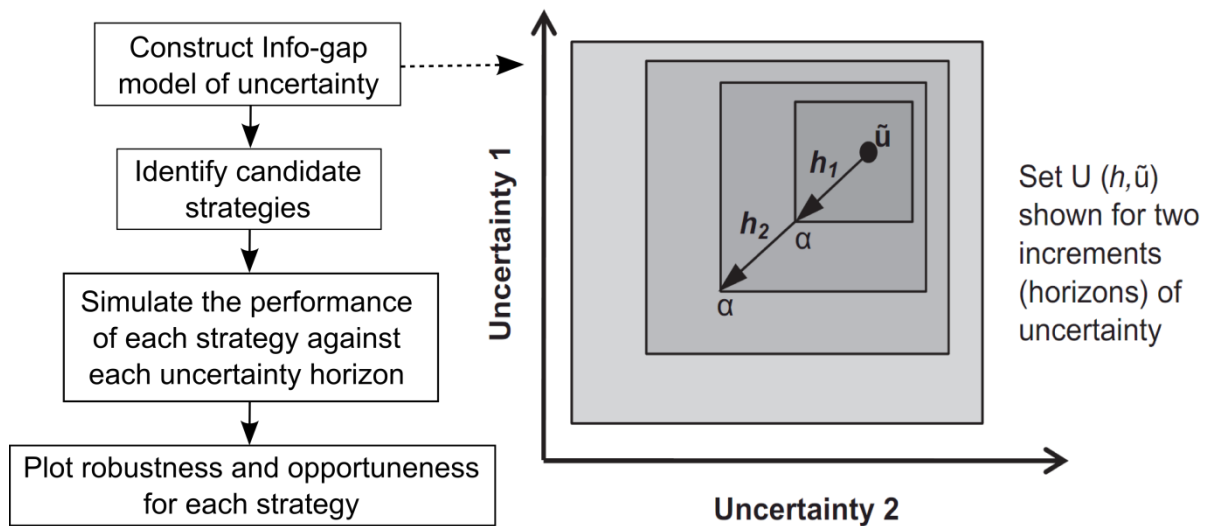


Figure 1-4. Info-gap approach framework (adapted from Hall et al., 2012a). The schematic of an Info-Gap uncertainty model (adapted from Matrosov et al., 2013b) shows the scaling (h) of each horizon of uncertainty (α) from the best estimate (\tilde{u}). The uncertainty model can also be asymmetric.

Hine and Hall (2010) perform Info-gap analysis to assess the sensitivity of flood management alternatives to a flood model uncertainty in the River Trent catchment in the UK. Korteling et al. (2013) apply the Info-gap decision theory to evaluate robustness of supply and demand management interventions under supply, demand and energy cost uncertainty for the Drift reservoir supply system in Cornwall, UK and compare the approach to the current water supply system planning in the UK. Hall et al. (2012a) compare the Robust Decision Making (RDM) (Lempert et al., 2003) approach and Info-gap theory for identifying robust climate policies aiming to reduce greenhouse gas emissions. The study concludes that both approaches provide similar results but different insights for the performance and vulnerabilities of the considered policies. Similarly, Matrosov et al. (2013b) compare the RDM and Info-gap methodologies using the River Thames basin water supply capacity expansion case study in the UK. They argue for joint application of the two approaches which reveals additional important information about the system that would not be available if only one method was implemented.

Although the Info-gap method provides the means to compare the robustness and opportuneness of alternative strategies simultaneously, it does not quantify their vulnerabilities (Matrosova et al., 2013b). The method also assumes that the best estimate of uncertainty can be identified; however, in the situations of deep uncertainty such estimate may be difficult to determine. Info-gap thus seeks local robustness in the subset of uncertainty around the best estimate instead of global robustness in the whole uncertainty space (Herman et al., 2014; Matrosova et al., 2013b). Decisions are assumed to be known prior to the analysis (Hall et al., 2012a).

1.3.2.3. Robust Decision Making

Robust Decision Making (RDM) is a planning framework designed to help decision makers formulate robust plans for the future under conditions of ‘deep’ uncertainty (Lempert and Collins, 2007b). RDM favours robustness over optimality and assumes a strategy that is able to satisfy minimum performance criteria (‘satisfice’) over a wide range of plausible futures is preferred by planners. ‘Deep’ uncertainty refers to the fact that analysts either do not know or do not agree on the probability distributions that govern one or more sources of uncertainty.

RDM is multi-step process that requires a significant stakeholder engagement. The process begins with the selection of one or more candidate strategies. Often it makes sense for the current system to be one of the candidate strategies assessed (the ‘baseline’); strategies proposed or favoured by planners are obvious choices for other candidate strategies. A system simulation model is used to simulate the performance of the candidate strategy under a wide spectrum of plausible futures, where each future is a combination of uncertain parameters (e.g., level of sustainability reductions, climate scenarios and demand levels). Performance of the system can be evaluated using one or multiple performance criteria that have the approval of stakeholders. Decision-maker approved performance thresholds then help determine if a strategy evaluated by simulating it under a particular scenario is a success or failure. At this stage the scenario discovery process (Bryant and Lempert, 2010; Groves and Lempert, 2007; Lempert et al., 2006) is run. Typically, a statistical data mining algorithm (such as the Patient Rule Induction Method, PRIM) (Friedman and Fisher, 1999) is used to determine the vulnerable realm of the preferred strategy, i.e., which combinations of future conditions or ‘scenarios’, cause the strategy to fail in one or more ways. Planners are meant to use this information to discard or further improve the candidate strategy leading to progressively improved strategies that hedge against those conditions which most

frequently cause unacceptable system failures. The new strategies can be resubmitted into the RDM framework and the process repeated iteratively until a suitably robust strategy is found. Figure 1-5 illustrates the RDM framework.

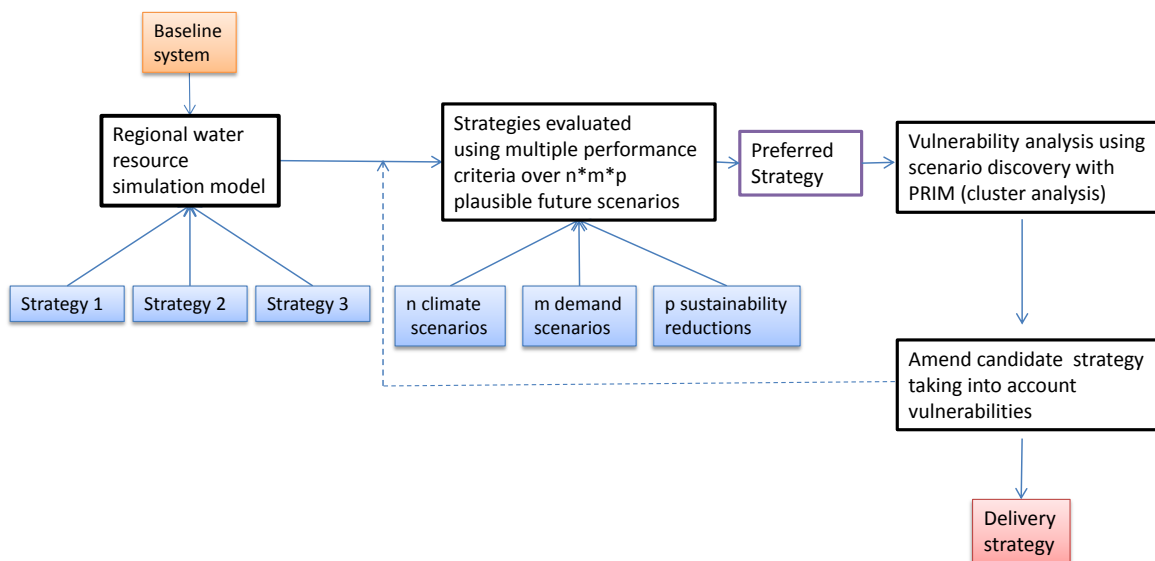


Figure 1-5. Schematic of an RDM framework implementation (designed by Evgenii Matrosov). Candidate strategies and the baseline (current) system are submitted into the robust decision making framework. The strategies are simulated under a multitude of scenarios (covering for example climate change, demand and sustainability reduction uncertainties) and their performance is compared. A preferred strategy is selected to undergo a vulnerability analysis to determine under what future conditions the preferred strategy is likely to fail. Ameliorations to the strategy can then be proposed before resubmitting the improved strategy back into the scenario simulation step.

Groves and Lempert (2007) use RDM to identify vulnerabilities of the California department of Water Resources' California Water Plan (CWP). Lempert and Groves (2010) apply RDM to identify climate change vulnerabilities of the Inland Empire Utilities Agency's 2005 Integrated Water Resource Plan and to develop a more robust plan including adaptive strategies. RDM approach was also investigated in UK studies; Matrosov et al. (2013a; 2013c) compare the RDM approach to the economic optimization and the Info-Gap analysis, respectively, when applied to the Thames basin capacity expansion case study.

These studies however do not emphasize how decision alternatives should be generated in support of the decision-making process. Multi-objective Robust Decision Making (MORDM) proposed by Kasprzyk et al. (2013) uses MOEA optimization to generate trade-offs across a diverse set of planning alternatives prior to assessing their robustness. This overcomes the possibility of the candidate strategies fed into the RDM framework to be infeasible or severely suboptimal (Reed et al., 2013). Herman et al. (2015) apply the MORDM framework to a "Research Triangle" region of North

Carolina in the US to optimize and assess the robustness of four interconnected water utilities strategies. The robustness of candidate strategies is however still assessed post-optimization, i.e., the robustness is not explicitly incorporated into the search for candidate strategies process itself.

1.3.2.4. Risk-based analysis

Risk may be defined as the quantification of uncertainties that may have adverse impact on a water resource system performance (Vucetic and Simonovic, 2011). Quantifying risk involves consideration of three important aspects: what can happen, how likely it is to happen, and what would the consequences be (Simonovic, 2009). The risk-based approach explicitly considers the probability or likelihood and consequences of adverse effects (Hall et al., 2012b).

The risk-based water resource investment planning approach involves several steps (e.g. Borgomeo et al., 2014). First, a probability distribution of future projections such as temperature and precipitation is estimated and sampled. For each such sample a number of realizations of future conditions are produced. These future conditions are used as input into a water resource system simulation model to evaluate a predefined set of alternative investment plans. Based on the simulation output a probability of failure for each alternative plan is estimated. Because the probability of failure cannot be predicted precisely a distribution of such probabilities is estimated and used to calculate the probability of failure (Hall et al., 2012b). The alternative plans are then compared based on their ability to cost-effectively reduce the probability of failing.

Jones (2001) and Johnson and Weaver (2009) describe a risk-based approach where risks are identified and managed using GCM projections. Hall et al. (2012b) propose a risk-based approach to incorporate UKCP09 projections (Murphy et al., 2009) into water resource planning in England and Borgomeo et al (2014) apply this approach to the London's water supply system planning problem in the River Thames basin, UK. Turner et al (2014a) highlight the benefits of using the risk-based approach when compared to the UK's conventional planning approach using the Ennerdale supply system case study in West Cumbria, UK.

Although the risk-based approach incorporates uncertainty into the planning process by extensive sampling and is able to connect the results directly with risk indicators used in practice (Borgomeo et al., 2014), it has several limitations. For instance, the probability distribution of uncertainties that this approach relies on requires a prior knowledge (Vucetic and Simonovic, 2011); this may, however, not be appropriate for situations of

deep uncertainty (Knight, 1921) where assigning probabilities to future states is problematic (Kasprzyk et al., 2013; Lempert, 2002; Lempert et al., 2003; Walker et al., 2013). Turner and Jeffrey (2015) conducted a survey between UK's water practitioners and found that many indicated "distrust in the plausibility of synthetic droughts generated by stochastic models" and prefer designing a system whilst considering real and tangible events. The probabilistic metrics are also perceived difficult to communicate to stakeholders (Turner and Jeffrey, 2015). Despite these limitations on the use of probabilities, risk based approaches are promising and are viable option for aiding water resource plan decision-making. Hall and Borgomeo (2013) argue: "transparently implemented risk analysis provides a mechanism for exposing the implications of uncertainty for outcomes that people value. It provides a structure for integrating multiple perspectives and objectives with respect to water resources systems in a way that, at its best, provides a platform for deliberative decision processes and expert critique".

1.3.3. Planning approaches seeking flexibility

1.3.3.1. Real options

Real options allow for recourse, i.e., change, in a physical design or operations of a system to respond to changing conditions (Jeuland and Whittington, 2014). Such options may arise from operational flexibility or from the possibility of delaying investments until more information about future conditions becomes available (Steinschneider and Brown, 2012). Real options therefore provide for and value adaptive flexibility. The concept of real options originated in the field of finance (Myers, 1984) but since then it has become a recognized approach for climate change adaptation investment decisions (Dobes, 2008; Linquti and Vonortas, 2012; Woodward et al., 2014). The benefits of applying real options analysis in water resource planning include not only reduced or delayed financial costs to water companies but may provide better security of supply and environmental standards to water companies' customers and communities for lower water bills (NERA, 2012).

Decision Trees and Dynamic Programming are the most widely applied methods for real options analysis (Cardin and de Neufville, 2008; NERA, 2012). Figure 1-6 illustrates a real options approach based on a decision tree analysis. Intervention strategies are represented as decision trees with multiple paths into the future, rather than single paths fixed over the planning horizon (Woodward et al., 2014). The yellow rectangles represent a decision which could be taken or not. The green circle illustrates

a plausible future condition associated with the probability of its severity. Based on how this future condition unfolds another decision is considered, creating a tree like pathways. Each pathway is associated with the net present value of the whole plan on the pathway. An adaptable intervention strategy therefore consists of paths at each planning period, where each path corresponds to a set of intervention measures.

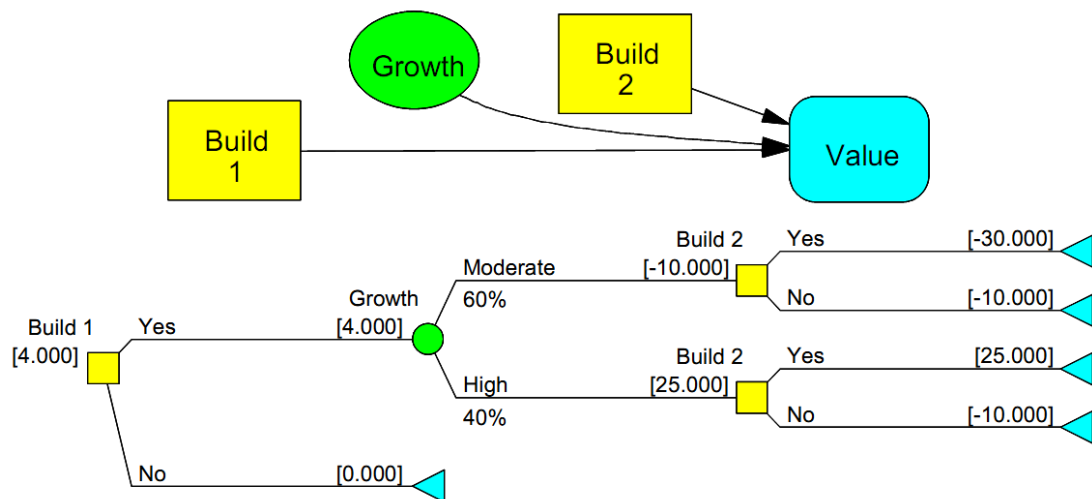


Figure 1-6. Example of a decision tree approach (adapted from NERA, 2012)

Jeuland and Whittington (2014) combine the real options analysis with sensitivity analysis in the form of RDM to a multipurpose dam case study on the Blue Nile river in Ethiopia. The assumed changes and probabilities of 7 future hydrological and 3 demand conditions are incorporated in the form of scenarios. The alternative designs that include the selection, sizing, and sequencing of dams as well as reservoir operating rules are identified a priori. The approach then uses Monte Carlo simulation to produce the downside risk (10th percentile of the cumulative distribution of simulated Net Present Value (NPV)), expected value, and upside potential (90th percentile of the NPV distribution) of alternative designs. These are then transformed into relative measures which are used for comparison between the alternatives using RDM principles to identify robust solutions.

Woodward et al. (2014) combine the concepts of real options with multi-objective optimization to assess robustness of potential flood risk management alternatives in the River Thames estuary in the UK. The flexibility of an option is evaluated as the difference between options with embedded flexibility, i.e., real options, and an option identified via deterministic optimization (where only historical conditions are considered). The decision tree approach was used to create alternative design pathways

where intervention measures were allowed to be brought into effect at the beginning or the middle of the planning horizon. The latter is where the pathways diverge.

All of these studies incorporate probabilistic distribution of uncertainties which, as already discussed, may not be appropriate in cases of deep uncertainty and consider only monetary objectives. A report investigating real options approach for the application to the UK water resource planning (NERA, 2012) identified several benefits and limitations of this technique. In particular, the approach is able to evaluate alternative plans more accurately than the current practice. It also provides more realistic view of the future thus often reducing conflicts and enquiries about long-term plans that in the current practice do not embed flexibility. The potential limitations include computational practicality in terms of evaluating many possible alternatives and the complexity of results that may require more time and effort in communication of the results. The approach, however, was assessed using mathematical programming technique which is currently applied in practice and whose limitations were discussed in section 1.2.3.1. The computational complexity could be addressed by the use of more efficient optimization techniques such as multi-objective evolutionary algorithms (discussed in section 1.2.3).

1.3.3.2. Dynamic Adaptive Policy Pathways

Proposed by Haasnoot et al. (2013), Dynamic Adaptive Policy Pathways combines two methods for decision making under uncertainty that incorporate flexibility – Adaptive Policymaking (Walker et al., 2001) and Adaptation Pathways (Haasnoot et al., 2012).

The Adaptive Policymaking (APM) is a theoretical approach for developing contingency planning to adapt a basic plan according to new information when it becomes available (Walker et al., 2001). It argues for the importance of monitoring and pre-specification of responses to when a plan or policy no longer achieves satisfactory performance (Kwakkel et al., 2010). Signposts are used to track the performance and signpost triggers are used to determine when the additional actions should be implemented. The general idea is to design a basic plan with immediate actions, establish a monitoring system, track the signposts and adapt the basic plan once the trigger values are detected. Example applications are demonstrated by e.g., Kwakkel et al. (Kwakkel et al., 2010), who apply the APM principles to the Schiphol Airport long-term development case study, and Hamarat et al. (Hamarat et al., 2014), who combine the APM approach with multi-objective robust optimization to assess possible

adaptation of EU energy production towards renewable energy generation and lower carbon emissions considering 46 plausible future conditions.

Adaptation Pathways is an analytical approach to develop sequencing of possible actions to adapt to changing external conditions (Haasnoot et al., 2012). Adaptation tipping points (ATPs) (Kwadijk et al., 2010) are used to specify conditions under which a plan is no longer meeting its objectives, a plan’s “sell-by date”, which are scenario dependent. When such ATP is reached, additional actions are required, which results in a sequence of possible actions after each ATP in form of pathways or adaptation trees. This leads to the Adaptation Pathways map that defines alternative paths that satisfy a pre-specified minimum performance level to arrive to the same desired point in the future (Haasnoot et al., 2013). An example of such map is shown in Figure 1-7. The ATP points (or terminals) illustrate when the plan requires adaptation and the transfer stations indicate the available transfers from one pathway to another. The example shows that some actions are required in the near future. However, choosing action B may be inadequate as this plan quickly reaches its ATP and requires additional actions. Taking action C involves a risk; if scenario X is realized, this plan will also need to adapt with additional actions (shown by the green dashed line in Figure 1-7). Decision-makers can thus make an informed decision and choose a dynamic adaptive plan which is able to achieve their intended objectives despite the myriad of uncertainties.

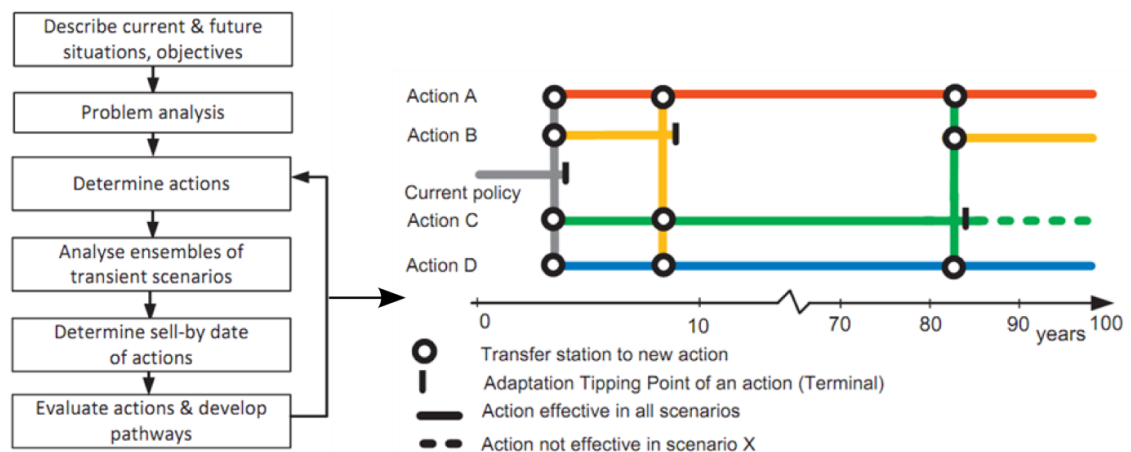


Figure 1-7. Adaptation Pathways approach framework (adapted from Haasnoot et al., 2012) and Adaptation Pathways map (adapted from Haasnoot et al., 2013)

The Dynamic Adaptive Policy Pathways approach consists of a transient scenario analysis where vulnerabilities and opportunities in a system under uncertainty are identified. Different actions to address these vulnerabilities are specified and the Adaptation pathways map is produced. The preferred plan is the chosen from the map

and a monitoring system is put in place to track the plan's performance. Haasnoot et al. (2013) demonstrate the approach on the long-term water management problem in the lower Rhine Delta in Netherlands. Future uncertainties are represented by two climate change scenarios and two socio-economic scenarios; the possible interventions include flood management actions, supply water actions such as modifications to reservoir levels, and demand reduction actions. Kwakkel et al. (2014) extend this approach with the use of multi-objective robust optimization to identify promising adaptation pathways. The methodology is illustrated on a hypothetical flood risk management case study considering a range of climate and land use change, fragility of dikes, flood damage, and policy uncertainties.

The Dynamic Adaptive Policy Pathways approach stimulates and aids the inclusion of adaptation into planning by explicitly identifying actions that may need to be implemented now to keep options open into the future and actions that can be postponed (Haasnoot et al., 2013). However, stakeholders, policy and decision makers in the UK prefer any changes to the established planning process to be introduced gradually; this approach currently poses too big a challenge to be implemented in practice.

1.3.4. Summary

Each of the planning approaches described above (apart from the Capacity expansion which is already used by water resource planners in the UK) was assessed for suitability to this research project. Several criteria in order of their importance included the ease of embedding the method into the current planning approach in the UK, the ease of explaining and visualizing the solutions, the ease of explaining the method to stakeholders, computational complexity and if the method could provide automatically linked simulation with optimization with search for robustness and flexibility. Table 1-2 summarizes the benefits and limitations of each planning approach against the criteria. The Risk-based analysis and the proposed approach in this thesis have been found to be the most suitable methods for the current UK planning approach improvements. The latter however is proposed to be embedded step by step introducing minimal required changes to the current planning approach in each step to allow for easier and smoother transition which is illustrated in Figure 1-8.

Table 1-2. Summary of the planning approaches' suitability for this project.

Criteria	Ease of embedding into UK planning	Results communicability to stakeholders	Approach communicability to stakeholders	Computational complexity	Automatic search for robustness and flexibility
Decision Scaling	Medium	Medium	Medium	Medium	No
Info-Gap	Medium	Medium	Low	Medium	No
RDM	Medium	Medium	Low	Medium	No
Risk-based analysis	Medium	Medium	Medium	High	Yes
Adaptation pathways	Low	Low	Low	High	Yes
Real options	High	Low	Medium	High	Yes
Proposed approach	High	Medium	Medium	High	Yes

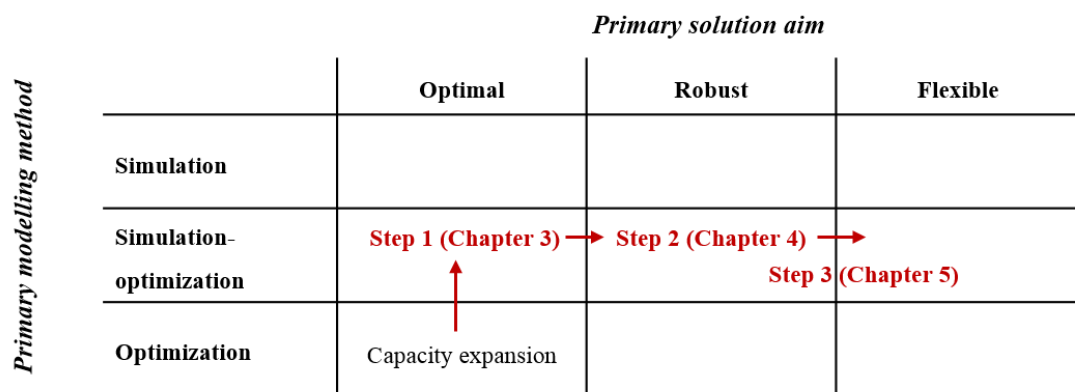


Figure 1-8. Proposed approach step-wise improvements to the current planning approach in the UK.

1.4. Case study

1.4.1. Thames basin description

The Thames basin is located in the south-east of England and is the driest part of Britain with an average annual precipitation of just 708mm (assessed between 1970 and 2000 on a major part of the catchment upstream of Teddington Weir shown in Figure 1-9 by grey separating line using the National River Flow Archive monthly precipitation records available upon request) whilst the national average is 897mm (British Geological Survey). The sub-catchment water balance analysis conducted here instead

of the whole Thames catchment is due to the limited data availability (precipitation record and licensed abstraction data). The total precipitation in summer (June, July and August) is on average 35mm lower than the precipitation in winter (December, January, February) when assessed between 1970 and 2000. Only a fraction of precipitation turns into the effective rainfall, i.e. the amount of precipitation stored in the soil from the rainfall after evapotranspiration and runoff. Based on the simplified precipitation-effective rainfall relationship (Figure 1-10) the effective rainfall in the Thames basin represents approximately 40% of the rainfall in winter and 35% of the rainfall in summer (Figure 1-11). In reality, the effective rainfall is influenced by many factors such as climate, soil type and structure, topography, etc. and such data should be used to provide more accurate effective rainfall estimation.

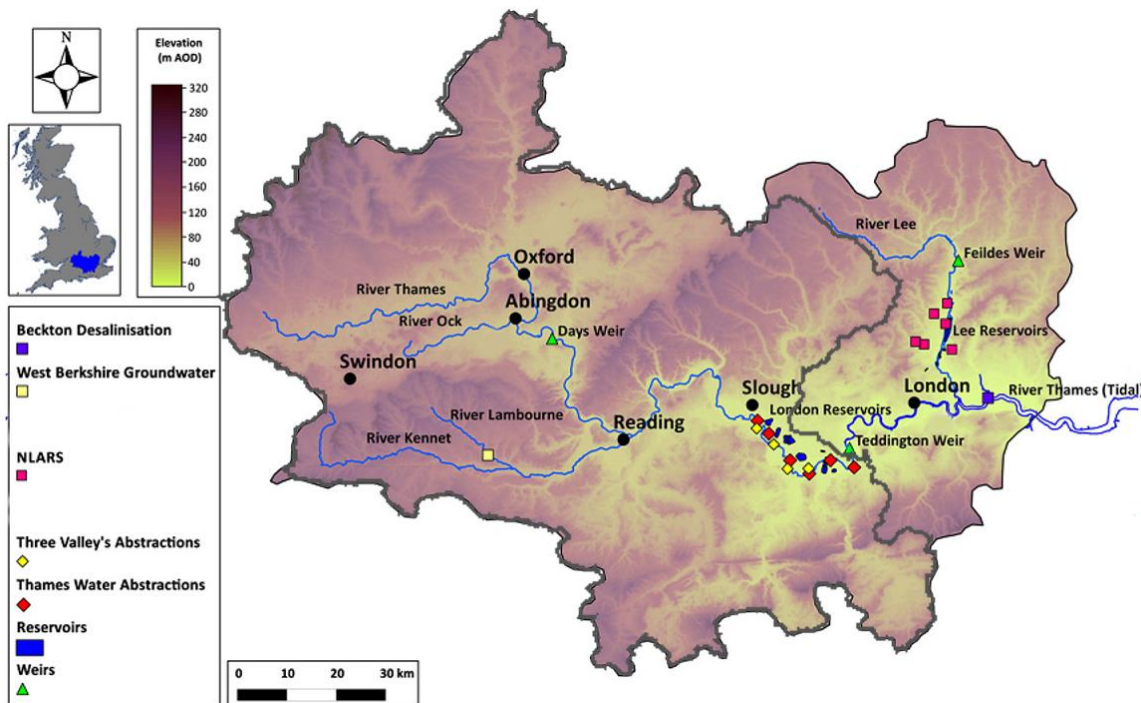


Figure 1-9. River Thames basin schematic showing the River Thames, its tributaries and major urban areas (adapted from Matrosov et al., 2011). The sub-catchment upstream of the Teddington Weir shown by grey line was used for the effective rainfall and CAMS estimations. Reservoirs are located to the west of London on the River Thames (London Reservoirs) and in the Lee Valley (Lee Reservoirs) and are all interconnected and referred to as London Aggregate Storage (LAS). WBGW is located in the south-west of the basin whilst NLARS in the Lee Valley. The desalination plant is in the Thames Estuary east of London.

The population density in the basin is four times higher than that of the rest of England. Water from the River Thames is used to supply a large proportion of the domestic and industrial water needs. The Catchment Abstraction Management Strategies (CAMS) regulated by the Environment Agency (EA) specify the abstraction licenses in the basin which restrict the daily and annual volume of water each license holder is allowed to abstract from the river (Environment Agency, 2010). The Thames basin CAMS licenses

upstream of the Teddington Weir obtained from the EA were used to estimate the proportion of the effective rainfall being depleted for public water supply. On average 690 ML/d is licensed for public water supply abstraction upstream of Teddington Weir (the licensed volumes vary between months of the year). The sub-catchment upstream of the Teddington Weir covers an area of 9,948km² (Centre for Ecology & Hydrology). 1 mm of rain corresponds to 1 litre of water over surface area of 1 m². From this relationship the volume of effective rainfall per month over the whole sub-catchment was calculated and compared to the licensed abstraction average monthly volumes. It was found that the public water supply licensed abstraction constitutes approximately 32% of the effective rainfall which corresponds with Thames Water's estimations that more than half of the effective rainfall is licensed for abstraction and around 80% of that, i.e. approximately 40% of the effective rainfall, is used for public water supply (Thames Water, 2014).

More than half of the effective rainfall is licensed for abstraction and around 80% of that, i.e. approximately 40% of the effective rainfall, is used for public water supply (Thames Water, 2014).

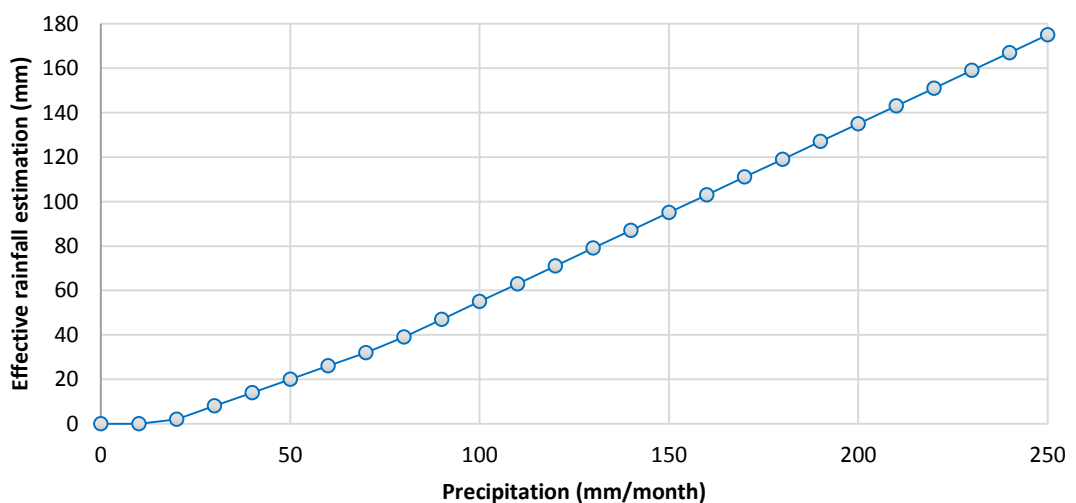


Figure 1-10. Simplified precipitation/effective rainfall relationship (Natural Resources Management and Environmental Department).

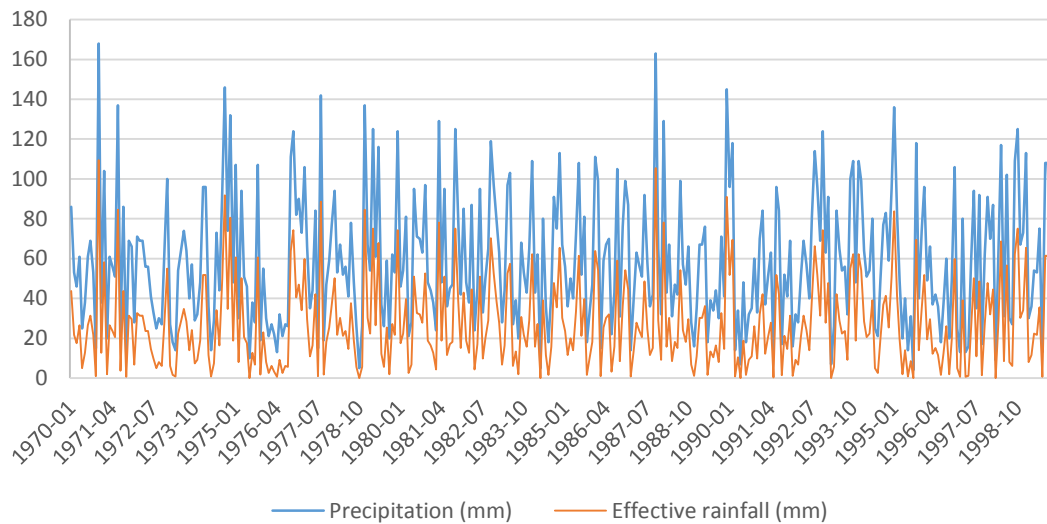


Figure 1-11. Precipitation in the River Thames basin upstream of Teddington Weir between 1970 and 2000 (blue line) and the estimated effective rainfall (orange line).

Water availability in the region is threatened by possible changes in rainfall patterns. The UK Climate Projections (UKCP09) (Murphy et al., 2009) estimate a 15% increase in winter precipitation and an 18% decrease in summer in the London area under the SRES A1B medium emissions scenario when compared to the 1961-1980 baseline conditions (Environment Agency, 2009). Thames Water Utilities Ltd. (TWUL), which manages most of the Thames basin water resources, projects a 25% increase in population in the region by 2040 (Thames Water, 2014). This “expected” future is nevertheless highly uncertain. From the precipitation records of the sub-catchment it was found that on average summers between 1970 and 2000 were drier than summers between 1940 and 1970 (average total summer rainfall of 156mm compared to 179mm) and winters were wetter in 1970-2000 than in 1940-1970 (average total winter rainfall of 191mm compared to 181mm). However, in the period between 2000 and 2014 both summers and winters were wetter (average total rainfall of 175mm and 211mm, respectively) than summers and winters between 1970 and 2000. This suggests that climate change may drive the precipitation patterns in either direction.

Water resources in the Thames basin are comprised of reservoirs, aquifers and the River Thames. The groundwater provides for 20% and 70% of public water supply for London and Thames Valley, respectively (Thames Water, 2014) and plays a major role in recharging and maintaining high quality of rivers, streams and wetlands within the basin. The basin is divided into individual Water Resource Zones (WRZs) from which six are managed by Thames Water Utilities Ltd. (TWUL). The majority of the surface water supply is provided by 23 interconnected reservoirs on River Thames (south-west

of London) and River Lee in Lee Valley (London Reservoirs and Lee Reservoirs in Figure 1-9, respectively) which constitute a combined storage of 200 Mm³. Additional supply is provided by the North London Artificial Recharge Scheme (NLARS in Figure 1-9), a conjunctive surface – groundwater scheme to recharge the aquifer during droughts, the West Berkshire Groundwater Scheme (WBGW in Figure 1-9), used during dry periods, and a desalination plant in the Thames estuary (Beckton Desalination Figure 1-9).

The non-linear seasonal Lower Thames Control Diagram (LTCD) shown in Figure 1-12 specifies when drought-alleviating supply schemes should be activated based on the London Aggregate Storage (LAS) volumes. The LTCD also dictates when the minimum environmental flows in the Thames downstream of all abstractions at Teddington (Figure 1-9) should be lowered and when water-use restrictions are imposed. For instance, if the LAS level drops below Demand Level 1 (blue dashed line in Figure 1-12), the Intensive media campaign to promote reduced water use is put in place. If the LAS level drops further below the Demand Level 2 (green dotted line in Figure 1-12), the campaign is enhanced and sprinkler/unattended hosepipe ban is established. The thresholds vary depending on the period of the year. The Levels of Service (LoS) specify the maximum frequency of imposing the associated water-use restrictions on customers (table in Figure 1-12).

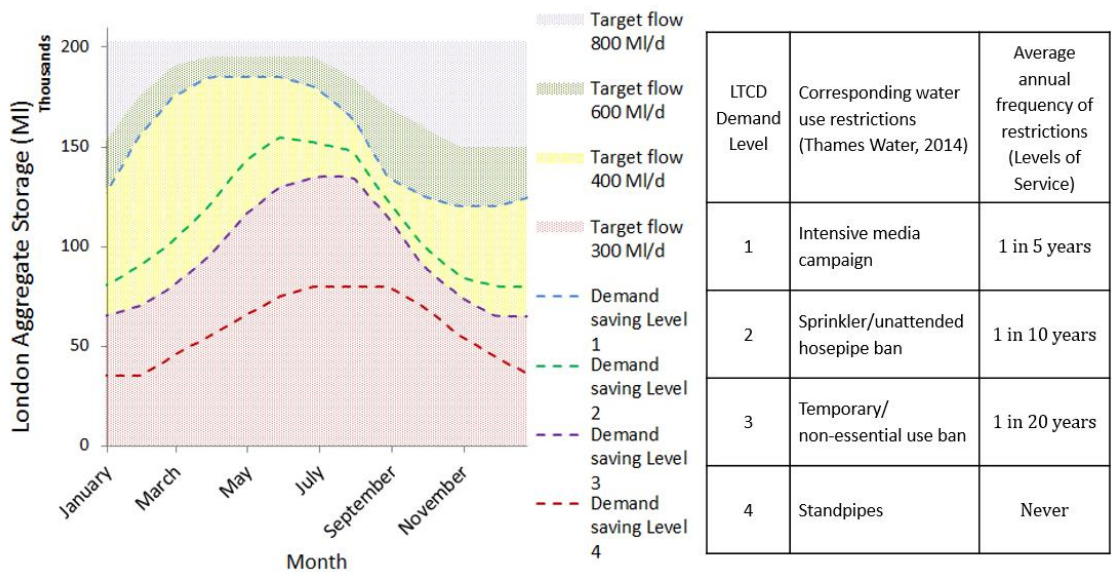


Figure 1-12. Lower Thames Control Diagram (LTCD) relating the London aggregate storage levels on the vertical axis, minimum environmental flows at Teddington Weir (shaded areas), and water-use restrictions (dotted lines) throughout a year (horizontal axis). The table shows the associated water use restrictions and desired Levels of Service.

1.4.2. Current planning approach in the UK

Water supply in the UK is managed by several private water companies whose activities are regulated by the non-departmental public body Environment Agency (EA). Their financial investments and prices for customers are regulated by the economic water industry regulator Ofwat. Every five years water companies must produce Water Resources Management Plans (WRMPs) where they demonstrate their plans to maintain supply-demand balance for the next 25-30 years (Environment Agency, 2012). The planning implies an estimation of future supply and demand, where the former is defined as ‘Water Available for Use’ (WAFU) which consists of the supply system yield of ‘deployable output’ (DO), anticipated reductions in licensed water abstractions, losses and short-term outage allowance (Matrosov et al., 2013a). Deployable output (DO) is the maximum rate at which a system can supply water throughout a dry period at a given reliability level (i.e., Levels of Service) and an estimated uncertainty (Hall et al., 2012b). DO is obtained by simulating the water resource system using historical records and averaging the daily output of supply options during droughts. The uncertainty is incorporated using a safety margin called headroom which aggregates all sources of uncertainty into an annual estimate to reduce vulnerability at low cost (Hallegatte, 2009; UKWIR, 2002). A headroom allowance is used as a ‘buffer’ between WAFU and demand (Environment Agency, 2012) where the latter is estimated as water to be delivered increased by the distribution system losses (Matrosov et al., 2013a). Water companies set their ‘target headroom’ so they can guarantee the desired service reliability, i.e., Levels of Service, to their customers. Planners then apply the Economics of Balancing Supply and Demand (EBS D) approach, where the main focus is to find appropriate balance between available water supply and demand management interventions and the customer needs to maintain the supply-demand balance seeking the least-cost plan (UKWIR, 2002). Once companies identify a list of available and feasible supply and demand interventions, their financial (capital and operating costs), environmental and social costs are estimated and an optimization algorithm is applied to identify the least-cost schedule of the supply and demand interventions. The social and environmental impacts are monetized and aggregated into the single cost objective. For practical reasons companies use discrete costing and sizing of interventions rather than continuous cost curves. A mixed integer linear programme such as one formulated by Padula et al. (2013) is typically implemented in the EBS D approach.

A stochastic extension of the EBSD approach called the ‘intermediate approach’ (UKWIR, 2002) has been previously developed to consider wider range of supply uncertainties. The identified optimal least-cost plan is assessed through Monte Carlo simulation using a probability distribution of DO to ensure the plan satisfies the chosen target reliability levels (Levels of Service). However, the water industry regulators that set out guidelines for water resource management plans now require consideration of climate change impacts and their uncertainties (Environment Agency, 2012) as well as uncertainties associated with estimations of future socio-economic and other conditions (Ofwat, 2013). In their latest WRMPs water companies employed a scenario testing approach where the identified least-cost plan was tested against plausible future scenarios, including the changes in DO, demand levels, energy prices, etc., and subsequently amended to deliver final least-cost plan (Thames Water, 2014). Each source of uncertainty was however considered separately; their combined effects were not taken into account.

The regulators and water companies realize that such simple assessment of risks and uncertainties may lead to the lack of transparency in the decision making process (Hunt and Wade, 2016). In particular, the current approach does not adequately address important planning goals such as the resilience of plans to different futures, trade-offs between multiple performance metrics and the influence of uncertainties on investment decisions (Hunt and Wade, 2016). The variety and complexity of different available approaches to planning under uncertainty make it difficult for planners to choose one that would require the lowest level of transition whilst providing the most desired outcomes. The single least-cost objective approach may introduce bias into the decision making process as well as limits the exploration of the many possible combinations of supply and demand options and is potentially unsuitable for the high variability and uncertainty in future states. For instance, Padula (2015) demonstrates the diversity of near-optimal solutions for the Water Resources of South East England (WRSE) capacity expansion problem using the EBSD approach. The study found 240 near-optimal solutions within 10% of the least-cost optimal plan. The error of margin in cost estimations often exceeds 10% (Yeomans and Huang, 2003) thus focusing on only a single least-cost objective may potentially results in an inaccurate and conservative solution to a highly complex problem. Recently non-EBSD planning approaches seeking system robustness have been investigated for the Thames basin (Matrosov et al., 2013a; 2013b) as mentioned in section 1.3 but the variety and complexity of different available approaches to planning under uncertainty make it difficult for

planners to choose one that would require the lowest level of transition whilst providing the most desired outcomes.

1.5. Research question and objectives

The challenge of long-term human-natural resource system planning is to identify high value portfolios of human interventions whilst considering the two main challenges described previously: future uncertainty and multiple concurrent societal goals. This identification process is severely complicated by the exponentially large number of alternative combinations of schemes available to manage future resources. This project aims to provide an answer to the question:

How can:

- 1. the uncertainty of future conditions and**
- 2. multiple concurrent societal goals**

be addressed to provide an efficient and straightforward practical implementation for the real world water resource systems planning problems?

This research focuses on improving the water resource management and planning process in the UK by addressing the issues identified in previous sections. In particular, it intends to overcome cognitive biases in the decision making process by introducing an optimization approach that considers multiple conflicting objectives explicitly without the need of prior knowledge about how they interact and conflict with each other. Trade-off analysis has some, but limited, prior history of inclusion in water resource planning regulations (California Department of Water Resources, 2008; UKWIR, 2016). Here the aim is to provide a visually communicable approach which enables stakeholder deliberation about benefits achievable by the water system and its engineered assets that is compatible with the resilience and participatory aspirations of UK water planning (Environment Agency, 2015). From a policy perspective the trade-offs and broader performance requirements help to avoid the myopia of least-cost decision making (Herman et al., 2015). Results aid policy makers to orient their investment strategies towards their key requirements and aspirations.

Water planners and regulators in the UK recognize the limitations of the current approach as described in section 1.4.2 and are actively seeking to improve the statutory planning framework (Defra, 2011). This project intends to reflect the necessity of the current water planning policy changes that are being considered. Several theoretical

approaches have been developed to incorporate uncertainties into decision making as described in section 1.3.2. Many of these are complex and require multiple iterative processes to deliver desired and practical outcomes. Application of such frameworks by water system planners will require them to understand and accept the benefits of embedding the search for robustness within automated investment filtering approaches which historically only considered cost. The goal of this project is to communicate to water resources planners the increase in understanding and judgement they can obtain by incorporating uncertainty into automated intervention evaluation methods. This project proposes to introduce the many-objective simulation based optimization that incorporates multiple sources of uncertainty and the use of interactive visual analytics to the current water resource management and planning in the UK, as well as demonstrate the benefits of this approach compared to the current practice.

1.6. Outline of the thesis

The next chapter describes the methodology used over the course of the project. In particular, both the simulation and optimization models chosen for the study as well as the simulation-optimization framework built from those are described in detail. The Interactive River-Aquifer Simulation 2010 (IRAS-2010) model used to simulate a water resource system is presented together with its adjustments and extensions required for the Thames basin case study conducted throughout this project. The chapter proceeds with a description of the Epsilon Non-dominated Sorting Genetic Algorithm II (ϵ -NSGAI) heuristic algorithm used for many-objective optimization. The chapter concludes by presenting the simulation-optimization framework designed from the two above mentioned models as a screening tool for decision making under uncertainty covered by this thesis.

Chapters 3 to 5 cover the individual studies undertaken throughout the research project to address the research question. Table 1-3 provides a summary of these chapters including the author contributions (initials shown in brackets following tasks), applied planning approach and models, data and data sources.

Table 1-3. Summary of individual project studies with author contributions

	Chapter 3	Chapter 4	Chapter 5
Main contribution	Evgenii Matrosov (EM) & Ivana Huskova (IH)	IH	IH
Case study	River Thames basin		
Approach	Many-objective optimization	Multi-scenario many-objective optimization	Scheduling
Model used	IRAS-2010 simulation model connected to ϵ -NSGAI multi-objective evolutionary algorithm		
Model improvements	Thames basin representation in IRAS-2010 (EM) MPF (EM) Improvements of IRAS-2010 and calibration against TWUL's WARMS simulation model (IH) Connecting IRAS-2010 with ϵ -NSGAI (IH) Modification of ϵ -NSGAI for the MPF (IH)	MPF adjustments (IH) Modification of ϵ -NSGAI for the MPF and multiple scenarios (IH)	Extension of the simulation model to accommodate new resource options and schedules (EM+IH) MPF adjustments (IH) Modification of ϵ -NSGAI for the MPF and multiple scenarios (IH)
Scenarios of future conditions	Historical river flow record (1970 – 2000) Demand (2035) Energy (2035) No sustainability reduction (current state)	Future Flows (11 x 2020 – 2050) Demand (2 x 2035s) Energy (2 x 2035s) Sustainability reductions (2 x 2035s)	Bootstrapped Future Flows (4 x 110 x 2020 – 2070) Demand (2020 – 2070) Energy (2020 – 2070) No sustainability reduction (current state)
Scenario data sources	Flow record – NRFA Demand – TWUL Energy price - DCE	FFs – NRFA and HR Wallingford Demand, energy & sust. reduction scenarios – TWUL + DCE	FFs - NRFA and HR Wallingford Demand and energy – TWUL + DCE
Flow data manipulation	Denaturalization of flows based on CAMS licenses (IH)	Denaturalization of flows based on CAMS licenses (IH)	Denaturalization of flows based on CAMS licenses (IH) Bootstrapping (IH)
Visualization/image manipulation software used	Aerovis, Matlab, Excel, Gimp, Inkscape		

*MPF = Mathematical problem formulation

Chapter 3 presents the first step of changing the traditional water resource system planning approach using the screening tool described in Chapter 2. A deterministic study of the Thames basin water supply system expansion that considers many conflicting system's performance objectives and a single "most probable" scenario of future conditions based on historical trends. We will show the benefits of considering multiple objectives concurrently when compared to a single least cost objective approach. The chapter also provides findings about how such planning approach may be communicated to decision makers and stakeholders. By doing so decision makers are given the opportunity to decide the balance between many system goals a posteriori as well as justify the choice of their final portfolio to interested parties. A part of this study was published in the *Journal of Hydrology* (Matrosov et al., 2015).

Chapter 4 incorporates multiple sources of uncertainty in a form of scenarios into the problem analysed in the previous chapter to identify robust portfolios of supply and demand management interventions for the Thames basin. The potential future portfolios are evaluated here against scenarios of plausible climate impacted hydrological conditions, water demands, environmentally motivated abstraction reductions, and energy prices. The results obtained using this approach are compared to those obtained using the deterministic (single scenario) conditions. The benefits of considering multiple sources of uncertainty whilst searching such as perfect foresight bias reduction are highlighted and discussed. The results analysis again focuses on the most effective approach to communicate such findings to a wider audience. This study was published in the *Global Environmental Change* (Huskova et al., 2016).

Chapter 5 then looks at how a time continuation may be incorporated into the many-objective search for robust plans, i.e. schedules, of supply and demand management interventions. We will discuss how a major drought event and its time occurrence within the considered hydrological flows scenario ensemble affects the optimization. The study proposes a scenario ensemble manipulation technique - a bootstrapping method that respects the non-stationary trend of climate change scenarios and ensures even distribution of the major stress event in the scenario ensemble is proposed. Using such scenario ensemble reduces the possibility of optimizing the intervention schedules against perfect foresight. We demonstrate how the visual analysis of solutions can aid decision making by investigating the implied performance trade-offs and how the individual interventions and their schedules present in the robust plans affect the system's behaviour. Multiple plans with similar initial actions may be combined into a

coherent intervention schedule over time allowing switching to other plans within the first decade.

Chapter 6 concludes the thesis and its findings and identifies further research steps that may be undertaken in future.

2. Chapter 2 – Methodology

2.1. Simulation model

2.1.1. Interactive River-Aquifer Simulation (IRAS-2010)

The Interactive River-Aquifer Simulation (IRAS-2010) is an open-source and computationally efficient rule-based water resource system simulation model (Matrosov et al., 2011). A water resource system is represented by a network of nodes and links, where the former represent a reservoir, aquifer, gauge or consumption site, etc., and the latter defines natural or engineered connections between the nodes (example network is shown in Figure 2-1). Each of the model components is defined by parameters associated with its characteristics, e.g. a maximum capacity of a reservoir, flow time-series of a gauge site, etc., which guide the simulation of water distribution throughout the system. During each user defined sub time-step water storage, flow, allocation and consumption are determined using four consecutive algorithm loops (Figure 2-1). At first, demand deficit is calculated, which determines the required storage releases. Second, the model calculates the total mass balance for all non-aquifer and non-wetland nodes. The third and fourth loop then determines the flows to and from aquifer and wetland nodes and their storage, respectively. The model is able to generate multiple performance metrics, such as energy consumption and hydropower generation.

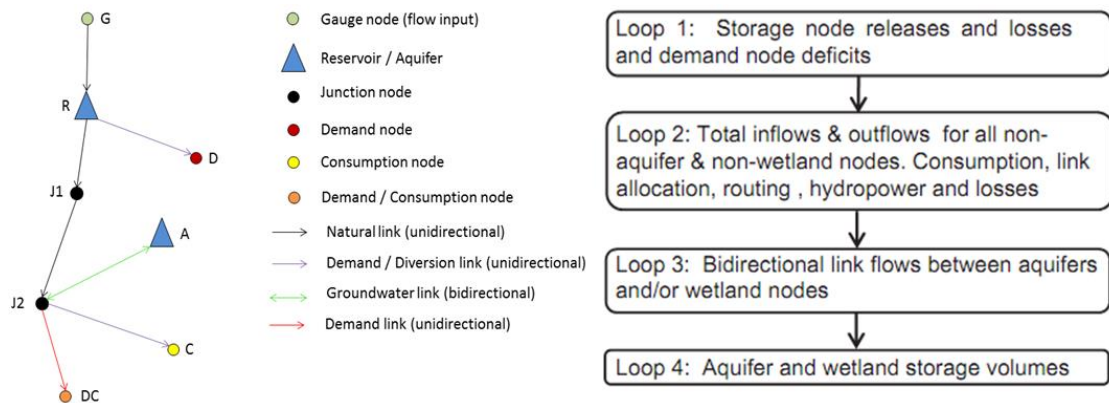


Figure 2-1. IRAS-2010 example water resource system network representation. The four consecutive loops illustrate the algorithm procedure (adapted from Matrosov et al., 2011).

IRAS-2010 model requires input data such as network description and node/link parameters, the modelling time horizon and time steps, gauge nodes flow data in each time step, etc. The model is able to generate output in the form of multiple performance metrics, such as energy consumption and hydropower generation, as well as time series of any node inflows/outflows or storage levels. The model was chosen for this project due to its ability to represent complex water system element interactions and operating

rules and its fast runtimes (Matrosov et al., 2011). The latter is particularly important here as the model needs to evaluate many possible combinations of interventions during a single optimization run (section 2.3).

2.1.2. Thames basin water supply system in IRAS-2010

The Thames basin existing water resource system represented in the Thames IRAS-2010 model is shown in Figure 2-2 and is based on the Thames model created by Matrosov et al (2011). There are three points of inflow into the system represented by gauge sites: Day’s Weir and Lower Thames on the River Thames, and Feildes Weir on the River Lee. The Rye-Meads represents the treated effluent input from the Rye Meads water treatment works with monthly profile (Table 0-1 in Appendix). The interconnected Thames and Lee reservoirs are aggregated into a single London Aggregate Storage node (LAS). The model incorporates the LTCD operating rules (Figure 1-12). The detailed description of each model component is included in the Appendix.

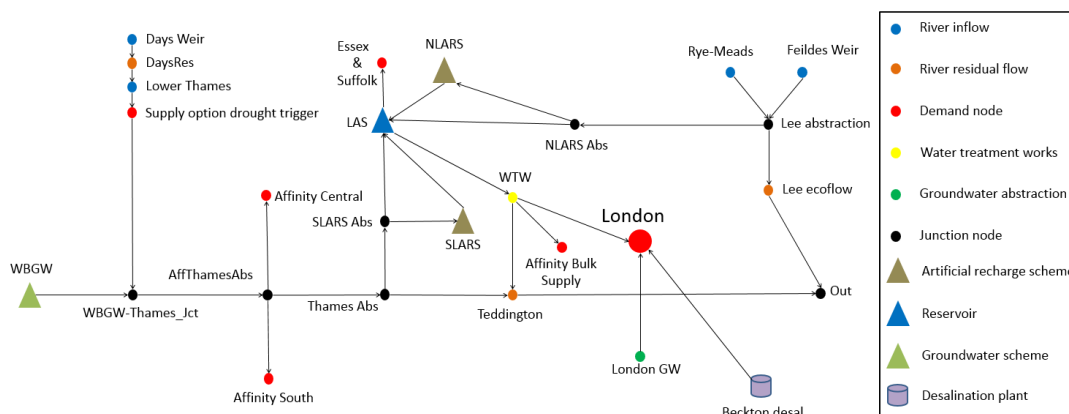


Figure 2-2. IRAS-2010 Thames model components network representation showing the existing supply options.

The Thames IRAS-2010 model was calibrated against TWUL’s simulation model to capture the TWUL’s practices as closely as possible using naturalised historical river flow records (1920-2005) and baseline demand (2,175 Ml/d). The Water Resources Management System (WARMS) model (Mountain, 2009) consists of series of mathematical simulation models that calculate the DO within the Thames basin. The Thames IRAS-2010 model provides coarser representation of the system than the WARMS model where some supply infrastructure options are aggregated into a single node (such as the London Aggregate Storage including all River Thames and River Lee reservoirs) and most supply option’s operational rules are simplified. Figure 2-3 illustrates the simulated LAS storage levels by the WARMS and IRAS-2010 Thames

models (shown by grey and black lines, respectively). The trend of levels corresponds between the models but the LAS volume obtained by IRAS-2010 Thames model does not drop as low as in WARMS apart from drought periods when it drops slightly lower. This can be seen in Figure 2-4 where during 1934 the IRAS-2010 Thames model (black line in Figure 2-4) indicates the LTCD Demand Level 4 failure while the WARMS model does not (grey line in Figure 2-4).

Figure 2-5 illustrates the simulated and gauged river flow comparison at Teddington Weir. The simulated flow is highly comparable between the WARMS and IRAS-2010 Thames models and the observed flows obtained from NRFA (red dashed line in Figure 2-5). Both IRAS-2010 Thames and WARMS models show slightly higher flows than the historic observed records in some wet periods and lower flows in some dry periods. These differences between the gauged and modelled flow result from the simplified hydrological representation of the basin, particularly in the IRAS model, including the lack of flow routing and stream-aquifer interaction. The latter in particular may be causing lower modelled river flows in dry periods when in reality aquifers drive the river base flows in summers after being themselves replenished by winter rainfall.

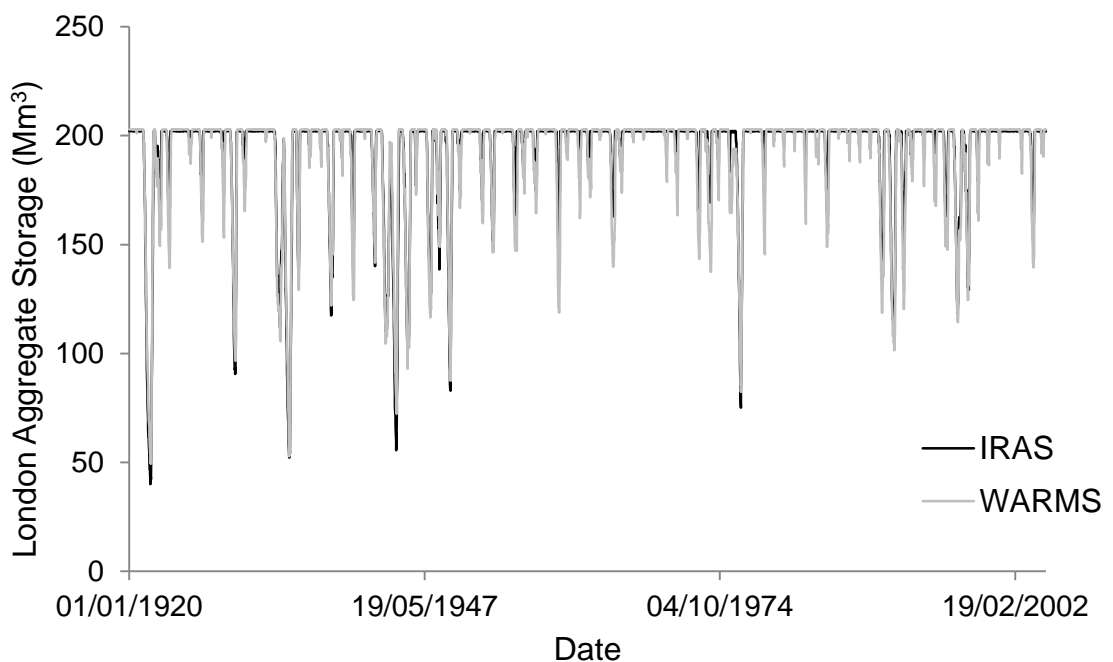


Figure 2-3. Simulated London Aggregate Storage (LAS) levels comparison between the WARMS and IRAS-2010 Thames models.

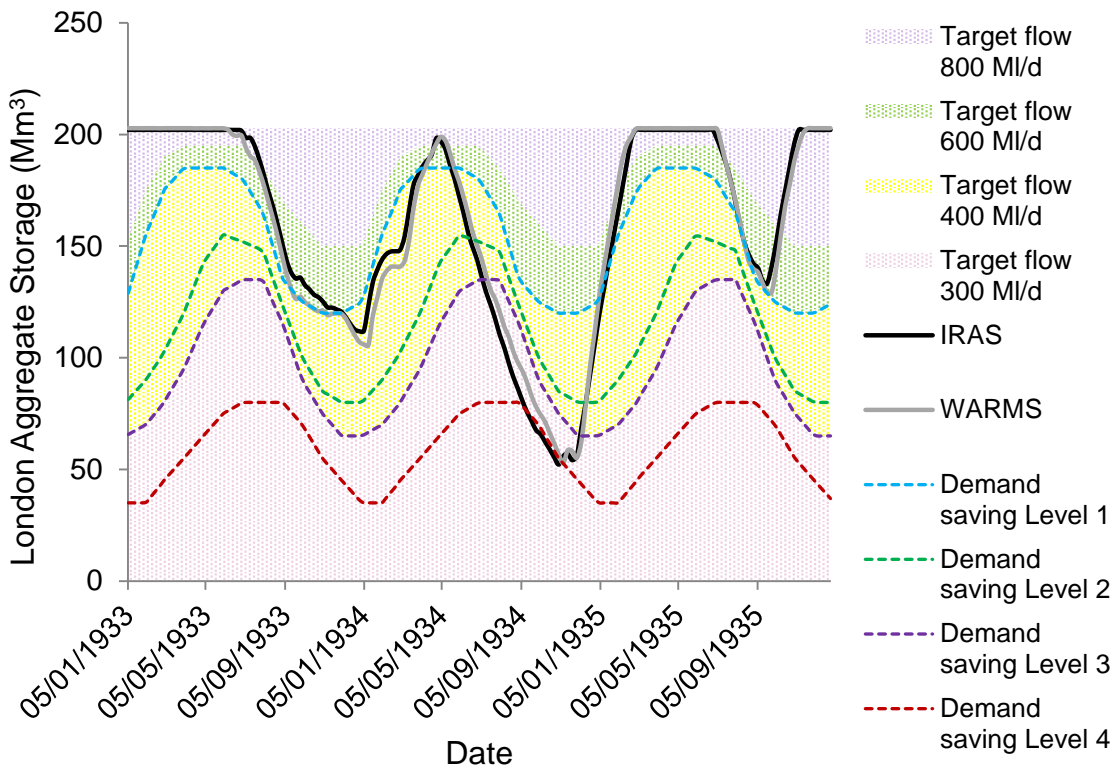


Figure 2-4. LAS drawdown simulated by WARMS and IRAS-2010 Thames models (shown by grey and black lines, respectively) between 1933 and 1936 illustrated against the LTCD.

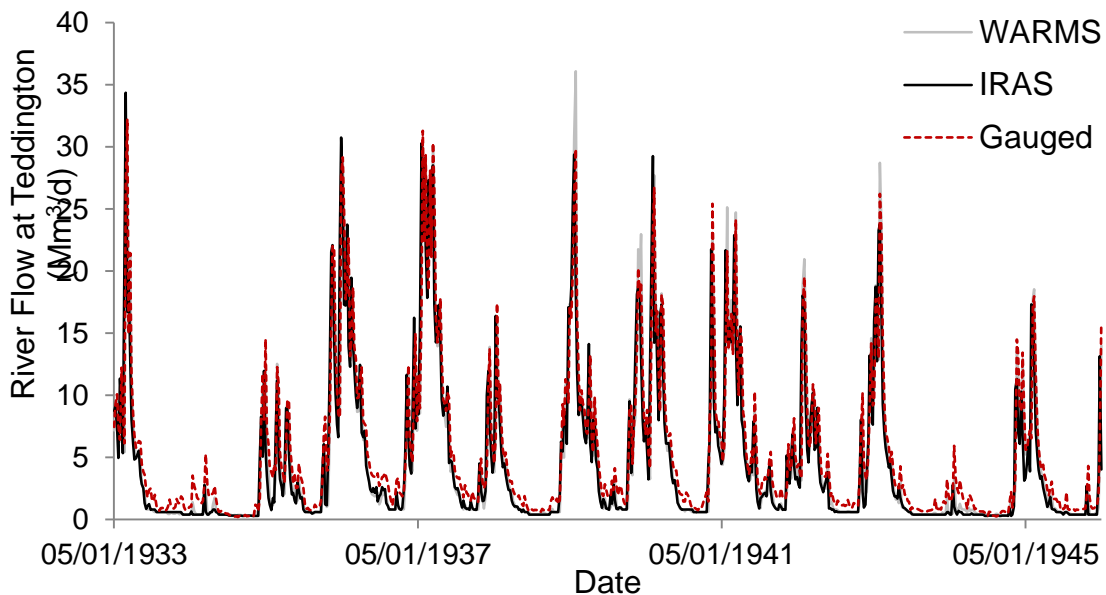


Figure 2-5. Simulated (WARMS and IRAS-2010 Thames models) and gauged Thames river flow at Teddington Weir during 1933 – 1945.

The calibration results suggest that the Thames IRAS-2010 model is able to emulate the TWUL’s simulation model very closely and may be used to simulate the Thames basin water resource system to investigate planning approach proposed here.

2.2. Optimization model

The optimization in this study is performed using the Epsilon-dominance Non-dominated Sorting Genetic Algorithm II (ϵ -NSGAI) (Deb et al., 2002; Kollat and Reed, 2006), a type of MOEA. It was chosen for its search effectiveness and efficient parallel performance (Hadka and Reed, 2012; Kollat and Reed, 2006; Reed et al., 2013; Tang et al., 2006). ϵ -NSGAI employs non-dominated sorting, epsilon-dominance archiving (Laumanns et al., 2002) and adaptive population sizing tournament selection. The ϵ -dominance archive sorts solutions based on the user specified levels of significant precision for the objectives (i.e., the minimum magnitude of change in the objectives that the user cares about). The adaptive population sizing reduces the need to investigate the most suitable initial population size a priori (Kollat and Reed, 2006). The algorithm consists of a series of connected runs between which the population size is adjusted with the introduction of new random solutions. Initially, the algorithm starts the search with a small number of candidate solutions. Over successive generations of each connected run, high quality solutions are passed into the epsilon-dominance archive. The archived solutions are injected into the population at the beginning of the next run and used to automatically adjust the search population size. A quarter of this population size is comprised of the archived solutions while the remaining three quarters are randomly generated solutions (Kollat and Reed, 2006). This ensures that high-quality solutions stored in the archive are not lost during the search and lowers the possibility of stalling at local optima during the search. ϵ -NSGAI has been demonstrated as a suitable and effective tool for complex many-objective optimization problems (Kollat and Reed, 2006; Reed et al., 2013).

2.3. Simulation-optimization framework

The IRAS-2010 simulation model was connected to the ϵ -NSGAI algorithm via a C++ wrapper code that runs the simulation model within the ϵ -NSGAI and exchanges required parameters between the two models. The framework's pseudo-code is shown in Figure 2-6. The initial random population of decision variables based on the user defined input (i.e., how many variables, what bounds, etc.) is generated by the ϵ -NSGAI using uniform random sampling. The variables are passed onto the IRAS-2010 model as input parameters which performs the simulation of water resource system and generates required user defined performance measures. These are fed back to the evolutionary algorithm as objective and constraint values which are used to assign the "fitness" of each candidate solution. Next, non-dominated sorting is performed and

“survived” solutions are archived. The algorithm then applies its genetic variation operators of crossover and mutation, where the former combines genetic information of two individuals (parents) while the latter perturbs a genetic code of a single individual (parent) to create new individual (child) for the next generation of decision variables. This represents one generation of the heuristic search process. The operator parameters such as the probability of crossover and mutation are user defined. The next generation of decision variables is again passed to the simulator and the loop is repeated until the termination criteria are met. The termination criteria are set as the maximum number of function evaluations (FEs) where one FE represents one simulation of a single candidate solution and which are determined by the solutions’ “evolution” observation. Sufficient number of FEs occurs when the solutions converged towards and are diversifying along the Pareto optimal front (the front no longer moves spatially between the generations and is only smoothing out).

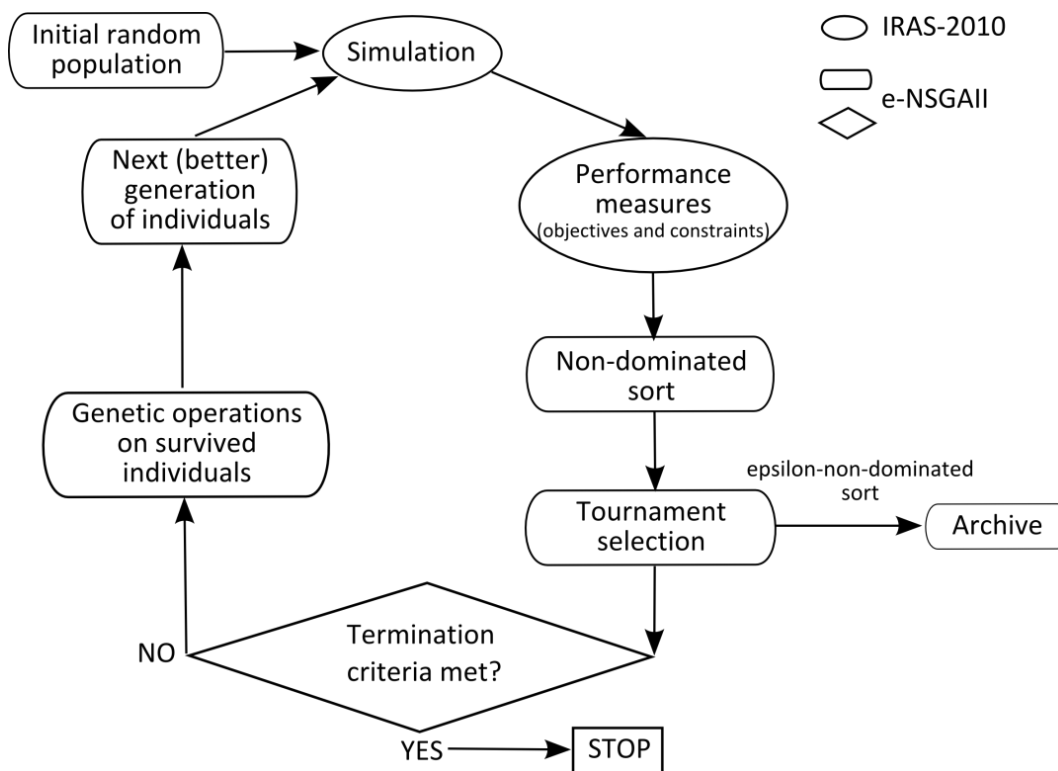


Figure 2-6. Schematic of the IRAS-2010- ϵ -NSGAI framework. The ϵ -NSGAI generates random initial population of decision variables which are passed onto IRAS-2010 as input variables. IRAS-2010 then simulates the system and provides performance measures that are fed back to the ϵ -NSGAI as objective and constraint values. ϵ -NSGAI then evaluates the fitness of solutions, stores the most fit solutions in archive and performs genetic operations on these solutions to generate next generation of decision variables that are again passed to the simulation model. The process repeats until the termination criteria are met.

2.4. Implementing many-objective robust optimization into the current planning approach

To demonstrate the implementation of the approach proposed by this thesis into the current planning practice in the UK the implementation is here performed in three gradual steps.

First, the simulation-optimization framework described in section 2.3 is used to perform a many-objective optimization of the Thames basin water supply system considering new possible supply and demand management interventions and financial, engineering and environmental performance metrics. The portfolios of interventions, i.e., combinations of interventions, are evaluated for their performance against a single scenario of future conditions represented by historical climate conditions and a single value for demand growth and energy price estimation for 2035 under existing environmental regulations to reflect the traditional use of a single future scenario in the current practice. This is referred to a deterministic approach in the following text. Visual analytics of the obtained trade-offs is used to demonstrate the benefits of considering many objectives explicitly and how such analysis helps decision makers to navigate the trade-offs and gain knowledge about how their preferences interact and conflict with each other. For simplicity only a static snapshot of the system's performance in 2035 without time continuation was considered, i.e., how the plausible portfolios would perform in 2035.

Second, multiple scenarios of future conditions are incorporated into the many-objective optimization using the same problem formulation, i.e., decisions, objectives and constraints, and static approach. The portfolios are assessed against 88 possible scenarios of variable future conditions agreed with TWUL. The scenario ensemble contains different combinations of climate change impacts on river flows, demand growth levels, changing energy prices and stricter environmental conditions. Visual analytics is used to compare the obtained trade-offs with the deterministic optimization trade-offs from the first step to highlight the benefits of incorporating uncertainties into the optimization process.

Third, the considered new supply and demand management interventions are updated according to the latest TWUL's WRMP options. A time continuation consideration is added to the analysis to allow for scheduling of interventions over time, i.e., when the interventions should be built or implemented, which the current WRMPs need to

provide. The trade-offs here consist of intervention plans where a plan represents a combination of interventions and their schedules over a planning time horizon. Visual analytics is used to first assess the impacts of considered scenarios on the timing of interventions and second to aid decision making in choosing a robust and flexible plan.

The exact methodology, results analysis and discussion for each step is provided in more detail in the following chapters.

3. Chapter 3 – Deterministic many-objective optimization

3.1. Introduction

Most environmental systems are complex and require considering multiple conflicting system goals. Planning that considers multiple system goals and their trade-offs is a valuable addition to the decision making process (Reed and Kasprzyk, 2009). A new generation of heuristic search methods can be linked to system simulators to identify the Pareto optimal set of design alternatives. Pareto optimal signifies optimal in a multi or many-objective sense, i.e., the set of decisions which cannot be improved upon for one objective without simultaneously lowering performance in another. Pareto optimal solutions are also non-dominated which indicates they are better than all other solutions in at least one objective (Coello Coello, 2007; Kollat and Reed, 2006). Pareto optimal solutions can be presented in trade-off plots (Fleming et al., 2005) where stakeholders can select an appropriate balance of systems goals and visualise the trade-offs different decisions imply.

This chapter investigates the trade-offs revealed by a many-objective optimization approach to planning future water supply system expansion investments in the Thames basin. Optimal combinations of supply and demand management interventions, i.e., portfolios, are evaluated against a range of performance measures including the financial, engineering and environmental performance of the system. Considering many objectives explicitly reveals information about the system that would remain hidden when only a single objective is considered. The trade-offs analysed here show that the engineering and environmental performance of the system can be improved with relatively modest investments. Visualizing the performance metrics progressively aims to help decision makers navigate the trade-offs and learn how their preferences conflict. Visualizing the interventions present within the Pareto optimal portfolios against the trade-offs reveals how individual interventions cluster in certain parts of the trade-off space and how they affect the performance of the system.

The contribution of this chapter is to demonstrate the benefits of employing the many-objective optimization and visual analysis in the current planning approach in England and Wales. Such approach reveals information that would remain hidden if the planning problem were solved using the traditional lower-dimensional analysis such as the least-cost EBSD approach currently used by the English water sector (Padula et al., 2013).

Visualizing the performance trade-offs and how the portfolios of interventions and interventions themselves are distributed within those trade-offs gives planners valuable information about what system performances are achievable and what portfolios can lead to those levels of performance.

Section 3.2 describes the applied problem formulation, i.e., which decisions, objectives and constraints were considered, and future conditions. Section 3.3 provides the optimization results and their analysis and section 3.4 the discussion of findings. The chapter concludes with section 3.5.

3.2. Methodology

3.2.1. Problem formulation

The London water supply problem was formulated to demonstrate the benefits of incorporating many performance objectives within the optimization of alternative investment portfolios. This section describes the objectives, decisions, and constraints used in the formulation. The performance objectives in this study consider the financial (capital, $f_{CapCost}$, and energy, f_{Energy} , cost), engineering (supply deficit, f_{SupDef} , reliability, f_{SupRel} , and resilience, f_{SupRes}) and environmental (eco-deficit, f_{Eco}) performance of the system. Some of the objectives used in the previous study (Matrosov et al., 2015) were changed after a consultation with stakeholders. In particular, the operating cost objective here includes only the cost of energy required to operate the system to assess the effects of possible energy price change explicitly. The resilience objective that minimizes the duration of failures considers the maximum duration of failure here instead of the average duration in the previous study. The environmental performance is assessed by comparing the natural and simulated flows in the river Thames rather than using the shortage index associated with a fixed river flow volume as was the case previously. The storage vulnerability objective maximizing the minimum aggregate storage level in the previous study is not included here as the reliability and resilience objectives were considered sufficient to assess the London's aggregate storage performance. The same proposed future supply and demand management interventions are considered as decisions as in Matrosov et al (2015) with the difference of modelling the River Severn Transfer based on the actual River Severn flows rather than assuming constant supply and of not considering demand management interventions for other WRZ than London. The latter is due to TWUL not having the ability to influence demand management in these zones.

The feasibility of portfolios is constrained by the mutual exclusivity of certain supply interventions and by meeting the minimum Levels of Service (Figure 1-12). The problem formulation is defined by Equation 3-1:

$$\text{Minimize } \mathbf{F}(\mathbf{x}) = (f_{CapCost}, f_{SupDef}, f_{SupRes}, -f_{SupRel}, f_{Eco}, f_{Energy})$$

$$\mathbf{x} \in \{Y_i, Cap_i\}$$

$$Y_i \in \{0,1\} \quad \forall i \in \Omega$$

subject to $c_k \leq FR_k$

$$\sum_{i \in ME} Y_i \leq 1$$

3-1

where \mathbf{x} is a vector representing a portfolio of supply and demand interventions, Y_i is a binary variable representing the inclusion of intervention i in portfolio \mathbf{x} (1 means the intervention is included and 0 not included), Cap_i is a real variable associated with the capacity/release value of intervention i , Ω represents the whole decision space, c_k is a constraint associated with Level of Service (LoS) k , FR_k is the value of maximum failure frequency allowed for LoS k , and ME represents the set of mutually exclusive interventions. The individual decisions, objectives and constraints are described in more detail in the following subsections.

3.2.1.1. Decisions

This study considers 7 new supply and 5 demand management interventions for the London's Water Resource Zone (WRZ) chosen from the TWUL's proposed feasible intervention list (Thames Water, 2014). The supply interventions include the Upper Thames Reservoir (UTR), River Severn Transfer (RST), Northern Transfer (NT), Columbus transfer (CT), South London Artificial Recharge Scheme (SLARS), a water reuse scheme and a new desalination plant. Demand management options for London WRZ include active leakage control, a pipe repair campaign (i.e., main pipes replacement), water efficiency improvements, installation of meters, and implementation of seasonal tariffs. The Upper Thames Reservoir, River Severn Transfer, and Northern Transfer supply interventions are mutually exclusive where only one of these interventions can be implemented within a single portfolio. The interventions are shown in Figure 3-1 and are described in more detail in Table 3-1. The uncertainty in available release or demand savings (deployable output in EBSD approach) was not considered here as the supply interventions' releases are simulated

during the optimization, i.e. their release changes during the modelling time horizon based on water availability in the system, their storage levels and operating rules.

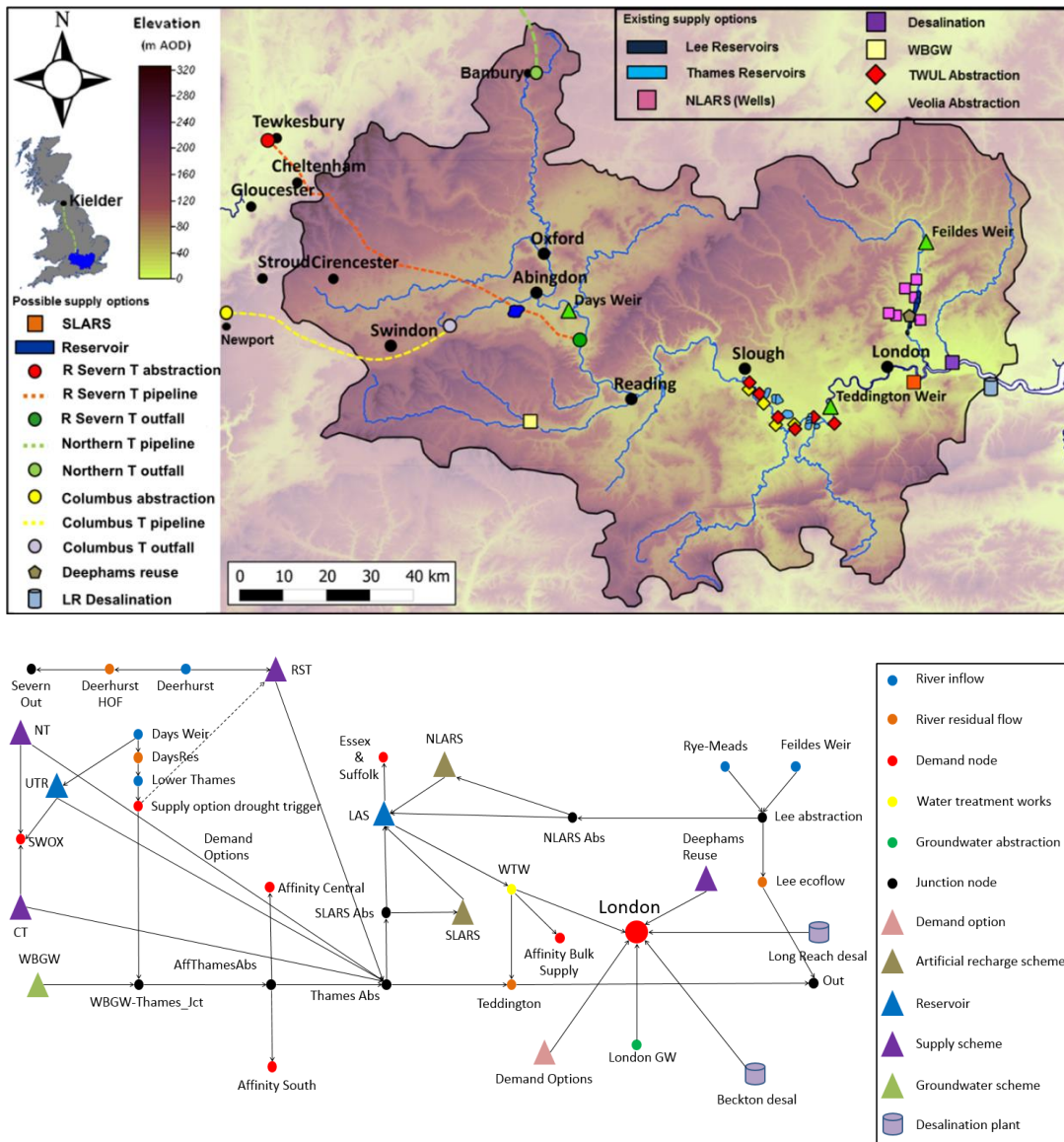


Figure 3-1. Current and new possible supply and demand interventions considered as decisions. The upper panel shows the location of interventions in the Thames basin whilst the lower panel shows the extended Thames IRAS-2010 simulation model schematic.

Table 3-1. Supply and demand management interventions considered as decisions.

Intervention	Description	Capacity or release
<i>Demand management interventions</i>		
Active Leakage Control (ALC)	Enhanced levels of “Find and Fix”, implementation of further pressure management, and trunk main leakage management	2 – 50 ML/day reduction in demand
Pipe repair campaign (Pipes)	Replacement of water mains, communication pipes and supply pipes to reduce leakage in the distribution system.	165.1 ML/day reduction in demand
Enhanced efficiency improvements (EFI)	Water efficiency campaigns, retrofitting and household and commercial customer audit programmes	11.6 ML/day reduction in demand
Installation of smart meters (Meters) with seasonal tariffs (Tariffs)	Installing smart meters in properties with application of seasonal tariffs. Tariffs are considered as a decision conditional on implementing Meters.	88.7 ML/day reduction in demand
<i>Supply interventions</i>		
Upper Thames Reservoir (UTR)	A proposed reservoir which would release water into the Thames during times of low flow and provide constant supply to a neighboring area.	30-150 ML
River Severn Transfer (RST)	A proposed unsupported water transfer (i.e. without intermediate storage) that would bring water from the River Severn to the Thames during periods of low flow. The transferred volume depends on the Hands of Flow (HOF) condition for River Severn and maximum transfer capacity.	300 ML/day if Severn flow is above 2,490 ML/d 0 – 240 ML/day if Severn flow is below 2,490 ML/d but above 1,800 ML/d 0 ML/day if Severn flow is below 1,800 ML/d
Northern Transfer (NT)	A proposed water transfer that would bring water from Northern England to the Thames during periods of low flow.	74 ML/day
South London Artificial Recharge Scheme (SLARS)	A proposed conjunctive use surface-groundwater recharge scheme that would function analogous to the existing NLARS.	5 – 24 ML/day
Deepham Reuse Scheme (DRS)	A proposed indirect water reuse scheme that would provide additional treatment	25 – 95 ML

	of wastewater from the Deepham's water treatment works which would be pumped into the surface storage reservoir	
Columbus Transfer (CT)	A proposed water transfer scheme that would bring water from the Dwr Cymru Welsh Water area to the River Thames during periods of low flow.	39 ML/day
Long Reach Desalination (LRD)	A possible reverse osmosis treatment plant that would desalinate brackish groundwater leaking from the Thames Tideway and the Chalk aquifer underlying the Thames.	15 ML

3.2.1.2. Objectives and constraints

The capital cost objective ($f_{CapCost}$), as in Matrosov et al (2015), is the annualized capital cost of implementing new supply and demand interventions in a portfolio normalized to each intervention's expected design life. This is to provide equal comparison between interventions that have unequal design lives. For instance, it may be more practical to implement more expensive reservoir that remains functional for 80 years than less expensive desalination plant that would however need to be rebuilt after 25 years. The capital cost of each implemented intervention is therefore divided by its design life in years to assess how much it would cost per year if we assume its total capital cost requirement would be spread over the intervention's life. The total annualized capital cost of a portfolio is minimized:

$$\text{Minimize } f_{CapCost} = \sum_i [(CapCost_i / DL_i) * Y_i]$$

3-2

where $CapCost_i$ is the capital cost of implementing intervention i and the DL_i is the design life of intervention i .

The supply deficit (f_{SupDef}) objective represents the maximum annual deficit [%] experienced by the London demand and is minimized:

$$\text{Minimize } f_{SupDef} = \max_t [((DT_t - M_t) / DT_t) * 100\%]$$

3-3

where DT_t is the London's demand target for year t and M_t is the demand met during year t .

Resilience is defined by how quickly the system recovers from a failure (Moy et al., 1986). The supply resilience objective (f_{SupRes}) is assessed on the LAS node and the failure occurs when the LAS storage level drops below the LTCD Demand level 3 threshold and the non-essential use ban is brought into effect (Figure 1-12). The objective aims to minimize the maximum time period over the whole time horizon required to recover from the failure, which refers to a period during which the Demand level 3 restrictions are in place:

$$\text{Minimize } f_{SupRes} = \max D$$

3-4

where D is the failure duration in weeks.

The supply reliability objective (f_{SupRel}) is also assessed on the LAS node and aims to minimize the frequency of failures [%] (Hashimoto et al., 1982). This is similar to temporal reliability (Kiritskiy and Menkel, 1952), The reliability therefore maximizes the proportion of time over the whole time horizon when the LAS level is above the LTCD Demand Level 3 threshold and the Demand level 3 restrictions are not brought into effect:

$$\text{Maximize } f_{SupRel} = (1 - (F_s/S)) * 100\%$$

3-5

where F_s is the number of time-steps (weeks) during which the system was in failure, and S is the total number of time-steps within the modeling time horizon.

The eco-deficit objective (f_{ECO}) (Vogel et al., 2007) represents the difference between the naturalized low flows and simulated low flows [%] (low flows here denote the flows under Q_{70} , i.e., flows that are not exceeded 70% of the record time) at the Teddington Weir on the River Thames. The naturalized flows here refer to the river flow where there are no TWUL's abstractions; the objective therefore assesses direct impact of TWUL's abstractions and return flows on the river itself. The higher the difference (i.e., deficit), the more the environmental conditions of the river deteriorate due to lower water levels than the natural state. Eco-deficit of 0% implies no deficit while 100% eco-deficit is the largest possible deficit:

$$\text{Minimize } f_{Eco} = (|AN_{Q70} - AS_{Q70}|/AN_{Q70}) * 100\%$$

3-6

where AN_{Q70} is the area under the naturalized flow duration curve (FDC) and AS_{Q70} is the area under the simulated FDC. A flow duration curve (FDC) is a graphical representation of the overall variation of a streamflow, usually showing the probability of exceedance on the horizontal axis and the magnitude of flow on the vertical axis. FDCs provide an estimate of the percentage of time of the considered record during which the flow exceeds a particular magnitude.

The energy objective (f_{Energy}) quantifies the cost of the average annual energy use of the whole supply system including the existing and implemented possible supply interventions:

$$\text{Minimize } f_{Energy} = \left((1/T) * \sum_{t=1}^T \sum_i E_{i,t} \right) * UP$$

3-7

where $E_{i,t}$ is the energy requirement to operate the supply intervention i over each year t , T is the total number of years and UP represents the unit price of 1 kWh. The $E_{i,t}$ is based on the release of the particular supply intervention during year t :

$$E_{i,t} = R_{i,t} * ER_i$$

3-8

where $R_{i,t}$ is the release of the supply intervention i during year t (ML) and ER_i is the energy requirement for a mega liter of intervention's i release (kWh/ML).

The constraints ensure satisfactory reliability of the aggregate surface storage (assessed on LAS) that complies with the TWUL specified LoS (Figure 1-12) and are based on the occurrence reliability definition (Kiritskiy and Menkel, 1952):

$$c_k = [1 - (F_k/T)] * 100\%$$

3-9

where k denotes a particular LoS level, F_k is the number of years during which the storage volume dropped below the LoS level k . The constraints limit how often storage volumes drop below the LTCD demand levels to the maximum frequency of occurrence specified by TWUL's Levels of Service (Figure 1-12).

The algorithm implements a constraint based tournament operator where feasible solutions are always preferred to infeasible solutions. In general, simulations that do not meet these constraints are considered infeasible and are not passed into the archive of the MOEA. However, if all solutions are infeasible, the constrained tournament selection promotes solutions with the smallest aggregate constraint violations (Deb et al., 2002).

3.2.2. Scenario of future conditions and computational experiment

The deterministic optimization was performed using a 30-year historical time-series of river flows (1970-2000) with a weekly time-step. As in Matrosova et al (2015) this implies that we use 30 years of historical hydrology to represent hydrological conditions that we assume to be representative of those that may occur in the year 2035. This 30-year period was chosen to reflect the 25-30 year planning time horizon of WRMPs and due to the presence of a major drought between 1975 and 1976 when severe water rationing measures were imposed (CIWEM, 2016).

The water use demand for 2035 of 2,325 Ml/d was estimated by TWUL (Thames Water, 2014) based on the WRPG recommendations to incorporate the population growth estimations from local authorities and several assumptions such as continuation of the current metering policies, maintaining leakage at the 2015 levels, etc. (Environment Agency et al., 2012). This value is adjusted for each month of the year by applying monthly factors (Table 0-2 in Appendix) used by the Environment Agency's commercial Aquator model. The energy cost estimate for 2035 of 13p/kWh uses the Department of Climate and Energy medium forecasts for industrial energy prices (Thames Water, 2014). No sustainability reductions, i.e., environmentally motivated reductions in licensed abstraction volumes, were considered; the historical trend suggests TWUL's licenses will not change by 2035 (Thames Water, 2014).

The MOEA optimization was run for 25,000 function evaluations (FEs) 50 times, each with a different random seed value to lessen the influence of random number generation on the results. As the "true" Pareto optimal set is unknown, close approximation to this set was sought (section 1.2.3.1). The reference set (obtained by non-dominated sorting of the 50 solution sets where any dominated solution, i.e., a solution that does not perform better against any objective when compared to the other solutions, thus is not Pareto optimal, is discarded) was almost identical to the Pareto optimal solutions obtained from a single seed analysis suggesting the results are very close approximation to the true Pareto optimal solutions.

3.3. Results

3.3.1. Performance trade-offs analysis

The many-dimensional visualization offers a rich view into high performing combinations of interventions and their impacts. This analysis shows how progressively visualizing the performance dimensions helps communicate many-dimensional trade-offs and aids stakeholder understanding and deliberation.

Firstly, lower dimensional optimization approach results are shown to analyse the implications of many-objective optimization on decision making process. Water companies incorporate the operational, environmental and social cost in addition to the capital cost into the single cost objective. Because the environmental and social costs are very difficult to estimate and the estimations might not be accurate we are not considering these in the single cost objective optimisation here. The purpose of this analysis is to highlight the provision of many alternative plans as well as the process of learning about the system's behaviour. Therefore, the single cost objective in our study consists of only the capital cost of portfolios. Considering only a single cost objective would provide a single least cost solution shown in a two-dimensional plot in Figure 3-2a. The horizontal axis represents the capital cost while the vertical axis the reliability performance metric. The reliability of the system is constrained to reflect at least the minimum required Levels of Service (LoS), i.e. the maximum return periods of imposing demand restrictions as specified in Figure 1-12. This constraints the reliability metric here that reflects the LoS Level 3, to a minimum of 95% (return period of 1 in 20 years). However, many times when the London Aggregate Storage falls below the Demand Saving Level 3 (Figure 1-12), it also falls below the Demand Saving Level 4 when standpipes would be imposed. The optimization constraints here ensure such demand restriction is never imposed as the LoS Level 4 states (Figure 1-12). To never allow for LoS Level 4 failure (i.e. Level 4 reliability to be lower than 100%), the LoS Level 3 reliability as a result is constrained by the optimization to 99.2%. Although the solution requires the lowest possible capital investment while maintaining the specified Levels of Service, its supply reliability performance may still be improved upon. Optimizing for capital investments and supply reliability explicitly results in a trade-off curve between these conflicting objectives (Figure 3-2b); improving the system's reliability requires higher investments. The trade-off curve provides information about how much more capital is required to improve the reliability of the supply by a certain amount. Achieving perfect reliability for the lowest possible cost, however, might not

satisfy every decision maker preferences. Considering many different objectives provides decision makers with better insight into the system's behaviour and many alternative solutions to the problem where improvement in one objective reduces the performance in one or more other objectives.

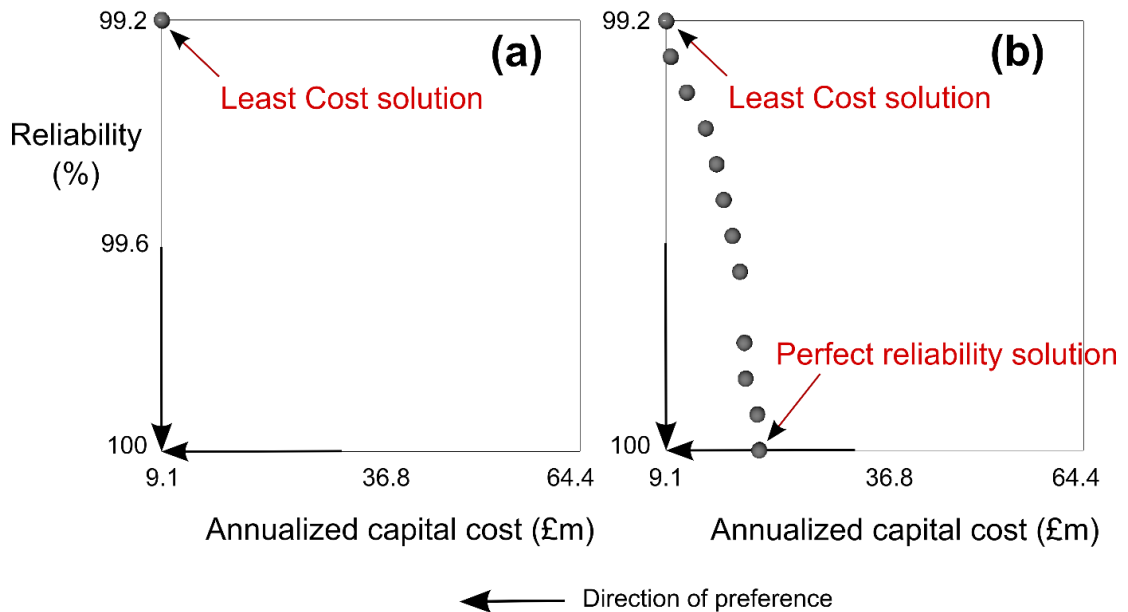


Figure 3-2. Single objective (plot a) and two objective (plot b) deterministic optimisation results. Plot b illustrates the trade-off between the capital cost and supply reliability objectives; improving reliability performance of the system requires higher capital investments.

Figure 3-3a shows the full set of Pareto optimal portfolios obtained from the six objective optimisation. This two dimensional representation however does not provide sufficient insight into how these portfolios differ, potentially hiding decision relevant information. The two distinct fronts here show seemingly identical performance. Visualizing the Pareto approximate solutions in many dimensions helps to understand how the objectives and plans conflict and interact with each other. We show how building the understanding of these interactions progressively via visualization analytics may aid decision making.

The colour scale in Figure 3-3b distinguishes the portfolios according to their environmental performance, i.e. the eco-deficit objective value. The red points represent the highest eco-deficit, i.e., the worst environmental performance, while the blue points show the lowest achievable eco-deficit, i.e., the lowest environmental impact. Portfolios with the same level of reliability differ in terms of their environmental performance; reducing the eco-deficit requires higher capital investment.

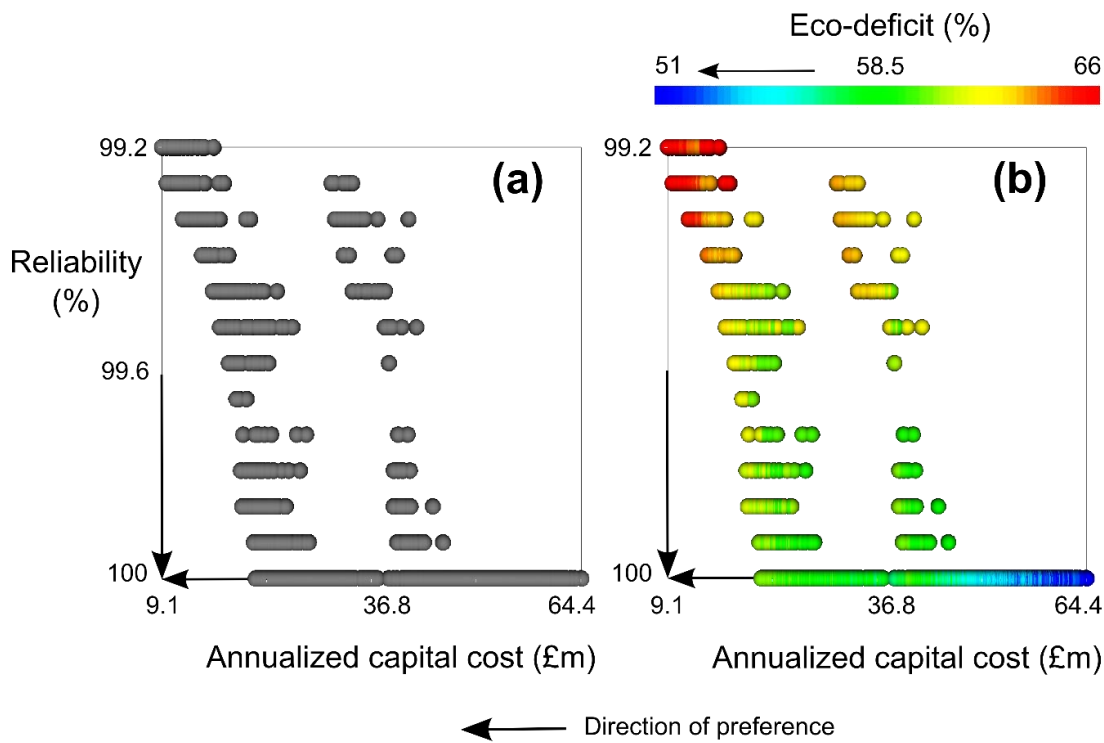


Figure 3-3. The full set of Pareto approximate portfolios obtained from the six objective optimization shown in two dimensions (plot a) and three dimensions (plot b). Adding the colour scale to visualize the environmental performance further distinguishes between the portfolios. The red solutions illustrate the highest eco-deficit while the blue solutions show the lowest eco-deficit.

This three dimensional representation provides better means for the analysis but is still not sufficient to reveal all the information available to decision makers. We can explore the objective space further by adding supply deficit objective values as a “depth” into the three dimensional plot (Figure 3-4a) and rotating the view such that the interactions between all shown objectives is clearly visible (Figure 3-4b). The figure reveals two distinct “fronts” with one front skewed to the right, i.e., higher capital costs (shown on x axis in Figure 3-4) are required to achieve identical reliability between the right and left fronts. By improving the reliability of the system (downward direction on the vertical axis) one can also decrease supply deficits (shown on y axis in Figure 3-4). Nevertheless, many perfect reliability solutions (at the bottom plane of the cube in Figure 3-4) exhibit varied supply deficit that decreases with higher capital investment.

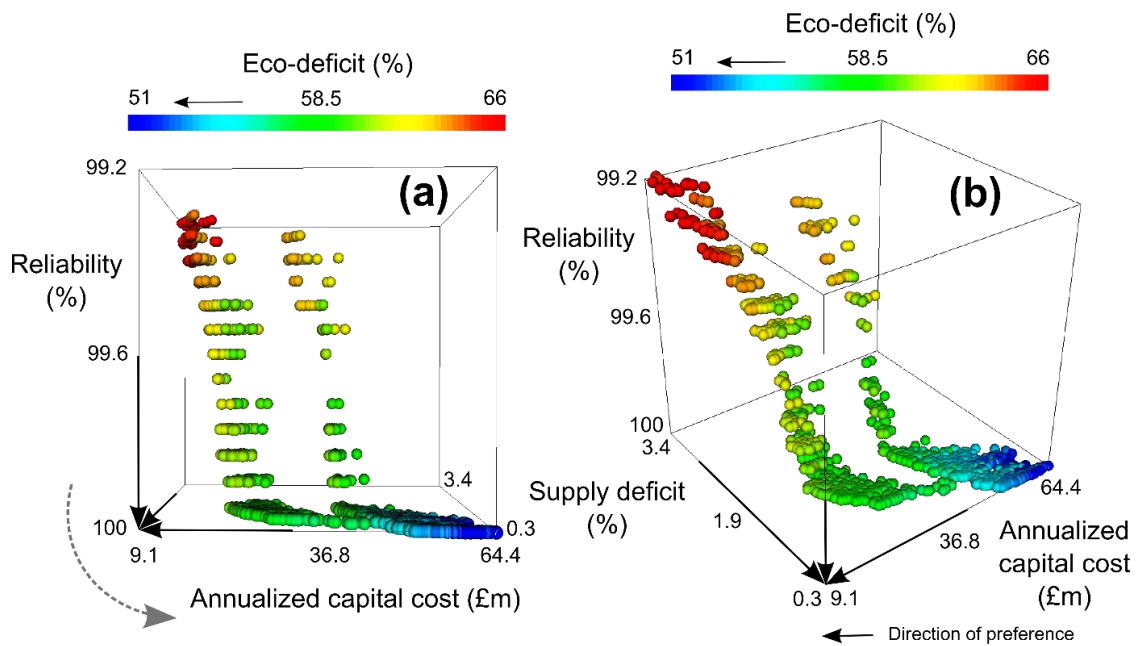


Figure 3-4. Adding 4th dimension, supply deficit, as a “depth” into three dimensional plot (plot a). The view in plot b indicates that improving the reliability also lowers the supply deficit.

To incorporate the two remaining objectives, supply resilience and energy cost, the shape of the points representing the Pareto optimal solutions was changed to cones in Figure 3-5. The orientation of the cones in Figure 3-5 shows the resilience of the portfolios where the cones pointing upwards indicate the worst resilience, i.e., the longest maximum duration of LTCD Demand Level 3 failure, while the cones pointing downwards show the best achievable resilience. This performance objective is strongly correlated with reliability; improving the system’s supply reliability also increases the supply resilience, i.e., reduces the duration of the failure state.

Visualizing the energy cost objective, however, reveals potentially unexpected information about the system. This objective is represented by the size of the cones in Figure 3-5b where the bigger the cone the higher the average annual operating cost the portfolio requires. Both of the two distinct fronts (discussed further in section 3.3.2) indicate that improving the system’s engineering and environmental performance requires higher energy use. More importantly, the portfolios on the left hand side front in Figure 3-5b exhibit higher energy cost requirements than the portfolios on the right hand side of the plot. Although the latter require higher capital investment to achieve similar engineering performance, these portfolios are also able to achieve lower eco-deficit (colour in Figure 3-5b) than the former. Furthermore, lower average annual energy cost requirements might influence the total long-term cost of a portfolio.

Decision makers who prefer the system with perfect reliability and good environmental

performance that require relatively low energy use may choose a plan from the portfolios in the lower part of the right hand side front in Figure 3-5b.

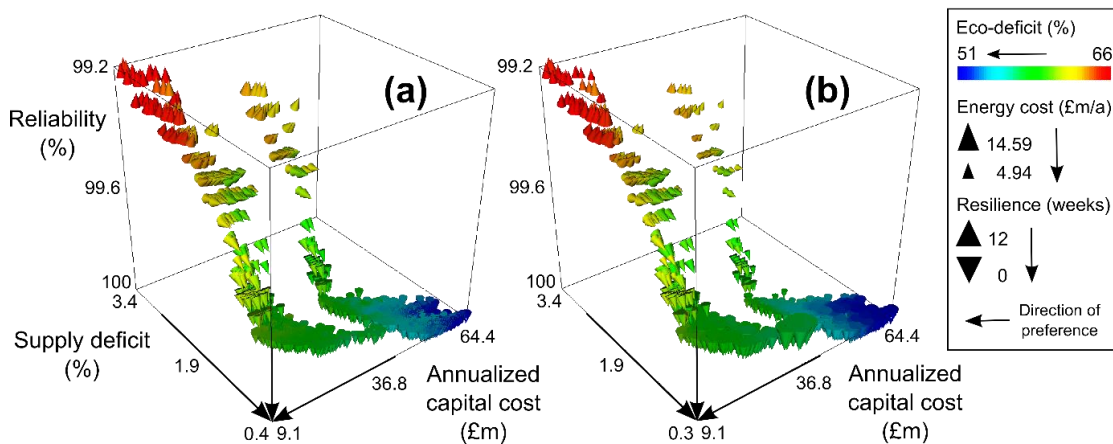


Figure 3-5. Visualizing the resilience (plot a) and energy cost (plot b) objectives by the orientation and size of the cones, respectively. Cones pointing upwards indicate worst resilience while cones pointing downwards the best resilience; the bigger the cone the higher energy use the portfolio requires. Improving the reliability of the system (vertical axis) also increases its resilience but requires higher capital investment and energy use. The two distinct fronts differ in the portfolio energy requirements where the portfolios on the right hand side front require higher capital cost but exhibit lower energy cost than the portfolios on the left hand side front.

3.3.2. Portfolio analysis

The results of the many-objective optimization may be analysed further to assess how the individual interventions within the portfolios affect the system's performance. As noted by Tsoukias (2008), decision makers find the strict mathematical separation of decisions and objectives to be a false construct that can limit decision relevant insights. Figure 3-6 displays a combination of both decisions (the intervention choices) and a subset of performance metrics. The cardinal axes show the capital cost, supply deficit and reliability metrics as in Figures 3-4 and 3-5. Similarly, the size of the cones depicts the energy cost requirements. The colour in Figure 3-6a shows the implementation of the strategic mutually exclusive supply interventions; the blue portfolios build none of these, the green portfolios build the Upper Thames Reservoir (UTR) and the red portfolios build the River Severn Transfer (RST). None of the Pareto optimal portfolios build the Northern Transfer (NT). When none of these new supply interventions are implemented portfolios require the lowest capital investment but have the worst supply deficit and reliability. Most of the Pareto optimal portfolios implement the UTR and only a fraction implement the RST. The latter (red points in Figure 3-6a) exhibit perfect reliability but these portfolios require the highest operating energy use, possibly making them impractical in the long-term. The orientation of cones in Figure 3-6a indicates implementation of the Pipe repair demand management intervention; cones pointing

upwards depict portfolios that include the Pipe repair campaign while cones pointing downwards show portfolios that do not. Both panels show a combination of portfolios with and without the Pipe repair campaign creating the two distinct fronts. Portfolios implementing this intervention require higher capital investment but exhibit better environmental performance (colour of cones in Figure 3-5) and demand lower energy use (size of cones in Figures 3-5b and 3-6) than the portfolios on the left front. This suggests the demand management interventions may help improve the system's performance with reduced energy consumption.

Panel b of Figure 3-6 illustrates implementation of the Long Reach desalination plant (shown by colour) and the Deephams Reuse Scheme (shown by the orientation of the cones). Portfolios building the desalination plant (red cones in Figure 3-6b) require higher capital investment than portfolios that do not (blue cones in Figure 3-6b) but the former improve the environmental performance (shown by colour in Figures 3-4 and 3-5) for the same levels of supply deficit and reliability than the latter. The building the reuse scheme influences the energy cost requirements; portfolios implementing the reuse scheme (cones pointing upwards in Figure 3-6b) generally require higher energy cost to operate (shown by the size of the cones) than portfolios not implementing the reuse (cones pointing downwards in Figure 3-6b).

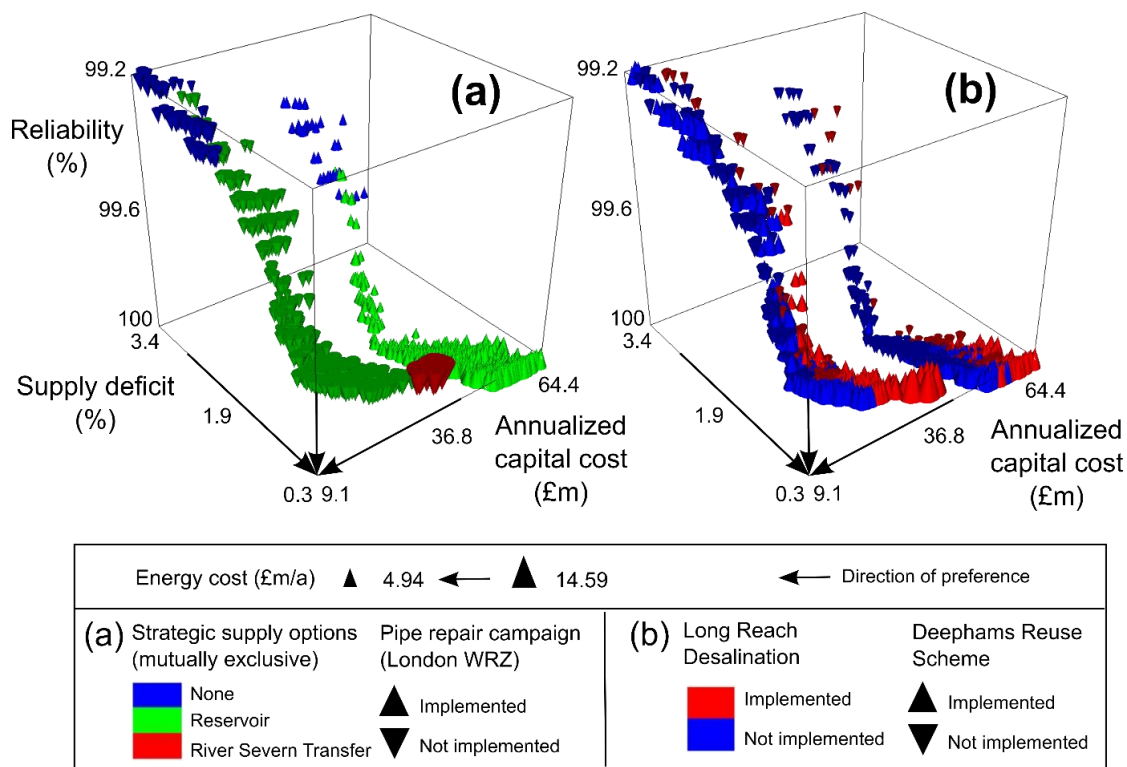


Figure 3-6. Pareto optimal portfolio composition analysis. The cardinal axes show the same performance metrics as in Figures 3-4 and 3-5 and the size of the cones refers to the energy cost. The colour in panel a shows the implementation of the strategic mutually exclusive supply interventions; blue portfolios do not implement any, green portfolios build the reservoir and red portfolios build the River Severn Transfer. The orientation of the cones in panel a depicts the implementation of the Pipe repair campaign; cones pointing upwards implement the campaign, cones pointing downwards do not. The colour in panel b shows the Long Reach desalination plant implementation; red portfolios build the plant, blue portfolios do not. The orientation of the cones in panel b illustrates the Deephams Reuse scheme implementation; cones pointing upwards build the scheme, cones pointing downwards do not.

To analyse how the individual combinations of interventions, i.e. portfolios, affect the performance of the system five representative portfolios are singled out based on their performance. These are highlighted in Figure 3-7. The Least Cost portfolio requires the lowest initial investment, builds the least infrastructure and shows the worst engineering and environmental performance. The Reuse portfolio builds the Deephams reuse scheme and achieves the same engineering performance than the Pipe repair portfolio implementing the Pipe repair campaign instead with lower capital cost but higher energy cost requirements. The RST portfolio builds the River Severn Transfer supply intervention, exhibits perfect reliability and resilience but requires the highest energy cost to operate. The Highest cost portfolio implements all supply and demand management interventions and achieves the best engineering and environmental performance but requires the highest initial investment. Please note that even this best

performing portfolio cannot achieve 0% supply deficit (its supply deficit is 0.3%), i.e. result in any supply-demand balance surplus.

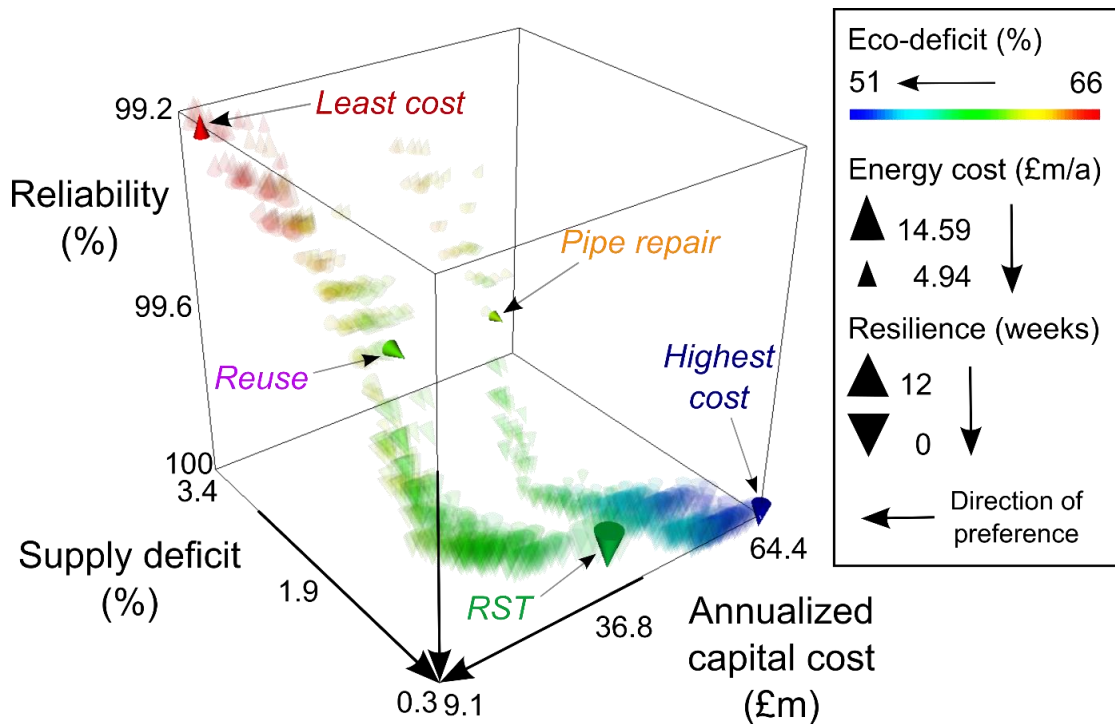


Figure 3-7. Five representative portfolios singled out for further analysis. The Least Cost solution requires the lowest initial investment, performs the worst against the engineering and environmental metrics and builds the least infrastructure. The Reuse portfolio builds the reuse scheme and achieves the same level of engineering performance than the Pipe repair portfolio implementing the Pipe repair campaign with lower capital investment but higher energy cost requirements than the latter. The RST portfolio builds the River Severn Transfer, has perfect reliability and resilience but requires highest energy cost. The Highest cost portfolio achieves the best engineering and environmental performance but requires the highest initial investment.

Table 3-2 details the individual supply and demand management interventions present in each representative portfolio as well as the TWUL's WRMP14 Least Cost and final plan interventions. The current TWUL's WRMP, WRMP14, considered slightly updated resource and demand management options as well as many small surface water and groundwater schemes. The cost included NPV of the capital, operating and environmental and social costs that is different from the capital cost in our study that represents average annual undiscounted capital investment only. Furthermore, the interventions in WRMP14 plans are scheduled over time whilst our study considers only a static snapshot of the system in 2030s. Small schemes such as groundwater schemes providing little supply volumes were not considered in our study for simplicity. Nevertheless, our results still bear some resemblance to the WRMP14 least cost and final plans for London. The latter is a revised more expensive strategy that is more sustainable and deliverable than the actual least cost plan identified by the EBSD model

(Thames Water, 2014). The former included similar SLARS capacity than our Least Cost, updated transfers volume than our Least Cost, and a reuse scheme with higher volume and different location than the Deephams Reuse considered in our study, which was not available at the time of our study. The Least Cost plan here does not implement a reuse scheme. The demand management interventions in WRMP14's least cost plan provide much higher demand savings than Least Cost plan in our study. It is however important to note that the EBSD model assumes an intervention is able to provide the constant ML/day supply as DO every day of its operation whilst the IRAS simulation model is able to simulate more realistic release of each intervention based on the water availability in the system.

Table 3-2. Five selected representative portfolio composition compared to the current TWUL's WRMP14 final plan

Solution	Least Cost	Reuse	Pipe repair	RST	Highest Cost	WRMP14 Least-Cost	WRMP14 Final Plan
<i>Supply interventions (ML/day)</i>							
UTR/RST/NT	×	UTR (149.5)	UTR (75.2)	RST (300)	UTR (149.9)	×	×
SLARS	22.7	×	17.1	23.4	22.2	23	18
Deephams Reuse	×	62	×	94.5	95.0	150 ¹	150 ¹
Columbus Transfer	39	×	×	39	39	34 ²	34 ²
Long Reach Desalination	×	×	×	15	15	×	×
Small GW schemes	-	-	-	-	-	14.4	14.4
Other reductions*	-	-	-	-	-	0	5.7
<i>Demand management interventions (ML/day demand reduction)</i>							
Active Leakage Control	49.2	49.7	49.6	49.8	49.6	212.2 ³	20
Pipe repair campaign	×	×	165.1	×	165.1		39
Efficiency	×	11.6	×	11.6	11.6		13
Meters	88.7	88.7	88.7	88.7	88.7		28.8 ⁴
Tariffs	☑	☑	☑	☑	☑		☑

* Includes commercial reduction from competition and TWUL's building water reduction

¹Beckton Sewage Treatment Works (not available at time of this study)

²2 transfer schemes (each of 17ML/d) represented in this study as Columbus Transfer

³Leakage, metering and water efficiency all together

⁴Resulting from different metering options not available at the time of this study

The WRMP final plan implements SLARS with similar capacity to our Pipe repair portfolio, a reuse scheme with again higher volume and different location than the Deephams Reuse considered in our study, small local transfers and groundwater schemes, other savings and all demand management interventions (with updated demand saving estimates not available at the time of our study). Nevertheless, the WRMP14 states that “three options (transfers, re-use and storage) are proposed to be taken forward for more detailed study in AMP6 to give future flexibility...” (Thames Water, 2014) which would bear more resemblance to our RST and Highest Cost portfolios.

Figure 3-8 shows the performance metrics of the selected portfolios on a parallel axis plot. Each vertical line represents an axis for a specific metric with the preferred direction of optimization to be at the bottom of the plot. Each coloured horizontal line then represents a particular portfolio – the Least Cost portfolio is shown in red, Reuse in purple, Pipe repair in yellow, RST in green, and the Highest Cost in blue. The performance metric value is located where a coloured line crosses a corresponding vertical axis. Where the coloured lines cross each other between the vertical axes there is a trade-off between the adjacent axes, i.e. corresponding metrics. The Least Cost solution in our study builds only two small supply interventions (SLARS and Columbus transfer) and two demand management interventions (ALC and Meters with Tariffs). The Reuse portfolio builds large UTR and small reuse scheme with ALC, Efficiency, and Meters with Tariffs. The more expensive Pipe repair portfolio builds small UTR and SLARS with ALC, Meters with Tariffs, and Pipe repair campaign. The Pipe repair campaign implementation results in higher capital cost but lower energy cost when compared to the Reuse portfolio. The difference between the RST and Highest Cost portfolios is that the former build RST instead of UTR and does not implement the Pipe repair campaign, which results in lower capital cost but worse supply deficit and environmental performance as well as significantly higher energy cost when compared to the Highest Cost portfolio performance.

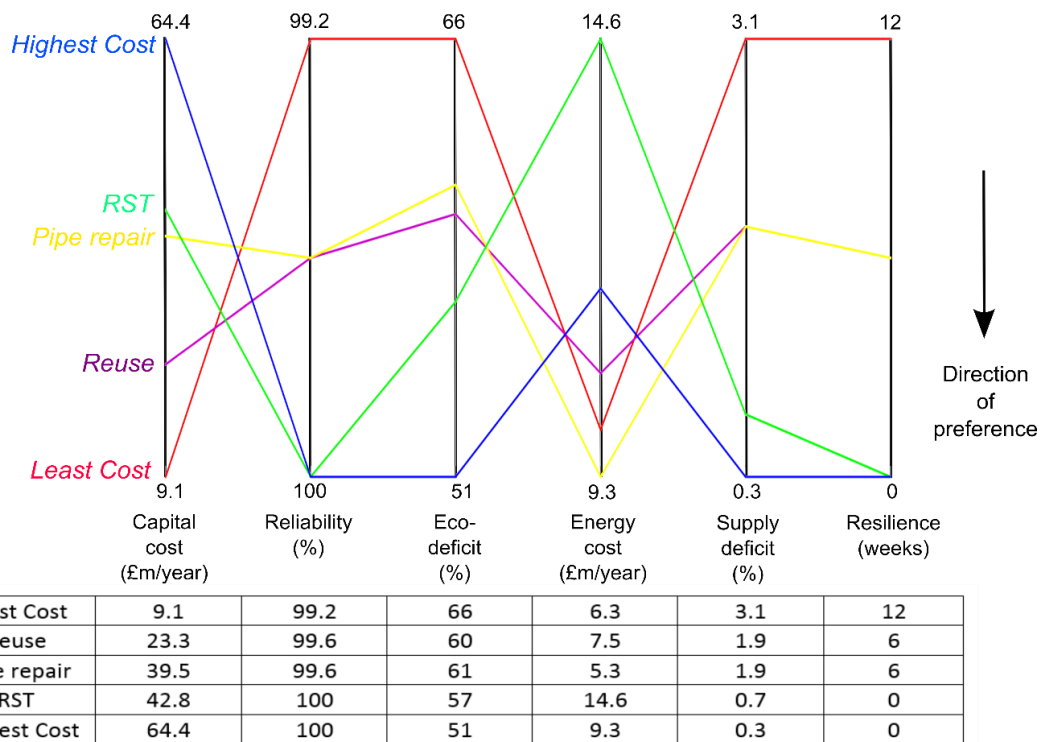


Figure 3-8. Five selected representative portfolio performance comparison on a parallel axis plot. The vertical axes represent performance metrics where the preferred (best) performance is at the bottom of axes whilst the worst performance is at the top. The coloured lines show the five selected portfolios and the table shows each portfolio’s metric values.

The volumetric glyph and parallel plots show the performance objectives of each solution evaluated over the whole of a simulation run. The use of a simulation model in this optimization approach allows for direct performance comparison between any of the Pareto optimal plans. Figure 3-9 shows some of the simulated results for the London aggregate storage node for each of the five selected portfolios. The plot serves as a reminder that each cone or point in the Pareto-approximate plots is backed up by a detailed and realistic system simulation. The Highest Cost portfolio sees the least drawdown of the London Aggregate Storage (LAS) node. The Least Cost portfolio (red line in Figure 3-9) performs most poorly; the RST and Highest Cost portfolios (green line and dark blue dashed line in Figure 3-9, respectively) have the lowest drawdown not crossing the LTCD Demand Level 1 (shown by the light dashed blue curve) with the latter maintaining higher level of the LAS storage in autumn 1997.

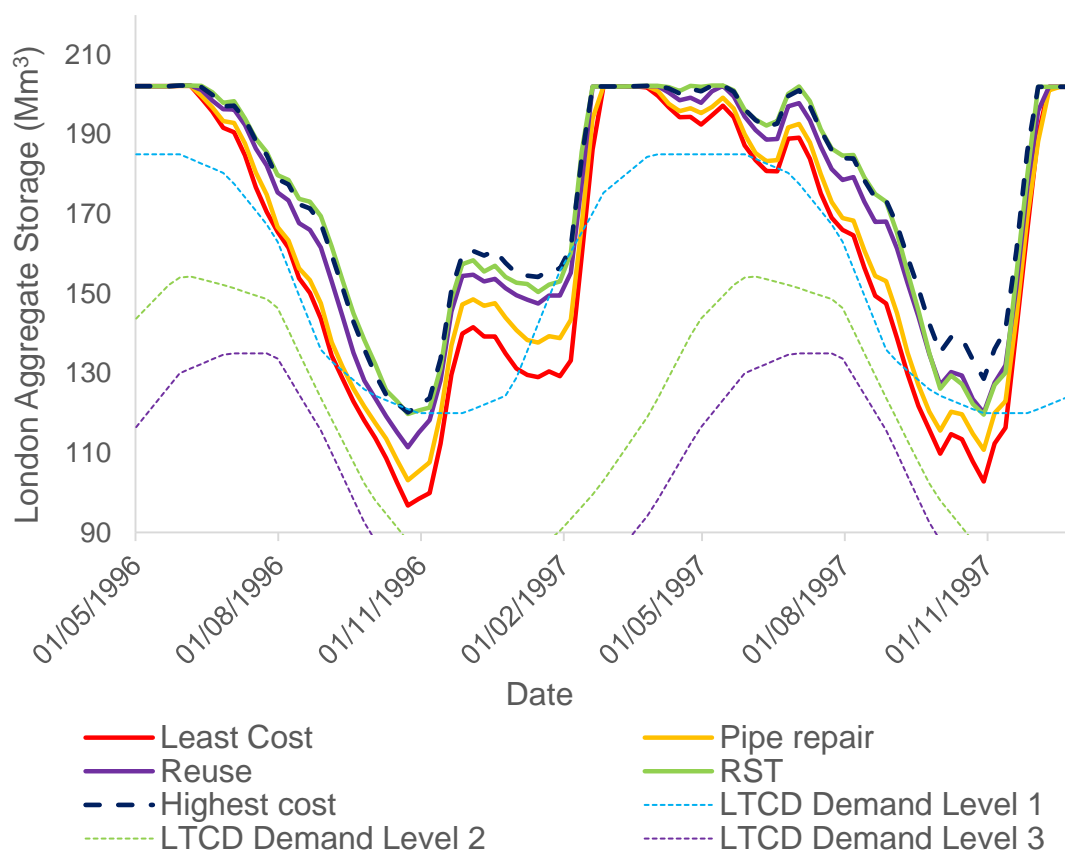


Figure 3-9. Simulated London Aggregate Storage drawdown for the five representative portfolios.

3.4. Discussion

3.4.1. Many-objective optimization

Water resource systems serve stakeholders with complex and varying interests who may have differing preferences regarding how the system should be able to adapt in the context of future uncertainty (Heffernan, 2012). It is therefore desirable to integrate these multiple needs in the decision making process (Simpson, 2014) and provide decision-makers with the ability to consider the broader consequences of various decisions (Loucks, 2012). Multi-objective optimization allows planners to incorporate different and often conflicting preferences into decision making. Optimizing for these preferences explicitly, without the need to monetize and aggregate them into a single objective, allows decision makers to visually assess the trade-offs that different investments imply. Trade-offs can facilitate stakeholder deliberations post optimization and provide planners with a rich view into high performing intervention portfolios that otherwise would remain hidden if lower dimensional analysis (monetary only) was used. In the Thames basin, reducing capital investments negatively affects the engineering and environmental performance of the system Figure 3-5). Higher capital investment results in maintaining good engineering and environmental performance

whilst saving on energy costs. Decision makers who value reliability and good environmental performance without a large increase in energy use may choose a plan from the portfolios in the lower part of the right front in Figure 3-5.

3.4.2. Visual analytics

Visualizing the Pareto optimal set of solutions in the many-dimensional objective space allows decision makers to discover how the different system performance criteria conflict and interact with each other. Visualization of trade-offs in multiple dimensions is well suited for situations where stakeholders have diverse interests. For instance, an environmental regulator could be interested in how different portfolios impact the environmental flows downstream of abstraction sites while water companies could be interested in seeing how well portfolios meet service reliability requirements.

Visualizing and exploring the Pareto optimal portfolios progressively, as was shown in Figures 3-3 – 3-5 may aid the learning and decision making process and help justify to interested parties why a certain plan was selected. Decision makers are given the opportunity to decide the balance between performance preferences in the planning process a posteriori.

The analysis presented here demonstrated that it is important to exploit visual analytics to promote linked views of both performance objectives and investment decision variables simultaneously. Figure 3-6 showed how the Thames system's Pareto optimal portfolios 'cluster' into distinct suites of water supply and demand management interventions. Visualizing these diverse groups of portfolios in performance space provides decision makers with a rich perspective on key decision trade-offs and significant flexibility when choosing alternatives for further consideration. Decision makers can quickly build a mental map of the consequences of including certain interventions in their plans. The parallel axes plot in Figure 3-8 allows for visualizing multiple dimensions (performance metrics) "in parallel" on a single plot. Such representation is particularly suitable for demonstrating to decision makers how a small number of solutions can be compared directly against many performance metrics.

3.4.3. Uncertainty of future supply and demand

A limitation of the application described here is its consideration of one set of future conditions: it assumes historical inflows are representative of future plausible ones and that future demands, energy prices and abstraction license conditions are known. The historical record used in this study contains several stress events and therefore provides a useful stress test for future system designs. A 30-year historical hydrological record is

used in the current planning framework English water companies use which was also applied here. This deterministic study provides a baseline against which results from a future stochastic or multi-scenario optimization seeking robustness could be compared.

3.4.4. Practical use of the proposed approach

The current modelling to assist water supply-demand planning in the UK uses single objective least-cost optimization subject to reliability constraints (Padula et al., 2013). In the approach proposed here, the use of a water resource simulator allows performance metrics to be measured in diverse units familiar to stakeholders who may not agree on how or whether metrics should be monetized. As such the approach presented here is a contribution towards improved water planning for water utilities. Matrosov et al. (2013a,b) apply simulation-based water planning approaches on a UK case-study (Robust Decision Making and Info-Gap Analysis) and contrast them to the current regulator approved least-cost optimization approach. Borgomeo et al. (2014) present a risk-based framework that uses simulation to incorporate climate change projections into water resource planning. These simulation-based system design approaches allow considering engineering, economic and environmental performance in greater detail, but they do not consider all combinations of proposed interventions as economic optimization does. A few options with ranges of possible capacities (even if coarsely discretized) quickly lead to an exponential number of possible intervention portfolios to try. Simulation based approaches such as those applied by Matrosov et al (2013 a,b) can be criticized for choosing to evaluate in depth portfolios of options that are to some extent arbitrarily defined. The approach presented here frees planners from having to choose *a priori* which portfolios of interventions (at fixed capacities) to evaluate; instead here the search for the most promising groupings of options and their capacities is automated.

If trusted simulators are used in the proposed analysis, and performance metrics used in the optimization have been defined with stakeholders (Herman et al, 2015), the Pareto optimal solutions will likely be of interest to decision makers. The IRAS-2010 Thames basin simulator used in this study was shown to accurately emulate the TWUL's simulation model WARMS (section 2.1.2) and the performance metrics were discussed with TWUL.

3.5. Conclusion

Water resource system and water supply planning are inherently multi-objective problems where decision makers must balance complex priorities such as costs, reliability, ecosystem services, etc. Single-objective planning such as least cost optimization gives planners only part of the picture when designing real systems where many aspects of system performance are relevant. Even if all system goals can and have been translated to one commensurate unit system (typically monetary), planners would lack the ability to understand the trade-offs embodied by different plans. This chapter presented Thames basin water resources supply system design optimization problem with 7 simultaneous objectives: minimizing capital and operating costs while maximizing environmental performance and engineering performance metrics such as supply deficit, resilience and reliability. The objectives were subject to regulatory supply reliability constraints.

Visual analytics was used to explore the Pareto optimal solutions in a multi-dimensional trade-off space. Adding dimensions progressively helps decision makers to navigate the trade-off space and gain understanding of how their preferences interact and conflict. Multi-dimensional plots aid analysts and decision makers see how individual interventions affect performance of the system in each dimension. Portfolios which share certain interventions were seen in some cases to cluster in some parts of the decision space showing that choosing certain options leads to certain types of performance. Conversely, other parts of the Pareto optimal front revealed that quite different portfolios had similar performance. Together the graphics underline the complexity of selecting interventions in complex human-natural systems when many metrics of performance are relevant and the richness of information communicable through a multi-objective search-based approach. The visual analytics graphics allow stakeholders and decision makers to assess trade-offs between objectives and show how different interventions and portfolios of interventions map to those trade-offs.

4. Chapter 4 – Multi-scenario many-objective optimization

4.1. Introduction

This chapter describes a planning approach that explicitly considers both multiple sources of uncertainty and multiple evaluation objectives. In the proposed system design screening framework here the goal of robustness and resilience is incorporated explicitly into an automated intervention selection process. This contrasts with common approaches where robustness and resilience are evaluated post-optimization using sensitivity analyses (e.g. Thames Water, 2014). This provides analysts with a high performing set of robust system designs and the associated trade-offs in benefits implied by intervention choices. The benefits of incorporating multiple sources of uncertainty into a multi-objective decision making process are demonstrated; the analysis shows how considering only historical data can lead to poorly performing system designs under hydrological futures considered plausible by national climate model results (Centre for Ecology & Hydrology, 2015).

This study proposes a multi-scenario multi-objective decision-making approach which addresses some limitations of the current planning approach. Several conflicting performance goals including the financial, engineering and environmental performance are considered explicitly. Multiple sources of uncertainty in the form of scenarios considered relevant by stakeholders are used in an automated search for robust combinations of interventions. The ensemble of scenarios consists of climate change impacted hydrological flows, plausible water demands, environmentally motivated abstraction reductions, and future energy prices. The approach is demonstrated by exploring portfolios of alternative water infrastructure and conservation investments for London's water supply for an estimate of conditions in 2035. Visual analytics is used to investigate the trade-offs between performance goals and communicate the influence of specific interventions on a portfolio's performance. Robust portfolios from a multi-scenario search are compared to those developed when considering only historical conditions to highlight the benefits of explicitly considering multiple futures within the investment portfolio search. Visualizing the individual interventions implemented in the identified portfolios from both single and multi-scenario search aids the exploration of how the options affect the robustness of the system. The proposed multi-scenario efficient trade-off analysis is a valuable investment screening tool for utility planners

identifying robust infrastructure and conservation investment bundles that provide benefits over a wide range of future conditions. Such an approach is particularly valuable where decisions on resource development are contested and trade-offs need to be negotiated with stakeholders interested in a diverse set of definitions for desirable system performance.

The approach is described in section 4.2 which details the optimization formulation and the scenarios of future conditions. Results are presented in section 4.3 and discussed in section 4.4. The chapter concludes with section 4.5.

4.2. Methodology

4.2.1. Problem formulation

In the multi-scenario optimization portfolios are identified as robust when they perform satisfactorily well over the considered range of external conditions in the form of scenarios. The performance metrics are calculated for each future scenario in the same way as for the deterministic case. We then calculate the average and the worst 95th percentile of values obtained from all scenarios to assess performance across the ensemble of scenarios. The percentile values here do not have a probabilistic interpretation but refer to the fraction of considered cases where an outcome occurs. Water planners are typically risk averse and will want to consider system performance under stressful conditions. The worst 95th percentile performance value reflects how a candidate solution would perform if nearly worst-case conditions occurred and is applied to metrics related to system failure (in our study, deficit, reliability and resilience).

The feasibility of portfolios is again constrained by the mutual exclusivity of certain supply interventions and by meeting the minimum Levels of Service across the ensemble of scenarios (Figure 1-12). In this work we assume water managers are interested in solutions that are able to satisfy today's minimum performance levels over a wide range of plausible future conditions. For this reason, current Levels of Service are applied to all future scenarios as constraints. The failure frequency, i.e., the maximum allowed frequency of imposing demand restrictions (Figure 1-12), is calculated for each scenario. If a candidate solution violates any of the constraints in any scenario, it is not brought forward into the trade-off space. Keeping the current Levels of Service limits the solutions to only those that would be acceptable under current planning goals. This does not consider that, in response to a changing climate,

future managers may decide 2015-era Levels of Service are too strict. The problem formulation is of the same format as defined by Equation 3-1 in section 3.2.1.

4.2.1.1. Decisions

The same decisions as in the deterministic approach described in the previous chapter in section 3.2.1.1 are considered here to be able to directly compare the portfolios.

4.2.1.2. Objectives and constraints

The objectives and constraints here are calculated in the same way as for the deterministic optimization (section 3.2.1.2) with the difference of statistical analysis of the values across multiple scenarios considered here. The equations are therefore adjusted as follows.

The capital cost objective ($f_{CapCost}$) is assessed as in the deterministic optimization and as described by Equation 3-2. The capital cost of a portfolio remains the same across all possible futures as it depends only on the implemented decisions.

The supply deficit (f_{SupDef}) objective represents the maximum annual deficit [%] experienced by the London demand and is minimized:

$$\text{Minimize}_{P_{95}} \left[f_{SupDef} = \max_t \left[\left(\frac{DT_t - M_t}{DT_t} \right) * 100\% \right] \right]_P$$

4-1

where P represents the percentile of the set of objective values across the whole ensemble of scenarios, P_{95} is the value at the worst 95th percentile, DT_t is the London's demand target for year t and M_t is the demand met during year t .

The supply resilience objective (f_{SupRes}) is assessed on the LAS node and the failure occurs when the LAS storage level drops below the LTCD Demand level 3 threshold and the non-essential use ban is brought into effect. The objective aims to minimize the maximum time period over the whole time horizon required to recover from the failure, which refers to a period during which the Demand level 3 restrictions are in place:

$$\text{Minimize}_{P_{95}} \left[f_{SupRes} = \max D \right]_P$$

4-2

where D is the failure duration in weeks.

The supply reliability objective (f_{SupRel}) is also assessed on the LAS node and maximizes the proportion of time over the whole time horizon when the LAS level is above the

LTCD Demand Level 3 threshold and the Demand level 3 restrictions are not brought into effect:

$$\text{Maximize}_{P_{95}} [f_{SupRel} = (1 - (F_s/S)) * 100\%]_P$$

4-3

where F_s is the number of time-steps (weeks) during which the system was in failure, and S is the total number of time-steps within the modelling time horizon.

The eco-deficit objective (f_{ECO}) (Vogel et al., 2007) represents the difference between the naturalized low flows and simulated low flows [%] (low flows here denote the flows under Q_{70} , i.e., flows that are not exceeded 70% of the record time) at the Teddington Weir on the River Thames. The naturalized flows here refer to the river flow where there are no TWUL's abstractions; the objective therefore assesses direct impact of TWUL's abstractions and return flows on the river itself. The higher the difference (i.e., deficit), the more the environmental conditions of the river deteriorate due to lower water levels than the natural state. Eco-deficit of 0% implies no deficit while 100% eco-deficit is the largest possible deficit:

$$\text{Minimize}_{Average} [f_{Eco} = (|AN_{Q70} - AS_{Q70}|/AN_{Q70}) * 100\%]_P$$

4-4

where AN_{Q70} is the area under the naturalized flow duration curve (FDC) and AS_{Q70} is the area under the simulated FDC. The eco-deficit metric calculation for each scenario simulation is associated with the difference between natural and simulated (after all abstractions and return flows to the system) low flows, which are defined as flows that are exceeded more than 70% of the flow record (flows below Q_{70}). This percentage deviation is different at different flows. The traditional Environmental Flow Indicators in the UK are assessed against Q_{10} , Q_{30} , Q_{70} and Q_{95} . The Q_{70} and Q_{95} flows are generally projected by the Future Flows to decrease (Centre for Ecology & Hydrology). As the difference between the flow duration curves is usually very small towards the 100% the Q_{70} was chosen in this project to reflect the eco-deficit metric.

The energy objective (f_{Energy}) quantifies the cost of the average annual energy use of the whole supply system including the existing and implemented possible supply interventions:

$$\text{Minimize}_{Average} \left[f_{Energy} = \left((1/T) * \sum_{t=1}^T \sum_i E_{i,t} \right) * UP \right]_p$$

4-5

where $E_{i,t}$ is the energy requirement to operate the supply intervention i over each year t , T is the total number of years and UP represents the unit price of 1 kWh. The $E_{i,t}$ is based on the release of the particular supply intervention during year t and is calculated in the same way as detailed in Equation 3-8.

The constraints ensure satisfactory reliability of the aggregate surface storage (assessed on LAS) that complies with the TWUL specified LoS (Figure 1-12) and are calculated for each scenario in the same way as specified by Equation 3-9. If a solution violates any constraint in any scenario it is considered unsatisfactory and not robust.

4.2.2. Scenarios of future conditions

One of the most widely applied approaches to incorporate uncertainties into planning is using scenarios of plausible future conditions. The economic regulator for the UK water industry Ofwat (Ofwat, 2013) requires water companies to assess key risks of their proposed plan. Planners evaluate these risks post optimization by testing their preferred plans against plausible futures using scenario simulation. However, the considered resource options' daily supply (deployable output) used in the search for least-cost portfolio is still estimated considering only baseline historical conditions. TWUL identified and used for scenario testing four external conditions with the highest potential to adversely impact their water resources system, based on Ofwat's recommendations (Thames Water, 2014). These include climate change impact on hydrological flows, demand growth, sustainability reductions from stricter environmental regulations and energy prices. The scenarios for the four uncertainties were selected by TWUL to span the range of conditions that they would like their system to be able to respond to (Thames Water, 2014). For the purpose of our study we use the same scenarios as identified by TWUL and consider all of their possible combinations for the simplicity and ease of communication. The ensemble, which is incorporated within the optimization, includes 11 hydrological flow scenarios, 2 demand levels, 2 sustainability reductions levels and 2 energy price scenarios resulting in the total of 88 scenarios of future conditions (Table 4-1).

Table 4-1. Future scenarios. All combinations of future conditions were considered in the multi-scenario robust optimization

Uncertainty dimension	Number of scenarios	Future conditions
Hydrology	11	See section 4.2.2.1
Water demand	2	2,325 ML/day
		2,558 ML/day
‘Sustainability reductions’ to water licenses	2	No reduction (current licensed)
		Total of 175 ML/day
Energy unit price	2	13 p/kWh
		35 p/kWh
Total number of scenarios	88	

4.2.2.1. Supply side scenarios

The WRPG guidelines (Environment Agency et al., 2012) require assessing the effects of climate change on the supply availability and recommend four different approaches to do so. Two of these approaches use 11 Future Flows (FFs) hydrological flow scenarios. The FF scenarios represent equally probable hydrological scenarios characterized by future climate change impacted river flow time-series. The time-series were developed by the ‘Future Flows and Groundwater Levels’ project (Prudhomme et al., 2013) and are available from the National River Flow Archive (NRFA) online database (Centre for Ecology & Hydrology, 2012). The scenarios were 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 (Hadley Centre for Climate Predictions and Research, 2008). The model was run for the UK climate projections under the historical and medium emissions scenario (SRES A1B) and was also used to derive the UK Climate Projections scenarios produced in 2009 (UKCP09) (Murphy et al., 2009). TWUL applied FFs for their scenario testing (Thames Water, 2014). The SRES emission scenarios (IPCC, 2000) provide emission projections assuming no mitigation policies; the IPCC has recently produced the Representative Concentration Pathways (RCP) scenarios that take into account the current legislation on air pollutants projecting lower anthropogenic emissions (Kirtman et al., 2013). Climate projections obtained using the RCP scenarios may therefore provide different magnitude of change for temperature and precipitation.

The flow time-series for the Thames basin were generated by the hybrid hydrological model CLASSIC (Crooks and Naden, 2007), a semi-distributed grid-based rainfall–

runoff model that uses a combination of regionalized and catchment calibrated parameters. The entire time series of all 11 members of the Future Flows scenario ensemble (*afgcx*, *afixa*, *afixc*, *afixh*, *afixi*, *afixj*, *afixk*, *afixl*, *afixm*, *afixo*, and *afixq*) covers the period between 1950 and 2098 (Prudhomme et al., 2013).

This study uses a 30-year period (2020 - 2050) of all 11 scenarios for simulating demands and energy prices estimated for 2035 where each of these 30 years is assumed to represent possible conditions in the year 2035. The study considers only conditions at the projected planning year of 2035. Using transient flow time-series may not be appropriate as time continuation is not represented. We used the Mann-Kendall trend test to detect and confirm any transient characteristics of all 11 scenarios. The Mann-Kendall trend test (Kendall, 1975; Mann, 1945) is a non-parametric test widely used to detect significant trends in time-series. It is insensitive to outliers thus particularly suitable for hydrologic time-series trend analysis (Hamed, 2008). A significant statistical trend is present when the absolute value of Kendall's *tau*, which ranges between -1 and 1, is near 1 (Helsel and Hirsch, 2002). The analysis of the whole 148-year period confirmed the presence of a trend in all scenarios with the risk of rejecting the H_0 or "no trend" hypothesis lower than 0.5%. Two scenarios (*afixc* and *afixh*) showed increasing trend in flow volumes over time (i.e., increasing year by year) while the other 9 were characterized by a decreasing trend. However, the test cannot confirm the presence of a trend with significance level of 5% or higher in 6 scenarios between 2020 and 2050 while the absolute value of the Kendall's *tau* statistic with the same significance level for the other 5 scenarios does not exceed values above 0.1. Due to the short time span this period may be used for an analysis that is concerned only with a static snapshot of a system's performance in time (Ferguson et al., 2013; Knapp and Trainor, 2013). This study uses the 30-year period (2020 - 2050) of all 11 scenarios for simulating demands and energy prices estimated for 2035 where each of these 30 years is assumed to represent possible conditions in the year 2035.

The left panel of Figure 4-1 shows the flow duration curves (FDCs) for low flows at Teddington (low flows here denote flows below Q_{70}). A flow duration curve (FDC) is a graphical representation of the overall variation of a streamflow, usually showing the probability of exceedance on the horizontal axis and the magnitude of flow on the vertical axis. FDCs provide an estimate of the percentage of time of the considered record during which the flow exceeds a particular magnitude. The FFs scenarios reflect the period from 2020-2050 while the historical record (shown by a red dashed line in

the left panel of Figure 4-1) reflects the years 1970-2000. The latter was chosen for the deterministic study due to the high impact drought in 1976 (Burke et al., 2010) which required extreme water demand saving measures and water rationing. The left panel of Figure 4-1 indicates the low flows of the historical record fall in the middle of the FFs scenarios where the *afixh* scenario is the wettest and the *afixa* scenario the driest.

The pattern of flows, particularly the duration and timing of extreme events, can also affect the water supply systems performance. These patterns are not seen in the FDCs. The right panel of Figure 4-1 illustrates the difference in flow patterns across the 11 FFs scenarios compared to the historical flow record for an example two year period. There is a large variation of peak and low flows between scenarios. For instance, the *afixm* scenario (shown by the yellow line in the right panel of Figure 4-1) follows the historical record (shown by the red dashed line in the right panel of Figure 4-1) in 2025 but exhibits higher flows in winter 2026 and lower flows in winter 2027 than the historical series. Scenarios *afgcx* and *afixj* (dark blue and green lines in the right panel of Figure 4-1, respectively) show high flows in spring 2025 when the historical record exhibits low flows.

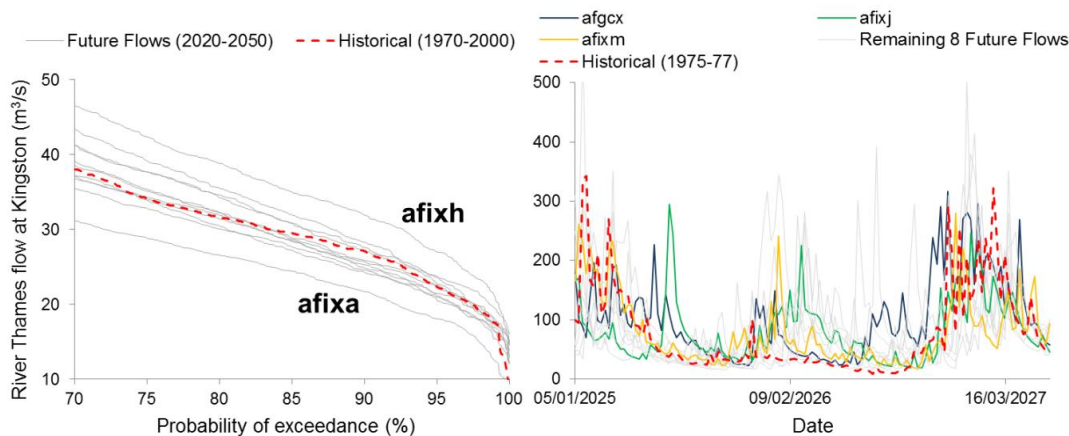


Figure 4-1. Flow duration curve comparison for low flows (below Q70) between the Future Flows scenarios (2020-2050) and the historical flows (1970-2000, shown by the red dashed line) at Teddington Weir in Kingston on the River Thames (left panel). The *afixa* scenario is the driest while the *afixh* the wettest. The right panel illustrates the hydrological flow pattern comparison between the Future Flows scenarios (2025-27) and the historical flows (1975-77, shown by the red dashed line).

4.2.2.2. Socio-economic and regulatory scenarios

The scenarios representing the socio-economic and regulatory uncertainties for the year 2035 were chosen based on TWUL's estimates (Thames Water, 2014) and the Ofwat's recommendations (Ofwat, 2013). The socio-economic uncertainty is represented by two demand projection scenarios and two energy prices scenarios. The two demand scenarios use the estimate of demands for 2035 of 2,325 MI/d, as in the deterministic

approach in Chapter 3, and 2,558 ML/d, a 10% increase. These values are adjusted for each month of the year by applying monthly factors used by the Environment Agency's commercial Aquator model. The demand of 2,325 ML/d was estimated by TWUL (Thames Water, 2014) based on the WRPB recommendations to incorporate the population growth estimations from local authorities and several assumptions such as continuation of the current metering policies, maintaining leakage at the 2015 levels, etc. (Environment Agency et al., 2012). The 10% increase is used by TWUL to account for the errors in estimates (Thames Water, 2014).

The energy price scenarios include an energy cost of 13p/kWh and 35p/kWh. The estimate of 13p/kWh was applied in the deterministic approach and uses the Department of Climate and Energy medium forecasts for industrial energy prices. The increase to 35p/kWh was estimated by TWUL by doubling the forecasted price to account for possible carbon price increases, network replacements and upgrades, energy price increases, etc. (Thames Water, 2014).

The institutional uncertainty is represented by two sustainability reduction scenarios. These reflect a possible reduction in the licensed abstraction volumes for water companies. TWUL currently abstracts from several locations on the River Thames and River Lee. The IRAS-2010 Thames model aggregates the surface water abstractions to a single abstraction node upstream of Teddington Weir on the River Thames and downstream of Feildes Weir on the River Lee, as well as a single groundwater abstraction point for the whole basin. The reductions are therefore applied to these single abstraction nodes. One scenario assumes no license change (i.e., that the company will be able to abstract the current volumes in 2035 as was considered in the deterministic study) while the other includes a reduction of 25 ML/d in groundwater and 100 ML/d and 50 ML/d in surface water from the River Thames and River Lee, respectively, provided by the Environment Agency as a plausible future reduction (Thames Water, 2014).

4.2.3. Computational experiment

The MOEA algorithm in the multi-scenario optimization was run for 50,000 FEs with 10 random seeds. In the multi-scenario runs, a higher number of function evaluations than in the deterministic optimization (section 3.2.2) were required due to the computational complexity of solving that case. Fewer random seeds (10) were used here than in the deterministic case (50) in order to reduce the computational burden. The

obtained reference set again closely resembles the Pareto optimal solutions from a single seed analysis suggesting a close approximation to the true Pareto optimal set.

4.2.4. Comparison with deterministic approach

Least-cost optimal plans are typically identified using baseline historical conditions and tested against multiple realizations of future conditions, particularly in the UK planning context (Environment Agency et al., 2012; Thames Water, 2013). Linking to this standard evaluation scheme a many-objective approach is applied here considering a range of supply and demand management interventions as decisions and a combination of financial, engineering and environmental objectives (detailed in sections 3.2.1 and 4.2.1). A deterministic baseline described in Chapter 3 was developed using only historical hydrological conditions and demands estimated for the year 2035 (i.e., a single deterministic scenario of the future) as a preliminary screening for the Thames basin water supply and demand investments. Here a multi-scenario many-objective optimization approach that incorporates multiple plausible realizations of future conditions of concern to planners with the same problem formulation as in the deterministic approach, with the only difference being that the objective values are assessed across the ensemble of scenarios, is implemented. Decisions are evaluated against all possible combinations of considered future changes in external conditions; solutions that work well across the multiple future states are sought via the multi-objective multi-scenario optimization. The results of the two approaches are then compared. Lastly, solutions from the deterministic optimization are subjected to the multiple scenarios of the 2nd problem. Deterministic solution performance is contrasted with that of the multi-scenario solutions to assess the advantages of considering multiple futures whilst searching. Figure 4-2 illustrates the steps performed in this study.

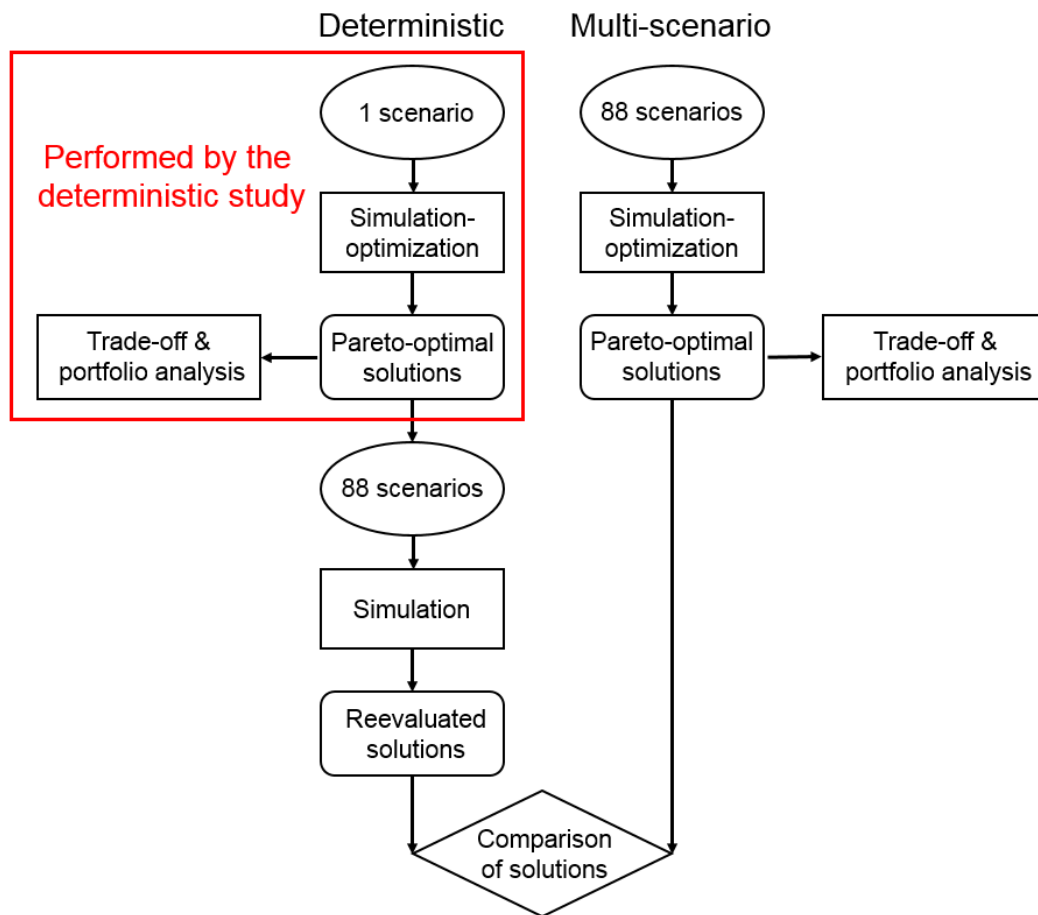


Figure 4-2. Flow chart showing the steps of the approach followed in this study. Two separate optimizations, deterministic (left), described in Chapter 3, and multi-scenario (right), were performed and the results analysed. The deterministic solutions were then simulated against the multiple scenarios and their performance was compared to that of the multi-scenario solutions.

4.3. Results

4.3.1. Comparison of deterministic and multi-scenario optimization results

4.3.1.1. Portfolio performance

Figure 4-3 illustrates how the Pareto optimal front changes when we incorporate multiple sources of uncertainty in the form of scenarios into the optimization. The individual objectives are represented as for the deterministic analysis in Figure 3-5. The cardinal axes show the capital cost, supply deficit and reliability and the arrows point towards the direction of preference, i.e., ideal solution. The colour of the cones shows environmental performance; blue cones exhibit the best environmental performance whilst the red cones the worst. The orientation of the cones depicts the resilience and their size the energy cost requirements; cones pointing downwards of the smallest size have the best resilience and require the lowest energy cost and vice versa. The translucent points here show the deterministic optimization results analysed in the previous chapter while the full coloured points show the multi-scenario optimization

Pareto optimal portfolios. The figure indicates the uncertainties cause the objective space to shrink and shift slightly towards the right hand side of the cube, i.e., towards higher capital investment. Achieving absolute reliability under a range of plausible futures requires higher capital investment than when only deterministic conditions are considered. The range of the objective values is lower for the multi-scenario solutions than for the deterministic solutions. For instance, the annualized capital cost of portfolios varies between £18.2m/a and £65.6m/a for the former while the latter has values between £9.1m/a and £64.4m/a. This suggests that the higher variability of external conditions requires higher capital investment to maintain good engineering and environmental performance.

The multi-scenario optimization solutions (full-coloured cones in Figure 4-3) achieve similar levels of reliability and resilience in varied conditions with better environmental performance at the expense of higher capital and operating costs as compared to the deterministic solutions (translucent cones). It is worth noting, however, that the highest energy cost value does not significantly exceed the highest value obtained by deterministic optimization. The similar engineering performance of the two Pareto optimal sets of portfolios can be explained by the Levels of Service constraints ensuring the acceptability of the system's behaviour under varying future conditions. The two distinct fronts present in the multi-scenario results differ in terms of the operating cost requirements as was the case in the deterministic solution set (Figure 3-5).

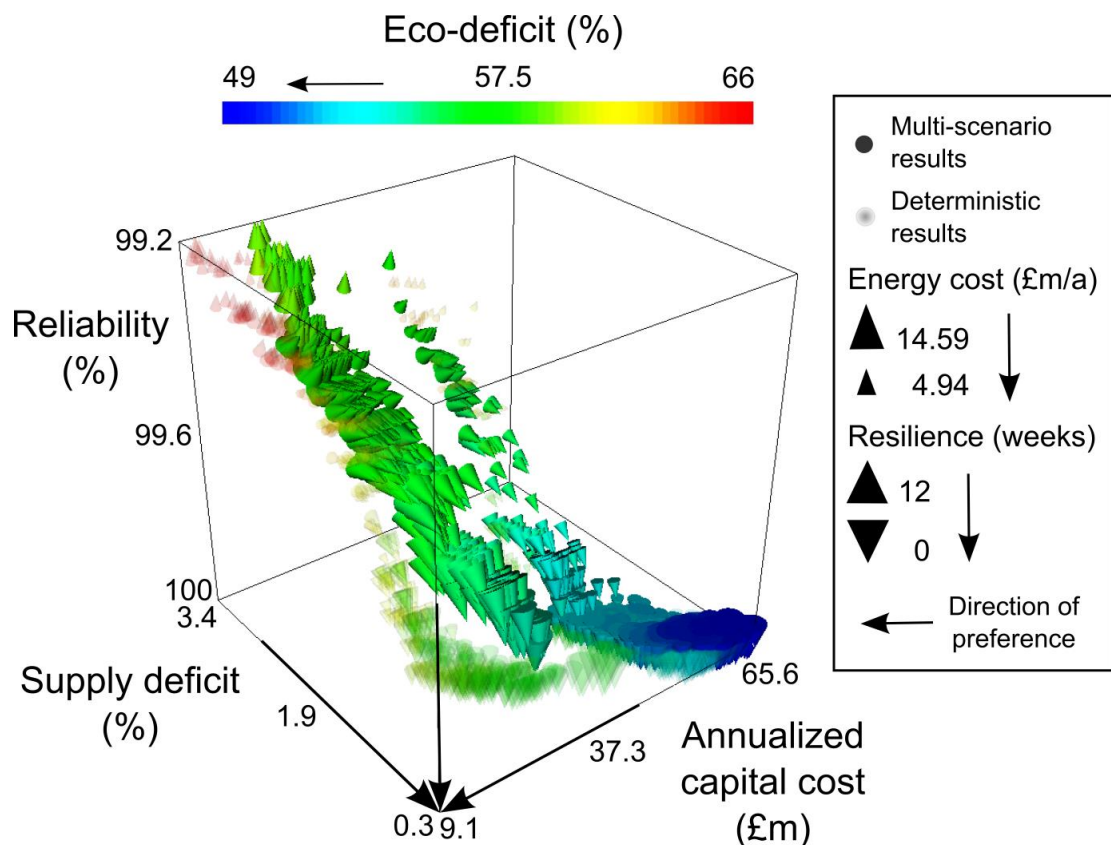


Figure 4-3. Multi-scenario Pareto optimal portfolio trade-offs (full colour cones) compared to the deterministic Pareto optimal portfolio trade-offs (translucent cones). The multi-scenario optimization objective space shrinks and shifts towards higher capital and energy cost requirements (i.e., the full colour cones positioned further from the ideal point on the capital cost axis and bigger than the translucent cones). These multi-scenario efficient portfolios attain good engineering performance despite the higher variability of stresses while outperforming the deterministic portfolios in the ecological objective (colour scale). Please note that the translucent deterministic solutions and the full coloured multi-scenario solutions were evaluated against different future conditions and are therefore not directly comparable. The plot highlights how the optimal space changes and shifts when multiple sources of uncertainty are considered.

4.3.1.2. Portfolio composition

Figure 4-4 compares portfolio composition (i.e., how interventions map to the performance objective space) between the deterministic (left) and multi-scenario (right) results in the same view as shown in Figure 4-3. The size of the cones illustrates the energy cost requirements of portfolios. The colour represents the implementation of the mutually exclusive supply options; green cones show portfolios that include the Upper Thames Reservoir (UTR), the red coloured portfolios incorporate the unsupported River Severn Transfer (RST), and blue cones depict portfolios that do not implement any of these. The deterministic Pareto optimal portfolios implement a combination of these. When none of these new supply interventions are implemented portfolios require the lowest capital investment but have the worst supply reliability. Most of the Pareto optimal portfolios implement the UTR and only a fraction implement the RST. The

latter (red points in Figure 4-4) exhibit perfect reliability but these portfolios require the highest operating energy use, possibly making them impractical in the long-term. None of the multi-scenario Pareto optimal portfolios (right panel in Figure 4-4) implement the transfer intervention which requires higher capital and operating costs than the reservoir; all build the UTR reservoir.

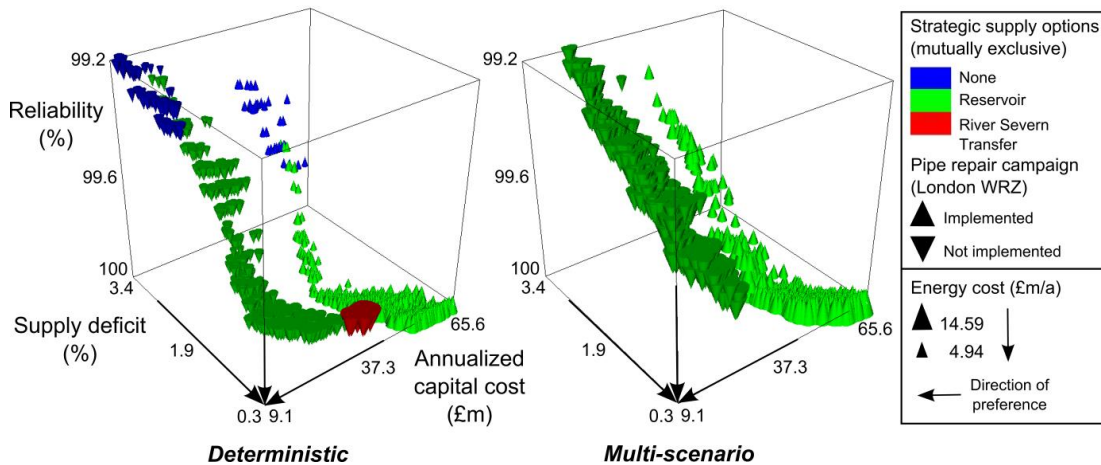


Figure 4-4. Comparison of portfolio composition between the deterministic and multi-scenario Pareto optimal solutions. The cardinal axes show the same objectives as in Figure 4-3. Cone size represents the portfolio energy cost while colour shows which of the mutually exclusive supply interventions was implemented. Cone orientation indicates whether or not each portfolio implemented the London pipe repair campaign. Implementing (lighter coloured cones pointing upwards) or not implementing (darker coloured cones pointing downwards) the pipe repairs divides the trade-off space into two distinct fronts.

The orientation of cones in Figure 4-4 indicates implementation of the Pipe repair demand management intervention for the London Water Resource Zone (WRZ); cones pointing upwards depict portfolios that include the Pipe repair campaign while cones pointing downwards show portfolios that do not. Both panels show a combination of portfolios with and without the Pipe repair campaign creating the two distinct fronts. Portfolios implementing this intervention require higher capital investment but exhibit better environmental performance (colour of cones in Figure 4-3) and demand lower energy use (size of cones in Figure 4-4) than the portfolios on the left front. This suggests the demand management interventions may help improve the system's performance with reduced energy consumption. All of the multi-scenario Pareto optimal solutions implement all the other demand management interventions for the London WRZ (i.e., active leakage control, efficiency improvement, metering, and seasonal tariffs). Demand management interventions may therefore be considered to increase the robustness of plans against uncertain future conditions.

4.3.2. How deterministic solutions would perform under uncertainty

Intervention portfolios developed whilst considering only historical conditions (i.e., deterministic optimization) might not perform well under conditions that are possible in an uncertain future. To demonstrate the potential bias in this approach we select six representative solutions (supply and demand management portfolios) from the deterministic Pareto optimal front. The six portfolios are highlighted in Figure 4-5 by full colour points while the translucent points depict the whole set of Pareto optimal solutions from the deterministic (left) and multi-scenario (right) optimization. The portfolios are distinguished by indicative names reflecting their capital investment requirements or implementation of one of the mutually exclusive supply interventions. The Least Cost portfolio does not implement any of the mutually exclusive strategic supply interventions and requires the lowest capital investment. The Reservoir 1 and 2 portfolios build the UTR, exhibit the same performance against the reliability objective but differ in the capital investment requirements. The more expensive Reservoir 2 portfolio implements the Pipe repair campaign demand management intervention for the London WRZ, while the cheaper Reservoir 1 portfolio does not. The Reservoir 3 portfolio also implements the UTR and Pipe repair campaign but requires even higher capital investment which results in perfect reliability. The Transfer portfolio implements the RST and achieves 100% reliability. The Highest Cost portfolio achieves perfect reliability by implementing all considered supply (including UTR) and the majority of demand interventions and requires the highest capital investment.

The six solutions were simulated under the same 88 scenarios that were used in the multi-scenario optimization. When subjected to the multi-scenario conditions only two of the six portfolios satisfy the LoS constraints as calculated over the scenario ensemble. The performance of these two portfolios (Reservoir 3 and Highest Cost) under multiple future conditions is shown in the right panel in Figure 4-5 (full colour points) and compared to the multi-scenario Pareto optimal portfolios (translucent points in the right panel of Figure 4-5). These two solutions exhibit worse reliability performance under the 88 future scenarios than they did under the deterministic analysis. In fact, both of these portfolios exhibit worse performance in all other objectives under uncertainty (summarized in Table 4-2). The operating costs show the highest difference indicating that to satisfy the Levels of Service under higher variability of conditions the system would need to operate more intensively resulting in higher operating expenditure.

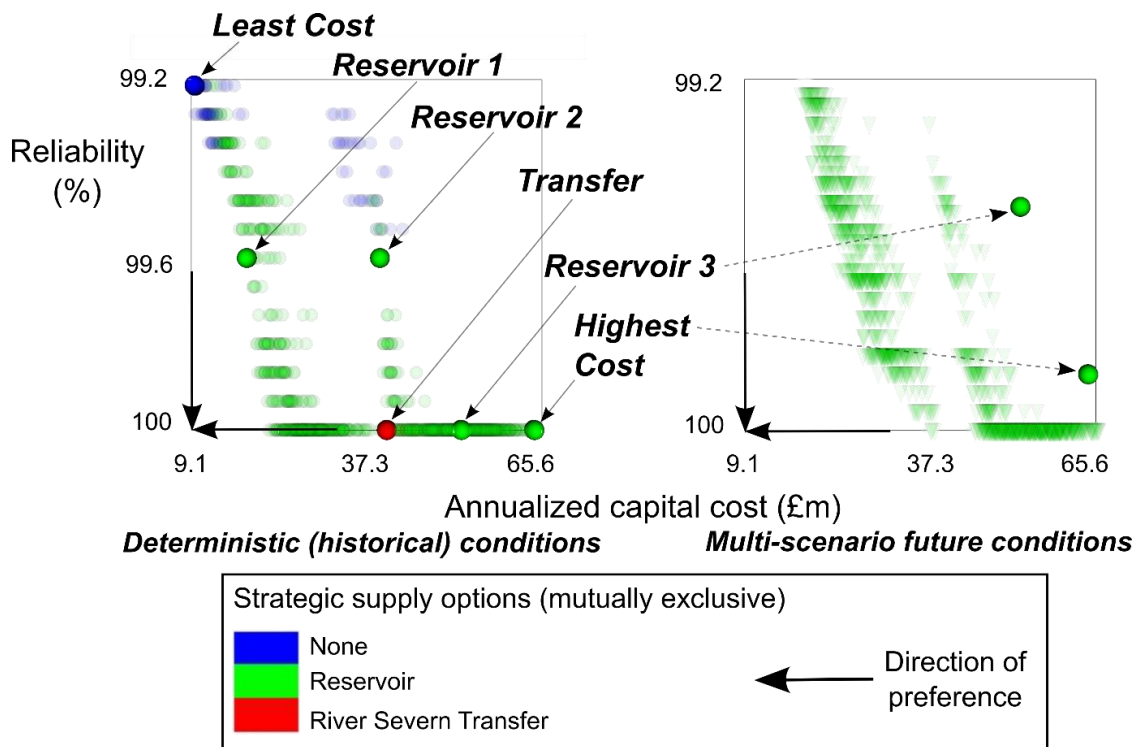


Figure 4-5. Six representative deterministic (left) Pareto optimal portfolios (large full colour spheres in the left panel) were simulated under the 88 future scenarios. The performance of these solutions over the future scenarios is compared to that of the multi-scenario Pareto-approximate optimal solutions (full colour spheres vs translucent cones, respectively, in the right panel). Only two portfolios (Reservoir 3, Highest Cost) satisfy the LoS constraints when subjected to the multiple scenarios but are dominated by other portfolios (they show higher capital costs than portfolios with the same reliability). Please note that while these two solutions were Pareto optimal under deterministic conditions, they are not Pareto optimal under the 88 possible scenarios. The two-dimensional plots are projections of a six-objective frontier onto a two-dimensional surface and as such show only the trade-off between the two plotted dimensions.

Table 4-2. Performance comparison of the Reservoir 3 and Highest Cost portfolios depicted in Figure 4-5 between the deterministic and multi-scenario conditions.

Objective	Reservoir 3		Highest Cost	
	<i>Deterministic</i>	<i>Multi-scenario</i>	<i>Deterministic</i>	<i>Multi-scenario</i>
Supply deficit (%)	1.20	2.63	0.35	1.35
Supply resilience (weeks)	0	8	0	2
Supply reliability (%)	100	99.50	100	99.87
Eco-deficit (%)	56	57	51	54
Energy cost (£m/a)	5.56	7.87	9.30	13.69

To illustrate the importance of incorporating uncertainty directly into the optimization the whole deterministic Pareto optimal set of solutions was simulated over the 88 scenarios. Only 40% of this set satisfied LoS constraints when calculated over all 88

plausible future scenarios. These surviving solutions were then sorted amongst each other to preserve only the dominating solutions in the set, discarding majority of these solutions. Only 3% of the original deterministic Pareto optimal solutions were left.

While these solutions were Pareto optimal under deterministic conditions, they are not Pareto optimal under the 88 possible scenarios.

Figure 4-6 illustrates how the performance of these remaining solutions compares to that of the multi-scenario Pareto optimal solutions. The latter are shown as opaque while the former are depicted by translucent points. The two panels show two different views of the same solution sets. When subjected to the 88 future scenarios, the remaining deterministic solutions (translucent spheres in Figure 4-6) are dominated by the multi-scenario Pareto optimal solutions (full colour spheres in Figure 4-6), i.e., they can no longer be considered Pareto optimal. The translucent portfolios require higher capital investment and energy use (shown by the size of points in Figure 4-6) to achieve the same levels of reliability than the full coloured portfolios (that are located in the same position regarding the vertical axis of Figure 4-6a). The latter also require lower capital investment and energy use to maintain the same levels of supply deficit than the former, also exhibiting better environmental performance (shown by colour in Figure 4-6). This is particularly visible in Figure 4-6b where the same set of portfolios as in Figure 4-6a is shown in different view; the reliability and supply deficit axes were switched and the plot rotated anticlockwise. The full coloured spheres require lower capital and operating cost as they are closer to the ideal point with respect to the capital cost axis and of lower size than the translucent spheres.

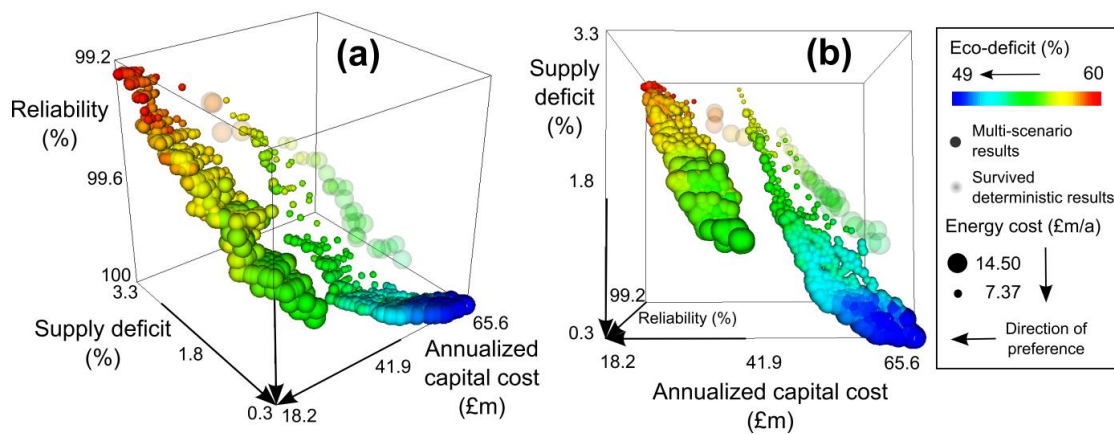


Figure 4-6. Deterministic Pareto optimal solutions that comply with the LoS constraints under the multi-scenario conditions (translucent points) and the multi-scenario Pareto optimal solutions (full coloured points) visualized together. The cardinal axes show the same objectives as Figures 4-3 and 4-4. Colour represents the environmental performance of portfolios while the size of the points indicates their energy costs. The deterministic solutions are dominated by the multi-scenario efficient solutions (i.e., their positions, colours, and sizes are further away from the ideal point than the multi-scenario solutions). Whilst deterministic solutions were Pareto optimal under historical conditions, they are not Pareto optimal under the 88 plausible scenarios.

4.4. Discussion

4.4.1. Incorporating uncertainty into many-objective optimization

When planning under uncertainty planners should ensure their system is able to cope with a wide range of plausible futures. This study illustrates that taking into account multiple performance objectives and planning for robustness can be achieved concurrently. Deterministic optimization the Thames water resource system interventions considering only the historical flow record was compared to a multi-scenario optimization which considered multiple sources of uncertainty. It was found that using historical flow records to assess future system investments can provide biased information about individual portfolios, i.e., make them seem favourable when in fact they do not perform well in many alternate plausible futures. Figure 4-5 illustrated how the performance of six representative solutions from the deterministic optimization analysis changes subject to multiple sources of uncertainty. Only two solutions remain feasible (Reservoir 3 and Highest Cost in Figure 4-5) but show worse performance against the optimized objectives than suggested by the deterministic approach (Table 4-2). In total 60% of portfolios considered Pareto optimal in the deterministic analysis fail under the wider set of future conditions with only 3% of the original set surviving non-dominated sorting (see the first paragraph of section 3.3). Figure 4-6 showed that the multi-scenario portfolios perform better with respect to the environmental and economic objectives than the survived deterministic portfolios. By incorporating

uncertainty directly into the optimization process one identifies robust solutions that perform well under a range of plausible future states.

4.4.2. Visual analytics

Visualizing the Pareto optimal set of solutions in the many-dimensional objective space allows decision makers to discover how the different system performance objectives conflict and interact with each other. Many objectives may be represented by other visualization techniques such as parallel plots (Rosenberg, 2015). The many-dimensional trade-off scatter plots presented here highlight the interactions and conflicts between the objectives for the purpose of this study. In our experience communicating the information provided by many-objective trade-off plots to decision makers is best done by visualizing dimensions progressively. The many-dimensional plot of Figure 4-3 only represents the final stage of the exploration. The progressive introduction of dimensions within trade-off plots is explored in Chapter 3. Visualizing and exploring the Pareto optimal portfolios progressively may aid the learning and decision making process and help justify to interested parties why a certain intervention was selected. Decision makers are given the opportunity to decide the balance between performance preferences a posteriori. Visual analytics can provide the means to compare the deterministic and multi-scenario optimization objective spaces as well as how and why their Pareto optimal portfolios differ.

When multiple scenarios of future conditions are incorporated into the search for optimal portfolios the Pareto optimal front shrinks and shifts slightly towards higher capital investment than when only a single scenario is considered (Figure 4-3). Achieving absolute reliability under a range of plausible futures requires higher capital investment than when only a single scenario is considered. Higher variability of external conditions requires higher capital investment to maintain good engineering and environmental performance. The similar engineering performance (supply reliability and resilience) of the two Pareto optimal sets of portfolios can be explained by the Levels of Service constraints ensuring the acceptability of the system's behaviour under a single and varying future conditions. This indicates that planners can achieve the desired service levels in uncertain future but with portfolios implementing higher capacity interventions that require higher capital and operating costs than what was suggested by the portfolios evaluated against only a single future scenario.

Robust interventions can be identified by their presence in the Pareto optimal solutions obtained from the multi-scenario optimization. Figure 4-4 showed that although some

deterministic Pareto optimal portfolios implement the unsupported River Severn Transfer instead of the Upper Thames Reservoir, none of the multi-scenario portfolios select the more expensive and less reliable transfer. In contrast, the UTR is implemented in all of the multi-scenario portfolios. This suggests that, given how the system is currently modelled, the reservoir intervention improves the system design's robustness against a variety of future conditions. Similarly, the Pipe repair demand management intervention improves the system's performance under the considered range of future conditions. Further analysis showed that all the other demand management interventions are implemented in all the robust portfolios in the London WRZ. Water companies generally prefer implementing supply-side measures to plan for future deficits (Charlton and Arnell, 2011) but our results suggest that reducing demand by implementing demand management interventions increases plan robustness. These interventions do not require energy unlike the majority of supply interventions, do not rely on uncertain hydrological flows and are likely appropriate strategies for relatively water scarce systems in the face of uncertainty.

4.4.3. Limitations and future work

Future conditions in this study were represented in a limited way. The set of 11 Future Flow scenarios is recommended for the climate change impact assessment in the UK by regulators and used in the Thames basin water resource system planning (Environment Agency et al., 2012; Thames Water, 2014). The 30-year flow time-series used here (2020-2050) may be considered quasi-stationary at best; just over half of the scenarios do not exhibit transient characteristics during this time period. Transient time-series, where the probability distribution that characterizes the flow at any given time period changes progressively as time moves forward, are not appropriate for studies considering a static snapshot of a system's performance in time. The sample of water demand, energy prices and sustainability reductions was suitable in the particular planning context (chosen in consultation with stakeholders) but it does not represent a wide range of possibilities; only 2 different states for each were represented. The shortcomings of using a limited number of scenarios as well as estimates based on the extrapolations of current socio-economic trends to consider uncertainty of future conditions are acknowledged. If a low number of scenarios is used or future conditions are sampled incorrectly, the Pareto optimal solutions obtained using such limited future conditions may not exhibit robustness characteristics and perform unsatisfactorily under a different set of future conditions. The scenarios of future conditions should be

identified carefully and represent as wide a range of possible futures for the specific problem as possible. The scenarios used in this study were identified by TWUL as posing the highest risk to their system and covering the maximum and minimum impact ranges of the possible future conditions in 2030s (Thames Water, 2014). It was accepted to use only the lower and upper bounds of future demands, energy prices, and sustainability reductions here as the water supply system was constrained to maintain the specified Levels of Service. Sampling between those ranges would influence the results substantially as they were meant to maintain the service levels for both lower and upper bounds. A different approach would be to allow the system fail in some conditions when a bigger sample of futures covering more extreme conditions is used which is applied in the following chapter. The purpose of the study is to highlight the possible improvements to the current planning approach in England, one of which is using the scenarios to identify the robust portfolios instead of evaluating the deterministic least-cost portfolio against each of those separately. In future, a larger more diverse scenario set could be sampled and more advanced sampling techniques could be used.

Identifying robust combinations of assets is valuable but it does not fully serve the planning processes where investments must be chosen and prioritized over time. The approach as applied here did not recommend a schedule of implementation (as does the current EBSD approach); this is left to future work which will need to consider, and trade-off, the value of flexibility (Woodward et al., 2014) and adaptation (Haasnoot et al., 2013; Hamarat et al., 2014).

The proposed approach is computationally intensive, even when only 88 scenarios are considered. Our multi-scenario optimization ran in 46 hours on 96 CPU cores. Further increasing the number of possible future scenarios increases the number of their combinations exponentially. Evaluating each candidate portfolio against such a large ensemble poses significant computational challenges. The ability of the MOEA optimization algorithm to converge to the true Pareto optimal front becomes increasingly difficult to demonstrate. Here we performed a random seed analysis for the multi-scenario optimization with 10 different random seeds (see Kollat and Reed (2006) for more details) while the deterministic optimization random seed analysis checked the approximation to the true Pareto optimal set using 50 random seeds. As more scenarios are used, it might be increasingly harder to verify the approximation sufficiently.

4.5. Conclusion

This chapter proposed an approach to identify and visually display robust plans for water resource systems that meet many financial, engineering and ecological goals. The approach was applied to identifying portfolios of new water supplies and demand management interventions that could meet London's estimated water supply demands in 2035. Proposed portfolios were evaluated against the following metrics: annualized capital cost, maximum annual supply deficit, supply resilience, supply reliability, hydro-ecological deficits and annual average energy cost. Future portfolios were also assessed against multiple scenarios of future climate change impacted hydrological flows, water demands, environmentally motivated abstraction reductions, and energy prices. To identify the most robust portfolios amongst the many available options a search algorithm (many-objective evolutionary algorithm) linked to a water resource system simulator was used. The Pareto optimal portfolios identified as robust in this study are considered robust to the scenarios used. If a different set of future conditions was used, the approach could potentially identify different portfolios as robust to the particular set. The scenarios of future conditions to be considered in the search for robust portfolios should therefore reflect the plausible conditions that may occur in a particular study area as well as the decision makers' aspirations of which conditions they would like their system to be robust to.

Results were presented via many-dimensional visualizations that help decision-makers consider how the performance objectives trade-off with each other for the portfolios identified as Pareto optimal. Plots can also show how options are distributed within the Pareto front and how they influence the system's performance. The study was designed to show the benefits of considering multiple plausible futures to optimize a complex system, rather than a single deterministic scenario. Only 3% of deterministic Pareto optimal solutions perform satisfactorily well under the set of plausible future conditions chosen by stakeholders in our study. Multi-scenario optimization identified portfolios that dominate those suggested by deterministic optimization. Exploring the Pareto optimal portfolios of supply and demand interventions helps identifying robust interventions that provide benefits over a wide range of futures including those with conditions similar to today.

5. Chapter 5 – Scheduling

5.1. Introduction

The current planning approach for London's water supply planning utilizes least cost optimization of future intervention schedules with limited uncertainty consideration. The plans are identified using historical flow records and linear interpolation of a past trend in population growth, i.e. a single scenario approach. The uncertainties associated with future supply and demand are simply incorporated using an aggregated safety buffer called headroom (Environment Agency, 2012; Padula et al., 2013). The multi-scenario optimization approach described in the previous chapter demonstrated how such limited representation of uncertainties could potentially provide biased information and lead to inefficient planning strategies. The study optimised for static portfolios that perform well under a static snapshot of future conditions (for year 2035). It did not consider transient hydrological change stemming from climate change progression and for this reason did not consider the scheduling of interventions. In practice, water utilities need to schedule the implementations of investments whilst minimizing their capital and operating costs and ensuring that the supply-demand balance is maintained and ecosystem services are kept in good health in the future. Delaying investments can reduce costs and provides more time for obtaining better information about future but may result in a risk of near future failure (Kang and Lansey, 2014).

Only few multi-objective studies have addressed the water supply capacity expansion scheduling problem to this date. Mortazavi et al. (2015) applied a multi-objective evolutionary algorithm using multiple scenarios of future conditions to optimize the capacity expansion scheduling and operating rules of the Canberra headworks system in Australia. Three objectives were considered, financial, engineering and social, where the latter two were monetized. The study used unique optimization for each future scenario and as such robustness across scenarios was not considered. Kang and Lansey (2014) used a multi-period multi-scenario optimization (MPMSO) where first a set of single-scenario single objective deterministic problems were solved. Common decisions between the multiple results were identified and the MPMSO model was then used to determine the optimal compromise solution. Beh et al. (2015) followed a similar approach of identifying optimal plans for each considered scenario deterministically with the exception of considering multiple objectives. The obtained optimal plans were then assessed for robustness and flexibility post-optimization and the recommendations

for implementation at a particular planning period were made based on the performance trade-offs, robustness and flexibility indicators and common interventions. The approach was demonstrated on the Adelaide water supply system in Australia.

Borgomeo et al. (2016) employ multiple nonstationary climate model inputs into multi-objective optimization to assess trade-offs between the financial cost of the simplified London's water resource system capacity expansion scheduling and the probabilistic risk of exceeding the target frequency of water use restrictions. The risk-based approach incorporates uncertainty into the planning process by extensive sampling and is able to connect the results directly with risk indicators used in practice (Borgomeo et al., 2014). However, the probability distribution of uncertainties that this approach relies on requires a prior knowledge (Vucetic and Simonovic, 2011); this may, however, not be well suited for situations of deep uncertainty (Knight, 1921) where assigning probabilities to future states is problematic (Kasprzyk et al., 2013; Lempert, 2002; Lempert et al., 2003; Walker et al., 2013).

The approach in this chapter optimizes future water supply system investments schedules considering robustness in addition to multiple discounted performance objectives explicitly. The candidate plans of scheduled investments are evaluated against a bootstrapped ensemble of 110 transient hydrological scenarios. The approach is demonstrated on London's water supply system case study for a 50 year planning time horizon. A many-objective robust optimization that explicitly considers the robustness of candidate plans (how well plans maintain desired levels of service) across a selection of future scenarios is then applied. Six objectives, including financial, engineering and environmental performance and robustness indicators are used in the automated search for high value scheduled portfolios of investment options. The future scenario ensemble is generated by random resampling of the chosen equally probable scenarios to ensure even time distribution of the major stress event within the modelled time horizon. The resampling method respects the nonstationary trend of the original scenarios. The ensemble size is kept small to enable computational tractability with real world water system simulators. Because the scheduling problem implies the passage of time we have discounted all engineering and environmental performance (Pearce et al., 2003) in addition to the financial performance to take into account human time preferences. Visual analytics is used to help decision makers select a subset of promising scheduled portfolios of interventions. Once a cluster of plans with stakeholder acceptable trade-offs is identified, the plans are analysed for their diversity

and how they can be combined into a coherent intervention schedule over time. The flexibility of the Pareto optimal plans are assessed post-optimization; a plan is considered flexible if its staged investments allow switching to other plans within the first decade.

The next section describes the scheduling approach, problem formulation and the scenarios of future conditions. Two experiments conducted to investigate the impact of major drought event within the hydrological scenarios together with proposed random resampling method (5.2.3) and the assessment of the engineering and environmental objectives (5.2.4) are also described here. The results obtained from the recommended approach are presented and analysed in section 5.3. Section 5.4 provides discussion of the results and approach and section 5.5 concludes this chapter.

5.2. Methodology

5.2.1. Scheduling of interventions

Despite requiring plans to plan for the next 25 years, the EA guidelines (Environment Agency et al., 2012) recommend that companies consider a long-term perspective beyond the 25-year planning horizon to “make companies’ systems more resilient to future uncertainties” and “to allow efficient, sustainable water resources planning to meet the needs of customers and the environment”. This study considers a 50 year planning time horizon, twice as long as the planning time horizon in WRMPs. The time-horizon is divided into 5 year planning periods. New interventions can only be activated at the beginning of each 5 year planning period. Interventions follow the “one-off” rule (Beh et al., 2015; Borgomeo et al., 2016; Mortazavi-Naeini et al., 2015), i.e., once an intervention is implemented, its capacity and operating rules do not change for the remainder of the time horizon. Following Beh et al. (2015), we take into account interventions’ lifespans by deactivating them once they reach their expected design lives. This study does not consider the refurbishment of interventions that have reached their design lives. In contrast to the previous studies, the construction period of interventions is incorporated into the simulation; an intervention becomes operational in the simulation model only after its construction period has passed. As the water supply system’s performance beyond the planning time horizon is not considered, the interventions are only allowed to be scheduled such that they become operational within the planning time horizon. Mutually exclusive interventions are modelled such that if any scheme from the mutually exclusive interventions is implemented in any planning

period, the remaining interventions from the same group can no longer be implemented within the remainder of the time horizon.

5.2.2. Original problem formulation

The scheduling problem addressed in this study considers multiple performance and robustness objectives. The performance objectives include the financial (f_{Capex}, f_{Energy}), engineering (f_{SupRes}) and environmental performance (f_{ECO}) of the water supply system. Originally only the financial performance was discounted using a discount rate of 4.5% (Environment Agency, 2012; Thames Water, 2014) and an average value across scenarios of future conditions was considered. The robustness objectives (f_{LOS3}, f_{LOS4}) reflect how well a plan of intervention schedules satisfies desired performance thresholds over the considered future states. The supply deficit and reliability used in the previous two chapters are not considered here after consultation with TWUL as those studies showed strong correlation of these two metrics with the supply resilience metric. Furthermore, the reliability metric is here reflected by the robustness objectives.

The decision vector consists of 3 components for each decision: if an intervention should be implemented (S_i), when (T_i) and at what capacity (Cap_i). To reduce the search space complexity, the time and capacity components of the decision vector are simplified. Interventions are scheduled in 5 year periods within the planning time horizon and their capacities in ML considered only as integer values. Mutual exclusivity of some interventions is handled via the first component of the decision vector, i.e., the selection integer variable. For instance, if two interventions are mutually exclusive, only a single selection decision variable defines which of these is selected, e.g., 0 means none of these is selected, 1 means intervention 1 is selected, and 2 means intervention 2 is selected. This reduces the need for mutual exclusivity constraint employed in the previous two studies (Chapters 3 and 4).

No constraints are posed on the feasibility of portfolios as only feasible combinations of interventions are generated. Furthermore, the uncertainties associated with future conditions make posing constraints on the performance of the system somewhat arbitrary; instead, the robustness metrics (f_{LOS3}, f_{LOS4}) serve as an indicator of how well the system would perform under considered plausible conditions. By this the approach aims to improve the decision making process by stimulating the exploration of all available possibilities and subsequent interrogation and negotiation of trade-offs

between decision makers and stakeholders. The problem formulation is defined by Equation 5-1 below:

$$\text{Minimize } \mathbf{F}(\mathbf{x}) = (f_{Capex}, f_{Energy}, f_{SupRes}, f_{Eco}, -f_{LoS3}, -f_{LoS4})$$

$$\mathbf{x} \in \{S_i, T_i, Cap_i\}$$

$$S_i \in \{0,1\} \forall i \in Ind, \text{ and } S_i \in \{0,1,2\} \forall i \in ME$$

5-1

where \mathbf{x} is a decision vector consisting of 3 components for each considered intervention. S_i refers to the selection of intervention i where $S_i = 1$ if selected, 0 if not for individual options (*Ind*); for mutually exclusive options (*ME*) $S_i = 1$ if intervention 1 is selected, 2 if intervention 2 is selected, and 0 if none of those are selected. T_i refers to the implementation planning period of intervention i , where a planning period occurs each 5 years within the planning time horizon, i.e., there are 10 planning periods within the 50 year planning horizon. The last component of the decision vector \mathbf{x} , Cap_i , refers to the capacity of intervention i .

5.2.2.1. Decisions

This study considers 8 new supply and 5 demand management interventions for the London's Water Resource Zone (WRZ) that were updated after consultation with TWUL based on the constrained list of options considered for the upcoming WRMP19. The supply interventions include the Upper Thames Reservoir (UTR), River Severn Transfer (RST), Oxford Canal Transfer (OCT), South London Artificial Recharge Scheme (SLARS), Deephams and Beckton water reuse schemes and a Long Reach and South Estuary desalination plants. Demand management options for London WRZ include active leakage control, a pipe repair campaign (i.e., main pipes replacement), water efficiency improvements, installation of meters, and implementation of seasonal tariffs. The Upper Thames Reservoir and River Severn Transfer, as well as the reverse osmosis (RO) and non-reverse osmosis (nonRO) reuse supply interventions are mutually exclusive where only one of these interventions can be implemented within a single portfolio. The interventions are shown in Figure 5-1 and are described in more detail in Table 5-1.

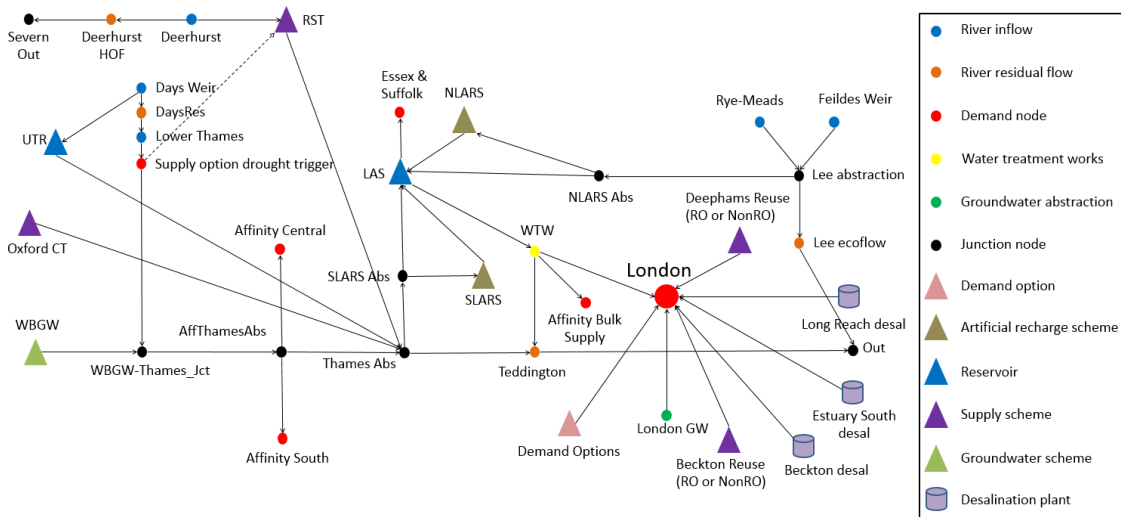
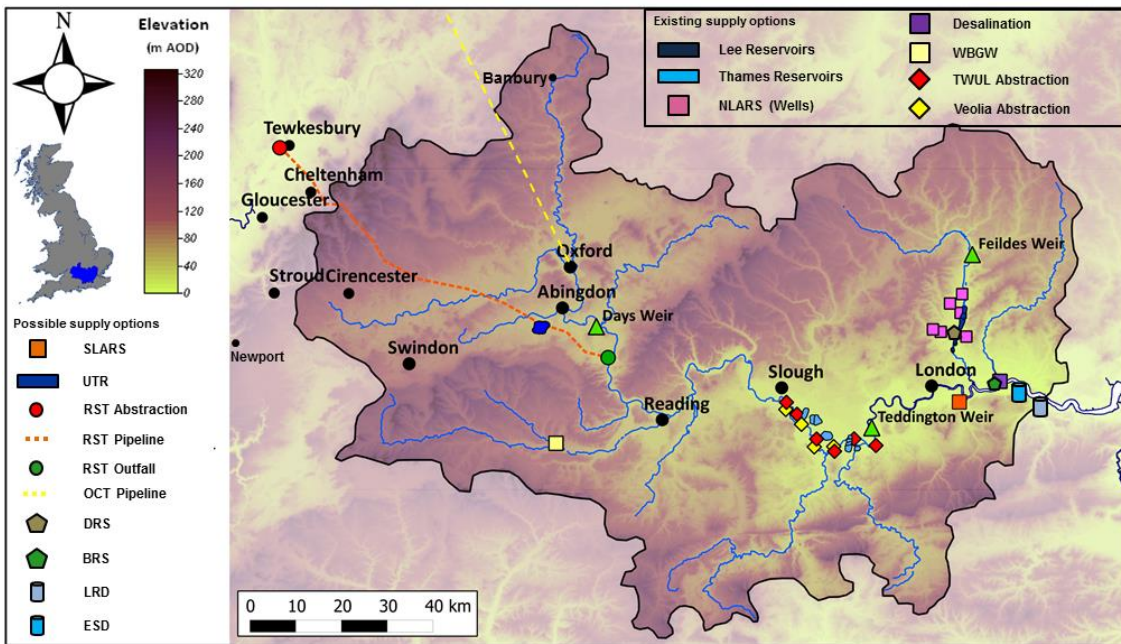


Figure 5-1. Current and new possible supply and demand management interventions considered in the scheduling study. The upper panel shows the schematic of the Thames basin water supply system extension whilst the lower panel shows the same system as modelled in the Thames IIRAS-2010 simulation model.

Table 5-1. Supply and demand management interventions considered in the scheduling study.

Intervention	Capacity (ML)	Construction period (years)	Design life (years)	Mutual exclusivity and other conditions
<i>Supply interventions</i>				
Upper Thames Reservoir (UTR)	30 - 150 (in 5 step integer intervals)	10	80	Yes, with RST
River Severn Transfer (RST)	Maximum of 300 ML/day based on River Severn Hands Off flow conditions	12	60	Yes, with UTR
South London Artificial Recharge Scheme (SLARS)	2 - 26	5	60	No
RO/nonRO Deephams Reuse Scheme (DRS)	25 – 60 (in 5 step integer intervals)	6	60	Yes, RO with nonRO
RO/nonRO Beckton Reuse Scheme (BRS)	50 – 150 (in 5 step integer intervals)	6	60	Yes, RO with nonRO
Oxford Canal Transfer (OCT)	17	12	60	No
Long Reach Desalination (LRD)	15	4	25	No
Estuary South Desalination (ESD)	50 – 150 (in 5 step integer intervals)	6	25	No
<i>Demand management interventions</i>				
Active Leakage Control (ALC)	2 – 50 (ML/day saving)	N/A	25	No
Pipe repair campaign (Mains)	165.1 (ML/day saving)	N/A	60	No
Enhanced efficiency (Eff)	11.6 (ML/day saving)	N/A	25	No
Smart metering (Meters)	88.7 (ML/day saving)	N/A	60	No
Seasonal tariffs (Tariffs)	Monthly profile of demand savings	N/A	N/A	Only available if Meters implemented

5.2.2.2. Objectives and constraints

The capital cost objective (f_{Capex}) represents the total discounted capital cost investment requirements of implementing new supply and demand interventions taking into

account their construction periods and design life. The capital cost assessment is based on the calculations applied in the EBSD framework (Padula et al., 2013). The undiscounted financial cost of interventions is spread over their construction period which provides annual cash flows; the future cash flow value is then evaluated at the end of the construction period:

$$fcc_i = \sum_{t=0}^{CP_i-1} \frac{ufc_i}{CP_i} * (1 + i_c)^t$$

5-2

where fcc_i is the financial capital cost of intervention i , ufc_i is the undiscounted financial cost of intervention i depending on its capacity or release rate, CP_i is the construction period of intervention i , i_c is the discount rate and t refers to a yearly time step. Future capital costs are then annualized over option's design life:

$$afcc_i = fcc_i * \frac{i_c(1 + i_c)^{DL_i}}{(1 + i_c)^{DL_i-1}}$$

5-3

where $afcc_i$ is the annualized financial capital cost of intervention i and DL_i is the design life of intervention i in years. The total capital cost of portfolio then represents the sum of annualized and discounted capital costs of all selected interventions:

$$\text{Minimize } f_{Capex} = \sum_i (afcc_i * S_i)$$

5-4

The energy cost objective (f_{Energy}) is the total discounted energy cost requirement to operate the whole water supply system over the whole planning time horizon:

$$\text{Minimize } f_{EnergyAverage} = \left(\frac{1}{T} \sum_{t=1}^T \sum_i E_{i,t} * UP_t * (1 + i_c)^{t-1} \right)_P$$

5-5

where where P represents the percentile of the set of objective values across the whole ensemble of scenarios, $E_{i,t}$ is the energy requirement in kWh to operate supply option i during year t , UP_t is the unit price (£) per kWh in year t , and T is the total number of

years in the planning time horizon. The energy requirement $E_{i,t}$ depends on the supply option's i release during year t :

$$E_{i,t} = R_{i,t} * ER_i$$

5-6

where $R_{i,t}$ refers to the total volume (ML) released by supply option i during year t , and ER_i is the energy required to release 1 ML associated with supply option i . If an option is not selected, its release will remain 0 ML over the whole planning time horizon thus its energy cost requirement will be £0.

Resilience is defined by how quickly the system recovers from a failure (Moy et al., 1986). The supply resilience objective f_{SupRes} is assessed on the LAS node and the failure occurs when the LAS storage level drops below the LTCD Demand level 3 threshold and the non-essential use ban is brought into effect (Figure 1-12). The metric is calculated for each scenario and an average value is taken as the final metric as follows:

$$Minimize_{Average} [f_{SupRes} = maxD]_P$$

5-7

where D is the failure duration in weeks.

The eco-deficit objective (f_{ECO}) (Vogel et al., 2007) represents the difference between the naturalized low flows and simulated low flows [%] (low flows here denote the flows under Q_{70} , i.e., flows that are exceeded 70% of the record time) at the Teddington Weir on the River Thames. The naturalized flows here refer to the river flow were there no TWUL's abstractions; the objective therefore assesses direct impact of TWUL's abstractions and return flows on the river itself. The higher the difference (i.e., deficit), the more the environmental conditions of the river deteriorate due to lower water levels than the natural state. Eco-deficit of 0% implies no deficit while 100% eco-deficit is the largest possible deficit. Similarly to the supply resilience metric eco-deficit is calculated for each scenario and an average value is taken as the final metric as follows:

$$Minimize_{Average} f_{ECO} = \left[(|AN_{Q70} - AS_{Q70}| / AN_{Q70})_P * 100\% \right]_P$$

5-8

where AN_{Q70} is the area under the naturalized flow duration curve (FDC) and AS_{Q70} is the area under the simulated FDC.

The robustness objectives (f_{LoS3} and f_{LoS4}) are applied here as satisficing robustness indicators used similarly in other urban water supply studies (e.g., Beh et al., 2015; Herman et al., 2014; Paton et al., 2014a; Paton et al., 2014b). These metrics here assess how well a candidate plan satisfies the desired Levels of Service across future scenarios as a fraction of the considered scenario ensemble in percent. The Level 3 demand restrictions (non-essential and hosepipe use ban in Figure 1-12) are currently limited to once in 20 years, while the Level 4 restrictions (standpipe in Figure 1-12) are not allowed to occur anytime. The frequency of occurrence is calculated using annual reliability metric:

$$AR_k = \left(1 - \frac{F_k}{T}\right) * 100\%$$

5-9

where AR_k is the annual reliability of level k , F_k is the number of years during which the LAS level dropped below level k , and T is the total number of years in the planning time horizon. The f_{LoS3} and f_{LoS4} then reflect in how many scenarios (in %) the Level 3 and 4 LoS, respectively, were maintained (Equations 5-10 and 5-11, respectively):

$$f_{LoS3} = \left(\frac{NS_{(AR_3 \geq 95\%)}}{J}\right) * 100\%$$

5-10

$$f_{LoS4} = \left(\frac{NS_{(AR_4 = 100\%)}}{J}\right) * 100\%$$

5-11

where NS_m is the number of scenarios where the condition m occurs and J is the total number of scenarios in the scenario ensemble.

5.2.2.3. Flexibility indicator

A flexibility indicator is calculated for each Pareto optimal plan. The flexibility metric aims to reflect how flexible a plan is within the first 10 years of the planning time horizon, i.e., if planners have a possibility to “switch” to a different plan schedule within the first ten year period if the near future unfolds differently than anticipated. A plan schedule represents a “path” over time specifying which interventions to build when. If a plan shares the same schedule with other plans at the beginning of the

planning time horizon, it is considered more flexible than plans with unique schedules. The degree of flexibility depends on how many plans within the Pareto optimal set a plan shares its schedule with. The flexibility indicator metric (*FI*) is calculated as follows:

$$FI = \left(\frac{NP_{10}}{NP} \right) * 100\%$$

5-12

where NP_{10} is the number of plans present in the Pareto optimal set that a plan shares the same schedule with in the first 10 years of the planning time horizon, and NP is the total number of plans in the Pareto optimal set of plans. Please note that the flexibility indicator reflects only how many other plans within the Pareto optimal set a plan shares the same schedules with within the first decade of the planning time horizon. It does not indicate how well a plan is able to adapt to changing future conditions.

5.2.3. Scenarios of future conditions

This study uses an ensemble of 11 equi-probable Future Flows (FF) scenarios (Prudhomme et al., 2013) represented by climate change impacted river flow time-series for the UK as the basis for our hydrology scenarios. The scenarios are considered equally probable to occur in future as the probabilities of their occurrence cannot be estimated. The FF ensemble represents 148 years (1950 - 2098) of transient climate change and is recommended by regulators (Environment Agency et al., 2012) to be used when performing the sensitivity analysis on their proposed least-cost plans. TWUL tested their 2014 WRMP with the FF ensemble (Thames Water, 2014). Section 4.2.2.1 in Chapter 4 provides a detailed description and analysis of the ensemble. This study uses a 50 year segment of the full time-series (2020-2070) with weekly time-step of all 11 FF scenarios. Similar to the multi-scenario approach (section 4.2.2.1) a Mann-Kendall trend test (Kendall, 1975; Mann, 1945) was performed here on the 11 50 year time-series to confirm that the shorter series displayed the nonstationary characteristics of the full 150-year set. The absolute value of Kendall's *tau* did not exceed 0.2 for any of the 11 scenarios suggesting only a weak climate change trend. This allows for a time series resampling method to be applied in this study which justification is provided in section 5.2.3.1 and which is described in more detail in section 5.2.3.2.

The scheduling study here employs transient water demand and energy prices with a single socio-economic scenario to focus the investigation on the impacts of the

hydrological uncertainty. The London demand for 2020 was estimated to be 2,125 ML based on the expected population growth and household water use (Thames Water, 2014) and was assumed to increase by 12.5 ML each year reaching 2,750 ML in 2070 (Thames Water, 2014). The demand is again adjusted each month using the monthly profiles factors (Table 0-2 in Appendix). The energy price for 2020 was estimated to be 8.9 p/kWh in 2020 based on the Committee on Climate Change (CCC) estimations (CCC, 2014) for industrial sectors and was assumed to increase nonlinearly (based on values in 2013, 2020, and 2030 as provided by the CCC).

5.2.3.1. Major stress event and drought manipulation

The FF scenarios used in this study were analysed for major stress events that may potentially influence the scheduling of interventions. The most extreme drought event in the considered 50-year planning time horizon (2020 - 2070) was found to occur in the *afixa* scenario between 2040 and 2045 (Figure 5-2). Three dry winters appear in this five year period, consecutively in 2040/41 and 2041/42, and in 2043/44 where the dry winters are also preceded by dry summer months. The dry winters pose a significant strain on the London's water supply system as most storage supply schemes use the winter periods to replenish their storage levels deployed during drier summer months (Thames Water, 2014). This 5-year period of the *afixa* scenario was identified as the most extreme event in the FF ensemble. The occurrence of extreme hydrological stress events cannot be predicted and can occur under even mild climate change scenarios. A single major drought event within a scenario ensemble may bias the scheduling towards the exact period where it occurs in the ensemble. The timing of this particular drought was found to have a significant impact on the resultant schedules present in the Pareto optimal plans obtained from the many-objective robust optimization. The experiment confirming this bias is described below.

To assess the effect of the most extreme drought position in time four scenario ensemble cases were designed. Case 1 applied the original ensemble of 11 Future Flow scenarios described above and used by water companies for scenario testing of their preferred plans. In Case 2, the most extreme drought was "shifted" to the beginning of the planning time horizon within the scenario where it originally occurs (Figure 5-2). This was done by "cutting out" the 2040-2045 period from the *afixa* scenario time series and "pasting" this five year period at the beginning of the time series to represent the 2020-2025 period whilst shifting the 2020-2040 period in time to represent the 2025-2045 period instead. All the other scenarios within the ensemble remained unchanged.

In Case 3, the same drought was “shifted” to the end of the planning time horizon in the same way as described above with all the other scenarios unchanged. Case 4 then used only the single scenario where the drought occurs, i.e., the *afixa* scenario, in its original form ignoring all the other scenarios within the ensemble. The scheduling optimization problem using the original problem formulation (section 5.2.2) was then solved for each case separately.

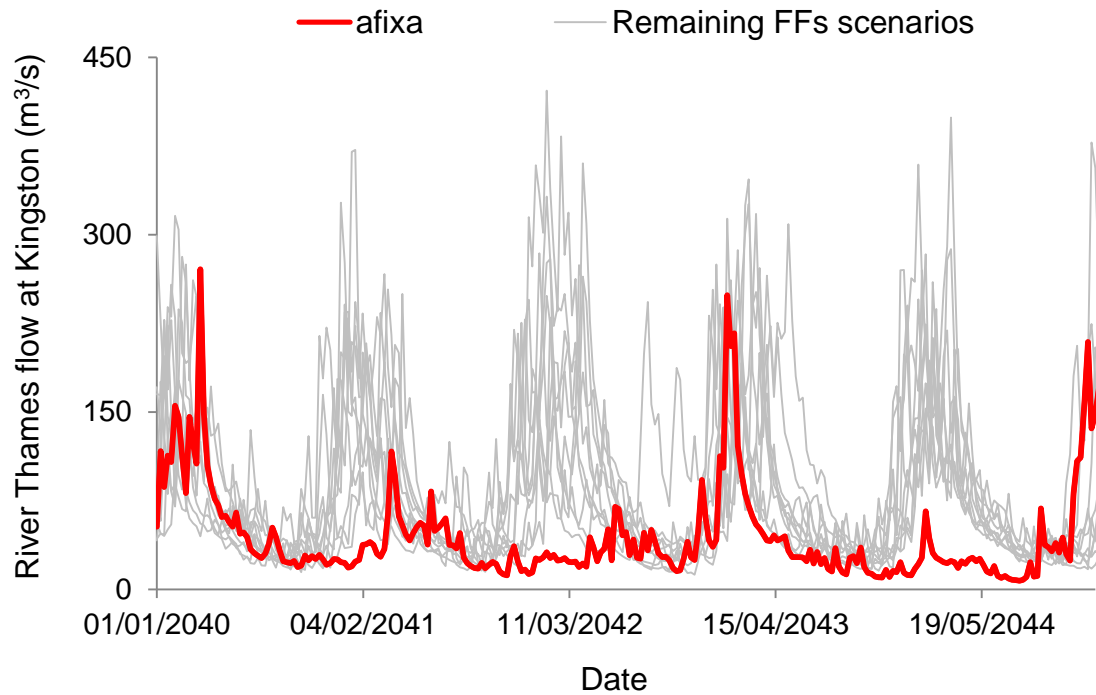


Figure 5-2. Afixa scenario drought between 2040 and 2045 identified as the most extreme event in the 50 year planning time horizon (2020-2070) of the Future Flows (FF) scenario ensemble.

Figure 5-3 summarizes the schedules present in the Pareto optimal fronts obtained for the 4 experimental scenario ensemble cases. The individual bars represent the implementation of interventions where the colour corresponds with a particular intervention (as shown in the legend), the position of bars on the x axis refers to the planning period and the height of a bar illustrates how many plans implement the intervention at a particular planning period.

In Case 1 majority of the supply interventions are mostly implemented in the 2035 planning period, just before the *afixa* drought occurs. The demand management interventions are implemented in 2040 as they do not require a construction period, apart from the metering (brown colour in Figure 5-3) which appears to be equally spread over the first half of the planning time horizon. In Case 2 the implementation of the demand management interventions is significantly shifted to the first planning period of 2020 with 80% of Pareto optimal plans implementing metering in 2020. Case

3 sees a slight shift in intervention implementation towards the second half of the planning horizon. Meters (brown colour in Figure 5-3) are still mostly implemented in 2020 and OCT transfer (light green colour in Figure 5-3) in 2040. Case 4 differs significantly from the other three cases. There is a substantial spike of supply intervention implementation across the Pareto optimal plans in 2035 and demand intervention implementation in 2040, just before the drought occurs. Only few plans implement any intervention after 2040.

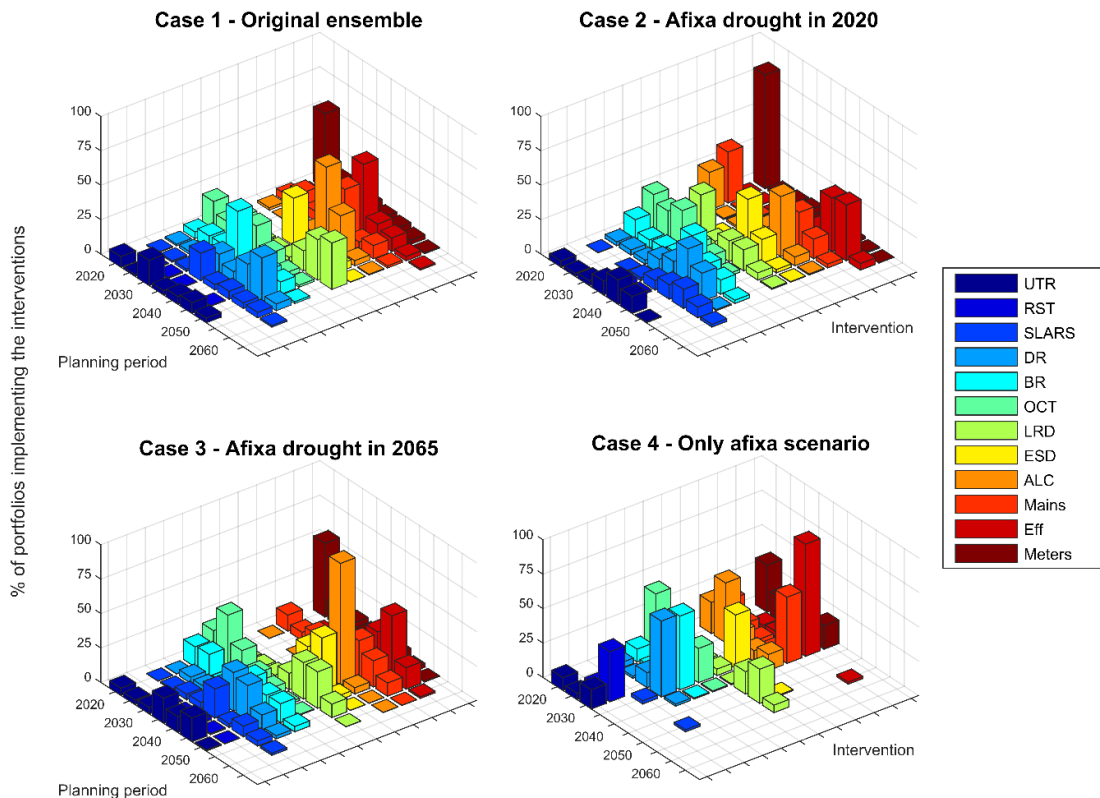


Figure 5-3. Schedules of interventions occurring across the Pareto optimal plans obtained in the drought manipulation experiment. The x axis shows the 5 year planning periods, the y axis and the colour of the bars depicts individual interventions, whilst the vertical axis as well as the height of the bars corresponds to the fraction of the Pareto optimal plans that implement a particular intervention in a particular planning period.

5.2.3.2. Scenario resampling

To reduce the extreme event timing bias investigated above a bootstrapping method ensuring that the major stress event occurs evenly across the planning time horizon whilst preserving the transient climate change signal of each scenario is proposed here.

Bootstrapping is a statistical technique of random resampling with replacement originally developed by Efron (1979). This study employs local block bootstrapping (LBB) (Papadoditis and Politis, 2002) which was developed as a modification of the block bootstrap to address resampling of nonstationary time series where the non-

stationarity is due to a slowly changing stochastic structure or where local but not global stationarity is present. As mentioned previously in section 5.2.3, the Mann-Kendall analysis of the FF scenarios used in this study confirmed a weak trend in the 50-year segment of the entire 150 year time series but showed local stationarity when a 30-year segment was analysed (section 4.2.2.1). To preserve these characteristics, the 50-year FF time series are here recommended to be resampled using the LBB method to only resample blocks of consecutive data, e.g., hydrological years that are in close proximity to each other within the whole record. The method has been shown to capture the distribution of nonparametric trend estimators and resample nonstationary data with local stationarity without the need for de-trending the data (Dowla et al., 2013). A rigorous description of the LBB method is provided in Paparoditis and Politis (2002).

This study considers a 50-year planning time horizon (2020-2070) split into 5-year planning periods at the start of which interventions can be implemented. To reduce the bias of the extreme *afixa* drought event between 2040 and 2045 10 different sets of the original 11 scenarios were generated ensuring that the *afixa* drought occurs in a different 5-year period in each *afixa* scenario within each new ensemble while still preserving the trend of the original *afixa* time series. The 10 remaining scenarios were also bootstrapped to make each new ensemble ensuring that their respective trends were maintained. This resulted in 10 sets of 11 scenarios creating an ensemble of 110 scenarios in total.

The scenarios were generated following the recommendations of Paparoditis and Politis (2002). The block size b was set to 5, i.e. the time series were resampled in 5 year blocks, and the real number B (where $B \in (0,1]$ and $b*B$ is an integer) to 0.2 for our sample size n of 50 years within a single scenario. The LBB algorithm was then used to generate new bootstrapped samples of the 50-year time series. Each bootstrapped scenario was analysed using the Mann Kendall trend analysis (Kendall, 1975; Mann, 1945) to check if the trend present in the original scenario was preserved within the 5×10^{-3} difference in the direction of the original scenario's Sen slope. The Sen slope is an estimation of the changing nature of the time series and specifies the median slope joining all pairs of observation points. A difference of 5×10^{-3} in the Sen slope between the original time series and the bootstrapped time series implies that the trends seen in both time series are very similar. If the Sen slope of the time series was outside the permitted bounds, the bootstrapped scenario was discarded and new scenario was generated. In addition, the bootstrapped *afixa* scenarios were checked for the drought's

position in time; if the drought appeared in new 5-year period not yet represented in the newly generated ensembles and the trend preservation condition was met, the bootstrapped scenario was kept, otherwise it was discarded. The procedure was repeated until 10 different sets of 11 bootstrapped scenarios were produced ensuring that the *afixa* drought occurred within each 5-year planning period over the 10 sets of scenarios within the ensemble.

To investigate the effects of the proposed bootstrapping method on the scheduling approach four different bootstrapped ensembles were generated (4 ensembles each containing 110 scenarios, in total 440 scenarios). Figure 5-4 shows the flow duration curves of the resampled *afixa* scenarios (grey lines) compared to the original *afixa* scenario (shown by the red line). The resampled *afixa* scenarios vary in the magnitude of low flows as well as in their distribution across the bootstrapped ensembles ensuring that the different scenarios vary hydrologically and are distributed relatively equally around the original *afixa* scenario. The four ensembles were used in four separate many-objective robust optimization runs to investigate the impacts of different problem formulations described in the following section (5.2.4) and in the final approach detailed in section 5.2.6.

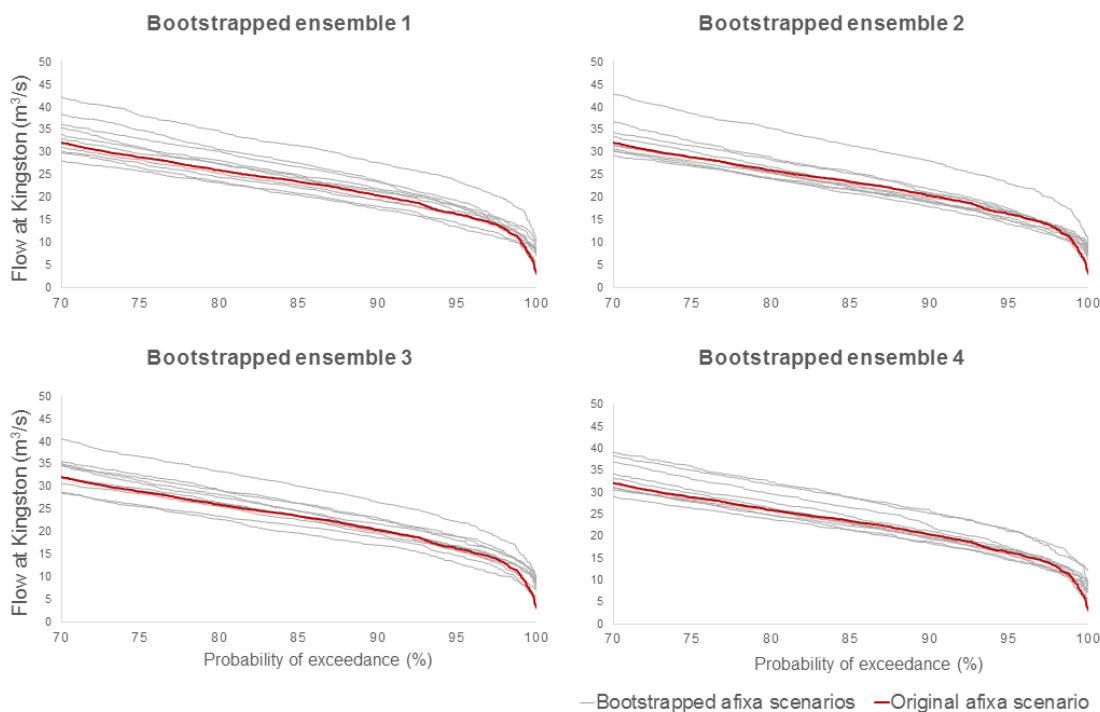


Figure 5-4. Flow duration curves showing low flows (i.e., flows with the probability of exceedance 70% of the record time and higher) of the bootstrapped afixa scenarios (grey lines), where the major drought event occurs, compared to the original afixa scenario (red line) from the original ensemble of 11 Future Flows scenarios.

5.2.4. Investigated problem formulations

5.2.4.1. Original objective values across scenarios

The bootstrapped ensembles described in the previous section were first applied in the many-objective robust optimization using the original problem formulation (section 5.2.2). Figure 5-5 shows the obtained Pareto optimal schedules of interventions where the axes, colours and bars represent the same dimensions as in Figure 5-3. Despite a slight difference, the schedules seem to follow the same pattern. In all four Pareto optimal sets, the metering (brown bars in Figure 5-5) is mostly implemented in the first planning period, efficiency (dark red bars) in 2045, ALC (orange bars) in 2045, ESD (yellow bars) in 2040, and LRD (green bars) in 2050. SLARS implementation (light blue bars in Figure 5-5) tends to focus around the middle of the planning horizon, while the BRS implementation (light turquoise bars) around the beginning of the planning horizon. The UTR implementation (dark blue bars in Figure 5-5) is evenly spread across the first 30 years of the planning horizon in all four sets. These results suggest that using the bootstrapped scenarios reduces the extreme drought event timing bias on the optimal scheduling of interventions and the random resampling does not affect the optimization results.

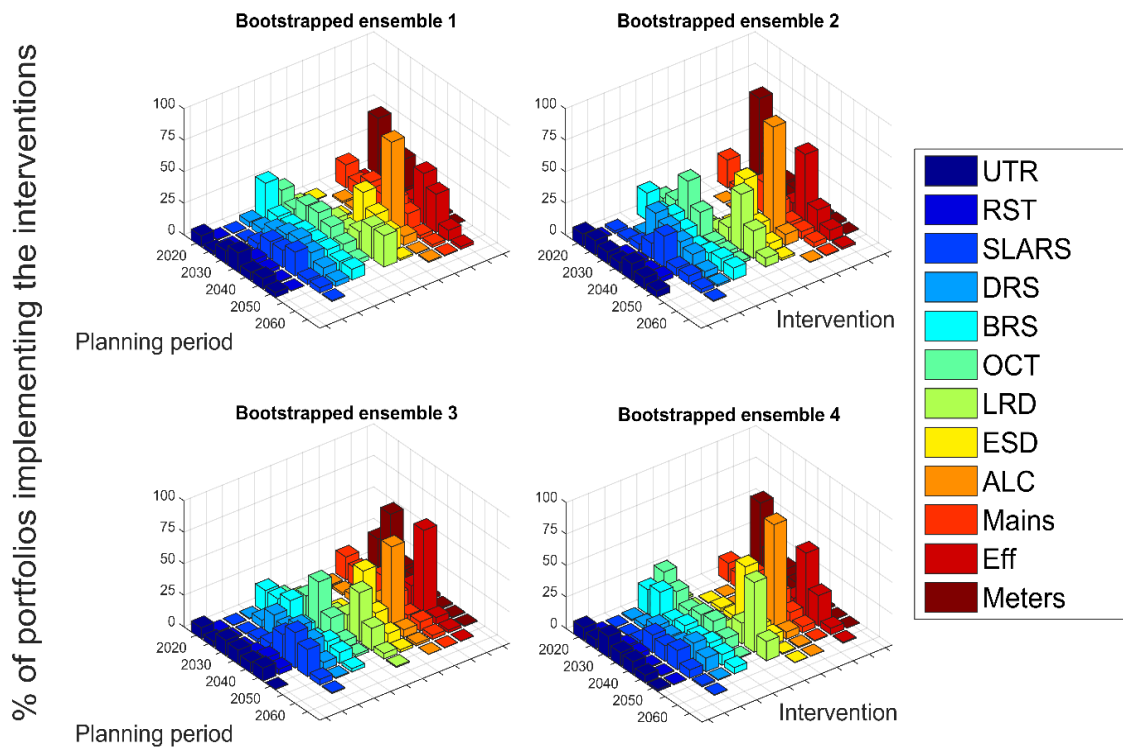


Figure 5-5. Schedules of interventions within the Pareto optimal plans obtained using the bootstrapped scenario ensembles and original objective values. The bars and axes represent the same dimensions as shown in Figure 5-3.

Nevertheless, the plan flexibility assessment using the flexibility indicator measure (section 5.2.2.3) revealed that the majority of plans in all four Pareto optimal sets of plans recommended "doing nothing" within the first two planning periods, i.e., the first 10 years of the planning time horizon. This contradicts with the usual planner intention where a planner would like to know what immediate actions he or she should take. Furthermore, it indicates that calculating the performance metrics such as resilience and eco-deficit over the whole planning time horizon when time continuation is considered may not represent the performance adequately. For instance, if the system performs poorly when the drought occurs earlier in the planning time horizon but very well in the rest of the planning time horizon the overall performance is balanced out whilst the discounted financial metrics force the investments to be delayed.

5.2.4.2. Average worst 5 year engineering and environmental performance

To address this issue the problem formulation was changed to assess the worst 5 year (or the worst planning period) engineering and environmental performance, i.e., supply resilience and eco-deficit, within a single scenario whilst keeping the assessment across scenarios average to avoid planning for the worst case scenario only. By doing so the resilience and eco-deficit performance metrics reflect the worst planning period (i.e., 5 year) performance encountered during the planning time horizon (i.e., 50 years).

The Equations 5-7 and 5-8 were changed as shown by Equations 5-13 and 5-14, respectively:

$$\text{Minimize}_{Average} \left[f_{SupRes} = \max_T D_j \right]$$

5-13

where j represents a five year period within the planning time horizon T , and D_j is the failure duration in weeks in period j . The supply resilience metric minimizes the average maximum duration of a failure across all periods within the planning time horizon across all scenarios in the ensemble.

$$\text{Minimize}_{Average} \left[f_{ECO} = \max_T \left\{ \left(|AN_{Q70} - AS_{Q70}| / AN_{Q70} \right)_j * 100\% \right\} \right]$$

5-14

where AN_{Q70} is the area under the naturalized flow duration curve (FDC) and AS_{Q70} is the area under the simulated FDC. The final eco-deficit metric minimizes the average worst deficit across all periods that occurred in the planning time horizon across all scenarios in the ensemble.

Using this formulation results in most flexible Pareto optimal plans in all four sets implementing Meters in the first 10 years of the planning time horizon. However, using different bootstrapped scenario ensembles within the optimization creates different schedules present in the Pareto optimal sets, i.e. the recommendations are affected by the random resampling of scenarios. In practice that would mean that if decision makers used a single ensemble of resampled scenarios, they would obtain different solutions than if they used a slightly different bootstrapped ensemble generated in the same way. Figure 5-6 shows the four Pareto optimal schedules obtained using the worst five year performance assessment of the resilience and eco-deficit objectives. The difference between the sets is more significant than in Figure 5-5. In particular, the ESD implementation (yellow bars) spikes in 2040 for the ensemble 1 but gets distributed between 2040 and 2055 for the other three ensembles. The LRD implementation (light green bars) spikes in 2040 for ensembles 2 and 4, but is more evenly distributed for ensembles 1 and 3. The OCT and SLARS implementation (greenish-blue bars and light blue bars, respectively) spikes in different periods for each ensemble. The remaining intervention schedules also show some degree of difference between ensembles. This suggests that the worst 5 year performance occurs in different planning periods between the ensembles and assessing this performance as it stands is not suitable for optimization across randomly resampled scenarios.

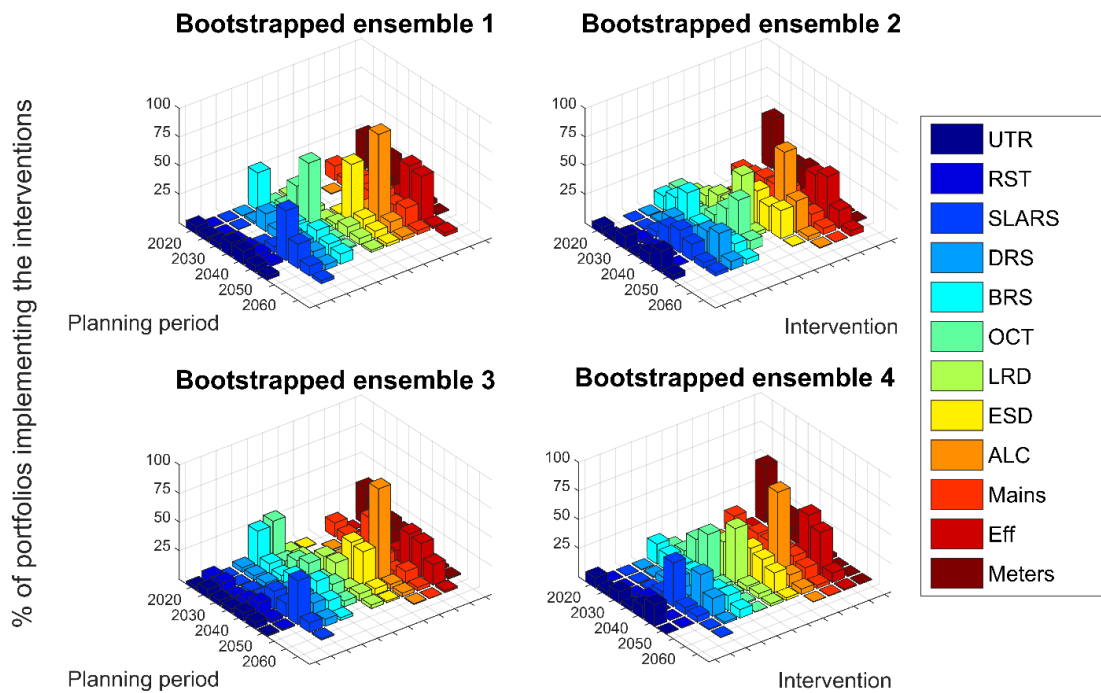


Figure 5-6. Schedules of interventions within the Pareto optimal plans obtained using the bootstrapped scenario ensembles and average of the worst 5 year engineering and environmental performance. The bars and axes represent the same dimensions as shown in Figure 5-3 and Figure 5-5.

5.2.4.3. Combination of discounting and worst 5 year performance

Discounting only financial performance in time with the engineering and environmental performance temporally undistinguished delays investments that may prove effective in short term. This results in unequal consideration of the multiple criteria over time resulting in potentially biased solutions as demonstrated above. The financial performance is discounted here as water companies are required to discount the financial aspects of their strategies when planning for the next 25-30 years (Environment Agency, 2012). Therefore, to reduce the temporal inequalities between objectives this study proposes to discount the engineering and environmental performance. Pearce et al. argue that if people's preferences count and if people perceive future risks to be regarded as of lower consequence than current risks, those preferences should be incorporated in the policy making.

The resilience and eco-deficit objective is discounted here for each five year period of the planning time horizon using the same discount rate of 4.5% as applied to the financial objectives. The resilience and eco-deficit objective value in a particular scenario then refers to the worst discounted five year performance value that occurs within the planning horizon. The final value across scenario ensemble is taken as the average value of the above. This allows for considering adverse events such as system failures that occur within near future to be of greater impact than events occurring in distant future as new technology or information may become available to prepare for adverse events more effectively.

Equations 5-13 and 5-14 were updated as follows:

$$\text{Minimize}_{Average} \left[f_{SupRes} = \max_T \{ D_j * (1 + i_c)^{-j} \} \right]$$

5-15

where j represents a five year period within the planning time horizon T , D_j is the failure duration in weeks in period j , and i_c is the discount rate. The supply resilience metric minimizes the average discounted maximum duration of a failure across all periods within the planning time horizon across all scenarios in the ensemble.

$$\text{Minimize}_{Average} \left[f_{ECO} = \max_T \left\{ \left[\left(|AN_{Q70} - AS_{Q70}| / AN_{Q70} \right)_j * 100\% \right] * (1 + i_c)^{-j} \right\} \right]$$

5-16

where AN_{Q70} is the area under the naturalized flow duration curve (FDC), AS_{Q70} is the area under the simulated FDC, and i_c is the discount rate. The final eco-deficit metric

minimizes the average discounted worst deficit across all periods that occurred in the planning time horizon across all scenarios in the ensemble.

This updated problem formulation ensures that the most flexible plans within the four Pareto optimal sets implement the ALC and Meters within the first decade of the planning time horizon. The optimal schedules from the four optimizations using the four bootstrapped scenario ensembles shown in Figure 5-7 are more similar than when undiscounted worst 5 year engineering and environmental performance was considered (Figure 5-6). In particular, ALC (orange bars), Mains (light red bars), Meters (brown bars), and OCT (light green bars) are mostly implemented in 2020, ESD (yellow bars) in 2040, and LRD (green bars) in 2045 with small degree of variation between the rest of the considered interventions.

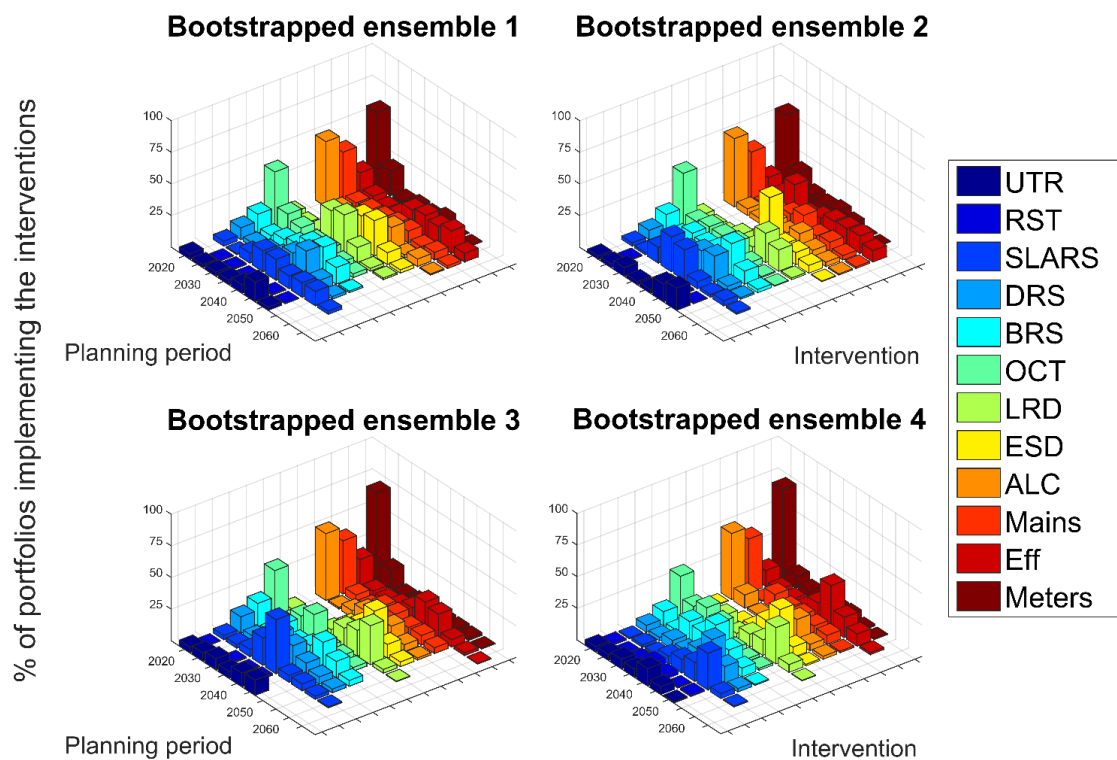


Figure 5-7. Schedules of interventions within the Pareto optimal plans obtained using the bootstrapped scenario ensembles and average of the discounted worst 5 year engineering and environmental performance. The bars and axes represent the same dimensions as shown in Figure 5-3, Figure 5-5, and Figure 5-6.

5.2.5. Summary of the investigations

The similarity of schedules within Pareto optimal plans was also assessed more formally using the the Kolmogorov-Smirnov (KS) test. The KS test is a non-parametric test to assess the equality of continuous one-dimensional sample with a known probability distribution sample or another sample (Massey, 1951). The latter, often

termed two-sample KS test, was used here. The test either confirms or rejects a null hypothesis that the two datasets are from the same continuous distribution, i.e. are likely to follow the same pattern.

The schedules of interventions consist of integer values (i.e., the implementation years) and each Pareto approximate set contains different number of portfolios. For these reasons the schedules of each intervention within the Pareto set were converted into percentiles such that if e.g., a 90th percentile of an intervention's implementation is 2050, that corresponds to 90% of portfolios within the Pareto set implementing the intervention by 2050. These percentiles were then used in the two-sample KS test such that percentile dataset of an intervention from one Pareto set was compared to the percentile dataset of the same intervention from another Pareto set. In the case of comparing four Pareto sets, six two-sample KS tests were performed to compare all possible pairwise combinations. The final similarity comparison metric was then designed to correspond to the percentage of the pairwise combinations where the null hypothesis of the KS test, in this case that the schedules are likely to follow the same pattern, was confirmed.

Figure 5-8 shows the percentage metric of the similarity of schedules across scenario ensembles (vertical axis) for each intervention (horizontal axis). The lines correspond to each investigated case and the points summarize the average similarity across all interventions for each investigated case where the colour of a point corresponds to the colour of a line for each case. Larger scenario ensembles, containing 220 scenarios and generated randomly in the same way as the bootstrapped ensembles consisting of 110 scenarios, were also investigated to assess if more scenarios within ensemble would provide better similarity of the Pareto optimal schedules (orange line and point in Figure 5-8). Using these larger ensembles did not improve the similarity of schedules and the optimizations required longer computational time to converge. All cases apart from the original problem formulation used with 110 bootstrapped scenario ensemble (light blue dashed line) show no similarity for the RST schedules. The best similarity of schedules across all bootstrapped ensemble cases is achieved for the BRS supply and Mains demand management interventions. The most varying schedule similarity across all cases can be seen for the UTR supply and Eff demand management interventions. The average percentage of similarity across all interventions (shown by points in Figure 5-8) shows the lowest similarity of only 14% for the drought experiment case (green point). The 110 bootstrapped scenario ensemble with the average discounted worst 5 year

performance case (red point) exhibits the same average similarity of 63% that the 110 bootstrapped scenario ensemble with the original problem formulation case (light blue point). The latter was however found to result in most flexible optimal schedules “doing nothing” within the first decade of the planning time horizon (section 5.2.4.1). The larger bootstrapped scenario ensemble size of 220 scenarios (orange point) shows slightly lower average schedule similarity of 57% than the 110 bootstrapped scenario ensemble using the same “final” problem formulation (red point). For this reason and because of the increased computational complexity of the former it is recommended to use the minimal required ensemble size to reduce the major drought event timing bias which is in this case 110 scenarios.

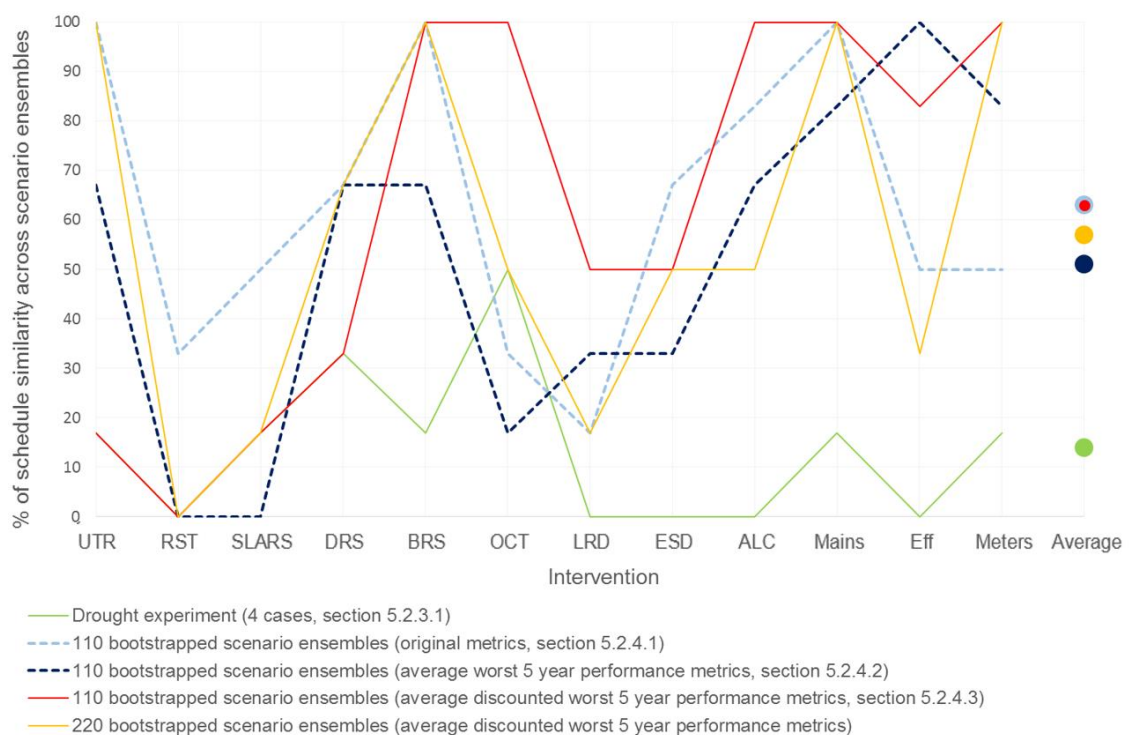


Figure 5-8. Similarity of schedules across scenario ensembles. The lines illustrate the investigated scenario ensembles cases and the points show the average schedule similarity across all considered interventions for each investigated case; the colour of a point corresponds with the colour of a matching case.

The trade-offs obtained by using the chosen problem formulation of discounting the worst 5 year performance for the resilience and eco-deficit metrics (described in section 5.2.4.3) and the four 110 bootstrapped scenario ensembles were assessed for similarity. Figure 5-9 shows the four trade-off sets where the horizontal axes show the total discounted capital cost, the vertical axes the discounted resilience and the aggregated robustness metric is shown by the colour scale. The axes were scaled to show the minimum and maximum values from all four sets of trade-offs. There is a slight

variation between the upper and lower objective value bounds between the four sets. The trade-off curves are however very similar only differing in the number of solutions found. This together with the previous findings that these trade-off solutions are also similar in the schedules they implement is here considered as satisfactory validation that the results obtained from the recommended approach are only slightly sensitive to the proposed random resampling of the hydrological flow scenarios.

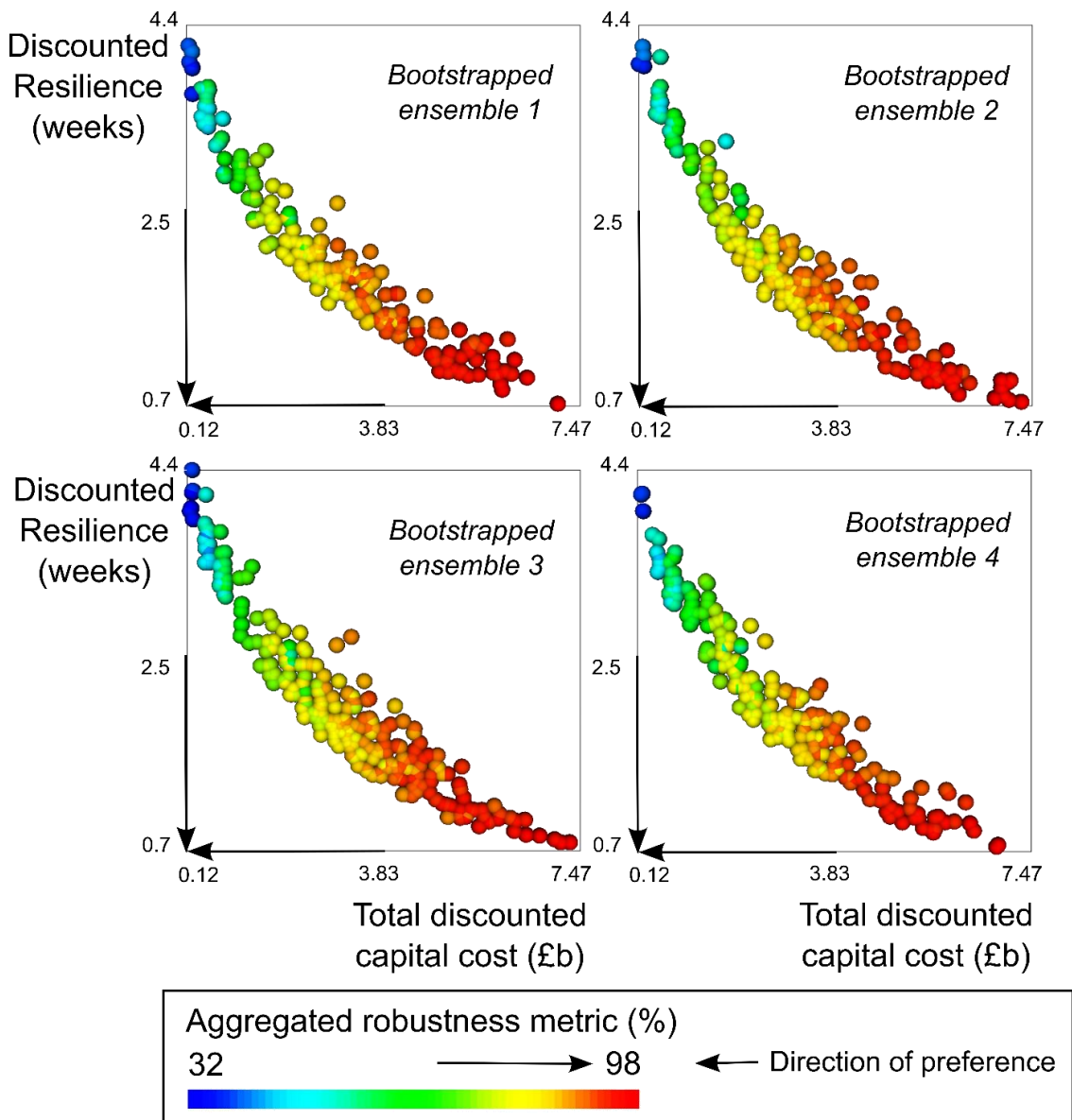


Figure 5-9. Trade-offs obtained from four 110 bootstrapped scenario ensembles using the discounted worst 5 year performance problem formulation.

5.2.6. Final recommended approach

Following the major drought event and problem formulation investigation detailed in sections 5.2.3 and 5.2.4 the final approach recommended here employs the scenario bootstrapping method (section 5.2.3.2) to generate ensembles of 110 scenarios and the problem formulation as detailed in section 5.2.2 with the equations 5-7 and 5-8 for

calculating the resilience (f_{SupRes}) and eco-deficit (f_{ECO}) objectives replaced by Equations 5-15 and 5-16, respectively.

The four optimizations using the four bootstrapped ensembles of 110 scenarios produced similar Pareto optimal fronts ensuring that the bootstrapping method provides consistent optimization results. Each of the four unique Pareto optimal solution sets was considered to be optimal for one respective ensemble (110 scenarios) only. In order to produce one final set of Pareto optimal plans, each of the plans that made up the four optimal solution sets was simulated over all 4 ensembles (in total 440 scenarios). The performance of each plan over the 440 scenarios was calculated identically to how it was calculated over the 110 scenarios within the optimization. The resultant simulation solutions were then sorted to keep only those that were non-dominated (Kollat and Reed, 2006) resulting in one final Pareto optimal solution set.

5.3. Results

Despite the optimization problem formulation discounting the non-financial performance of the system, the visual interrogation of results uses non-discounted non-financial performance. Decision makers are generally interested in how their system would perform over the considered planning time horizon. Thus to assess the performance trade-offs the engineering and environmental performance of the Pareto optimal plans is converted to reflect the worst experienced resilience and eco-deficit, i.e., without discounting the future performance.

5.3.1. Recommended trade-off set

The recommended Pareto optimal set of plans obtained by simulating the four Pareto optimal sets from the four bootstrapped ensembles against combined bootstrapped 440 scenario ensemble and non-dominated sorting is shown in Figure 5-10. The cardinal axes represent the total discounted energy cost requirements (f_{Energy}), total discounted capital cost requirements (f_{Capex}), and undiscounted supply resilience (f_{SupRes}) to reflect the worst 5 year period duration of occurred failure experienced by a plan. The arrows point towards the direction of preference; the ideal solution would lie in the lower left hand side corner of the cube. Such solution is not possible to achieve due to the trade-off between the financial and engineering performance. Improving the resilience of the system requires higher capital investment. However, plans of the same capital cost requirements and resilience levels differ in their energy requirements. The colour illustrates the undiscounted environmental performance of portfolios (f_{Eco}); the red plans

exhibit the worst eco-deficit while the blue plans the lowest eco-deficit. The environmental performance seems correlated with the engineering performance of the system but some plans of the same resilience levels and capital cost requirements with higher energy cost requirements achieve lower eco-deficit than plans of lower energy cost. The size of the points refers to the aggregated robustness indicator, which shows the average robustness of the two considered metrics f_{LoS3} and f_{LoS4} . The indicator is strongly correlated with the resilience; the bigger the point the more robust the plan is. The two distinct fronts visible in this particular many-dimensional view are created by implementation of the RO/nonRO Deephams reuse scheme. Plans from the right hand side front implement the RO DRS which requires much higher energy to operate than the nonRO DRS scheme. In contrast, the majority of plans implement only nonRO Beckton reuse scheme.

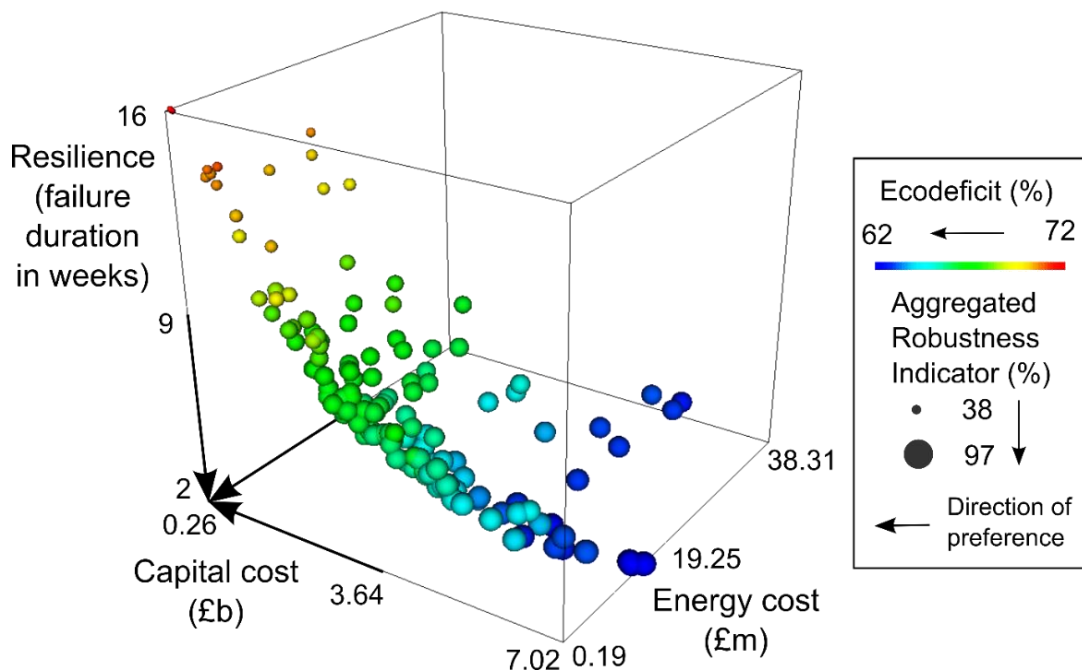


Figure 5-10. Recommended set of Pareto optimal plans and their performance trade-offs. The cardinal axes reflect the total discounted capital cost, energy cost and undiscounted supply resilience. The undiscounted eco-deficit is shown by colour; blue plans exhibit lowest deficit whilst red plans the highest deficit. The size of the points refers to the aggregated robustness metric for Demand Level 3 and Level 4 LTCD violations; the bigger the point the more robust the plan is. The arrows point towards the direction of preference.

The variety of plan schedules within the recommended Pareto optimal plans is illustrated in Figure 5-11. The horizontal axis shows the individual interventions whilst the vertical axis shows the planning periods. The lowest label on the vertical axis refers to no implementation, i.e., where an intervention is not implemented within the planning time horizon at all. The lines in Figure 5-11 illustrate the individual schedules

and the size of the points refers to the number of plans where a particular intervention occurs in a particular planning period. The colour of the lines shows the Upper Thames Reservoir capacity where plan schedules shown in blue build the smallest reservoir present in the Pareto optimal plans (90 ML) whilst the red lines the biggest reservoir (150ML).

Figure 5-11a illustrates schedules of all Pareto optimal plans from the recommended set. It can be seen that majority of schedules does not include the RST transfer supply intervention and about half of the plans do not implement the UTR reservoir and ESD desalination plant. Plans that do implement ESD built it from 2040 onwards. All plans include the implementation of Meters and ALC demand management interventions and the majority do so at the beginning of the planning time horizon. Figure 5-11b illustrates the diversity of plans where the most controversial intervention, the UTR reservoir, is implemented (coloured lines in Figure 5-11b). Most of these plans build the reservoir bigger than 130 ML. It is worth noting that all these plans always implement all demand management interventions in various planning periods.

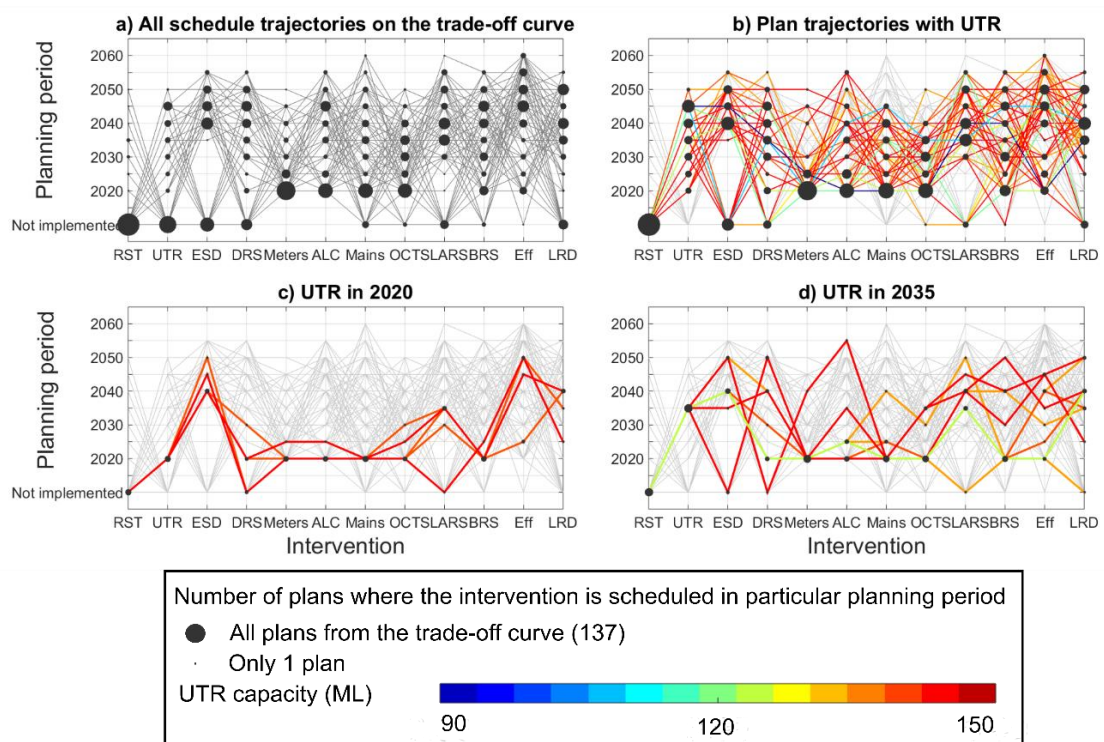


Figure 5-11. Schedules within the recommended Pareto optimal plans. The horizontal axis shows interventions whilst the vertical axis refers to the planning periods. A single line then illustrates the schedule of a single plan. The size of the points refers to the number of plans implementing an intervention at a particular period; the bigger the point the more plans the intervention occurs in in the particular planning period. Panel a) illustrates schedules of all Pareto-approximate plans from the recommended set. Panel b) highlights schedules of plans that implement the UTR reservoir. Panels c) and d) then “brush” the schedules further where the highlighted plans build UTR in 2020 and 2035, respectively. The colour of the lines in panels b, c, and d refers to the reservoir capacity.

The schedules can be “brushed” further to explore plans that implement UTR in particular period. For instance, Figure 5-11c shows all plan schedules where UTR is built at the beginning of the planning horizon. The colour of the lines shows that all of these plans build the reservoir of the highest capacity (140 – 150 ML). Most of these plans also schedule the Meters, ALC, Mains and the BRS reuse scheme for the beginning of the planning horizon. Figure 5-11d shows schedules where UTR is built 15 years later, in 2035. There is a greater variety of schedules than when UTR is built in 2020 (Figure 5-11c) as well as the implemented reservoir capacity (shown by the colour scale).

5.3.2. Deliberation of the preferred schedule

The trade-offs may be interrogated in terms of how the individual interventions and their schedules affect the system’s performance. Figure 5-12a illustrates the implementation and schedules of the most controversial supply interventions, i.e. the mutually exclusive UTR reservoir and RST transfer. The cardinal axes in Figure 5-12 show the same metrics as in Figure 5-10. The orientation of the cones illustrates the implementation of the interventions: cones pointing upwards show plans implementing the RST transfer, cones pointing sideways show plans implementing the UTR reservoir, and translucent cones pointing downwards show plans that do not implement any of those. Plans implementing these supply interventions provide better engineering and environmental performance spanning across almost the whole range of the capital and energy cost requirements than plans not implementing these interventions. The colour scale in Figure 5-12 refers to the schedules of the two interventions; dark blue plans build the interventions in the earliest possible period, i.e., 2020, whilst the light green plans build them in 2055. None of the plans build these interventions later than 2055 due to their long construction period requirements (10 years for UTR and 12 years for RST, see Supplementary material). The earlier these interventions are built the better engineering and environmental performance the plans exhibit but the higher the initial investment is required. It is worth noting that plans implementing the transfer in the same period as plans implementing UTR generally require lower initial investment but show worse performance in resilience and eco-deficit than the latter.

The plans may be “brushed” based on the preferred performance and schedules to identify a smaller cluster of promising plans that balance stakeholder preferences. For instance, if decision makers would like to preserve good environmental and engineering performance of the system, they would consider plans building either UTR or RST.

However, due to the controversy of these interventions decision makers may want to delay their implementation. Furthermore, decision makers may also want to consider minimizing the total energy cost requirements of the system over the planning horizon. Figure 5-12b shows a cluster of promising plans that satisfy such preferences (full coloured cones). These plans schedule the UTR or RST interventions' construction to 2030 or later, maintain the eco-deficit to a maximum of 65% and maximum duration of failure of 5 weeks and require total operating cost lower than £12m. Five plans are singled out based on their similar schedules in the first decade and labeled for further analysis: Least Cost (LC), Delayed Supply (DS), Least Energy (LE), High Performance (HP), and High Energy (HE).

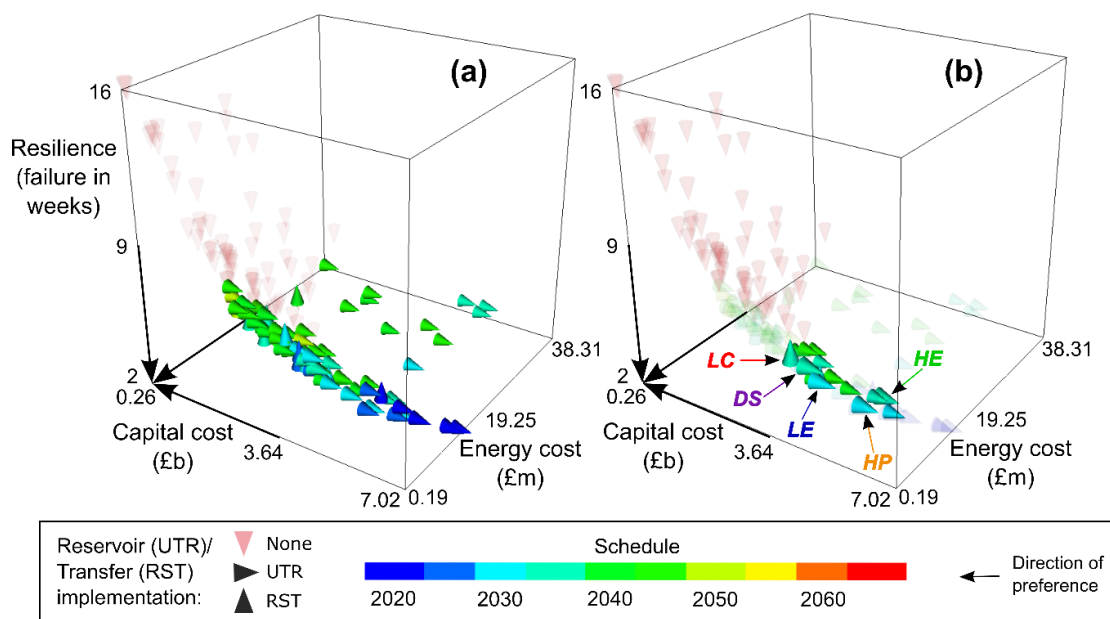


Figure 5-12. Reservoir (UTR)/Transfer (RST) implementation and schedules (panel A). The cardinal axes show the same performance metrics as in Figure 5-10. The arrows point towards the direction of preference. The orientation of the cones illustrates the implementation of these supply interventions: cones pointing upwards refer to plans implementing RST, cones pointing sideways refer to plans building UTR, and the translucent cones pointing downwards refer to plans that do not implement any of those. The colour scale refers to the scheduling of the UTR and RST interventions; dark blue colour refers to the earliest possible planning period (2020) whilst the dark red colour refers to the latest planning period (2065). Panel B shows a cluster of promising plans as a subset of plans from panel A chosen for further analysis where the UTR/RST implementation is delayed till 2030 and further with maximum energy cost of £12m, maximum eco-deficit of 65% and maximum duration of failure (resilience) of 5 weeks. Five plans are singled out based on their similar schedules in the first decade and labelled for further analysis (see Figure 5-13 and Figure 5-14Error! Reference source not found.).

Figure 5-13 shows a parallel axes plot of the cluster plans performance. The vertical axes illustrate performance metrics with the best performance at the bottom and the worst at the top. The horizontal lines represent all plans from the cluster shown in Figure 5-12b. When the lines cross between two vertical axes it signifies that there is a

trade-off between the two metrics. For instance, there is a clear trade-off between the capital cost and resilience, resilience and energy cost, energy cost and eco-deficit, and Level 4 robustness indicator and flexibility. In contrast, the eco-deficit and robustness indicator for the LoS Level 3 seem almost correlated. The coloured lines illustrate five candidate plans selected for further analysis (labelled cones in Figure 5-12b). The Least Cost plan (red colour) requires the lowest capital investment, is the most flexible of all plans within the cluster but has the lowest Level 3 robustness and the worst eco-deficit. The Delayed Supply plan (purple colour), implementing only small demand management interventions and Oxford Canal Transfer at the beginning of the planning time horizon and delaying all investments in the supply interventions until 2035, shows the worst resilience and low robustness and flexibility. This plan was chosen based on the resilience and eco-deficit metrics; it has the worst resilience out of all plans within the cluster and worst eco-deficit together with the LC plan but requires higher capital and energy cost investment than the latter. The Least Energy plan (blue colour) requires the lowest energy cost of the cluster plans, lies in the middle on the capital cost requirements axis but exhibits low engineering and environmental performance. The High Performance plan (orange colour) shows good resilience, low eco-deficit and high Level 3 robustness when compared to the other four singled out candidate plans but exhibits the lowest flexibility (there is no other plan within the whole Pareto-approximate set that has the same schedule within the first 2 planning periods). Lastly, the High Energy plan (green colour) requires the highest capital and energy cost out of the five candidate plans but shows the highest Level 4 robustness, average flexibility, and good engineering and environmental performance.

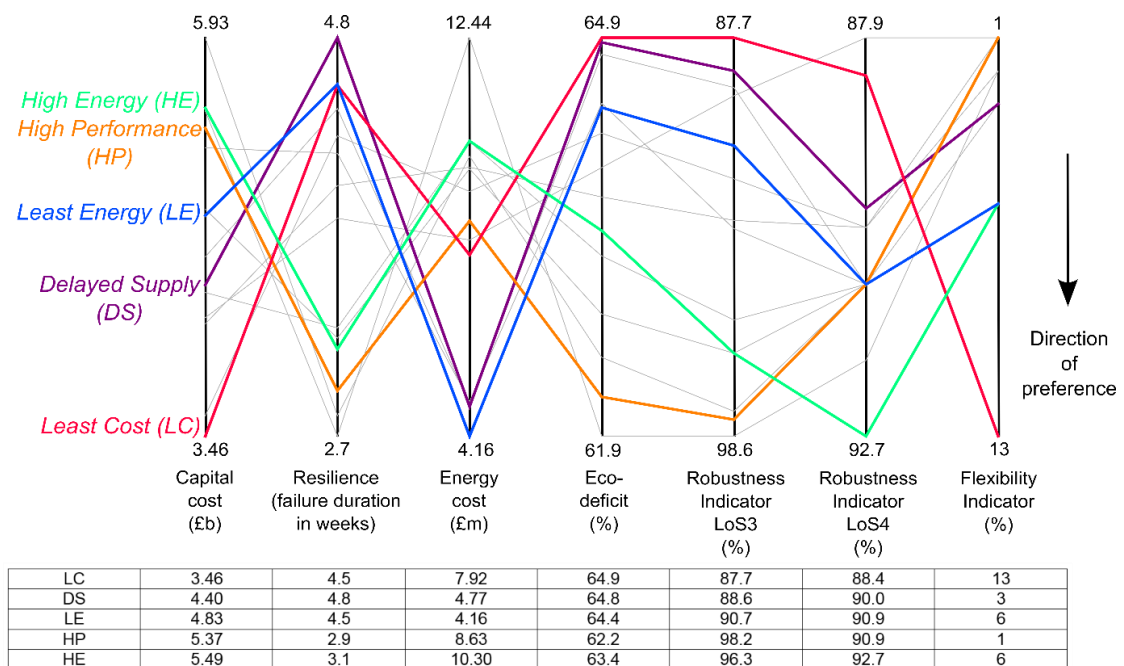


Figure 5-13. Parallel axes performance plot of plans from the cluster of promising plans shown in Figure 5-12b. The vertical axes represent performance metrics and the arrow points towards the direction of preference; the best performance is at the bottom of axes whilst the worst performance at the top. The coloured lines highlight five singled out candidate plans. The table shows the metric values for the five candidate plans.

The five singled out candidate plans may be combined into a plan strategy based on their intervention schedules (Figure 5-14). The horizontal axis in Figure 5-14 shows the “time continuation” and the boxes represent implementation of an intervention in a particular planning period. Each coloured line refers to a single plan whilst coloured intervention names belong to the same coloured plan; black intervention names mean that the particular intervention is implemented within multiple plans. A coloured box signifies where the plan schedule of the same colour ends.

The Least Cost plan (red line in Figure 5-14) implements only Meters in 2020 and continues with other interventions from 2030; it does not share the same schedule within the first 10 years with any other of the singled out candidate plans. The plan also builds the River Severn Transfer (RST) in 2035 instead of the reservoir. In contrast, the Least Energy and High Energy plans (blue and green lines in Figure 5-14, respectively) share the same schedule in the first 10 years, i.e., both plans introduce the Meters and Mains demand management interventions in 2020 and diverge only in 2030 where the Least Energy plan builds the UTR reservoir and LRD desalination plant whilst the High Energy plan builds the BRS reuse scheme. This would allow decision makers to take common immediate actions whilst leaving them more alternative plan schedules to follow in future. The two plans differ in their energy cost requirements considerably

which is caused by the High Energy plan implementing the energy intensive desalination plants (LRD and ESD) and reuse schemes (DRS and BRS) earlier in the planning time horizon than the Least Energy plan. The High Performance and Delayed Supply plans (orange and purple plans in Figure 5-14, respectively) both implement ALC and OCT in addition to Meters and Mains in 2020. The former then builds DRS reuse in 2025 and UTR in 2030 whilst the latter does not introduce any supply intervention until 2035 which results in the plan's poor performance (Figure 5-13) when compared to the other four candidate plans.

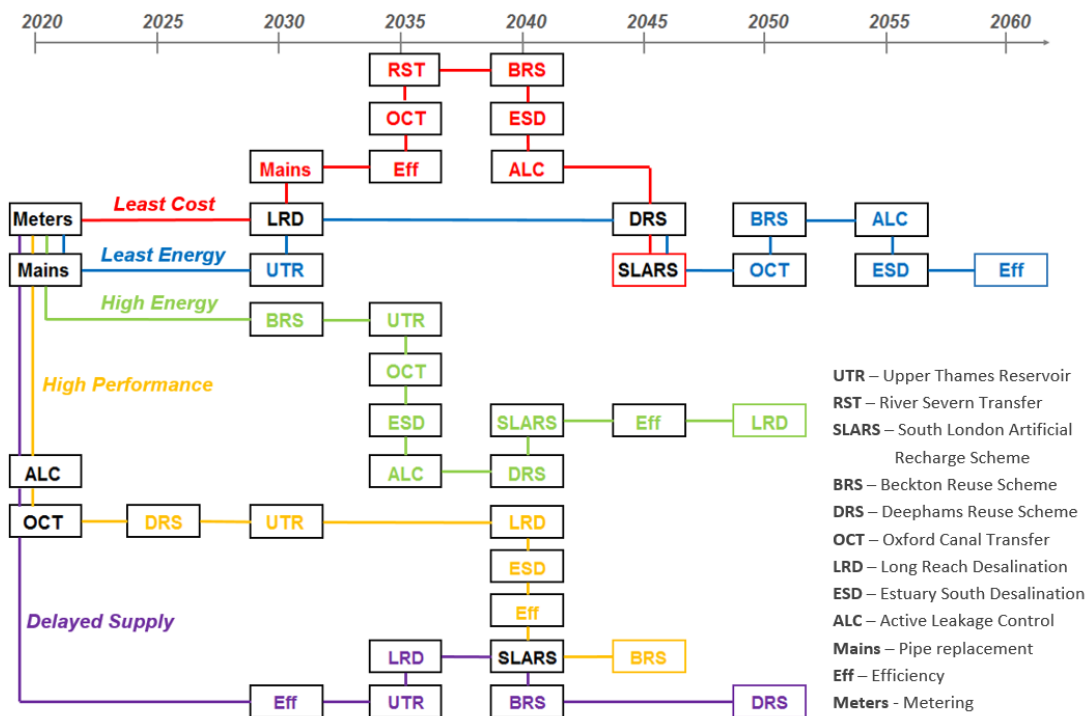


Figure 5-14. Five candidate plans selected from the cluster of promising plans shown in Figure 5 11b. The horizontal axis shows individual planning periods and the coloured lines track the different plans. The boxes represent implementation of individual interventions; a coloured box signifies the end point of a particular plan. Intervention names and boxes shown in black signify that multiple plans implement the intervention in the particular period.

5.4. Discussion

5.4.1. Bootstrapping

The scenarios of future hydrological conditions used in this study were chosen based on the current practice and regulator recommendations. Nevertheless, using only the original ensemble of the 11 Future Flow scenarios showed that a major stress event time occurrence projection may bias the scheduling of interventions (section 5.2.3.1). This study therefore proposed a scenario manipulation technique based on a bootstrapping method to generate a wider ensemble where such stress event is considered to occur at

any point in time. Evaluating the candidate solutions against such scenario ensemble ensures the Pareto optimal plans are robust to a wide range of future conditions. Based on the robustness metric indicators planners are given the opportunity to trade-off the financial requirements of plans with their long-term ability to maintain the desired levels of service where stress events may occur unexpectedly. The ensemble was kept small for practical purposes; larger ensembles did not result in higher quality solutions (section 5.2.5). Real world water resource system planning problems are complex and planners typically need to make decisions fast whilst not having access to high-performing clusters that can perform millions of system evaluations.

The investigation into the resampling influence on the Pareto optimal solutions (sections 5.2.4 and 5.2.5) showed that the problem formulation, i.e. the objective value calculations across the scenarios, can influence the schedules within the Pareto optimal solutions. The four different bootstrapped scenario ensembles were generated in the same way redistributing the major drought event equally across the planning time horizon in each ensemble. Nevertheless, the noise in random resampling may still have some influence what solutions are obtained from using each ensemble. The investigation of trade-offs obtained from using the four different bootstrapped scenario ensembles shown in Figure 5-9 confirmed that this noise is sufficiently low to cause substantial differences if the recommended problem formulation is used. Generating scenarios in different way as well as using a different problem formulation may result in greater sensitivity of solutions to the resampling noise and a sensitivity analysis technique should be used to assess the extent of the solutions' sensitivity.

5.4.2. Discounting performance

The supply and demand intervention plans were optimized for discounted financial, engineering and environmental performance. Financial discounting to value and price future financial assets for today has long been applied in planning (Frederick et al., 2002). Society values future gain or loss lower than the same gain or loss occurring now (Pearce et al., 2003). This, however, holds true not only for the financial aspect of assets but for all associated benefits and dis-benefits. In the case of a water supply system this includes the ability to provide sufficient levels of service as well as minimize the negative environmental impacts. As the traditional least cost approach monetizes the social and environmental impacts and aggregates all metrics into a single financial objective it could be argued that such approach already considers the time discounting of future non-financial performance. The many-objective optimization however

considers all metrics separately where usually only the financial metrics are discounted (e.g., Beh et al., 2015; Borgomeo et al., 2016). This results in unequal performance valuation of the system in future, i.e., the cost of future assets is lower today if they are implemented later in time but the risks associated with their future performance such as supply failures are valued the same today as at any point in future.

The conducted experiments in section 5.2.4 also revealed that discounting only the financial performance results in delaying the investments as much as possible as near future poor performance of the system is considered of lower concern than bigger failure in e.g. 25 years from now. As Olson and Bailey argue (Olson and Bailey, 1981) zero discounting logically implies the impoverishment of the current generation. Furthermore, the uncertainty associated with future conditions predictions such as climate change and population growth tends to increase with the length of the projections time span. This implies that predictions about near future may be more accurate than predictions about distant future. Thus a water supply system failure in near future may be of more concern to planners than the failure in distant future as there is more time available to prepare for the latter through technological advancements, more sophisticated prediction methods, etc. This study therefore discounts all considered performance metrics using the same discount rate to ensure their equal temporal assessment.

5.4.3. Plan analysis

The trade-off analysis and deliberation of the preferred plan schedule presented in this study aim to show how the results of the many-objective robust optimization may be used for decision making. Firstly, the performance of the whole Pareto optimal front may be assessed using multi-dimensional visual analytics to provide information about the system's performance trade-offs (Figure 5-10). In this case improving the robustness, resilience and environmental performance of the system requires higher capital investment but not necessarily higher energy use; plans with the same capital cost differ in their energy cost requirements. It is worth noting that higher energy use does not result in higher robustness. Figure 5-10 showed that plans located towards right hand side on the energy cost axis (i.e., higher energy cost) are of lower size (i.e., lower robustness) than plans located towards left (i.e., lower energy cost) that are of the same capital cost and resilience but different eco-deficit. Planners may therefore want to consider less long-term cost alternatives that provide better resilience and robustness with slightly worse environmental performance.

The investigation of the Pareto optimal plan schedules illustrated in Figure 5-11 provides decision makers with insight into the high-performing combinations of interventions and their schedules. For instance, planners may hypothesize that building a single large intervention such as a reservoir right at the beginning of the planning time horizon would mean smaller interventions do not need to be implemented for several years to follow if at all. However, the results here suggest that such plans are not optimal under a wide range of future hydrological conditions as all Pareto optimal plans that build the UTR reservoir in 2020 implement several smaller interventions in 2020 or 2025 (Figure 5-11c). Furthermore, these plans build the reservoir of the highest considered capacity (colour of lines in Figure 5-11c). In contrast, planners may believe that delaying the reservoir implementation inevitably requires implementing most of the other considered interventions at the beginning of the planning horizon for the system to perform satisfactorily. The results here however suggest that plans which build UTR in e.g. 2035 (Figure 5-11d) provide a variety of both UTR capacity and other intervention scheduling. Such information helps decision makers to acquire more knowledge about their system's behaviour.

The Pareto optimal plans may then be interrogated in terms of what interventions are implemented and when they should be built. In the Thames basin the most socially and economically controversial intervention is the Upper Thames Reservoir which in this study is considered mutually exclusive with the River Severn Transfer. Therefore, these two interventions and their schedules may be mapped to the trade-off surface as shown in panel A of Figure 5-12b. By doing so decision makers are provided with the information of how the individual decisions affect their system's performance and this may help to narrow down the whole set of alternative solutions to a cluster of few (Figure 5-12b). The plans within the identified cluster may then be analysed in more detail by e.g. choosing a small number of promising solutions with similar performance that share similar intervention schedules in the first decade and comparing their relative performance (Figure 5-13). Mapping and combining the intervention schedules of such plans against time frame as illustrated in Figure 5-14 results in a schematic of a flexible plan that provides multiple choices over time. Choosing to implement interventions that are shared between multiple plans in the first five year planning period such as Meters and Mains for Least Energy and High Energy plans or Meters, Mains, ALC and OCT for High Performance and Delayed Supply plans in Figure 5-14 allows switching between these plans within the first five years. If for example planners chose to implement the Delayed Supply plan but the demand management interventions it

implements would not deliver anticipated demand savings within the first five years, the High Performance plan could instead be implemented by building the DRS scheme in the following five year planning period. The latter plan shows higher resilience and robustness indicating that switching to this plan would improve the system's performance. Nevertheless, all five plan combined into the single schematic exhibit similar performance when compared to the other Pareto optimal plans (Figure 5-12b) thus switching between these plans would not violate overall optimality. This allows decision makers to select not one but multiple plans with the same immediate actions whilst providing more flexibility in which actions to implement in the following planning periods. However, the current planning approach in the UK is repeated every five years the approach proposed here may also be repeated after the first five year planning period which may result in different paths after the initial period as the new data become available (i.e. scenarios of future conditions, cost of interventions, etc.). The plan schematic presented here is meant to show planners they can combine multiple plans with similar initial investments when considering initial decisions.

5.5. Conclusion

This chapter proposed an approach to identify and visually deliberate robust plans for water resource systems that meet many financial, engineering and ecological goals. The approach was applied to identifying plans of new water supply and demand management intervention schedules that could meet London's estimated water supply demands in the next 50 years. Plans were evaluated against the following discounted metrics: capital and energy cost, and supply resilience and hydro-ecological deficits; two robustness indicators were also considered. Future plans were assessed against multiple scenarios of future climate change impacted hydrological flows. These were generated by bootstrapping method that respects the non-stationary trend of climate change scenarios and ensures even distribution of the major stress event in the scenario ensemble. Using such scenario ensemble reduces the possibility of optimizing the intervention schedules against perfect foresight.

Results were presented via many-dimensional trade-off visualizations that help deliberation of preferred plan between stakeholders. The trade-offs interrogation in terms of what interventions individual plans implement and when provides decision makers with information about how the interventions affect the system's behaviour. The set of Pareto optimal plans may be narrowed down based on their performance and

intervention schedules. Promising plans that share similar intervention schedules in the first decade were combined into a coherent flexible plan that provides multiple choices over time. This allows decision makers to select not one but multiple plans with the same immediate actions whilst providing more flexibility in which actions to implement in the following planning periods.

6. Chapter 6 – Conclusions

6.1. Summary

Water supply planning in many major world cities faces several challenges associated with but not limited to climate change, population and economic growth and environmentally motivated regulations. Long-term plans to maintain supply-demand balance and ecosystem services require careful consideration of uncertainties associated with future conditions. In addition, such plans must meet multiple demands of a range of stakeholders whose preferences often conflict. Understanding these conflicts necessitates exploration of many alternative plans to identify possible compromise solutions and important system trade-offs. The current approach for London's water supply planning in the UK utilizes least cost capacity expansion of future plans of intervention schedules with limited consideration of uncertainty beyond a supply-demand buffer. The traditional capacity expansion approach typically requires simplified aggregated models that have difficulties in representing non-linearities and if multi-objective it limits the weighting or prioritization of objectives 'a posteriori'. The single least-cost objective approach may introduce bias into the decision making process as well as limits the exploration of the many possible combinations of supply and demand options and is potentially unsuitable for the high variability and uncertainty in future states.

Recently developed planning under uncertainty approaches that evaluate many plausible candidate strategies and consider trade-offs between multiple water supply system performance criteria have been mostly applied to hypothetical or simplified case studies. The simulation-based planning approaches are typically applied to predefined strategies to assess their vulnerabilities and robustness. If these predefined strategies are desired to balance multiple societal goal such as reliability of the associated water supply system and its environmental impacts in addition to the required investments the search process for such strategies has to be performed prior to the robustness assessment. The existing simulation-optimization based planning approaches that link these two steps together have some limitations when considered for the application to the current planning approach in practice. Firstly, the methodology they employ represents too big a challenge to be incorporated into the UK's planning process 'as is'. Secondly, the results obtained by using these approaches are in general too complex for decision makers to understand, let alone justify their choices arising from such results to

regulators. The variety and complexity of different available approaches to planning under uncertainty make it difficult for planners to choose one that would require the lowest level of transition whilst providing the most desired outcomes. Application of such frameworks by water system planners will require them to understand and accept the benefits of embedding the search for robust plans that perform well under wide range of future conditions within automated investment filtering approaches.

This thesis described a step-wise approach of introducing the many-objective robust optimization of water supply system expansion investments to UK's water industry regulators, planners and stakeholders. Chapter 3 presented the first step of implementing the many-objective optimization to the Thames basin water supply planning problem. Six performance objectives were considered explicitly including the financial, engineering and environmental performance. Historical records were used to represent conditions in 2035. The performance trade-offs were visualized progressively to help decision makers become familiar with many-objective analysis, navigate the trade-offs and reveal information that would remain hidden if lower dimensional analysis was used. Individual interventions within the Pareto optimal portfolios were mapped on the trade-off space to reveal how the interventions themselves affect the system's performance.

Multi-objective optimization linked to simulation allows planners to incorporate different and often conflicting preferences into decision making explicitly as well as reducing the need to choose *a priori* which portfolios of interventions at fixed capacities to evaluate. Instead of estimating the deployable output of each supply scheme by using a simulation model separately and using this information in separate optimization model with discrete scheme capacities the proposed approach automates the search for the most promising portfolios of interventions and their capacities. Visualizing the trade-offs helps planners to decide on appropriate balance between different planning goals and assess the consequences of including certain interventions in their plans. In Chapter 4 multiple sources of future uncertainty were implemented in the same many-objective optimization problem in the form of scenarios. All possible combinations of 11 scenarios of future hydrological conditions, 2 demand growth scenarios, 2 energy price growth scenarios and 2 sustainability reduction scenarios were considered to represent conditions considered plausible to occur in 2035. The objectives were proposed to be assessed across scenarios as average for the environmental impact and energy cost requirement and as 'nearly' worst-case for the engineering performance. Different

objective assessment as well as using different scenario set could potentially lead to different results. The objectives and scenarios were discussed with decision makers to ensure the results reflect their planning efforts. The candidate portfolios were constrained to maintain the desired service reliability (Levels of Service) across all considered futures. The results were compared to those obtained from the deterministic optimization described in Chapter 3. Visual analytics was used to highlight the benefits of incorporating uncertainties whilst searching for the robust portfolios.

The previous chapters considered only a static snapshot of the Thames basin water supply system's performance in a single year (2035). Chapter 5 then introduced time continuation to incorporate the scheduling of interventions into the many-objective robust optimization. A planning time horizon of 50 years (2020 – 2070) was considered. The decisions were updated according to the latest TWUL's WRMP and the six objectives considered included discounted financial, engineering and environmental performance as well as robustness metrics reflecting how well the candidate plans of intervention schedules would perform across the considered future scenarios. A bootstrapping method that respects the non-stationary trend of climate change scenarios and ensures even distribution of the major stress event in the hydrological flows scenario ensemble within the planning time horizon was proposed. Results were presented via many-dimensional trade-off visualizations to help planners make a decision based on Pareto optimal plans' performance and intervention schedules. Promising plans that share similar intervention schedules in the first decade were combined into a coherent flexible plan that provides multiple choices over time.

6.2. Findings

This thesis examined how the challenges of incorporating multiple societal goals and uncertainty consideration may be addressed to provide efficient and straightforward practical implementation for the real world water resource system planning problems. The goals considered and optimized for in the studies included the initial capital investment requirements of implementing new infrastructure and demand management interventions, their operating cost requirements, the supply reliability and resilience of the water supply system, the environmental impacts of the new infrastructure and demand savings on the river flows and a measure of plan's robustness to a range of future scenarios. The studies presented in Chapters 3, 4, and 5 and summarized above demonstrated the implementation of the many-objective robust optimization that considers both multiple performance criteria and a wide range of future conditions for

the Thames basin water supply system expansion planning problem. The findings from each study are summarised below.

Chapter 3 demonstrated that optimizing for multiple preferences explicitly is well suited for situations where stakeholders have diverse interests and allows decision makers to visually assess the trade-offs that different investments imply. Visualizing and exploring the trade-offs progressively aids the learning and decisions making process. In the Thames basin, reducing capital investments negatively affects the engineering and environmental performance of the system. Higher capital investment results in maintaining good engineering and environmental performance whilst saving on energy costs. Visualizing performance objectives and investment decisions simultaneously reveals how individual decisions affect the system's performance. Building the unsupported River Severn Transfer instead of the reservoir requires lower initial investment but significantly higher operating costs; implementing the pipe repair campaign intervention requires higher capital costs but provides energy cost savings. The approach presented here frees planners from having to choose *a priori* which portfolios of interventions to evaluate and the trade-off exploration findings may help justify to interested parties why a certain strategy was selected.

Chapter 4 demonstrated that taking into account multiple performance preferences and planning for robustness can be achieved concurrently. Such approach identifies robust solutions that perform well under a wide range of future conditions. The analysis here showed that sing only a single future scenario based on historical records might suggest future system investments that are optimal for the specific future condition but are unlikely to perform well under a range of plausible future conditions. Robust interventions can be identified by their presence within the identified robust portfolios. The results suggest that, given how the system is currently modelled, building the reservoir and reducing demand by implementing the demand management interventions are likely appropriate strategies for the Thames basin water supply system in the face of uncertainty.

In Chapter 5 where time continuation is considered the investigations revealed that a presence of a single major drought event within the hydrological flow scenarios may bias the scheduling of interventions towards the timing of this drought. Ensuring even distribution of such event within the considered scenario ensemble reduces such bias significantly. Based on the robustness metric indicators planners are given the opportunity to trade-off the financial requirements of plans with their long-term ability

to maintain the desired levels of service where stress events may occur unexpectedly. The investigation also showed that discounting only financial performance of the system results in delaying investments with unequal consideration of the engineering and environmental performance over time. Discounting all considered performance metrics equally ensures that the robust plans perform satisfactorily within near future as well as over the whole planning time horizon. The visual trade-off analysis provides insights of not only how the individual intervention implementation affects the system's performance but how also their sequencing over time changes the performance. Building the reservoir and implementing demand management interventions early improves the robustness, resilience and environmental performance of the system, requires higher capital investment but not necessarily higher energy use. In general, higher plan's energy use does not results in higher plan's robustness. This chapter also demonstrates how some Pareto optimal plans of intervention schedules may be combined into a single coherent plan that provides multiple choices in the first five years of the plan implementation. The current planning approach in the UK is repeated every five years; the approach proposed here may also be repeated after the first five year planning period which may result in different paths following after the initial period due to updated input data (i.e. scenarios of future conditions, cost of interventions, etc.). The plans that may be combined implement the demand management interventions in the first five years which suggests that reducing demand at the beginning of the planning time horizon may provide planners with higher flexibility of which supply interventions and when to implement in the following periods. The coherent plan schematic presented here is meant as a recommendation for planners to consider combining multiple plans with similar initial investments when designing their preferred strategy.

6.3. Limitations

This thesis focused on investigating the implementation of many-objective robust optimization approach into the current water supply system planning practice in the UK. A single case study of the Thames basin water supply system planning problem was used throughout the project. Some findings, benefits and limitations discussed here may not directly apply to other water resource planning problems that may require the use of other specific performance metrics (e.g., hydropower performance, irrigation, etc.) and scenarios of future conditions not discussed here.

Future conditions in this study were represented in a limited way; only a limited number of scenarios as well as estimates based on the extrapolations of current socio-economic trends to consider uncertainty of future conditions were employed. The Pareto optimal portfolios identified as robust in this study are considered robust to the scenarios used. If a different set of future conditions was used, the proposed approach could potentially identify different portfolios as robust to the particular set. The climate change impacted scenarios used throughout this thesis may also underrepresent the true complexity of the potential effects of climate change on hydrology. These scenarios are currently recommended by the regulators as one of the approaches for scenario testing and are used by water companies. Increasing the number of possible future scenarios increases the number of their combinations exponentially. Evaluating each candidate portfolio or plan against such a large ensemble poses significant computational challenges that many water companies are not technologically and temporally equipped to undertake. The purpose of this thesis is to highlight the possible improvements to the current planning approach in England. The approach proposed here was therefore designed to resemble the current practice as close as possible and offer a relatively straightforward methods of implementation.

6.4. Future work

This thesis proposed a methodology of implementing the many-objective robust optimization in the water supply system expansion planning. Despite representing the real water supply system the approach has not yet been implemented in practice. A project to include this approach in TWUL's WRMP19 based on the methodology presented here is currently being undertaken.

The scheduling of interventions as proposed in this thesis does not take into account the value of flexibility (Woodward et al., 2014) and adaptation (Haasnoot et al., 2013; Hamarat et al., 2014) explicitly. Approaches seeking plans of supply and demand management interventions represented as dynamic trajectories over time, which are able to be adapted to the changing environment whilst considering many system goals and plausible futures, may be more suited to situations of deep uncertainty. The robust plans were optimized for considering static robustness here and were assessed for flexibility post-optimization. Searching for dynamic robustness involves searching for plans that are able to adapt as conditions change (Walker et al., 2013). One possible method is the Adaptation Pathways approach (Haasnoot et al., 2012) described in section 1.3.3.2. Instead of optimizing the exact planning period when an intervention should be built or

implemented the search would optimize an adaptation tipping point (Kwadijk et al., 2010) of each intervention within each plan, i.e., a condition which when “observed” would signal the need to implement the specific intervention in order to maintain the desired service levels in future. The tipping points may be in the case of the Thames basin water supply system specified as the frequency of occurrence of certain LTCD Demand level failure. For instance, if the sprinkler/hosepipe use ban (LTCD Demand level 2 failure) is imposed more than once within the first decade of the planning time horizon, a reuse scheme should be built to maintain desired service levels in the next 80 years. This would result in a plan consisting of an adaptation pathways map specifying trigger conditions for each intervention within the plan. Such rules to guide the implementation of interventions as the future unfolds may result in more flexible strategies where a decision is made based on observations on how the future is actually unfolding.

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Appendix – Thames IRAS-2010 components

This Appendix provides the Thames IRAS-2010 simulation model components description as illustrated in Figure 2-2.

Day's Weir and Lower Thames inputs

The naturalised flow sequences we use are those for Day's Weir and Teddington. The lower Thames input is derived by simply subtracting Day's Weir flows from Teddington flows, making no allowance for time of travel downstream. The model is run on a weekly time-step. This calculation depends on the assumption that flow from Day's Weir reaches Teddington in less time than one time-step.

WBGW (West Berkshire Groundwater Scheme)

WBGW release water into the Thames when the Demand Level 2 restriction line on the Lower Thames Control Diagram (LTCD) is crossed. When invoked, the scheme can release 66 MI/d for 18 months. The scheme is represented in the model as a reservoir of capacity 18x30x66 MI (one month=30 days). WBGW is refilled using an input of 0.2 m³/s which represents natural GW infiltration.

AffThamesAbs

This is the sum of Affinity abstractions from the Thames to its Central and Southern WRZs (Affinity Central and Affinity South, respectively, in Figure 2-2). This is set as a constant amount representing the sum of abstraction licences, 405.4 MI/d. However, to account for the return flows the Affinity abstraction was reduced by 30% to 283.8 MI/d.

Thames Abs

The Thames Nominal Intake component represents combined abstractions at Datchet, Wraysbury, Laleham, Walton, Hampton, the Thames-Lee tunnel and Surbiton. We assume that Thames Water will be able to take the maximum aggregate daily licensed value (5455 MI/day) if it is available and needed. An annual license of 663716 MI can be implemented. Abstraction is also constrained by the minimum environmental flow at Teddington, as set by the LTCD.

LAS (London Aggregated Storage)

In our model all the London reservoirs are aggregated into one reservoir with total capacity of 202 828 MI. In the WARMS model they are lumped into three: north Thames reservoirs, south Thames reservoirs and Lee Valley reservoirs. In fact, the Thames and Lee storage is connected by the Thames-Lee tunnel with a capacity of 410 MI/d (flow goes only in 1 direction: Thames-Lee). Splitting the reservoir in the modelling would introduce considerable extra complication.

Besides the Thames abstractions there are currently two other inputs to the aggregate storage. One is the North London Artificial Recharge Scheme (NLARS) which only supplies water in dry situations when an LTCD control curve is crossed (please see description of ‘NLARS’ for details). The other is the combined intake from the Lee, component NLARS_abs. Because there is more than one input, the Aggregated Storage component has a supply order, calling on the Lee first, then the Thames and finally NLARS.

Groundwater, in the representation, is considered as supplying demand directly rather than adding to storage. Demand calls on groundwater first and is always considerably more than it can supply.

Feildes Weir (Lee input)

These are the denaturalised flow time-series for Feildes Weir. The TWUL abstractions are aggregated into a single node located below Feildes Weir inflow point. We assume all TWUL Lee abstraction points (Chingford South, Chingford supply channel, Enfield lock, Enfield lock navigation, Keids Weir) are indeed downstream of Feildes Weir.

Rye-Meads (Rye Meads treated effluent input)

The input here is a monthly profile repeated in each year based on the WARMS model shown in Table 0-1.

Table 0-1. Rye-Meads effluent monthly profile

Month	Release (Ml/d)	Month	Release (Ml/d)	Month	Release (Ml/d)	Month	Release (Ml/d)
January	75.9	April	75.9	July	82.8	October	74.4
February	77.4	May	76.7	August	77.4	November	74.4
March	76.7	June	77.4	September	76.7	December	74.4

Lee abstraction (Lee nominal intake)

Lee abstraction to LAS. The Lee intake is similar to the Thames nominal intake. Hands-off flow after abstraction (Lee ecoflow node) is set to 34 Ml/d. The constraints on the abstraction are the annual and daily licences: 238,119.5 Ml annually and 2,636.7 Ml/d daily as sums of all TWUL licences on the River Lee. The pumping capacity is however limited to 1,171 Ml/d; the maximum daily abstraction is therefore set to reflect the pumping capacity.

Essex & Suffolk (Essex and Suffolk Water Bulk Supply)

Thames Water provides a bulk supply of raw water to Essex and Suffolk of 91 Ml/d on average.

To this average demand, Thames Water applies a monthly. We apply the same profile expressed as proportions of 91.

Thames water also has to make available raw water to Three Valleys for pollution incidents on an emergency basis, and as sweetening flow in the connecting tunnel to their Iver WTW. This is included as an export of a constant 10 MI/d.

WTW (Nominal Treatment Works, Returns to River)

Losses from the treatment works are expressed as a percentage of the amount treated, currently set to 7.2% of which 88% is fed back to the Thames at Teddington. The River Thames WTW returns its losses to the river above Teddington but some losses go to the River Lee.

If the potential losses at each WTW (below) are added, the total losses come to 113 MI/d. In that case 88% of the losses would go to the Thames and 12% to the Lee.

Affinity Bulk Supply

There is a binding bulk supply agreement for the provision of 10 MI/d to Three Valleys Water at Fortis Green which is a constant amount with no associated profile.

NLARS (North London Artificial Recharge Scheme)

The use of the NLARS resource depends on the Lower Thames Control Diagram. It is called upon when the level 1 demand savings line is crossed (same as the 600/400 MI/d environmental flow line).

NLARS release is set to vary between 80 MI/d and 130 MI/d based on its current available storage. The annual license is set to 55,000 MI. As in the EA AQUATOR model we assume that NLARS can operate continuously for 16 months. To incorporate the annual license we model NLARS as a reservoir of capacity equal to the total amount that might be extracted from it (limited by the annual licence prorated to 16 months), assuming 30 days per month. This results in a capacity of 73.3 Mm³ (55,000 MI 16 months/12 months).

When the LAS is at 99% of capacity (ample water supply), NLARS is recharged using a diversion from Lee abstraction-LAS link. In reality, the Lee reservoirs recharge NLARS but it would be difficult to model it in IRAS as it would result in circular flow. The way we model it does not affect the model and better represents the fact that NLARS recharge originates from the Lee reservoirs (no recharge comes from Thames reservoirs). The recharge rate is 60 MI/day.

London GW (London aggregated groundwater)

This is set to the sum of the London groundwater DOs (432 MI/d) from the latest WRMP, adjusted by +8 MI/d to 440 MI/d. Groundwater is assumed to feed demand directly because losses are included in the DO calculation (and because demand always exceeds groundwater supply). London GW includes the CHARS scheme. For the baseline simulation the time varying GW output was used based on the time-series used in WARMS.

London (London demand)

London demand is modelled as the expected demand in 2050 as given in the Thames Water WRMP. A monthly profile obtained from the EA's AQUATOR model is used (Table 0-2). This demand is reduced when LTCD restrictions are invoked. Demand reductions for each successive LTCD level were obtained from the EA's AQUATOR model.

Table 0-2. Monthly factors for London's demand

Month	1	2	3	4	5	6	7	8	9	10	11	12
Factor	0.989	0.977	0.965	0.964	1.006	1.014	1.043	1.056	1.001	0.975	0.99	1.02

Teddington (Teddington Weir)

The environmental flow normally required at Teddington Weir is 800 MI/d but can be reduced in increments according to the LTCD.

Beckton desal (Beckton desalination plant)

This node is modelled as an infinite reservoir that releases water straight into London when the Thames flow at Teddington goes below 3,000MI/d.

Junction nodes (black nodes)

The junction nodes serve only as "connections" between other nodes, i.e. their mass balance follows the relationship $\sum_j inflow_{ji} = \sum_j outflow_{ij}$, where i represents the junction node and j represents any other node connected to node i via link ij (where i is the upstream node) or ji (where j is the upstream node).