Advances in Water Resources 161 (2022) 104117

Contents lists available at ScienceDirect

Advances in Water Resources

journal homepage: www.elsevier.com/locate/advwatres

Trade-off informed adaptive and robust real options water resources planning

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ARTICLE INFO

Keywords:
Water resource systems planning
Adaptive infrastructure planning
Real options analysis
Robust decision making
Multi-objective search
Stakeholder-driven environmental planning

ABSTRACT

Planning water resource systems is challenged primarily by two realities. First, uncertainty is inherent in the predictions of future supplies and demands due for example to hydrological variability and climate change. To build societal resilience water planners should seek to enhance the adaptability and robustness of water resource system interventions. Second, water resource developments typically involve competing interests which implies considering the trade-offs and synergies implied by the highest performing combinations of development options is useful. This work describes a real options based planning framework that generates adaptive and robust water system design alternatives able to consider and trade-off different goals. The framework can address different types of uncertainties and suggests the highest performing designs across multiple evaluation criteria, such as financial costs and water supply service performance metrics. Using a global city's water resource and supply system as a demonstration of the approach, we explore the trade-offs between a long-term water management plan's infrastructure services (service resilience, reliability, vulnerability) and its financial costs under supply and demand uncertainty. The set of trade-off solutions consist of different investment plans which are adaptive and robust to future changing conditions. Results show that the highest performing plans lower net present value (NPV) of needed investments by up to 18%, while maintaining similar performance across the other objectives. The real option value of delaying investments as much as possible approaches up to 14% of total NPV.

1. Introduction

Planning future interventions in water resource systems faces unprecedented challenges due to climate change, socioeconomic growth and increased urbanization (Milly et al., 2008; Brekke et al., 2009; Best, 2019). The services and performance of future water resource systems are impacted by the uncertain nature of long-term future conditions. Unpredictable changes in water demands and future hydrological flows and their potentially amplified hydrologic variability increases the risks of future water supply failures (Fletcher et al., 2019; Schewe et al., 2019) and the sophistication required to prevent them (Salas et al., 2018). Equally, both service providers (utilities, river basin organizations, etc.) and their customers and stakeholders have grown in sophistication, increasingly demanding their interests be considered in the decision-making process (Carr et al., 2012; van Bruggen et al., 2019).

The benefits of certain characteristics water planning have become increasingly clear. Firstly considering the multiple objectives of water systems (Hitch, 1960; Banzhaf, 2009; Reed et al., 2013; Paton et al., 2014; Kasprzyk et al., 2013) and thereby achieving multi-dimensional efficiency (i.e., the ability to appropriately trade-off the benefits implied by the best solutions) is typically appropriate. Second, in the face of multiple uncertainties (Smith et al., 2019; Harou et al., 2020) with different levels of predictability, achieving resilience (i.e., recovering quickly from stress or failure), robustness (i.e., performing acceptably across a variety of plausible conditions) and adaptability (i.e., meeting system requirements by responding to changing conditions) have become core objectives of water planning (Dessai and Hulme, 2007; Charlton and Arnell, 2011; Castelletti et al., 2010; Reed et al., 2013; Wise et al., 2014; Maier et al., 2014; Kwakkel et al., 2015; Herman and Giuliani, 2018). We expand on these below.

To capture different stakeholder interests, water resources management can be strengthened by multi-criteria approaches which help reconcile competing water interests (e.g., Hurford et al., 2020; Geressu et al., 2020). Performance measures of interest when evaluating water intervention options include ones that describe economic or

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https://doi.org/10.1016/j.advwatres.2021.104117
Received 31 August 2021; Received in revised form 29 November 2021; Accepted 23 December 2021
Available online 12 January 2022
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financial performance, water supply security metrics such as reliability and resilience (Hall et al., 2019; Brown et al., 2020), or other social and environment impact measures. The development of multi-objective optimization approaches, identifying plans that represent the best achievable trade-offs and synergies between objectives (Kollat and Reed, 2007b), has made this approach practicable for real system design problems (e.g., Matrosov et al., 2015). Multi-objective evolutionary algorithms (MOEAs) have found a wide range of applications in water resources planning under uncertainty (Reed et al., 2013; Maier et al., 2014).

A water supply development plan of a water utility typically proposes a set of supply augmentation and/or demand reduction (water conservation) interventions over a planning time horizon (Yakowitz, 1982; Luss, 1982; Padula et al., 2013). Plans aimed at performing well under a single scenario are likely to have sub-optimal performance in other scenarios (Ben-Haim, 2006; Huskova et al., 2016). Instead, approaches aiming at robustness (Lempert, 2003; Lempert et al., 2006) evaluate plans over multiple plausible futures simulated concurrently (Kang and Lansey, 2012) to select actions that are insensitive to a wide range of outcomes. Because many designs are possible, optimization can help automate the search for efficient and robust water supply portfolios for capacity expansion (Kasprzyk et al., 2013; Mortazavi-Naeini et al., 2014; Huskova et al., 2016).

A robust but fixed plan that performs well under a range of plausible futures has the disadvantage of not considering future water planners' ability to adapt to future conditions as they manifest. Such 'static' plans quickly become out of date as new information is gained, even just a few years after a plan is written. For instance, Huskova et al. (2016) introduced a robust planning approach in the presence of trade-offs between conflicting objectives, but it is not adaptive and does not allow for learning over time (Trindade et al., 2019). Hall et al. (2020) use a risk-based framework that identify plans that robustly achieve targets for tolerable risk and other performance objectives under varying climate scenarios. Other examples include the work of Kasprzyk et al. (2013), Mortazavi-Naeini et al. (2014, 2015), Beh et al. (2017), Borgomeo et al. (2018) and Geressu and Harou (2019). Adaptive approaches on the contrary produce multiple strategies, each optimal for different trajectories or 'pathways' (Haasnoot et al., 2013), that are developed to dynamically address uncertainty over time allowing for modifications to investment strategies as new information about uncertain conditions becomes available (Charlton and Arnell, 2011; Paton et al., 2014; Woodward et al., 2014; Beh et al., 2015; Maier et al., 2016; Gorelick et al., 2019; Herman et al., 2019; Erfani et al., 2018).

Recent literature has investigated quantitative evaluation of adaptation through adaptive pathways and Real Options Analysis (ROA). Adaptive strategies implement adaptation by optimizing signposts and triggers that dictate the activation of the next action on a pathway (Haasnoot et al., 2012; Kwakkel et al., 2015; Herman and Giuliani, 2018; Trindade et al., 2019) and have been applied to flood risk, infrastructure sequencing, drought management and stormwater management (Ranger et al., 2013; Zeff et al., 2016; Manocha and Babovic, 2018). Dynamic Adaptive Policy Pathways (DAPP) identify adaptive strategies under an uncertain future (Haasnoot et al., 2013; Kwakkel et al., 2015) by prescribing continuous monitoring and adaptation (Johnson and Geldner, 2019). Rule-based planning frameworks face the challenge of selecting useful indicators and thresholds that define when an action is triggered. To address this issue, Murgatroyd and Hall (2021) introduced a framework for optimal rule-based planning strategies that helps planners identify a set of candidate indicators based on their ability to predict future risk of failure in a water supply system. In this strand of research, where signposts associated with measuring the actual values of uncertain factors are used to select options, recent studies have sought to develop adaptive plans that can also respond robustly to changing conditions (Molina-Perez et al., 2019; Groves et al., 2021).

ROA enables adaptation by considering present investment decisions that are allowed to be corrected in subsequent modeled planning stages responding to changes in uncertainty over time (Dixit and Pindyck, 1995; Dittrich et al., 2016) and is implemented through different techniques including decision trees, lattices, Monte Carlo analysis (Trigeorgis, 1996; Lander and Pinches, 1998; Chow and Regan, 2011; De Neufville and Scholtes, 2011) and multi-stage stochastic optimization programs (Zhao et al., 2004; De Weck et al., 2004; Wang and De Neufville, 2005a,b; Erfani et al., 2018). In water resources management, ROA has been applied in various studies to examine the implications of future uncertainties when irreversible investment commitments are considered (Woodward et al., 2014; Ray and Brown, 2015; Marques et al., 2015; Beh et al., 2015; Erfani et al., 2018). While the adaptability feature of both approaches (ROA and adaptive pathways) are considered over the planning horizon, ROA exercises the adaptability at pre-defined decision stages whilst adaptive pathway approaches do so based on the state of the system and its threshold values.

The use of ROA methods for evaluating flexible strategies in long-term climate change adaptation decisions has been both encouraged (Buurman and Babovic, 2016; Hino and Hall, 2017; Wreford et al., 2020; Erfani et al., 2020; Ginbo et al., 2020) and contested (Kwakkel, 2020). Thus far there have been limitations to the implementation of ROA principles for infrastructure planning and scheduling. First, ROA as a single-objective approach is limited in capturing diverse stakeholder values. For instance, Erfani et al. (2018) optimized adaptive plans using a single least cost objective and an aggregate supply–demand formulation which cannot accommodate tangible performance-based outcomes (Hall et al., 2012; Padula et al., 2013; Brown et al., 2015). Second, as suggested by Herman et al. (2020), adaptive frameworks are dependent on an uncertainty specification which is quantified either as a probability distribution or an ensemble of realizations. When assigning probabilities to future scenarios is not possible, the use of ROA is considered to be impractical (Shortridge and Camp, 2019; Kwakkel, 2020). In Zhang and Babovic (2012), Woodward et al. (2013) and Marques et al. (2015), all uncertain future conditions are represented by probability distributions, without consideration of robustness. In other works where uncertainty is represented as a set of alternative future states of the world, (e.g., Jeuland and Whittington, 2014; Ray et al., 2018) robustness is addressed a posteriori by re-evaluating pre-defined system configurations over multiple future climatic and non-climatic uncertainties.

This paper introduces a simulation–optimization framework that addresses known ROA limitations and combines ROA principles with robustness analysis to enable adaptive and robust infrastructure planning while exploring the trade-offs between multiple objectives. We extend the classical multistage stochastic 'capacity expansion problem' (Ruszczyński and Shapiro, 2003) where corrective decisions allow the model to compensate for insufficient or excessive investment made at earlier decision stages. This way, water plans identified are adaptive in that they flexibly activate, delay, and replace interventions to adapt to the future uncertainties and are robust in that they perform satisfactorily well over a range of plausible future conditions. Uncertainties are either represented by a scenario tree where each scenario represents a probabilistically weighted future state aiming for adaptation, or through a range of plausible equiprobable future states aiming for robustness. We consider multiple objectives to explore trade-offs inherent in society's conflicting goals for water resources systems and to help identify synergies ('co-benefits') between different measures of performance.

The next section describes the proposed approach, the scenario tree construction, and the adaptive and robust multi-objective optimization formulation. Section 3 describes an application to a global city, in Section 4 the case study's results are presented and discussed in Section 5. Section 6 concludes the paper.

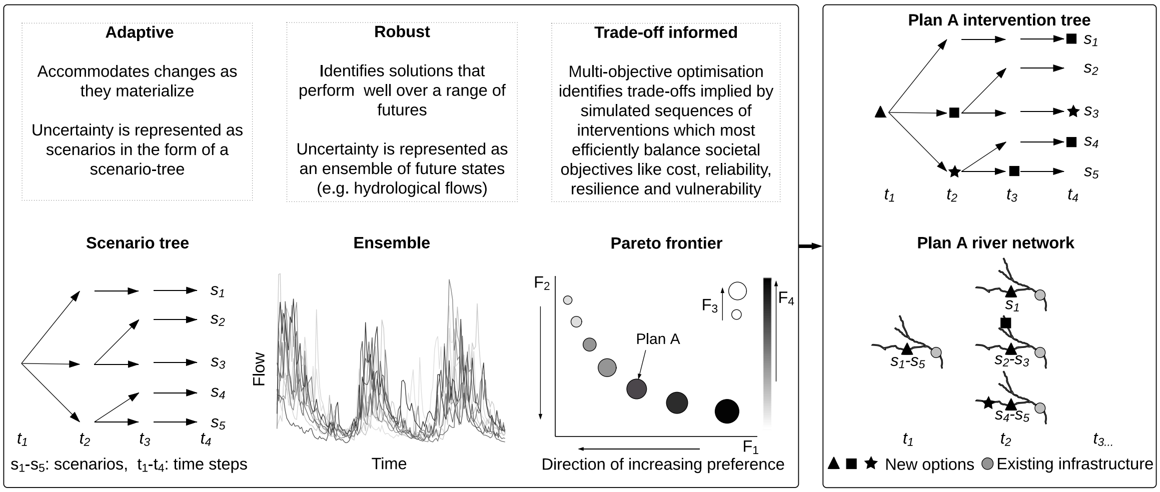

Fig. 1. Visual summary of the proposed framework for trade-off informed real options based adaptive and robust water resource system design. The left panel summarizes the framework's attributes and methods; and the right panel its main output. Uncertainty is represented through a scenario tree and as a set of alternative future states. Multi-dimensionally Pareto-efficient adaptive and robust intervention plans are identified through multi-objective optimization for stakeholder deliberation. For example, stakeholders may feel that solution 'A' represents an appropriately balanced mix of the 4 performance measures. The right panel shows the tree of intervention decisions (shapes drawn over the river basin) implied by Plan A over time increments t_1, t_2 etc. that efficiently balance the 4 objectives and are adaptive (to the uncertainty of the 5 scenario tree scenarios) and robust (to the ensemble of plausible futures).

2. Method

The proposed framework seeks both adaptability and robustness in addressing uncertainty and multi-dimensional efficiency for dealing with competing societal goals. We build ROA principles into the planning framework by using a scenario tree to enable adaptability of the investment decisions that can be modified to accommodate changes as they materialize (Maier et al., 2016). ROA principles involve various options, such as delaying investments in the interest of acquiring information, evaluating phased investments and modifying or abandoning actions. Through the consideration of an ensemble of future states, robustness is built into the planning framework by ensuring solutions perform acceptably well over a range of future conditions (Herman et al., 2015; Maier et al., 2016). Fig. 1 shows an overview of the proposed framework. We use a physically-based water resource system simulation which for different plans tracks multiple performance metrics over time. The water resource system simulations are coupled with a Multi-Objective Evolutionary algorithm (MOEA) (Coello et al., 2007; Nicklow et al., 2010) to identify those adaptive plans on the scenario tree that are also robust across an ensemble of future states and that appropriately trade-off various decision-relevant interests.

2.1. Trade-off formulation for adaptive and robust planning

For adaptive analysis we randomly generate a set of multiple forecasted values of the uncertain parameter and use a scenario tree construction technique to generate a scenario tree. We construct the scenario tree by implementing an optimization problem that minimizes the so-called probability distance between the uncertainty sets following the algorithm presented by Gröwe-Kuska et al. (2003). The problem takes the original uncertainty set and produces a scenario tree out of it for multistage decision making. The original uncertainty set in our study is the demand uncertainty that is defined by the bounds of urban water demand forecasting models. The algorithm optimally creates a scenario tree by successively bundling the tree nodes into separate sets to be represented by a new node while maintaining the probability information of the constructed tree as close as possible to the original uncertain stochastic process. The quality of the constructed tree is controlled by a metric that calculates the percentage of information lost known as relative probability distance (Heitsch and Römisch, 2011). This is set to 5% in this study, as we assume that this is an acceptable loss of information. The tolerance indicates how well the constructed tree approximates the original stochastic process and consequently determines the number of scenarios that are embedded in the scenario tree. Erfani et al. (2018) demonstrated this scenario tree construction method in a water supply capacity expansion problem.

The multi-objective search algorithm then uses the scenario tree to implement ROA principles as discussed above. While this enables adaptive water resource investment decisions, the plans are not necessarily robust to uncertainty. To seek for robustness the framework has the ability to represent uncertainty as an ensemble of future states and exploit them to identify adaptive plans that are also robust to these uncertainties. To achieve this, the framework searches for plans across an ensemble of future states on each branch of the scenario tree using a predefined robustness measure. Different measures of robustness have been used in the literature (Lempert et al., 2006; Herman et al., 2015; McPhail et al., 2018) each of which allows stakeholders to achieve a different performance requirement.

2.2. Mathematical formulation

Below we formulate the multi-objective optimization problem that allows implementation of ROA principles for adaptive and robust planning. Let N be the set of nodes on the scenario tree that structures the evolution of the uncertain parameters and $\mathbf{z}$ be a vector of the uncertain parameters that are represented as an ensemble of future states. The formulation below obtains optimal investment decisions for each node of the scenario tree that are robust to $\mathbf{z}$:

$$Minimize\ F(\mathbf{x}|\mathbf{z}) = (f_1, \ldots, f_k), \tag{1}$$

$s.t.$

$$\sum_{i \in ME} dS_{n,i} \leq 1, \qquad \forall n \in N_t, \tag{2}$$

$$dS_{n,i} \in \{0, 1\}, \qquad \forall n \in N_t, i \in I, \tag{3}$$

$$\mathbf{x} \in \{dS_{n,i}\}. \tag{4}$$

In the above formulation, $F(\mathbf{x}|\mathbf{z})$ is the vector of k-objective functions, $f_i \forall i = 1 \ldots k$, that each is aggregated based on the robustness metric used over an ensemble of $\mathbf{z}$ states, $\mathbf{x}$ is a decision variable vector representing a set of interventions, k is the number of objectives for trade-off analysis, I is the set of all interventions, N_t is the set of nodes belonging to stage t, $dS_{n,i}$ is a binary variable denoting if intervention

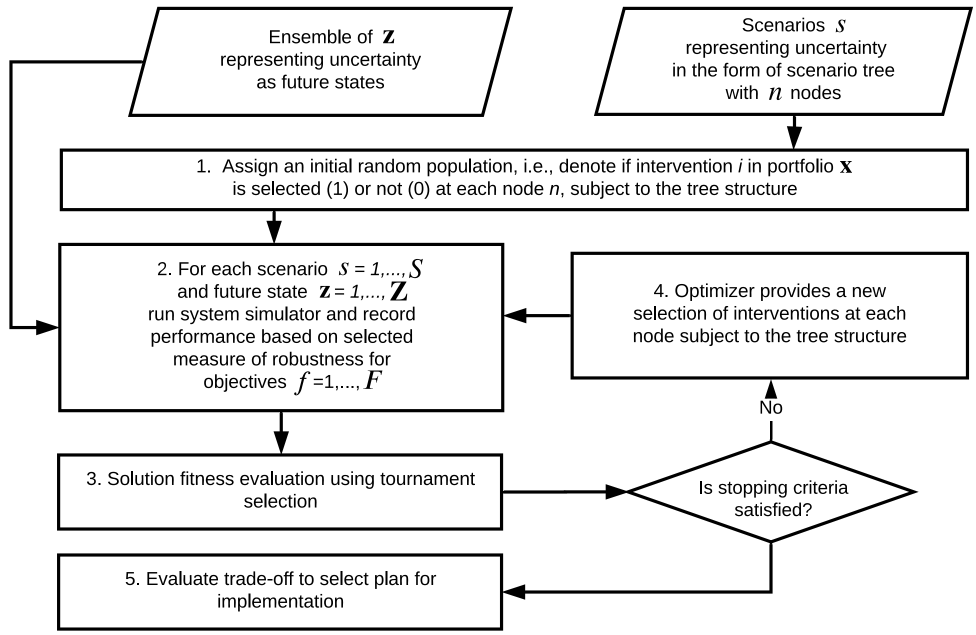

Fig. 2. Flow chart for multi-objective, real options based adaptive and robust planning.

i in portfolio $\mathbf{x}$ is selected or not in node n of the scenario tree and ME represents the set of mutually exclusive interventions.

Fig. 2 shows a flowchart of the proposed framework. In step 1 the search algorithm generates an initial random population of candidate plans on the scenario tree. Each plan is a portfolio of interventions sequenced over time (at each node of the tree). A plan could involve for instance a mix of supply-side and demand-side interventions, each with their associated costs and different impacts on supply capacity expansion and demand reduction respectively. The population is generated making sure that plans have the same interventions on the node they share, to prevent an implemented option from becoming unavailable in subsequent stages of the scenario tree. Each option has a construction lead time that establishes the period between the decision to implement an option and becoming operational. In step 2, each plan in the population is passed to a water resource system simulator to be evaluated over an ensemble of future conditions $\mathbf{z}$. These future conditions could include hydrological flows or demand forecasts over the planning period. The performance of each solution relative to the objective functions is evaluated in each simulated scenario. This results in different performance metrics across $\mathbf{z}$ that are then aggregated and passed to the search algorithm as objective function values (step 3). Analysts can specify a stopping criterion which if satisfied terminates the search process, like a pre-defined number of iterations or a convergence metric. Until then the search algorithm employs population update strategies to select interventions for the next evolution (step 4). This results in a set of adaptive and robust plans that trade-off multiple objectives (step 5). The different efficient plans generate a Pareto-frontier allowing planners to examine the trade-offs, for example between investment costs and different facets of system performance.

3. Application

3.1. Background

We apply the proposed trade-off informed framework for adaptive and robust planning to the London urban water supply area, which is located in the Thames river basin in southeast England. The water supply is managed by Thames Water, a private water utility serving 15 million customers across London and the Thames Valley. The region has a relatively high population density and faces a projected 25% increase in population by 2040 (Thames Water, 2014; Environment Agency, 2013). However, the actual population growth is uncertain making it a suitable case study to investigate the use of the proposed approach.

Furthermore, water utilities and regulators in England and Wales are considering a move from a traditional single-objective least cost optimization approach (UKWIR, 2016; Padula et al., 2013) to identifying a 'best value' plan that balances multiple performance criteria and seeks adaptability (Thames Water, 2019; Environment Agency, 2021). This is because single-objective approaches require all metrics to be aggregated ('commensurated') into a single metric (typically monetary) and their preferences over one another explicitly articulated in a single metric. This results in a single optimized solution that can potentially lead to imbalanced and unpopular decisions (Matrosov et al., 2015). Multi-objective approaches allow incorporating different metrics with different units of measure without a need to either aggregate them or pre-specify their preferences. This results in a set efficient (i.e., 'best available') trade-off solutions. Hence, the proposed multi-objective approach is likely to be appealing to water utility planners in the UK and beyond.

This study uses a 2020–2070 planning period in which water supply management intervention decisions are made every 5 years following water company regulation in England and Wales. We consider 11 new supply (of type reservoir, transfer, waste water reuse, desalination) and 4 new demand management interventions (of type active leakage control, pipe repair, water efficiency, metering) for the global city's water resource system shown in Table 1. Each option has characteristics related to its ability to store and or manage water, construction period, design life and mutual exclusivity. Unlike aggregated supply–demand modeling approaches where interventions' contributions to supply expansion or demand reduction is a single number (yield) in the optimization (Padula et al., 2013; Erfani et al., 2018), in this approach physically-based supply interventions and their operating rules are simulated over time whilst demand management options reduce aggregate annual demand.

Release from supply options during droughts occur according to London's seasonal Lower Thames Control Diagram (LTCD) (refer to Matrosov et al., 2011). Release from reservoir and groundwater options is subject to available storage while desalination and reuse options release water indefinitely as needed. The storage capacity of modular supply interventions can be expanded at a future stage by paying a

Table 1
Supply and demand management interventions considered in the London case study. RE: release or reduction to average annual demand in Ml/d, EXP: release in Ml/d for expanded capacity of modular reservoir, CP: construction period in years, DL: design life in years, ME: mutual exclusivity.

Intervention	Code	RE/EXP	CP	DL	ME
		Supply interventions			
Reservoir	RES	267[a]	10	80	TRF, RESm
Reservoir modular	RESm	176/267[b]	10	80	TRF, RES
Inter basin river transfer	TRF	300[c]	12	60	RES, RESm
Artificial recharge scheme	ARS	26[d]	5	60	–
Reuse scheme A	RSA	60	6	60	RSAn
nonRO reuse scheme A	RSAn	60	6	60	RSA
Reuse scheme B	RSB	150	6	60	RSBn
nonRO reuse scheme B	RSBn	150	6	60	RSB
Canal tranfer	CTR	17	12	60	–
Desalination A	DEA	15	4	25	–
Desalination B	DEB	150	6	25	–
		Demand interventions			
Active Leakage Control	ALC	50	0	25	–
Pipe Repair Campaign	PIP	165.1	0	60	–
Enhanced Efficiency	EFF	11.6	0	25	–
Smart Metering	MET	88.7	0	60	–

[a]Supply contribution corresponds to a RES capacity of 150 Mm^3.
[b]Supply contributions corresponds to initial RESm capacity of 100 Mm^3 then expanded to 150 Mm^3 if required.
[c]Supply contribution is dependent on if flow on the Inter basin river transfer is above the minimum environmental flow.
[d]Supply contribution corresponds to a storage reservoir of 14.04 Mm^3 capacity. The ARS groundwater scheme is modeled as a storage reservoir in order to limit the length of time it can output.

relevant expansion cost. For instance, the proposed Reservoir can be built with a fixed (RES) or modular (RESm) storage capacity, listed in Table 1 as two separate interventions that are mutually exclusive, i.e., at most one of the two interventions can be selected. The non-modular RES intervention builds a 150 Mm^3 reservoir that releases 267 Ml/d when activated during droughts (periods of low storage and low flow in the Thames). The modular RESm intervention initially builds a reservoir of 100 Mm^3storage capacity which can be expanded to 150 Mm^3 at a later decision stage if required. For the modular option, the utility has to pay a premium upfront to reserve the right for further expansion (see Erfani et al. (2018) for a synthetic example of a reservoir option demonstrating this ROA principles).

This study uses the Interactive River Aquifer Simulation (IRAS-2010) model of the regional water resources and supply system (Matrosov et al., 2011) which tracks flows and storages spatially with a weekly time-step. Options that provide or save less than 10 Ml/day were ignored, and lead times of options related to design and planning permission were not considered. Therefore, results in Section 4 are approximate and attempts to compare them directly with TWUL's published plan, which considers more detailed data, would not be valid.

3.2. Addressing uncertainties

In this study we use a scenario tree to structure the uncertainty about future water demands for adaptive planning, where branching is allowed from one demand scenario to another. However, each member of the hydrologic ensemble (presented in Section 3.2.2) is independent, and therefore the time-series associated with one ensemble member can only be compared with the same ensemble member time-series for a different time slice (Prudhomme et al., 2013). Each future flow time-series represents a unique condition of climate uncertainty and therefore once a simulation begins under one time-series, that same time-series must be used until the end of the planning period to maintain the hydrological consistency of each supply state. This implies a scenario tree cannot be used to represent the supply-related uncertainty in this case and future climate change supply impacts are represented as an ensemble of equally likely hydrological flow time-series. In our case study, the ensemble of streamflows included nonstationary hydrological conditions where extreme hydrologic events, like droughts, can be experienced at any point of the planning horizon. If a scenario reduction technique were used to bundle hydrological scenarios, that would potentially result in droughts happening in consecutive time periods for some branches of the tree and therefore biasing the timing of activation for interventions. Following the framework discussed earlier, this implies the planning decisions made in this application will be adaptive to demand uncertainty and robust to supply uncertainty.

The proposed approach does not prescribe how uncertainties should be represented, allowing planners to decide, based on the structure of the data, whether to seek adaptability (scenario tree) or robustness (ensemble of future states). Adaptability allows for learning over time while robustness ensures the plan performs acceptably under a wide range of plausible future conditions. In most cases how to structure the uncertainty modeling is dictated by available data or the nature of the problem. For instance, if in a hydrological time-series the temporal correlation were weak, supply uncertainty could be represented as a scenario tree where time slices from different time-series would be mixed and matched to create branches of the tree (Heitsch and Romisch, 2005; Latorre et al., 2007; Séguin et al., 2017) therefore allowing adaptive decisions to learn from supply variability. If not, hydrological flows could be represented as spatially and temporally coherent future time-series.

3.2.1. Demand uncertainty scenario tree

The demand scenario tree is extracted out of the London demand uncertainty space as shown in Fig. 3(a). The demand uncertainty is approximated by 21 scenarios, shown in Fig. 3(b) (it is also drawn out in panel (a)). Let T be the assumed time horizon and $t \in T$ the decision points spaced at regular time intervals. The decision in t_1, which is the same for all scenarios, is called the 'here-and-now' decision and is made in the first time step before any uncertainty is realized. In the subsequent decision points, 'wait-and-see' decisions are made with the information about uncertainty which is revealed in previous stages. These decisions are adaptive in that they can vary with the uncertain parameters and can take different values in each scenario. For instance, in the context of our example, at t_2, the demand uncertainty of the first stage is revealed. We make the decision in t_2 for each scenario with the benefit of knowing the value of the uncertain parameter in t_1, but with no other knowledge of future data. This proceeds until we make the decision in the last time period T with the benefit of knowing the values of the uncertain parameter at $T-1$. Therefore adaptive decisions are not

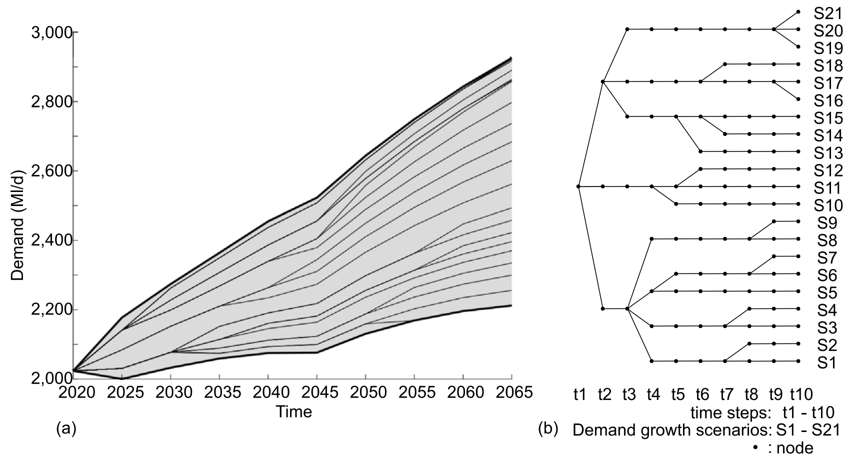

Fig. 3. (a) Demand uncertainty approximated using a scenario tree. (b) Scenario tree extracted from demand uncertainty.

locked in that they are modified based on new information. The 'here-and-now' decisions are also robust to supply uncertainty since they are optimized based on an aggregation of a hydrological ensemble so that it performs acceptably well. Robustness, however, treat solutions as locked by aggregating their performance given a set of ensembles.

Non-anticipative constraints link 'here-and-now' and 'wait-and-see' decision variables belonging to different scenarios. For instance, at t_2, the demand uncertainty is represented by three decision nodes implying that the three investment decisions are the same within some subgroups of scenarios which are indistinguishable based on the information available up to that point. It can be seen that the subgroups of scenarios S_1 - S_9, S_{10} - S_{12} and S_{13} - S_{21} share common investment decisions at t_2. This is enforced by non-anticipative constraints that ensure investment decisions at time t only utilize any information that is available up to this stage. The proposed methodology exploits the tree structure to provide flexibility in allowing initial water resource investment decisions to adapt to future changes in water demand (Erfani et al., 2018). This multi-period decision process enables the virtual planners (implied by this model-based approach) to modify or delay investment plans as information on future demand is gradually revealed.

3.2.2. Climate projections uncertainty

To illustrate the water resource systems' behavior during the eventual future climate change impacted supplies, supply uncertainty is represented by a set of transient climate change forced daily river flow and monthly groundwater levels for the UK (Prudhomme et al., 2013) available from the National River Flow Archive online database. The scenarios represent equally probable hydrological flows and 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. The dataset consists of an ensemble of 11 equally probable flow time-series for the Thames basin between 1950 and 2098 (Prudhomme et al., 2013).

3.3. Case study formulation

The case study problem formulation uses the following vector of objective functions:

$$F(\mathbf{x}|\mathbf{z}) = (f_1, f_2, -f_3, -f_4), \tag{5}$$

where $\mathbf{z}$ is the ensemble of hydrological flows and f_1 - f_4 are the objectives considered for trade-off analysis.

The first objective, f_1, minimizes the total capital and operational cost of implementing new supply and demand interventions in a portfolio. The cost is annualized and discounted with discount rate r over the planning time horizon and weighted by the probability p_n (derived from the scenario tree construction algorithm) that node n is realized using,

$$f_1 = \sum_{t\in T, n\in N_t, i\in I} \frac{p_n}{(1+r)^t} \times \frac{tC_i}{DL_i} \times dS_{n,i}, \tag{6}$$

where tC_i is the total discounted cost (capital and operational) of implementing intervention i in node n at time stage t and DL_i is the design life of intervention i. The costs are normalized to each intervention's expected design life by dividing the investment cost of each intervention by its expected lifetime. The use of total investment cost per year allows for equal comparison between interventions that have unequal design lives.

The second objective, f_2, maximizes system service resilience which is defined by how quickly the system recovers from a failure (Moy et al., 1986). A definition of a failure is problem dependent; in this study, a failure associated with the service resilience objective (Eq. (7)) occurs when the London Aggregate Storage level drops below a certain threshold (LTCD level 3) and a non-essential water use ban is imposed. The aim of the objective is to minimize the maximum duration of the imposed partial water use ban. The average discounted maximum duration of the failure across all scenarios, weighted by their probability w_s, is then minimized using,

$$f_2 = \sum_{s\in S} w_s \times \max_t \left((1+r)^{-t} \times D_{s,t}\right), \tag{7}$$

where w_s is the probability of scenario occurrence, $D_{s,t}$ is the duration of failure in scenario s in time t. The probability of scenario occurrence is derived based on the probabilities of the scenario tree nodes and is calculated by multiplying all state transition probabilities on the scenario path (Eq. (8))

$$w_s = \prod p_n, \quad \forall n \in N_s, N_s \subset N, \tag{8}$$

where N is the set of all nodes on the demand scenario tree and N_s is the set of nodes that belong to the path of scenario s.

The third objective, f_3, is to maximize system reliability which is calculated based on how frequently the system fails. The average discounted frequency of no-failures across all scenarios, weighted by their probability w_s, is maximized using,

$$f_3 = \sum_{s\in S} w_s \times \left(1 - \sum_{t\in T} (1+r)^{-t} \times \frac{Z_{s,t}}{|TS_t|}\right) \times 100\%, \tag{9}$$

where $Z_{s,t}$ is the number of time-steps (weeks) the system was in failure in time period t in scenario s and $|TS_t|$ is the number of time-steps (weeks) in time t. We choose to minimize LTCD level 2 failures where a water saving media campaign is imposed to reduce demand.

The fourth objective, f_4, reflects how well a plan meets a desired Level of Service (LoS) requirement over the considered future scenarios.

Table 2
Algorithm parameters and objective ϵ values for the London case study.

Algorithm parameters	Values
Initial population size	512
Population scaling factor (for injection)	0.25
Number of generations per run	50
Probability of crossover p_c	1.0
Probability of mutation p_m	0.5
Distribution index for SBX crossover	15
Distribution index for polynomial mutation	20
Objectives	**Epsilon**
f_1	1,000 k£
f_2	0.1 weeks
f_3	0.5%
f_4	0.5%

We calculate the fraction of future scenarios where a plan performs within the desired LoS,

$$f_4 = \sum_{s \in S} \frac{k_s}{|S|} \times 100\%, \tag{10}$$

where the binary variable k_s is 1 if a plan in a scenario performs within a required LoS or 0 otherwise and $|S|$ is the total number of scenarios. Since the time dimension is not present in Eq. (10), the performance of this objective is not discounted. An objective in our case study is to minimize the number of scenarios in which LTCD level 3 failure frequency exceeds 1 in 20 years (Eq. (10)).

We implicitly optimize vulnerability (i.e. limiting the magnitude of failure) by using objectives relating to different LTCD failure levels (LoS3 resilience, LoS2 reliability and LoS3 return period requirement). Thames Water uses these different failure levels as thresholds to implement escalating supply and demand management measures. In this application robustness is sought both by ensuring insensitivity to future conditions by optimizing the average performance over an ensemble of futures (for total cost, system service resilience and system reliability) and by minimizing LTCD level 3 failure occurrences that exceed a 1 in 20-year frequency. For the climate impacted flow scenarios, the average statistic was selected to provide a relatively stable performance.

The performance objectives of cost, reliability and service resilience are all discounted to not bias financial metrics within the search. The financial costs are net present values (NPV) of capital and operational expenditures incurred by implementing new interventions and using them. If only financial metrics were to be discounted in multi-objective problems, expensive and high performing assets would tend to get selected only towards the end of the planning period as they would offer high benefit at a largely discounted cost. The use of equal rates of discount for both monetary and non-monetary performance is suggested in literature when benefits are hard to monetize (Keeler and Cretin, 1983). Therefore, the engineering performance objectives were discounted using the same discount rate as the financial objective to ensure an equal rate of time preference. These were calculated in accordance with the UK government's 'Green Book' discount rates, which reflect the rate at which society values the present compared to the future (Treasury, 2003). To identify the approximate Pareto frontier, we use the Epsilon-Dominance Non-dominated Sorting Genetic Algorithm II (e-NSGAII) (Kollat and Reed, 2006) that has been shown to effectively solve complex many-objective optimization problems (Reed et al., 2013). Further computational details of how the search process was conducted are found in the supplementary materials (see Appendix A).

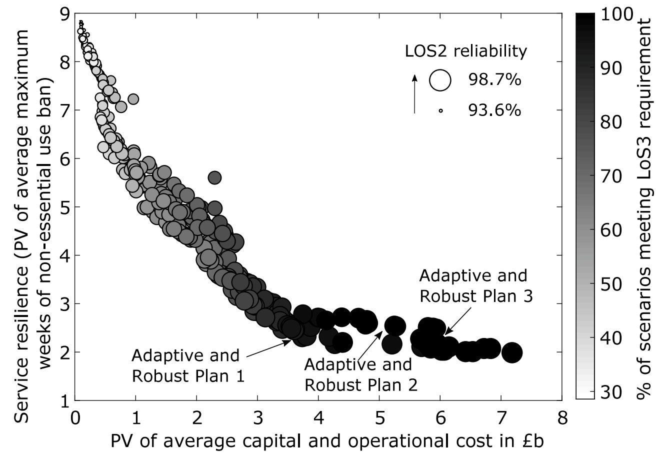

Fig. 4. Plot of the non-dominated approximately Pareto optimal set. Each Adaptive and Robust Plan corresponds to a 50 year plan. The present values for cost and service resilience reduction are shown. The direction of preference (minimization) is downward. The size of the points shows undiscounted reliability. The colorbar shows the percentage of scenarios that meet the LoS3 return period requirement.

4. Results

4.1. Solving the multi-objective adaptive and robust water resource planning problem

Fig. 4 shows the approximately Pareto-optimal adaptive and robust water resources city plans projected onto the two dimensional cost-service resilience trade-off space. Each of the 329 points represents a unique Pareto-approximate adaptive and robust plan proposing a set of investment options for each decision node of the scenario tree over the 50-year planning period. The size of the points shows the reliability objective, i.e., the average percentage of years in a solution that did not have an LTCD level 2 failure while its color shows the percentage of scenarios that meet the LoS3 return period.

The investment cost is lower for adaptive and robust plans with lower service resilience, reliability and fraction of scenarios that meet required LoS return period, implying that more investment is required to improve performance of the infrastructure service objectives. The Pareto-approximate space is roughly divided into three 'zones' with respect to their performance across the objectives. If a decision maker requires that the percentage of scenarios that meet the LoS3 return period is at least 90%, then they must choose a solution from the third zone, observed in the right portion of the Pareto front. Our analysis is seeking to identify which infrastructure choices can achieve magnitudes of potential failures deemed acceptable by stakeholders.

Three efficient solutions (points on the Pareto front in Fig. 4) are singled out for further analysis to reflect different plausible preferences of decision makers. The adaptive and robust plans that correspond to these selected solutions are referred to as ARP 1, ARP 2 and ARP 3. ARP 1 is the 'lowest cost' solution where at least 90% of scenarios achieve LoS3 failures occurring at most every at most 1 in 20 years. ARP 3 is a 'high cost' solution where all scenarios meet the LoS3 return period requirement while ARP 2 displays an example of a 'balanced' solution between the conflicting objectives. More risk-averse decision makers may select ARP 3 where financial performance (low cost) is traded in to obtain higher performance in infrastructure services (service resilience, reliability and vulnerability).

The investment trajectories for the three selected plans of the Pareto front, together with their performance values in terms of four objectives, are shown in Fig. 5. The tree consists of 21 possible investment trajectories for each adaptive and robust plan based on the demand scenarios depicted in Fig. 3(b). Decisions to invest in a set of interventions are made at the beginning of each time interval t. Since decision points are spaced at 5-year time intervals, an activated intervention becomes available either at the same or in a future time interval depending on the length of its construction period.

Fig. 5 details the short-term (t_1 - t_4, i.e. decisions made in 2020, 2025, 2030 and 2035) investment decisions of the three adaptive and robust plans (represented by black, gray and white boxes), showing whether a portfolio that consists of an intervention (1–11) or a combination thereof is activated at the beginning of each 5-year time interval under different demand scenarios differentiated by demand thresholds. The potential supply-side and demand-side water resource options that can be activated at each node of the tree are detailed in Table 1. Demand threshold values displayed on each branch indicate which path is optimal for a given demand at each interval. For instance, if the planner considers that demand for water in 2025 is most likely to be less than 2030 Ml/d (low demand growth), then the lower path is the best intervention response. If demand is between 2030 Ml/d and 2084 Ml/d (moderate demand growth) then the middle path is optimal, whilst if demand is 2084 Ml/d or greater (high demand growth) then the upper path should be selected. The interventions that are activated at the beginning of the tree (root node) should be implemented in the first time period and are selected in all demand scenarios.

The most pressing concern of water planners is short-term investment decisions, i.e., what to do now. However, these near-term decisions must be compatible with future investments and the resulting investment trajectories of which they are a part must demonstrate long-term water supply security under different future scenarios. Initial investment trajectories resulting from differing near-term decisions can follow a range of future branches based on future decisions. The decision determining which subsequent branch a planner should follow can be taken as new information on demand growth becomes available. Such results enable adaptive investment planning where initial investment decisions can be postponed and adjusted according to future possible demand conditions. The scenario tree approach results in 'wait-and-see' strategies that seek to delay interventions until they are required. This 'wait-and-see' strategy is a manifestation of real-options-based principles. The opportunity to defer investments enables planners to reduce overall intervention costs and make more informed investment decisions as new information is unveiled.

The ability to defer investments enables planners to reduce overall intervention costs. For example, as seen in Fig. 5, for all three adaptive and robust plans, the decision in 2025 (t_2) to invest (further increase supply or reduce demand) is postponed for later if demand is expected to be low or moderate. If demand in 2025 is expected to be high, then planners can invest in further actions (infrastructure or demand management) depending on which adaptive and robust plan they select.

Each adaptive and robust plan has alternative sets of interventions scheduled for implementation. For instance, as shown in Fig. 5, at the root node ARP 1, 2 and 3 activate portfolio 1, 2 and 3 respectively consisting of the same mix of demand management options, namely Active Leakage Control (ALC), Smart Metering (MET) and Pipe repair campaign (PIP). In the more expensive ARP 2 and 3 a large supply scheme is also selected alongside the demand management interventions. Portfolio 2 builds River Severn Transfer (RST) while portfolio 3 builds RES. The interventions selected in 2020 (t_1) are active across all 21 scenarios. In 2025 (t_2), if demand is low, no further investment is suggested for the short-term period until 2035 (t_4) where all adaptive and robust plans activate Canal transfer (portfolio 7). If demand in 2025 is moderate, Reuse scheme B (RSB) is activated either in 2030 (t_3) or 2035 (t_4), depending on the adaptive and robust plan. If demand in 2025 is high, the initial portfolios are all expanded differently but in 2030 (t_3) the same Reuse scheme A is activated in all adaptive and robust plans. In practical applications, at the next decision stage (i.e., 5 years later) the optimization should be performed again with the newly available demand scenarios that could be different from the original ones (Creaco et al., 2013).

To gain more insight on how the Pareto-approximate adaptive and robust plans differ, we plot in Fig. 6 the long-term (t_1 - t_{10}) investment decisions for the fixed size reservoir ('RES') across the three selected adaptive and robust plans. In the 'low cost' ARP 1, RES is activated in high demand growth scenarios (scenarios 16–21) midway through the 50 year planning period. In the more 'balanced' ARP 2, RES is activated earlier on in the same scenarios as ARP 1, as well as in others (11 out of 21 scenarios). In ARP 3, RES is built across all scenarios (21 out of 21) as it is activated in the first time period. The ability to defer or avoid an expensive or potentially controversial option shows the benefit of combining multi-objective optimization with ROA.

Fig. 7 depicts the activation frequency of the interventions across the 21 demand scenarios in each time step for the long-term planning problem. The combination of interventions in each adaptive and robust plan, the time of their implementation as well as its activation frequency across the scenarios is plotted. As expected from Fig. 5, Active leakage control (ALC), Pipe Repair (PIP) and Metering (MET) are activated in all scenarios in all three adaptive and robust plans from the start of the planning period. This suggests that these demand interventions are robust across the multi-objective trade-off as well as supply demand uncertainty, indicating that demand management should be put in place early in the planning period. Larger interventions such as TRF and RES are activated in all three adaptive and robust plans at different points and frequency across the scenarios. While ARP 1 suggest their activation midway through the planning period, ARP 2 and 3 activates large interventions earlier and at a higher frequency across the scenarios. This indicates that the development of both large supply schemes is recommended at some point during the next 50 years, above a certain demand growth level. Below that level, ROA helps planners avoid unnecessary costly investments.

4.2. Activation comparison of large interventions

To examine the selection of the two large interventions (RES and TRF), we compare their activation across all Pareto-approximate solutions. Fig. 8 shows the same Pareto-approximate solution set as Fig. 4, displaying the values of three objectives (cost, resilience and reliability). The color here corresponds to the activation frequency of the two large interventions across the 21 scenarios during the planning period. A black circle informs that by the end of the planning period, the intervention is selected all 21 scenarios, while a white circle reports that the intervention is not selected in any. The interventions display a different activation ratio across the 329 solutions; RES is selected in 155 of solutions while TRF in all 329 by the end of the planning period. However, above a certain level of resilience (2.8 weeks), RES is always selected and the frequency of its activation increases for more resilient solutions. In the case of TRF, some solutions with high resilience do not require the intervention to be active in all scenarios at a high frequency. This shows that, to achieve a certain required level of resilience, RES must be selected relatively early in the planning period (high frequency of scenarios where intervention is activated shown by the black color) while the activation of TRF could be postponed for later and activated only under certain demand conditions.

4.3. Metrics for adaptability assessment

To help evaluate solutions and quantify what has been gained by this analysis we adopt two metrics from the field of stochastic programming (Birge and Louveaux, 1997; Escudero et al., 2007), namely Value of the Stochastic Solution (VSS) and Expected Value of Perfect Information (EVPI), into decision-relevant metrics of adaptability and flexibility in water planning decisions. To examine the implications on adaptability and flexibility across the cost-resilience trade-off, we compare the same three 5-year plans (i.e. ARP 1, 2 and 3) from the previous section. VSS and EVPI enable comparing the plans in terms of their ability to adapt to changing conditions and in terms of

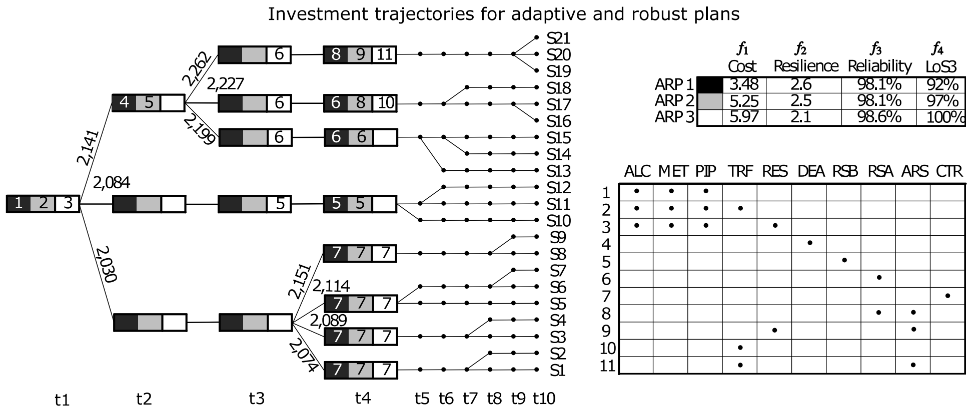

Fig. 5. Resulting investment trajectories for three selected optimized Adaptive and Robust Plans (ARP 1-3) for the short-term period (next 15 years). At each stage, a decision to activate a portfolio of supply demand interventions is made. Each portfolio consists of a combination of interventions including Active Leakage Control (ALC), Smart Metering (MET), Pipe repair campaign (PIP), Inter basin river transfer (TRF), Reservoir (RES), Desalination A (DEA), Reuse scheme B (RSB), Reuse scheme A (RSA), Artificial recharge scheme (ARS), Canal Transfer (CTR). A planner uses the threshold values (in Ml/d) on each arc to select which path to follow out of the 21 demand scenarios (S1–S21) based on how they believe demand growth for the next decision period will evolve.

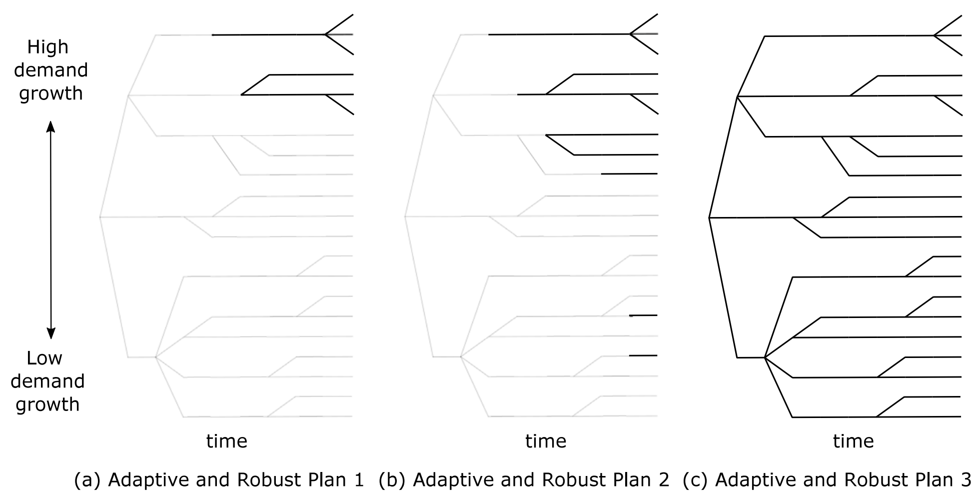

Fig. 6. Activation of RES across the three selected Pareto solutions. The darkened branches (black line) in the tree indicate in which scenario and at which time RES becomes active.

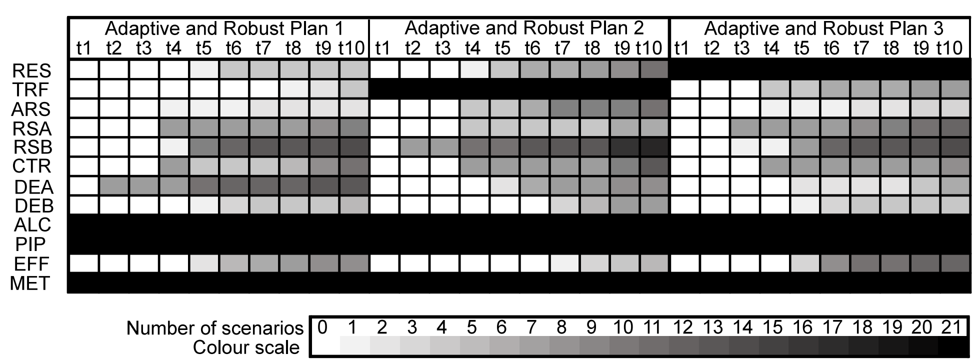

Fig. 7. Activation frequency of interventions across the 21 demand scenarios for the long-term plan. Activated interventions include Reservoir (RES), Inter basin river transfer (TRF), Artificial recharge scheme (ARS), Reuse scheme A (RSA), Reuse scheme B (RSB), Canal transfer (CTR), Desalination A (DEA), Desalination B (DEB), Active Leakage Control (ALC), Pipe repair campaign (PIP), Water efficiency (EFF), Smart Metering (MET).

the value gained from delaying irreversible investment commitments respectively. This follows Erfani et al. (2018) who use the VSS and EVPI metrics to quantify the benefits of adaptability and flexibility for a single objective water resource planning approach. Appendix B details the calculation of VSS and EVPI for the multi-stage formulation proposed here.

The VSS and EVPI for the three plans as a percentage of the total cost of each adaptive and robust plan are shown in Fig. 9. In this case-study VSS illustrates the difference made by using the robust multi-objective multistage approach which explicitly allows for periodical adaptation to different future demand conditions instead of ignoring the uncertainty around the demand values in each stage. Stated in a different way, VSS quantifies the cost of not recognizing the uncertainty

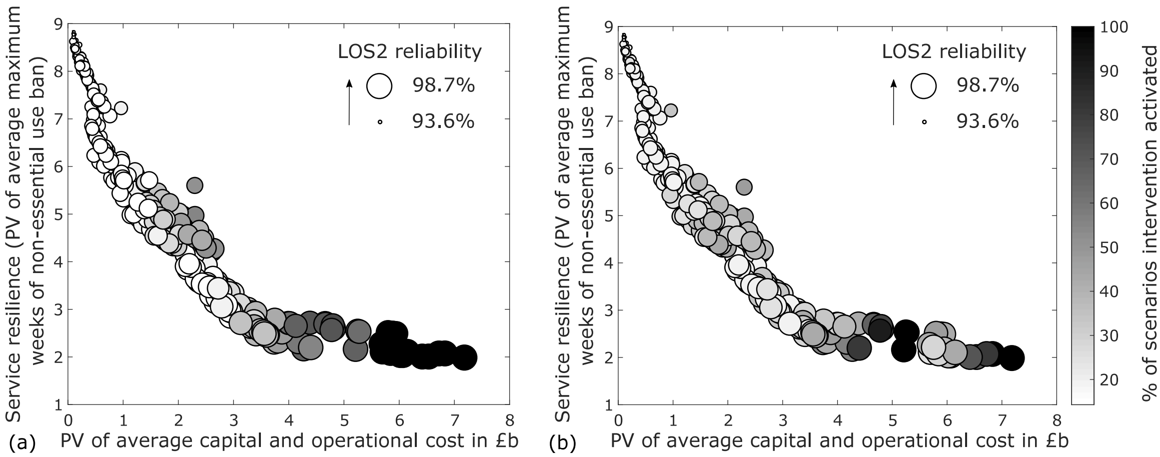

Fig. 8. Activation frequency of two large interventions, (a) Reservoir (RES) and (b) Inter basin river transfer (TRF), across the 21 demand scenarios by the end of the planning period.

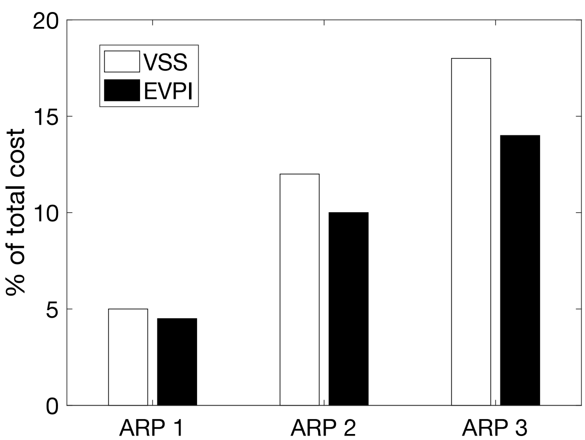

Fig. 9. VSS and EVPI values as percentage of the total cost for three selected optimal Adaptive and Robust Plans (ARP).

and therefore ignoring the adaptability advantage. For the London case study, VSS, expressed as a percentage of the total cost, is higher for the most resilient and reliable ARP 3 (18%) compared to ARP 1 (12%) and ARP 2 (5%). This indicates seeking an adaptive and robust city planning approach can have considerable financial value.

In this case study, EVPI estimates the value of improving demand forecasting. Again, the higher EVPI for ARP 3 (14%) compared to ARP 1 (10%) and ARP 2 (4.5%) shows that for the more resilient and reliable adaptive and robust plan, there is high value in investing in demand forecasts.

5. Discussion

To illustrate the benefits of the proposed adaptive and robust multi-stage multi-objective approach applied to London's water supply planning, three efficient, adaptive and robust plans were selected and compared. In all three of these plans, three demand management interventions are recommended for implementation in 2020. They should be implemented regardless of demand growth since they are selected at the beginning of the tree. Large supply interventions are only activated in 2020 in the more expensive ARP 2 and 3, which provide better performing services than ARP 1. If demand in 2025 is below 2,141 Ml/d then the previously selected interventions remain active without the need to invest. However, if 2025 demand in 2020 is predicted as more than 2,141 Ml/d, further investment is required to maintain desired levels of service in ARP 1 and 2. By the end of the planning period, all three selected optimal adaptive and robust plans implement both large supply interventions (RES and TRF) in the top path of the tree (the one with the least favorable supply–demand balance) showing that, under higher demand conditions, the selection of the two large schemes occurs across the multi-objective trade-off (regardless of preference). These high level results summarize how the approach works and how its results, which consider many different decision-maker and societal priorities, and many different futures, are interpreted.

As encouraged by Wreford et al. (2020), this study shows the applicability of scenario-based ROA methods to adaptive climate change infrastructure investment analysis. The use of a scenario tree is appropriate for cases where planning is performed regularly over discrete time intervals, as is often the case in water supply and river basin planning, where agencies emit planning reports on a regular basis (e.g., every 5 years in our case study country).

Since plans are regularly re-optimized in each 5-year water supply planning cycle, the only consequential decision is the decision made in the first decision time-step. The initial planning decisions are optimally adapted to future conditions by modifying or delaying investments as more information on future conditions is gradually revealed. This definition of adaptability is unique to a multistage stochastic implementation of ROA.

The applicability of ROA for climate change adaptation studies has been challenged because of concerns that assigning weights to scenarios in ROA is problematic (Shortridge and Camp, 2019) and that expected values are not meaningful summaries of option value (Kwakkel, 2020). The proposed approach represents adaptation by applying ROA principles without having to assign probabilities to each scenario. For instance, in this study, the scenarios were randomly generated from the uncertainty space using a scenario tree construction method. That is, the scenario tree construction could generate multiple trees from the same uncertainty source data with different number of nodes at each time step with a calculated probability, as well as different branching structure. On the topic of expected value, this is not a required attribute of our approach which allows consideration of multiple metrics; indeed, our case study does not use expected values for all objectives.

Multistage stochastic solutions are adaptive in that 'here-and-now' ($t = t_1$) planning decisions that do not depend on future observations are corrected through 'wait-and-see' ($t > t_1$) decisions for each realization of the scenarios in subsequent pre-determined stages in the time-horizon (Birge and Louveaux, 2011). Multistage stochastic models use sequential (multi-period) decision making, but not all sequential decision making is multistage stochastic; examples of sequential decision making include the scheduling formulations of Padula et al. (2013), Beh et al. (2015), Borgomeo et al. (2016) and Borgomeo et al.

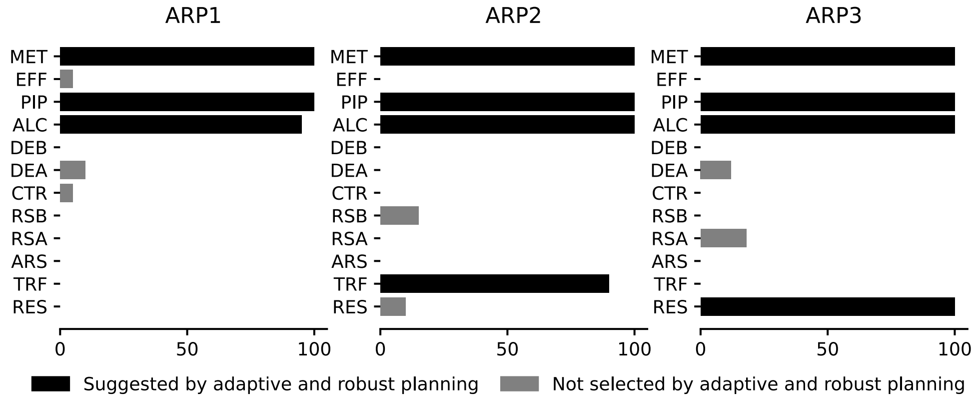

Fig. 10. Activation frequency of interventions for adaptive and robust solutions 1, 2 and 3 in planning decision period t_1 using 30 scenario trees.

(2018). What makes 'multistage stochastic' different from other multi-period decision making is the inclusion of a sequence of 'wait-and-see' decision variables that are used as 'recourse' to 'here-and-now' planning decisions to capture the evolving information over time. DAPP solutions can react to the state of the system using signposts and triggers at any moment of a simulation, not at pre-specified time-steps.

Methods aiming to inform management decisions usually involve assumptions and limitations around the uncertainties. In our case, the supply data used independent non-stationary climate scenarios that did not allow us to mix time slices of different hydrological time-series and hence they could not be used to construct a scenario tree for adaptive supply analysis. We therefore produced plans adaptive to demand and robust to supply uncertainty. The proposed framework as explained in Section 2.2 however is general and could consider multi-dimensional scenario trees where the evolution of different sources of uncertainties, not just demand, are considered. Uncertain parameters could include the probability of hydrological scenarios as well as economic aspects such as discount rates. The way that uncertain dimensions of the decision problem are modeled must be informed by problem structure and data availability.

Note that following Huskova et al. (2016), and to limit the number of function evaluations necessary for the optimization to converge, each intervention in our application had a fixed capacity (i.e., the size of investments is not optimized) (Table 1). Alternative capacities for the same interventions could be added as new interventions if just a few sizes are being considered. Optimizing the capacity of interventions across their entire range would result in more efficient, adaptive and robust plans, but is left to future work.

5.1. Sensitivity analysis

We test the sensitivity of the proposed actions of the three selected adaptive and robust plans to the use of different scenario trees. The London case study was run for thirty different and optimally generated scenario trees from the stochastic London demand distribution from the same uncertainty source. From each run, we select an adaptive and robust plan that exhibits a similar trade-off between the four objectives according to ARP1, 2 and 3. The results of the sensitivity analysis, shown as a bar chart in Fig. 10, illustrate the activation frequency of the options in the first planning decision period (t_1). For all three adaptive and robust plans, most interventions suggested by the planning approach have a high frequency of selection (more than 80%) indicating that recommendations are not sensitive to the structure of the scenario tree when extracted from the same uncertainty space. This finding is in accordance with the stability theory of multistage stochastic programming that suggests that multistage stochastic model results are stable with respect to the perturbation of the stochastic input process (Heitsch et al., 2006; Heitsch and Römisch, 2009).

5.2. Robustness analysis

We perform a regret-based analysis of the selected adaptive and robust plans to assess the deviation from optimality when simulated under a different ensemble of flow scenarios. To create the new ensemble of hydrological flows we resample the nonstationary time series via bootstrapping, as per Paparoditis and Politis (2002) for resampling of nonstationary time series.

Fig. 11 shows box plots of normalized values of regret across the 4 objectives for ARP1, 2 and 3. Regret R for a criteria c is calculated as the difference in the performance P of the portfolio in the best performing scenario s_b, $P_c(s_b)$, and that of the performance of the same plan in the scenario in question s, $P_c(s)$, given by:

$$R_c = P_c(s_b) - P_c(s). \tag{11}$$

The adaptive and robust plan with smaller infrastructure options (ARP1) performs best in cost regret while the more expensive ARP2 has the highest cost regret values because the options activated early in the planning period incur high operational cost values.

6. Conclusions

Given unknown future water supply and demand conditions, growing global populations, and the push to invest in infrastructure to prevent the worst impacts from climate change, the problem of intervening in water resource systems under uncertainty has taken on a renewed urgency. Considering conflicting objectives while addressing uncertainties in developing human–natural resource systems has become a frontier problem of water science. By explicitly accommodating the aspiration for adaptability, robustness and the need to balance different water system goals, we feel the proposed approach is a useful contribution to water management.

This paper proposed an approach for multi-objective, real options based adaptive and robust planning of water interventions under uncertainty. A scenario tree is extracted to represent the uncertain parameters which can be branched from one state to another, and the uncertainties that cannot be defined by the scenario tree are considered as an ensemble of future states. A multi-objective search engine uses an independent water resource simulator to identify optimal interventions for each node of the structured scenario tree and evaluate the plans over an ensemble of future conditions. The obtained Pareto-approximate investment plans are adaptive and robust to the uncertainties considered.

The framework was demonstrated on London's water resource system. Demand uncertainty was represented through a scenario tree while supply uncertainty through an ensemble of hydrological flows. Demand growth threshold values inform decision makers which investment trajectory would be best to follow to optimize cost, service resilience, reliability and vulnerability of the water supply system.

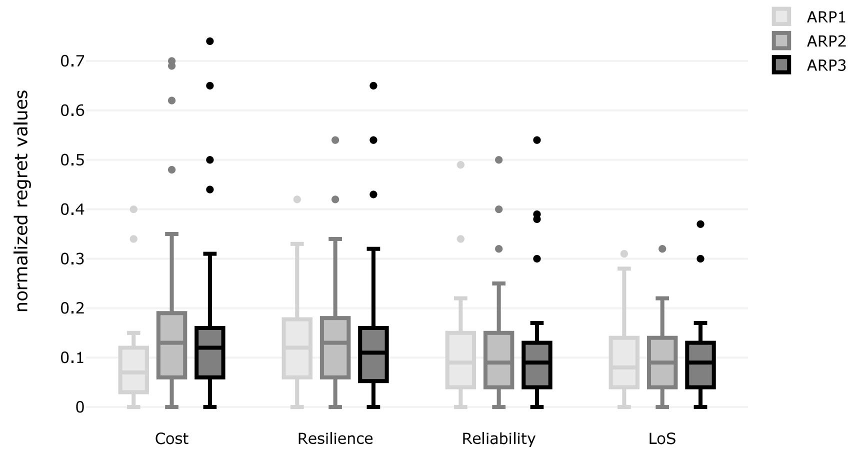

Fig. 11. Box plots of regret for each of the four objectives. The median regret is represented by the horizontal line in each box, the top and bottom of the boxes represent the upper and lower quartiles respectively. Points represent outliers.

The plans are robust in that they are insensitive to different future hydrological conditions and adaptive in that commitments being made in the short-term allow for choosing future actions based on how future demand growth unfolds. The application of this real options based definition of adaptability to a multi-objective water infrastructure planning problem in combination with robust optimization is novel. For regulated utilities with a regular planning cycle, the proposed adaptive and robust water infrastructure approach is institutionally appropriate since our definition of adaptability uses a set of pre-determined time-steps.

To demonstrate the use of the outputs of the proposed planning framework, three Pareto-approximate solutions were selected and compared. Depending on how the planner believes short-term demand growth will evolve and their preference on the multi-objective performance trade-off, they select which plan to implement, including whether interventions should be delayed.

The flexibility and adaptability assessment of the three adaptive and robust plans quantified the benefit of considering supply and demand uncertainty by calculating the stochastic value (i.e., expected loss of using a deterministic solution) and the value of knowing more about the future. For more costly plans that provide higher performance in infrastructure services (service resilience, reliability and vulnerability), the importance of handling uncertainty and having better information increases. In our case, London's net present value of required investments was reduced by up to 18%. Also the option value of best delaying investments to wait for better predictions was shown to be worth up to 14% of total NPV. These results help quantify the value of a ROA approach.

This paper shows global cities can and should appropriately balance their investment-performance trade-off, and that explicitly optimizing robustness and adaptability of water supply systems can increase future service levels at a lower cost. Increased societal resilience in the face of climate change is an aspiration of many cities world-wide as they look to invest in resource security. This paper describes a new route for investing in complex real-world water systems despite future uncertainties in a systematic, transparent and beneficial manner.

CRediT authorship contribution statement

Kevis Pachos: Conceptualization, Methodology, Software, Writing – original draft, Validation, Visualization. **Ivana Huskova:** Methodology, Software. **Evgenii Matrosov:** Methodology, Software, Writing – review & editing. **Tohid Erfani:** Conceptualization, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Julien J. Harou:** Conceptualization, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Funding from Thames Water, the UCL Department of Civil, Environmental and Geomatic Engineering doctoral training scheme and UKRI's FutureDAMS project (ES/P011373/1) are gratefully acknowledged. Anna Wallen and Chris Lambert provided comments that improved the paper. Data used in this study is available in the Technical appendices on the Thames Water website: https://www.thameswater.co.uk/about-us/regulation/water-resources.

Appendix A. Computational implementation

To solve the problem explained in Section 3.3, we use the Epsilon-Dominance Non-dominated Sorting Genetic Algorithm II (e-NSGAII) (Kollat and Reed, 2006). We ran the multi-objective optimization ten times each starting from a unique population using different random seed value to account for the variability of the initial populations and to best approximate the Pareto front. Previous studies have used similar number of seeds to reduce the computational burden while ensuring that the influence of random number generation on the results is insignificant (Huskova et al., 2016). The initial population size was set to 512 and the algorithm operator parameters were chosen according to previous study recommendations (Kollat and Reed, 2007a; Matrosov et al., 2015). Each optimization was run for 25,000 function evaluations or until a convergence metric was satisfied. Table 2 summarizes the algorithm parameters including the objective ϵ values used for the case study. The ϵ values were selected to capture the minimum level of precision desired in differentiating between the performance of one portfolio alternative and another in each objective (1000, 0.1, 0.5 and 0.5 for cost, resilience, reliability and fraction of scenarios that meet required LoS respectively). To determine each run's convergence, we used a hypervolume metric (Zitzler, 1999) as the termination criterion, which is widely used in multi-objective optimization problems as it captures the diversity and convergence of solutions (Reed et al., 2013). Fig. A.12 shows how the search algorithm has converged after 120 generations.

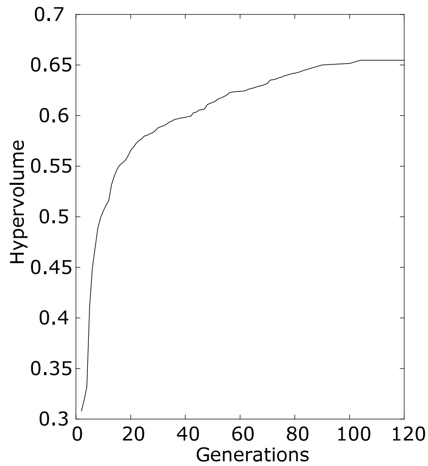

Fig. A.12. Hypervolume progress during the search.

Appendix B. Computational insight on the metrics used to evaluate the multi-period MOEA

The value of the stochastic solution (VSS) is calculated for each plan by replacing the decision variables (i.e. activation of intervention in each planning interval) with expected values and comparing the cost requirements between the two. By fixing the first stage interventions and solving for all the scenarios, the MOEA will generate a new set of Pareto adaptive and robust plans. The expected value of perfect information (EVPI) is estimated by computing the cost difference between the expected value with perfect information and the expected value with current information for each Pareto adaptive and robust plan. In order to allow comparison of VSS and EVPI values we select plans with the same level of resilience, reliability and fraction of scenarios that meet required LoS.

The calculations of VSS and EVPI in multi-stage problems are explained below. These two metrics were developed for the case of two-stage problems (Birge and Louveaux, 1997), and have been extended to multi-stage problems (Escudero et al., 2007). We calculate their values in a multi-stage framework with two objectives, for each Pareto approximate solution individually.

VSS and EVPI are calculated using the cost values of the solutions that correspond to a given level of resilience, reliability and fraction of scenarios where a plan performs within the desired LoS. VSS is calculated by solving the 'mean-value' problem resulting in a Pareto set of first stage solutions. EVPI is determined by computing the cost difference between the expected value with perfect information and the expected value with current information.

For the minimization model the following inequalities are satisfied,

$$WS \leq AP \leq EV, \tag{B.1}$$

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

From Eq. (B.1), EVPI and VSS are calculated as follows,

$$EVPI = AP - WS, \tag{B.2}$$

$$VSS = EV - AP. \tag{B.3}$$

To calculate the EVPI, non-anticipative constraints are relaxed at each time step so that decisions are made with perfect information about the future. From Eq. (B.2), the difference $AP - WS$ displays the value of perfect information. From Eq. (B.3), the difference $EV - AP$, known as the VSS, indicates the benefit of finding different solutions for each scenario by solving the stochastic program than to assume lack of uncertainty.

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

For any multi-stage stochastic program, the following relations hold:

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

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

The value of the stochastic solution is defined in t, denoted by VSS_t, as

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

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

$$VSS = \sum_{t \in T} VSS_t, \tag{B.4}$$

and,

$$EVPI = \sum_{t \in T} EVPI_t. \tag{B.5}$$

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