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Screening robust water infrastructure investments and their trade-offs under global change: A London example

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ABSTRACT

We propose an approach for screening future infrastructure and demand management investments for large water supply systems subject to uncertain future conditions. The approach is demonstrated using the London water supply system. Promising portfolios of interventions (e.g., new supplies, water conservation schemes, etc.) that meet London's estimated water supply demands in 2035 are shown to face significant trade-offs between financial, engineering and environmental measures of performance. Robust portfolios are identified by contrasting the multi-objective results attained for (1) historically observed baseline conditions versus (2) future global change scenarios. An ensemble of global change scenarios is computed using climate change impacted hydrological flows, plausible water demands, environmentally motivated abstraction reductions, and future energy prices. The proposed multi-scenario trade-off analysis screens for robust investments that provide benefits over a wide range of futures, including those with little change. Our results suggest that 60 percent of intervention portfolios identified as Pareto optimal under historical conditions would fail under future scenarios considered relevant by stakeholders. Those that are able to maintain good performance under historical conditions can no longer be considered to perform optimally under future scenarios. The individual investment options differ significantly in their ability to cope with varying conditions. Visualizing the individual infrastructure and demand management interventions implemented in the Pareto optimal portfolios in multi-dimensional space aids the exploration of how the interventions affect the robustness and performance of the system.

1. Introduction

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 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. Moreover, 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.

Instead of defining "optimality" under historical or narrowly defined conditions, planners have recently been seeking "robustness" for planning under uncertainty (Ben-Haim, 2000; Haasnoot et al., 2013; Herman et al., 2015; Lempert et al., 2003). Robustness as a planning goal is well suited to situations where the probabilities that govern uncertain future states are uncertain themselves. Such uncertainties are known as 'deep' or Knightian uncertainties (Knight, 1921). For example, assigning probabilities to population growth or the effects of climate change on systems is problematic (Walker et al., 2013). A robust system is one that performs well or satisfactorily well over a broad range of plausible future conditions rather than optimally in one. Robustness is

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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, 2012). Planning approaches seeking robustness have also been investigated in the UK's water resource planning context (Borgomeo et al., 2014; Korteling et al., 2013; Matrosov et al., 2013a, 2013b) but none of those explored the implications of many-objective decision-making and how the trade-offs change when multiple sources of uncertainty are considered. Recently, dynamic robustness (Walker et al., 2013) that specifically considers the value of flexibility and adaptation has been explored using the Dynamic Adaptive Policy Pathways approach for pre-specified strategies (Haasnoot et al., 2013; Urich and Rauch, 2014) and in multi-objective optimization (Hamarat et al., 2014; Kwakkel et al., 2014). 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. In our study we focus on demonstrating how performance trade-offs between investment packages change when uncertainties are considered within complex real-world water systems. Our goal is to communicate to policy makers the increase in understanding and judgement they can obtain by incorporating uncertainty into automated intervention evaluation methods.

Urban water supply planners have commonly employed narrowly defined, least-cost decision frameworks to guide capacity expansions 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 increases the likelihood that policies are viewed as performing poorly (McConnell, 2010) and maladaptative. 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).

Simple capacity expansion approaches such as least-cost yield planning (Padula et al., 2013) are being renewed in many areas of resource management to incorporate the planning approaches described above. The current UK approach does not consider a portfolio's robustness, cost, and social and environmental acceptability explicitly (Dessai and Hulme, 2007). Water planners and regulators recognize the limitations of the current approach and are actively seeking to improve the statutory planning framework (Defra, 2011). Our study aims to reflect the necessity of the current water planning policy changes that are being considered. These include a move from solely least-cost solutions to planning for resilience and robustness against a wide range of plausible future conditions whilst considering wider impacts of decisions beyond cost (Environment Agency, 2015). However, the current water supply system planning framework (Padula et al., 2013) requires water companies consider intervention yields, i.e., the maximum daily water supply an intervention can provide, based on historical flow data. This paper describes a planning approach that explicitly considers both multiple sources of uncertainty and multiple evaluation objectives. We show 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 and Hydrology, 2015). In our proposed system design screening framework 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.

Trade-off analysis has some, but limited, prior history of inclusion in water resource planning regulations (e.g. California Department of Water Resources, 2008; UKWIR, 2016). Here we seek 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). Our study demonstrates the importance of understanding how benefit trade-offs change when diverse sources of uncertainty are considered. 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.

Our 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. We use visual analytics 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. We believe 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 the Methods section. Section 3 introduces the Thames basin water resource system, planning context, and details the optimization formulation and the scenarios of future conditions. Results are presented in Section 4 and discussed in Section 5.

2. Methods

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 we apply a many-objective approach considering a range of supply and demand management interventions as decisions and a combination of financial, engineering and environmental objectives (detailed in Section 3.1). A deterministic baseline is 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. We then implement 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 above, with the only difference being that the objective values are assessed across the ensemble of scenarios. 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. Fig. 1 illustrates the steps performed in this study.

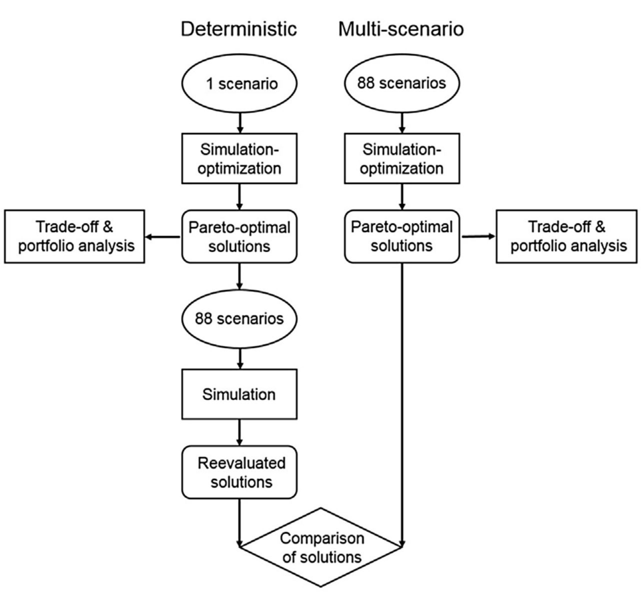

Fig. 1. Flow chart showing the steps of the two approaches followed in the study. Two separate optimizations, deterministic (left) and multi-scenario (right), were performed and the results analyzed. The deterministic solutions were then simulated against the multiple scenarios and their performance was compared to that of the multi-scenario solutions.

2.1. Simulation-Optimization framework

This study applies a multi-objective evolutionary algorithm (MOEA) linked to a water resource system simulator where the simulator is used to assess the performance of different portfolios. MOEAs are heuristic global search algorithms that simulate the process of natural evolution and are able to optimize over many objectives (Coello Coello et al., 2007). Rather than generating a single optimal solution, MOEAs produce Pareto optimal sets of solutions, i.e., solutions which cannot be further improved in one objective without simultaneously reducing performance in another (Coello Coello et al., 2007; Kollat and Reed, 2006). 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), hence our use of the term 'Pareto-approximate' or 'approximately Pareto optimal'. For simplicity this is referred to as Pareto optimal in the following text. MOEAs coupled with simulation have been shown to be suitable for complex water resource management and planning applications (Maier et al., 2014; Nicklow et al., 2010; Reed et al., 2013), including reservoir operation (Chang et al., 2005; Chang and Chang, 2009; Giuliani et al., 2014; Hurford et al., 2014), and urban water supply operation (Cui and Kuczera, 2003, 2005). This study utilizes the Epsilon-dominance Non-dominated Sorting Genetic Algorithm II (ε-NSGAII) (Kollat and Reed, 2006), a description of which is provided in the Supplementary material.

The MOEA is linked to an Interactive River-Aquifer Simulation 2010 (IRAS-2010) (Matrosov et al., 2011) model of the Thames basin water resource system. The MOEA generates decision variables such as reservoir capacity which are passed to the simulation model as input in addition to other input variables such as inflows, network composition, operating rules, etc. The latter then simulates the system quantifying flow and storage at system nodes (reservoirs, junctions, abstractions, aquifers, treatment and desalination plants, etc.) and links (rivers, pipes, water transfers) using a weekly time step. Performance metrics such as supply reliability are calculated at the end of the simulation and passed to MOEA as objective values. The optimization objectives can therefore be explicitly based on the physical performance of the system. IRAS-2010 Thames model has been shown to successfully emulate a model maintained by the environmental regulator Environment Agency (Matrosov et al., 2011). Surface storage in the basin is aggregated into a single reservoir node, the London Aggregate Storage (LAS), while the main demand in the system is represented by the London aggregate demand.

3. Case study

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 500 mm (Wilby and Harris, 2006). The population density is four times higher than that of the rest of England, which results in more than half of the effective rainfall being used for the public water supply (Merrett, 2007). 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. The Thames basin with existing and possible new water resource infrastructure is shown in Fig. 2. A description of the supply and

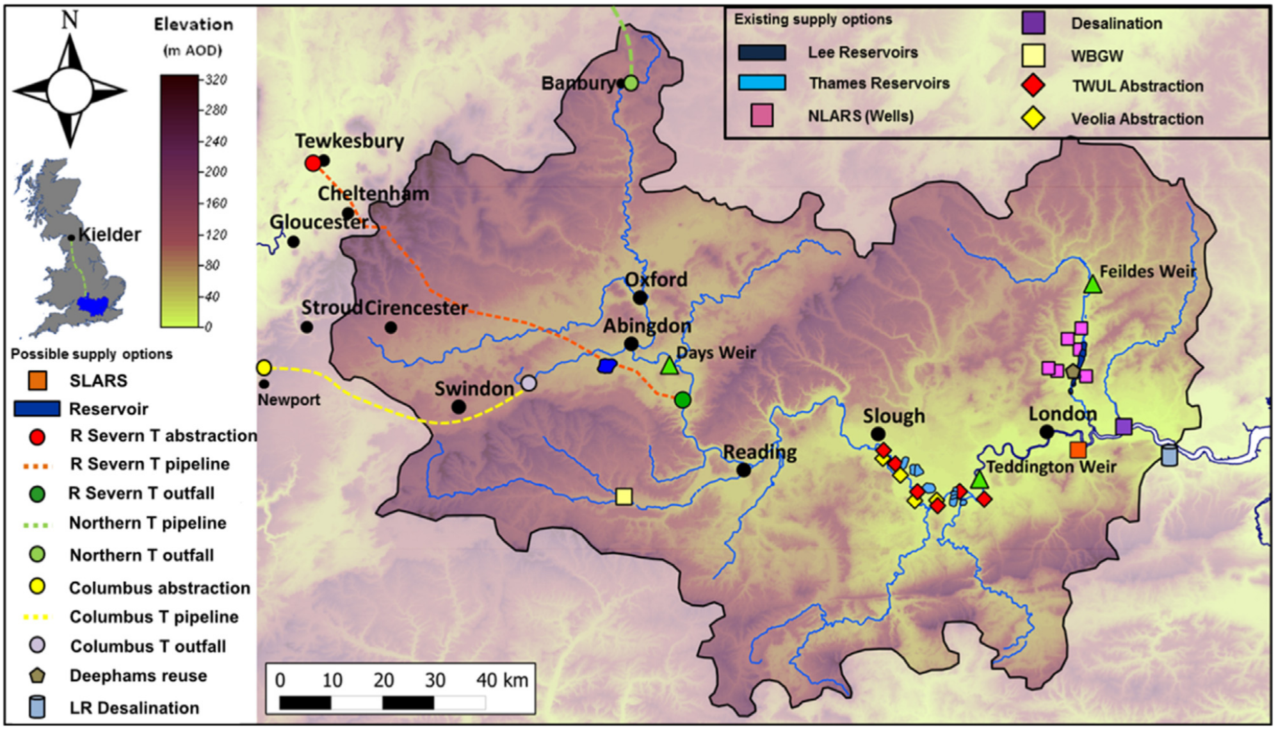

Fig. 2. Current and possible future supply options in the River Thames basin (adopted from Matrosov et al., 2015).

demand management interventions as well as the basin is provided in the Supplementary material.

The non-linear seasonal Lower Thames Control Diagram (LTCD) (refer to Matrosov et al., 2011; and the Supplementary material) 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 should be lowered and when water-use restrictions are imposed. The thresholds vary depending on the period of the year. The Levels of Service (LoS) then specify the maximum frequency of imposing the associated water-use restrictions on customers (Table 1), which are used as constraints in our problem formulation (Section 3.1).

Planners use the 'Economics of Balancing Supply and Demand' (EBSD) framework (Padula et al., 2013; UKWIR, 2002) to identify the least-cost portfolio of new water supply and conservation interventions. EBSD is a planning method that seeks to minimize the financial costs of meeting future water demands over a 25–30 year planning horizon given portfolios of different supply and demand management interventions and Levels of Service. Although the current least-cost planning guidelines do consider financial, social and environmental costs, they require monetization and aggregation of all criteria (Environment Agency et al., 2012; Padula et al., 2013). The Water Resources Planning Guidelines (WRPG) (Environment Agency et al., 2012) encourage water companies to iterate over the identified least-cost plan to find the optimum balance between the financial, environmental and social costs as well as non-monetary environmental benefits. The final plans are tested for their supply reliability and resilience. These tests are however performed post-optimization. Our proposed approach explicitly takes into account these metrics within the optimization and helps to identify plans that demonstrate all of these characteristics. The metrics are described in the following section and the Supplementary material.

3.1. Many-objective problem formulation

The London water supply problem described above 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

Table 1
Constraint values based on LTCD diagram and TWUL's Levels of Service (Thames Water, 2014).

LTCD Demand Level	Average annual frequency of restrictions	Constraint value referring to supply reliability
1	1 in 5 years	$C_1 \geq 80\%$
2	1 in 10 years	$C_2 \geq 90\%$
3	1 in 20 years	$C_3 \geq 95\%$
4	Never	$C_4 = 100\%$

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). These include the Upper Thames Reservoir, River Severn Transfer, Northern Transfer, Columbus transfer, South London Artificial Recharge Scheme (SLARS), a water reuse scheme and a new desalination plant (Fig. 2). Demand management options 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.

This study considers two formulations: a deterministic approach and a multi-scenario approach. The deterministic approach where the portfolios are evaluated against a single future scenario based on historical conditions uses a single value for each objective. 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, reliability and resilience).

The feasibility of portfolios is constrained by the mutual exclusivity of certain supply interventions and by meeting the minimum Levels of Service across the ensemble of scenarios (Table 1). 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 frequency of imposing demand restrictions (Table 1), 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 defined by Eqs. (1)–(3):

$$\text{Minimize } \mathbf{F}(\mathbf{x}) = \left(f_{CapCost}, f_{SupDef}, f_{SupRes}, -f_{SupRel}, f_{Eco}, f_{Energy}\right) \quad (1)$$

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

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

$$\text{subject to } C_k \leq FR_k \quad (2)$$

$$\textstyle\sum_{i \in ME} Y_i \leq 1 \quad (3)$$

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 in each scenario allowed for LoS k, and ME represents the set of mutually exclusive interventions. The individual objectives and constraints are described in more detail in the Supplementary material.

3.2. 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 preferred least-cost portfolio is still identified 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 2).

3.2.1. 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 FFs 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 and 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

Table 2
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 3.2.1
Water demand	2	2325 ML/day 2558 ML/day
'Sustainability reductions' to water licenses	2	No reduction (current licensed) Total of 175 ML/day reduction
Energy unit price	2	13 p/kWh 35 p/kWh
Total number of scenarios	88	

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. A more detailed description, analysis and justification of the used time-series is provided in the Supplementary material.

3.2.2. 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 2325 Ml/d and 2558 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 2325 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). 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 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) 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).

3.3. Computational details

The deterministic optimization was performed using a 30-year historical time-series of river flows (1970–2000) with a weekly time-step and demand and energy estimates for the year 2035. As in Matrosov 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. 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 2.1). 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.

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 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.

4. Results

4.1. Deterministic optimization analysis

In this section we present the deterministic optimization results where only a single future scenario based on historical conditions is considered. The many-dimensional visualization offers a rich view into high performing combinations of interventions and their impacts (as demonstrated in Matrosov et al. (2015)). That study showed how progressively visualizing the performance dimensions helps communicate many-dimensional trade-offs and aids stakeholder understanding and deliberation. In this paper we assume stakeholders are familiar with multi-dimensional trade-off interpretation and show plots with all dimensions of performance (six) concurrently and focus on displaying graphically the benefits of incorporating uncertainty explicitly within investment screening. The Pareto optimal solutions here differ slightly from the solutions in our previous study due to different objectives used and the shorter simulation period in the former.

Fig. 3 shows the full set of Pareto optimal portfolios obtained from the six objective optimization. The figure reveals two distinct "fronts" with one front skewed to the right, i.e., higher capital costs (shown on x axis in Fig. 3) 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 Fig. 3). Nevertheless, many perfect reliability solutions (at the bottom plane of the cube in Fig. 3) exhibit varied supply deficit that decreases with higher capital investment. The color scale distinguishes the portfolios according to their environmental performance, i.e., the eco-deficit objective. 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. The orientation of the cones in Fig. 3 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 Fig. 3 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 4.2.2) 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 Fig. 3 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 (color in Fig. 3) than the former. Furthermore, lower average annual energy cost requirements might influence the total long-term cost of a portfolio.

4.2. Comparison of deterministic and multi-scenario optimization results

4.2.1. Portfolio performance

Fig. 4 illustrates how the Pareto front changes when we incorporate multiple sources of uncertainty in the form of scenarios into the optimization. The individual objectives are represented as defined in Fig. 3. The translucent points show the deterministic optimization results analyzed in the previous section while the full colored 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-colored cones in Fig. 4) 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

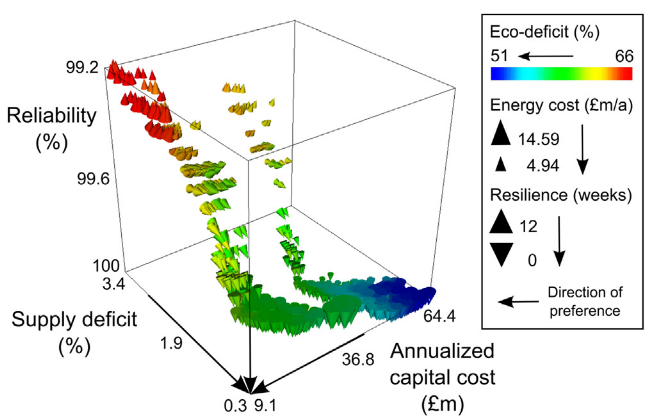

Fig. 3. Pareto optimal portfolios obtained by deterministic optimization. The principal axes show the capital cost, supply deficit and reliability objectives. The eco-deficit objective is depicted by the color scale; the red solutions illustrate the highest eco-deficit while the blue solutions show the lowest eco-deficit. The orientation of the cones illustrates the resilience of portfolios and the size of the cones the energy cost requirements. Cones pointing upwards indicate worst resilience while cones pointing downwards the best resilience; the bigger the cone the higher energy use the portfolio requires. The arrows point towards the direction of preference, i.e., the ideal point would lie in the lower central corner of the cube and its cone would be of the smallest size, blue color and pointing directly downwards. Given the inherent trade-offs between the objectives, such performance cannot be achieved. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

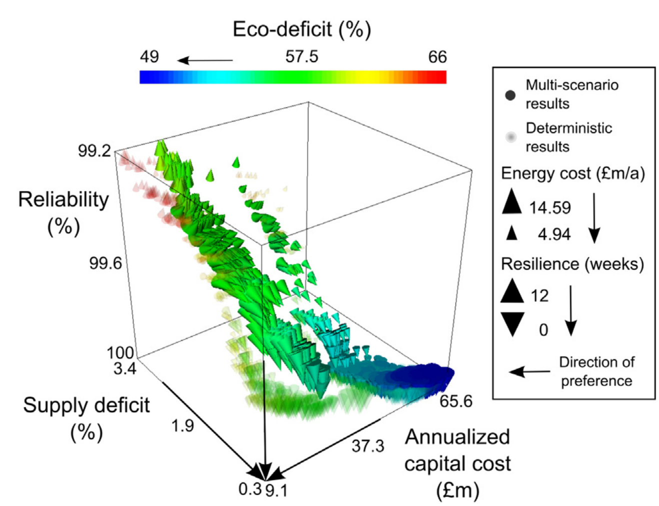

Fig. 4. Multi-scenario Pareto optimal portfolio trade-offs (full color cones) compared to the deterministic Pareto optimal portfolio trade-offs (translucent cones). The multi-scenario optimization objective space shrinks and shifts towards higher capital and energy cost requirements (i.e., the full color 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 (color scale). Please note that the translucent deterministic solutions and the full colored 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.(For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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 behavior 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 (Fig. 3).

4.2.2. Portfolio composition

Fig. 5 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 Figs. 3 and 4. The size of the cones illustrates the energy cost requirements of portfolios. The color represents the implementation of the mutually exclusive supply options; green cones show portfolios that include the Upper Thames Reservoir (UTR), the red colored 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 Fig. 5) 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 Fig. 5) implement the transfer intervention which requires higher capital and operating costs than the reservoir; all build the UTR reservoir.

The orientation of cones in Fig. 5 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 (color of cones in Fig. 4) and demand lower energy use (size of cones in Fig. 5) 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. 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 Fig. 6 by full color 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

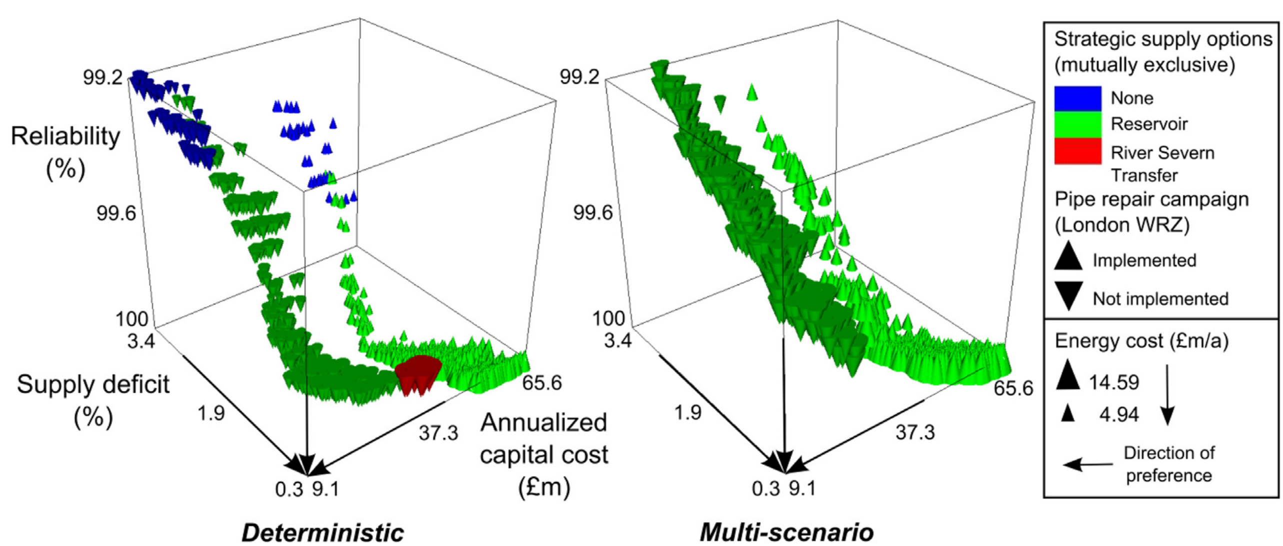

Fig. 5. Comparison of portfolio composition between the deterministic and multi-scenario Pareto optimal solutions. The cardinal axes show the same objectives as in Figs. 3 and 4. Cone size represents the portfolio energy cost while color shows which of the mutually exclusive supply interventions was implemented. Cone orientation indicates whether or not each portfolio implemented the London pipe repair campaign. Implementing (lighter colored cones pointing upwards) or not implementing (darker colored cones pointing downwards) the pipe repairs divides the trade-off space into two distinct fronts.(For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

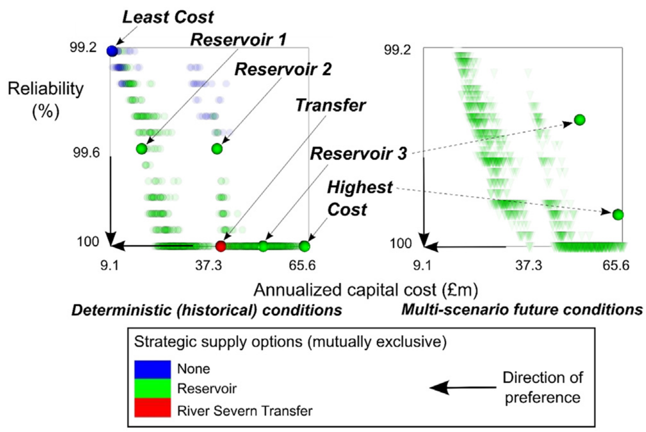

Fig. 6. Six representative deterministic (left) Pareto optimal portfolios (large full color spheres in the left panel) were simulated under the 88 future scenarios. The performance of these solutions over the future scenarios is compared to that of the multi-scenario Pareto-approximate optimal solutions (full color 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.(For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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 Fig. 6 (full color points) and compared to the multi-scenario Pareto optimal portfolios (translucent cones in the right panel of Fig. 6). 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 3). 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.

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.

Fig. 7 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 Fig. 7) are dominated by the multi-scenario Pareto optimal solutions (full color spheres in Fig. 7), 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 Fig. 7) to achieve the same levels of reliability than the full colored portfolios (that are located in the same position regarding the vertical axis of Fig. 7a). 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 color in Fig. 7). This is particularly visible in Fig. 7b where the same set of portfolios as in Fig. 7a is shown in different view; the reliability and supply deficit axes were switched and the plot rotated anticlockwise. The full colored 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.

5. Discussion

5.1. 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 (Fig. 3). 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 Fig. 3.

Table 3
Performance comparison of the Reservoir 3 and Highest Cost portfolios depicted in Fig. 6 between the deterministic and multi-scenario conditions.

Objective	Reservoir 3		Highest Cost	
	Deterministic	Multi-scenario	Deterministic	Multi-scenario
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

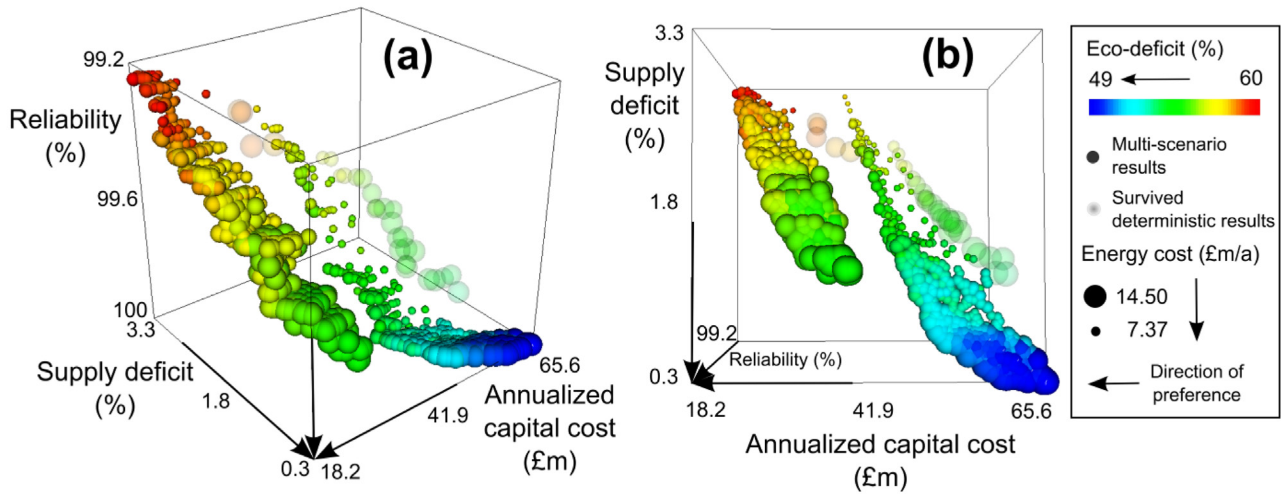

Fig. 7. Deterministic Pareto optimal solutions that comply with the LoS constraints under the multi-scenario conditions (translucent points) and the multi-scenario Pareto optimal solutions (full colored points) visualized together. The cardinal axes show the same objectives as Figs. 3, 4 and 5. Color 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, colors, 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.(For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

5.2. Incorporating uncertainties into many-objective optimization

When planning under uncertainty planners should ensure their system is able to cope with a wide range of plausible futures. Our study illustrates that taking into account multiple performance objectives and planning for robustness can be achieved concurrently. Deterministic optimization of 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. We found that using historical flow records to assess future system investments can provide biased information about individual portfolios, i.e., make them seem favorable when in fact they do not perform well in many alternate plausible futures. Fig. 6 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 Fig. 6) but show worse performance against the optimized objectives than suggested by the deterministic approach (Table 3). 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). Fig. 7 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.

5.3. 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 Fig. 3 only represents the final stage of the exploration. The progressive introduction of dimensions within trade-off plots is explored by Matrosov et al. (2015). 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.

Robust interventions can be identified by their presence in the Pareto optimal solutions obtained from the multi-scenario optimization. Fig. 5 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 modeled, 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.

5.4. 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 (see Supplementary material). 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. We acknowledge 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. 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 h 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.

6. Conclusions

This paper 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 we used a search algorithm (many-objective evolutionary algorithm) linked to a water resource system simulator.

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.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.gloenvcha.2016.10.007.

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