WR2143

Comparison of Robust Optimization and Info-Gap Methods for Water Resource Management under Deep Uncertainty

TOM ROACH[1]; ZORAN KAPELAN[2]; RALPH LEDBETTER[3]; MICHELLE LEDBETTER[4]

[1]Research Engineer, Centre for Water Systems, College of Engineering, Mathematics, and Physical Sciences, Univ. of Exeter, North Park Rd., Harrison Building, Exeter, EX4 4QF, UK (corresponding author). Email: tpr202@ex.ac.uk

[2]Professor, Centre for Water Systems, College of Engineering, Mathematics, and Physical Sciences, Univ. of Exeter, North Park Rd., Harrison Building, Exeter, EX4 4QF, UK

[3]Senior Hydrologist, HR Wallingford, Howbery Business Park, Crowmarsh Gifford, Wallingford, Oxfordshire, OX10 8BA, UK

[4]Mathematician, Smith Institute, Surrey Technology Centre, Surrey Research Park, Guildford, Surrey GU2 7YG, UK

Abstract

This paper evaluates two established decision making methods and analyses their performance and suitability within a Water Resources Management (WRM) problem. The methods under assessment are Info-Gap decision theory (IG) and Robust Optimisation (RO). The methods have been selected primarily to investigate a contrasting local vs global method of assessing water system robustness to deep uncertainty but also to compare a robustness model approach (IG) with a robustness algorithm approach (RO), whereby the former selects and analyses a set of pre-specified strategies and the latter uses optimisation algorithms to automatically generate and evaluate solutions. The study presents a novel *area*-based method for IG robustness modelling and assesses the applicability of utilising the Future Flows climate change projections in scenario generation for water resource adaptation planning. The methods were applied to a case study

resembling the Sussex North Water Resource Zone in England, assessing their applicability at improving a risk-based WRM problem and highlighting the strengths and weaknesses of each method at selecting suitable adaptation strategies under climate change and future demand uncertainties. Pareto sets of robustness to cost are produced for both methods and highlight RO as producing the lower costing strategies for the full range of varying target robustness levels. IG produced the more expensive Pareto strategies due to its more selective and stringent robustness analysis, resulting from the more complex scenario ordering process.

1 Introduction

Current water management systems work under the assumption that natural systems fluctuate within an unchanged envelope of variability (Milly et al. 2008). However, substantial anthropogenic change of the Earth's climate is modifying patterns of rainfall, river flow, glacial melt and groundwater recharge rates across the planet, undermining many of the stationarity assumptions upon which water resources infrastructure has been historically managed (IPCC 2007). This is creating a potentially vast range of possible futures that could threaten the reliability of vital regional water supplies. This combined with increased urbanisation and rapidly growing regional populations is putting pressures on finite water resources (Environment Agency 2013). Water companies and utilities worldwide are now under pressure to modernise their management frameworks and approaches to decision making in order to identify more sustainable and cost-effective water management adaptations that are reliable in the face of uncertainty.

Water management regulatory frameworks differ around the world but in many countries similar plans are developed under the auspices of Integrated Water Resources Management (IWRM) programmes. For instance, water utilities in the UK are required to produce Water

Resource Management Plans (WRMPs) every five years that outline their long-term strategies for maintaining a secure water supply to meet anticipated demand levels. These plans justify any new demand management or water supply infrastructure needed and validate management decisions (Environment Agency et al. 2012). Similar IWRM planning is fostered around the world as recommended by the Global Water Partnership (GWP) with the vision of a water secure world (Falkenmark and Folke 2000), including increasing regard given to sustainable water planning and policy in developing countries (Bjrklund 2001). Modern day IWRM planning is a multi-objective problem where decision makers are required to develop strategic *adaptation* plans to maximise the security of water supplies to future multiple uncertainties, whilst minimising costs, resources usage, energy requirements and environmental impact (Charlton and Arnell 2011; Environment Agency 2013).

The current approach within the UK, as stated in the Environment Agency's (EAs) Water Resources Planning Guideline for England and Wales (Environment Agency et al. 2012) and the Economics of Balancing Supply and Demand (EBSD) (NERA 2002), is to produce a "best estimate" of future deployable output (or system yield). Using climate change projections and regional population forecasts, the aim is to deliver an acceptable (i.e. target) level of service for the least cost given the projected changes in supply and demand. This produces a single best estimate of the future supply-demand balance over time and encourages a "predict and provide" type approach to WRM over a single projected future or pathway (Lempert and Groves 2010). Target Headroom (Environment Agency et al. 2012) is then added as a "safety margin", defined as "the minimum buffer that a prudent water company should allow between supply and demand to cater for specified uncertainties in the overall supply-demand resource balance" (UKWIR 1998) and is calculated by applying probability density functions (pdfs) to all sources of uncertainty in supply and demand (Hall et al. 2012a). However, the current EBSD approach does not fully explore the wider range of possible futures, the so called “deep” uncertainties (Walker et al. 2013a), or the full range of potential solutions and trade-offs. Nor does it promote examination and security against the more extreme projected scenarios; such as severe changes in individual supply source availability at peak demand periods (Environment Agency et al. 2012) or highly unexpected events (the so called black swans) (Bryant and Lempert 2010). It does not encourage the most *robust* or *flexible* strategies to be derived, but instead satisfies a single projected supply-demand balance over a short timescale of 25 years.

To overcome this, extensive international research is being carried out to test and evaluate a wide range of prospective Decision Making Methods (DMMs), i.e. *frameworks* and *approaches*, which demonstrate notable potential in handling “deep” uncertainties in regard to WRM adaptive planning. Walker et al. (2013a) defines the point at which uncertainties become “deep” as when one can enumerate multiple plausible alternatives of the future but cannot rank the alternatives in terms of perceived likelihood. In this paper “deep” uncertainty is defined as above and a DMM, in a WRM context, denotes any method that helps a decision maker identify the “best” adaptation strategy(ies) over a long term planning horizon that are either automatically generated or selected from a range of pre-defined solutions.

Popular DMMs include approaches such as; Robust Decision Making (Lempert and Collins 2007), Robust Optimisation (Ben-Tal et al. 2009), Decision Scaling (Brown 2010) and Info-Gap decision theory (Ben-Haim 2006), with a summary of such methods given by Ray and Brown (2015). The majority of established DMMs are developed to evaluate the *robustness* of a system, strategy or decision. Walker et al. (2013b) produced a review of conceptual approaches for handling deep uncertainties and concluded that further work needed to be done on the systematic *comparison* of approaches and computational tools for handling *robust* planning to better derive the potential strengths and weaknesses of the various approaches. Comparisons of Info-Gap and Robust Decision Making for WRM found the methods selected differing “best” solutions (Matrosov et al. 2013), which was also demonstrated by Hall et al. (2012b) when both methods were applied to evaluate robust climate policies. Furthermore an evaluation of robustness measures from different DMMs discovered each DMM ranked solutions to differing performance levels (Herman et al, 2015). Numerous more individual and comparative DMMs studies have been conducted within the context of WRM adaptive planning with specific attention to a measure of *robustness* (Ghile et al. 2014; Haasnoot et al. 2013; Jeuland and Whittington 2014; Kwakkel et al. 2014; Lempert and Groves 2010; Li, et al. 2009; Moody and Brown 2013; Paton et al. 2014a; Tingstad et al. 2013; Turner et al. 2014a; Whateley et al. 2014), including investigations into risk-based metrics for analysing adaptation strategy performance (Borgomeo et al. 2014; Brown and Baroang 2011; Hall et al. 2012a; Kasprzyk et al 2012; Turner et al. 2014b) and various new scenario-based methods for ordering and mapping the deep uncertainties within modern WRM problems (Beh et al. 2015a; Kang and Lansey 2013; 2014; Nazemi et al. 2013; Singh et al. 2014; Weng et al. 2010). However further testing and comparison of DMMs on real world case studies could be highly beneficial especially in regard to evaluating alternative definitions and calculations of system *robustness* to uncertainty, the methods of scenario generation and the process of adaptation strategy selection and evaluation.

This paper presents a comparison of Info-Gap (IG) and Robust Optimisation (RO) methods. Both methods are tested on a real world WRM adaptation case study, with the primary aim to investigate a contrasting local vs global method of *robustness* assessment. The methods chosen also allow a comparison of a robustness tool (IG) with an algorithm approach (RO), whereby the former selects and analyses a set of pre-specified strategies and the latter uses optimisation algorithms to automatically generate and evaluate solutions.

Examples of the application of IG decision theory in the development of long-term water management strategies can be found in Hipel and Ben-Haim (1999), Woods et al. (2011), Korteling et al. (2013), Matrosov et al. (2013) and in the development of robust climate policies in Hall et al. (2012b). IG was found to resolve a lot of the weaknesses in current WRM predictive target headroom approaches by analysing multiple plausible representations of the future and establishing a suitable robustness measure to uncertainty; however it was not clear how the local assessment method itself impacted on the differing solutions produced in regard to alternative methods, nor is it clear as to the impact attributed to the origin of the IG analysis.

Examples of the application of RO in the development of long-term water management strategies can be found in Kwakkel et al. (2014), Giuliani et al. (2014), Herman et al. (2014), Kang and Lansey (2013) and Beh et al. (2015b) and for adaptive policymaking in Hamarat et al. (2012). Within this research it was found that RO could handle complex, deeply uncertain problems with large numbers of possible solutions. It was also able to derive candidate strategies of more precise sequencing over the planning horizon than more traditional approaches.

This study presents a novel *area*-based method for IG robustness modelling. The *area*-based methodology is designed to improve the IG robustness search process for handling uncertainties based on discrete scenario projections that are not monotonically increasing. Incrementally sampling uncertainties in proportional increases across all uncertain variables leads to a number of scenario combinations being ignored (Matrosov et al. 2013). The *area*-based method advances this by assessing all potential scenario combinations within each incrementally expanding robustness analysis (see section 2.5). Furthermore the applicability of utilising the Future Flow climate change projections (Prudhomme et al. 2012) in scenario generation for water resource adaptation planning is demonstrated.

2 Methodology

First the general WRM problem is described followed by the concepts of risk, robustness, strategies and costs before giving a brief description of the two decision making methods under review. The case study is then outlined followed by results and discussion exploring the performance of each method and evaluating the varying concepts of robustness.

2.1 Water Resource Management Problem

The WRM problem is defined here as the long-term water resources planning problem of supply meeting future demand. The aim is to, for a given long-term planning horizon, determine the best adaptation strategy (i.e. set of interventions scheduled across the planning horizon) that are required to upgrade the existing regional WRM system that will satisfy the multiple objectives of maximising the robustness of future water supply whilst minimising the total cost of interventions required. Robustness of water supply (see section 2.3) is evaluated across a number of different, pre-defined supply and demand scenarios which are used to represent uncertain future climate change and population growth. The above problem is solved by using the two different decision making methods, each with its specific implementation. The results obtained by using the different decision making methods are compared after all solutions are re-evaluated using the definitions of risk, robustness and costs outlined below.

A water resource network model has been developed that simulates, using a daily time step, the supply and demand balance of a regional water supply system over a pre-established time horizon. Different future scenarios and adaptation strategies can be input to the system, analysing the performance of each system combination via risk of water deficit results. The simulation model is written in the Python programming language, and scenarios and strategies can either be input manually or selected automatically using an optimisation algorithm (see section 2.5).

2.2 Risk of a Water Deficit

The failure of the WRM system is defined here as water supply not meeting the demand required. The risk of water deficit (R_d) is defined in Eq. (1) in the likelihood x magnitude form:

$$R_d = \left(\frac{\sum_{j=1}^{N_j} d_j}{T}\right) \times \sum_{j=1}^{N_j} \Delta V_j \tag{1}$$

Where: (d_j) = a day with a water deficit; (T) = the total number of days in the planning horizon; (ΔV) = the volume of a water deficit recorded in day j (Ml); (j) = the time step index and (N_j) = the total number of timesteps in the planning horizon.

The circumstances that entail a 'water deficit' occurring are dependent on the system under study. For instance, in the case study to follow (section 3) a deficit day is counted if the water in the main reservoir falls below an unacceptable (threshold) level. This is allowed to occur occasionally so far as the likelihood and magnitude of occurrence (calculated above as a single risk-based metric) does not exceed a desired target level of system performance (r_c). The risk level of the system must remain at or below this level ($i.e. R_d \leq r_c$) for the system to be deemed as performing acceptably under a given future scenario.

2.3 Robustness of Water Supply

Robustness is commonly described in WRM literature as the degree to which a water supply system performs at a satisfactory level across a broad range of plausible future conditions (Groves et al. 2008). Robustness of long-term water supply is defined here as the fraction (i.e.

percentage) of future supply and demand scenarios that result in an acceptable system performance (Paton et al. 2014a; 2014b; Beh et al. 2015b), i.e. as follows:

$$Rob = \left({}^{S}\!/_{U} \right) \tag{2}$$

Where: (S) = the number of scenarios in which the system performs at an acceptable level of risk and (U) = the total number of scenario combinations (of supply and demand) considered. For example, if 90 (S) out of 100 (U) scenarios are deemed to have been met acceptably then the robustness of the water supply is 0.9, i.e. 90%. The acceptable performance level is defined as a risk of water deficit [see Eq. (1)] being below the target level of risk which is pre-specified for the duration of the long-term planning horizon.

2.4 Adaptation Strategies

Different adaptation strategies (q) can be produced by employing different combinations of various water resource options (intervention options) arranged over a long-term planning horizon. The total costs of strategies in the form of Net Present Values (NPVs) are derived using Eq. (3).

$$NPV_q = \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} \left[\frac{C_i}{(1+r)^{(j-1)dt}} + \frac{O_{ij}dt}{(1+r)^{(j-1)dt}} \right] \tag{3}$$

Where: (i) = the intervention option index, (N_i) = the total number of intervention options in the strategy (C_i) = the estimated capital cost of intervention option i (£M), (O_i) = the estimated operation cost of intervention option i (£M/yr), (r) = the annual discount rate (a rate of 0.03 selected for this investigation), (j) = the time step index, (dt) = the timestep duration (years) and (N_j) = total number of timesteps in the planning horizon.

2.5 Decision Making Methods

Info-Gap Decision Theory (IG)

Info-Gap (IG) decision theory is a non-probabilistic decision theory that seeks to optimise robustness to failure, or opportunity for windfall success, under deep (or "severe") uncertainty (Ben-Haim 2001). IG favours robustness of *satisficing* in its approach to decision making. A strategy of *satisficing* robustness can be described as one that will satisfy the minimum performance requirements (performing adequately rather than optimally) over a wide range of potential scenarios even under future conditions that deviate from the best estimate (Ben-Haim 2001; 2010). This concept of satisficing minimum requirements is similar to that of setting constraints in Robust Optimisation, however IG evaluates the robustness of an adaptation strategy as the greatest level of localised uncertainty that can be negotiated while maintaining these specified performance requirements (Hipel and Ben-Haim 1999). The Info-Gap robustness function, Eq. (4), expresses the robustness to uncertainty ($\hat{\alpha}$) of an adaptation strategy (q) as the <u>max</u>imum horizon of uncertainty (α) explored over a range of potential future scenarios of supply and demand ($u \in U$), for which the <u>max</u>imum risk of water deficit (R_d) occurring [calculated using Eq. (1)] rises no greater than the target level of water deficit risk (r_c), i.e. minimal risk requirements are always satisfied (Ben-Haim 2006):

$$\hat{\alpha}(q, r_c) = \max\left\{\alpha\colon \left(\max_{u \epsilon U(\alpha,\tilde{u})} R_d(q,u)\right) \leq r_c\right\} \qquad (4)$$

Where (u) = an individual discrete scenario combination (of supply and demand) and (U) = the total range (number) of scenario combinations considered. The Info-Gap robustness analysis begins from a "most likely" scenario combination ($\tilde{u}$) before expanding the analysis out over widening uncertain parameters (α). Fig. 1 gives a diagrammatic representation of the Info-Gap assessment exploring two uncertain vectors (supply (*U1*) and demand (*U2*)) until the target (unacceptable) level of system performance is exceeded (r_c). Opportuneness is also displayed, calculated as the shortest distance of uncertainty traversed to reach a highly desirable outcome (r_w).

A novel *area*-based method for IG robustness modelling of uncertain future supply and demand scenarios is presented in Fig. 2. This method is introduced in order to directly utilise the discrete Future Flow scenario projections (Prudhomme et al. 2012) within the IG analysis which traditionally uses continuous uncertainty variables. Each flow projection is highly variable, thus defining each horizon expansion as a function of increasing *distance* (α) cannot easily be established. The *area*-based method (Fig. 2) aims to solve this issue by first ordering the scenarios (both supply and demand) by their rank of severity (see section 3.2). A "most likely" scenario combination $(\tilde{u})$ is selected; however, the IG analysis now expands out over all adjacently ranked scenarios (the next higher and lower ranked scenarios of supply and demand) in an asymmetric search pattern until no more immediate adjacent scenarios satisfy (r_c) (Fig. 2). This robustness search technique allows more scenario combinations to be analysed and allows the robustness search to continue until all scenario expansion routes end in system failure. This calculates the expanding horizon of uncertainty (α) as a function of total *area* rather than as a function of maximum *distance* (Fig. 3) and the IG robustness level is calculated as a sum of all successful (α') deviations (total no. of local scenarios (u) satisfied):

$$\hat{\alpha}(q, r_c) = \sum_{u=\tilde{u}}^{U} \alpha' \left\{\alpha: \left(\max_{u \epsilon U(\alpha,\tilde{u})} R_d(q,u)\right) \leq r_c \right\} \quad (5)$$

In order to later compare the IG results with those of the RO assessment you then calculate the overall robustness to uncertainty as a percentage over all futures scenarios considered using Eq. (2), where $(\hat{\alpha} = S)$.

The severity ranking of demand scenarios is straightforward as they are typically projected in a severity order. However the supply scenario ranking and ordering can be performed in a number of ways. For this methodology each supply scenario is tested on the baseline historical water supply system configuration, with the level of system risk calculated and used to assign relative severity ranks to the scenarios.

The selection of an appropriate starting point ($\tilde{u}$) within a theoretically unbounded region of uncertainty is a highly debated subject (Sniedovich 2007; 2012). For this analysis the median scenarios of supply and demand (following rankings as stated above) are selected for the primary IG run (defined as U_{mid}). However, positions in the upper and lower quartile of scenario severity (defined as U_{high} and U_{low} respectively) are also tested in order to quantify the sensitivity of the ($\tilde{u}$) selection. The number of start points selected for examination is deemed appropriate given the complexity of the case study and range of uncertainty examined. The range in supply and demand uncertainty is selected with great care and by considering a wide array of different data/information sources to produce a range of genuinely likely scenarios, as advised by Sniedovich (2007), detailed fully in section 3.2.

Robust Optimisation (RO)

Robust Optimisation (RO) involves the application of appropriate optimisation algorithms to solve problems in which a specific measure of robustness is sought against uncertainty (Ben-Tal et al. 2009; see Eq. (2) for the defintion used here). Optimisation can be defined as trying to find the best solution amongst a set of possible alternatives without violating certain constraints (Walker et al. 2013b). It is mostly employed to identify a single best estimate solution to a single objective problem (Bai et al. 1997). However, when dealing with multi-objectives and deep uncertainties this predictive approach cannot be used, since often a theoretically “optimum” solution does not exist (Bankes 2011; Rosenhead et al. 1973). RO can overcome this difficulty by finding the best solutions as a set of global Pareto-optimal robust solutions across the full horizon of uncertainty (Coello 1999; Deb and Gupta 2006), leaving trade-offs among the various objectives out of the optimisation process and in the hands of the final decision maker (Ben-Tal and Nemirovski 1998; 2000; Bertsimas and Sim 2004). Although this approach is also not without its drawbacks, i.e. when deliberating on final trade-offs, as discussed by Beh et al. (2015b); however methods exist to aid the final decision process, such as value path plots (Geoffrion et al. 1972) and visual analytics (Reed and Kollat 2013). A detailed review of different aspects of optimisation within the WRM context can be found in Maier et al. (2014).

A wide range of optimisation techniques are available for RO including, but not limited to: Genetic Algorithms (Deb and Pratap 2002; Kollat and Reed 2006), Particle Swarm Optimisation (Zarghami and Hajykazemian 2013), Ant Colony Optimisation (Dorigo et al., 1996), Shuffled Frog Leaping Algorithms (Eusuff and Lansey 2003), Generalised Reduced Gradient Algorithms (Frank and Wolfe 1956), Linear Programing Techniques (Borgwardt 1987) or combined process approaches such as Many-Objective Visual Analytics (Fu et al. 2013), Many-Objective Robust Decision Making (MORDM) (Herman et al. 2014) or Borg Multi-Objective Evolutionary Algorithms (MOEA) (Hadka and Reed 2012).

For this WRM problem, the objective functions are the minimisation of cost [Eq. (3)] and maximisation of robustness [Eq. (2)]. The optimising algorithm selected for this study is the NSGAII, as its high performance and capabilities in handling multi-objective problems is well documented (Deb and Pratap 2002; Kollat and Reed 2006; Nicklow et al. 2009).

The WRM daily time-step supply and demand simulation model (see section 2.1) is combined with the NSGAII optimisation algorithm, set-up using the R-programming language.

The algorithm requires three main data inputs; a pool of potential new intervention options (see section 3.2) from which to form combinations of new adaptation strategies, and the range of potential supply and demand scenarios. The NSGAII algorithm automatically forms a population of strategies and analyses their performance across all scenario combinations of supply and demand in the simulation model to the two objectives of cost and robustness. The best performing strategies are then carried forward, mutated at random (based on selected probabilities) and then re-analysed over several generations, with the aim of ultimately identifying the Pareto set of results for robustness vs cost, where all non-dominated strategy results are discovered. The parameters used for the RO analysis are listed in section 3.2 and further explanation of the NSGAII operation can be found in Deb and Pratap (2002).

RO differs in its robustness analysis to IG in that it has been set up to assess the 'global' robustness of a strategy rather than performing a 'local' robustness examination. It tests a strategy's performance over all potential scenario combinations when calculating robustness [Eq. (2)] rather than isolating a most likely scenario and performing a localised examination.

3 Case Study

This section aims to compare the contrasting mechanisms and outputs of two DMMs analysed (Info-Gap and Robust Optimisation) on a real world WRM case study of the Sussex North Water Resource Zone in the UK. It also assesses the applicability of using the Future Flows climate change projections in supply scenario generation for water resource adaptation planning.

3.1 Case Study Description

IG and RO are applied to a case study of Southern Water's Sussex North Water Resource Zone (SNWRZ) shown in Fig. 4, a region in the South East of England that was listed as a region under “a serious level of water stress” (Environment Agency 2007). The existing water resources for the SNWRZ system are shown in Fig. 4 and listed in Table 1.

Water from all sources is treated at the Hardham Water Treatment Works (WTW). The minimum deployable output (MDO), which defines the water resource availability at the point at which it is most physically constrained and typically occurs in early autumn before the onset of winter recharge, is used to define the availability of new resource options (Southern Water 2009; 2014). The priority order for abstraction of each resource (shown in Table 1) is based directly on the SNWRZ system order (Southern Water 2009). On each daily time step of the simulation model – river abstraction occurs first and reservoir abstraction last in order to meet the required demand. This allows the reservoir resource to remain as reserve storage until required (e.g. when demand levels are high or river flow levels are low). The aim of the WRM problem analysed here is to, for a given long-term planning horizon, determine the best adaptation strategy(ies) to upgrade the existing regional WRM system that will *maximise* the robustness of future water supply whilst *minimising* the total cost of interventions required [as defined in Eq. (2) and (3)].

3.2 Case Study Set-Up

The water resource simulation model (described in section 2.1) is set up for the Sussex North Water Resource Zone to simulate the daily supply-demand balance of the water system over a 50 year planning horizon. A 50 year planning horizon has been selected to incorporate more climate change and demand uncertainty over time than a typical 25 year UK water company planning horizon.

Adaptation Strategies

A list of new potential water supply resources for the Sussex North Water Resource Zone was taken from Southern Water’s WRMP ‘feasible’ options list (Southern Water 2009). This included the range of options derived from the final phase (Phase 3) of resource investigation and appraisal carried out by Atkins (2007). This created a pool of potential intervention options (see Table 2), from which adaptation strategies can be formed by implementing different combinations of the new supply options, arranged over the 50 year planning horizon. The planning horizon is further sub-divided into 10 year construction periods, producing five potential operational start points for each option within a strategy. This is to reduce the number of potential combinations of strategies, allowing swifter optimisation and easier pre-selection of strategies for the application of IG theory.

The total cost of a strategy is calculated using the Net Present Value (NPV) approach shown in Eq. (3). The variation in water treatment costs of each individual resource option are included in the calculation of projected operational costs; however the uncertainties in changing water resource quality and the changing operational costs of individual options over time are not incorporated in this investigation due to low available data on these aspects. It should be noted that energy and water treatment costs are also highly variable and liable to change over time, but these uncertainties are beyond the scope of this investigation. The intervention options in Table 2 include the list of potential new 'supply' additions to the system. Demand side options are also important considerations for addressing the supply-demand balance. However, due to the Sussex North Water Resource Zone being classified as a "serious water stress area" (Environment Agency 2007), compulsory Universal Metering (UM) of all properties has already been initiated and a set leakage program is underway, therefore further demand side options are not included as potential intervention options in this analysis. New resource options (Table 2) are implemented in the simulation model between existing supply resources 3 and 4 (Table 1). This allows reserve groundwater and stored water at Weir Wood reservoir to remain as storage until required.

Supply Scenarios

There are various state-of-the art methods for producing scenarios to represent alternative plausible future conditions of a system (Mahmoud et al. 2009). In this analysis the application of using Future Flow scenarios (Prudhomme et al. 2012) to generate future projections for the region's major contributing river flows and reservoir inflows is tested. The Future Flows project utilises the latest projections from the UK Climate Impact Programme (UKCIP) from the Met Office Hadley Centre. They provide 11 plausible realisations (all equally likely) of the river flows at various river gauging stations across England, Wales and Scotland and account for the impact of climate change to 2100 under a Medium emission scenario.

The closest gauging site for Sussex North is at Iping Mill on the river Rother upstream of the Hardham extraction point (see Fig. 4). The flow data required downstream of the gauging station are extrapolated using a monthly flow factoring method (Arnell and Reynard 1996), which perturbs the historic river flow data to match the flow changes projected at the upstream gauge. Flow factors describe the percentage change in monthly average river flows over a 30 year historic period (1961-1990) with those of a 30 year future period at Iping Mill. The limitation of a flow factor approach is that the historical sequencing of drought events is unchanged (Diaz-Nieto and Wilby 2005), such that if a drought event occurs after 10 years historically it would appear in every climate change scenario after 10 years and force a similar pathway of adaptation strategies. In order to test the adaptation strategies against a range of different naturally varying scenarios, the historical flows are resampled (Ledbetter et al. 2012) using 3 month seasonal blocks (Dec-Feb, Mar-May, Jun-Aug and Sep-Nov) to create new realisations of historical climate. In order to then impose the transient climate change signal of the Future Flows scenario within the resampled historical sequences a rolling flow factor method is devised to produce factors for each year of 2015-2064. For example, to create flow factors for 2015 a future flow period from 2000-2029 is compared with the 1961-1990 baseline, for 2016 the future averaging period is advanced a single year to 2001-2030. The flow factors are then used to perturb the historic resampled river flow data at Hardham (Fig. 4) to provide 72 discrete supply scenarios. The same flow factors were used to perturb the inflows to Weir Wood reservoir and flows in the River Arun to ensure the system is modelling the same patterns of weather and climate change throughout the system at the same time. As the likelihoods of the different scenarios is not quantifiable the supply uncertainty is classified as “deep” (Walker et al. 2013a). However, IG theory still requires the selection of a “most likely” scenario starting point for the analysis despite the deep uncertainties. The selection of these starting points is detailed in section 2.5 and evaluated in Section 4.

The reliability of future groundwater and imported water from the Portsmouth region are not projected to be significantly impacted upon by the regions climate change projections so their current MDO values are taken as consistent daily inputs to supply over the full planning horizon (Southern Water 2009).

Demand Scenarios

Demand Scenarios for the Sussex North region have been produced using data from Southern Waters WRMP 2010-35 (Southern Water 2009), which includes data to 2035 that is then extrapolated to 2060 using the same rate of change increases as those within the 2030-2035 data. They consist of 4 scenarios based on varying success levels following the enforced introduction of Universal Metering in the region (see Table 3). This requires full metering of all properties and non-household businesses by 2015 and the scenarios illustrate the projected effect of this introduction from a pessimistic demand increase to more optimistic results and also include scenarios of low leakage increases and high leakage increases following the implementation of the regional leakage program (Southern Water 2009).

The annual demand projections (in 5 year intervals) given in Table 3 are interpolated to produce yearly average demands. The annual average demand is then multiplied by monthly factors to reflect the changing seasonal demand averages employed by Southern Water (2009; 2014). These values are then used to create four 50 year daily time-step demand scenarios.

Acceptable System Performance Level

Each adaptation strategy that is tested in the simulation model over a given future scenario combination of supply and demand projections will result in a specific risk of a water deficit value [Eq. (1)]. For the SNWRZ this risk level (as described in section 2.2) is calculated once all supply sources have been maximised, with the system entering a 'water deficit' when the last source, Weir Wood reservoir reaches a threshold level of 1155Ml (Southern Water 2009). The likelihood and magnitude of occurrences [calculated as a single risk metric, Eq. (1)] must not exceed a target level of system performance (r_c). This target level of system performance has been determined by calculating the risk of a water deficit occurring over the previous 50 years of historic data. As the system has been deemed acceptable by customers over this period (Southern Water 2009), maintaining the system at its current level of historic risk is considered as acceptable system performance. The existing system, when tested in the simulation model with historic flows/in-flows, recorded 20 days of water deficits over the 50 year period (18263 days) and registered a total combined water deficit of 388Ml. Applying Eq. (1), this resulted in the target level of system risk (r_c) of 0.425.

Decision Making Methods Application

The following final parameters were selected for the RO NSGAII algorithm following testing of numerous combinations for optimal optimisation: population size (200); no. of generations: (500); selection bit tournament size (2); mutation probability (per gene – 0.2); crossover probability (single point – 0.7). Adaptation strategy generation, testing, ranking, mutation and ultimate Pareto strategy identification is an automatic process carried out by the NSGAII algorithm during the RO procedure after 500 generation assessments.

For IG, multiple adaptation strategies are manually pre-specified from the range of potential option combinations and evaluated using the IG robustness model created. Either a subset of preferred strategies can be selected by the user or several thousand strategy combinations generated either using complete enumeration (generate all possible combinations) or using random generation (generate a specified number of combinations at random). The latter was carried out for this analysis using a random generation tool created in Python (as complete enumeration yielded too many combinations for feasible computation testing). The scenario generation tool created 28,000 individual adaptation strategies (of different intervention option combinations and varying sequencing of the options across the time horizon). Each strategy is then evaluated using the IG robustness model. The resulting strategy robustness vs cost results are then ranked to identify a set of IG Pareto strategies. This is a non-traditional step in the IG process; however it allows for easier comparing of the two DMM results.

4 Results and Discussion

For each DMM the 72 supply and 4 demand scenarios (i.e. a total of 288 possible scenarios) were modelled with the adaptation strategies, leading to the identification of Pareto optimal sets for both decision making methods (RO and IG-U_{mid}), trading-off the robustness of water supply and the NPV of total cost (see Fig. 5).

As it can be seen from Fig. 5, when compared to RO, the IG method produces higher-cost Pareto strategies for all robustness levels. The distribution of Pareto strategies across the range of robustness is also lower for the IG analysis, with no Pareto strategies recorded between 20-60% robustness levels. The reason for both occurrences is due to the IG's local robustness analysis and the method of ordering the scenarios. Examining the uncertainty region from a local point outwards requires multiple-adjacent scenarios to be satisfied in order for the robustness search to continue. This leads to more stringent localised target risk requirements than those placed on global robustness. As the analysis expands outward in an area calculation of satisficing scenarios, occasionally imperfectly ordered scenarios can lead to isolated regions of much higher requirements, which can pre-maturely end the robustness analysis. The reason for this is that several scenarios beyond these regions may have been satisfied by a strategy had they been reached. Fig. 6 depicts a simplified example of this 'blocking' effect using two example scenarios.

The scenario profiles illustrate the changing water deficit levels projected on the current water system over time. Scenario 2 is calculated as having the higher risk of water deficit value (R_d), so is ranked and ordered as more severe than scenario 1. When example strategy A is tested over scenario 1, system performance is classed unsatisfactory since scenario 1's greatest deficit period occurs early in the planning horizon and is not being met by strategy A's adaptation strategy. However, it would have satisfied scenario 2, but this scenario is not examined as the IG assessment is stopped following failure to satisfy Scenario 1. Consequently IG theory would favour strategy B as it provides sufficient additional water to the system to satisfy both scenarios, but has a trade off as being the more expensive strategy. RO's global assessment incorporates each successful scenario (e.g. Scenario 2 for Strategy A) in the robustness calculation regardless of severity ordering and so can more easily satisfy target robustness levels.

Fig. 6 highlights the difficulty in ordering discrete scenarios into a range of severity, when the individual scenarios are so variable and complex in their constituent parts (i.e. including 50 year river flow sequences). This presents a potential weakness of utilising an ensemble of discrete projections for scenario generation with the IG method. Matrosov et al. (2013) tackled this issue by using continuous variables of monthly perturbation factors that diverged out from their median flow factor set at structured intervals whereas. Hall et al. (2012b) adopted an ellipsoid uncertainty model combined with an interval-bounded model to uniformly scale the uncertainty. These approaches were not applied in this case study as the purpose was to test the applicability of using Future Flow scenarios (Prudhomme et al. 2012).

The IG results (Fig. 5) also indicate that a strategy of do nothing (spending 0 million) produces a 0% robust system and a sharp increase (spending over 60 million) is required to gain just a 2% robust system. This is due to the IG analysis using the median severity scenarios of supply and demand as a starting point, placing numerous hard to satisfy scenarios in direct proximity to the starting location. However, it could be argued that a solution of low robustness is not desirable so only the solutions of higher robustness (i.e. the IG results >60% robustness on Fig. 5) are significant to the final decision maker.

Fig. 7 presents the breakdown of intervention options within all the Pareto strategies ranked above 60% robustness for both RO and IG methods. It shows the percentage of Pareto strategies that feature each option (a), including graphs showing the year of construction of each option as a percentage of occurrences (b).

It highlights several interventions as being the most cost effective options following their inclusion in all the Pareto strategies (e.g. option H – a new river Arun abstraction point including a small scale storage reservoir; and option I – a new pipeline for transfer of excess winter water to refill Weir Wood reservoir). The main difference between the IG and RO Pareto strategies is IG's regularly selection of a large new reservoir (option A) to be constructed early in the planning horizon (2015) to increase overall system robustness (explained previously via Fig. 6.) whereas RO repeatedly selects option B (an effluent re-use scheme) early in the planning horizon (providing less water than option A but for less initial cost earlier in the planning horizon) before additionally adding options G and/or F (Aquifer storage and a new abstraction point on the river Adur) later in the planning horizon to increase water supply as more frequent deficit periods are projected over time.

The adaptation strategy's generation process, using samples rather than full enumeration for IG, did not contribute to a difference in the Pareto strategies identified as significantly as expected, although RO was able to identify several strategies that were not among the pre-specified set used in the IG analysis. The low impact of the strategy generation process is likely due to this case study's relatively small pool of intervention options examined and using a planning horizon segmented into 10 year construction periods. It is expected that a more complex case study with a larger pool of potential options will lead to more variation in the final Pareto strategies identified – this is an aspect for further investigation.

Fig. 8 presents the Pareto strategies selected by the IG robustness analysis following variation of the initial starting point of the robustness analysis ($U_{mid,}$ U_{high} and U_{low} in the scenario severity index). It reveals that the variation of start point did not alter the final Pareto strategies identified significantly, as can be seen by the largely overlapping IG Pareto fronts. The main variation can be seen in the strategies identified below 50% robustness, where lower costing strategies are more readily identified by U_{low}. This is because the larger robustness areas will encompass all the starting points regardless of their location within the region of uncertainty; however strategies of lower robustness will be identified at a more cost effective rate from a lower severity start point. This also implies that the starting point becomes more impacting the larger the uncertainty region becomes.

Southern Water's current water resource adaptation plan for the Sussex North WRZ (Southern Water 2009; 2014) includes option H (a new river Arun abstraction point including a small scale storage reservoir) which has been constructed and is now in use as of 2015, as well as plans for Options I (new pipeline to refill Weir Wood reservoir), G (aquifer storage) and B (the effluent re-use scheme) scheduled for 2018, 2020 and 2026 respectively. These options were also frequently selected within the DMM Pareto strategies however the overall plans differ, as both IG and RO produced Pareto strategies recommending more water to be added to the system earlier in the planning horizon to ensure higher levels of overall system robustness. Although this may seem an obvious statement qualitatively the DMMs provide quantitative information as to *how much more water* and *where* and *when* it needs to be added to the existing system to achieve a specific level of robustness. The larger initial resource options recommended also highlight the effect of examining multiple scenarios rather than planning to a single projection of supply and demand. The current UK industry planning methods assume a linear scaling of climate change between present day and the end of the planning horizon (Environment Agency et al. 2012) that ignores the variability from droughts, which these methods explicitly capture in this study. Therefore, by varying climate change and droughts you naturally plan for a wider range of robustness. It could also be argued that current methods do not evaluate for robustness given they typically only use central deterministic scenarios. The 5 year cycle of water company WRMPs also means that large investments are typically deferred whilst low impact, low costs measures are implemented, as it is very hard to get large infrastructure development past the regulators. The more substantial resources recommended early in the planning horizon by both DMMs highlight these potential issues in current practice. The results could also be linked with the longer planning horizon considered in this assessment, whereby higher initial costs are traded for greater long term system robustness – an aspect for further investigation. The selection of the most suitable risk-based (or resilience-based (DEFRA 2013)) metric as well as an appropriate selection of target system performance, are also likely to heavily influence the final Pareto strategies obtained.

Computational aspects of the methods (complexity and time) have not been examined in detail in this study as the computational setup is considered very specific to this case study. Further case study assessments would better reveal the computation strengths and weaknesses of each method.

5 Conclusions

This paper provides a comparison of two DMMs for integrated water resource management under deep uncertainty. The Robust Optimisation and Info-Gap methods were applied and compared on the case study of Sussex North Water Resource Zone in the UK with the aim to solve a specific WRM problem driven by the maximization of robustness of long-term water supply and minimisation of associated costs of adaptation strategies, all under a range of uncertain future supply/demand scenarios. The results obtained lead to the following key conclusions:

1. The two DMMs analysed produced different Pareto adaptation strategy recommendations to each other and to the strategies derived using the current UK engineering practice.
2. Robust Optimisation generally produced lower costing Pareto strategies than IG for all ranges of desired system robustness due to RO's less stringent method of global analysis.
3. Info-Gap's local analysis proved problematic to construct and assess using discrete scenarios and likely contributed to the higher costing strategy recommendations.
4. Optimisation, although not applied to the IG methodology here is likely to be required at some stage of planning when dealing with larger data sets and a larger pool of potential intervention options.
5. The location of the starting points of the IG analysis did not significantly alter the Pareto strategy results obtained, especially at higher robustness levels. However this could be associated to case study complexity and should be examined on more complex case studies to further explore this pivotal aspect of the theory
6. The variation in the Pareto strategies derived highlight how the current industry standard for water supply system adaptation planning could benefit by applying a wider range of decision methodologies and assessment tools (especially those that quantify a level of system 'robustness') as well as a more encompassing investigation into potential future uncertainties and alternative methods for scenario generation.

It is recommended that further analysis of IG and RO methods be undertaken on more complex case studies, utilising a larger pool of intervention options and a greater number of scenario projections, as well as consideration of additional planning objectives and uncertainties, before above conclusions could be generalised, including computational conclusions on the DMMs. Additionally the metrics of system risk are likely to influence the evaluation of adaptation strategies and the comparison between DMMs. Further work should be considered to assess the impact of re-defining risk and target system performance in terms such as reliability, resilience and vulnerability (Hashimoto et al. 1982; Yazdani et al. 2011); leading to the potential development of a novel DM framework for complex WRM planning under uncertainty, that may utilise (perhaps hybridize) features from a range of DMMs with the aim to exploit advantages and minimise disadvantages of existing methods (e.g. using optimisation to select and test more strategy combinations, combined with new vulnerability map or scenario discovery methodologies (e.g. Singh et al. 2014) with objectives set up to examine the trade-offs between robust and flexible solutions across multiple-objectives). The flexibility of solutions is another aspect not explored within the approaches presented here. In practice evaluating only fixed rather than adaptable strategies limits the range of potential long-term trade-offs explored. This limitation can be overcome by combining these DMMs with modern approaches such as Real Options (Jeuland and Whittington 2014), Adaptive Pathways (Kwakkel et al. 2014) or Adaptive Multi-Objective Optimal Sequencing (Beh et al. 2015b).

Acknowledgments

This work was financially supported by the UK Engineering and Physical Sciences Research Council, HR Wallingford and The University of Exeter through the STREAM Industrial Doctorate Centre. The authors are grateful to Dr Steven Wade, now at the Met Office, and Chris Counsell of HR Wallingford for providing data for the Sussex North case study.

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Tables

Table 1. SNWRZ existing water resources

Resource Abstraction Priority	Resource Description	Minimum Deployable Output (MDO) In Ml/d	Projected by Southern Water to be Affected by Climate Change?
1	River Rother/Arun Abstraction	40[a]	Significantly
2	Groundwater Sources	11.05[b]	Not significantly
3	Portsmouth Water Import	15[b]	Not significantly
4	Reserve Groundwater at Hardham	36.96	Not significantly
5	Weir Wood Reservoir Storage	21.82	Significantly

[a]Dependent on minimum residual flows in the river Rother (MRFs)
[b]Set at a constant value

Table 2. New water resource supply options available for the SNWRZ

Option	Resource Option Description	Minimum Deployable Output (Ml/d)	Estimated Capital Costs (£M) (2015)	Estimated Annual Operational Costs (£M/yr) (2015)
A	Surface storage reservoir with combined river Rother/Arun feed	26	47.8	0.21
B	Effluent re-use Scheme- MBR at Ford WWTW	19	36.7	0.16
C	Tidal river Arun desalination plant- 20Ml/d	20	34.6	0.34
D	Tidal river Arun desalination plant - 10Ml/d	10	24	0.27
E	Hardham WTW winter transfer to coast	4	17.1	0.12
F	River Adur abstraction point	5	11.2	0.07
G	Aquifer storage on the Sussex coast	5	10.8	0.06
H	River Arun abstraction point (below tidal limit) and small storage reservoir	11.5	10.2	0.07
I	Winter Refill of Weir Wood Reservoir	3	3.2	0.02

Table 3. Demand scenarios for the SNWRZ (Ml/d)

	Year Beginning – Average Daily Demand[a] (in Ml/d)									
Scenario Name	2015	2020	2025	2030	2035	2040	2045	2050	2055	2060
UM (pessimistic)	69.7	69.6	69.8	70.4	71.0	71.6	72.3	73.2	74.1	75.2
UM (optimistic)	67.2	67.5	68.2	69.2	70.1	70.9	71.8	72.5	73.2	73.8
UM (low leakage)	67.1	67.3	67.9	68.7	69.4	70.2	70.7	71.3	71.7	71.9
UM (high leakage)	68.7	69.0	69.5	70.1	70.9	71.6	72.6	73.7	75.1	76.7

[a]Demand values are the Dry Year Annual Average (DYAA) levels which are then fluctuated monthly throughout each year based on seasonal demand ratios (Southern Water 2009)

Figures

Fig. 1. Info-Gap robustness and opportuneness models

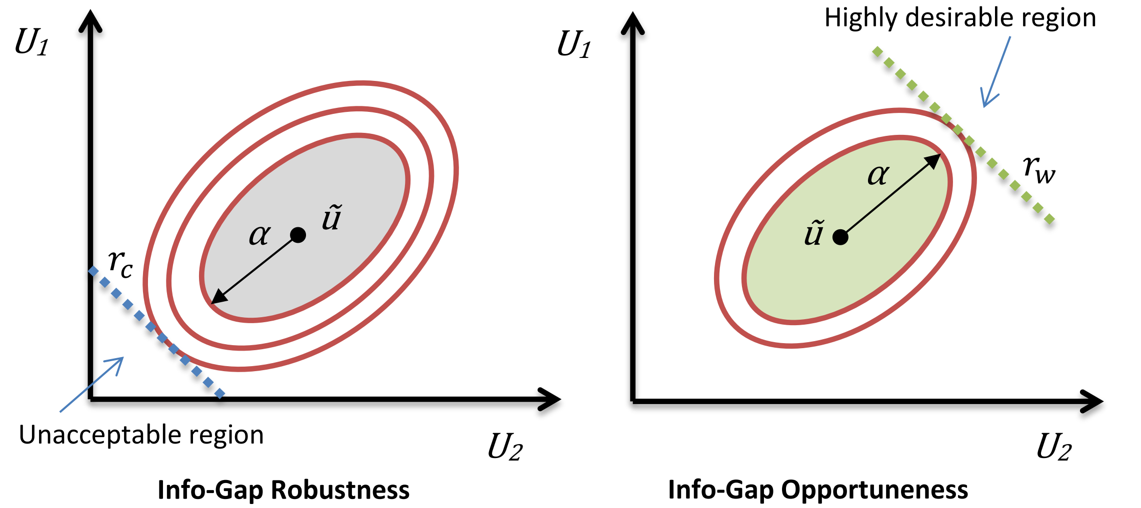

Fig. 2. Info-Gap robustness model – utilising discrete scenario area-based robustness mapping to search the uncertainty region

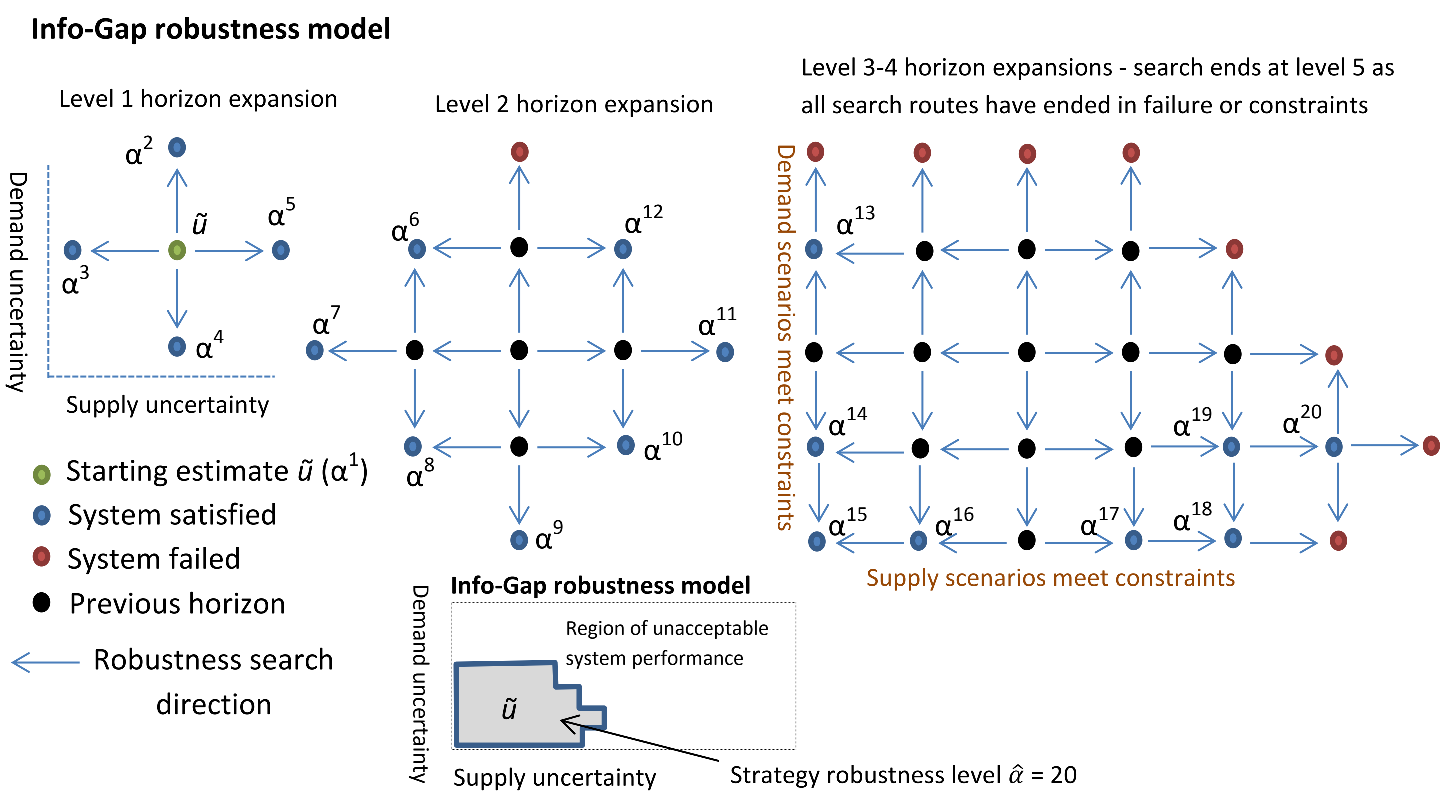

Fig. 3. Example of two adaptation strategies tested using the Info-Gap *area*-based robustness model

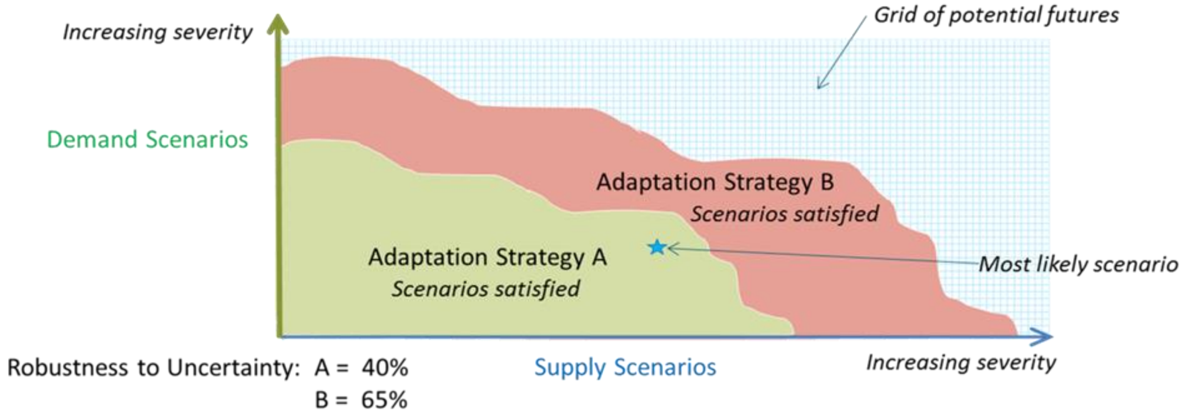

Fig. 4. Southern Water: Sussex North Water Resource Zone (SNWRZ) and surrounding territories – including network schematic. Map from Southern Water's annual report and accounts 2014-15 (Southern Water 2015)

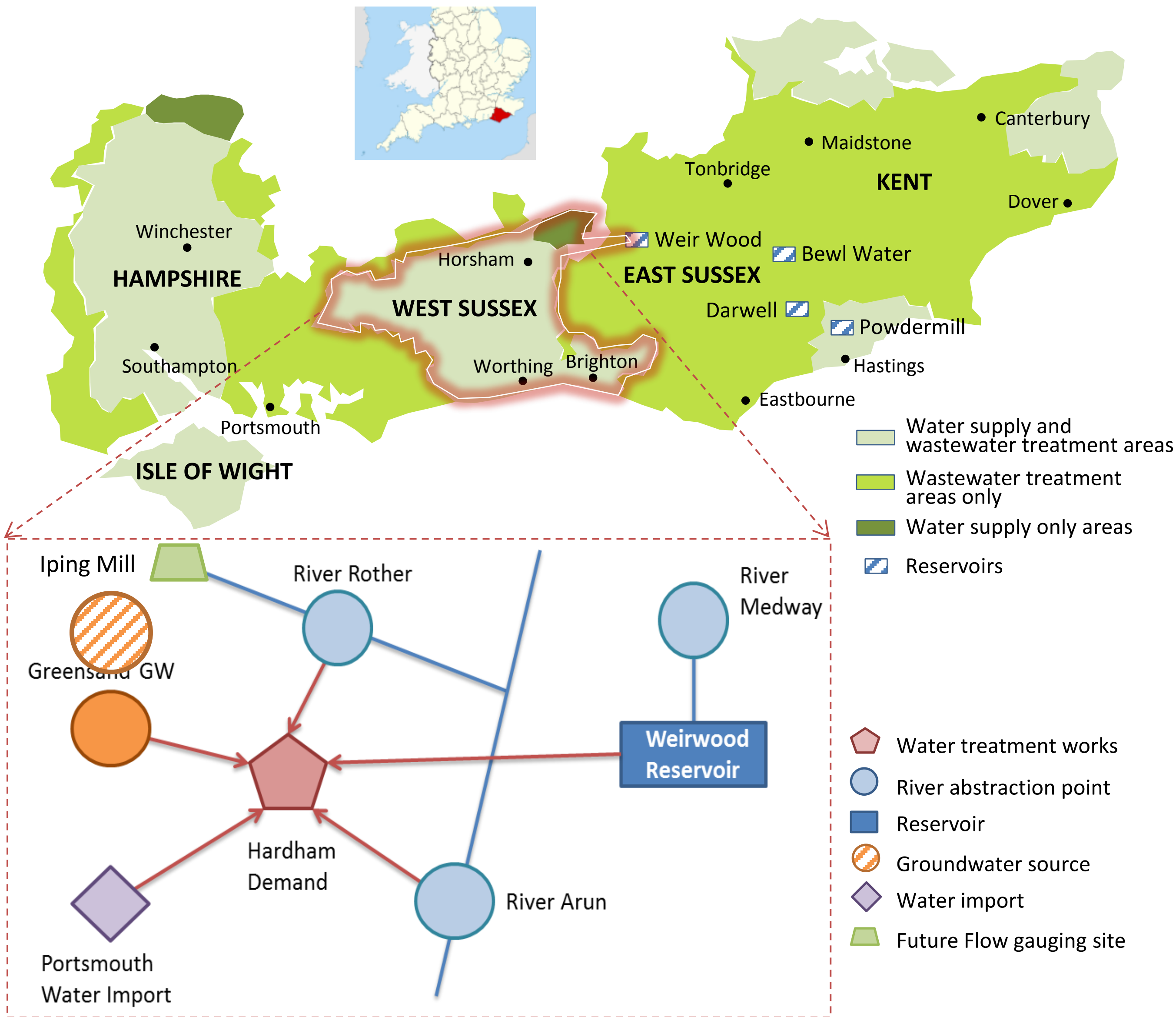

Fig. 5. Pareto sets identified by the Info-Gap and Robust Optimisation methods

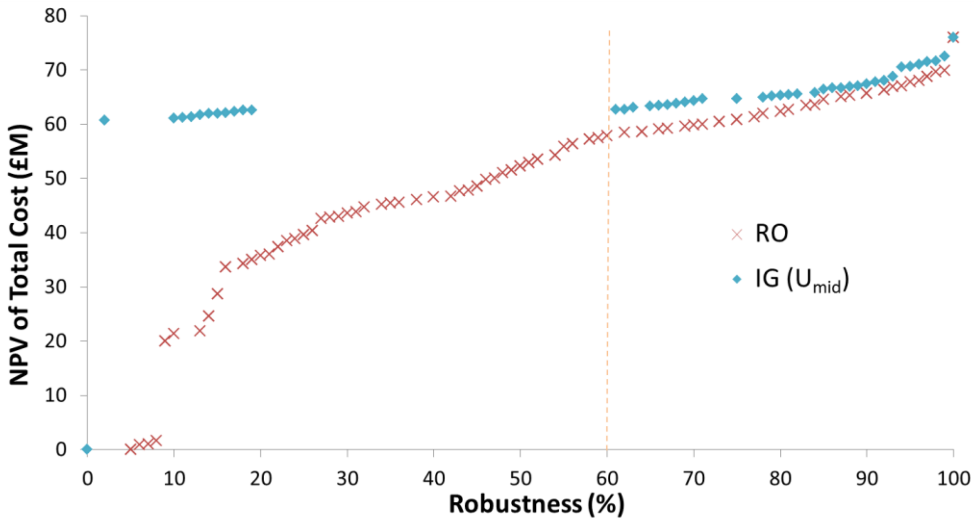

Fig. 6. Example of a scenario ordering arrangement that would prematurely end an Info-Gap robustness search. Explained via two scenario water deficit profiles and the respective water added to the system by two adaptation strategies. Strategy A has not satisfied scenario 1 but would have satisfied scenario 2

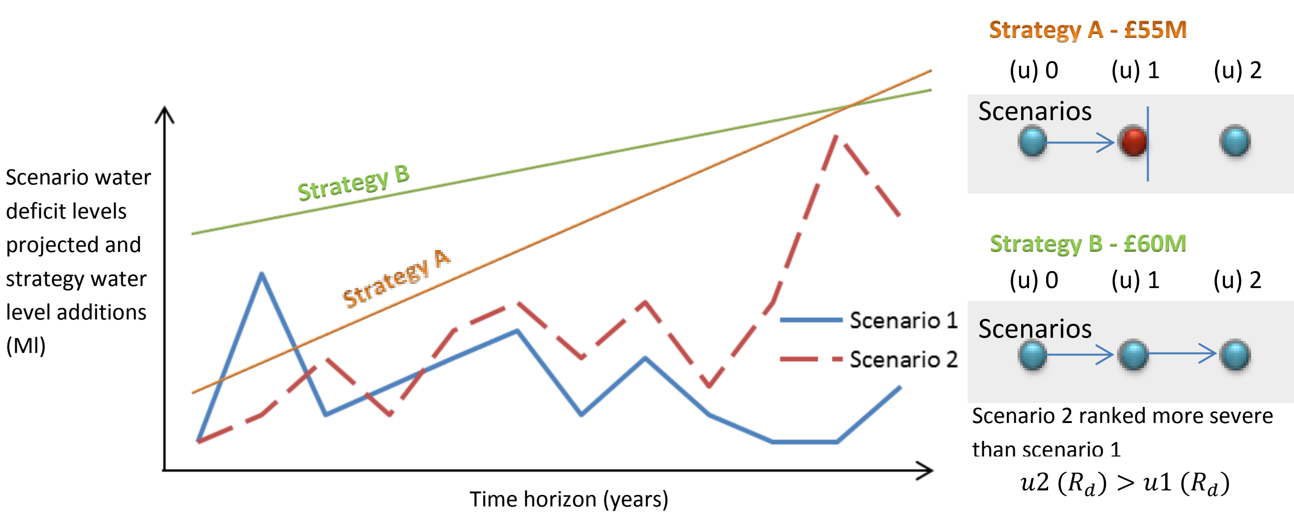

Fig. 7. (a) Individual intervention option components that feature in the Pareto strategies ranked above 60% robustness for Info-Gap and Robust Optimisation methods as a percentage of occurrences, and their year of implementation (b) also as a percentage of occurrences

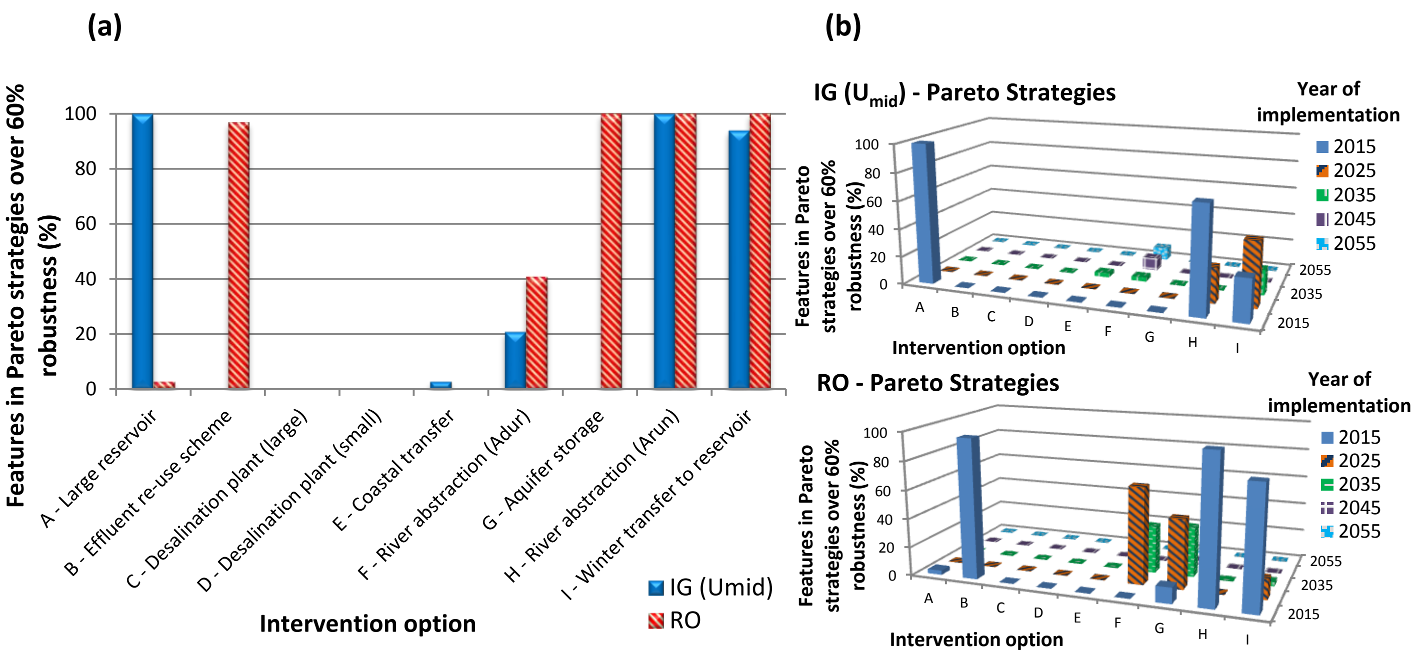

Fig. 8. Pareto strategies identified by Info-Gap following variation of the initial start point of the analysis (denoted as U_{low}, U_{mid} and U_{high})