APPLYING INFO-GAP DECISION THEORY TO WATER SUPPLY SYSTEM PLANNING: APPLICATION TO THE THAMES BASIN

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Abstract

Projected disparities between water supply and potable demand drive infrastructure capacity and water efficiency investments in the water utilities industry to meet demand whilst minimising associated costs and environmental impacts. The uncertainty surrounding many of these projections complicates stochastic modelling. Info-Gap Decision Theory (IGDT) offers decision makers a different approach to infrastructure planning. Here we use this framework to assess the relative performance of 20 supply infrastructure portfolios meant to meet demand in the Thames Basin up to 2035. Rather than planning for an optimal system, IGDT is used to identify the most robust system: the system that can cope with the greatest amount of climate change, demand and energy cost variability whilst maintaining pre-defined reservoir operation, environment and cost performance requirements.

Keywords
Info-Gap, water supply, infrastructure planning, severe uncertainty

1. INTRODUCTION

Water utilities in England and Wales develop Water Resources Management Plan' (WRMPs) to guarantee the supply-demand balance and justify new supply infrastructure, demand management options and infrastructure replacement [1]. WRMPs are completed every 5 years and use a 25 year strategic planning horizon [2].

The uncertainty of variables used in the supply-demand balance (e.g. water availability, unrestricted demand, restricted demand and losses) can be described as deeply uncertain [3], with experts unable to characterise or agree on the probability distributions describing them. Under such conditions it may be better to plan for robustness rather than optimality ([4]. A robust management strategy is one that performs *adequately* under a wide-range of plausible futures [5]. These futures consist of combinations of uncertain projected system parameters (e.g. water availability, population growth and operational costs). This paper applies IGDT to water supply planning in the Thames Basin.

2. DECISION MAKING UNDER UNCERTAINTY

2.1 Introduction to IGDT

IGDT characterises future uncertainty as a series of nested sets defined by the variable $\tilde{u}$ representing our best estimate of the future variable, u. The disparity between u and $\tilde{u}$ is scaled by h, which represents an increment or 'horizon' of uncertainty. This is parameterised such that $h: h \geq 0$. The Info-Gap uncertainty model is constructed as a nested set based on $\tilde{u}$ and h such that $U\ (h, \tilde{u})$. For water resources planning, decision makers may have a range of possible management strategies (q_i) available. At every increment of uncertainty (α - as outlined above and scaled by h) a management option will give a certain level of performance, Π, such that, $\Pi(q_i, h)$.

There is a maximum and minimum level of performance achieved for each management option at each increment of uncertainty (figure 1). For a decision maker, the pertinent question is how much uncertainty (how many of these increments α, scaled by h) can the system absorb whilst still maintaining a minimum level of performance; defined as *robustness* ($\hat{h}$). The inverse of this is *opportuneness* ($\hat{\beta}$); which is the performance improvement achieved when conditions are more benign than our central estimate.

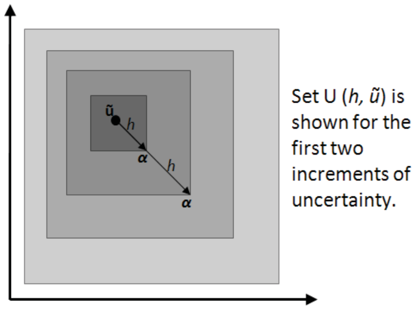

Figure 1. Schematic of an Info-gap uncertainty model

2.2 Thames Application

2.2.1 Hydrological Flows and Climate Change

Hydrological flows are available for the River Thames and River Lee from the late 19th century. These capture significant periods of drought from in the '20s, '30s and '40s in addition to years of high water availability. We use naturalised gauge data from the River Thames at Days Weir and Teddington Weir and the River Lee at Feildes Weir from 1920 [6]. In the absence of stochastically generated flows we assume that any 25 year section of the historical record may occur between now and 2035 subject to climate change perturbation; we utilise the full 85year record in our simulations to reflect this [7].

UKCP09 has produced 10,000 projections for the climate for the 2020s [1]. For each of these projections a different climate change scenario is produced. Here we use the upper, lower and mid scenarios [2] to derive and constrain the Info-Gap uncertainty model used to produce monthly factors to weight the historical flow in River Thames and Lee for climate change.

2.2.2 Potable Water Demand

Current trends in water demand suggest it is going to increase due to a rising population. This may be compounded by increasing per capita consumption [8]. However, current planning policy and building regulations [9] [10] set per capita efficiency targets that will reduce per capita demand, including aspirational *water neutrality* targets [11].

Here we take stochastic water demand foresting for London for the 2020s [2] and fit them to a gamma distribution with shape 310.98, and scale 6.9. An Info-Gap uncertainty model is built around this central estimate of demand, $Y|x = 0.5$ (2044.51 Ml/day) with the increments of uncertainty derived conditional from the underlying gamma distribution such that: $x = 0.525, 0.550, 0.575 \ldots\ldots .0.975$. The same intervals are used to sample the left-side of the gamma distribution.

2.2.3 Energy Costs

Minimum and maximum energy price estimates valid until the 2030s were obtained from an AECOM internal report (AECOM, *pers.comm*). Moreover, it was assumed that water utilities may offset energy costs in the future through renewable energy micro-generation that qualifies for a Feed-in-Taffif (FiT) [12]. In the absence of more information, a uniform distribution with minimum and maximum of £0.08 and £0.22/kWh respectively is used. A central estimate of £0.13/kwh is taken.

2.2.4 Performance Criteria

To perform Info-Gap analysis we use three performance criteria; storage reliability, environmental performance and total cost. Storage reliability is based on a combined emergency storage level of 45Mm^3 for all London [11]. Below this level the system is classed as being in failure. Total cost is a summation of fixed and variable operating costs and capital costs for the operation of each supply option [13] [2]. We take the most expensive 15% of simulations to be failures as a preliminary threshold. Environmental performance relates to the flow in the River Thames at Teddington. A failure occurs when flows drop below 800Ml/day. The severity and duration of failures are used to calculate a Shortage Index for each simulation. We take the worst performing 15% of simulations to be failures as above. For further details on the simulation of these performance measures see [14].

2.3 Uncertainty, Robustness and Opportuneness Function

Taking the convention u_1= climate change perturbation Info-Gap uncertainty model, u_2= water demand Info-Gap uncertainty model and u_3= energy cost Info-Gap uncertainty model; κ_l and κ_r scale and, σ_r and σ_l bound the right (upper) and left (lower) intervals of the Info-Gap model respectively. The three-dimensional Info-Gap uncertainty model incorporating the Info-Gap models for u_1, u_2 and u_3 becomes:

$$U(h,\tilde{u}) = \{u\colon \max[\sigma_l\,,(1-\kappa_l h)\tilde{u}_{i,j}] \le u_{i,j} \le \min[\,\sigma_r,(1+\kappa_r h)\tilde{u}_{i,j}]\}\; h \ge 0, i = 1,2,3\;, j = 1, 1-12 \tag{1}$$

where:
κ_l = [0.01,0.025,0.5] = scaling factors for the left hand side of the Info-Gap model for u_i
κ_r = [0.01,0.025,1.5] = scaling factors for the right hand side of the Info-Gap model for u_i
σ_l = [1.2, 1914.81,8] = the lower boundaries of the Info-Gap model for u_i
σ_r = [0.8, 2391.88,22] = the upper boundaries of the Info-Gap model for u_i

The Info-Gap uncertainty model (eq. 1) is developed for three dimensions (variables) and structures the sampling of the uncertain space α, between our best estimate $\tilde{u}$ of the future variable, u, scaled by h. For a decision maker, knowing how bad our future estimate ($\tilde{u}$) of u can be, whilst still providing a minimum level of performance (in this case reservoir operation, environmental flow and total cost) is the important question. This becomes the robustness function:

$$\hat{\hat{h}}\big(\Pi_c(Res_o, Cost_t, Env_p), q\big) = \; max\left\{h\colon \left(\min_{u_i\in u(h)} \Pi_{Res_o,Cost_t,Env_p}\;\; (u_{1,2,3}, q)\right) \ge \Pi_c(Res_o, Cost_t, Env_p)\right\} \tag{2}$$

where:
Res_o= Minimum reservoir storage threshold
$Cost_t$ = Maximum cost threshold
Env_p= Minimum environmental flow requirements

A decision maker may also ask how great a performance windfall might be received should the 2020s be more benign (e.g. wetter, less potable demand and lower energy costs) than expected. This becomes the opportuneness function:

$$\hat{\hat{\beta}}\big(\Pi_r(Res_o, Cost_t, Env_p), q\big) = \; min\left\{h\colon \left(\max_{u_i\in u(h)} \Pi_{Res_o,Cost_t,Env_p}\;\; (u_{1,2,3}, q)\right) \ge \Pi_r(Res_o, Cost_t, Env_p)\right\} \tag{3}$$

2.4. System Simulation

The Thames Basin water resource management system is modelled using IRAS-2010, an open source, rule-based water resource simulation model [14]. Using a weekly time-step the IRAS-2010 Thames model simulates the operation of 20 (19 future options and the current supply portfolio) potential infrastructure portfolios outlined in Thames Water's latest Water Resource Management Plan (WRMP) [2]. These include current supply infrastructure and combinations of new options including; an Upper Thames Reservoir (UTR) with capacities of 75, 100 or 150Mm^3, a River Severn Transfer (RST) of up to 315Ml/day, and aquifer storage and recovery scheme in south London (SLARS).

3. RESULTS AND DISCUSSION

The IRAS-2010 simulation was embedded within the Info-Gap robustness (eq.2) and opportuneness (eq.3) functions to assess the performance of each infrastructure option under ever increasing uncertainty in the input variables. The structure of the simulations was slightly altered from the two Info-Gap functions (eq, 2 and 3) such that the simulation would continue for all 20 increments of uncertainty rather than stopping at the point of failure. This provides further information about how the system would operate if we were to alter our performance requirements in the future

3.1. Robustness Analysis

For each infrastructure portfolio, robustness analysis consisted of 20 simulations (full grid sample of 20 demand and 20 flow factor ensembles as defined by equation 2). Post processing added 20 energy cost intervals, increasing the total number of results to 1600 for each infrastructure portfolio.

Initial results show that portfolio options 1-6 (including the current supply portfolio) failed to meet our minimum performance requirements for the central estimate scenario. All 6 failed due to a lack of reservoir capacity. A further 6 portfolio options failed after only 2 increments of uncertainty. These fall into two groups. The first included portfolio options 7-10 which failed again as a result of reservoir operation. These options did included a UTR (either 75 or 100Mm^3), but this reservoir only marginally improved their robustness (even with the highest capacity of desalination plant (140Ml/day and SLARS activated). The second group includes portfolio options 19 and 20, which failed as a result of total costs rather than reservoir operation. Both these options include the RST and the highest capacity desalination plant, with SLARS activated in one and de-activated in the other.

Robustness curves for the remaining 8 infrastructure portfolios are plotted in figure 3. These curves provide a relatively easy way of comparatively assessing the performance of the 8 most robust infrastructure portfolios. Options 15-18 visibly perform better at all horizons of uncertainty in terms of reservoir operation and environmental performance. These four options are however more costly, particularly options 17 and 18, which fail to meet our cost requirements after 7 horizons of uncertainty. Considering the absolute robustness of each infrastructure portfolio is the minimum robustness achieved for the 3 performance measures: portfolio 15 = 5, portfolio 16 = 5, portfolio 17 = 6, and portfolio 18 = 7 (portfolios 10 – 14 = 3).

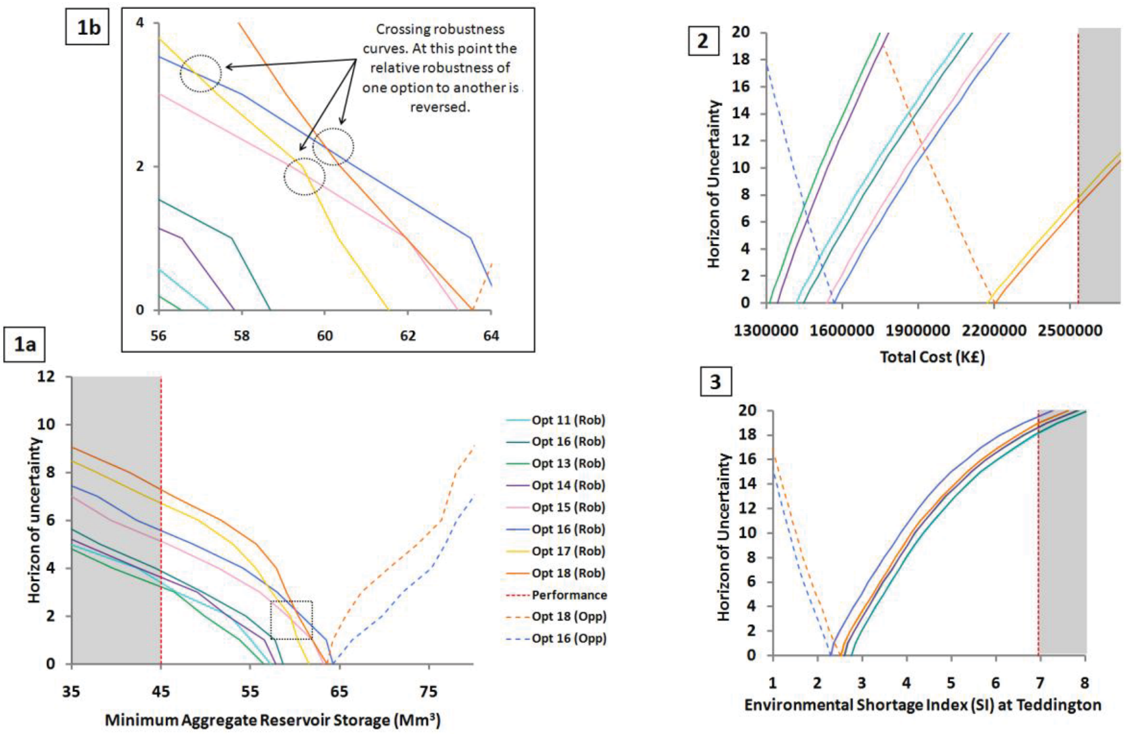

Figure 2. Robustness curves for the 8 best performing infrastructure portfolios and opportuneness curves for option 16 and 18. Results for reservoir performance (1a and 1b), cost (2) and environmental performance (3) are shown. Grey areas indicate region where system performance is below our current requirements.

From 20 portfolio options, 4 are significantly more robust. Overall, option 18 the most robust to uncertainty. This option includes the RST, SLARS and a lower capacity desalination plant (80ml/day). However, this comes at a risk of both higher costs and slightly lower environmental performance at each increment of uncertainty. At

7 horizons of uncertainty, energy costs are £0.165/kwh and demand is 2191Ml/day. A decision maker must as how likely this combination of energy costs and demand will be in 2020s. Another pertinent question is whether reservoir performance requirements could be relaxed (to say a minimum of 36Mm^3). This is the benefit completing all simulations.

Figure 3 shows that option 16 for instance can maintain minimum performance requirements to 7 horizons of uncertainty if reservoir performance can be relaxed. This scenario would also ensure both lower costs and better environmental performance at every horizon of uncertainty (figure 2). Option 16 includes a 140Ml/day desalination plant, 150Mm^3 UTR and SLARS. Interestingly, at 0-2 horizons of uncertainty option 16 actually performs better in terms of reservoir performance than option 18. The crossing of the robustness curves at this point (figure 4) shows that option 18 becomes more robust than option 16 above 2 increments of uncertainty. In this situation it is still quite difficult between options 16 and 18 (with options 15 and 17 being identical except for the absence of SLARS).

3.2. Opportuneness Analysis

Opportuneness analysis (eq. 4) aids this process by allowing the decision maker to see how much performance reward they might achieve should the future be more benign than our central estimate projection. As can be seen in figure 2 (panel 1a) (dotted lines), as conditions become less harsh (as *h* increases) the relative difference between options 16 and 18 is similar. Opportuneness curves for total cost show the gap closing towards horizon 20 between options 18 and 16, but option 18 is always more expensive. Option 16 also gives greater rewards for both environmental performance and reservoir operation for all increments of uncertainty. This is particularly significant for reservoir performance between uncertainty horizons 0 and 2. Between these intervals, where conditions are marginally more benign than our central estimate, the opportuneness curve for option 16 is less steep. This indicates that a greater performance reward is received for each interval or uncertainty when compared to option 18.

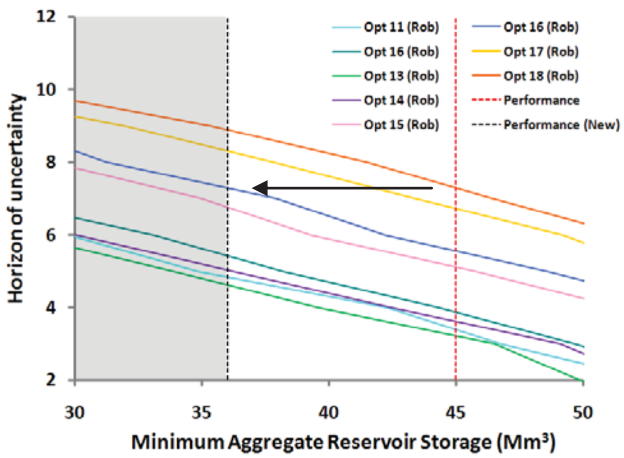

Figure 3. Demonstraton of how a reduction in minimum reservoir storage requirements from >45 to >36Mm^3 improves the robustness of option 16 to level similar to that achieved by option 18 for the original minimum storage requirement (>45Mm^3).

4. Discussion

IGDT was used to assess the relative performance of 20 infrastructure portfolio options to maintain the supply-demand balance in the Thames water resource system into the 2020s. Robustness curves show options 16 and 18 maintain minimum performance requirements under a larger amount of uncertainty than all other possible infrastructure portfolios. Robustness analysis shows that option 16 offers more robustness to small amounts of uncertainty (horizons 0-2), this is shown by options 16 having a steeper robustness curve than option 18 for all 3 performance criteria. Above 2 intervals of uncertainty robustness curves for option 16 and 18 cross. At this point option 18 becomes more robust than option 16 with respect to reservoir operation. Option 16 remains more robust for both environmental performance and total costs for all horizons of uncertainty.

Continuing robustness analysis beyond the point where a portfolio fails to meet our 3 performance requirements provides trade-off information to decision makers. A 22% reduction in minimum reservoir storage requirements enables option 16 to achieve the same robustness as option 18, with greater environmental performance and less total cost. Opportuneness curves further highlight that option 16 provides greater reward under less harsh futures.

This paper demonstrates that IGDT helps assess the robustness of various infrastructure portfolio options to uncertainty in our projections of water availability, demand and energy costs. Initial analysis suggests options 16 and 18 are best to maintain supply-demand balance in the Thames Basin. Further analysis of the trade-offs between our 3 performance requirements, changing reservoir operation requirements and opportuneness analysis identify option 16 as the most robust infrastructure portfolio from an initial shortlist of 20. This portfolio includes current supply infrastructure plus desalination (140Ml/day), UTR (150Mm^3) and SLARS. These results are preliminary; demand management options have not yet been considered.

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