Energy system planning using minimax regret

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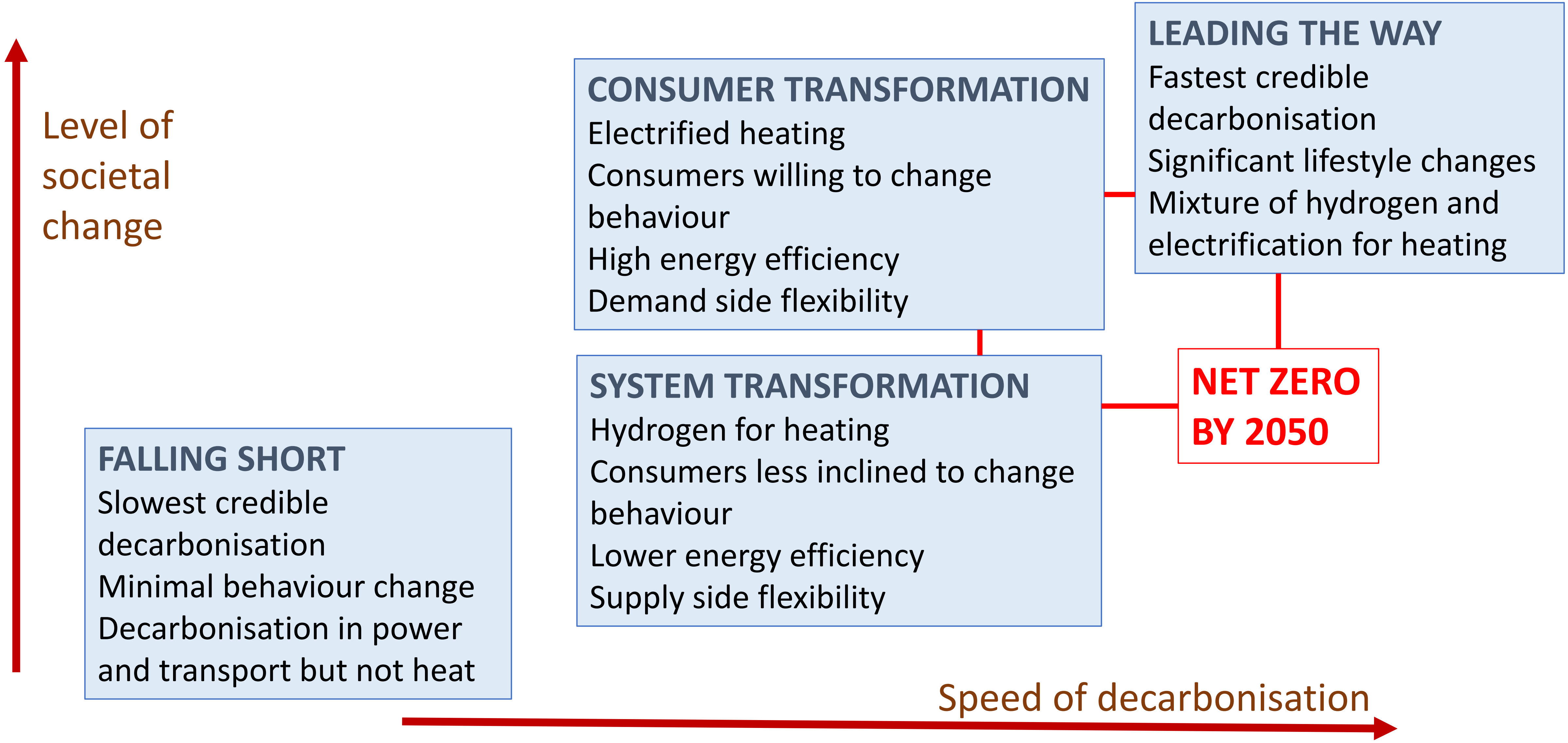
National Grid ESO Future Energy Scenarios



Using Future Energy Scenarios for planning

- Build detail around each scenario:
  - A path over time
  - What is implied for different parts of the UK
  - Possible variations due to weather conditions year by year
- FES are updated on an annual basis – but no major changes year to year.
- Use the FES consistently for all planning purposes (transmission planning, network enhancement and capacity procurement)

- BUT… What are the probabilities of different scenarios?

Why use minimax for planning?

- Decisions involve time horizons of decades with substantial uncertainty on what will happen
- The nature of uncertainty (e.g. involving future government decisions) makes it very hard to assign probabilities to scenarios
- Planning decisions need to be made with a clear procedure and in an objective way -- to avoid any suggestion of bias or favouritism
- Minimax rules avoid the need for subjective judgements on probabilities
- Also it is appropriate for planners to be risk averse.

Why use regret based rules?

- Regret is the additional cost in a given scenario from one decision in comparison with the best possible decision
- Minimizing regret is a heuristic people seem to use in practice. ("How bad will this decision look after the fact, when I find out that a better choice was available.")
- Different scenarios may have different (large) societal costs that don't depend on the decision made, with relatively smaller costs from the planning decisions. Then minimax cost ends up being determined by the outcomes in the worst scenario (even if decisions make only a small difference in that scenario).
- National Grid ESO in fact use minimax regret (“least worst regret”) for all decisions

Problems

- Problems with regret-based rules:
  - Regret is a relative cost measure, and this leads to examples with behaviour which seems wrong (i.e. breaks axioms we expect).
  - We may not have transitivity and we may not have the independence of irrelevant alternatives
- Problems with minimax rules:
  - Whether it is minimax cost or minimax regret the same problem occurs: The decision we take is critically dependent on the exact choice of scenarios that we consider.
  - This is a familiar problem with robust optimisation where the choice of uncertainty set is vital. Often it is the extreme (and hence unlikely scenarios) that determine the choice made

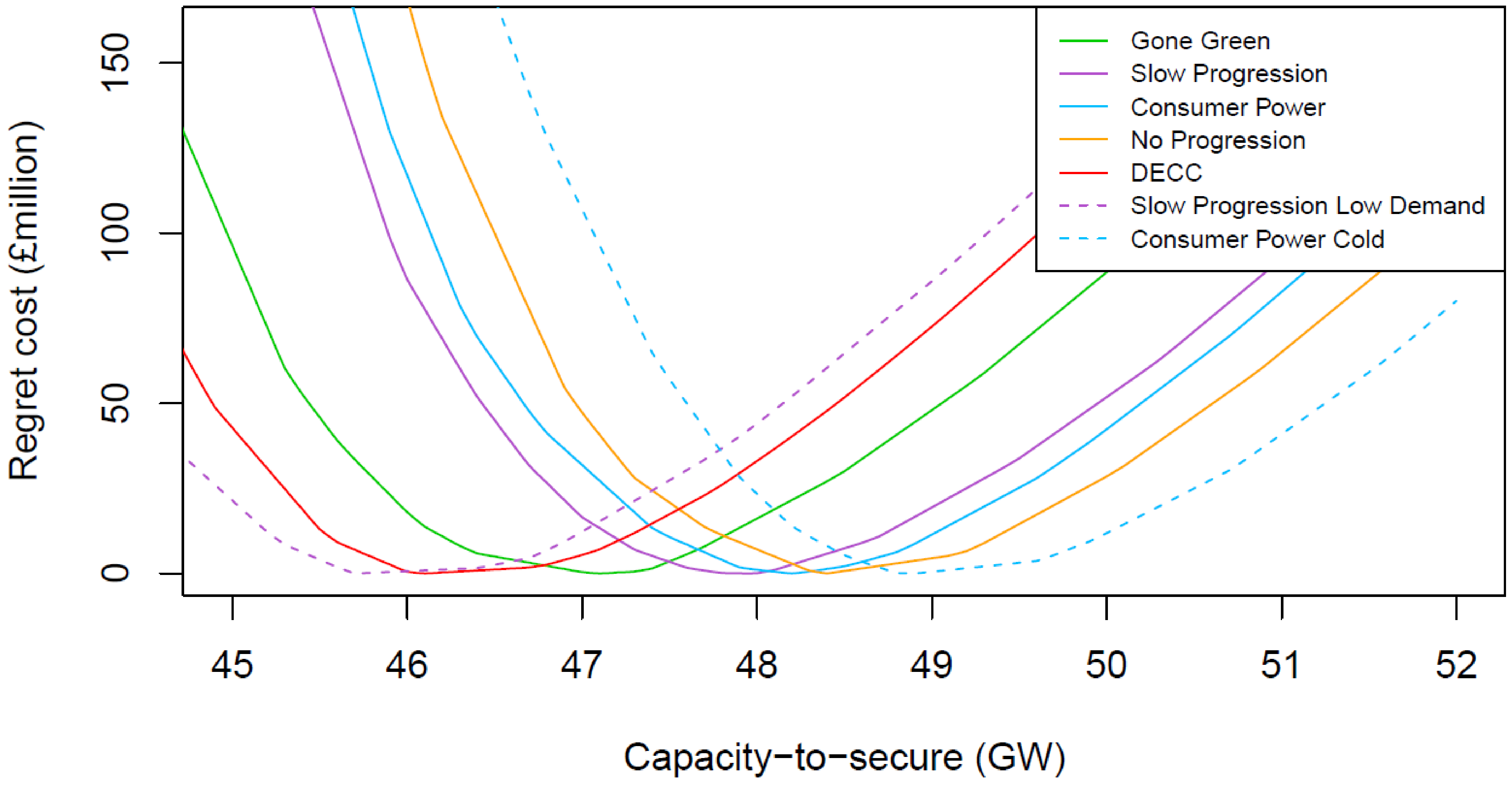
Framework

- S is the set of possible scenarios.
- Decision vector $x \in D \subset R^{\mathrm{n}}$.
- $C_i(x)$ is the cost if x is chosen and scenario i occurs.
- Define the regret function
$$R_i(x) = C_i(x) - \inf_{z \in D} C_i(z).$$
- Minimizing expected regret is the same as minimizing expected cost.
- The minimax regret rule solves
$$\min_{x \in D} \max_{i \in S} R_i(x).$$

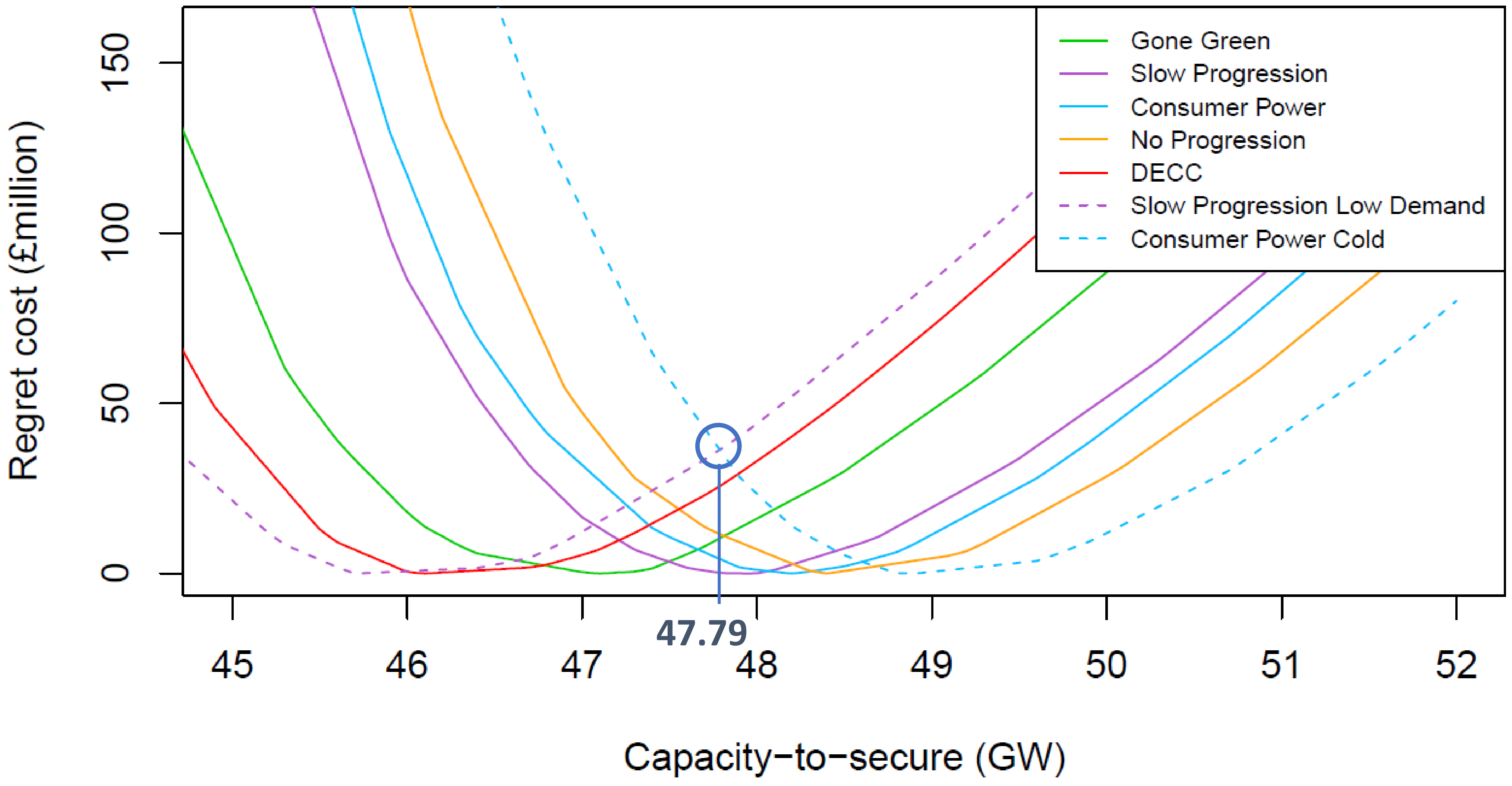
Application to electricity capacity procurement

- National Grid ESO produces an annual Electricity Capacity Report recommending a generation capacity-to-secure, via a capacity auction. Look at data for 2015 ECR.
- For each i in the scenario set S, there is a cost function C_i given by $C_i(x) = \mathrm{VOLL} \times \mathrm{EEU}_i(x) + \mathrm{CONE} \times x$,
- Here x is the generation capacity to be secured and $\mathrm{EEU}_i(x)$ is the corresponding expected energy unserved over the given winter.
- VOLL=£17,000 /MWh is the value of lost load and CONE= £49,000/MW is the cost of new entry
- $\mathrm{EEU}_i(x)$ are approximately of the form $\exp(-\lambda(x - a_i))$
- In that year National Grid used a set of 5 core scenarios, with 7 variant scenarios for each of the two central core scenarios. 19 scenarios in total.

Minimax regret capacity



Minimax regret capacity



An approach via robustness

- Minimax decision rules are also robust versions of expected cost minimisers. We suppose that there is an uncertainty set which is a convex subset P_A of the set of all probability measures.
- An important case occurs when P_A is defined by a matrix A of constraints:
$$P_A = \{p_i, i \in S \mid Ap \leq 0, p_i \geq 0, \sum p_i = 1\}.$$
- Using P_A allows the definition of a partial ordering amongst the probabilities of different scenarios, $p_i \geq p_j$. We may take these inequalities to link scenarios in the same family grouped around a single core scenario
- In this case the scenario set S may be partitioned into m disjoint components $S = S_1 \cup S_2 \ldots S_m$, and the matrix A is such that each constraint (corresponding to some row of A) involves only scenarios within a single component of S

Using this for capacity procurement

- Add back the missing variant scenarios associated with the other three core scenarios
- The scenario set S is partitioned as $S = \bigcup_{i=1}^{5} S_i$, where each S_i contains eight scenarios – the parent core scenario, labelled $i1$ and a further seven variant scenarios, or sensitivities, labelled ij for $j = 2, \ldots, 8$.
- Add constraints to limit the probabilities of variant scenarios $0.1p_{i1} \leq p_{ij} \leq p_{i1}$ (Write this as $p_{ij} \in G$)
- Define for each core scenario i the worst regret under these constraints:

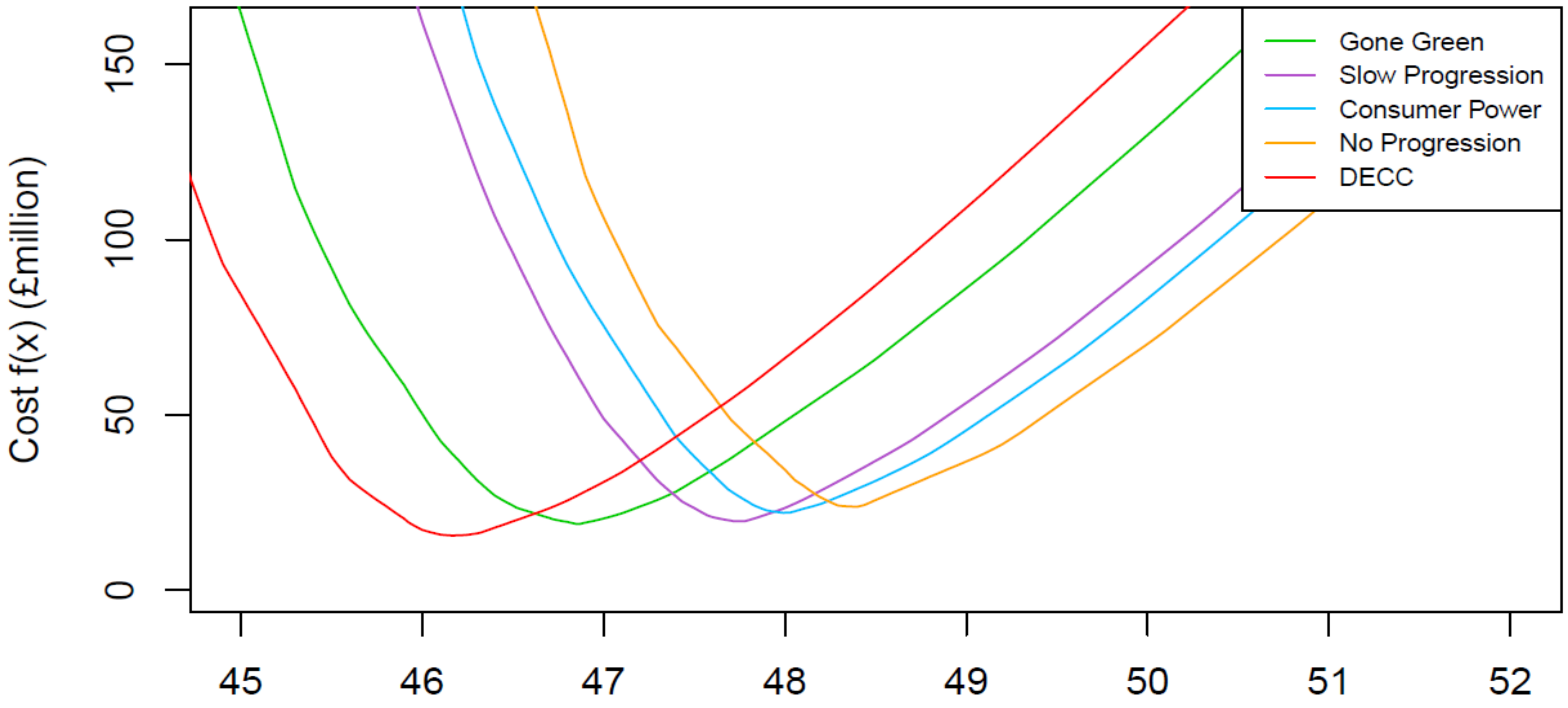
$$f_i(x) = \max_{p_{ij} \in G:\, \sum p_{ij} = 1} \sum_{ij \in S_i} p_{ij} R_{ij}(x)$$

where $R_{ij}(x)$ is the regret function associated with the scenario ij.

- Then the robust optimisation problem is: $\min_{x \in D} \max_{i=1,\ldots,5} f_i(x)$.

The resulting analysis

- Each f_i function is the worst regret under the core scenario and its variants.



- The optimal capacity-to-secure, is then $x = 47.65$ GW (a little less than the 47.79 GW obtained from the minimax regret analysis of the 2015 ECR)

The theory behind this. Part 1

- For the full story see the arXiv preprint arXiv:2203.01420
- It is impossible to use regrets and still get IIA: the independence of irrelevant alternatives property which states: adding a new decision possibility can't change the previous best option unless the new possibility becomes the best choice

Proposition: If the decision space D has at least three points, and the decision is made by minimising a continuous non-decreasing function of the set of regrets $\{R_i(x): i \in S\}$ over $x \in D$ and satisfies the IIA property, then the decision process is equivalent to minimising the expected costs for some set of probabilities $p_i, i \in S$.

The theory behind this. Part 2

- We can be precise about the number of scenarios that will end up determining the solution. Let $K \subseteq S$ be any subset of the scenarios and let the problem
$$P(K) = \min_{x \in D} \max_{i \in K} f_i(x)$$
have optimal solution $x^*(K)$.
- We can take f_i as R_i or C_i. We get the original problem when $K = S$

Proposition: Suppose the decision set $D \subseteq R^n$ is convex; $x^*(K)$ is uniquely defined for all K; and f_i is quasiconvex for each $i \in S$. Then there is a subset K with $n + 1$ elements where $P(K)$ has the same value as $P(S)$ and $x^*(K) = x^*(S)$.

Conclusions

- Minimax regret is often used in practice for infrastructure planning - for good reasons.
- Problem A: Failure of Independence of Irrelevant Alternatives.
  - This is impossible to avoid - need to be careful about possible gaming of the decision process
- Problem B: Everything depends on a small number of scenarios.
  - Best approach is to think of variants of a small number of core scenarios and include information on relative probabilities between core and variant scenarios.