

Lecture 3

Probabilistic Reliability

with

Info-Gap Uncertainty

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1 *Reliability Assessment with Info-Gaps*

1.1 *Introduction*

§ Facts of life:

- Things go **wrong**.
- Systems **fail**.
- **Loss** or **injury** occurs.

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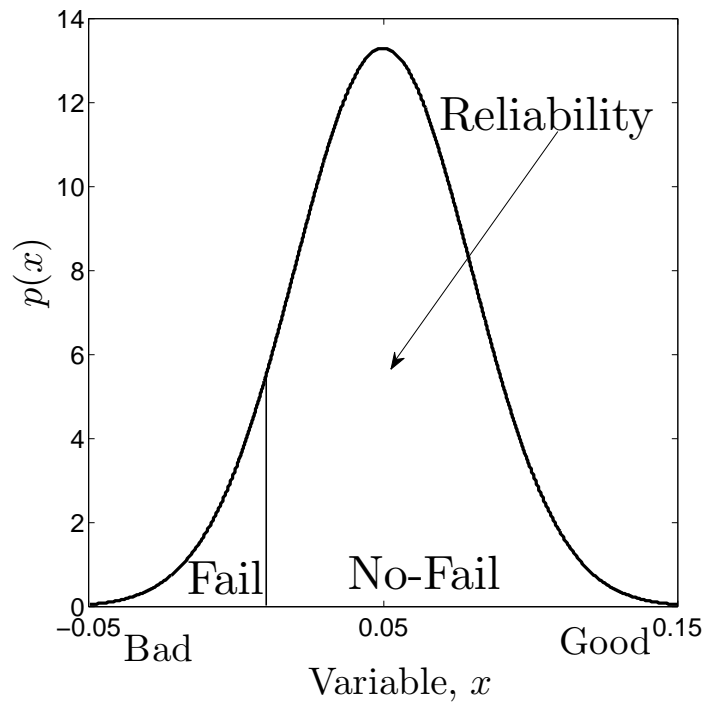
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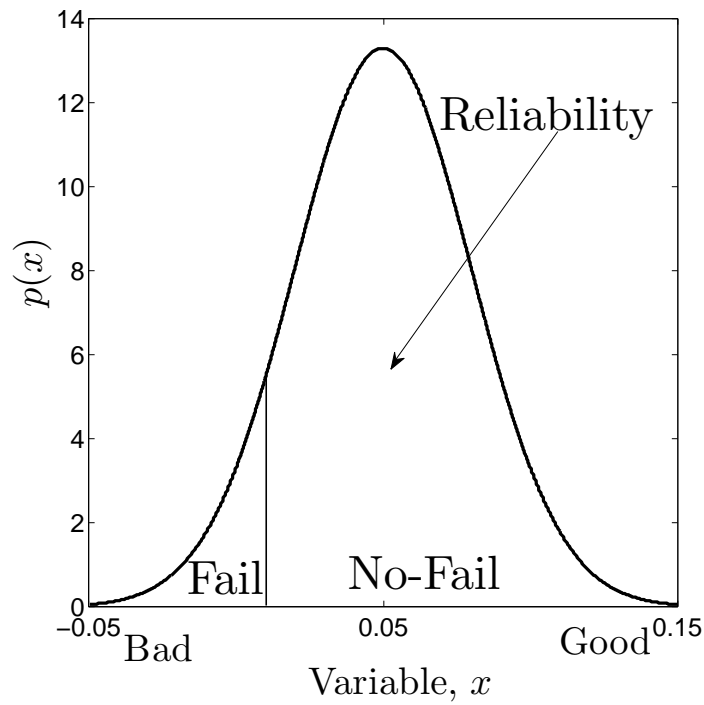
§ Methodology: Info-gap decision theory.

1.2 *The Problem*



§ **Reliability:** Area under **no-fail** part of curve.

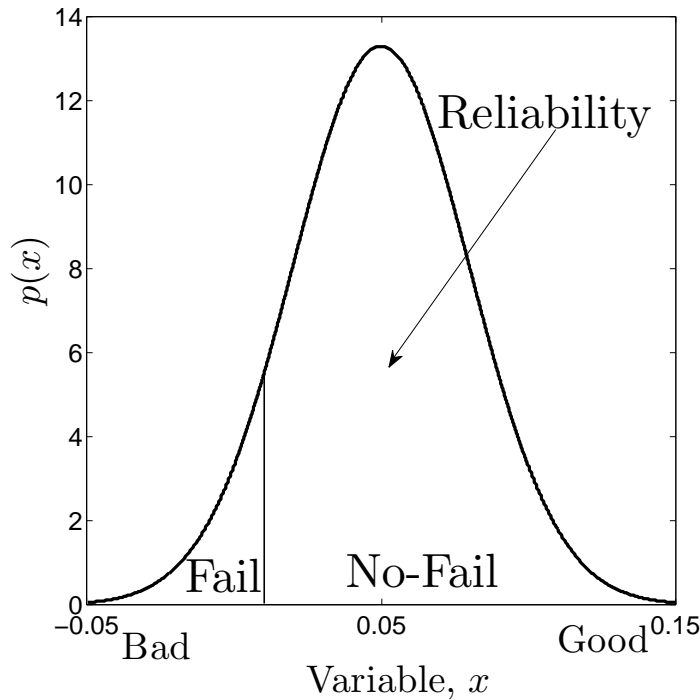
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§ **Good news:** “**Fail**” area usually **very small**.

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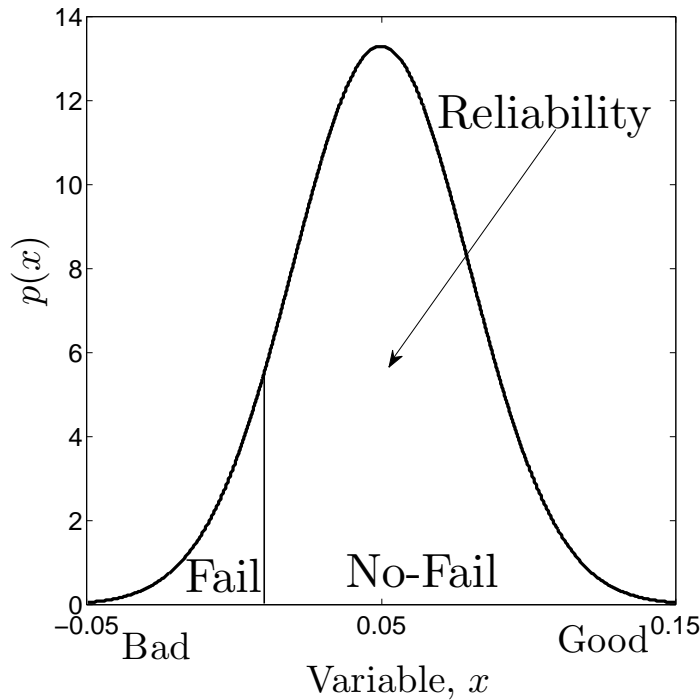
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- **Hard to estimate** reliability.
- **Sensitive to error** in probability function.

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§ **Good news:** Info-gap theory.

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 - Data are revised.
 - Shackle-Popper indeterminism.
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- **Past vs future:**
 - Processes vary in time.
 - Data are revised.
 - Shackle-Popper indeterminism.
- **Joint probabilities:**
 - Uncertain common-mode failures.
 - Uncertain correlations.

§ Two foci of uncertainty:

- **Statistical fluctuations:**
 - Randomness, “noise”.
 - Estimation uncertainty.
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- **Knightian uncertainty:**
 - Surprises.
 - Structural changes.
 - **Historical** data used to predict **future**.

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- **Statistical fluctuations:**
 - Randomness, “noise”.
 - Estimation uncertainty.
- **Knightian uncertainty:**
 - Surprises.
 - Structural changes.
 - **Historical** data used to predict **future**.

§ Info-gap theory to manage

Knightian uncertainty.

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2 *Zoonotic Disease*

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$$x(t) = a\sqrt{t} \quad (1)$$

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§ New zoonotic disease:

- Moving up an estuary from the sea.
- Distance of disease front from sea seems to be:

$$x(t) = a\sqrt{t} \quad (2)$$

- Our town located distance x_c from the sea.
- Estimated time of arrival:

$$t_c = \left(\frac{x_c}{a}\right)^2 \quad (3)$$

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§ New zoonotic disease:

- Moving up an estuary from the sea.
- Distance of disease front from sea seems to be:

$$x(t) = a\sqrt{t} \quad (4)$$

- Our town located distance x_c from the sea.
- Estimated time of arrival:

$$t_c = \left(\frac{x_c}{a}\right)^2 \quad (5)$$

§ The problem: eq.(1) highly uncertain.

-

§ New zoonotic disease:

- Moving up an estuary from the sea.
- Distance of disease front from sea seems to be:

$$x(t) = a\sqrt{t} \quad (6)$$

- Our town located distance x_c from the sea.
- Estimated time of arrival:

$$t_c = \left(\frac{x_c}{a}\right)^2 \quad (7)$$

§ The problem: eq.(6) **highly uncertain.**

- We require time T for intervention.
- **Probability of failure:** $P_f(T) = \text{Prob}(t_c < T)$.

§ $p(a)$ = PDF for a :

$$p(a) = \lambda e^{-\lambda a}, \quad a \geq 0 \quad (8)$$



§ $p(a) = \text{PDF for } a:$

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- **Probability of failure:** $P_f(T) = \exp(-\lambda x_c / \sqrt{T})$
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§ $p(a) = \text{PDF for } a:$

$$p(a) = \lambda e^{-\lambda a}, \quad a \geq 0 \quad (10)$$

- **Probability of failure:** $P_f(T) = \exp(-\lambda x_c / \sqrt{T})$
- **The problem:** $\tilde{\lambda} = \text{estimate of } \lambda$; **highly uncertain.**

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§ $p(a) = \text{PDF for } a:$

$$p(a) = \lambda e^{-\lambda a}, \quad a \geq 0 \quad (11)$$

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§ **Info-gap model of uncertain λ :**

$$\mathcal{U}(h) = \left\{ \lambda : \lambda \geq 0, \left| \frac{\lambda - \tilde{\lambda}}{s} \right| \leq h \right\}, \quad h \geq 0 \quad (12)$$

- **Non-probabilistic uncertainty.**
- **No known worst case.**

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- **Non-probabilistic uncertainty.**
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§ **Robustness:** maximum tolerable uncertainty.

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Maximum horizon of uncertainty in λ with
acceptable probability of failure:

$$\hat{h}(T) = \max \left\{ h : \left(\max_{\lambda \in \mathcal{U}(h)} P_f(T) \right) \leq P_c \right\} \quad (15)$$



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Maximum horizon of uncertainty in λ with acceptable probability of failure:

$$\widehat{h}(T) = \max \left\{ h : \left(\max_{\lambda \in \mathcal{U}(h)} P_f(T) \right) \leq P_c \right\} \quad (16)$$

• **Recall info-gap model of uncertainty:**

$$\mathcal{U}(h) = \left\{ \lambda : \lambda \geq 0, \left| \frac{\lambda - \widetilde{\lambda}}{s} \right| \leq h \right\}, \quad h \geq 0 \quad (17)$$

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$$\widehat{h}(T) = \max \left\{ h : \left(\max_{\lambda \in \mathcal{U}(h)} P_f(T) \right) \leq P_c \right\} \quad (18)$$

• **Recall info-gap model of uncertainty:**

$$\mathcal{U}(h) = \left\{ \lambda : \lambda \geq 0, \left| \frac{\lambda - \widetilde{\lambda}}{s} \right| \leq h \right\}, \quad h \geq 0 \quad (19)$$

§ **Robust satisficing:**

- **Satisfice performance and**
- **Maximize robustness to uncertainty.**
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Maximum horizon of uncertainty in λ with acceptable probability of failure:

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• **Recall info-gap model of uncertainty:**

$$\mathcal{U}(h) = \left\{ \lambda : \lambda \geq 0, \left| \frac{\lambda - \widetilde{\lambda}}{s} \right| \leq h \right\}, \quad h \geq 0 \quad (21)$$

§ **Robust satisficing:**

- **Satisfice performance** and
- **Maximize robustness** to uncertainty.
- Not min-max (minimizing a worst case).
- Not putative outcome optimization: $\min P_f$.

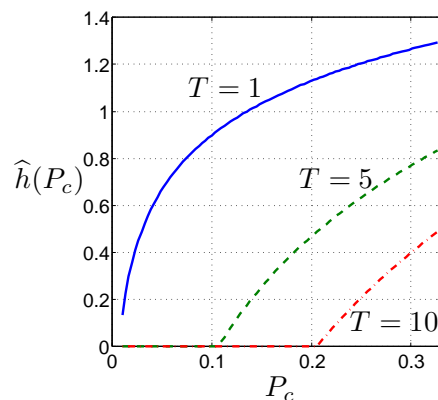


Figure 1: Robustness curves with $T = 1$ (solid), $T = 5$ (dash) and $T = 10$ (dot-dash) with parameter values: $\tilde{\lambda} = 1/2$, $s = 0.3$, $x_c = 10$.

§ Robustness function:

$$\hat{h}(T) = \frac{1}{s} \left(\tilde{\lambda} + \frac{\sqrt{T}}{x_c} \ln P_c \right) \quad (22)$$

- **Trade off:** P_c up (**bad**) $\iff \hat{h}$ up (**good**).

-

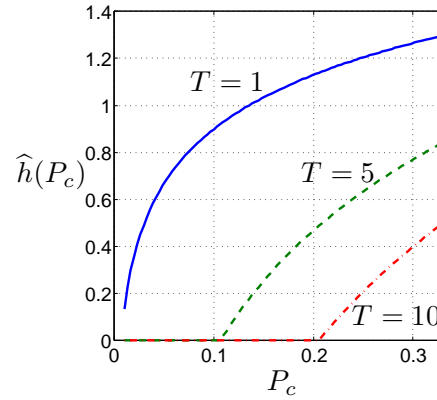


Figure 2: Robustness curves with $T = 1$ (solid), $T = 5$ (dash) and $T = 10$ (dot-dash) with parameter values: $\tilde{\lambda} = 1/2$, $s = 0.3$, $x_c = 10$.

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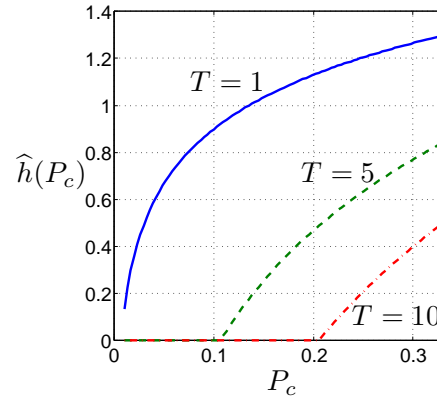


Figure 3: Robustness curves with $T = 1$ (solid), $T = 5$ (dash) and $T = 10$ (dot-dash) with parameter values: $\tilde{\lambda} = 1/2$, $s = 0.3$, $x_c = 10$.

§ Robustness function:

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- **Trade off:** P_c up (**bad**) $\iff \hat{h}$ up (**good**).
- **Zeroing:** No robustness at predicted P_f .
- \hat{h} **up** as required intervention time, T , **reduced**.

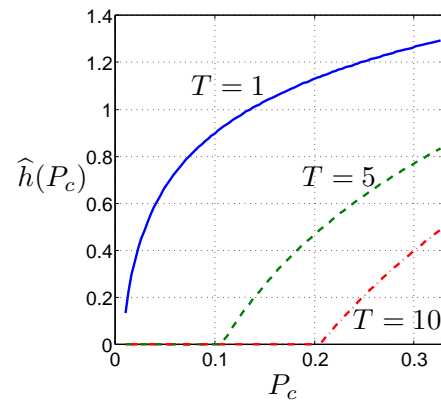


Figure 4: Robustness curves with $T = 1$ (solid), $T = 5$ (dash) and $T = 10$ (dot-dash) with parameter values: $\tilde{\lambda} = 1/2$, $s = 0.3$, $x_c = 10$.

§ What do the robustness numbers mean?

-

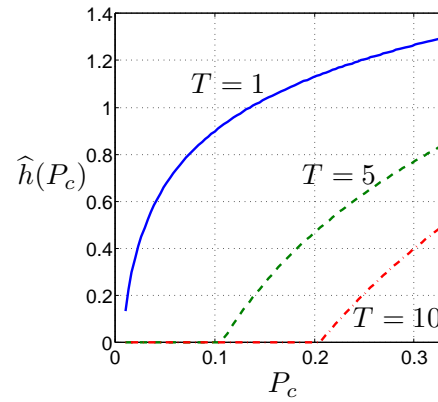


Figure 5: Robustness curves with $T = 1$ (solid), $T = 5$ (dash) and $T = 10$ (dot-dash) with parameter values: $\tilde{\lambda} = 1/2$, $s = 0.3$, $x_c = 10$.

§ What do the robustness numbers mean?

- **Example:** $(P_c, \hat{h}, T) = (0.2, 0.45, 5)$.
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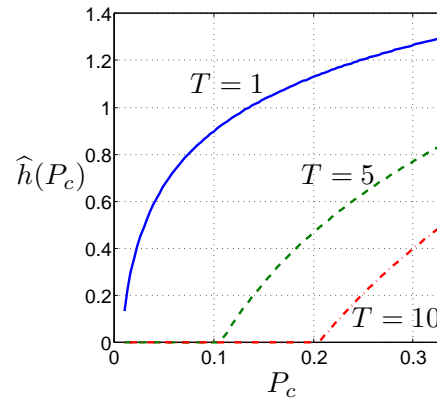


Figure 6: Robustness curves with $T = 1$ (solid), $T = 5$ (dash) and $T = 10$ (dot-dash) with parameter values: $\tilde{\lambda} = 1/2$, $s = 0.3$, $x_c = 10$.

§ What do the robustness numbers mean?

- **Example:** $(P_c, \hat{h}, T) = (0.2, 0.45, 5)$.
- If $P_f = 0.2$ is ok, then prep time T guaranteed if $\tilde{\lambda}$ errs no more than $\pm 0.45s$.
-

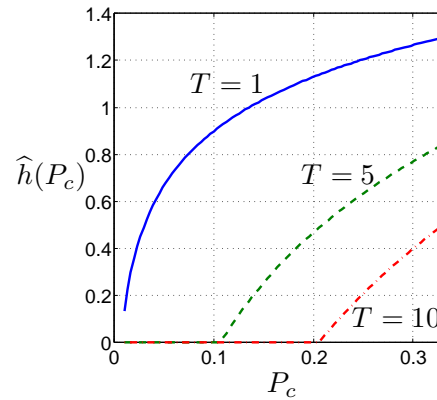


Figure 7: Robustness curves with $T = 1$ (solid), $T = 5$ (dash) and $T = 10$ (dot-dash) with parameter values: $\tilde{\lambda} = 1/2$, $s = 0.3$, $x_c = 10$.

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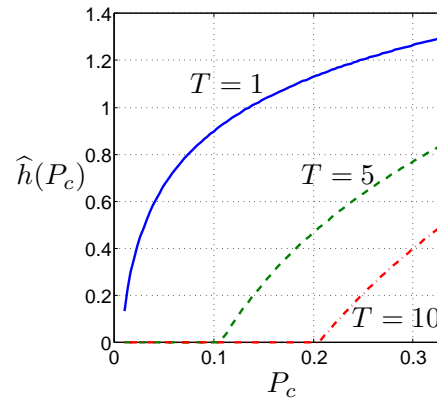


Figure 8: Robustness curves with $T = 1$ (solid), $T = 5$ (dash) and $T = 10$ (dot-dash) with parameter values: $\tilde{\lambda} = 1/2$, $s = 0.3$, $x_c = 10$.

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- **Low robustness** for this T and P_c .
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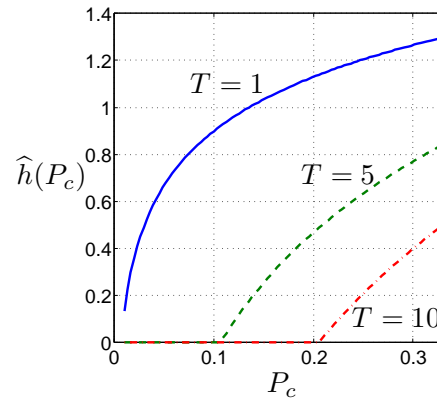


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- **Low robustness** for this T and P_c .
- **Expl:** $(P_c, \hat{h}, T) = (0.2, 1.1, 1)$: **moderate robustness**.

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- Choose between two possible interventions:
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 - I_1 : new and innovative technologies (NaI).
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- I_1 **predicted to be better** than I_2 :

$$\tilde{\lambda}_1 > \tilde{\lambda}_2 \quad (25)$$

Recall: $P_f(T) = \exp(-\lambda x_c / \sqrt{T})$.

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§ Innovation dilemma:

- Choose between two possible interventions:
 - I_1 : new and innovative technologies (NaI).
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- I_1 **predicted to be better** than I_2 :

$$\tilde{\lambda}_1 > \tilde{\lambda}_2 \quad (26)$$

Recall: $P_f(T) = \exp(-\lambda x_c / \sqrt{T})$.

- I_1 **more uncertain** than I_2 :

$$\frac{s_1}{\tilde{\lambda}_1} > \frac{s_2}{\tilde{\lambda}_2} \quad (27)$$

Hence the dilemma.

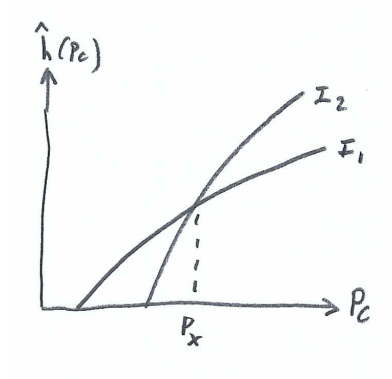


Figure 10: Crossing robustness curves showing preference reversal.

- **Robustness curves cross:**
Potential for **preference reversal**.

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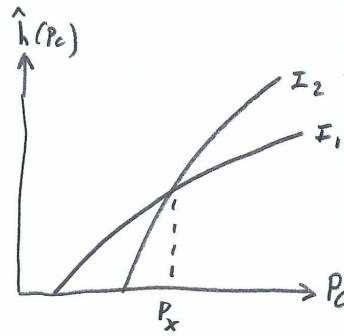


Figure 11: Crossing robustness curves showing preference reversal.

- **Robustness curves cross:**
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- **How to choose? Robust satisficing.**
Satisfice probability of failure. Maximize robustness:

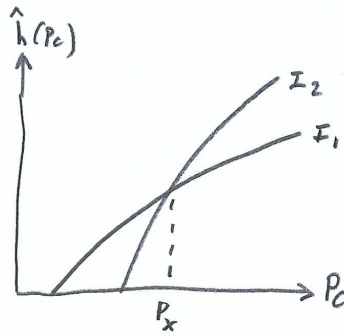


Figure 12: Crossing robustness curves showing preference reversal.

- **Robustness curves cross:**

Potential for **preference reversal**.

- **How to choose? Robust satisficing.**

Satisfice probability of failure. Maximize robustness:

I_1 preferred if $P_c < P_x$.

I_2 preferred if $P_c > P_x$.

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- Choose between alternative interventions.
- **Innovation dilemma:**
 - New & innovative: **seems better, more uncertain.**
 - State of the Art: **seems worse, less uncertain.**
- Resolution: robust satisficing.

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Any Questions?