Informing the Delineation of Input Uncertainty Space in Exploratory Modelling Using a Heuristic Approach

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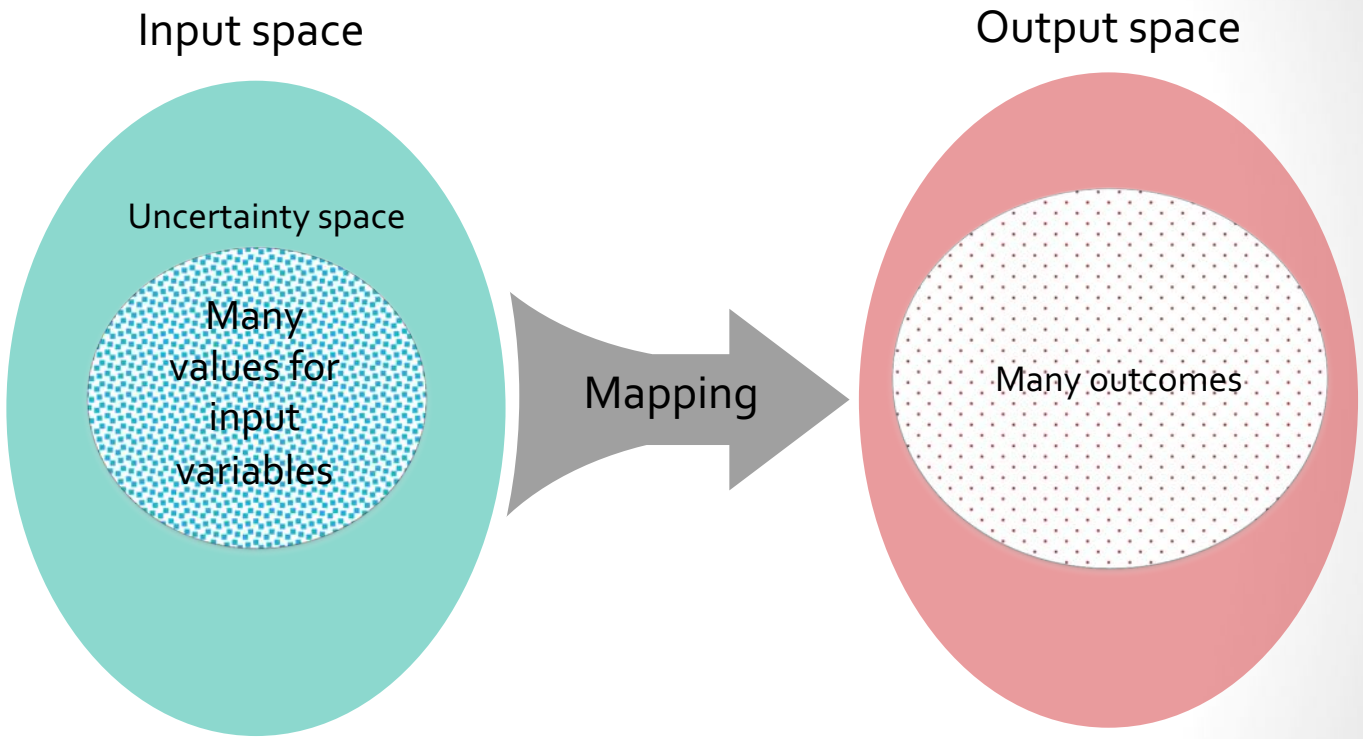
Outline

- Background
- Methods & Results
- Conclusions

~ Background ~

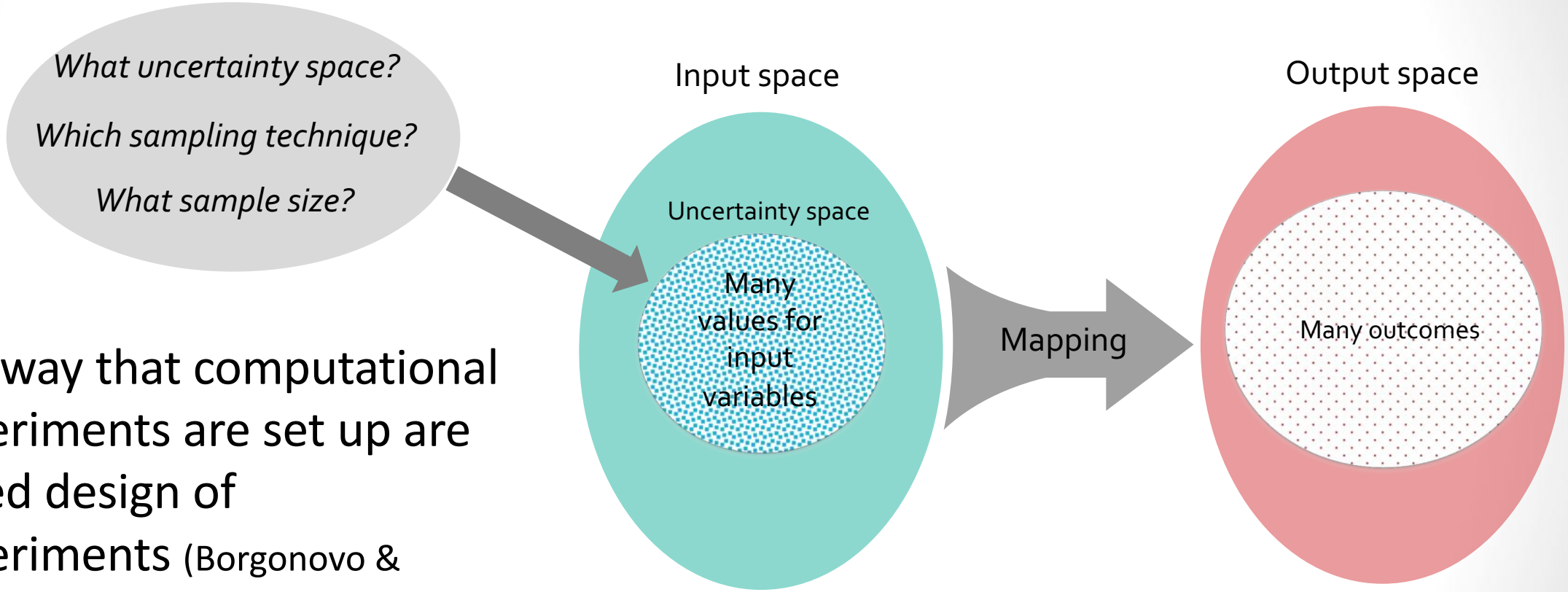
Exploratory modelling

Exploratory modelling is a meta-approach for *mapping* from an *input space* to an *output space* using computational experimentations (Bankes 1993).



Bankes, S. (1993). Exploratory modeling for policy analysis. *Operations Research, 41*(3), 435-449.

Design of experiments



The way that computational experiments are set up are called design of experiments (Borgonovo & Plischke 2016).

Borgonovo, E. and E. Plischke, Sensitivity analysis: A review of recent advances. European Journal of Operational Research, 2016. 248(3): p. 869-887.

Design of experiments

What uncertainty space?

Which sampling technique?

What sample size?

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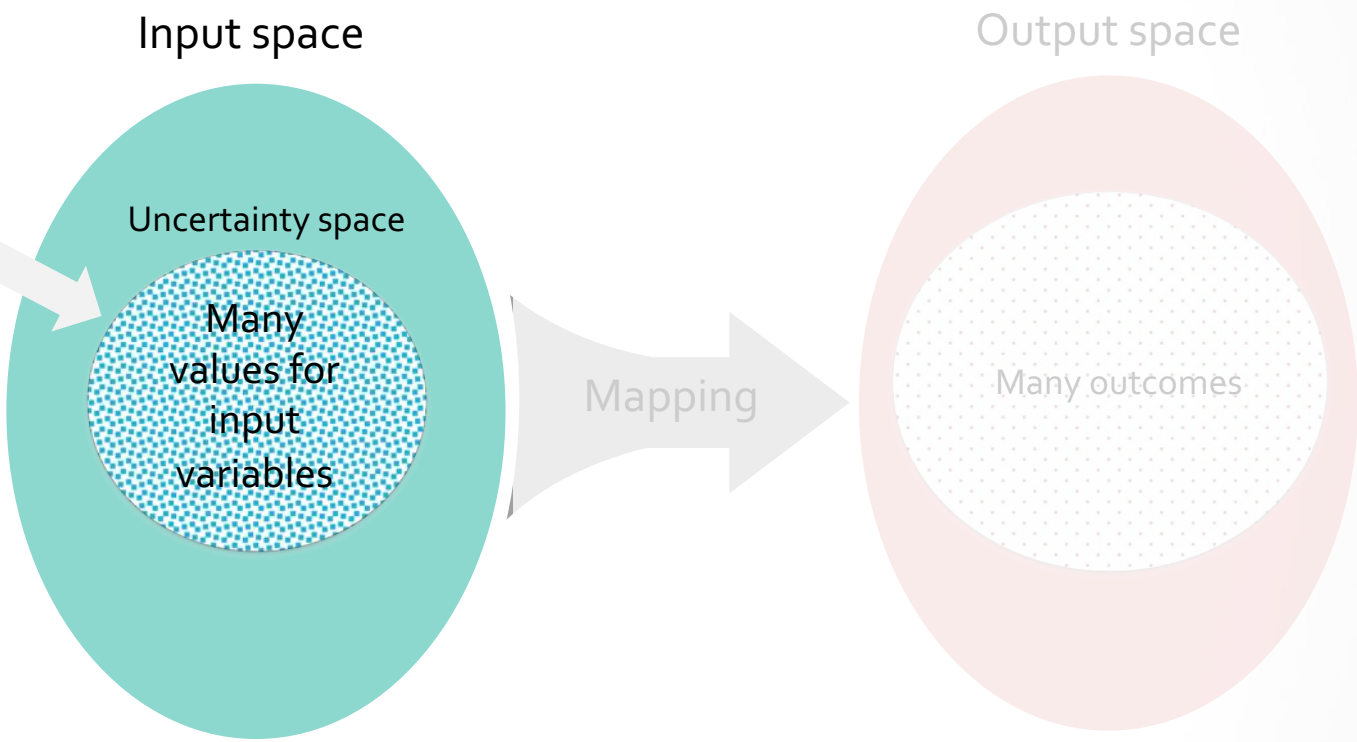

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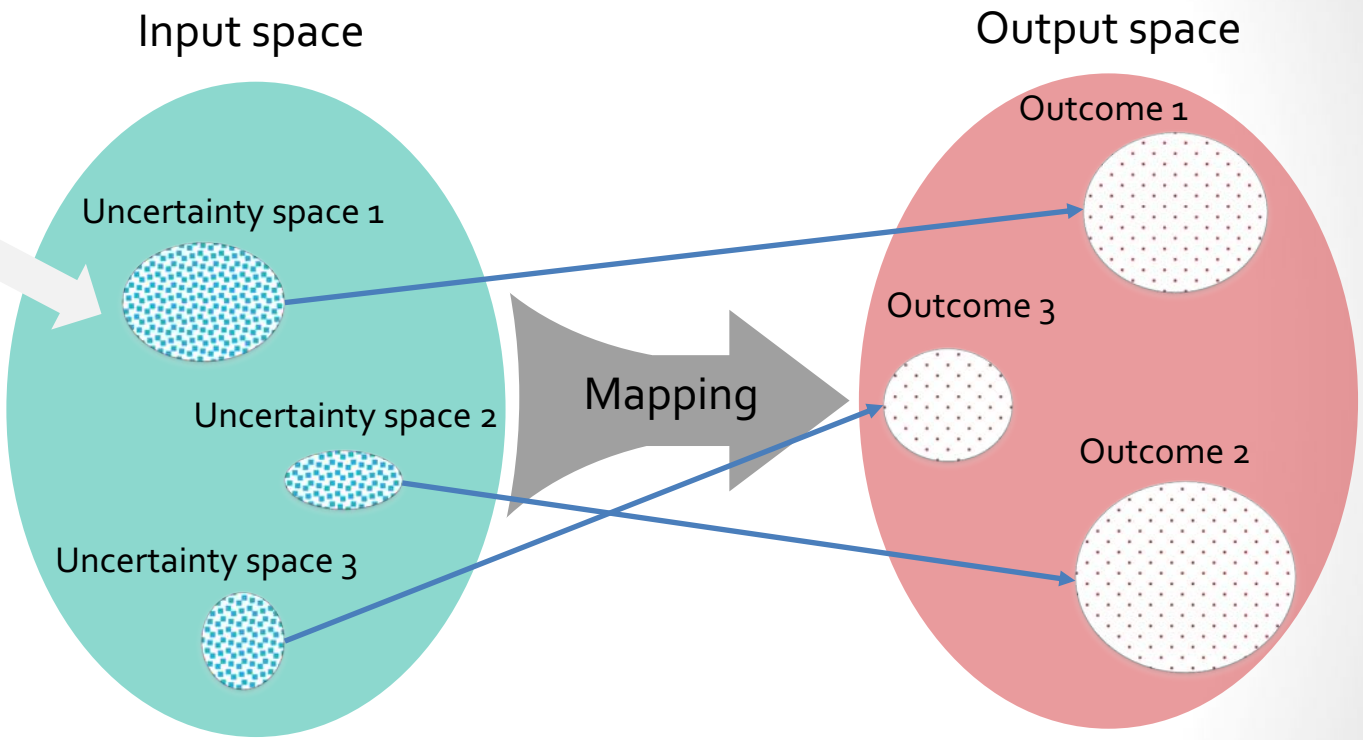

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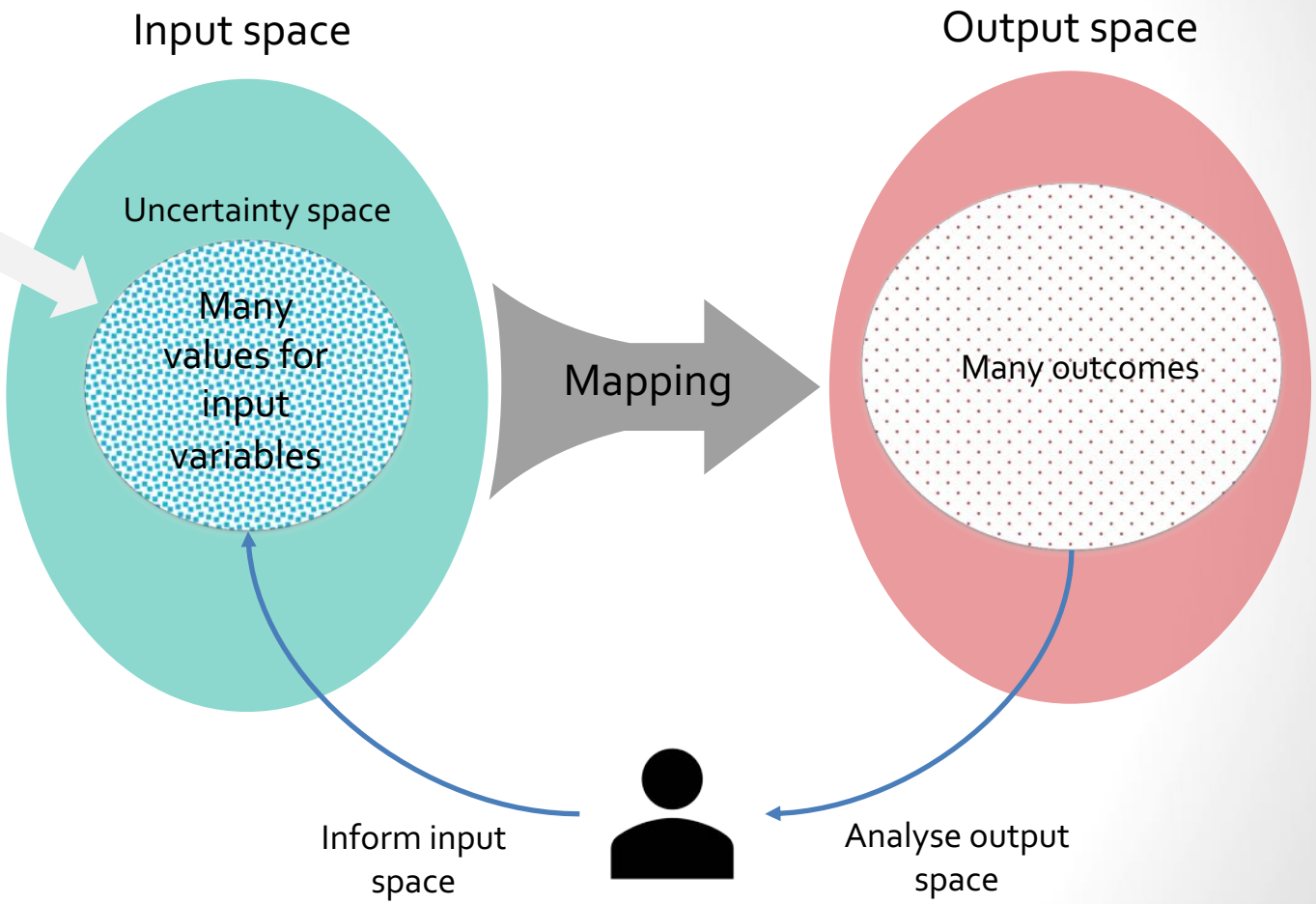

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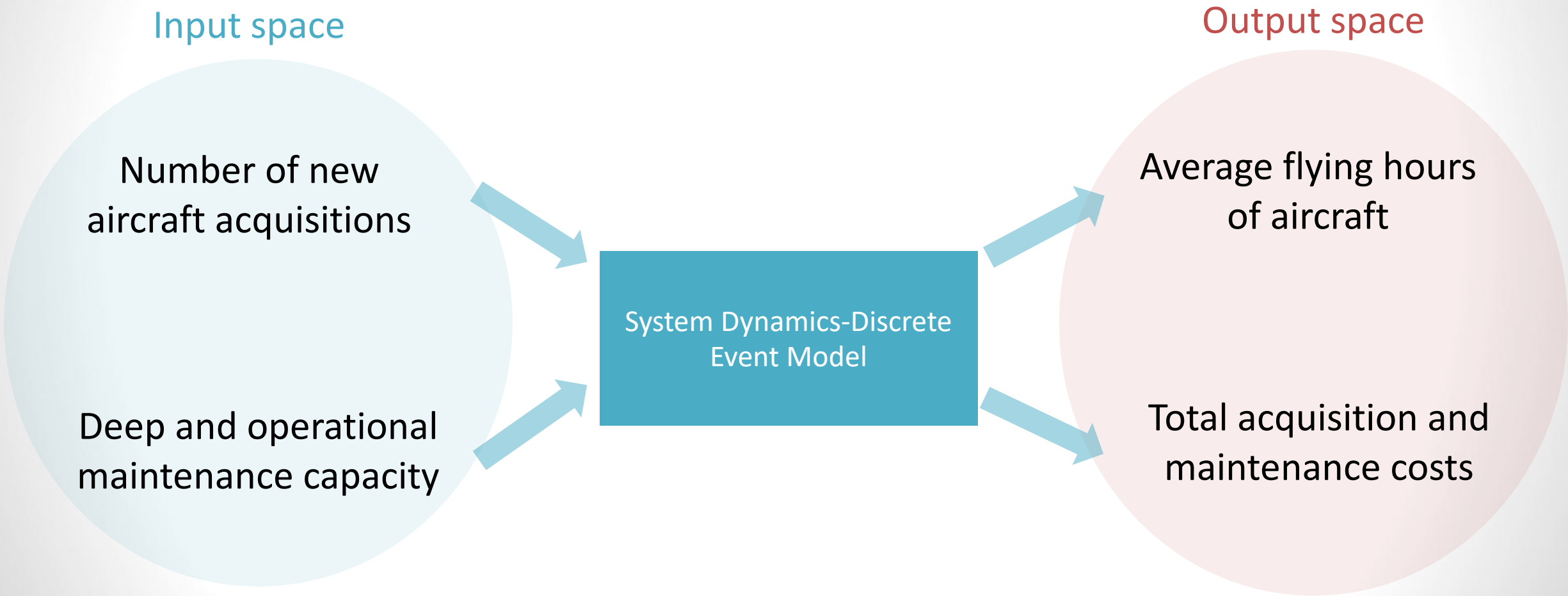
Research questions

Question 1: How sensitive is the output solution space to changes in the input uncertainty space?

Question 2: How can we inform the delineation of the input uncertainty space by screening a behaviour of interest in the output solution space?

~ Methods & Results ~

Capability acquisition and maintenance management of aircraft fleets



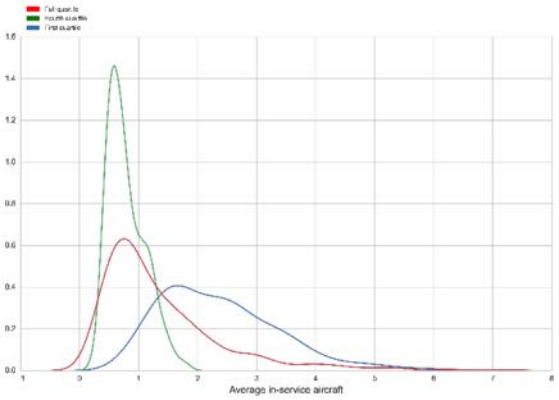
Alternative boundaries of uncertainty space

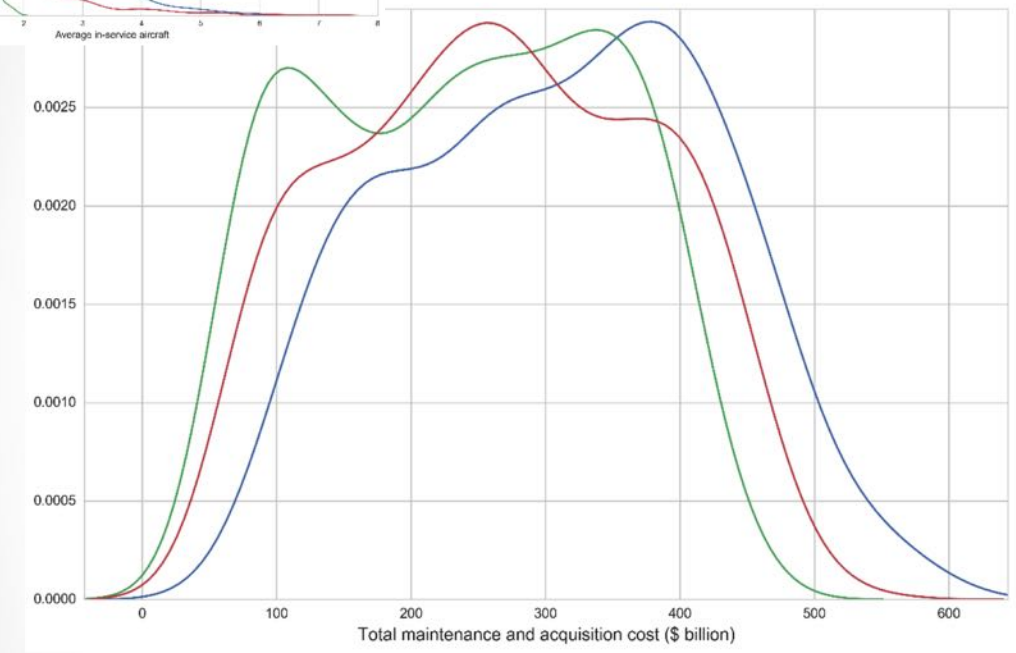
Three subsets of the uncertainty space :

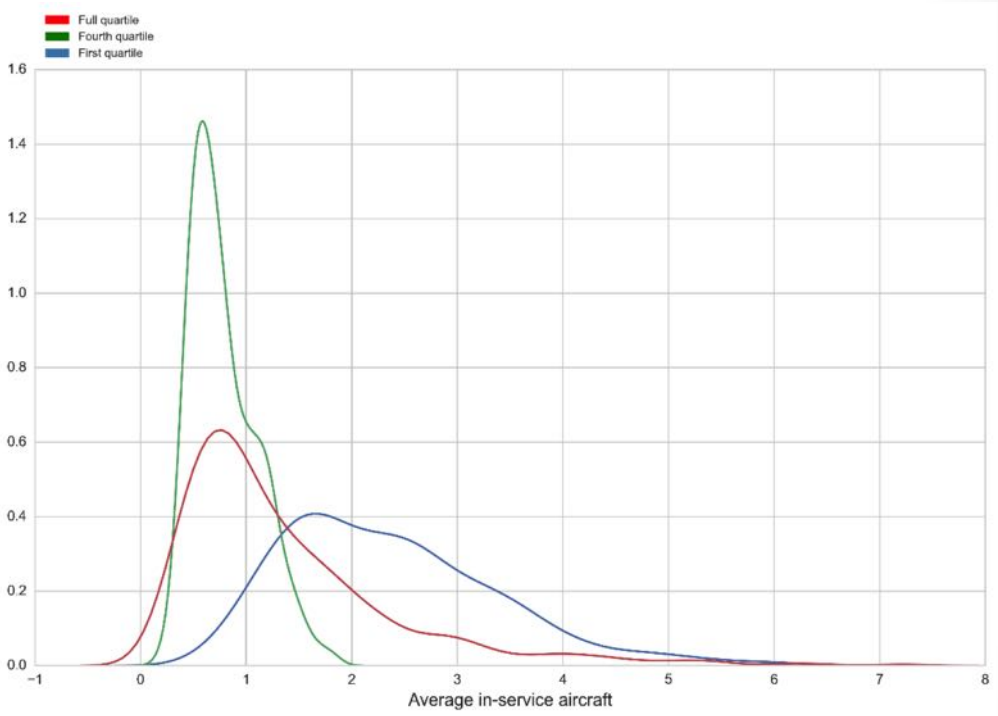
- Full range
- First quartile
- fourth quartile

Critical uncertainty factor	Range of variation
The risk that an aircraft is lost during operation	0.00026 – 0.00234
Lifetime of aircraft	37440 – 336690 (hour)
Total required flying hours	12 – 200 (hour/week)
Expected time spent by an aircraft in Capability Assurance Program (CAP)	8 – 45 (week)
Time between CAP events	16 – 40 (week)
Expected time spent by an aircraft in DM (Time in DM)	5 – 25 (week)
Time (flying hours) between DM events	200 – 1800 (hour)
Expected time spent by an aircraft in OM (Time in OM)	3 – 15 (week)
Time between OM events	50 – 450 (hour)
CAP available capacity	1 – 7 (aircraft)
Number of purchased aircraft	1 – 7 (aircraft)
OM available capacity	1 – 7 (aircraft)
DM available capacity	1 – 7 (aircraft)

ificance of the uncertainty space: KDEs & ANNOVA







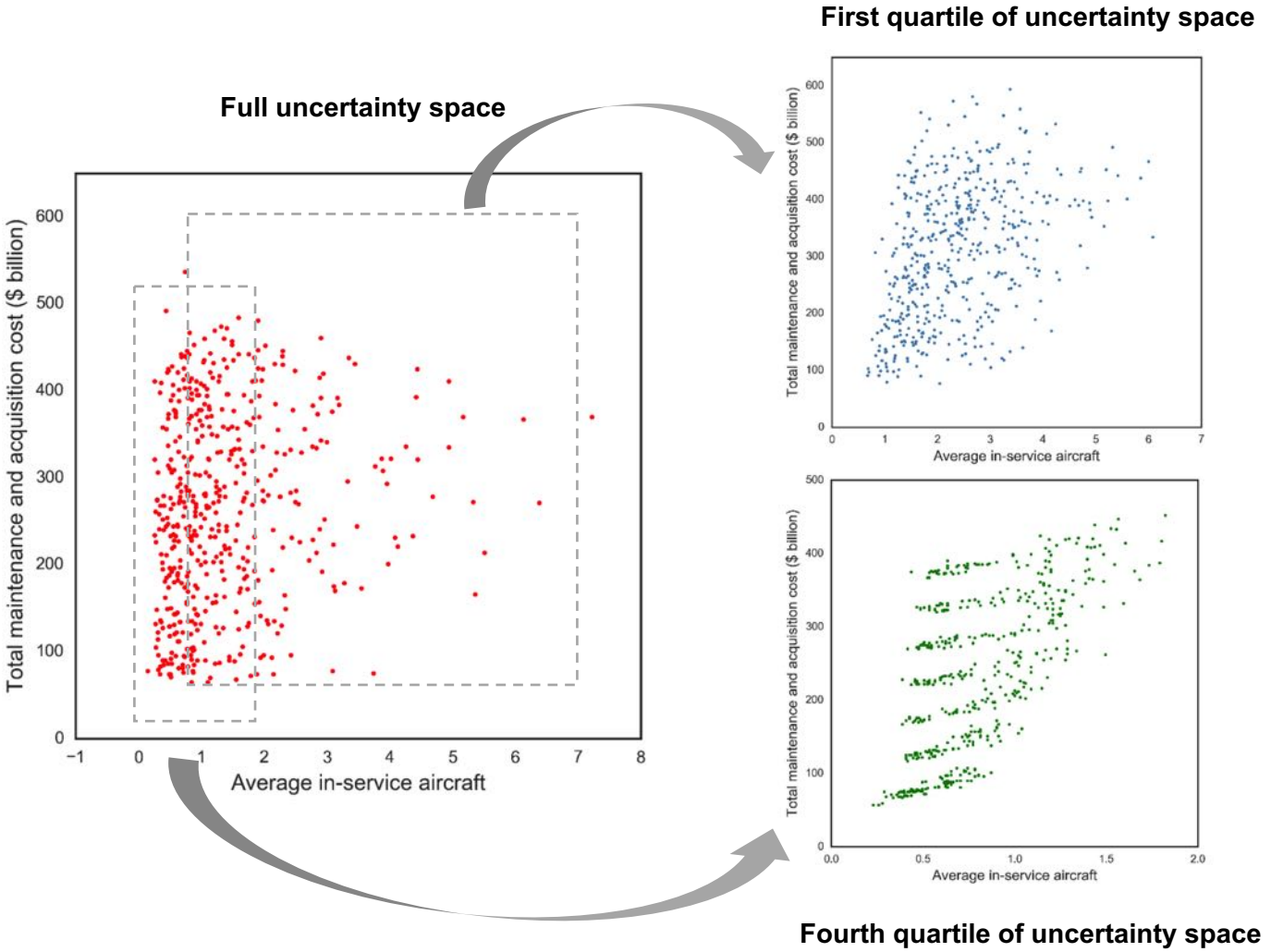
ANOVA SUMMARY for distribution of total costs

Ensemble	*Average*	*Variance*	*F*	*P-value*	*F critical*
Full range	264.484	12688.114	50.297	< 0.001	3.002
First quartile	308.946	13644.183			
Fourth quartile	238.402	11610.105			

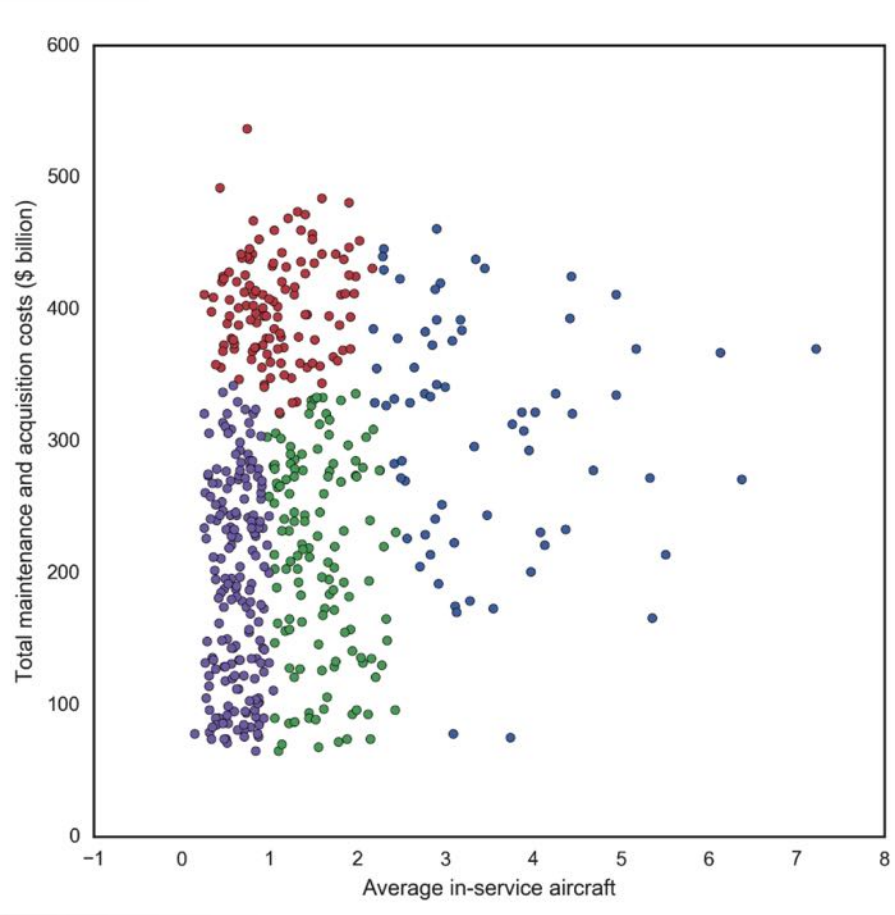
ANOVA SUMMARY for distribution of in-service aircraft

Groups	*Average*	*Variance*	*F*	*P-value*	*F critical*
Full range	1.379	1.102	426.463	< 0.001	3.002
First quartile	2.363	1.015			
Fourth quartile	0.792	0.099			

The significance of the uncertainty space: Scatterplots



Informing the delineation of uncertainty space



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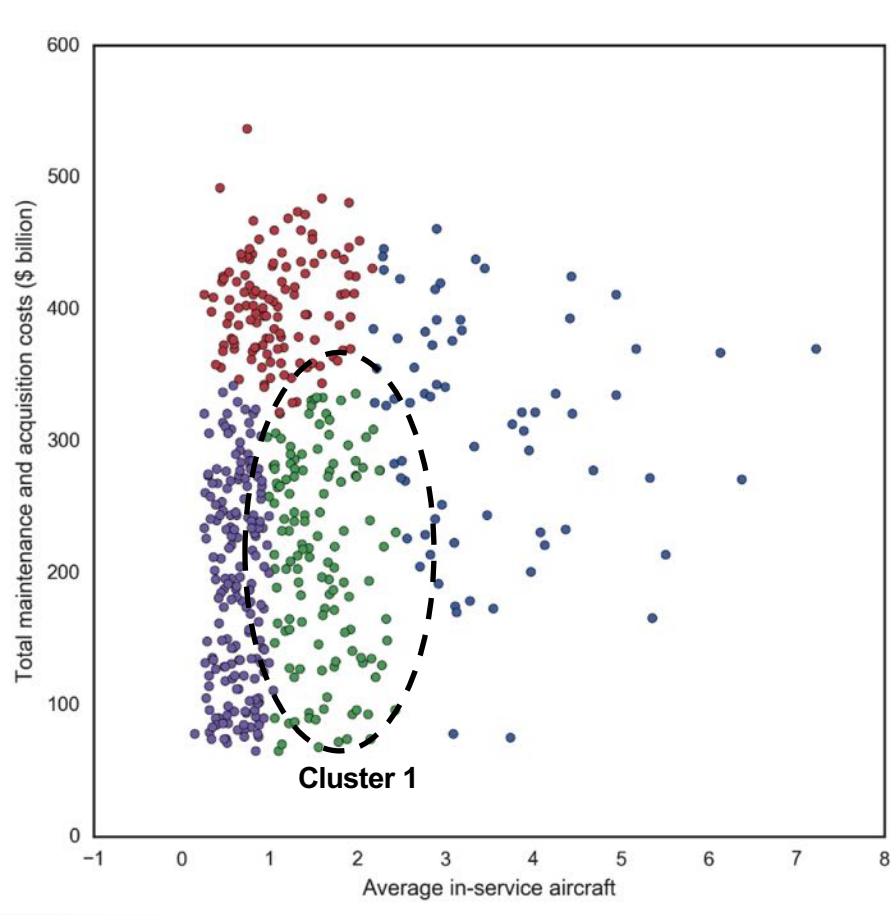

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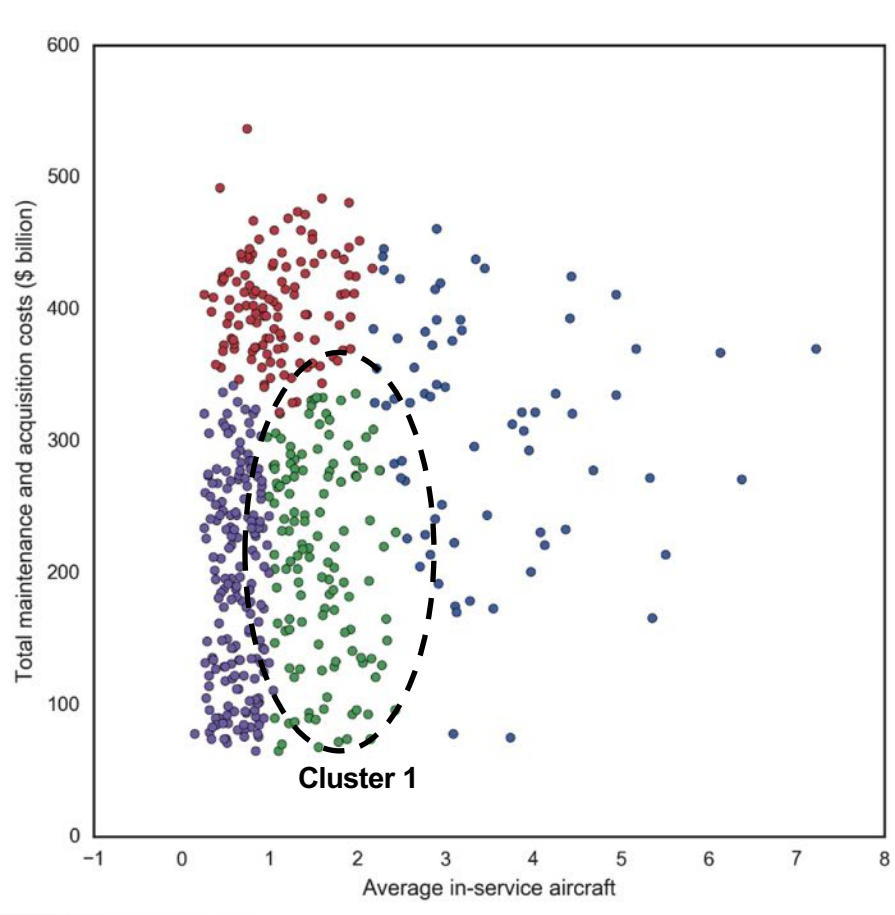
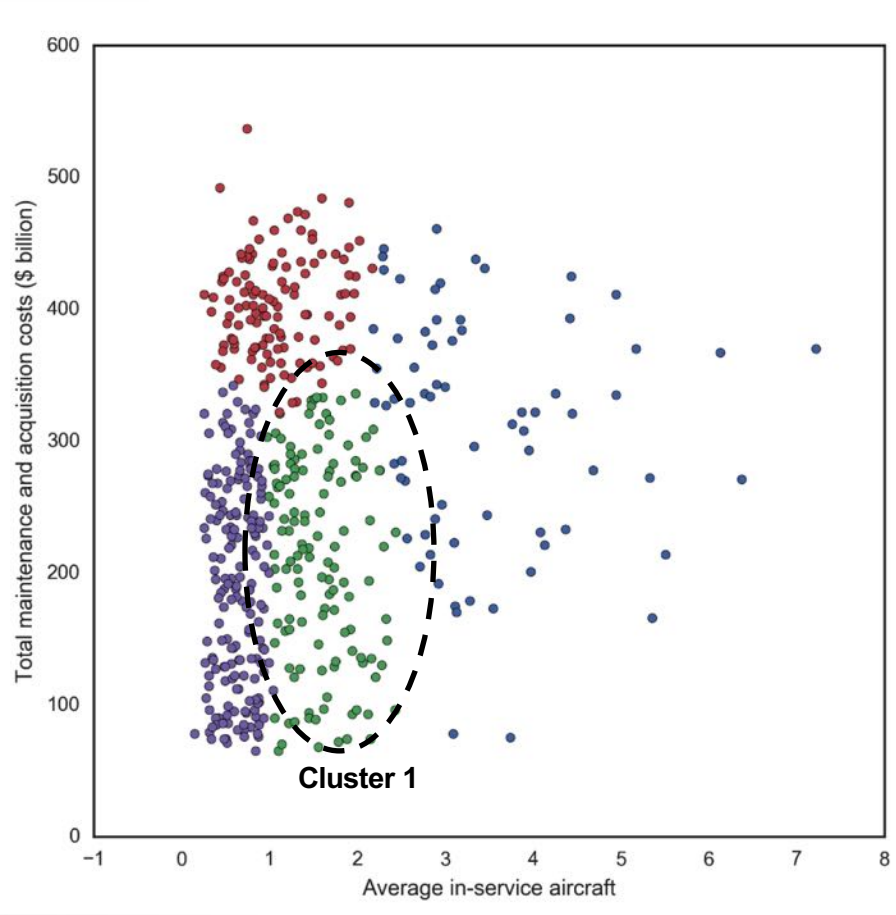


Scenario Discovery

What area of the input uncertainty space is responsible for Cluster 1?

Informing the delineation of uncertainty space



Scenario Discovery

What area of the input uncertainty space is responsible for Cluster 1?

Measure of merits	***Uncertainty***	***Range***	***P-value***
Coverage: 0.33	Number of purchased aircraft	2 – 5 (aircraft)	5.7e-07
Density: 93.30	Required flying hours	22 – 130 (hour/week)	6.8e-6
	Time spent in OM	4.2 – 14 (week)	1.3e-3
	OM available capacity	3 – 7 (aircraft)	1.5e-3
	CAP available capacity	2 – 7 (aircraft)	2.7e-3

Informing the delineation of uncertainty space

Results of scenario discovery

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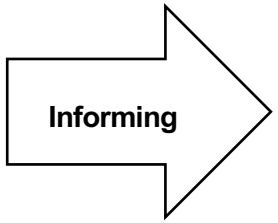

Modified uncertainty space leading to model behaviour in Cluster 1

Critical uncertainty factor	Range of variation
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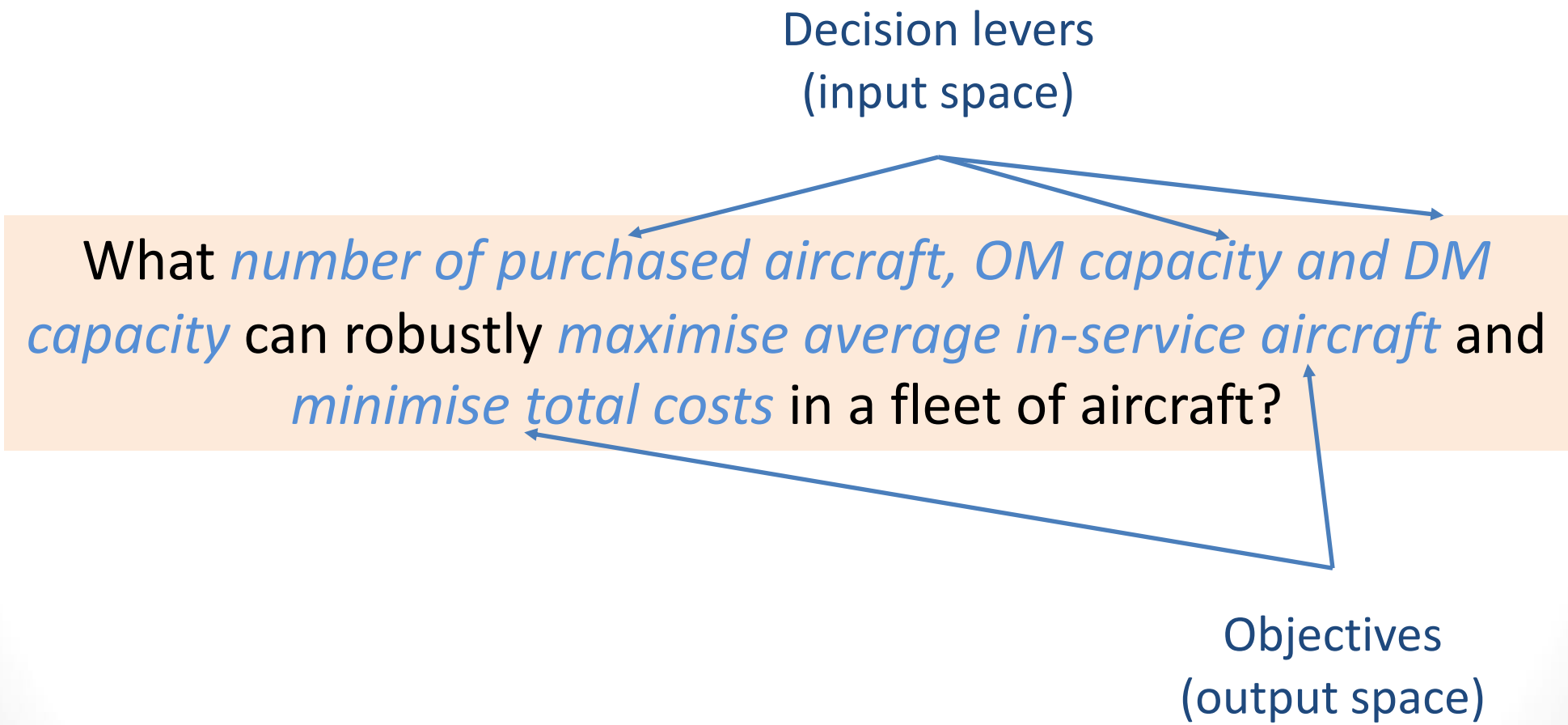
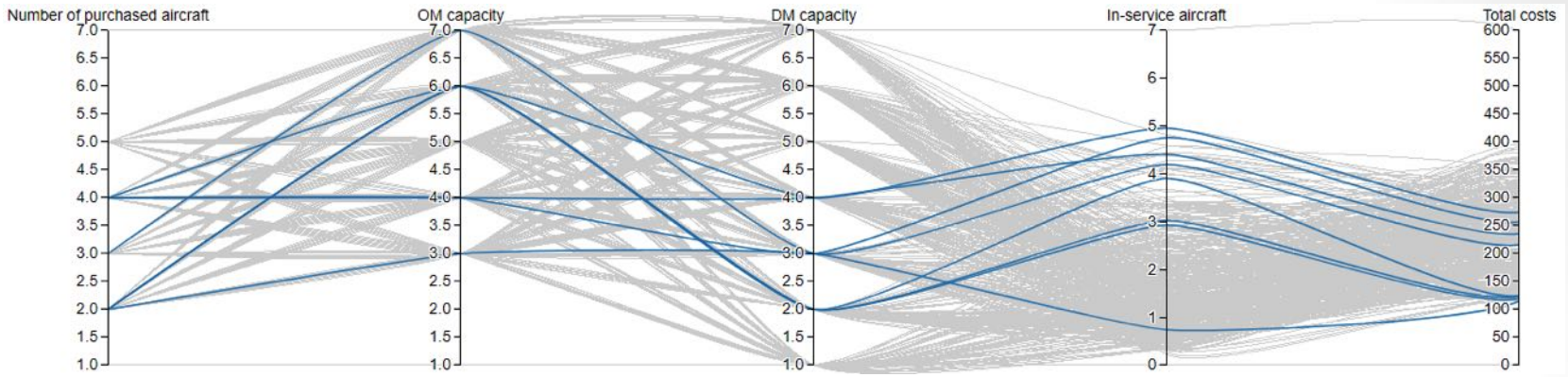
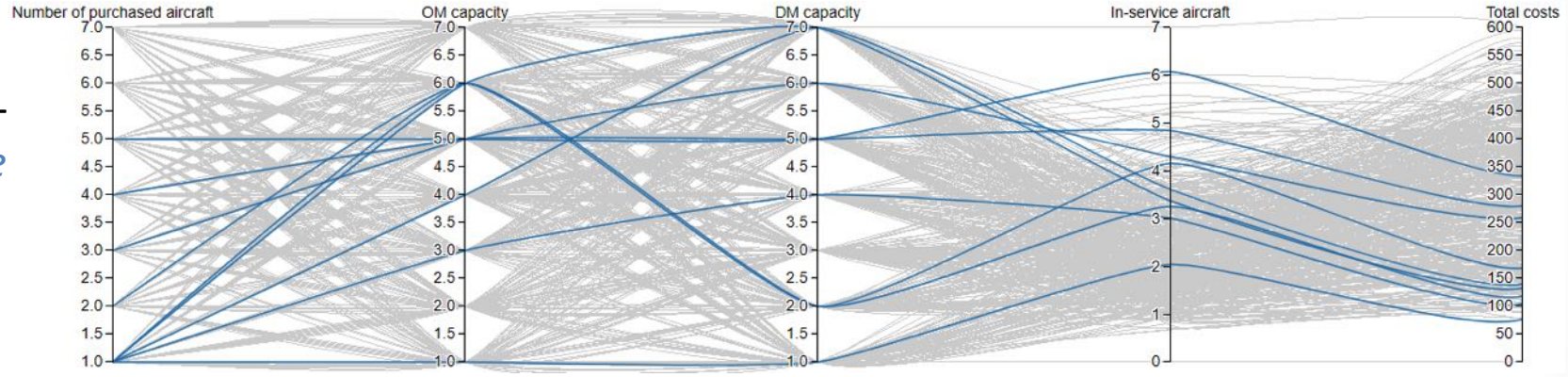
How much does the informed uncertainty space improve the confidence of results?



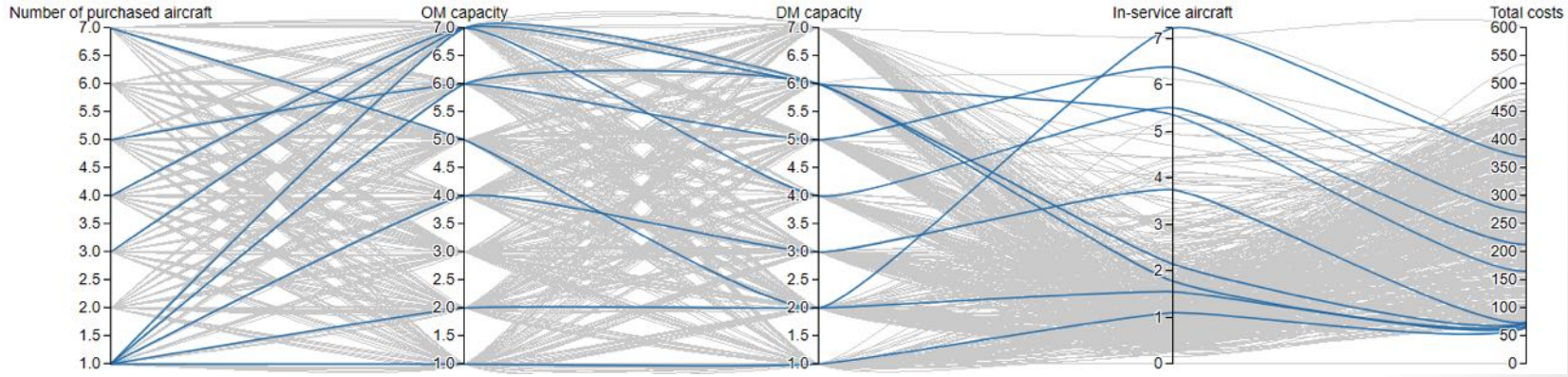
Pareto optimal solutions –
Informed uncertainty space



Pareto optimal solutions –
First quartile uncertainty space



Pareto optimal solutions –
Full uncertainty space



Robustness metrics

First robustness metric

Dispersion of decision levers

$$f_i(x) = Min\ (\mu_i + 1)(\sigma_i + 1)$$

Second robustness metric

Deviation of objectives from a threshold

$$f_i(x) = \begin{cases} Min\ (-\mu_i, \sum_{k=1}^{k} (x_k - threshold)^2 [x_k > threshold]\ ) \\ Max\ (\mu_i, -\sum_{k=1}^{k} (x_k - threshold)^2 [x_k < threshold]\ ) \end{cases}$$

Kwakkel, J. H., Eker, S., & Pruyt, E. (2016). How Robust is a Robust Policy? Comparing Alternative Robustness Metrics for Robust Decision-Making. In M. Doumpos, C. Zopounidis & E. Grigoroudis (Eds.), Robustness Analysis in Decision Aiding, Optimization, and Analytics (pp. 221-237). Cham: Springer International Publishing.

Robustness metrics

	Cluster 1	First quartile	Full range
Mean (in-service aircraft)	3.619	3.853	3.864
Mean (total costs)	183.375	179.444	152.778
Undesirable deviation from the threshold (in-service aircraft)	16.320	17.430	49.479
Undesirable deviation from the threshold (total costs)	141903	194765	293827
Dispersion (Purchased aircraft)	7.467	7.6182	11.397
Dispersion (OM capacity)	14.369	14.285	18.649
Dispersion (DM capacity)	6.900	16.577	13.946

~ Conclusions ~

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- Moving towards the *real-time* monitoring of the output space and controlling of the input space.
- Developing a simple and quick *control model* to relate output space to input space.
- Going beyond uncertainty space and *informing other aspects in design of experiments* (sample size, sampling technique, etc.).

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