

Overview of my research projects

Khalil Al Handawi, PhD

Technical presentation

May 18, 2023

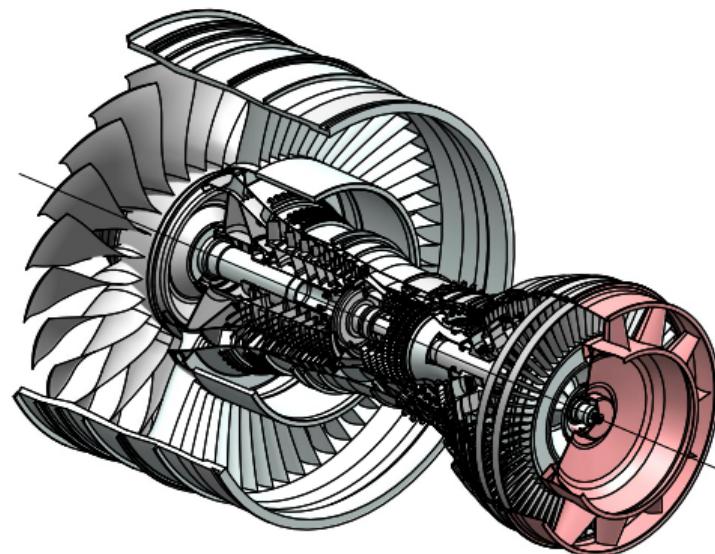
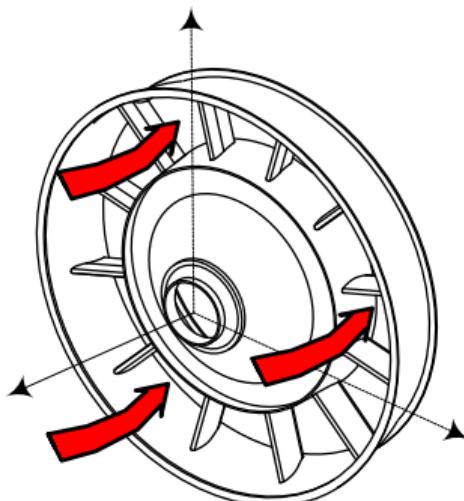
About me

- Khalil Al Handawi (*he/him/il*)
 - Experience with simulation based design
 - Experience with scientific computing
 - Experience with optimization and simulation research
- Born and raised in Abu Dhabi, United Arab Emirates
- Moved to Montréal in 2017
- Obtained a doctorate in mechanical engineering from McGill University



The challenge

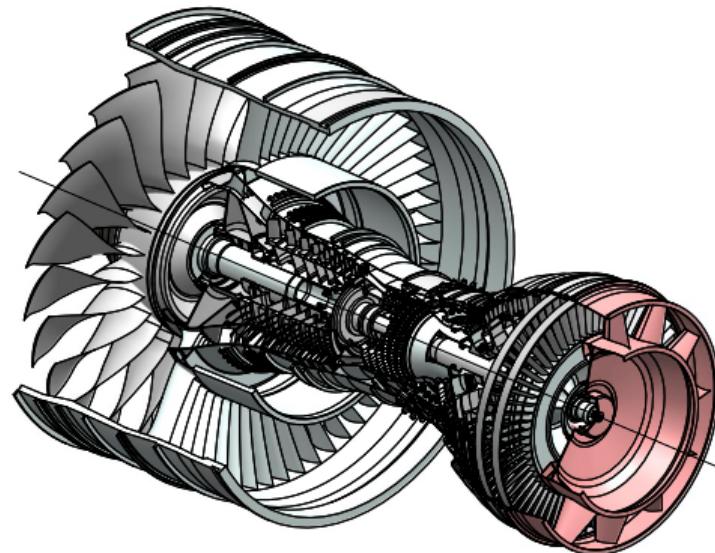
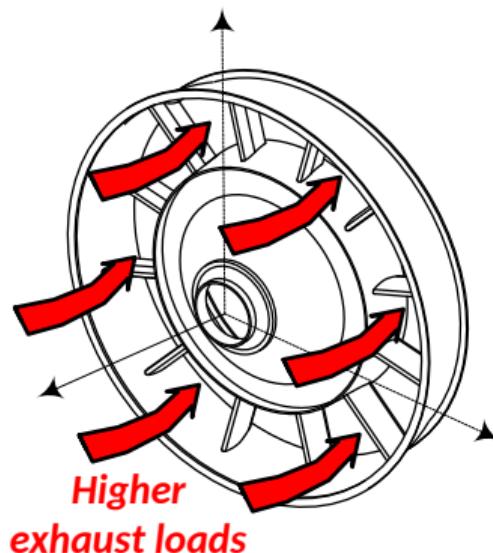
- This is a Turbine Rear Structure (TRS) under thermal loading



An aeroengine

The challenge

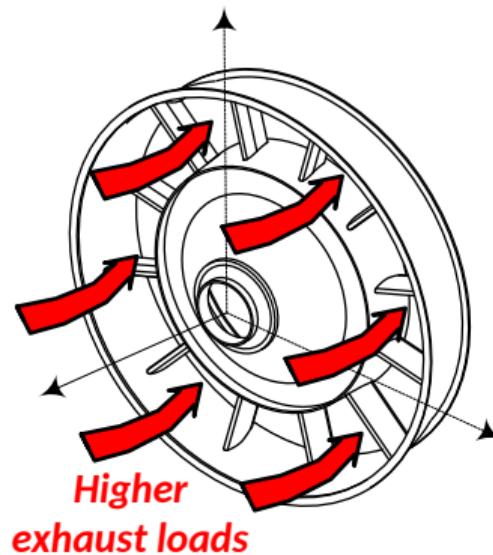
- This is a Turbine Rear Structure (TRS) under thermal loading
- Over its lifetime, design requirements can change



An aeroengine

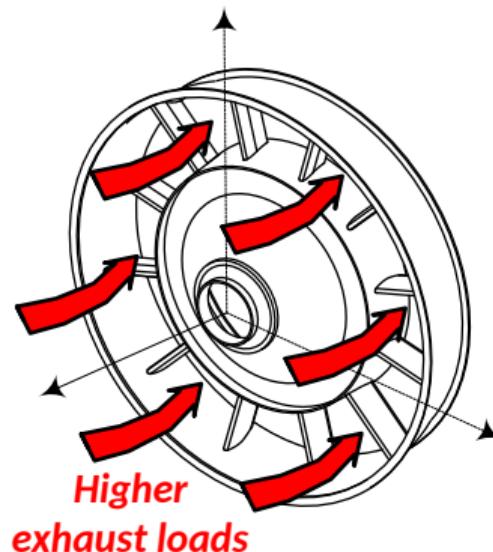
The opportunity

- Disposal or redesign can be sub-optimal options



The opportunity

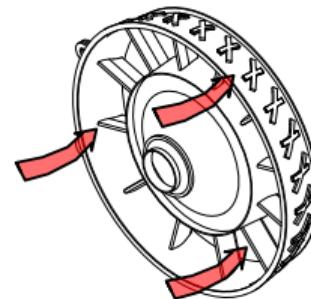
- Disposal or redesign can be sub-optimal options
- Additive remanufacturing may be a better option to extend useful lifetime



AM Remanufacturing of TRS

Change absorption through scalability

When the applied loads change:



Change absorption through scalability

When the applied **loads change**:



Change absorption through scalability

When the applied **loads change**:

A design can be **changed**:

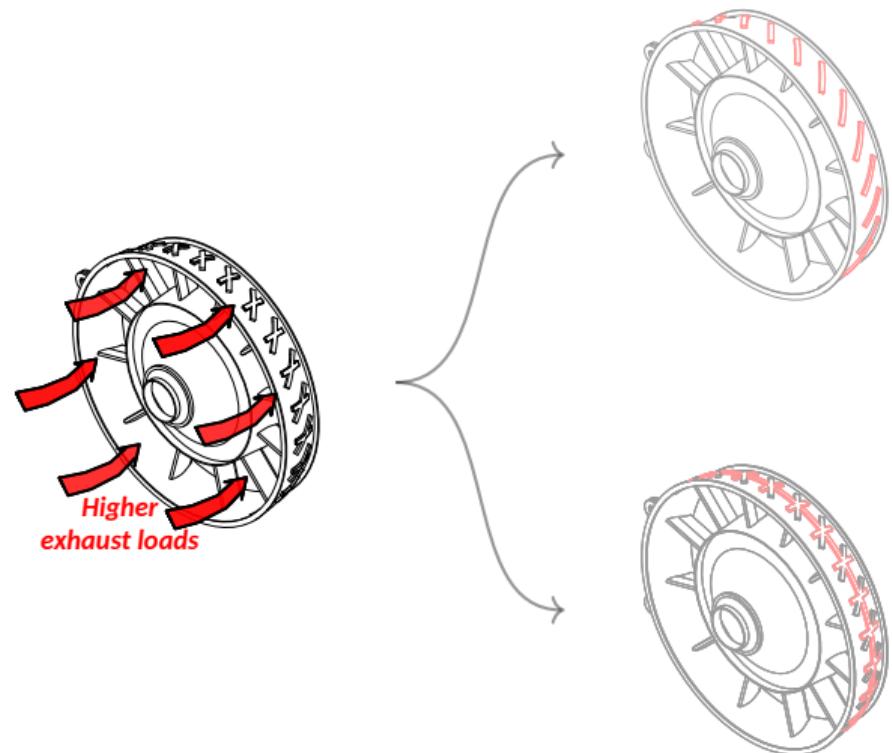


Change absorption through scalability

When the applied **loads change**:

A design can be **changed**:

- *Scalability*: the ability to change to accommodate stricter requirements¹

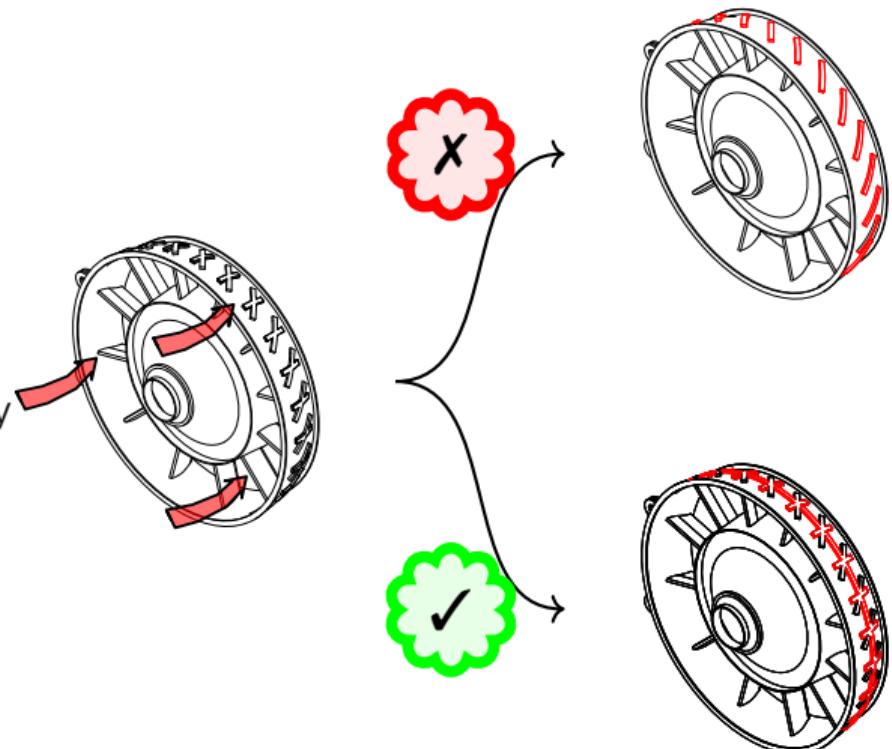


Change absorption through scalability

When the applied **loads change**:

A design can be **changed**:

- *Scalability*: the ability to change to accommodate stricter requirements ¹
- Successful *remanufacturing*: enabled by scalability of components ²



[1] A. Ross et al., 2008 , *Systems Engineering*

[2] K. Xing et al., 2007 , *International Journal of Advanced Manufacturing Technology*

Change absorption through scalability and remanufacturing ¹

Parametric design optimization problem formulation

Remanufacturing variables are included in the design optimization problems and changing requirements are modeled by parameters \mathbf{p}

Design optimization problem

$$\underset{x}{\text{minimize}} \quad f(x; p) = -n_{\text{safety}}(x; P_{\text{load}})$$

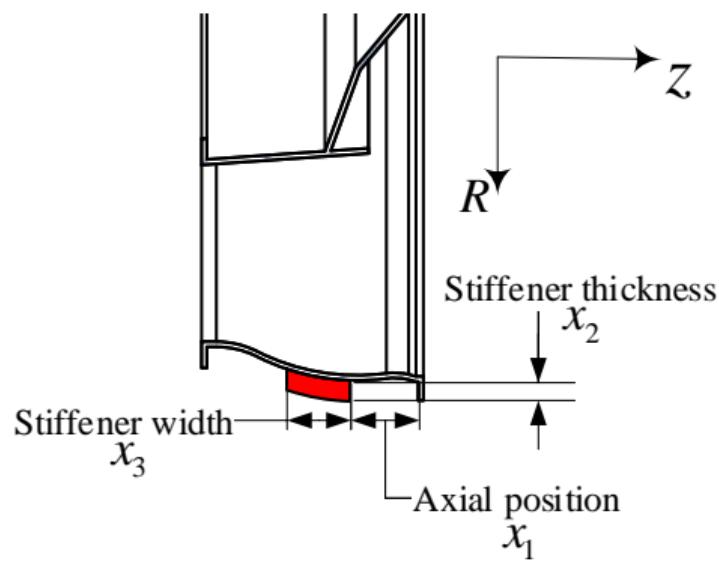
$$\text{subject to } \begin{aligned} g_1(x; p) &= x_3 + x_1 - W_{\text{total}} \leq 0 \\ g_2(x; p) &= T_m - T_{\text{deposit}} \leq 0 \end{aligned}$$

Changing requirements

W_{total} = width of base part

T_m = Melting temperature of deposit

P_{load} = Pressure load on outer casing



Conditions for scalability

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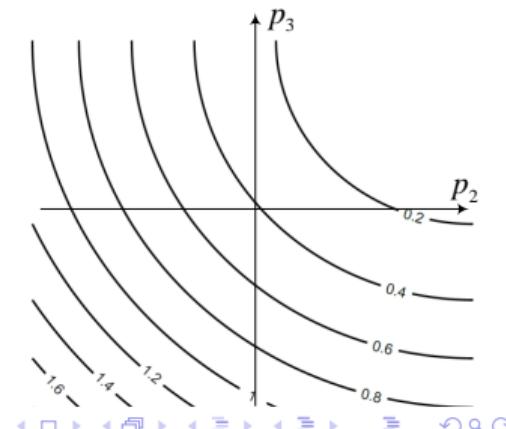
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Let us consider one variable and two parameters
For an optimal design to be scalable, the product of



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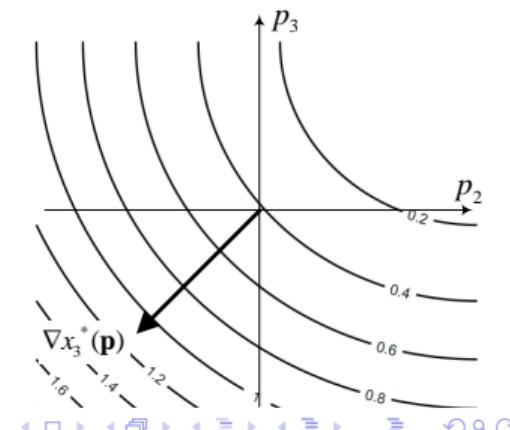
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$J = \text{Direction of change}$



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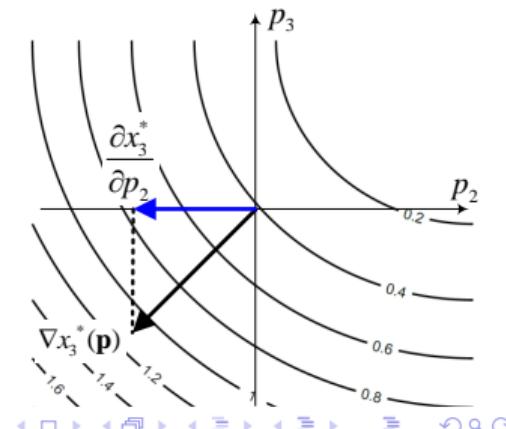
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J=Direction of change

$$\left[\frac{\partial x_3^*}{\partial p_2} \right]$$

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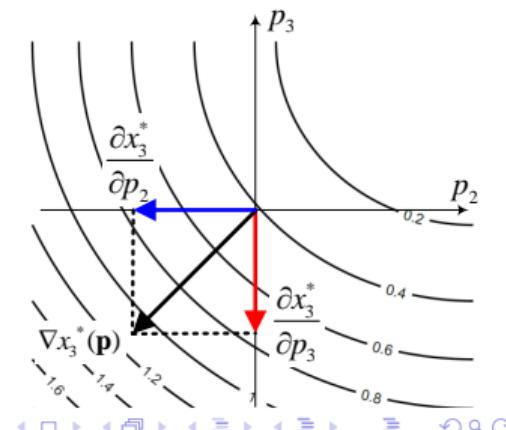
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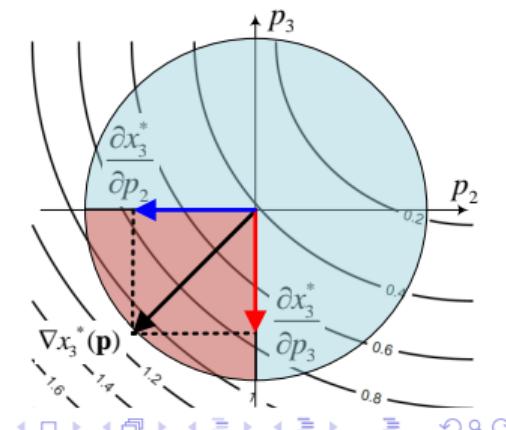
P_{load} = Pressure load on outer casing

N =Change effect J =Direction of change

$$\begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix} \times \begin{bmatrix} \partial x_3^* / \partial p_2 \\ \partial x_3^* / \partial p_3 \end{bmatrix}$$

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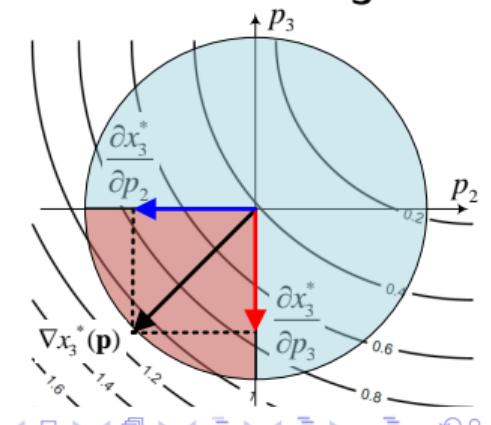
$$\times \begin{bmatrix} 1 \end{bmatrix} \geq 0$$

Let us consider one variable and two parameters
For an optimal design to be scalable, the product of

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must be greater or equal to zero

Scalable design!



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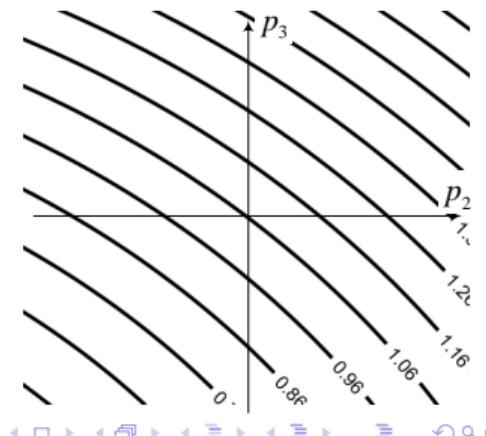
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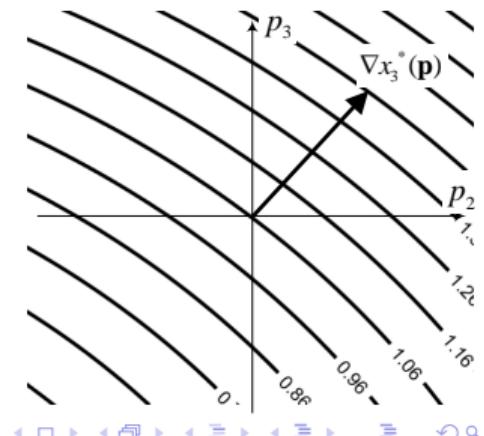
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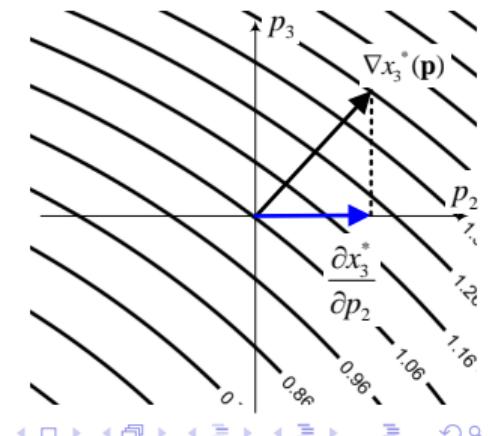
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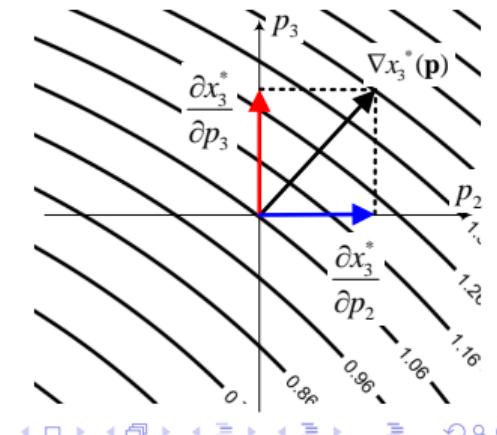
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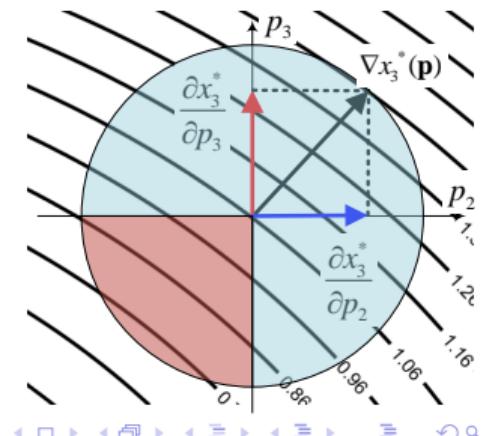
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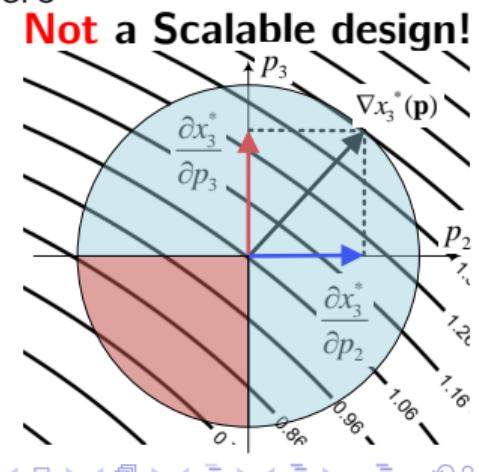
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Our full example: **4** variables and **3** parameters

N=Change effect

$$\begin{bmatrix} n_1 & 0 & 0 \\ 0 & n_2 & 0 \\ 0 & 0 & n_3 \end{bmatrix}$$

J=Direction of change

$$\begin{bmatrix} \partial x_1^* / \partial p_1 & \partial x_2^* / \partial p_1 & \partial x_3^* / \partial p_1 & \partial x_4^* / \partial p_1 \\ \partial x_1^* / \partial p_2 & \partial x_2^* / \partial p_2 & \partial x_3^* / \partial p_2 & \partial x_4^* / \partial p_2 \\ \partial x_1^* / \partial p_3 & \partial x_2^* / \partial p_3 & \partial x_3^* / \partial p_3 & \partial x_4^* / \partial p_3 \end{bmatrix}$$

M=Monotonicity

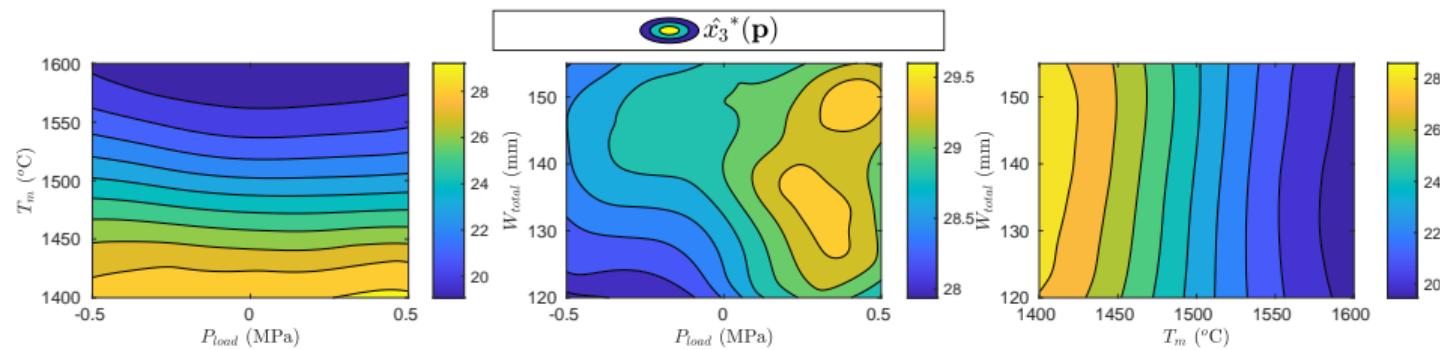
$$\begin{bmatrix} m_1 & 0 & 0 & 0 \\ 0 & m_2 & 0 & 0 \\ 0 & 0 & m_3 & 0 \\ 0 & 0 & 0 & m_4 \end{bmatrix} \geq 0$$

Response surface of parametric optimal solutions and scalable designs

- Computing the components of $\mathbf{J}(\mathbf{p})$ can be prohibitively expensive

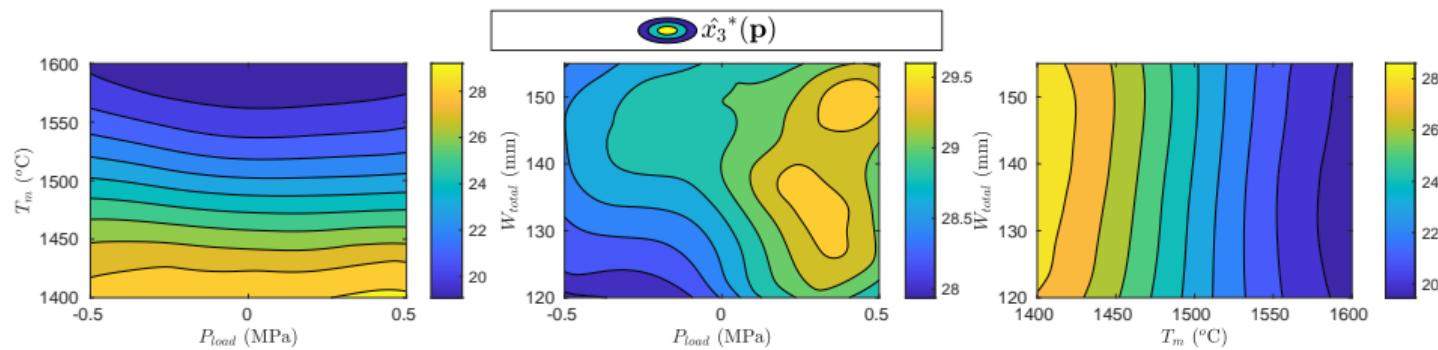
Response surface of parametric optimal solutions and scalable designs

- Computing the components of $\mathbf{J}(\mathbf{p})$ can be prohibitively expensive
- Response surface $\hat{\mathbf{x}}^*(\mathbf{p})$ can be obtained from parametric optimal designs
 $\mathbf{X}^* = \{\mathbf{x}^*(\mathbf{p}_1) \ \mathbf{x}^*(\mathbf{p}_2) \ \cdots \ \mathbf{x}^*(\mathbf{p}_k)\}$
(we use kernel smoothing)



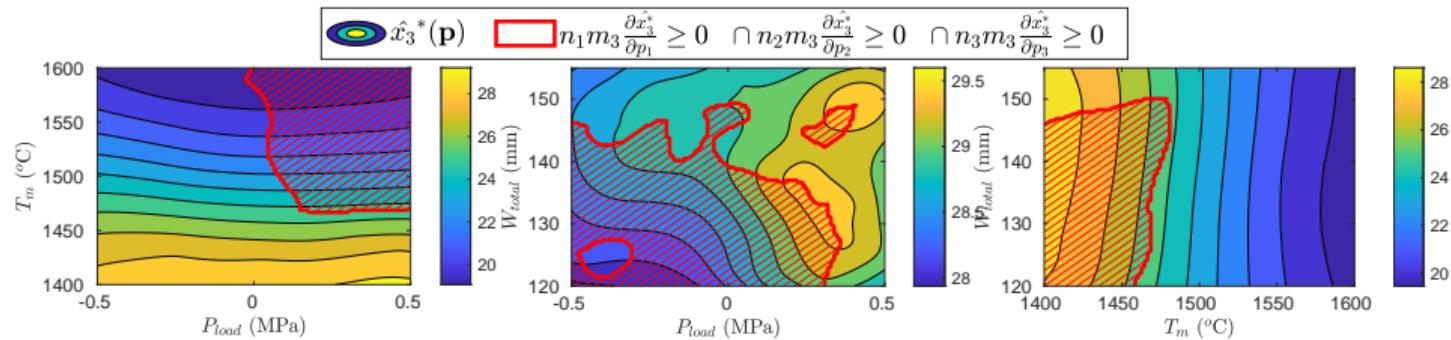
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- Jacobian $\mathbf{J}(\mathbf{p})$ of $\hat{\mathbf{x}}^*(\mathbf{p})$ estimated from the derivatives of the kernel basis functions

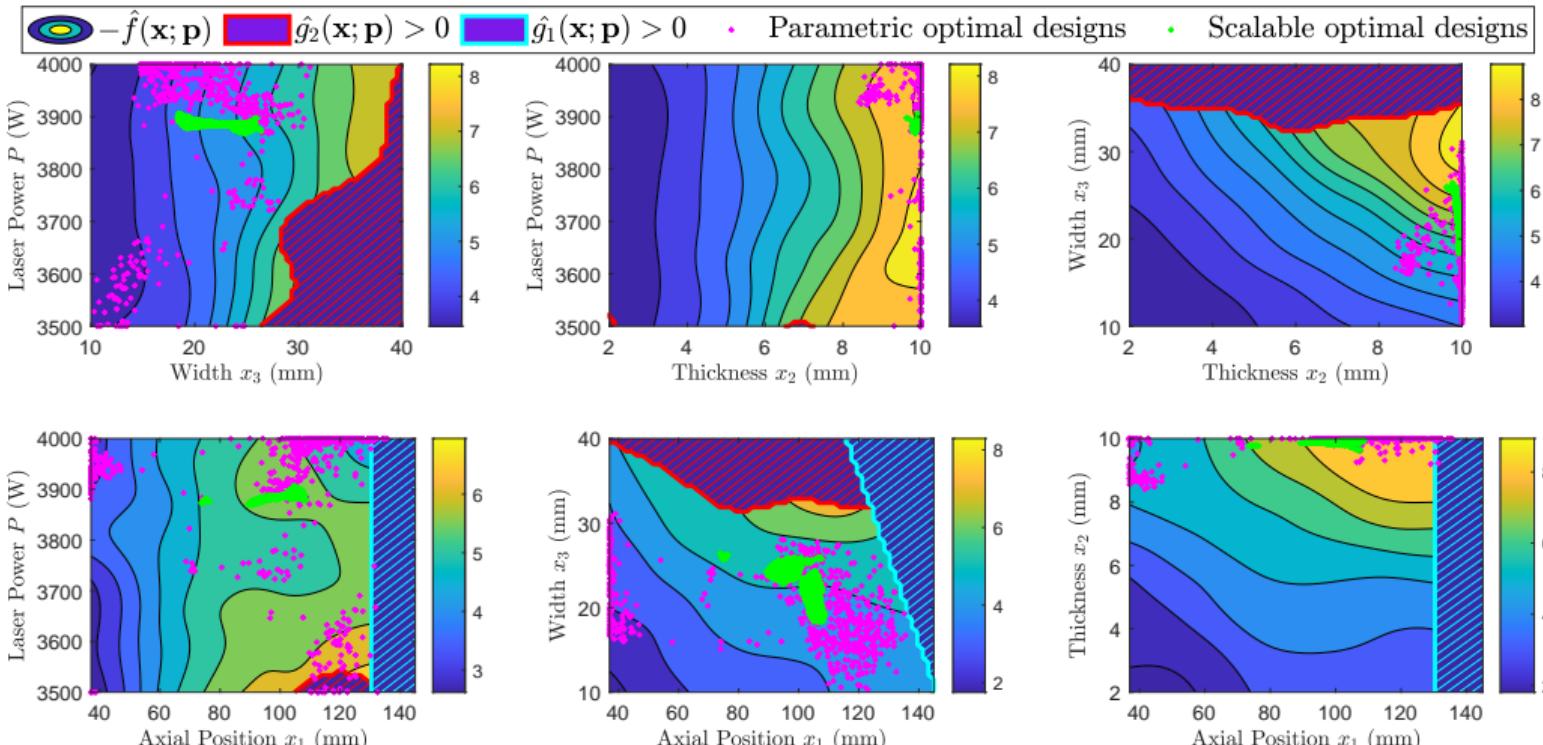


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- Jacobian $\mathbf{J}(\mathbf{p})$ of $\hat{\mathbf{x}}^*(\mathbf{p})$ estimated from the derivatives of the kernel basis functions
- Scalable optimal designs given by $\mathbf{N}\mathbf{J}(\mathbf{p})^T \mathbf{M} \geq \mathbf{0}$.



Map scalable optimal design set to design space

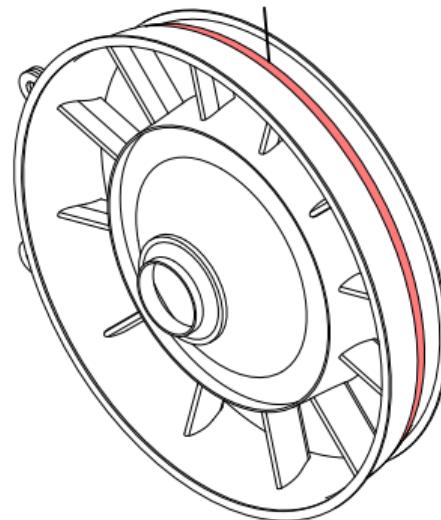


Using design margins to absorb change in requirements¹

Quantifying capability, buffer, and excess

- Failure criterion: Factor of safety $n_{\text{safety}}(\mathbf{T})$

Safety factor evaluation domain

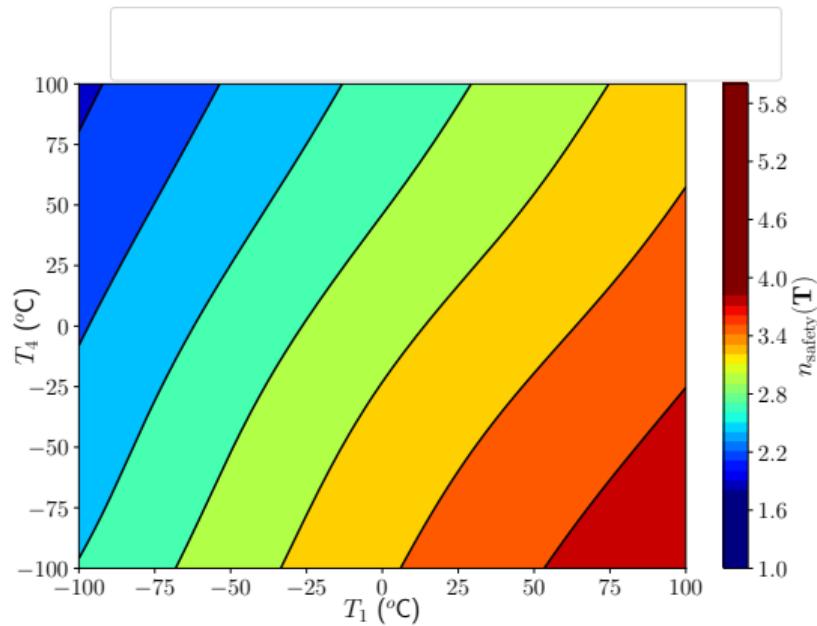


Failure domain

Quantifying capability, buffer, and excess

We focus on one 2D projection

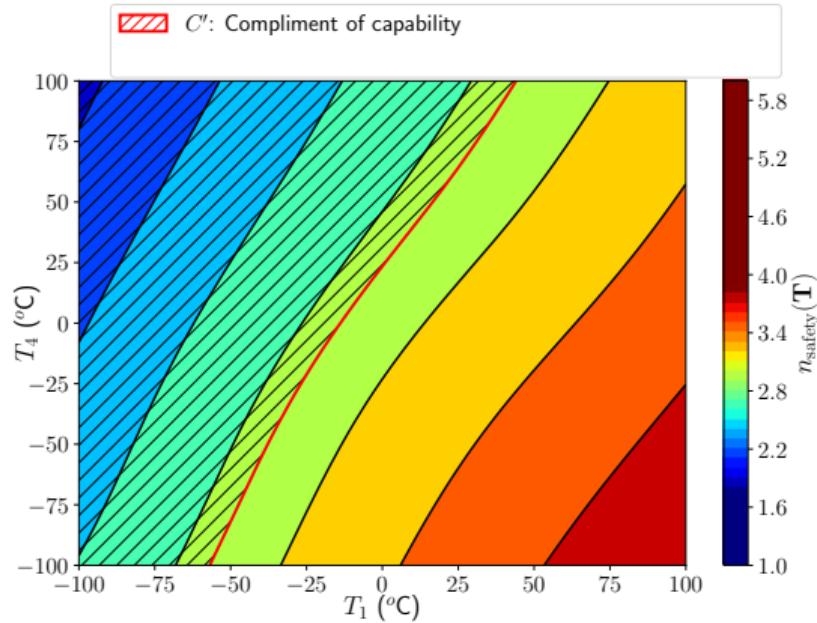
- *Failure criterion:* Factor of safety $n_{\text{safety}}(\mathbf{T})$ represented using isocontours



Quantifying capability, buffer, and excess

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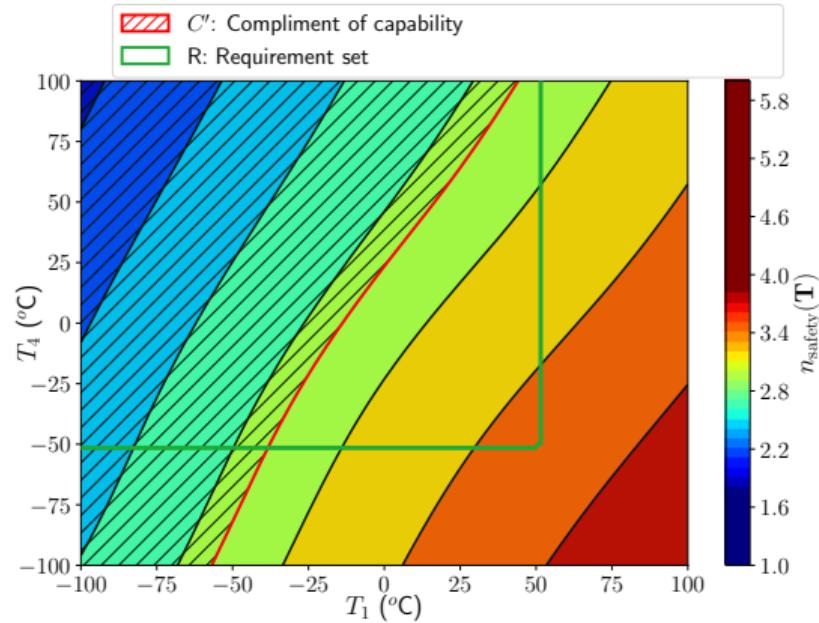
- *Failure criterion:* Factor of safety $n_{\text{safety}}(\mathbf{T})$ represented using isocontours
- *Capability:* Loads that **can** be satisfied



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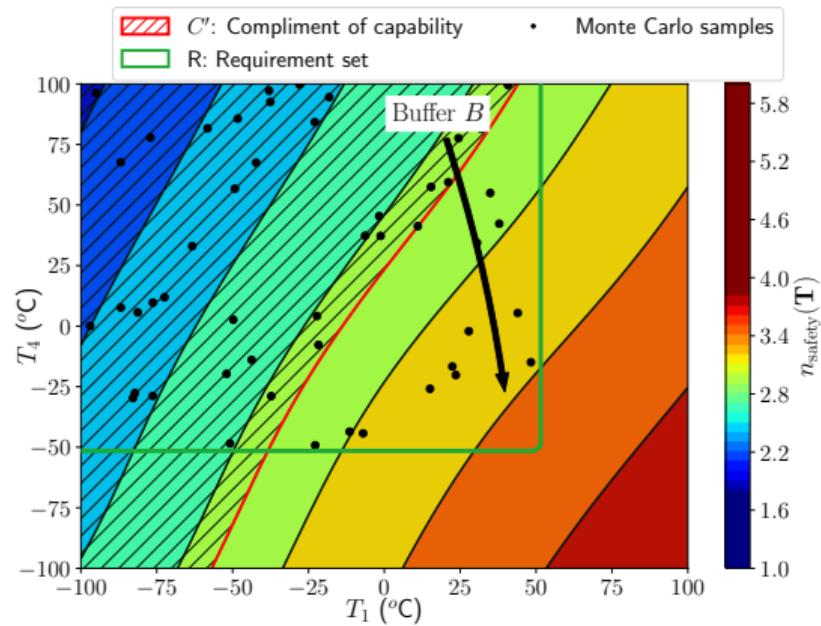
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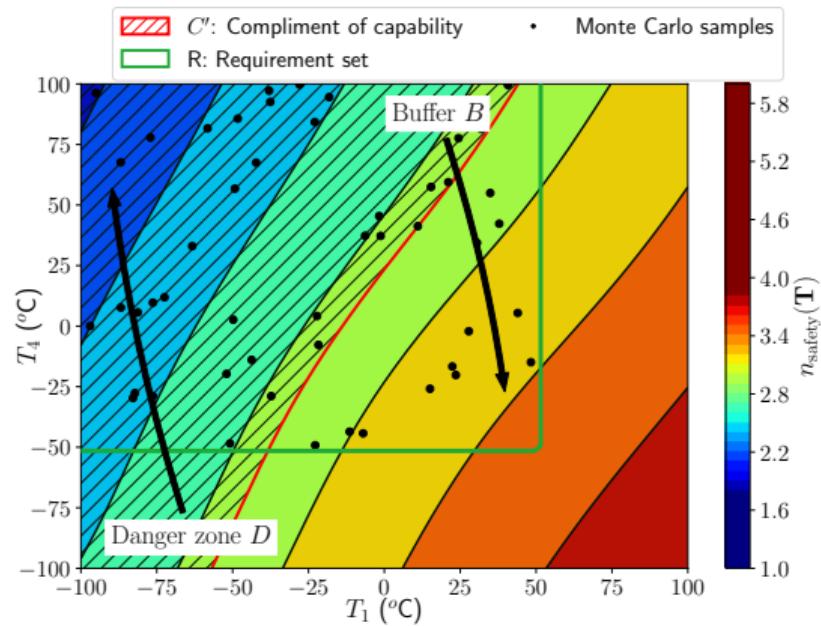
- *Failure criterion:* Factor of safety $n_{\text{safety}}(\mathbf{T})$ represented using isocontours
- *Capability:* Loads that **can** be satisfied
- *Requirements:* Loads that **must** be satisfied
- *Buffer:* Portion of requirement **satisfied**



Quantifying capability, buffer, and excess

We focus on one 2D projection

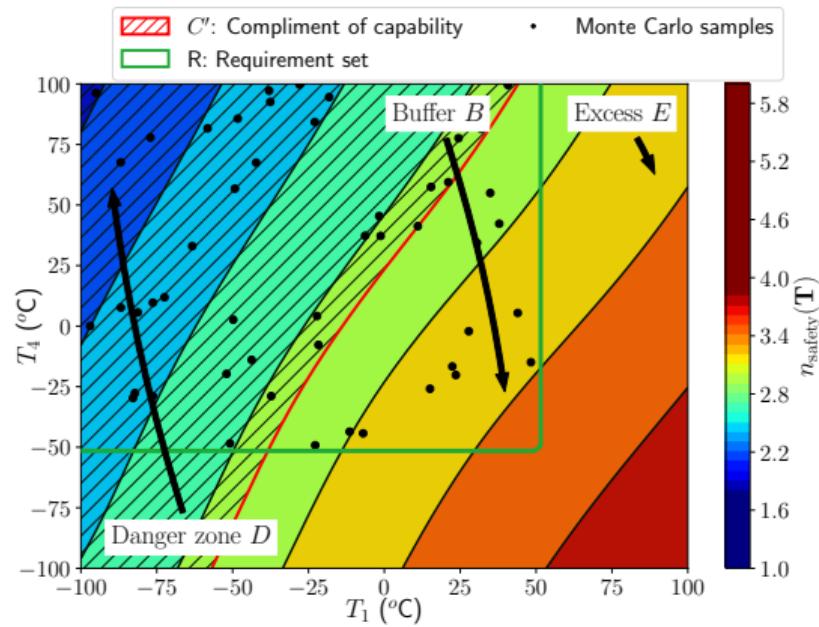
- *Failure criterion:* Factor of safety $n_{\text{safety}}(\mathbf{T})$ represented using isocontours
- *Capability:* Loads that **can** be satisfied
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- *Buffer:* Portion of requirement **satisfied**
- *Danger:* Portion of requirement **not satisfied**



Quantifying capability, buffer, and excess

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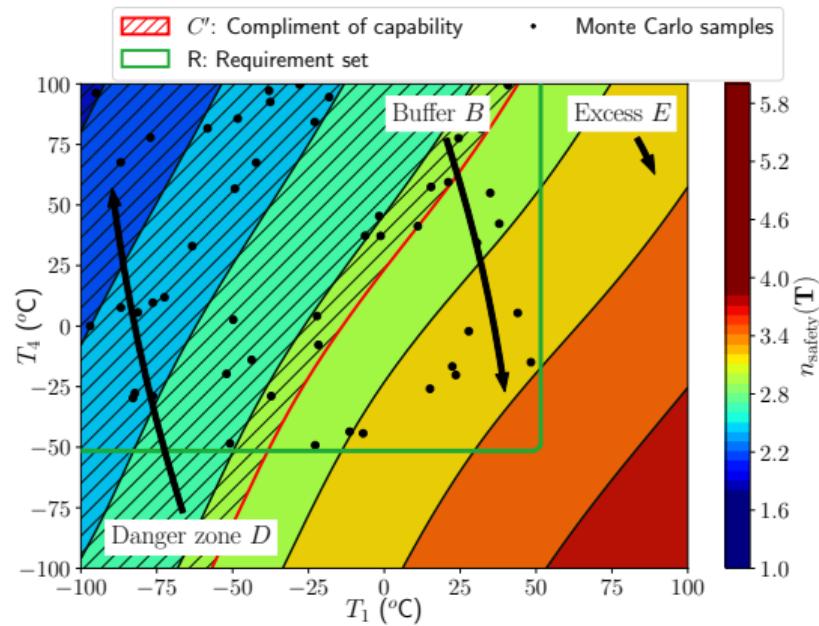
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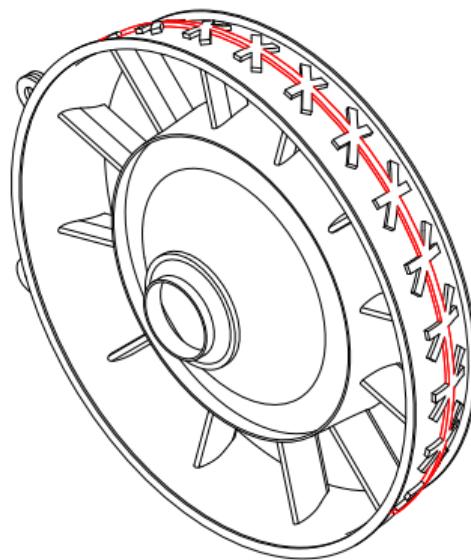
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- *Reliability:* $\mathbb{P}(\mathbf{T} \in C)$ estimated using Monte-Carlo integration



Considering redesign when buffer is insufficient

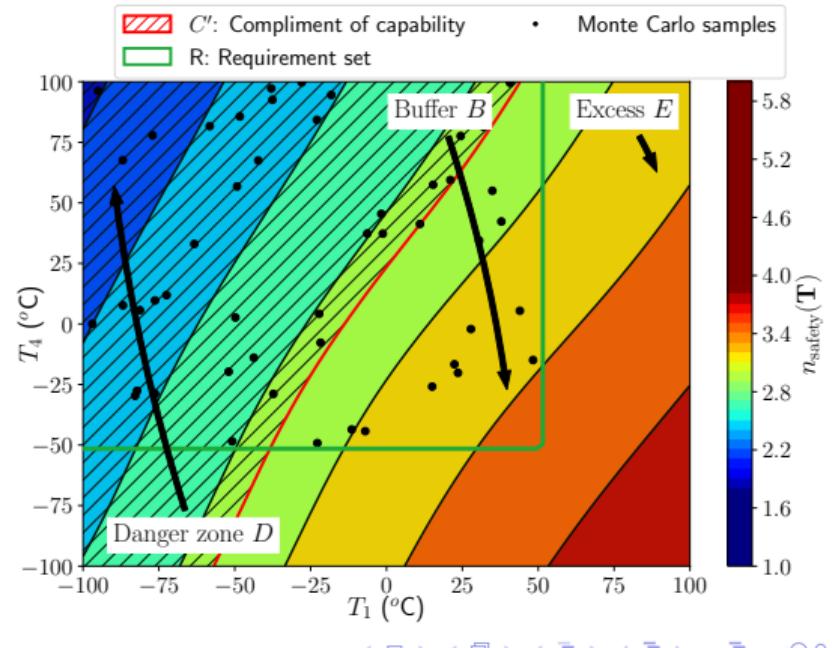
Going back to our baseline design we can calculate these metrics as follows:

$$c = 1, \mathbf{D} = [1, 2, 4]$$



Turbine Rear Structure (TRS)

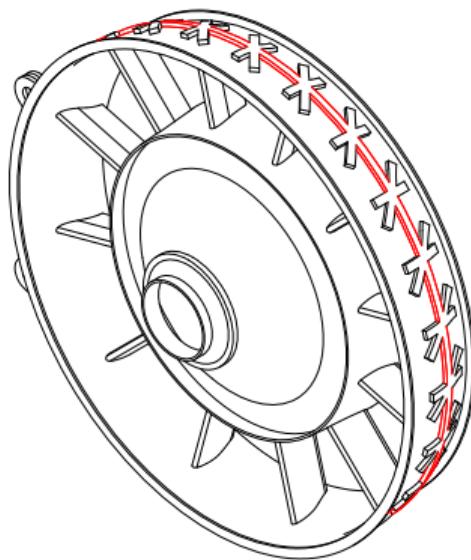
Reliability	Excess	Weight
0.3089	0.529	13.9



Considering redesign when buffer is insufficient

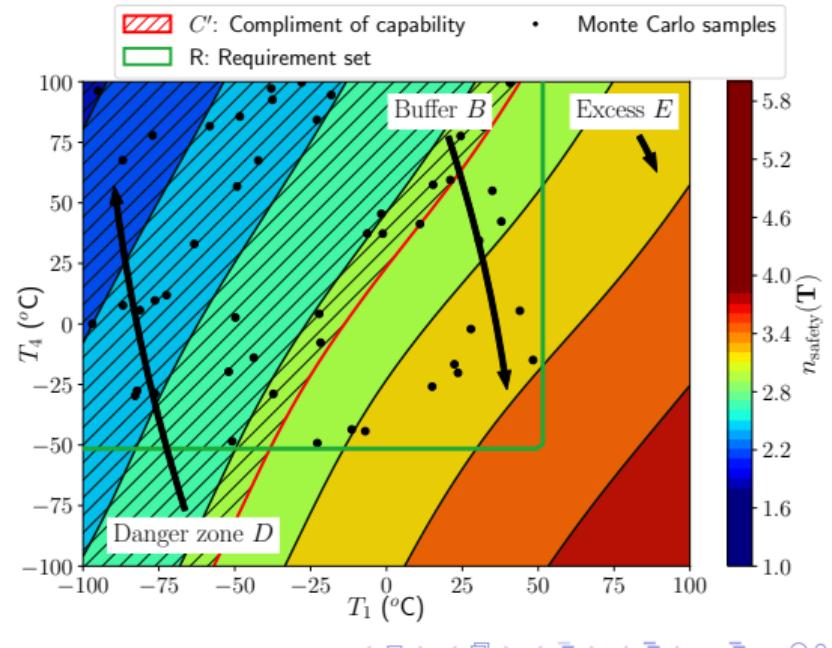
Consider depositing more material

$$c = 1, \mathbf{D} = [1, 2, 4, 0]$$



Turbine Rear Structure (TRS)

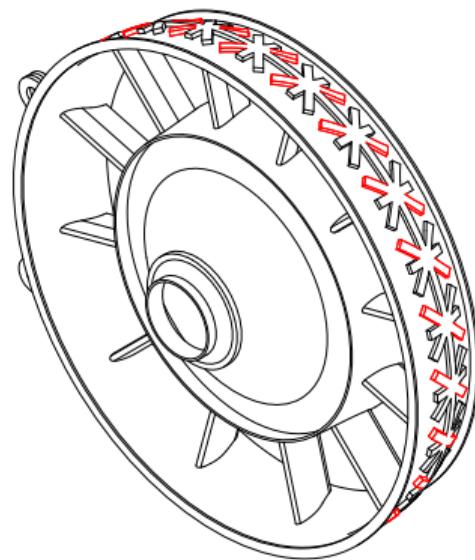
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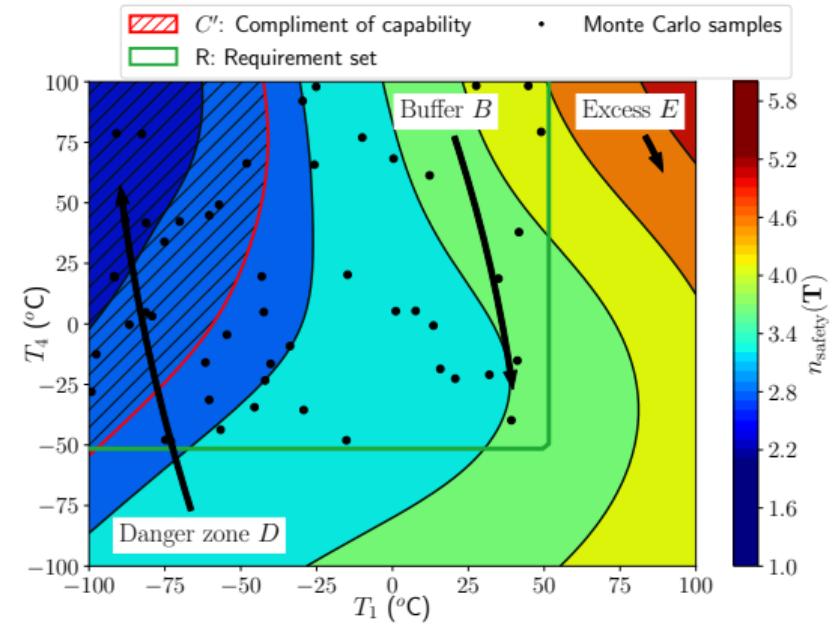
Reliability increases

$$c = 1, \mathbf{D} = [1, 2, 4, 0]$$



Turbine Rear Structure (TRS)

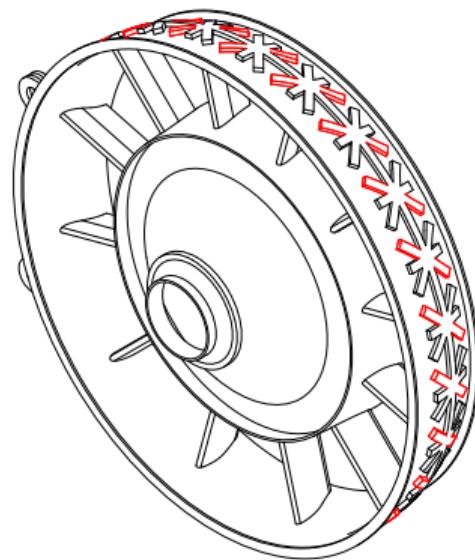
Reliability	Excess	Weight
0.759($\uparrow 145\%$)	0.856($\uparrow 62\%$)	18.5($\uparrow 33\%$)



Considering redesign when buffer is insufficient

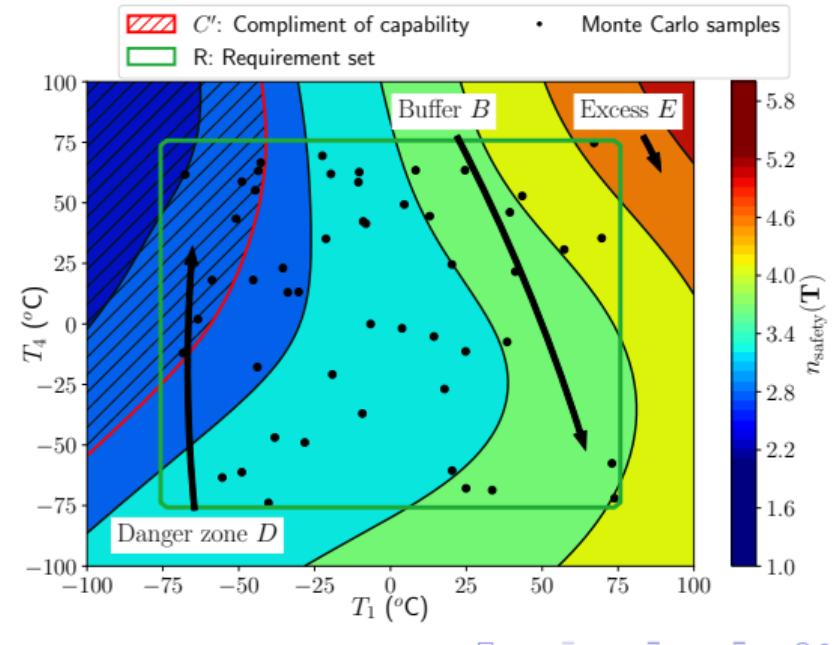
However, requirements can change as well!

$$c = 1, \mathbf{D} = [1, 2, 4, 0]$$



Turbine Rear Structure (TRS)

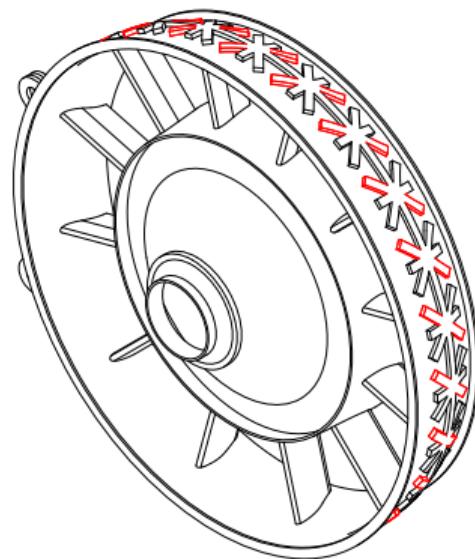
Reliability	Excess	Weight
0.943($\uparrow 24\%$)	0.754($\downarrow 12\%$)	18.5



Considering redesign when buffer is insufficient

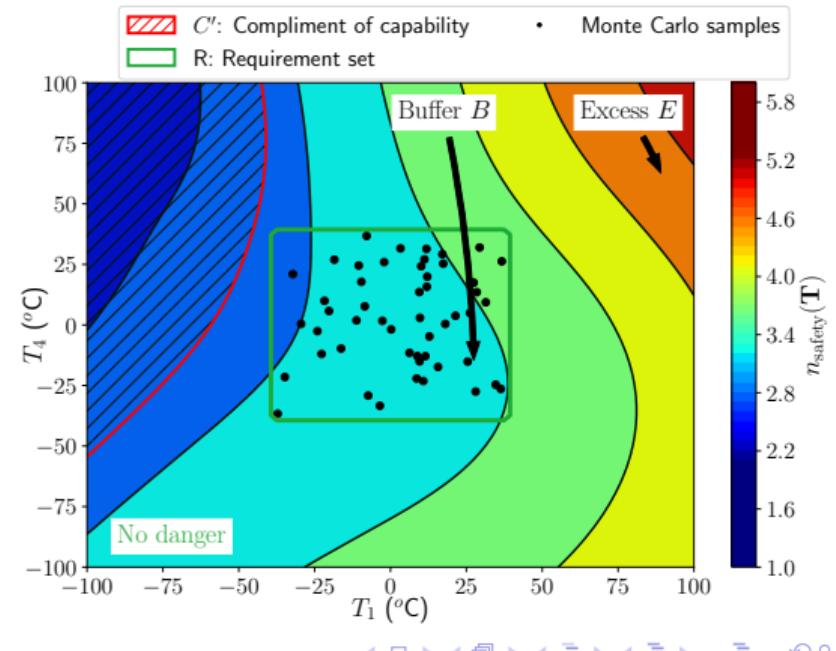
However, requirements can change as well!

$$c = 1, \mathbf{D} = [1, 2, 4, 0]$$



Turbine Rear Structure (TRS)

Reliability	Excess	Weight
1.00($\uparrow 6\%$)	0.871($\uparrow 15\%$)	18.5



Optimizing when and how much change is needed

Formulate optimization problem to minimize total excess while being reliable

Objective and constraints

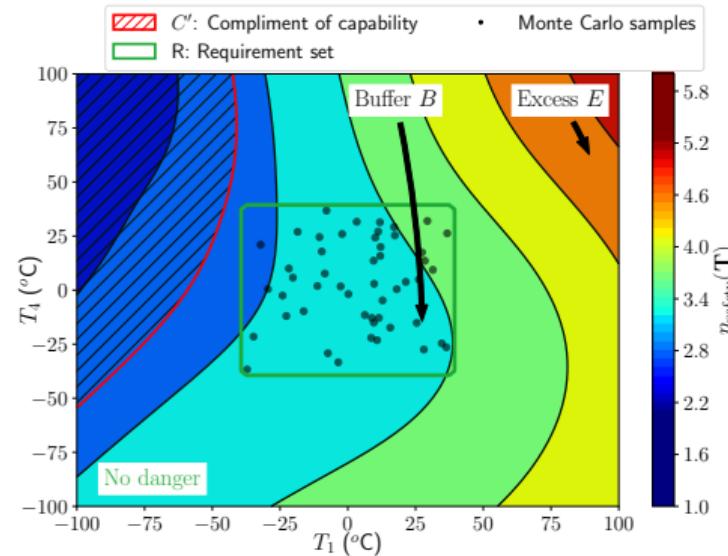
minimize $\text{excess}(c, D; \text{requirement arc})$
subject to $\text{reliability}(c, D; \text{requirement arc})$
over The set of feasible design decisions
 (404 possible combinations)

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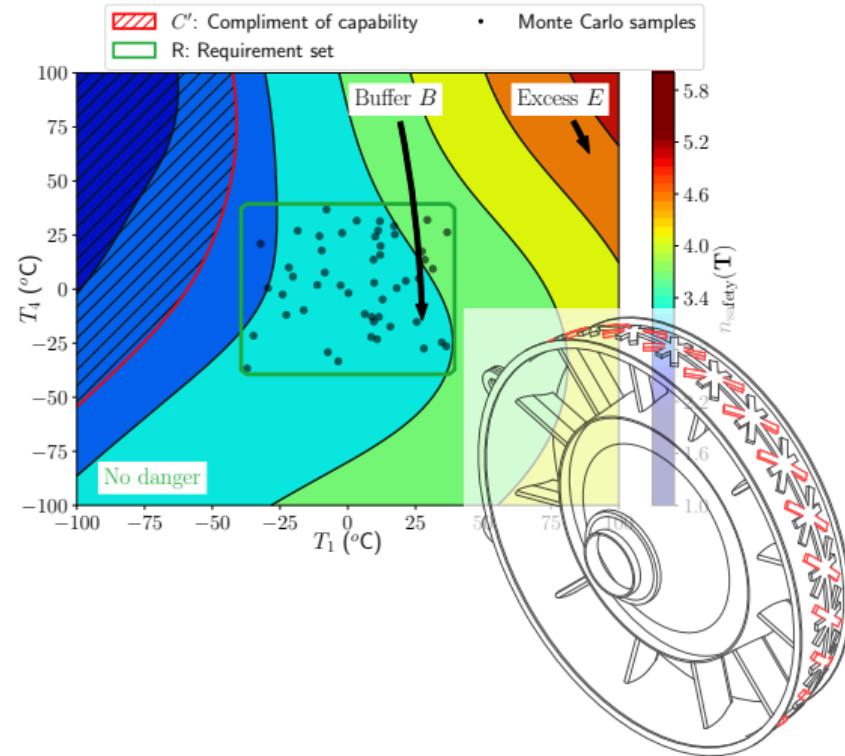
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Design variables

$c \in \{"\text{wavy}", "\text{hatched}", "\text{tubular}"\}$
 $D = [\text{decision}_1, \text{decision}_2, \dots]$
 $\text{decision} \in \{-1, 0, 1, 2, 3, 4\}$



Optimizing when and how much change is needed

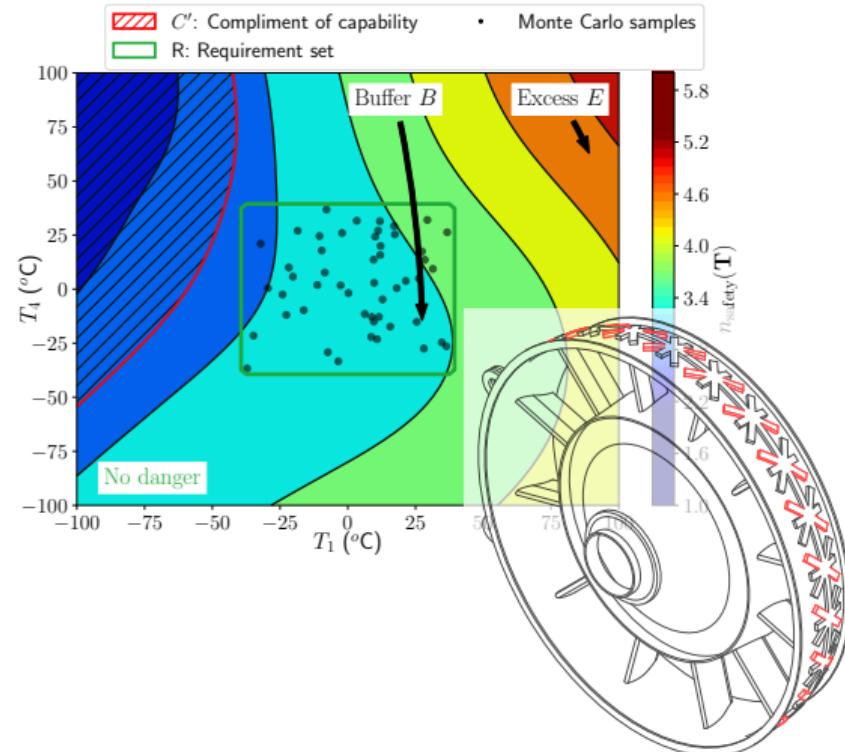
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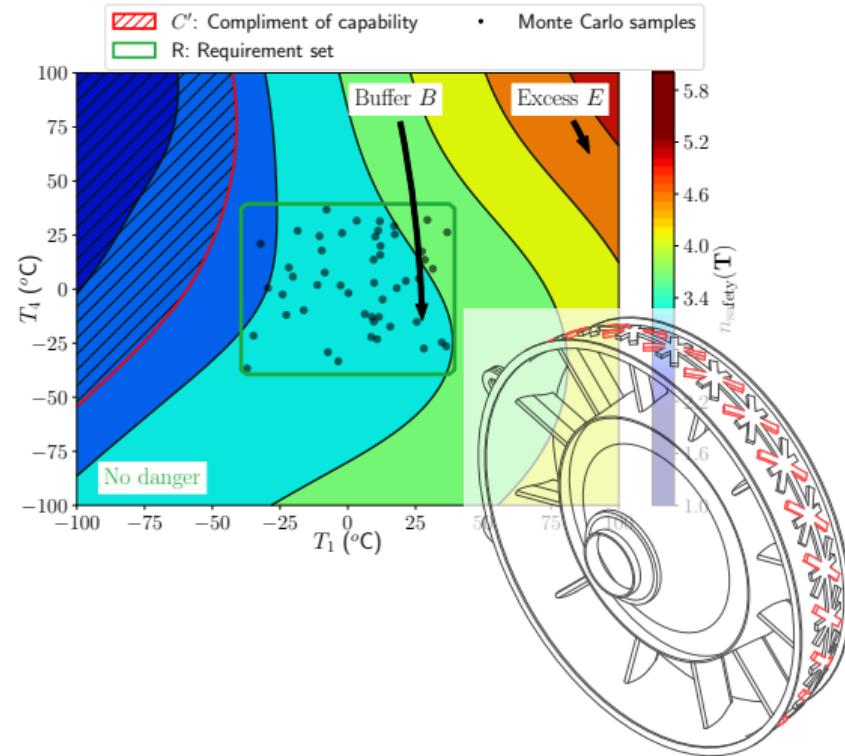
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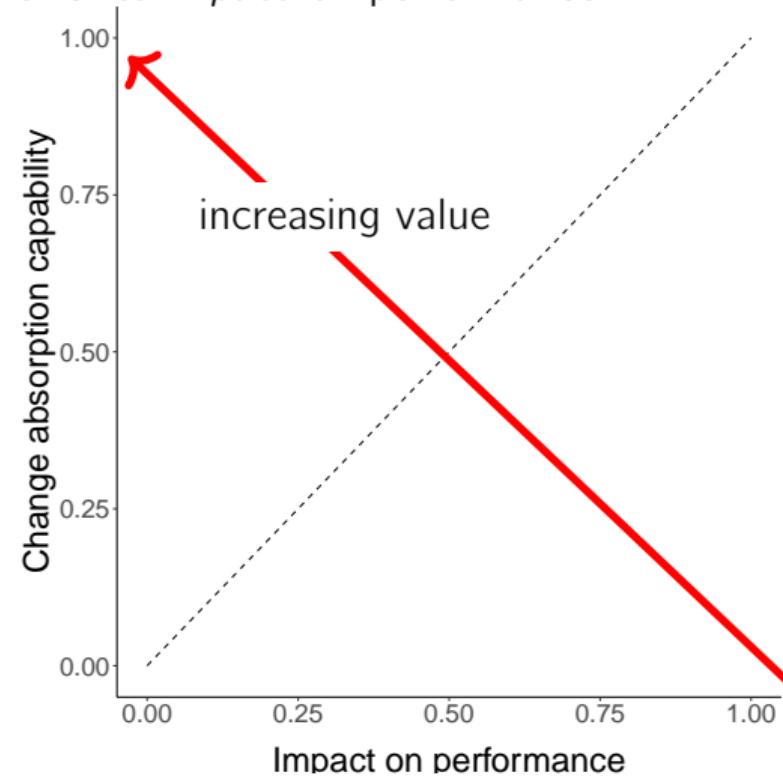
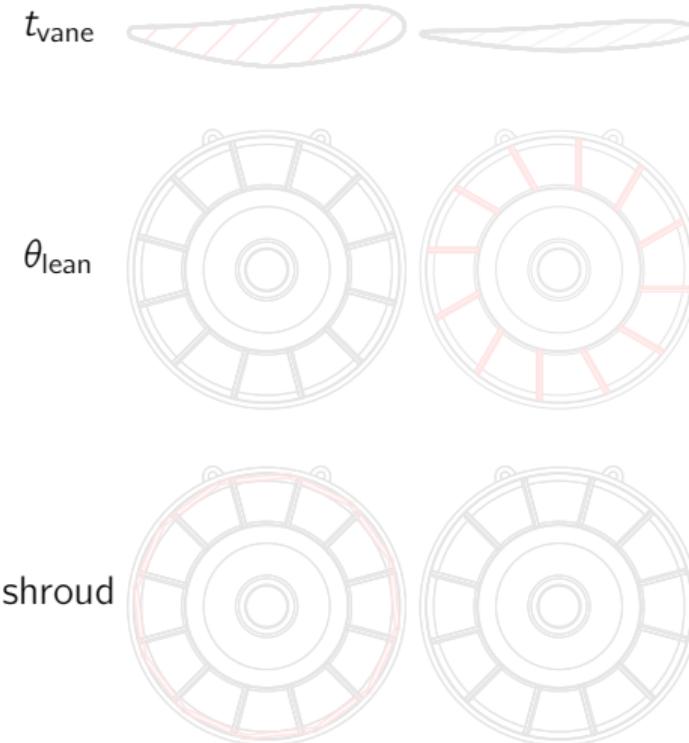
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Margin value-driven design space exploration

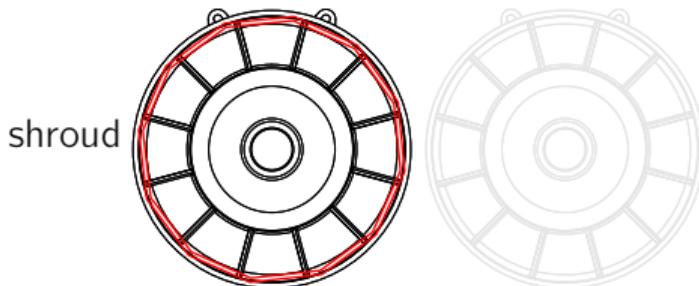
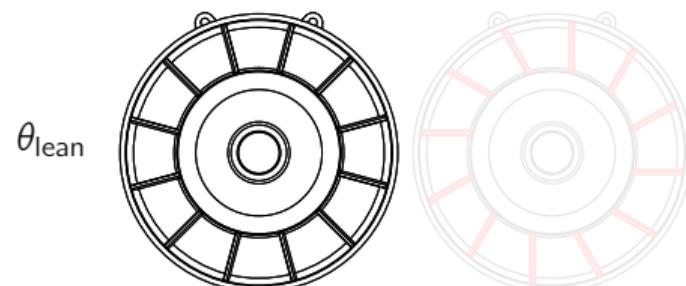
Change absorption through design margins

We quantify the change *absorption* capability **and** its *impact* on performance



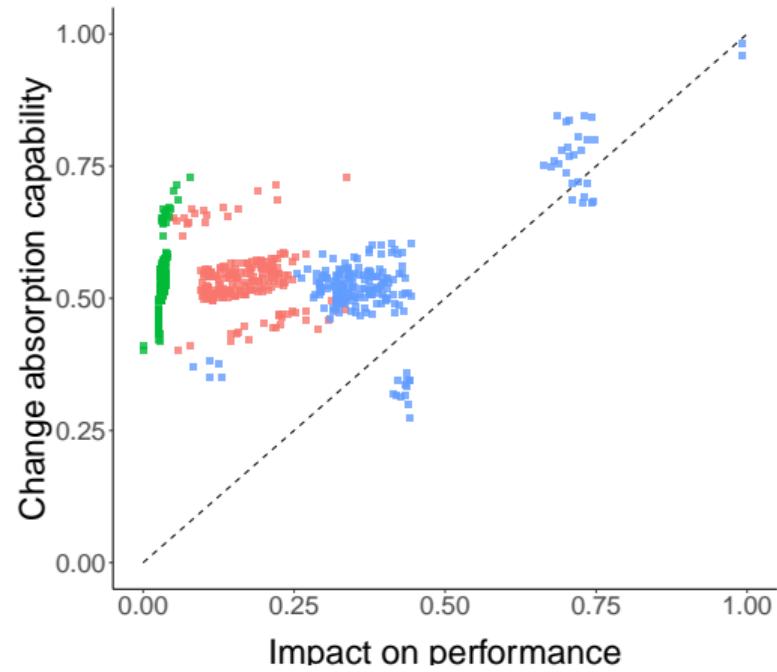
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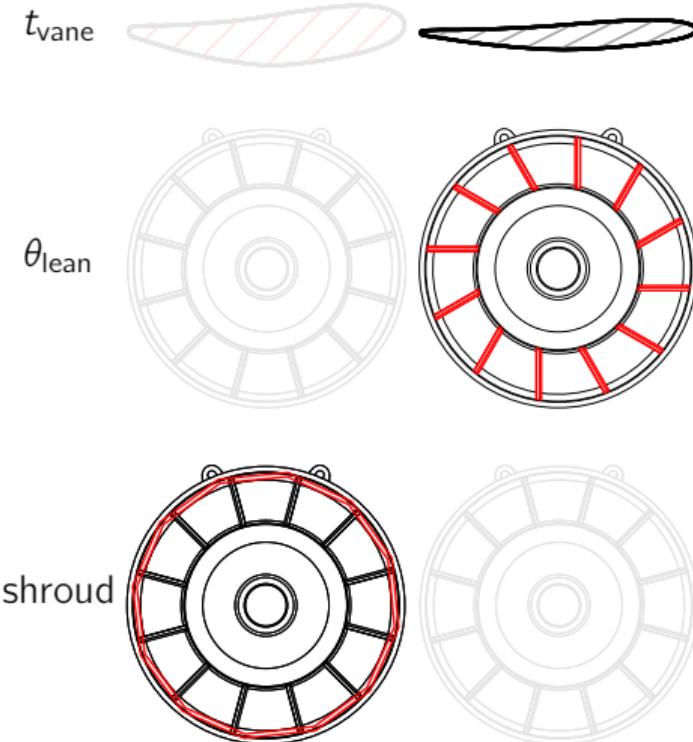
margin node • W_{vane} ● material ● n_{struts}

concept ■ 1A

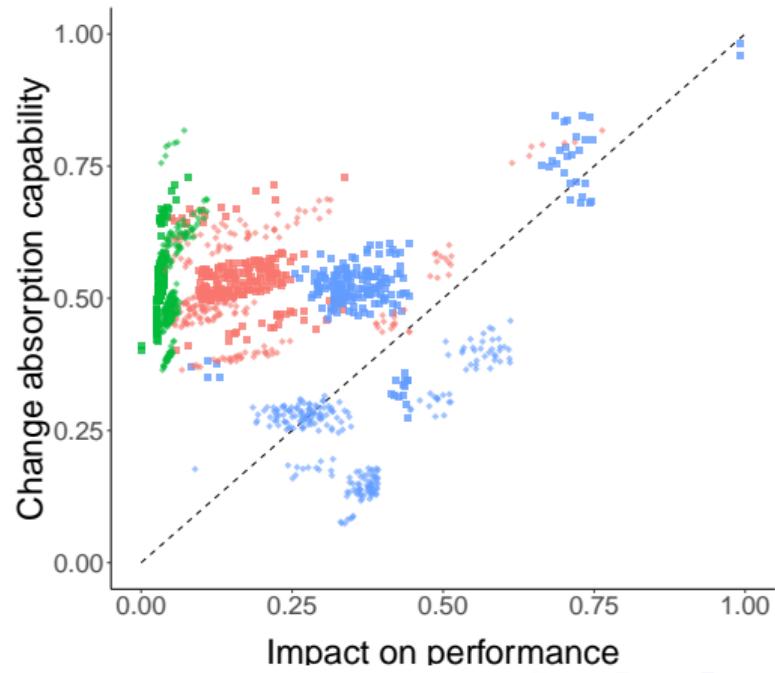


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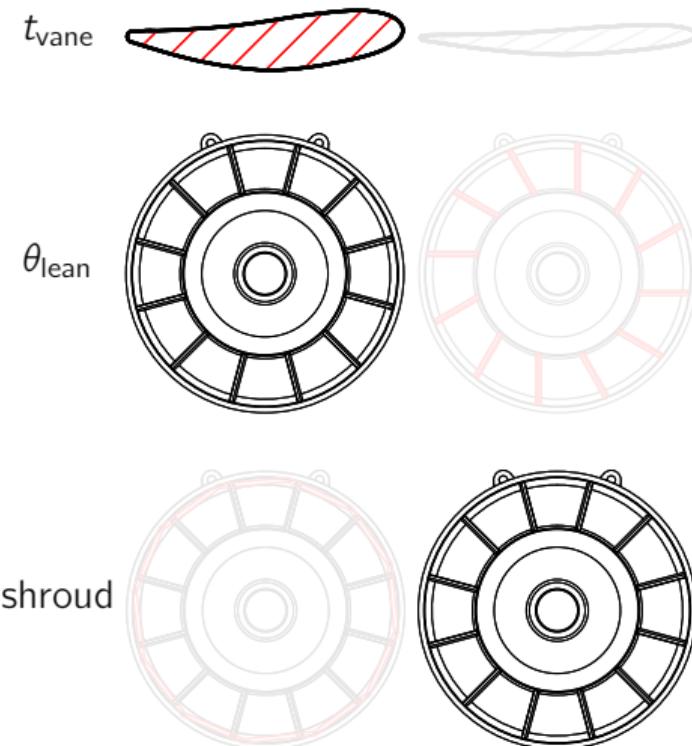


concept ■ 1A ◆ 1B
margin node ● W_{vane} ● material ● n_{struts}



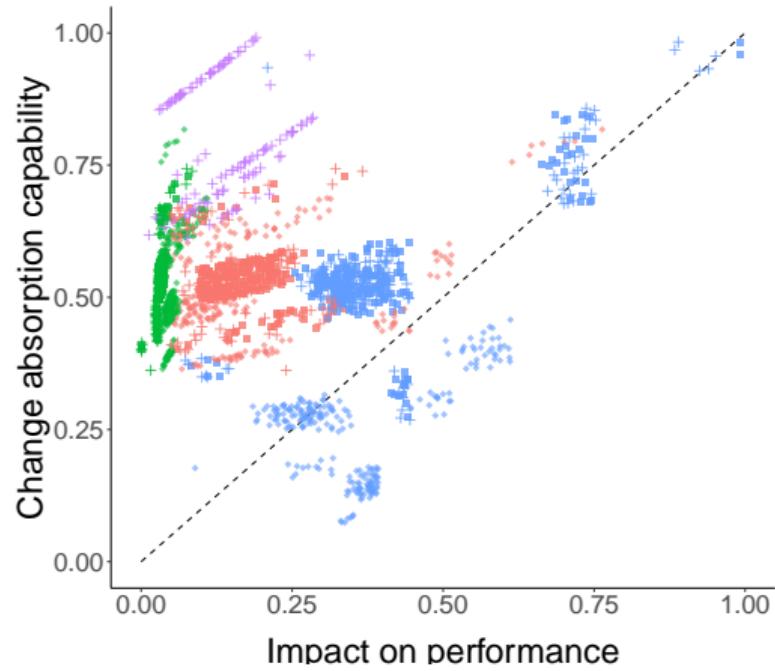
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margin node ● W_{vane} ● material ● n_{struts} ● t_{shroud}

concept ■ 1A ♦ 1B + 2A

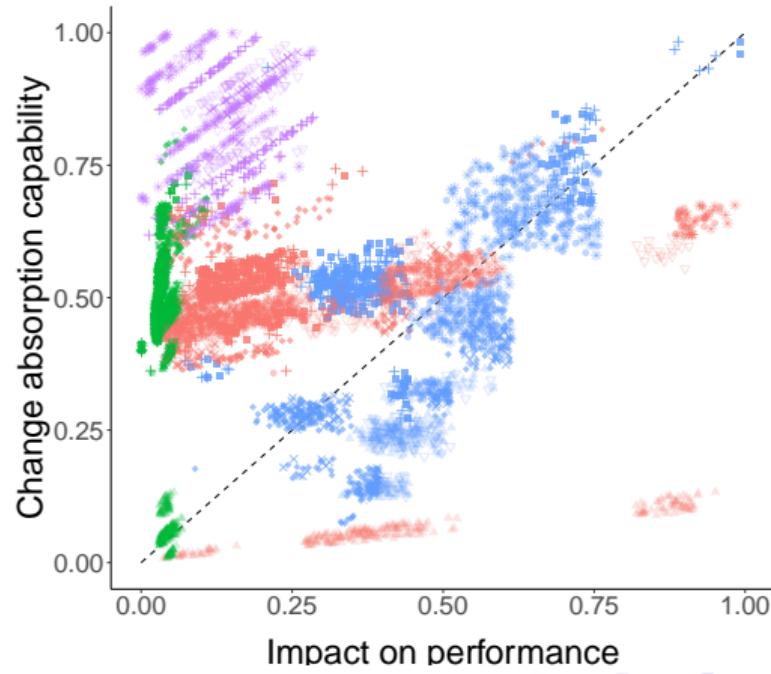
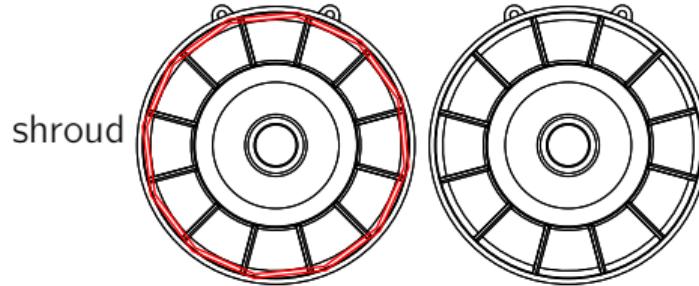
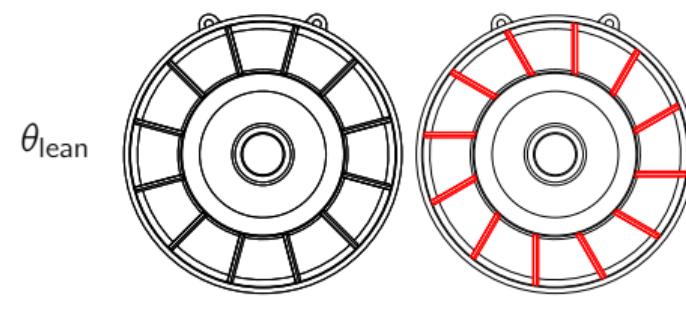


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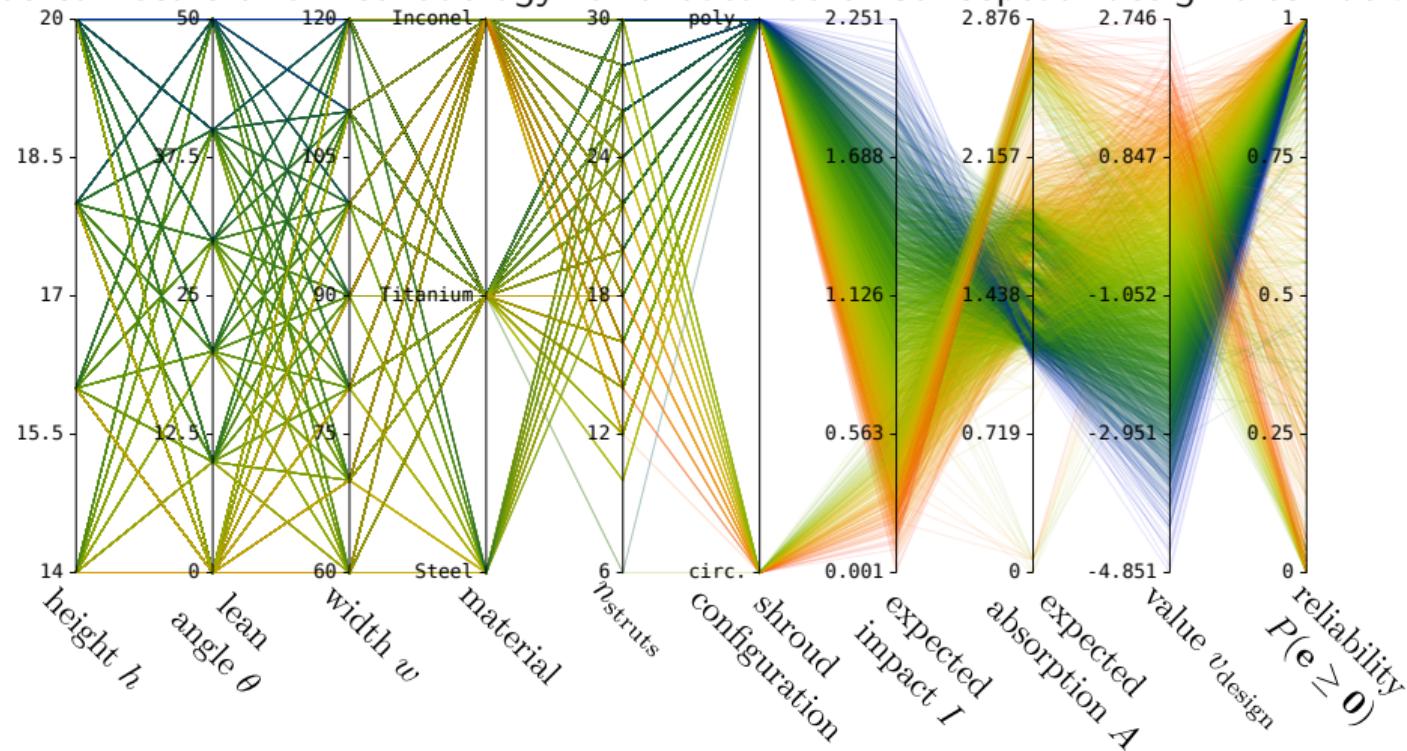


concept ■ 1A ♦ 1B ● 1C ▲ 1D + 2A × 2B * 2C ▽ 2D
margin node ● W_{vane} ● material ● n_{struts} ● t_{shroud}



Change absorption through design margins

We can scale this methodology for thousands of conceptual design alternatives



Conclusion and summary

We demonstrated how a change in design requirements can be absorbed using:

(a) Design **changeability**:

- Using a special kind of flexibility known as *scalability*,
- which is an enabler for *remanufacturing*

(b) Design **margins**:

- By identifying *excess* and *buffer*,
- and optimizing away excess

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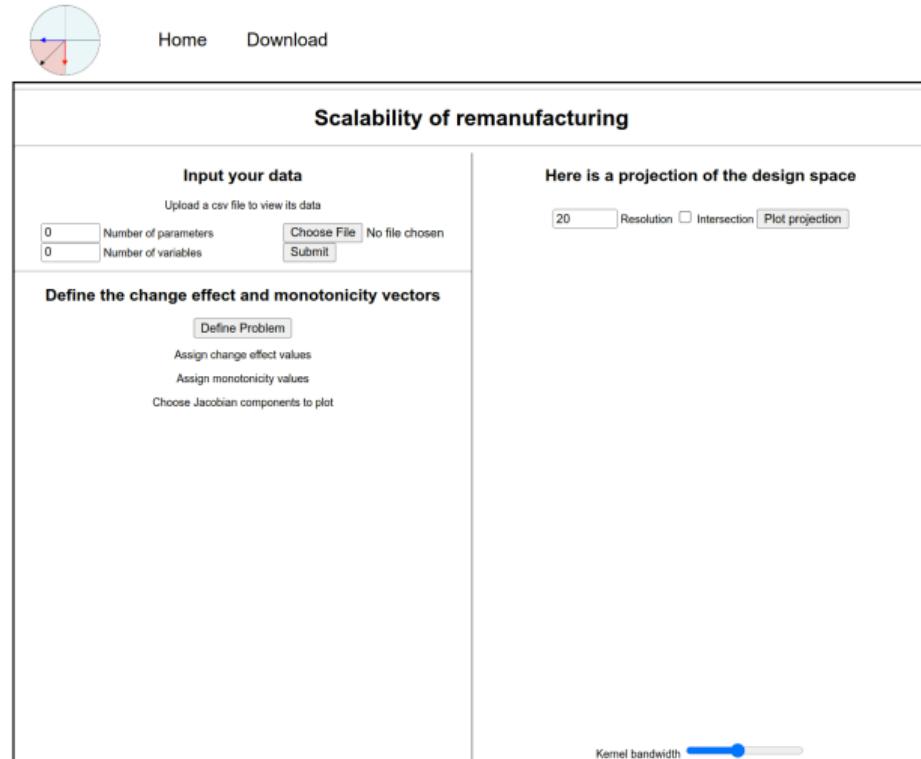
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Thank you for your time

Software tools for assisting designers

Scale AM: an open-source tool for scalability assessment [1,2]

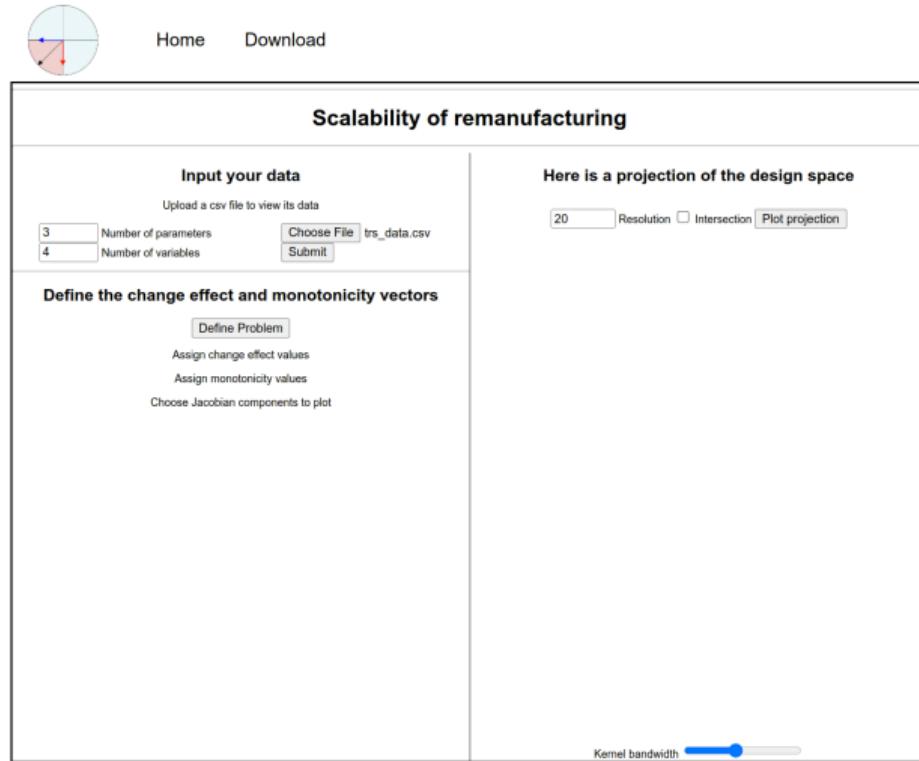


[1] K. Al Handawi, 2022 , https://github.com/khbalhandawi/scale_AM_webapp

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Scale AM: an open-source tool for scalability assessment [1,2]

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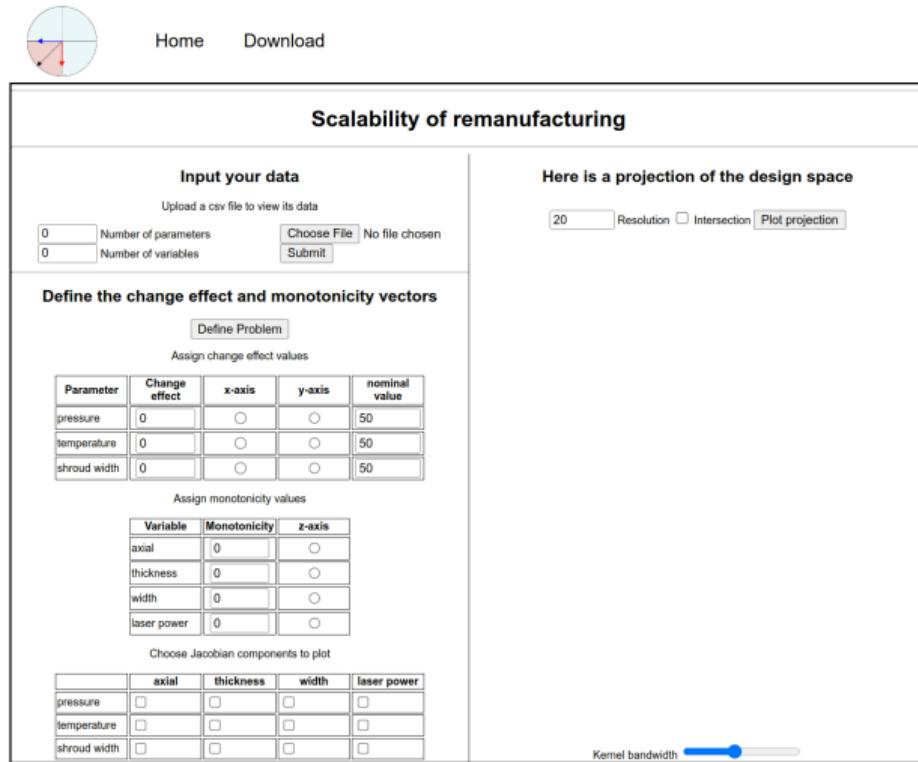


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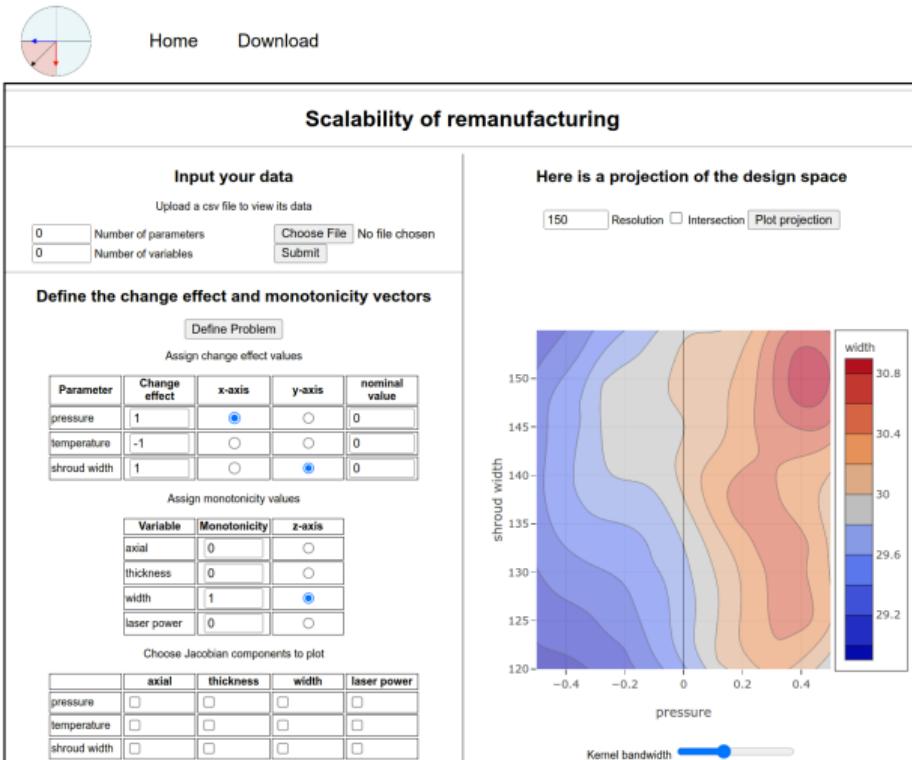


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- Takes as input DoE data
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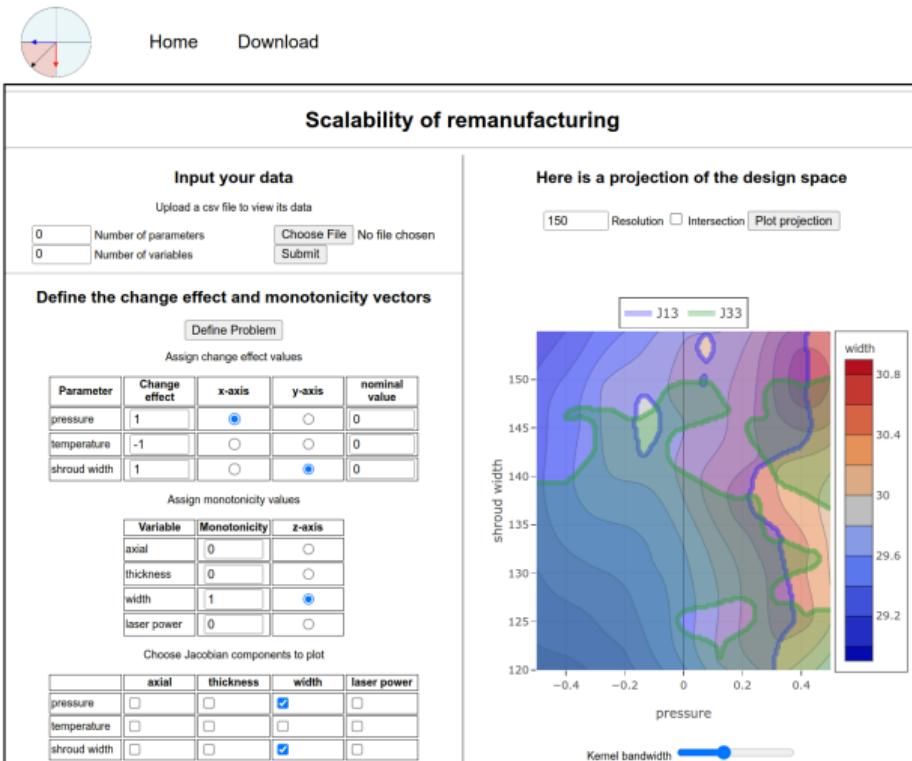


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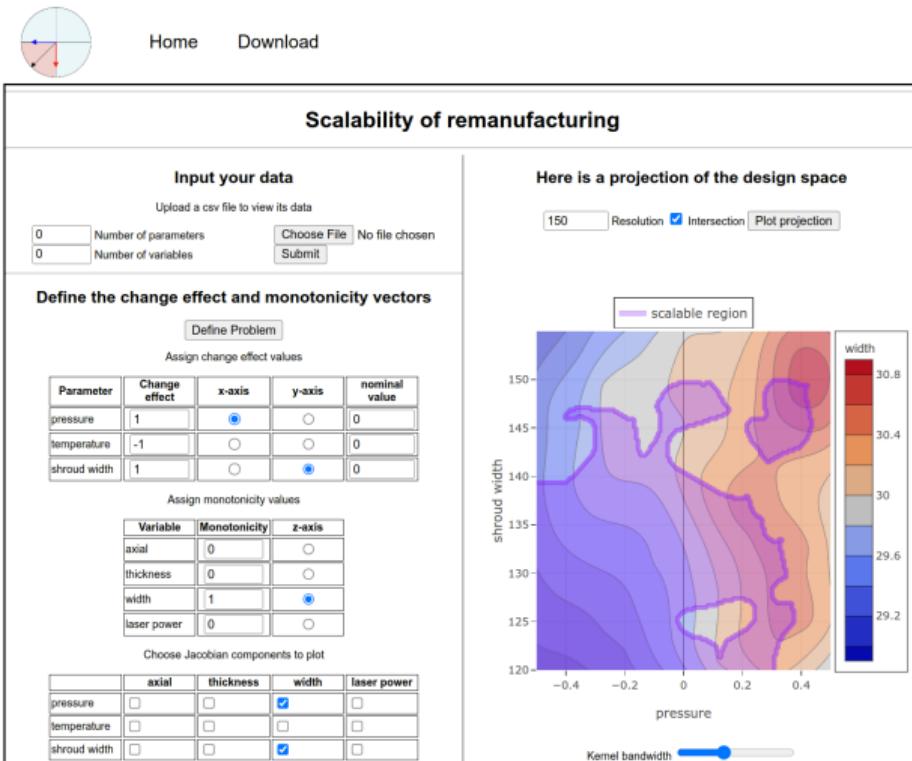


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Other projects: Graph representation of aviation network

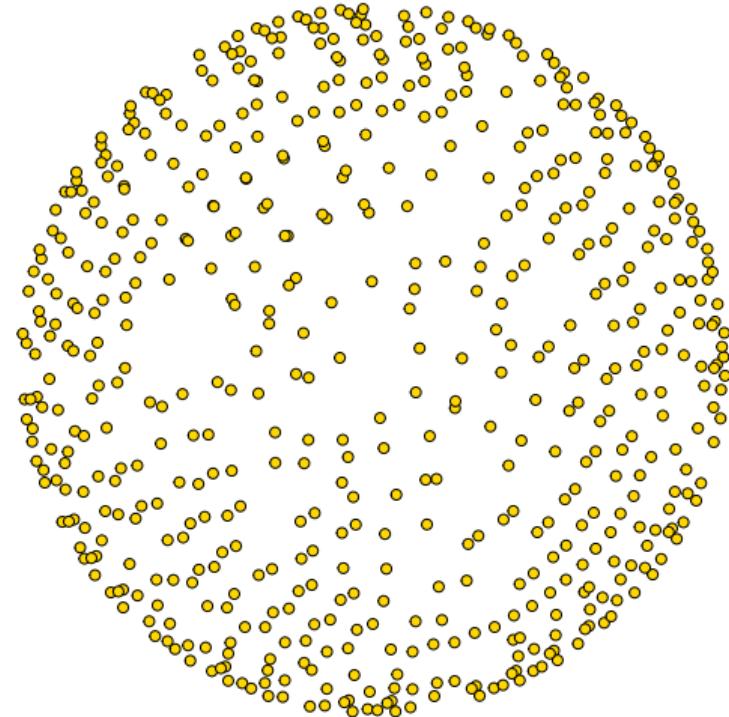
Overview of graphs

- **Nodes:** represent the airlines
- Edges: represent the codesharing
- Edge weights given by thickness of lines
- Node strength: sum of incoming edge weights at each node (size of nodes)
- We identify large communities

Finding optimal community structure

$$\min_{\{A_1, \dots, A_K\} \in \mathcal{V}^K} -Q(A_1, \dots, A_K)$$

where $K \in \mathbb{N}$, \mathcal{V} : Nodes
 Q : modularity



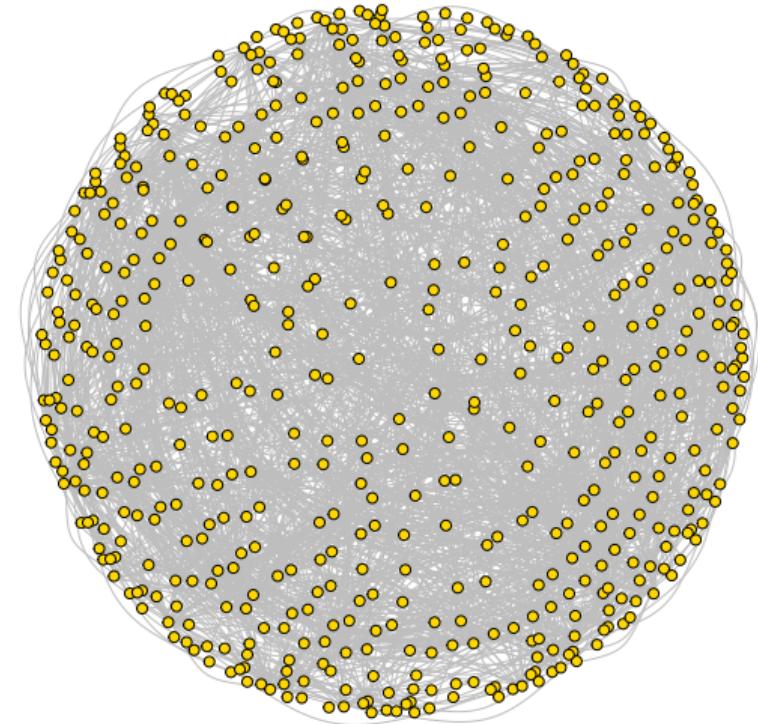
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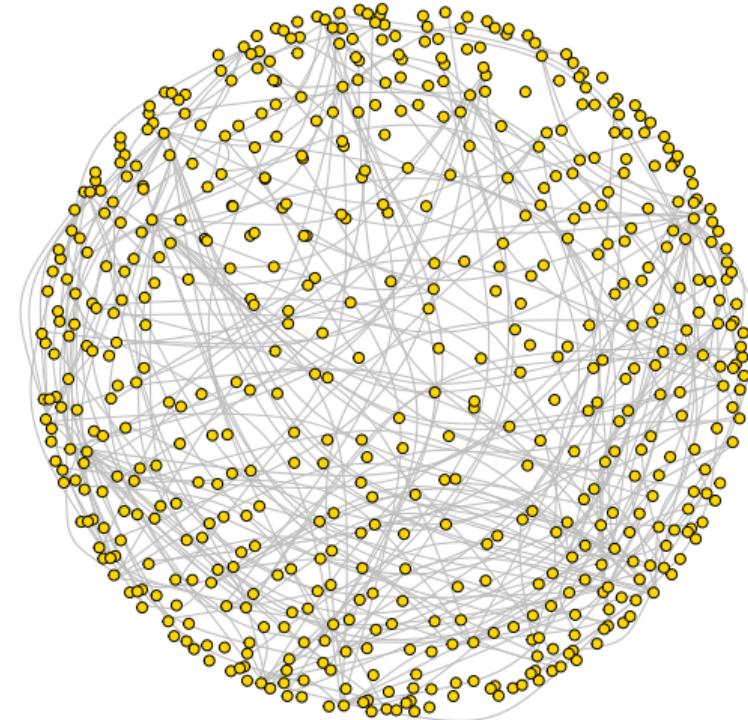
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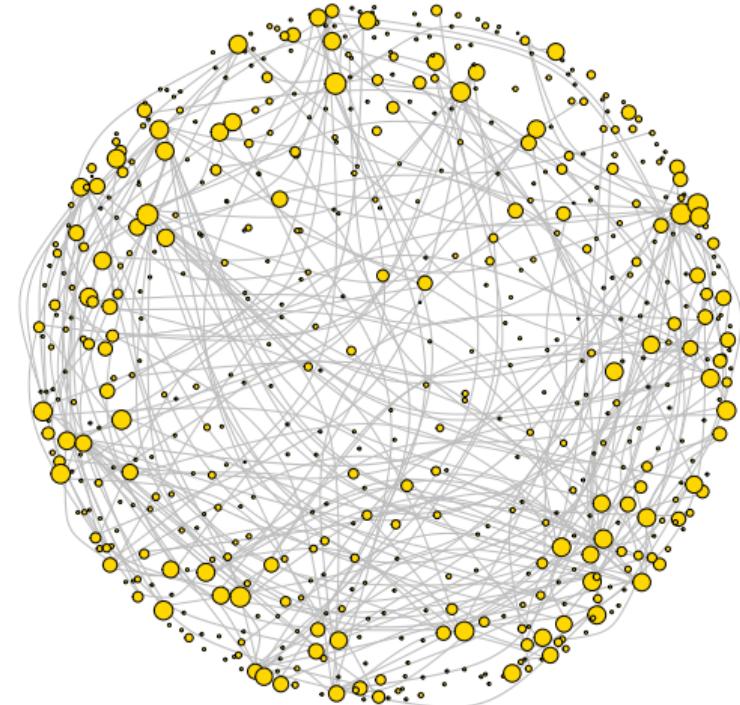
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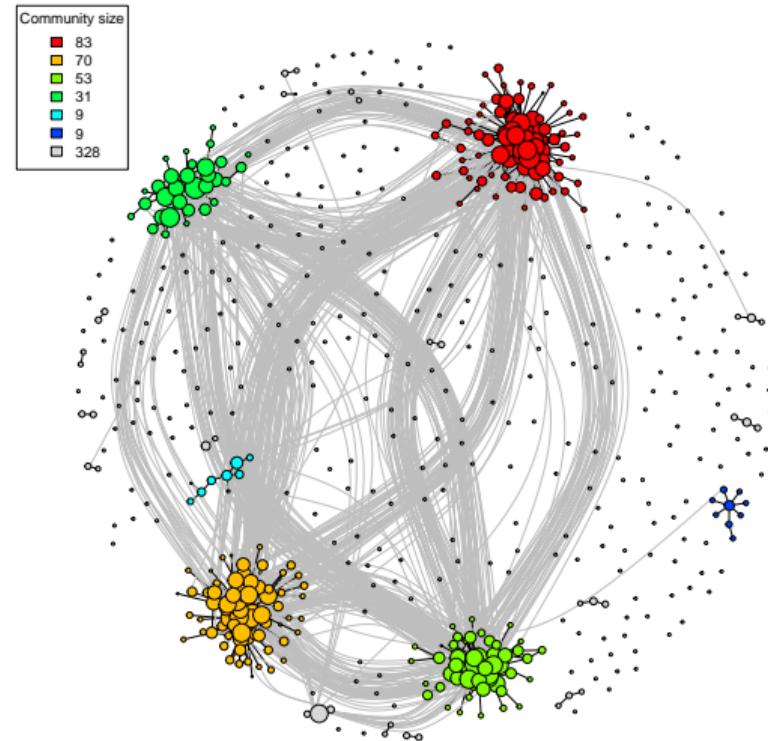
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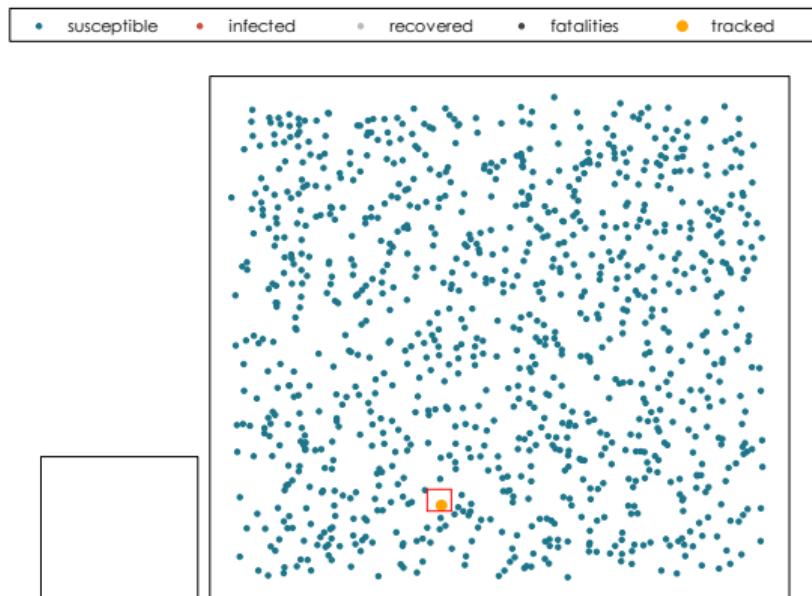
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Optimization of public health models using artificial life models

Public health policy-making problem formulation

What is the **cost** of public health interventions?

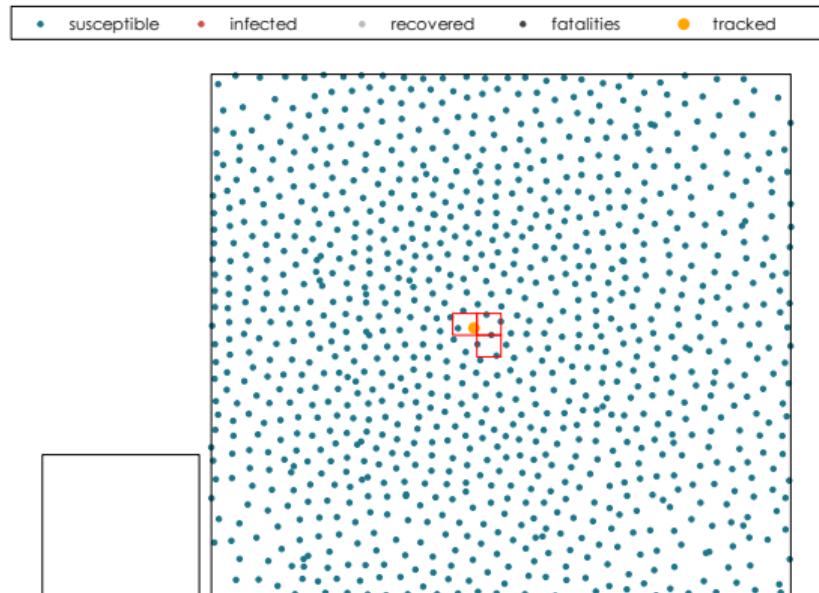
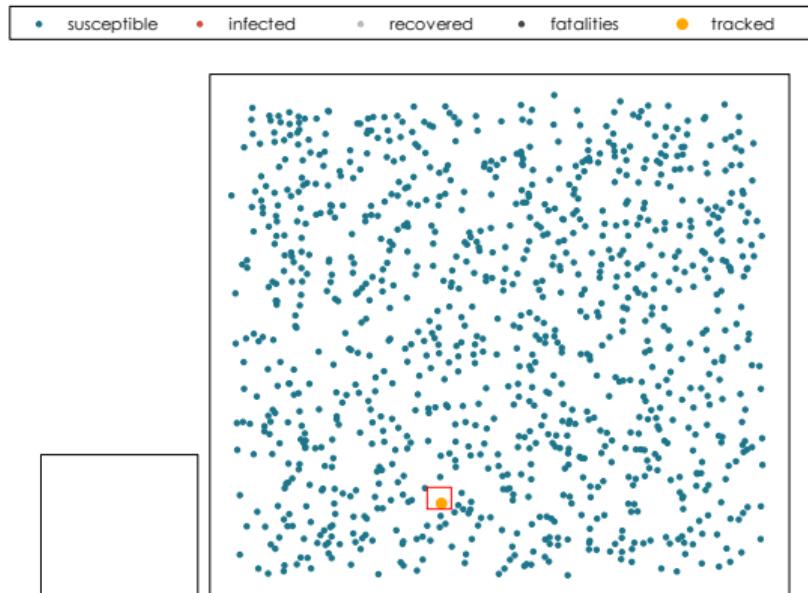
No interventions applied



Public health policy-making problem formulation

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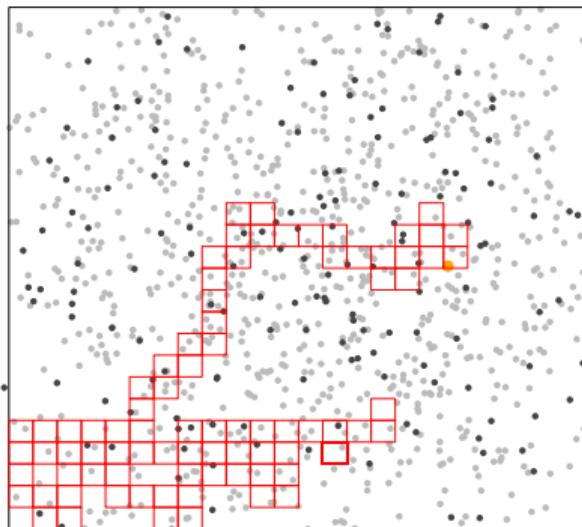
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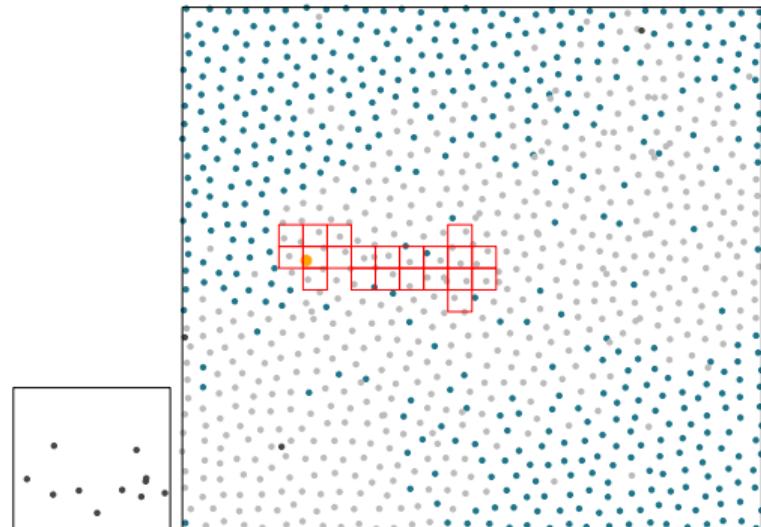
No interventions applied

• susceptible • infected • recovered • fatalities • tracked



with intervention

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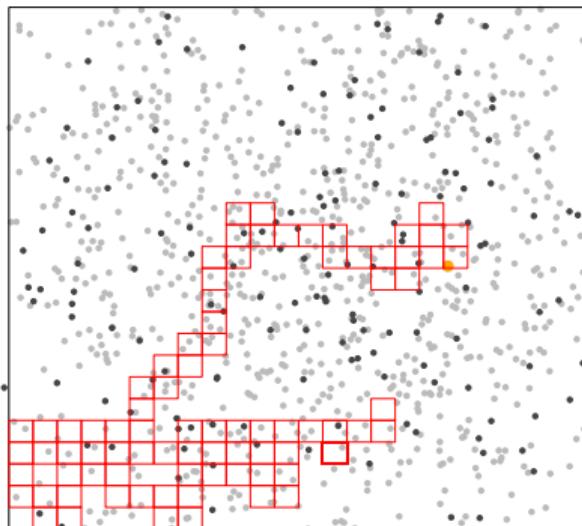


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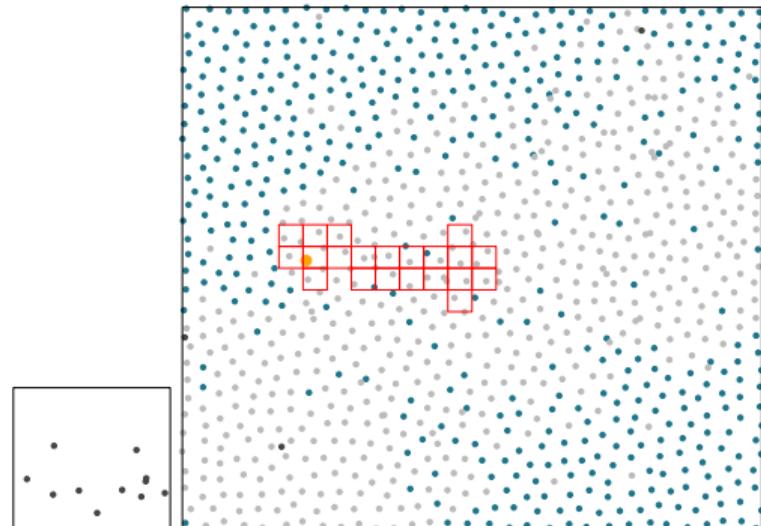
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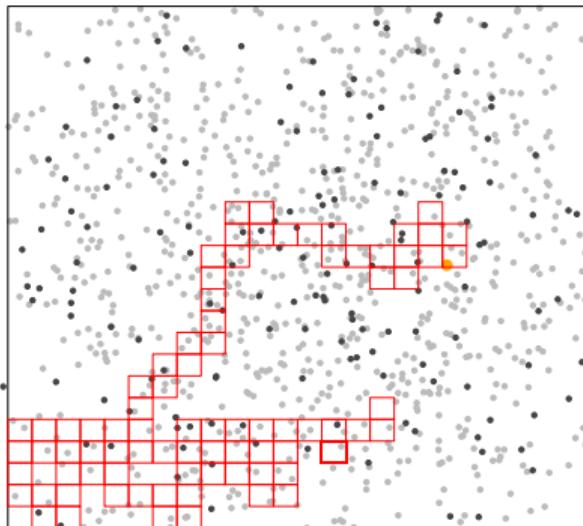


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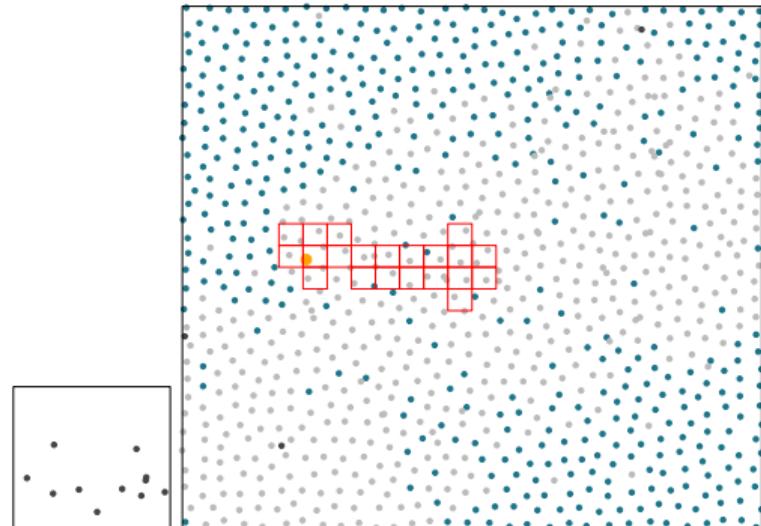
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with intervention

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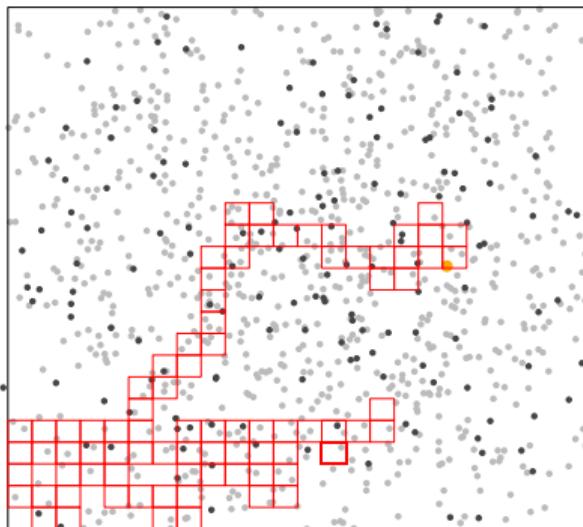


Public health policy-making problem formulation

What is the **cost** of public health interventions?

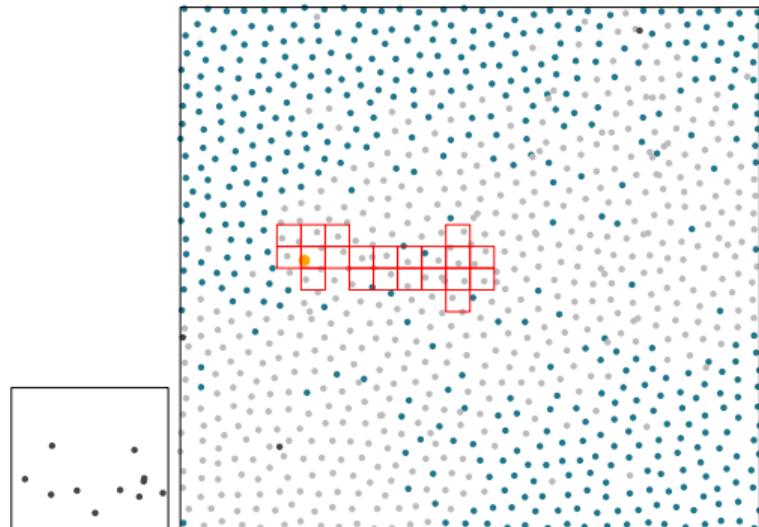
No interventions applied

● susceptible ● infected ● recovered ● fatalities ● tracked



with intervention

● susceptible ● infected ● recovered ● fatalities ● tracked



Optimization problem

Objective and constraints

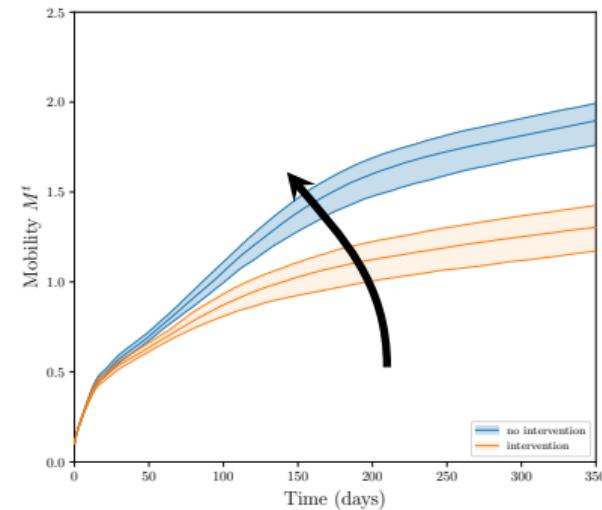
$$\min_x \quad f(x) = -M^T$$

subject to

where $x = [n_E, S_D, n_T]^T$

Design variables

- n_E : Number of essential workers
- S_D : Social distancing factor
- n_T : Number of tests daily



Optimization problem

No gradient information available, blackbox is expensive and noisy

Objective and constraints

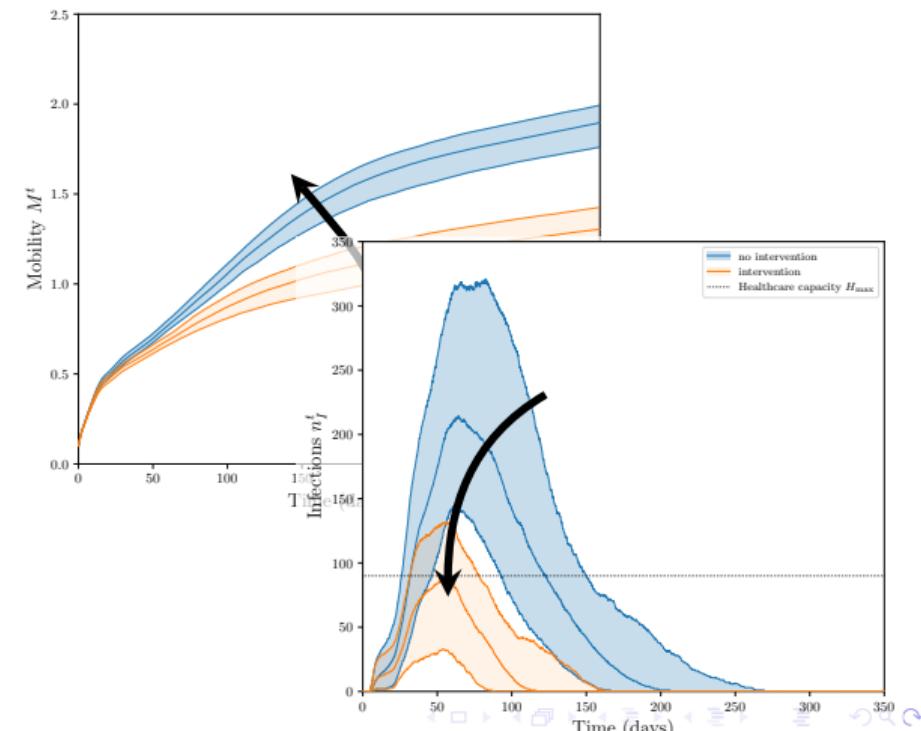
$$\min_x \quad f(x) = -M^T$$

$$\text{subject to} \quad c(x) \equiv n_{I,\max} - H_{\max} \leq 0$$

$$\text{where} \quad x = [n_E, S_D, n_T]^T$$

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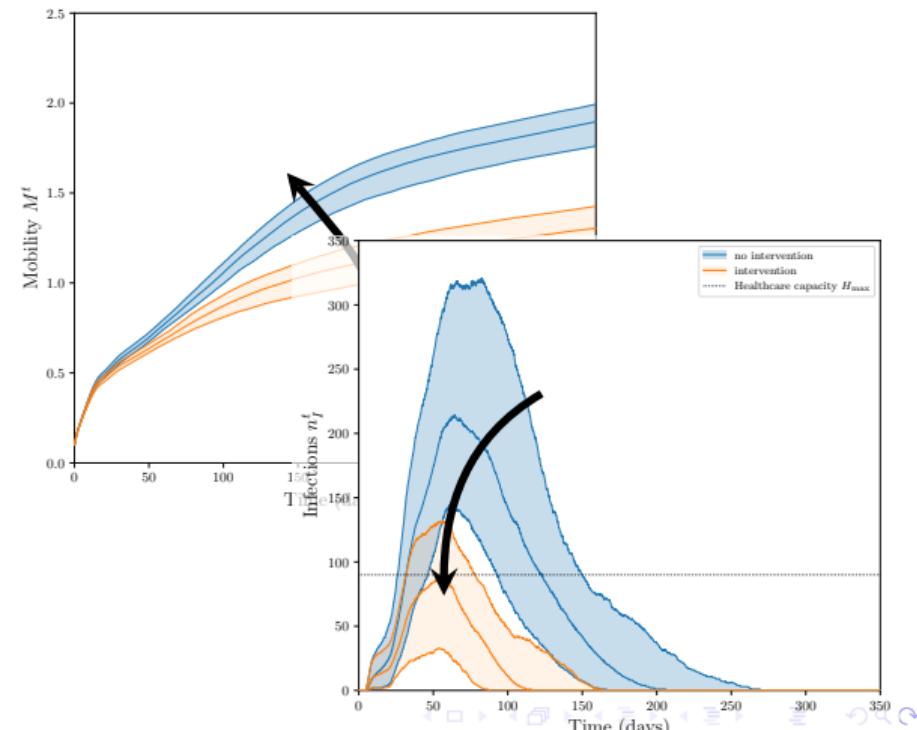
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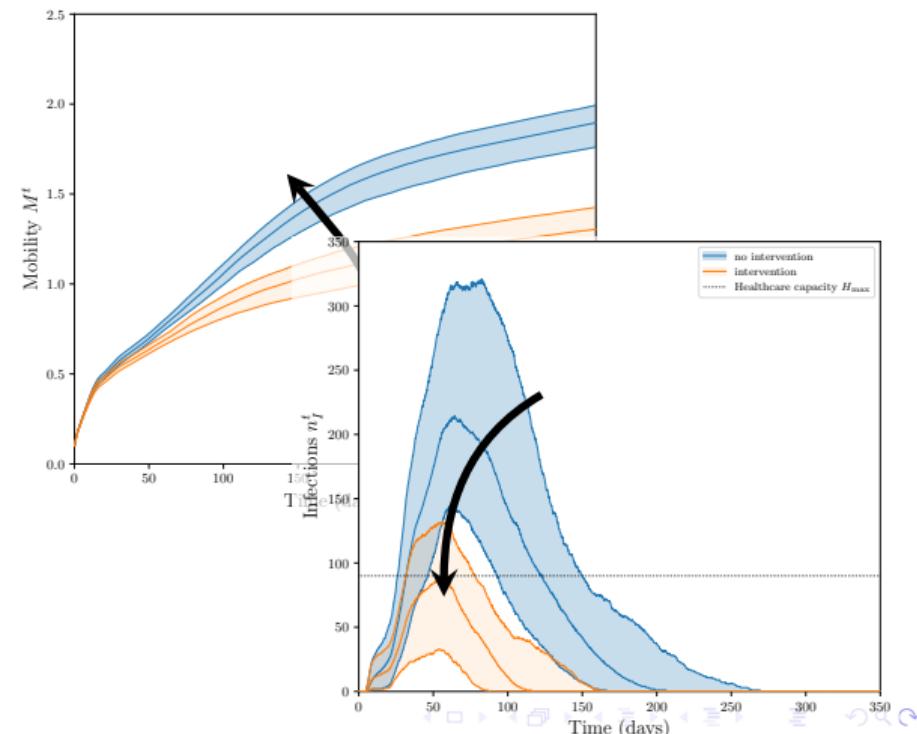
$$\min_x \quad f(x) = \mathbb{E}_{\Theta} [f_{\Theta}(x) = -M^T]$$

$$\text{subject to} \quad c(x) = \mathbb{E}_{\Theta} [c_{\Theta}(x) \equiv n_{I,\max} - H_{\max}] \leq 0$$

where $x = [n_E, S_D, n_T]^T$, Θ : realizations

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Randomly seeded parameters

- Initial conditions
- Interactions, demographics

