Overview of my research projects

Khalil Al Handawi, PhD

Technical presentation

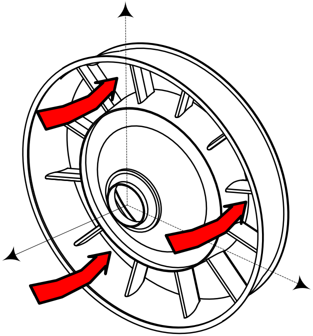
May 18, 2023

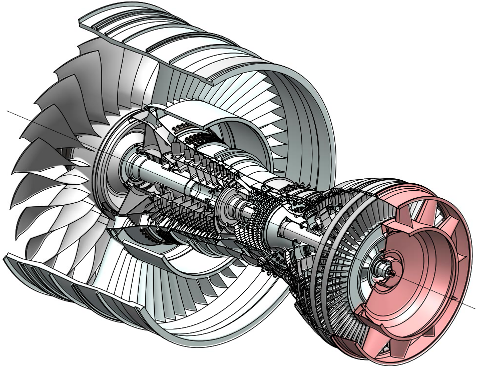
About me

- 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

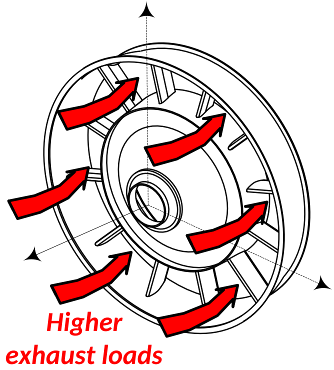


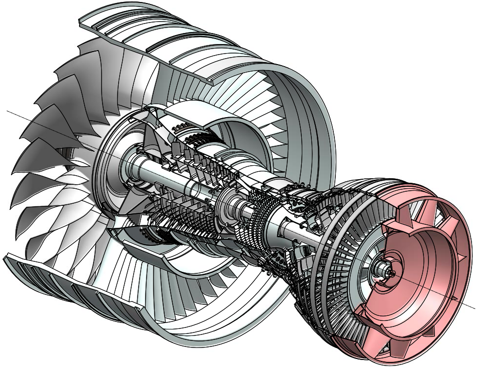


An aeroengine

The challenge

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

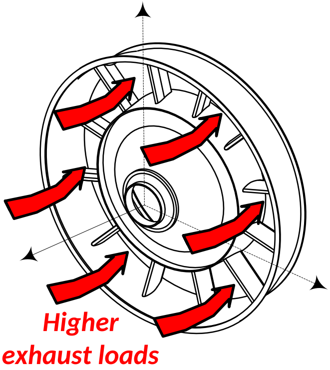




An aeroengine

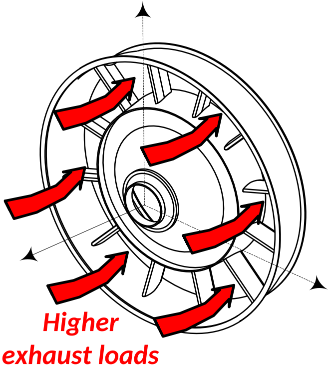
The opportunity

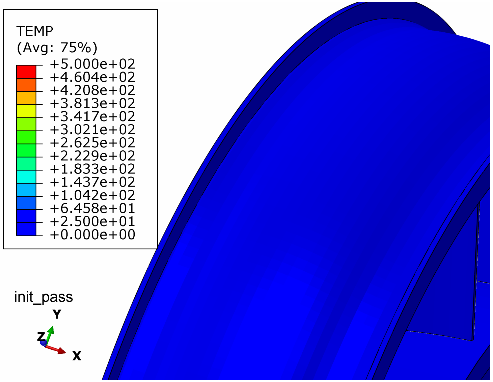
- Disposal or redesign can be sub-optimal options



The opportunity

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

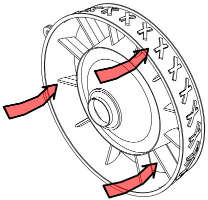




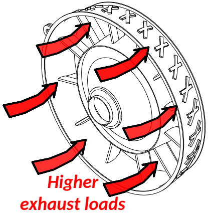
AM Remanufacturing of TRS

Change absorption through scalability

When the applied loads change:



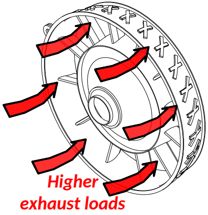
When the applied **loads change**:



Change absorption through scalability

When the applied **loads change**:

A design can be **changed**:

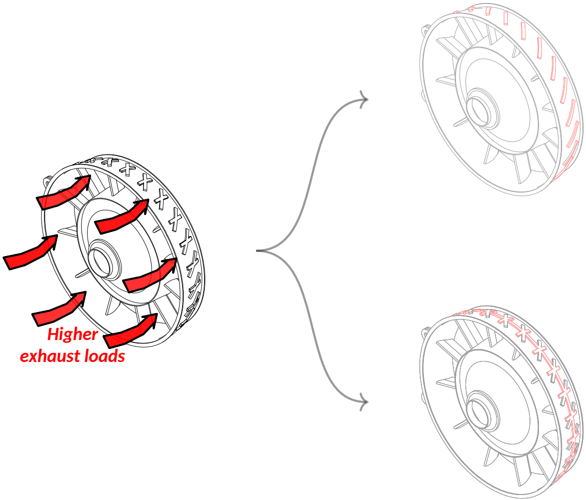


Change absorption through scalability

When the applied **loads change**:

A design can be **changed**:

- *Scalability*: the ability to change to accommodate stricter requirements [1]

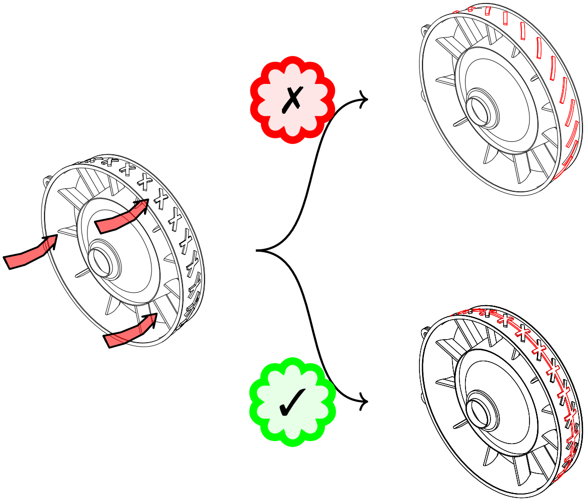


[1] A. Ross et al., 2008 , *Systems Engineering*

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]

[1] K. Alhandawi et al., 2020 , *Journal of Mechanical Design*

Parametric design optimization problem formulation

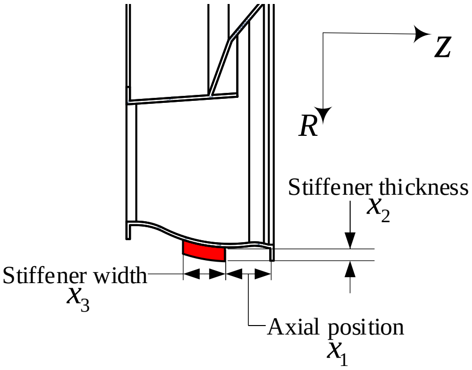
Remanufacturing variables are included in the design optimization problems and changing requirements are modeled by parameters **p**

Design optimization problem

$$\begin{aligned} \underset{\mathrm{x}}{\text{minimize}} \quad & f(\mathrm{x};\mathrm{p}) = -n_{\mathrm{safety}}(\mathrm{x}; P_{\mathrm{load}}) \\ \text{subject to} \quad & g_1(\mathrm{x};\mathrm{p}) = x_3 + x_1 - W_{\mathrm{total}} \leq 0 \\ & g_2(\mathrm{x};\mathrm{p}) = T_m - T_{\mathrm{deposit}} \leq 0 \end{aligned}$$

Changing requirements

$$W_{\mathrm{total}} = \text{width of base part}$$
$$T_m = \text{Melting temperature of deposit}$$
$$P_{\mathrm{load}} = \text{Pressure load on outer casing}$$



Conditions for scalability

Design optimization problem

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\end{aligned}
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Changing requirements

$W_{\text{total}} = \text{width of base part}$

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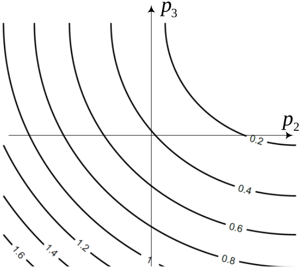
Let us consider one variable and two parameters

For an optimal design to be scalable, the product of



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Changing requirements

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W_{\text{total}} &= \text{width of base part} \\
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$$\overbrace{\begin{bmatrix} \quad & \quad \end{bmatrix}}^{\text{J=Direction of change}}$$

Let us consider one variable and two parameters

For an optimal design to be scalable, the product of

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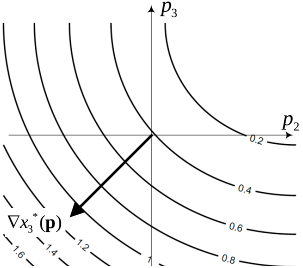

Conditions for scalability

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

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$$W_{\text{total}} = \text{width of base part}$$

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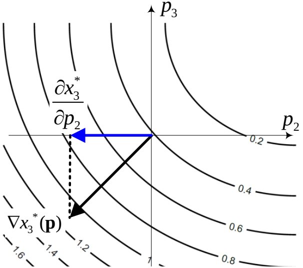
Let us consider one variable and two parameters

For an optimal design to be scalable, the product of

- the **direction of change**

$$\overbrace{\begin{bmatrix} \partial x_3^* / \partial p_2 \\ \\ \end{bmatrix}}^{\text{J=Direction of change}}$$



Conditions for scalability

Design optimization problem

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

$$\text{subject to} \quad g_1(x; p) = x_3 + x_1 - W_{\text{total}} \leq 0$$

$$g_2(x; p) = T_m - T_{\text{deposit}} \leq 0$$

Changing requirements

W_{total} = width of base part

T_m = Melting temperature of deposit

P_{load} = Pressure load on outer casing

$$\overbrace{\begin{bmatrix} \partial x_3^* / \partial p_2 \\ \partial x_3^* / \partial p_3 \end{bmatrix}}^{\text{J=Direction of change}}$$

Let us consider one variable and two parameters

For an optimal design to be scalable, the product of

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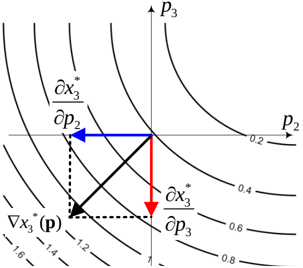

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$$
\underbrace{\begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix}}_{\text{N=Change effect}} \times \underbrace{\begin{bmatrix} \partial x_3^* / \partial p_2 \\ \partial x_3^* / \partial p_3 \end{bmatrix}}_{\text{J=Direction of change}}
$$

Let us consider one variable and two parameters

For an optimal design to be scalable, the product of

- the **direction of change**
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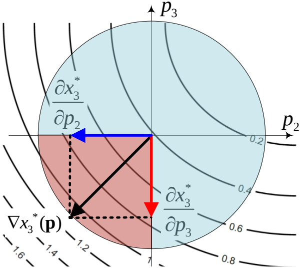

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Let us consider one variable and two parameters

For an optimal design to be scalable, the product of

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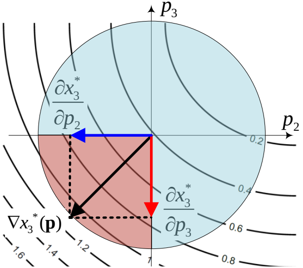
must be greater or equal to zero

$$\overbrace{\begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix}}^{\text{N=Change effect}} \times \overbrace{\begin{bmatrix} \partial x_3^* / \partial p_2 \\ \partial x_3^* / \partial p_3 \end{bmatrix}}^{\text{J=Direction of change}} \times \overbrace{\begin{bmatrix} 1 \end{bmatrix}}^{\text{M=Monotonicity}} \geq \mathbf{0}$$

Scalable design!



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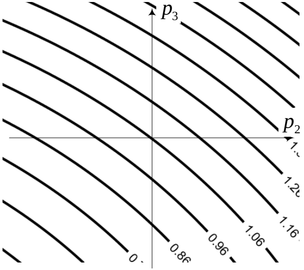

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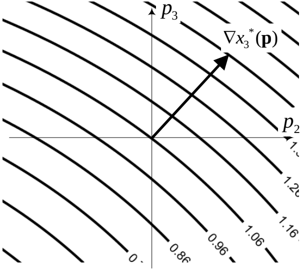

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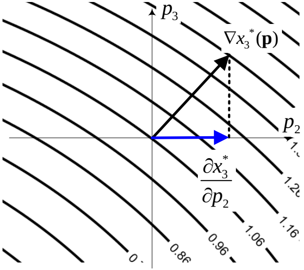

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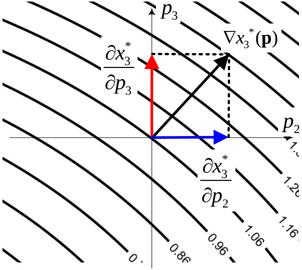

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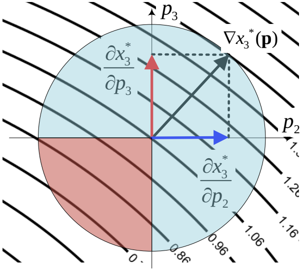

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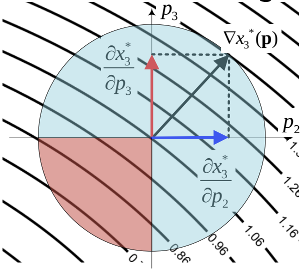
Not a Scalable design!



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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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Our full example: 4 variables and 3 parameters

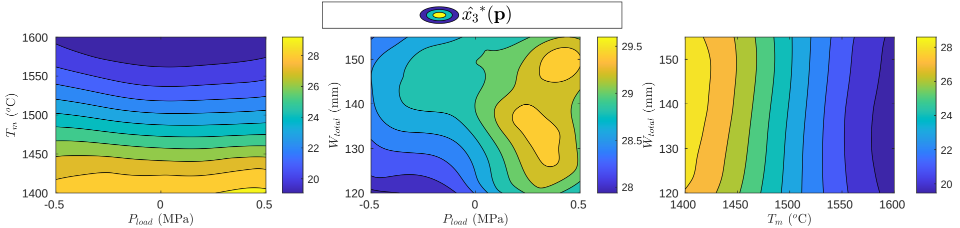
$$\underbrace{\begin{bmatrix} n_1 & 0 & 0 \\ 0 & n_2 & 0 \\ 0 & 0 & n_3 \end{bmatrix}}_{\text{N=Change effect}} \times \underbrace{\begin{bmatrix} \partial x_1^*/\partial p_1 & \partial x_2^*/\partial p_1 & \partial x_3^*/\partial p_1 & \partial x_4^*/\partial p_1 \\ \partial x_1^*/\partial p_2 & \partial x_2^*/\partial p_2 & \partial x_3^*/\partial p_2 & \partial x_4^*/\partial p_2 \\ \partial x_1^*/\partial p_3 & \partial x_2^*/\partial p_3 & \partial x_3^*/\partial p_3 & \partial x_4^*/\partial p_3 \end{bmatrix}}_{\text{J=Direction of change}} \times \underbrace{\begin{bmatrix} m_1 & 0 & 0 & 0 \\ 0 & m_2 & 0 & 0 \\ 0 & 0 & m_3 & 0 \\ 0 & 0 & 0 & m_4 \end{bmatrix}}_{\text{M=Monotonicity}} \ge \mathbf{0}$$

Response surface of parametric optimal solutions and scalable designs

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

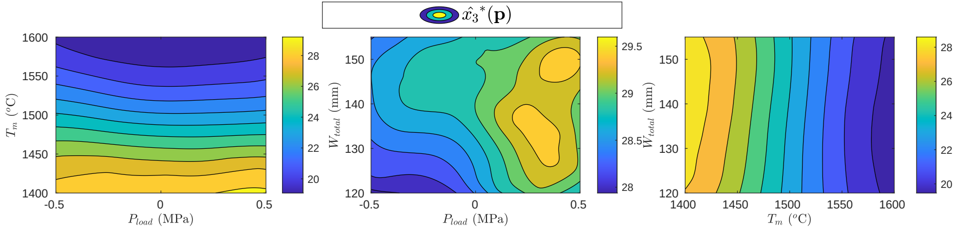
Response surface of parametric optimal solutions and scalable designs

- 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)



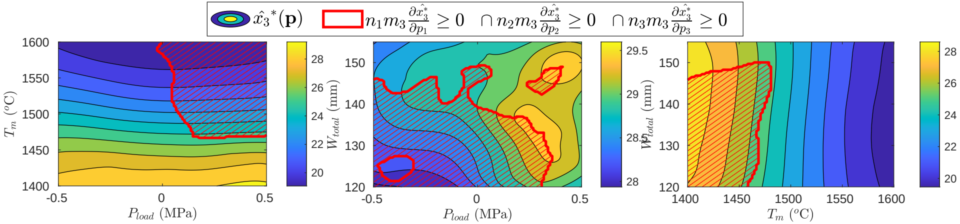
Response surface of parametric optimal solutions and scalable designs

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

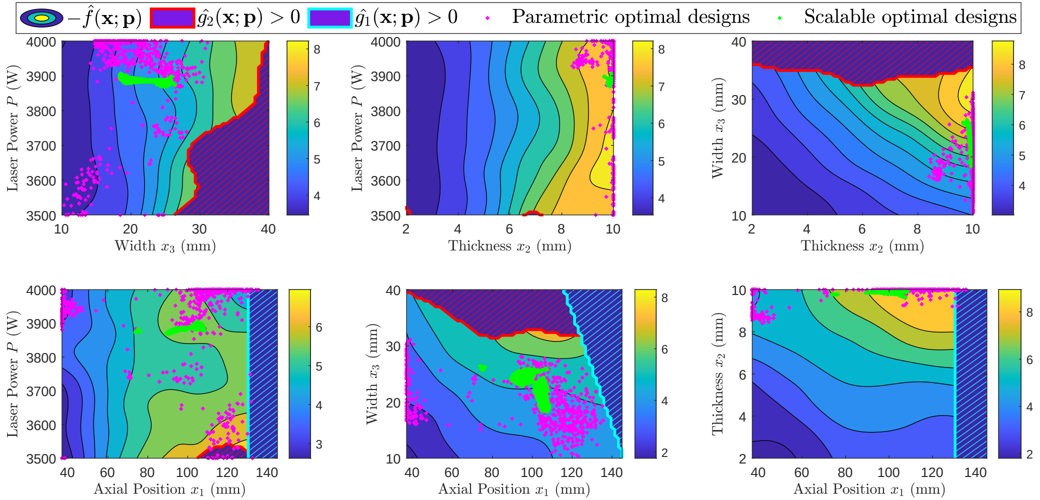


Response surface of parametric optimal solutions and scalable designs

- 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)
- 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 $\mathbf{N}\mathbf{J}(\mathbf{p})^{\mathrm{T}}\mathbf{M} \geq \mathbf{0}$.



Map scalable optimal design set to design space

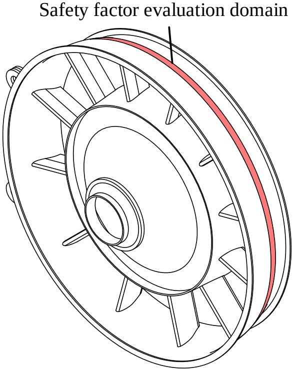


Using design margins to absorb change in requirements [1]

[1] K. Al Handawi et al., 2021 , *Journal of Mechanical Design*

Quantifying capability, buffer, and excess

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



Failure domain

Quantifying capability, buffer, and excess

We focus on one 2D projection

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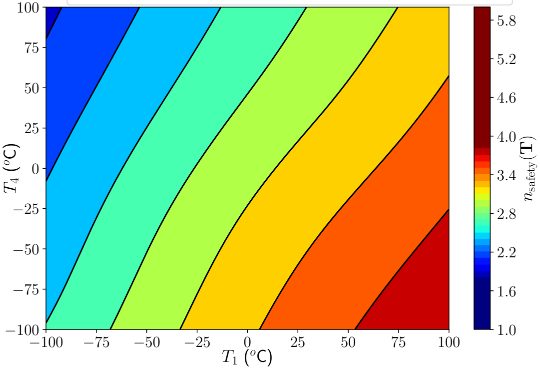

Quantifying capability, buffer, and excess

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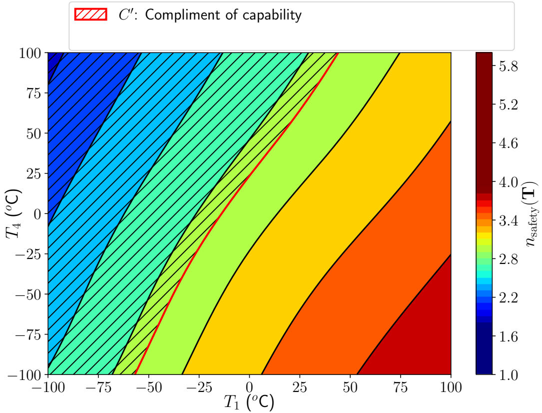

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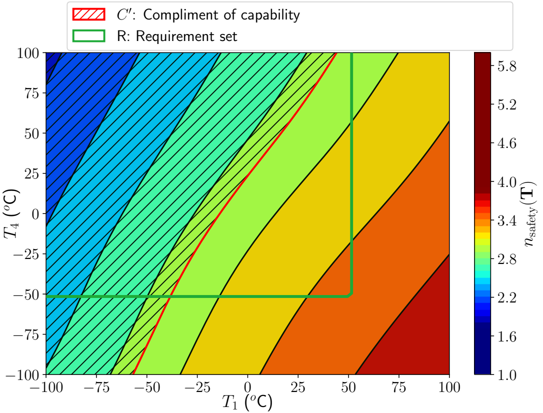

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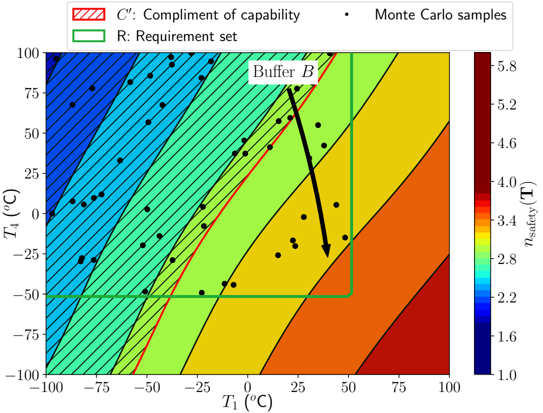

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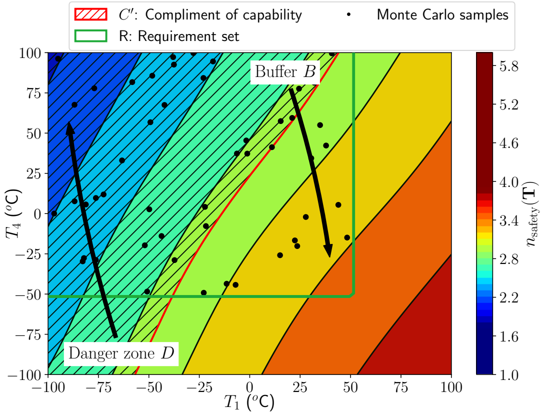

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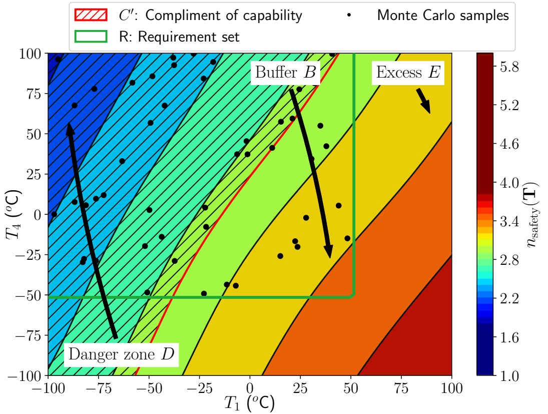

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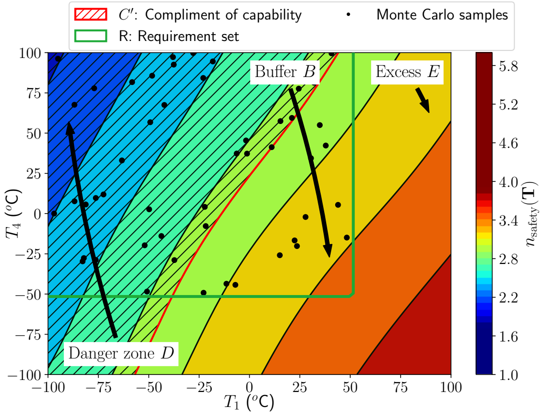
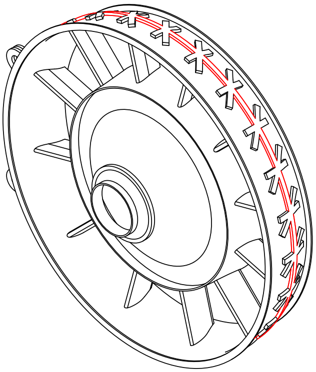
- *Reliability*: $\mathbb{P}(\mathbf{T} \in C)$ estimated using Monte-Carlo integration



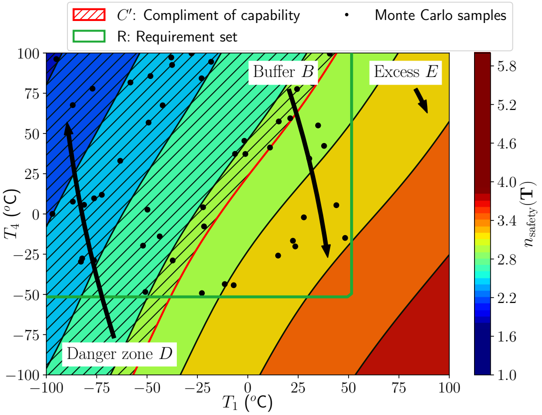
Going back to our baseline design we can calculate these metrics as follows:

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



Turbine Rear Structure (TRS)

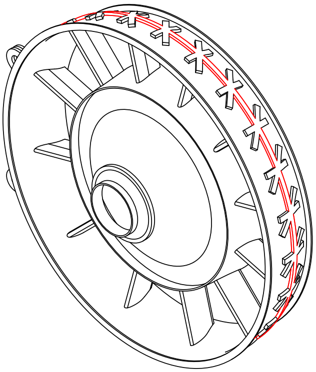
Reliability	**Excess**	**Weight**
0.3089	0.529	13.9



Considering redesign when buffer is insufficient

Consider depositing more material

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



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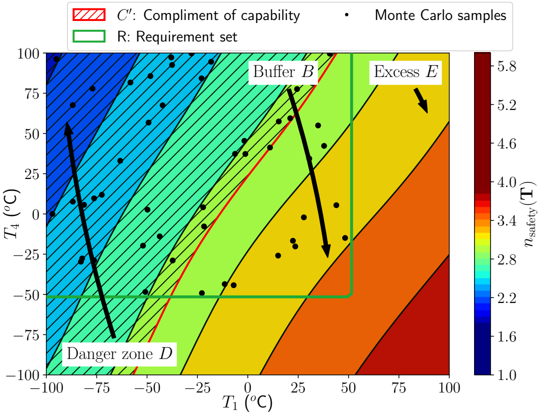
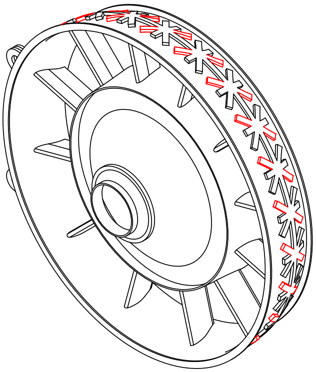


Considering redesign when buffer is insufficient

Reliability increases

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



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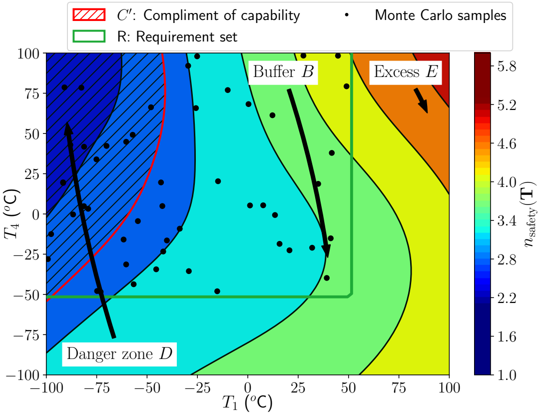
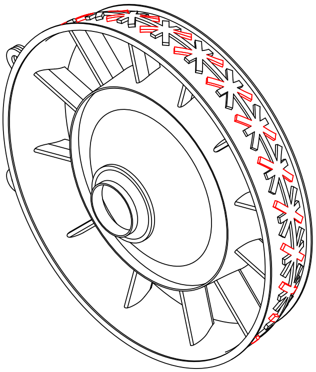


Reliability	Excess	Weight
0.759(↑ 145%)	0.856(↑ 62%)	18.5(↑ 33%)

Considering redesign when buffer is insufficient

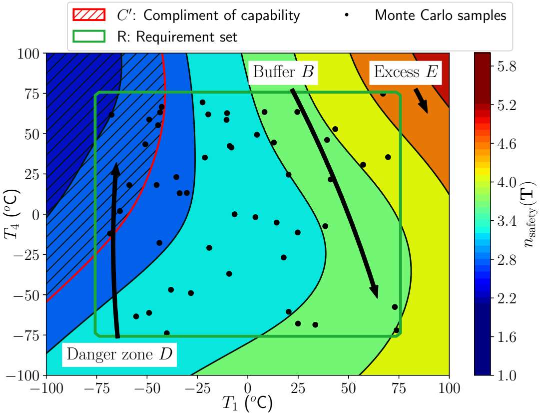
However, requirements can change as well!

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



Turbine Rear Structure (TRS)

Reliability	Excess	Weight
0.943(↑ 24%)	0.754(↓ 12%)	18.5



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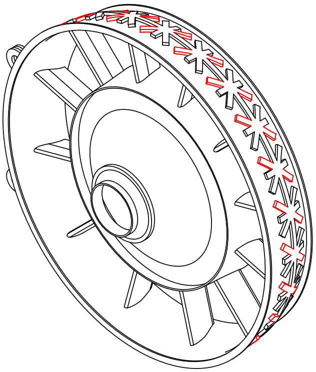

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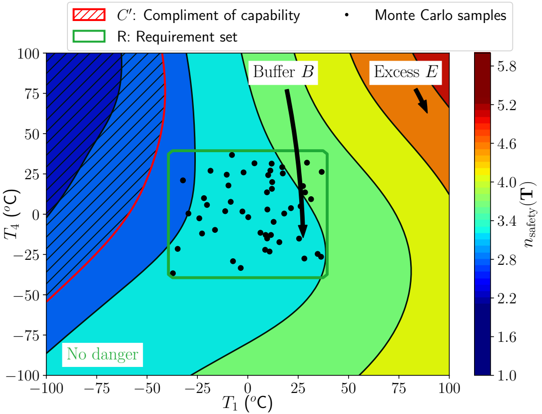

Reliability	Excess	Weight
1.00(↑ 6%)	0.871(↑ 15%)	18.5

Optimizing when and how much change is needed

Formulate optimization problem to minimize total excess while being reliable

Objective and constraints

minimize	excess(c, D; requirement arc)
subject to	*reliability*(c, D; requirement arc)
over	The set of feasible design decisions
	(404 possible combinations)

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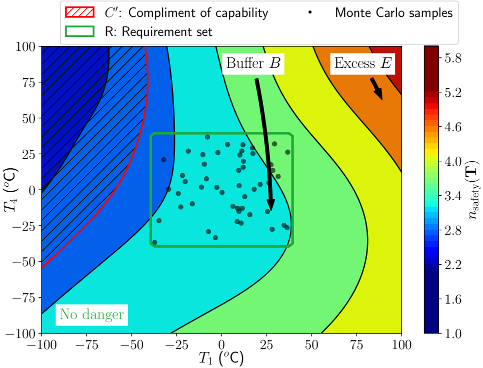

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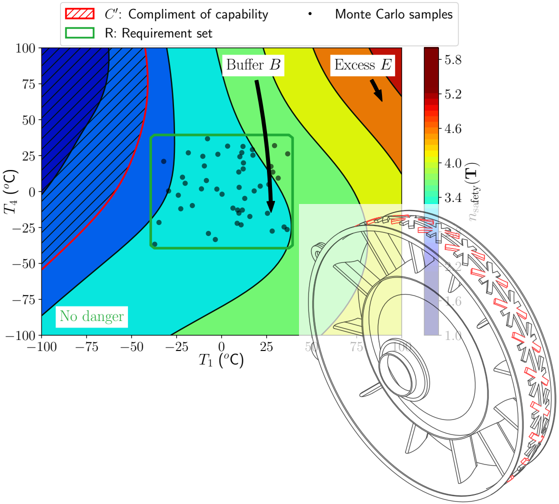
Design variables

$c \in \{\text{"wavy"}, \text{"hatched"}, \text{"tubular"}\}$

$\mathrm{D} = [\mathrm{decision}_1, \mathrm{decision}_2, \cdots]$

$\mathrm{decision} \in \{-1, 0, 1, 2, 3, 4\}$



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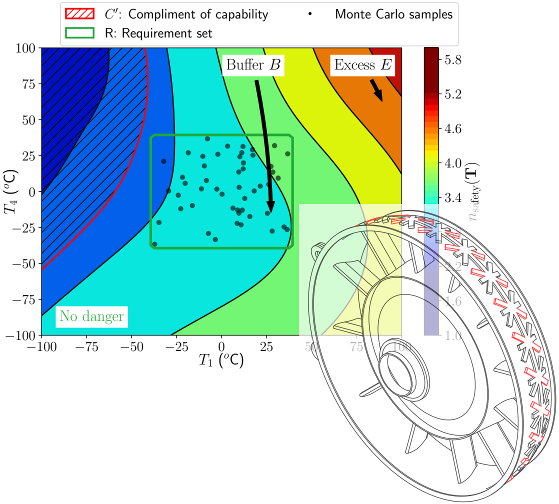

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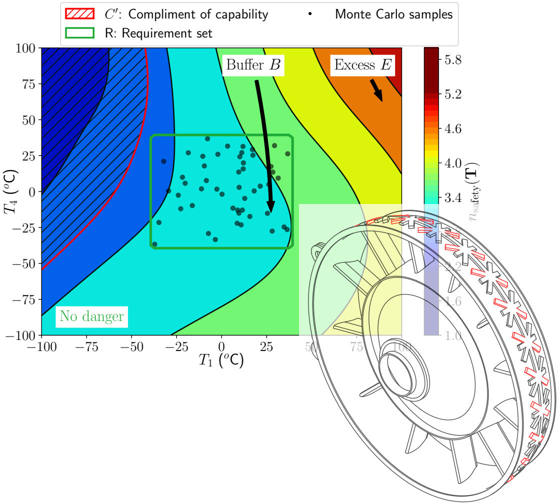
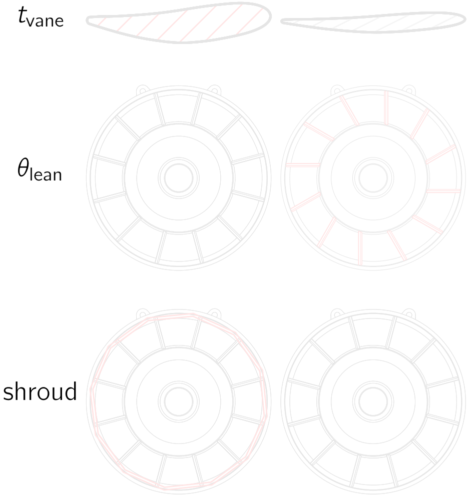
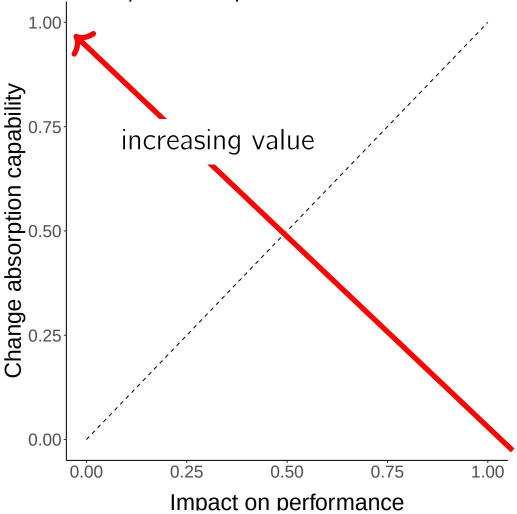


Margin value-driven design space exploration

Change absorption through design margins

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





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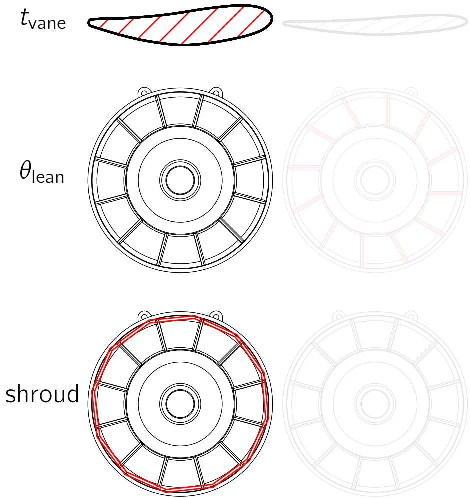
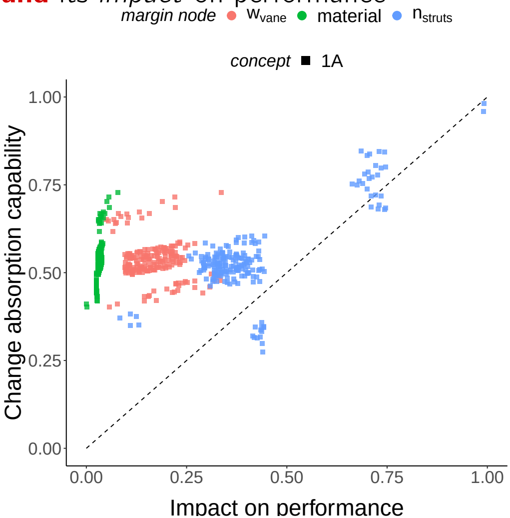


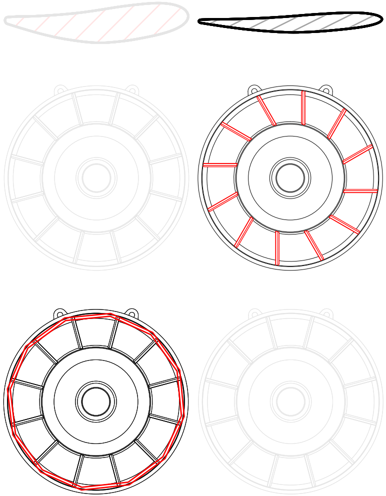


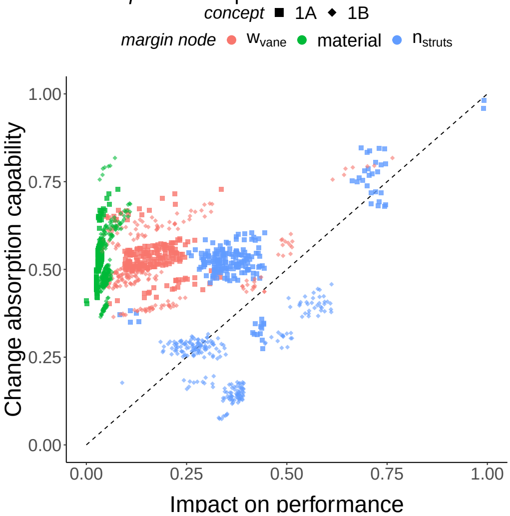
We quantify the change *absorption* capability **and** its *impact* on performance

t_{vane}

θ_{lean}

shroud





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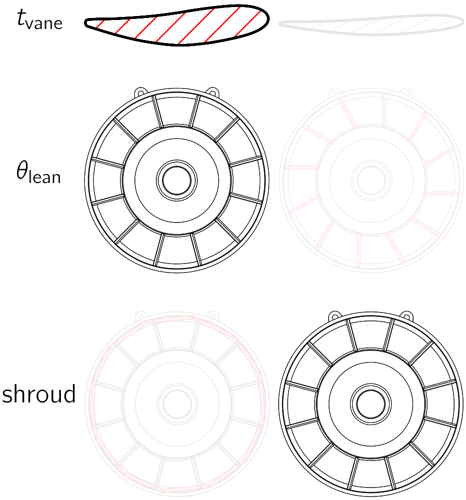

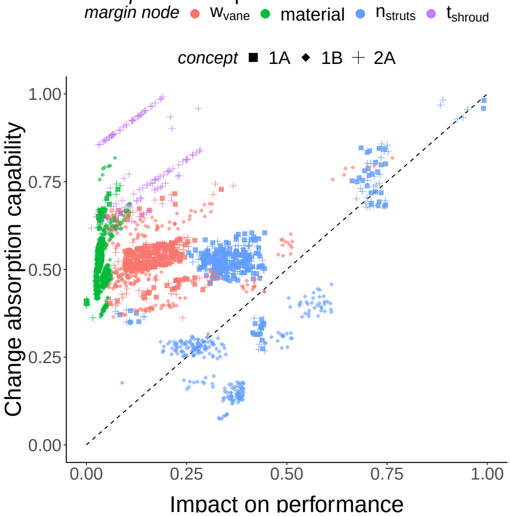

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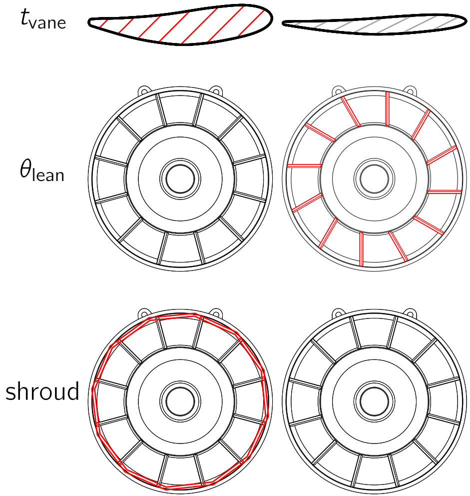
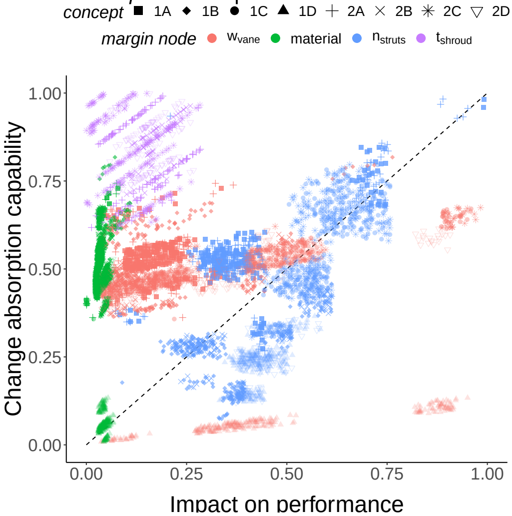
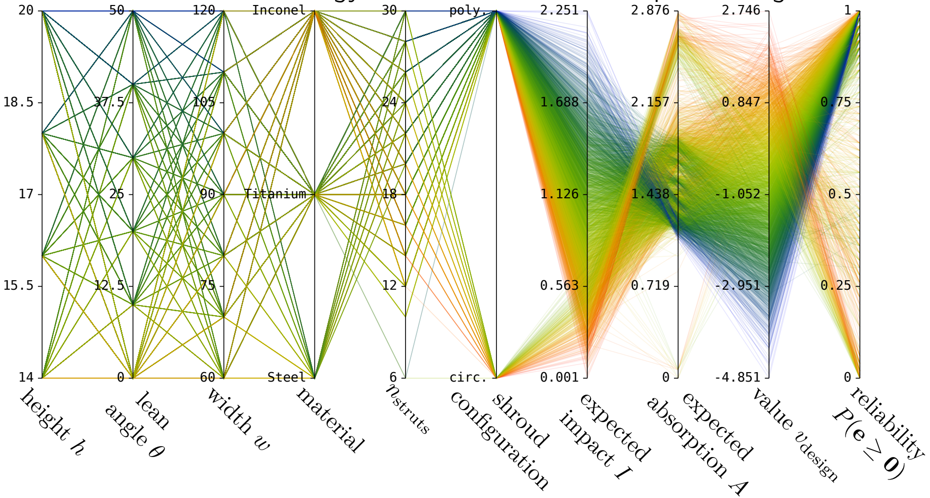




Change absorption through design margins

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**:
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Other projects: Graph representation of aviation network

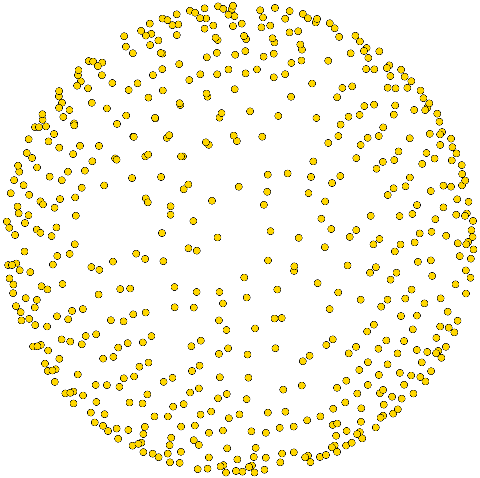
- Nodes: represent the airlines
- Edges: represent the codesharing
- Edge weights given by thickness of lines
- Node strength: sum of incoming edge weights at each node (size of nodes)
- We identify large communities
- Compare them to **six** airline alliances

Finding optimal community structure

$$\min_{\{\mathcal{A}_1,\cdots,\mathcal{A}_K\}\in\mathcal{V}^K} \quad -Q(\mathcal{A}_1,\cdots,\mathcal{A}_K)$$

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

Q : modularity



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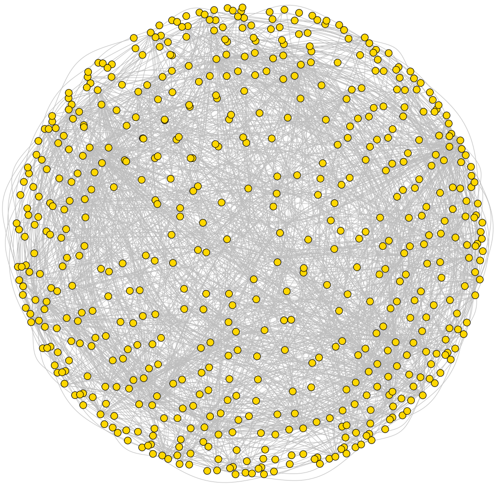

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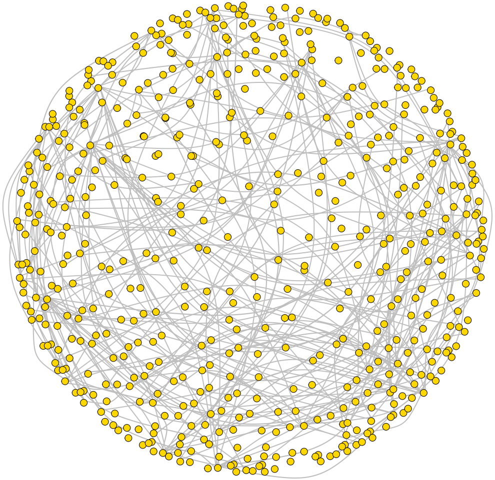

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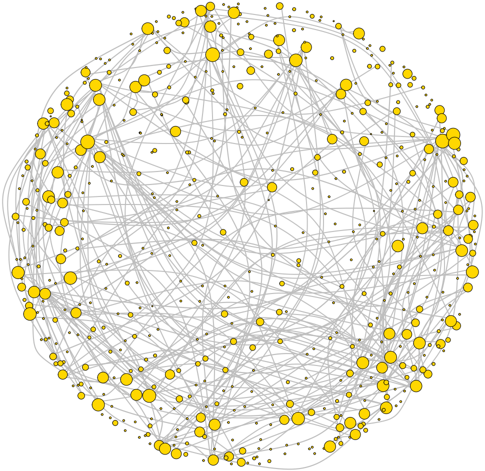

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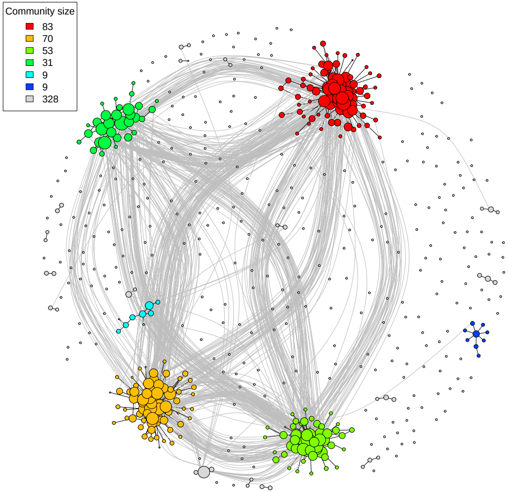

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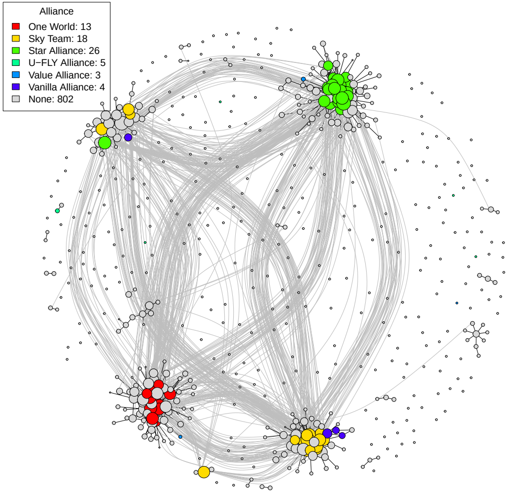

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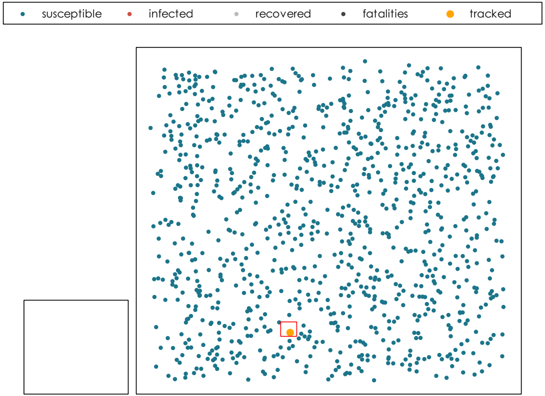
Optimization of public health models using artificial life models

Public health policy-making problem formulation

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

No interventions applied



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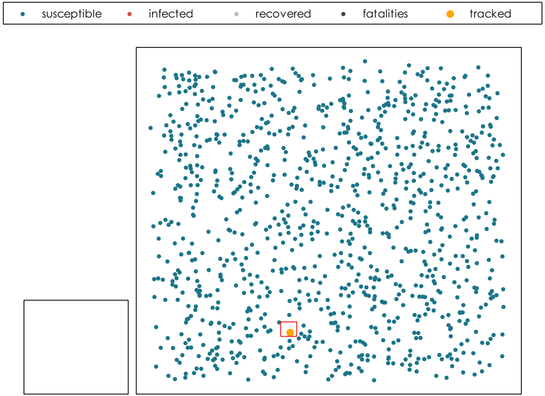
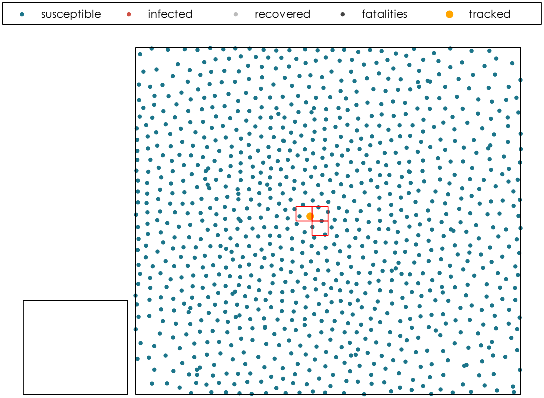


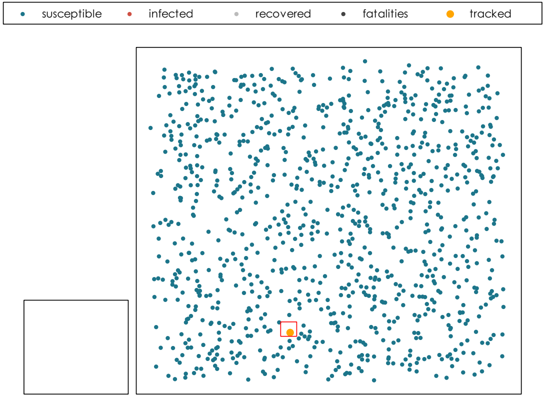
with intervention



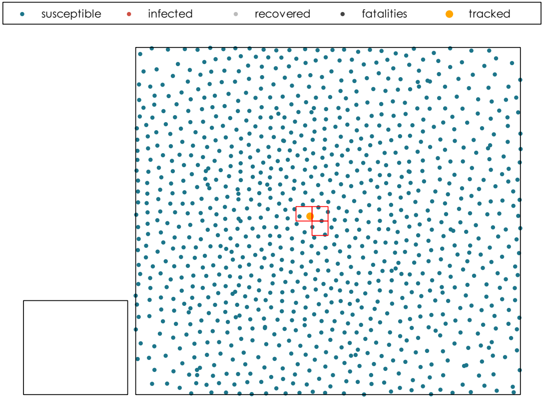
Public health policy-making problem formulation

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

No interventions applied



with intervention



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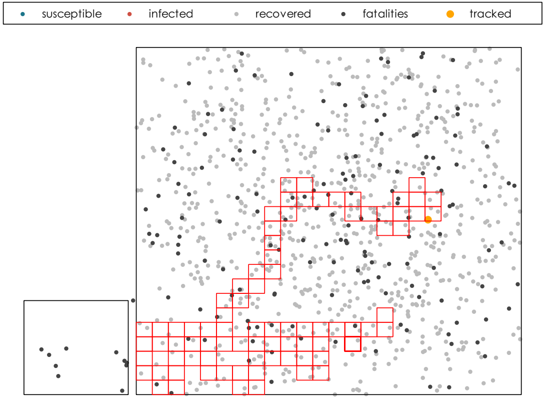
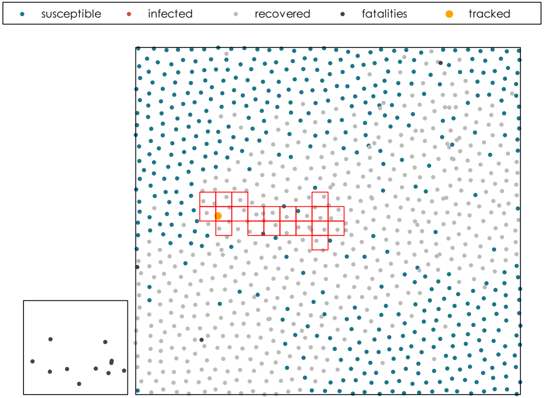


with intervention



Optimization problem

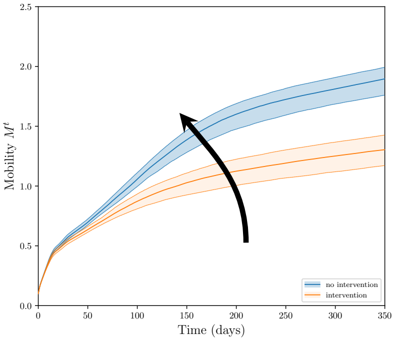
Objective and constraints

$$\min_{x} \quad f(x) = -M^T$$
subject to

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

Design variables

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



Optimization problem

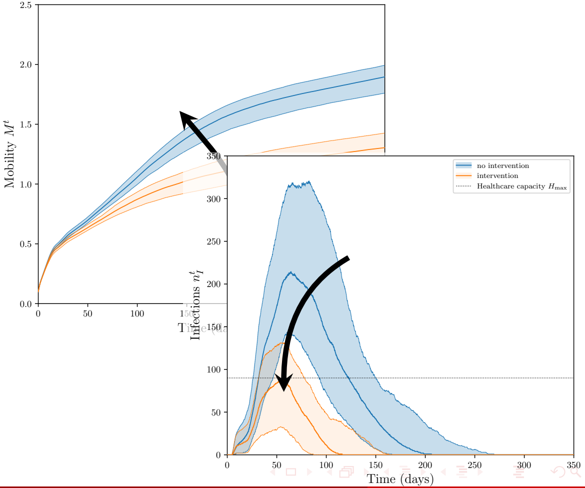
No gradient information available, blackbox is expensive and noisy

Objective and constraints

$$\begin{aligned} \min_{x} \quad & f(x) = -M^T \\ \text{subject to} \quad & c(x) \equiv n_{I,\max} - H_{\max} \leq 0 \\ \text{where} \quad & x = [n_E, S_D, n_T]^T \end{aligned}$$

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

$$
\begin{aligned}
\min_{\mathrm{x}} \quad & f(\mathrm{x}) = -M^T \\
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\text{where} \quad & \mathrm{x} = [n_E, S_D, n_T]^T
\end{aligned}
$$

Design variables

- n_E : Number of essential workers
- S_D : Social distancing factor
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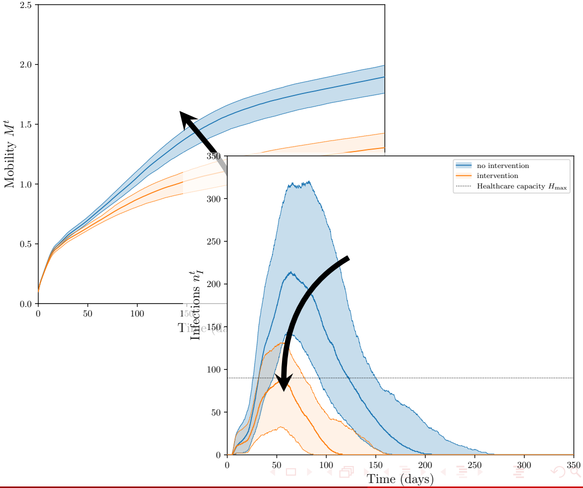


Optimization problem

No gradient information available, blackbox is expensive and **noisy**

Objective and constraints

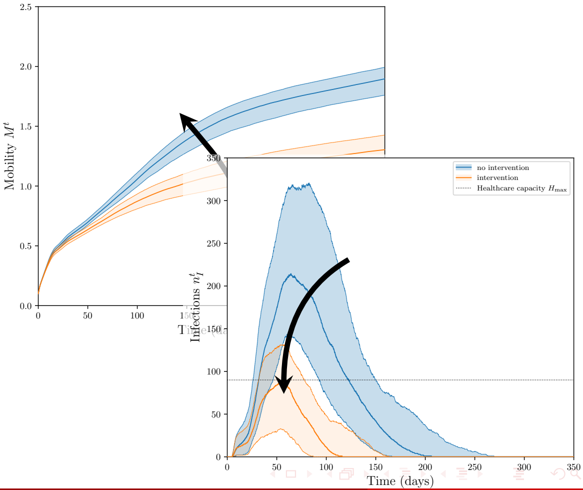
$$\min_{x} \quad f(x) = \mathbb{E}_{\Theta}\left[f_{\Theta}(x) = -M^T\right]$$

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

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

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

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

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

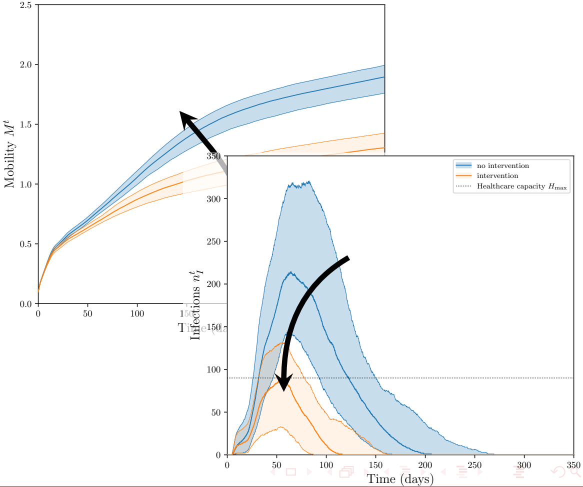
$$\text{where} \quad x = [n_E, S_D, n_T]^T, \ \Theta\text{: realizations}$$

Design variables

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

Randomly seeded parameters

- Initial conditions
- Interactions, demographics



Thank you for your time