Product reliability optimization under plate sheet forming process variability

B. Van Doninck, M. Imholz, M. Faes, D. Moens

1 KU Leuven - Dept. of Mechanical Engineering
2 Flanders Make
1 Outline

1 Introduction

2 Coupled process-product simulation

3 RBDO vs. IBDO

4 Conclusions and outlook
1  Reliability in engineering design

- advanced virtual design techniques
1  Reliability in engineering design

▶ advanced virtual design techniques $\leadsto$ highly optimised parts
1. Reliability in engineering design

- advanced virtual design techniques → highly optimised parts
- enabled by advances in materials and manufacturing engineering

- Topology Optimised wing (Nature)
- Additive Manufacturing micro lattice (Boeing)
- Topology optimised multi-material bionic arm (U Nottingham)
1 Reliability in engineering design

- advanced virtual design techniques \(\xrightarrow{\sim} \) highly optimised parts
- enabled by advances in materials and manufacturing engineering

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1 Reliability in engineering design

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Topology Optimised wing (Nature)  
Additive Manufacturing micro lattice (Boeing)  
Topology optimised multi-material bionic arm (U Nottingham)

$\rightarrow$ need for high-fidelity models incorporating physics, material behaviour, etc.
1 Reliability in engineering design

- advanced virtual design techniques \(\leadsto\) highly optimised parts
- enabled by advances in materials and manufacturing engineering
- need for high-fidelity models incorporating physics, material behaviour, etc.
1 Reliability in engineering design

▶ advanced virtual design techniques ⇔ highly optimised parts
▶ enabled by advances in materials and manufacturing engineering
⇔ need for high-fidelity models incorporating physics, material behaviour, etc.
▶ example: Additive Manufacturing

Figure: Intra-variability

Figure: Inter-variability
1 Probabilistic reliability analysis

Main idea

"Employ non-deterministic models to explicitly compute probability of failure"

model of structure:

\[ y = m(x), \quad m : \mathbb{R}^{n_x} \rightarrow \mathbb{R}^{n_y} \]
1 Probabilistic reliability analysis

Main idea
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model of structure:

\[ \mathbf{y} = m(\mathbf{x}), \quad m : \mathbb{R}^{n_x} \rightarrow \mathbb{R}^{n_y} \]

probability of failure:

\[ P_f = P(\mathbf{y} \in \mathcal{F}) = \int_{\mathbb{R}^{n_y}} \mathbb{I}_{\mathcal{F}}(\mathbf{y}) f_{\mathbf{y}}(\mathbf{y}) d\mathbf{y} \]

with:

\[ \mathbb{I}_{\mathcal{F}} = \begin{cases} 0 & \iff \mathbf{Y} \text{ is below safety treshold} \\ 1 & \iff \mathbf{Y} \text{ above safety treshold} \end{cases} \]
1 Interval analysis

Main idea

“Bound the non-determinism in the model between a crisp upper and lower bound”
1 Interval analysis

Main idea

”Bound the non-determinism in the model between a crisp upper and lower bound”

- interval uncertain parameters $\rightarrow x^I \in \mathbb{IR}^{nx}$
- compute bounds on output quantities $y \in \mathbb{R}^{ny}$
  $\mapsto$ extrema of realization set of uncertain responses:
  $$\tilde{y} = \left\{ y_j \mid y_j = m(x_j), x_j \in x^I \right\}$$
1 Design optimization

Reliability based design optimization

\[
\begin{align*}
\text{minimize} & \quad y^o(x) \\
\text{subject to} & \quad P_f(y^p(x)) < c
\end{align*}
\]  \hspace{1cm} (1)

Interval based design optimization

\[
\begin{align*}
\text{minimize} & \quad y^o(x) \\
\text{subject to} & \quad y^p(x) > b \\
& \quad \underline{y}^p(x) < c
\end{align*}
\]  \hspace{1cm} (2)
1 Challenge and presentation goals

Observation

Variability and uncertainty often stems from (complex) production process influences
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Two main questions:

⇝ how can we include data we have on these advanced processes into the product design optimization?
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Variability and uncertainty often stems from (complex) production process influences

Two main questions:

⇝ how can we include data we have on these advanced processes into the product design optimization?

⇝ should we, given a dataset, follow an interval or a probabilistic optimization approach?
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2 Case introduction

- Deep drawn (Erichsen) steel cup
  → structure representative for sheet metal forming
- Relevant parameters:
  - production process: blank-holder force, deep draw distance, initial plate thickness
  - material parameters: Young’s modulus, elastic strength, hardening law parameters

Figure: Erichsen cup
2 Process and product simulation models

Process model:

- First principle based $\rightarrow$ too expensive
- Random Forrest model
- 100 combinations of production parameters
- Off-line thickness measurement of entire cup
- 5 zones of different thickness thinning are considered
- Trained using SciKit Learn

Figure: Thickness measured over Erichsen cup
2 Process and product simulation models

Process model:
- First principle based $\sim$ too expensive
- Random Forrest model
- 100 combinations of production parameters
- Off-line thickness measurement of entire cup
- 5 zones of different thickness thinning are considered
- Trained using SciKit Learn

Product model:
- Linear elastic Finite Element model
- First 10 eigenmodes
- MSC Nastran
- 1401 CQUAD4 and 49 CTRIA3 elements
2 Coupling of the models

(a) Measured product shape as reference
(b) Division in 5 zones of different thinning
(c) Apply thinning as predict by Random Forrest model to each zone
(d) Mesh morphing to account for e.g. drawing depth or account for flange wrinkling by means of a fitted analytical model
2 Implementation

- Implemented using Python, Noesis Optimus and MSC Nastran
- Input parameters: process, material, initial plate thickness
- Output: first 10 flexible resonance frequencies
- Computation of Sobol indices to detect sensitive parameters
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3 Reliability based design optimization: set up

- Variability in initial plate thickness
- Variable parameters:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Distribution</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial plate thickness</td>
<td>Normal</td>
<td>$\mathcal{N}(0.7734, 0.012)$ mm</td>
</tr>
<tr>
<td>Clamp holding force</td>
<td>deterministic</td>
<td>45 N</td>
</tr>
</tbody>
</table>

- Goal: minimize total mass of cup
- Constraint: $f_1 > 3500$ Hz with $\beta > 3$ (FORM)
- Sequential Quadratic Programming with BFGS approx. of Hessian
3 Reliability based design optimization: results

- 3 runs of SQP, totaling 78 deterministic evaluations
- result:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Mean Value</th>
<th>Var.</th>
</tr>
</thead>
<tbody>
<tr>
<td>m</td>
<td>Mass</td>
<td>65.8 g</td>
<td>0.824 g</td>
</tr>
<tr>
<td>t</td>
<td>Plate thickness</td>
<td>0.927 mm</td>
<td>0.011 mm</td>
</tr>
<tr>
<td>$f_1$</td>
<td>Eigenfrequency 1</td>
<td>3613.0 Hz</td>
<td>37.6 Hz</td>
</tr>
</tbody>
</table>

average thickness increased from 0.773 mm to 0.927 mm
3 Interval based design optimization

- Uncertainty in initial plate thickness
- Variable parameters:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial plate thickness</td>
<td>Interval</td>
<td>[0.754; 0.794] mm</td>
</tr>
<tr>
<td>Clamp holding force</td>
<td>deterministic</td>
<td>45 N</td>
</tr>
</tbody>
</table>

- Goal: minimize total mass of cup
- Constraint: $f_1 > 3500 \ Hz$
- Interval propagation: Transformation method
- Sequential Quadratic Programming with BFGS approx. of Hessian
3 Interval based design optimization: results

- 3 runs of SQP, totaling 12 deterministic evaluations
- result:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Lower bound</th>
<th>Upper bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>$m$</td>
<td>Mass</td>
<td>63.47 g</td>
<td>66.38 g</td>
</tr>
<tr>
<td>$t$</td>
<td>Plate thickness</td>
<td>0.893 mm</td>
<td>0.934 mm</td>
</tr>
<tr>
<td>$f_1$</td>
<td>Eigenfrequency 1</td>
<td>3500 Hz</td>
<td>3633 Hz</td>
</tr>
</tbody>
</table>
3 Comparison of the approaches

- computational cost of RBDO > IBDO
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- safety margins rather comparable
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  ⇔ highly case dependent
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  ⇔ by construction
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Conclusions

▶ Coupled approach linking process to product simulation
▶ Application to industrial use case
▶ Comparison of Reliability based and interval based design optimization

Outlook (ongoing)

▶ Fitting interval and random fields to data (X)
▶ Redo RBDO and IBDO with these fields