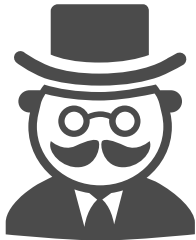




# Uncertainty in Finance



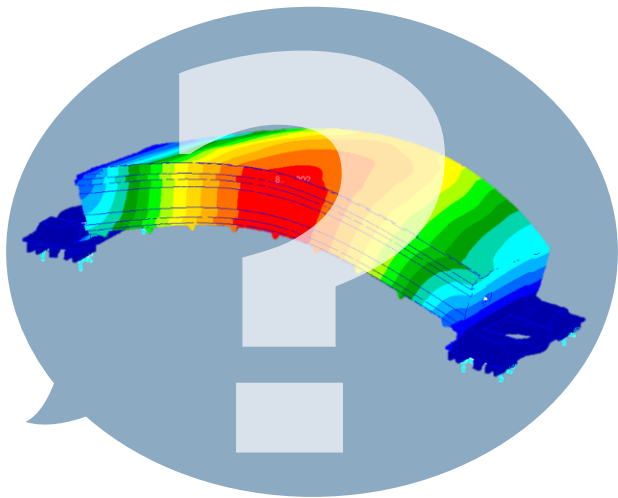
# Uncertainty in Finance



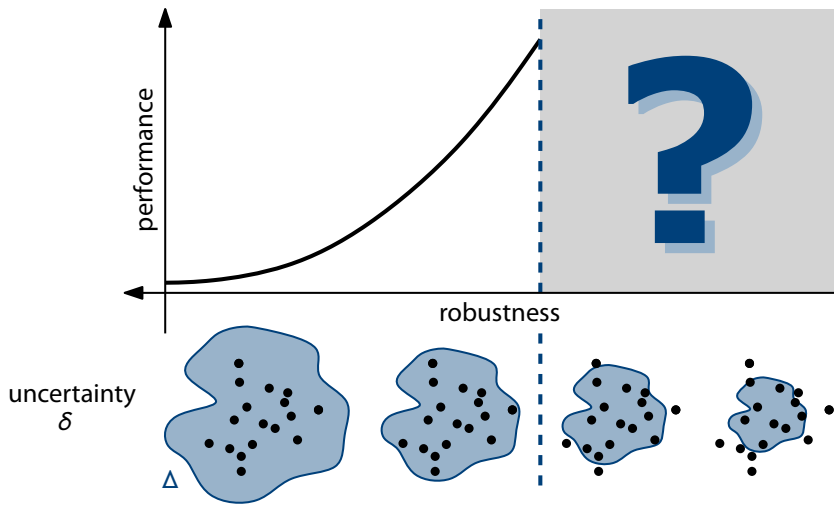
# Uncertainty in Engineering



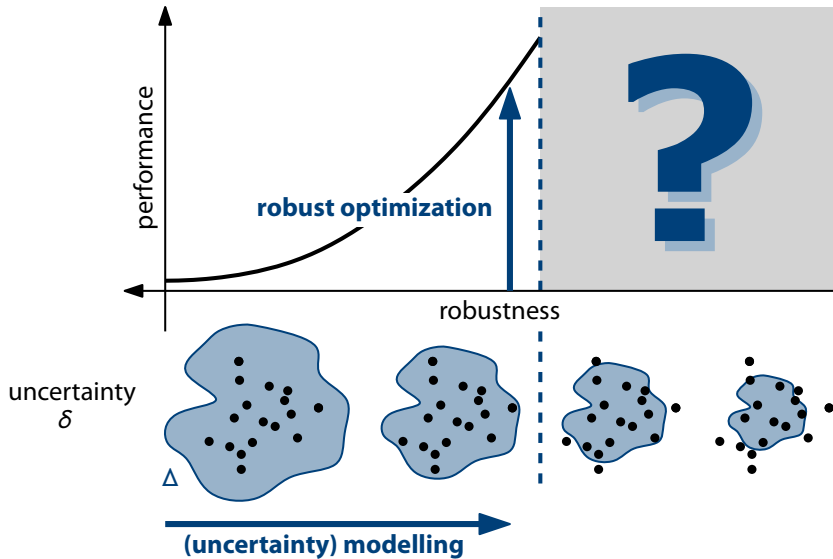
# Uncertainty in Engineering



# The General Picture



# The General Picture



# Robust Optimization

Find the solution (portfolio, control, design ...),

that is adequate for all possible  $\delta$  in  $\Delta$ ,

and guarantees the highest performance.



# Robust Optimization

Find the solution (portfolio, control, design ...),

↔ optimization variable  $x$

that is adequate for all possible  $\delta$  in  $\Delta$ ,

and guarantees the highest performance.

# Robust Optimization

Find the solution (portfolio, control, design ...),

↪ optimization variable  $x$

that is adequate for all possible  $\delta$  in  $\Delta$ ,

↪ constraints  $f_i(x, \delta) \geq 0$ , for all  $\delta \in \Delta$ ,  $i = 1, \dots, m$

and guarantees the highest performance.

# Robust Optimization

Find the solution (portfolio, control, design ...),

↪ optimization variable  $x$

that is adequate for all possible  $\delta$  in  $\Delta$ ,

↪ constraints  $f_i(x, \delta) \geq 0$ , for all  $\delta \in \Delta$ ,  $i = 1, \dots, m$

and guarantees the highest performance.

↪ maximize  $\gamma$  subject to  $f_0(x, \delta) \geq \gamma$ , for all  $\delta \in \Delta$

# Robust Optimization

Find the solution (portfolio, control, design ...),

↪ optimization variable  $x$

that is adequate for all possible  $\delta$  in  $\Delta$ ,

↪ constraints  $f_i(x, \delta) \geq 0$ , for all  $\delta \in \Delta$ ,  $i = 1, \dots, m$

and guarantees the highest performance.

↪ maximize  $\gamma$  subject to  $f_0(x, \delta) \geq \gamma$ , for all  $\delta \in \Delta$



maximize  $\gamma$   
 $x, \gamma$

subject to  $f_0(x, \delta) \geq \gamma$ , for all  $\delta \in \Delta$   
 $f_i(x, \delta) \geq 0$ , for all  $\delta \in \Delta$ ,  
 $i = 1, \dots, m$

**1**

***Beyond the original raison d'être***

**2**

***Solving robust optimization problems***

**3**

***Results in applications***

# Motion Planning



# Motion Planning



# Motion Planning

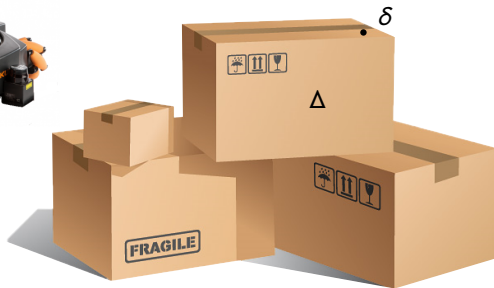




# Motion Planning



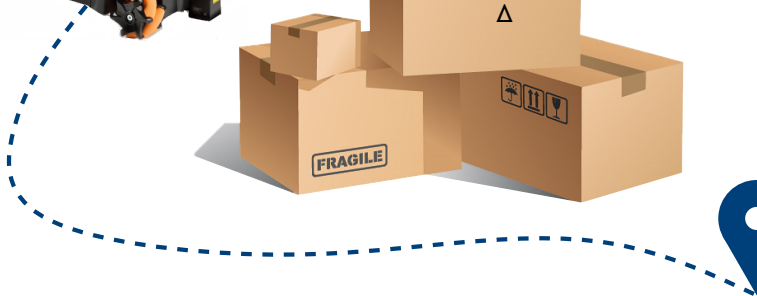
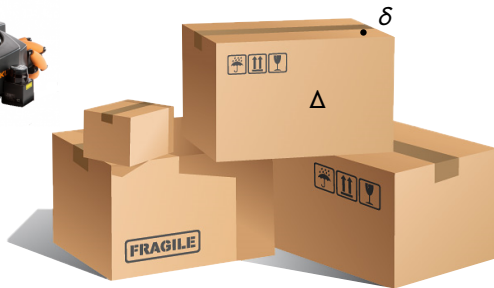
collision avoidance:  
 $\text{dist}(\text{KUKA}, \delta) \geq \epsilon, \forall \delta \in \Delta$



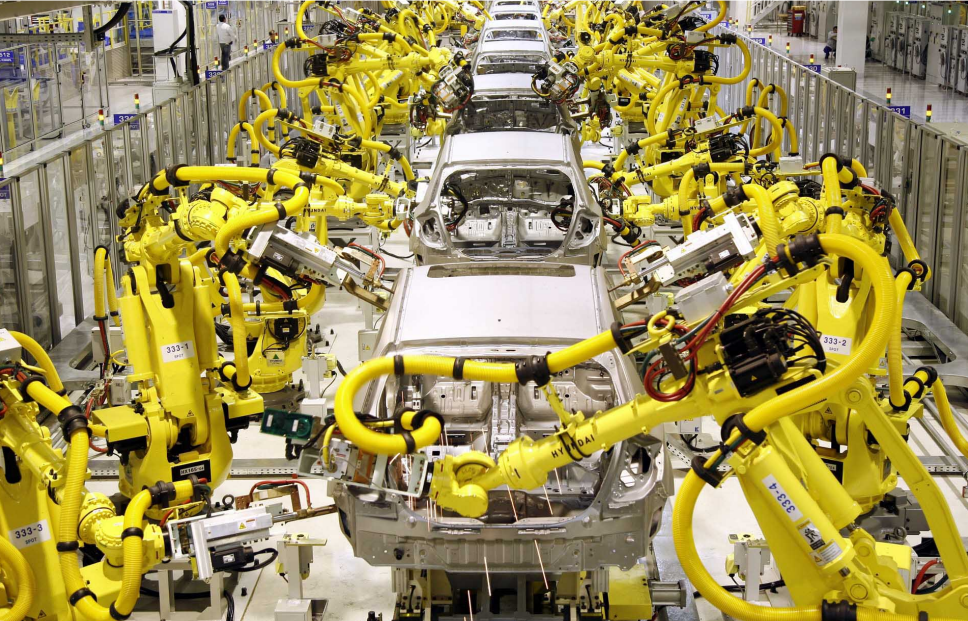
# Motion Planning



collision avoidance:  
 $\text{dist}(\text{KUKA}(t), \delta) \geq \epsilon, \quad \forall \delta \in \Delta$   
 $\forall t \in [0, T]$



# Motion Planning



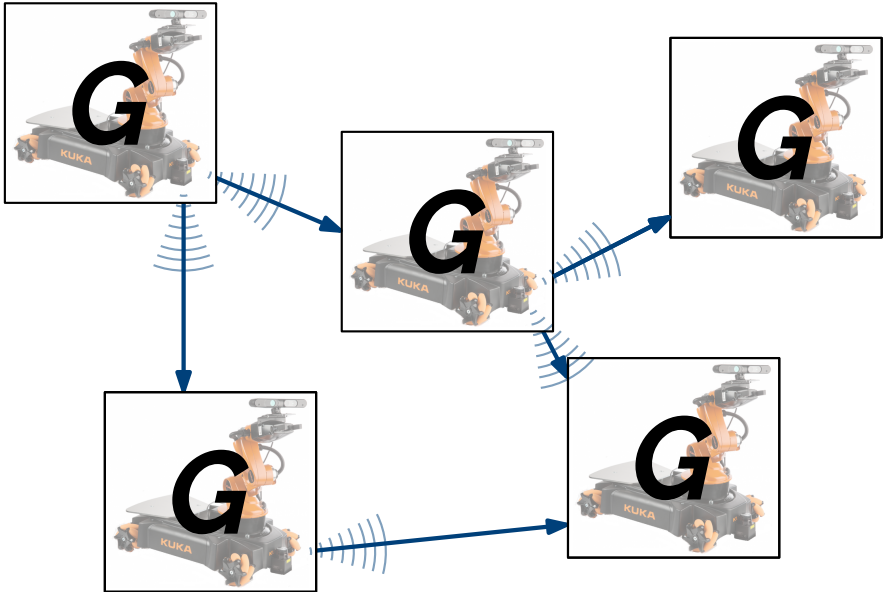
# Interconnected Systems



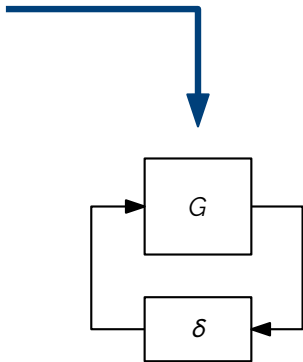
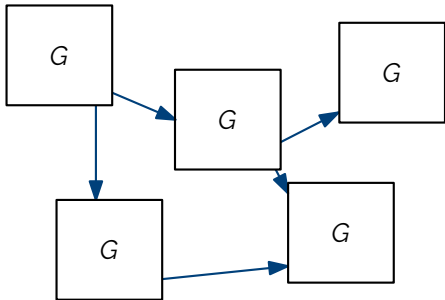
# Interconnected Systems



# Interconnected Systems



# Interconnected Systems



$\Delta \sim$  interconnection

# Interconnected Systems





# Parametric Programming

maximize  $f_0(x, \delta)$   
subject to  $f_i(x, \delta) \geq 0, \quad i = 1, \dots, m$



$x^{\text{opt}}(\delta)$   
for  $\delta \in \Delta$

# Parametric Programming

$$\begin{array}{ll} \underset{x}{\text{maximize}} & f_0(x, \delta) \\ \text{subject to} & f_i(x, \delta) \geq 0, \quad i = 1, \dots, m \end{array}$$



$$\begin{array}{l} x^{\text{opt}}(\delta) \\ \text{for } \delta \in \Delta \end{array}$$

Trade-off analysis

↔  $\delta$ : weight on objectives

$$f_0(x, \delta) = \sum_k \delta_k f_{0,k}(x)$$



# Parametric Programming

$$\begin{array}{ll} \underset{x}{\text{maximize}} & f_0(x, \delta) \\ \text{subject to} & f_i(x, \delta) \geq 0, \quad i = 1, \dots, m \end{array}$$



$$\begin{array}{l} x^{\text{opt}}(\delta) \\ \text{for } \delta \in \Delta \end{array}$$

Linear parameter varying control

↔  $\delta$ : measurable parameters affecting the system dynamics



# Parametric Programming

$$\begin{array}{ll} \underset{x}{\text{maximize}} & f_0(x, \delta) \\ \text{subject to} & f_i(x, \delta) \geq 0, \quad i = 1, \dots, m \end{array}$$



$$x^{\text{opt}}(\delta) \\ \text{for } \delta \in \Delta$$

Computing approximation  $\hat{x}(\delta)$  of  $x^{\text{opt}}(\delta)$

$$\hat{x}(\delta) = x_0 + x_1 \delta + x_2 \delta^2 \dots$$

↪ solve robust optimization problem to compute coefficients

$$\begin{array}{ll} \underset{x_0, x_1, \dots}{\text{maximize}} & \int_{\Delta} f_0(\hat{x}(\delta), \delta) d\delta \\ \text{subject to} & f_i(\hat{x}(\delta), \delta) \geq 0, \quad \text{for all } \delta \in \Delta, \\ & i = 1, \dots, m \end{array}$$

**1**

***Beyond the original raison d'être***

**2**

***Solving robust optimization problems***

**3**

***Results in applications***

# The Main Challenge

$$f(x, \delta) \geq 0, \text{ for all } \delta \in \Delta$$

# The Main Challenge

$$f_x(\delta) \geq 0, \text{ for all } \delta \in \Delta$$

# The Main Challenge

$$f_x(\delta) \geq 0, \text{ for all } \delta \in \Delta$$



there exists no  $\delta$  in  $\Delta$  for which  $f_x(\delta) < 0$



# The Main Challenge

$$f_x(\delta) \geq 0, \text{ for all } \delta \in \Delta$$



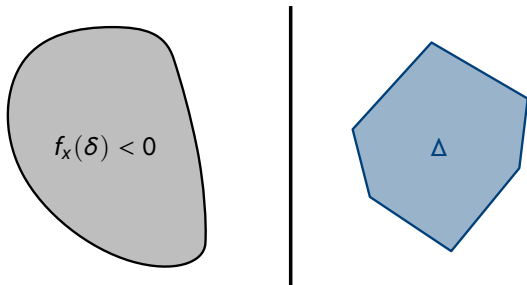
there exists no  $\delta$  in  $\Delta$  for which  $f_x(\delta) < 0$



$$\{\delta \mid f_x(\delta) < 0\} \cap \Delta = \emptyset$$

# Few Cases: Tractable Reformulation

## Linear separation



## Quadratic separation

- S-procedure, Kalman-Yakubovich-Popov lemma ...

# Otherwise: Relaxations

$$f(x, \delta) \geq 0, \text{ for all } \delta \in \Delta$$












$$\mathcal{F}_\Delta(x) \geq 0$$

*relaxation*

# Otherwise: Relaxations

## A novel scheme for constructing relaxations

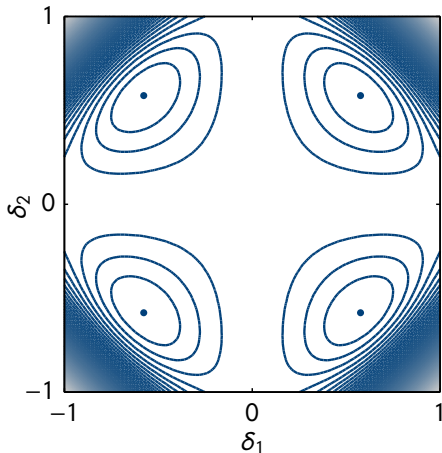
- more general than existing schemes

	Pólya	sum-of-squares	<b>new</b>
$f_x(\delta)$	polynomial	polynomial	piecewise polynomial
$\Delta$	  	  	  

# Otherwise: Relaxations

## A novel scheme for constructing relaxations

- more general than existing schemes
- computationally more efficient than existing schemes



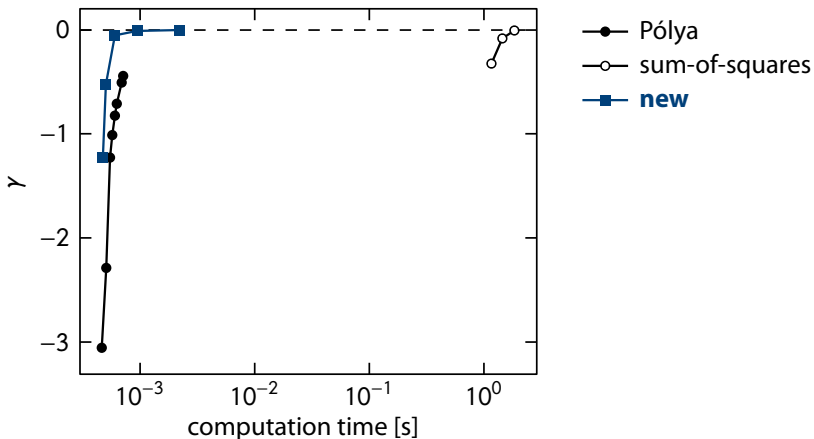
maximize  $\gamma$

subject to  $f(\delta) \geq \gamma$ , for all  $\delta \in \Delta$

# Otherwise: Relaxations

## A novel scheme for constructing relaxations

- more general than existing schemes
- computationally more efficient than existing schemes



# B-spline Relaxations

## Overall idea

- B-splines: piecewise polynomial basis functions  $B_\alpha$ 
  - partition of unity on  $\Delta$ :  $\sum_{\alpha \in \alpha} B_\alpha(\delta) = 1, \forall \delta \in \Delta$
  - positive on  $\Delta$ :  $B_\alpha(\delta) \geq 0, \forall \delta \in \Delta$

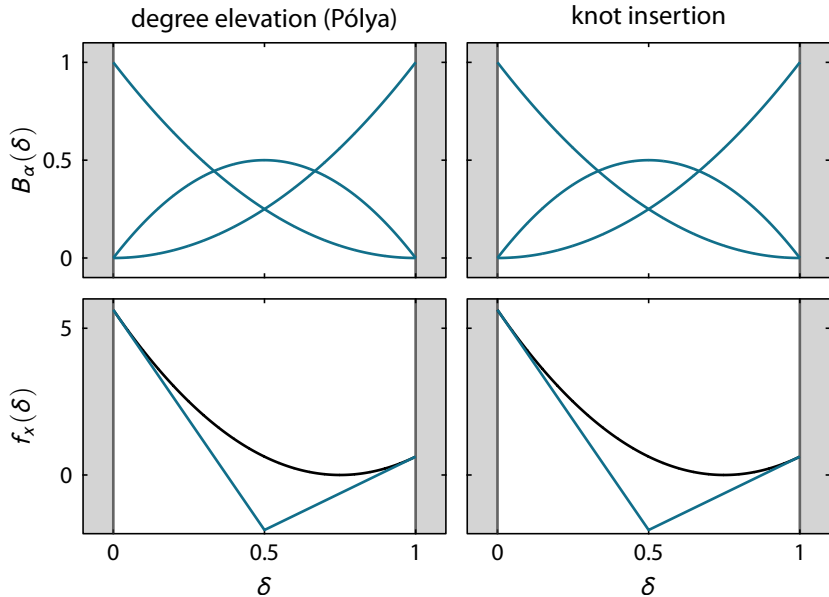
- relaxation:  $f(x, \delta) = \sum_{\alpha \in \alpha} c_\alpha(x) B_\alpha(\delta) \geq 0, \forall \delta \in \Delta$



$$c_\alpha(x) \geq 0, \forall \alpha \in \alpha$$

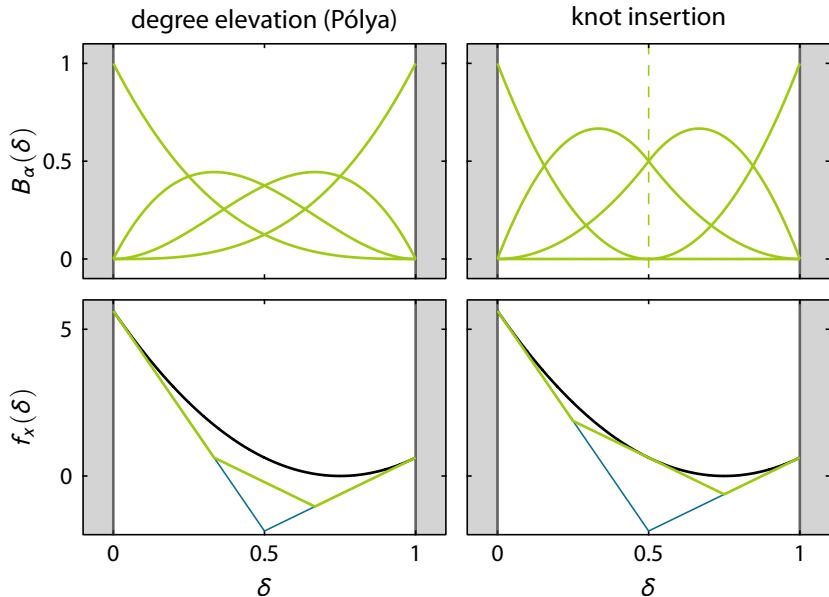
- refinement: higher-dimensional B-spline bases
  - piecewise polynomial of higher degree
  - piecewise polynomial on finer grid

# B-spline Relaxations

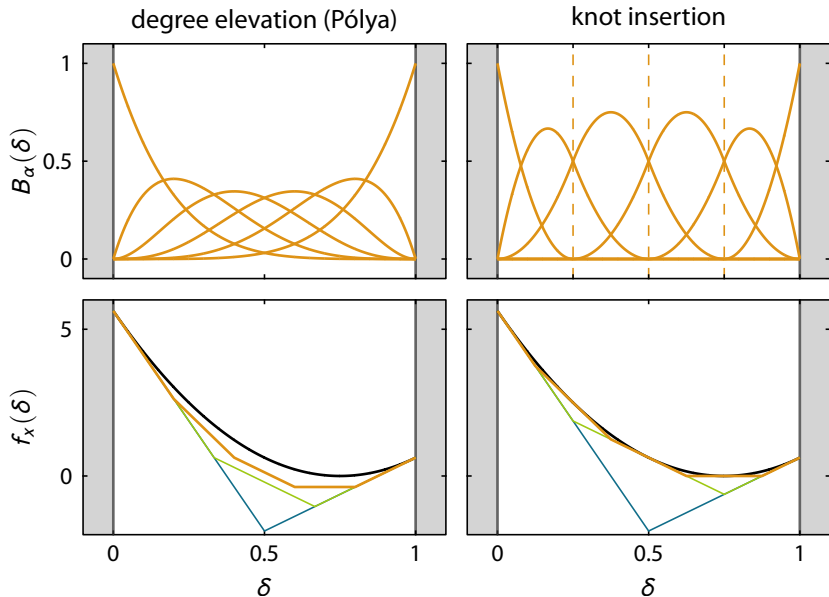




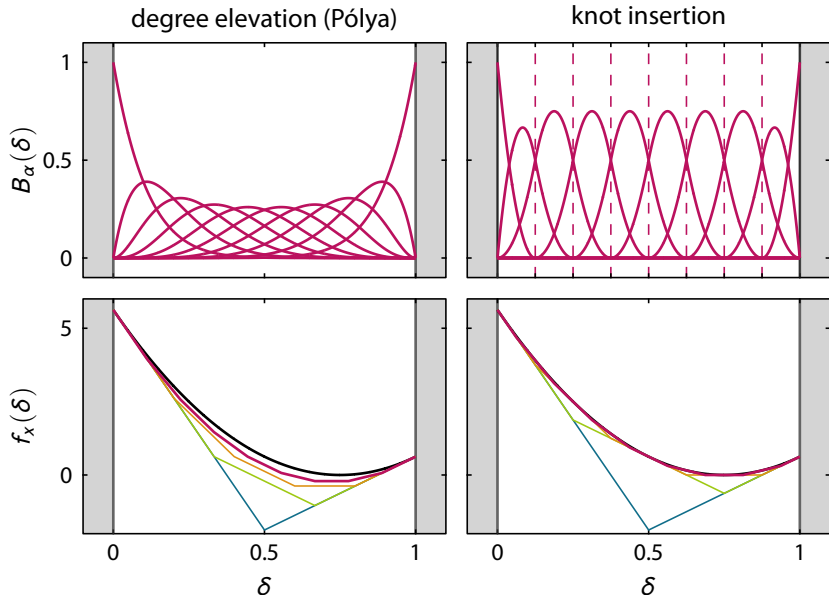
# B-spline Relaxations



# B-spline Relaxations



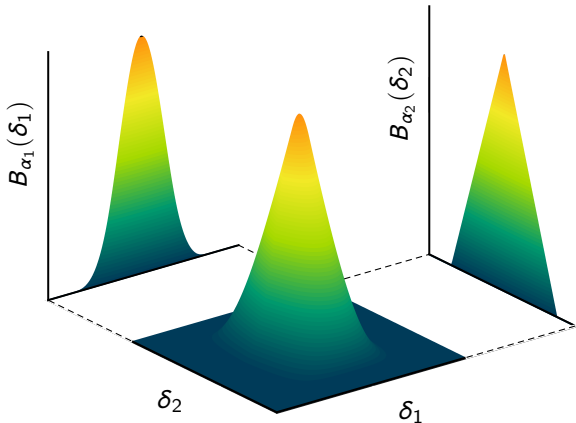
# B-spline Relaxations



# B-spline Relaxations

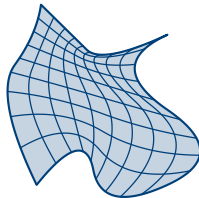
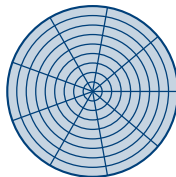
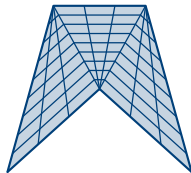
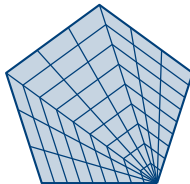
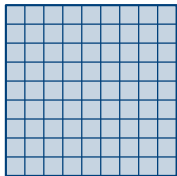
## Tensor product B-splines

$$B_{\alpha}(\delta) = B_{\alpha_1}(\delta_1)B_{\alpha_2}(\delta_2)$$



# B-spline Relaxations

Towards non-hyperrectangular domains



**1**

***Beyond the original raison d'être***

**2**

***Solving robust optimization problems***

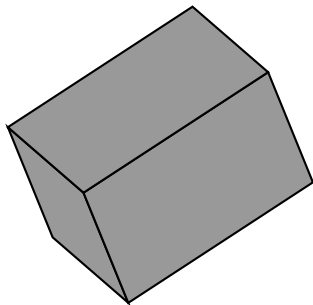
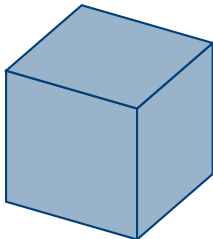
**3**

***Results in applications***

# Motion Planning

## Avoiding collision

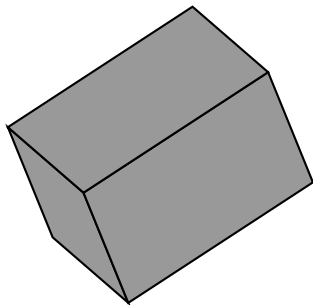
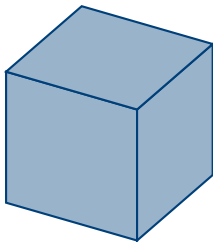
- exact reformulation using linear separation



# Motion Planning

## Avoiding collision

- exact reformulation using linear separation





# Motion Planning

## Avoiding collision

- exact reformulation using linear separation

## Enforcing constraints at all times

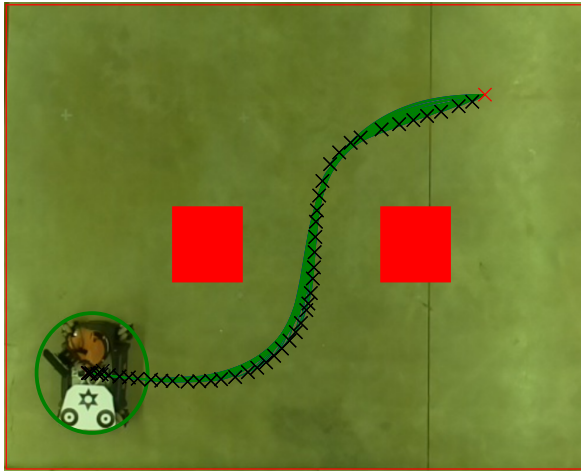
- B-spline parametrization of motion trajectory
- novel relaxation scheme for efficient constraint satisfaction

# Motion Planning

20 ms for simple kinematic models

# Motion Planning

20 ms for simple kinematic models

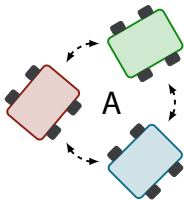


# Motion Planning

## Extension to multi-agent motion planning

- optimization distributed over agents using ADMM
- 1 ADMM iteration per update

B

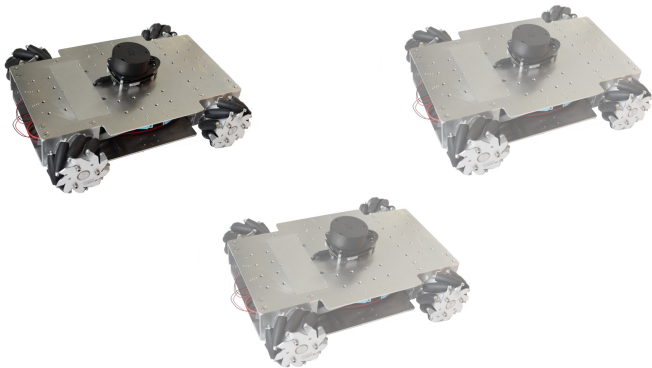


# Motion Planning

40 ms for simple kinematic models

# Motion Planning

40 ms for simple kinematic models

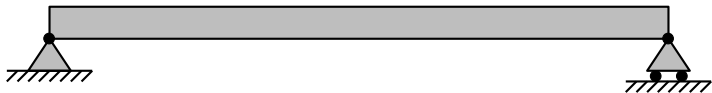


# Interconnected Systems

Application in vibro-acoustics

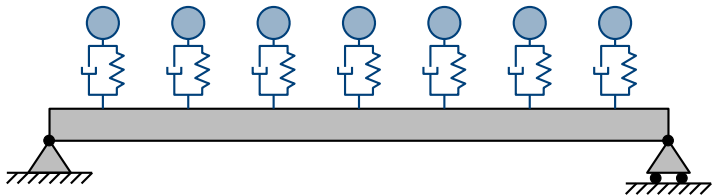


# Interconnected Systems

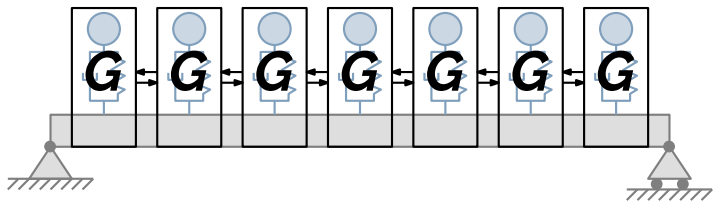




# Interconnected Systems

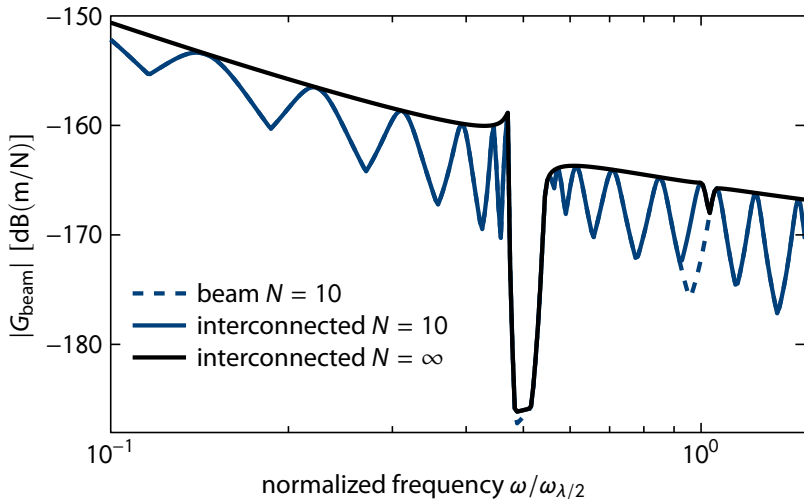


# Interconnected Systems



# Interconnected Systems

Efficient analysis using quadratic separation



# Parametric Programming

## A novel B-spline based framework

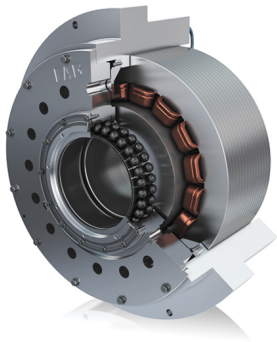
- B-spline parameterized  $\hat{x}(\delta)$  for high flexibility
- novel relaxation scheme for low conservatism

# Parametric Programming

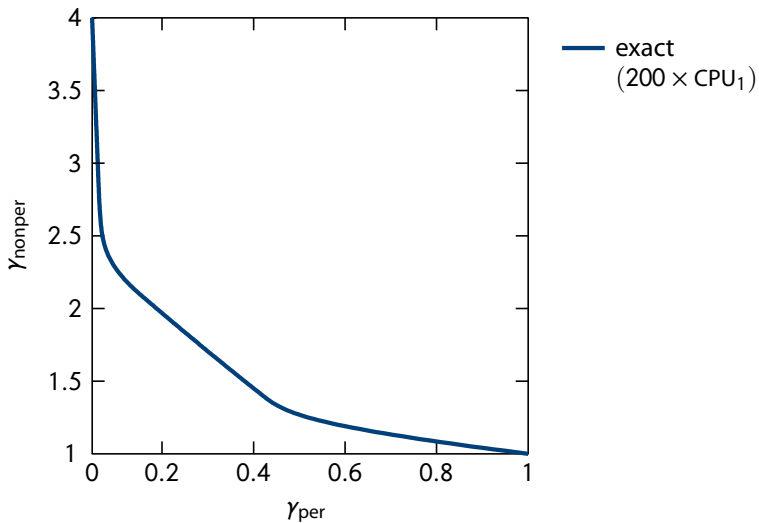
## A novel B-spline based framework

- B-spline parameterized  $\hat{x}(\delta)$  for high flexibility
- novel relaxation scheme for low conservatism

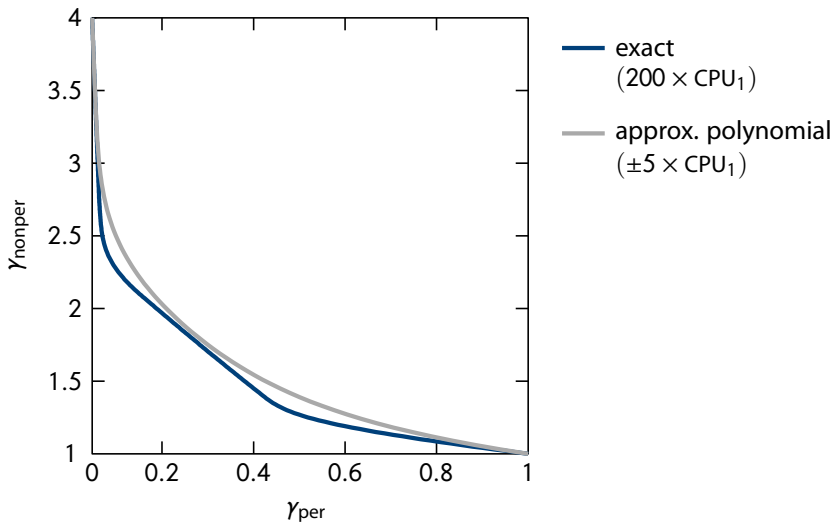
## Trade-off analysis in active bearing control



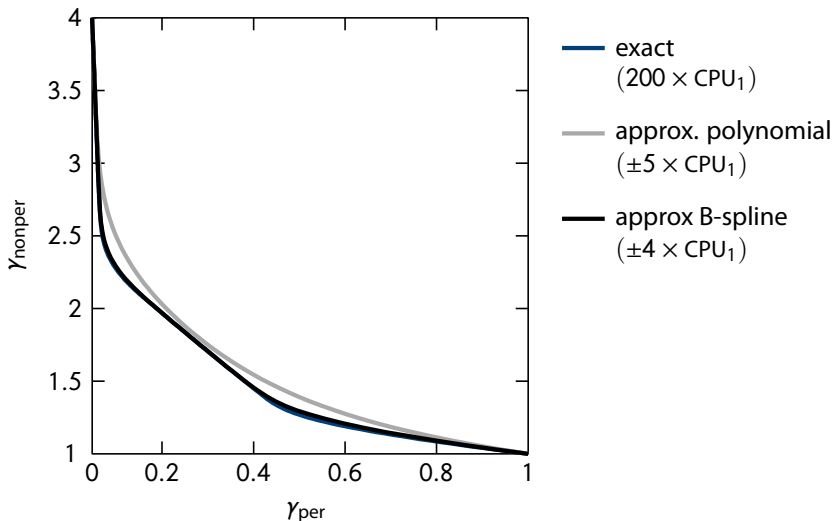
# Parametric Programming



# Parametric Programming



# Parametric Programming





# Conclusion

**1**

***Robust optimization  
has many applications in engineering***

**2**

***General and effective strategy  
for solving robust optimization problems***

**3**

***Results in applications***

# Thank You!

The MECO research group  
Wannes Van Loock, Ruben Van Parys, Tim Mercy

Claus Claeys, Elke Deckers



