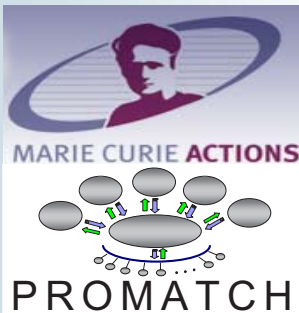




Nonlinear MPC via Novel Multiparametric Programming Techniques



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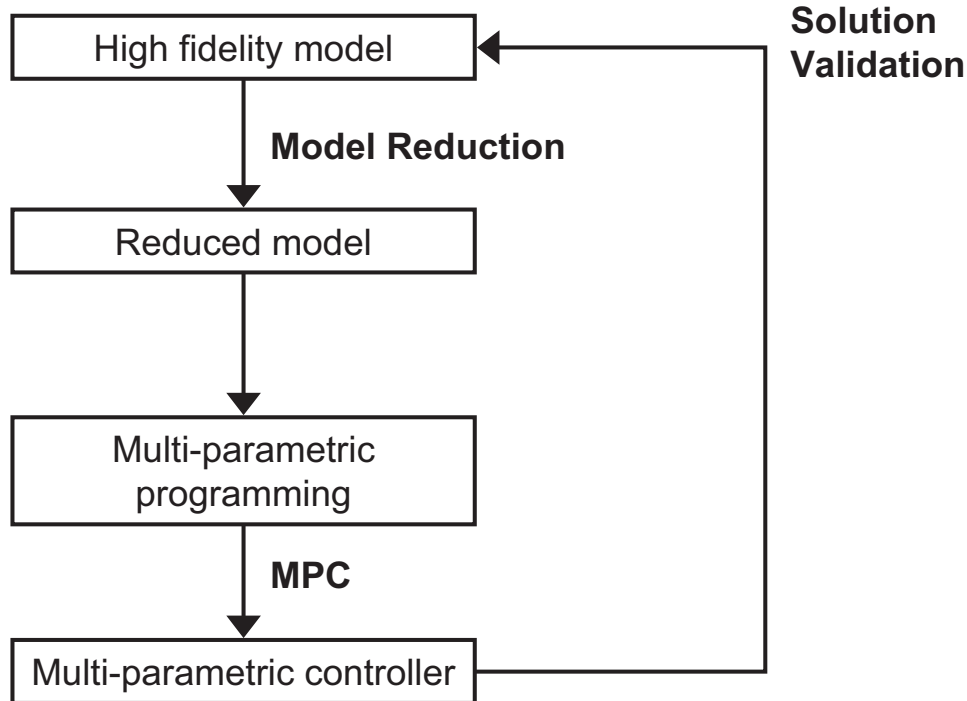
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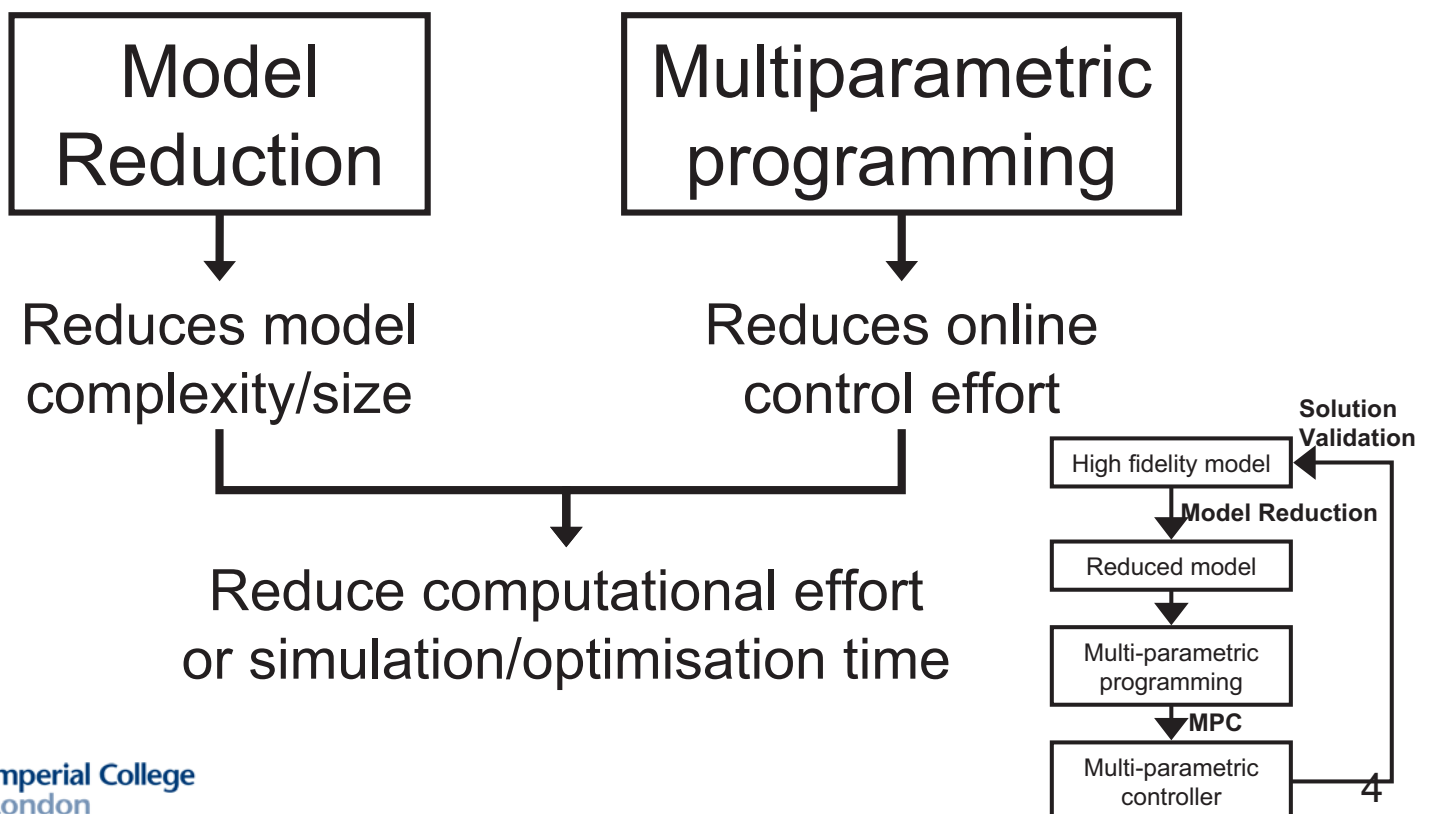
Outline

- Framework and objectives
- Nonlinear Multiparametric discrete-time MPC
 - Formulation & overall strategy
 - Off-line strategy
 - Parametric Algorithm
 - On-line strategy
 - Research and Development Achievements
- Concluding remarks and future work

Framework and objectives



Framework and objectives



Nonlinear Multiparametric discrete-time MPC

- Formulation & overall strategy
- Off-line strategy
- Parametric Algorithm
- On-line strategy

Formulation & overall strategy

Traditional MPC:

\min_U Objective Function ($U, x(t), z(t)$)
s.t. Dynamic Model ($U, x(t), z(t)$) \longrightarrow
 Process Constraints ($U, x(t), z(t)$)
 Initial Conditions

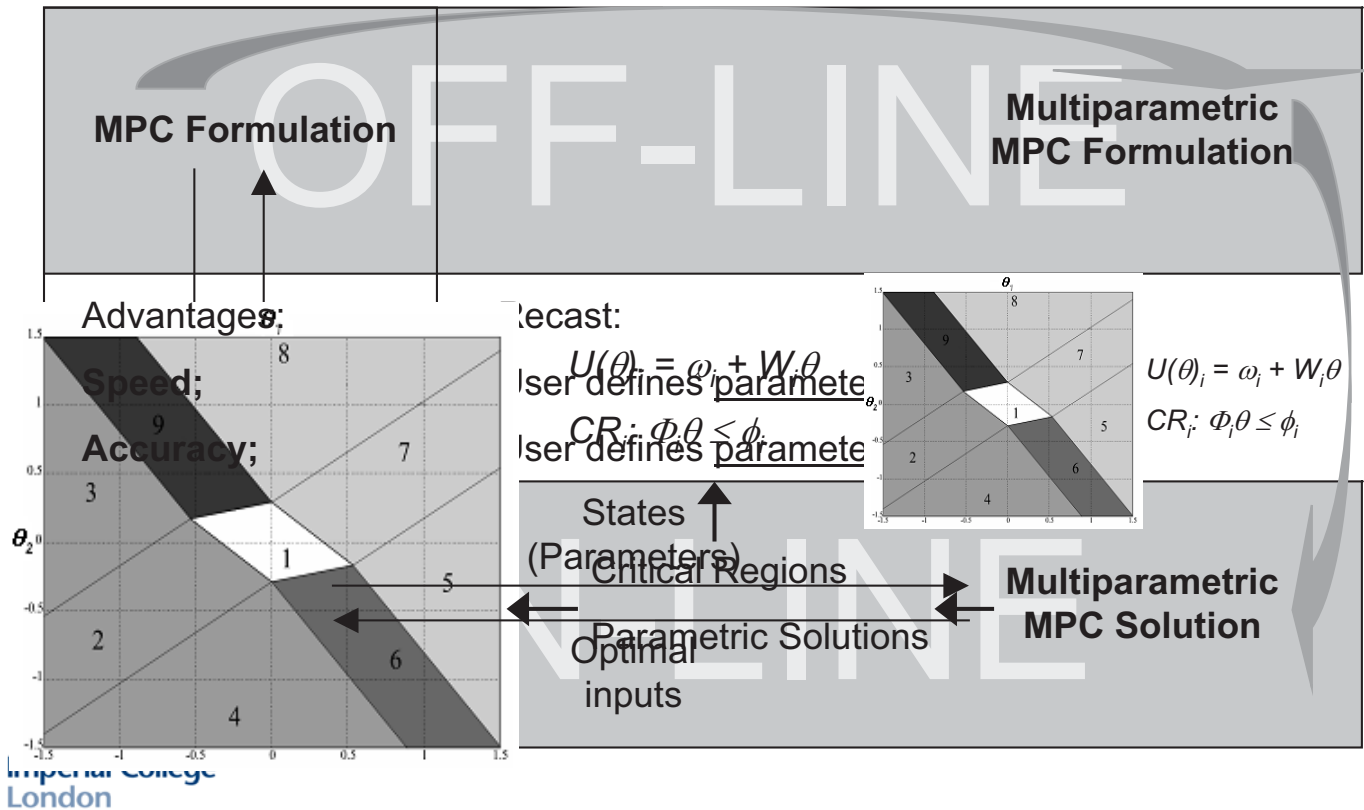
- Requires specification of initial conditions
- Optimal inputs calculated for the vector of initial conditions

Multiparametric MPC:

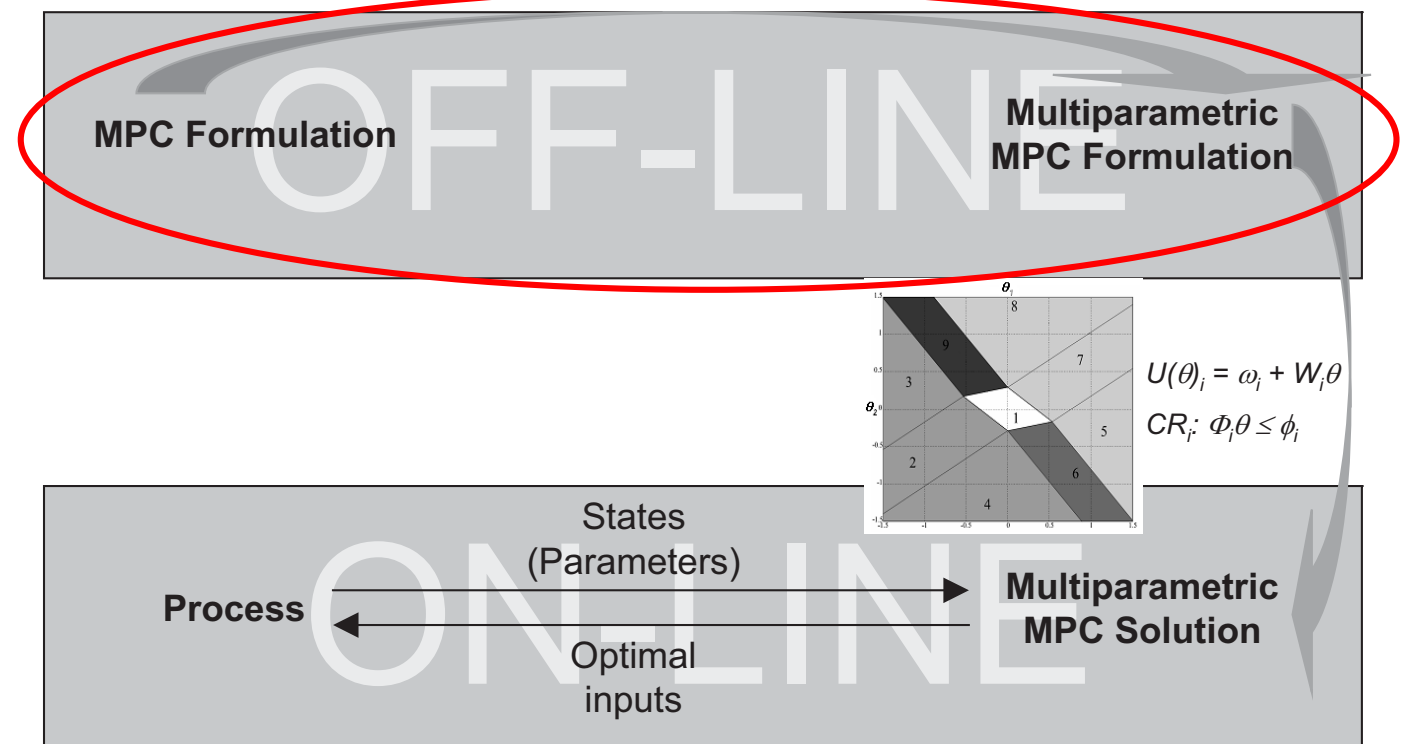
\min_U Objective Function (U, θ)
s.t. Dynamic Model (U, θ) \longrightarrow
 Process Constraints (U, θ)
 Parameter Space Definition

- States/disturbances recast as parameters (θ)
- The space of expected parameters defined as an independent space
- Problem is solved for all combinations of parameters (semi-infinite problem)

Formulation & overall strategy



Off-line strategy



Off-line strategy

1) Select parameters

- 1) States
- 2) Load disturbances

2) Define parameter space

- 1) e. g. Reactor temperature between 25 and 75C

$$\min_U \text{Objective Function } (U, x(t), z(t))$$

$$s.t. \text{ Dynamic Model } (U, x(t), z(t))$$

Process Constraints $(U, x(t), z(t))$

Initial Conditions

$$\min_U \text{Objective Function } (U, \theta)$$

$$s.t. \text{ Dynamic Model } (U, \theta)$$

Process Constraints (U, θ)

$$\min_U \text{Objective Function } (U, \theta)$$

$$s.t. \text{ Dynamic Model } (U, \theta)$$

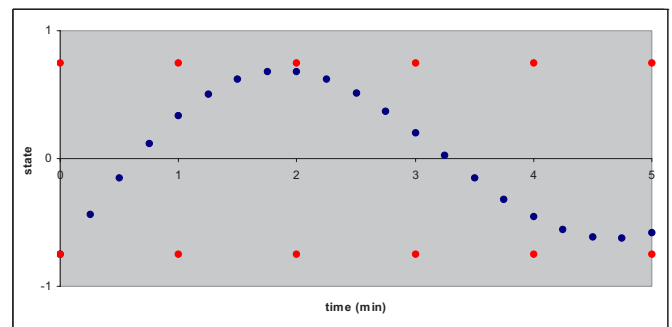
Process Constraints (U, θ)

Parameter Space Definition

Off-line strategy

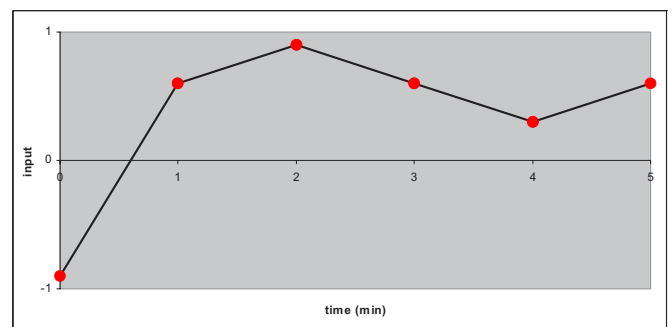
3) Discretise time domain

- 1) Need to express state constraints with finite number of equations



4) Discretise controls and load disturbances

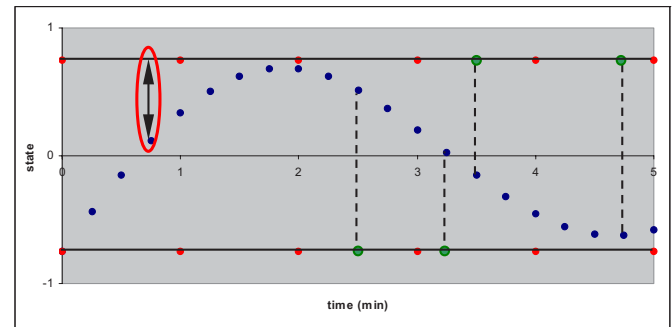
- 1) Control vector parameterization



Off-line strategy

5) Assess constraints

- 1) Formulate candidate point constraints
- 2) Solve relaxed optimisation problem
- 3) Add new constraints to mp-NLP problem



$$\min_{U, \theta} \text{Objective Function } (U, \theta)$$

$$s.t. \text{ Dynamic Model } (U, \theta)$$

$$\text{Process Constraints } (U, \theta)$$

$$\max_i (\text{Process Constraint Violation})_i,$$

$$(\text{Process Constraint Violation})_i^{\max} > \epsilon_r$$

$$\theta \in \Theta$$

11

Off-line strategy

$$\min_U \text{Objective Function } (U, \theta)$$

$$s.t. \text{ Dynamic Model } (U, \theta)$$

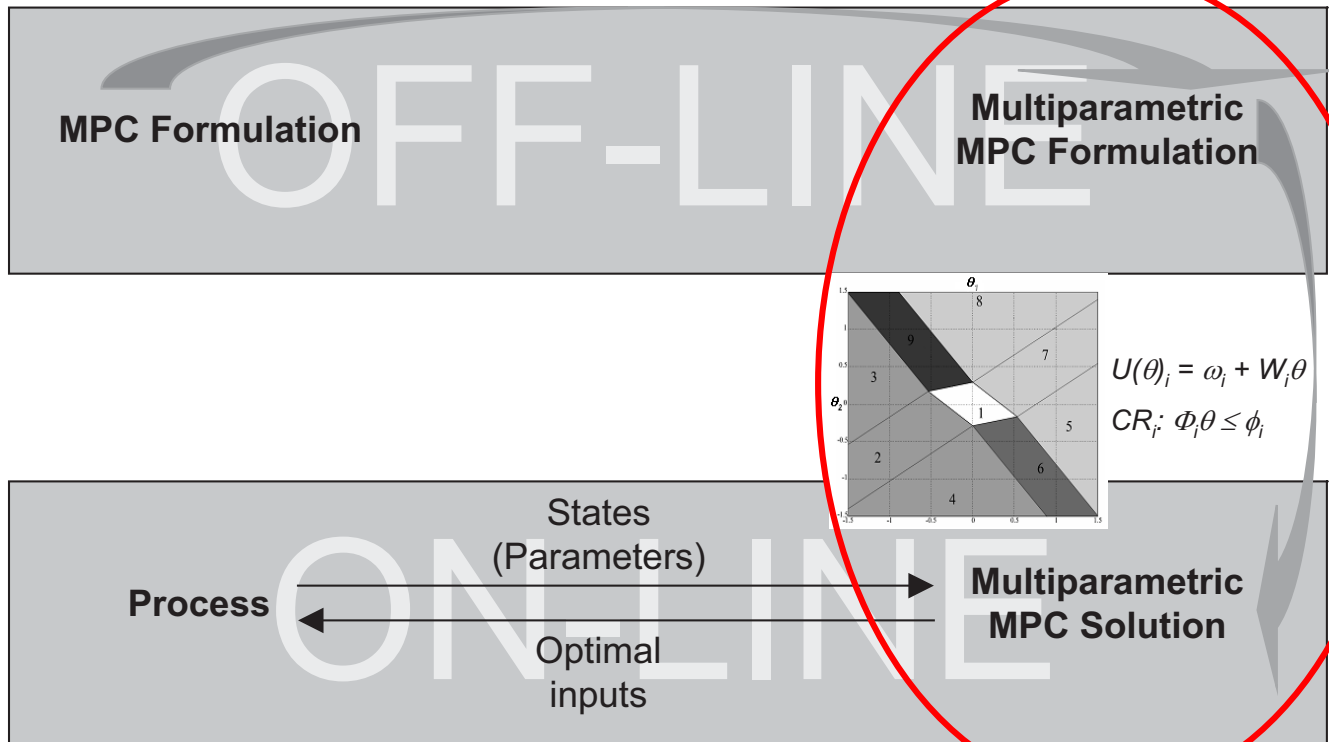
$$\text{Process Constraints } (U, \theta)$$

$$\text{Parameter Space Definition}$$

- Vector of inputs (finite)
- Inputs parameterized
- States discretised in time
- Vector of constraints (finite)

12

Parametric Algorithm



Parametric Algorithm

- Driven by accurate active-set characterization of parameter space
- Vertex search method
- Valid for convex formulations

Parametric Algorithm

- Components of the new algorithm
 - Search of vertices
 - Construction of critical regions
 - Approximation of optimal solutions

Parametric Algorithm

Problem formulation:

$$\min_{x_1, x_2} x_1^3 + 2x_1^2 - 5x_1 + 6x_2^2 - 3x_2 - 6$$

s.t.

$$2x_1 + x_2 \leq 2.5 + \theta_1$$

$$0.5x_1 + x_2 \leq 1.5 + \theta_2$$

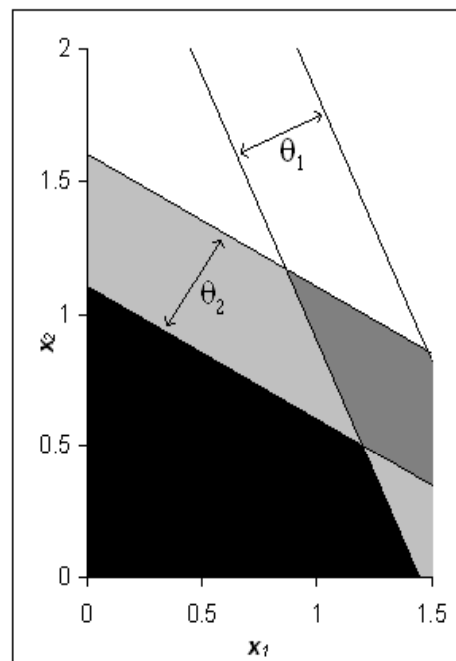
$$x_1 \geq 0$$

$$x_2 \geq 0$$

$$0 \leq \theta_1 \leq 1$$

$$0 \leq \theta_2 \leq 1$$

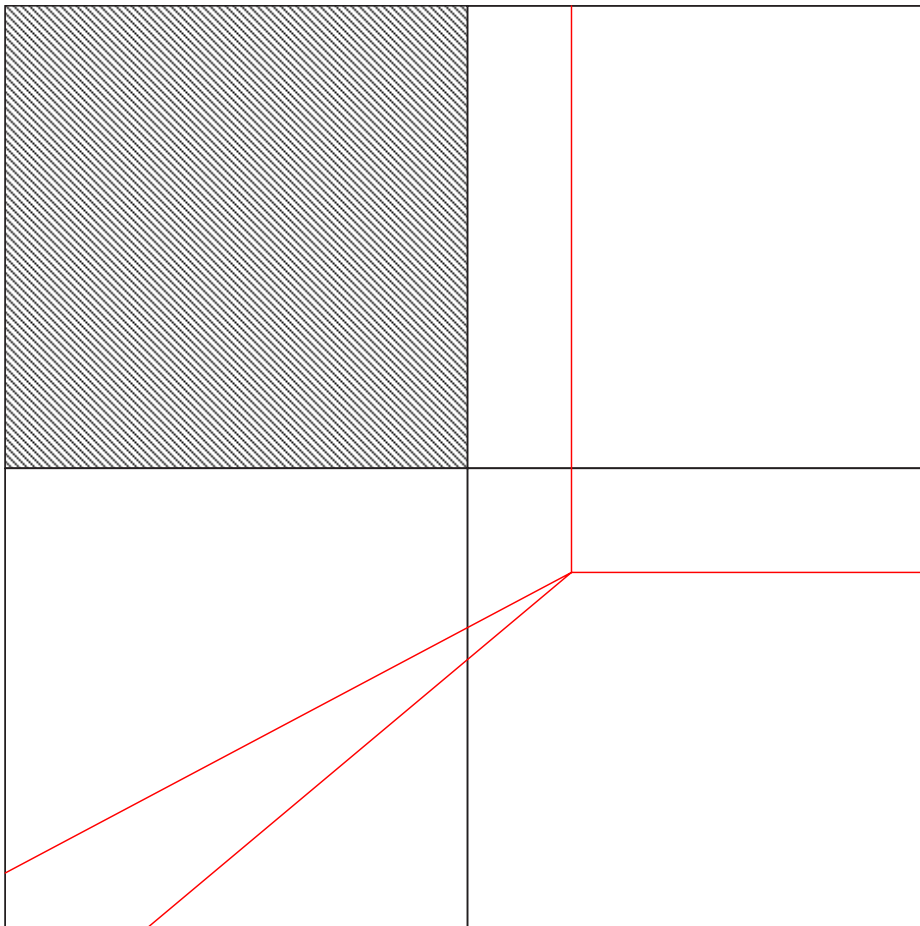
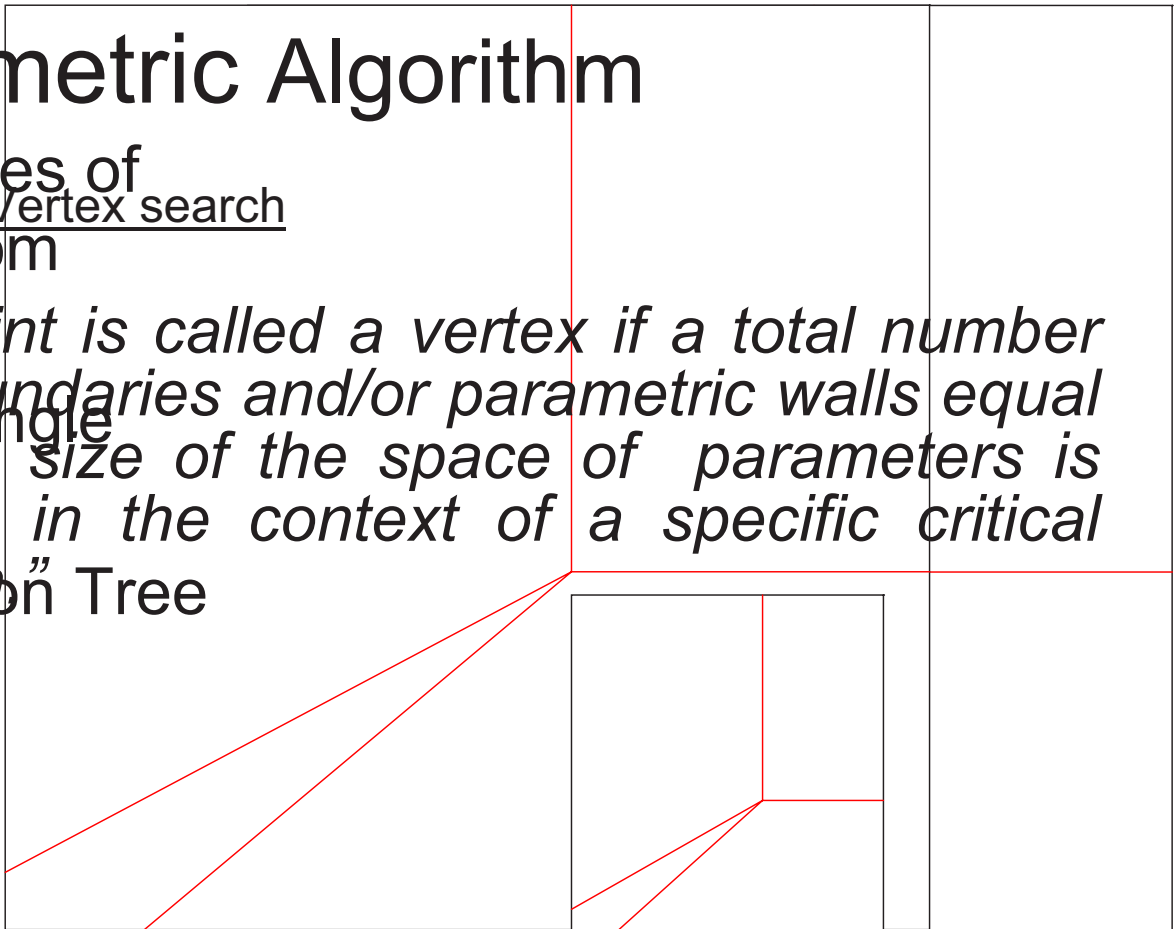
Feasible (\mathbf{x}) space:

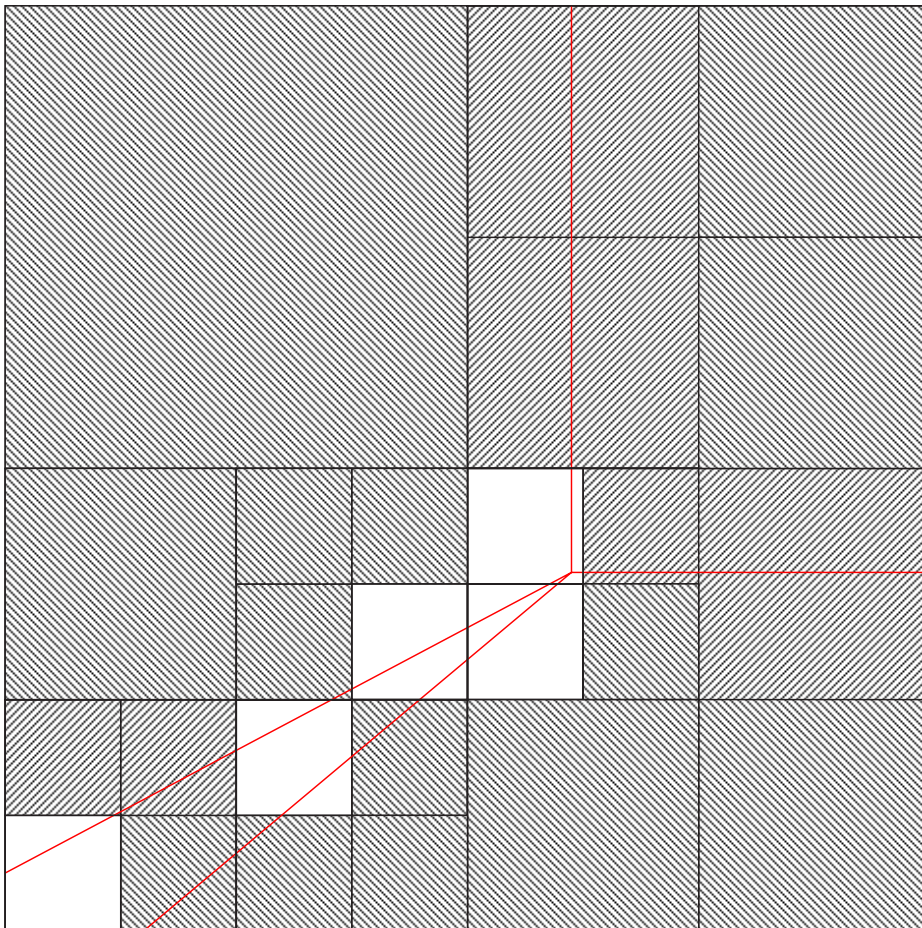
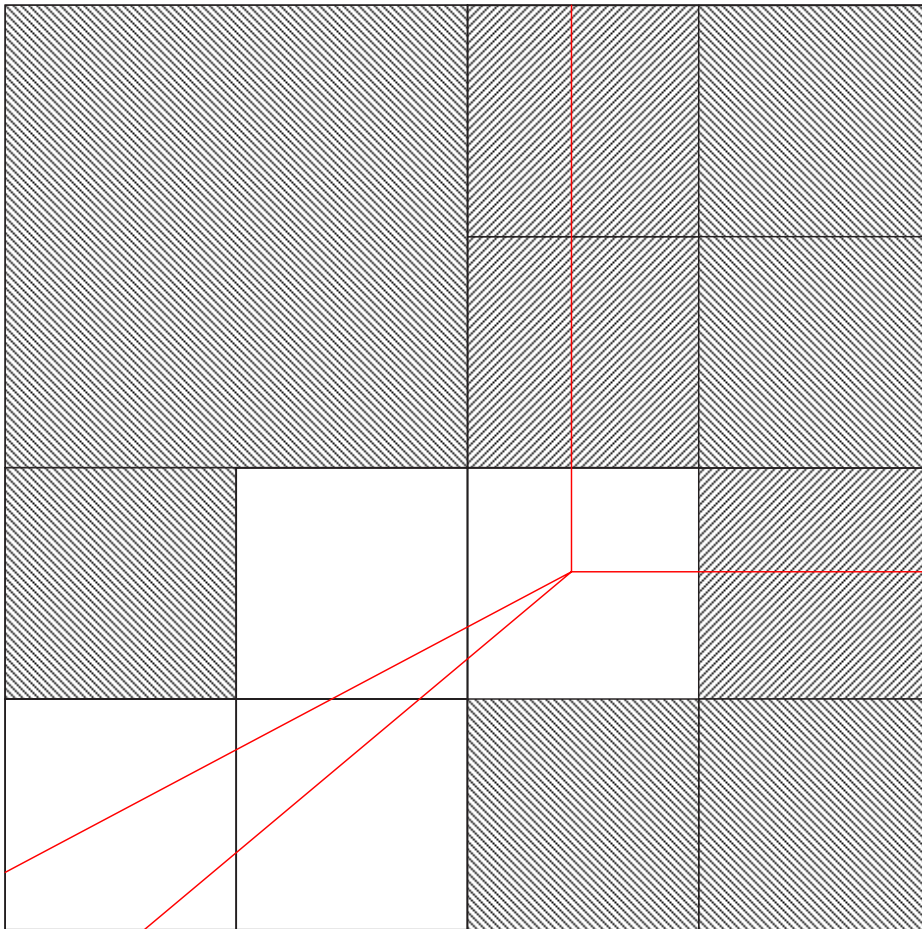


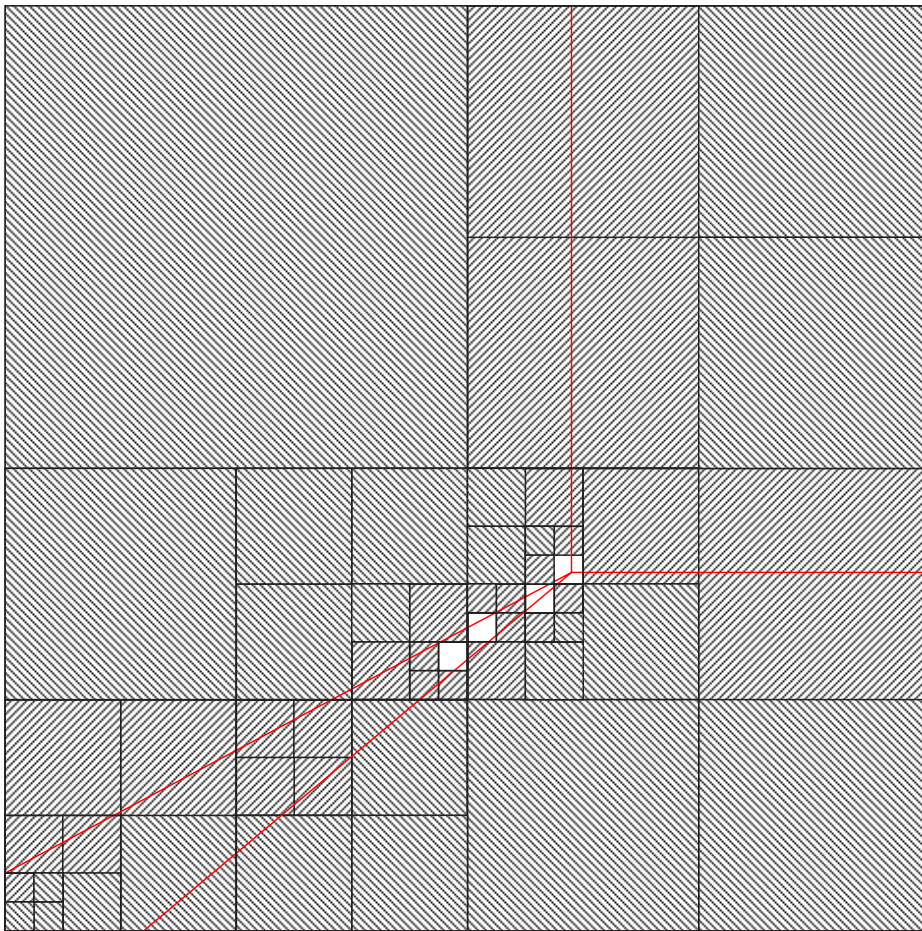
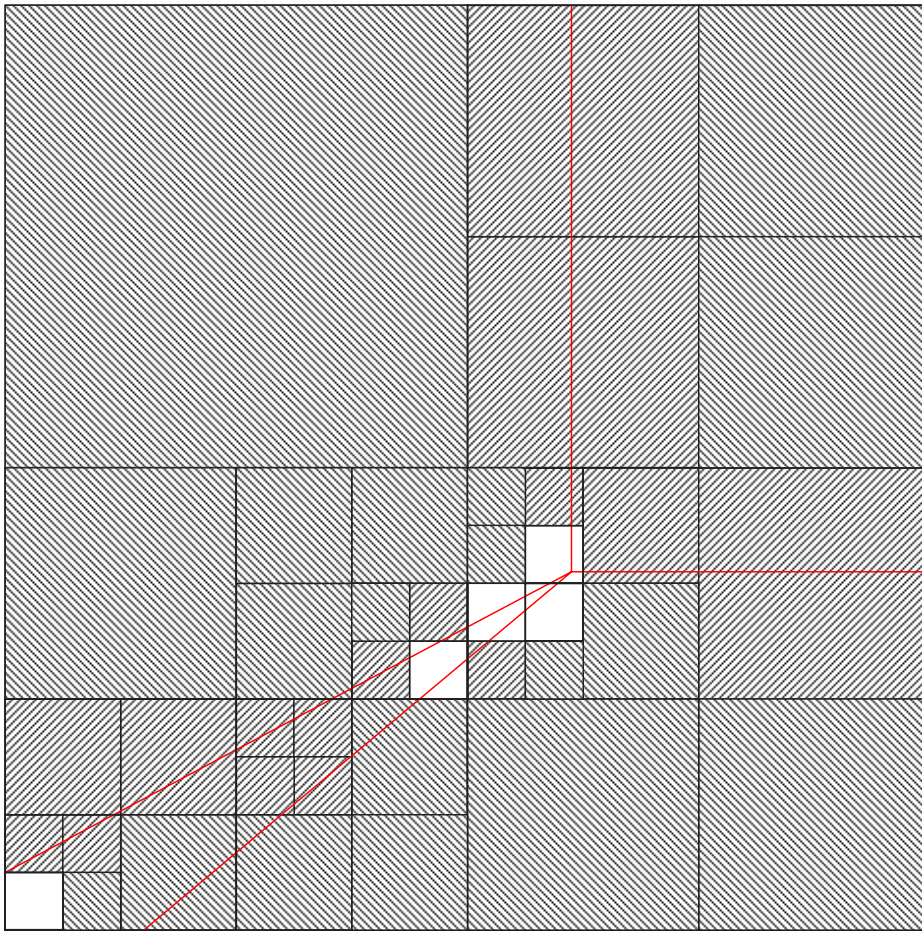
Parametric Algorithm

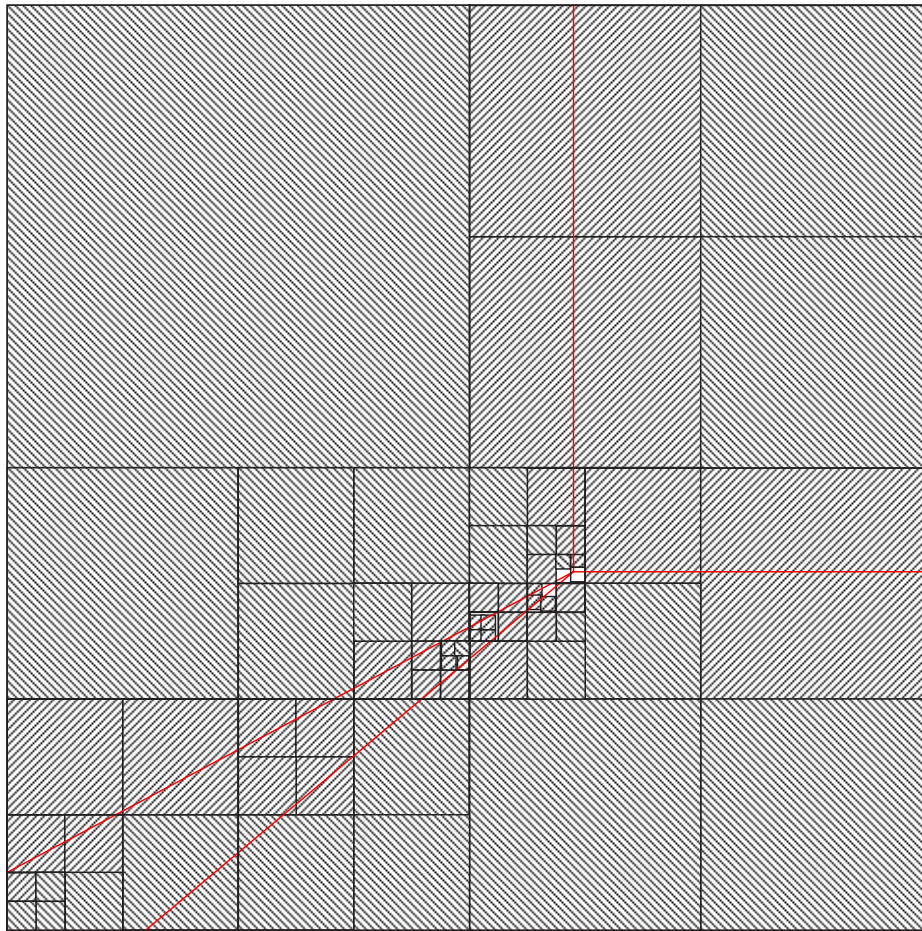
- Degrees of freedom
Stage 1: Vertex search

- *“A point is called a vertex if a total number of boundaries and/or parametric walls equal to the size of the space of parameters is active in the context of a specific critical region”*







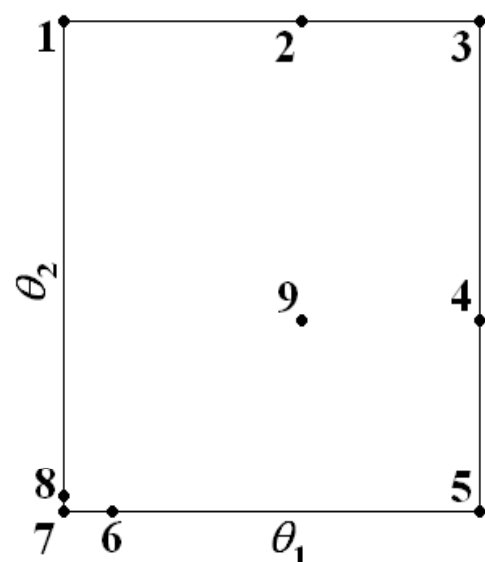


Parametric Algorithm

Stage 1: Vertex search

- The vertices are just points of the parameter space!
- How to use this information to approximate the critical regions?

Parameter space (Θ):
Found Vertices



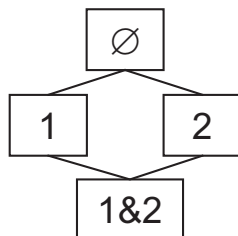
Parametric Algorithm

Stage 2: Boundary construction

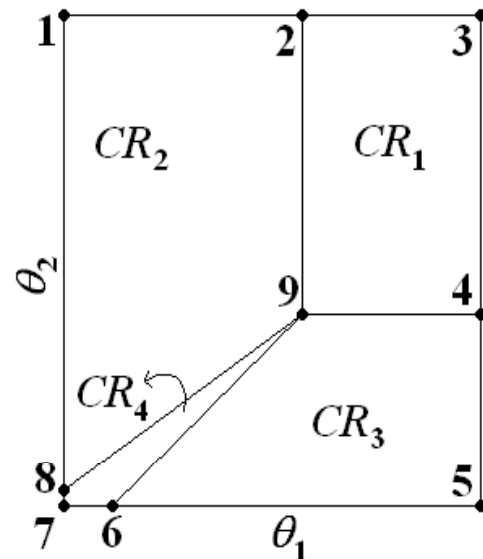
- We assess all the active sets in the vicinity of each of the found vertices

Vertex	1	2	3	4	5	6	7	8	9
Active	1	\emptyset	\emptyset	\emptyset	2	2	1&2	1	\emptyset
Constraint	1	1	\emptyset	2	2	1&2	1&2	1&2	1&2

- This information enables one to derive a list of all existing boundaries between active sets, based on the **solution tree**:



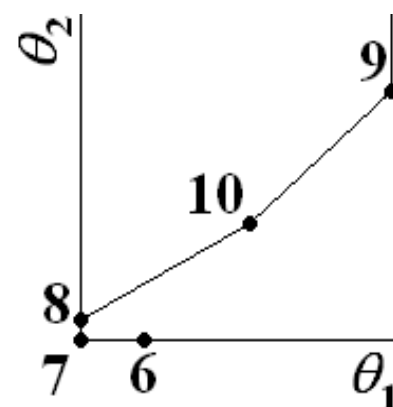
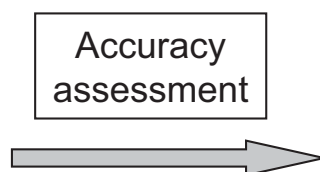
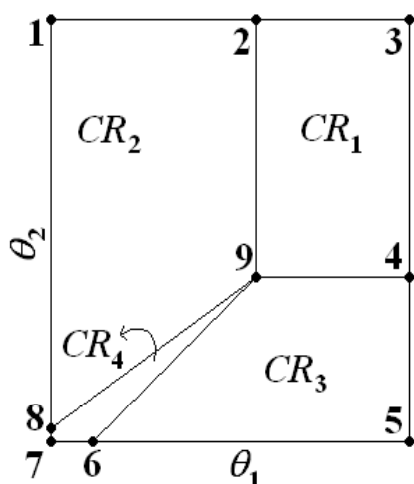
Parameter space (Θ): Found Vertices



Parametric Algorithm

Stage 2: Boundary construction

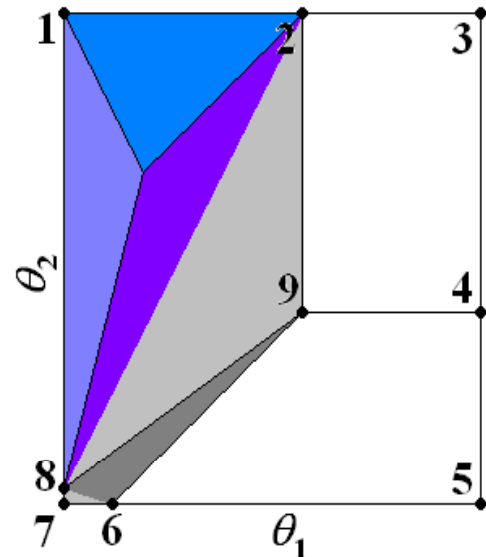
- We take the vertices found for each boundary and create linear approximations, based on the defined solution tree
- The accuracy is assessed



Parametric Algorithm

Stage 3: Parameterization of optimal solutions

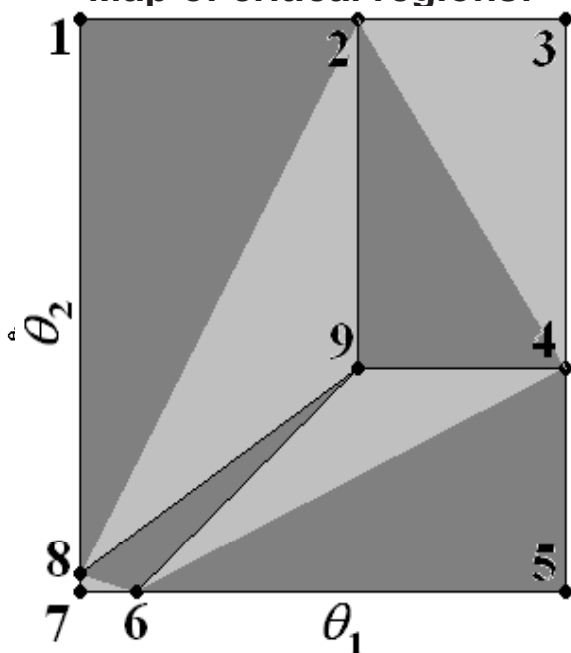
- Convex hulls
- Linear Interpolation
- Assess the error
- Create partitions



Parametric Algorithm

Final Solution:

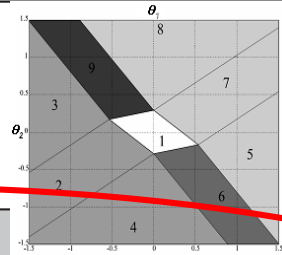
Map of critical regions:



Name	Value
parametricWalls	{m_ParametricWalls=[4]({m_ID=1 m_Index=1 m_Value=0.0000000000000000})}
optimisationProblem	{m_OptimalSolution=[0] m_LagrangeVectorFlags=[0] mse={...} ...}
criticalRegionsDomain	[8]([3]({m_NormalVector=[2](0.31622776601683794,0.94868329805051377) m
[0]	{m_NormalVector=[2](0.31622776601683794,0.94868329805051377) m
[0]	{m_NormalVector=[2](0.31622776601683794,0.94868329805051377) m_Cc
m_NormalVector	[2](0.31622776601683794,0.94868329805051377)
m_Constant	-0.029646353064078555
m_Sign	-1
[1]	{m_NormalVector=[2](0.0000000000000000,1.0000000000000000) m_Cor
m_NormalVector	[2](0.0000000000000000,1.0000000000000000)
m_Constant	0.0000000000000000
m_Sign	1
[2]	{m_NormalVector=[2](1.0000000000000000,0.0000000000000000) m_Cor
m_NormalVector	[2](1.0000000000000000,0.0000000000000000)
m_Constant	0.0000000000000000
m_Sign	1
[1]	[3]({m_NormalVector=[2](-0.63059257030990912,0.77611404462871458) r
[2]	[3]({m_NormalVector=[2](0.85260144214626254,-0.52256174836100766) r
[3]	[3]({m_NormalVector=[2](1.0000000000000000,0.0000000000000000) m_
[4]	[3]({m_NormalVector=[2](-0.40905590409290915,0.91250932451495126) r
[5]	[3]({m_NormalVector=[2](-0.63059257030990912,0.77611404462871458) r
[6]	[3]({m_NormalVector=[2](0.82530726124983178,0.56468391559199016) m
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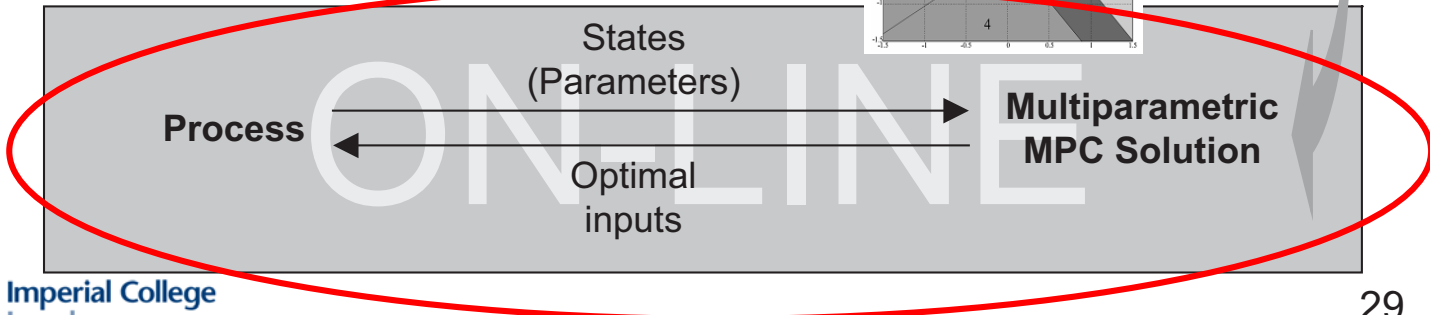
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[0]	[3](0.66666700000000001,-0.66688000000000003,0.6666699999999999)
[1]	[3](-0.333867000000000002,1.3311999999999999,1.1667000000000001)
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[6]	{m_ParametricSolutions=[2]([3](5.5511200000000000e-016,5.5511200000000000
[7]	{m_ParametricSolutions=[2]([3](0.000000000000000000,0.0000000000000000)

On-line strategy

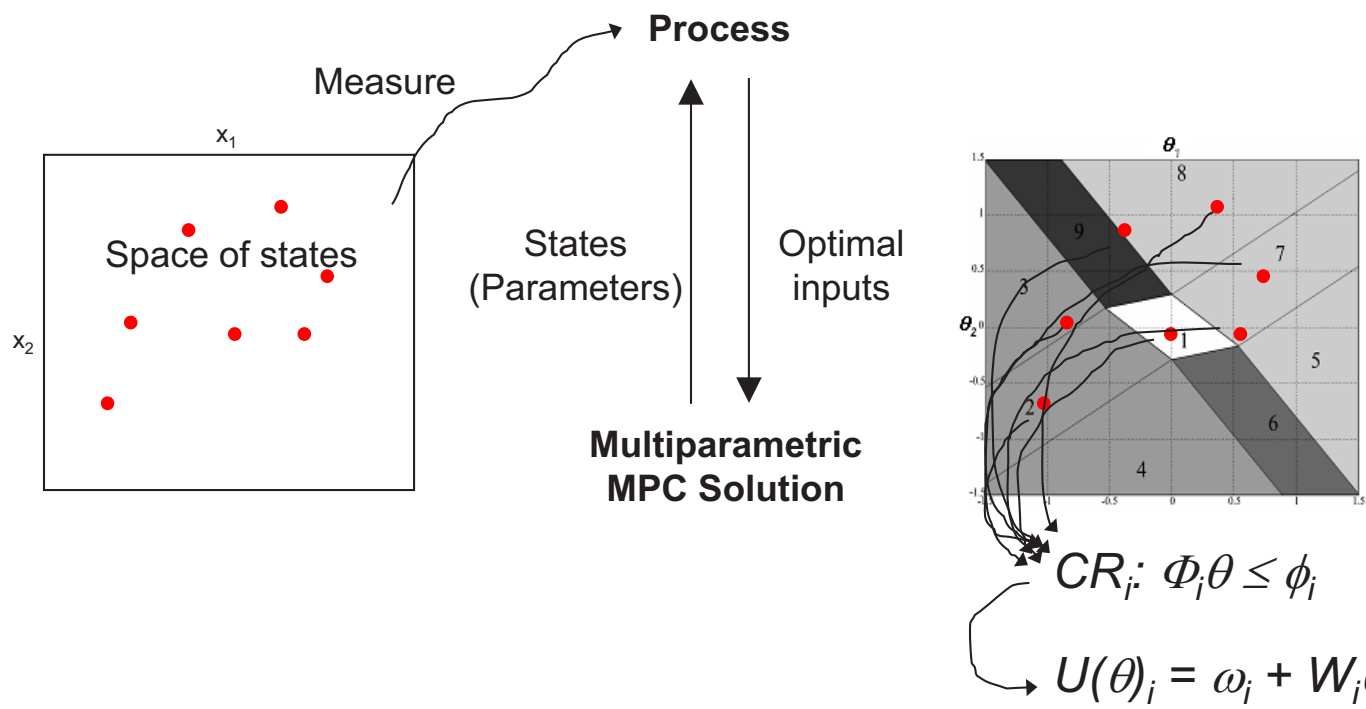


$$U(\theta)_i = \omega_i + W_i \theta$$

$$CR_i: \Phi_i \theta \leq \phi_i$$

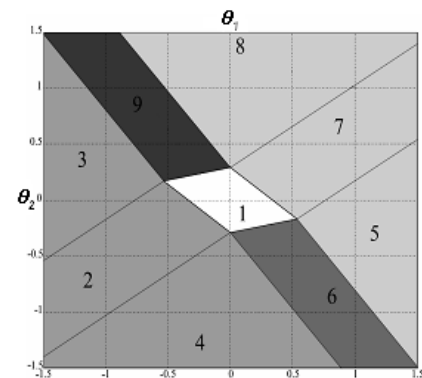


On-line strategy



On-line strategy

- Performs only linear calculations
- Consists of an input-output methodology based on the multiparametric solution



$$CR_i: \Phi_i \theta \leq \phi_i$$

$$U(\theta)_i = \omega_i + W_i \theta$$

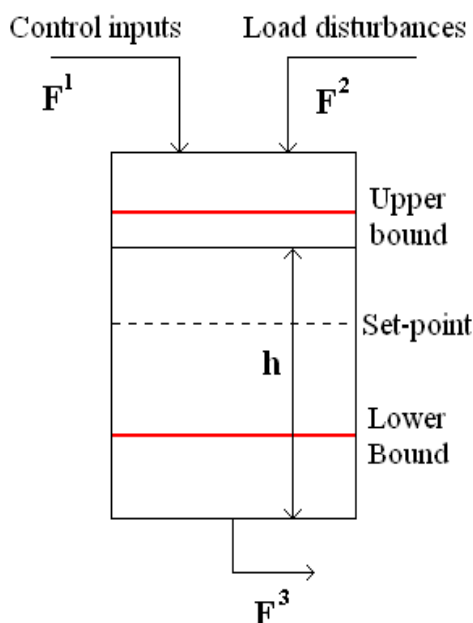
Research and Development Achievements

- Theoretical framework completed
 - On-line strategy
 - Parametric Algorithm
 - Off-line strategy
- Software has been developed (C++/gPROMS)
 - Parametric Solver (Implementation of Algorithm)
 - Off-line strategy

Concluding remarks

- A novel framework for the use of Multiparametric MPC has been developed;
- Theoretical and practical developments have been made for each of its components;
- Novel developments on the Parametric Solver will enable to solve more complex problems;
- Small chemical engineering problem solved;
- Further testing will enable to improve the methodology.

Example



- F^1 – control stream
- F^2 – load disturbance
- F^3 – outlet stream (gravity)
- Problem defined for a control horizon of 3 time units

Example

Problem formulation:

$$\min_{F_1^1, F_2^1, F_3^1} P(h_3 - h^{sp})^2 + \sum_{i=0}^2 Q(h_i - h^{sp})^2 + R(u_{i+1} - u_i)^2$$

$$s.t. \quad h_{l+1} = h_l + D_l \cdot \Delta t, \quad l \geq 0$$

$$D_l = \frac{F_l^1 + F_l^2 - C_D \sqrt{h_l}}{A}, \quad l \geq 0$$

$$h_0 = h_0; \quad u_0 = u_0; \quad (F_2^1 \quad F_2^2 \quad F_2^3)^T = (\theta_1 \quad \theta_2 \quad \theta_3)^T;$$

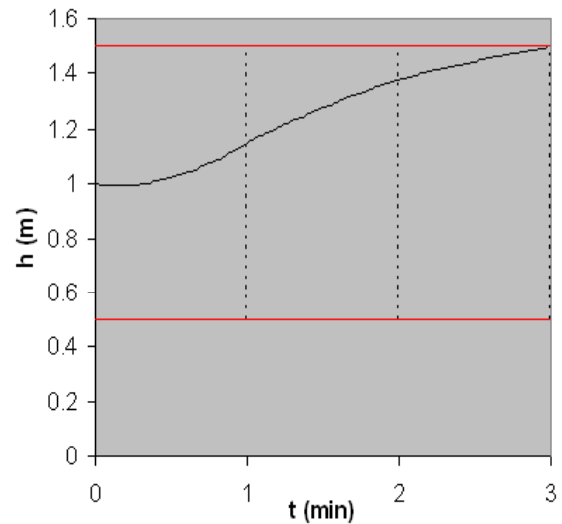
$$h^{\min} \leq h_r \leq h^{\max}, \quad r \geq 1;$$

$$(0 \quad 0 \quad 0)^T \leq (F_1^1 \quad F_1^2 \quad F_1^3)^T \leq (1.5 \quad 1.5 \quad 1.5)^T$$

$$(0 \quad 0 \quad 0)^T \leq (\theta_1 \quad \theta_2 \quad \theta_3)^T \leq (1 \quad 1 \quad 1)^T$$

Example of optimal solution

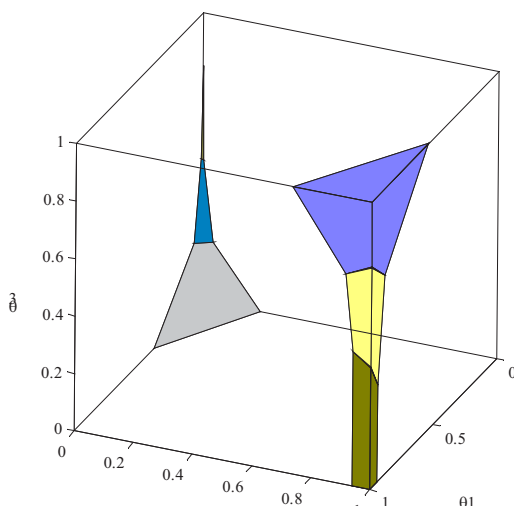
$$((\theta_1 \quad \theta_2 \quad \theta_3)^T = (1 \quad 1 \quad 1)^T):$$



Example

Final Solution:

Map of critical regions:



Parametric solutions for Critical Region 1:

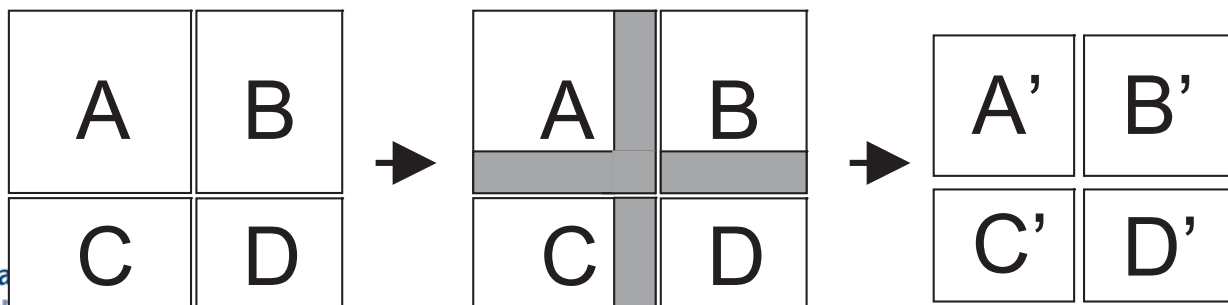
$$\begin{cases} F_1^1 = 1.029 - 0.284\theta_1 - 0.278\theta_2 - 0.010\theta_3 \\ F_2^1 = 1.385 - 0.473\theta_1 - 0.466\theta_2 - 0.019\theta_3 \\ F_3^1 = 1.461 - 0.513\theta_1 - 0.509\theta_2 - 0.025\theta_3 \end{cases}$$

Reduction of the control/optimisation model

- Given a linear state space, we seek to decrease the number of states

Balanced Truncation - fundamentals

- From a dynamics point of view, we want to neglect the states which are harder to reach and harder to observe
- Using a balanced realization, to reduce a system from order n to $n-p$, we neglect the last p states.



Reduction of the control/optimisation model

- Order of reduction, p , is defined (size = n)

- x_1 – first $n-p$ components of x
- x_2 – last p components of x

- Relevant partitions of the states vector and matrices are made

$$\min_U J(U, \bar{x}(t)) = \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix}_{t+N_y|t}^T \begin{pmatrix} P_{11}^b & P_{12}^b \\ P_{21}^b & P_{22}^b \end{pmatrix} \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix}_{t+N_y|t} + \sum_{k=0}^{N_y-1} \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix}_{t+k|t}^T \begin{pmatrix} Q_{11}^b & Q_{12}^b \\ Q_{21}^b & Q_{22}^b \end{pmatrix} \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix}_{t+k|t} + u_{t+k}^T R u_{t+k}$$

s.t. $y_{min} \leq y_{t+k|t} \leq y_{max}, k = 1, \dots, N_c$
 $u_{min} \leq u_{t+k} \leq u_{max}, k = 0, 1, \dots, N_c$

$$\begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix}_{t|t} = \begin{bmatrix} \bar{x}_1(t) \\ \bar{x}_2(t) \end{bmatrix}$$

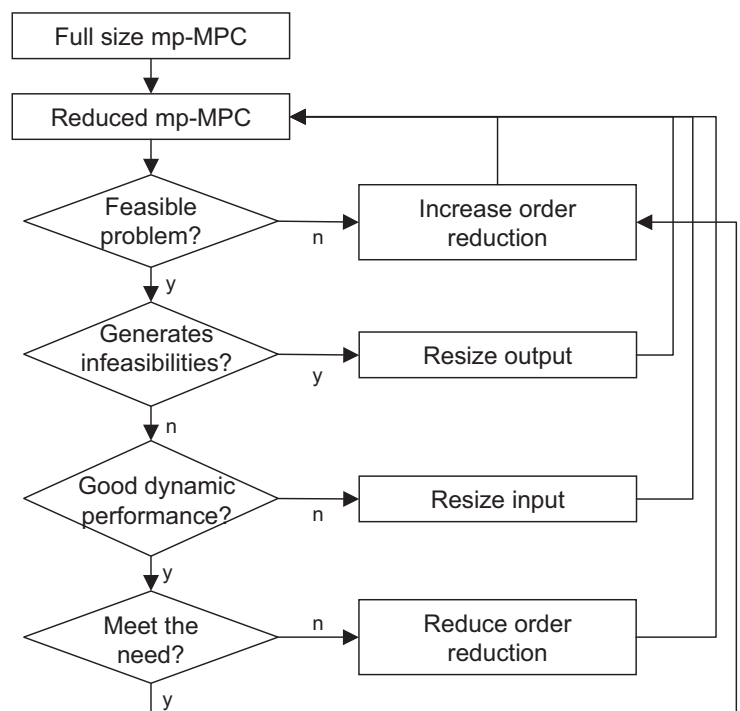
$$\begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix}_{t+k+1|t} = \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix}_{t+k|t} + \begin{pmatrix} B_1 \\ B_2 \end{pmatrix} u_{t+k}, k \geq 0$$

$$y_{t+k|t} = \begin{pmatrix} C_1 & C_2 \end{pmatrix} \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix}_{t+k|t}, k \geq 0$$

$$u_{t+k} = \begin{pmatrix} K_1 & K_2 \end{pmatrix} \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix}_{t+k|t}, N_u \leq k \leq N_y$$

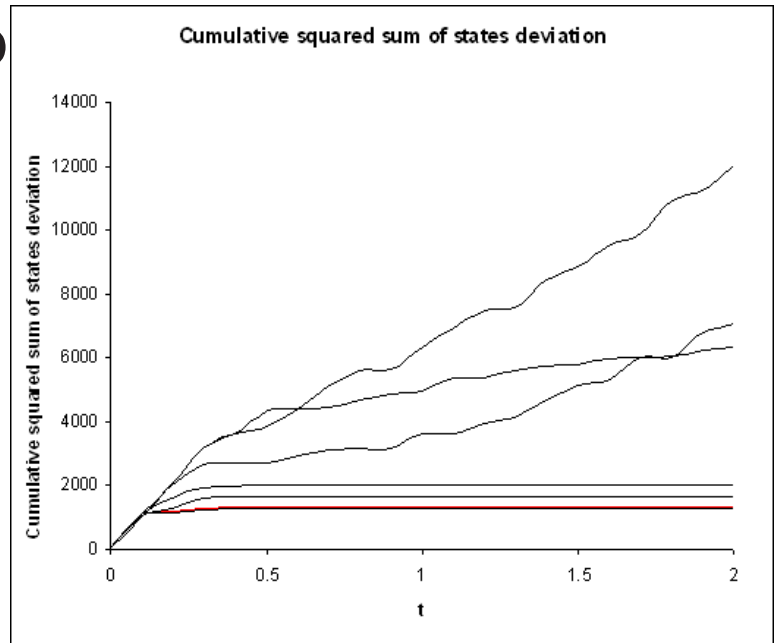
Combined Balanced Truncation/ mp control – framework

- Iterate with order reduction
- Objective: find the minimum order reduction for which feasibility and optimality are guaranteed



Illustrative example

- Full size closed loop response is close to open loop response
- Reasonable performance for small order reductions
- Appropriate control design is key!



Optimal Model Reduction order:
from 30 to 20 states