Parameter identification for combined quasi-static / electromagnetic forming processes by mathematical optimization

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HELMUT SCHMIDT UNIVERSITÄT
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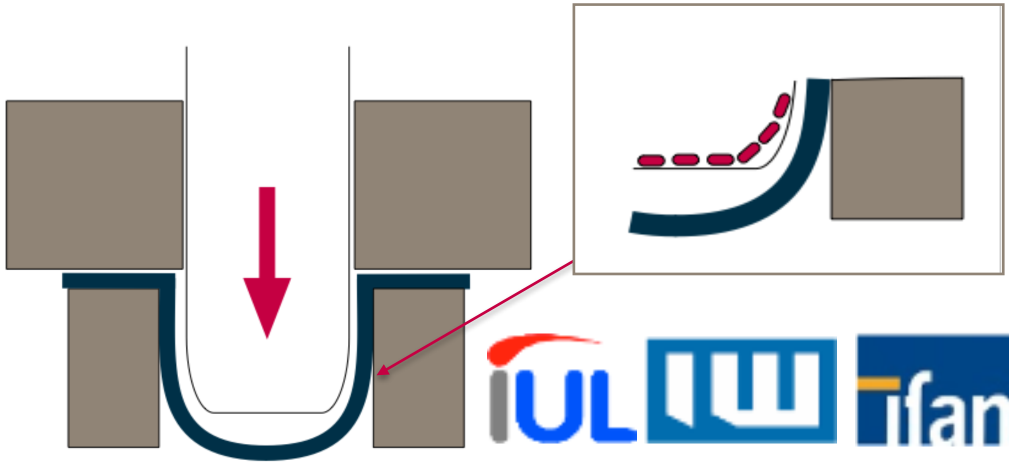
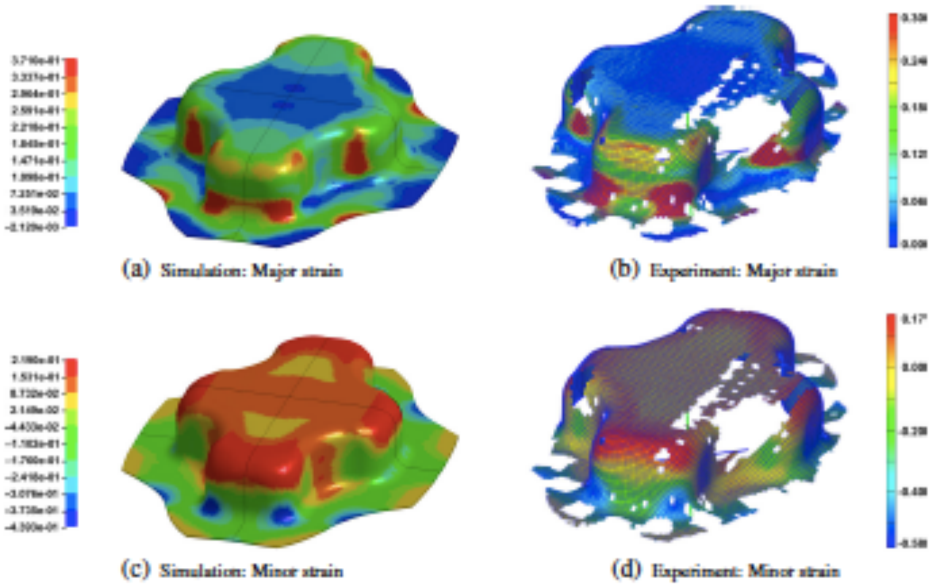
PAK 343
Methodenplanung

Theoretische Elektrotechnik

Combining fast and quasi-static forming methods

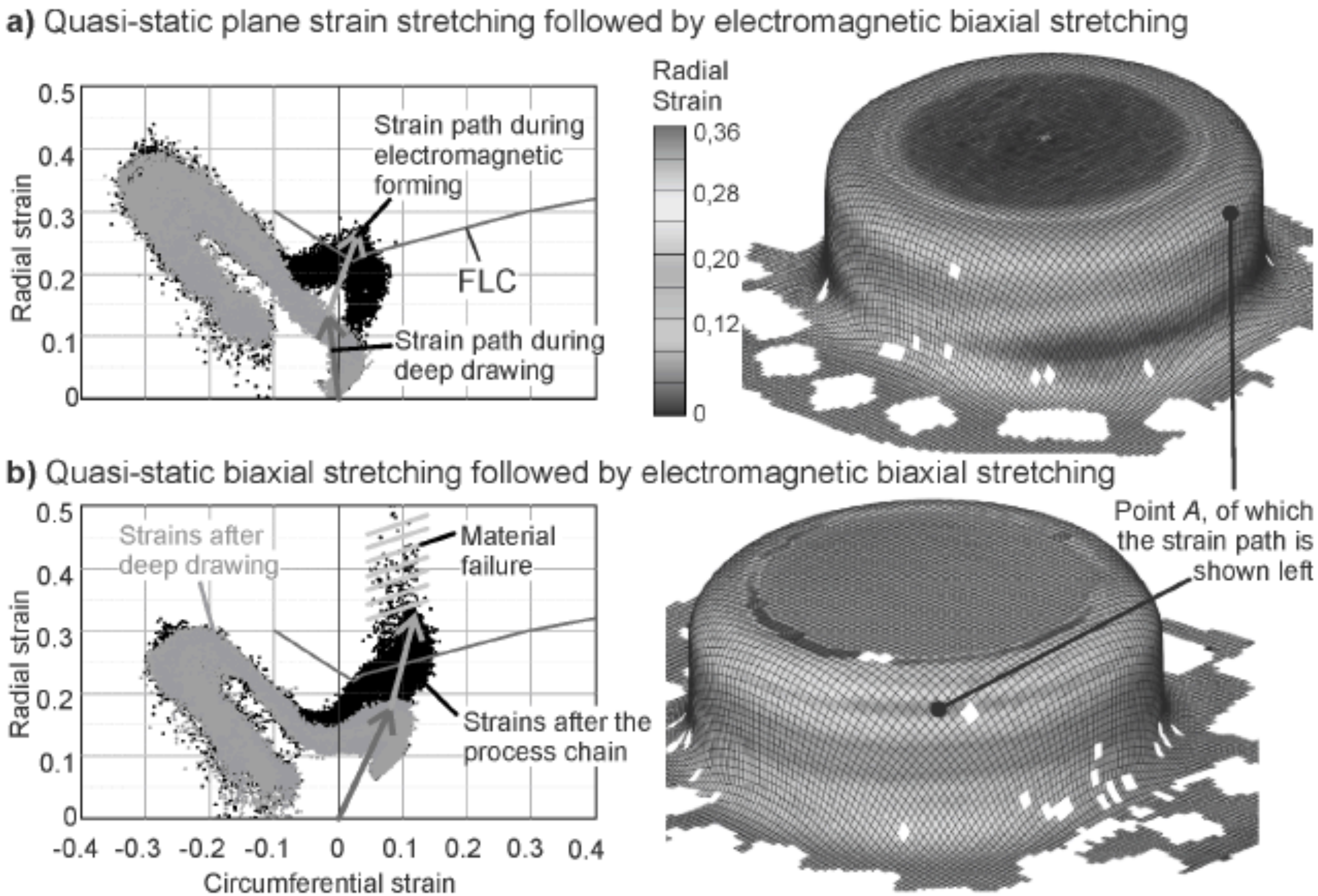




Motivation

- Combination of two methods may increase the freedom of design
- Integration in existing tools is possible
- Profit from advantages of a contact-free method
- Design of tailored processes for complicate forming tasks
- Combination of fast and quasi-static methods yields forming beyond quasi static forming limits

Enhanced formability due to combination with impulse methods



Material: EN A-5083

Experimental results

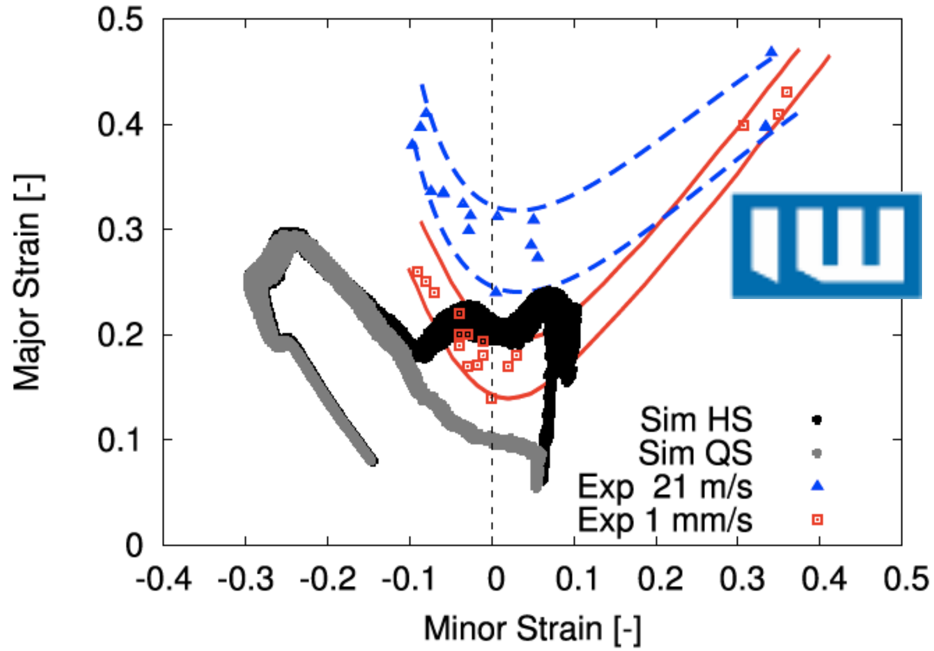
Kiliclar, Y., Demir, O.K., Engelhardt, M., Rozgic, M., Vladimirov, I.N., Wulfinghoff, S., Weddeling, C., Gies, S., Klose, C., Reese, S., Tekkaya, A.E., Maier, H.J., Stiemer, M., 2016:

Experimental and numerical investigation of increased formability in combined quasi-static and high-speed forming processes.

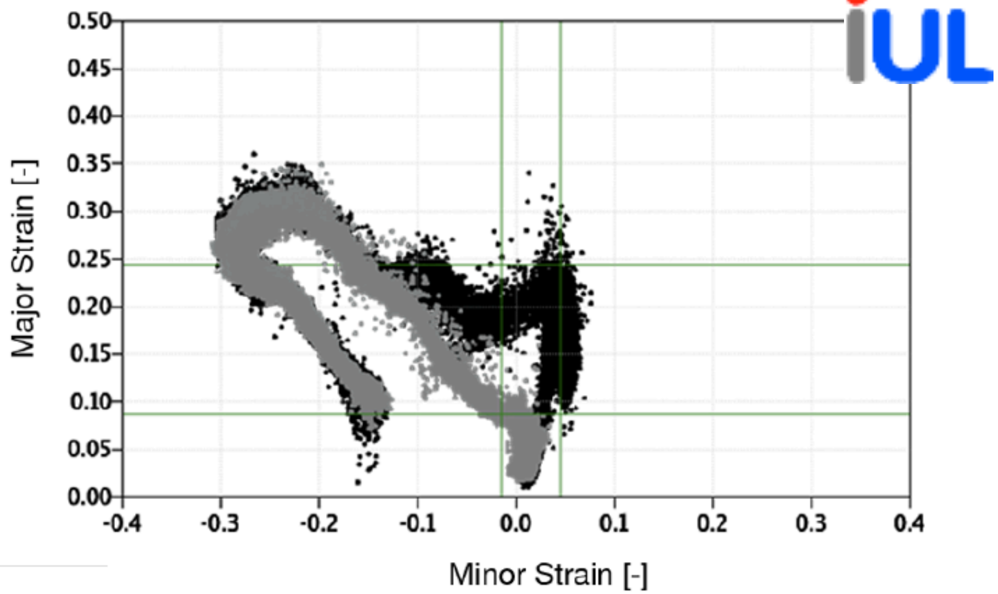
Journal of Materials Processing Technology, Volume 237, S. 254-269.

On the quality of simulation results and the usability of FLCs

Simulated with LS-DYNA



(a) Simulation



(b) Experiment

Corresponding strain rates: 1000 1/s 0.1 1/s

Kiliclar, Y., Demir, O.K., Engelhardt, M., Rozgic, M., Vladimirov, I.N., Wulfinghoff, S., Weddeling, C., Gies, S., Klose, C., Reese, S., Tekkaya, A.E., Maier, H.J., Stiemer, M., 2016:

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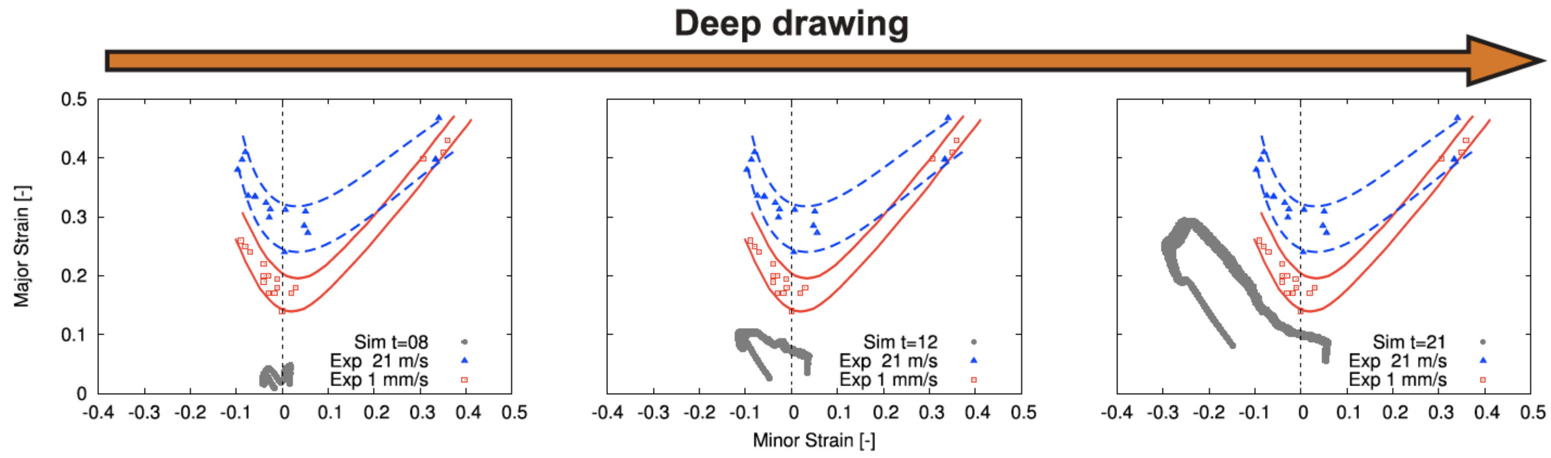
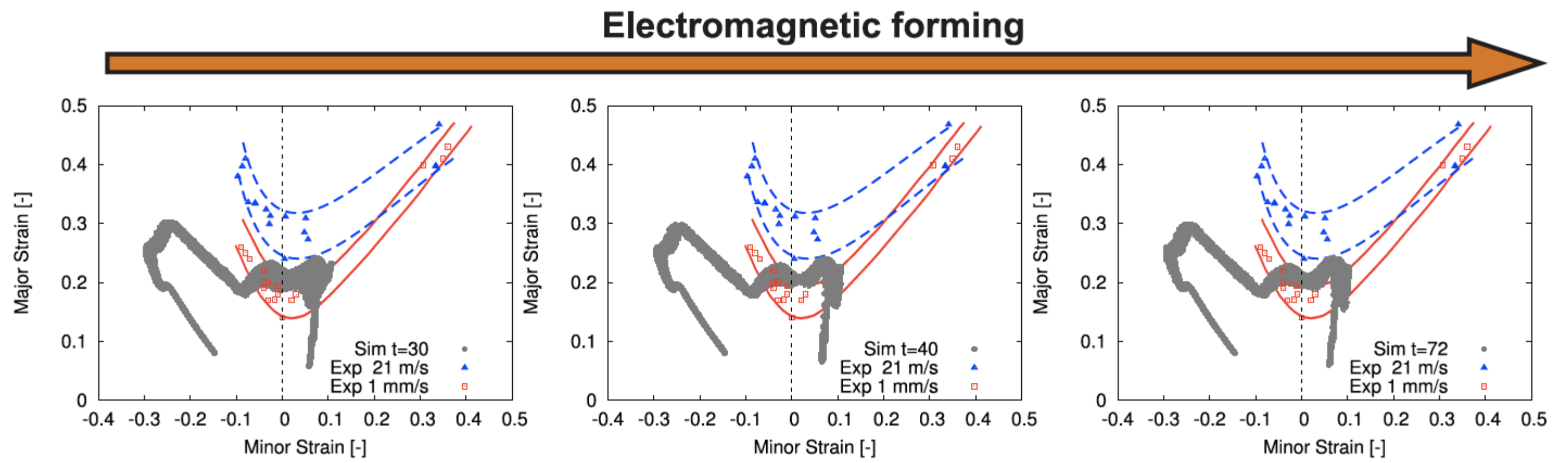
Evolution of strains



(a) Initial deep drawing step



(b) Subsequent high-speed forming step

FLCs by

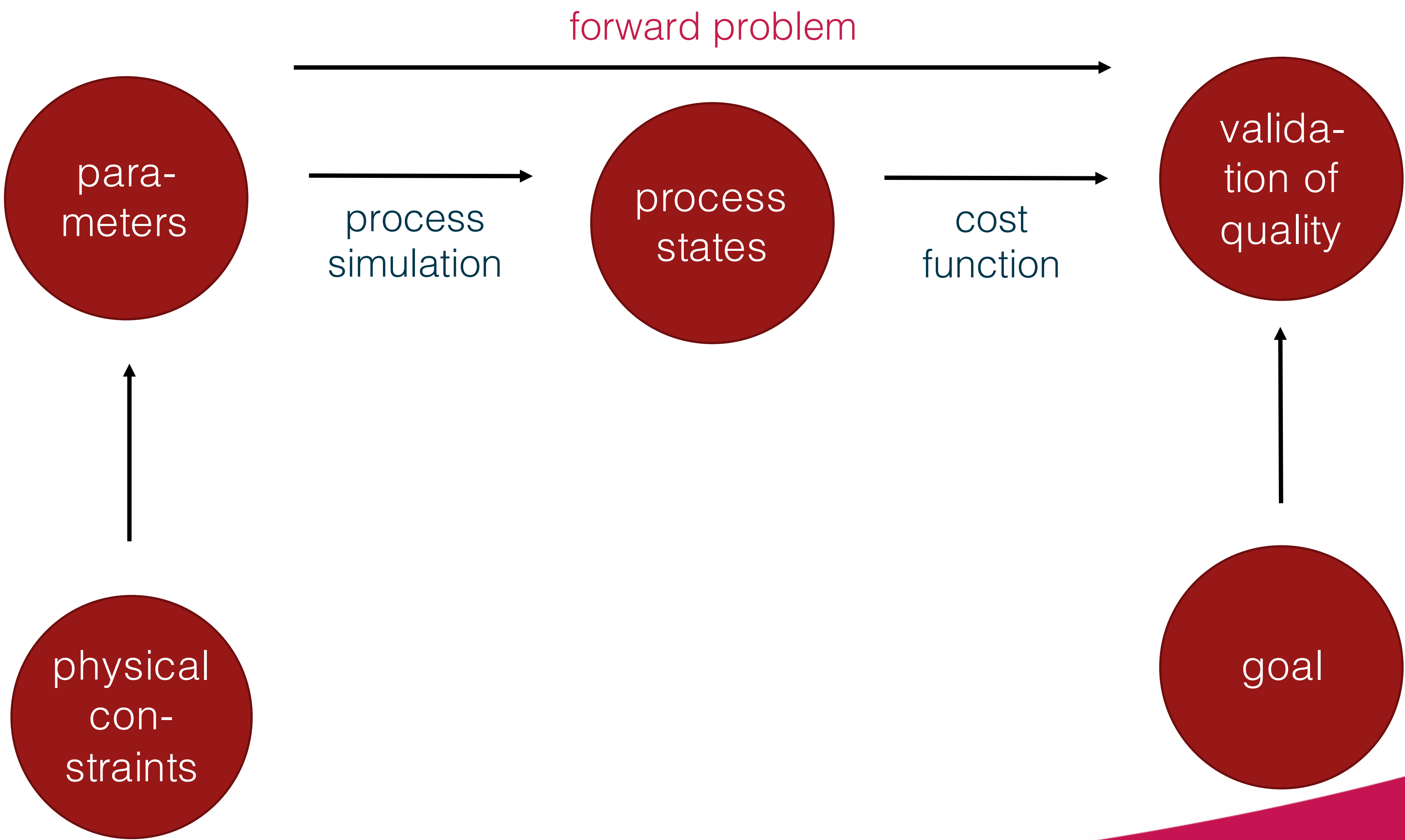
Need for mathematical optimization

- Mathematical Optimization can generally be used to solve identification problems, e.g., to identify

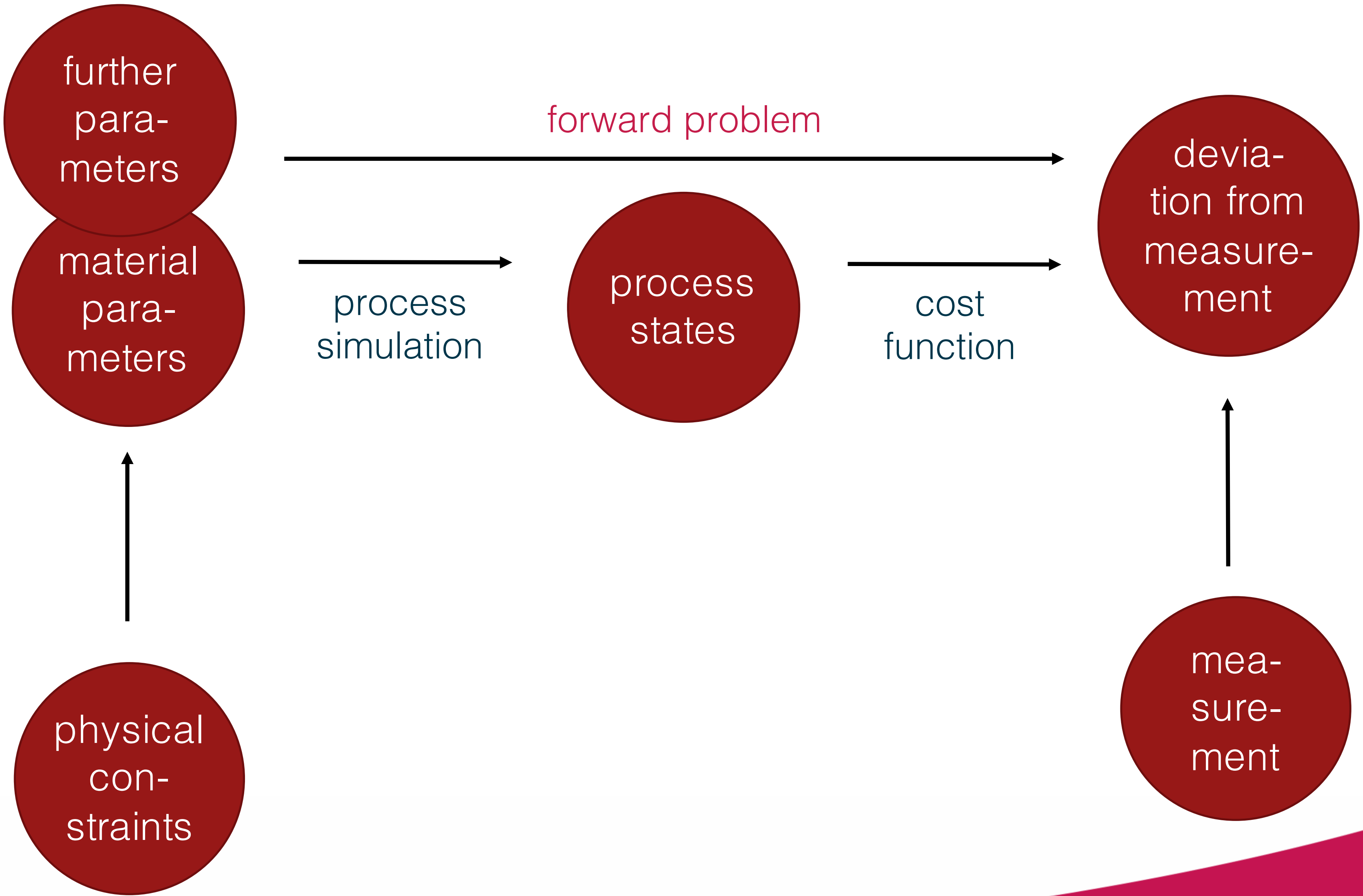
- process parameters that lead to a process with favorable properties (e.g., an extension of forming limits)

- internal parameters of the employed material model

Mathematical optimization for general identification problems



Mathematical optimization for material parameters



One model for all stages

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Stress-strain Relation

$$S = \mu\left(C_{\mathrm{p}}^{-1} - C^{-1}\right) + \frac{\lambda}{2}\left(\det C\,(\det C_{\mathrm{p}})^{-1} - 1\right) C^{-1}, \quad X = c\left(C_{\mathrm{p_i}}^{-1} - C_{\mathrm{p}}^{-1}\right)$$

$$Y = CS - C_{\mathrm{p}}X, \quad Y_{\mathrm{kin}} = C_{\mathrm{p}}X$$

C Cauchy-Green tensor

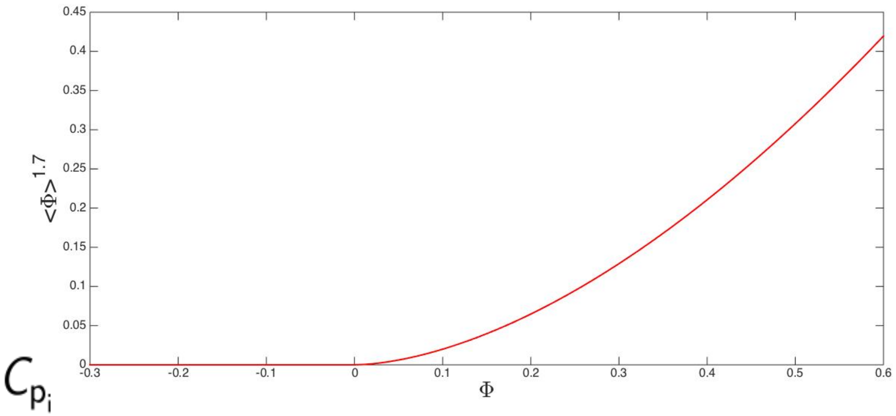
Hill-type yield function

$$\Phi = \sqrt{Y^{\mathrm{D}} \cdot \left(\tilde{\mathcal{A}}\left[(Y^{\mathrm{D}})^{\mathrm{T}}\right]\right)} - \sqrt{\frac{2}{3}}\left(\sigma_{\mathrm{y}} + Q\left(1 - e^{-\beta\kappa}\right)\right)$$

With a tress like tensor Y derived from the second Piola-Kirchoff tensor S and backstress X

Plastic multiplier (Perzyna formulation)

$$\dot{\Lambda} = \frac{\langle\Phi\rangle^{m}}{\eta}$$



Isotropic hardening

$$\dot{\kappa} = \sqrt{\frac{2}{3}}\dot{\Lambda}$$

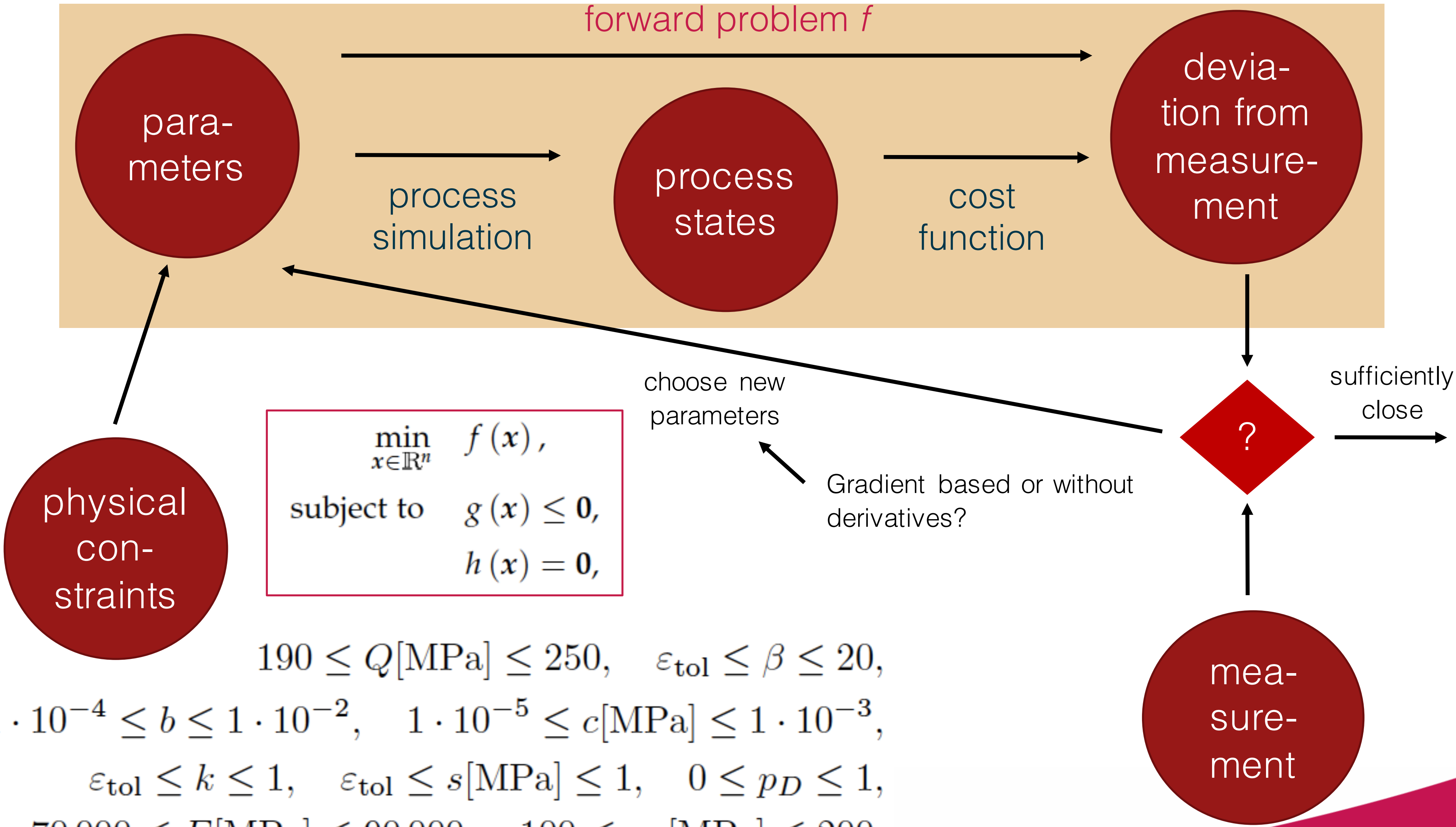
Kinematic hardening

$$\dot{C}_{\mathrm{p_i}} = 2\dot{\Lambda}\frac{b}{c}Y_{\mathrm{kin}}^{\mathrm{D}}C_{\mathrm{p_i}}$$

Damage (Lemaitre)

$$\dot{D} = \sqrt{\frac{2}{3}}\frac{\dot{\lambda}}{1-D}\left(\frac{Y_0}{s}\right)^{k} < \kappa - p_D >$$

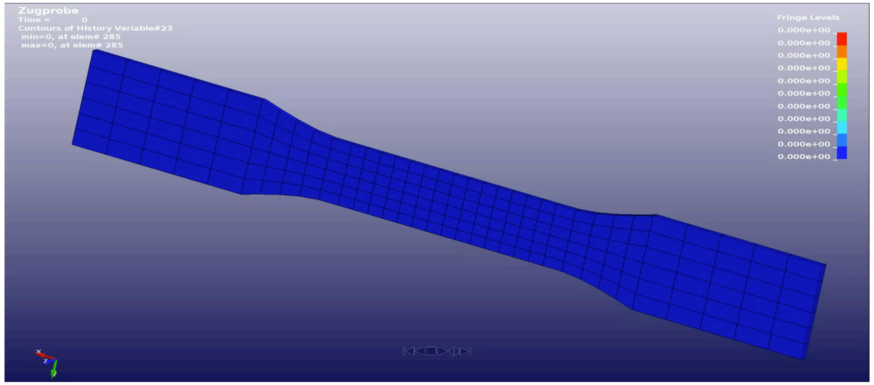
The inverse problem

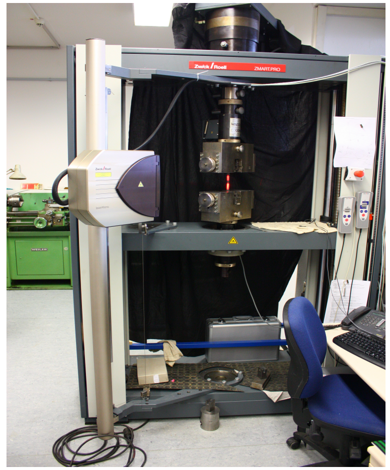


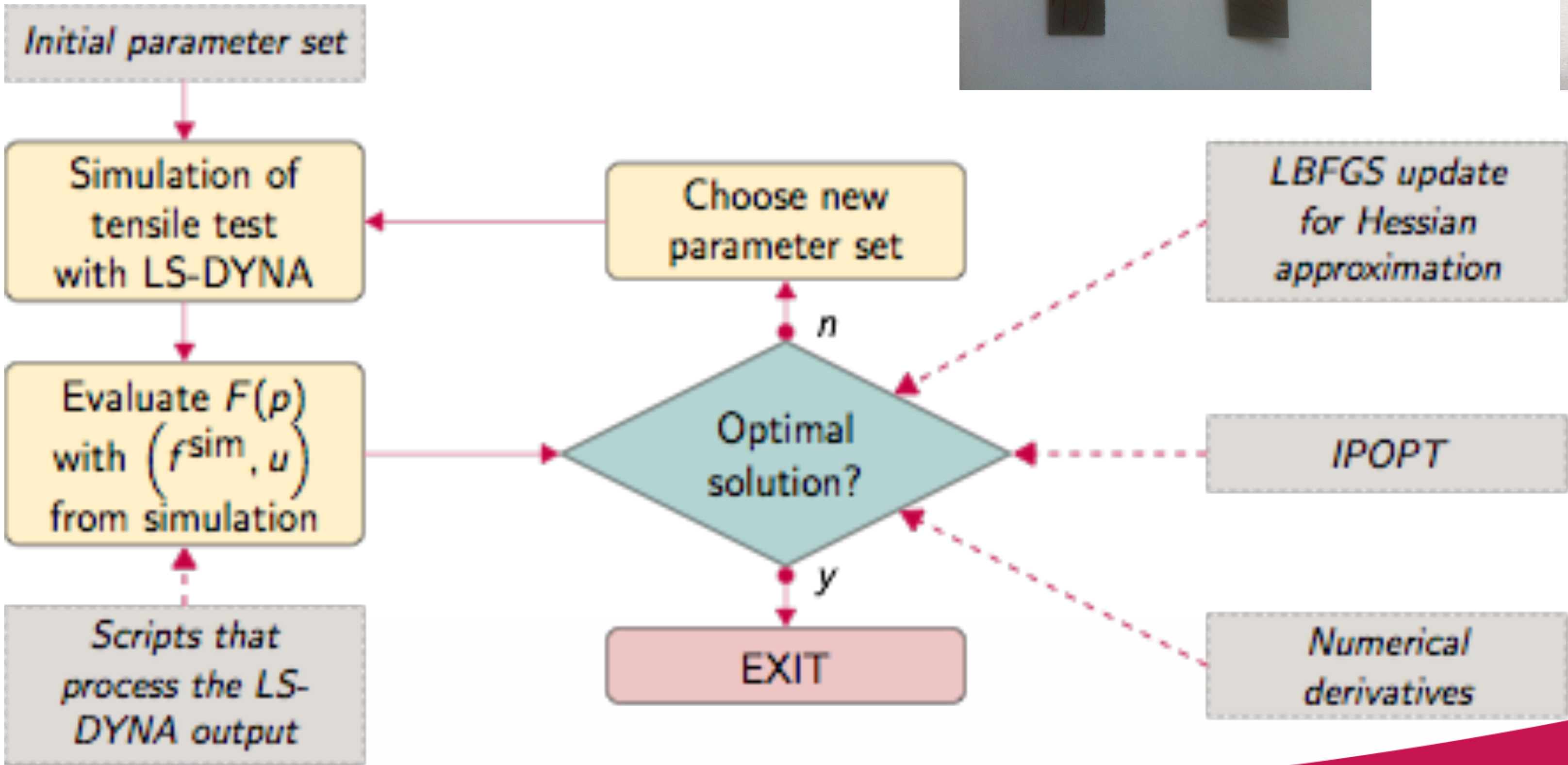
$$\min_{x \in \mathbb{R}^n} \quad f(\boldsymbol{x}),$$
$$\text{subject to} \quad g(\boldsymbol{x}) \leq \mathbf{0},$$
$$h(\boldsymbol{x}) = \mathbf{0},$$

$$190 \leq Q[\mathrm{MPa}] \leq 250, \quad \varepsilon_{\mathrm{tol}} \leq \beta \leq 20,$$
$$1 \cdot 10^{-4} \leq b \leq 1 \cdot 10^{-2}, \quad 1 \cdot 10^{-5} \leq c[\mathrm{MPa}] \leq 1 \cdot 10^{-3},$$
$$\varepsilon_{\mathrm{tol}} \leq k \leq 1, \quad \varepsilon_{\mathrm{tol}} \leq s[\mathrm{MPa}] \leq 1, \quad 0 \leq p_D \leq 1,$$
$$70\,000 \leq E[\mathrm{MPa}] \leq 90\,000, \quad 100 \leq \sigma_{\mathrm{y}}[\mathrm{MPa}] \leq 200.$$

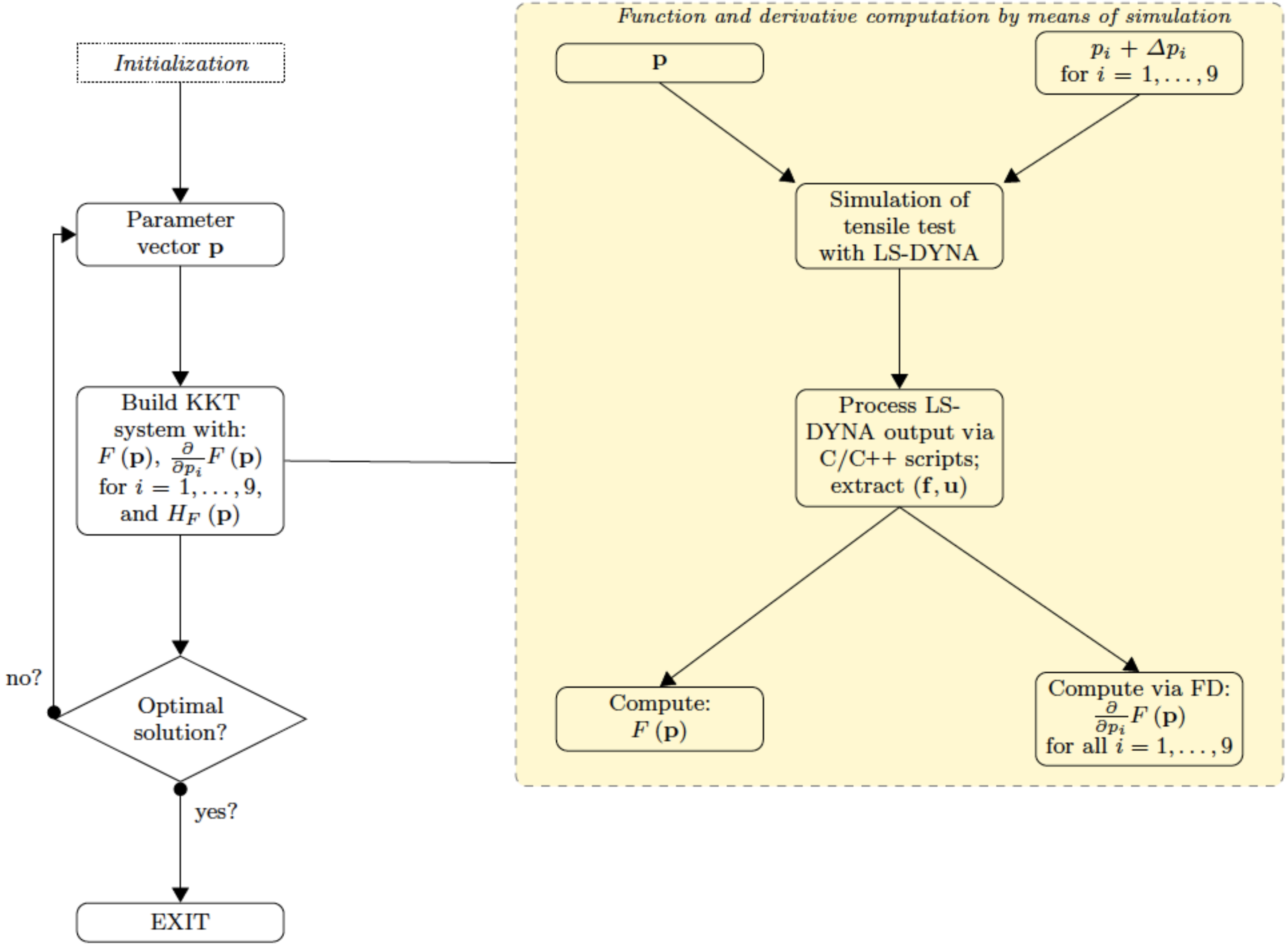
Identification of the material model





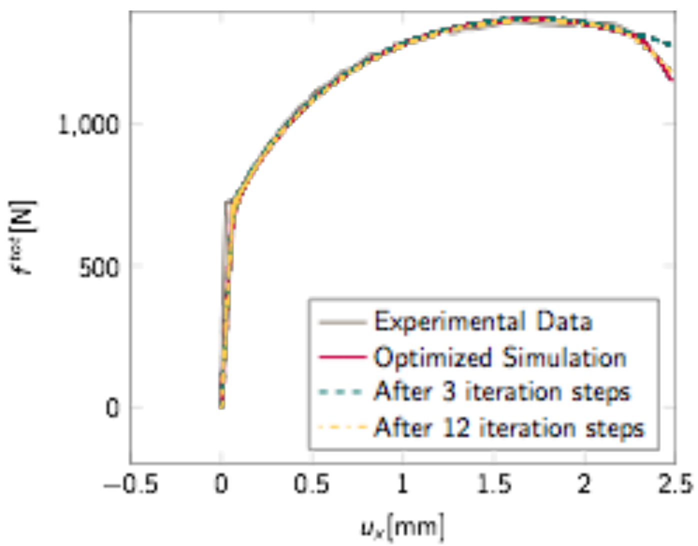


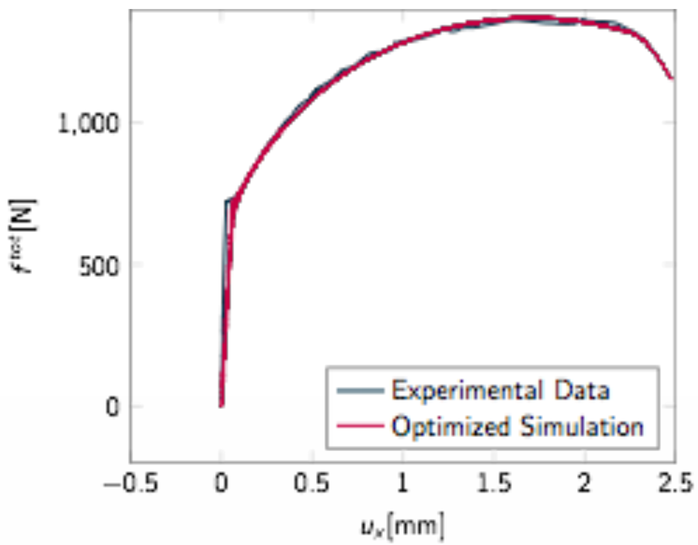
The algorithm with numerical computation of derivatives

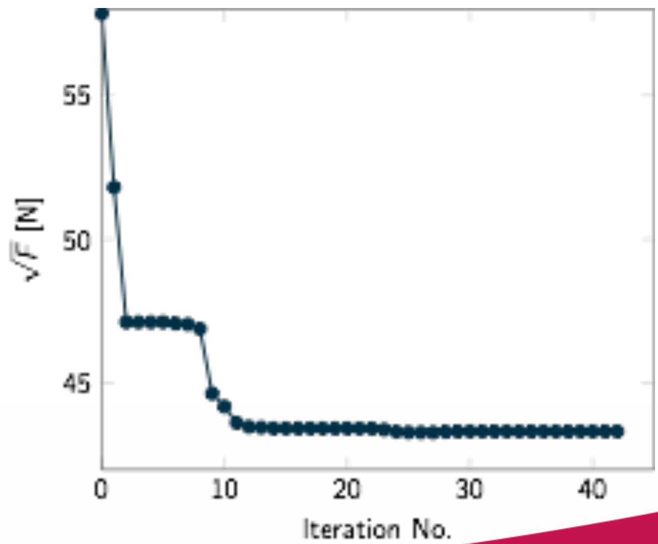


Model identification

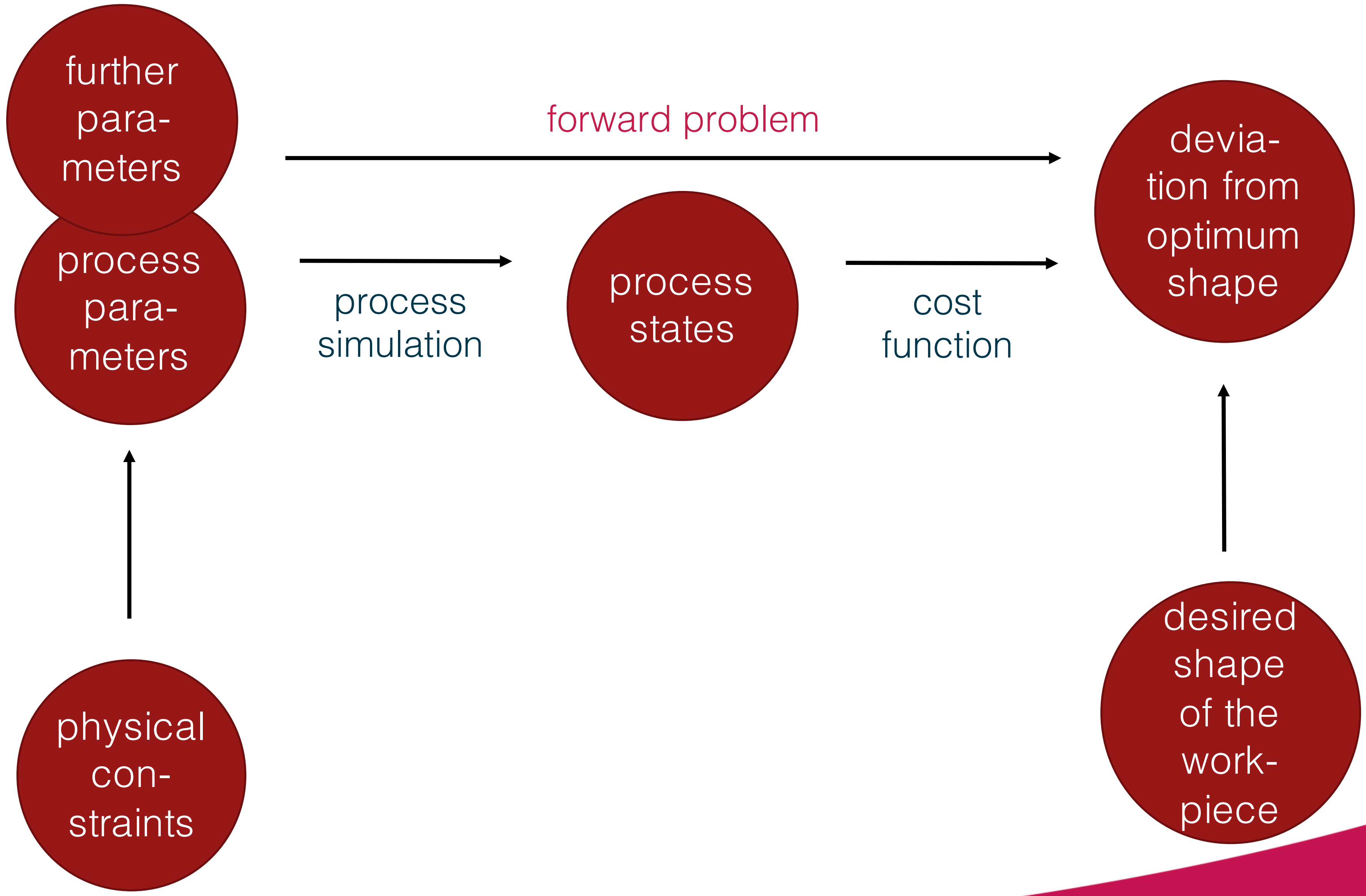
Young's modulus	E	$8{,}089\text{x}10^{4}$ MPa
Yield stress (von Mises)	σ_y	$1{,}185\text{x}10^{2}$ MPa
Backstress (isotropic)	Q	$1{,}604\text{x}10^{2}$ MPa
Hardening parameter (isotropic)	β	$1{,}265\text{x}10^{1}$
Hardening parameter (kinematic)	b	$5{,}124\text{x}10^{-3}$
Equivalent stress (kinematic hardening)	c	$4{,}598\text{x}10^{-4}$ MPa
Strain-rate-exponent	k	$4{,}694\text{x}10^{-1}$
Equivalent strain for damage model	s	$2{,}680\text{x}10^{-1}$
Threshold for damage	p_D	$6{,}306\text{x}10^{-1}$







Mathematical optimization for process parameters



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The coupled model

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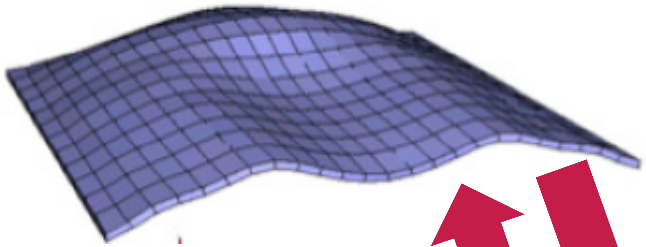
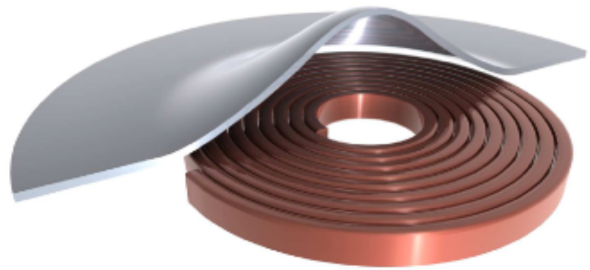
Mechanical model





Lorentz force density $f = \kappa_p \frac{\partial A}{\partial t} \cdot \nabla \times A$

Joule heating $p_{\text{Joule}} = \kappa_p \left| \frac{\partial A}{\partial t} \right|^2$

Spatial distribution of conductivity κ_p

Eddy current equation for the magnetic vector potential *A*

$$\nabla \times \left(\frac{1}{\mu} \nabla \times \mathbf{A} \right) + \kappa_\mathrm{p} \frac{\partial \mathbf{A}}{\partial t} = -\kappa_\mathrm{p} \nabla \varphi_\mathrm{p}$$

Electric scalar potential $\Delta \varphi = 0$

for Coloumb gauge $\nabla \cdot A = 0$

The coupled model

Weak form of electromagnetic equations

$$\int_\Omega \left(\frac{1}{\mu}\nabla\times\mathbf{A}\cdot\nabla\times\tilde{\mathbf{A}} + \sigma\overset{*}{\mathbf{A}}\cdot\tilde{\mathbf{A}}\right) = -\int_S \sigma\tilde{\mathbf{A}}\cdot\nabla\phi$$

$$\int_S \nabla\phi\cdot\nabla\tilde{\phi} = 0$$

$\mathbf{f}_\mathrm{L} = \det(\nabla\xi)(\mathbf{J}\times\nabla\times\mathbf{A})$

Lorentz-force

Joule heating

$\boldsymbol{\xi}, v$

Weak form of mechanical force balance

$$0 = \int_{B_\mathrm{r}} \{\varrho\ddot{\boldsymbol{\xi}} - \boldsymbol{f}_\mathrm{L}\}\cdot\boldsymbol{\xi}_* + \int_{B_\mathrm{r}} \boldsymbol{K}(\nabla\boldsymbol{\xi})^{-\mathrm{T}}\cdot\nabla\boldsymbol{\xi}_*$$

Material model

Unknown fields

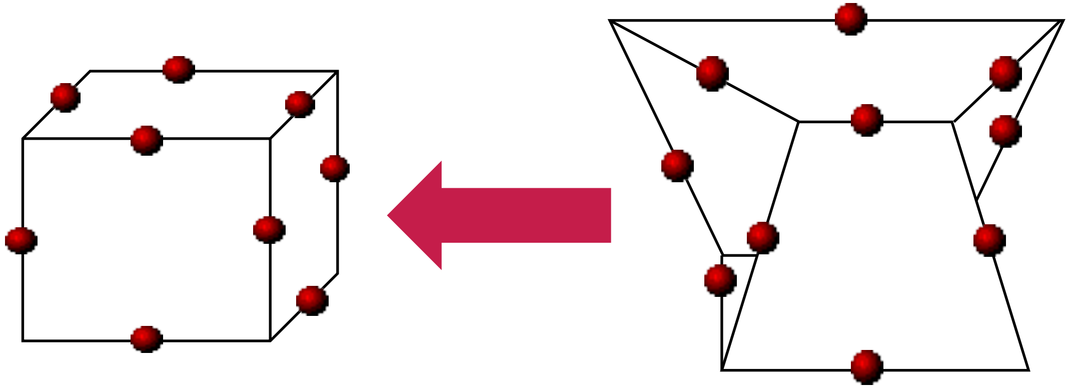
Vektorpotential **A**
Skalarpotential **Φ**
Deformation **ξ**

FE-simulation

Nédélec-elements

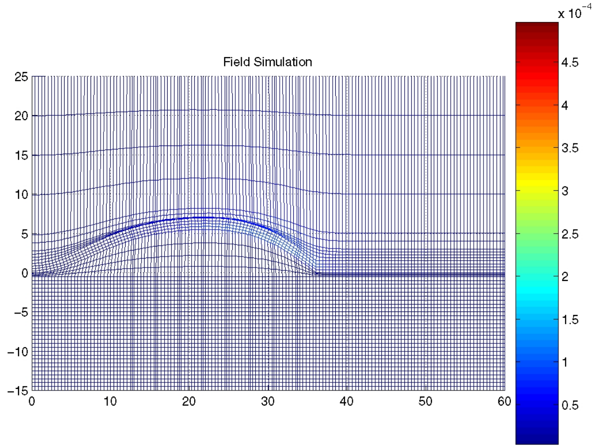
$$\int_{\Gamma_i} \mathbf{a}_e \cdot \mathbf{t}_i \,, \quad i = 1, \ldots, 12$$

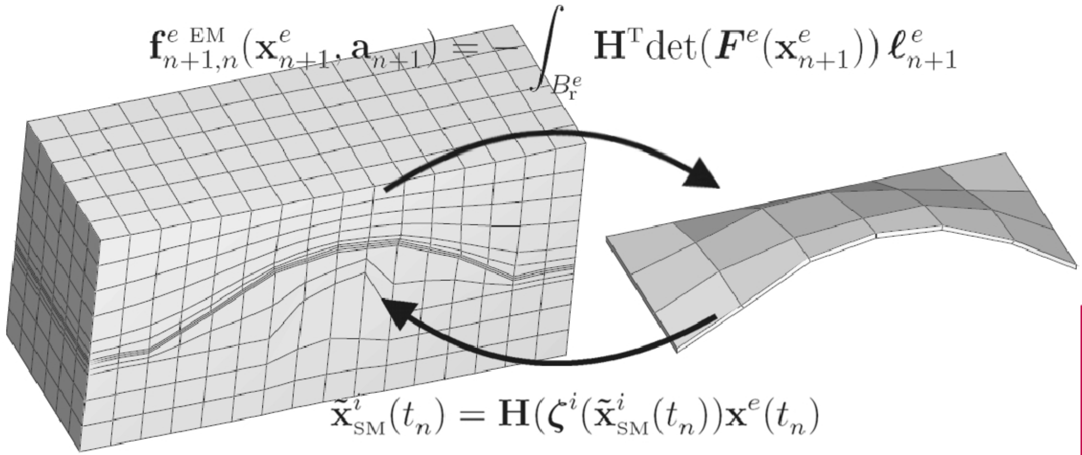
$\mathbf{t}_i$: tangential vector



Either in the full area of interest or only in the conducting material, while boundary-elements are used in the air-gap

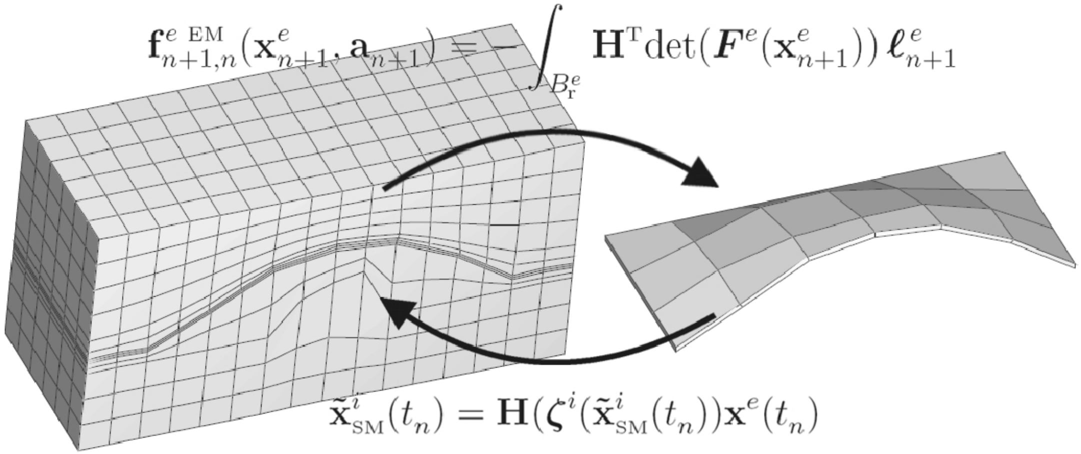
Arbitrary Langrangian Eulerian Formulation

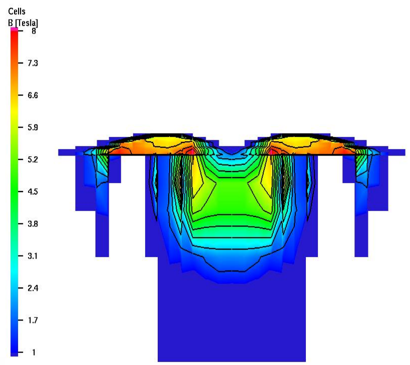


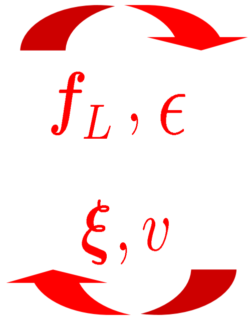


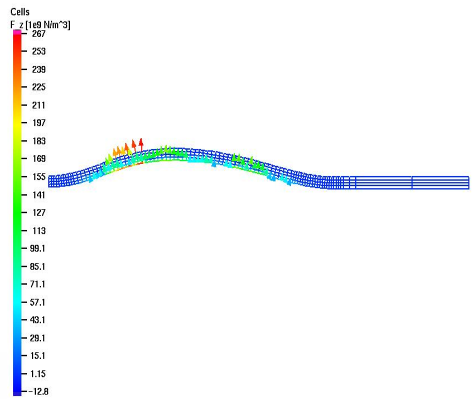
Algorithmic coupling

Explicit vs. implicit schemes

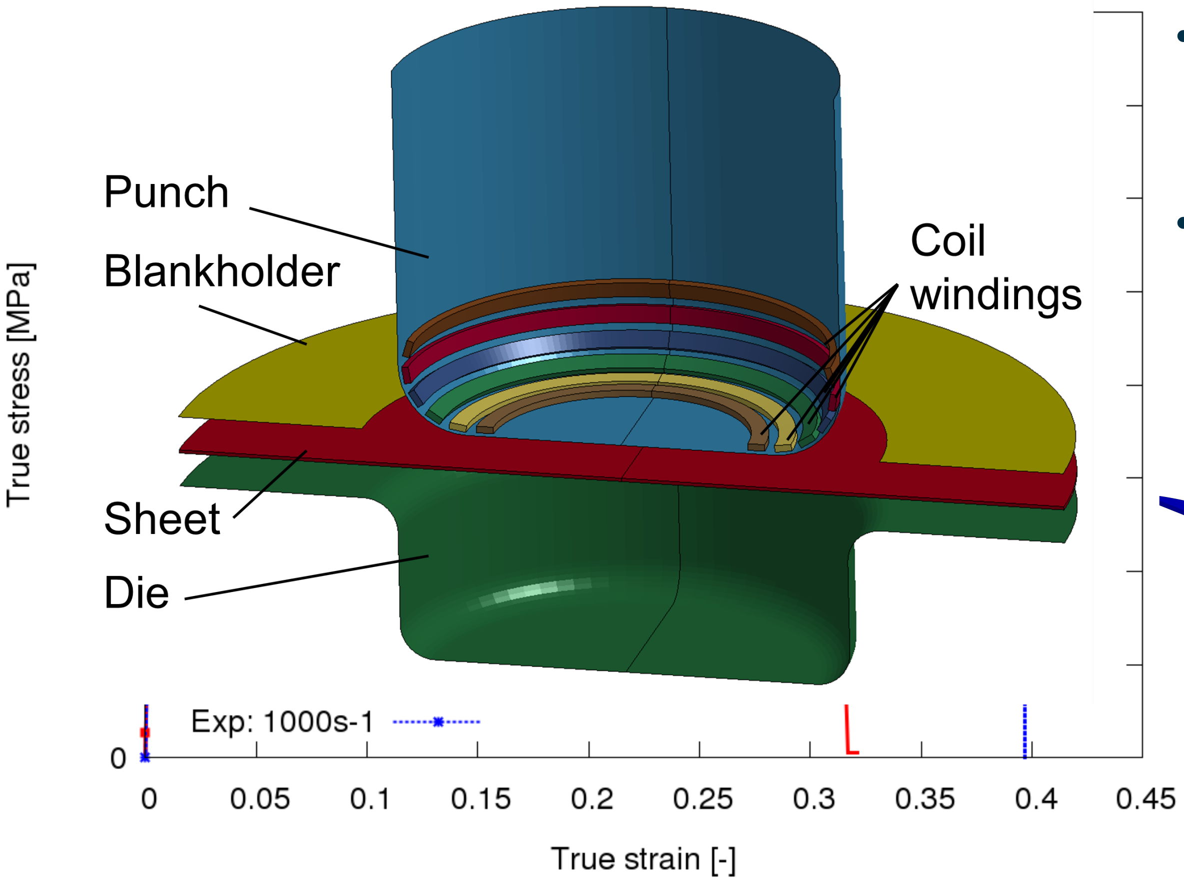




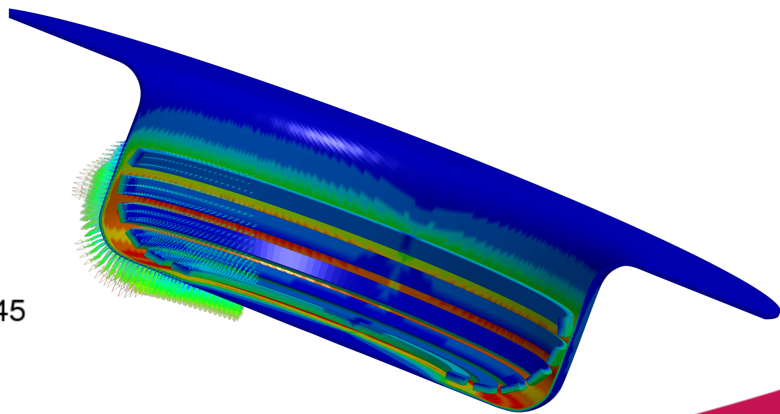




Validation and verification

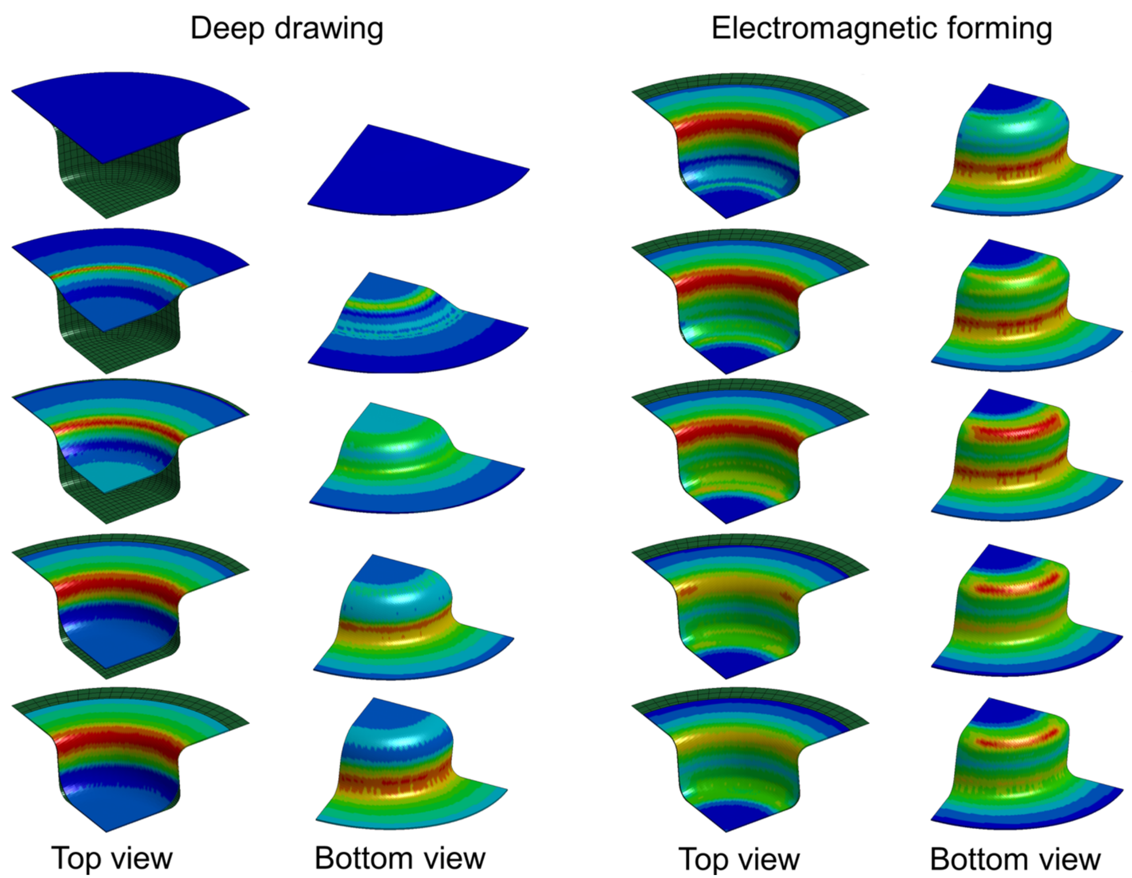


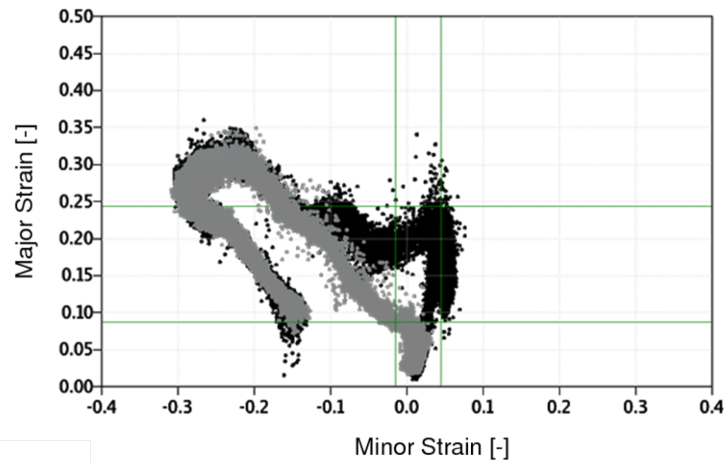
- Comparison to stress-strain curves (with evolution model for damage threshold)
- Application to complex situation (cup drawing)

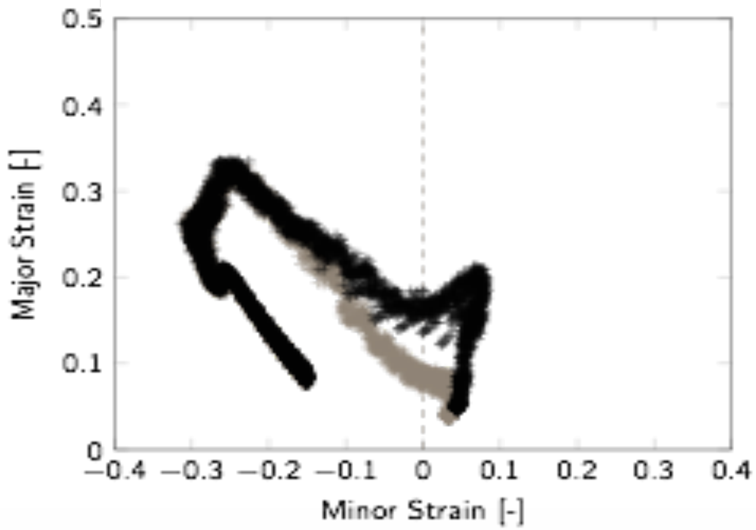


Simulation: Yalin Kiliclar with LS-DYNA

Combined forming of a round cup

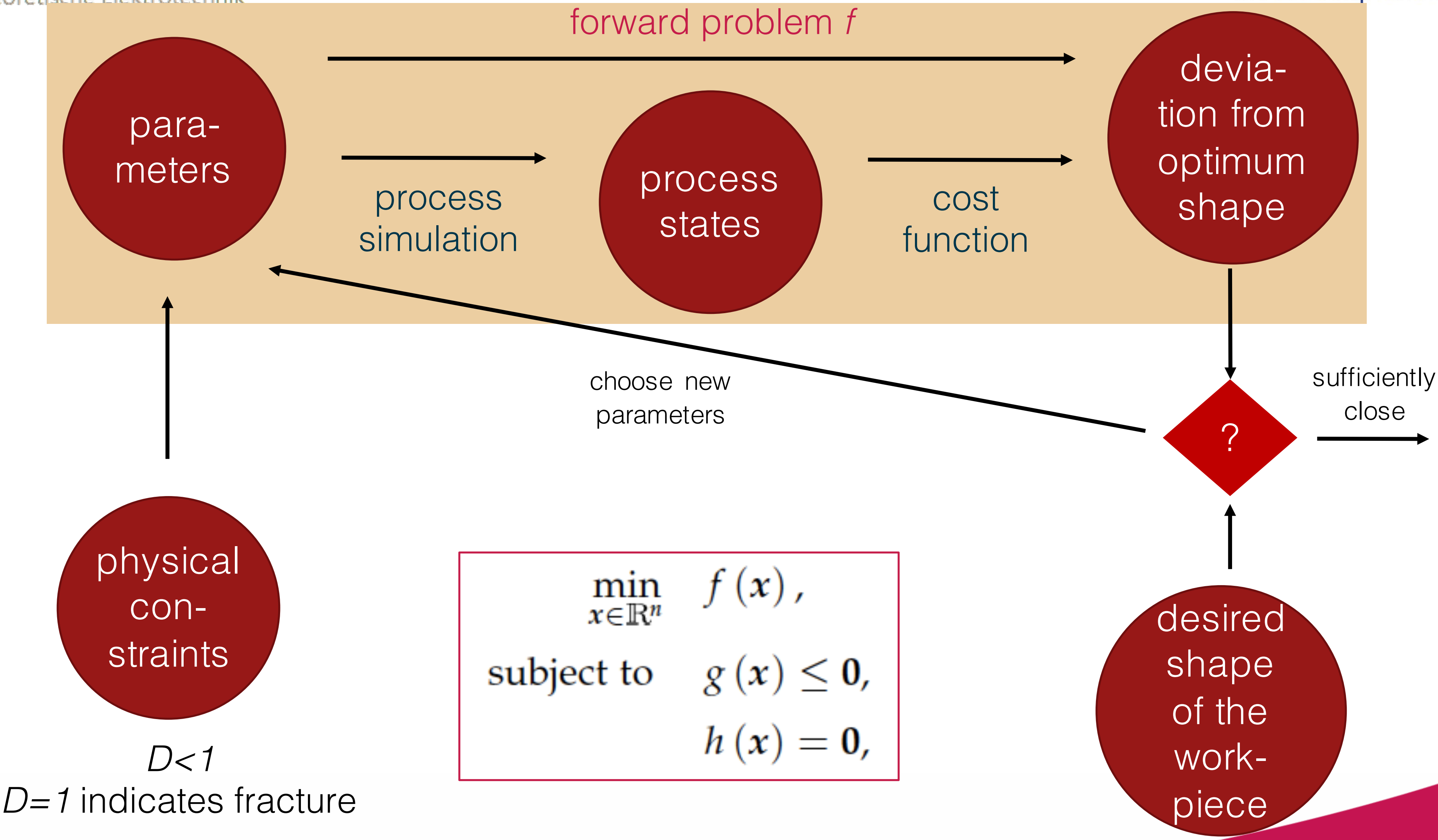






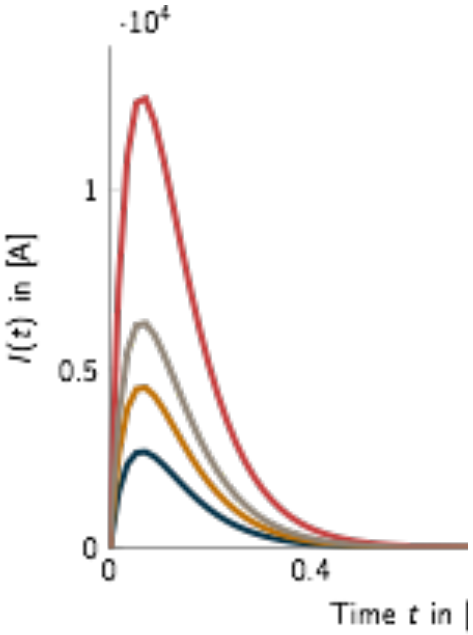
Simulation: Yalin Kiliclar with LS-DYNA

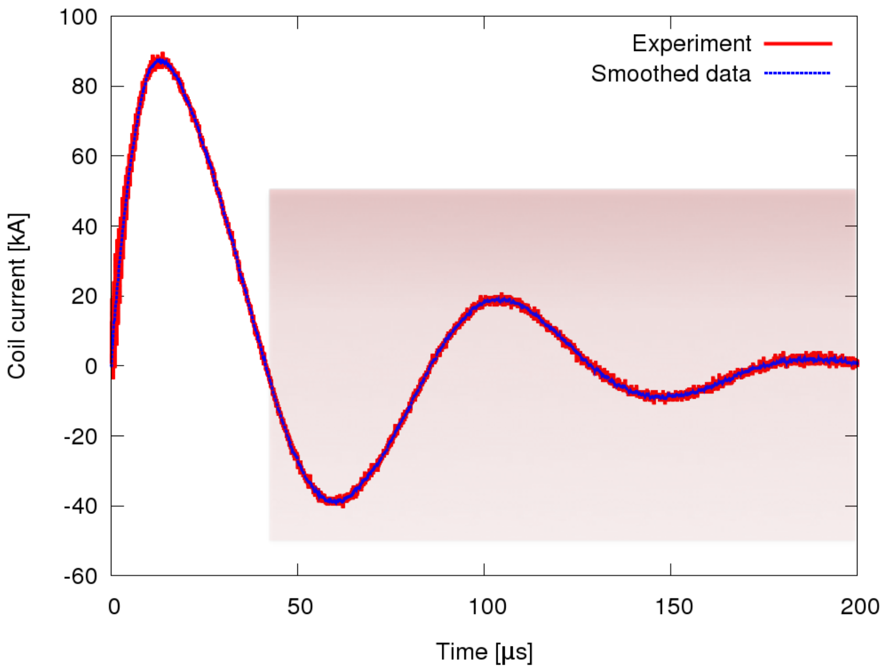
The inverse problem



$$\begin{aligned} \min_{x \in \mathbb{R}^n} \quad & f(x), \\ \text{subject to} \quad & g(x) \leq 0, \\ & h(x) = 0, \end{aligned}$$

Example: identification of optimum current





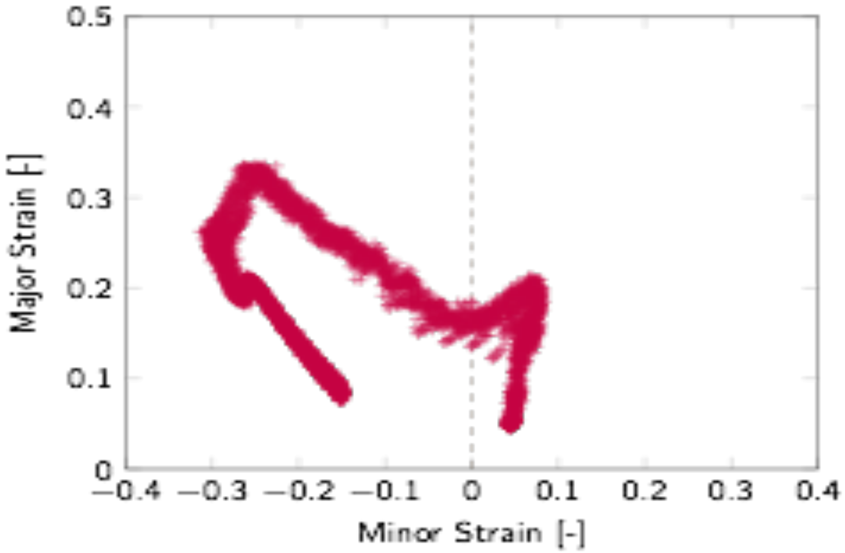
- Only the first half wave is relevant for forming
- Remaining energy absorbed by coils
- Try novel approach to reduce wear and energy consumption

→ Double exponential pulse as mathematical model

$$I(t) = I_\alpha e^{-\alpha t} + I_\beta e^{-\beta t}$$

Example: identification of optimum current

- Maximize the radius at bottom edge
  → Maximize the first principle strain
- Avoid damage
  → Constrain the damage variable in all elements
- Technically reasonable current
  → Constrain the current at each time step (here: 125 000 A)

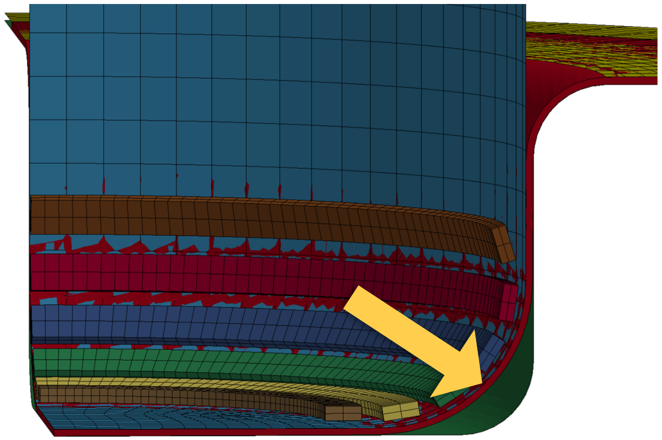


$$\min_{(I_\alpha, I_\beta, \alpha, \beta)^\top \in \mathbb{R}^4} \quad -\sum_{j=1}^{m} \varepsilon_1^j \left(I_\alpha, I_\beta, \alpha, \beta\right),$$

$$\text{subject to} \quad D_j\left(I_\alpha, I_\beta, \alpha, \beta\right) \leq 1 - p, \quad \forall\, j = 1, \ldots, m,$$

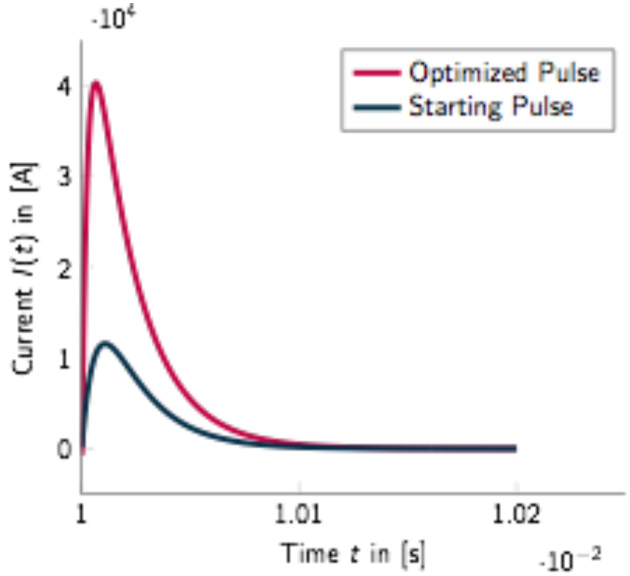
$$I_\alpha e^{-\alpha t_i} + I_\beta e^{-\beta t_i} \leq I_{\max}, \quad \forall\, i = 1, \ldots, N.$$

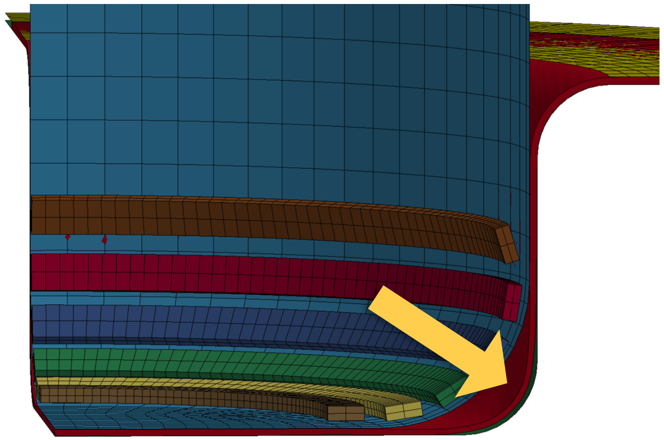
Example: identification of optimum current



$r = 20\,\text{mm}$

$d = 0.91\,\text{mm}$





$r = 15.35\,\text{mm}$

$d = 0.85\,\text{mm}$

$$I_\alpha = -65570.2\,\text{A}$$

$$I_\beta = 64867.8\,\text{A}$$

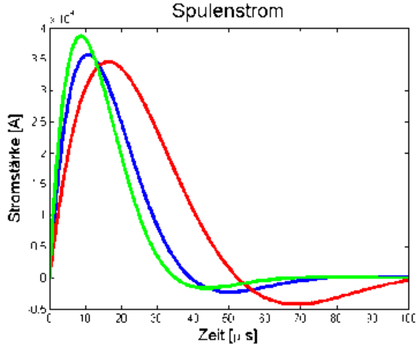
$$\alpha = 6878.78$$

$$\beta = 973.021$$

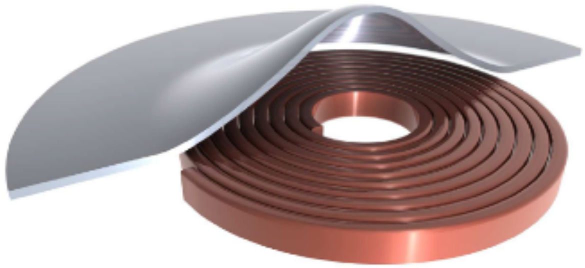
Optimization Method:
IPOPT as implemented by
Wächter und Biegler

Process identification I

available power

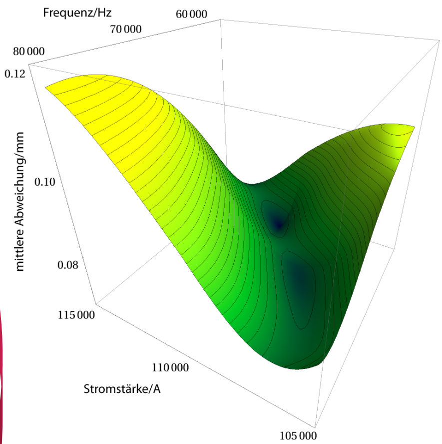


tool properties

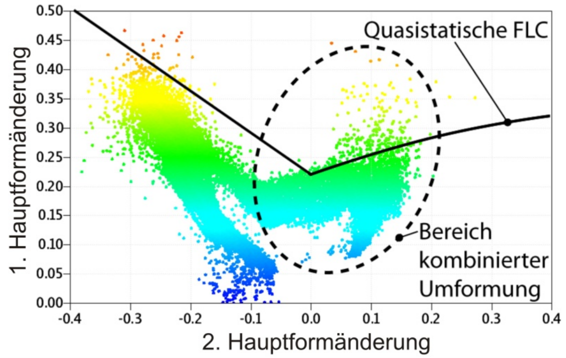


economical reasons

choose process parameters



no damage

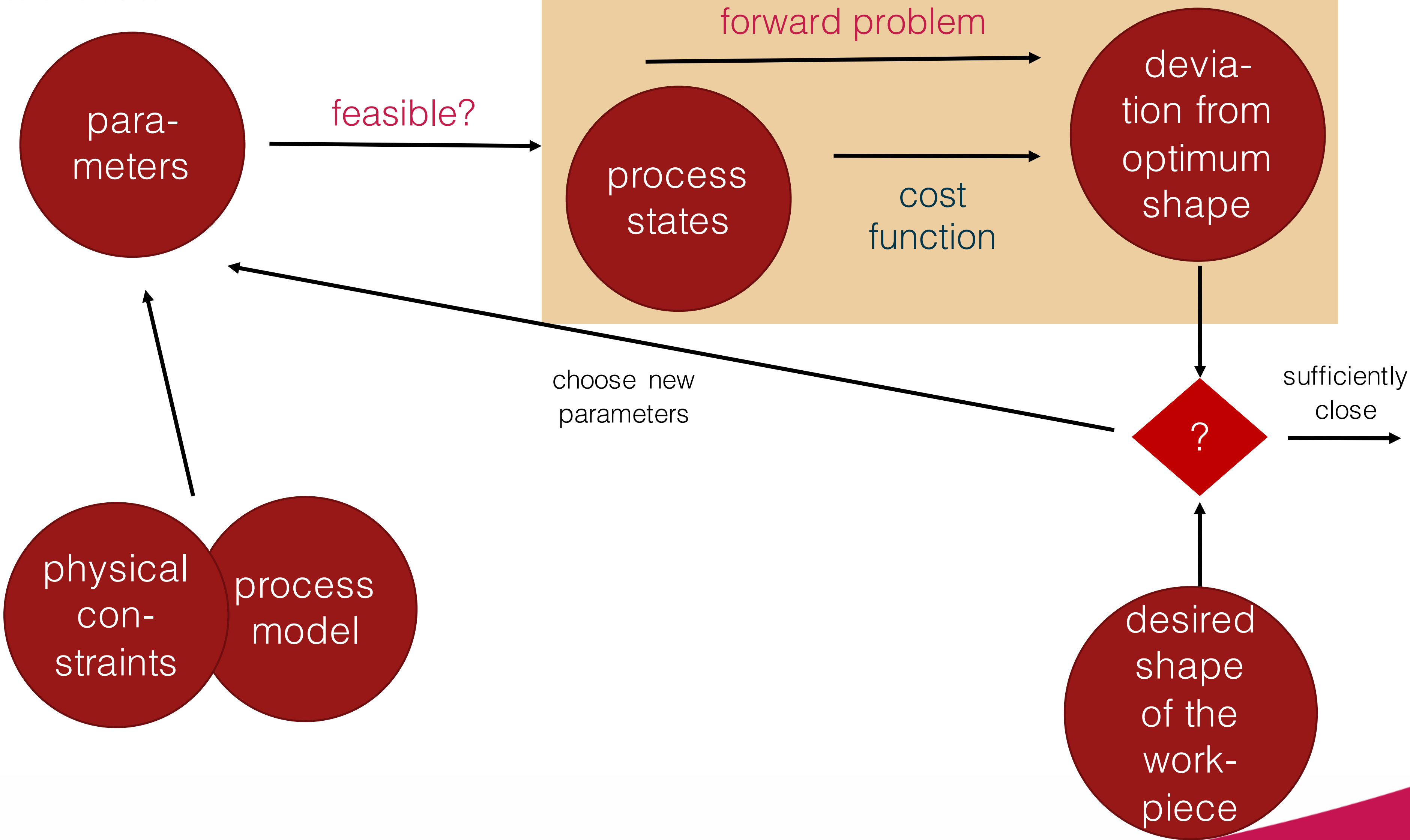


solve process model
→ deformation field

compute deviation to optimum shape

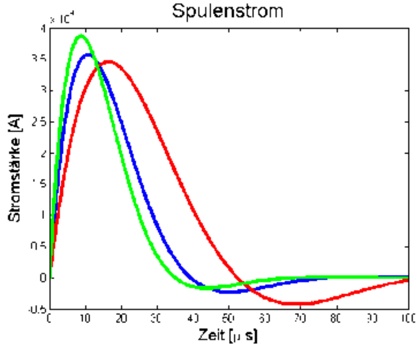
Iterate until parameters yield a sufficiently good result

The inverse problem II

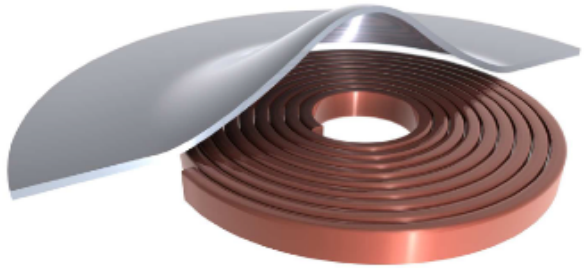


Process identification II

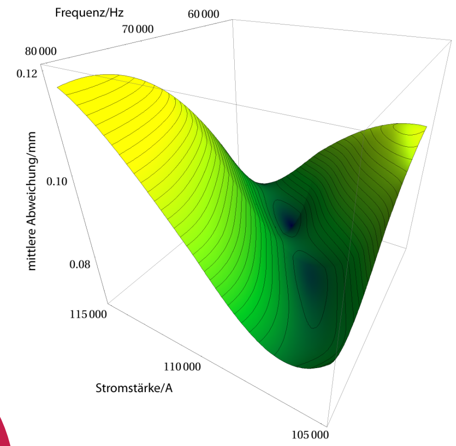
available power



tool properties

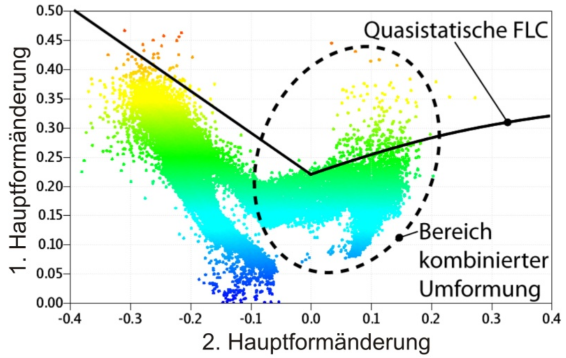


economical reasons



process model

no damage



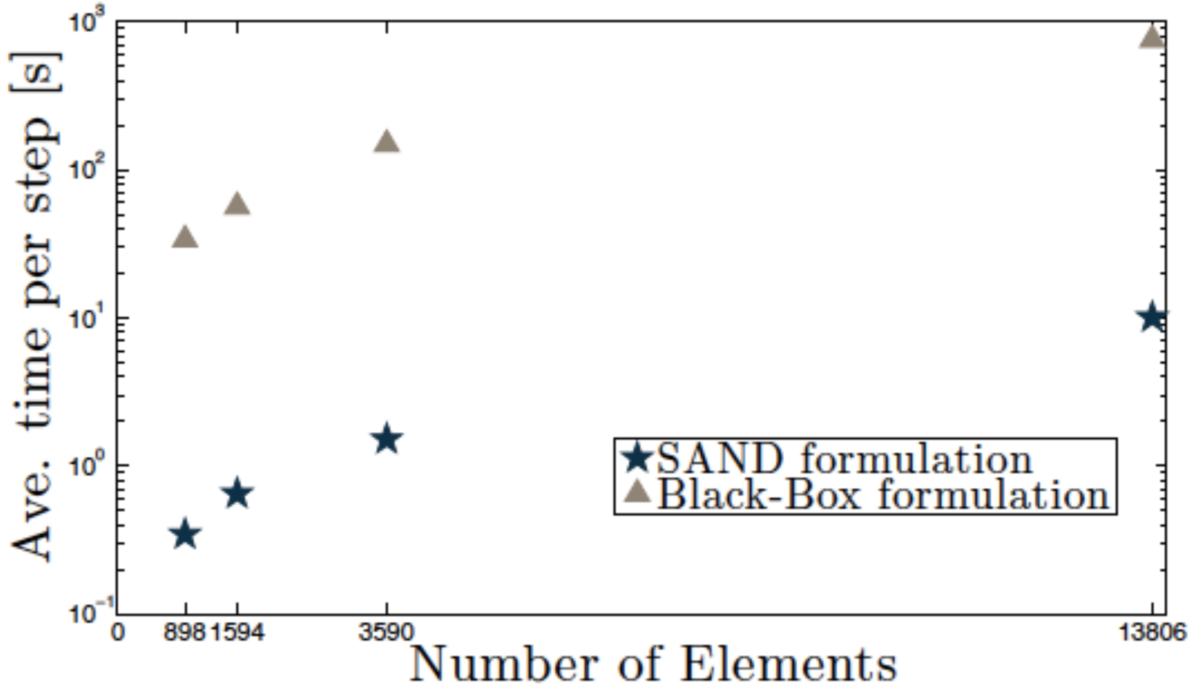
choose process parameters

compute deviation to optimum shape

Iterate until parameters yield a sufficiently good result

Comparison of the methods

- Scheme I allows for a black-box-use of solver and optimizer
- Scheme II requires internal data of the simulation code
- Scheme II is much faster
- Scheme II has not been implemented for the complete problem
- Scheme II produces a huge number of constraints, but simple cost function



Computation time for scheme I and II for a simple mechanical identification problem

Optimization Method: IPOPT as implemented by Wächter und Biegler

Algorithmic aspects

- Practically, the discrete system of equations with the overall stiffness-matrix of the finite-element model as system matrix is not solved, but given to the optimizing algorithm as constraints
- Also, nonlinearities can be handled by the optimization algorithm
- A large number of constraints can be treated, since only a few of them is active at a certain stage of the algorithmic procedure
- Active set strategies: Only the active constraints need consideration
- Use of simple auxiliary problems in certain areas of the parameter space (trust region methods)

Shape optimization

Optimization problem

$$\Phi(\vec{u}_{\min}) = \min_{\vec{p}\in P, \vec{u}_{\vec{p}}\in V} \Phi(\vec{u}_{\vec{p}}),$$

$$\text{s.t. } \Lambda_{\vec{p}}\vec{u}_{\vec{p}} = \vec{f}_{\vec{p}}$$

with cost function

$$\Phi(\vec{A}_{\vec{p}}) = \int_0^T \int_C \left| \kappa_{\vec{p}} \frac{\partial \vec{A}_{\vec{p}}}{\partial t} \times (\nabla \times \vec{A}_{\vec{p}}) - \vec{f}_{\mathrm{ideal}} \right|^2 \mathrm{d}V \mathrm{d}t$$

such that MQS Maxwell equations hold

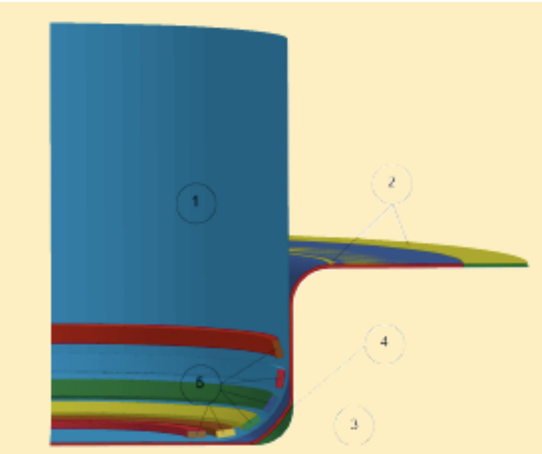
$$\nabla \times \left(\frac{1}{\mu} \nabla \times \vec{A}_{\vec{p}} \right) + \kappa_{\vec{p}} \frac{\partial \vec{A}_{\vec{p}}}{\partial t} = -\kappa_{\vec{p}} \nabla \varphi_{\vec{p}}$$

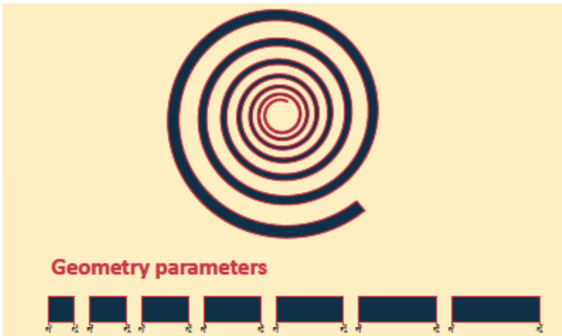
$$\mathrm{div}\, \vec{A} = 0$$

Discretized version

$$\vec{f}_{\mathrm{comp}}(\vec{r}) = \sum_{k\in M} a_k^{(n)} \vec{b}_k(\vec{r})$$

$$\Phi(\vec{q}) = \sum_{n=1}^{N} \sum_{\vec{q}\in Q} w_n w_{\vec{q}} \left| \vec{f}_{\mathrm{comp}}(\vec{q}) - \vec{f}_{\mathrm{ideal}}(\vec{q}) \right|^2$$





Summary

- The benefits of high speed forming as part of a process chain can be increased by simulation based method planning
- Virtual planning of complicated processes can efficiently be performed by a full integration of the simulated model into the optimization framework via restrictions – however, then the simulation tool cannot be used as a black-box solver anymore
- Optimization algorithms that can cope with a high number of constraints are available
- Material optimization can be treated with the same algorithm
- Vision: standardized computer software for design problems (inverse problems)