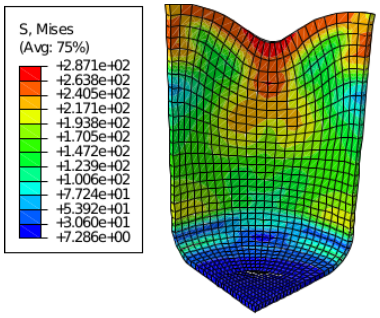
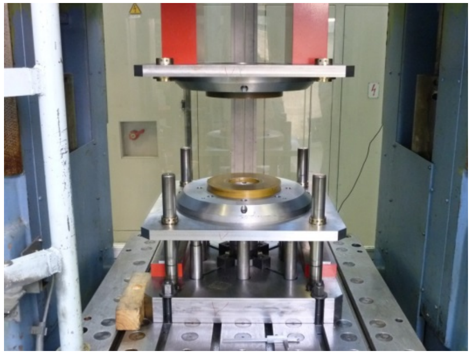
OPTIMIZATION PROBLEMS IN MATERIALS PROCESSING

Melanie.Senn@iwm.fraunhofer.de



Fraunhofer
IWM



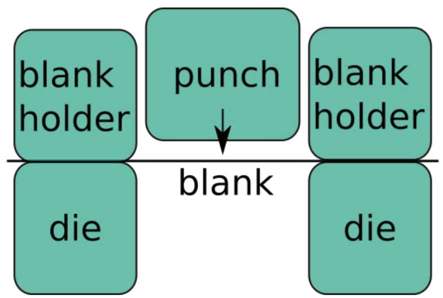
Optimization problems in materials processing

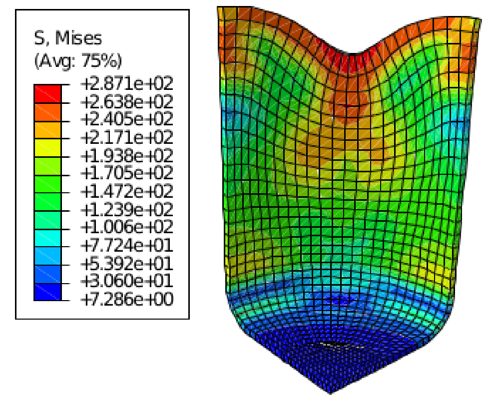
1. Time-independent parameters
    1. Optimization of model / process parameters
       Example: mimimization of spring-back in draw bending
2. Time-dependent parameters
    1. Deterministic
       Example: optimization of step sizes in incremental hole drilling
    2. Stochastic (under uncertainty)
       Example: optimal control of blank holder force in deep drawing

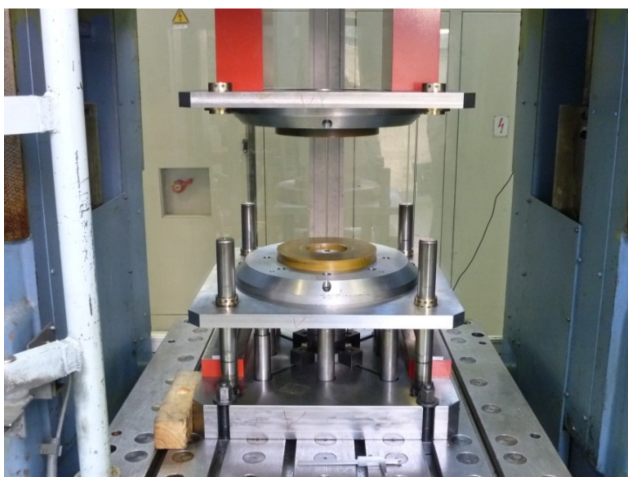
Fraunhofer
IWM

2.2 Optimal control in deep drawing: process overwiew

- Controlled variable:
  stress distribution (sheet)
- Control parameter:
  blank holder force (machine)

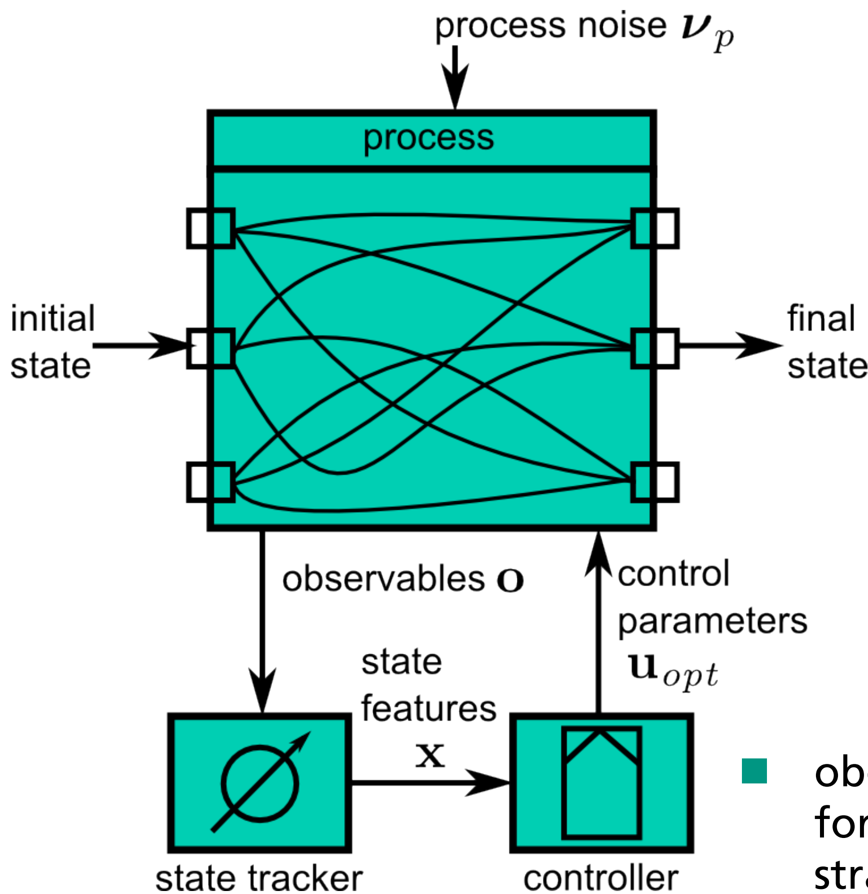


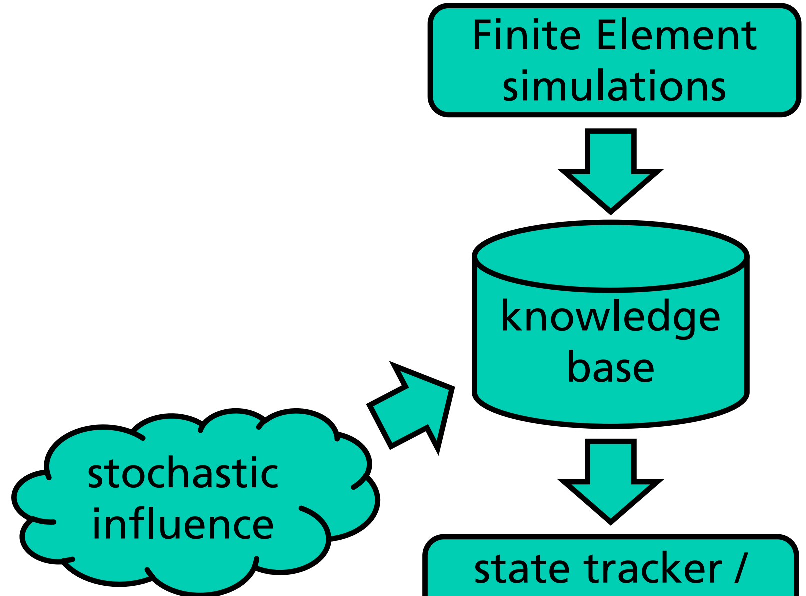




Fraunhofer IWM

2.2 Optimal control in deep drawing: generic model + data

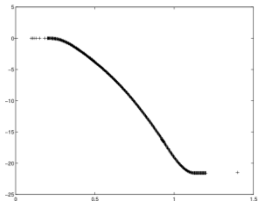




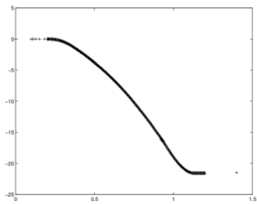
- obervables:
  forces, displacements, strains
- state:
  von Mises stresses
- control parameter:
  blank holder force
- process noise:
  friction, anisotropy

2.2 Optimal control in deep drawing: state tracker model

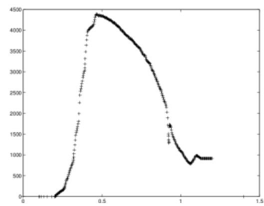
sheet displacement (x) [mm / s]



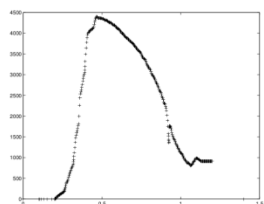
sheet displacement (y) [mm / s]



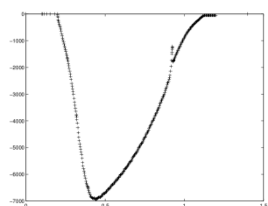
punch force (x) [N / s]

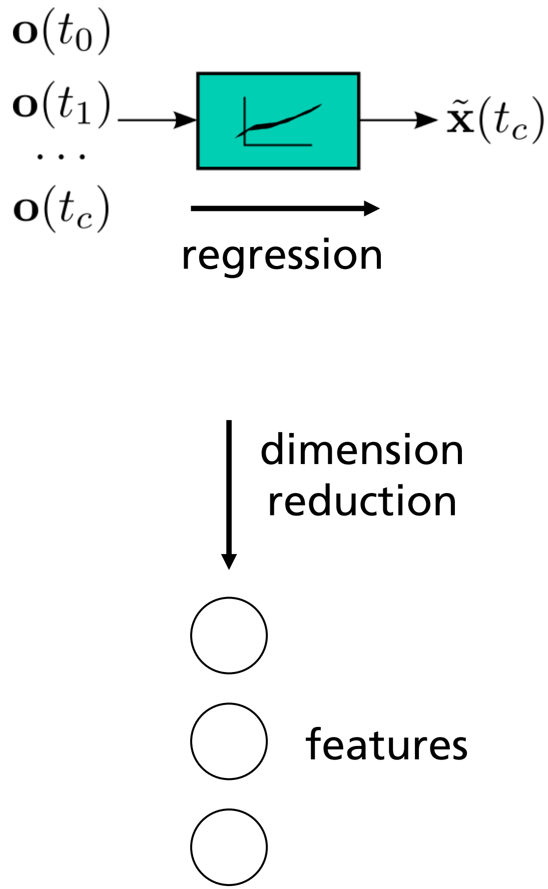


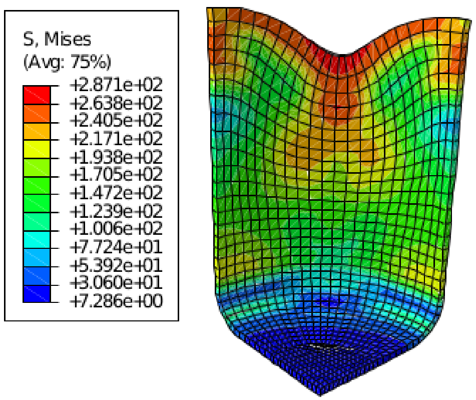
punch force (y) [N / s]



punch force (z) [N / s]

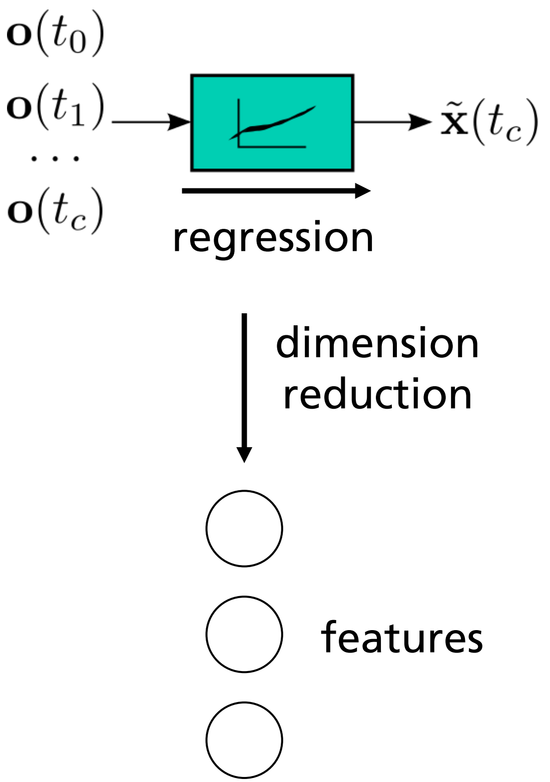




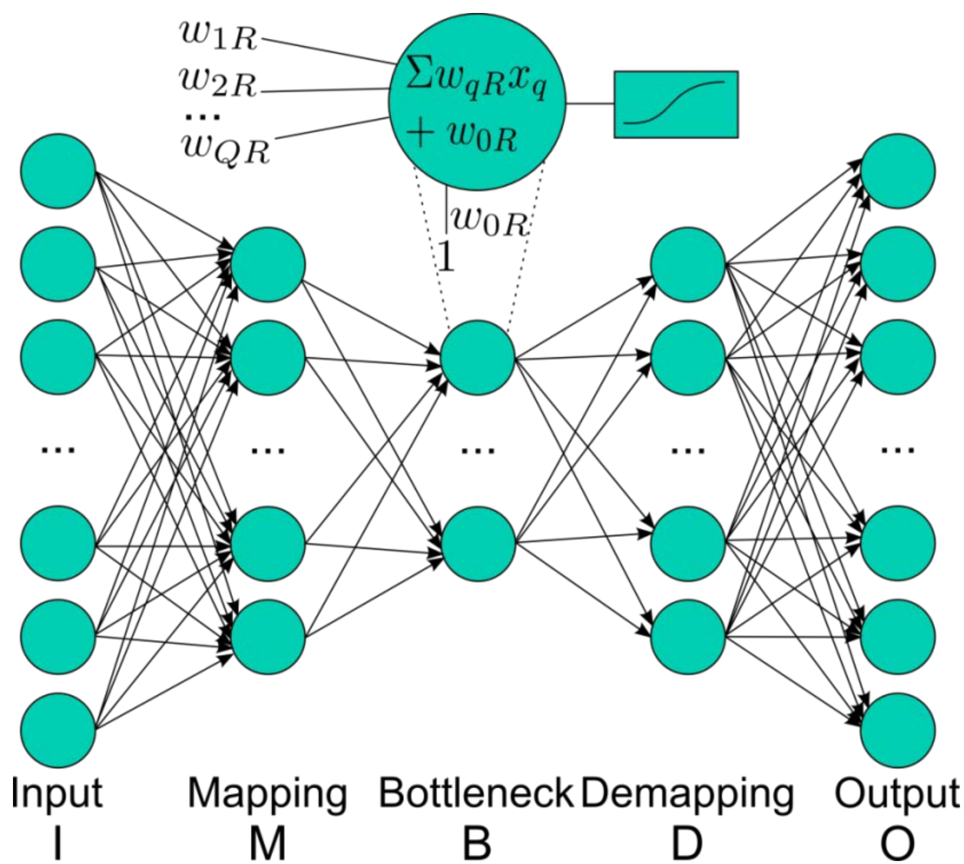


Fraunhofer IWM

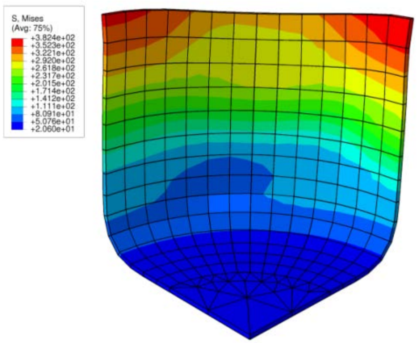
2.2 Optimal control in deep drawing: state tracker model



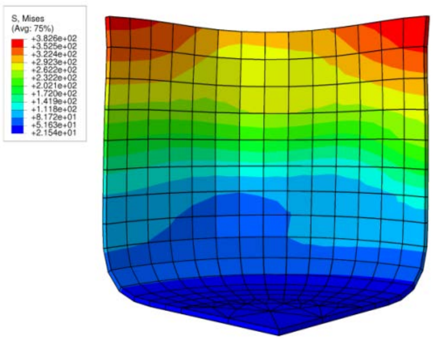
Principal Function Approximator



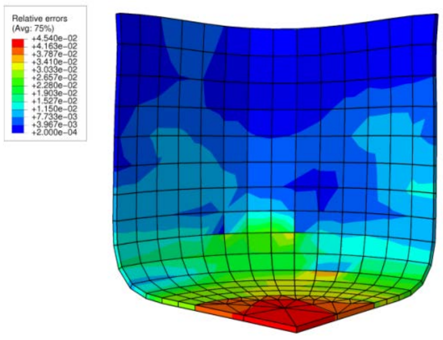
2.2 Optimal control in deep drawing: state tracker results



von Mises stresses
(simulation)



von Mises stresses
(prediction)



relative error [0, 0.0454]
(prediction vs. simulation)

Principal Function Approximator

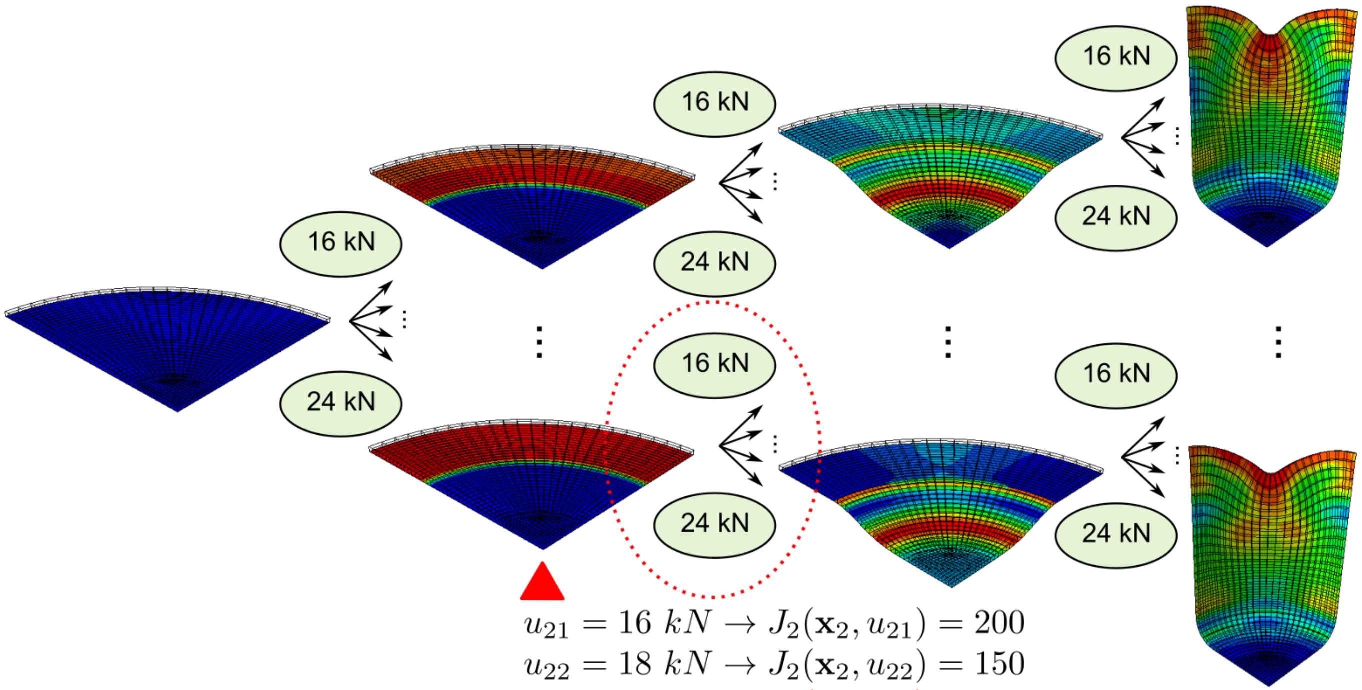
100 samples: 80% training, 20% test, 5-fold cross validation

Relative error mean: 0.0082

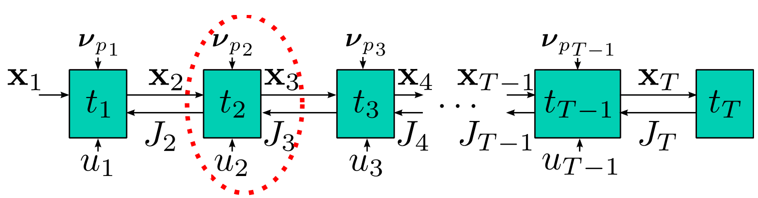
Relative error max: 0.1292

Fraunhofer IWM

2.2 Optimal control in deep drawing: controller model



$$u_{21} = 16\ kN \rightarrow J_2(\mathbf{x}_2, u_{21}) = 200$$
$$u_{22} = 18\ kN \rightarrow J_2(\mathbf{x}_2, u_{22}) = 150$$
$$u_{23} = 20\ kN \rightarrow J_2(\mathbf{x}_2, u_{23}) = 130$$
$$u_{24} = 22\ kN \rightarrow J_2(\mathbf{x}_2, u_{24}) = 170$$
$$u_{25} = 24\ kN \rightarrow J_2(\mathbf{x}_2, u_{25}) = 190$$



t: decision point in time, J: cost function, u: control parameter

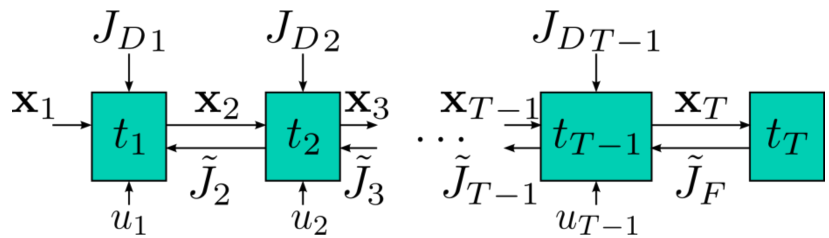
x: state / state features (controlled variable), v_p: process noise

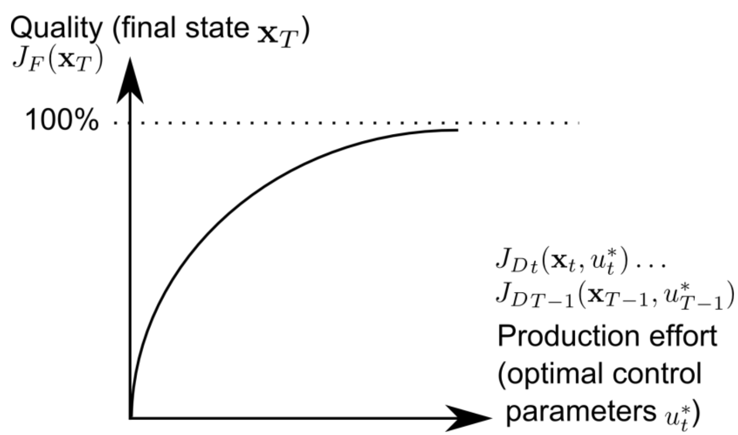
Fraunhofer IWM

2.2 Optimal control in deep drawing: controller model

- Bellman equation

$$u_{t\,opt}(\mathbf{x}_t) = \underset{u_t \in U_t}{\arg\min}\{J_{D\,t}(\mathbf{x}_t, u_t, \mathbf{x}_{t+1}) + \langle \tilde{J}_{t+1}(\mathbf{x}_{t+1})\rangle\}$$





2.2 Optimal control in deep drawing: controller results

- State transitions $\boldsymbol{x}_{t+1} = \boldsymbol{f}_t(\boldsymbol{x}_t, u_t, \boldsymbol{v}_{p_t})$
  - Artificial Neural Network (deterministic) + noise model (**μ,Σ**)
- Costs
  - Local costs J_{D_t}, final costs J_F (user-defined functions)
  - Total costs $\tilde{J}_{t+1}$ (Artificial Neural Network)

comparison of controllers by total applied costs J_{D_1}+ ... + J_{D_T}+ J_F

	classical DP	backward ADP	forward ADP
relative cost difference (in %)*	4.96	8.43	8.85

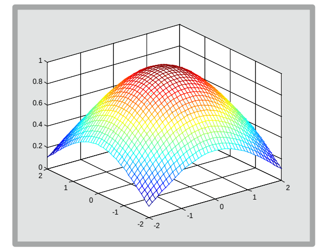
*w.r.t. deterministic cost minimum,
100 stochastic paths

→ decrease in complexity

DP: Dynamic Programming, ADP: Approximate Dynamic Programming

2.2 Optical strain measurement

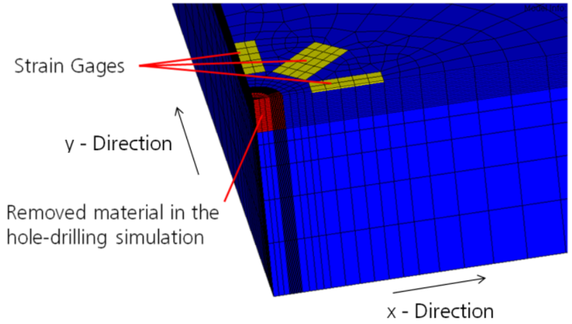
- Digital Image Correlation
  - Evaluate experiments after execution (e. g. tensile tests)
  - Determine material properties (e .g. Youngs modulus)
  - Sub-pixel accuracy
- Statistical methods (centroid)
  - High measurement rate
  - Base for closed-loop strain control

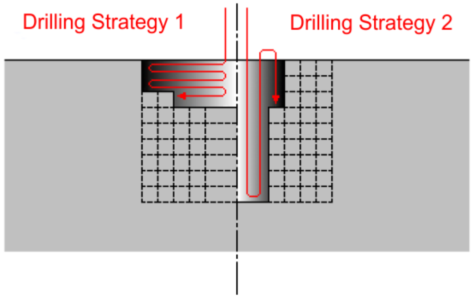


Fraunhofer IWM

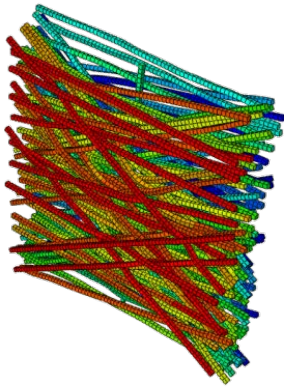
2.1 Parameter optimization in finite element simulations

- Optimization of step sizes in incremental hole drilling



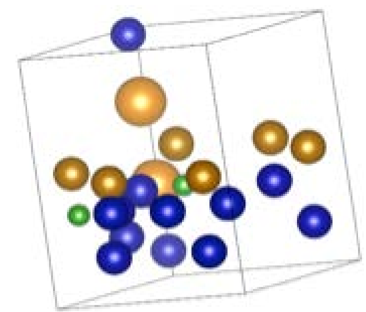


- Optimization of fiber orientations in fiber-reinforced composites

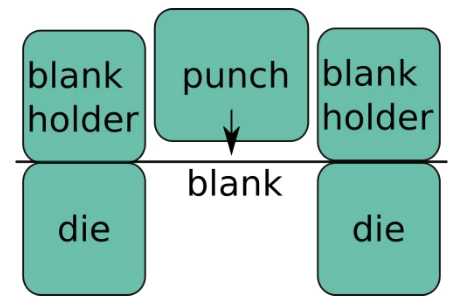


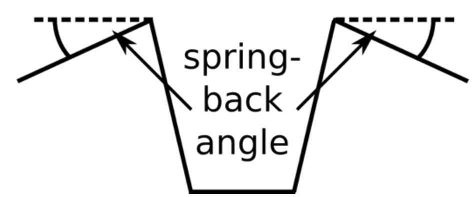
Fraunhofer IWM

1.1 Material and process design



- High-throughput screening
  - Complex parameter optimization problems
  - Find correlations between atomic structure and magnetic properties
- Integrated surrogate modeling approach
  - Design of Experiments (DoE)
  - Surrogate modeling (e.g. Artificial Neural Networks)
  - Parameter optimization w.r.t. desired result (e.g. Genetic Algorithms)
  - Example: mimimize spring-back in draw bending
  - Conventional / sequential DoE





Fraunhofer IWM

Summary and outlook

- Optimization problems in materials processing
  - Time-dependent / time-independent
  - Deterministic / stochastic
- Establish field of „process optimization“at IWM
  - Existing problems / new challenges

Thank you for your attention!

Questions?

Fraunhofer
IWM