

Verbesserung der Vorhersagegenauigkeit des Werkstoffflusses bei der Simulation von kombinierten Fließpressverfahren durch Parameterkalibrierung

Improvement of material flow prediction of combined cold forging processes by parameter calibration

10th Weimar Optimization and Stochastic Days 2013

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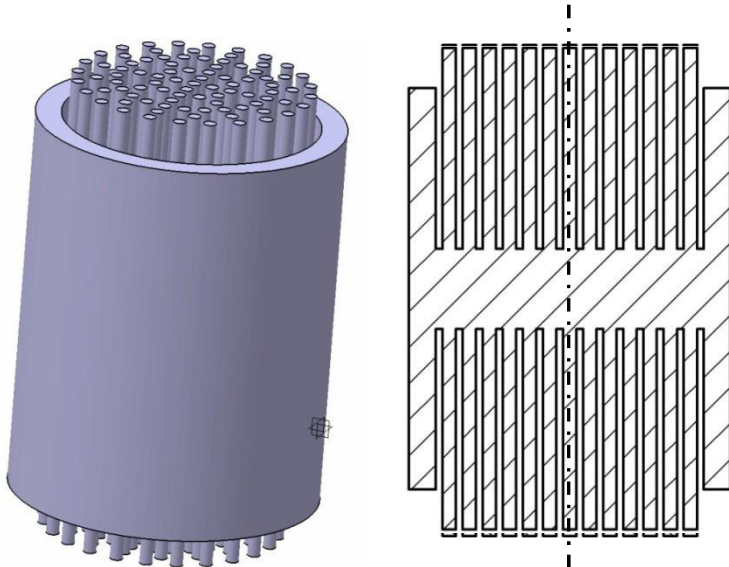
Agenda

- 1** Introduction
- 2** Experiments on backward-rod-backward-cup-extrusion
- 3** Sensitivity analysis of FEA simulations of backward-rod-backward-cup-extrusion
- 4** Inverse parameter calibration of FEA settings and comparison to experimental data
- 5** Conclusions

Introduction

Problem and objective

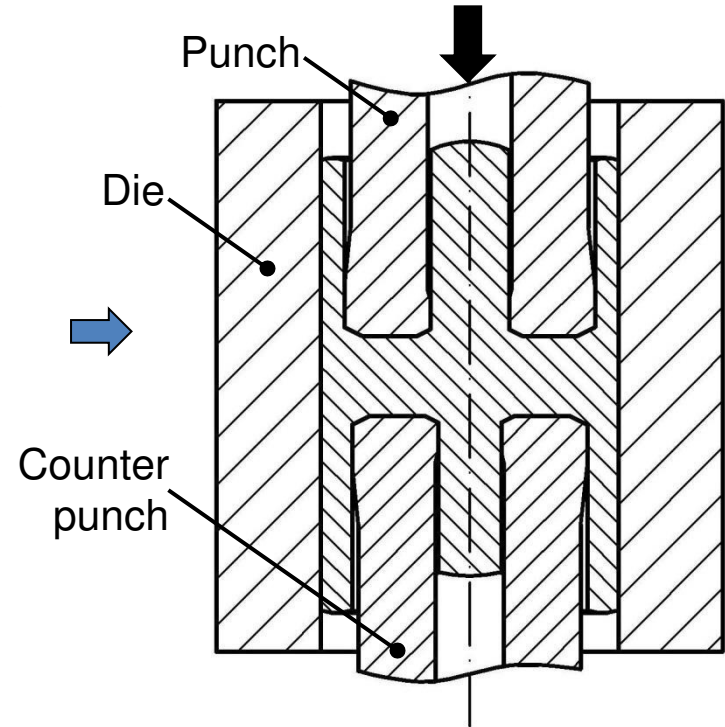
Heat dissipator



Academic part



Cold forging process



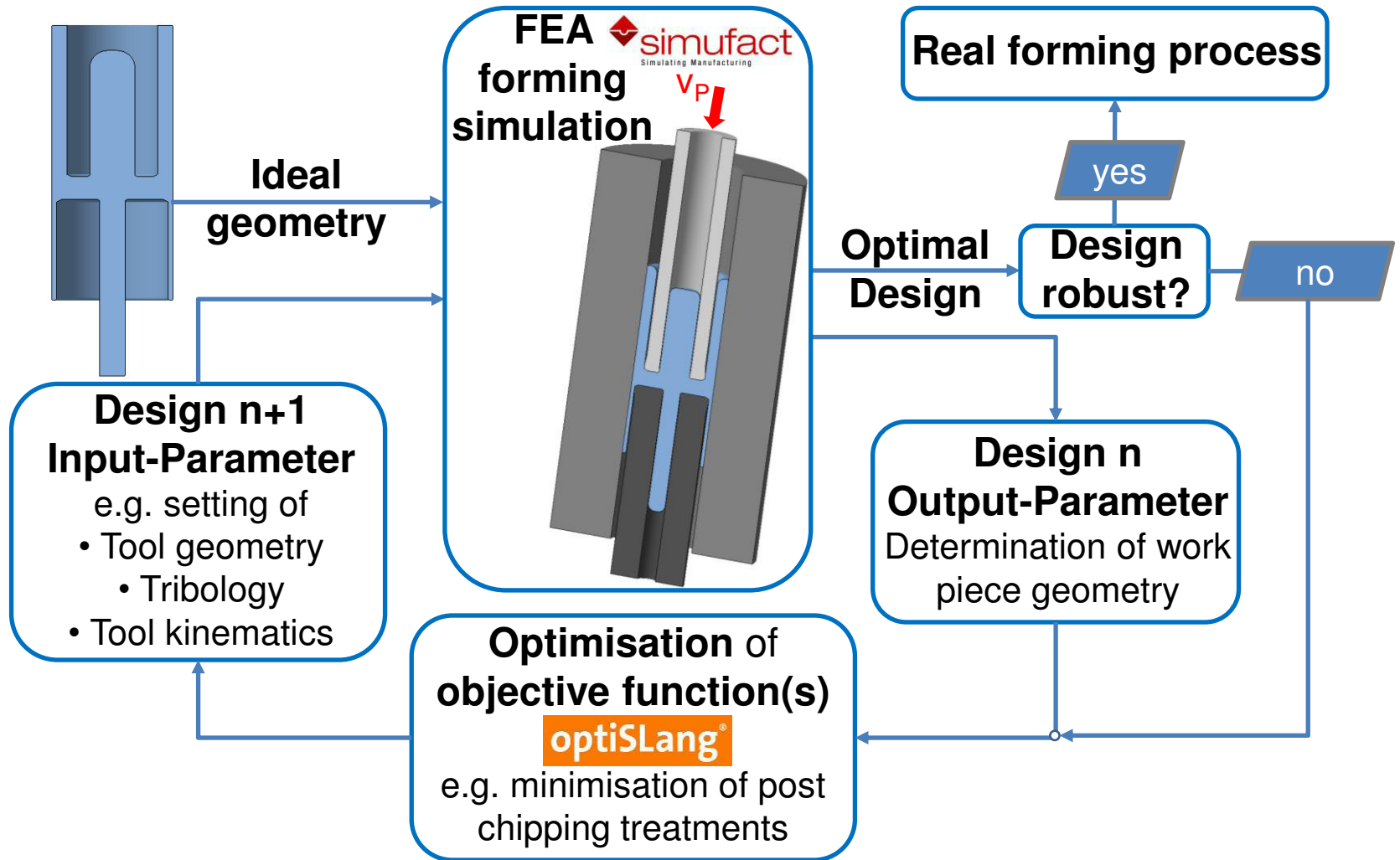
Challenge:

Production of the heat dissipator

- Requirements:**
- Combined cold forging process
 - One forming stage / One stroke
 - No mechanical stops

Introduction

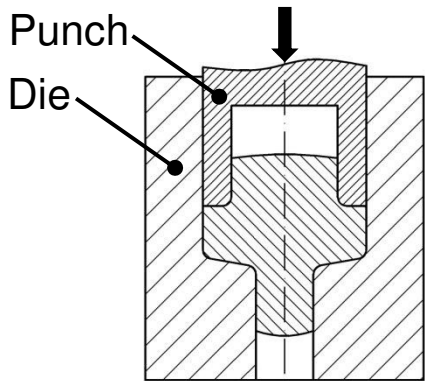
Procedure during automatic process optimisation



Introduction

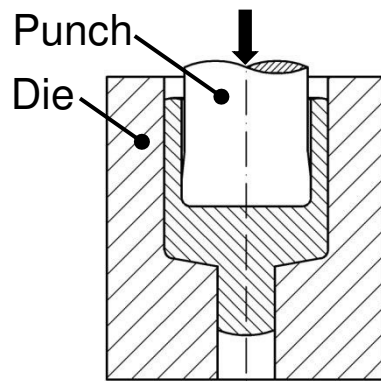
Material flow in combined cold forging processes

Forward-Rod-Backward-Rod-Extrusion



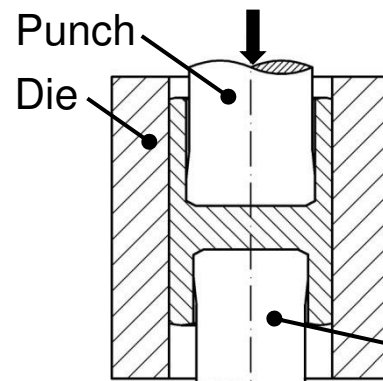
- $\epsilon_{A, BR}$
- Punch radius

Forward-Rod-Backward-Cup-Extrusion



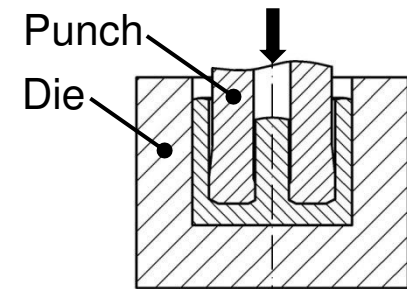
- $\epsilon_{A, FR}$ und $\epsilon_{A, BC}$
- Punch radius
- Die shape
- Material
- Friction

Forward-Cup-Backward-Cup-Extrusion



- $\epsilon_{A, FC}$ und $\epsilon_{A, BC}$
- Punch land lengths
- Punch tip radii
- Punch tip angles
- Billet height
- Material
- Friction
- Press kinematics
- Floating or driven die

Backward-Rod-Backward-Cup-Extrusion



- Material
- Friction

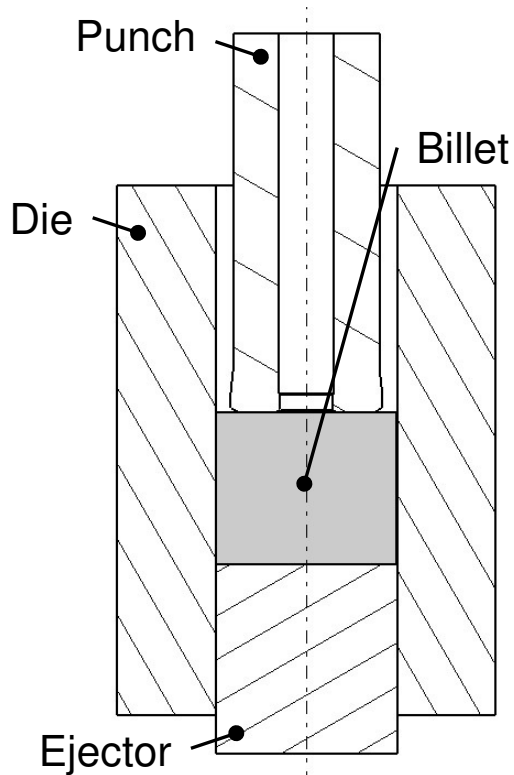
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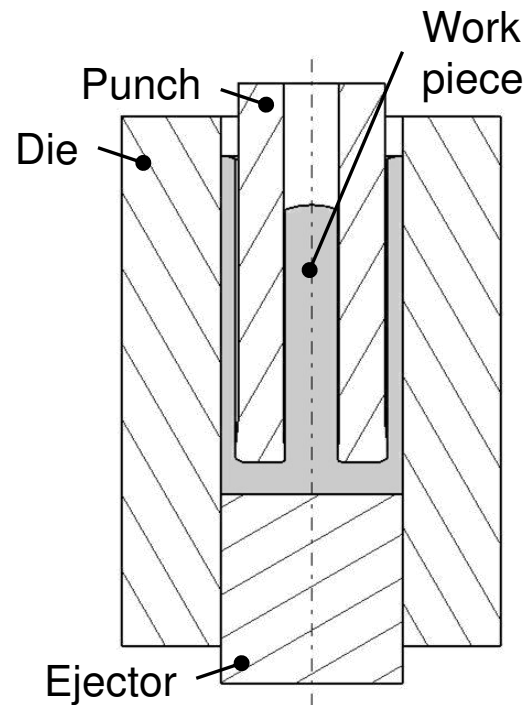
Experiments on backward-rod-backward-cup-extrusion

Process steps

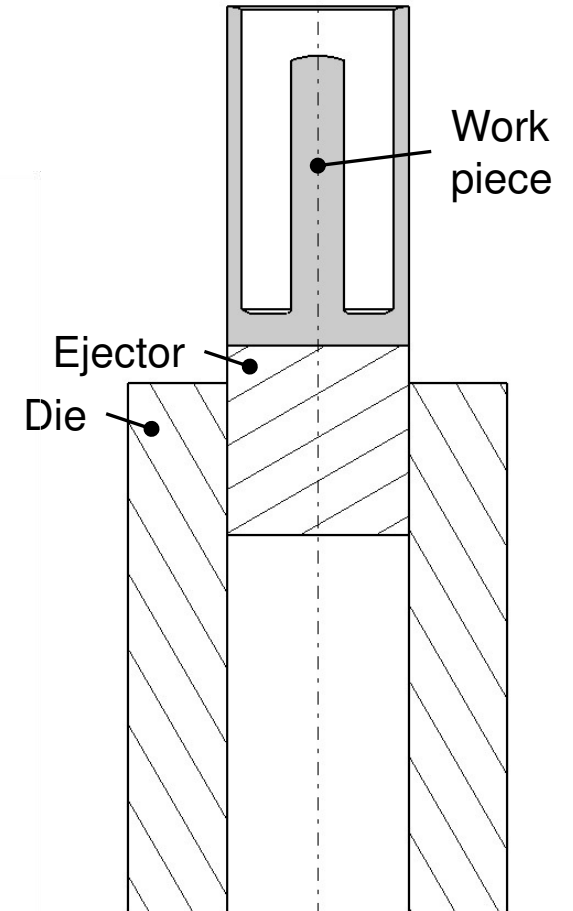
1) Loading



2) Forging



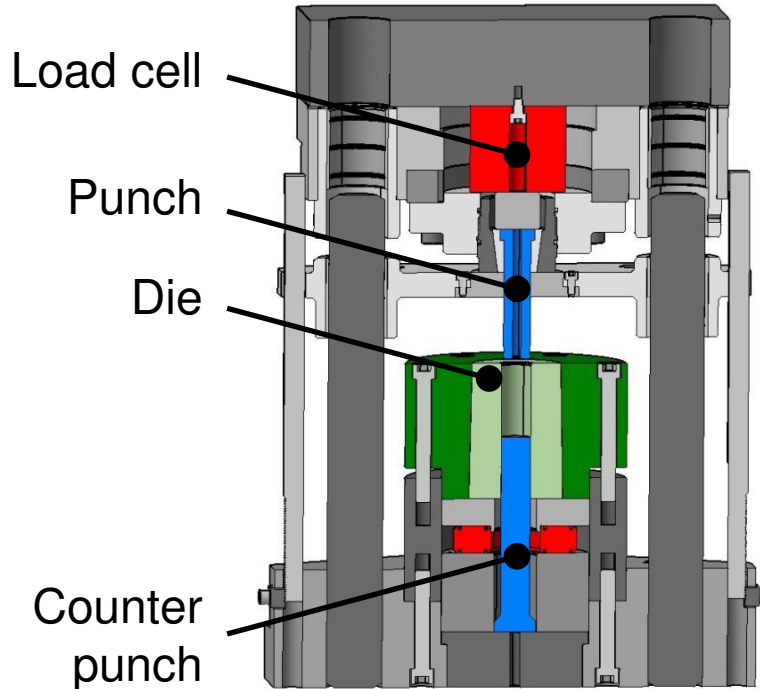
3) Ejecting



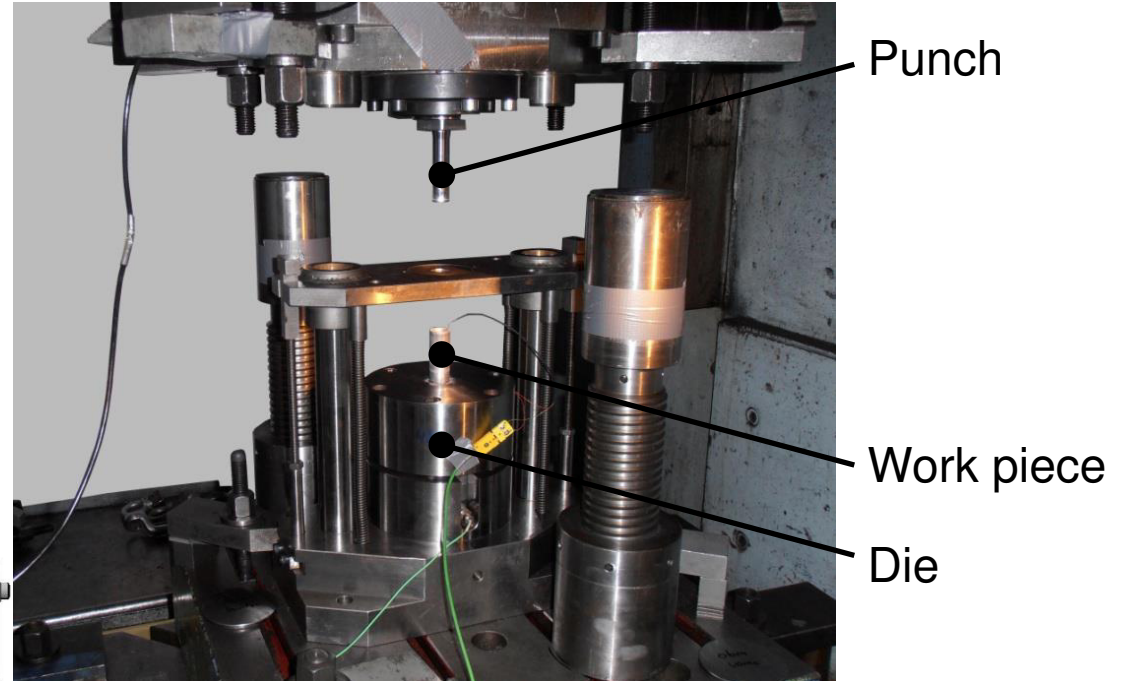
Experiments on backward-rod-backward-cup-extrusion

Test tool setup

Tool scheme

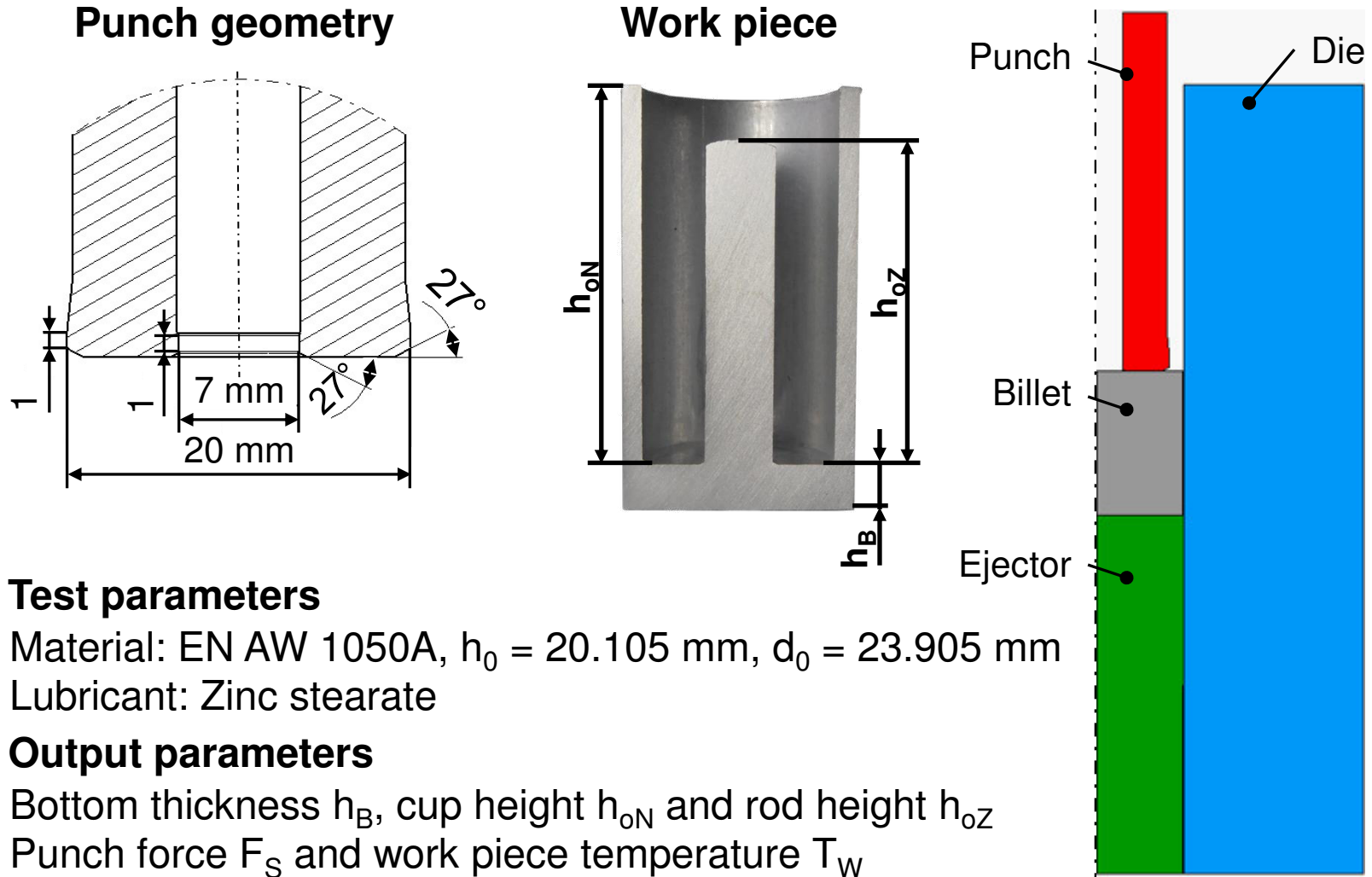


Assembled in 6.000 kN hydraulic press



Experiments on backward-rod-backward-cup-extrusion

Test parameters and output parameters



Test parameters

- Material: EN AW 1050A, $h_0 = 20.105$ mm, $d_0 = 23.905$ mm
- Lubricant: Zinc stearate

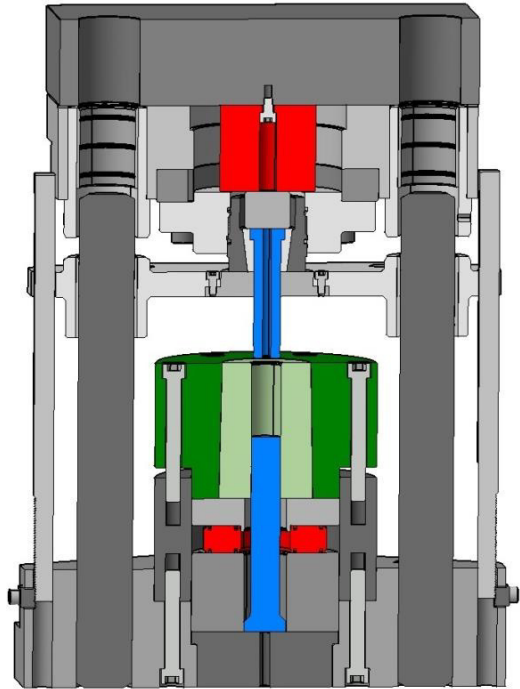
Output parameters

- Bottom thickness h_B , cup height h_{oN} and rod height h_{oZ}
- Punch force F_S and work piece temperature T_W

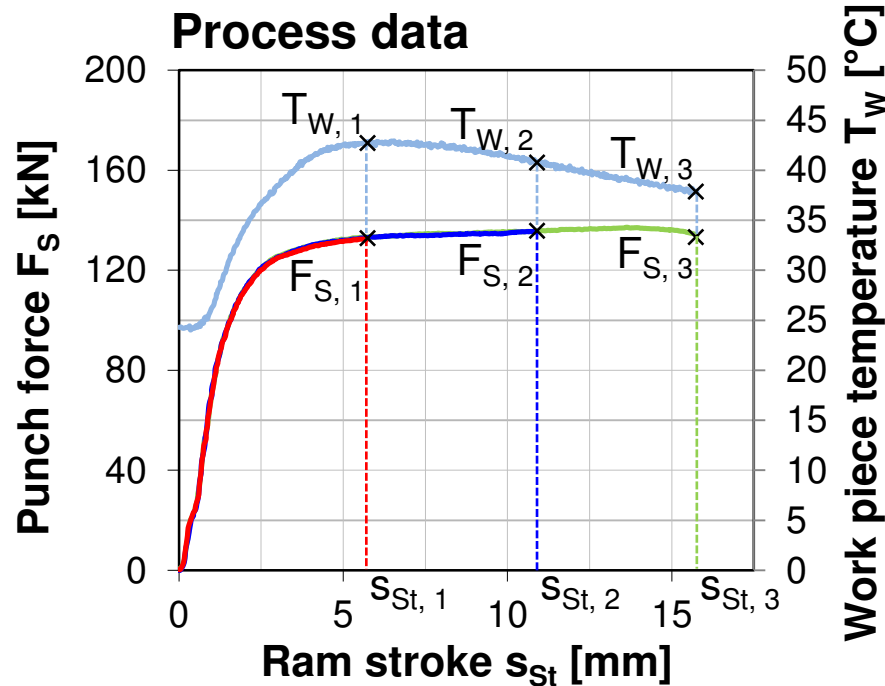
Experiments on backward-rod-backward-cup-extrusion

Experimental data

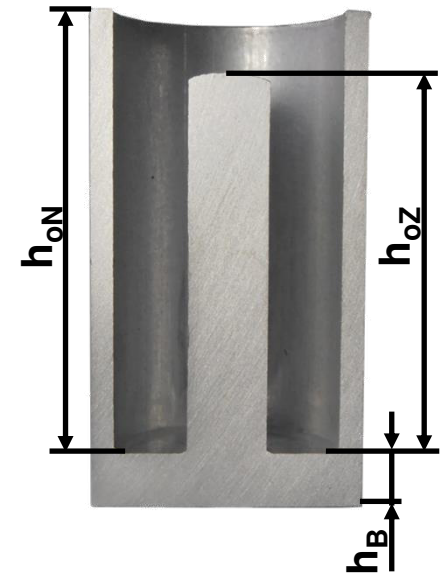
Tool scheme



Process data



Work piece

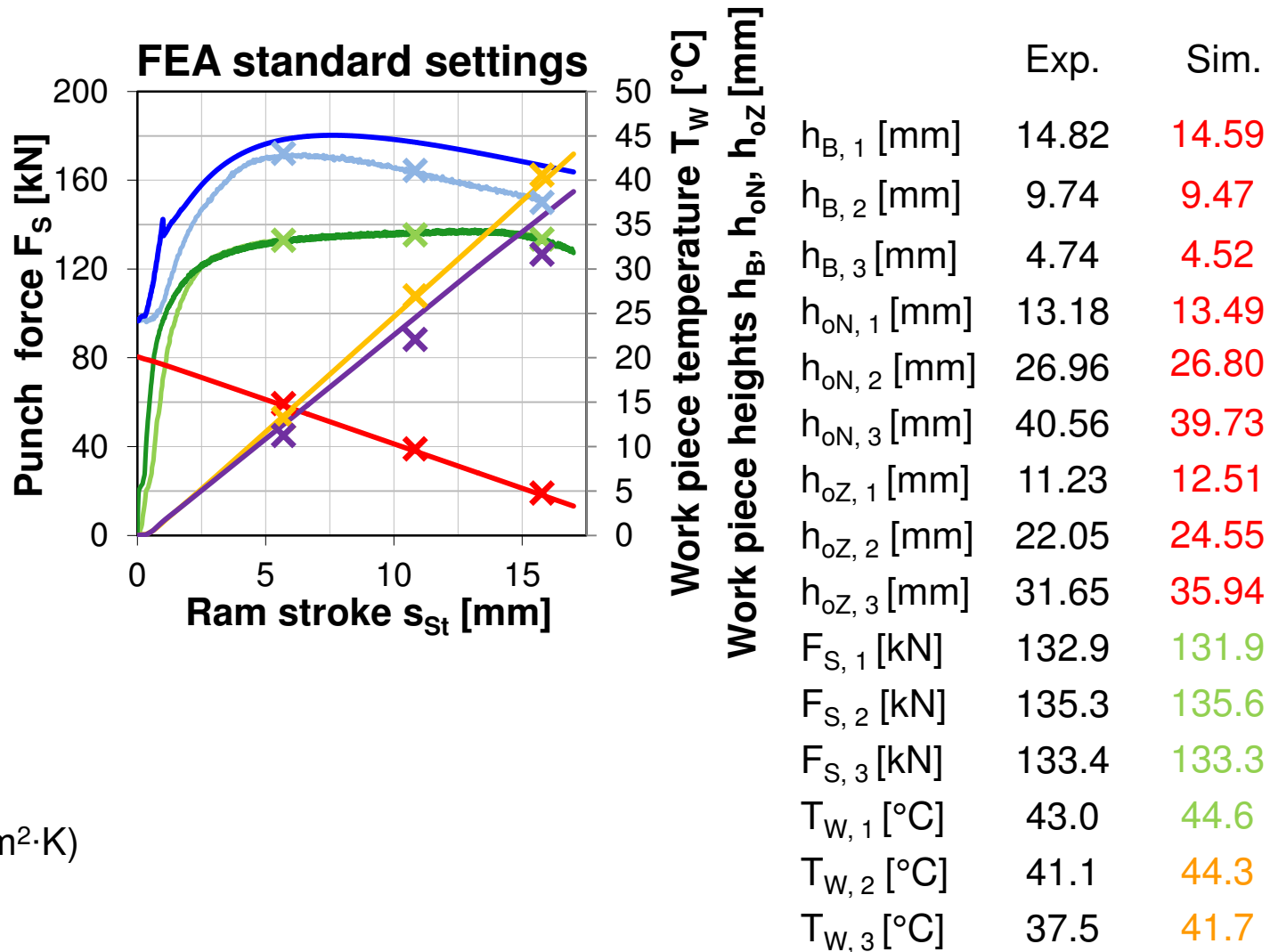


$$s_{St,1} [\text{mm}] = 5.71 \quad s_{St,2} [\text{mm}] = 10.84 \quad s_{St,3} [\text{mm}] = 15.78$$

$h_{B,1} [\text{mm}] = 14.82$	$h_{oN,1} [\text{mm}] = 13.18$	$h_{oZ,1} [\text{mm}] = 11.23$	$F_{S,1} [\text{kN}] = 132.9$	$T_{W,1} [^{\circ}\text{C}] = 43.0$
$h_{B,2} [\text{mm}] = 9.74$	$h_{oN,2} [\text{mm}] = 26.96$	$h_{oZ,2} [\text{mm}] = 22.05$	$F_{S,2} [\text{kN}] = 135.3$	$T_{W,2} [^{\circ}\text{C}] = 41.1$
$h_{B,3} [\text{mm}] = 4.74$	$h_{oN,3} [\text{mm}] = 40.56$	$h_{oZ,3} [\text{mm}] = 31.65$	$F_{S,3} [\text{kN}] = 133.4$	$T_{W,3} [^{\circ}\text{C}] = 37.5$
with $\Delta h_B = 0.1 \text{ mm}$	with $\Delta h_{oN} = 0.1 \text{ mm}$	with $\Delta h_{oZ} = 0.1 \text{ mm}$	with $\Delta F_S = 5 \text{ kN}$	with $\Delta T_W = 3 \text{ }^{\circ}\text{C}$

Experiments on backward-rod-backward-cup-extrusion

Experiments vs. FEA simulation



$D = \infty$ N/mm
 $\mu = 0.03$
 $m = 0.18$
 $\alpha = 20000$ W/(m²·K)
 $V = 0.750$

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Sensitivity analysis of FEA simulations

Way of procedure

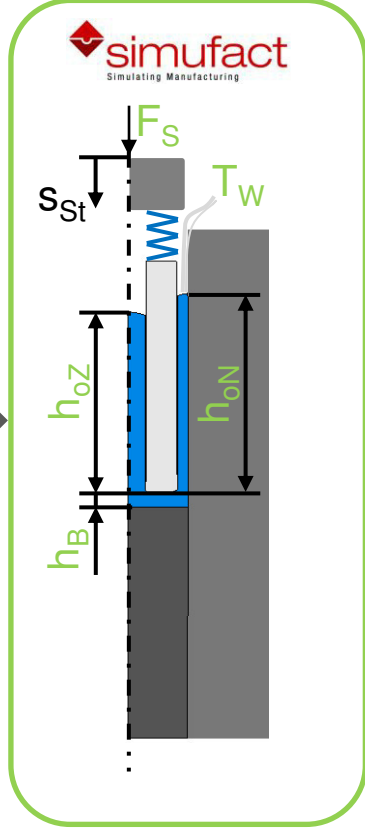
Stiffness \mathbb{W}
 $D = 200000 \text{ N/mm}$
 $D = 700000 \text{ N/mm}$

Friction
 T_R
 $m = 0$
 $\mu = 0.001$
 σ_N

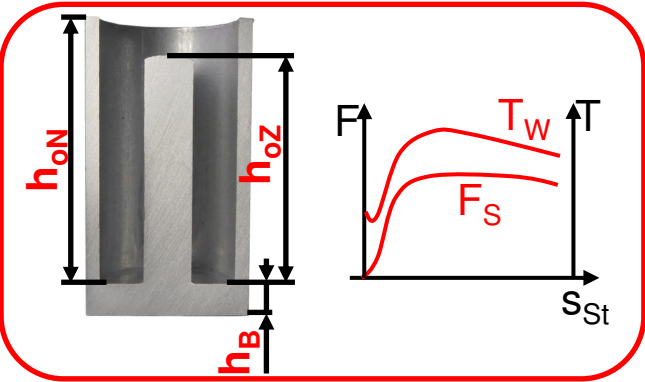
Dissipation  $v = 0.5$
 $\alpha = 20000 \text{ W/(m}^2\cdot\text{K)}$
 $\alpha = 80000 \text{ W/(m}^2\cdot\text{K)}$

Heat transfer
 \dot{Q}
 T_1 A T_0

Parameter



Sensitivity analysis (DOE and MOP)



Forming experiments

$h_{B,i}$ $h_{oN,i}$ $h_{oZ,i}$ $F_{S,i}$ $T_{w,i}$

$h_B = f(s_{St})$
 $h_{oN} = f(s_{St})$
 $h_{oZ} = f(s_{St})$
 $F_S = f(s_{St})$
 $T_w = f(s_{St})$

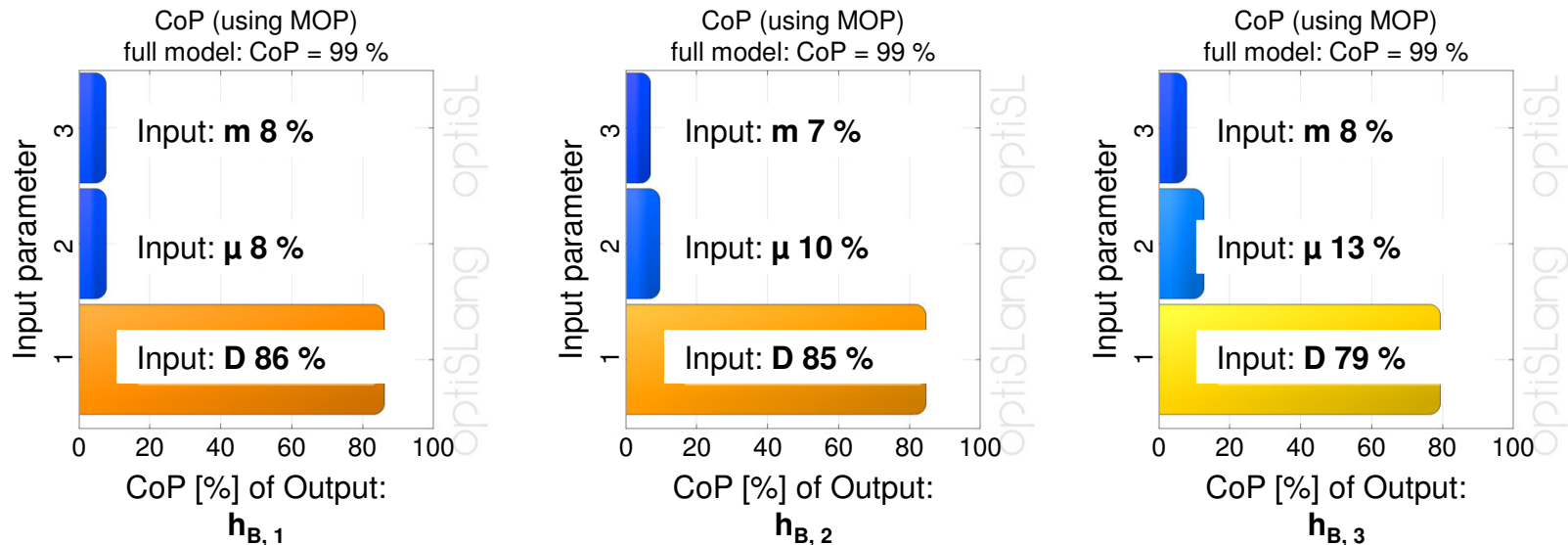
Target function(s)

Inverse parameter calibration (MOP and FEA)

Sensitivity analysis of FEA simulations

MOP results: Work piece bottom thickness

MOP settings: 5 input parameters, 77 support points, 39 test points, Δ CoP = 0.03

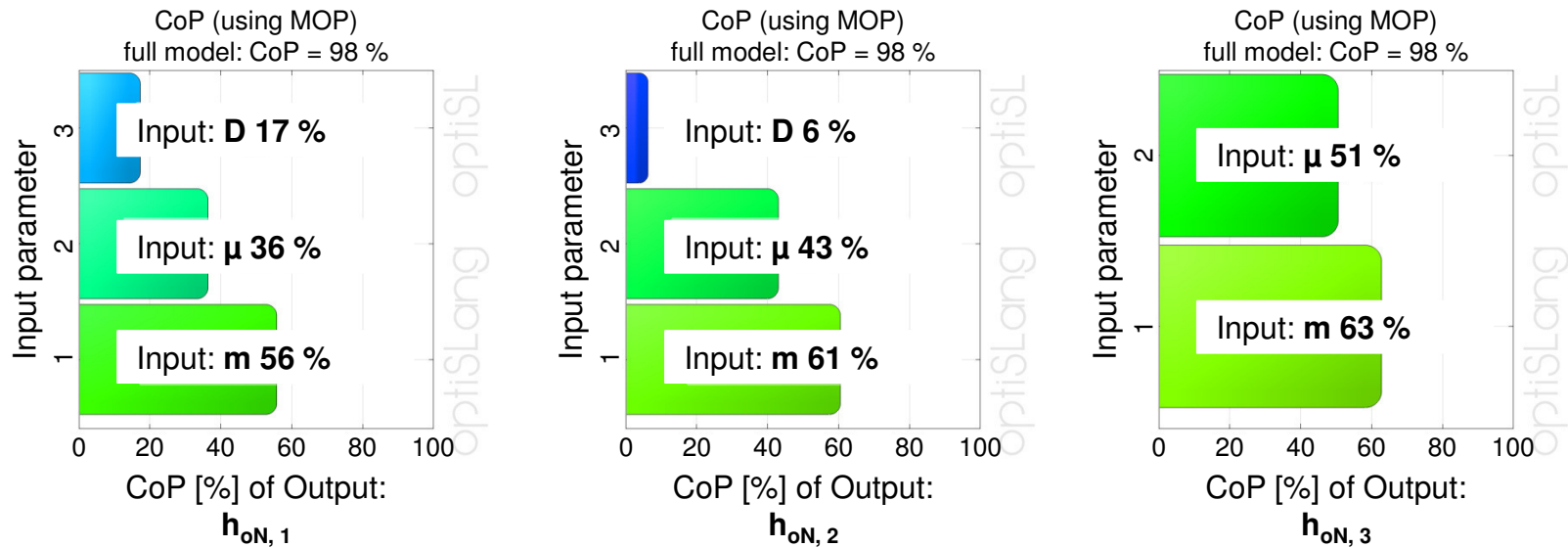


- Work piece bottom thickness $h_{B,i}$ depends mainly on the press and tool stiffness D
- $h_{B,i}$ depends also on the friction parameters μ and m
- Very good Coefficients of Prognosis
- Strong correlation between $h_{B,1}$, $h_{B,2}$ and $h_{B,3}$

Sensitivity analysis of FEA simulations

MOP results: Cup height

MOP settings: 5 input parameters, 77 support points, 39 test points, Δ CoP = 0.03

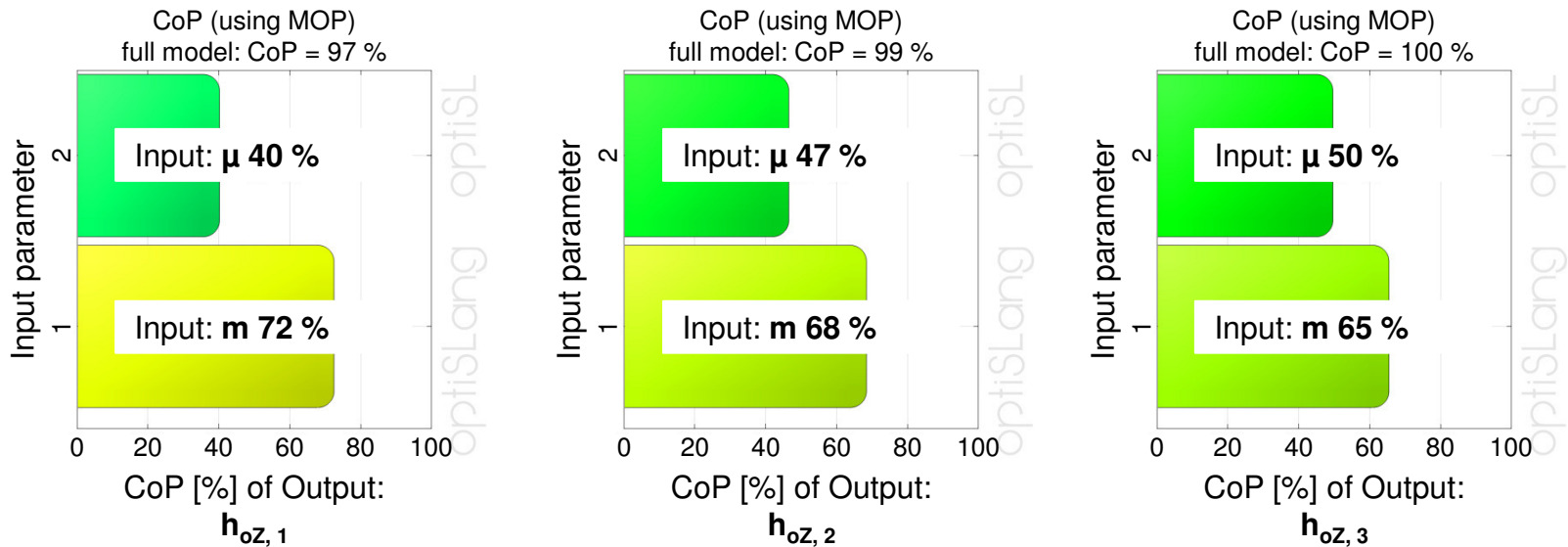


- Cup height $h_{oN,i}$ depends mainly on the friction parameters μ and m
- $h_{oN,1}$ and $h_{oN,2}$ depends also on the press and tool stiffness D
- Very good Coefficients of Prognosis
- Strong correlation between $h_{oN,1}$, $h_{oN,2}$ and $h_{oN,3}$

Sensitivity analysis of FEA simulations

MOP results: Rod height

MOP settings: 5 input parameters, 77 support points, 39 test points, Δ CoP = 0.03

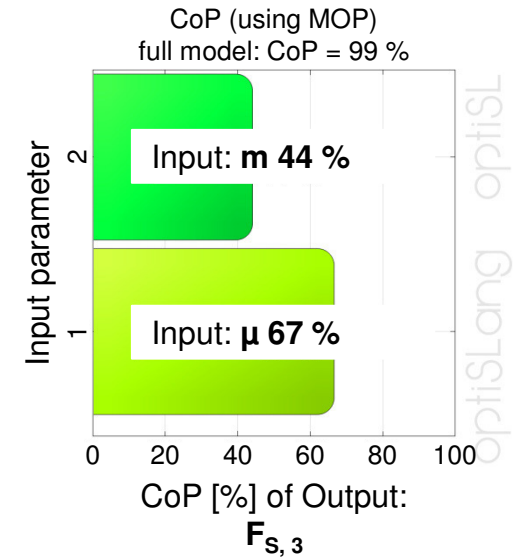
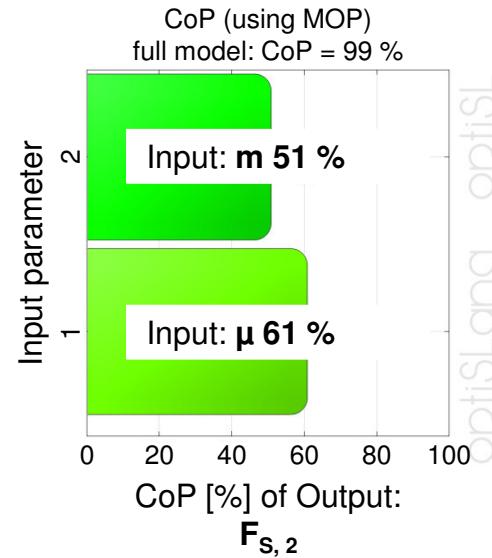
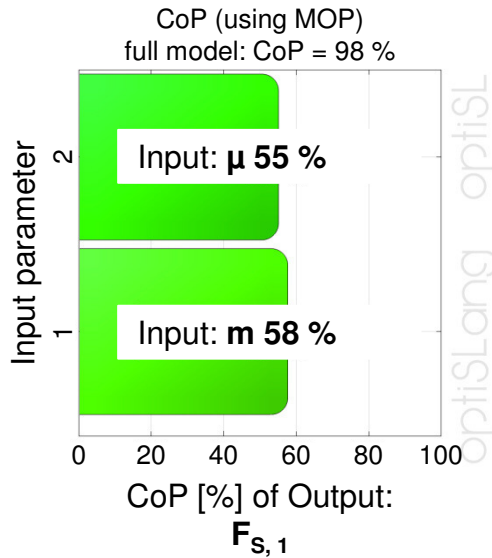


- Rod height $h_{oz,i}$ depends on the friction parameters μ and m
- Very good Coefficients of Prognosis
- Strong correlation between $h_{oz,1}$, $h_{oz,2}$ and $h_{oz,3}$

Sensitivity analysis of FEA simulations

MOP results: Punch force

MOP settings: 5 input parameters, 77 support points, 39 test points, Δ CoP = 0.03

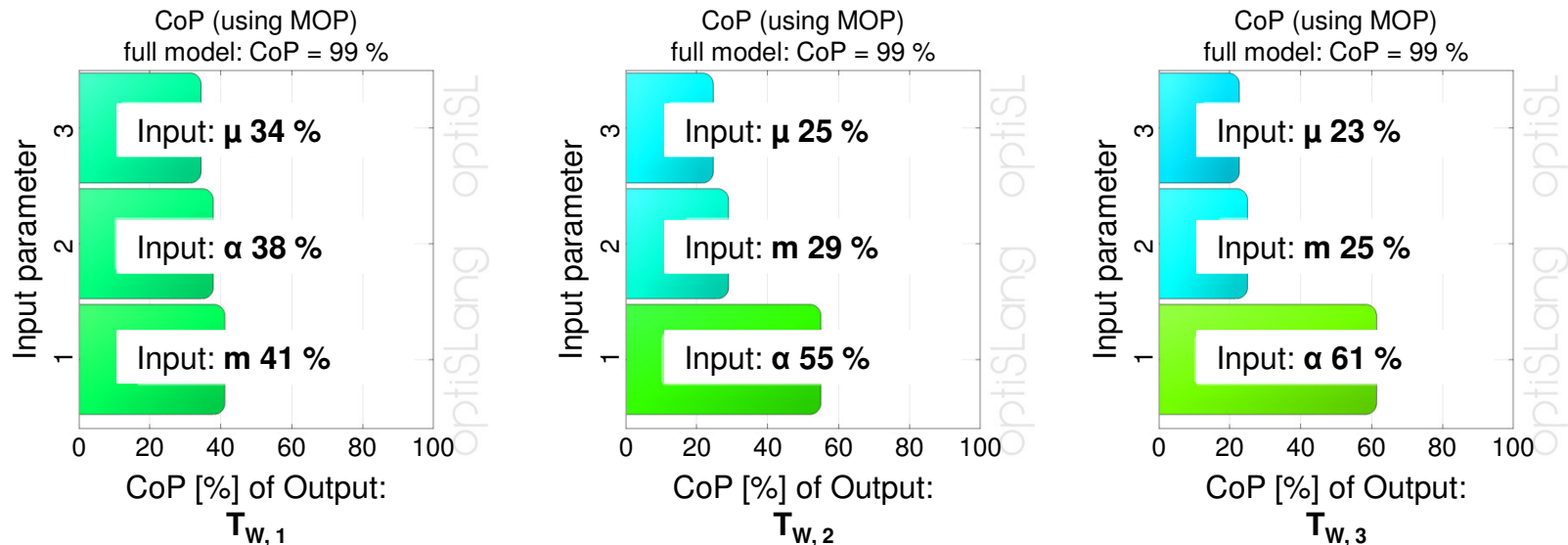


- Punch force $F_{S,i}$ depends on the friction parameters μ and m
- Very good Coefficients of Prognosis
- Strong correlation between $F_{S,1}$, $F_{S,2}$ and $F_{S,3}$

Sensitivity analysis of FEA simulations

MOP results: Work piece temperature

MOP settings: 5 input parameters, 77 support points, 39 test points, Δ CoP = 0.03



- Work piece temperature $T_{w,i}$ depends on the heat transfer coefficients α and friction parameters μ and m
- Very good Coefficients of Prognosis
- Strong correlation between $T_{w,1}$, $T_{w,2}$ and $T_{w,3}$

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- 5** Conclusions

Inverse parameter calibration of FEA settings

Way of procedure

Stiffness \mathbb{W}
 $D = 350000 \text{ N/mm}$
 700000 N/mm

Friction

 $m = 0.2$
 $\mu = 0.001$

Dissipation
 $v = 0.5$
 1

Heat transfer
 $\alpha = 20000 \text{ W/(m}^2 \cdot \text{K)}$
 $80000 \text{ W/(m}^2 \cdot \text{K)}$

Parameter

simufact
 Simulating Manufacturing

Sensitivity analysis (DOE and MOP)

Forming experiments

$h_{B,i}$ $h_{oN,i}$ $h_{oZ,i}$ $F_{S,i}$ $T_{W,i}$

$h_B = f(s_{St})$
 $h_{oN} = f(s_{St})$
 $h_{oZ} = f(s_{St})$
 $F_S = f(s_{St})$
 $T_W = f(s_{St})$

Target function(s)

Inverse parameter calibration (MOP and FEA)

Inverse parameter calibration of FEA settings

Objective functions

Bottom thickness failure: $Err_{h_B} = \frac{1}{3} \cdot \sum_{i=1}^3 \left(\frac{h_{B,i \text{ exp}} - h_{B,i \text{ sim}}}{0.1 \text{ mm}} \right)^2$ with $\Delta h_B = 0.1 \text{ mm}$

Material flow failure: $Err_{h_{oN}} = \frac{1}{3} \cdot \sum_{i=1}^3 \left(\frac{h_{oN,i \text{ exp}} - h_{oN,i \text{ sim}}}{0.1 \text{ mm}} \right)^2$ with $\Delta h_{oN} = 0.1 \text{ mm}$

Material flow failure: $Err_{h_{oZ}} = \frac{1}{3} \cdot \sum_{i=1}^3 \left(\frac{h_{oZ,i \text{ exp}} - h_{oZ,i \text{ sim}}}{0.1 \text{ mm}} \right)^2$ with $\Delta h_{oZ} = 0.1 \text{ mm}$

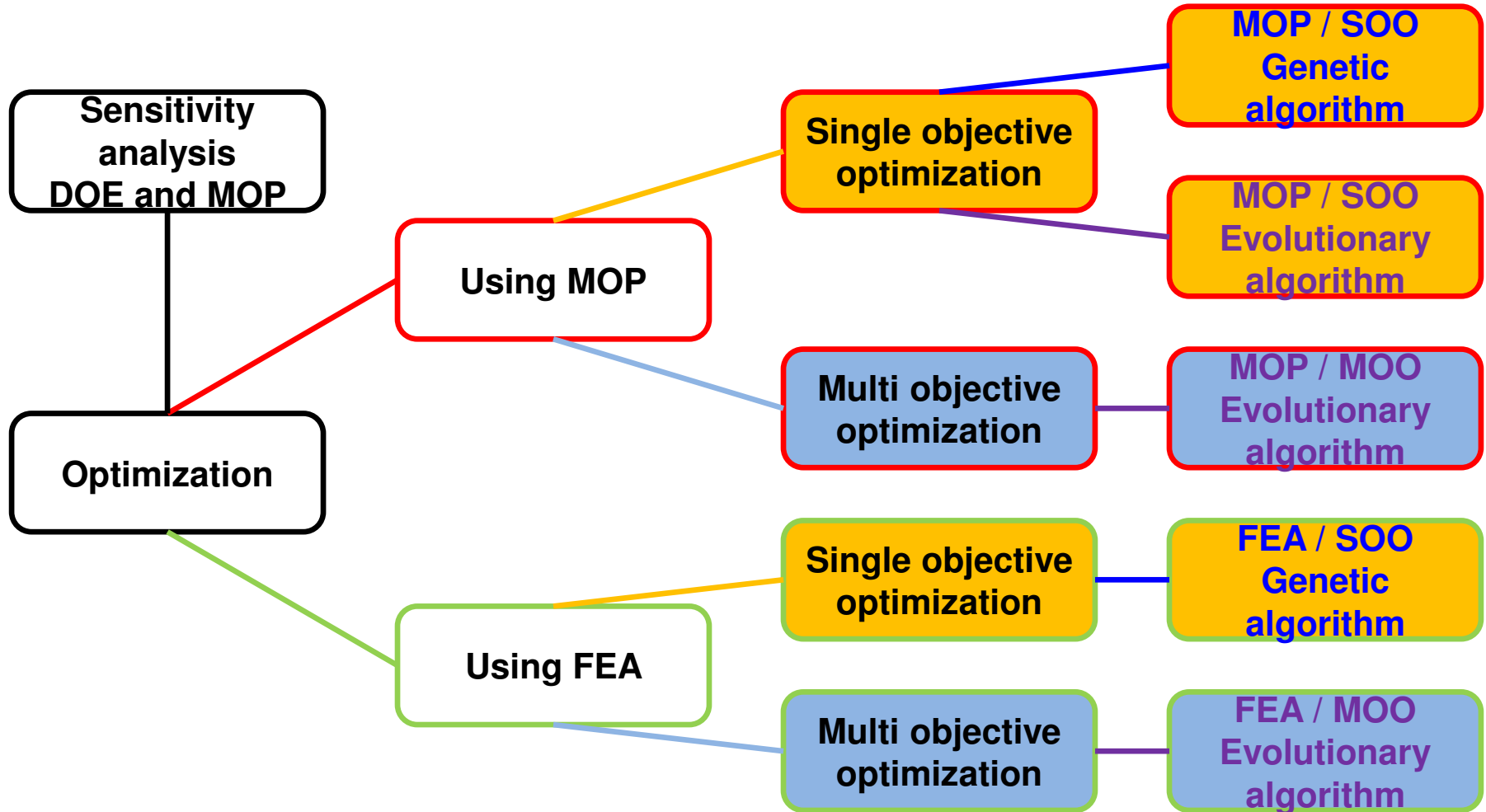
Force failure: $Err_{F_S} = \frac{1}{3} \cdot \sum_{i=1}^3 \left(\frac{F_{S,i \text{ exp}} - F_{S,i \text{ sim}}}{5 \text{ kN}} \right)^2$ with $\Delta F_S = 5 \text{ kN}$

Temperature failure: $Err_{T_W} = \frac{1}{3} \cdot \sum_{i=1}^3 \left(\frac{T_{i \text{ exp}} - T_{i \text{ sim}}}{3 \text{ }^\circ\text{C}} \right)^2$ with $\Delta T_W = 3 \text{ }^\circ\text{C}$

Failure sum: $Err = Err_{h_B} + Err_{h_{oN}} + Err_{h_{oZ}} + Err_{F_S} + Err_{T_W}$

Inverse parameter calibration of FEA settings

Conducted variants



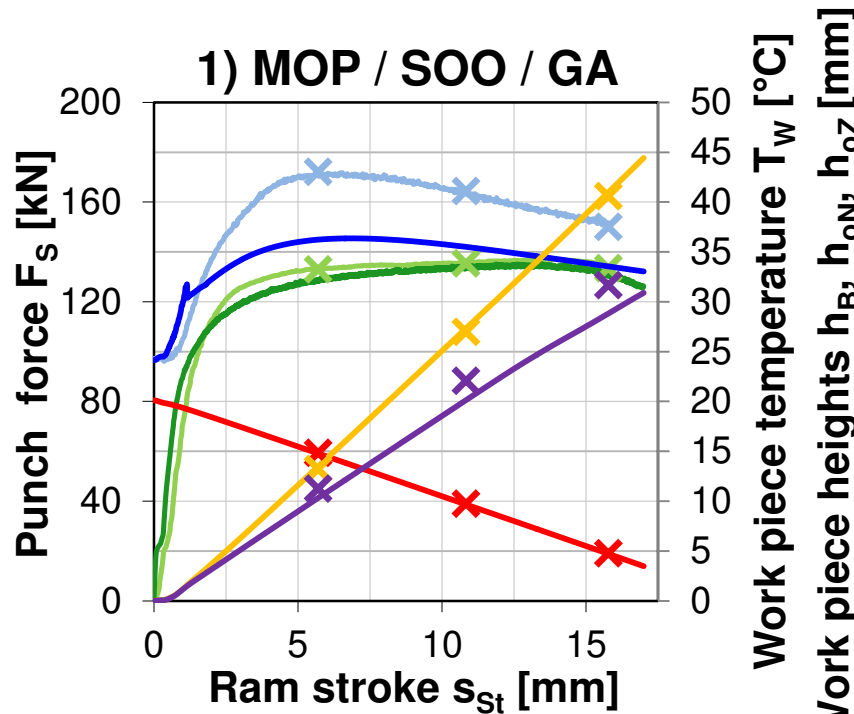
Inverse parameter calibration of FEA settings

Input parameters after calibration runs

	D [N/mm]	μ [-]	m [-]	α [W/(m²·K)]	V [-]	Err [-]
MOP / SOO Genetic algorithm	684060	0.001	0.118	25894	0.5	3.73
MOP / SOO Evolutionary algorithm	684420	0.001	0.119	26878	0.5	3.73
MOP / MOO Evolutionary algorithm	547670	0.006	0.042	34749	0.791	38.66
FEA / SOO Genetic algorithm	640890	0.023	0.040	68257	0.738	9.27
FEA / MOO Evolutionary algorithm	593550	0.022	0.053	29368	0.587	26.89

Inverse parameter calibration of FEA settings

MOP / Single objective optimization / Genetic algorithm



Exp. Sim.

h_B × —

h_{oN} × —

h_{oZ} × —

F_S × —

T_W × —

	Exp.	Opt.	Sim.
$h_{B,1}$ [mm]	14.82	14.76	14.77
$h_{B,2}$ [mm]	9.74	9.63	9.66
$h_{B,3}$ [mm]	4.74	4.68	4.71
$h_{oN,1}$ [mm]	13.18	13.32	13.50
$h_{oN,2}$ [mm]	26.96	26.98	27.35
$h_{oN,3}$ [mm]	40.56	40.38	41.00
$h_{oZ,1}$ [mm]	11.23	11.21	10.34
$h_{oZ,2}$ [mm]	22.05	21.96	20.14
$h_{oZ,3}$ [mm]	31.65	31.68	28.83
$F_{S,1}$ [kN]	132.9	128.2	128.1
$F_{S,2}$ [kN]	135.3	131.5	133.6
$F_{S,3}$ [kN]	133.4	128.2	130.3
$T_{W,1}$ [°C]	43.0	42.4	36.2
$T_{W,2}$ [°C]	41.1	41.1	35.5
$T_{W,3}$ [°C]	37.5	38.1	33.5

$D = 684060 \text{ N/mm}$

$\mu = 0.001$

$m = 0.118$

$\alpha = 25894 \text{ W/(m}^2\cdot\text{K)}$

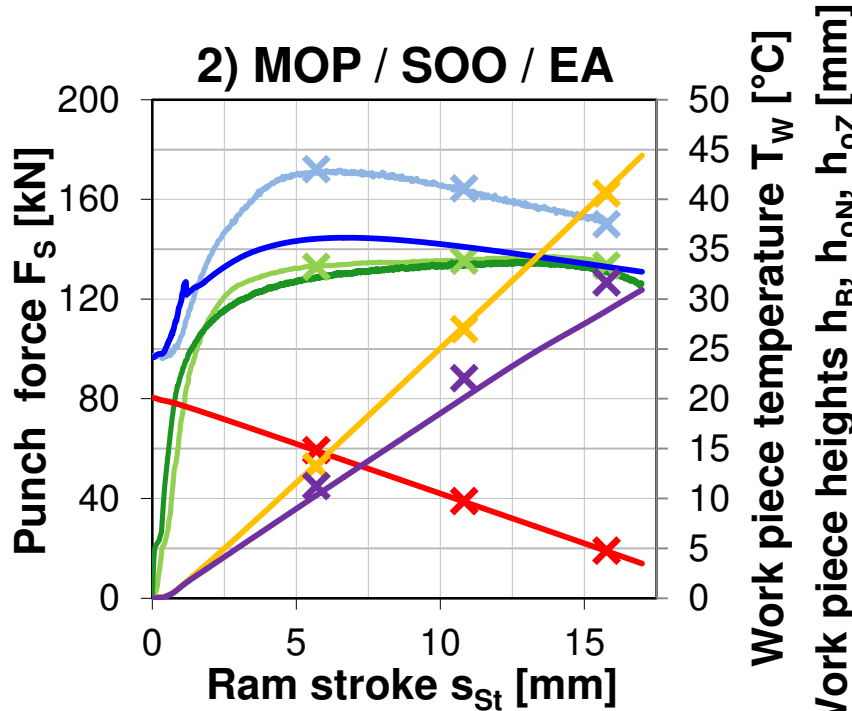
$V = 0.500$

	Opt.	Sim.
Err_{h_B}	0.84	0.34
$\text{Err}_{h_{oN}}$	1.71	14.86
$\text{Err}_{h_{oZ}}$	0.30	412.88
Err_{F_S}	0.85	0.48
Err_{T_W}	0.03	3.44
Err	= 3.73	= 432.00

Inverse parameter calibration of FEA settings

MOP / Single objective optimization / Evolutionary algorithm

	Exp.	Sim.
h_B	✗	—
h_{oN}	✕	—
h_{oZ}	✕	—
F_S	✕	—
T_W	✕	—



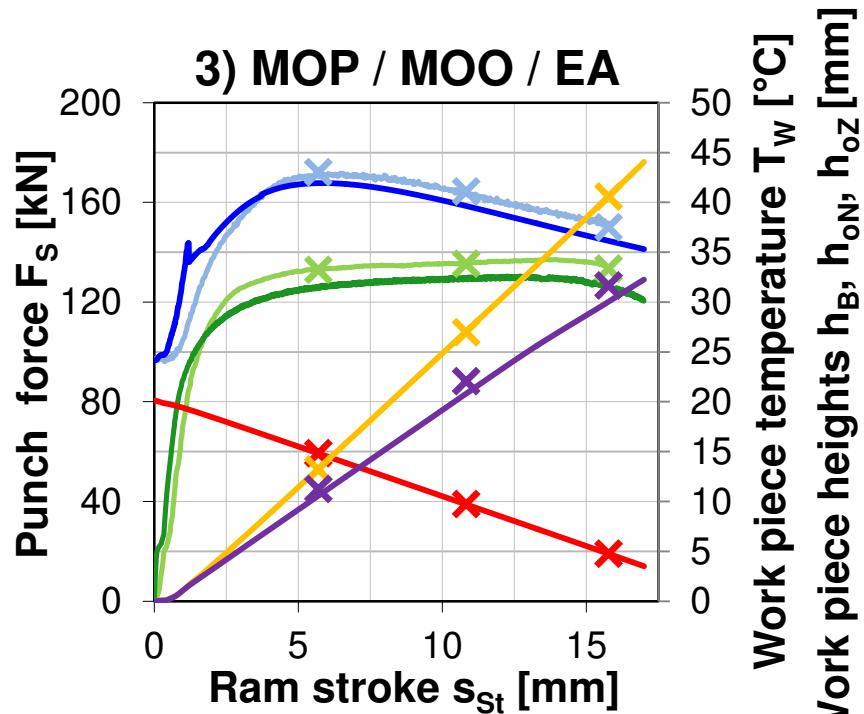
$D = 684420 \text{ N/mm}$
 $\mu = 0.001$
 $m = 0.119$
 $\alpha = 26878 \text{ W/(m}^2\cdot\text{K)}$
 $V = 0.500$

	Opt.	Sim.
Err_{h_B}	= 0.84	= 0.33
$Err_{h_{oN}}$	= 1.72	= 13.34
$Err_{h_{oZ}}$	= 0.30	= 412.51
Err_{F_S}	= 0.84	= 0.38
Err_{T_W}	= 0.03	= 3.74
Err	= 3.73	= 430.30

	Exp.	Opt.	Sim.
$h_{B,1}$ [mm]	14.82	14.76	14.77
$h_{B,2}$ [mm]	9.74	9.63	9.66
$h_{B,3}$ [mm]	4.74	4.68	4.71
$h_{oN,1}$ [mm]	13.18	13.32	13.50
$h_{oN,2}$ [mm]	26.96	26.98	27.35
$h_{oN,3}$ [mm]	40.56	40.38	41.00
$h_{oZ,1}$ [mm]	11.23	11.21	10.34
$h_{oZ,2}$ [mm]	22.05	21.96	20.14
$h_{oZ,3}$ [mm]	31.65	31.68	28.83
$F_{S,1}$ [kN]	132.9	128.2	128.1
$F_{S,2}$ [kN]	135.3	131.5	133.6
$F_{S,3}$ [kN]	133.4	128.2	130.3
$T_{W,1}$ [°C]	43.0	42.3	36.2
$T_{W,2}$ [°C]	41.1	41.0	35.5
$T_{W,3}$ [°C]	37.5	38.0	33.5

Inverse parameter calibration of FEA settings

MOP / Multi objective optimization / Evolutionary algorithm



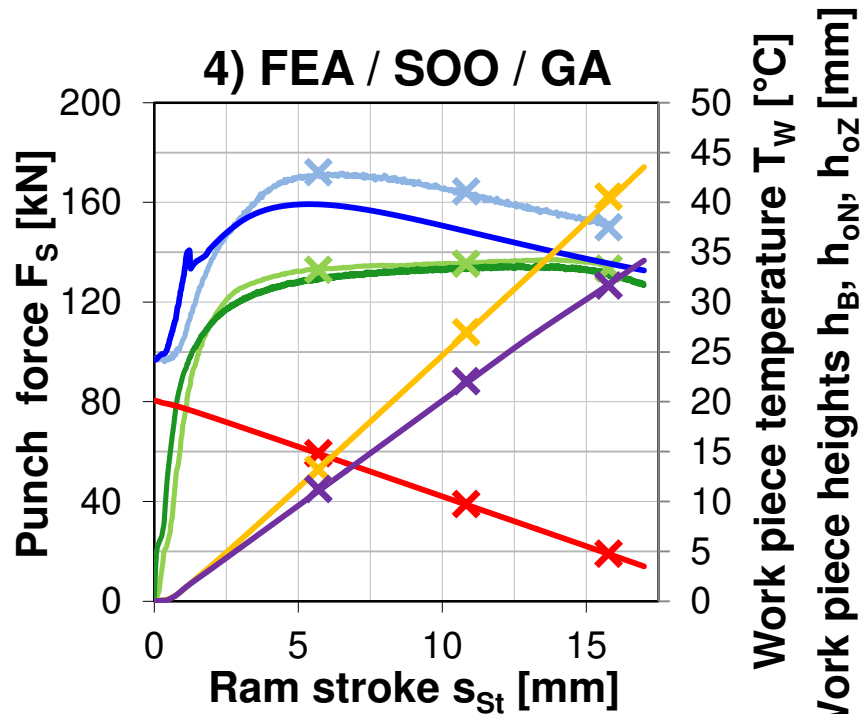
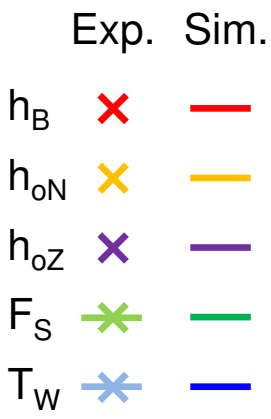
$D = 547670 \text{ N/mm}$
 $\mu = 0.006$
 $m = 0.042$
 $\alpha = 34749 \text{ W/(m}^2\cdot\text{K)}$
 $V = 0.791$

	Opt.	Sim.
Err_{h_B}	0.29	0.08
$Err_{h_{oN}}$	17.62	1.60
$Err_{h_{oZ}}$	20.64	146.93
Err_{F_s}	0.07	1.84
Err_{T_w}	0.04	0.19
Err	= 38.66	= 150.64

	Exp.	Opt.	Sim.
$h_{B,1}$ [mm]	14.82	14.83	14.81
$h_{B,2}$ [mm]	9.74	9.71	9.69
$h_{B,3}$ [mm]	4.74	4.77	4.74
$h_{oN,1}$ [mm]	13.18	13.07	13.32
$h_{oN,2}$ [mm]	26.96	26.55	27.10
$h_{oN,3}$ [mm]	40.56	39.89	40.64
$h_{oZ,1}$ [mm]	11.23	10.95	10.60
$h_{oZ,2}$ [mm]	22.05	21.94	20.84
$h_{oZ,3}$ [mm]	31.65	32.32	30.06
$F_{S,1}$ [kN]	132.9	130.6	125.6
$F_{S,2}$ [kN]	135.3	135.3	129.9
$F_{S,3}$ [kN]	133.4	133.4	126.0
$T_{w,1}$ [°C]	43.0	42.6	41.9
$T_{w,2}$ [°C]	41.1	41.3	39.6
$T_{w,3}$ [°C]	37.5	38.3	36.1

Inverse parameter calibration of FEA settings

FEA / Single objective optimization / Genetic algorithm



$D = 640890 \text{ N/mm}$
 $\mu = 0.023$
 $m = 0.040$
 $\alpha = 68257 \text{ W/(m}^2\cdot\text{K)}$
 $V = 0.738$

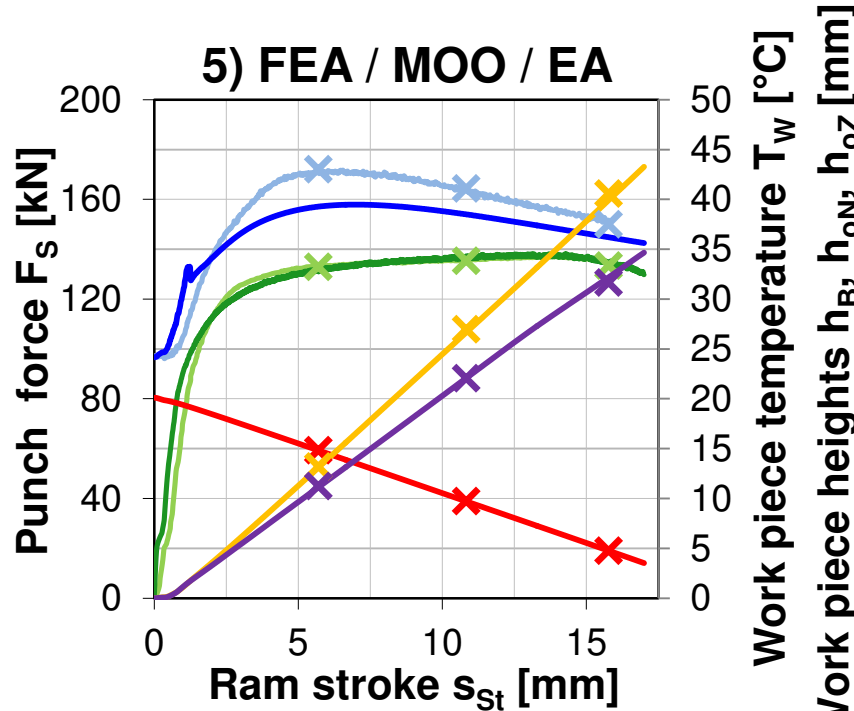
	Opt.	Sim.
Err_{h_B}	= 0.20	= 0.20
$Err_{h_{oN}}$	= 4.88	= 4.88
$Err_{h_{oZ}}$	= 2.47	= 2.47
Err_{F_S}	= 0.28	= 0.28
Err_{T_W}	= 1.44	= 1.44
Err	= 9.27	= 9.27

	Exp.	Opt.	Sim.
$h_{B,1}$ [mm]	14.82	14.79	14.79
$h_{B,2}$ [mm]	9.74	9.67	9.67
$h_{B,3}$ [mm]	4.74	4.72	4.72
$h_{oN,1}$ [mm]	13.18	13.26	13.26
$h_{oN,2}$ [mm]	26.96	26.87	26.87
$h_{oN,3}$ [mm]	40.56	40.21	40.21
$h_{oZ,1}$ [mm]	11.23	11.06	11.06
$h_{oZ,2}$ [mm]	22.05	21.88	21.88
$h_{oZ,3}$ [mm]	31.65	31.78	31.78
$F_{S,1}$ [kN]	132.9	129.3	129.3
$F_{S,2}$ [kN]	135.3	133.4	133.4
$F_{S,3}$ [kN]	133.4	130.9	130.9
$T_{W,1}$ [°C]	43.0	39.8	39.8
$T_{W,2}$ [°C]	41.1	37.1	37.1
$T_{W,3}$ [°C]	37.5	33.9	33.9

Inverse parameter calibration of FEA settings

FEA / Multi objective optimization / Evolutionary algorithm

	Exp.	Sim.
h_B	✗	—
h_{oN}	✕	—
h_{oZ}	✕	—
F_S	✕	—
T_W	✕	—



$D = 593550 \text{ N/mm}$
 $\mu = 0.022$
 $m = 0.053$
 $\alpha = 29368 \text{ W/(m}^2\cdot\text{K)}$
 $V = 0.587$

	Opt.	Sim.
Err_ h_B	= 0.07	Err_ h_B = 0.07
Err_ h_{oN}	= 15.94	Err_ h_{oN} = 15.94
Err_ h_{oZ}	= 9.98	Err_ h_{oZ} = 9.98
Err_ F_S	= 0.08	Err_ F_S = 0.08
Err_ T_W	= 0.82	Err_ T_W = 0.82
Err	= 26.89	Err = 26.89

	Exp.	Opt.	Sim.
$h_{B,1}$ [mm]	14.82	14.81	14.81
$h_{B,2}$ [mm]	9.74	9.70	9.70
$h_{B,3}$ [mm]	4.74	4.75	4.75
$h_{oN,1}$ [mm]	13.18	13.14	13.14
$h_{oN,2}$ [mm]	26.96	26.68	26.68
$h_{oN,3}$ [mm]	40.56	39.94	39.94
$h_{oZ,1}$ [mm]	11.23	11.15	11.15
$h_{oZ,2}$ [mm]	22.05	22.09	22.09
$h_{oZ,3}$ [mm]	31.65	32.20	32.20
$F_{S,1}$ [kN]	132.9	130.9	130.9
$F_{S,2}$ [kN]	135.3	136.7	136.7
$F_{S,3}$ [kN]	133.4	134.6	134.6
$T_{W,1}$ [°C]	43.0	39.3	39.3
$T_{W,2}$ [°C]	41.1	38.5	38.5
$T_{W,3}$ [°C]	37.5	36.2	36.2

Agenda

- 1** Introduction
- 2** Experiments on backward-rod-backward-cup-extrusion
- 3** Sensitivity analysis of FEA simulations of backward-rod-backward-cup-extrusion
- 4** Inverse parameter calibration of FEA settings and comparison to experimental data
- 5** Conclusions

Conclusions

- Material flow in combined cold forging processes is influenced by a variety of process parameters
- For automatic process optimisation it is necessary to exactly know which parameters can be used to influence the material flow
- Another requirement for automatic process optimisation is to exactly predict the real material flow by FEA
- Inverse parameter calibration can be used to achieve more proper FEA models or at least more proper FEA model settings
- Results using MOP are not satisfying in the current case
- Parameter calibration using FEA is very time-consuming
- Suitable cascaded procedure should be developed

Thank you for your attention!

