Identification of Nonlinear Mechanical Model Parameters Based on Softcomputing Methods

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Doctoral Thesis Defense

Outline

- Motivation
- Forward mode of identification
  - Error function definition and optimization
  - Meta-modelling of computation model or error function
  - Proposed methods
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    - Niching strategy CERAF for multi-modal optimization
    - Meta-modelling of error function by Radial Basis function Network
  - Applications:
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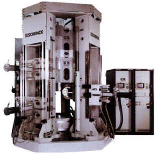
    - Parameters identification of continuum-discrete damage model capable of representing localized failure
- Inverse mode of identification
  - Inverse model development
  - Proposed methodology: Neural network, Genetic training, LHS training data preparation, Stochastic sensitivity analysis
  - Application to identification of microplane model M4 parameters
- Conclusions

Motivation

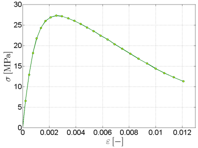
Goal:

to find parameters X^M of a given computational model M to match outputs Y^M from the model with results Y^E from the experiment E

? $\longrightarrow$

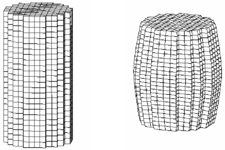


$\longrightarrow$



Inputs X^E — Experiment E — Outputs Y^E

$E, \nu, \ldots$ $\longrightarrow$



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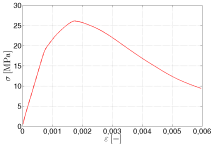


Inputs X^M — Model M — Outputs Y^M

Forward (classical) mode of identification

- based on the definition of an error function $F(X)$ of the difference between outputs of the model Y^M and experimental measurements Y^E, i.e.

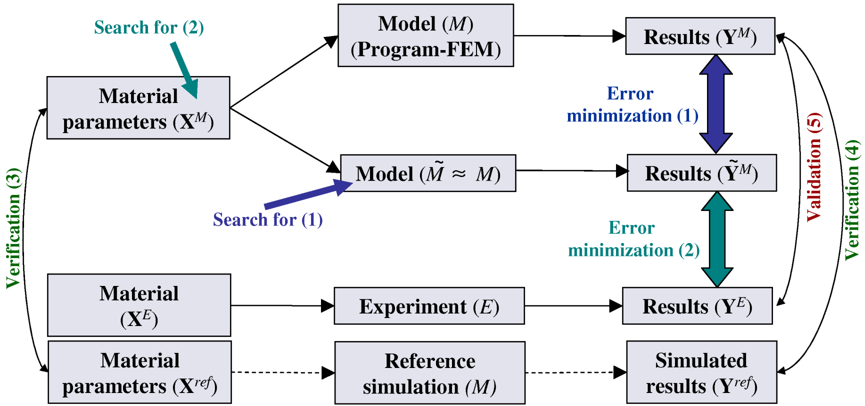
$$F(X) = \|Y^E - M(X)\|. \tag{1}$$

- leads to minimization of the error function $F(X)$
- general in all possible aspects:
  - multi-modality of the error function → multi-modal optimization (niching strategies [Mahfoud, 1995])
  - error function polluted by a noise or experimental error → introduction of stochastic parameters or regularization of the error function [Iacono et al.,2006, Mahnken and Stein, 1996]
  - more than one experiment for one material → e.g. multi-objective optimization [Coello,2004, Coello,2000, Miettinen, 1999]

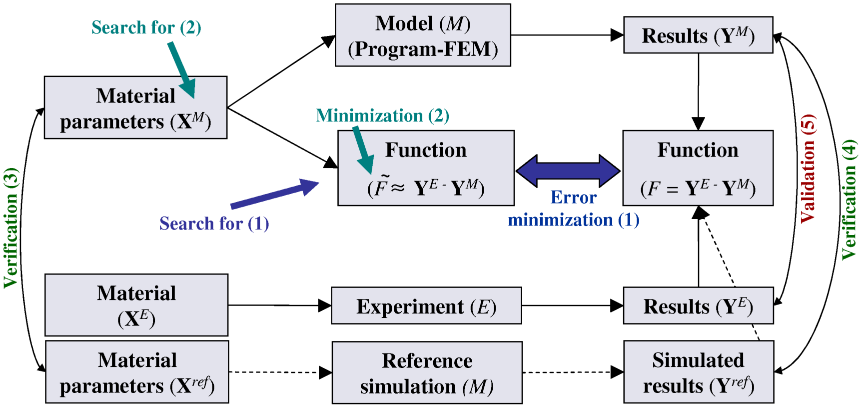
Forward mode of identification

- The computationally expensive optimization should be repeated for any change in data, e.g. even for small change in an experimental setup. This feature handicaps the forward mode from an automatic and frequent usage.
- The need for a huge number of error function evaluations
  - $\rightarrow$ parallel decomposition and parallel implementation [Cantú-Paz,2001];
  - $\rightarrow$ computationally inexpensive meta-model $\tilde{M}$ of the computational model M
    - (−) computationally exhausting meta-model determination;
    - (−) complex mapping $X^M \longrightarrow Y^M$
    - (+) once determined meta-model could be used for parameters identification for new measurements;
  - $\rightarrow$ computationally inexpensive meta-model $\tilde{F}$ of the error function F
    - (+) simpler mapping $X^M \longrightarrow F(X^M)$
    - (−) often leads to multi-modal problem

Meta-modelling of computational model $\tilde{M}(X) \approx M(X)$



Meta-modelling of error function $\tilde{F}(X) \approx F(X)$



Meta-modelling tools

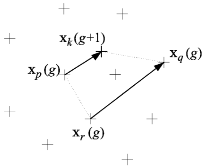
Design of experiments	Model choice	Model fitting	Sample techniques
(Fractional) Factorial	Polynomial (Linear, quadratic)	Least squares regression	Response surface methodology [Toropov and Yoshida,2005]
Central composite	Radial basis function network	Weighted least squares regression	**Proposed forward mode technique**
D-optimal	Realization of stochastic process	Best linear predictor	Kriging [Jin,2003]
Random selection	Functions and terminals	Genetic algorithm	Genetic programming [Toropov and Yoshida,2005]
Latin Hypercube	Splines (Linear, cubic)		**Proposed inverse mode technique**
Selected by hand	Multi-layer perceptron	Back Propagation	Neural networks [Pichler et al.,2003]
Orthogonal array	Decision tree	Entropy	Inductive learning

Proposed forward mode methods - Genetic algorithms

- operate on a "population" of feasible solutions

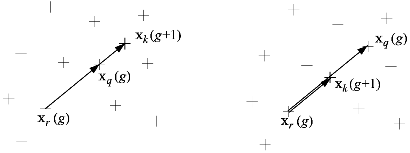
SADE algorithm [Hrstka and Kučerová, 2003]

- mutation
- local mutation
- cross-over
- tournament selection
- 5 parameters



GRADE algorithm

- mutation
- cross-over
- tournament selection
- 3 parameters

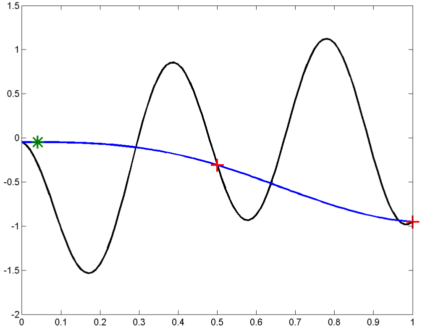


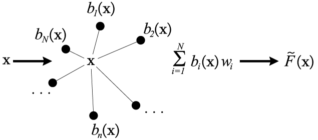
Improvements of robustness of genetic algorithms - niching strategy CERAF

- multi-start algorithm with memory
- creating of adaptive radioactive zones "CEntres RAdioactiF"
- [Hrstka and Kučerová,2004]

Improvements of effectivity of genetic algorithms - Radial Basis Function Network

- meta-model of objective function: $F(\mathbf{x}) \approx \tilde{F}(\mathbf{x}) = \sum_{i=1}^{N} b_i(\mathbf{x}) w_i$
- interpolation by Gaussian functions: $b_i(\mathbf{x}) = e^{-\|\mathbf{x}-\mathbf{c}_i\|^2/r}$
- iterative refinement near optimum





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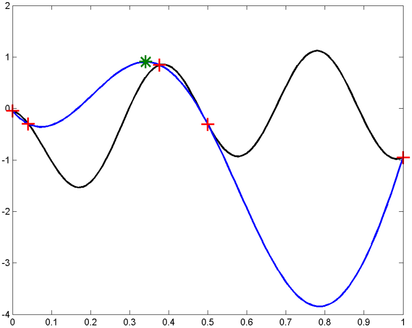

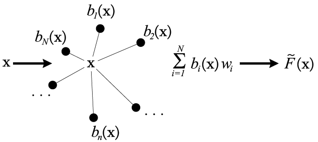

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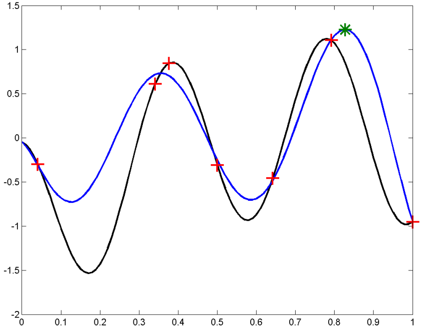

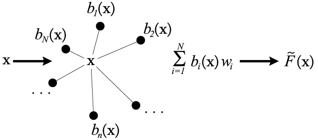

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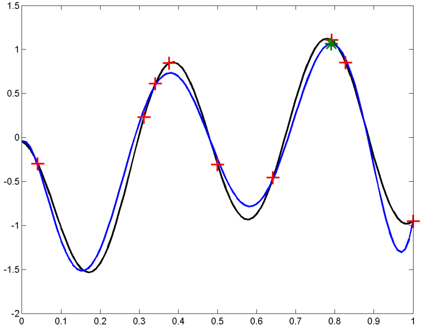

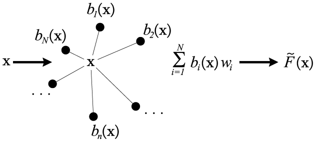

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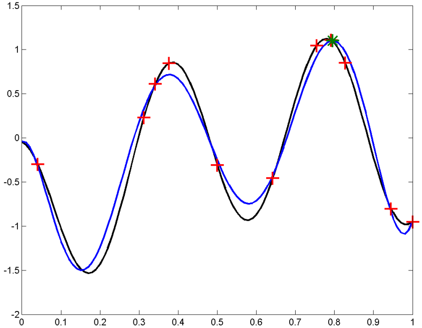
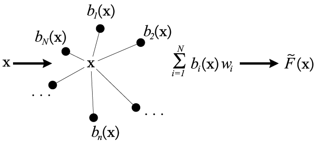




Proposed forward mode methods - Comparison

Test function	N	SADE		GRADE		GRADE+CERAF		GRADE+RBFN	
		SR %	ANFC	SR %	ANFC	SR %	ANFC	SR %	ANFC
F1	1	100.0	61	100.0	61	100.0	60	100.0	23
F3	1	100.0	87	100.0	97	100.0	94	96.7	159
Branin	2	100.0	668	100.0	371	100.0	368	100.0	43
Camelback	2	100.0	306	100.0	223	100.0	222	100.0	61
Goldprice	2	100.0	634	100.0	360	100.0	358	11.6	472
PShubert1	2	100.0	1518	100.0	5501	100.0	1844	2.1	466
PShubert2	2	100.0	1043	100.0	1403	100.0	970	2.5	530
Quartic	2	100.0	534	100.0	341	100.0	339	100.0	77
Shubert	2	100.0	682	100.0	649	100.0	654	18.0	506
Hartman1	3	100.0	478	100.0	319	100.0	320	99.9	63
Shekel1	4	100.0	7719	100.0	33776	100.0	3434	0.0	-
Shekel2	4	100.0	4595	100.0	13522	100.0	2638	0.0	-
Shekel3	4	100.0	4127	100.0	10857	100.0	2650	0.0	-
Hartman2	6	71.2	57935	60.8	165622	100.0	10284	97.7	163
Hosc45	10	100.0	7759	100.0	2265	100.0	2274	-	-
Brown1	20	91.1	160515	100.0	209214	100.0	195250	-	-
Brown3	20	100.0	60554	100.0	36339	100.0	36429	-	-
F5n	20	94.4	26786	99.8	7197	100.0	7259	-	-
F10n	20	66.4	227577	70.3	90687	98.2	289702	-	-
F15n	20	97.5	48533	99.4	23358	100.0	24894	-	-

Optimal control and optimal design of structures undergoing large deformations and rotations

Optimal design

$$\mathbf{K}(\mathbf{u},\mathbf{d})\mathbf{u} = \mathbf{f}$$

Prescribed:

- external loading $\mathbf{f}$
- desired shape $\mathbf{u}$ or other constraints

Unknown:

- design variables $\mathbf{d}$
  (structural properties)

Optimal control

$$\mathbf{K}(\mathbf{u})\mathbf{u} = \mathbf{f}(\mathbf{c})$$

Prescribed:

- structure $\mathbf{K}$
- desired shape $\mathbf{u}$

Unknown:

- control variables $\mathbf{c}$
  (external loading)

Traditional formulation

Constrained optimization

$$\min_{\mathbf{x}} J(\mathbf{u},\mathbf{x})$$

subject to

$$\mathbf{f}^{int}(\mathbf{u}(\mathbf{x}),\mathbf{x}) - \mathbf{f}^{ext}(\mathbf{x}) = \mathbf{0}$$

Simultaneous formulation

Unconstrained optimization

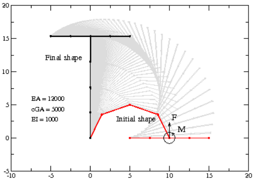
$$\max_{\boldsymbol{\lambda}} \min_{\mathbf{u},\mathbf{x}} L(\mathbf{u},\mathbf{x},\boldsymbol{\lambda})$$

where

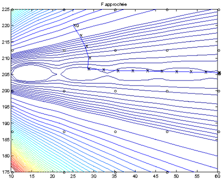
$$L(\mathbf{u},\mathbf{x},\boldsymbol{\lambda}) =$$
$$= J(\mathbf{u},\mathbf{x}) + \boldsymbol{\lambda}^T \left(\mathbf{f}^{int}(\mathbf{u},\mathbf{x}) - \mathbf{f}^{ext}(\mathbf{x})\right)$$

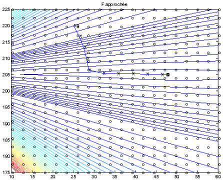
Optimal control of a cantilever structure - traditional formulation

Definition of T letter problem

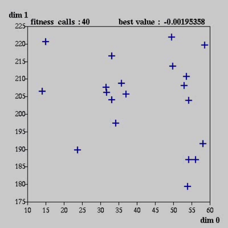


Diffuse approximation based gradient method





GRADE

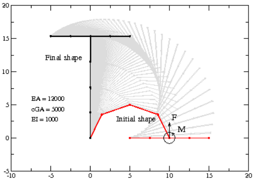


RBFN + GRADE

Statistics

Optimal control of a cantilever structure - traditional formulation

Definition of T letter problem



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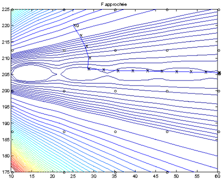

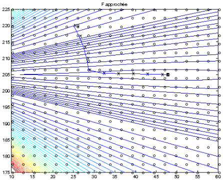

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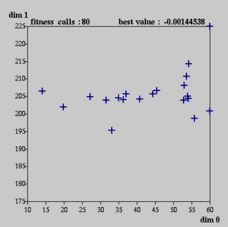

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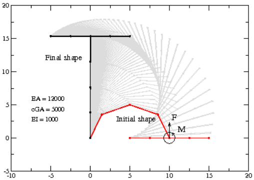

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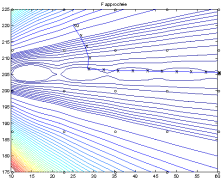

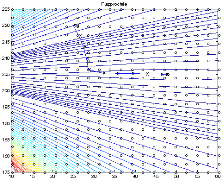

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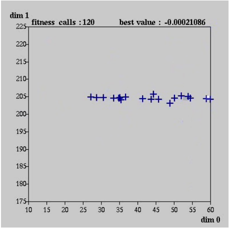

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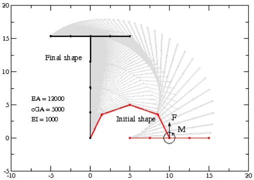

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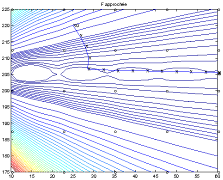

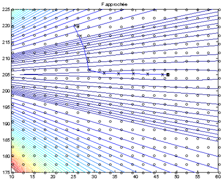

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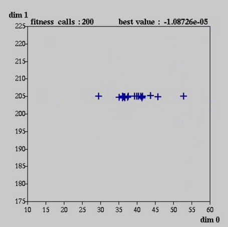

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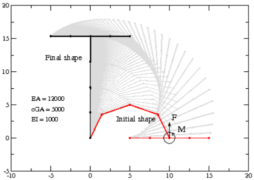

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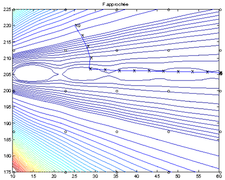

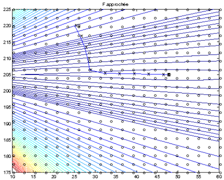

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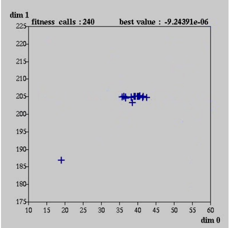

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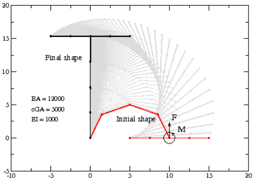

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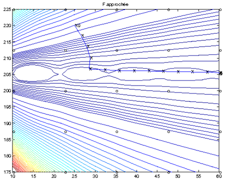

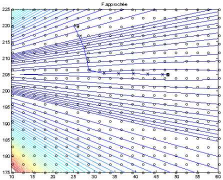

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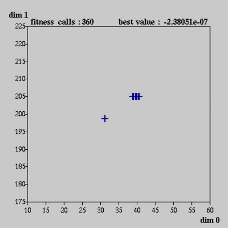

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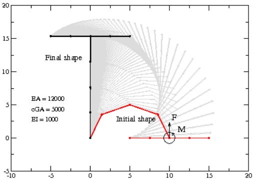

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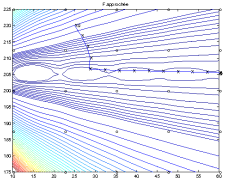

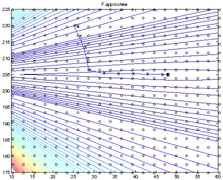

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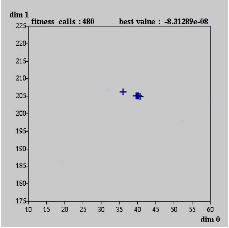

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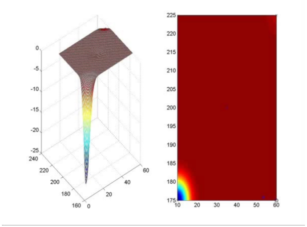

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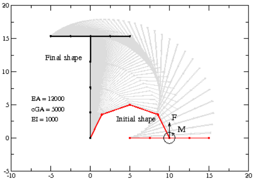
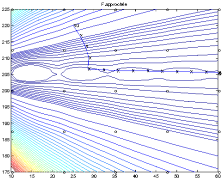
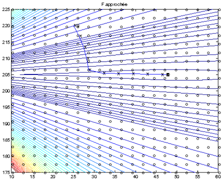
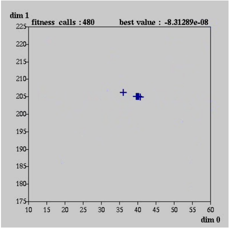


Diffuse approximation based gradient method

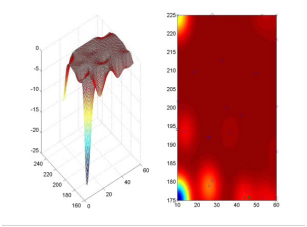




GRADE



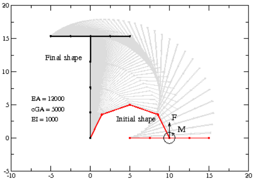
RBFN + GRADE



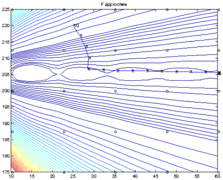
Statistics

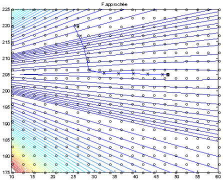
Optimal control of a cantilever structure - traditional formulation

Definition of T letter problem

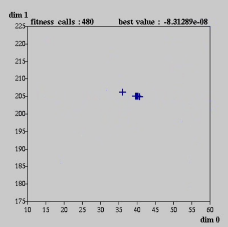


Diffuse approximation based gradient method

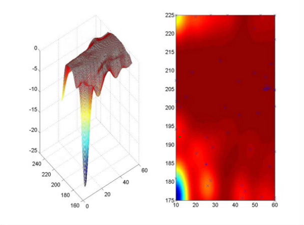




GRADE



RBFN + GRADE



Statistics

Optimal control of a cantilever structure - traditional formulation

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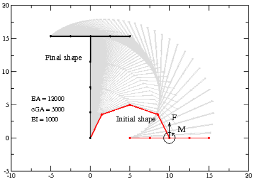
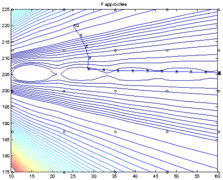
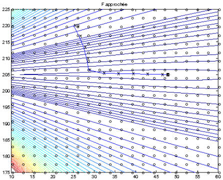
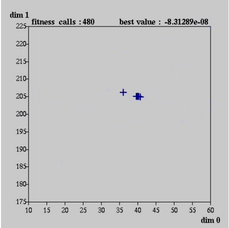


Diffuse approximation based gradient method

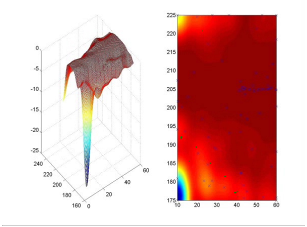




GRADE



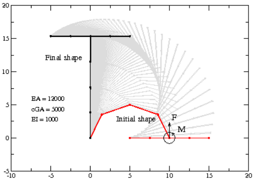
RBFN + GRADE



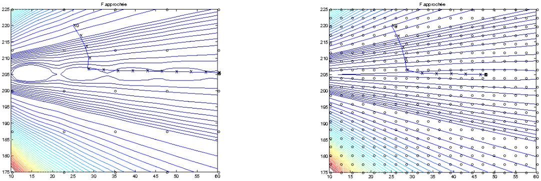
Statistics

Optimal control of a cantilever structure - traditional formulation

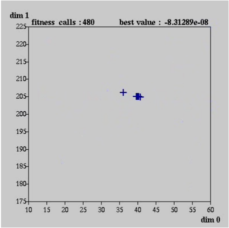
Definition of T letter problem



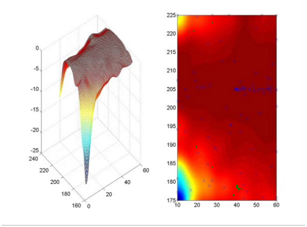
Diffuse approximation based gradient method



GRADE



RBFN + GRADE



Statistics

Diffuse approximation:

Func. calls: 25 : $\Delta F = 20.00$
(Grid: 5×5) $\Delta M = 0.26$
Func. calls: 400 : $\Delta F = 7.44$
(Grid: 20×20) $\Delta M = 0.03$

GRADE:

Func. calls: 512 : $\Delta F = 0.10$
$\Delta M = 0.00$

RBFN + GRADE:

Func. calls: 104 : $\Delta F = 0.10$
$\Delta M = 0.00$

Optimal control of a cantilever structure - simultaneous formulation

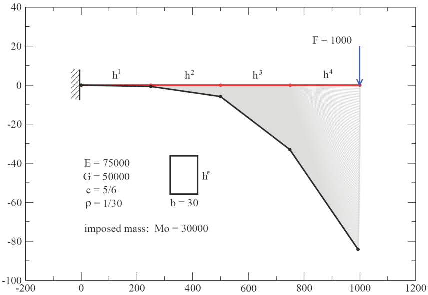
Karush-Kuhn-Tucker optimality condition:

$$
\begin{aligned}
0 &= \mathbf{r}_\lambda^T \delta\boldsymbol{\lambda} = \left(\frac{\partial L(\cdot)}{\partial \boldsymbol{\lambda}}\right)^T \delta\boldsymbol{\lambda} := \left[\mathbf{f}^{int}(\mathbf{u},\mathbf{c}) - \mathbf{F}_0\mathbf{c}\right]^T \delta\boldsymbol{\lambda} \\
0 &= \mathbf{r}_u^T \delta\mathbf{u} = \left(\frac{\partial L(\cdot)}{\partial \mathbf{u}}\right)^T \delta\mathbf{u} := \left(\frac{\partial J(\mathbf{u},\mathbf{c})}{\partial \mathbf{u}}\right)^T \delta\mathbf{u} + \boldsymbol{\lambda}^T\mathbf{K}\delta\mathbf{u} \quad \Rightarrow \boldsymbol{\lambda} \\
0 &= \mathbf{r}_c^T \delta\mathbf{c} = \left(\frac{\partial L(\cdot)}{\partial \mathbf{c}}\right)^T \delta\mathbf{c} := \left(\frac{\partial J(\mathbf{u},\mathbf{c})}{\partial \mathbf{c}}\right)^T \delta\mathbf{c} - \boldsymbol{\lambda}^T\mathbf{F}_0\delta\mathbf{c}
\end{aligned}
$$

$\min_{\mathbf{u},\mathbf{c}} \mathbf{r}^T\mathbf{r}; \quad \mathbf{r}(\mathbf{u},\mathbf{c}) = (\mathbf{r}_c, \mathbf{r}_\lambda)$ ...solved by GRADE algorithm

Formulation	Traditional	Simultaneous
Number of variables	2	23
ΔF	0.10	0.03
ΔM	0.00	0.04
Func. calls	512	37701
One func. call [s]	0.006946	0.00004935
Total time [s]	3.559	1.861

Optimal design of shear deformable cantilever



Limit thickness	h_1	h_2	h_3	h_4
Min	30	30	15	15
Max	60	60	35	35

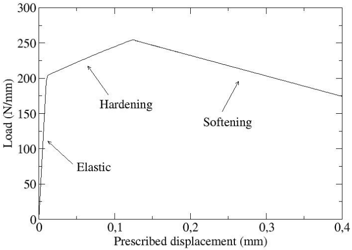
GRADE algorithm results

Thickness	h_1	h_2	h_3	h_4
Optimal	43.8	35.9	26.3	14.2

Formulation	traditional	simult.
Variables	4	19
$\Delta\ h_1$	0.019	0.005
$\Delta\ h_2$	0.018	0.004
$\Delta\ h_3$	0.016	0.004
$\Delta\ h_4$	0.013	0.002
Func. calls	3497	313006
One f. call [s]	0.0021	0.0000276
Total time [s]	7.344	8.640

Parameter identification of continuum-discrete damage model capable of representing localized failure

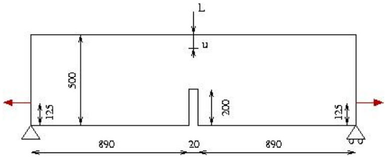
- Relatively simple model capable of describing the diffuse damage mechanism as well as propagation of macrocracks proposed by [Brancherie and Ibrahimbegović, 2003]
- Three stages of concrete behavior
  - elastic,
  - plastic hardening,
  - continuum as well as discrete softening due to damage

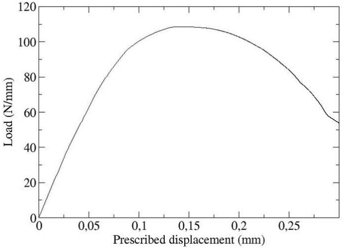


- 6 parameters with the following extreme values:

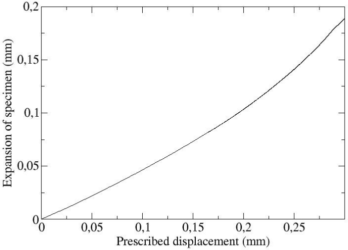
$E\in(25.0, 50.0)$ GPa	$\bar{\sigma}_f\in(1.0, 5.0)$ MPa	$\bar{\bar{\sigma}}_f\in(\bar{\sigma}_f + 0.1, 2\bar{\sigma}_f)$ MPa
$\nu\in(0.1, 0.4)$	$\bar{K}\in(10.0, 10000.0)$ MPa	$\bar{\beta}\in(0.1\bar{\bar{\sigma}}_f, 10.0\bar{\bar{\sigma}}_f)$

Sequential identification from three-point bending test



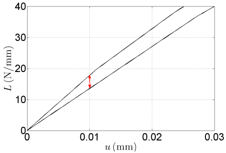


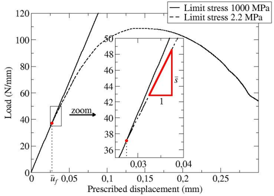
- easy to perform in lab
- heterogeneous strain field
- solving three simpler identification steps is more efficient than the full-scale problem
- using only a subset of simulations

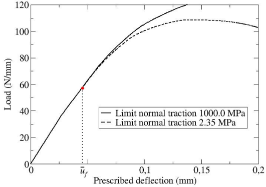


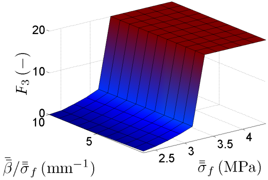
Sequential identification from three-point bending test

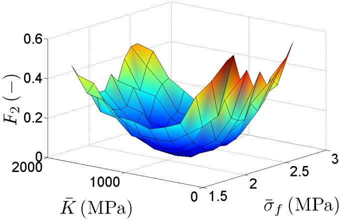
- 1^{st} stage: E and ν identification:
  $F_1 = (L_{ref}(u) - L(u))^2 w_1 + (\Delta l_{ref}(u) - \Delta l(u))^2 w_2$
  $u = 0.01$ mm
- 2^{nd} stage: $\bar{\sigma}_f$ and $\bar{K}$ identification:
  $F_2 = \left(\bar{u}_{f,ref} - \bar{u}_f\right)^2 w_3 + \left(\bar{s}_{ref} - \bar{s}\right)^2 w_4$
  $\bar{s} = (L(\bar{u}_f + 0.01\text{mm}) - L(\bar{u}_f + 0.005\text{mm}))/0.005\text{mm}$
- 3^{th} stage: $\bar{\bar{\sigma}}_f$ and $\bar{\bar{\beta}}$ identification
  $F_3 = \left(\bar{\bar{u}}_{f,ref} - \bar{\bar{u}}_f\right)^2 w_5 + \left(L_{ref}(u) - L(u)\right)^2 w_6$
  $u = 0.15$ mm







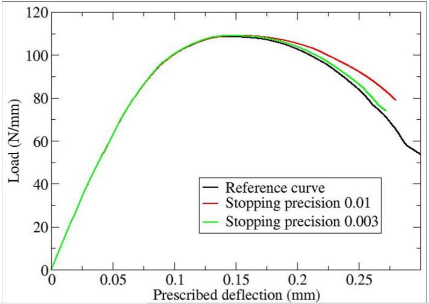




Results obtained by RBFN + GRADE method

F	Prec.	NSR	Max NFC	Ave NFC	Par.	MaxErr [%]	AveErr [%]
F_1	10^{-5}	100	32	16	E	1.23	0.41
					ν	2.20	0.16
F_2	10^{-2}	94	140	29	$\bar{\sigma}_f$	2.58	0.87
					K	2.49	0.78
	10^{-3}	80	140	47	$\bar{\sigma}_f$	0.59	0.30
					K	1.54	0.49
F_3	10^{-2}	92	140	37	$\bar{\bar{\sigma}}_f$	1.32	0.47
					$\bar{\bar{\beta}}$	12.21	2.34
	3×10^{-3}	76	143	47	$\bar{\bar{\sigma}}_f$	0.67	0.33
					$\bar{\bar{\beta}}$	2.68	0.26

- Prec. - stopping precision
- NSR - number of successful runs
- Max NFC - maximal number of function calls
- Ave NFC - average number of function calls
- Par. - parameter
- MaxErr - maximal error
- AveErr - average error



Inverse mode of identification

- ***existence of an inverse relationship*** between Y and X;

$$\Rightarrow \text{determination of its } \boldsymbol{approximation}\ M^{INV}$$
$$X^M = M^{INV}(Y^M).$$

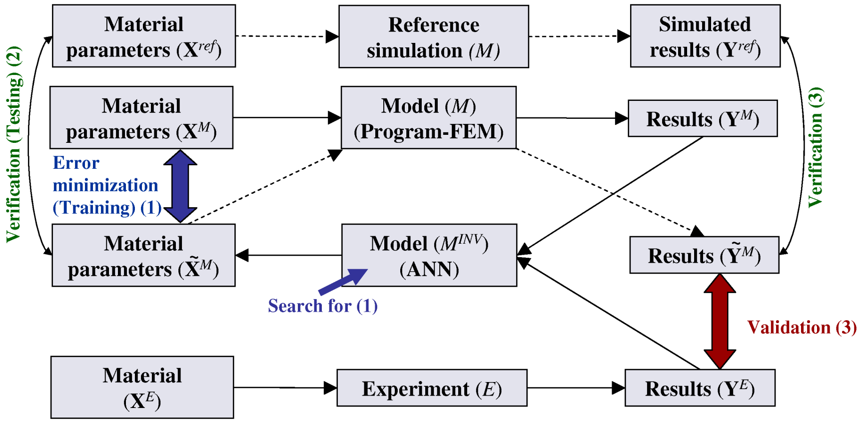
(+) ***enables automatic and frequent usage***;

(−) ***exhausting search*** for the inverse relationship;

(−) ***inability to solve multi-modal problem***;

- data with noise → ***stochastic parameters*** [Lehký and Novák,2005, Fairbairn et al.,2000];
- ***more experiments*** for one material → e.g. sequential, cascade or iterative processes.

Schema of inverse mode of identification



Inverse mode of identification

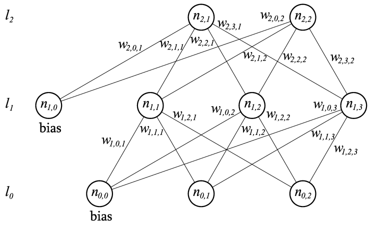
Solutions of prediction errors:

- ***guess of an expert*** $\longrightarrow$ reduction of the definition domain [Novák and Lehký, 2006];
- ***cascade neural networks***: predictions of some inputs x_i used as known for next inverse model predicting other inputs x_j $\longrightarrow$ reduce the complexity of M^{INV} [Waszczyszyn and Ziemianski,2005] or [Kučerová et al., 2007];
- ***sequential refining***: predictions of all inputs X in one step used to reduce the definition space in following steps [Most et al., 2007].

All these methodologies **disables automatic and frequent usage**.

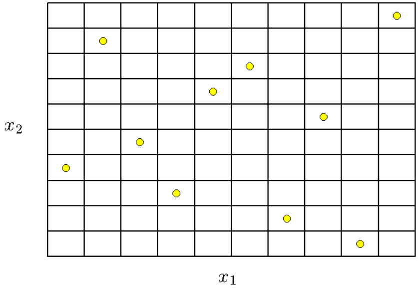
Proposed inverse mode method

Approximation of M^{INV} by multi-layer perceptron:



with log-sigmoid activation function: $f_{\mathrm{act}}(\Sigma) = \frac{1}{(1+e^{-\alpha\Sigma})}$

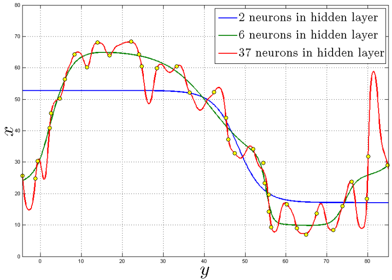
Training data chosen by Latin Hypercube Sampling method optimized by Simulated Annealing using software package FREET [Novák et al.,2003]

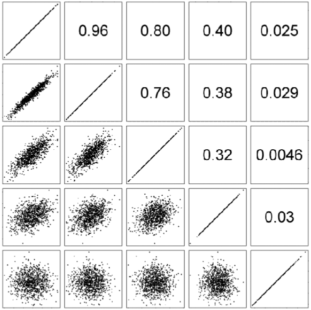


Proposed inverse mode method

Training process is governed by GRADE algorithm; overtraining is controlled comparing the errors on training and testing data.

Input data are chosen by hand with respect to stochastic sensitivity analysis performed using Pearson product moment correlation coefficient.



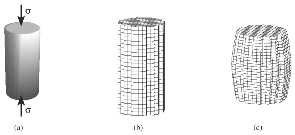


Microplane model M4 [Bažant et al., 2000]

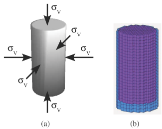
- Advantages:
  - Three-dimensional model
  - Tensional and compressive softening
  - Loading, unloading and cyclic loading
  - Realistic simulations of engineering structures
- Disadvantages:
  - Large amount of data needs to be stored
  - The strain-to-stress map is not smooth
  - Very expensive analysis
  - 7 parameters need to be adjusted: $E, \nu, k_1, k_2, k_3, k_4, c_{20}$
  - 5 parameters without simple physical interpretation

$\Rightarrow$ Difficult to determine values from an experiment

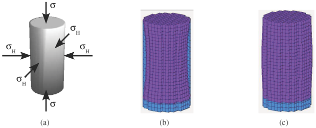
- Caner and Bažant,2000 proposed 3 tests for all parameters estimation:
  - Uniaxial compression test



  - Hydrostatic compression test

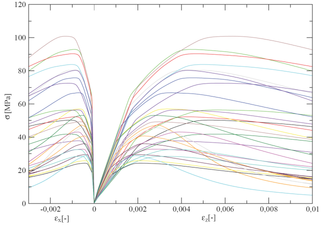


  - Triaxial compression test

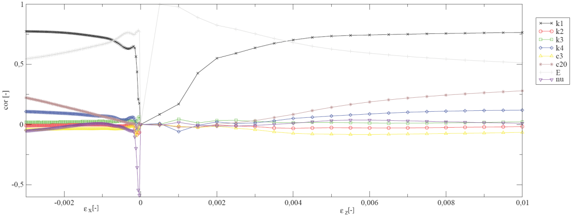


Uniaxial compression test

Bundle of 30 simulation
(LHS method + Sim. Annealing)



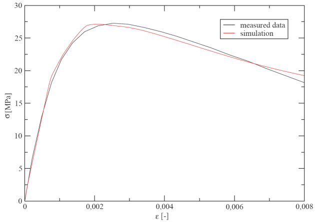
Stochastic sensitivity analysis
(Pearson's product moment correlation coefficient)



- 1^{st} stage: E, ν, k_1 identification
- 2^{nd} stage: c_{20} identification
  (new 40 simulations needed)

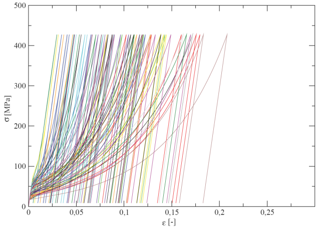
Parameter	ANN	Input values
k_1	4 - 2 - 1	$\sigma_{x,2}$, $\sigma_{z,peak}$, $\epsilon_{z,peak}$, E
c_{20}	4 - 3 - 1	$\sigma_{x,100}$, $\sigma_{z,20}$, E, k_1
E	3 - 2 - 1	$\sigma_{z,1}$, $\sigma_{z,2}$, $\sigma_{z,3}$
ν	4 - 3 - 1	$\sigma_{x,1}$, $\sigma_{x,2}$, E, k_1

Validation

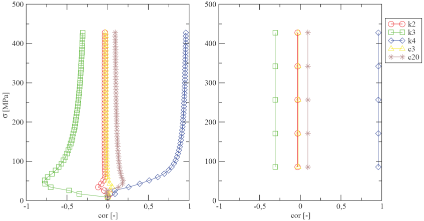


Hydrostatic compression test

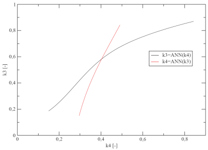
Bundle of 60 simulation
(E, ν, k_1 fixed)



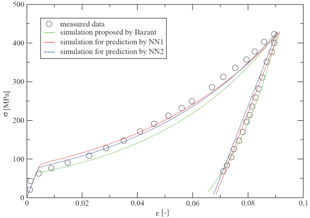
Stochastic sensitivity analysis
Loading part × Unloading part



k_3 (ANN1)	4 - 2 - 1	k_4, ϵ_{peak}, ϵ_{yield}, $\epsilon_{load,25}$
k_3 (ANN2)	5 - 2 - 1	k_4, ϵ_{peak}, ϵ_{yield}, $\epsilon_{load,16}$, $\epsilon_{load,36}$
k_4	3 - 2 - 1	k_3, ϵ_{peak}, $\epsilon_{unload,4}$

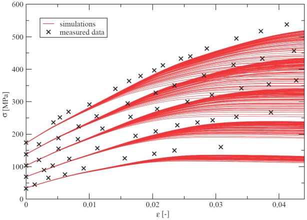


Validation

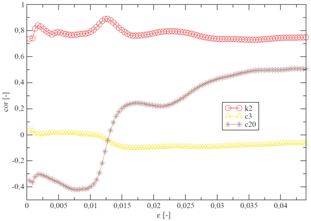


Triaxial compression test

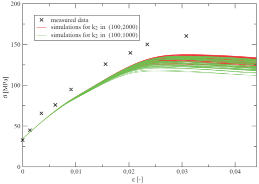
Bundle of 60 simulation (E, ν, k_1, k_3, k_4 fixed)



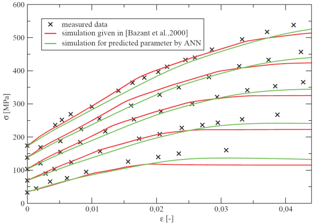
Stochastic sensitivity analysis



k_2	3 - 2 - 1	σ_{peak}, σ_{29}, σ_{100}



Validation



Conclusions

- An ***insight into procedures*** suitable for parameters identification was presented.
- ***Basic notation and classification*** is introduced.
- ***Two basic modes*** of an inverse analysis are described:
  - a forward mode leading to an optimization of an error function;
  - an inverse mode leading to an inverse model development.
- Forward mode methods and applications:
  - ***Two genetic algorithms*** were proposed as a robust and reliable optimization algorithms.
  - One ***niching strategy*** was development in order to increase the reliability of genetic algorithms.
  - ***Interpolation of error function*** based on radial basis function network was introduced to improve effectivity of genetic algorithms.
  - Examples of ***optimal control and optimal design*** were solved.
  - Parameters of one ***damage model*** were successfully identified.

Conclusions

- An inverse methodology was proposed consisting of:
  - Inverse model based on ***layered artificial neural network***,
  - ***Latin Hypercube Sampling*** design of experiments optimized by ***Simulated Annealing*** applied for ANN training data preparation,
  - ***Stochastic sensitivity analysis***,
  - ***Genetic training*** of ANN.
- Sequential parameters identification of ***microplane model M4*** was shown.