# Fortschritt-Berichte VDI

# VDI

Reihe 20

Rechnerunterstützte Verfahren Dipl.-Ing. Nikola Aulig, Darmstadt

Nr. 468

# Generic Topology Optimization Based on Local State Features

ian

Berichte aus dem

Institut für Automatisierungstechnik und Mechatronik der TU Darmstadt

eneriert durch IP '18.219.189.2 ellen und Weitergeben von Ko

https://doi.org/10.51202/9783186468208-I Generiert durch IP '18.219.189.247', am 30.04.2024, 19:37:59. Das Erstellen und Weitergeben von Kopien dieses PDFs ist nicht zulässig.

# Generic Topology Optimization Based on Local State Features

Dem Fachbereich Elektrotechnik und Informationstechnik der Technischen Universität Darmstadt zur Erlangung des akademischen Grades eines Doktor-Ingenieurs (Dr.-Ing.) genehmigte Dissertation

von

### Dipl.-Ing. Nikola Aulig

geboren am 6. Februar 1984 in Karlsruhe

Referent: Prof. Dr.-Ing. J. Adamy Korreferent: Prof. Dr. rer. nat. B. Sendhoff Tag der Einreichung: 30. November 2016 Tag der mündlichen Prüfung: 4. Mai 2017

> D17 Darmstadt 2017

https://doi.org/10.51202/9783186468208-I Generiert durch IP '18.219.189.247', am 30.04.2024, 19:37:59. Das Erstellen und Weitergeben von Kopien dieses PDFs ist nicht zulässig.

# Fortschritt-Berichte VDI

### Reihe 20

Rechnerunterstützte Verfahren Dipl.-Ing. Nikola Aulig, Darmstadt

Nr. 468

Generic Topology Optimization Based on Local State Features

Berichte aus dem

Institut für Automatisierungstechnik und Mechatronik der TU Darmstadt



#### Aulig, Nikola Generic Topology Optimization Based on Local State Features

Fortschr.-Ber. VDI Reihe 20 Nr. 468. Düsseldorf: VDI Verlag 2017. 216 Seiten, 78 Bilder, 12 Tabellen. ISBN 978-3-18-346820-1, ISSN 0178-9473, € 76,00/VDI-Mitgliederpreis € 68,40.

**Keywords:** Topology Optimization – Concept Design – Local State Features – Evolutionary Computation – Design Sensitivities – Prediction – Machine Learning – Vehicle Crashworthiness

The work at hand addresses engineers, designers and scientists who face the challenging task of devising concept structures in a virtual product design process that involves more and more sophisticated physical simulations. Using methods of evolutionary optimization and machine learning, this dissertation explores a novel generic topology optimization algorithm, which is able to provide concept designs even for problems involving complex, blackbox simulations. A self-contained learning component utilizes physical simulation data to generate a search direction. The generic topology optimization is studied in conjunction with statistical models such as neural networks or support vector regression. In empirical experiments, the novel method reproduces reference structures with minimum compliance and provides innovative solutions in the domain of vehicle crashworthiness optimization.

#### Bibliographische Information der Deutschen Bibliothek

Die Deutsche Bibliothek verzeichnet diese Publikation in der Deutschen Nationalbibliographie; detaillierte bibliographische Daten sind im Internet unter <u>http://dnb.ddb.de</u> abrufbar.

#### Bibliographic information published by the Deutsche Bibliothek

(German National Library) The Deutsche Bibliothek lists this publication in the Deutsche Nationalbibliographie (German National Bibliography); detailed bibliographic data is available via Internet at http://dnb.ddb.de.

D 17

#### © VDI Verlag GmbH · Düsseldorf 2017

Alle Rechte, auch das des auszugsweisen Nachdruckes, der auszugsweisen oder vollständigen Wiedergabe (Fotokopie, Mikrokopie), der Speicherung in Datenverarbeitungsanlagen, im Internet und das der Übersetzung, vorbehalten.

Als Manuskript gedruckt, Printed in Germany. ISSN 0178-9473 ISBN 978-3-18-346820-1

### Acknowledgements

The presented research was conducted at the Honda Research Institute Europe GmbH (HRI-EU). The institute provided a unique and excellent personal, scientific and technical environment that made this particular thesis possible.

First of all, I thank my supervisor Markus Olhofer for his ideas, scientific and formal support and continuous, optimistic attitude over all the years. I thank the HRI-EU president Prof. Bernhard Sendhoff for important advice and guidance, despite of his full calender and the formal, long-term commitment to this project. Special thanks for guidance and encouragement go to Prof. Jürgen Adamy from the Control Methods and Robotics (RMR) department, who offered to supervise the dissertation in a collaboration between the Technische Universität Darmstadt and HRI-EU. Most of all, I am thankful for the trust, which these three scientists put in me.

I would like to express my thanks to many colleagues and friends for their valuable support: Mariusz Bujny, Duane Detwiler, Fabian Duddeck, Giles Endicott, Michael Gienger, Lars Gräning, Thomas Guthier, Martina Hasenjäger, Matthew Kent, Ingolf Lepenies, Stefan Menzel, Emily Nutwell, Matthias Platho, Edgar Reehuis, Tobias Rodemann, Andrea Schnall, Olga Smalikho, Till Steiner, Thomas Weisswange, and all my colleagues from the Complex System Optimization and Analysis Group. Thank you for your - scientific and non-scientific - comments, ideas, discussions, encouragements, distractions, collaborations and too many other things to list them all. Some of these, as well as Damien Schlarb, Svenja Schlarb, Friedrich Schenk helped to improve the language throughout this document. Furthermore, I would like to thank the administrative and technical staff at HRI-EU and RMR for their support, especially Birgit Heid for organizing formalities and Burkhard Zittel for maintaining the computational cluster. I thank Prof. Andrew Ng for his excellent online lecture on machine learning.

Finally, I am very grateful to all my other friends, my parents and family, and especially Andrea Schnall for their invaluable support, comprehension and, most of all, just for being there all these years.

# Contents

Sy	mbc	ols and	Abbreviations	Х	IV
$\mathbf{A}$	bstra	nct		XV	VII
Zι	ısam	menfa	ssung	XV	III
1	Inti	roduct	ion		1
<b>2</b>	Fun	damei	ntals		8
	2.1	Backg	round: Topology Optimization of Continuum Stru	ıc-	
		tures	· · · · · · · · · · · · · · · · · · ·		8
		2.1.1	General Problem Formulation		9
		2.1.2	Early Topology Optimization		10
		2.1.3	Topology Optimization Approaches		13
	2.2	Densit	ty-based Topology Optimization		15
		2.2.1	Problem Formulation		15
		2.2.2	The Minimum Compliance Problem		17
	2.3	Evolu	tionary Computation		21
		2.3.1	Evolution Strategies		23
		2.3.2	Covariance-Matrix Adaptation Evolutionary Stra	tegy	26
	2.4	Summ	1ary		27
3	$\mathbf{Str}$	ucture	Representations for Evolutionary Computat	tion	29
	3.1	Repre	senting the Structure		29
	3.2	Grid I	Representation		31
		3.2.1	Bit-Array Encoding		31
		3.2.2	Real-Valued Array Encoding		34
	3.3	Geom	etric Representation		34
		3.3.1	Voronoi-cells		34
		3.3.2	Material-Mask Overlay		35
		3.3.3	Graph Representation		36
		3.3.4	Level Set Methods		39

	3.4	Indire	ect Representation	39
		3.4.1	Lindenmayer System	39
		3.4.2	Gene Regulatory Network	41
		3.4.3	Compositional Pattern Producing Network	41
	3.5	Discu	ssion	42
	3.6	Summ	hary of Contribution	47
<b>4</b>	Тор	ology	Optimization by Predicting Sensitivities	48
	4.1	Gener	ric Update-Signal Model	48
		4.1.1	Introduction	48
		4.1.2	Replacing Sensitivities	50
		4.1.3	Local State Features	54
	4.2	Enclo	sing Topology Optimization	58
		4.2.1	Improvement Threshold	60
	4.3	Explie	cit Evolutionary Learning	63
		4.3.1	Neural Network Approximation Model	65
		4.3.2	Piecewise-Constant Model	67
		4.3.3	Optimization with CMA-ES	72
		4.3.4	Computational Flow	73
	4.4	Samp	ling and Supervised Learning	74
		4.4.1	Sensitivity Estimation by Finite-Difference Sampling	75
		4.4.2	Aggregated Sensitivity-Sampling	78
		4.4.3	Sensitivity Regression Model	80
		4.4.4	Computational Flow	81
	4.5	Summ	hary of Contribution	82
<b>5</b>	$\mathbf{Stu}$	dies o	n the Minimum Compliance Problem	84
	5.1	Refere	ence Problem	84
		5.1.1	Linear Static LSF	86
	5.2	NE/P	CM-TOPS Experiments	88
		5.2.1	Results LSF Vector I	90
		5.2.2	Results LSF Vector II	94
		5.2.3	NE/PCM-TOPS Results Discussion	97
	5.3	SVR/	LIN-TOPS Experiments	100
		$5.3.1^{'}$	Results LSF Vector I	102
		5.3.2	Results LSF Vector II	102
		5.3.3	Intermediate LIN/SVR-TOPS Results Discussion	106
		5.3.4	Mesh-Independency Study	108
		5.3.5	Alternative LSF	110
		5.3.6	Experiments with Aggregated Sampling	111

	$5.4 \\ 5.5$	Overall Discussion	$116 \\ 119$
6	Тор	ology Optimization of Crashworthiness Objectives	121
	6.1	State-of-the-art	121
	6.2	Maximum Energy Absorption Beam	126
		6.2.1 Beam Model and Optimization Set-up	126
		6.2.2 Optimization Results	130
	6.3	Minimum Intrusion Frame	136
		6.3.1 Frame Model and Optimization Set-up	136
		6.3.2 Optimization Results	140
	6.4	Summary of Contribution	149
7	Con	clusions	150
	7.1	Main Results	150
	7.2	Future Directions	153
$\mathbf{A}$	The	orv	155
	A.1	Adjoint Sensitivities	155
	A.2	Sensitivity Regression Models	157
		A.2.1 Linear Regression	157
		A.2.2 Support Vector Regression	157
	A.3	Compliance Topology Optimization	159
	A.4	Correlation Coefficient	159
в	Con	apliance Studies Results	161
С	Cras	shworthiness	172
Bi	bliog	raphy	177

# List of Figures

1.1	Classification of the research focus of this thesis in between knowledge and data-driven approaches	5
1.2	Graphical overview of the main components of the thesis.	6
2.1	Illustration of the three fields within structural optimization.	10
2.2	General design space of a topology optimization problem	11
2.3	General design space of a topology optimization problem	11
	and density approach.	12
2.4	Computational flow for density-based topology optimization.	19
2.5	Examples for topology optimization	20
2.6	The working principle of an evolutionary algorithm	23
3.1	Proposed categories of representations for structures in a	
	topology optimization scenario	32
3.2	Grid Representation.	33
3.3	Voronoi cell representation.	35
3.4	Material mask representation.	36
3.5	Graph representation.	37
$3.6 \\ 3.7$	Constructive solid geometry representation	39
	cellular division process.	40
3.8	Cellular growth model based on motile polarized cells and	
	voxelization.	42
3.9	CPPN representation for structure	43
4.1	Overview of the structure of Chap. 4. The chapter intro-	
	duces a generic topology optimization concept with different	
	learning and modelling approaches	49
4.2	The concept of standard gradient-based topology optimiza-	
	tion compared to the concept of generic topology optimization.	51
4.3	Local state features: Example for displacements of element	
	nodes when a finite element analysis is performed	57

4.4	Example for Local State Features of cantilever structure	58
4.5	Computational Flow of TOPS and TOPS with improvement	61
4.6	The "Check Design Improvement" Step of TOPS with Im-	01
	provement Threshold.	62
4.7	The optimization process of updating the structure based	
	on local state features and model	65
4.8	A feed-forward Multi-Layer-Perceptron with one hidden	
	layer as update-signal model, processing Local State Fea-	
	tures as input. A single model provides update-signals for	~ -
1.0	all elements in the design space	67
4.9	Example for LSF space and element clusters by choosing 4	<u> </u>
4 10	Prototype elements.	69 71
4.10	The computational flow for TOPS with complicit evolution	11
4.11	ary tuning of the update signal model with CMA ES	72
1 19	The idea of TOPS with sensitivity-sampling	77
4.12	The computational flow for TOPS based on supervised	
1.10	learning of regression models with finite difference sampling	
	of sensitivities.	82
5.1	Minimum compliance cantilever reference problem: design	
	space (left) and reference solution (right). $\ldots$	85
5.2	The relation of several LSFs of $\mathbf{s}_i^1$ and corresponding elemen-	
	tal sensitivity shown for all elements of the initial structure.	
	The sensitivity can take several values for a nodal displace-	
	ment component $s_{i1,2} = u_{i1,2}$ , yet it is clearly related to the	00
<b>۲</b> 0	strain energy density $s_{i10}^2 = \text{SED}_i$ by a linear function	88
0.3	the NE/DCM TOPS rung for LSE Vector I	01
5 /	The compliance of the mean and best run versus the number	91
0.4	of function evaluations for NE/PCM-TOPS on LSE Vector I	92
5.5	The number of function evaluations for NE/PCM-TOPS	52
0.0	learning steps, over the iterations of the topology optimiza-	
	tion. $\ldots$	93
5.6	Optimized structures obtained for NE/PCM-TOPS for LSF	
	Vector I	93
5.7	Empirical correlation coefficients for update-signals with	
	sensitivities for NE/PCM-TOPS and LSF Vector I	94

5.8	Optimized compliance values and required evaluations of the NE/PCM-TOPS runs for LSF Vector II
5.9	The compliance of the mean and best run versus the number of function evaluations for NE/PCM-TOPS on LSF Vector
5.10	II
	learning steps, over the iterations of the topology optimiza- tion 97
5.11	Optimized structures obtained for NE-TOPS and PCM- TOPS for LSF Vector II
5.12	Empirical correlation coefficients for update-signal with sen-
	sitivities and LSF Vector II
5.13	Comparison of the resulting compliance (left) and the re- quired evaluations (right) for PCM-TOPS with $P = 13$ for
	LSF Vector I and a reduced LSF Vector I
5.14	Optimized compliance values and required evaluations of the runs obtained in the different experiments with
	LIN/SVR-TOPS and LSF Vectors I and II 103
5.15	Optimized structures for LIN/SVR-TOPS with LSF Vector I.104 $$
5.16	The number function evaluations of LIN/SVR-TOPS re-
	quired for learning, over the iterations of the topology op-
	timization for LSF Vector I
5.17	Optimized structures obtained for LIN/SVR-TOPS for LSF
	Vector II
5.18	The number function evaluations of LIN/SVR-TOPS re-
	quired for learning, over the iterations of the topology op-
- 10	timization for LSF Vector II
5.19	Best optimized structures of SVR-TOPS with LSF Vector
5 00	II for different mesh sizes
5.20	Required evaluations of SVR-TOPS with LSF Vector II for
	different mesh sizes. The dashed line shows the evaluations
F 01	required by the run that resulted in the best structure 109
0.21	TODE with LEE Victors Lts IV
E 00	Optimized atmatunes of SVD TODS with alternative LSE
0.22	voctors including voctors L and II for completeness 112
5 92	Resulting structures from SVR_TOPAS for increasing val
0.40	ues of the group size parameter N <sub>a</sub> and increasing numerical
	noise 11/
	nonoc

5.24	The variance of the noise versus the mean compliance of the optimized structures obtained from running SVR-TOPAS	
	for several group sizes	115
$\begin{array}{c} 6.1 \\ 6.2 \end{array}$	Clamped beam subject to rigid cylindrical pole crash Energy absorption versus the number of iterations respec-	127
	TOPS-PCM.	131
6.3	Optimized structure for beam crash energy maximization.	132
0.4	PCM-TOPS and HCA results for beam crash energy max-	100
6.5	Optimized structures obtained by all 15 PCM-TOPS runs	132
	for the maximum energy beam, ordered by decreasing	
6.6	$E_{\rm abs}/\rm kNm$ , starting from the highest	133
	optimization.	134
6.7	The optimized update-signals colour-coded onto the beam	105
	structure for different iterations.	135
6.8	Illustration of intrusion during a side pole impact	136
6.9	The model of frame subject to the crash with a rigid pole.	137
6.10	of a rigid pole.	138
6.11	Intrusion versus the number of iterations (top), respectively	
	evaluations (bottom) for frame intrusion minimization with	
0.10	TOPS-PCM, shown for the best and the mean run	141
6.12	Optimized thickness distribution of the frames subject to intrusion minimization by PCM-TOPS and by HCA	142
6.13	Deformation of the optimized frames subject to intrusion	
	minimization by PCM-TOPS and by HCA, seen from the	
	front	143
6.14	Deformation of the optimized frames subject to intrusion minimization by PCM TOPS and by UCA scen from the	
	side	144
6.15	The average z-displacement $\bar{u}_z(t)$ of the intruding node set	
	$\mathcal{G}_{I}$ during the crash, of the frame subject to intrusion mini-	
	mization for the initial and the optimized designs by PCM-	
	TOPS and HCA. For PCM-TOPS, the mean of the runs is	
	plotted with bars indicating the standard deviation	145

6.16	The empirical correlation coefficient between update-signals and LSFs plotted over the iterations for the frame structure
	optimization
6.17	The optimized update-signals colour-coded onto the frame structure for different iterations
B.1	The optimized structures resulting of running NE-TOPS on the minimum compliance cantilever problem, for LSF
	Vector I
B.2	The optimized structures resulting of running PCM-TOPS on the minimum compliance cantilever problem, for LSF
	Vector I
B.3	The optimized structures resulting of running NE-TOPS on the minimum compliance cantilever problem, for LSF
	Vector II
B.4	The optimized structures resulting of running PCM-TOPS on the minimum compliance cantilever problem, for LSF
	Vector II
$C_{1}$	Strain-stress curves for the non-linear material models used
0.1	in the crash simulations 173
C.2	The optimized update-signals depending on the LSFs for
	the energy absorption beam
C.3	The optimized update-signals depending on the LSFs for
	the minimum intrusion frame

# List of Tables

5.1	Parameter settings for the plane stress minimum compliance
	cantilever reference problem
5.2	Parameter settings for NE/PCM-TOPS experiments 89
5.3	Parameter settings for LIN/SVR-TOPS experiments 101
5.4	Group size parameter for SVR-TOPAS that results in the
	lowest compliance for a given noise value
5.5	Overview of TOPS approaches and findings
6.1	Specifications for clamped beam model subject to pole crash.128
6.2	Specifications of PCM-TOPS for beam crash energy absorp-
	tion
6.3	Specifications for clamped frame subject to rigid pole crash. 137
6.4	Specifications of PCM-TOPS for frame intrusion minimiza-
	tion
B.1	Minimum, mean and maximum compliance and number of
	evaluations obtained by the different experiments on the
	compliance cantilever problem
B.2	Minimum, mean and maximum compliance and number of
	evaluations obtained by the different experiments on the
	compliance cantilever problem relative to the reference 169
C.1	Material constants of the elastic-plastic material model of
	the frame problem in Sec. 6.3

# Symbols and Abbreviations

### Symbols

- $\rho$  Density, topology optimization design variable
- *F* Objective function
- u State vector
- G Constraint
- $\Omega$  Design domain
- **x** Point in design domain
- V Volume of structure
- *L* Number of extra constraints
- $\rho$  Vector of densities, topology optimization design variables
- N Number of finite elements in design space mesh
- *E* Material Young's modulus
- *p* Penalization coefficient
- c Compliance
- l Load vector
- **K** Stiffness matrix
- f Volume fraction
- v Finite element volume
- $\mu$  Number of parent individuals
- $\rho$  Number of parent individuals used for creating new offspring individuals
- $\kappa$  Individual lifetime
- $\lambda$  Number of offspring individuals
- heta Vector of ES design variables, update-signal model parameters
- k Iteration number
- $\Theta$  Number of search dimensions in ES
- **z** Random mutation vector
- **C** Covariance matrix of ES mutation operator
- $\mathcal{N}$  Normal distribution
- $\sigma$  Standard deviation of normal distribution, global step size
- $\sigma$  Vector of strategy parameters
- z Random mutation number

au	Learning parameter
m	Distribution mean
$\mathbf{v}$	Adjoint state vector
S	Update-signal model
J	Number of LSFs
$\mathbf{s}_i$	LSF Vector
u	Nodal displacement
В	OC-input
m	Move limit
$\eta$	OC damping parameter
$\widehat{S}$	Filtered update-signal model
Λ	Lagrange multiplier for volume constraint
$\widehat{H}$	Sensitivity filter weights
$r_{\min}$	Sensitivity filter radius
$\Delta F$	Design improvement
M	Number of evluations
g	MLP activation function
H	Number of hidden neurons
$\mathcal{V}$	Data set of LSF samples
с	LSF prototype
P	Number of LSF prototypes
$\Psi$	Mapping from LSF space to finite set of indices
ζ	Cluster index
$\epsilon$	Finite difference step length
T	Number of training samples
y	Prediction target
${\mathcal{G}}$	Set of element or node ids
$\hat{k}$	SVR kernel function
Ĺ	Number of support vectors
ν	Poisson's ratio
SED	Strain energy density
$\varrho'$	Volumetric mass density
$\sigma_{ m Y}$	Yield stress
$E_{\rm h}$	Elasticity hardening modulus
q	Penalization coefficient for plasticity
$E_{abs}$	Energy absorption
IED	Internal energy density
r	Simulation residual
t	Time

I Intrusion

### Abbreviations

BESO	Bi-directional Evolutionary Structural Optimization
CMA	Covariance Matrix Adaptation
CPPN	Compositional Pattern Producing Network
EA	Evolutionary Algorithm
$\mathbf{EC}$	Evolutionary Computation
$\mathbf{ES}$	Evolution Strategy
ESL	Equivalent Static Load
FD	Finite Difference
FEA	Finite Element Analysis
HCA	Hybrid Cellular Automata
LIN	Linear Regression
LSF	Local State Feature
LSM	Level Set Method
MLP	Multi-Layer Perceptron
NE	Neuro-Evolution
NEAT	Neuro Evolution for Augmenting Topologies
OC	Optimality Criteria
PCM	Piecewise-Constant Model
RBF	Radial Basis Function
SERA	Sequential Element Rejections and Admissions
SVR	Support Vector Regression
SIMP	Solid Isotropic Material with Penalization
TOPAS	Topology Optimization by Predicting Aggregated Sensitivities
TOPS	Topology Optimization by Predicting Sensitivities

### Abstract

The automatic creation of optimal concepts for mechanical structures in the computer-aided design process has become an important area of research. Continuum topology optimization methods determine the distribution of material within a pre-defined design space and, thus, not only the shape, but also the fundamental geometric layout of a structure. For this task, the majority of the existing, numerical optimization methods requires mathematical gradient information. However, when addressing optimization problems that involve highly non-linear or black-box simulations, it can be difficult to obtain satisfactory results or gradient information at all. In order to provide design concepts also for these types of problems, this thesis presents a generic topology optimization approach. The novel method realizes a self-contained learning component that utilizes physical simulation data to generate a search direction. Based on a continuous problem formulation, every design variable is improved iteratively by a learned update-signal. The individual update-signals are computed from local state features and substitute sensitivities of the design variables. Evolutionary optimization or supervised learning adapt the model parameters for determination of the update-signals to the chosen optimization goal. In empirical studies, the novel method reproduces reference structures with minimum compliance. When applied to a practical problem from the challenging domain of vehicle crashworthiness optimization, specifically the minimization of intrusion, it provides superior design concepts when compared to a frequently applied heuristic method. The results confirm that the proposed method is capable to yield innovative solutions to so far unsolved topology optimization problems.

## Zusammenfassung

Die automatische Erstellung von optimalen Entwurfskonzepten für mechanische Strukturen im rechnergestützten Entwicklungsprozess ist ein wichtiger Forschungszweig. Methoden der Topologieoptimierung bestimmen die Materialverteilung in einem vordefinierten Entwurfsraum und daher nicht nur die Form, sondern auch die grundsätzliche geometrische Ausgestaltung einer Struktur. Die Mehrheit der verfügbaren numerischen Optimierungsmethoden benötigen hierfür mathematische Gradienteninformation. Betrachtet man jedoch Optimierungsprobleme, die stark nichtlineare oder Blackbox-Simulationen beinhalten, kann es schwierig sein, zufriedenstellende Ergebnisse oder überhaupt Gradienteninformation zu erhalten. Um auch für solche Probleme Entwurfskonzepte zu finden, wird in dieser Dissertation ein generischer Topologieoptimierungsansatz präsentiert. Die neue Methode realisiert eine eigenständige Lernkomponente, welche in der Lage ist, aus physikalischen Simulationsdaten eine Suchrichtung zu erstellen. Basierend auf einer kontinuierlichen Formulierung des Problems wird jede Entwurfsvariable durch ein gelerntes Updatesignal iterativ verbessert. Die individuellen Updatesignale berechnen sich aus lokalen Zustandsmerkmalen und ersetzen die Sensitivitäten der Entwurfsvariablen. Evolutionäre Optimierung oder überwachte Lernverfahren passen die Modellparameter zur Bestimmung der Updatesignale an das gewählte Optimierungsziel an. In empirischen Studien reproduziert die neue Methode Referenzstrukturen mit minimaler Nachgiebigkeit. Bei der Anwendung auf ein Problem aus dem anspruchsvollen Gebiet der Optimierung des Fahrzeug-Unfallverhaltens, speziell der Minimierung der Eindringtiefe, liefert sie überlegene Entwurfsvorschläge im Vergleich mit einer häufig verwendeten heuristischen Methode. Die Ergebnisse bestätigen, dass die vorgeschlagene Methode in der Lage ist, innovative Losungen für bisher ungelöste Topologieoptimierungsprobleme zu erzeugen.