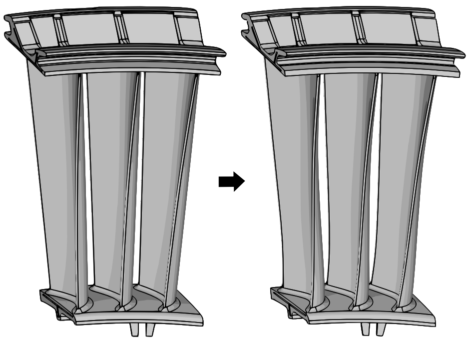
Ilya Arsenyev

Efficient Surrogate-based Robust Design Optimization Method

Multi-disciplinary Design for Aero-turbine Components



Fachgebiet für Computational Mechanics
Prof. Dr.-Ing. Fabian Duddeck
Technische Universität München

TECHNISCHE UNIVERSITÄT MÜNCHEN

Ingenieurfakultät Bau Geo Umwelt
Professur für Computational Mechanics

Efficient Surrogate-based Robust Design Optimization Method.

Multi-disciplinary Design for Aero-turbine Components.

Ilya Arsenyev

Vollständiger Abdruck der von der Ingenieurfakultät Bau Geo Umwelt der Technischen Universität München zur Erlangung des akademischen Grades eines

Doktor-Ingenieurs

genehmigten Dissertation.

Vorsitzender: Prof. Dr.-Ing. Kai-Uwe Bletzinger

Prüfer der Dissertation:

1. Prof. Dr.-Ing. habil. Fabian Duddeck
2. Prof. Dr.-Ing. habil. Ronald Mailach
3. Prof. Dr.-Ing Tom Verstraete

Die Dissertation wurde am 27.06.2017 bei der Technischen Universität München eingereicht und durch die Ingenieurfakultät Bau Geo Umwelt am 01.12.2017 angenommen.

Schriftenreihe des Fachgebiets für Computational Mechanics

Band 7

Ilya Arsenyev

Efficient Surrogate-based Robust Design Optimization Method

Multi-disciplinary Design for Aero-turbine Components

Shaker Verlag
Aachen 2018

Bibliographic information published by the Deutsche Nationalbibliothek
The Deutsche Nationalbibliothek lists this publication in the Deutsche Nationalbibliografie; detailed bibliographic data are available in the Internet at http://dnb.d-nb.de.

Zugl.: München, Techn. Univ., Diss., 2017

Copyright Shaker Verlag 2018
All rights reserved. No part of this publication may be reproduced, stored in a retrieval system, or transmitted, in any form or by any means, electronic, mechanical, photocopying, recording or otherwise, without the prior permission of the publishers.

Printed in Germany.

ISBN 978-3-8440-6090-4
ISSN 2193-2700

Shaker Verlag GmbH • P.O. BOX 101818 • D-52018 Aachen
Phone: 0049/2407/9596-0 • Telefax: 0049/2407/9596-9
Internet: www.shaker.de • e-mail: info@shaker.de

Abstract

This work continues the recently intensified research aimed to propose efficient methods for the optimization of industrial turbine components under the presence of uncertainties. Improvement and automation of the multi-disciplinary simulation process combined with optimization and optimization under uncertainty (OUU) techniques should bring considerable reduction of development time, while improving the design. The first deliverable of this work is a new multi-disciplinary analysis (MDA) chain, which includes aerodynamic, thermal and structural analysis followed by fatigue life prediction. Accurate three-dimensional transient thermal analysis is introduced, to the knowledge of the author, for the first time into the automatic MDA chain within this work. The transient thermo-mechanical analysis results into a significant increase of computational costs, which limits the total number of system evaluations for further deterministic optimization and OUU applications. This motivated the development and implementation of efficient optimization and OUU methods, capable of solving expensive engineering problems within a very limited amount of system evaluations.

In this work, robustness of an objective function together with reliability with respect to design constraints are requested simultaneously in order to consider the design as robust, leading to the concept of Reliability-Based Robust Design Optimization (RBRDO). Special attention is paid to efficient adaptive surrogate-based methods, aimed at solving computationally demanding engineering problems. A novel Efficient Global Optimization with Performance Measure Analysis (EGOPMA) method for inverse reliability analysis with the help of Gaussian process surrogates is proposed to be used within the RDO framework. The method is capable to obtain the first order Probabilistic Performance Measures (PPM) for non-linear functions within a very limited number of system evaluations. This allowed formulating the novel RBRDEGO method, which combined efficiency and global properties of the EGO method for optimization with the proposed EGOPMA for reliability assessment and sampling-based robustness quantification. Special attention is paid to handling noisy simulation-based results and missing data from failed simulations as well as to the ability of the method to exploit parallelism of an industrial computational environment.

Comparison with the latest state-of-the-art methods provided validation of the RBRDEGO method and indicated its high efficiency. The method was successfully applied to realistic high-dimensional simulation-based problems, such as aerodynamic 3D shape of a single vane.

Finally, a synergy of the main deliverables of this research enabled a multi-disciplinary reliability-based robust design optimization of the LPT vane cluster with the help of the developed MDA process chain and proposed RBRDEGO. The optimization of the vane design led to a significant reduction of the stage losses, while respecting all the multi-disciplinary constraints. RBRDO allowed to include effects of shape and loads uncertainty into the optimization, so that an obtained optimal design also satisfies robustness requirements. The optimum was validated using Monte-Carlo random sampling, which confirmed the robustness of the design and the accuracy of the method.

Zusammenfassung

Diese Arbeit setzt die in jüngerer Zeit intensivierte Forschung im Bereich von effizienten Optimierungsmethoden unter Unsicherheit für industrielle Turbinenentwicklung fort. Verbesserung und Automatisierung von multidisziplinären Simulationsketten wurden realisiert in Verbindung mit Methoden für die Optimierung unter Unsicherheit (OUU) mit dem Ziel der Reduktion der Entwicklungszeit sowie der gleichzeitigen Verbesserung des Designs. Daraus resultiert als erstes Ergebnis dieser Arbeit eine neu entwickelte Prozesskette für die multidisziplinäre Analyse (MDA), die Simulationen der Aerodynamik, der transienten thermischen Analyse, der Strukturmechanik und der Lebensdauer kombiniert. Soweit dem Autor bekannt wurde hier zum ersten Mal eine detaillierte drei-dimensionale transiente thermische Analyse in eine voll automatisierte Optimierungskette integriert. Die so etablierte MDA-Kette führt zu einem hohen Rechenaufwand, der die Zahl von Systemberechnungen deutlich begrenzt, die noch industriell akzeptabel wäre. Dieser hohe Rechenaufwand motivierte die Entwicklung von effizienten OUU Methoden, die aufwändige technische Optimierungsprobleme nun innerhalb industriell umsetzbarer Zeit lösen können.

In dieser Arbeit wird die Robustheit der Zielfunktion zusammen mit der Zuverlässigkeit bezüglich der Design-Nebenbedingungen berücksichtigt, was zum Konzept der Reliability-based Robust Design Optimization (RBRDO) führt. Hierbei werden besonders effiziente adaptive Ersatzmodell-basierte Methoden betrachtet (Efficient Global Optimization with Performance Measure Analysis, EGOPMA), die durch Verwendung von mathematischen Modellen die Optimierung und die Robustheitsanalyse beschleunigen. Speziell wurde hier eine neue EGOPMA-Methode für die inverse Zuverlässigkeitsanalyse mittels Ersatzmodellen auf Basis von Gauß-Prozessen vorgeschlagen. Die neu entwickelte Kombination dieses Ansatzes mit der etablierten adaptiven Gauß-Prozess-basierten Optimierungsmethode EGO (Efficient Global Optimization) ermöglicht jetzt die effiziente RBRDO von komplexen Problemen mit einer sehr niedrigen Zahl von Simulationen. Spezielle Verfahren wurden zusätzlich beachtet zur Beherrschung des numerischen Rauschens und zur Stabilisierung betreffs irregulär beendeter

Berechnungen. Eine Parallelisierung des Verfahrens wurde ermöglicht, um die Methode im Kontext von industriell hoch parallelisierten HPC-Umgebungen (High Performance Computing) anwendbar zu machen. Vergleiche mit modernsten RBRDO-Methoden und mit realistischen Anwendungsbeispielen inklusive einer 3D-aerodynamischen Formoptimierung eines Schaufelclusters zeigen die hohe Effizienz der entwickelten und implementierten Vorgehensweise.

Die Hauptergebnisse dieser Forschungsarbeit ermöglichen in Zukunft die multi-disziplinäre RBRDO eines Schaufelclusters einer Niederdruckturbine durch die Kombination der implementierten MDA-Prozesskette mit der neu entwickelten Methode. Im Beispiel hat die Optimierung selbst dann noch eine signifikante Reduktion der aerodynamischen Verluste gebracht auch wenn alle multi-disziplinären Nebenbedingungen mit einem gewünschten Zuverlässigkeitsniveau unter stochastischer Form- und Lastvariation erfüllt werden mussten. Das abgeleitete Optimum wurde mithilfe eines Monte-Carlo-Samplings validiert, so dass die Designzuverlässigkeit und Verfahrensgenauigkeit bestätigt werden konnte.

Acknowledgements

I would like to thank my supervisor Prof. Dr. Fabian Duddeck for giving me the opportunity to conduct my doctoral research at the chair of Computational Mechanics of the Technische Universität München, for his help, availability, interesting meetings and discussions. I would like to thank Dr. Andreas Fischersworring-Bunk for his support and guidance of my work in the MTU Aero Engines.

A special thank goes to Giulia Antinori for sharing with me the problems and difficulties but also the successes and fun of working on the topic of robust design optimization for low pressure turbines applications.

My appreciation goes especially to Dave Cloud for the positive attitude and confidence he always showed despite all the difficulties; to Daniel Theurich and Michael Junge for their help and support in getting familiar with structural and thermal mechanics processes within turbine design; to Frank Vöse for his help in getting used to completely new MTU working environment; to all my colleagues in MTU Aero Engines for their continuous help and support they provided and for creating very nice working environment and sharing their knowledge.

I would also like to thank my colleagues at the chair of Computational Mechanics, Daniel Weigert, Stefan Erschen, Lailong Song, Simon Moessner, Simon Hesse, Gesche Fender, Pablo Lozano, Duo Zeng, Koushiar Komeilizadeh, Erich Wehrle for the nice time and interesting discussions we had.

I would like to thank my wife Anna and the whole of my family for the infinite support and strong encouragement they always provided to me.

Dedicated to my family.

Contents

Acronyms

2D	Two-dimensional.
3D	Three-dimensional.
AL	Augmented-Lagrangian.
AMV	Advanced Mean Value method.
ANN	Artificial Neural Network.
ASA	Adaptive Simulated Annealing.
BC	Boundary Condition.
BFGS	Broyden–Fletcher–Goldfarb–Shanno algorithm.
BLUP	Best Linear Unbiased Predictor.
CAD	Computer-aided Design.
CBS	Constraint Boundary Sampling.
CDF	Cumulative Distribution Function.
CEI	Constrained Expected Improvement.
CFD	Computational Fluid Dynamics.
CMGEI	Clustered Multiple Generalized Expected Improvement.
CV	Cross-validation.
DIRECT	Dividing Rectangles method.
DOE	Design of Experiments.
DOF	Degree of Freedom.
EGO	Efficient Global Optimization.
EGOPMA	Efficient Global Optimization with Performance Measure Analysis.
EGRA	Efficient Global Reliability Analysis.
EI	Expected Improvement.
EO	Engine Order.
ES	Evolutionary Strategy.

EWC	End Wall Contouring.
FEM	Finite-element Method.
FORM	First Order Reliability Method.
FP	Feasibility Probability.
GA	Genetic Algorithm.
GEI	Generalized Expected Improvement.
GP	Gaussian Process.
HMV	Hybrid Mean Value method.
HPC	High-pressure Compressor.
HPT	High-pressure Turbine.
HTC	Heat Transfer Coefficient.
LE	Leading Edge.
LHD	Latin-Hypercube Design.
LHS	Latin-Hypercube Sampling.
LOOCV	Leave-one-out Cross-validation.
LPC	Low Pressure Compressor.
LPT	Low Pressure Turbine.
MC	Monte-Carlo.
MCMC	Markov Chain Monte-Carlo.
MCS	Monte-Carlo Sampling.
MDA	Multi-disciplinary Analysis.
MDO	Multi-disciplinary Optimization.
MLE	Maximum Likelihood Estimation.
MOGA	Multi-objective Genetic Algorithm.
MPFP	Most Probable Failure Point.
MPP	Most Probable Point.
MPPIR	Most Probable Point of Inverse Reliability method.
MPTP	Minimum Performance Target Point.
MSE	Mean Square Error.
NSGA2	Nondominated Sorting Genetic Algorithm II.
OUU	Optimization under Uncertainty.
PDF	Probability Density Function.

PMA	Performance Measure Analysis.
PPM	Probabilistic Performance Measure.
PS	Pressure Side.
RANS	Reynolds-averaged Navier-Stokes.
RBF	Radial Basis Function.
RBRDEGO	Reliability-based Robust Design Efficient Global Optimization.
RBRDO	Reliability-based Robust Design Optimization.
RDO	Robust Design Optimization.
RIA	Reliability Index Analysis.
RMSE	Root Mean Square Error.
RSM	Response Surface Method.
SA	Simulated Annealing.
SBGO	Surrogate-based Global Optimization.
SBLO	Surrogate-based Local Optimization.
SKE	Secondary Kinetic Energy.
SLHS	Symmetrical Latin-Hypercube Sampling.
SORA	Sequential Optimization and Reliability Assessment.
SORM	Second Order Reliability Method.
SQP	Sequential Quadratic Programming.
SS	Suction Side.
SVR	Support Vector Regression.
TE	Trailing Edge.
TKE	Turbulent Kinetic Energy.
TMF	Thermo-mechanical Fatigue.
TO	Take-off.
TUM	Technische Universität München.
WEI	Weighted Expected Improvement.

List of Symbols

$\mu(\cdot)$	Mean of an uncertain quantity.
$\sigma^2(\cdot)$	Variance of an uncertain quantity.
$E[\cdot]$	Expectation operator.
$\boldsymbol{x}$	Vector in multi-dimensional space.
$\boldsymbol{X}$	Matrix of points $\boldsymbol{x}$.
C	Covariance.
R	Correlation.
σ_z^2	Gaussian process variance.
n	Dimension of the space.
N	Number of points or observations.
f	Arbitrary function.
y	Observation of a function at a point $\boldsymbol{x}$.
$\boldsymbol{\beta}$	Regression coefficients.
$\boldsymbol{F}$	Regression matrix.
$\boldsymbol{r}$	Correlation vector between selected point and other training points.
$\boldsymbol{R}$	Correlation matrix.
I	Unit diagonal matrix.
σ_n^2	Noise variance.
τ	Nugget term.
$\boldsymbol{\theta}$	Vector of hyperparameters.
ν	Parameter of Matèrn correlation function.
Γ	Gamma function.
K_ν	Modified Bessel function of the second kind.
γ	Parameter of exponential correlation function.
$p(\cdot\|\cdot)$	Conditional probability.

L	Likelihood function.
ψ	Reduced likelihood function.
y_{min}	Current optimal solution of an optimization problem.
$I(\cdot)$	Improvement w.r.t. current optimum.
$P[\cdot]$	Probability.
$\mathbf{\Phi}$	Normal distribution CDF.
ϕ	Normal distribution PDF.
g	Order of GEI.
w	Weight in WEI.
I_c^g	Generalized improvement with constraints.
F	Gaussian process of the objective function.
g_i	Constraint function i.
G_i	Gaussian process of constraint i.
$\sigma_{g_i}^2$	Variance of G_i.
P	Penalty term.
$\mathbf{\Psi}$	Augmented-Lagrangian penalty function.
λ_i	Lagrange multiplier.
p	Penalty parameter.
μ	Penalty parameter.
V	Constraint violation.
$\hat{y}$	Gaussian process approximation of a function.
$\hat{f}$	Gaussian process approximation of an objective function.
$\hat{g}_i$	Gaussian process approximation of a constraint function.
β	Reliability index.
β_{HL}	Hasofer-Lind reliability index.
U	Standard normal space.
$\boldsymbol{u}$	Point in U.
T	Transformation from X into U space.
$\boldsymbol{n}$	Unit vector or normal vector.
P_f	Failure probability.
ϵ	Small constant.
$\boldsymbol{v}$	Point in uncertain space.

h	Enthalpy.
s	Entropy.
ς	Losses.
c_p	Specific heat at constant pressure.
c_v	Specific heat at constant volume.
R	Ideal gas constant.
T	Temperature.
σ	Stress.
E	Elastic modulus.
f	Frequency.
E_t	Total energy per unit volume.
e	Internal energy per unit mass.
Q	Heat generation per unit volume.
$\boldsymbol{u}$	Flow velocity vector.
p	Pressure.
ρ	Density.
$\boldsymbol{f}$	Body force per unit volume.
$\boldsymbol{\sigma}$	Stress tensor.
$\boldsymbol{\tau}$	Deviatoric part of stress tensor - shear stress tensor.
μ	Dynamic viscosity coefficient.
κ	Bulk viscosity coefficient.