FEA information

WORLDWIDE NEWS

February 2004

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Dr. Ted. Belytschko **US**	**Dr. Bhavin V. Mehta** **US**	**Dr. Taylan Altan** **US**	**Dr. David Benson** **US**
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Articles

Editor	**Trent Eggleston**
Editor – Technical Content	**Arthur B. Shapiro**
Technical Writer	**Dr. David Benson**
Technical Writer	**Uli Franz**
Graphic Designer	**Wayne Mindle**
Feature Director	**Marsha J. Victory**

Updated Overview of Some LS-OPT Features

Dr. Nielen Stander

www.crashoptimization.com

Introduction

LS-OPT is a standalone Design Optimization and Probabilistic Analysis package with an interface to LS-DYNA. In the "conventional design" approach, a design is improved by evaluating its "response" and making design changes based on experience or intuition. This approach does not always lead to the desired result, that of a 'best' design, since the design objectives are often in conflict. It is therefore not always clear how to change the design to achieve the best compromise of these objectives. A systematic approach can be obtained by using an inverse process of first specifying the criteria and then computing the 'best' design according to a formulation. The improvement procedure that incorporates design criteria into a mathematical framework is referred to as Design Optimization This procedure is often iterative in nature and therefore requires multiple simulations.

No two products of the same design will be identical in performance, nor will a product perform exactly as designed or analyzed. A design is typically subjected to Structural variation and Environmental variation input variations that cause a variation in its response that may lead to undesirable behavior or failure. In this case a Probabilistic Analysis, using multiple simulations, is required to assess the effect of the input variation on the response variation and to determine the probability of failure.

To run and control multiple analyses simultaneously, LS-OPT provides a simulation environment that allows distribution of simulation jobs across multiple processors or networked computers. Each job running in parallel consists of the simulation, data extraction and disk cleanup. Measurements of time remaining or performance criteria such as velocity or energy are used to measure job progress for LS-DYNA's explicit dynamic analysis calculations.

The graphical preprocessor LS-OPT*ui* facilitates definition of the design input and the creation of a command file while the postprocessor provides output such as approximation accuracy, optimization convergence, tradeoff curves, anthill plots and the relative importance of design variables. The postprocessor also links to LS-PrePost to allow the viewing of the model representing a chosen simulation point.

Typical applications for LS-OPT are

Design Optimization

System Identification

Probabilistic Analysis

Future versions of LS-OPT will combine optimization and probabilistic analysis features in Reliability-Based Design Optimization.

Capabilities

Optimization

The Optimization capability in LS-OPT is based on Response Surface Methodology and Design of Experiments. The D-Optimality Criterion is used for the effective distribution of sampling points for effective generalization of the design response. A Successive Response Surface Method allows convergence of the design response. Neural Networks provide an updateable global approximation that is gradually built up and refined locally during the iterative process. A Space Filling sampling scheme is used to update the sampling set by maximizing the minimum distances amongst new and existing sampling points.

LS-OPT allows the combination of multiple disciplines and/or cases for the improvement of a unique design. Multiple criteria can be specified and analysis results can be combined arbitrarily using C or FORTRAN type mathematical expressions.

Response Surface Methodology

Response surface methodology (RSM) is a collection of statistical and mathematical techniques useful for developing, improving and optimizing the design process. RSM encompasses a point selection method (also referred to as Design of Experiments, Approximation methods and Design Optimization to determine optimal settings of the design dimensions. RSM has important applications in the design, development, and formulation of new products, as well as in the improvement of existing product designs.

In LS-OPT, Response Surface Methodology is used both in Optimization and Probabilistic Analysis as a means to reduce the number of simulations. In the latter procedure, RSM is also used to distinguish deterministic effects from random effects.

Probabilistic Analysis

LS-OPT enables the investigation of stochastic effects using Monte Carlo simulation involving either direct FE Analysis or analysis of Surrogate models such as Response Surface Methodology or neural networks. As an input distribution, any of a series of statistical distributions such as Normal, Uniform, Beta, Weibull or User-defined can be specified. Latin Hypercube sampling provides an efficient way of implementing the input distribution. Histograms and influence plots are available through the postprocessor (Version 2.2).

Instability/Noise/Outlier Investigations (Version 2.2)

Some structural problems may not be well-behaved i.e. a small change in an input parameter may cause a large change in results.

LS-OPT computes various statistics of the displacement and history data for viewing in the LS-DYNA FE model postprocessor (LS-PrePost). The methodology differentiates between changes in results due to design variable changes and those due to structural instabilities (buckling) and numerical instabilities (lack of convergence or round-off). Viewing these results in LS-PrePost allows the engineer to pinpoint the source of instability for any chosen response and therefore to address instabilities which adversely affect predictability of the results.

Tradeoff

A tradeoff study enables the designer to interactively study the effect of changes in the design constraints on the optimum design. E.g. the safety factor for maximum stress in a beam is changed and the designer wants to know how this change affects the *optimal* thickness and displacement of the beam.

Variable Screening

For each response, the relative importance of all variables can be viewed on a bar chart together with their confidence intervals. This feature enables the user to identify variables of lesser importance that can be removed from the optimization, thereby contributing to time saving while having little effect on the final result.

Glossary

Design of Experiments

A point selection method for determining the number and locations of sampling points in the Design Space. A simulation is done at each sampling point.

Approximation

A simple mathematical function acting as a substitute (or surrogate model) to generalize the (often highly complex) Response variation across the Design Space.

The result obtained from an analysis (e.g. Finite Element Analysis) of a product or process. The response is used as a criterion in Design Optimization or Probabilistic Analysis.

Design Optimization

The process of setting the design variables, typically the dimensions, of a product to minimize or maximize the value of its Response. A more general form of optimization includes specified limits on other responses (constrained optimization).

Probabilistic Analysis

The analysis of a set of different designs with a specified distribution in order to determine the characteristics (such as the mean and standard deviation) of the Response distribution.

Design Space

The region between the lower and upper limit for each of the design variables. These are specified to prevent the occurrence of designs with extreme of nonsensical dimensions (such as negative thicknesses).

Region of interest

A part of the Design Space considered being of interest for design exploration or Design Optimization.

Design Variable

An independent variable or dimension which forms part of the description of a design. Typical design variables are thickness dimensions, geometrical dimensions or values of material constants.

D-Optimality Criterion

A criterion that determines how well the coefficients of the design Approximation are estimated. The changes in the locations of the sampling points to maximize this criterion maximizes the confidence in the coefficients of the Approximation model.

Robust

A robust product performs consistently on target and is relatively insensitive to parameters that are difficult to control. A robust design minimizes the noise transmitted by the noise variables.

Noise variable

A parameter of a product that has some degree of uncontrollability while the product is being manufactured or used in the field up to the end of its lifetime.

Response Noise

The random component of a response variation that can be caused by instability of the structure (such as buckling), numerical roundoff during analysis or modeling effects such as Finite Element meshing or lack of convergence during analysis

Successive Response Surface Method

The successive response surface method is an iterative method which consists of a scheme to assure the convergence of an optimization process. The scheme determines the location and size of each successive Region of interest in the Design Space, builds a response surface in this region, conducts an Design Optimization and will check the tolerances on the Responses and design variables for termination. When using neural networks instead of polynomials as a Surrogate model, the Approximation is updated instead of newly constructed in each iteration. Consequently, the final approximation has a global representation that can be used for optimization, tradeoff studies or probabilistic analysis.

Structural variation

Variation in the dimensions or material properties of a product.

Environmental variation

Variation in the loads such as force (perhaps due to impact) and temperature considered in the design of a product.

System Identification

The determination of system parameters such as material constants to minimize the difference between computational responses and experimental results. The purpose is to identify the system parameters of a model by using experimental results of a physical experiment.

Surrogate model

Approximation

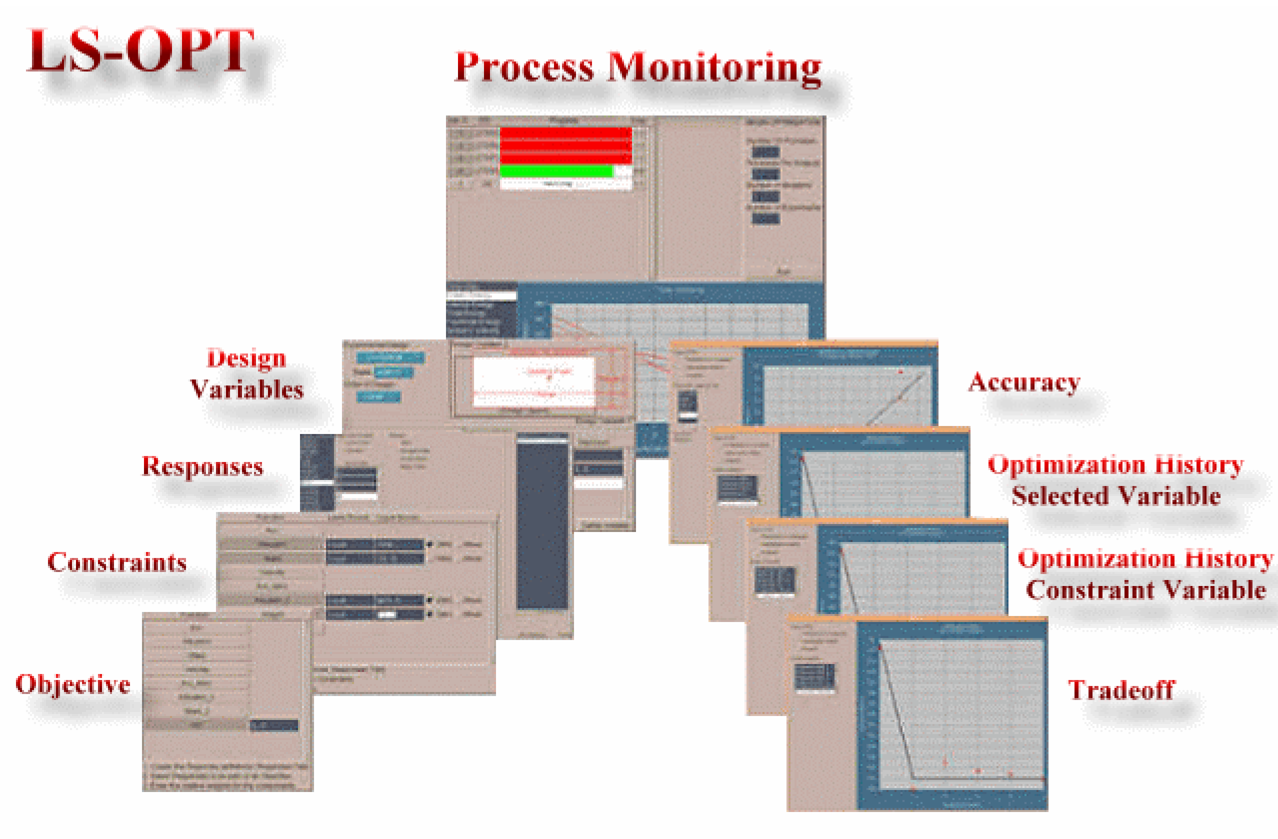
LS-OPT is delivered with LS-DYNA at no charge.

LS-OPT User's Manual Version 2 including shipping

$140 International

$70.00 USA

To order contact vic@lstc.com



At Intel's Developer Forum held in San Francisco, CEO Craig Barrett discussed Digital Technology Transforming Industries, Organizations.
Digital Technology Transforming Industries, Organizations.

Silicon and Solutions Drive Change, Increase Productivity, Create Opportunity. Topics include 64-bit Memory Extensions, HyperThreading (HT), Intel® Centrino™ mobile technology and more...

SAN FRANCISCO, Feb. 17, 2004 - Intel Corporation CEO Craig Barrett today described how the pervasive use of digital technology and continued technology advancement are driving the fundamental transformation of commerce, entertainment and communications worldwide. Speaking to more than 4,800 technology industry engineers, developers and designers at the Intel Developer Forum (IDF), Barrett described the changes taking place and the significant opportunities being created by technology for organizations and individuals.

"As organizations around the world look to information technology to increase productivity and performance, we're entering a period of rapid change driven by investment in new technology," said Barrett. "The transformation we're seeing with the convergence of computing and communications, with businesses continuing to embrace technology, and with the way entertainment is delivered and consumed, will begin to be applied to areas such as health care, life sciences, genomics, and new forms of computational innovation. Digital technology and silicon will be at the center of innovation as new opportunities, new fields of endeavor and new business models emerge to benefit from this transformation."

"At the same time, as digital technology becomes more pervasive, we must avoid making it overly complex for end-users. Intel and the industry must focus on developing solutions -- not just technical features -- that meet customer requirements and which can be more easily implemented at lower cost in enterprises, the digital home and in wireless communications."

The Intel Itanium® processor family is a notable example of the company's solutions-oriented approach to enterprise computing. Through industry collaboration and investments in software support and other important complementary technologies, the Itanium processor family is gaining momentum with key customers and improving business productivity. Intel sold more than 100,000 Itanium processors in 2003 and major system installations are being deployed at many Fortune 500 companies.

"Acceptance of the Itanium processor in key areas such as the financial services industry is extremely gratifying," Barrett said. "More and more firms in a variety of industries are realizing the performance, reliability, scalability, manageability and other benefits of Itanium-based platforms."

In other areas of computing, Intel is focused on meeting new opportunities by developing technologies and platforms for a broad range of customer needs that go beyond sheer chip speed. Intel has already brought to market technologies such as HyperThreading (HT) and Intel® Centrino™ mobile technology that provide end-user benefits in addition to better performance.

The company has also announced plans to bring the benefits of LaGrande technology (LT) to enhance secure computing; Vanderpool technology (VT), which would increase system reliability, flexibility and responsiveness; and other technologies to improve processing of digital media, packet processing, runtime performance, and data mining and synthesis. In the future, Intel processors will also incorporate other enhancements that will benefit the overall platform.

Beginning in the second quarter, Intel will introduce 64-bit memory extension technology to its IA-32 architecture for server and workstation processors. The 64-bit extension technology is one of a number of platform innovations Intel plans to deliver, or already is delivering to this segment of the market. Others include Intel Hyper-Threading technology, PCI Express, DDR2 memory support, enhanced power management and SSE3 instructions.

"Intel has the resources, flexibility, breadth of support and technical prowess to provide customers with the features they require for their computing needs," Barrett said. "Offering a broad lineup of solutions means that when combined with the Itanium processor family - which is designed specifically for business critical high-end server, and technical computing market segments -- we can provide leadership solutions from top to bottom in a variety of 64-and 32-bit configurations."

Intel is also focusing resources and attention on the transformation taking place in the home environment. The growing use of digital technology in the home is creating new opportunities for companies that can provide value and increased capabilities at lower cost for consumer electronic devices. Likewise, broadband wireless technology is transforming computing and communications. Much like Intel's Centrino mobile technology has changed the way businesses and individuals can now use technology, next generation cellular technologies along with new communications standards such as WiMax will further accelerate the convergence of computing and communications and improve productivity.

"Silicon technology is the engine driving the transformation of commerce, entertainment, education and science," Barrett said. "Intel's investments in R&D, manufacturing capacity and worldwide markets combined with our focus on providing customers a broad range of solutions, means the opportunities for growth and innovation are limited only by our own imaginations."

More information available on the following websites:

Intel in Manufacturing: http://www.intel.com/go/manufacturing
64-bit memory extensions: http://developer.intel.com/technology/64bitextensions/
HyperThreading (HT): http://www.intel.com/products/ht/hyperthreading.htm
Intel® Centrino™ mobile technology: http://www.intel.com/products/mobiletechnology/index.htm

The TopCrunch Project
www.topcrunch.org

The TopCrunch project was initiated to track the aggregate performance trends of high performance computer systems and engineering software. Instead of using a synthetic benchmark, actual engineering software applications are used with real data and are run on high performance computer systems. The data are available for download in the form of data files for our current software suite. With time, we expect to track the evolution of delivered performance as a function of enhancements in both software algorithms and hardware. The results of the benchmarks are available as submitted, and may be searched by data, code name, and year. Summaries and overall rankings are posted twice per year following the precedent set by TOP500.

FAQ:

Who runs TopCrunch?

Prof. David Benson at UCSD runs TopCrunch, with support from his students, post-docs, research engineers, and web site support from the Jacobs School of Engineering.

How do I contact TopCrunch?

For web site related problems, click on "webmaster" at the bottom of the page. For issues associated with the benchmarks themselves, contact dbenson@ucsd.edu.

Who funds TopCrunch?

TopCrunch is supported by DARPA HPCS through a subcontract from the USC Information Sciences Institute.

Why do you use production codes for the benchmarks?

The objective is to track the aggregate computing performance available to scientists and engineers. Synthetic benchmarks are usually more highly optimized than production codes because they are much smaller and simpler codes, and therefore don't reflect real world performance. Research codes are generally not available to the broad range of people we would like to see perform the benchmarks, lack the breadth we are seeking, and the limited resources of the developers means that they can't provide the support required for non-specialists to use them.

How are the benchmark codes chosen?

The benchmarks are chosen to reflect the types of calculations performed in the mechanical and aerospace communities. Therefore, codes associated with structural dynamics (LS-DYNA), fluid flow (CTH), and materials science (SPaSM) have been chosen. These codes have different challenges to address in terms of domain decomposition, message passing, load balancing, and dynamic memory allocation that makes the comparison of their relative scaling interesting. Additional codes may be added in the future.

How are the benchmarks problems chosen?

The benchmark problems are chosen to reflect current engineering practice in the real world, and to have a structure that allows them to be scaled up as computer performance grows. The problems are not intended to be optimal analyses, i.e., the fastest possible choice of options to achieve a particular solution, because engineers rarely have time to optimize their analyses in real life. For example, the accuracy of the stress distribution in a structural element increases with the number of Gaussian quadrature points, but at the expense of speed. For a given level of accuracy, there is, therefore, a choice that maximizes speed. It is, however, common engineering practice to use more points than absolutely necessary because an inaccurate solution will require rerunning the analysis, which effectively doubles its cost and more than doubles the wall clock time to get an acceptable answer. The same general observation holds true for many other analysis choices to be made.

How do I obtain the benchmark codes?

The codes are available directly from their authors, and are not available on this site. The contact information is given on the code description pages.

How do I run the benchmark problems?

The general command lines required for executing a program are given on the code description pages, along with pointers to additional documentation for the codes.

Can I change the problem data?

No! Aside from the number of processors, no changes are permitted. As discussed, the problems are chosen to represent current industrial practice, and are not optimized for performance. Our goal is to track software and hardware performance, not analyst performance!

How do I obtain technical support for running the problems?

Technical support for running the codes is available through the software providers. If a particular problem downloaded from this site doesn't run, contact David Benson.

How do I submit the benchmark results?

Mail the ASCII output files from the analyses, which contain the timings, to Administrator. The entire file must be submitted, not just the timings.

How does TopCrunch prevent people from cheating?

We can't. We try to avoid obvious cheating by requiring the ASCII output files, but we recognize that a determined cheater can readily edit the output. We reserve the right to withdraw or not post results that appear suspicious, and to require benchmarkers to provide additional proof such as the binary restart and plot files. But we explicitly don't warranty the accuracy of the benchmark results. If you feel that results posted here are incorrect, please contact the Administrator.

Can I run the benchmark problems with my own code?

As one objective of the site is to track software advances, competition between codes is welcomed. However, in the interests of fairness, if you wish to have your results posted, you must

Run a model that is identical in all respects to the benchmark model. This includes, but is not limited to, element formulation, the number of integration points, time step scaling, material models, and domain decomposition (including the specification of contact surfaces).

Be willing to supply us with access to the results for verification and provide a version of the code to a platform of our choice under our control to run your data file and program independently at no cost to us.

Should I buy my computer based on the posted results?

We recognize that these results may be useful to some users in making basic decisions about their computing requirements. However, be aware of the following caveats:

The performance of a computer is the result of many aspects of the system, including the chip, the available memory, the connection between the processors (e.g., Gigabit Ethernet vs. Myrinet), the version of the operating system, the version of MPI, and the particular version of the benchmark code.

The performance is also subject to the particular circumstances under which it was performed, e.g., a benchmark run in a single user mode will usually be faster than one that was run with other users on the system.

We explicitly don't warrant the accuracy of the numbers posted on this site.

February Updated Conference News
By LSTC and ETA
LS-DYNA Conference May 2-4 2004

Keynote Speakers:

Dr. Priya Prasad
Ford Technical Fellow, Manager
Vehicle Safety R & D
Ford Motor Company

Dr. Ted Belytschko
Walter P. Murphy Professor
Northwestern University

Larry J. Achram, Vice President
Virtual Engineering & Crossfire
DaimlerChrysler

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Register On Line: www.ls-dynaconferences.com

Conference Only		
	Registration	$ 450
	Early Registration (prior to 04/16)	$ 400
	Student Rate (with valid ID)	$ 275

Conference & Training Seminar May 5th & 6th		
	Registration	$ 900
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Training Seminar Only May 5th & 6th		
	Registration	$ 450
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	Student Rate (with valid ID)	$ 275

Conference Registration Includes

1. **Conference Proceedings and Sessions**
2. **Continental Breakfast, Lunch, Refreshments**
3. **Reception and Conference Banquet**
4. **Admittance to Exhibition**

Training Seminar Registration Includes:

1. **Hands-on workshop w/Seminar Handouts**
2. **Continental Breakfast**
3. **Lunch**
4. **Refreshments**

Pre-Conference Seminar: VPG3.0: a new pre/post environment for LS-DYNApc
3:00 p.m. – May 2nd

SEMINARS – May 5th & 6th

- **Advanced Crashworthiness** — **Paul DuBois (Consultant)**
- **Heat Transfer Analysis** — **Arthur Shapiro, Ph.D. (LSTC)**
- **Implicit Analysis** — **Bradley Maker, Ph.D. (LSTC)**
- **LS-OPT** — **Nielen Stander, Ph.D. (LSTC)**
- **LS-PrePost** — **Philip Ho (LSTC)**
- **Metal Forming** — **Xinhai Zhu, Ph.D. (LSTC)**
- **ALE/Eulerian & Fluid Structure Interaction** — **Mhamed Souli, Ph.D (Univ. de Lille)**

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Educational Participants & Contributing Authors		
USA	Dr. T. Belytschko	Northwestern University
USA	Dr. D. Benson	Univ. California – San Diego
USA	Dr. Bhavin V. Mehta	Ohio University
USA	Dr. Taylan Altan	The Ohio State U – ERC/NSM
USA	Prof. Ala Tabiei	University of Cincinnati
USA	Tony Taylor	Irvine Aerospace Inc.
Russia	Dr. Alexey I. Borovkov	St. Petersburg State Tech. University
Italy	Prof. Gennaro Monacelli	Prode – Elasis & Univ. of Napoli, Federico II

Special Announcements and Highlights of News Pages

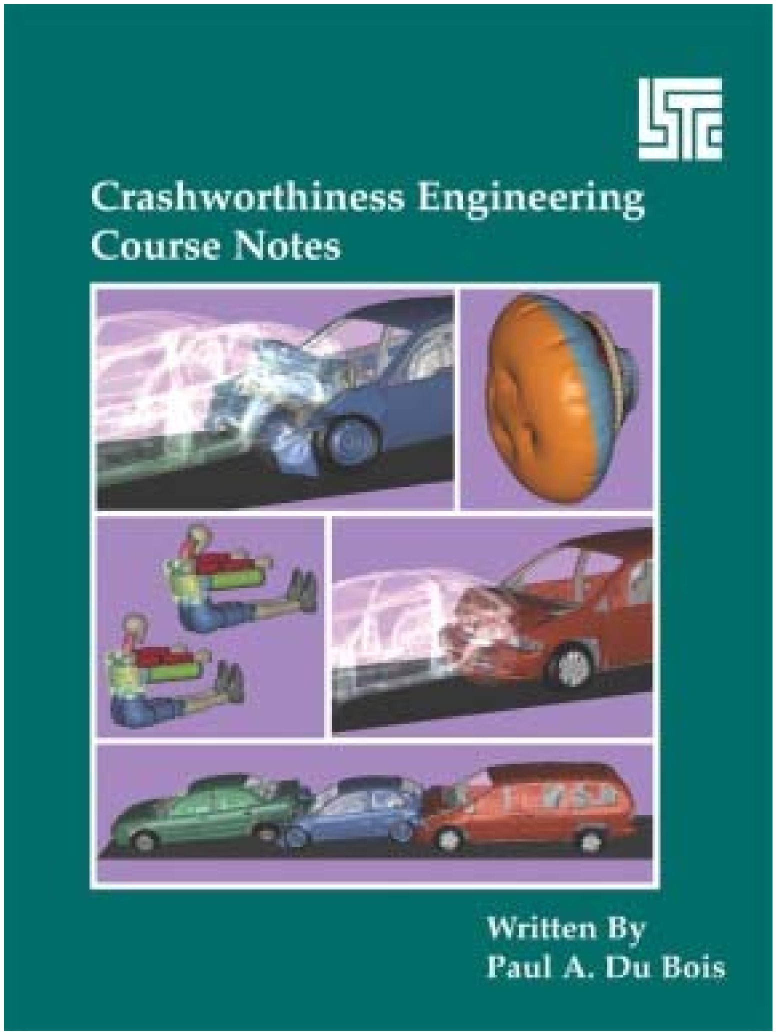
Posted on FEA Information and archived one month on the News Page

January 5th	LSTC	On line registration available
	MSC.Software	Dytran
	JRI	Nike-Works
	DYNAmore	Distributor - Germany
January 11th	SGI	SGI® Altix™
	ETA	DYNAFORM pc
	Altair – Italy	Distributor - Italy
January 18th	Oasys	Courses
	HP	Linux for HP workstations
	Numerica	Distributor - Italy
January 26th	INTEL	The Intel® Itanium® 2 processor
	Fujitsu	PRIMERGY
	MSC.Software China	Distributor China

2004	
Mar 08-11	SAE 2004 World Congress & Exhibition - Detroit, MI
May 2-3	8th International LS-DYNA Users conference will again be held at the Hyatt Regency Dearborn, Fairlane Town Center, Dearborn, MI hosted by LSTC and ETA
May 10-12	OPTECH04, Optimization Technology Meeting 2004
May 24-26	2004 ANSYS Users Conference and Exhibition to be held in Pittsburgh, Pennsylvania, U.S.A.

First Time Available in a Bound Edition
Limited Published Quantity

Crashworthiness Engineering Course Notes
Paul A. Du Bois

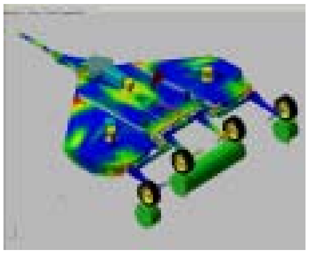


This first edition will be available to purchase on line in two weeks. To reserve a copy in advance contact Marsha Victory – vic@lstc.com

Pricing Includes Shipping (US currency) :

US	**$ 75.00**
International	**$100.00**

Durability Analysis Helps John Deere Cut Rotary Cutter Development Time in Half

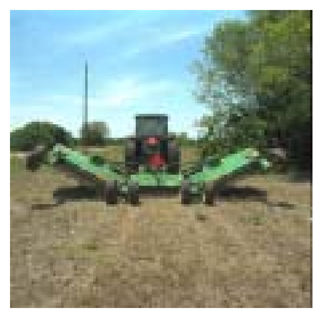


The implementation of durability analysis at John Deere Welland Works, Welland, Ontario, was one of the key factors in reducing development time for their rotary cutter systems. On the last two product generations, each design and test cycle was completed in one or two weeks using a virtual prototype instead of several months required by physical prototypes. As a result, development on a 20-foot cutter was reduced from about two to four years and most recently to one year.

One of the most time-consuming aspects of the cutter systems' development in the past was the lengthy process of building physical prototypes, testing them for durability, then redesigning several parts and starting all over again. In the last several years, Deere engineers have streamlined this process by building a virtual prototype of the entire cutter, including finite-element representations of the most fatigue-sensitive components.

Deere's virtual prototyping procedure mimics a physical durability test of its rotating drum. The virtual tests produce stress time-histories that are used by durability analysis software to make fatigue life predictions. These predictions have proven very accurate when compared to physical testing. "Using the new method, we have reduced the number of physical prototypes from three or four previously, down to two, and now one on our two most recent designs," said Terry Ewanochko, Product Engineer for John Deere Welland Works. "These time savings made a big contribution to the dramatic reductions in the development cycle on our latest products."

The 15-foot and 20-foot Flex-Wing rotary cutters made by John Deere are used by farm operators, road side maintenance companies and municipalities for turf and grass mowing, pasture clipping, knocking down and shredding stalks and clearing out brush. For this heavy-duty work, the cutters must be extremely durable. The cutter assembly consists of three articulated sections, the center and two wings, as well as rotating cutting blade sets, and support wheels. The sectional design floats to follow the ground contour, allowing uniform cutting height on hilly terrains while preserving the full cutting width of 15 feet or 20 feet.



For more convenient transporting the wings can be folded to reduce the width of the cutter. A tractor that provides a mechanical power take-off together with hydraulic lines tows the cutter. The power take-off drives the rotating cutters while the hydraulic lines drive the actuator cylinders that are used to control the cutter height and wing lift. The wings and center structure are fabricated using a double-deck steel plate construction concept. The center and wing axles, and lower hitch arm, are also fabricated. Continuous-seam and stitch welding provides extra strength for greater durability and provides manufacturing benefits over bolts and rivets.

Previous design process

Traditionally, Deere has relied upon a series of physical tests to ensure the survivability of these products when subjected to static and cyclic loadings. The most important is performed on a bump-test fixture, which simulates the jarring and twisting impact a cutter experiences when running over large bumps and rocks. The cutter is attached to a grounded drawbar while the wheels ride on rotating drums - one for the center section and one for each of the wings. Triangular-shaped cleats attached to the drums are used to simulate bumps. "In the past, we had to keep building new prototypes and testing them on this fixture until we were satisfied with their life," Ewanochko said. "The problem was that prototypes are very expensive and take a long time to build and test. When we found problems with one or more major structural components we would have to redesign and rebuild the prototype, and start the testing again several times. This build-and-break process had to continue until the quality level was acceptable."

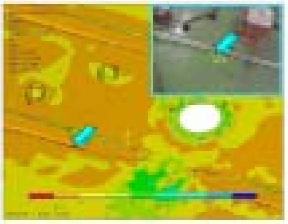
Virtual prototyping method

Deere engineers believed the process could be improved while they were creating several small component-level virtual prototyping models. "We hired MSC.Software Corporation as consultants to use their ADAMS (MSC.Adams) multibody simulation software to simulate the performance of several components," Ewanochko said. "We were impressed with the ability of the software to generate component-load profiles that can be used as input for fatigue analysis software. We decided to move to the next level by developing a prototype of the complete rotary cutter and modeling its performance on the bump test fixture."

Utilizing the MSC.Adams/Durability product enabled complete integration of key virtual prototyping techniques such as finite element analysis, multi-body simulation, and fatigue life prediction. The initial MSC. Adams model of the cutter and test fixture was generated in the Pro/ENGINEER environment using the embedded product MSC.Adams MECHANISM/Pro. This software package is seamlessly integrated within Pro/ENGINEER, so the consultants were able to perform kinematics analysis to validate the model without leaving the CAD environment, then perform one-button transfer to MSC.Adams where full dynamic simulations were performed.

MSC.Software engineers finalized the model by adding higher-fidelity features such as contacts, bushings, motions, couplers, and more complex joints for the bump test. The flexibility characteristics of the structural parts were modeled by generating finite element meshes of these components using Pro/MECHANICA and exporting them in the format used by ANSYS finite element software. ANSYS was then used to generate flexible body modal neutral files that contain the modal mass, stiffness, and deflection characteristics using a modal representation of the component. The orthonormalized modes, including static correction modes, were computed within ANSYS and then transferred to MSC.Adams, which modeled the flexible body deformations as a linear combination of mode shapes.

The dynamic bump test was simulated in the virtual prototyping environment by first reaching static equilibrium for one second, then accelerating the drum operating speed. Using the full finite element models of critical components, Deere engineers obtained local stresses with the MSC.Adams solution. The mode shape participation factors were used as the scalars on the stress solution of each mode shape in a linear superposition to represent the component's instantaneous stress shape. This superposition was performed at every node in the finite element model for each time step in the simulation, making it possible to define a stress time-history at every location in the flexible component models. The modal coordinates, or scaling factor time-histories, were output from MSC.Adams for each component in a format that is directly readable by FE-Fatigue, a popular durability analysis software package from nCode. Also, the stress solution for each mode shape was solved in ANSYS and exported to FE-Fatigue.



FE-Fatigue then performed the stress superposition at every node for the purpose of life prediction. This involved automatic, multi-channel peak/valley extraction and rainflow cycle counting, followed by the damage sum.

Results: time savings and design improvements

"The results of the durability analysis showed good correlation with our physical test results on an initial prototype, giving us the confidence to predict service lives based on the virtual prototype simulation," Ewanochko said. "As a result, we integrated the virtual prototyping process midway into the development cycle of our new 20-foot rotary cutter and from the very beginning of our latest 15-foot rotary cutter. On the 20-foot cutter, we had already produced one physical prototype when we created the virtual one. After validating the virtual prototype against the physical prototype, we finalized the design with the virtual prototype, and only one more physical prototype was required to complete the design. Experimental testing of this prototype further verified the predictions that we had generated with the virtual prototype. The big advantage was that we completed each design and test cycle using the virtual prototype in only one or two weeks. This is compared to several months required in the past when we had to actually build the design in order to determine whether or not it would work. As a result of these improvements, and others in different areas of the design process, we were able to reduce the development on the 20-foot cutter to about two years. This was only half as much time as we had ever been able to do previously, based on the best time-compression techniques used in the past. On the 15-foot cutter, we used virtual prototyping from Day 1. As a result, we only needed one physical prototype and are on track to complete the design in only one year. Compressing the time cycle also meant that we were able to evaluate many more design concepts than we could in the past, including innovative approaches that we probably couldn't have spent the time and money to test in the past."

MSC.Software Note:
Excerpt from the website of MSC.Software

MSC.Software Helps Chery Automobile Company Improve Vehicle Development with Virtual Product Development

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Emerging Chinese Automotive Company Turns to MSC.Software Professional Services Team for Vehicle Development Process Consulting

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SANTA ANA, Calif. - February 18, 2004 - MSC.Software Corp. (NYSE: MNS), …today announced a multi-phase, enterprise consulting services engagement with Chery Automobile Company Ltd. (Chery). …Chery is currently building an automotive engineering research institute (AERI) as the first phase of a long-term program for product line expansion. The services being provided by MSC.Software are linked to detailed planning and requirements for the new technical facilities…."

Stander, N. and Craig, K.J. On the robustness of a simple domain reduction scheme for simulation-based optimization, Eng. Comput., Vol. 19 (4), pp. 431-50, 2002

ON THE ROBUSTNESS OF A SIMPLE DOMAIN REDUCTION SCHEME FOR SIMULATION-BASED OPTIMIZATION

Nielen Stander[1] and K.J. Craig[2,*]
[1] Livermore Software Technology Corporation,
7374 Las Positas Rd, Livermore, CA 94550, USA
nielen@lstc.com
[2] Multidisciplinary Design Optimization Group (MDOG), Department of Mechanical and Aeronautical Engineering, University of Pretoria, Pretoria 0002, South Africa
ken.craig@eng.up.ac.za

* Professor. Currently on sabbatical leave at Livermore Software Technology Corporation.

Abstract

This paper evaluates a Successive Response Surface Method (SRSM) specifically developed for simulation-based design optimization, e.g. that of explicit nonlinear dynamics in crashworthiness design. Linear response surfaces are constructed in a subregion of the design space using a design of experiments approach with a *D*-optimal experimental design. To converge to an optimum, a domain reduction scheme is utilized. The scheme requires only one user-defined parameter, namely the size of the initial subregion. During optimization, the size of this region is adapted using a move reversal criterion to counter oscillation and a move distance criterion to gauge accuracy. To test its robustness, the results using the method are compared to SQP results of a selection of the well-known Hock and Schittkowski problems. Although convergence to a small tolerance is slow when compared to SQP, the SRSM method does remarkably well for these sometimes pathological analytical problems. The second test concerns three engineering problems sampled from the nonlinear structural dynamics field to investigate the method's handling of numerical noise and non-linearity. It is shown that, despite its simplicity, the SRSM method converges stably and is relatively insensitive to its only user-required input parameter.

Keywords: Simulation-based optimization, response surface methodology, multipoint approximations, design of experiments, crashworthiness.

Introduction

The success of finite element simulation to augment or even replace physical experimentation in design has accelerated the development of simulation-based optimization in recent years. While having its origins in the statistics of physical experimentation, response surface methodology (RSM) (Box & Wilson, 1951, Myers and Montgomery, 1995) has been the primary gradient-free simulation-based approach available. The general unavailability of analytical gradient information in analysis codes arises from the complexity of the non-linear finite element formulation. While not requiring any code enhancement, an alternative approach by means of finite differences may result in spurious gradients, not suitable for gradient-based optimization. For these reasons, and because of the noise-filtering properties of RSM, it has become particularly popular for impact design applications such as crashworthiness or metal forming where the response can be highly nonlinear.

As analysis methods for impact dynamics began to take hold in industry in the late eighties, design optimization methods of impact design followed in the mid 1990's. Among the topics studied are occupant safety (Etman *et al*, 1996, Etman, 1997), component-level optimization (Marklund, 1999, Akkerman *et al*, 2000), airbag-related parameter identification (Stander, 2000) and full-vehicle simulation (Sobieszczanski-Sobieski et al, 2000). The response surface method appeared in several forms, e.g. a successive response surface method (Toropov, 1989, Etman *et al*, 1996, Kok & Stander, 1999, Stander, 2001) and an updated response surface method (Schramm & Thomas, 1998, Sobieszczanski-Sobieski *et al*, 2000). Toropov (1989) experimented with linear and multiplicative approximations for his iterative multipoint approximation method and applied weighted least squares fitting and reduction of the subregion size based on function accuracy. In later work, Toropov presented refinements of his method in the form of indicators for move limit strategies. These criteria have been incorporated in a multipoint approximation strategy known as MARS (Toropov, 1998). The methodology of Etman (1997) uses a successive linear approximation approach with a saturated experimental design ($n + 1$ points, with n the number of design variables) within a subregion of the design space. To determine the location and size of each new subregion, a complex heuristic is used, based on oscillation, the accuracy of the response surface and constraint activity. More recently, Sobieszczanski-Sobieski et al (2000) conducted a full-vehicle simulation of a multidisciplinary nature while using a single set of higher-order response surfaces. In a metal-forming application Kok & Stander (1999) used a successive linear response surface method while Akkerman *et al* (2000) demonstrated the use of a similar but slightly enhanced successive approximation method to a knee bolster design with shape variables and involving transient mesh adaptivity.

While these studies demonstrate optimization capability by means of examples, there appears to be a dearth of studies that assess accuracy and robustness in design optimization in nonlinear dynamics. Against this background, the present paper outlines a simple, dual criterion successive response surface method (SRSM) that requires a single user-defined parameter. Furthermore, a deeper investigation is conducted into the convergence properties of the method (SRSM) as applied to a large set of algebraic test problems as well as a smaller set of simulation-based problems. For the algebraic problems, the SRSM method is compared to the more standard Successive Linear Programming (SLP) method where both use the same adaptive domain reduction approach.

The motivation for the method proposed in the paper is derived from the requirements for simulation-based optimization (Craig & Stander, 2001):

1. *Robustness and accuracy*. In practical applications, it is important that the optimization method produces an answer to engineering accuracy or at least an immediate and significant improvement of the objective.
2. *Efficiency*. The number of expensive simulation-based function evaluations required for each design iteration must be limited. Direct optimization methods without approximations or evolutionary algorithms like the genetic algorithm are usually disqualified due to the large number of function evaluations required.
3. *Parallelization*. To improve efficiency, modern simulations run on multiple computers and/or processors. The optimization method must therefore be parallelizable. This disqualifies e.g. sequential line searches.
4. *Noise*. The step-size dilemma of gradient-based methods must be addressed as this impacts both robustness and efficiency. A noise filtering capability may avoid local optima.
5. *Infeasibility*. The algorithm must be able to start from and handle intermediate infeasible designs if they can be simulated. It must also be able to provide a best compromised design if no feasible design is possible within the constraints specified.
6. *Global optimum.* This requirement is probably the strictest of all those listed. If an algorithm has features that at least provide the possibility of not terminating on the first local optimum it finds, then this will be desirable in practical applications. The study of true global optimization algorithms lies outside the scope of this paper.
7. *Ease of use.* The number of user-selected parameters must be kept to a minimum.

A method that successfully addresses most of these requirements is the Successive Response Surface Method (SRSM) based on *oscillation* and *move distance* criteria and first described in Stander (2001). This algorithm uses RSM (Myers & Montgomery, 1995), i.e. a Design of Experiments approach, to construct linear response surfaces on a subregion from a *D*-optimal subset of experiments. Linear functions are used to minimize the number of simulations required, especially for a very large number of variables. Successive subproblems are solved using a multi-start variant of the dynamic trajectory method, LFOPC (Snyman, 2000). To select the optimum, multi-starts are performed from the locations coinciding with the subset of experimental design points. The size of each successive subregion is adapted based on contraction and panning parameters designed to alleviate oscillation and prevent premature convergence. To prevent remote designs from affecting the accuracy of the subregional optimum, simulation results from previous iterations are not incorporated and each response surface is strictly based on the results of a *D*-optimal experimental design within the current subregion. Infeasibility is handled automatically when it occurs through the construction and solution of an auxiliary problem to bring the design within the subregion if possible. The method handles noisy responses automatically through the selection of an initially large subregion and a typically 50% over-sampling of experiments in the implementation of the *D*-optimality criterion (Roux, Stander & Haftka, 1998). As the optimum is approached, the subregion is contracted automatically, implying that inaccuracies in the sensitivity information do not cause large departures from the previous design. Therefore this handling of the *step-size dilemma* (Haftka & Gürdal, 1990) also provides an inherent move limit to the algorithm. The use of an adaptive subregion or trust region is not new, e.g., in Lin *et al* (2000), Pérez *et al* (2000), and Alexandrov *et al* (1997), the ratio of the simulated (actual) objective function reduction to that of the approximated objective function reduction in each design step is used as a measure to adjust the trust region size.

The SRSM method has proved itself to be robust but only moderately efficient if convergence to a tight tolerance is required. The over-sampling required for each response surface, although fully parallelizable, implies that it requires 50% more function evaluations for each design iteration than the minimum required by gradient-based algorithms. This method, although by no means a global optimization algorithm, may be more likely to find a lower local optimum than local approximation (gradient) methods due to its 'wider' perspective of the design space as embodied in the response surface. However, experimentation with multi-start designs on suitable test problems is required to verify this.

The aim of this study is also to illustrate that the SRSM method provides an accurate yet efficient and robust optimization methodology to address both smooth and noisy simulation-based problems. The test cases are therefore chosen accordingly and are grouped in two main categories. The first is a random collection of analytical and sometimes pathological problems from Hock & Schittkowski (1981) that are often used for testing optimization algorithms. These examples possess reliable gradient information, so one would expect a good local approximation method to perform well. The second category contains simple but general structural optimization problems for testing the algorithm's ability to handle practical engineering problems. These are a nonlinear explicit dynamic crash optimization problem of a simplified car, a material identification problem that employs the nonlinear implicit analysis of a tensile test specimen, and an occupant safety-related head impact problem. The problems in the second category exhibit various degrees of noise and nonlinearity and are therefore ideal to demonstrate the handling of these characteristics.

Methodology of Successive Response Surface Method (SRSM)

Consider the general nonlinear optimization problem:

$$\text{Minimize } f(\boldsymbol{x}),\ \boldsymbol{x} \in R^n \tag{1}$$

subject to the inequality constraints

$$L_j \le g_j(\boldsymbol{x}) \le U_j; \quad j = 1,2,\ldots,m \tag{2}$$

and simple bounds on the design variables

$$x_{il} \le x_i \le x_{iu}; \quad i = 1,2,\ldots,n \tag{3}$$

where L_j and U_j refer to the upper and lower bounds on each of the inequality constraints, and x_{il} and x_{iu} the lower and upper bounds on each of the design variables, n is the number of design variables, and m the number of inequality constraints. Note that equality constraints can be written as two inequality constraints in the form of Equation 2 with L_j equal to U_j.

Refer to Roux, Stander & Haftka (1998) and Stander (2001) for a detail description of the Successive Response Surface Method (SRSM). The method, as implemented in LS-OPT (Stander, 1999), has a number of features that makes it robust and suitable for the solution of practical problems:

- The *D*-optimal experimental design is used to best utilize the number of available runs. Over-sampling of 50% is used to maximize the predictive capability (Roux, Stander & Haftka, 1998) of the response surfaces.
- Linear approximations are constructed using linear regression on all the points of the current iteration. Unit weighting is used for the regression.
- An adaptive domain reduction method is applied as described in detail below.
- An auxiliary problem that minimizes the maximum constraint violation is solved to enforce feasible designs.

The SRSM method uses a region of interest, a subspace of the design space, to determine an approximate optimum. A range is chosen for each variable to determine its initial size. A new region of interest centers on each successive optimum. Progress is made by moving the center of the region of interest as well as reducing its size. Figure 1 shows the possible adaptation of the subregion.

The starting point $\boldsymbol{x}^{(0)}$ will form the center point of the first region of interest. The lower and upper bounds $(x_i^{rL,0}, x_i^{rR,0})$ of the initial subregion are calculated using the specified initial range value $r_i^{(0)}$ so that

$$x_i^{rL,0} = x_i^{(0)} - 0.5r_i^{(0)} \text{ and } x_i^{rU,0} = x_i^{(0)} + 0.5r_i^{(0)} \qquad i = 1, 2\ n \tag{4}$$

where n is the number of design variables. The modification of the ranges on the variables for the next iteration depends on the oscillatory nature of the solution and the accuracy of the current optimum.

A contraction parameter γ is firstly determined based on whether the current and previous designs $\boldsymbol{x}^{(k)}$ and $\boldsymbol{x}^{(k-1)}$ are on the opposite or the same side of the region of interest. Thus an oscillation indicator c may be determined in iteration k as

$$c_i^{(k)} = d_i^{(k)} d_i^{(k-1)} \tag{5}$$

where

$$d_i^{(k)} = 2\Delta x_i^{(k)} / r_i^{(k)}; \quad \Delta x_i^{(k)} = x_i^{(k)} - x_i^{(k-1)}; \quad d_i^{(k)} \in [-1;1] \tag{6}$$

The oscillation indicator (purposely omitting indices *i* and *k*) is normalized as $\hat{c}$ where

$$\hat{c} = \sqrt{|c|}\, sign(c)\,. \tag{7}$$

The contraction parameter γ is then calculated as

$$\gamma = \frac{\gamma_{\text{pan}}(1+\hat{c}) + \gamma_{\text{osc}}(1-\hat{c})}{2}\,. \tag{8}$$

The parameter γ_{osc} is typically 0.5-0.7 representing shrinkage to dampen oscillation, whereas γ_{pan} represents the pure panning case and therefore unity is typically chosen.

The accuracy is estimated using the proximity of the predicted optimum of the current iteration to the starting (previous) design. The smaller the distance between the starting and optimum designs, the more rapidly the region of interest will diminish in size. If the solution is on the bound of the region of interest, the optimal point is estimated to be beyond the region. Therefore a new subregion, which is centered on the current point, does not change its size. This is called panning (Figure 1(a)). If the optimum point coincides with the previous one, the subregion is stationary, but reduces its size (zooming) (Figure 1(b)). Both panning and zooming may occur if there is partial movement (Figure 1(c)). The range $r_i^{(k+1)}$ for the new subregion in the (k + 1)-th iteration is then determined by:

$$r_i^{(k+1)} = \lambda_i r_i^{(k)}; \quad i = 1, 2\,, n; \quad k = 0, 2\,, niter \tag{9}$$

where λ_i represents the contraction rate for each design variable. To determine λ_i, $d_i^{(k)}$ is incorporated by scaling according to a zoom parameter η, typically 0.5, that represents pure zooming and the contraction parameter γ to yield the contraction rate

$$\lambda_i = \eta + \left|d_i^{(k)}\right|(\gamma - \eta) \tag{10}$$

for each variable independently (see Figure 2). This criterion replaces function error and feasibility-based criteria frequently employed in earlier response surface formulations (Etman, 1997, Toropov, 1998).

For the Successive Linear Programming (SLP) method used for comparison in the results section, linear response surfaces are constructed using the gradient at the current point. The subregion is centered on this point while its adaptive properties are governed by the same heuristics as the SRSM method.

Test cases

The move limit heuristics of the SRSM and SLP methods are set to $\gamma_{\text{pan}} = 1.0$, $\gamma_{\text{osc}} = 0.6$ and $\eta = 0.6$ for all the test cases below unless indicated otherwise.

Hock and Schittkowski problems

37 arbitrarily selected Hock problems and one problem from Svanberg (1995, 1999) are used in this benchmark with the same starting designs being used for testing all the algorithms. The problems are all analytical expressions with analytical gradients but the gradients are computed numerically to emulate a simulation-based environment to align the test with the thrust of this paper. Five of the problems (Nos. 2, 15, 16, 17, 20) are variations of the Rosenbrock problem ($f = 100(x_2 - x_1^2)^2 + (1 - x_1)^2$), while the number of design variables ranges between 2 and 21. All the selected problems are constrained optimization problems.

Small car crash problem

This problem (Figure 3) consists of a simplified vehicle moving at a constant velocity of 15.64m.s^{-1} (35mph) and impacting a rigid pole. The nonlinear finite element structural solver LS-DYNA (LSTC, 2000) is used to perform a simulation of the crash using the explicit dynamic analysis method. The simulation duration is 50ms. The objective is to minimize the Head Injury Criterion (HIC) (NHTSA, 2000) over a 15ms interval of a selected point subject to an intrusion constraint of 550mm of the pole into the vehicle at 50ms. This criterion is based on linear head acceleration and was designed to minimize skull fracture/brain injury due to head contacts with the vehicle interior (NHTSA, 2000). The design variables are the shell thickness of the car front (t_{hood}) and the shell thickness of the bumper (t_{bumper}).

Material identification problem (Müller, 2000)

In a material identification problem the optimization process uses experimentally measured data to calibrate a constitutive model. A non-linear simulation is performed with the model parameters as input, and the discrepancy of the simulated and measured results is used as a minimization criterion. In this example, the parameters of a power-law material model of a tensile test specimen are determined using the experimental reaction force, *F* and elongation, *u*. The stress-strain history of the specimen (Figure 4) is simulated using LS-DYNA (LSTC, 2000) and the objective is defined as the least-squares difference between the simulated and measured force-elongation history. The design variables in this problem are the two material parameters in the power-law model, as defined in Equation 11.

$$\sigma_y = K\varepsilon^r = K(\varepsilon_{yp} + \varepsilon^p)^r \qquad (11)$$

where ε_{yp} is the elastic strain to yield and ε^p is the effective plastic strain (logarithmic). The strength coefficient, *K* and strain-hardening exponent, *r* are used as design variables.

Head impact problem (Balasubramanyam, 2001)

This problem is outlined in Figure 5. Shown is a Free Motion Headform (FMH) impacting the A-pillar of a vehicle covered on the interior with plastic trim. The aim of the optimization is to reduce the Head Injury Criterion,

$$\text{HIC-d} = 166.4 + 0.75466*\text{HIC} \tag{12}$$

(as measured at the FMH's center of gravity) by modifying the trim design. The five design variables used are the trim thickness, rib height and thickness, number of ribs and rib span (distance between the first and last rib). Note that the inclusion of the number of ribs as a design variable makes this an integer-based optimization problem. Adaptive meshing is incorporated in the parameterization of the mesh through the TrueGrid (XYZ, 2000) preprocessor to ensure good mesh quality for all possible designs. Note that this is an unconstrained minimization problem as no limits are placed on e.g. the intrusion into the trim or on the mass of the trim.

Results and discussion

Hock and Schittkowski problems

The results for the 38 problems are summarized in Tables I and II. The results obtained using Powell's Sequential Quadratic Programming (SQP) method as reported by Hock and Schittkowski are given in Table I, while the results for the SRSM and SLP method are given in Table II. *n* is the number of design variables.

Convergence is defined in terms of the objective function, with the number of iterations required for 1% and 0.01% convergence given in Tables I and II. The error on the objective is defined as

$$f_{err} = \frac{\left| f_{act} - f^* \right|}{1 + \left| f_{act} \right|} \times 100\% \tag{13}$$

where f_{act} is the exact objective function value (Hock, 1981) and f^* is the computed optimum.

For the SQP results, only final convergence values are available, and the iterations to this final value and the error are given. Note that for each iteration, the objective function, constraint function(s) (if present) and their gradients must be evaluated. SRSM employs $1.5(n + 1) + 1$ *D*-optimal design points for each iteration, while the SLP method uses a small finite-difference step size (10^{-6}), therefore requiring only $n + 1$ evaluations for the numerical gradient. For all the problems, unless otherwise indicated, the original subregion is 25% of the design space in each variable. No problems other than those reported here were attempted.

The result of the twelve-corner polytope problem of Svanberg (1995, 1999) is also given in Tables I and II. Svanberg listed the optimum as 280, found in about 150 iterations (50 outer with about 3 inner iterations each) to an accuracy of 10^{-6} using the Method of Moving Asymptotes (MMA) algorithm. Astonishingly, the SLP method finds this optimum to within 10^{-2} in 7 and to within 10^{-4} in 8 iterations.

Summary of tabled results:

- The SQP method fails to find a local minimum in 2 of the 37 problems it was tested on.
- The SRSM method fails to find a local minimum in 5 of the 38 problems with modification to the default heuristics only required once for convergence.
- The SLP method fails to find a local minimum in 4 of the 38 problems.

For three of the problems where SQP and SLP failed to converge to the global optimum (Problems 16, 33, and 63), SRSM performed better. E.g. for Problem 16, SRSM found the optimum in 80 iterations, but only through the alteration of γ_{pan} in Equation 8 from the default value of 1.0 to 1.2. This is the only such amendment in this study. The SQP method, on the other hand, found the global optimum in Problems 13 and 20, while SRSM and SLP converged to local minima. Both SQP and SLP found the correct optimum in Problem 15, while SRSM converged to a local minimum. It should be emphasized that the results presented are for a single starting design for each problem, and that the ability of some of the algorithms to find the global optimum whilst others found local optima, is based on chance.

Small car crash problem

The starting design and optimum design values of the small car crash problem are shown in Table III together with the bounds on the design variables. Note that the initial design is infeasible due to the violation of the intrusion constraint.

The optimization history for the small car crash problem is shown in Figure 6 for the objective (HIC) and in Figure 7 for the design variables (t_{hood} and t_{bumper}). The correct minimal HIC-value is approximately 106 with zero violation of the intrusion. The effect of the only parameter that the user must select in SRSM, the range of the initial subregion, is also shown in Figure 6. It can be seen that the initial subregion size has an effect on the initial convergence, but that the heuristics of the algorithm removes the influence of this parameter by the 8th iteration, making it robust to this selection for this example.

The effect of the initial range is more pronounced on the history of the design variables (see Figure 7), as the initial linear response approximation is less accurate for the larger ranges (4 and 5mm). As soon as the zooming parameter is activated, the subregion becomes smaller and the approximations more accurate, resulting in reduced oscillation in the design variable values as convergence is approached.

Figure 8 shows that simulation results and the response surface predictions converge by about the fourth iteration for an initial range of 2.0mm. The comparison is interesting because it shows the response surface accuracy and the degree of noise present in the problem.

Material identification problem

The starting design and optimum design values of the material identification problem are shown in Table IV together with the bounds on the design variables.

The optimization history for the design variables is given in Figure 9 as a function of the initial range. It can be seen that although SRSM is sensitive to this parameter, the algorithm is robust. The stable convergence rate can also be viewed in the objective function (least-squares error) history plot in Figure 10.

Head impact problem

The starting design and optimum design values of the head impact problem are shown in Table V together with the bounds on the design variables.

The objective function history is given in Figure 11. The solid line represents the result interpolated from the response surface while the solid squares indicate the simulated objective at the current design. As the optimization progresses, the difference between these two diminishes due to the improvement in the approximation. Figure 11 also demonstrates that although SRSM does not include an integer optimization method, it succeeds in the present example in converging to a solution likely to be near an optimum. This example seems to have more noise than the crash problem.

The initial and optimum designs are compared side by side in Figure 12. The reduction in HIC-d is due to a more gradual deceleration of the Free Motion Headform (FMH) upon impact. Figure 13 illustrates how the optimum design cushions the impact by removing the peak in the acceleration curve.

Conclusions

A Successive Response Surface Method (SRSM), specifically tailored for simulation-based optimization, was presented in this paper and tested on a variety of test cases.

The following conclusions can be drawn:

1. The SRSM method performed surprisingly well on the analytical test problems, even though it only used linear approximations. Convergence was in general slower than for SQP, but the contracting subregion helped the algorithm to move into close proximity of the optimum. In general, progress to the region of the optimum is rapid, followed by an expected slow convergence to a higher accuracy.
2. In the engineering test cases, the SRSM method exhibited stable convergence characteristics and the robustness of the method proved to be insensitive to the selection of the initial subregion size.

3. In the final test case, SRSM was able to successfully include an integer variable in the optimization process. Although the success rate of this application is not evident, it is an indication that SRSM is able to deal with the noise induced by approximating a continuous variable with an integer. A more rigorous approach would be to conduct a discrete optimization of the approximate subproblem.
4. An SLP algorithm based on the same domain reduction scheme as SRSM proved to be successful for coarse convergence although it is expected to be successful only for smooth analytical problems.

Finally, the results in this paper demonstrate that, when considering coarse convergence properties, the performance of the Successive Response Surface Method does not differ dramatically from other, more established algorithms such as SQP. While the failure of numerical gradient-based methods such as SQP is well documented for noisy problems, it has been shown that SRSM has the potential of obtaining, with a reasonable degree of accuracy and without experimentation with user-selected parameters, converged optimization solutions to these problems. This makes the algorithm ideal for multidisciplinary optimization problems in which multi-point approximations are suitably constructed for noisy functions (e.g. from crash simulations) and analytical gradients are available for smooth functions (e.g. modal frequencies).

Acknowledgements

The authors would like to thank Suri Balasubramanyam, Mike Burger and Tobias Müller for their assistance in setting up the example problems. The support of the South African National Research Foundation, Grant no. GUN2046904, for the sabbatical of the second author at the Livermore Software Technology Corporation, is gratefully acknowledged.

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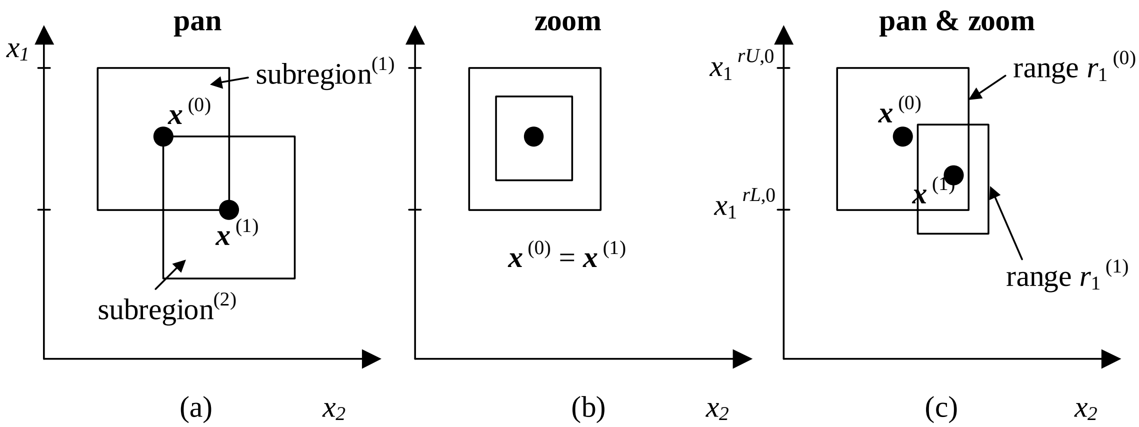

Figure 1 – Adaptation of subregion in SRSM: (a) pure panning, (b) pure zooming and (c) a combination of panning and zooming

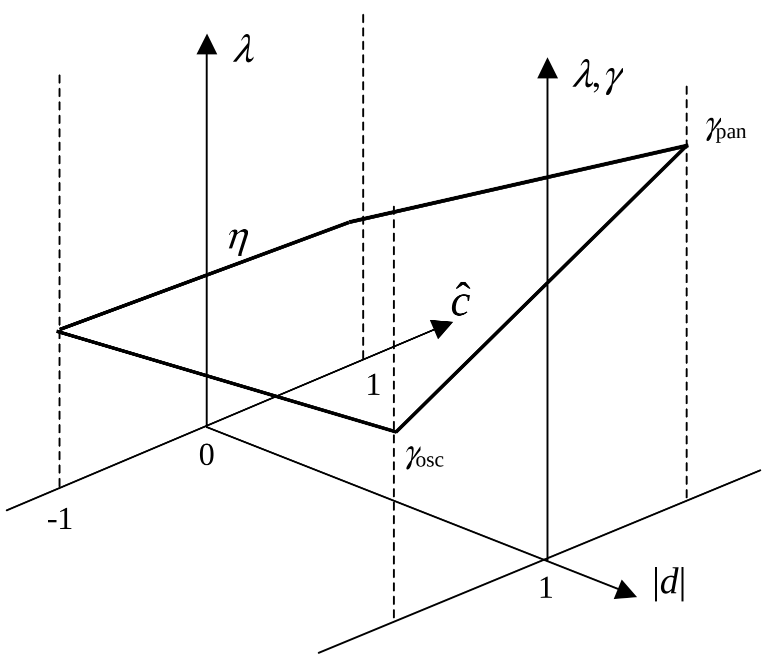

Figure 2 – The sub-region contraction rate λ as a function of the oscillation indicator $\hat{c}$ and the absolute move distance $|d|$

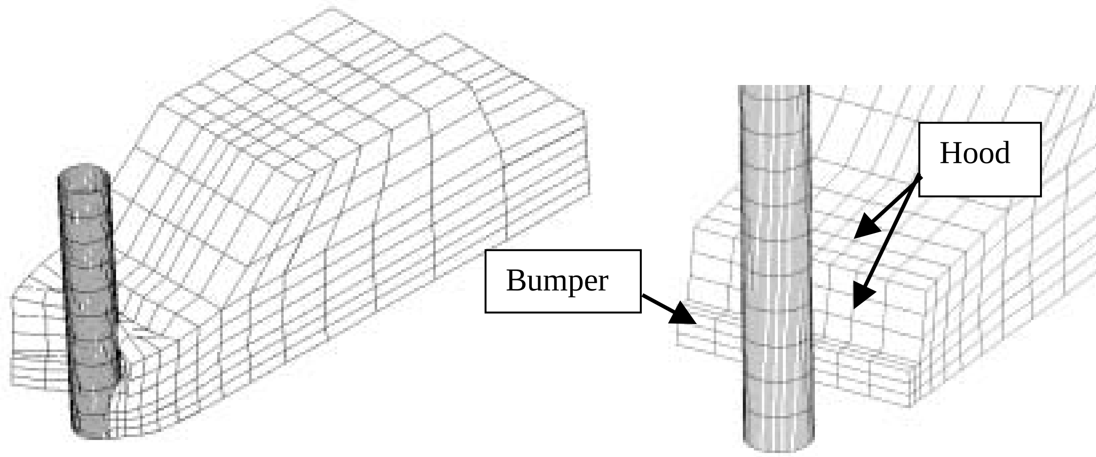

Figure 3 – Small car crash: geometry of deformed (50ms) and undeformed shape

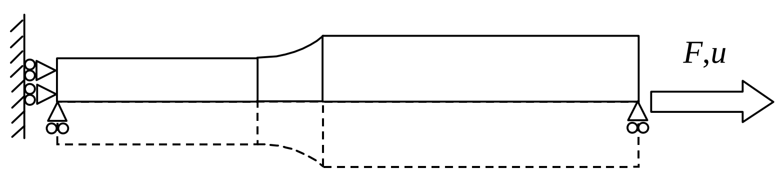

Figure 4 – Quarter symmetric model of test specimen

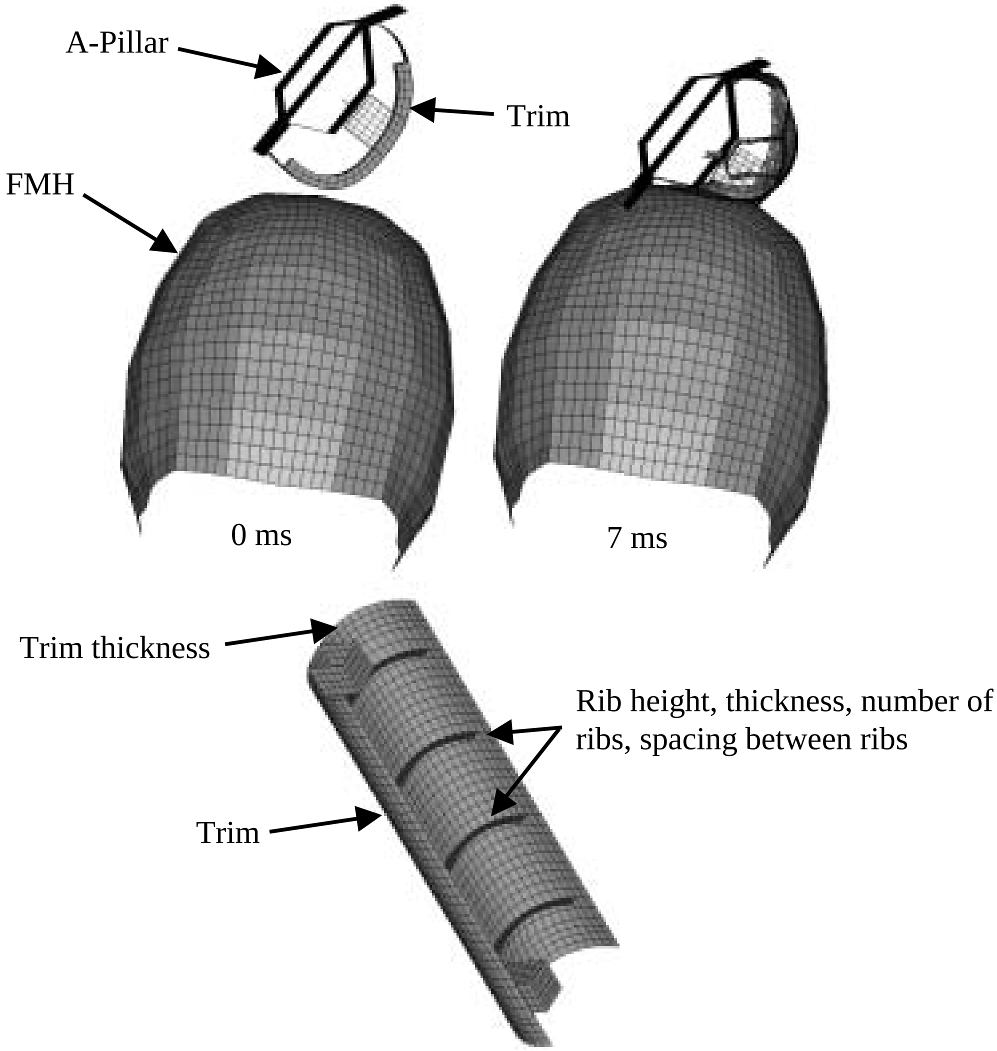

Figure 5 – Head impact problem: Design variables and trim deformation due to impact of FMH

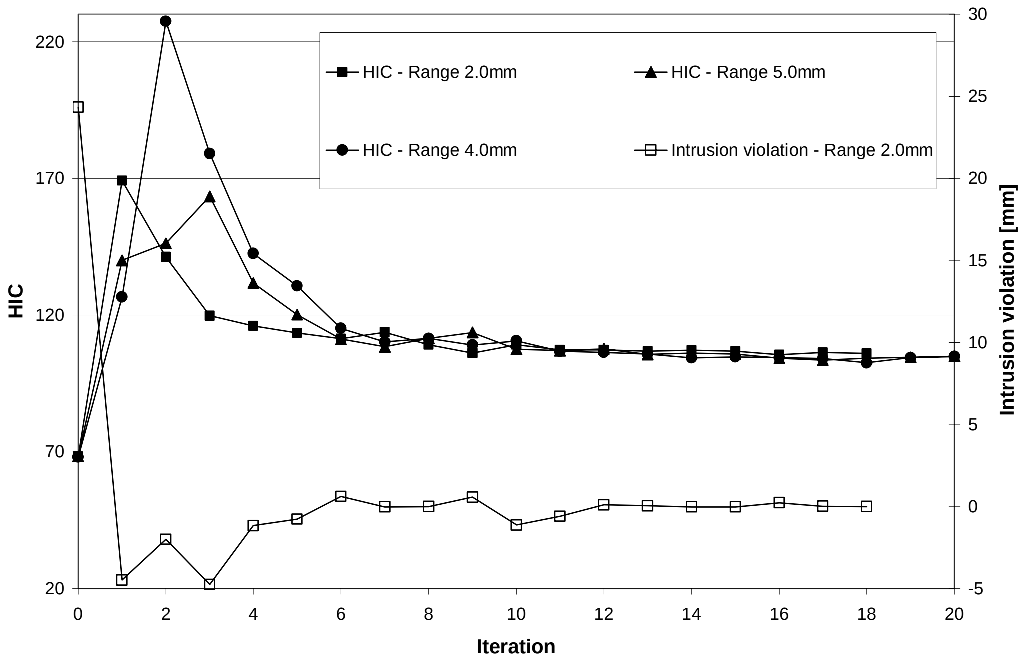

Figure 6 – Small car crash: Optimization history of HIC and intrusion

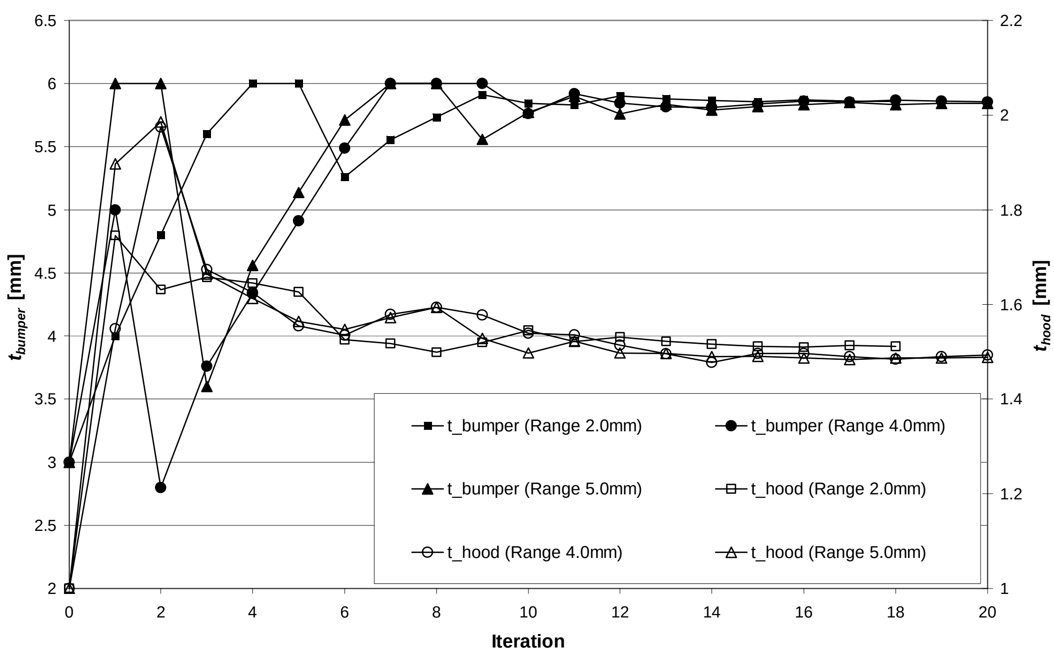

Figure 7 – Small car crash: Optimization history of t_{hood} and t_{bumper}

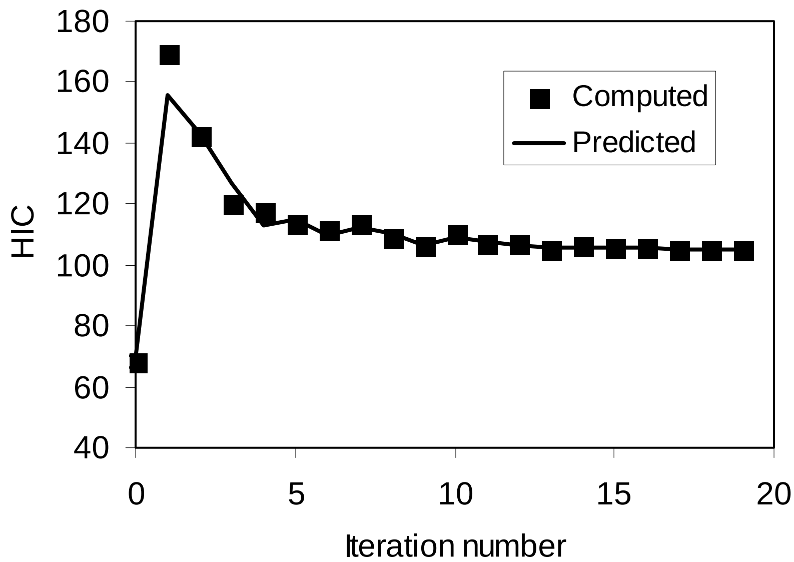

Figure 8 – Small car crash: Optimization history of HIC — simulation results (dots) and response surface results (line). Initial range = 2.0mm.

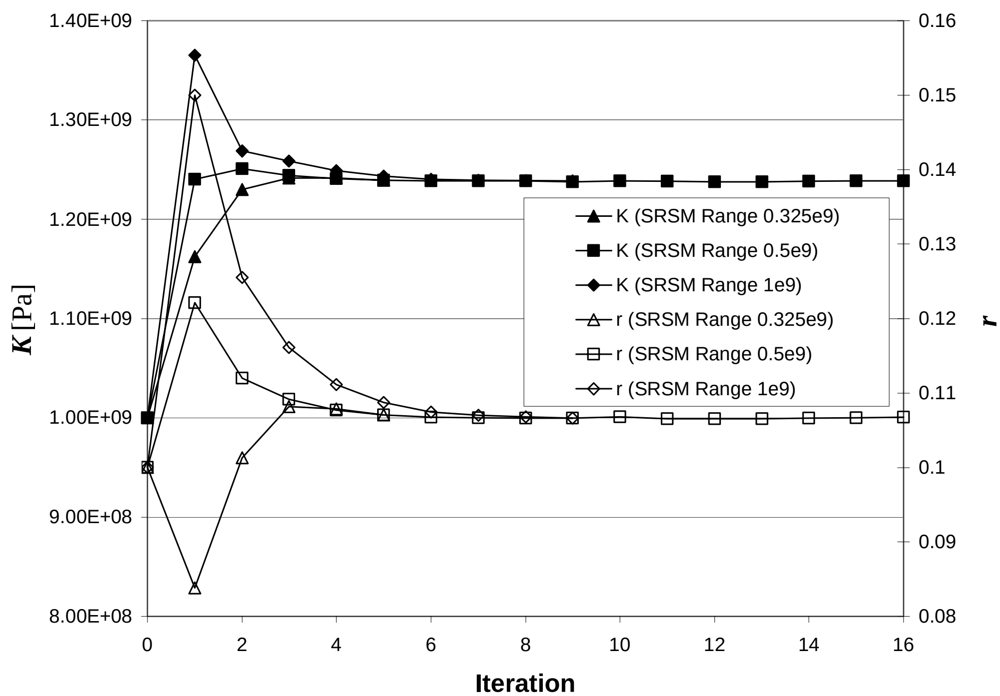

Figure 9 – Material Identification: Optimization history of design variables as a function of initial range on K (range on r = 0.05)

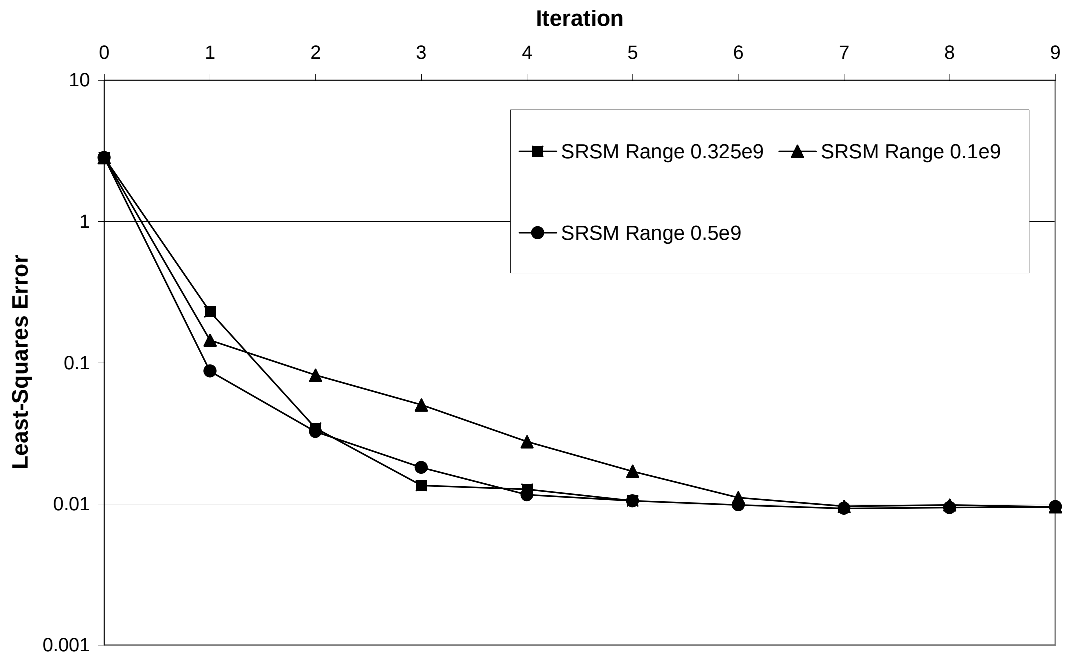

Figure 10 – Material Identification: Optimization history of least-squares error for SRSM

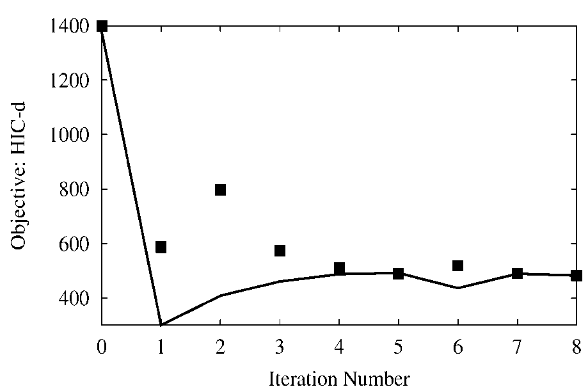

Figure 11 – Objective function history for head impact problem. The squares represent simulation results and the solid line the response surface interpolations at the predicted optima after each iteration.

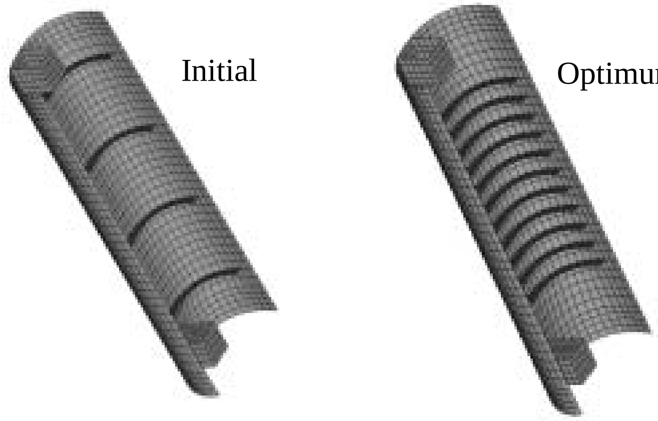

Figure 12 – Head impact problem: Initial and optimum trim designs

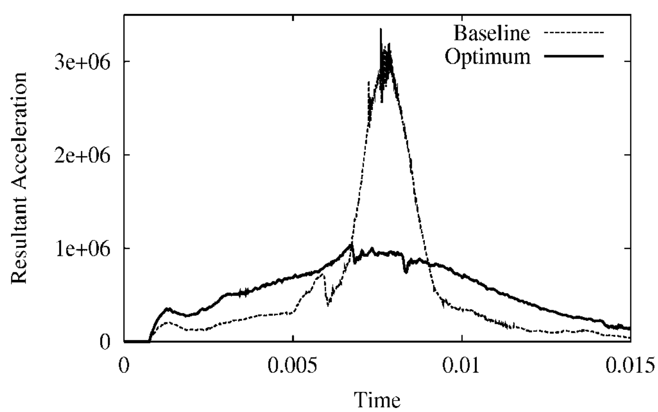

Figure 13 – Head impact problem: Initial (baseline) and optimum FMH acceleration versus time

Problem #	*n*	f_{act}	SQP		
			f^*	Niter	f_{err}
2	2	0.0504	28.4	-	-
10	2	-1	-1	12	5e-8
12	2	-30	-30	12	1e-8
13	2	1	1	45	5e-8
14	2	1.39	1.39	6	8e-9
15	2	307	307	5	1e-8
16	2	0.25	23.1[+]	-	-
17	2	1	1	12	1e-8
20	2	38.2	38.2	20	5e-9
22	2	1	1	9	1e-8
23	2	9	9	7	1e-8
24	2	-1	-1	5	1e-8
26	3	0	0	19	4e-8
27	3	0.04	0. 04	25	2e-8
28	3	0	0	5	3e-21
29	3	-22.6	-22.6	13	9e-11
30	3	1	1	14	1e-8
31	3	6	6	10	1e-8
32	3	1	1	3	1e-8
33	3	-4.59	-4[+]	-	-
36	3	-3300	-3300	4	1e-8
45	5	1	1	8	1e-8
52	5	5.33	5.33	8	6e-9
56	7	-3.46	-3.46	11	1e-8
60	3	0.0326	0.0326	9	3e-8
61	3	-144	-144	10	2e-8
63	3	952[¥]	962[+]	-	-
65	3	0.954	2.8	-	-
71	4	17.0	17.0	5	2e-8
72	4	728	728	35	1e-8
76	4	-4.68	-4.68	6	3e-9
78	5	-2.92	-2.92	9	3e-9
80	5	0.0539	0.0539	7	8e-10
81	5	0.0539	0.0539	8	2e-9
104	8	3.95	3.95	19	8e-9
106	8	7050	7050	44	1e-5
108	9	-0.866	-0.697[+]	-	-
12-corner polytope[#]	21	280	280	150	1e-6

Table I – Hock and Schittkowski problems (SQP): number of iterations Niter corresponding to objective f^* (error f_{err} and known optimum f_{act})

¥ SRSM found a lower optimum than that listed in Hock & Schittkowski (1981)

\+ Converged to local optimum # Obtained by MMA (Svanberg 1995, 1999), not SQP

Problem #	n	f_{act}	SRSM			SLP		
			f^*	Niter (1%)	Niter (0.01%)	f^*	Niter (1%)	Niter (0.01%)
2	2	0.0504	6.55	-	-	0.524	-	-
10	2	-1	-1	13	18	-1	24	27
12	2	-30	-30	5	11	-30	5	7
13	2	1	0.76	-	-	0.781	-	-
14	2	1.39	1.39	9	13	1.39	4	5
15	2	307	360^+	-	-	306	5	-
16	2	0.25	$0.25^\$$	68	79	23.1^+	-	-
17	2	1	1	8	11	1	6	6
20	2	38.2	40.2^+	-	-	40.2^+	-	-
22	2	1	1	8	12	1	5	5
23	2	9	9	13	18	9	1	2
24	2	-1	-1	2	2	-1	2	2
26	3	0	0	15	22	0	9	11
27	3	0.04	0.079	-	-	0.072	-	-
28	3	0	0	10	14	0	11	12
29	3	-22.6	-22.6	7	16	-22.6	5	9
30	3	1	1	9	10	1	9	12
31	3	6	6	8	15	6	8	11
32	3	1	1	1	1	1	2	2
33	3	-4.59	-4.59	4	9	-4^+	-	-
36	3	-3300	-3300	5	5	-3300	5	5
45	5	1	1	6	6	1	6	6
52	5	5.33	5.33	9	15	5.33	6	11
56	7	-3.46	-3.46	15	25	-3.46	10	12
60	3	0.0326	0.0326	11	15	0.0326	11	23
61	3	-144	-144	6	11	-144	4	6
63	3	$952^¥$	952	2	8	962^+	-	-
65	3	0.954	0.954	18	22	0.954	14	16
71	4	17.0	17.0	4	10	17.0	2	5
72	4	728	728	34	53	820^+	-	-
76	4	-4.68	-4.68	5	13	-4.68	3	8
78	5	-2.92	-2.92	20	28	-2.92	9	12
80	5	0.0539	0.0539	7	11	0.0539	1	6
81	5	0.0539	0.079	-	-	0.0539	4	6
104	8	3.95	3.95	8	14	3.95	8	18
106	8	7050	7050	8	13	7049	4	5
108	9	-0.866	-0.866	27	32	-0.675^+	-	-
12-corner polytope	21	280	279	7	-	280	7	8

Table II – Hock and Schittkowski problems: number of iterations (Niter) corresponding to objective f^* (SRSM and SLP)

\$ $\gamma_{pan} = 1.2$ + Converged to local optimum

¥ SRSM found a lower optimum than that listed in Hock & Schittkowski (1981)

	Minimum	Initial	Maximum	Optimum
t_{hood} [mm]	1	1	6	1.51
t_{bumper} [mm]	1	3	6	5.85
HIC		68.33		106.78
Intrusion violation [mm]		24.34		0

Table III – Small car crash: Design variable upper and lower bounds; initial and optimum values of objective, design variables and constraint

	Minimum	Initial	Maximum	Optimum
K [GPa]	0.7	1	2	1.23865
r [-]	0.01	0.1	0.2	0.106726

Table IV – Material Identification: Design variable upper and lower bounds; initial and optimum values of design variables

	Minimum	Initial	Maximum	Optimum
Trim thickness [mm]		2		2.9
Rib thickness [mm]	0.8	1	1.8	0.8
Rib height [mm]	6	6	15	6.5
Number of ribs [-]	4	4	16	11
Rib span [mm]	130	180	180	140
HIC-d		1400		482

Table V – Head Impact Problem: Design variable upper and lower bounds; initial and optimum design values of objective and design variables