LS-OPT®: Status and Outlook

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LS-DYNA Users Forum, Göteborg, Sweden
October 9, 2014
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- Enhancements in 5.1
- Outlook
LS-OPT: Brief overview

- **Optimization**
  - Direct and Metamodel-based

- **Reliability and Robustness (RBDO)**

- **Process Optimization**

- **Multiple solvers, pre-, post-processors**

- **Network-based**
  - Job scheduling
  - Monitoring
  - Control

- **Parameter Identification (Materials, Systems)**
**LS-OPT Methodology**

- **Metamodel-based Optimization/Reliability**
  - Discrete-Continuous problems (Sizing/Shape)
  - Benefits derived from metamodels
    - Build a global model of the design for graphical exploration
    - Stochastic methods inexpensively applied
      - Reliability and Robustness Analysis/Optimization
      - Global Sensitivity Analysis
      - Outlier Analysis
      - Tolerance Optimization

- **Direct Optimization**
  - Global Optimization
  - Integer (category, material), Discrete-Continuous, Multi-Objective
Vehicle MDO: Setup and model detail

6 Crash Modes + Body Dynamics Mode:
- approximately 3 million element models

Allen Sheldon, Ed Helwig (Honda R&D)
Objective:
Minimize Mass

Constraints:
- **Front NCAP:**
  - Decelerations
  - Intrusions
- **Front Offset:**
  - Intrusions
  - Cabin Integrity
- **SICE:**
  - Intrusions
- **Side Pole**
  - Intrusions
- **Roof Crush:**
  - Force
- **Rear ODB**
  - Intrusions
  - Fuel System Clearance
- **NVH:**
  - Body Stiffness
  - Body Frequency

35 Continuous Thickness Variables:
33% of BIW mass

Allen Sheldon, Ed Helwig (Honda R&D)
Optimization setup and results

**LS-OPT SRSM Settings:**

- **Optimization Strategy**
  SRSM (Domain Reduction)

- **Metamodel**
  Radial Basis Function Network (global)

- **Point Selection**
  Adaptive Space Filling
  54 points per iteration

**Gauge Changes**

- Optimization was **aggressive** with a significant initial mass reduction.
- Then optimization **converges** as constraints are satisfied.
- Final step shows some increase in mass as variables are switched to discrete values.

- Gauge changes are non-intuitive.
- Some parts have significant gauge up values.
- Rear portion of structure saw significant gauge down.

Allen Sheldon, Ed Helwig (Honda R&D)
Calibration of material 125

9 parameters
5 tension/compression cases

Optimum
Mismatch history

Start
New Features
Multi-level Optimization

- Subdivision of problem into levels
- Nesting the optimization problem
- Variables and responses are transferred between levels
- Inner level optimization is done for each outer level sample
Multi-level Optimization: Why?

- **Organization.** Easier to organize the problem as a collection of subsystems

- **Efficiency.** Solution algorithm takes advantage of the subproblem type
  - Can match optimization methods with variable types, e.g. materials (categorical), sizing/shape (continuous).

- **Robustness and accuracy.** Smaller sub-problems are typically solved in a relatively low-dimensional space

- **Critical framework for rational decomposition methods:** *Analytical Target Cascading*
  - Iterative method which resolves *inconsistencies* between individual processes with *shared* variables

- **Applications:** System Optimization (component sublevels), Product families, Tolerance optimization
Multi-level Optimization: Example -- Truck

6 Thickness design variables
6 Material categorical variables
Multi-level Optimization: Example

Outer level: Continuous

Inner level: Discrete/Categorical

Variable setup

Material categories

thicknes transfer
Multi-level Optimization
Categorical variables: Material levels

Inner Rail Material Variables

- Baseline
- Mat_B (UNS31600)
- Mat_C (UNS30403)
- Mat_D (UNS31803)
Multi-level Optimization: Design Criteria

Variables
- Outer level: 6 thickness variables of main crash members
- Inner level: 4 material types (levels) for 6 main crash members

Minimize
- Mass

Criteria
- Intrusion < 721
- Stage 1 pulse < 7.5g
- Stage 2 pulse < 20.2g
- Stage 3 pulse < 24.5g
## Multi-level Optimization: SRSM/GA vs. GA only

<table>
<thead>
<tr>
<th>Analysis Type</th>
<th>No. of DVs</th>
<th>Mass (Kg)</th>
<th>Reduction (%)</th>
<th>Cost (LS-DYNA runs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multilevel Optimization with thickness and discrete material variables</td>
<td>6 (thickness) + 6 part materials (4 discrete levels) = 12</td>
<td>Baseline: 138.1</td>
<td>Optimum: 122.2</td>
<td>Reduction: 11.6%</td>
</tr>
<tr>
<td>Direct optimization with both thickness and material variables (population size: 30)</td>
<td>6 (thickness) + 6 part materials (4 discrete levels) = 12</td>
<td>Baseline: 138.1</td>
<td>Optimum: 130.5</td>
<td>Reduction: 5.5%</td>
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<tr>
<td>Direct GA with thickness and discrete material variables (population size: 100)</td>
<td>6 (thickness) + 6 part materials (4 discrete levels) = 12</td>
<td>Baseline: 138.1</td>
<td>Optimum: 121.9</td>
<td>Reduction: 11.8%</td>
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</table>
Multilevel Optimization: Observations

- Multilevel more robust (possibly).
  - GA population size can significantly influence global optimality
- Multilevel allows metamodel creation for continuous variables
  - E.g. can apply robustness, tolerance optimization etc.
- Disadvantage: Multilevel more expensive.
  - Optimization could be streamlined, e.g. by adapting starting points for sublevel optimization. Hybridization of optimizer.
- Multilevel useful in other applications such as tolerance optimization: *Tolerance Optimization Using LS-OPT (Basudhar). Proceedings of this forum*
  - Also, Collaborative Design Optimization, Design of Product Families
Variable deactivation (iterative methods)

- **Optimization:** large number of function evaluations, especially in multi-level setup
- **Variables can be manually de-activated**
  - Save computational effort (variable screening)
  - Variable is frozen
  - Seamless restart

![Parameter Setup and Sampling Matrix](image)

![Optimization History](image)

Multiple entity plot
Parallel Neural Networks

- High metamodel accuracy required. Even with screening, appropriate metamodeling tools needed
- Feedforward Neural Networks
  - High accuracy global approximation. Good bias-variance compromise. Variance information available (illustrated below)
  - Expensive. Vehicle crash often 100+ responses. Solved independently due to nonlinearity. Reduction (as when linear) not possible.
    - Ensembles (sorting through hidden nodes to get the right order)
    - Committees (Monte Carlo method to improve prediction)
  - Ensembles and Committees are suitable for parallelization
Parallel Neural Networks: interface

**Functionality**
- similar to solver job monitoring.
- Jobs can be distributed.
Parallel Neural Networks

9 design parameters

Statistics

<table>
<thead>
<tr>
<th>Parameters</th>
<th>9</th>
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</thead>
<tbody>
<tr>
<td>Simulations</td>
<td>1997</td>
</tr>
<tr>
<td>Responses</td>
<td>15</td>
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<tr>
<td>Processors</td>
<td>8</td>
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</table>

Calculated times

<table>
<thead>
<tr>
<th>Type</th>
<th>Order</th>
<th>MC</th>
<th>Time (min.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>3</td>
<td>9</td>
<td>2.8</td>
</tr>
<tr>
<td>Default</td>
<td>5*</td>
<td>9*</td>
<td>10.6</td>
</tr>
<tr>
<td>Max</td>
<td>10</td>
<td>19</td>
<td>99.6</td>
</tr>
</tbody>
</table>
Excel stage type (substitution)

Inputs from LS-OPT to Excel fields

Histories/Responses of previous stages

Design variables
Excel stage type (extraction)

Excel fields as LS-OPT histories/responses
Third Party solvers: Example

Parameter definition (solver input file)

Minimization of residual

Variable setup
Third Party solvers: Example

Parameter definition (solver input file)

Variable setup

Minimization of residual

Optimal curve match

Courtesy: Aboozar Mapar, MSU
Graphical Features
(Viewer)
Design Point Categories

- Picking, displaying and saving designs of interest

Categories + Other “Other” points hidden
Histogram visualization

- Manual axis control of the region of interest
  - Range, step size
- Graphical visualization of properties (mean, std dev, feasibility range)
- Additional histogram types
  - Frequency
  - Probability / Relative Frequency = \( \frac{\text{Frequency}}{\text{Sample size}} \)
  - Probability Density Function (PDF) / Relative Frequency per Unit Width = \( \frac{\text{Probability}}{\text{Bin width}} \)
    (standard representation)
Histogram visualization – attributes

![Histogram visualization diagram with arrows pointing to attributes: Type, Mean, Std Dev, Constr. bound value, and Axis limits.](image-url)
Global Sensitivity Analysis (subregion)

- Sensitivities within specific design proximity
- Can set up multiple sub-regions interactively
Response-variables (development version)

- Transfer variables between design stages
Outlook
Outlook

♦ Multi-level Optimization
  - Funded by US Department of Energy
  - *Analytical Target Cascading* as a logical development path to provide a collaborative capability

♦ Viewer (post-processing, data mining)
  - Result table manipulation: integration of *categories* into tables, etc.
  - Speed improvements to Viewer displays
  - Virtual design displays: generate cluster of surrogate results

♦ Reliability
  - Probability Density Function approximation from empirical data
    - Kernel density approximation
  - Sequential reliability analysis
    - Convergence of probability of failure value
    - Adaptive sampling
  - Tolerance-based optimization – See paper by *Anirban Basudhar*
Outlook

◊ New applications for approximations
  - Domain reduction approaches for multi-objective optimization (MOO)
    - Extend work done for User’s Conference 2012
    - Classification-based Decision Boundaries
      - Support Vector Machines
      - Application in domain definition for binary and discontinuous responses
  - Multi-response metamodels
    - Spatial distribution of response locations
    - Biomechanical applications, e.g. using MRI spatial data for heart muscle calibration

◊ Metamodels: performance and usability
  - Multiple metamodel type displays: comparison of metamodels
Outlook

minated

Job scheduler

- LS-OPT job scheduler handles/monitors ~330 jobs in parallel (Linux limitation – number of open sockets).
- With MPP (e.g. 64 nodes/job) ~ 21,000 but capacity is now typically ~20,000 nodes

More solver types

- Matlab
- LS-TaSC
Other papers at this conference

- Tolerance Optimization Using LS-OPT (Basudhar)
- LS-OPT Current development: A perspective on multilevel optimization, MOO and classification methods (Stander, Basudhar) (Developers Forum, Sweden)
Current Releases

- Production (v5.1.0)
  http://ftp.lstc.com/user/ls-opt/5.1.0

- Development version
  http://ftp.lstc.com/beta/lsopt/5.2