New developments in LS-OPT

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Summary:

This paper provides an overview of current LS-OPT® development and focuses mainly on the following new features: (i) New wizards for LS-Dyna statistics and metamodel-based optimization, (ii) visualization of the Pareto Optimal Front (iii) new optimizers for metamodel optimization, (iv) generic result extraction, (v) algorithm settings, (vi) metamodel evaluation and (vii) improved experimental design for generating designs in reasonable space.

Keywords:

LS-OPT, LS-DYNA statistics, Pareto Optimal front, Multi-objective optimization, Metamodel-based optimization, Reasonable design space

1 Introduction: LS-OPT overview

In today's CAE environment it is unusual to make engineering decisions based on a single physics simulation. A typical user conducts multiple analyses by varying the design and uses the combined results for design improvement. LS-OPT® [1] provides an environment for design and is tightly interfaced to LS-DYNA® and LS-PREPOST® with the goal of allowing the user to organize input for multiple simulations and gather and display the results and statistics. More specifically, LS-OPT has capabilities for improving design performance in an uncertain environment and conducting system and material identification. These objectives can be achieved through the use of statistical tools and optimization. The individual tasks that can thus be accomplished are:

- Identify important design variables
- Find the optimal surface (Pareto front) for multi-objective problems
- Explore the design space using surrogate design models
- Identify sources of uncertainty in FE models
- Visualize statistics of multiple runs
- Optimize the design with consideration of uncertainties
- Conduct robust parameter design

The typical applications are: Multidisciplinary Design Optimization (crashworthiness, modal analysis, durability analysis, etc.), system and material identification (biomaterials, metal alloys, concrete, airbag properties, etc.) and process design (metal forming).

The main technologies available in LS-OPT are:

Experimental Design (DOE). D-Optimal design, Latin Hypercube sampling, Space Filling and others. DOE allows the user to automatically select a set of different designs to be analyzed. The main types mentioned here are each suited to a different type of analysis: *D*-Optimal for polynomials and sequential optimization, Latin Hypercube for stochastic analysis and Space Filling for Neural Networks.

Metamodels (approximations). Response Surface Methodology, Neural Networks and Kriging are provided. Both Feedforward Neural Networks and Radial Basis Function Networks are available. With these tools, the user can explore the design space and quantify the predictability of a response, i.e. identify sources of noisy response. A user-defined metamodel can also be specified by creating a dynamically linked library.

Variable screening [4] provides information on the relative importance of design variables.

Optimization. Used for automated design improvement. The Sequential Response Surface Method (SRSM) [5] is the principal iterative tool for finding a converged optimum and is very efficient. A similar methodology is used for finding a converged result using Neural Net updating with adaptive Space Filling. Multi-objective optimization [6] can be activated by selecting more than one objective together with the GA core solver. This combination will produce a Pareto front. Optimization with discrete variables is possible, as is combinatorial optimization. A direct multi-objective GA optimizer is used for the latter.

Probabilistic analysis includes Reliability Analysis, Outlier Analysis, Robust Parameter Design and Reliability-Based Design Optimization (RBDO). Reliability analysis allows the user to evaluate the probability of failure while Outlier Analysis allows the identification of parts of a model that contribute to noisy response and therefore may affect the overall predictability of the results. Robust Parameter Design and RBDO allow for defining robustness as an objective and the consideration of the probability of failure as a constraint option in optimization. The outlier analysis uses integrated LS-PREPOST features to visualize structural zones with unpredictable behavior [3].

Features are available to distribute simulation jobs across a network, using a variety of standard and user-defined queuing systems.

In the sections that follow, a number of new features are discussed, namely Radial Basis Function Networks, User-defined metamodels, a GA for direct combinatorial optimization and multi-objective optimization.

2 Strategies for metamodel-based optimization

There are three recommended strategies for automating the metamodel-based optimization procedure. A schematic of the different strategies is shown in Figure 1. These strategies apply to the tasks: Metamodel-based Optimization and RBDO. The setup for each strategy was possible in Version 3.3 but selection was complicated and has been simplified in Version 3.4 by introducing a special panel in the GUI (see Figure 2). Selecting a strategy will change the available options and default settings in other panels such as the sampling and run panels.

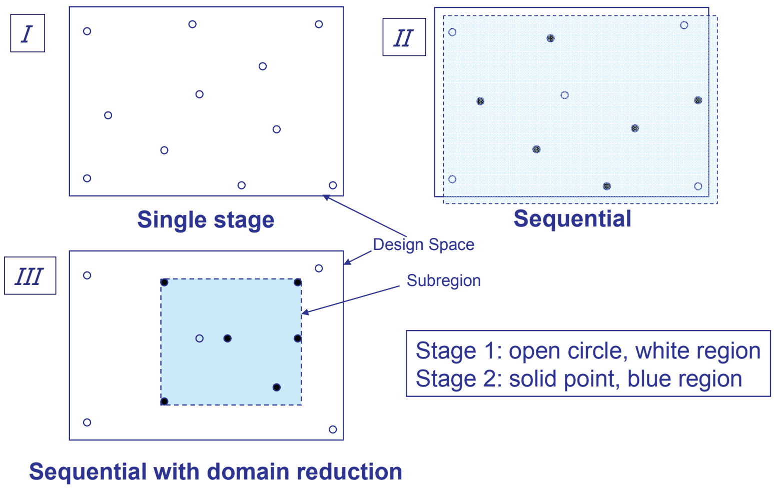

Figure 1: Schematic of metamodel-based optimization strategies in LS-OPT

2.1 Single stage

In this approach, the experimental design for choosing the sampling points is done only once. A typical application would be to choose a large number of points (as much as can be afforded) to build metamodels such as RBF networks using the Space Filling sampling method. This is probably the best way of sampling for Space Filling since the Space Filling algorithm positions all the points in a single cycle.

2.2 Sequential strategy

In this approach, sampling is done sequentially. A small number of points is chosen for each iteration and multiple iterations are requested. The approach has the advantage that the iterative process can be stopped as soon as the metamodels or optimum points have sufficient accuracy. It was demonstrated in Reference 7 that, for Space Filling, the Sequential approach had similar accuracy compared to the Single Stage approach, i.e. 10 × 30 points added sequentially is practically as good as 300 points created in a single step. Therefore both the Single Stage and Sequential Methods are good for design exploration using a surrogate model. For instance when constructing a Pareto Optimal Front, the use of a Single Stage or Sequential strategy is recommended in lieu of a Sequential strategy with domain reduction.

Both the previous strategies work better with metamodels other than polynomials because of the flexibility of metamodels such as neural networks to adjust to an arbitrary number of points.

2.3 Sequential strategy with domain reduction

This approach is the same as that in the previous section but in each iteration the domain reduction strategy is used to reduce the size of the subregion. During a particular iteration, the subregion is used to bound the positions of new points. This method is typically the only one suitable for polynomials. There are two approaches to Sequential Domain Reduction strategies. The first is global and the second, local.

2.3.1 Sequential Adaptive Metamodeling (SAM)

As for the sequential strategy *without* domain reduction, sequential adaptive sampling is done and the metamodel constructed using all available points, including those belonging to previous iterations. The difference is that in this case, the size of the subregion is adjusted (usually reduced) for each iteration. This method is good for converging to an optimum and *moderately* good for constructing global approximations for design exploration such as a Pareto Optimal front. *The user should however expect to have poorer metamodel accuracy at design locations remote from the current optimum.*

2.3.2 Sequential Response Surface Method (SRSM)

SRSM is the original LS-OPT automation strategy and allows the building of a new response surface (typically linear polynomial) in each iteration. The size of the subregion is adjusted for each iteration. Points belonging to previous iterations are ignored. This method is only suitable for convergence to an optimum and cannot be used to construct a Pareto optimal front or do any other type of design exploration. Therefore the method is ideal for system identification.

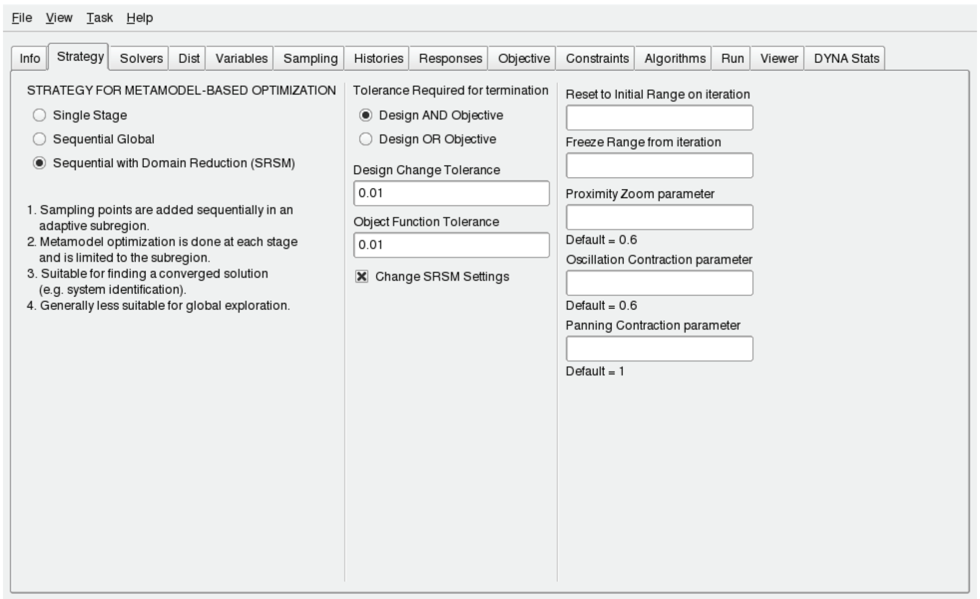

Figure 2: Optimization strategy panel

3 Reasonable design space

In some cases, especially when a parametric preprocessor is used there is a potential for unreasonable designs to be created due to conflicts created by certain combinations of parameter values. Such designs typically also cause LS-DYNA error terminations. A reasonable design space approach has always been available using the "Move" option in the Constraints panel of the GUI, but failed if the center point of the design space was not a reasonable design. An improved method is now provided. The constraints for the reasonable design space are specified in the Constraints panel with the "Move" flag selected. The feature is limited to explicit composites (i.e. composites not dependent on response surfaces) and (as previously) the D-Optimality criterion. The figure illustrates an example in which three iterations are done with the constraints REAS1 and REAS2 selected as defining the reasonable design space. Constraint C3 is only used for the optimization phase.

This feature has been migrated to Version 3.3.

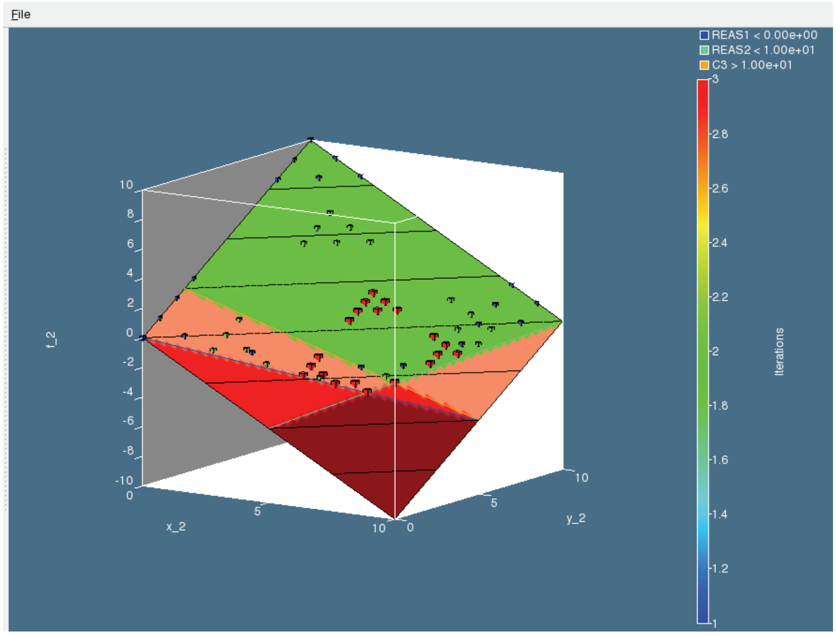

Figure 3: Reasonable experimental designs defined by constraints REAS1 and REAS2.

4 Generic result extractor

Since LS-OPT is sometimes used in an MDO mode, a need often arises to, in addition to LS-DYNA, run solver programs for which LS-OPT does not have a standard interface. A software tool has therefore been developed to quickly identify and tag result fields in a text-based solver output file and then have LS-OPT extract the appropriate result after simulating any design. For instance a NASTRAN or Madymo text output file can be tagged for extracting selected results. A special response type, for which the appropriate tag is specified, is provided in the Responses tab of the GUI. The result extractor is activated from within LS-OPT.

5 Metamodels

5.1 Kriging (updated)

The Kriging metamodel has been a feature of LS-OPT since Version 2 but has recently been updated to provide a speedier metamodel building phase. A few advanced options have been added to the Kriging selection namely the two types of correlation functions (exponential and Gaussian) as well as the trend functions (constant, linear, or quadratic) that segregate the large- and small-scale components of the response. The robustness of the metamodel building methodology has also been improved by implementing a scheme to deal with design points close to one another.

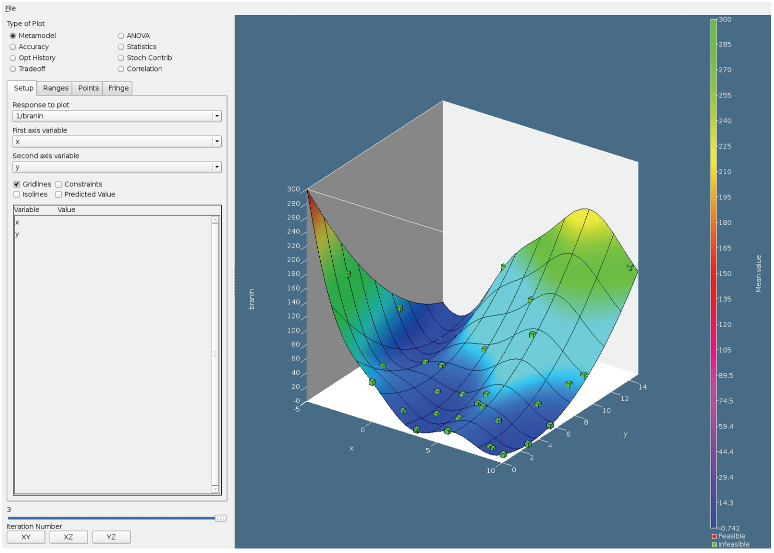

Figure 4: Two dimensional rendering of a Kriging model in LS-OPT®

6 Metamodel optimizers

Until Version 3.4 the two optimizers available for metamodel optimization were the gradient-based algorithm LFOPC (Leapfrog Optimizer for Constrained problems) and the Genetic Algorithm (GA). The LFOPC algorithm is highly accurate and robust but can be time consuming for large optimization problems. This deficiency is largely due to the fact that LFOP is a local optimizer and therefore requires a multi-start approach in an attempt to find a global optimum. The GA was implemented for Version 3.3 to address multi-objective non-convex constrained optimization problems. The GA also serves as a global optimization technique for single–objective optimization problems. Another popular global optimization method Adaptive Simulated Annealing (ASA) is added to address the global optimization problem more efficiently. The ASA algorithm is based on the algorithm by Ingber [8].

The main deficiency of global optimization techniques is the high computational expense. To improve the computational efficiency of global optimization, a hybrid approach that exploits the beneficial features of both global (global optimization) and local (fast convergence) optimizers is adopted. In this approach, a global optimizer is used with limited computational budget to drive the search to the global optimal region. Next, the sub-optimal solution from the global optimizer is used as the starting point for local optimizer to converge to the global optimal solution. Based on the global optimizer, two hybrid variants have been added, namely (i) Hybrid GA and (ii) Hybrid ASA. For both hybrid approaches, firstly GA or ASA is run as global optimizer followed by a single LFOPC run.

7 Algorithm settings

In Version 3.4, a feature has been added for advanced users to choose an optimization algorithm and change the optimization algorithm settings for LFOPC, GA and ASA. In addition to this feature, the user is also allowed to modify the parameters for SRSM (Sequential Response Surface Method) (see Figure 2).

8 Visualization of the Pareto Optimal Front

Displaying the Pareto optimal front for a problem with only 2 objectives is very simple. However for three or more objectives, more sophisticated display mechanisms are required. Two approaches are taken to visualize the Pareto Optimal Front. The first is to allow the display for problems with 2 and 3 objectives. See Figure 5 for a 3-dimensional display. A fourth quantity can be displayed using a color index. For multi-objective problems with a larger number of objectives, a multi-axial plot is used as shown in Figure 6. The function or variable bounds can be adjusted to isolate a suitable Pareto optimal point or points.

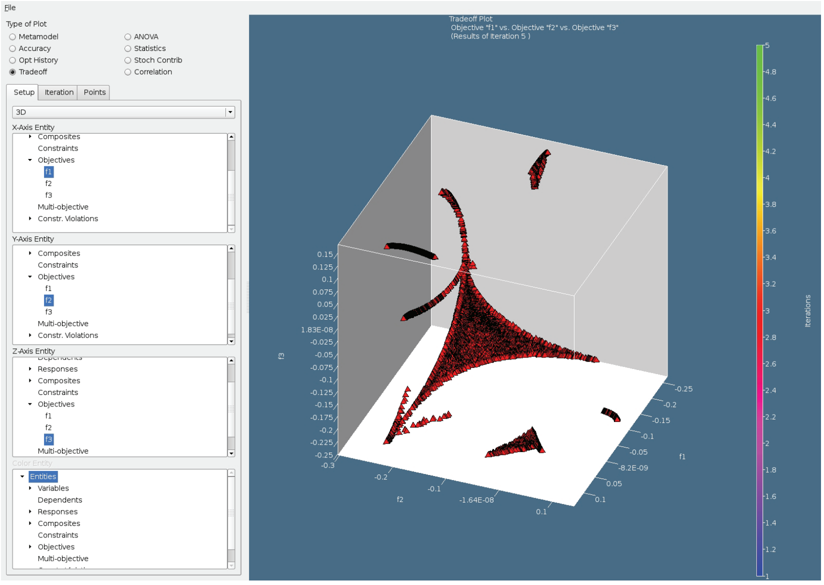

Figure 5: Pareto Optimal Front for triple objective optimization problem (LS-OPT GUI)

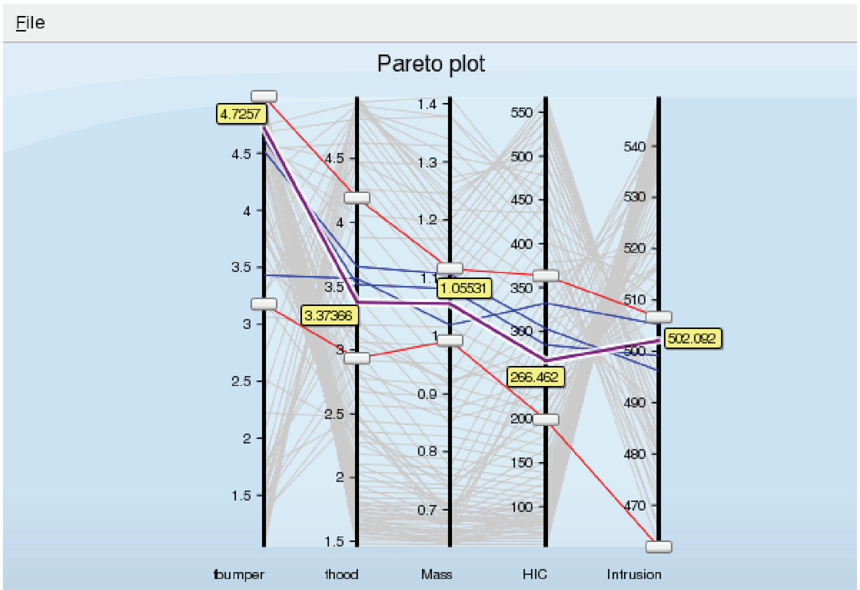

Figure 6: Pareto Optimal Front based on multi-axial plot.

9 LS-DYNA statistics wizard

LS-OPT can display statistical results visually in LS-PREPOST on the structure. This ability has been completely redesigned to allow:

- A shorter learning curve. The GUI wizard and outlay guides a user through the creation of a plot.
- Increased usability. The capability was re-organized focus on plots as the central entity. These plots can be edited, displayed, computed in a batch fashion, and refined further (for example, in a bifurcation analysis).
- Re-use and sharing of an investigation method. The plots created during the analysis of a structure is saved in a database. This database can be re-used in similar studies. For example, a metal forming group have to set up their investigation methodology only once and re-use this set-up for a number of similar metal forming studies.

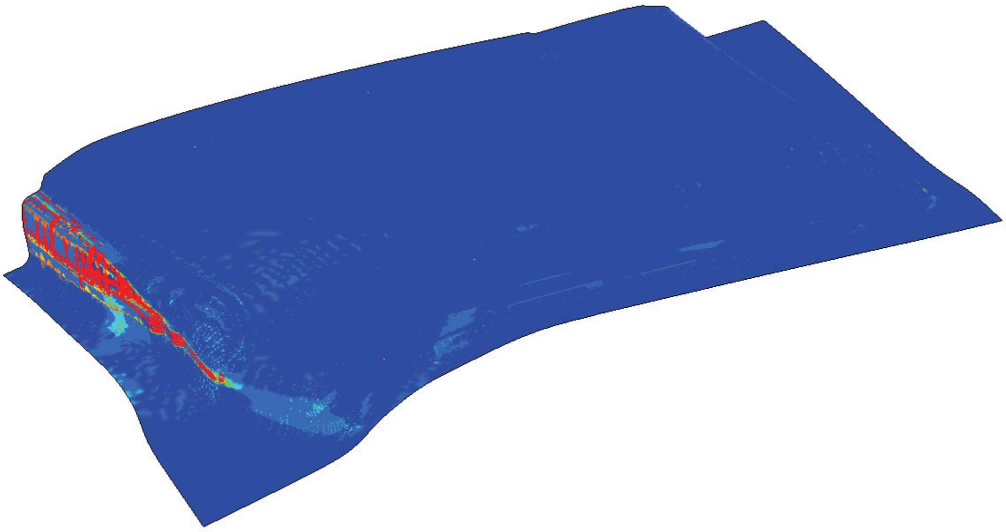

Figure 7: Standard deviation of plastic yield of a metalforming problem. The creation of plots of statistical quantities like these has been simplified by the new GUI.

10 Miscellaneous features

The Extended Results database is now also available as a .csv (comma separated variables) file for importing into spreadsheet programs such as Microsoft Excel (migrated to Version 3.3).

A feature has been added to evaluate design points using an existing metamodel. A .csv file containing all the interpolated design results is produced. The feature can be selected under the "Evaluate Metamodel" tab in the "Solvers" panel. The repair feature: "Analyze checkpoints" is used to do the evaluation using an existing database (migrated to Version 3.3).

11 Conclusion

LS-OPT Version 3.4 presents a significant step forward for design with LS-DYNA by providing a friendlier interface as well as refining and accelerating the existing methods for probabilistic analysis and optimization. New features such as extended visualization of the Pareto Optimal Front and a generic result extractor have been added.

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