

## New Features in LS-OPT<sup>®</sup> Version 3

Nielen Stander and Willem Roux  
*Livermore Software Technology Corporation*

### Abstract

*An overview of LS-OPT features is given with special emphasis on new features available in LS-OPT Version 3.1. The main features added to Version 3 include discrete optimization, 3-D metamodel plotting, additional statistics features, and a simplification of parameter identification. LS-OPT is now available for MS Windows<sup>®</sup>.*

### Introduction and 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
- Optimize the design
- Explore the design space using surrogate design models
- Identify sources of uncertainty in FE models
- Visualize statistics of multiple runs

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 and Neural Networks are the most important. With these tools, the user can explore the design space and quantify the predictability of a response, i.e. identify sources of noisy response.
- *Variable screening* [4] provides information on the relative importance of design variables.

- *Probabilistic analysis* includes Reliability and Outlier Analysis [3]. The former allows the user to evaluate the probability of failure while the latter allows the identification of parts of a model that contribute to noisy response and therefore affect the predictability of the results. The outlier analysis uses integrated LS-PREPOST features.
- *Optimization*. Used for automated design improvement. The Successive Response Surface Method (SRSM) [5] is the principal iterative tool for finding a converged optimum. A similar methodology is used for finding a converged result using neural net updating.

Features are available to distribute simulation jobs across a network, using a queuing system.

## New Features

### *LS-OPT for Windows*<sup>®</sup>

Released in December 2005 as Version 3.0, LS-OPT for Windows incorporates a new Application Program Interface (LS-API) to speed up development and facilitate porting.

### *Stochastic fields*

Stochastic fields are used to randomly perturb a spatial property. With this capability, a set of perturbed models can be created for a stochastic analysis. LS-DYNA Version 971 [2] provides the capability to perturb (i) geometry and (ii) shell thickness using eigen or displacement modes or harmonic functions. Examples are shown below:

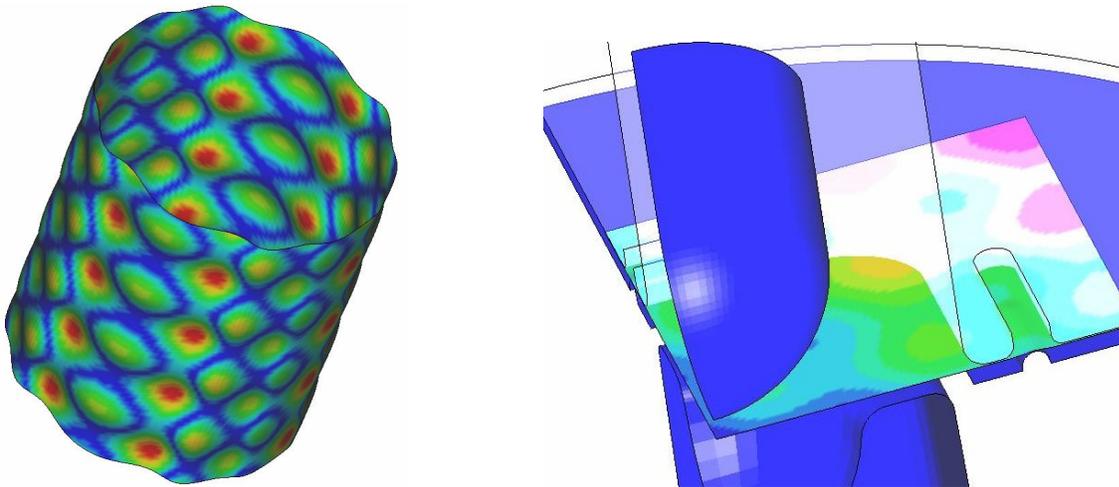


Fig 1: (a) Geometric perturbations of a cylinder and (b) thickness perturbations of a sheet metal blank

### *3-D visualization of metamodels*

In Version 3.1 a new feature is provided for the three-dimensional visualization of metamodels. The fringe types are function value and variance (standard deviation). The latter is important particularly for neural networks, where some variation may occur in regions of sparse information or noise.

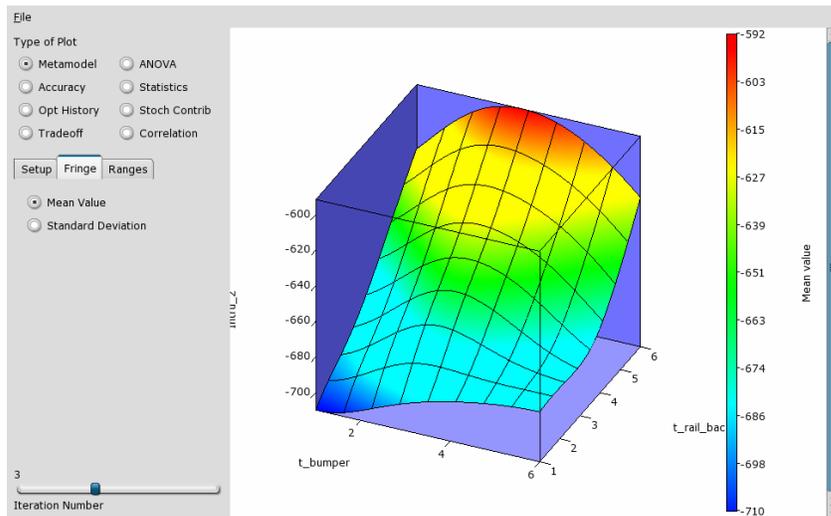


Fig. 2: Response plot using a Neural Network metamodel. The mean response of 9 committee members is shown.

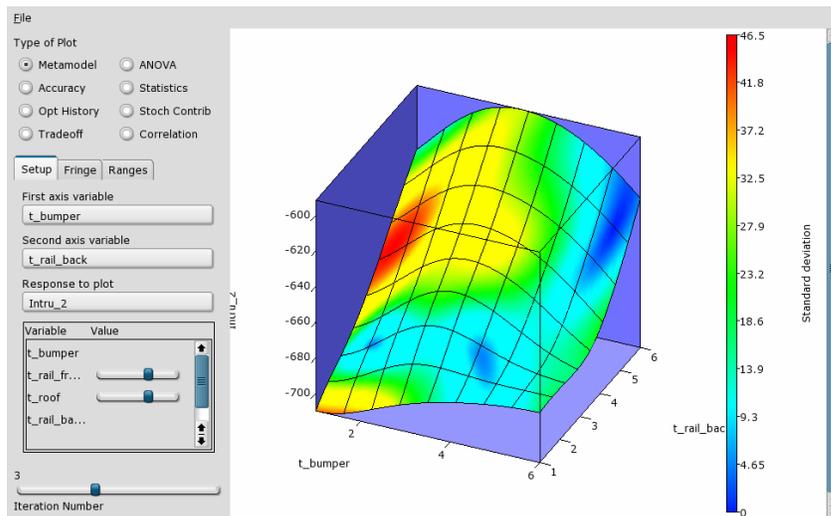


Fig. 3: Response metamodel plot with superimposed standard deviation (9 committee members)

**Discrete Optimization**

In Version 3.1 a mix of continuous and discrete variables can be incorporated in SRSM.

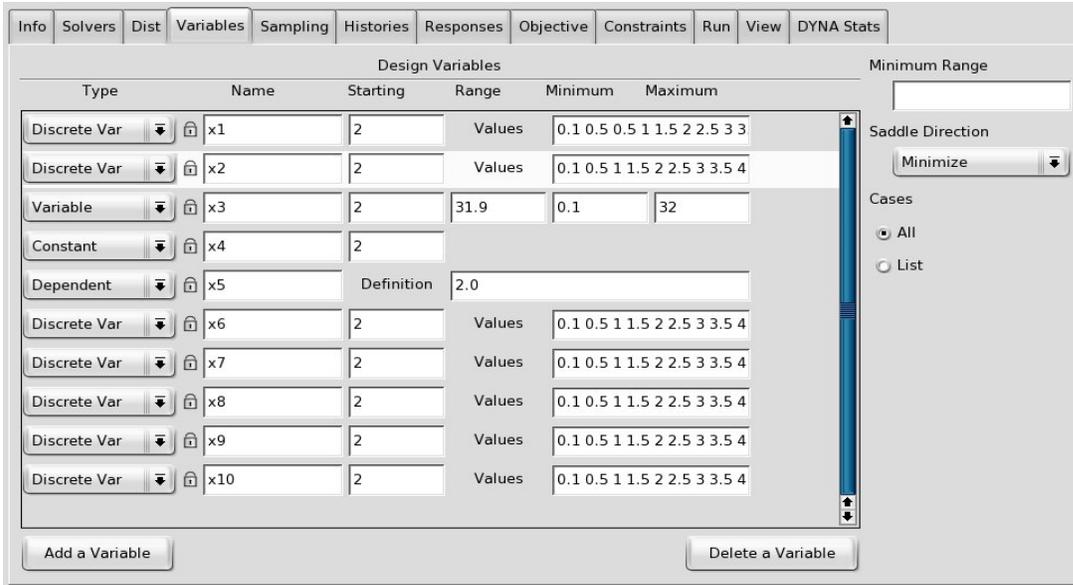


Fig 4: The variables panel showing the specification of discrete variables

**Improved visualization of statistical results**

The LS-PREPOST visualization of statistical quantities based on multiple runs has been extended. Changes include:

- The variation of any *d3plot* response can be investigated.
- The histories of all the LS-DYNA runs can now be plotted.
- An automated bifurcations identification procedure is available.

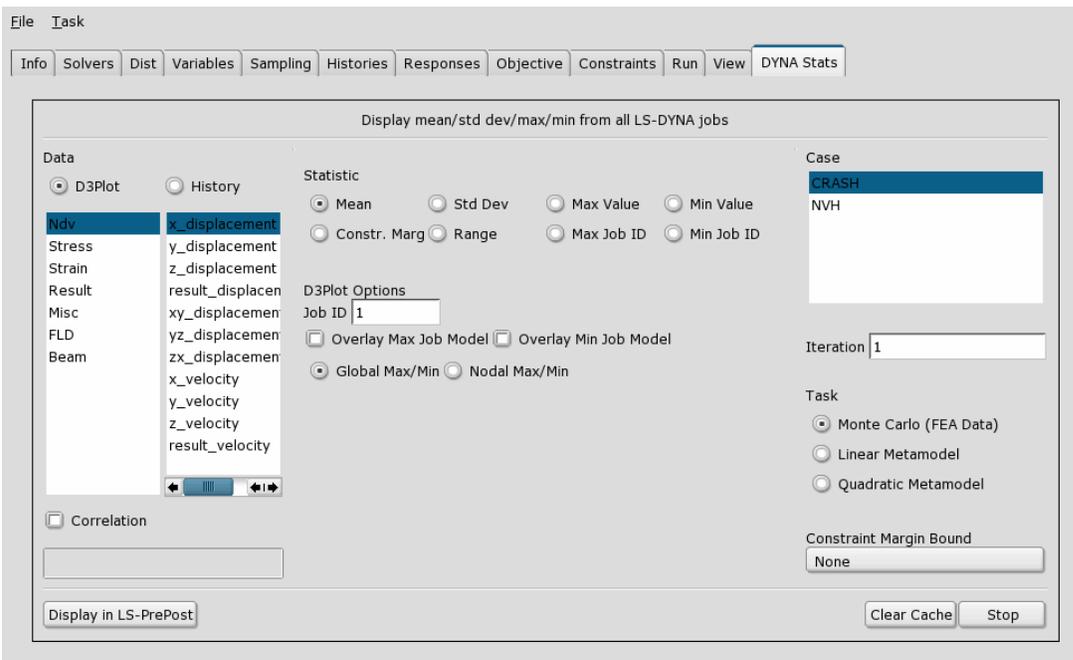


Fig. 5: The DYNA Statistics panel. The panel is used to investigate the variation of d3plot results and LS-OPT histories. The procedure includes tight integrated with LS-PREPOST visualization. Instability analysis and display of probabilistic (six-sigma) safety margins are also possible.

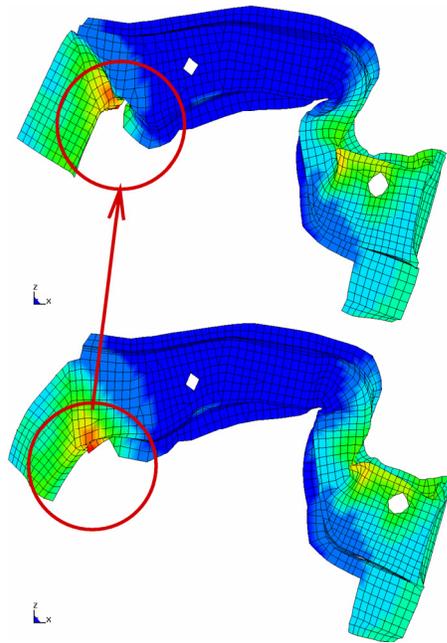


Fig. 6: Standard deviation of displacement residuals superimposed on outlier deformed states.

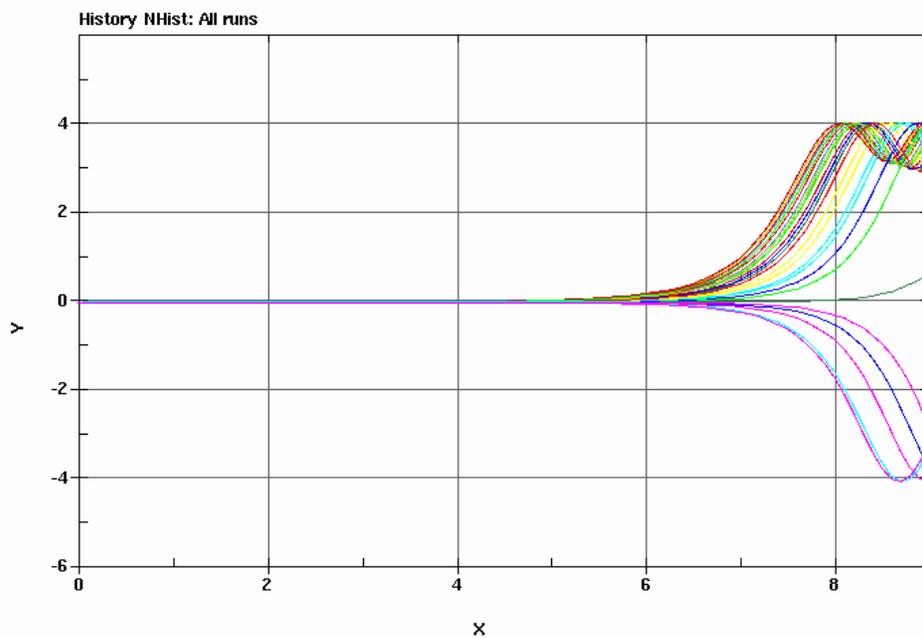


Fig. 7 The LS-OPT histories of all the LS-DYNA run can be viewed simultaneously.

### ***Reliability-based design optimization (RBDO)***

Reliability-based design optimization (RBDO) is the computation of an optimum design subject to probabilistic bounds on the constraints. The probabilistic bound is usually interpreted as a six-sigma context; for example, the failure of only one part in a million is acceptable.

**System Identification**

System and material parameter identification has been automated by enabling the importing of test curves. The methodology is response surface-based (see Fig. 6), i.e. a response surface is constructed for each test point (or interpolated point) resulting in a single response surface history curve consisting of  $P$  points being incorporated into a composite function:

$$\frac{1}{P} \sum_{p=1}^P W_i \left( \frac{F_i(\mathbf{x}) - G_i}{s_i} \right)^2 = \frac{1}{P} \sum_{p=1}^P W_i \left( \frac{e_i(\mathbf{x})}{s_i} \right)^2$$

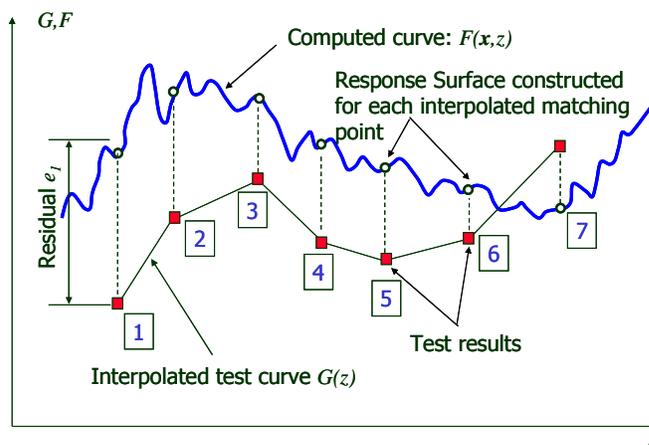


Fig. 6: Disagreement of Test and Computed curves to be reduced by optimization of the Mean Squared Error of the residuals.

The feature uses three new keywords:

Get test data:

```
History 'testcurvename' file "testfilename"
```

Construct crossplot:

```
History 'curvename' {Crossplot (
    history_x_name, history_y_name,
    [numpoints, begin, end] )}
```

Construct error norm of curve mismatch:

```
Composite 'name' {MeanSqErr (
    'testcurvename', 'curvename',
    [numpoints, begin, end,
    weighting_type, scaling_type,
    weighting_value, scaling_value,
    weighting_curve, scaling_curve] )}
```

***Improvement of neural networks***

Feedforward neural networks were introduced in Version 2 of LS-OPT to provide a more flexible option for creating surrogate models for design. For Version 3 these have been improved for more robust prediction. The Feedforward NN's in LS-OPT have the following advantages:

1. Complex functions can be modelled. NN's provide an increase in complexity commensurate with an increase in the number of data points.
2. NN's are more flexible than the standard application of polynomials because these typically require a minimum number of runs for a specific order polynomial, and these numbers may be far apart for a large number of design variables. E.g. 10 variables require at least 11 runs for a linear response surface and 66 for quadratic. A NN automatically adopts the complexity of form dictated by the number of points and the degree of nonlinearity of the function.
3. A sequential response surface scheme such as SRSM in LS-OPT typically ends up with a local linear approximation of the response (i.e. they are piece-wise accurate). NN's are useful for making approximations across the design space. This allows wider exploration using the *Metamodel* or *Trade-off* features in the Viewer.
4. Neural networks tend to smooth and not interpolate (intercept each point). The smoothing property is required to filter or quantify noise.
5. Neural Network Committees: Because NN's are created using a nonlinear regression procedure which uses a random starting point to compute the NN weights, slightly different NN's are often created using the same analysis result set. This allows for (i) generating a centered net based on the mean of a *committee* of nets and (ii) generating variance information for the committee. Figure 3 shows the point-wise variance of a neural net.

A disadvantage of neural nets is that they are more costly to generate, especially for a large number of variables.

**References**

1. Stander, N., Roux, W.J., Eggleston, T. and Craig, K.J. LS-OPT Version 3.1 User's Manual, Livermore Software Technology Corporation, March 2006.
2. Hallquist, J.O. LS-DYNA User's Manual, Version 971.
3. Roux, W.J., Stander, N., Günther, F and Müllerschön, H. Stochastic analysis of highly nonlinear structures, *International Journal for Numerical Methods in Engineering*, Vol. 65:1221-1242, 2006.
4. Craig, K.J. and Stander, N., Dooge and Varadappa, S. Automotive crashworthiness design using response surface-based variable screening and optimization, *Engineering Computations*, Vol. 22:38-61, 2005.
5. Stander, N. and Craig, K.J. On the robustness of a simple domain reduction scheme for simulation-based optimization, *Engineering Computations*, Vol. 19:431-450, 2002.

