

LS-OPT[®] Status and Outlook

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Abstract

Features added to the recently released LS-OPT Version 5.2 are discussed. An outlook of the next version, which includes Statistical Classification and Digital Image Correlation, is given.

Introduction

LS-OPT has evolved significantly over a period of more than a decade to contain an array of advanced features for simulation-based optimization. The major features are as follows:

- Metamodel-based and Direct Optimization algorithms. Multi-Objective Optimization. Multi-level Optimization. Multidisciplinary and Multi-stage optimization.
- Probabilistic Analysis and Optimization features such as Reliability, Robustness, RBDO and Tolerance Optimization. FE model-based visualization of LS-DYNA[®] Statistics (using LS-PrePost[®]).
- Comprehensive LS-DYNA interface
- Post-processing which includes metamodel surface, scatter plot and statistical result displays
- Flow-chart-based GUI with job progress monitoring
- Parameter identification
- Simulation job distribution and monitoring. Secure proxy server.

A major enhancement of LS-OPT methodology is the addition of *Statistical Classification*. This is a general methodology which can be used to define a failure boundary or a constraint in the design space, collectively referred to as a *decision boundary*. Once trained, a decision boundary can be used for efficient decision making without actual expensive function evaluation. It can be used for reliability analysis, optimization (including probabilistic optimization and multi-objective optimization) or for defining regions of particular interest in the design space. A later section of the papers gives further insight into the classification method being implemented. The classification-based approach can be particularly useful in the presence of binary or discontinuous responses and multiple dependent failure modes.

As the user base of LS-OPT grew, it became apparent that a critical part of simulation-based design is material parameter identification. In order to enhance parameter identification capabilities, features such as Curve Mapping (2011) were added to LS-OPT. Current development in this direction is focused on providing identification features which use Digital Image Correlation (DIC) as an optical testing method. A section of this paper is dedicated to DIC-based parameter identification.

New features in Version 5.2

LS-OPT Version 5.2 was released in December 2015. The following major features are included:

1. A new integrated progress window has been created to unify Windows and Linux progress monitoring. The window features separate tabs for text output and thermometer type progress monitoring. Warnings and errors are displayed in a separate tab window. Global progress is displayed. The window can be hidden while the older option via the stage dialog LED is still available.

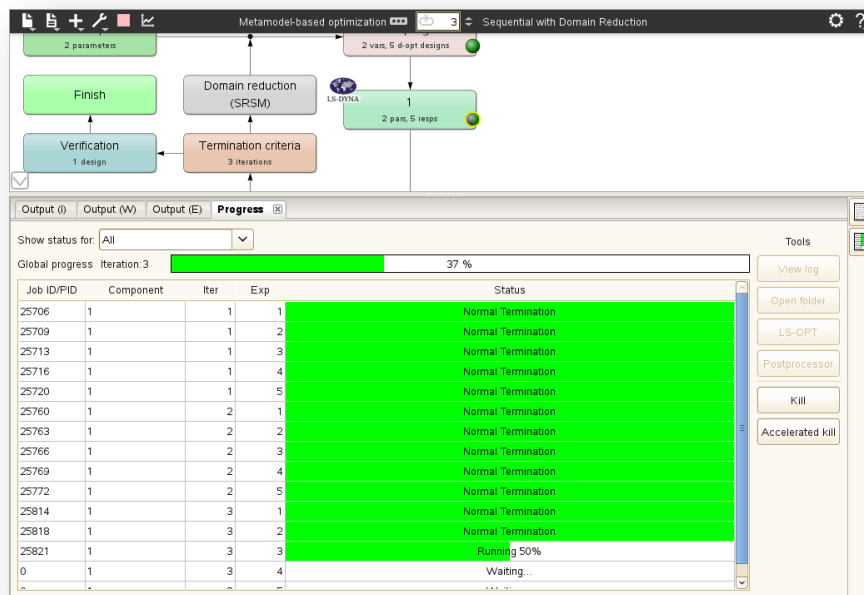


Figure 1: The integrated progress window has been created to unify Windows and Linux progress monitoring. Progress bars are live, and can be queried for job logs, post-processing and individual job control.

2. *Response variables* were created to allow the substitution of simulation results in input files of a child stage during a multi-stage process flow. In combination with previously introduced multi-level features, this feature allows the input files of a stage to be defined as derivatives of optimized variables produced by previous stages in a multi-stage/multi-level process. E.g. in a multi-level setup, an optimal design stage can be provided with optimal material parameters (substituted in the material card) generated by a parent material identification step. This process represents two optimization steps running in tandem with the second step using the optimal variables of the first step.

These parameters can be processed, using mathematical expressions, between stages in the process flow. All the response and history expressions are fully supported. Histories from simulation output can also be transferred to LS-DYNA input files as *DEFINE_CURVE data sets (as e.g. required for State Variable models in multi-scale parameter identification [1]).

- The generation and display of comparison metamodels. A set of different metamodels based on the same set of analysis results can be selected by the user for display. Parallel Neural Networks are also available as comparison metamodels.

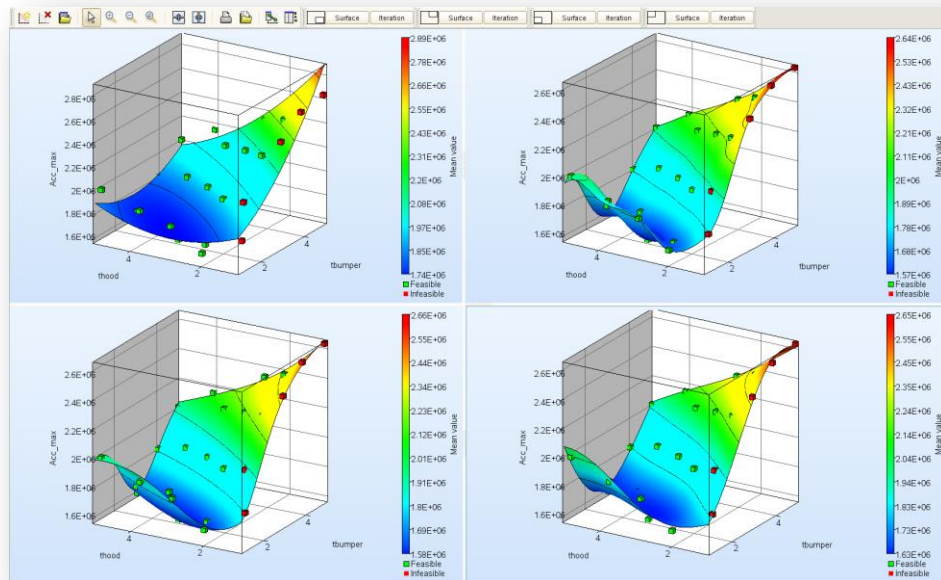


Figure 2: Display of comparison metamodels.

- Reliability statistics, e.g. as a result of direct or metamodel-based Monte Carlo analysis, can be extracted in a multilevel setup. This allows the setup of, for instance, tolerance optimization or robust design problems using the direct Monte Carlo method. Mean values, standard deviation as well as the probability of failure are supported for individual constraints as well as globally.

Other new features include:

- Matlab is supported as a solver type on the Windows platform.
- Navigation tools are available in the GUI for navigating between levels when using multilevel optimization. E.g. the input setup and progress can be accessed with full functionality for lower levels by navigating from the start (top) level.
- Histories can be displayed in three dimensions in which the third dimension is a variable.
- LS-OPT metamodels (DesignFunctions.x file format) can be imported. This is useful for problems in which a metamodel has already been constructed. Importing and optimization/Monte Carlo analysis can be executed as a single step to allow for automatic importation preceding the inner level analysis of a multi-level optimization.
- Parallelization is now automatic for extraction repair. The number of processors available on the local machine is automatically detected. Hence, mode tracking, a potentially costly extraction procedure, now runs in parallel.
- Box plot options are available for histogram displays (reliability analysis). This includes whisker type options for min./max., interquartile range, standard deviation and 9%/91%.

11. The FE postprocessor can be customized.
12. Features are available to encrypt the LS-OPT (.lsopt) input file.
13. The efficiency of the Curve Mapping algorithm for parameter identification involving hysteretic curves has been improved.
14. Features have been added to the GenEx text file extraction tool to simplify the selection and extraction of histories.
15. Retry and timeout attributes required by the job scheduler to handle abnormal termination can now be specified in the GUI.
16. Algorithms for curve differentiation have been improved [2] potentially allowing higher order curve derivatives in future versions. Irregular spacing of the history or crossplot curve is allowed.
Numerical integration functions have been unified.
17. History statistics are now displayed in the *Viewer*, in addition to *DynaStats*. Thus, the statistics can be viewed even if d3plot files are deleted. Additionally, non LS-DYNA history statistics are also displayed.
18. A response file option allows the specification of an output file with a single value that needs to be extracted (user-defined response). This feature solves a portability issue by obviating “type” (Windows) or “cat” (Linux) commands to write such a file to standard output as is required for user-defined responses.

Classification-based Design and Analysis

Several LS-OPT tasks use metamodel-based approximations in order to perform design optimization and probabilistic analysis. The basic idea is to replace expensive function evaluations, e.g. FE simulations, with inexpensive surrogate model or metamodel evaluations. These metamodel predictions then replace the objective and constraint function evaluations. However, the presence of discontinuous and binary responses hampers the construction of accurate metamodels [3]. To overcome such issues, the next version of LS-OPT will introduce a new entity, referred to as *classifier*. The use of classifiers represents a conceptual shift from the commonly used approach of metamodel-based prediction. Instead of the function values, the classification-based method relies only on the class of a sample, e.g. safe or failed. Once trained, a classifier provides a decision boundary that decomposes the design space into two regions (safe and failed), and thus predicts the class of any unknown design sample depending on its spatial position (e.g. at the question mark in Figure 3).

A popular machine learning technique known as support vector machine (SVM) [4] is currently being implemented in LS-OPT for constructing the decision boundaries. An SVM boundary is obtained as $s(\mathbf{x}) = 0$, where $s(\mathbf{x})$ is given in Eq. (1).

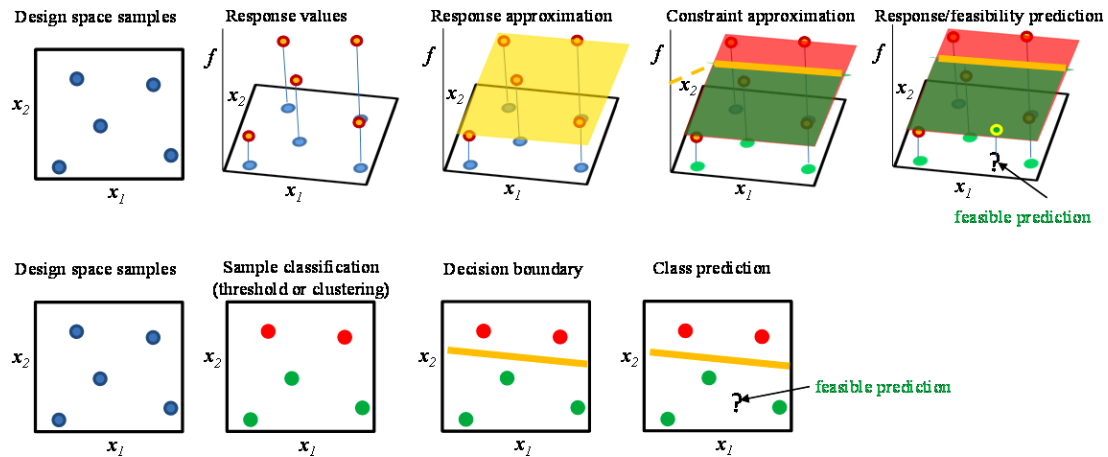


Figure 3: Summary of basic classification method (bottom) and comparison to metamodeling (top).

$$s(\mathbf{x}) = b + \sum_{i=1}^N \alpha_i y_i K(\mathbf{x}, \mathbf{x}_i) \quad (1)$$

Here, $y_i = \pm 1$ (e.g. red vs green) is the class label, α_i is the Lagrange multiplier for the i^{th} sample and b is the bias. A kernel K maps the design space and the feature space (a high-dimensional space consisting of basis functions as the variables, where the classifier is linear) and allows the SVM decision boundaries to be highly nonlinear in the design space. The evaluation of the sign of $s(\mathbf{x})$ at any unknown design is straightforward and inexpensive and gives the predicted class, making it suitable for use as an optimization constraint [5] or for reliability assessment [3,6].

In terms of LS-OPT terminology, a classifier will share some of the properties of several entity types, such as metamodels, composites and constraints. A classifier is defined as a composite of other entities, such as variables, dependents, responses, composites as well as other classifiers. In addition, depending on the method to assign class labels an upper and/or lower bound may also be specified as part of the classifier definition, similar to constraints. A classifier definition can also consist of multiple classifiers that are combined in either series or in parallel. Additionally the type of classification, initial parameters etc. are also specified in the classifier definition (Figure 4).

A decision boundary based on classification can be used as a deterministic or probabilistic constraint in deterministic optimization, probabilistic optimization or reliability analysis [3]. It can also be used to define a region of interest in the design space for further sampling [7]. The main advantages of using the classification-based method are as follows:

1. As evident in Figure 3, the classification-based method does not require the actual response values at the training samples; instead, it only requires the class ± 1 of the samples. As a result, it can be applied to problems with only binary pass/fail information available.
2. As the response values are not approximated and are instead classified, the method is unaffected by the presence of discontinuities.

3. A single classifier can represent multiple failure modes. This feature can be used to devise a mechanism in which only a few failure modes need to be evaluated at a sample to obtain the class label, thus increasing the efficiency. Additionally it automatically accounts for the dependence between different failure modes, which is often neglected by other methods.

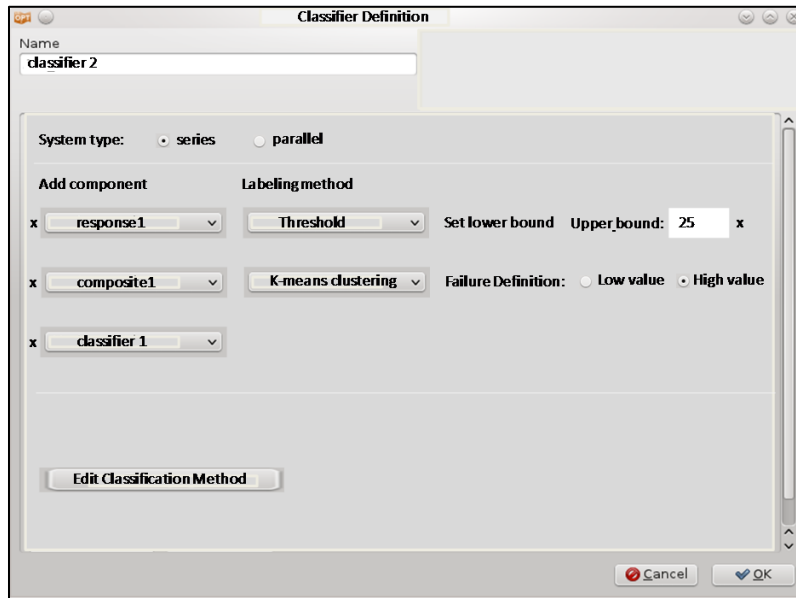


Figure 4: Proposed Classifier definition dialog in LS-OPT (top). The classification algorithm and algorithm parameters are specified in a separate dialog that opens upon clicking “Edit Classification Method”.

Digital Image Correlation

While LS-OPT has included parameter identification features since its first release, experimental methods for measuring material behavior have advanced significantly in the intervening years. A major current development activity is to significantly enhance these capabilities to empower LS-OPT to accommodate current testing techniques.

Digital Imaging Correlation (DIC) is an optical method which provides full-field displacement measurements for mechanical tests of materials and structures. It can be used to obtain temporal displacement, deformation or strain fields from an experimental coupon and can be combined with Finite Element Analysis to identify the constitutive properties of a material. The methodology for both DIC and its application to material parameter identification has been thoroughly researched since the early 1980s [8,9,10].

Because DIC-based parameter identification is an inverse process, optimization is used to obtain the parameters which will minimize the discrepancy between the measured field and the computed field. As expressed for instance in Mahnken *et al* [10] the functional used is:

$$f(\boldsymbol{x}) = \sum_{j=1}^n \|\boldsymbol{\varphi}_j(\boldsymbol{x}) - \tilde{\boldsymbol{\varphi}}_j\|^2$$

where $\boldsymbol{\varphi}_j(\boldsymbol{x})$ is a vector of nodal displacements (for computation and experiment(~)) at a number of observation points and n is the number of observation states. The functional can also be augmented to incorporate force-displacement measurements or any other functional resulting in a parameter identification based on a multi-scale DIC. Weighting is applied to compensate for differing units. Although DIC techniques can be used to derive strains, displacements appear to be the field of preference in material identification.

Using DIC in parameter identification has significant advantages. A common problem in material identification is that there is often too little information available to identify all the material parameters with sufficient certainty. This results in a solution in which some or all of the parameters identified have very large confidence intervals. This comes about because the user might have chosen to use limited information such as the force vs. displacement (purely global information) from a tensile test which means that the result is based on a single global history without specific information related to local deformation due to e.g. large strain plasticity or failure. Because DIC adds a spatial dimension to the problem, the constitutive properties can be identified as broadly and with as much certainty as can be achieved with the available data. (This, of course, does not relieve the analyst of the responsibility to design suitable tests or construct accurate Finite Element models to identify a particular material).

While DIC has become the norm for tensile testing, using 2-dimensional displacement fields, DIC type information can also be gathered from other types of imaging methods, e.g. 3-dimensional MRI (Magnetic Resonance Imaging). As a practical example, Fig. 5 depicts the FE model of the myocardium of the left ventricle used to calibrate its biomechanical constitutive properties [11]. In this example Green-Lagrange strains corresponding to a user-selected state were used to define the correlation field.

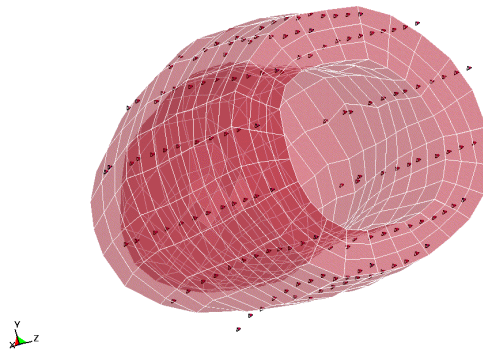


Figure 5: A set of MRI measuring points superimposed on the Finite Element model of a left ventricle myocardium[12].

While DIC-type calibration, as depicted in Fig. 5, has been conducted using LS-OPT in the past [12], the present implementation generalizes the feature to enable it to address a greater diversity of problems. The following features are being developed:

1. Multi-point responses and histories. This feature allows the user to specify a node, element or coordinate set instead of a single entity as is currently available.
2. The mapping of points to an FE model is key to the methodology. Hence definition of a coordinate set (e.g. the MRI measuring points shown in Figure 3) that can be used to match locations on the finite element model is supported. The LS-DYNA interface is therefore extended from specific node numbers to point coordinates. A rapid *exact nearest neighbor* search, capable of matching $10^7 \rightarrow 10^7$ points in reasonable time, based on part definition, is used to locate nodes or elements in the FE model.
3. Enhanced MSE functionals that can be used as objective functions for minimizing discrepancies.
4. The ability to interpolate fields within a finite element is incorporated into the mapping approach. In this case, the methodology does not rely on finding a nearest node, but can interpolate a displacement or strain in the nearest element. This is especially important for coarse meshes or high resolution DIC.
5. Error analysis to allow the user to assess the mismatch as well as the resulting uncertainty of the parameters.
6. Graphical features to enhance the prior inspection and editing of test results.
7. Discrepancy maps.

Examples will be presented at the conference.

Conclusion

The paper summarizes new LS-OPT features and discusses major features under development. Noteworthy is the introduction of Statistical Classification and the enhancement of parameter identification features for DIC-based testing.

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