In the last decades enormous progress has been made to simulate the realistic behavior of products with non-linear software running on high-performance hardware. Simulated behavior is now so accurate that for many products virtual prototypes are considered replacements for experimental testing. Because of the robustness of this new simulation technology, the use of optimization software to achieve (more) desirable model behavior is now standard industry practice.

In most optimization software the user has to define the design problem upfront in terms of objectives, constraints, and design variables. The ‘best design’ is then found iteratively by the algorithm. A limitation to this approach is that many business and technical requirements may be unknown to the engineer performing the study. As a consequence there is more emphasis on making the design tradeoffs transparent to customers and management. This means that the engineer not only has to come up with the ‘best design’, but also must identify and characterize a trade space of competitive choices. This practice requires orders of magnitude more simulations than deterministic optimization.

Furthermore, all deterministic optimization algorithms tend to push the simulated behavior of the product towards one or more constraints until the constraints are active. With a design sitting on one or more constraint boundaries even slight uncertainties in the problem formulation or changes in
the operating environment could produce failed, unsafe designs, and/or result in substantial performance degradation in real operating conditions. For this reason it is critical that stochastic effects are considered when designing real-world products using optimization, to ensure product quality, even though this requires additional orders of magnitude more simulations than deterministic optimization.

The purpose of this paper is to propose a “realistic optimal design” process that consistently creates products that meet their requirements over their lifecycle while deploying company resources (human, hardware, and software) in the most efficient manner. This process enables the creation of large trade studies and the inclusion of stochastic behavior characteristics inside the short industrial design cycles through the efficient use of HPC (High Performance Computing) resources and approximation technology.

The process presented here consists of the following steps: sampling the design space with Design of Experiments, converting the samples into an accurate approximation, and using Six Sigma optimization and/or multi-objective optimization on the approximated design space.

We will illustrate the process for the structural design of a nozzle adapter using the Isight optimization software with an Abaqus finite element model.

1: Methodology – Realistic Optimization and Simulation

In the last decades enormous progress has been made to simulate the realistic behavior of products with non-linear software running on high-performance hardware. Simulated behavior is now so accurate that for many products simulations with virtual prototypes are considered replacements for experimental testing. Because of the robustness of this new simulation technology, the use of optimization software to achieve (more) desirable model behavior is now standard industry practice. The time it takes to run these simulations is still in the order of minutes and hours, the same as it was twenty years ago.

Today’s product design processes require more and more transparency with respect to the tradeoffs between the different aspects of product behavior. Many customers now mandate transparency. A good example of this is the “Cost as an independent variable” Defense Department acquisition program [Ref 1] This of course makes the design work much more challenging as the engineer now not only has to come up with the ‘best design’, but also must articulate a well understood trade space of competitive choices.

In 1999 Balling [Ref. 2] coined the phrase “design by shopping” and we feel that this is a good description for this real-time activity. Real-time means that

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the trade-offs are generated within a few seconds. This obviously makes the deployment of optimization algorithms with high fidelity simulation infeasible for this application.

One approach which has emerged in support of trade space identification and ‘design by shopping’ is to create a set of Pareto optimal solutions using multi-objective optimization methods [Ref. 3]. For a set of Pareto optimal points it is not possible to make an improvement in one objective without making another objective worse.

![Figure 1: A Pareto front showing the Pareto optimal solutions and the dominated solutions.](image)

This concept is shown in Figure 1. For computationally inexpensive simulations the algorithms by Deb and others [Ref 4, 5] can be used directly to find the Pareto front. These Pareto sets and other up-front parametric studies can be used directly by management and customers ‘to shop for the best design’.

Unfortunately, the computational cost to directly apply multi-objective optimization to realistic simulation is still much higher than the daily turnaround time required for many design processes. Each optimization run has a dependency on the previous run(s) and requires a minimal number of iterations to converge, so it is not always possible to meet the design cycles through the use of HPC. Also, not many organizations own the hundreds of CPUs and commercial software licenses required to run so many simulations.

For individual problems it is of course always possible to tweak the optimization approach in order to reduce the computational expense as is evident by the large volume of academic benchmark studies [Ref 6]. Such finely tuned optimization methods are the domain of optimization experts and most optimization tools (like Isight) allow the integration of any expert methods. However, as Wolpert and Macready (Ref. 7) proved convincingly:

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"…for any [optimization] algorithm, any elevated performance over one class of problems is exactly paid for in performance over another class." This means that non-experts are more likely to do less well with such finely tuned methods. Robust multi-objective methods like AMGA [Ref. 5] are therefore preferred for standard engineering workflows, even if they sometimes come at greater computational cost.

The computational expense can be reduced to acceptable levels by the consistent applications of approximation algorithms such as Response Surface Methods [Ref 8] and Radial Basis Functions/Neural Nets [Ref 9]. The individual numerical simulations on which the approximation is based can be easily distributed over available HPC resources. The user has a consistent metric for the quality of the approximation through cross-validation.

Like all engineering methods, approximations are not a cure for all. A highly coupled non-linear problem with just 5 dimensions may well need thousands of samples in order to create an accurate approximation. Such problems may require a multi-step approach whereby empirical parameters for a simplified model are calibrated with a higher fidelity model or physical experiments. The simplified model now acts as an “approximation” to the high-fidelity model.

2: Methodology – Design for real world performance

Most real world engineered products and processes behave stochastically - involving chance or probability. Variation is inherent in material characteristics, loading conditions, simulation model accuracy, geometric properties, manufacturing precision, actual product usage, etc.

Applying direct stochastic optimization on realistic simulations will almost certainly result in an unacceptable cycle times, because the determination of stochastic behavior with acceptable accuracy requires thousands of simulations. This is made clear by the well-known dice experiment shown in Figure 2 [Ref. 10].

Figure 2: Dice experiment after 100 and 1000 throws
Even after 1000 experiments we still observe errors in excess of 5% in what obviously should be a uniform distribution. Accurate Monte Carlo simulations, like this dice experiment, which are typically used to calculate reliability, or probability of failure, are far more expensive than making an accurate approximation. There are of course other reliability methods such as FORM (Ref. 11) that require far fewer samples, but these types of methods make assumptions about the normality of the probability distributions and the ability to create accurate approximations of the design space with low order Taylor series that are often not valid.

Figure 3: Non-linear deflection of a cantilever beam with non linearity using the Alladin finite element analysis [Ref 12, 13]

Figure 3 shows the bilinear behavior of tip deflection of a composite beam as a function of a monotonically increasing tip load. This curve can be accurately approximated to an error of less than a few percent with just a few sample points. We can then compute the probability distribution of the approximated tip deflection as a function of a probability distribution of the tip load with thousands of Monte Carlo simulations. The time to evaluate the approximations is negligible since each evaluation only takes milliseconds.

Through this example it is easy to understand why the consistent use of approximations can reduce the cost of realistic optimization by two orders of magnitude. Further order of magnitude cost reductions are possible if the solver (like Abaqus) can provide gradient information to increase the accuracy of the approximation and if the optimization software (like Isight) can effectively deploy nested loops so that both the reliability method and the optimization method can utilize the same approximations.
3: Methodology – Standard Realistic Optimal Design Workflow

The realistic optimization process can now be described as a standard engineering workflow shown in Figure 4.

The left side of Fig. 4 shows the process to create a valid approximation of the simulated behavior. A valid approximation is one with a known an acceptable error as computed by cross-validation. This error should be less than the error in the simulation itself as it makes little sense to create an accurate approximation of an inaccurate simulation. The right side shows how this process is used inside of a Six Sigma (robust) optimization.

Figure 4: The standard process to create a Realistic Optimal Design (ROD) consisting of creating a valid approximation (left) and a Six Sigma optimization with a valid approximation (right).
a) Design of Experiment setup. We define a set of samples over the range of design variables that you expect to drive the performance attributes of interest. The sampling domain includes the expected best point and its operational variability. We employ DOE technique, like Optimal Latin Hypercube, that covers the design space evenly to achieve the best approximation accuracy.

b) Approximation and cross-validation setup. For the given sample points we need a highly reliable automatable method to generate accurate approximations. The Response Surface method with term selection, Radial Basis Functions and Kriging as available in the Isight software will all do well on most structural problems [Refs. 16, 17, 9]. The cross-validation method needs to be automatic and efficient as well. However, we also don’t want to “waist” too many function calls on error evaluation. For this purpose we recommend the leave-one-out cross-validation approach.

c) DOE execution on available computing cluster. Since the DOE sample points are independent from each other we can make good use of available HPC power.

d) Generation of the approximation and determination of the cross-validation error. If the error is greater than the target error the density of the sampling needs to be increased. For a single variable problem there is no difference between doubling the sample points in the same domain or halving the domain as far as density is concerned. However, as Figures 5 and 6 show, once the number of dimensions in the domain go up adding points to the sample is not nearly as efficient as reducing the domain space in every dimension. To enable reliability calculations, the minimum design space should at least comprise +/- 3 standard deviations from the mean design point. This means that about one in a thousand stochastic sample points will have to be extrapolated by the approximation.
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Figure 5: The effect of adding sample points to the accuracy of the 10 dimensional beam model approximation of simulated behaviour

Figure 6: The effect of reducing the domain to the accuracy of the 10 dimensional beam model approximation of simulated behaviour

e) Setup of the Six Sigma optimization consisting of a reliability technique and an optimization method. The Monte Carlo method with prescribed tight convergence criteria is preferred because of its ability to model (any) real world problems. It is recommended that the Monte Carlo method is used with fixed random number seeds to avoid random noise in the solution that will complicate the optimization process. Alternatively a very tight reliability method convergence criteria can used, but this can lead to an excessive number of stochastic sample points that have to be extrapolated. Any robust optimization method can be used in this workflow. Since we use approximations we are not concerned with computational cost and therefore robust methods such as genetic algorithms (Refs 5, 14) and hybrid methods (Ref 15) will work well. The optimization domain needs to be reduced by 3 sigmas for each of the design variable bounds to enable accurate reliability calculations.

f) A reliability method varies the stochastic parameters (inclusive of design variables) until the reliability method is converged. The optimization method iterates on the mean design point until the best point is found inside of the approximated space. If the point is found on the edge of the design variable domain the process of creating a valid approximation has to be repeated for a new domain that is centered on this best point. Some of the points of the previous sample may be reused.
4: Example – Design of a jet engine nozzle adapter

Figure 7 shows a jet engine adapter duct with a forward and aft flange. The sections are made from INCONEL 625, an alloy that possesses high strength at the high temperatures typical of a jet engine. It is planned that a thrust reverser and nozzle assembly will be mounted on the aft flange. Only preliminary estimates of the thrust reverser and nozzle weights are known. These estimates have a standard deviation of as much as 5%. The duct has to withstand Federal Airworthiness Regulations (FAR) emergency landing loads with a Factor of safety FOS of 2.

![Figure 7: Nacelle duct with thrust reverser and nozzle point loads](image)

As a first step a DOE (Design of Experiments) is configured with this Abaqus model. As part of the model a factor of safety (FOS) is calculated: the ratio of the yield strength to the maximum stress. The parameters that are expected to have an impact on the weight calculations (such as duct thicknesses and thrust reverser & nozzle weight) are varied over a range that is expected to include the final design. The computed factor of safety, the mass and the maximum von-Mises stress are selected as DOE responses. We sample the model 50 times using the Latin Hypercube technique.

Once the DOE is completed, the results are loaded in the Isight for Abaqus Visual Design post-processing tool. This tool automatically creates an approximation of the output parameters for the given inputs. The error analysis confirms that the von-Mises stresses can be predicted to within a few percent.

We now use the fast approximation as a surrogate for the full Abaqus simulation and optimize the adapter duct thicknesses in such a way that the...
weight is minimized while maintaining a FOS greater than 2. An “optimal”
duct weight of 40 lbs is found. To study the effect of variability, a Monte-Carlo
simulation is performed that samples material properties and thrust reverse
and nozzle weight according to their probability distributions around this
“optimal” point. Figure 9a shows the converged Monte Carlo simulation with
1900 sample points. It is now clear that half the designs won’t achieve the
required FOS target. The main reason for this is that the thrust reverser and
nozzle weights can exceed the preliminary design estimates and will therefore
load up the duct more. To address this problem a Six Sigma optimization is
performed whereby the weight is minimized while increasing the probability
that FAR is met to a value greater than 99.9%. This Isight workflow is shown in
Figure 8.

![Six Sigma Isight Realistic Optimal Design Workflow](image)

**Figure 8: The Six Sigma Isight Realistic Optimal Design Workflow**

A higher value is probably not rational because of other unknowns in the
certification process. Figure 9 shows the probability distribution of the factor of
safety before and after the Six Sigma optimization. We can now expect the
duct to meet the FAR, even with uncertainties in the thrust reverser and nozzle
weights. The Six Sigma optimization increased the duct weight by 3 lbs. If we
had shifted the probability distribution of Fig. 9a to the same location as Fig.
9b by scaling the structure linearly, we would have had to add 6.4 lbs.
CONCLUSION

In this paper we propose a “realistic optimal design process”. This process samples the simulated design space with the Design of Experiments method, converts these samples into an accurate approximation, and uses Six Sigma optimization on the approximated design space to find a realistic high quality design. A realistic high quality design meets its requirements over its lifecycle while deploying company resources (human, hardware, and software) in the most efficient manner.

The approach was illustrated by a structural design of a nozzle adapter using the Isight optimization software with an Abaqus finite element model.

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