Making Efficient and Effective Use of Simulation Results for Critical Design Decisions

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Abstract

The growth and maturity of finite element simulations have influenced the way people design new products or even identify root causes to observed failures. In many industries, the size and scale of the models are large and produce an incredible amount of data over the life of the program or activity. Similarly, the amount of computational power available today is unmatched. Oftentimes, this leads to a situation where it can difficult to navigate through all of the data and provide a consistent and accurate conclusion. This is especially true when facing a design challenge in which simulation is perfectly suited tool. However, without linking critical features of the model (such as material choice or some critical dimension in a complex part) to outcomes, decisions can be more conjecture than scientific conclusion. In this talk, we will go over some techniques to help aide in making better decisions at critical junctures using simulation results. These probability based analysis will help formulate our simulation test plans with more direction and do more with the data we collect.

Introduction

Mechanical design of products like mobile phones is a difficult task due to the sheer number of components and design decisions. In order to ship a high quality product, teams manage every little dimension, round, tolerance gap and material choice. Finite element simulations have proven over time to be an unmatched tool in its ability to avoid failures and aide in the design process. This is especially true when designing for drop events, which can be catastrophic. Finite element analysis tools allow us to simulate these types of events and optimize the design to improve the probability of survival. In some regions of the world, network carriers require certain minimum reliability performances to ensure low field failure rates. It is our goal as simulation engineers to ensure we not only meet these specification, but we provide unmatched quality and reliability to our customers around the world.

However, what we are keenly aware of is that simulation tools are inherently different than real world testing because they do not incorporate influences of uncertainty and variation. These complexities must be studied and understood to fully grasp how to couple simulation models to real world outcomes. In this manuscript, we will outline one case study of how SIMULIA-based tools can be used to improve our prediction capabilities and, as a result, allow us to make better design decisions.

This manuscript will focus on incorporating probability into simulation tools to better assess the real impact of a design decisions. The study will look at how to set-up the problem using iSight, how to collect the results and how to analyze the data in the mindframe of making a particular design decision. The discussion will also touch on the costs associated with this technique and the incremental costs associated with improved accuracy.

Problem Statement: Using Probability Analysis to Assess Part Change

Recently, smartphone drop simulation results have indicated some structural weaknesses that highlight risk to display assembly components; especially for perfect top and bottom drops.

Most often, the discussions is centered around the main display lens on the exterior surface, which can be either plastic or glass. When the phone is dropped, the impact angle with the floor as well as the curvature or shape of the device will significantly impact the dynamics of the phone. This curvature influences how energy will propagate through the device and whether it drives towards or away from specific components.

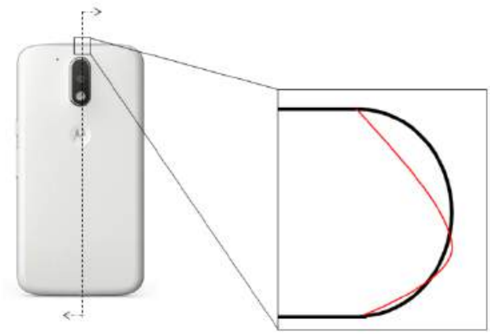

Figure 1. The exterior contour of the two different design concepts are compared. An adjustment is the contour is proposed in order prevent inertial loading towards the lens and help improve reliability.

With real hand drops, we know the probability of hitting exactly any particular angle is fairly low. That being said, the common approach for these kind of problems is to optimize for a particular ‘worst case.’ Questions have been raised about how the angular shape of the phone edge can truly influences the probability of failure and if optimizing the design based upon a single orientation is a suitable practice or leaves other important factors unaccounted for. This study will dig into that problem using computational tools.

Study Outline: Creating a Design of Experiments

In this study, geometric influences will be scrutinized in relation to a random drop targeting an orthogonal direction, (top drop). If the strain on the main display lens is too high, cracking will initiate, whether it is glass or plastic. This type of cracking is a major pain point for consumers and therefore an area of focus. This motivates us to ensure the highest reliability possible, which is not only influenced by the materials used but also the geometric design.

In order to simulate a random drop, we recreate an approximation of the system response, a Latin Hypercube DOE[i] is constructed within iSight. This model spaces out our simulation test points (n=10) equally in our design space. In this case, we are looking at varying two input (pitch and roll) and measuring the response of three output (max principle strain (LEP2) of the lens, touch panel and display panel peak strains). For our DOE, we define bounds of +/- 20 degrees around our target orientation, top drop (-90,0). The ten DOE-defined points plus one for the center point (n=11), are then put into the boundary conditions for our simulation models to define the random pitch and roll of a hand drop; this takes about a day and half to simulate, on average, using 12 cores per simulation.

Run #	Pitch	Roll
1	-70	11
2	-74	-2
3	-79	-7
4	-83	2
5	-88	20
6	-92	-11
7	-97	-16
8	-101	7
9	-106	-20
10	-110	16
11	-90	0

Table 1. Test points defined by a Latin Hypercube Design of Experiment (DOE) for ten equally spaced points, as well as the design center point (-90,0).

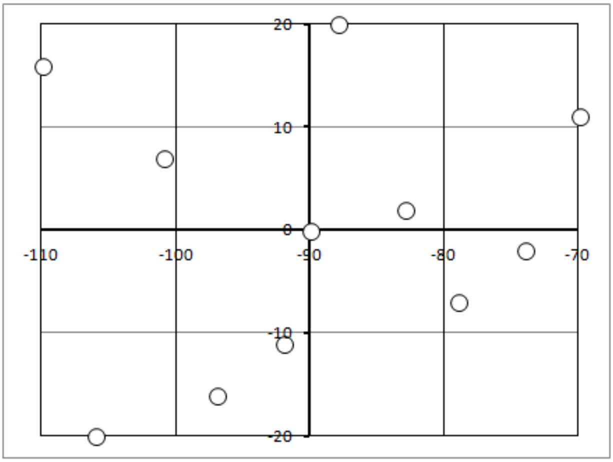

Figure 2. Visualization of the test points defined by their pitch (x-axis) and roll (y-axis).

These eleven points are then used to define an approximation model or response surface (RBF). This approximation model will allow us to sample our system much faster than running thousands of simulations (~0.01s vs 6 hrs).

Results: Monte Carlo Simulation

With the response surface model created, we run a Monte Carlo model[ii] to randomize our pitch and roll inputs. In this example, we define the pitch and roll as normal distributions with standard deviations of 10 degrees, centered about the target angle (-90,0).

On the output side, we track the max principle strain (LEP2) on the lens, touch and display panel. For this analysis, we want to know the probability of the touch and display failing as well as the failure strain criteria needed from the lens in order to get a failure rate of only 10%. In this manuscript, all strain values will be normalized by the estimated failure strain. Please note that although iSight will report a 100% pass rate for some situations, we downgrade this to 99% to account for probability of unobserved failures and knowing that in reality nothing has 100% certainly. This gets to the difference between a test probability and a real probability, in which the model has some inherent errors. Therefore we do a simple correction to ensure we account for a ~1% chance the model is provides a false negative.

We loop the model, randomizing the drop angles using a Monte Carlo, until it converges around 2,000 iterations. After convergence, we can analyze the output results shown in the image below.

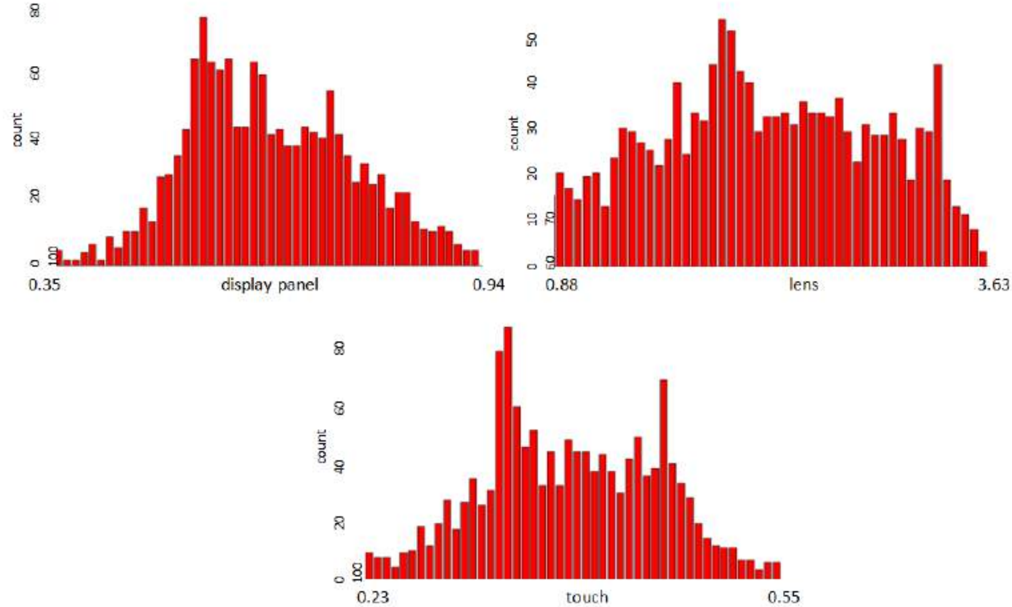

Figure 3. The outputs for the display panel, lens and touch are displayed. The histograms shows the types of distributions each output has after running the Monte Carlo simulation.

In this design, we observe that the risk of the touch and display failing are low (less than 1%) for some assumptions of their failure limits. The results from the lens indicates that we need a fairly robust lens design, in which the failure criteria is over 0.49.

Analyzing Exterior Contour Adjustment

In order to analyze the effects of the exterior contour adjustment changes of this nature made to the main housing part in order to drop the strain in bottom drop. However, once we run our Monte Carlo simulation to account for a randomized drop angle, we reach a different outcome.

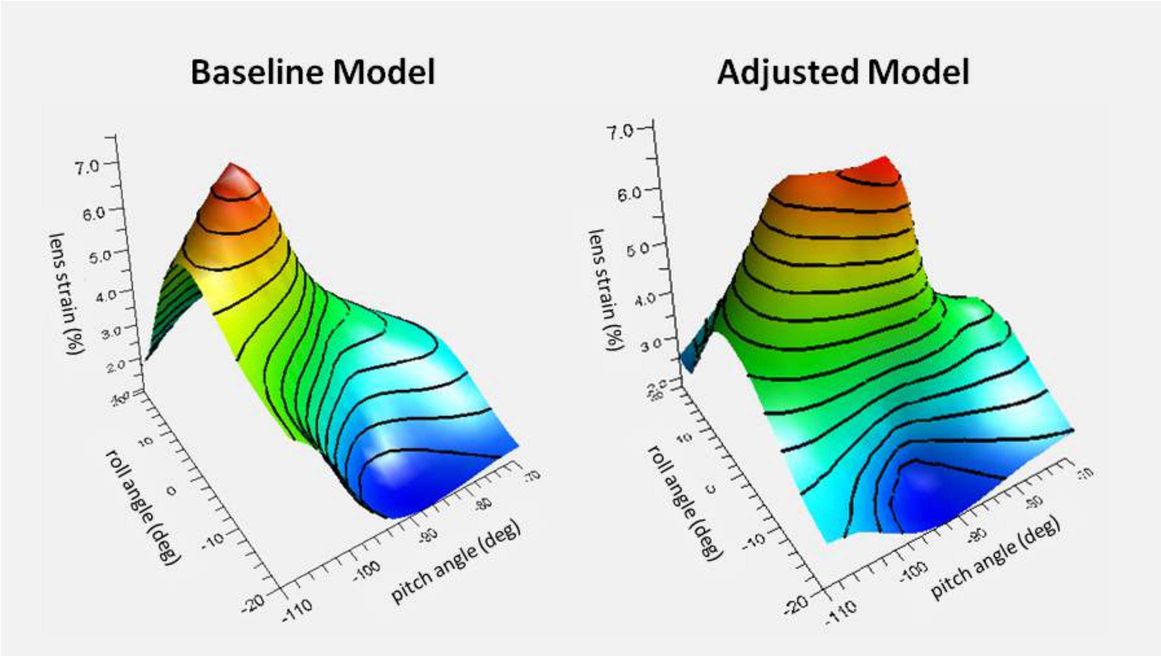

Figure 4. On the left hand side, we have the response surface for the plastic lens strain (LEP2) and on the right we have the response from the peak adjusted model. There are two main differences between these model: (a) the maximum strain in the peak adjusted model is higher(7.6% vs 7.3%) and (b) the global maximum is shifted from perfect bottom drop (-90,0) to (-110,8), approximately.

	Plastic Lens			display panel			Touch		
	LEP2 min/max	LEP2 mean +/- sigma	LEP2 @ 90% pass	LEP2 min/max)	LEP2 mean +/- sigma	prob pass @ 1.0%	LEP2 min/max	LEP2 mean +/- sigma	prob pass @ 2.0%
(baseline)	0.88 / 3.63	2.26 +/- 0.70	3.25	0.36 / 0.93	0.66 +/- 0.11	0.99	0.23 / 0.55	0.49 +/- 0.06	0.99
Peak adj.	0.21% / 3.63	1.83 +/- 0.82	3.05	0.29 / 0.80	0.61 +/- 0.07	0.99	0.16 / 0.55	0.35 +/- 0.04	0.99

Table 2. Summarized results from the three outputs contrast the results from the baseline and the exterior contour adjusted model.

Results: Assessing the Trade-Off of Larger DOEs

When running a design of experiments, the number of test points is intimately linked to the accuracy of your response surface. As more points are added, the fitting algorithm works better and the surface picks up more of the localized minimums and maximums within the global range. It was my goal to do some comparisons to determine the response surface errors when using an 11 or 21 point LHC DOE. Although more points is usually almost always better, it comes with a significant computational cost. These costs are compared in line with the accuracy.

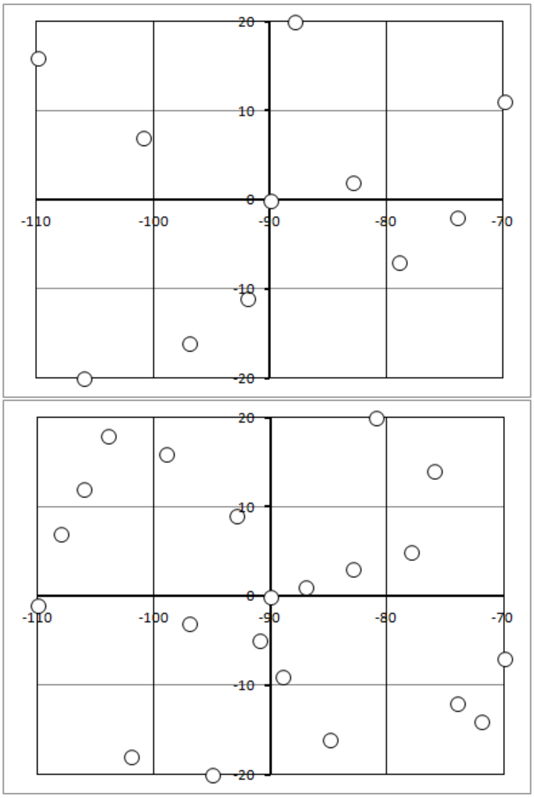

Figure 1. Visual comparison of an 11 pt DOE to a 21 pt DOE, varying pitch and roll over a 20 degree range.

		RBF Approximation Base Data Set	
		11 pt	21 pt
Validation Points (either cross validation or separate data set)	11 pt	display, 0.17 lens, 0.35 touch, 0.23	display, 0.18 lens, 0.22 touch, 0.22
	21 pt	display, 0.23 lens, 0.18 touch, 0.24	display, 0.19 lens, 0.21 touch, 0.25
Computation Cost	Wall Clock Example	26 hrs	44 hrs
	Total Cost	672 CPU hrs	1,344 CPU hrs

Table 1. Comparing the average error for 10 pt DOE and a 20pt DOE using an RBF model. For each original DOE, we are able to calculate the error based upon the same data set as fitting or an external data set, in this case the other DOE results. Additionally, the computation cost is outlined for the two options to balance the improvement in accuracy with more points.

Either alternatively or in addition to making a larger DOE study, more runs (simulations) were added around the global maximum in order to see the sensitivity of the results on the refinement level of the source data for response surface modeling. The goal of this approach was to understand if a Latin Hypercube DOE approach is sufficient in our case, where we have such an obvious global maximum that appears to rapidly increase/decrease with respect to angle.

A total of 8 more runs were added around (-90,0), our local max, with +/- degree change in both pitch and roll. The change in the response surface shape is compared in the figure below.

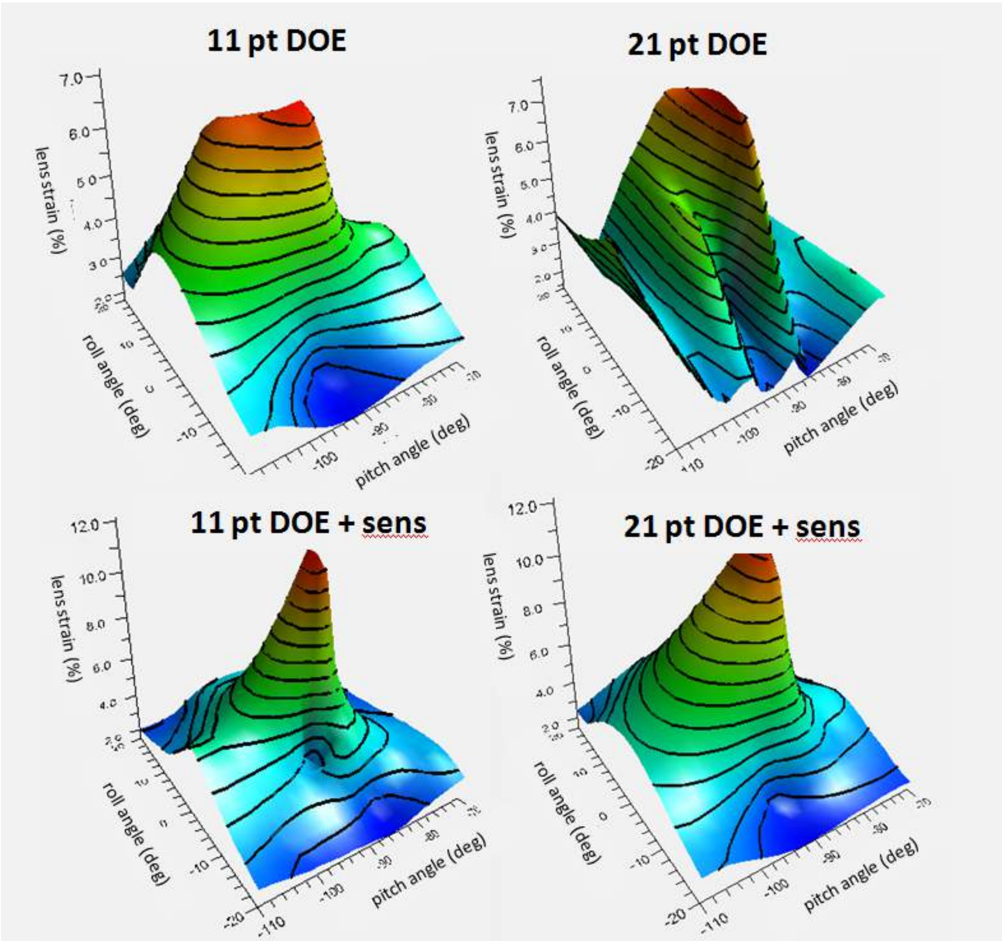

Figure 5. Comparison of the Lens response surface from the 11pt DOE (upper left), 21pt DOE (upper right), an 11pt DOE with 8 sensitivity runs (lower left) and a 21pt DOE with 8 sensitivity runs around the global max (lower right).

In the end, the results do change as a function of the additional runs, however on the order of 10-15% when you compare the global maximum and points in close proximity.

Conclusions

1) Shifting the exterior contour does drop strain in the target orientation, but shifts our peak strain to some other orientations.

When comparing the response surfaces of the two designs, this outcome is rather obvious. If we only analyzed the target orientation (-90,0), we observe a 40% drop in the peak strain on the lens, however it overlooks the fact that we might be shifting our worst case to some other orientation. In our DOE, we pick up on that shift which is shown in Figure 3. When we run these responses through our Monte Carlo model, the reduction in strain is much lower, about 18% by average and 14% by the failure criteria requirement.

	Top Drop - -90,0	Monte Carlo - 90% pass criteria	Monte Carlo - mean strain
(baseline)	3.65	3.25	2.26
Peak adj.	1.63	3.60	1.84
	-55%	**-6%**	**-18%**

Table 3. Strain results from a perfect top drop are compared to the 0.90 pass criteria for the random drop condition and the mean strain level; which indicates a much lower effect.

2) The probability of failure increases on our display panel after exterior contour adjustment.

After making our exterior contour adjustment, the model indicates that the probability of failure does not change for the other components. In terms of these components, the exterior contour adjustment is relatively outcome insensitive. Although this might seem like an unimportant outcome, it is important to check other components to ensure the change does not unintentionally increase risk in other areas of the design. In this particular case, we track the dynamics of the display panel and the touch layer. The results indicate that in these cases, the risk of failure is not influenced at all when the design change occurs. This is an important consideration to ensure a change or an optimization of one component does not sacrifice another.

3) Adding more point on your DOE does help accuracy, but comes at computational costs.

As we all expect, adding more training points to our response surface through making a larger DOE is helpful. However, when comparing the response surface fits and the Monte Carlo outputs, we are able to weigh the computational costs. The improvement realized is about 10-15%, which is good but effectively doubles our cost. In some conditions, when we are not resource limited, these changes are palatable, however in most conditions it would not be; especially when our simulations are large and complex. There is no right or wrong answer to this dilemma and likely deserves more study to determine where our error plateaus and we receive diminishing returns to define the best DOE size. That study in of itself, requires significant resources and must be done on a case by case basis.

Future Guidance and Conclusions

This case study provided an example of how locally optimizing based upon a single orientation can be flawed. Although if we were to analyze the exterior contour results simply on top drop we would see a drop in strain, we would overestimate the magnitude of the change significantly. Instead of getting a drop of about 40%, we instead realize only a marginal drop of 15%. This vast difference can change the narrative about a design change. When analyzing the results, we are able to realize that the global maximum of the lens strain simply shifts from -90,0 to -110,10. In this particular case, we would have to weigh the benefits of the ID change against other risks; such as increased probability of touch or OLED failure or even user perception of the device and feel in hand.

The conclusion of this study is that for future programs the influence of randomness should be considered when making a change such as exterior contour adjustment. Although the required simulations increases significantly, it can provide more relevant quantitative assessment of the design. This means this tool is most useful when a program is faced with a critical decision, such as an ID change.

**DISCLAIMER: values in this manuscript have been normalized to protect proprietary information. The numbers disclosed are shown in such as way that the conclusions and learning based upon the original values hold true.

[i] Runger, George. Engineering Statistics, New York, NY: Wiley. 2010
[ii] Keller, Paul. *Six Sigma Demystified*, New York, NY: McGraw Hill. 2005