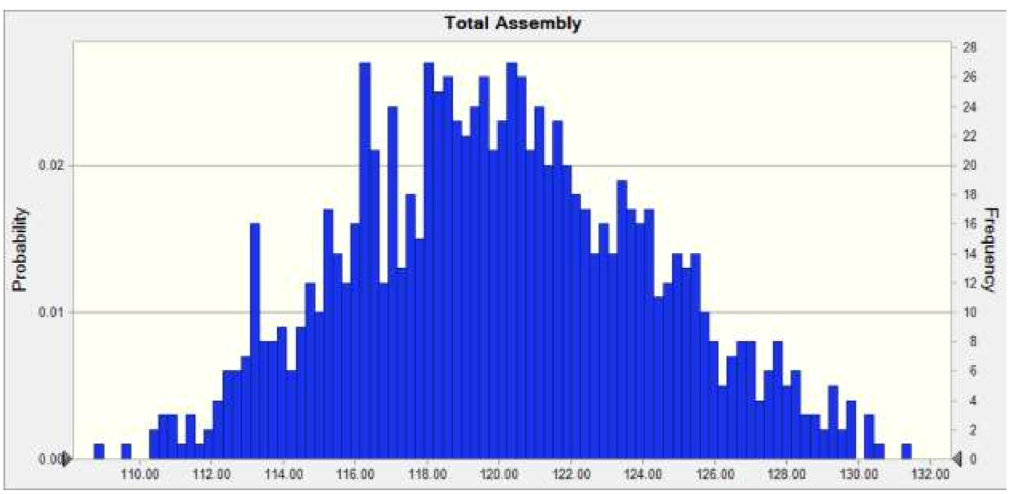
Introduction to Use of Monte Carlo Simulation to Enhance DFMA Results

32nd Annual International Forum on DFMA
Providence-Warwick, RI
June 6-7, 2017



AUTHOR:

KOHLER CO.

Adam Guenther North America NPI Manager

INTRODUCTION

The Design for Manufacture and Assembly (DFMA) method, as provided by the Boothroyd-Dewhurst software company, is an excellent tool for estimating the processing time and cost for new products. The net results, however, represent an ideal state and do not incorporate the variation of the systems which they represent. This paper will discuss the use of Monte Carlo Statistical modeling to expand upon the results of DFMA software modeling, providing better understanding of uncertainty and risk in product modeling.

DFMA INTRO

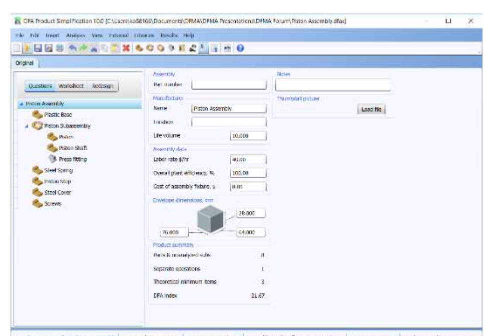
Those familiar with the BDI DFMA software understand the value the software provides. The method encourages collaboration in design engineering and improvement in product design in two ways:

1. Identifying the minimum "theoretical number" of parts and challenging teams to reduce part numbers.
2. Establishing "should be" costs of manufacturing options.

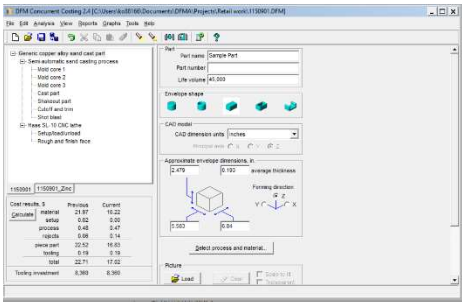
The software also improves efficiency of the process by significantly reducing analysis time and improving analysis accuracy.

Kohler's effort has largely been financed and led by one business unit, the Global Faucets Manufacturing Engineering and New Product Group. Led by champions and leaders within this group, the DFMA method has grown significantly, resulting in use in the design of all major products launches. Kohler currently uses six international licenses to support its Global business in Faucets, supporting development in the UK, Europe, China, India and North America.

The DFMA software contains two modules. The first module is the Design for Assembly (DfA) module. The module process estimates of cost and assembly time with specific focus on the number of parts (identifying the theoretical minimum number of parts), operations and plant labor and efficiency. From this, a DfA index score is produced, with can be compared with other potential product design.



The second module, Design for Manufacture (DfM), produces cost of manufacture for individual and assembled parts. Costs are generated based upon data entered by the user, database



entries, and software calculations, and can also include automated assemblies. From this analysis, a total cost of the product can be generated and alternatives evaluated.

BENEFIT OF DFMA TO NEW PRODUCT INTEGRATION (NPI)

DFMA does many things for New Product Integration (NPI). The Mission of the Global Faucets NPI group is “Improving Operations through new product launches”. The NPI leadership team has identified three critical behaviors which influence its ability to fulfill this mission:

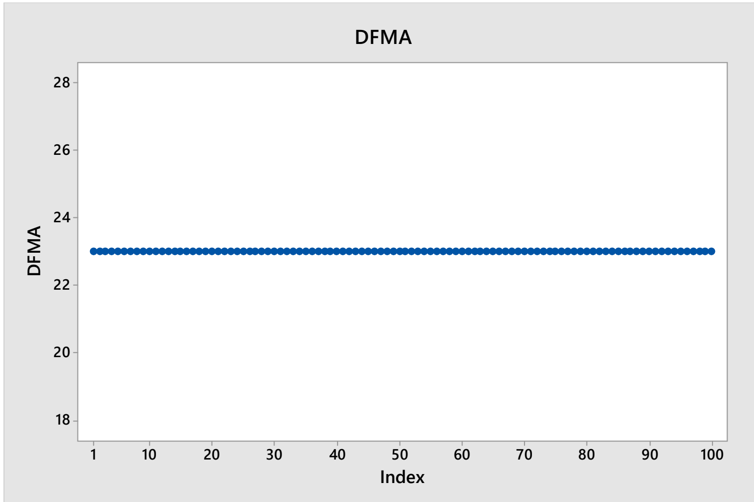
3. Tenacious Collaboration
4. Data-based Decision making
5. Identify and Eliminate Waste

DFMA drives the team behavior to focus on the elimination of waste in terms of unneeded parts and assembly operations, excessive and provides an ideal state assembly process. It completes this using best-in class data, in a collaborative, multi-disciplinary environment.

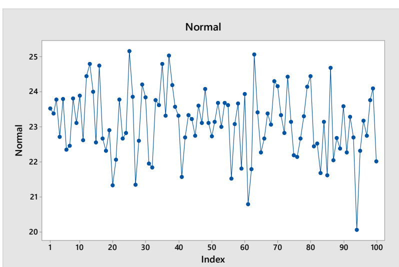
The NPI and New Product Development teams within Global Faucets are actively pursuing a Lean NPD method of new product development. As part of this method, events are utilized as a platform for bringing collaborative teams from all major professional competencies together to work together on various project deliverables. The DFMA method works excellently within this structure, facilitating discussions primarily during a Design Production Process Preparation (3P) event, but also throughout the development process, providing objective data upon which the team can make decisions concerning product design viability.

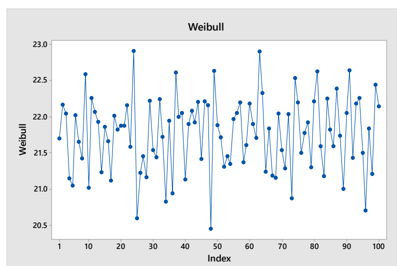
FINDING A GAP: PROCESS VARIATION

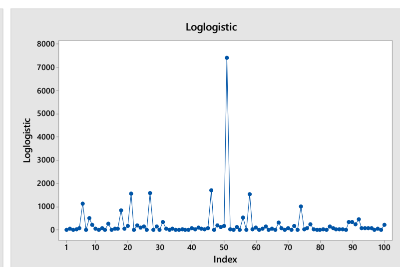
DFMA has been a highly successful method for Kohler. Even in that environment, it inherently has a limitation: it represents only the *central tendency* of any process. Represented graphically, repetitive runs of the process look like this:



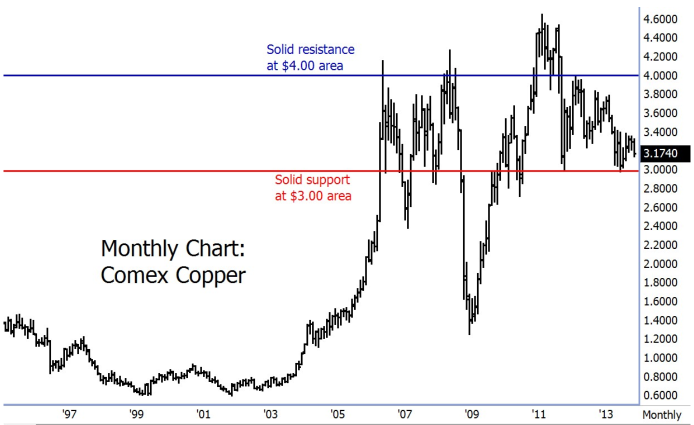
As any operator or manager of a process recognizes, actual results of repetitive process runs include *variation*. No process consistently produces results with no variation: every process includes it. The actual results for this process may look like this:







The gap between understanding the central tendency of a process and its variation is a common issue within process and product planning. This is not a criticism of the DFMA method: it does exactly what it is designed to do. Nevertheless, it cannot provide us the entire picture regarding the processes and products it represents due to the lack of ability to analyze the variation in the processes. An illustration of the real-world variation in a process which has significant impact on Global Faucets planning is commodity process pricing for copper[1]:



[1] Wycoff, Jim; "Special Report, Why the Meltdown in Copper Prices this Week is Very Important for Precious Metals, and Possibly Equity Markets"; Kitco.com, Nov 15, 2013. Available at: http://www.kitco.com/news/2013-11-15/Why-the-Meltdown-in-Copper-Prices-this-Week-is-Very-Important-for-Precious-Metals,-and-Possibly-Equities-Markets.html

Projecting the future state from 2005 for this commodity would have led to drastically incorrect decisions about product cost. This leaves a gap in decision making, even when using such highly informed tools as DFMA. One way to bridge this gap between the DFMA model and the real world is the addition of another statistical tool: Monte Carlo.

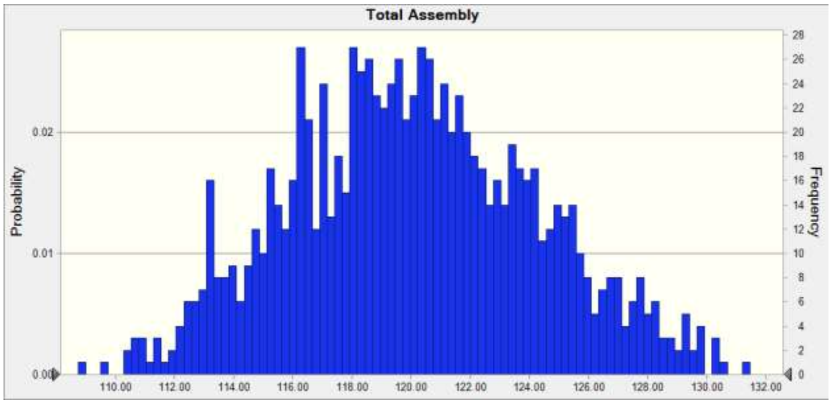
FILLING THE GAP: MONTE CARLO ANALYSIS

Monte Carlo simulation is a computerized mathematical technique, allowing it users to account for risk in a quantitative way, which facilitates data-based decision making.[2] It functions by utilizing random sampling of statistical distributions provided as assumptions in a model to produce thousands of potential results. The resulting data can be graphed and analyzed.

The increased understanding of the effects of variation gained by conducting this analysis can be invaluable. Frequently, associates are able to produce an estimate of a range of values for any parameter given a good/better best model. Based upon this range, Monte Carlo simulation provides the likelihood of any given result[3]. The resulting model and distribution can be analyzed for probabilities of success and failure. In practice, Monte Carlo takes a project team's decision making from a model that looks like this:

To one that looks like this:

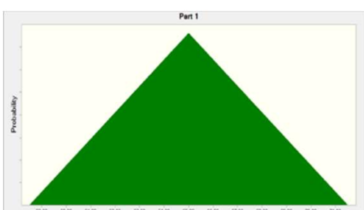
[2] Palisade Corp; "Monte Carlo Simulation"; Palisade.com, 2017, Accessed May 12, 2017. Available at:http://www.palisade.com/risk/monte_carlo_simulation.asp
[3] RiskAmp, "What is Monte Carlo Simulation", Riskamp,com, Accessed May 12, 2017. Available at: https://www.riskamp.com/files/RiskAMP%20-%20Monte%20Carlo%20Simulation.pdf

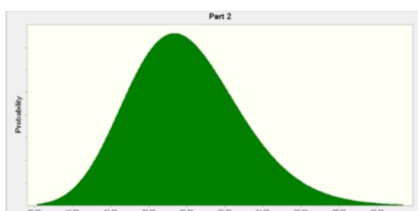


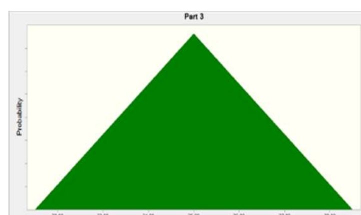
The additional granularity of the model provides for better decision making and improved project success.

HOW MONTE CARLO WORKS

Monte Carlo is statistical model using randomly generated data based upon distributions entered by a user (all analysis for this report is conducted using an Excel add-on for Monte Carlo called Crystal Ball. The Crystal ball software is available at this website: http://www.oracle.com/us/products/applications/crystalball/overview/index.html). An illustration of the method may be the best way to explain its use. Assume a process with three consecutive manufacturing steps in a linear fashion. There is no transition time between steps, so no additional time is added for transition. For the first and third process, all a good/better/best estimate is used which results in the use of a *triangular* distribution. For Operation 2, data exists, and so we can *map* a distribution.





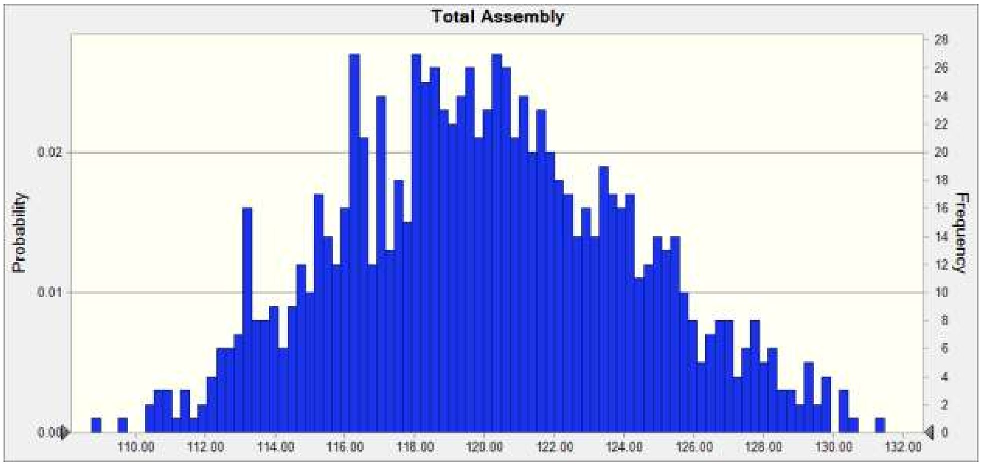


For Operation 1, we have only Best/Likely/Worse data. So we Use a *Triangular* distribution.

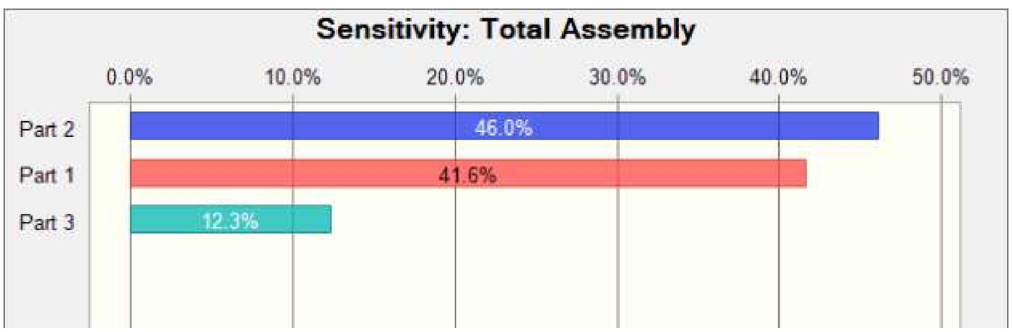
For Operation 2, we have a similar operation with data. So we can *FIT* a distribution using real data.

For Operation 3, we again have Best/Likely/Worse data. So we Use a *Triangular* distribution.

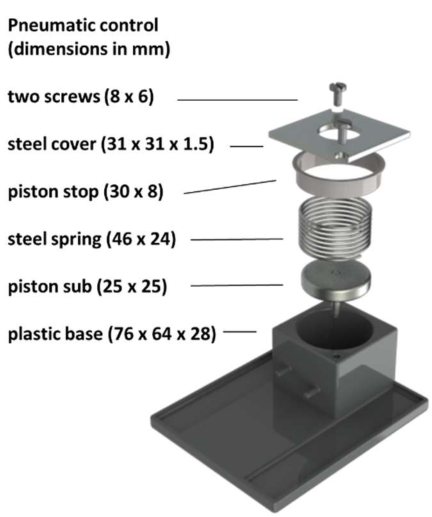
The statistical model is then produced by repetitive random sampling of these products, resulting in a distribution of possible results. The results of the simulation produces a distribution of potential results which looks like this:



Beyond this distribution, Crystal Ball provides us many other useful tools. One significant tool is the Sensitivity Analysis. This tool provides the user with a detailed analysis of which variable is contributing the largest amount to the variation in the finished modeled variable. An example is below: for our test case, the process is most sensitive to variation in the assembly time for Part 2, closely followed by the variation in Part 1.

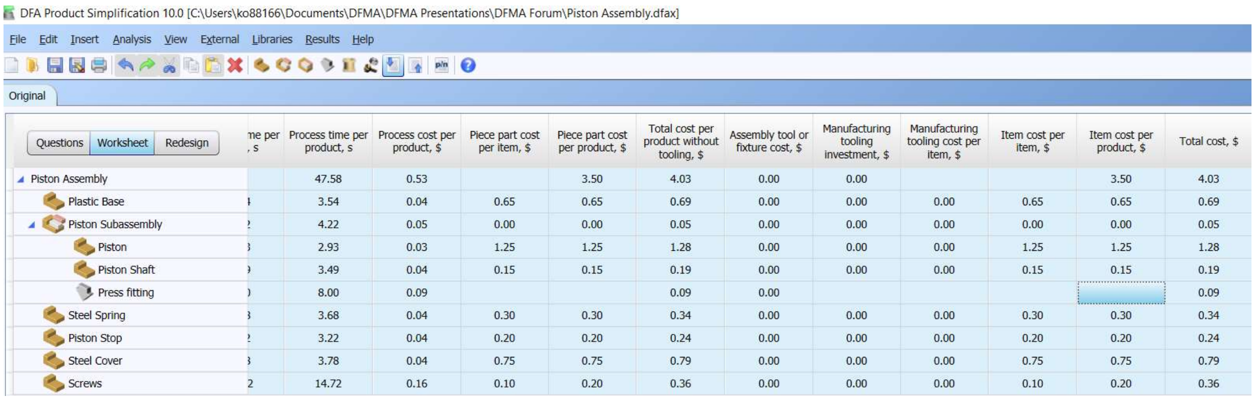


AN EXAMPLE



This process can be illustrated using a product which is an example frequently used during initial DFMA training with BDI. This product is a simple piston mechanism used in printers during the middle 20th century. The picture of this product is seen at left.

Typically, a DFMA trained associate would begin his or her work with this product by conducting a DFA analysis. The associate would insert each of the parts, any operations required, and answer all the questions involved (minimum part category, insertion difficulties, size and weight, etc.). Upon completion of this work, the software would produce a number of results, including a worksheet which would appear like this:


DFA Product Simplification 10.0 [C:\Users\ko88166\Documents\DFMA\DFMA Presentations\DFMA Forum\Piston Assembly.dfax]

File Edit Insert Analysis View External Libraries Results Help

Original

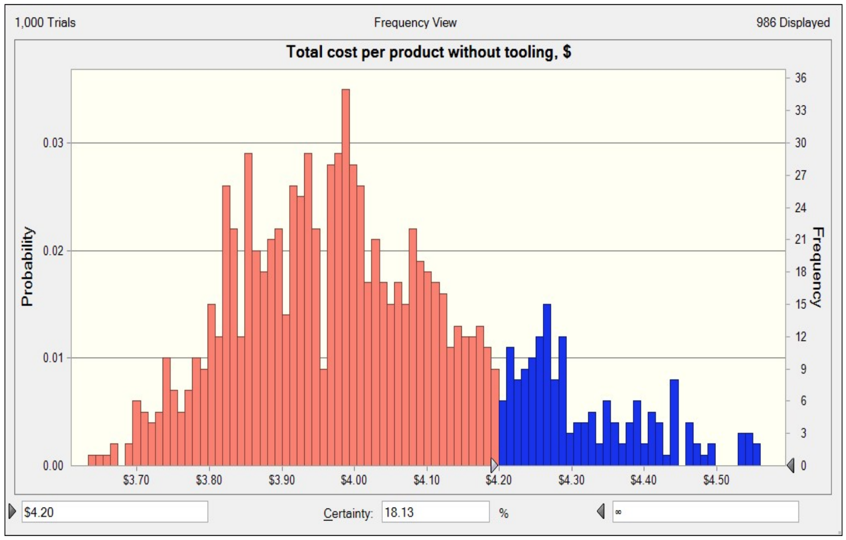
Questions Worksheet Redesign

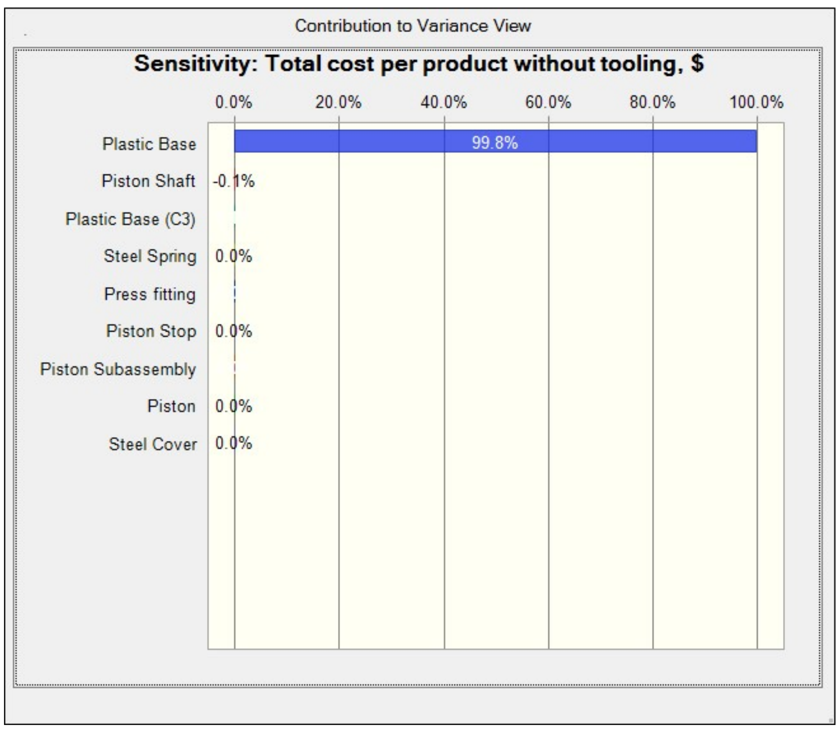
	me per , s	Process time per product, s	Process cost per product, $	Piece part cost per item, $	Piece part cost per product, $	Total cost per product without tooling, $	Assembly tool or fixture cost, $	Manufacturing tooling investment, $	Manufacturing tooling cost per item, $	Item cost per item, $	Item cost per product, $	Total cost, $
Piston Assembly		47.58	0.53		3.50	4.03	0.00	0.00			3.50	4.03
Plastic Base	4	3.54	0.04	0.65	0.65	0.69	0.00	0.00	0.00	0.65	0.65	0.69
Piston Subassembly	2	4.22	0.05	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.05
Piston	3	2.93	0.03	1.25	1.25	1.28	0.00	0.00	0.00	1.25	1.25	1.28
Piston Shaft	9	3.49	0.04	0.15	0.15	0.19	0.00	0.00	0.00	0.15	0.15	0.19
Press fitting	0	8.00	0.09			0.09	0.00					0.09
Steel Spring	3	3.68	0.04	0.30	0.30	0.34	0.00	0.00	0.00	0.30	0.30	0.34
Piston Stop	2	3.22	0.04	0.20	0.20	0.24	0.00	0.00	0.00	0.20	0.20	0.24
Steel Cover	3	3.78	0.04	0.75	0.75	0.79	0.00	0.00	0.00	0.75	0.75	0.79
Screws	2	14.72	0.16	0.10	0.20	0.36	0.00	0.00	0.00	0.10	0.20	0.36

Should the associate then desire to complete a Monte Carlo analysis, they would copy this worksheet into Excel and add the distribution assumptions and the calculated result. The resulting spreadsheet would appear as below, with the green cells the assumptions and the blue the calculated value. In this case, we are assembling a large number of purchased components along with one component we will manufacture: the plastic base. This product will have a lot of variation in pricing due to commodity pricing variation.

Name	Repeat count	Process time per entry, s	Process time per product, s	Process cost per product, $	Piece part cost per item, $	Piece part cost per product, $	Total cost per product without tooling, $
Piston Assembly			47.58	$ 0.53		3.5	4.03
Plastic Base	1	3.54	3.54	$ 0.04	$ 0.65	$ 0.65	$ 0.69
Piston Subassembly	1	4.22	4.22	$ 0.05	$ -	$ -	$ 0.05
Piston	1	2.93	2.93	$ 0.03	$ 1.25	$ 1.25	$ 1.28
Piston Shaft	1	3.49	3.49	$ 0.04	$ 0.15	$ 0.15	$ 0.19
Press fitting	1	8	8	$ 0.09		$ -	$ 0.09
Steel Spring	1	3.68	3.68	$ 0.04	$ 0.30	$ 0.30	$ 0.34
Piston Stop	1	3.22	3.22	$ 0.04	$ 0.20	$ 0.20	$ 0.24
Steel Cover	1	3.78	3.78	$ 0.04	$ 0.75	$ 0.75	$ 0.79
Screws	2	14.72	14.72	$ 0.16	$ 0.10	$ 0.20	$ 0.36
							$ 4.03

The net result in terms of pricing can be seen below, with both the variation and the sensitivity analysis visible.





Conducting this analysis would produce two key conclusions. First, although the product is on average profitable (this is the value we would normally make decisions upon), more than 18% of the time we would not meet the margin goals expected of the business. Also, the product is by far most sensitive to the variation in price of the plastic base. This should lead to risk mitigation for commodity pricing of the plastic, perhaps by hedging or through the use of material contracts. The cost of the part could also be potentially improved by using an alternate resin or via a different formation process, which the associate could examine using the DFM software and then assess using the Crystal Ball decision function.

CONCLUSION

Although the DFMA software is a monstrous step forward for modeling products and processes, it leaves a gap in terms of risk management and understanding of process variation. The use of Monte Carlo modeling can help to fill this gap.