IMPLEMENTING SIX SIGMA: ARE YOU GETTING RESULTS FAST ENOUGH?

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ABSTRACT

Six Sigma focuses on high return projects that will maximize customer satisfaction. Is every part of your Six Sigma effort providing a maximum return, including your software? Do your graphics come alive, helping you make key discoveries with the click of your mouse? Can you easily find relationships among numerous variables without sorting through pages of p-values? Do your designed experiments provide the maximum information using the minimal resources? The presentation covers concepts you typically don't learn in analytics training and presents techniques that shorten your journey from question to answer.

EXAMPLE 1: GRAPHS THAT LIVE

Six Sigma efforts seek to improve quality in the eyes of the customer and reduce scrap to three parts per million produced. This ambitious undertaking has decreased costs and increased customer satisfaction for hundreds of organizations worldwide. But a question remains: Are these organizations using software that lowers the cost of required Six Sigma data analysis itself?

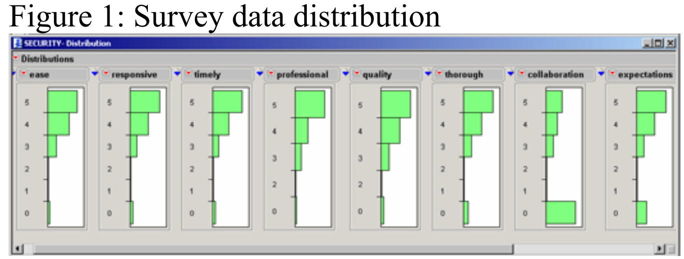
Does your Six Sigma software integrate graphics with your analytical reports making visualization a natural part of your analysis? Or do you find yourself often wondering what the appropriate graphical display would be to explore a particular problem? Do you spend time looking through books and old course notes trying to figure out how to get the right graphic, time that could be spent implementing solutions sooner?

In assessing the customers' view of quality, surveys are often used to pinpoint problem areas and measure success. What happens when your survey seems to tell you that everything is great, that everybody loves you? How do you analyze a survey to which 90% of respondents said you rank a 4 or 5 out of 5 in all categories? How do you find the value in the other 10% of the data? How do you sort through the data and find the gems?

The data in Figure 1 represent the partial results of a survey in which respondents were asked to rate a particular service on a scale of 0 to 5, 5 being highest. Zero indicated the respondent chose not to score that question. Under consideration were:

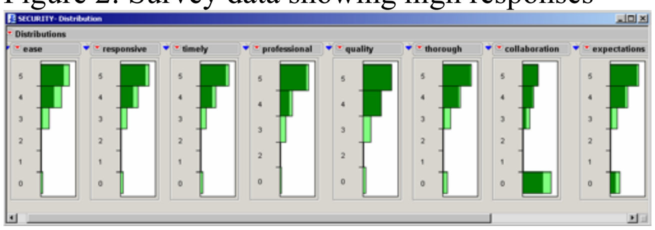
1. Ease of use
2. Responsiveness of provider
3. Timeliness of services
4. Professionalism of staff
5. Quality of service
6. Thoroughness of service
7. Collaboration by staff
8. Meeting requesters expectations
9. Value of service
10. Communication during service process

Figure 1: Survey data distribution



A quick plot of the data shows that most respondents scored all aspects of the service very favorably, except in the *collaboration* area for which many chose not to respond. Plots that come alive allow you to click on any bar on the graph and see where the records that comprise the bar appear in the bar graphs for other variables. In other words, with the click of the mouse you can immediately check if respondents who choose a 4 or 5 on one question had a tendency to choose a 4 or 5 on all questions. Figure 2 shows the 4 and 5 score for *quality* selected. Notice how most responses across all questions are also 4 and 5. These graphs allow you to click on any bar and see the relationships. The graphs are alive, not just pictures.

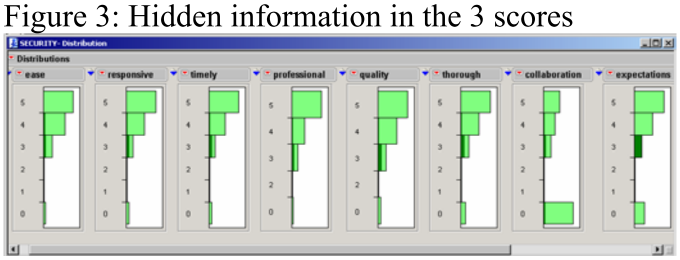
Figure 2: Survey data showing high responses



Because very few respondents selected a score of 1 it is difficult to draw any conclusions by focusing on the 1 scores. The 3 score, however, may hold useful information.

Figure 3 displays the distribution chart with the 3 score for *meeting expectations* highlighted. Notice that when the respondents selected 3 for *expectations* they most often responded with a 3 for the other questions. This could indicate a need to further discuss customer expectations versus results to get improvements where marginal service delivery is perceived.

Figure 3: Hidden information in the 3 scores



Following the approach used in Figure 3, you can quickly assess scoring relationships for other questions when respondents scored a 3. Table 1 displays a summary of that exploration.

Table 1: Service survey analysis results

	Ease	Responsive	Timely	Professional	Quality	Thorough	Collaboration	Expectations	Value	Communication
Ease	3	3_4	3_4	3_4	3_4	3_4	345	34	34	34_5
Responsive	3_4	3	3_4	3_4	3_4	3_4	345	3_4	3_4	345
Timely	3_4	3_4	3	3_4	3_4	3_4	345	3_4	3_4	345
Professional	34	3_4	3_4	3	3_4	3_4	45	3_4	3_4	345
Quality	3_4	3_4	3_4	3_4	3	3_4	345	3_4	3_4	34_5
Thorough	3_4	3_4	3_4	3	3	3	345	3_4	3	3_{45}
Collaboration	03	03	03	0_3	03	03	3	3_4	03	$_03_4$
Expectations	$_03_4$	$_03_4$	3	3_0	03	$_03_4$	34_5	3	3	3_{45}
Value	3_{45}	3_4	3_4	3_4	34	3_4	345	3_4	3	345
Communication	$_03_4$	$_03_4$	3	03	$_03_4$	$_03_4$	3_4	03	03	3

Table 2: Legend for Table 1

3	When respondent chose 3 on question shown on column…
03	Chose 0 and 3 almost equally
3_4	Chose mostly 3, sometimes 4
34	Chose 3 and 4 equally
$_03_4$	Chose mostly 3, sometimes 0 or 4
3_{45}	Chose mostly 3, sometimes 4 or 5
0_3	Chose mostly 0, sometimes 3
345	Chose 3, 4, and 5 almost equally
34_5	Chose 3 and 4 almost equally, sometimes 5

To read Table 1, look down each column. The columns represent the questions. Looking at the first question – ease of requesting services – and looking at only the respondents who answered 3, the rows under *ease* show how the 3 respondents responded to other questions. The physical size of the response value shown corresponds to the relative number of times the response was chosen versus other responses. For example, when *ease* was 3, most other questions were responded to as 3 and some 4's, 3 and 4 equally, 0 and 3 equally, 3 with 0 and 4, or 4 and 5 chosen less frequently.

The cells of possible interest are in yellow. It appears that lower rankings on *collaboration, expectations*, and *communication* responses are driven by 3 or 0 rankings across all questions, except *collaboration*. This is true for *communication* with the exception of the relation between *communication* and *expectations* – here the ability to meet expectations remains high even when communication is rated a 3. While *collaboration* responses are generally high, *communication* responses of 3 seem to be related to low collaboration responses.

Instead of concluding that this service is completely acceptable as is, this organization should try to understand what is causing low responses on *collaboration, expectations* and *communication* in the presence of low responses to the other items. For example, is there a need for more corporate awareness of policy and practice related to this service? Are there specific incidents related to these responses? Are there staff or customer behaviors related to these events?

Without the ability to quickly assess responses through graphics, you would spend hours generating cross-tabulations on subsets of these data. Graphs that live also make it quick to subset data. Figure 4 reveals that using the right mouse on a bar of interest provides a pop-up menu allowing immediate data subsetting. Figure 5 displays the resulting table.

Figure 4: Subsetting directly from a graph

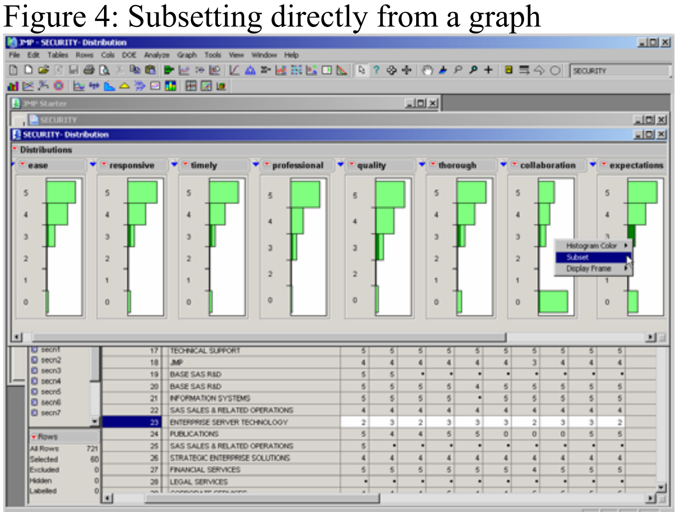
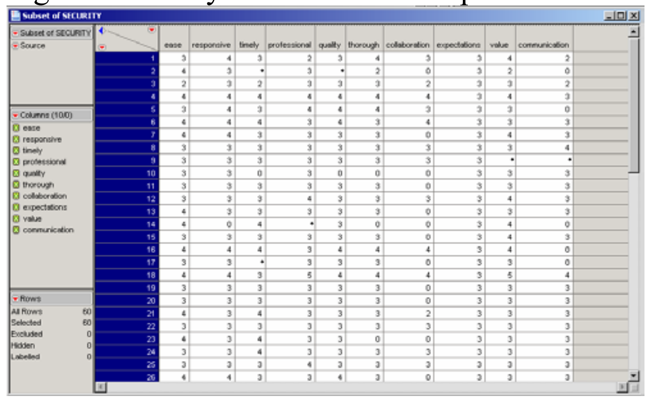


Figure 5: Survey data subset for Expectations = 3



You will add maximum value to your Six Sigma efforts by using software that integrates graphs into the standard statistical reports. Graphs that come alive at the click of your mouse enable you to explore data as quickly as you can think of the next path you want to take.

EXAMPLE 2: GROWING A TREE WITHOUT DIGGING A HOLE

Another challenge in analyzing data arises when you have numerous dependent variables that may have interactions. How much time do you spend massaging the data, looking for interactions among variables, examining lists of p-values, searching for answers? How is that time compounded when the response variable is categorical? Does the problem get worse when your response has multiple categorical values? What do you do when you suspect that interactions exist not only among the dependent variables, but for specific values of the dependent variables? The hole gets deeper and wider as the data grows.

Wouldn't it be nice to have one tool that sorted through all your variables searching for only the most predictive dependent variables? Couldn't you use one tool that finds the combination of values across all variables that maximizes predictions, handles missing data or gives simple rules describing hidden relationships?

Instead of getting stuck in an analytical hole, grow a tree. A decision tree, also known as recursive partitioning, provides a quick way to get to the relationships in many types of data. Let's look at an example.

Figure 6 displays graphs of approximately 50,000 records of historical data collected during polypropylene machining. You want to analyze this data to determine what situations result in good or bad machining (cuts). The distribution analysis in Figure 7 reveals no obvious patterns in machine speeds, saw tooth rating, sheet thickness, saw, or amount of lubricant used. The distribution analysis in Figure 7 shows possible relationships for good cuts with speed, saw teeth rating, and lubricant amount. Recursive partitioning finds the rules that define good and bad cuts.

Figure 6: Machining data with bad cuts highlighted

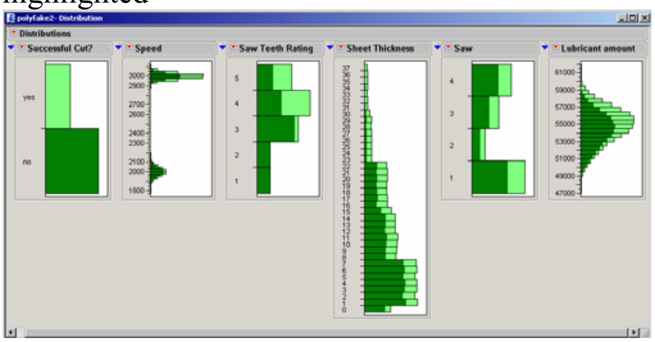


Figure 7: Machining data with good cuts highlighted

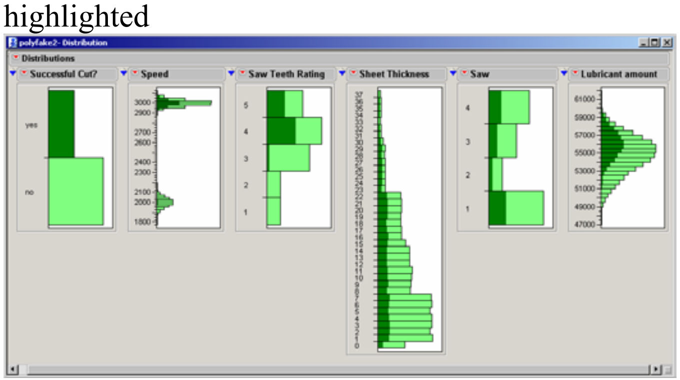


Figure 8 displays the recursive partitioning window before analysis begins. Recursive partitioning with a binomial response (good or bad cut) works as follows:

- Determine the proportion of good and bad cuts
- Display all data points as stacked bar graph – green are good cuts, red are bad cuts
- Split the data to find the subset of data that best separates the most good or bad cuts
- Repeat splitting finding further subsets of data that best separate good cuts from bad cuts
- Include in the analysis only variables and groupings that are predictive

Figure 8: Partitioning before any splits

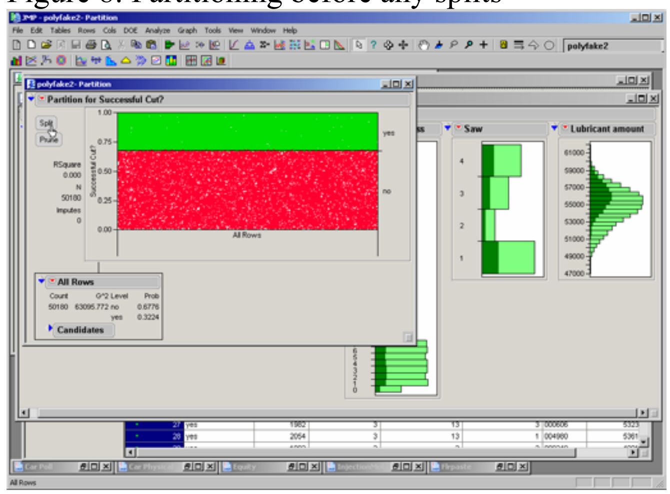


Figure 9: Predicting good and bad cuts with three splits

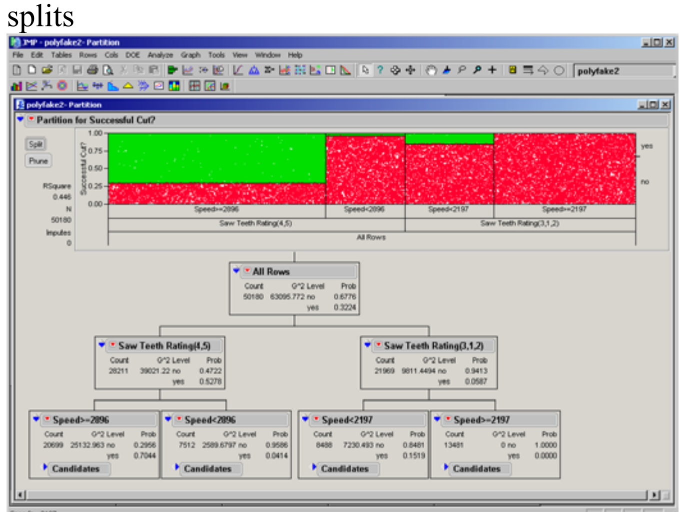
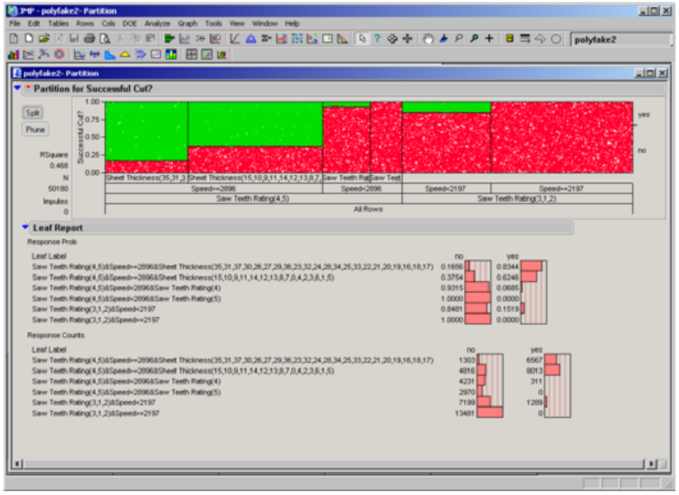


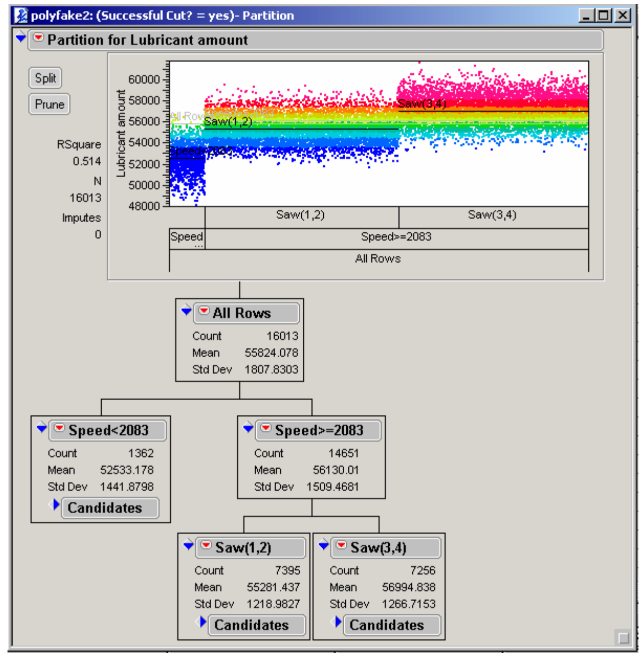
Figure 10: Predicting good and bad cuts with four rules



Figures 9 and 10 show that with three splits, four simple rules define situations under which good and bad cuts occur. The four rules have combinations of the categorical variables saw teeth rating and sheet thickness while dividing the continuous variable speed at several values, all to maximize prediction accuracy. With a few mouse clicks you have isolated four data subsets that describe good and bad cut situations. How long would this take with your current Six Sigma software?

Figure 11 shows partitioning with a continuous response variable. Here, the distribution graph was used to subset the good cut data. The analysis shows how lubricant amount relates to speed and saw. Because lubricant amount is continuous, the decision tree tries to find data subsets that predict mean values of lubricant amount.

Figure 11: Partitioning to predict lubricant amount



You will add maximum value to your Six Sigma efforts by using software that lets you quickly identify relationships, quickly determine predictive variables, and find interesting subsets of data.

EXAMPLE 3: DESIGNED TO SAVE MONEY

When designing experiments to find the optimal process setting or design new products, are you constrained by the limits of your software? Does your software let you define the questions you want to answer? Or does your software tell you the question it can answer and force your problem into a textbook example? Can you easily trade off predictability decisions for experimental runs? Can you select the number of runs you can afford and still have enough information to solve your problem?

Suppose you need to determine the best way to weld sections of polyamide together. You will vary the welding penetration, heating time, and hot-tool temperature. You want to use a response surface design for weld penetration and heating time, but you have several specific hot-tool temperatures to test. You can use a response surface for weld penetration and heating time, then replicate the design for all values of hot-tool temperature you need to test. However, the limited amount of time and experimental resources (materials, workers time, down time/opportunity costs) also need to be considered.

Assuming the costs in Table 3 for experimental resources you estimate the total experiment costs in Table 4.

Table 3: Experimentation costs

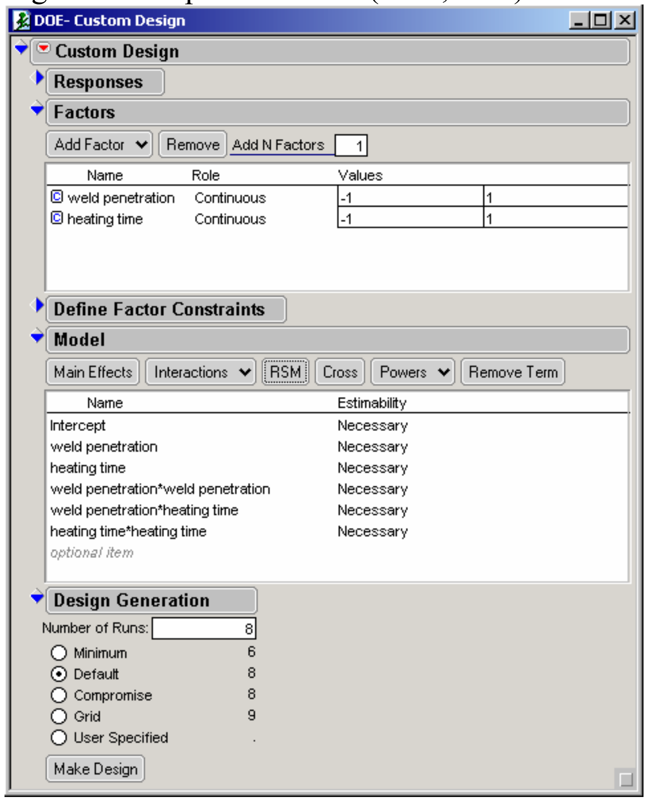
Resource	Cost
Workers time	$500
Materials	$500
Down time/Opportunity costs	$5,000
Total Cost per run	$6,000

Table 4: Total experiment costs

Number of Runs	Total Experiment Costs
1	$6,000
10	$60,000
50	$300,000
100	$600,000
150	$900,000

Looking at classical experimental design techniques, a response surface for weld penetration and heating time demands eight runs as shown in Figure 12. Replicating the design for four values of hot-tool temperature yields 32 runs; for eight hot-tool temperatures there would be 64 runs.

Figure12: Response surface (weld, time)



Using design tools that let you consider resource constraints, that let you define the problem not just look up a textbook answer, you can lessen the number of runs. Figure 13 shows that you can answer the four temperature hot-tool problem with 32 runs, or as few as 15 runs. Likewise, the eight temperature hot-tool problem can be addressed with 72 runs, or as little as 27 runs as shown in Figure 14. Table 5 details design costs for various numbers of runs using the cost of $6,000 per run.

Figure 13: Custom design, four hot-tool temps

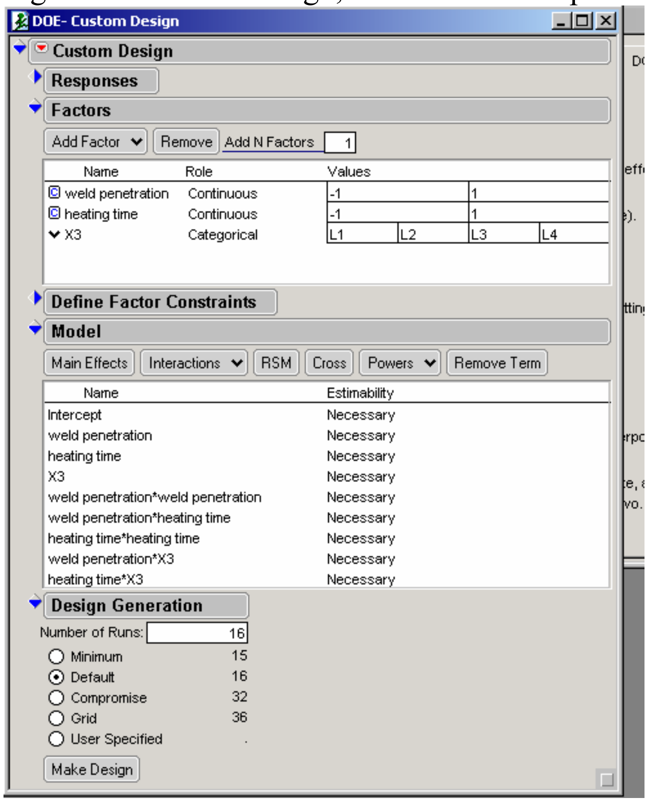
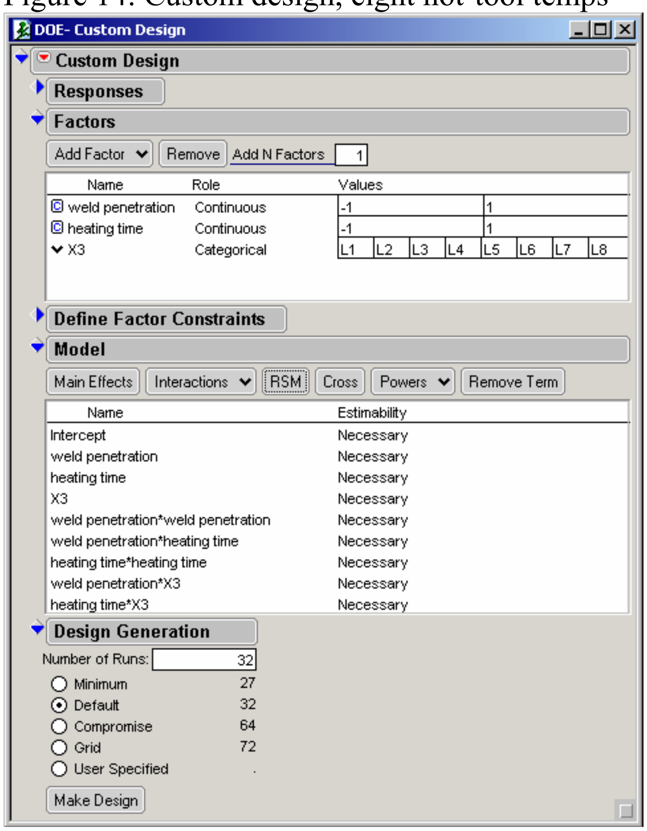


Table 5: Costs of experiments

Experiment	Runs	Cost ($6,000 per run)	Cost ($50,000 per run)
Response Surface (weld, time)	8	$48,000	$400,000
Response Surface replicated 4 hot-tool temps	32	$192,000	$1,600,000
Response surface replicated 8 hot-tool temps	64	$384,000	$3,200,000
Custom Design, 4 hot-tool temps, minimum runs	15	$90,000	$750,000
Custom Design, 8 hot-tool temps, minimum runs	27	$162,000	$1,350,000
Custom Design, 8 hot-tool temps, user specific runs	42	$250,000	$2,100,000

What if your experimental costs were higher, say $50,000 per run? The cost of textbook designs can get astronomically high very quickly. Wouldn't your Six Sigma commitment dictate searching for a more cost effective method for reducing costs? Choose software that minimizes time to collect data, minimizes time spent on analysis, and minimizes time required to reach the best answers.

Figure 14: Custom design, eight hot-tool temps



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