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JMPer Cable

Special Six Sigma Edition

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Six Sigma: Getting to the Root Cause

Christopher Nachtsheim, University of Minnesota
Bradley Jones, JMP Development

Six Sigma is an approach to business problem solving that is taking American industry by storm. The success stories compiled by its early adopters are impressive, spanning industries from high tech manufacturing to service providers and companies from the Fortune 100 to fast-food franchises.

The basic components of the Six Sigma approach are not new, but the packaging is. Six Sigma is a clever compilation of proven techniques from many previous management methods. The power comes from Six Sigma's integration of the team-based approach, customer orientation, financial motivation and assessment, tangible rewards for success, qualitative and statistical tools, and focus on short-duration, high-impact projects.

Most importantly, the support and active participation of top management is recognized as being integral to the success of any Six Sigma program. It's not just throwing money at the problem—although a financial investment is necessary. It's not just cheerleading from the sidelines—although visible leadership is required. It is providing the organizational structure and flexibility to let the project leaders (Black Belts) and team participants do their jobs. The Black Belt devotes full time to his/her project, seeing it through to completion. Management must also be willing to alter the normal flow of business operations to facilitate the completion of project assignments.

Six Sigma has elements of Deming's management and quality philosophy, but it is more. At Six Sigma's core is the fundamental cycle of engineering problem solving: Plan–Do–Check–Act. But Six Sigma also recognizes that the managerial and organizational aspects of change management are at least as important as the technical issues—thus the emphasis on top management involvement, the use of cross-functional teams, problem selection and definition, then standardizing and institutionalizing the resulting improvements.

The Six Sigma problem-solving tools are important. These methods fall naturally into two categories: qualitative and statistical. The qualitative toolkit includes process mapping techniques such as the integrated flow chart, team building techniques, and brainstorming tools such as cause-and-effect diagrams, interrelationship digraphs, failure modes effects analysis (FMEA), and affinity diagrams. The data analytical tools start with simple descriptive statistical summaries and graphs. Dot plots, box plots, histograms, pareto charts and tables of means, and standard deviations are examples. Control charts and process capability analyses are widely used and a bit higher on the sophistication scale, while discovering and quantifying relationships among variables can require more advanced statistical modeling tools such as ANOVA, regression, contingency tables and so forth.

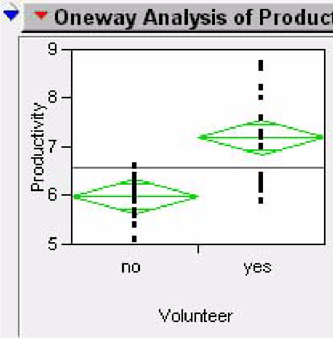
Six Sigma recognizes that simply establishing a correlation between variables of interest does not establish causation. A simple example can be used to illustrate this important—and often overlooked—point. Recently, programmers at a large insurance firm were given the option of attending a training workshop on object-oriented programming, and about half of the eligible programmers volunteered. Each year the productivity of all programmers is rated on a 10-point scale. The graph in Figure 1 compares the ratings of the programmers who attended the training with those who did not. The supporting statistical analysis shows that the observed difference in average productivity is highly statistically significant.

It is tempting to conclude that the increase in productivity was caused by the training. But this was simply an observational study of historical data. Causality does not necessarily follow. In this case, review of the prior-year's productivity scores revealed that the volunteers were already the most productive—so much for the effectiveness of the training.

So how do we establish causality? We must actively manipulate the variables we can control—as opposed to passively observing them—and quantify the effects. Because active manipulation of variables is built into design of experiments (DOE), it is the most powerful of the analytical tools in the kit of the Black Belt.

There are four phases in every Six Sigma project: identification, characterization, optimization, and institutionalization. Let's consider ways to apply DOE at each of these phases.

Oneway Analysis of Productivity By Volunteer



t-Test

Assuming equal variances

	Difference	t-Test	DF	Prob > |t|
Estimate	-1.2200	-4.776	28	<.0001
Std Error	0.2555			
Lower 95%	-1.7433			
Upper 95%	-0.6967			

Figure 1: The graph on the left shows a comparison of trained versus untrained programmers.

Identification: Recognize and Define

The first step in any Six Sigma project is the identification step. Here the focus is on developing an understanding of how variation in internal processes affects business results and customer satisfaction. Identification of critical-to-business processes facilitates project selection and problem definition, including establishing key progress metrics. In a manufacturing situation, a progress metric might be the amount of scrap and rework produced. In a service operation, it might be the number of customer complaints per week. Six Sigma emphasizes the importance of the voice of the customer in choosing progress metrics, where customers may be internal or external to the company. If the measure isn't on the customer's radar screen, it probably shouldn't be on yours.

An obvious application of DOE in the define step is in customer surveys. To establish price points for the standard package and 4 options, an automotive company designed a survey in the form of five-factor (25-2) experiment. In this way, the company was able to fix pricing to maximize revenue. Moreover they found out which features customers perceive to have the most value. This guided Six Sigma teams in choosing high impact process studies. Using DOE, surveys can also be fielded in ways to test for the effects of various customer demographic factors, such as age, gender, economic level, and so on.

Characterization: Measure, Analyze

The characterization step establishes the current performance levels for the key progress metrics and establishes goals for those metrics. This step frequently involves the development of integrated flowcharts of the current process and the determination of its statistical capability. Once the current process is well understood, goals and timelines for the project can be set.

DOE is frequently used in this step to help determine process capability, to compare alternative measurement methods, and/or to establish the validity of selected metrics. To establish process capability and to fully understand the current process, potential sources of variability, such as operators, shifts, raw material lots, and ambient conditions are systematically varied in a designed experiment. DOE can also be used to characterize the accuracy and precision of alternative measurement systems and to determine—in a validation stage—whether or not what is being measured is truly linked to the customer's perception of quality.

Optimization: Improve, Control

The optimization step is truly where the rubber meets the road in a Six Sigma project. Here, the process changes needed to affect the desired improvements are identified. In the words of Harry and Schroeder (2000), "Optimization identifies what steps need to be taken to improve a process and reduce the major sources of variation. The key process variables are identified through statistically designed experiments; Black Belts then use these data to establish what "knobs" must be adjusted to improve the process." DOE is the one tool that can effectively establish and quantify the causal relationships between variables that can be controlled—such as process steps, materials, equipment, training levels—and key process outputs such as defect rates, on-time deliveries, or scrap and rework. Once these relationships have been modeled statistically, they can be used to move the output metrics toward the stated goals.

When implemented, the improvements identified via DOE (or other methods) will lead to a new, improved level of process capability. Once this new level of process capability has been assessed, the savings to the corporation can be quantified.

Institutionalization: Standardize, Integrate

A successful optimization step will identify a new set of best practices for the management of a critical-to-business process. It's important that these best practices be standardized, communicated, and implemented throughout the organization. This is the essence of the institutionalization step.

DOE is used within the institutionalization step in a variety of ways. For example, the optimization step may have involved experimentation with a manufacturing process in a pilot plant or with a product receiving process in a particular distribution center. Scale-up from a pilot plant setting to full production or from one distribution center to all such centers may require fine tuning. Alternatively, it may be important to establish the sensitivity of key metrics to the control variables on a site-by-site basis. Such sensitivity and fine-tuning studies can be effectively carried out in the DOE framework.

Design for Six Sigma

It is useful to go even farther. In Design for Six Sigma (DFSS), a new business operation integrates DOE and Six Sigma from the outset. DOE becomes the analytical tool of choice for developing new products and implementing new systems. The potential savings from DFSS dwarf the alternative choice of implementing a process in the traditional way and using Six Sigma techniques to optimize it later.

Using DOE for Process Optimization: An Example

In the production of dense, multi-layered, printed circuit boards, a challenging, on-going problem is registration error. Registration refers to the alignment of electrical connections that must occur between layers of circuits. Warped, shrinkage, rotation, or other movements that occur during the lamination process can lead to registration error. If the registration error falls outside of the specification limits—from -12 to +12—the board will be defective. Factors that affect registration error can be divided into two groups: the constituents and operating conditions. The constituents are the epoxy and core materials and the operating conditions include such process settings as oven pressures and

Circuit Boards
Fit Model
Columns (4/0)
Temperature
Pressure
Supplier
Registration Error
Rows
All Rows 14
Selected 0
Excluded 0
Hidden 0
Labelled 0

	Temperature	Pressure	Supplier	Registration Error
1	275	20	cheap	-15.4
2	300	20	cheap	-18.1
3	325	20	cheap	-18.8
4	275	25	cheap	-6.6
5	300	25	cheap	-15.8
6	275	30	cheap	4.6
7	325	30	cheap	-17.1
8	275	20	pricey	-10.6
9	325	20	pricey	3.7
10	300	25	pricey	3.1
11	325	25	pricey	10.4
12	275	30	pricey	-13.9
13	300	30	pricey	6.1
14	325	30	pricey	13.6

Figure 2: A JMP data table of experimental runs.

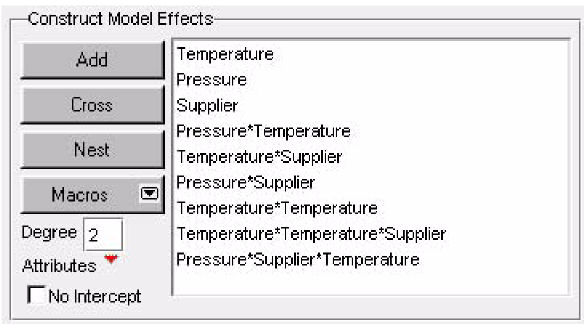


Figure 3: To analyze the data shown in Figure 2, the data should be entered into JMP's Fit Model dialog.

temperatures. The following, simplified example was adapted from some recently reported Six Sigma studies that targeted the reduction of registration error (McQuarry 1999, 2001).

There were two objectives articulated in the identification step of this Six Sigma project. One was to reduce the scrap rates due to registration error; another was cost reduction through the use of lower-cost materials. It was noted during the characterization step that two suppliers had been competing and that previous historical data had indicated that use of the low-cost supplier's epoxy led to high registration error rates. Using the current process, any potential savings due to the use of the low-cost epoxy were lost due to the associated high scrap rates. An experiment was designed with the goal of determining optimal process settings for each supplier's epoxy.

Figure 2 shows the data table from the experimental runs. Note that temperature and pressure were each tested at three levels. This was required to fit a quadratic response surface model in registration error. A full factorial design would take 18 runs. This was reduced to 14 runs through the use of a D-optimal design.

The model used to analyze the data in Figure 2 is entered into JMP's Fit Model dialog, as shown in Figure 3.

Figure 4 shows predicted registration error at the current process settings for the high-cost supplier. The process mean is 3.7 and the standard deviation is about 2.5. Recall that if the registration error falls outside of the specification limits—from -12 to 12—the board will be defective. The predicted scrap rate for this process (assuming a 1.5 standard deviation drift in the process mean—a standard Six Sigma calculation) is 3.44%.

Figure 5 shows that the mean registration error at the current process settings for the low-cost supplier is about -14.4. The scrap rate for this process is well over 50%—clearly not a capable process.

By contrast, Figures 6 and 7 show the optimal settings of temperature and pressure for each supplier. Figure 6 reveals that lowering the temperature from its current setting of 300 to 291, while raising the pressure from 25 psi to 29 psi moves the process mean for registration error to virtually zero. The scrap rate is 0.05%.

The big surprise is in Figure 7. Here, lowering the temperature to 281 and raising the pressure to 30 also with the low-cost epoxy also leads to a zero predicted registration error and a scrap rate of 0.05%.

In the institutionalization step, the improvement team recommended switching to the low cost supplier and standardizing on the optimal process settings. Substantial savings resulted from lower material costs and reduced scrap.

DOE and Six Sigma

Management methods evolve. Like total quality management (TQM), quality circles, re-engineering, and many other business fads, Six Sigma will eventually be replaced by something better. But it is important to recognize that the many of the techniques that make up the Six Sigma toolkit are proven tools that are here to stay. The design of experiments is one such tool. Invented in the early part of the 20th century, DOE has made contributions to virtually every area of science and technology. We applaud the developers and purveyors of Six Sigma methodology for recognizing DOE's role in quality improvement.

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McQuarry, G., "Control of Key Registration Variables for Improved Process Yields on Dense MLBs." *IPC Expo '99*, March 1999.

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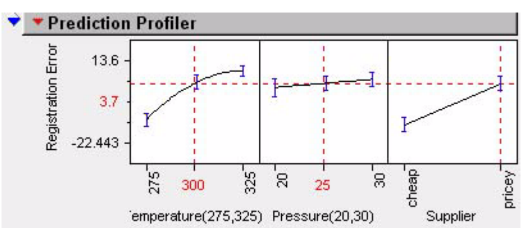


Figure 4: Registration error as a function of oven temperature, pressure, and supplier.

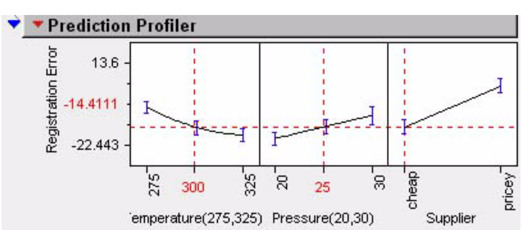


Figure 5: Predicted registration error at current process settings for low-cost epoxy.

DOE News

JMP-Starting High C_{pk} Levels in Multi-Layer Printed Circuit Board Production

Gray McQuarrie, GrayRock & Associates LLC

Creative use of design of experiments (DOE) can often reduce process variation, sometimes by orders of magnitude. The following case study shows how variation was reduced in the fabrication of multi-layer printed circuit boards by using a simply constructed DOE. The keys to success were:

- using only two control variables to produce a wide variety of different board compositions (circuit configuration and bonding sheets, described later)
- defining the experimental run sample sizes within the natural context of the manufacturing environment
- keeping the experiment small enough to ensure timely completion, but large enough to capture process capability information.

The composition of a multi-layer printed circuit board is similar to a multi-layer cake. Figure 8 illustrates a cross section of an eight-layer board. One board consists of three fiberglass cores with copper circuit images on both sides, fiberglass bonding sheets, and the outer-layer copper. The bonding sheets surrounding the cores are thin, woven glass sheets that are epoxy-resin coated. In the lamination process a book of many boards (many cakes, each with many

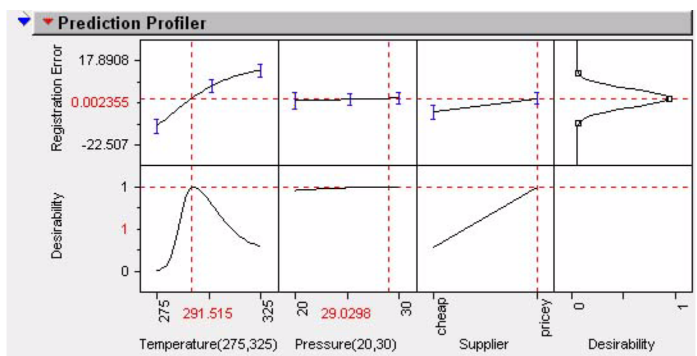


Figure 6: Optimal settings for the high-cost (current) supplier.

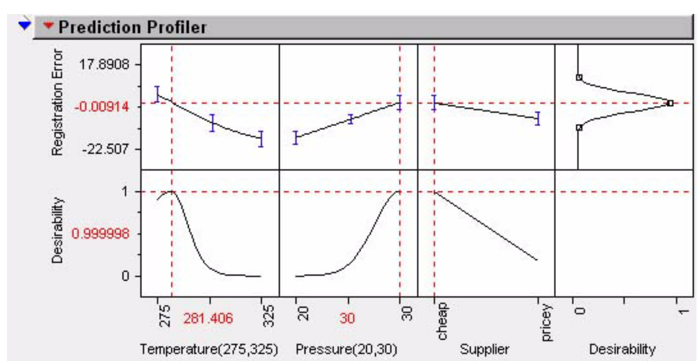


Figure 7: Optimal settings for the new cheap supplier.

layers) are subjected to high heat and pressure. This causes the resin in the bonding sheets to melt and polymerize, filling in the circuits and gluing the board together.

After multi-layer lamination (gluing the cake layers), each board has thousands of holes drilled vertically all the way through the board. Every one of the thousands of holes must line up to the required location in the circuit image layers or an electrical short will result during final electrical testing. This may not sound too difficult if we consider unmoving targets, but because cores move (grow or shrink) from the lamination step, we need to hit moving targets! We adjust (scale) each circuit image by growing the image or shrinking the image in order to compensate the core movement.

The cores in this case study were 18 inches long (X) and 24 inches wide (Y). Measuring targets were placed near each of the four corners of each of the three cores. From these targets (measured using an expensive, finely-tuned X-ray machine) data for movement in the X direction and Y direction are collected. Figure 9 shows the X and Y histograms and capability analyses for a population of 5 mil (0.005 inches thick) cores measured from a variety of eight-layer board compositions. Positive numbers indicate growth (in mils) and negative numbers indicate shrinkage. Both distributions show more than a 20-mil spread, which violates the given spread tolerance of 10 mils and leads to significant quality problems and scrapped product.

Using JMP's Capability Analysis feature in the Distribution platform, we can enter upper and lower bounds that define the acceptable spread and see the result of this scaling. If we scale all the 5-mil cores 10 mils (grow the artwork) in the X direction and 5 mils in Y, then the C_{pk} is 0.262 for X and 0.301 for Y (see Figure 10). This core variation is typical of the industry and the global scaling adjustment represents the standard industry scaling decision. How can DOE help us improve our C_{pk}s?

We could treat the surface copper, each layer of bonding sheet, each copper thickness on each core, the image of each core, the core thickness, as well as the book construction, the lamination press type, and the press parameters, all as experimental variables and construct a massive experiment that would take months to complete and analyze. Our analysis would likely be futile because the presence of high level interactions is not needed in our model. This approach is too complex and expensive, so we need to find a simpler way.

In any designed experiment, we have complete freedom to define our variables anyway we choose. Whenever something looks like a layer

What data needs to be collected in order to make a proper scaling decision?

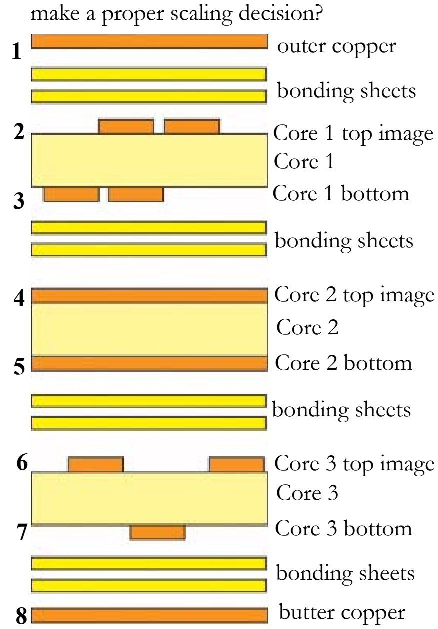


Figure 8: Illustration of a multi-layer printed circuit board.

Configuration	Core 1	Core 2	Core 3
Level 1	sig/ sig	grnd/ grnd	sig/ sig
Level 2	grnd/ grnd	sig/ sig	grnd/ grnd
Level 3	grnd/ sig	sig/ sig	sig/ grnd
Level 4	grnd/ sig	grnd/ grnd	sig/ grnd

Figure 9: Defining a circuit configuration.

Look for JMP at these Conferences and Trade Shows

Sept. 22-24	SESUG
Sept. 29- Oct. 2	NESUG
Oct. 6-8	SCSUG
Oct. 13-15	MWSUG
Nov. 10-14	AAPS

cake, the variables are highly connected and you need to be concerned about high-level interactions. For example, if a variable changes Core 3 movement, then Core 1 will move differently because of the physical connection.

RULE: When you see a layer cake in your system, stop and define variables at the cake layer level so that you step around the high level interactions.

For our multi-layer board cake, let us use a logical method that allows different cake compositions. Most cores have either signal circuits (little copper) or ground circuits (lots of copper). We have three cores in our cake where each core has two circuit choices (the top and bottom). We defined a circuit configuration factor with four levels to our eight layer boards. See Figure 9 for details.

For bonding sheets, we considered four types, ranging from thinnest to thickest: 1080, 2113, 2116, and 7628 (these numbers represent the glass supplier codes). For each board in our experiment, we used the same bonding material around each core.

We have reduced our problem down to two four-level categorical variables: circuit configuration (config) and bonding sheet (sheet).

A 16-run full factorial design was used for the model with main effects config and sheet, and their interaction, config*sheet.

The sample size decision was made based on the minimum standard production run. Each run represented one book of panels, which would provide 10 data points per core for a total of 480 data points in the experiment. Additionally, the experiment was blocked on specific presses and sets of panels blocked to be pressed at specific times. In this way, we could estimate the short-term capability using our experimentally derived scaling model. Even though we had a large data set, the production runs were easy to manage and easy to run through the factory, measurements were made quickly and were easy to track, and the cost of materials and labor was kept below $5,000.

Figure 10 shows the distribution of all of the data generated for Core 1 in the experiment. The experiment was able to explain 97.9% of the X variation observed in Figure 10 and 92% of the Y variation. Figure 12 shows the

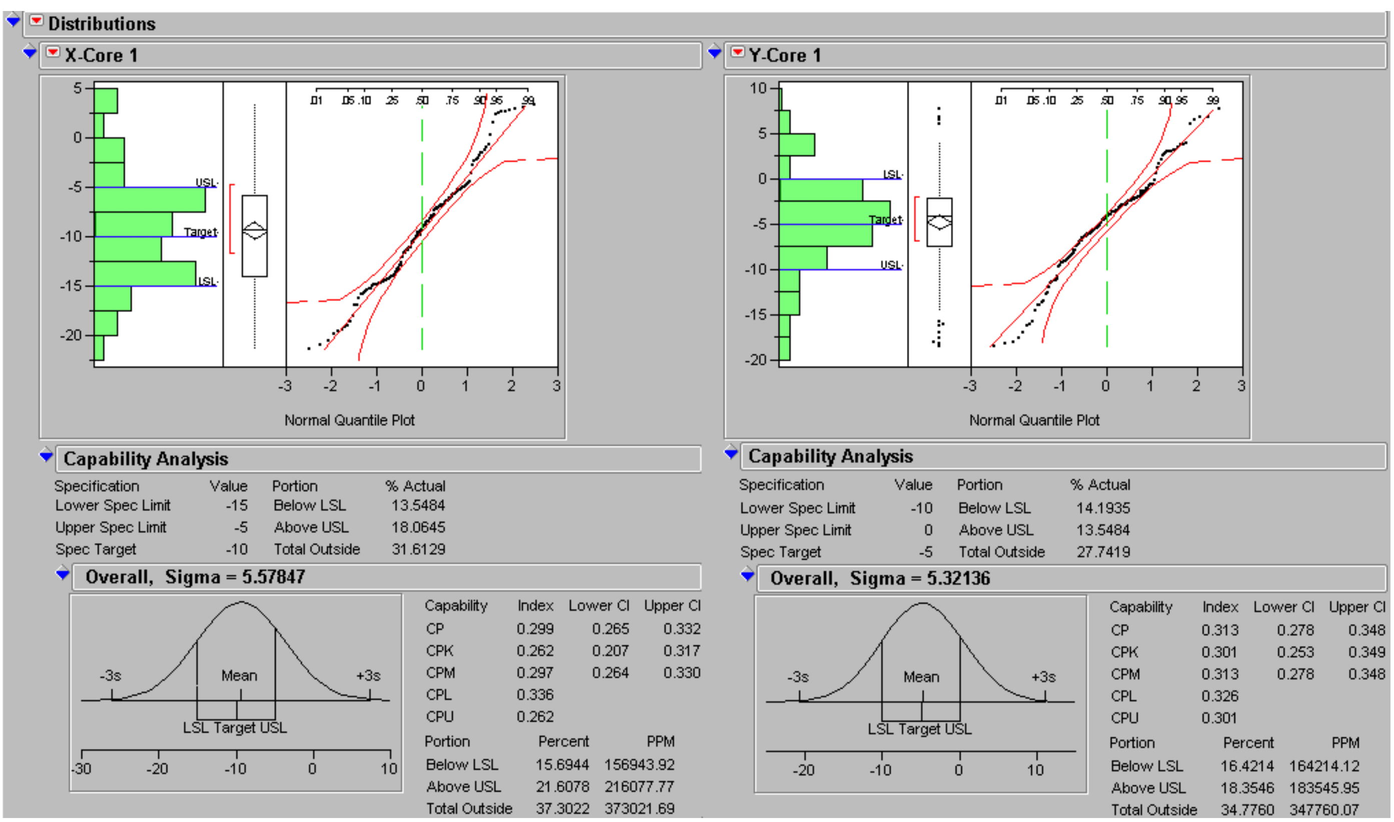


Figure 10: Distribution and capability analyses of X and Y core measurements.

residuals plot for Core 1 in the X and Y directions.

Figure 11 shows a JMP screening plot where all of the results for each core in each X and Y direction in our multi-layer board can be compared.

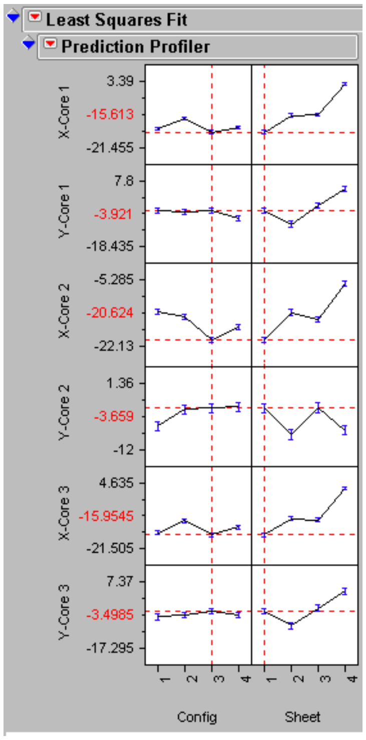


Figure 11: Comparison of responses using the prediction profiler.

Conclusion

For multi-layer boards that exactly match our experimental compositions, we have an approximate short term C_{pk} of 2.061 (0.0006 ppm) in the X direction and 1.11 (867 ppm) in the Y direction (Figure 12).

We match board compositions outside of the experimental study with the most similar composition in the experiment as a starting point, thereby reducing the size of feedback adjustments and further stabilizing the scaling process. These C_{pk}s would be lower than the board composition used in the experiment, but stand a better chance of improving after production adjustments.

This experiment also shows the need to improve the movement consistency of the cores in the Y direction. These types of simple (but not simple-minded) experiments win results with management.

Grayrock & Associates LLC specializes in the accelerated development of managers and engineers in the implementation of Lean and Six Sigma improvement efforts, large or small. Gray McQuarrie was on of the first wave of Black Belts certified by Allied Signal in the mid 1990s. Gray, along with Frank Delk, created the Lean Laboratory™, which provides clients powerful insights on how they can quickly and creatively make their own unique transition to a Lean operation.

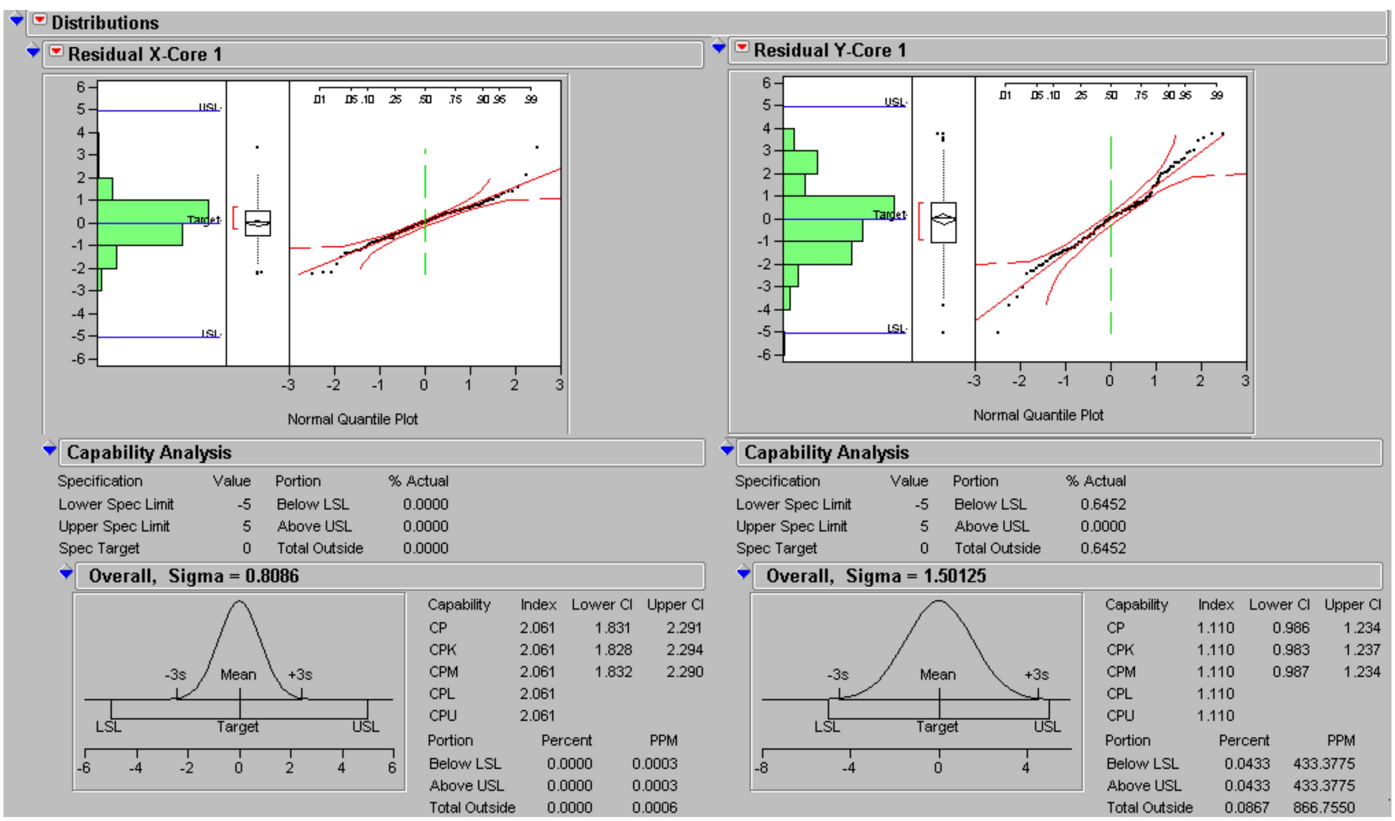


Figure 12: Histograms and capability analyses of residual X-Core 1 and Y-Core 1.

Directed Improvement in Product Reliability

John Sall, Executive Vice President, SAS Institute

Mark Bailey, SAS Statistical Training & Technical Services

All formalized or structured quality programs—including Six Sigma—use a defined process, such as Plan-Do-Check-Act (PDCA), to select an improvement project. This article addresses the topic of improving product reliability. Knowing how a product fails is an important first step toward making it more reliable.

Products often fail because of several different causes. If the causes are independent, they can be modeled by the *competing causes* model. Doganaksoy, Hahn and Meeker (2002) show that it is important to take these different modes into account, both to improve the reliability estimates and understand the opportunities for improving reliability itself. The data from their article is used in this article to illustrate features in JMP.

Doganaksoy, Hahn and Meeker's example involves developing a new insulator for armature bars in an electric generator. The insulator consists primarily of a dielectric material, mica, bonded together with an organic compound. Two kinds of failure studied are:

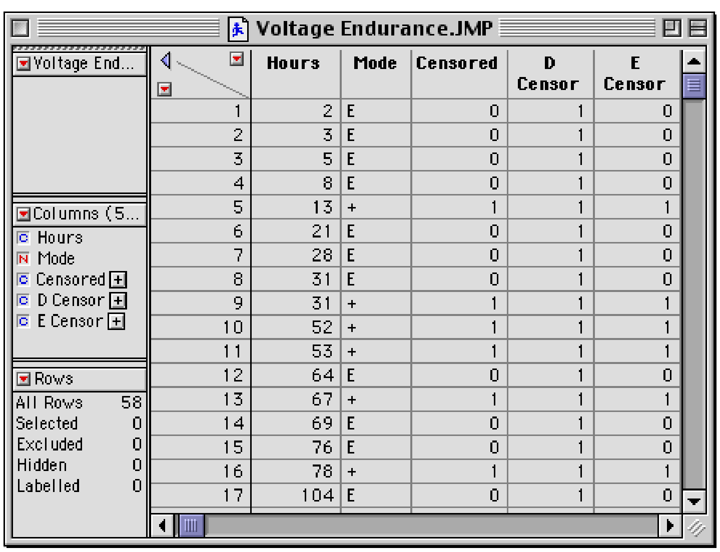
- Degradation of the organic binder (label D). This is a wear-out cause.
- Early failure due to a processing problem (label E). This is a defect cause.

A sample of 58 parts was subjected to a high stress voltage endurance life test. Figure 13 shows a partial listing of the data table.

Examine the Data

Hours is the time when the part was observed. Mode identifies which of two possible failures occurred. If the observation is censored, a '+' is shown. Three formula columns for censoring were added to the data table. These columns possess a zero for censored observations and a 1 for censored observations, as follows:

- Censored contains the formula Mode=="+", which indicates a censored event time.
- D Censor contains the formula Mode!="D", which indicates that the observation is either censored or fails for a cause that is not D.
- E Censor contains the formula Mode!="E", which indicates that the observation is either censored or fails for a cause other than E.



	Hours	Mode	Censored	D Censor	E Censor
1	2	E	0	1	0
2	3	E	0	1	0
3	5	E	0	1	0
4	8	E	0	1	0
5	13	+	1	1	1
6	21	E	0	1	0
7	28	E	0	1	0
8	31	E	0	1	0
9	31	+	1	1	1
10	52	+	1	1	1
11	53	+	1	1	1
12	64	E	0	1	0
13	67	+	1	1	1
14	69	E	0	1	0
15	76	E	0	1	0
16	78	+	1	1	1
17	104	E	0	1	0

Figure 13: Voltage endurance data table.

A Univariate Survival Analysis

To obtain a preliminary look at the failure distribution, select **Survival/ Reliability** under the **Survival and Reliability** command in the **Analyze** menu, as shown in Figure 14.

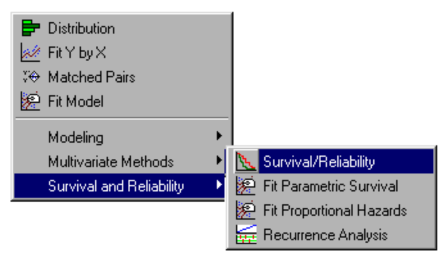


Figure 14: The Survival/Reliability command.

After you select the command, the Survival dialog (shown in Figure 15) opens for you to cast variables into the appropriate analysis roles.

Figure 15: The Survival/Reliability dialog.

The response (Y, Time to Event) is Hours, which is time to failure in this example. For an initial analysis, use the Censored variable in the Censor role.

After you click OK, the Survival platform provides a non-parametric (Kaplan-Meier) estimate of the failure curve. The portion of units failed at a given time is shown in the failure plot in Figure 16.

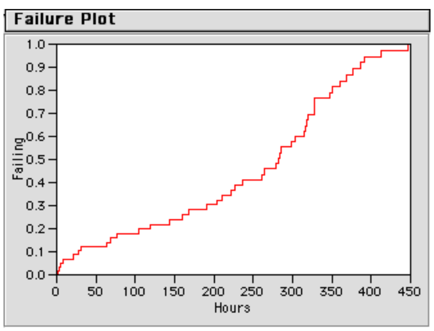


Figure 16: Omnibus analysis with no separate causes.

The number of units that failed steadily increases without exhibiting any special or unusual features. Some parts lasted almost 450 hours, while a few parts failed almost immediately. Thirteen parts did not fail by 450 hours. The mean time to failure is 244 hours.

Analysis by Each Failure Mode

It is important to remember that there are two kinds of failures. It is assumed that these two kinds of failures operate independently. If a unit fails for one failure mode, then we won't know when it would have failed for the other failure mode. That is, each failure becomes a censoring event for all the other failure modes. To account for this properly, invoke the Survival platform two more times, one for each failure mode, using the columns D Censor and E Censor, respectively, as censoring columns.

JMP then provides the non-parametric failure curves for the D and E failure modes, as shown in Figure 17.

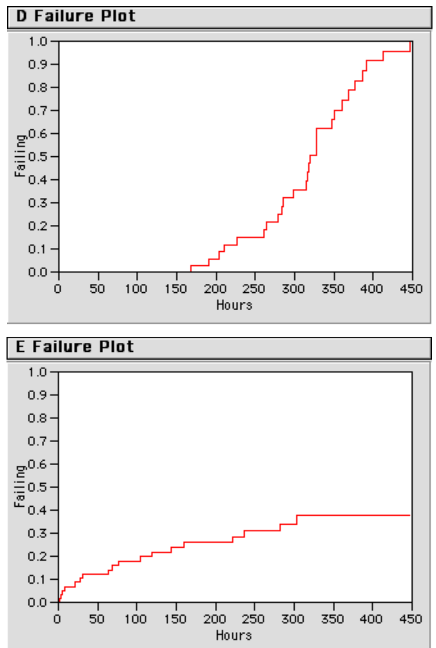


Figure 17: Non-parametric failure curves for the D and E failure modes.

Using the commands **Weibull Plot, Weibull Fit,** and **Fitted Distribution Plots** from the platforms' menus, you can display Weibull distributions for each failure mode (see Figures 18 and 19). In the examples in Figure 18, the plots have been scaled for comparison and the titles have been edited to keep track of the two analyses for the two failure modes.

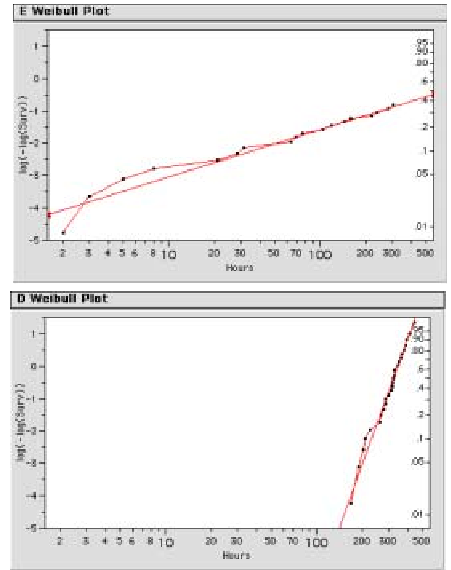


Figure 18: A Weibull distribution for each failure mode.

The Weibull plots (Figure 19) show the distributional fit for the two failure distributions, with fitted Weibull lines going through the points well.

JMP can overlay the fitted survival curve on the Kaplan Meier failure plot. To do this:

1. Right click in the fitted failure curve.
2. Select Edit Graphics Script.
3. Copy the script for drawing the fitted survival curve, and cancel the dialog.
4. Right-click on the Kaplan Meier graph.
5. Select Add Graphics Script.
6. Paste the script you just copied.
7. Change the expression from a survival curve into a failure curve by changing the YFUNCTION argument as shown below:

```
Pen Color(3); Y Function(1-
Exp(-(Time / 1170.5543408) ^
0.63530858565), Time)
```

E Weibull Parameter Estimates

same as Extreme-Value with Alpha=exp(Lambda), Beta=1/Delta

Parameter	Estimate	Lower 95%	Upper 95%	N Failed
Alpha	1170.5543	539.21538	4699.9246	18
Beta	0.6353086	0.3998794	0.9420287	18

D Weibull Parameter Estimates

same as Extreme-Value with Alpha=exp(Lambda), Beta=1/Delta

Parameter	Estimate	Lower 95%	Upper 95%	N Failed
Alpha	344.32883	321.05689	370.11551	27
Beta	5.6050384	4.1533682	7.2816374	27

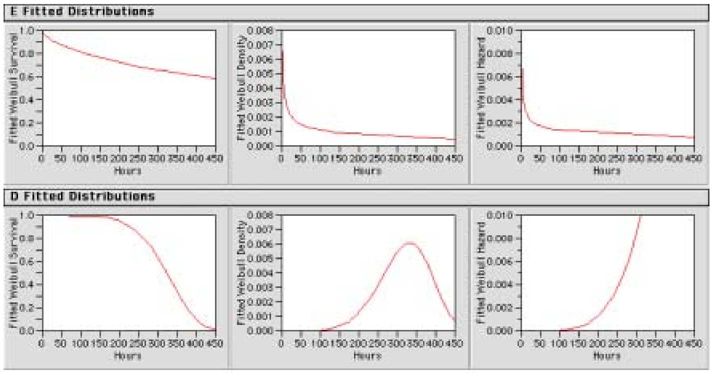


Figure 19: A Weibull fit (parameter estimates) and fitted distribution plots for each failure mode.

Figure 20 shows that the fitted failure distribution follows the nonparametric (Kaplan-Meier) fit well.

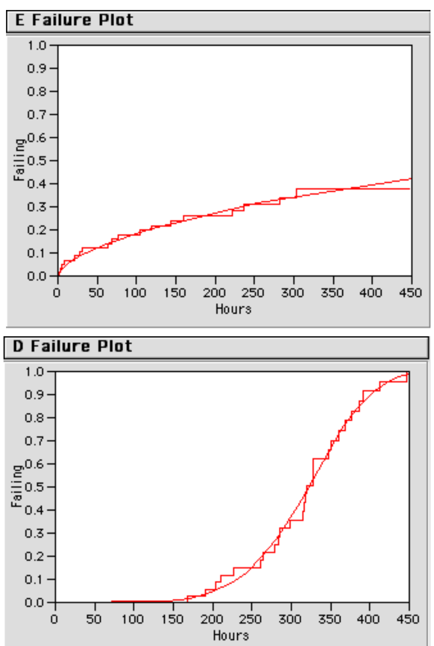


Figure 20: The distribution follows the fit.

Competing Causes Command

What if you have many modes of failure and want to see how competing causes work together for the combined distribution? The Competing Causes command in JMP serves to answer these questions. To continue with this example, invoke the Competing Causes command from the menu and select Mode as the competing cause code column. The output is a Weibull model fit to each failure cause. You can then

- fit a combined survival to the data, as shown in Figure 21.

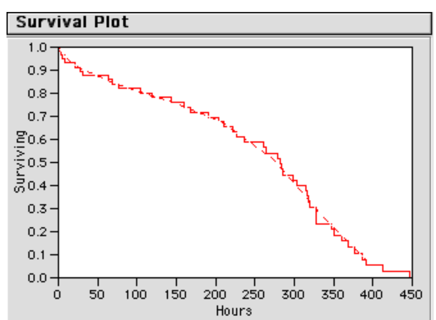


Figure 21: The combined Weibull fits with the survival (1-failure) plot.

- superimpose separate Weibull fits on a combined Weibull plot, as shown in Figure 22.

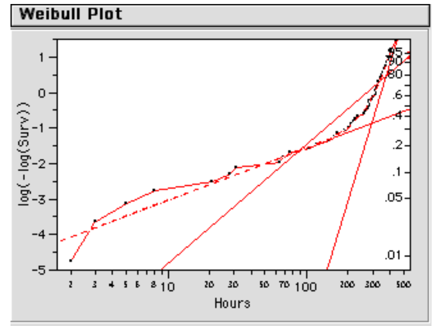


Figure 22: The separate Weibull fits superimposed on a combined Weibull plot.

- view the estimates, as shown in Figure 23. Note that in this example, the code "+" was not actually a failure code, but merely a censoring indicator. There were no "+" failures, so and this line is ignored.

Competing Causes

Weibull Parameter Estimates

Mode	Alpha	Beta		N Failed	N Censored
+	.	.	<2 events	0	58
D	344	5.60508234		27	31
E	1171	0.63531754		18	40

Figure 23: The competing causes' parameter estimates.

- view a combined fitted hazard curve, as shown in Figure 24. With competing causes from early and late failure modes, the curve is shaped like a bathtub. The early failures are bad components and the late failures are wear-out.

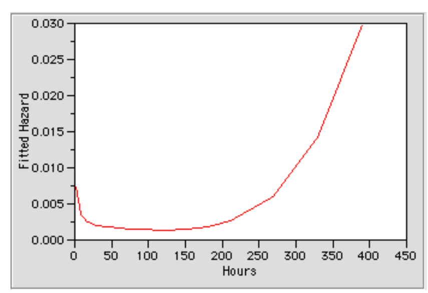


Figure 24: The bathtub-shaped hazard plot curve.

By examining all of the above, the current failure distribution is now known. The larger question might now be: "How can I affect the combined failure distribution if I can resolve one or more of the causes of failure?" JMP offers a way to simulate this situation with the Omit Causes command. If cause D is omitted, then the survival plot shows the fitted Weibull survival curve for cuase E only (see graph on left in Figure 25).

To resolve the early failure cause, use the Omit Causes command and select E, as shownin the graph on the right in Figure 25. This results in a new scenario, which resolves early failures.

Note that the hazard plots also change with respect to the omitted causes, as shown in Figure 26.

An analysis such as this helps to make a case for investing in the research to find a better binder that does not degrade. It also helps strengthen an argument for using a wear-in period to eliminate components with early failures. Numerical predictions from these survival models could be used in financial models of warranty or maintenance savings or return on investment (ROI).

References

Necip Doganaksoy, Gerald J. Hahn and William Q. Meeker, "Reliability Analysis by Failure Mode," Quality Progress 35(6)47-52, June 2002.

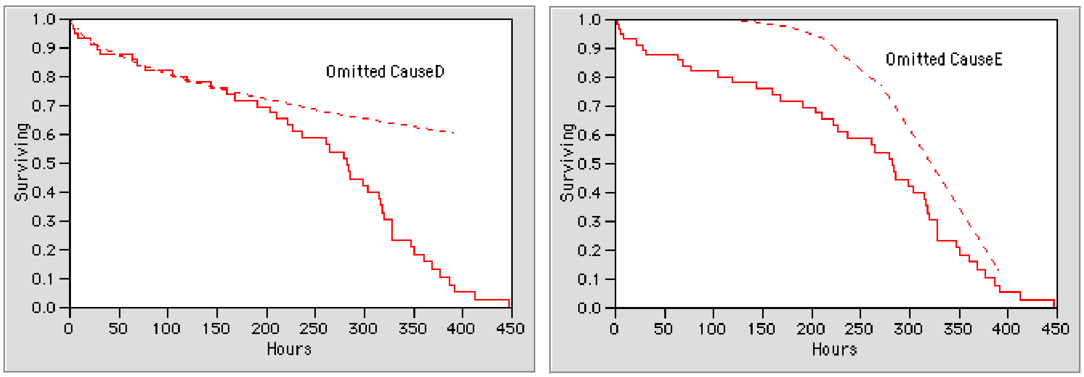


Figure 25: The Weibull curves with causes D and E omitted.

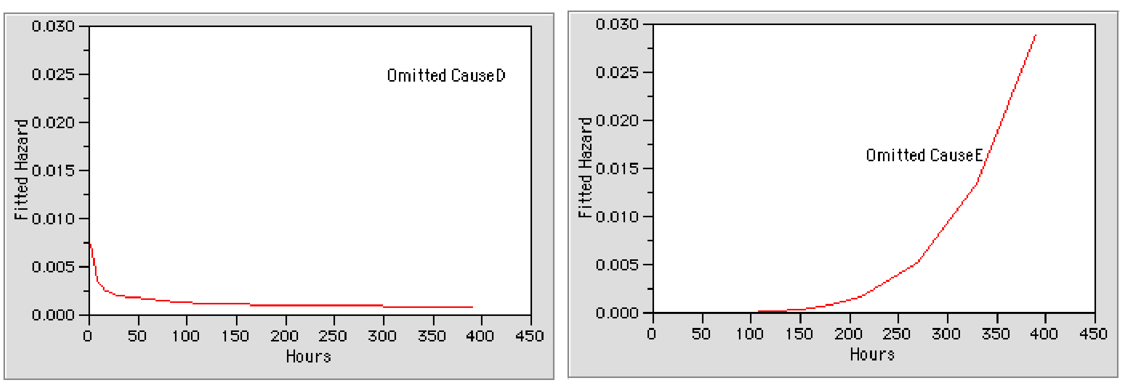
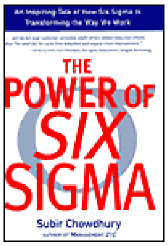


Figure 26: The hazard plots change with respect to the omitted causes.

Enjoy Chowdhury's "The Power of Six Sigma"

Chuck Boiler, JMP Sales and Marketing



Subir Chowdhury has created an entertaining parable used to infuse his audience with the business philosophy that is Six Sigma. His book, *The Power of Six Sigma*, achieves the goal of educating through a plausible lunch conversation between old friends who share contrasting career histories. Reminiscent of Plato's dialogues (but about one one hundredth the length or complexity), Socrates is played by Larry Hogan and Socrates' student by Joe Meter. These fictitious college buddies work in different divisions of The American Burger Company and their careers veer in opposite directions.

Larry's career is thriving. During lunch, Larry draws Joe into a dialogue about the nature of perfection from the standpoint of a customer who consumes a product or service. Larry builds a road map for Joe that describes how to get to this perfection and provides a non-technical description of the metrics of Six Sigma that won't put off those of us who took 'Math for Poets' in college.

The beauty of Chowdhury's approach is that it couches the Six Sigma methodology in a metaphor that is understandable to anyone who has ever eaten a pizza or been a customer. He couches it in a way that people at every level of the organization can understand.

The Power of Six Sigma rolls a Trojan Horse into the gates of every mind, releasing its contents, not of warriors, but of a powerful idea that can change the way companies think and act about quality. If you are new to Six Sigma or are the type that learns more from historical fiction than from history books, do yourself a favor and spend an hour reading this little book.

Subir Chowdhury is executive vice president of the American Supplier Institute. He is also the author of *Management 21C* and coauthor of *Robust Engineering and The Mahalanobis-Taguchi System*.

JMP + TLC = Great Six Sigma Training

JMP is parterning with California-based consulting firm Thomas A. Little Consulting (TLC) to establish a Six Sigma training curriculum built around the core principles of JMP.

Organizations working with TLC to implement a Six Sigma initiative receive training in all phases of the Six Sigma process. JMP's features address each of these phases, improve root cause identification, and suggest process improvement opportunities.

"Six Sigma represents a great opportunity to reach people who may not know how effective statistical software is as a tool to improve their business processes. We are pleased to announce this partnership with TLC as it will be an extremely effective way to generate success in this market." said John Chesebrough, JMP partner strategist.

TLC training delivers a common set of improvement tools and methodologies, standardized process analysis and measurement control systems, more predictable outcomes and timelines, and improved products and processes. Elimination of waste and reduction in cycle-time, lower costs, higher yields, improved customer satisfaction and increased profitability are all training objectives and goals of this proven, well established consulting firm.

"We consider JMP a critical element to the success of Six Sigma and integral in all of our consulting activities," said Dr. Thomas Little, founder of TLC. "JMP's fast, powerful and easy-to-use application software allows the user to collect relevant data, determine the root cause of problems, design experiments to improve performance and validate the effectiveness of improvement ideas."

Implementing Six Sigma in the Semiconductor Industry

Annie Zangi, JMP Development

Many semiconductor circuit board shops, wafer fabs, and post-fab operations have adopted the Motorola Six Sigma philosophy and have formed goals of attaining a Six Sigma level of quality by a particular date. Two quality measures, C_p and C_{pk}, the process capability indices, are described by AIAG (1995) as follows:

- C_p is the allowable tolerance spread to the actual spread of the data when the data follow a normal distribution.
- C_{pk} is used to evaluate both the spread and mean shift of the process.

Formulas for these indexes and the k factor, which quantifies the amount by which the process is off-center, can be found in Breyfogle (1997).

The formula for C_{pk} is written

$$Cpk = min\left(\frac{USL-\mu}{3\sigma}, \frac{\mu-USL}{3\sigma}\right)$$

The relationship between C_{pk} and C_p is

$$Cpk = Cp(1-k)$$

Six Sigma, defined by Motorola, proposes obtaining a minimum acceptable C_{pk} of 1.5, or 3.4 defective parts per million.

This article describes step-by-step how one company used JMP and the Six Sigma process to identify and correct problem areas in manufacturing.

The Technical Problem

Most of the published Statistical Process Control (SPC) theory is based on the normal distribution and assumes both that products are manufactured one unit at a time and that any random sample of these units can be considered independent. Unlike one-widget-at-a-time production, semiconductor manufacturing has numerous batch processes. Often, 200 or more wafers are simultaneously processed in the furnace. Then, each wafer is then divided into many individual chips. Clearly, chips coming from the same wafer—and even those from the same batch—are not independent of one another. Because the variance within a batch was not being considered, the unsuspecting engineers wound up with SPC charts containing incorrectly tight limits and many observations appearing out of control.

The Case Study

The "Acme" Semiconductor Co. began a Six Sigma process by putting together their team and analyzing the wafer manufacturing process. In particular, they studied the photolithographic process. Many engineers had been frustrated with the SPC requirements on this process and were ready to discontinue using them. When the team reached the step of performing process and measurement system capability studies, they found their process was not capable at the Six Sigma criteria.

The following steps use JMP to run the capability analysis for this case study. You can access the Wafers.jmp data table from the JMP web site (www.jmpdiscovery.com).

1. Open Wafers.jmp.
2. Select **Analyze > Distribution.**
3. Choose Photolithography as the Y Column, then click **OK**.
4. Click the red triangle icon on the histogram title bar to access the

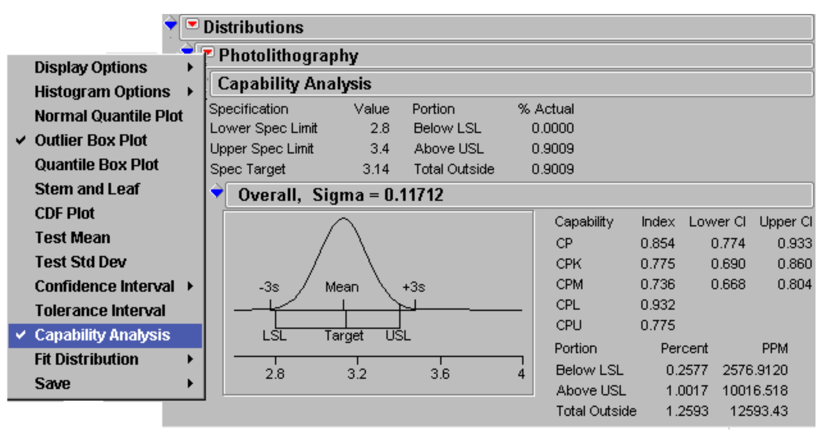


Figure 27: Click the red triangle icon and choose Capability Analysis.

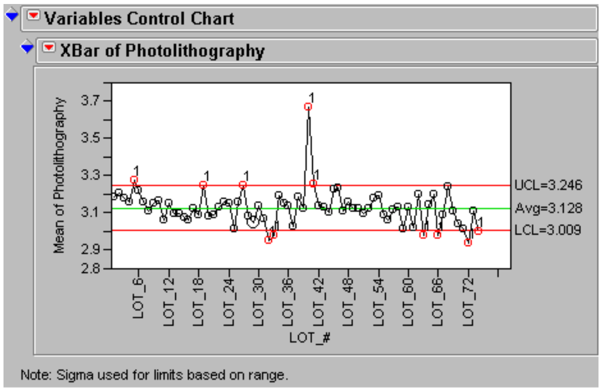


Figure 28: Mean chart of photolithography.

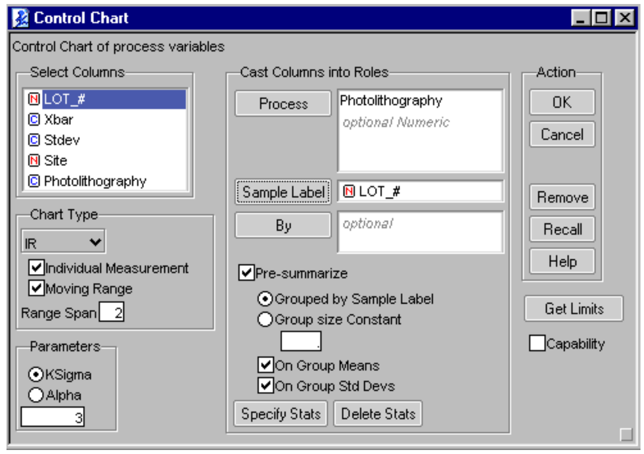


Figure 29: Launch dialog for IR control charts.

menu and choose Capability Analysis, as shown in Figure 27.

5. Set the Lower Spec Limit to 2.8, the Upper Spec Limit to 3.4, and the Target to 3.14.

As recommended by Six Sigma, the team examined the photolithographic process further through control charts. To see the results in Figure 28:

1. Select **Graph > Control Chart**.
2. Select Photolithography as the Process variable and LOT_# as the Sample Label.

Xbar and R charts summarize the results for three samples per lot, located at the top, middle, and bottom of each wafer.

Figure 28 shows that 11 out of 74 lots (~ 15%) failed test 1, or were beyond the control limits. It's no wonder the process engineers were discouraged. Since so many points failed this one test, no one dared suggest using any of the other Western Electric tests.

Is the Sigma Correct?

The team continued to study the charts and the resulting processes for several months. The charts looked horrible, but the actual percentages of bad chips weren't that far out of line. They realized that because the samples were not independent, the sigma used for the control charts was incorrect. Samples within the same lot are from three different positions within the same wafer, so it makes sense to plot the mean of these lots and to use the variation between them. The samples are not independent but the assumption is made that the wafers are. It is also useful to plot the standard deviation of each wafer, so that management can review the variation within each wafer.

Instead of using the Xbar chart with the sigma based on incorrectly assumed independent samples (0.06826), the team began using an X, or Individual, chart to plot the mean and standard deviation of the samples. This resulted in a sigma of 0.07834, giving wider limits.

Control Chart Example

The JMP Control Chart platform can presummarize data, such as the wafer samples, and plot the results. Run the control charts again as follows:

1. Select **Graph > Control Chart**.
2. Select Photolithography as the Process variable and LOT_# as the Sample Label.
3. Change the chart type to IR (Individual Measurement), as shown in Figure 29.
4. Check the Presummarize box.
5. Check both On Group Means and On Group Standard Deviations.

The charts in Figure 30 show that only one point fails test 1.

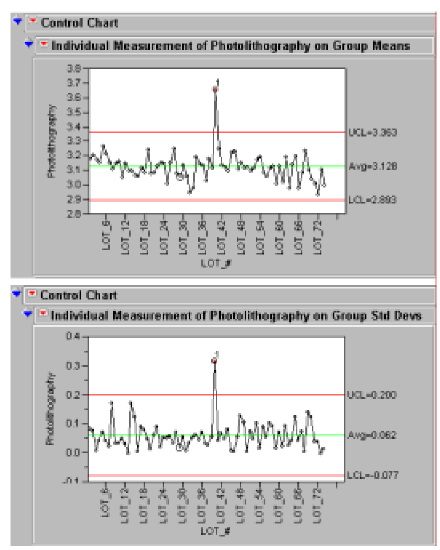


Figure 30: Individual (IR) charts for wafer data. Only one point failed test 1.

(continued)

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Further examination shows that only one chip within Lot 40 had a high value. The remaining points fell well within the upper and lower bounds.

The team then focused on the variability within wafers, making the chips more consistent across a wafer and bringing down the overall standard deviation. Reducing the within-wafer error ultimately moved the process into Six Sigma standard capability.

Notes

The data used in this article were obtained from Czitrom and Spagon (1997).

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Czitrom, V., and Spagon, P. "Statistical Case Studies for Industrial Process Improvement," *ASA-SIAM Series on Statistics and Applied Probability*. Philadelphia, PA, 1997.

About JMPer Cable

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JMPer Cable is mailed to JMP users who are registered users with SAS Institute. It is also available online at www.jmpdiscovery.com.

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