A lean approach to Measurement Systems Analysis

A JMP data visualization case study

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Abstract
Measurement System Analysis (MSA) is a prerequisite to top-notch experimentation, but sometimes economic pressures force us to do more with less and it's common to leave a formal MSA out of work plans. This paper suggests an alternate way forward – a lean approach that lets us use data collected for an experiment to also do a measurement *sanity check*.

Thankfully, JMP's unique implementation of Donald Wheeler's EMP III approach to MSA[1] allows us to do a measurement sanity check in lieu of a full MSA when we have a compelling reason to cut corners. The measurements made on replicate runs in a Designed Experiment are first visualized and then analyzed, providing valuable insight on the performance of our measurement system. If the quality of the replicate run data is poor, the collected data are chalked up to an MSA or process in need of further study. If the data quality is good, we continue with our analysis of the experiment data. This is a risk-free, no-cost shortcut done as an integral part of the experimental work.

The remainder of this paper describes a case study about the development of a new polymer orthotic brace design similar to the one shown in Figure 1. The case study has a dual emphasis on the EMP III measurement sanity check and the use of JMP's powerful data visualization tools to overcome obstacles. It is hoped that the reader can use this MSA shortcut and perhaps some of the data visualization methods described and to that end, the focus is on practical application, not theory.

Figure 1: Ankle-foot orthotic brace

Case Study Background

Note: this case study is based on actual events, but confidentiality requires modification of experiment details.

A team had to develop a new orthotic brace for a customer with difficult technical and commercial targets. Immediate orders were available so with the right design and process, significant margins were attainable. However once the inaugural order was placed, liquidated damages applied for late delivery, so the team was anxious about possible startup problems.

Machine time and raw materials were available for development work, but the team has to succeed within the limitations of existing production equipment and stock raw materials. As expected, they were also under heavy management pressure to minimize resource consumption. The design itself was novel, so the team had no experience or historical precedence on which to launch their work. To top it all off, the team was specifically told to skip a formal Measurement Systems Analysis.

This was a pressure-packed assignment that demanded lean thinking…

The Product & Process

Orthotic braces are used to treat a range of walking dysfunctions and are usually custom fit to each patient by a medical practitioner. The process used to make these braces include the following steps:

- ✓ Cast the patient's foot and prescribe the brace
- ✓ Create a mold to duplicate the patient's foot
- ✓ Modify the mold for therapeutic purposes
- ✓ Vacuum form the brace over the mold
- ✓ Fine finish the brace.

The first step is done by the practitioner while the other steps are usually done by a centralized brace fabrication facility.

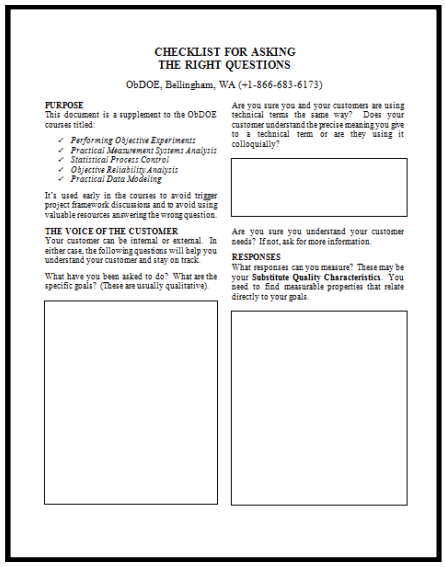
The Team

The development team was non-traditional as it consisted of an R&D Engineer, a Production Manager, a Process Engineer, an Inspector and some experienced Line Operators. The open-minded company management thought that a wide range of skills were needed to assure long term success and further believed it was important to develop people at all organizational levels.

Defining the Goal

This may seem like a trivial point, but experience strongly indicates that answering the wrong question is a common mistake in industrial experimentation. Knowing this, the team listened carefully to the Voice of the Internal Customer and to the Voice of the External Customer and began formulating their plan. Aided by a handy document titled *Checklist for Asking the Right Questions*[2] (Figure 2) their plan began to take shape.

For those that might find it useful, the checklist is available at www.obdoe.com.



CHECKLIST FOR ASKING
THE RIGHT QUESTIONS

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PURPOSE
This document is a supplement to the ObDOE courses titled:

- ✓ *Performing Objective Experiments*
- ✓ *Practical Measurement Systems Analysis*
- ✓ *Statistical Process Control*
- ✓ *Objective Reliability Analysis*
- ✓ *Practical Data Modeling*

It's used early in the courses to avoid trigger project framework discussions and to avoid using valuable resources answering the wrong question.

THE VOICE OF THE CUSTOMER
Your customer can be internal or external. In either case, the following questions will help you understand your customer and stay on track.

What have you been asked to do? What are the specific goals? (These are usually qualitative).

Are you sure you and your customers are using technical terms the same way? Does your customer understand the precise meaning you give to a technical term or are they using it colloquially?

Are you sure you understand your customer needs? If not, ask for more information.

RESPONSES
What responses can you measure? These may be your **Substitute Quality Characteristics**. You need to find measurable properties that relate directly to your goals.

Figure 2: ***Checklist for asking the right questions***

The Strategy & the Tactics

The basic strategy for the development work was simple:

Run a few….predict the rest.

Being knowledgeable about DOE, the team chose to move forward with a quadratic I-Optimal design created with JMP's Custom DOE designer. They noted with much satisfaction that I-Optimal DOE is itself very lean as it maximizes return on experimental resources and allows inclusion of a user-specified number of replicate runs. JMP does not force the experimenter to suffer the costs of full replicates or the limitations of replicating only center points. Strategy in hand, the team discussed tactics and gained consensus on the best way forward.

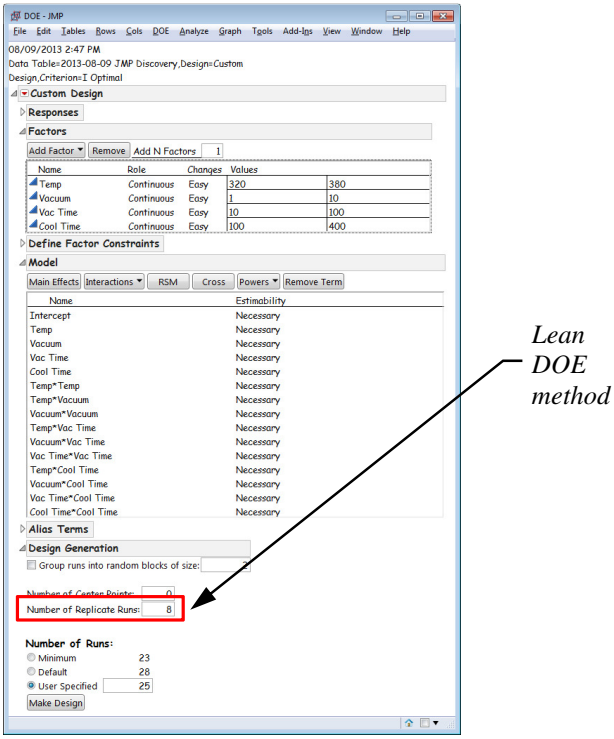
Experimental Factors & Responses

The team designed its experiment with 4 factors – temperature, vacuum, vacuum time and cooling time. The team maximized predictive ability by setting the factor ranges at the widest levels allowed by the equipment. The experiment had 2 responses - one technical response to be maximized (*Maximize This*) and one commercial response to be minimized (*Minimize That*)

Replication

The team knew that measuring response variation was critical so they decided on 8 replicate runs,

noting that the JMP Custom DOE designer allows easily augmentation of the design for more replicates, if needed. The experimental design input screen is shown in Figure 3. Note the *Number of Replicate Runs* field as it is a main advantage of I-Optimal DOE.



Lean DOE method

Figure 3: Design input screen

Figure 4 is the experiment plan. Only 25 trials are needed, <u>including the 8 replicate runs</u>.

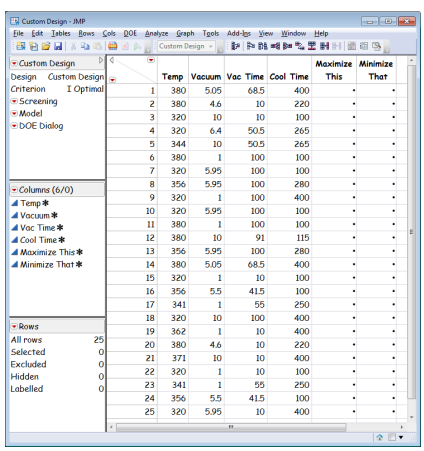


Figure 4: Experimental plan

At this point, the team had to get management approval for resources, a formidable barrier due to the understandable reluctance to spend money and disrupt production. However, the team had 2 barrier busters firmly in hand.

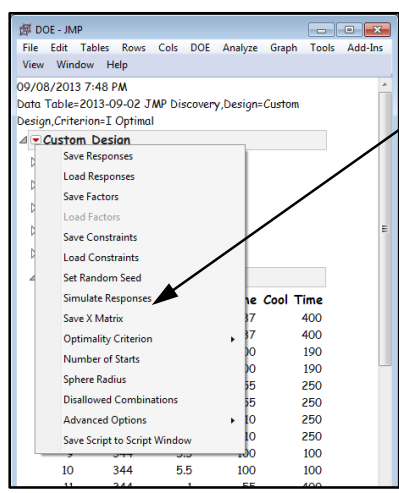
Barrier Buster #1

The team was focused on optimizing key physical brace properties but they knew that a design that was too costly to sell was pointless. So, by including *Minimize That* (i.e. cost) as an experimental response, they clearly demonstrated to the financial decision-makers their balanced technical-commercial approach to the product development work. The result was to ease the usual friction between those needing resources and those making the financial decisions.

Barrier Buster #2

Fortunately, JMP provides a simple way to anticipate the inevitable and important management question *what will success look like.*

Specifically, the team used JMP's Simulate Response feature (Figure 5) to simulate response data along with their design so they could "analyze" and visually demonstrate their experimental end game to the company CEO and CFO before beginning the experiment. The team explained how JMP's Sorted Parameter Estimates, Interaction Plots and other visual tools can provide profitable insight into a production process. And, the team did a live demonstration of JMP's Prediction Profiler showing how they could balance the technical & commercial goals.



Financial barrier cruise missile

Figure 5: Simulate response data

Implement the Plan

While it was tempting to immediately execute the approved plan, the team knew that good DOE practices include consideration of an important prerequisite – **checking the measurement system.** And, they were painfully aware of the technical risks associated with the management decision to skip a formal MSA.

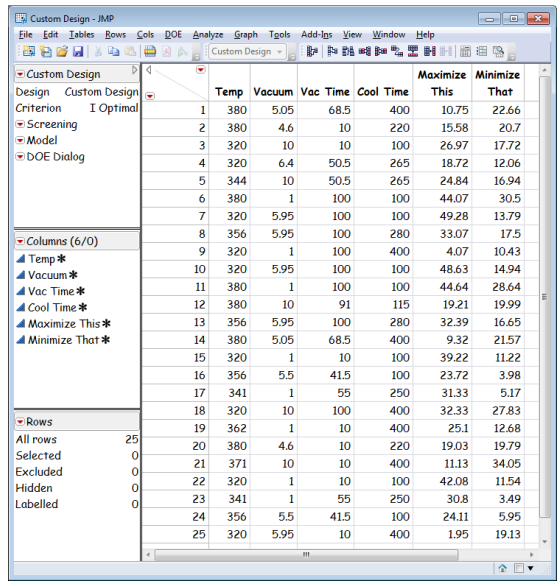
Validate measurement system (Part 1 of 2)

The team understood the decision to skip a formal MSA (*after all, they are full factorial experimental designs themselves!*) but they dreaded their vulnerability to misinterpretation of experiment results. Fortunately, JMP's Variability Chart and Dr. Donald J. Wheeler's EMP III method provided the perfect solution. Simply stated, the team planned to use their 8 replicate runs to do a measurement system sanity check. This approach also had another important advantage – that EMP III is probability-based and devoid of arbitrary decision rules. Their approach was risk-free and cost only a bit of time.

Collect the experimental data

When the team began running the experimental trials, they were asked by supervisory staff to perform the trials in batches. They were asked to run all Temp = 300°F first, the Temp = 340°F next, etc. The team used the JMP Custom DOE designer to visually walk the supervisors step-by-step through the experimental setup to explain where the random order came from. They further explained why randomization is important to negate the possible effect of variables that were not included as experimental factors – ambient temperature or material variation, for example. The supervisors understood and agreed. Again, JMP visualization saved the day.

Figure 6 shows the simulated response data. Note for example, that Trial 1 and 14 are the same set of conditions. These replicate runs present a fine opportunity for a measurement sanity check.



	Temp	Vacuum	Vac Time	Cool Time	Maximize This	Minimize That
1	380	5.05	68.5	400	10.75	22.66
2	380	4.6	10	220	15.58	20.7
3	320	10	10	100	26.97	17.72
4	320	6.4	50.5	265	18.72	12.06
5	344	10	50.5	265	24.84	16.94
6	380	1	100	100	44.07	30.5
7	320	5.95	100	100	49.28	13.79
8	356	5.95	100	280	33.07	17.5
9	320	1	100	400	4.07	10.43
10	320	5.95	100	100	48.63	14.94
11	380	1	100	100	44.64	28.64
12	380	10	91	115	19.21	19.99
13	356	5.95	100	280	32.39	16.65
14	380	5.05	68.5	400	9.32	21.57
15	320	1	10	100	39.22	11.22
16	356	5.5	41.5	100	23.72	3.98
17	341	1	55	250	31.33	5.17
18	320	10	100	400	32.33	27.83
19	362	1	10	400	25.1	12.68
20	380	4.6	10	220	19.03	19.79
21	371	10	10	400	11.13	34.05
22	320	1	10	100	42.08	11.54
23	341	1	55	250	30.8	3.49
24	356	5.5	41.5	100	24.11	5.95
25	320	5.95	10	400	1.95	19.13

Figure 6: Experimental plan with simulated data

Check: is the standard deviation "constant"?

Models assume that response standard deviation is "constant" at the repeated experimental points. There are 3 methods used to evaluate the homogeneity of the standard deviation. They are ① the Normal Probability Plot, ② the Residuals-by-Predicted Plot and ③ the Box-Cox Plot. The team was delighted that all 3 methods are visually-based. If 2 out of 3 pass the evaluation, then the team could assume the response variation to be constant. If 2 or more fail the test, the team might have to transform the response data.

Figure 7 is the Residuals-by-Predicted Plot. When reviewing this plot, the team looked for patterns that might indicate the standard deviation is not constant. Fortunately, this plot indicated no such patterns. Visual evaluation of the Normal Probability Plot and Box-Cox Plots provided good results a well and the team concluded that the standard deviation is indeed constant and that they could proceed.

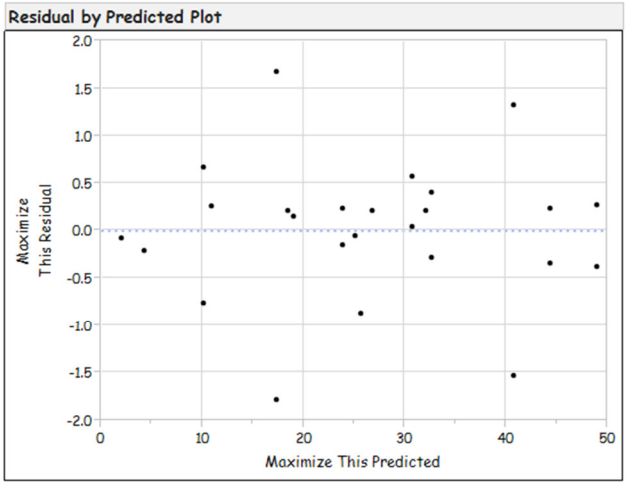


Figure 7: Residuals by Predicted for *Maximize This*

Validate measurement system (Part 2 of 2)

Upon review of the experiment data, the team ran into a problem. To perform the measurement sanity check, they needed an identifier to match the replicate runs together. Again, JMP provided a simple barrier buster and the team wrote a column formula as shown in Figure 8. Figure 9 shows the experimental plan with the trial identifier. (Note: a JMP Add-in to create the trial identifier is available at www.obdoe.com)

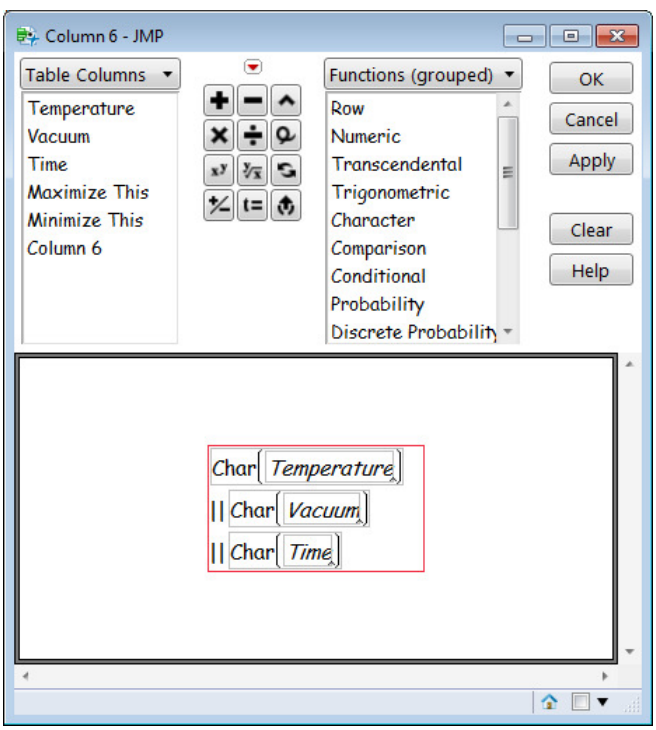
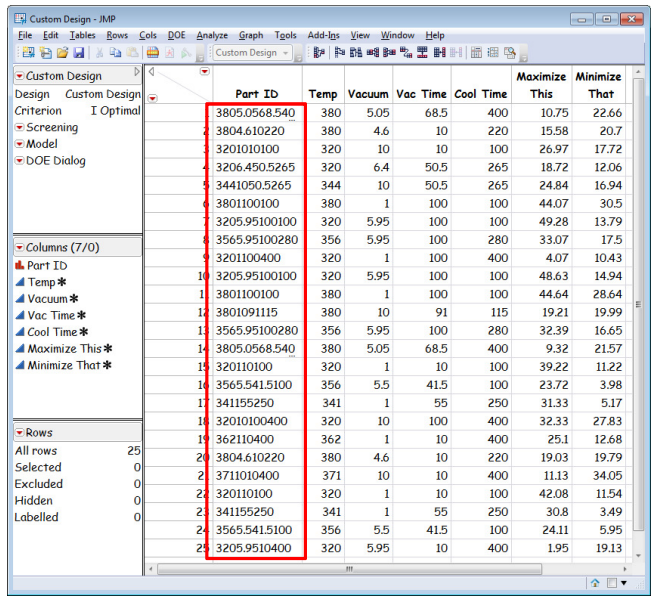


Figure 8: Column formula to create trial ID number



	Part ID	Temp	Vacuum	Vac Time	Cool Time	Maximize This	Minimize That
1	3805.0568.540	380	5.05	68.5	400	10.75	22.66
2	3804.610220	380	4.6	10	220	15.58	20.7
3	3201010100	320	10	10	100	26.97	17.72
4	3206.450.5265	320	6.4	50.5	265	18.72	12.06
5	3441050.5265	344	10	50.5	265	24.84	16.94
6	3801100100	380	1	100	100	44.07	30.5
7	3205.95100100	320	5.95	100	100	49.28	13.79
8	3565.95100280	356	5.95	100	280	33.07	17.5
9	3201100400	320	1	100	400	4.07	10.43
10	3205.95100100	320	5.95	100	100	48.63	14.94
11	3801100100	380	1	100	100	44.64	28.64
12	3801091115	380	10	91	115	19.21	19.99
13	3565.95100280	356	5.95	100	280	32.39	16.65
14	3805.0568.540	380	5.05	68.5	400	9.32	21.57
15	320110100	320	1	10	100	39.22	11.22
16	3565.541.5100	356	5.5	41.5	100	23.72	3.98
17	341155250	341	1	55	250	31.33	5.17
18	32010100400	320	10	100	400	32.33	27.83
19	362110400	362	1	10	400	25.1	12.68
20	3804.610220	380	4.6	10	220	19.03	19.79
21	3711010400	371	10	10	400	11.13	34.05
22	320110100	320	1	10	100	42.08	11.54
23	341155250	341	1	55	250	30.8	3.49
24	3565.541.5100	356	5.5	41.5	100	24.11	5.95
25	3205.9510400	320	5.95	10	400	1.95	19.13

Figure 9: Experiment plan with Part ID

With everything in place, the team ran their sanity check on the replicate runs. Defaulting to the visual, they first checked the Variability Chart as shown in Figure 10. This simple graph provided a fine overview of all of their response data and put their ability to replicate results into good visual perspective. They also used the Variability Chart to clearly explain results to staff not directly involved with the work.

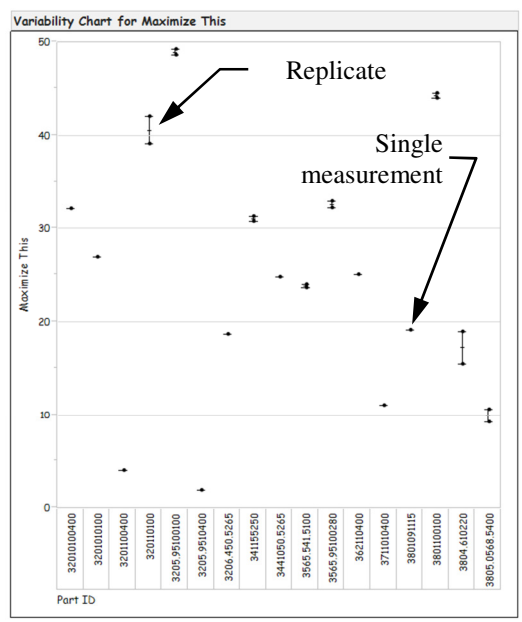


Figure 10: Variability Chart

The Variability Chart is informative, but it provides no way to numerically assess the

measurement system. JMP's EMP results (Figure 11) provided this necessary insight as follows.

EMP Results

EMP Test	Results	Description
Test-Retest Error	1.2354	Within Error
Degrees of Freedom	8	Amount of information used to estimate within error
Probable Error	0.8333	Median error for a single measurement
Intraclass Correlation	0.9948	Proportion of variation attributed to part variation

System Classification	
Current	First Class

Monitor Classification Legend

Classification	Intraclass Correlation	Attenuation of Process Signal	Probability of Warning, Test 1 Only*	Probability of Warning, Tests 1-4*
First Class	0.80-1.00	Less than 11%	0.99 - 1.0	1.0
Second Class	0.50-0.80	11% - 29%	0.88 - 0.99	1.0
Third Class	0.20-0.50	29% - 55%	0.40 - 0.88	0.92 - 1.0
Fourth Class	0.00-0.20	More than 55%	0.03 - 0.40	0.08 - 0.92

* Probability of warning for a 3 standard error shift within 10 subgroups using Wheeler's tests.

Figure 11: EMP Results for *Maximize This*

Test-Retest Error

The Test-Retest Error sheds numerical light on measurement repeatability. Normally, the Test-Retest error is used to evaluate operator repeatability, but for the EMP sanity check, we use it to better understand experimental response repeatability. In this case, the Test-Retest Error is 1.24 and quite small compared to the range of the experimental response variables. The team had good corroboration on their conclusions from the Variability Chart.

Probable Error

The Probable Error, introduced by Wilhelm Bessel in the early 1800's, is the standard deviation times 0.675 and is widely used in the EMP III measurement method instead of the standard deviation. Figure 12 is a visualization of the simple rationale behind the Probable Error calculation.

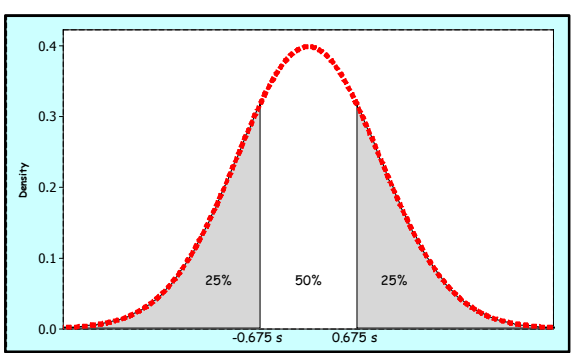


Figure 12: Distribution of measurement errors

In words, Probable Error is the median error for a single measurement. In this case, half of the measurement errors will be greater than 0.83 and half will be less than 0.83. The Probable Error compares favorably with the 2-50 range of values for *Maximize This.*

Intraclass Correlation

The Intraclass Correlation indicates the proportion of measurement variation that comes from repeat trials ("parts") rather than from the measurement system itself. The team noted a highly satisfactory value of 0.9948.

System Classification

The EMP III method provides a probability-based classification for the measurement system. In this case, the First Class Gauge classification gave the team a useful, probability-based assessment of their replicate runs.

Effective Resolution

JMP also provides information and recommendations regarding the effective resolution of the measurement system as shown in Figure 13. The team found that they could drop a digit from their measurements and make their data more meaningful.

Effective Resolution

Source		Value	Description
Probable Error	(PE)	0.6557	Median error for a single measurement
Current Measurement Increment	(MI)	0.01	Measurement increment estimated from data (in tenths)
Lower Bound Increment	(0.1*PE)	0.0656	Measurement increment should not be below this value
Smallest Effective Increment	(0.22*PE)	0.1442	Measurement increment is more effective above this value
Largest Effective Increment	(2.2*PE)	1.4424	Measurement increment is more effective below this value

Action: Drop a digit

Reason: The measurement increment of 0.01 is below the lowest measurement increment bound and should be adjusted to record fewer digits.

Figure 13: EMP III, effective resolution

A tough question from the boss

As it turned out, the company Engineering Director had automotive experience and was used to reviewing Gauge R&R data in the AIAG format. JMP has a visual summary specifically for that type of person as shown in Figure 14.

EMP Gauge R&R Results

Component	Std Dev	Variance Component	% of Total	20406080
Gauge R&R	1.235390	1.52619	0.517	
Repeatability	1.235390	1.52619	0.517	
Reproducibility	0.000000	0.00000	0.0	
Product Variation	17.136463	293.65835	99.5	
Interaction Variation	0.000000	0.00000	0.0	
Total Variation	17.180935	295.18454	100.0	

Figure 14: AIAG-style summary table

Check: does the model appear useful?

The Actual by Predicted plot provided a visual way to assess the ability of the model. The results were good (Figure 15).

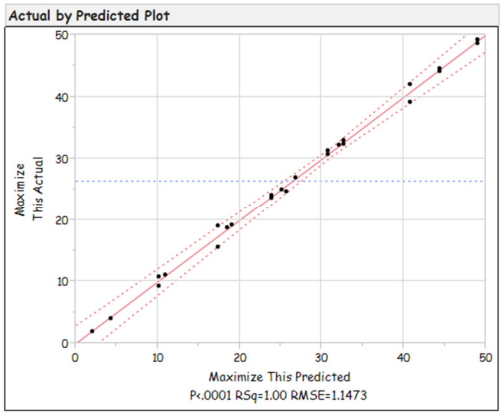


Figure 15: Actual by Predicted Plot

Gain process insight

The team pondered JMP's copious Fit Model output as a superb opportunity to gain valuable new process knowledge. For example, as shown in the Sorted Parameter Estimates (Figure 16), the team learned that the Cool Time and Vac Time main effects were the most significant on *Maximize This*. Conversely, the team also noted that the Temp*Vac Time interaction and Cool Time*Cool Time were least significant.

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Cool Time(100,400)	-9.00105	0.304559	-29.55	<.0001*
Vac Time(10,100)	6.916416	0.304957	22.68	<.0001*
Temp*Cool Time	6.6501681	0.357409	18.61	<.0001*
Temp*Vacuum	-6.871355	0.422915	-16.25	<.0001*
Vacuum*Cool Time	5.3855865	0.388362	13.87	<.0001*
Vacuum*Vac Time	5.0719734	0.399008	12.71	<.0001*
Vacuum*Vacuum	6.274606	0.526046	11.93	<.0001*
Vacuum(1,10)	-3.410766	0.335423	-10.17	<.0001*
Vac Time*Vac Time	6.0070911	0.614382	9.78	<.0001*
Temp(320,380)	-2.940415	0.308391	-9.53	<.0001*
Temp*Temp	-5.853776	0.634946	-9.22	<.0001*
Vac Time*Cool Time	-2.70379	0.356722	-7.58	<.0001*
Cool Time*Cool Time	-3.463395	0.599213	-5.78	0.0002*
Temp*Vac Time	-0.957093	0.358777	-2.67	0.0236*

Figure 16: Terms sorted by significance, *Maximize This*

The team also gained valuable insight into their process using the Interaction Profiler as shown in Figure 17. The team instantly saw a number of interactions for the *Maximize This* response variable including one between Temp and Vacuum. The team realized the profound value of this insight as process knowledge that's usually not found in an equipment manual and rarely learned by trial and error.

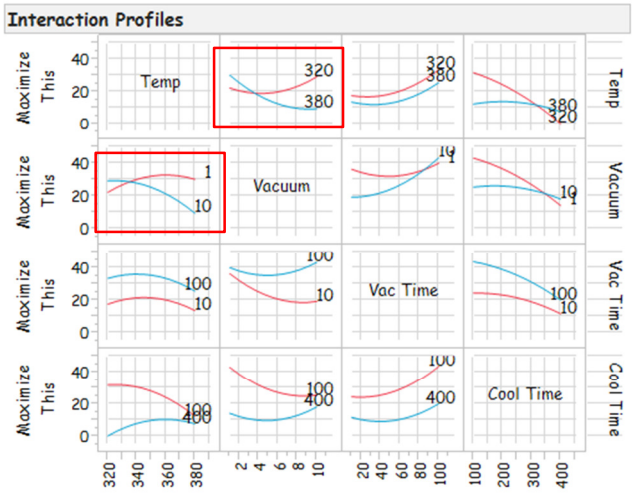


Figure 17: Interaction Profiler for *Maximize This*

Find a sweet spot

The highly visual JMP Prediction Profiler, shown in Figure 18, allowed the team to visualize different combinations of factor settings and instantly see the effect on their 2 response variables. After discussions and lively debate, the team, CEO and CFO reached consensus on the right balance between the *Maximize This* (Temp of 340°F, a Vacuum setting of 3, a Vac Time of 50, Cool Time of 130) and cost. At this point, everyone involved felt an overwhelming, gratifying level of accomplishment.

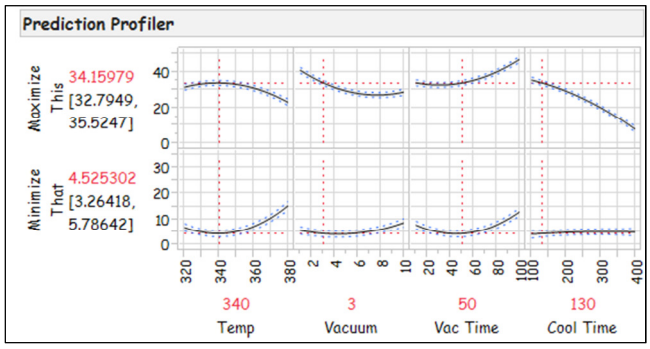


Figure 18: Prediction Profiler

Test the model and sweet spot
The next logical step was for the team to determine the prediction interval and use it to validate the model and the sweet spot. The validation was successful.

Another pause to gain process insight
Never passing on an opportunity to visualize data and gain more and more process insight, the team ran a Monte Carlo Simulation of 20,000 runs at the chosen sweet spot and visualized the distribution of the simulated results. This provided the team with an early indication of process capability. See Figure 19.

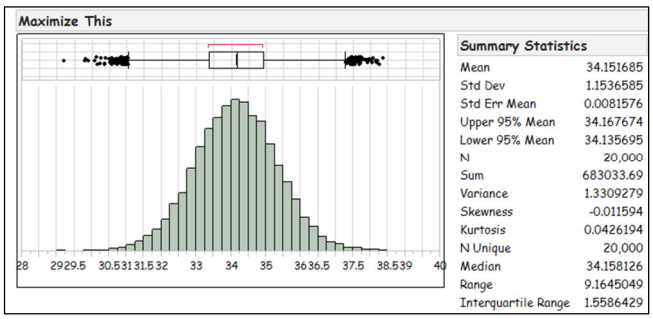


Figure 19: Results of Monte Carlo simulation

Step 5, Celebrate Success & Monitor Progress

The team did not view this work as a "project", per se, but rather as the beginning of many iterative cycles of learning about their new brace design and process. Hence, there was more work to do.

Process Behavior Study
The team was on a roll. They had valuable new knowledge in hand and a new process making high quality orthotic braces, creating happy customers and spinning profits. But they knew that entropy is merciless and that keeping the process running profitably required continuous learning and continuous improvement. Now was not the time for the team to take its eye off the proverbial ball. They needed a way to monitor their process.

The team settled on the use of an X-bar-R process behavior chart generated with JMP's Control Chart Builder. This chart is very visual as shown in Figure 20 and, most importantly, it was kept at the production line and reviewed multiple times per day by Line Operators and Supervisors. Should the process begin to shift or indicate unexpected variation, everyone would know quickly and they could avoid mass production of unacceptable braces.

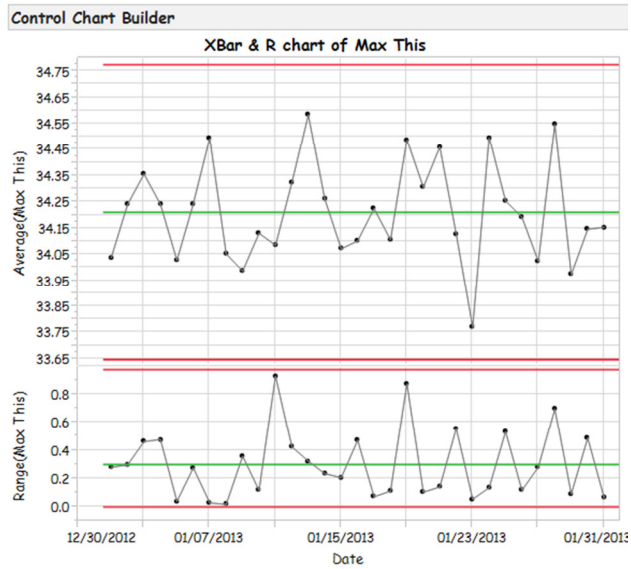


Figure 20: Voice of the Process, visualized

The team, recalling a video[5] they saw during their *Lean Statistical Thinking* workshop, realized that the data collected, analyzed and annotated by the Line Operators was a veritable gold mine of useful information. With that in mind, the team continuously examined the performance of the new process, annotated process changes and observed the effects of the process changes. As a result of their efforts, they further improved the process, further reduced waste and added much valuable knowledge on equipment maintenance to their ongoing Total Productive Maintenance program. Over time, additional iterative experiments were run to gain further process understanding, qualify new materials and reduce process variation.

Case Study Conclusion

I-Optimal DOE is a powerful tool that's useful across a broad range of industries and is well suited to lean manufacturing. EMP III is a superb Measurement Systems Analysis tool that should be used to fully evaluate measurement noise prior to the start of development work. But when MSA resources are unavailable, EMP III can also be

used to do a measurement systems sanity check on their experimental data and give a useful indication of measurement system performance.

Epilogue

The unusual makeup of the team presented a challenge even before the development work got started as some personnel were unfamiliar with the statistical methods deemed essential for the work. Instructional methods were sought to help these folks master the basics they'd need to participate up to their full potential.

A good first step

Many recent books on process improvement methods[3,4] provide convincing example after convincing example of the power of data visualization and with that in mind, the team leader arranged a hands-on workshop in *Lean Statistical Thinking*. The workshop started with a simple, visual exercise using pencil, eraser and a blank XMR process behavior chart (Figure 21). From this exercise, the team members learned firsthand the power of data visualization and why it was necessary to constantly think about separating possible signals from probable noise.

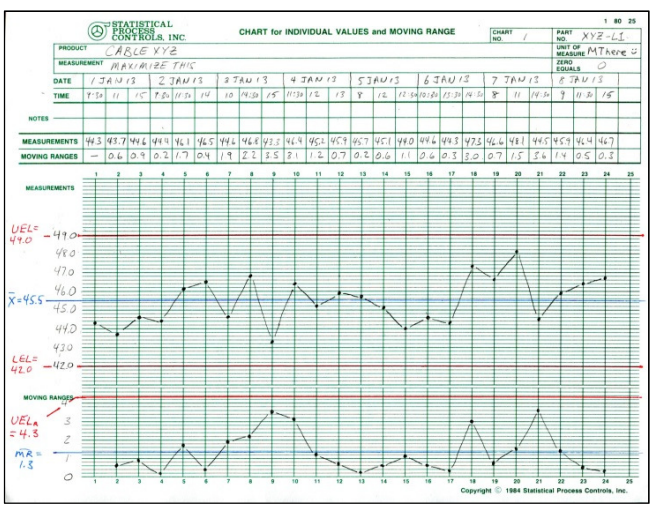


Figure 21: An effective barrier buster

Lean Statistical Thinking Exercise

Meanwhile, Anscombe's Quartet (Table 1) provided the team with a fine demonstration of the grave dangers lurking in data analysis based solely on descriptive statistics.

Table 1: Anscombe's Quartet

X1	Y1	X2	Y2	X3	Y3	X4	Y4
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89

<u>For all XY pairs in Table 1</u>

- ✓ X1, X2, X3, X4, Mean = 9.00, StDev = 3.317
- ✓ Y1, Y2, Y3, Y4, Mean = 7.50, StDev = 3.032

From a descriptive statistics viewpoint, all 4 paired datasets are equal. However, when viewed with JMP scatterplots (Figure 22), the team saw a remarkably different picture.

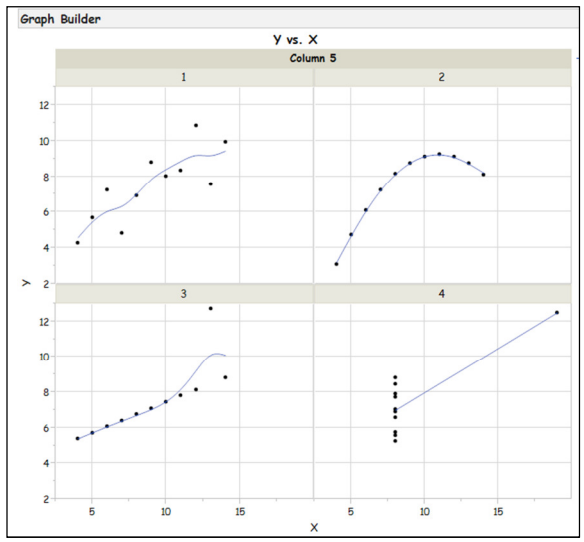


Figure 22: An effective team visualization exercise

The team leader found the Anscombe's Quartet visualization exercise so useful, he called it his *visualization slam dunk for beginners.*

From these and similar data visualization exercises, the team progressed inexorably from their historical reliance on descriptive statistics to enlightened data-driven discussion to the successful development work described above.

A Final Thought…

The author and his colleagues at ObDOE hope all readers found this case study provided at least

one idea that will help you overcome barriers and make your experiments leaner. Thanks for your time.

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