ROBUST OPTIMIZATION: SOME TOOLS BASED IN JMP® TO ENHANCE TRADITIONAL TAGUCHI METHODS

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ABSTRACT AND INTRODUCTION: WHY ROBUST OPTIMIZATION?

The idea behind Taguchi Robust Optimization experiments is very powerful: Given the product or process we are trying to optimize, there are some factors we can't control (or are difficult or expensive to control). Taguchi calls these noise factors and places them in an outer array which create the replicates in each row of the control factor DOE (or inner array). The signal-to-noise ratio (S/N ratio) analysis method is used to find the 'sweet spot' in the design where performance is minimally sensitive to variation of the noise factors.

								Noise Factors					
	Control Factors							N1		N2			
Run	A	B	C	D	E	F	G	Q1	Q2	Q1	Q2	SN	Mean
1	1	1	1	1	1	1	1	17.0	34.5	17.8	16.9	7.9	21.55
2	1	2	2	2	2	2	2	26.3	27.4	28.0	38.2	14.7	29.98
3	1	3	3	1	3	2	1	39.2	43.4	42.5	41.9	27.3	41.75
4	2	1	1	2	2	2	1	17.4	25.0	24.1	31.1	12.8	24.40
5	2	2	2	1	3	1	1	31.5	17.5	28.0	36.6	10.9	28.40
6	2	3	3	1	1	2	2	46.5	47.9	35.4	42.2	17.7	43.00
7	3	1	2	1	3	2	1	22.5	26.6	23.0	25.5	21.9	24.40
8	3	2	3	2	1	2	1	29.9	27.0	22.8	26.7	19.2	26.60
9	3	3	1	1	2	1	2	30.6	22.7	33.6	28.5	15.9	28.85
10	4	1	3	1	2	2	1	26.0	44.0	25.9	16.7	7.8	28.15
11	4	2	1	1	3	2	2	28.7	26.0	24.6	25.3	23.3	26.15
12	4	3	2	2	1	1	1	35.9	53.1	40.2	21.5	9.2	37.68
13	5	1	2	1	1	2	2	21.5	36.2	17.5	21.1	9.3	24.08
14	5	2	3	1	2	1	1	26.9	23.5	31.4	18.9	13.6	25.18
15	5	3	1	2	3	2	1	37.1	24.4	30.9	53.0	9.4	36.35
16	6	1	3	2	3	1	2	22.0	27.0	18.2	15.5	12.3	20.68
17	6	2	1	1	1	2	1	22.0	29.5	39.1	40.1	11.6	32.68
18	6	3	2	1	2	2	1	47.8	35.1	38.6	48.5	16.1	42.50

Inner array   Outer array

Fig. 1 – Example of a Taguchi DOE matrix with control and noise factors

Taguchi developed a menu of orthogonal arrays for the inner array (control factors). They are designed to break up interaction confounding patterns, they are efficient (can run lots of factors with minimal runs), and allow multiple levels per factor. However, there are some limitations of the traditional techniques (which have been around for 50 years):

- The Taguchi inner arrays do not allow for estimating interactions in control factors.
- The control factors have to be fitted to one of the Taguchi 'cookbook' arrays, which often results in empty columns and wasted resources (in contrast to JMP's Custom Design tool, which fits the most efficient matrix to the exact experimental factors).

- Traditional Taguchi examples don't lend themselves to more complex outer arrays for the noise factors (more on this later).

- Commercially available statistical software often is not very flexible for Taguchi DOE's, requiring manual Excel-based analysis for many experiments.

- The S/N ratio analysis method lacks traditional statistical metrics for separating signal from noise in the experiment (no 'p-values' are created).

This paper demonstrates how various tools in JMP can help alleviate the limitations in this list.

ALTERNATIVE TO 'COOKBOOK' ORTHOGONAL ARRAYS

Suppose we want to run the following experiment (all factor levels are categorical):

- 1 control factor with 2 levels and 7 control factors with 3 levels, 8 control factors total. (This would fully utilize a Taguchi $L_{18}\{2^1 \times 3^7\}$ orthogonal array, one of the more popular and useful of the Taguchi menu arrays.)

Let's create the DOE using the JMP Custom Design tool, using the above factor assumptions.

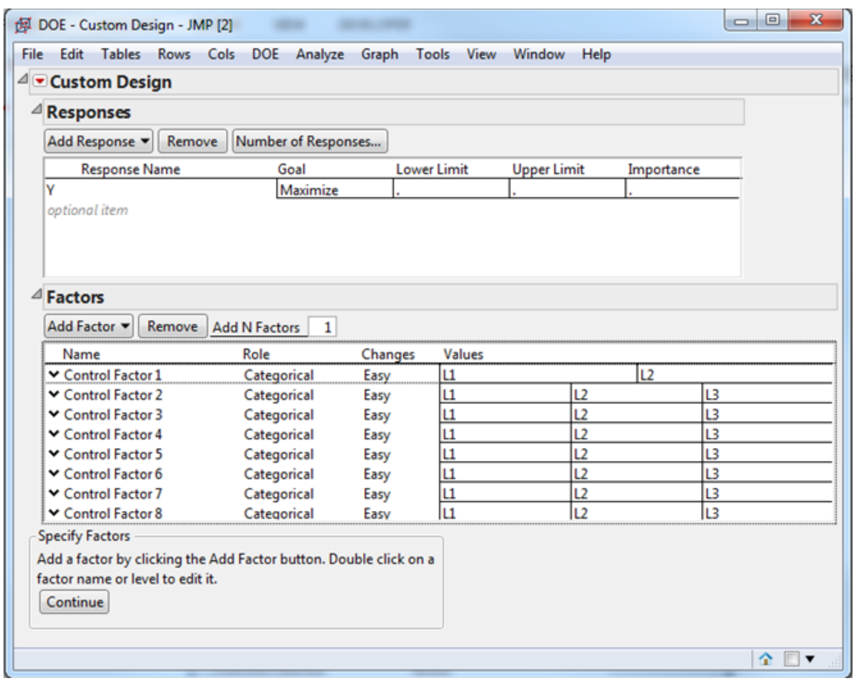
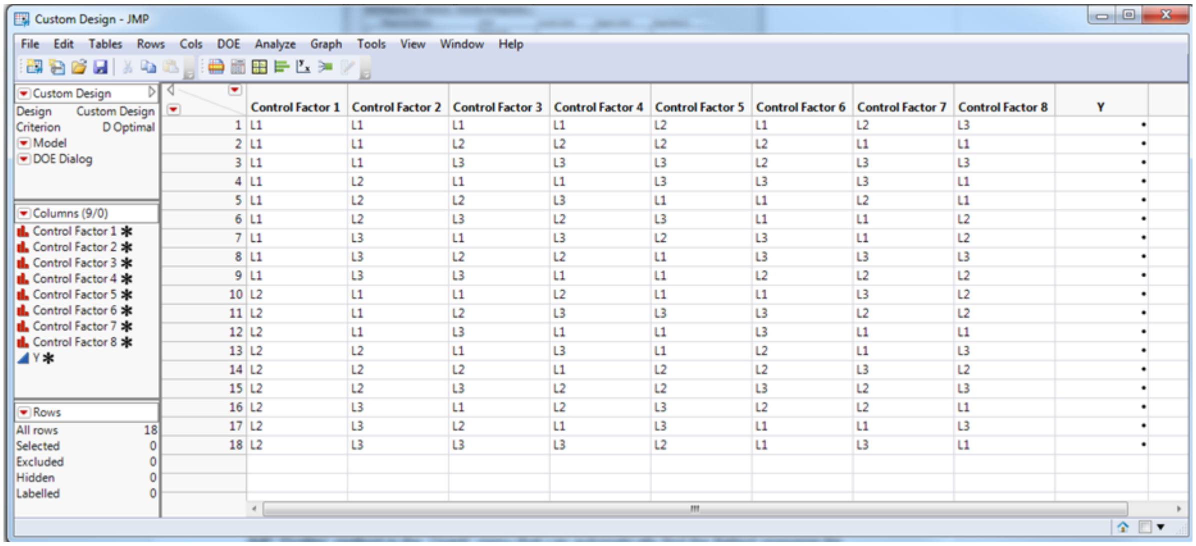


Fig. 2 – Custom Design Dialog Box, with 8 control factors

When the above settings are used to create a table, JMP chooses 18 runs as the default; <u>exactly the same</u> number of runs as a Taguchi $L_{18}(2^1 \times 3^7)$ orthogonal array. The resultant matrix is not identical to the Taguchi L_{18}, but it's close. It appears the Custom Design tool essentially replicated the $L_{18}(2^1 \times 3^7)$ orthogonal array (with minor differences in the fraction chosen from the full factorial space).



	Control Factor 1	Control Factor 2	Control Factor 3	Control Factor 4	Control Factor 5	Control Factor 6	Control Factor 7	Control Factor 8	Y
1	L1	L1	L1	L1	L2	L1	L2	L3	•
2	L1	L1	L2	L2	L2	L2	L1	L1	•
3	L1	L1	L3	L3	L3	L2	L3	L3	•
4	L1	L2	L1	L1	L3	L3	L3	L1	•
5	L1	L2	L2	L3	L1	L1	L2	L1	•
6	L1	L2	L3	L2	L3	L1	L1	L2	•
7	L1	L3	L1	L3	L2	L3	L1	L2	•
8	L1	L3	L2	L2	L1	L3	L3	L3	•
9	L1	L3	L3	L1	L1	L2	L2	L2	•
10	L2	L1	L1	L2	L1	L1	L3	L2	•
11	L2	L1	L2	L3	L3	L3	L2	L2	•
12	L2	L1	L3	L1	L1	L3	L1	L1	•
13	L2	L2	L1	L3	L1	L2	L1	L3	•
14	L2	L2	L2	L1	L2	L2	L3	L2	•
15	L2	L2	L3	L2	L2	L3	L2	L3	•
16	L2	L3	L1	L2	L3	L2	L2	L1	•
17	L2	L3	L2	L1	L3	L1	L1	L3	•
18	L2	L3	L3	L3	L2	L1	L3	L1	•

Fig. 3 – Custom Designer generated inner array (sorted left to right)

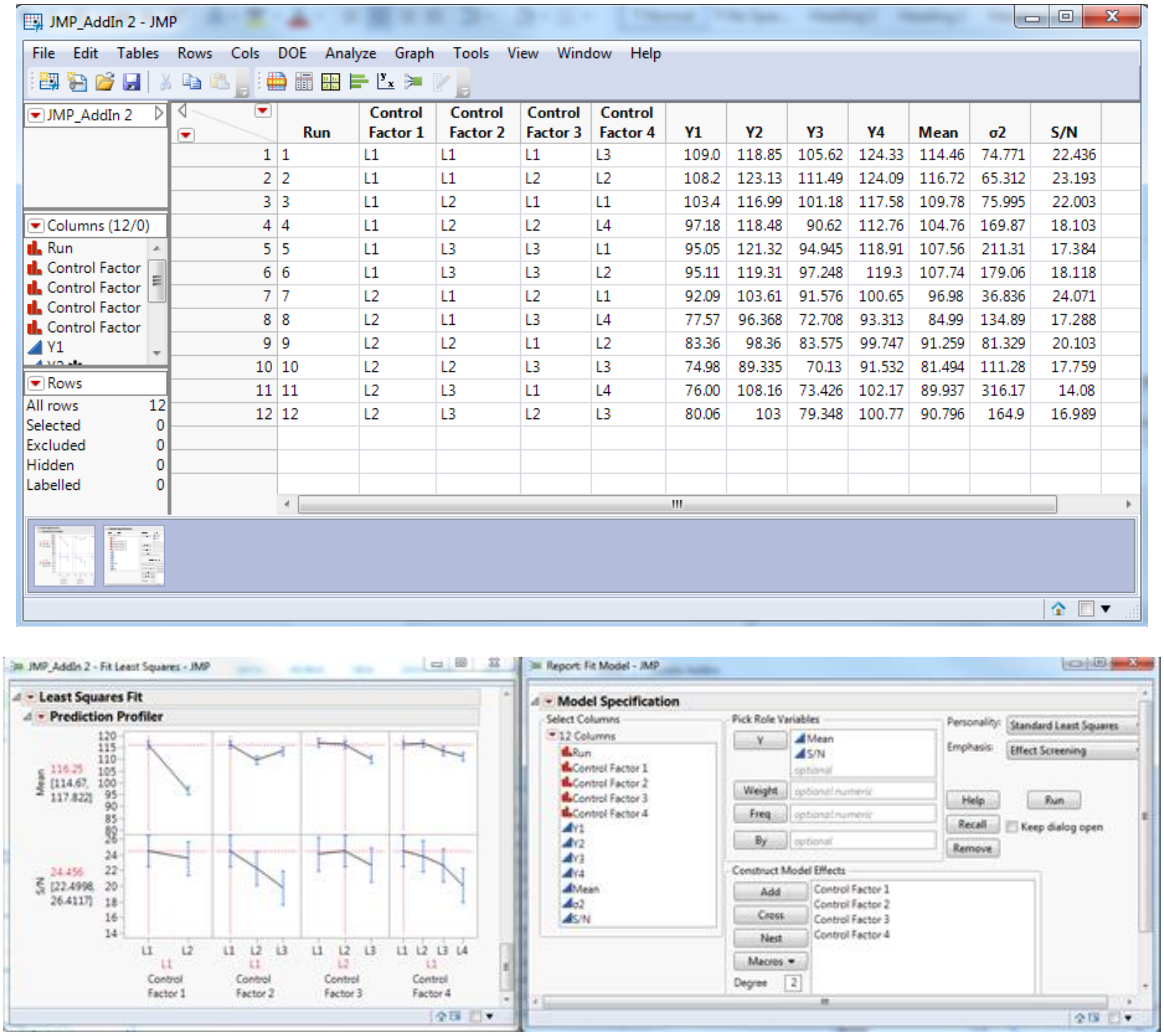
Note that a similar exercise can be used to create the outer array, which contains the noise factors. On some experiments, the outer array will be fairly simple. For more complex scenarios, with multiple noise factors and possibly with more than two levels per factor, the Custom Designer is a great tool for creating an outer array with minimal runs. An outer array created in this fashion is simply applied to each row in the inner array. The arrays can be exported to Excel to be joined together for the experiment.

This example demonstrates that inner arrays created by the JMP Custom Design tool can yield the same functionality as the Taguchi 'cookbook' arrays – with the important advantage that the array will be fitted to the chosen factors and levels rather than forcing the factors into a table from a book. Using the Custom Design tool also allows the flexibility to include interactions in the inner array, if those are of interest in the specific experiment being planned.

An additional JMP feature that can assist with the traditional Taguchi analysis is creating the mean and S/N ratio graphs from the DOE after the results have been recorded. After the experiment is executed and the resulting data entered into an Excel table, the mean and S/N ratio columns are calculated as usual. This completed DOE table can then be exported to JMP, and the Fit Model with Profiler can be used to create the mean and S/N graphs, eliminating the need to do the manual Excel calculations to create these graphs. (For those not familiar with the S/N ratio analysis method, the entries in the S/N column are calculated for each row using the formula below. The entries are in units of dB or decibels.)

$$\frac{S}{N} = 10\log\left(\frac{\bar{y}^2}{\sigma^2}\right)$$

where 'y-bar' is the average of all the noise factor entries in that row and σ^2 is the variance of those entries. The goal is to maximize the S/N ratio.)



Run	Control Factor 1	Control Factor 2	Control Factor 3	Control Factor 4	Y1	Y2	Y3	Y4	Mean	σ2	S/N
1	L1	L1	L1	L3	109.0	118.85	105.62	124.33	114.46	74.771	22.436
2	L1	L1	L2	L2	108.2	123.13	111.49	124.09	116.72	65.312	23.193
3	L1	L2	L1	L1	103.4	116.99	101.18	117.58	109.78	75.995	22.003
4	L1	L2	L2	L4	97.18	118.48	90.62	112.76	104.76	169.87	18.103
5	L1	L3	L3	L1	95.05	121.32	94.945	118.91	107.56	211.31	17.384
6	L1	L3	L3	L2	95.11	119.31	97.248	119.3	107.74	179.06	18.118
7	L2	L1	L2	L1	92.09	103.61	91.576	100.65	96.98	36.836	24.071
8	L2	L1	L3	L4	77.57	96.368	72.708	93.313	84.99	134.89	17.288
9	L2	L2	L1	L2	83.36	98.36	83.575	99.747	91.259	81.329	20.103
10	L2	L2	L3	L3	74.98	89.335	70.13	91.532	81.494	111.28	17.759
11	L2	L3	L1	L4	76.00	108.16	73.426	102.17	89.937	316.17	14.08
12	L2	L3	L2	L3	80.06	103	79.348	100.77	90.796	164.9	16.989

Fig. 4 – A Taguchi DOE with data, calculated mean and S/N columns, with Fit Model dialog box and the Prediction Profiler

With the DOE table in JMP, simply put the mean and S/N columns in as responses and the control factors as factors in the Fit Model dialog box, and create the profilers for both metrics.

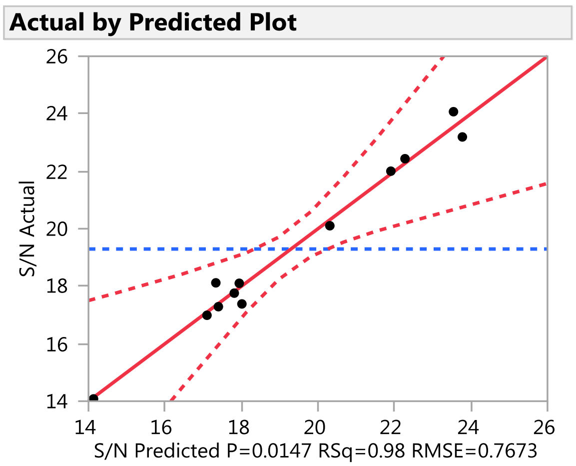
- Note these JMP graphs will be slightly different than the hand-calculated graphs. JMP is using the least-squares model rather than the actual data in the profiler; manual Excel calculations use the data. The differences are minor and only affect non-significant factor levels.

HOW ELSE CAN JMP HELP US WITH TAGUCHI EXPERIMENTS?

We have seen how the JMP Custom Design tool can help create more efficient inner and outer arrays. We have also demonstrated how JMP Fit Model can help automate the mean and S/N graphing analysis. Can JMP help with anything else? Recall one of the issues with the Taguchi

S/N ratio analysis method is the lack of traditional statistical metrics to separate signal from common cause variation.

Doing the analysis in JMP yields a solution to that problem. See Fig. 5 below for the Fit Model analysis from the above example. With a good RSquare fit in the regression plot, the ANOVA table showing statistical significance, and the Effect Tests table indicating Control Factors 2 and 4 as contributors to the S/N signal, we have a statistical metric that something is going on.



Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	8	99.45571	12.4320	21.1186
Error	3	1.76602	0.5887	Prob > F
C. Total	11	101.22173		0.0147*

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Control Factor 1	1	1	2.227050	3.7832	0.1470
Control Factor 2	2	2	40.746231	34.6085	0.0085*
Control Factor 3	2	2	6.615889	5.6193	0.0967
Control Factor 4	3	3	30.509915	17.2761	0.0214*

Fig. 5 – Actual by Predicted Plot with ANOVA and Effects Tests table for S/N ratio response

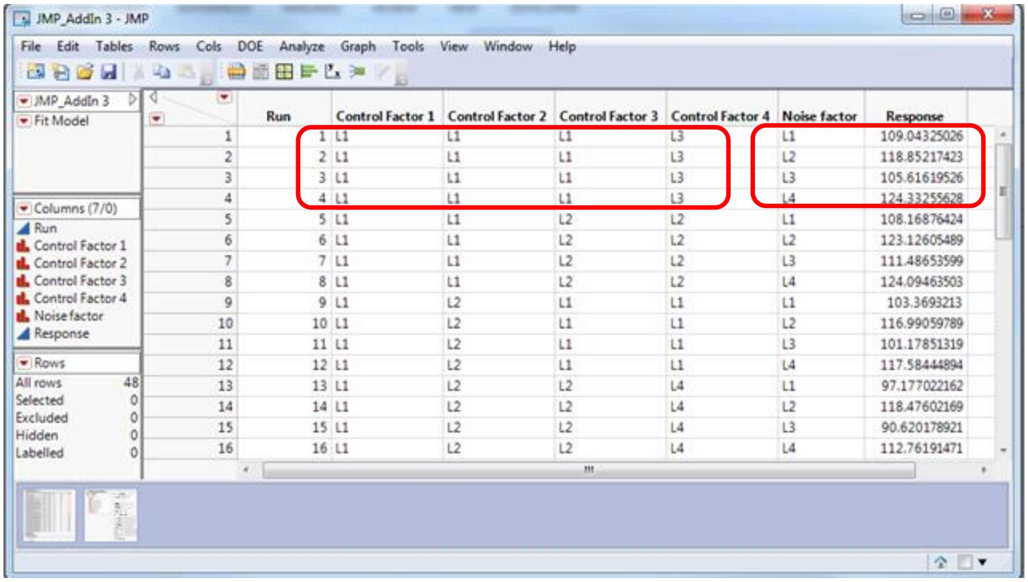
An alternate method for analyzing Taguchi DOEs

To consider another method to gain additional insight, we start by restating the goal of robust optimization in traditional DOE language:

- In Taguchi language: We want to find settings of the control factors that minimize the effect of the noise factors on the output.
- In traditional DOE language: We want to discover where there are interactions between the control factors and noise factors, and set the control factors to minimize the effect of those interactions on the output.

Given the way we have re-stated the problem, how might JMP assist in enhancing the Taguchi approach? The following example will demonstrate. (There are papers in the literature on the subject of combined array designs vs. inner-outer array designs. The example below is one method of doing combined array which specifically utilize the tools available in JMP.)

We start by creating a new table in JMP containing the same data as in the above example, but in this table, we will transpose the outer array data into a single column and create replicates for each inner array row to match up with the transposed data, as shown below. (Note that in this example, we are starting with an existing Taguchi inner-outer array. When designing a new experiment, the user can either design the inner and outer arrays separately and marry them as in this example, or utilize the individual crossing function in the Fit Model dialog boxes to create a single matrix with the control vs. noise factor interactions shown below. In the examples I evaluated, it resulted in the same number of runs, so this is a personal preference issue.)



	Run	Control Factor 1	Control Factor 2	Control Factor 3	Control Factor 4	Noise factor	Response
1	1	L1	L1	L1	L3	L1	109.04325026
2	2	L1	L1	L1	L3	L2	118.85217423
3	3	L1	L1	L1	L3	L3	105.61619526
4	4	L1	L1	L1	L3	L4	124.33255628
5	5	L1	L1	L2	L2	L1	108.16876424
6	6	L1	L1	L2	L2	L2	123.12605489
7	7	L1	L1	L2	L2	L3	111.48653599
8	8	L1	L1	L2	L2	L4	124.09463503
9	9	L1	L2	L1	L1	L1	103.3693213
10	10	L1	L2	L1	L1	L2	116.99059789
11	11	L1	L2	L1	L1	L3	101.17851319
12	12	L1	L2	L1	L1	L4	117.58444894
13	13	L1	L2	L2	L4	L1	97.177022162
14	14	L1	L2	L2	L4	L2	118.47602169
15	15	L1	L2	L2	L4	L3	90.620178921
16	16	L1	L2	L2	L4	L4	112.76191471

Fig. 6 – DOE data from Fig. 4 with outer array transposed and each row of inner array replicated to match transposed outer array data

With this table in JMP, we launch another Fit Model window. The response goes in the usual place, and for model effects, we include all the factors, including noise factor(s). Recalling the note above about how we are interested in interactions between the control and noise factors, we cross the noise factor with each control factor as shown in the dialog box below.

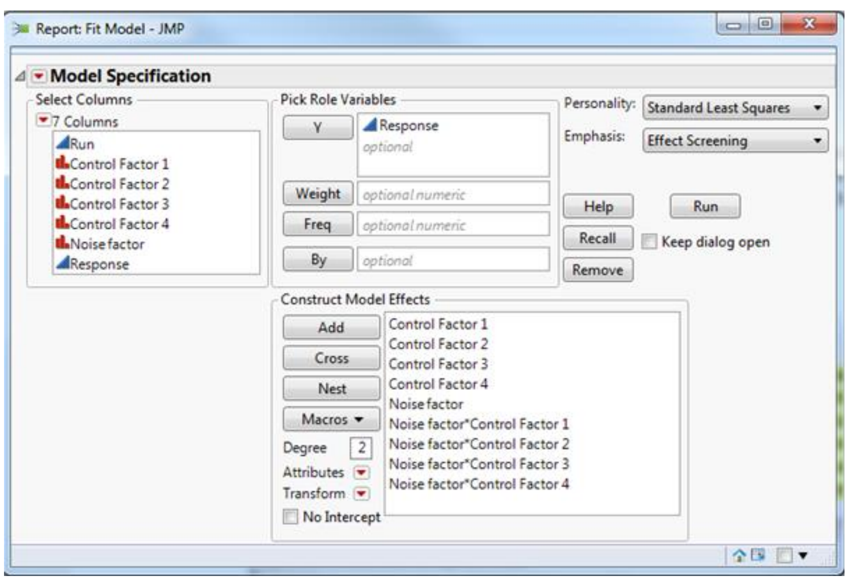
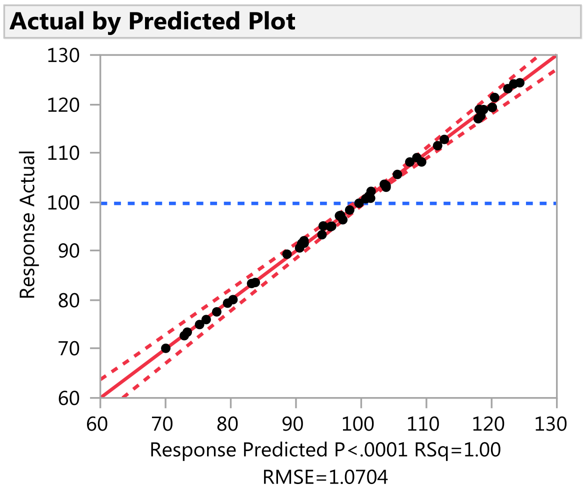


Fig. 7 – Dialog box for transposed data

Note the selection of “Effect Screening” for Emphasis.

As with any Fit Model run, a menu of various statistical analyses are made available. Fig. 7 shows the residual plot and ANOVA table, which indicate a good model fit and that signals exist in the data.



Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	35	11100.241	317.150	276.8246
Error	12	13.748	1.146	**Prob > F**
C. Total	47	11113.989		<.0001 *

Fig. 8 – Residual plot and ANOVA table

A new table in JMP 12, the Effect Summary, is shown in Fig. 8. Examination of this table answers the question: “Which interactions between the control factors and noise factor(s) are statistically significant?” This confirms our original guess from examination of the S/N graph that Control Factors 2 and 4 have significant interactions with the noise factor – but the PValue gives us confidence that these signals are real and that Control Factors 1 and 3 have less effect.

Effect Summary

Source	LogWorth	PValue
Control Factor 1	15.492	0.00000
Noise factor	14.571	0.00000
Control Factor 3	9.060	0.00000
Control Factor 2	8.420	0.00000
Control Factor 4	6.836	0.00000
Noise factor*Control Factor 2	6.100	0.00000
Noise factor*Control Factor 4	4.749	0.00002
Noise factor*Control Factor 3	1.177	0.06651
Noise factor*Control Factor 1	0.529	0.29561

Fig. 9 – Effect Summary graph

There is one more useful exercise that we can do with this alternate analysis. Now that we know that Control Factors 2 and 4 have significant interactions with the noise factor, can we determine which control factor setting yields the best process with this alternate analysis method? Remember our goal is to set the control factors such that the contribution of the noise factor(s) are minimized. This is easily accomplished by utilizing the Profiler created with Fit Model. Simply stated, we want to choose the settings of the significant control factors (2 and 4) such that the plot from the noise factor is as flat as possible. Simply move the sliders of the significant control factors across the range until the noise factor graph is flattest. Note that this exercise yields the same result as choosing the maximum S/N ratio from the traditional analysis.

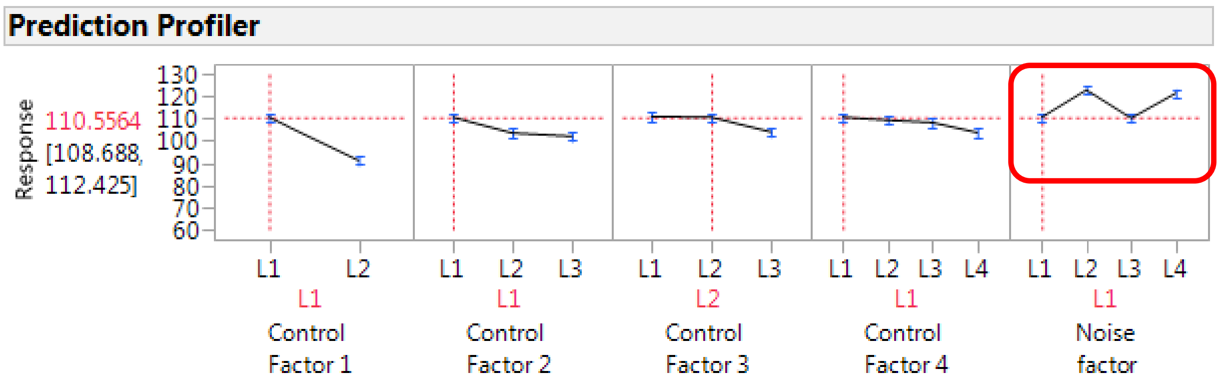


Fig. 10 – Profiler from experiment

Experienced JMP users will recall that there is an algorithm within the JMP 'Profiler' method in the 'Graph' menu that can automatically find the flattest response for noise factors. However, this only works if your noise factors are *numeric continuous*. As you will see, the specific Autoliv study discussed below required categorical noise factors.

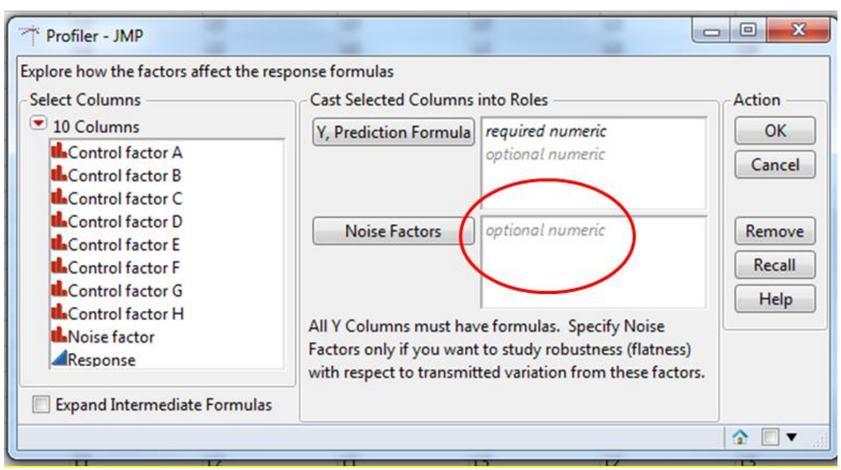


Fig. 11 – Noise factor function in JMP Profiler

Please see Appendix A for an example of why these statistical tests are important for analysis of robust optimization experiments, and an example where the alternate method yields a better prediction than the Taguchi S/N ratio analysis.

REAL WORLD EXAMPLE

Pyrotechnic airbag inflators utilize proprietary pyrotechnic chemicals to create rapid gas output for deploying automobile airbags. Repeatable performance (low variation) is essential to provide robust occupant restraint. Airbag inflator output is measured by deploying inside a sealed tank and recording the tank pressure output vs. time. Metrics of interest are:

- Onset (when the gas starts flowing after the electric signal is given)
- Rate of gas output during the deployment (referred to as slope)
- Maximum pressure when the reaction is complete

Inflator function is dependent on the chemical reactions of the various pyrotechnic materials, and also on the physical properties of mechanical components.

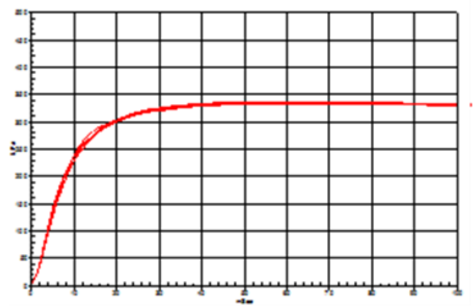


Fig. 12 – Typical sealed tank pressure curve from an airbag inflator

An important step in Taguchi Robust Optimization is determining the noise strategy. Most of the examples in the literature feature noise factors where the engineers have a good understanding of the effect of the noise factors on output, and can combine factors for a fairly simple outer array. But things are not always so simple. In this case, where we are looking at chemical reactions, the specific characteristics of components or materials which may cause a performance shift may not be measureable other than testing in the inflator.

In the case of optimization of an airbag inflator, Autoliv was interested in understanding how they could reduce the sensitivity of inflator output to lot-to-lot variation of certain influential components and pyrotechnic materials in production. We had a choice whether to use one of two different technologies for one of the components (both produced acceptable nominal performance).

We needed to answer the question: Which choice for the component in question would yield the most robust performance (least sensitive to lot-to-lot variation)?

For the inflator in question, four components were chosen to be included as noise factors in the outer array. These selections were plausible suspects, but it is important to note that we had to be exploratory; we didn't know for sure what the effect of lot-to-lot variation would be. One purpose of the DOE was to gain more specific understanding of these noise factors.

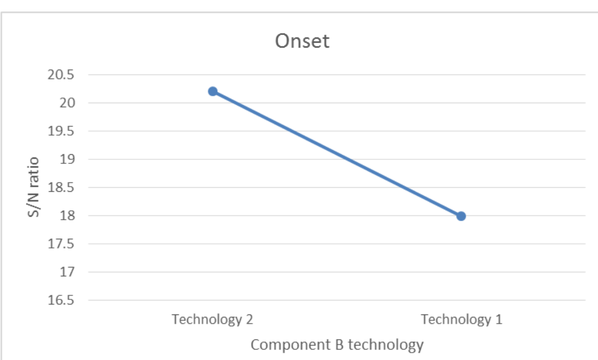
After giving the problem some thought, the team decided to pull samples from the production line once per week for six weeks, for each of the four selected components. This yielded an outer array of 4 noise factors, six levels per factor (4^6). The outer array was created using the JMP Custom Design tool. (Note that this experiment would not be feasible without using a relatively sparse array, given the number and levels of the noise factors. However, the JMP Custom Design tool makes this a trivial problem.) We chose an outer array with 92 runs for this experiment. (It could have been done with as few as 21.) Note this noise strategy is significantly more complex than typical examples of Taguchi DOE's in the literature.

For the control factors, the inner array was very simple: There was one factor with two levels. (Taguchi experiments with only one control factor are called "Robust Assessment" in the literature, but the evaluation method is identical.) For Component B, we wanted to know which of two technologies would result in an inflator that was least sensitive to lot-to-lot variation of the four components in the outer array.

Note that Component B is the control factor and is also one of the four factors in the outer array, so six lots of Component B were selected for each technology. 92 inflators were built and tested for each technology of Component B, or 184 total.

Fig. 9 shows the traditional Taguchi S/N analysis of the data (note the middle part of the DOE matrix has been hidden due to the width). Also, a few data cells are blank – one of the reasons we used more runs than were technically required was the probability of missing data. The dB gain for onset and slope metrics was significant, favoring Technology 2 for Component B. (Optimizing max pressure was not as important.)

Component B technology	Replicate #	1	2	3	4	88	89	90	91	92	σ	Mean	S/N	dB Gain
	Component A	F	A	E	C	C	C	D	B	C				
	Component B	A	D	D	A	B	F	E	D	B				
	Component C	C	A	B	F	D	B	A	E	F				
	Component D	A	C	A	B	C	D	E	F	A				
Technology 2	Onset	3.56	4.18	4.5	4.2	3.9	4.52	4.8	4.14	3.28	0.383329	3.92413	20.20344	**2.216331**
Technology 1		4.48	5.04	5.9	4.9	5.28	6.22			5.82	0.626224	4.966897	17.98711	
Technology 2	Max pressure	315	305	299	310	309	315	310	311	323	5.619654	311.0435	34.86223	**-1.69655**
Technology 1		314	312	317	316	311	311			320	4.653167	313.1034	36.55878	
Technology 2	Slope	8.90	8.52	8.31	8.86	8.68	9.40	8.18	8.86	9.18	0.398051	8.816175	26.90684	**2.40895**
Technology 1		9.37	8.55	9.01	8.85	8.64	8.34			8.36	0.523399	8.784706	24.49789	



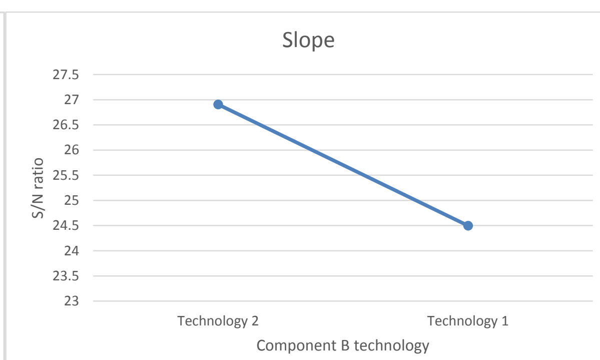


Fig. 13 – Taguchi S/N analysis of example

ANALYSIS OF DATA USING PROFILER METHOD IN JMP

The data from the above experiment was copied to a JMP data table (after transposing the outer array as noted above). The Fit Model dialog box was used to create the analysis; as before, crossing the control factor with each of the noise factors. Note ‘Emphasis’ is set to ‘Effect Screening’.

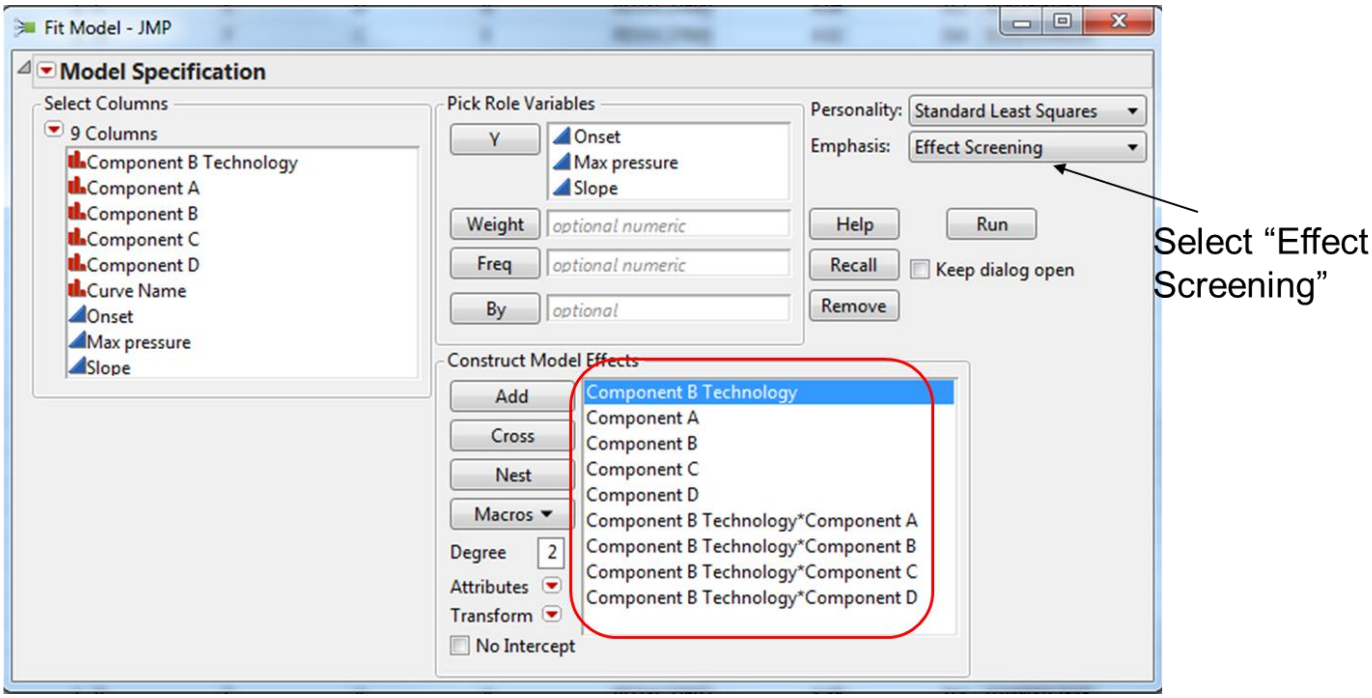


Fig. 14 – Fit Model dialog box of real world example. ‘Component B Technology’ is the control factor; Component A-D are noise factors

FIT MODEL OUTPUT

As noted above, the JMP analysis yield statistics that help decide whether any apparent signals are significant or not. Looking at the Effect Summary table, it shows some of the control factor to noise factor interactions are significant. (Other analysis tables, like the Sorted Estimates graph, are also useful for determining statistical significance.)

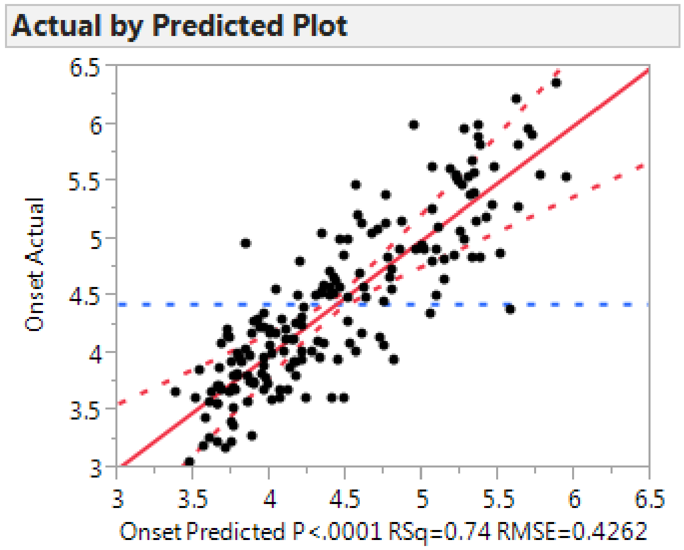


Fig. 15 – Residual plot shows relatively good model fit (onset shown)

Effect Summary

Source	LogWorth	PValue
Component B Technology	33.523	0.00000
Component C	9.779	0.00000
Component A	9.576	0.00000
Component B	1.584	0.02606
Component D	1.571	0.02683
Component B Technology*Component A	1.492	0.03222
Component B Technology*Component B	1.297	0.05049
Component B Technology*Component C	0.757	0.17507
Component B Technology*Component D	0.430	0.37140

Fig. 16 – Effect summary table show significant signals for the interactions

PROFILER ANALYSIS

In this example, there is only one control factor with two levels, so analysis is simple: we compare the noise factor profiles between Component B Technology 1 and Component B Technology 2. This analysis contains many interesting insights. Two are noted here:

- Refer to the green boxes below. Component A had an effect on onset; this was expected. Note also that the general 'shape' of the profile is similar between the top and bottom graphs. <u>However, the profile in the lower graph, Component B Technology 2, is significantly 'flatter' than with Component B Technology 1.</u> This is a clear sign that there is an interaction between Component A and Component B, and Component B Technology 2 dampens the effect of Component A lot-to-lot variation on the onset metric – exactly what we are looking for in a Robust Optimization DOE. This is especially surprising when you look at the profiles immediately to the right of the green highlighted cells: The lot-to-lot variation of Component B itself had little effect on variation of the onset metric.

- Referring to the red boxes below: The effect Component B lot-to-lot variation on the slope metric was significantly less with Technology 2 compared to Technology 1.

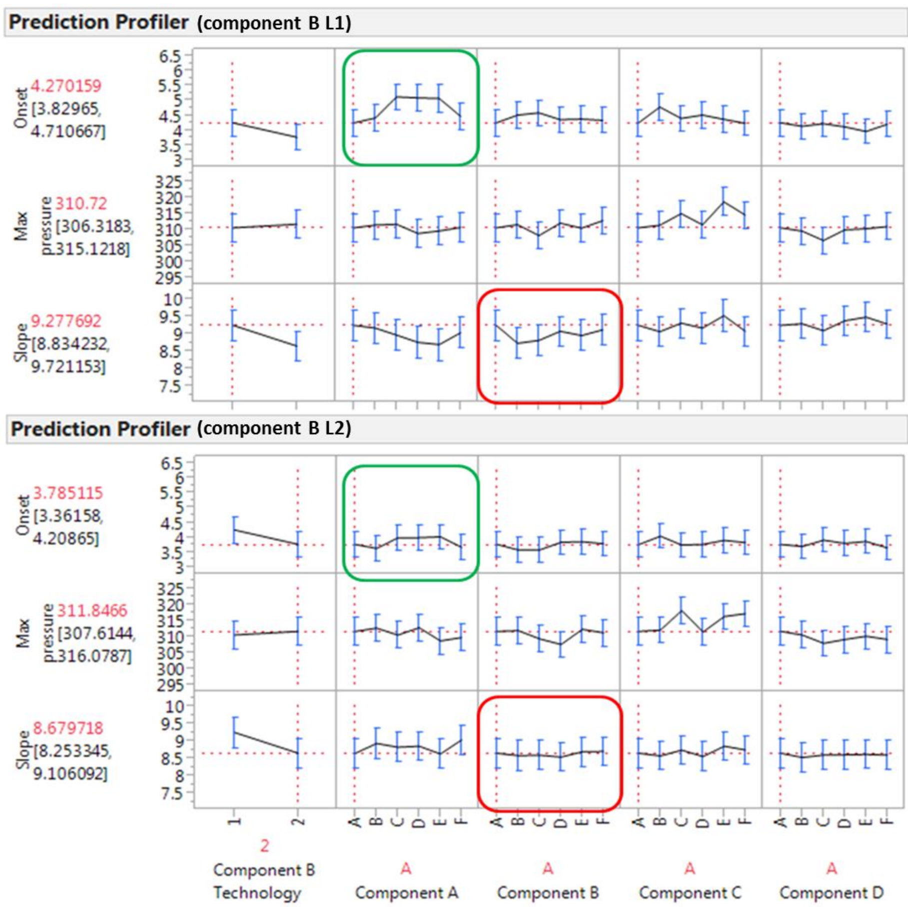


Fig. 17 – Profiler of example

There is an additional method to determine significance in addition to the statistical analysis provided automatically by Fit Model. In the red boxes above, the Profiler indicates that something is happening, but this wasn't strongly reflected by the p-values in the various Fit Model outputs for interactions in this case. However, using the profiler to capture the max and min slope values at each Component B Technology setting, and using the DF and mean square error values from the ANOVA table, a simple t-distribution calculation shows the min-max shift is significant with Technology 1 but not Technology 2.

Recalling the Taguchi S/N analysis above: The JMP based analysis agrees with the S/N ratio analysis that Component B Technology 2 is the better choice to minimize product variation for onset and slope. However, given the comparatively complex noise strategy, <u>the JMP Profiler analysis yielded significant detailed information about the noise factors which was not apparent from the simple Taguchi S/N ratio calculations</u>.

SUMMARY

Taguchi Robust Optimization is a powerful concept to create products and processes that are insensitive to variation in noise factors. The JMP-based analysis techniques presented here contribute several enhancements to the traditional S/N analysis method in the type of problems Autoliv deals with:

- Use of the Custom Design tool for the inner array allows more flexibility in choice of factors and less waste of resources (including selective investigation of two factor interactions).
- Use of the Custom Design tool for the outer array allows more flexibility in creating a noise strategy, <u>especially when the noise strategy is more complex</u>.
- Especially in the case of more complex outer arrays, the Profiler analysis method yields greater insight from the noise factors compared to the traditional S/N ratio method.
    - As noted earlier, example ‘Case Study 2’ in the Appendix demonstrates that with the specific data set, the Taguchi S/N method and the Profiler method do not agree, with the Profiler method producing the more correct answer.
- The JMP method provides statistical analysis of the output for significance.

A note for experienced Taguchi practitioners: Note this paper does not cover dynamic response DOE’s. We have not found good applications with airbag technology at Autoliv for dynamic response experiments. (Coming up with a rational ideal function where the input signal is energy stored in pyrotechnic chemicals is a problem we haven’t solved.) Figuring out how to extend these technique to dynamic DOE’s would be an interesting next step.

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APPENDIX – DISCUSSION OF IMPORTANCE OF STATISTICAL TESTS AND THE ALTERNATE METHOD FOR ANALYZING TAGUCHI EXPERIMENTS

Several dilemmas led to the following work in trying to better understand how to make the Taguchi Robust Optimization process more “robust”.

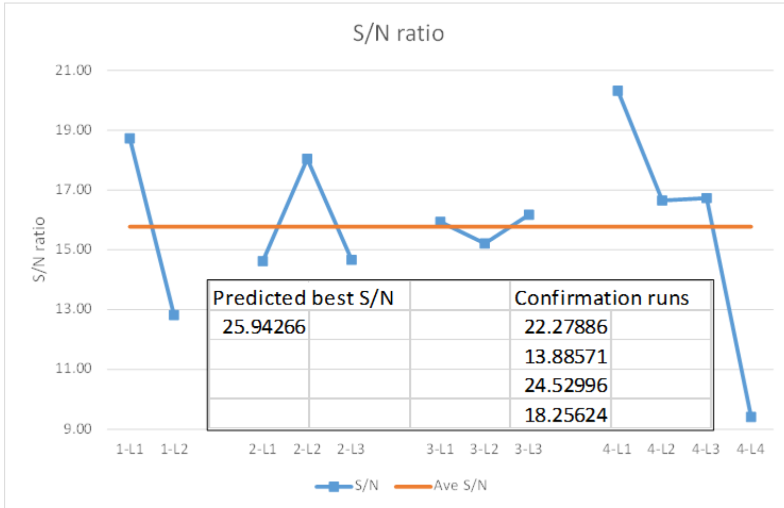
- Not infrequently when doing the confirmation runs for Taguchi DOE’s, the predicted S/N ratio gain does not replicate.
- While playing with simulated data in development of the main body of this paper, I stumbled onto a set of data where the traditional analysis of maximizing the S/N ratio and the alternate JMP-based Profiler analysis method gave very different answers. This was confusing. Was there something wrong, and how might the problem be detected? Which method actually gave the ‘right’ answer for this somewhat strange data set?

What follows will demonstrate how doing the extra analyses of Taguchi DOEs in JMP can find problems with data that can lead the experimenter astray.

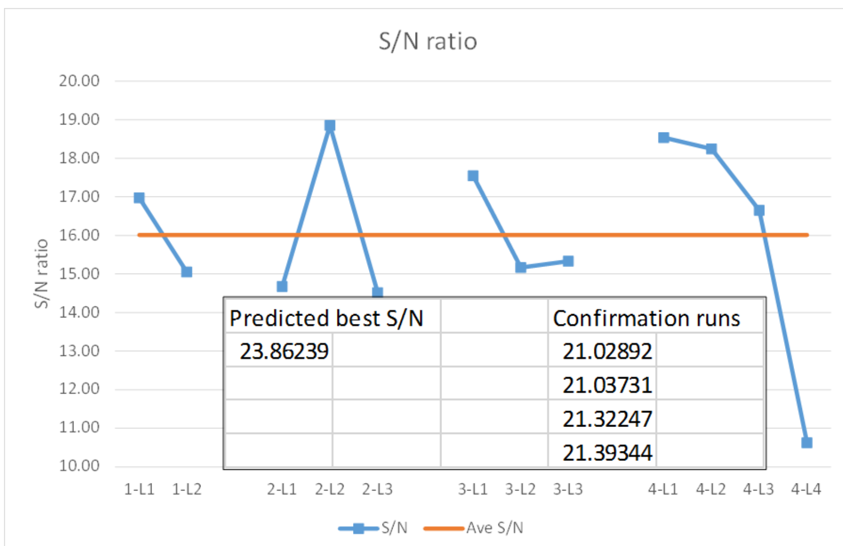
CASE STUDY 1

The following data comes from a simulation model using a Taguchi $L_{12}(2^1x3^3)$ categorical inner array, with a 4 level outer array. The overall mean of the model is set at 100. Common cause variation is simulated with a random number generator and a constant for sigma that can be changed to vary the magnitude of common cause variation. Lookup tables create the signals for the main effects and the noise factor/control factor interactions.

Two examples of data are shown below from the simulator. S/N ratio graphs were created for each example, a ‘best case’ prediction was made for each based on the best settings for the control factors per usual Taguchi practice, and then the simulator ran four confirmation runs to check against the prediction.



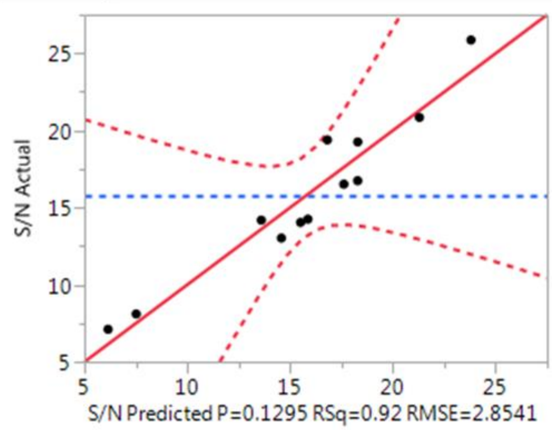
Example 1



Example 2

Although the S/N ratio graphs are similar between the two examples, note how much more consistent the confirmation runs were in Example 2 compared to Example 1. Can JMP help us understand the difference? For both examples, the Taguchi table was exported into JMP. With the S/N ratio output column as the response, below are the Actual by Predicted Plots for each, with the Summary of Fit and Analysis of Variance tables.

Actual by Predicted Plot



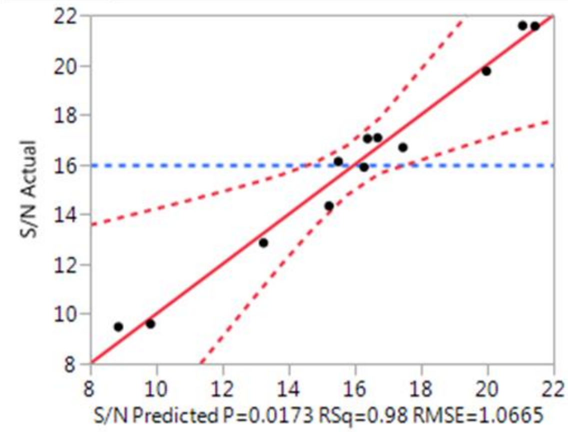
Summary of Fit

RSquare	0.919471
RSquare Adj	0.704727
Root Mean Square Error	2.854062
Mean of Response	15.77718
Observations (or Sum Wgts)	12

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	8	279.01906	34.8774	4.2817
Error	3	24.43701	8.1457	Prob > F
C. Total	11	303.45607		0.1295

Actual by Predicted Plot



Summary of Fit

RSquare	0.980494
RSquare Adj	0.928477
Root Mean Square Error	1.066486
Mean of Response	15.99334
Observations (or Sum Wgts)	12

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	8	171.51398	21.4392	18.8495
Error	3	3.41218	1.1374	Prob > F
C. Total	11	174.92616		0.0173*

The table on the left is Example 1, on the right is Example 2. Note two things especially: the "Prob > F" statistic and the Mean Square Error in the Analysis of Variance table.

The reader may have guessed by now the difference between the two examples: Everything in the simulator was the same except the magnitude factor for common cause standard deviation. The factor in Example 1 was set at 8; it was set at 2 for Example 2.

The rule-of-thumb tool for significance in the Taguchi method is any dB gain over 1 is worth investigating. The S/N ratio chart in Example 1 met this criteria for all the control factors except Control Factor 3. Example 1 predicted a significant signal for S/N ratio according to this rule of thumb. And yet, this did not predict the difficulty in replicating the results. The analysis in JMP did, by warning us that there was a great deal of common cause variation in the response.

Use of this simple tool in JMP should help prevent waste of resources attempting to replicate experimental results that are due mostly to chance causes.

CASE STUDY 2

The data below was a simulated data set from JMP, generated from a standard Taguchi $L_{18}(2^1x3^7)$ design selected from the 'Taguchi Arrays' tool in the DOE menu. Two noise factors were selected, and since noise factors in this tool only allow two levels, there were four columns in the outer array. For the purposes of the following analysis, the outer array was treated as one noise factor with four levels.

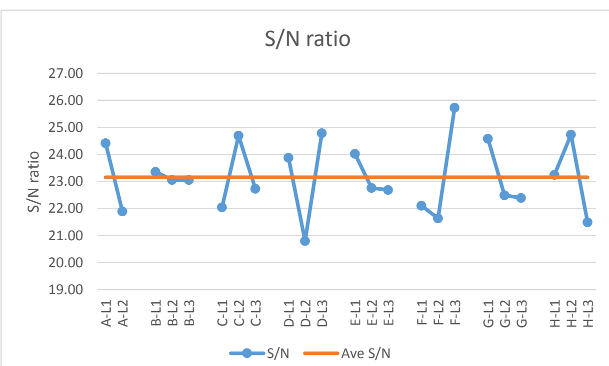
This particular simulated data set had some curious properties. When analyzed using the JMP-based Profiler method described above, it revealed that the noise factor/control factor interactions were just as numerous and had about the same magnitude as the main effects. It could easily be argued that this data set would never represent anything in the real world; however, it does highlight some striking differences between the traditional Taguchi analysis method and the 'minimize the noise factor profile' Profiler method described above.

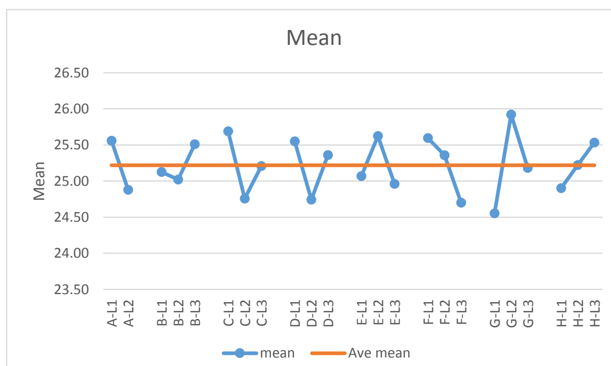
Here is the data table in Taguchi format from the simulator:

Run	Control Factor A	Control Factor B	Control Factor C	Control Factor D	Control Factor E	Control Factor F	Control Factor G	Control Factor H	Y1	Y2	Y3	Y4	Mean	σ2	S/N
1	L1	L1	L1	L1	L1	L1	L1	L1	27.27611	24.53889	25.49333	24.74333	25.51292	1.550076	26.23167
2	L1	L1	L2	L2	L2	L2	L2	L2	28.02611	25.84889	25.39333	23.84333	25.77792	2.983311	23.47797
3	L1	L1	L3	L3	L3	L3	L3	L3	23.82611	25.64889	24.37333	26.55333	25.10042	1.521431	26.1711
4	L1	L2	L1	L1	L2	L2	L3	L3	29.58778	25.17722	29.45	23.74	26.98875	8.882902	19.13811
5	L1	L2	L2	L2	L3	L3	L1	L1	21.53778	22.00722	23.64	23.48	22.66625	1.106049	26.66985
6	L1	L2	L3	L3	L1	L1	L2	L2	27.37778	24.54722	27.46	26.33	26.42875	1.838009	25.79806
7	L1	L3	L1	L2	L1	L3	L2	L3	24.26611	28.53389	27.50667	24.48667	26.19833	4.609947	21.72851
8	L1	L3	L2	L3	L2	L1	L3	L1	26.25611	23.99389	27.43667	26.16667	25.96333	2.058829	25.15101
9	L1	L3	L3	L1	L3	L2	L1	L2	27.05611	25.60389	23.74667	25.14667	25.38833	1.860473	25.39645
10	L2	L1	L1	L3	L3	L2	L2	L1	28.00389	21.72111	26.98667	25.95667	25.66708	7.618838	19.36864
11	L2	L1	L2	L1	L1	L3	L3	L2	23.46389	23.73111	23.25667	25.36667	23.95458	0.923929	27.93138
12	L2	L1	L3	L2	L2	L1	L1	L3	26.92389	28.47111	21.19667	22.33667	24.73208	12.34051	16.95188
13	L2	L2	L1	L2	L3	L1	L3	L2	25.55222	22.34278	28.82	22.35	24.76625	9.587374	18.06021
14	L2	L2	L2	L3	L1	L2	L1	L3	24.67222	22.80278	22.84	25.69	24.00125	2.028973	24.53192
15	L2	L2	L3	L1	L2	L3	L2	L1	27.54222	24.47278	25.07	24.03	25.27875	2.458617	24.1482
16	L2	L3	L1	L3	L2	L3	L1	L2	26.49389	24.57611	24.83333	24.14333	25.01167	1.057499	27.72005
17	L2	L3	L2	L1	L3	L1	L2	L3	27.84389	22.62611	27.97333	26.26333	26.17667	6.207199	20.42933
18	L2	L3	L3	L2	L1	L2	L3	L1	22.50389	28.81611	22.06333	23.91333	24.32417	9.590376	17.9024

Data from simulation

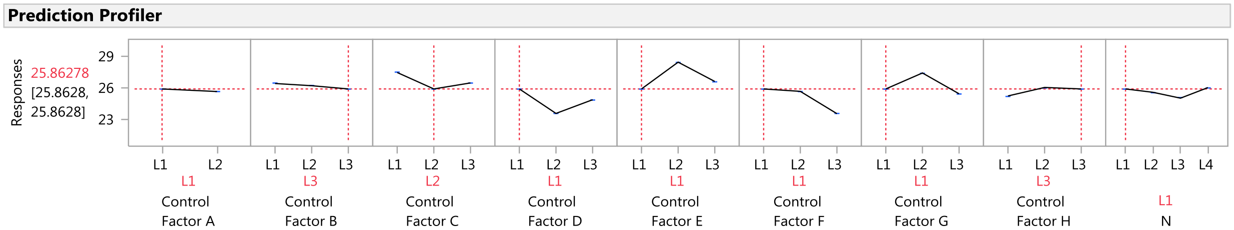
This table yielded the following Excel graphs using traditional Taguchi methods:





These graphs are fairly typical looking, and the S/N ratio graph is predicting (based on >1 dB gain) some significant improvement signals.

As described in the main body of the paper, the outer array was then transposed to create a new table, and this table was exported to JMP for analysis using the alternate Profiler method of minimizing the magnitude of the noise factor profiler. The result is shown below:



Optimized profiler from alternate JMP-based method

Working through both methods, here is the prediction for optimum control factor settings for each to achieve the most robust performance:

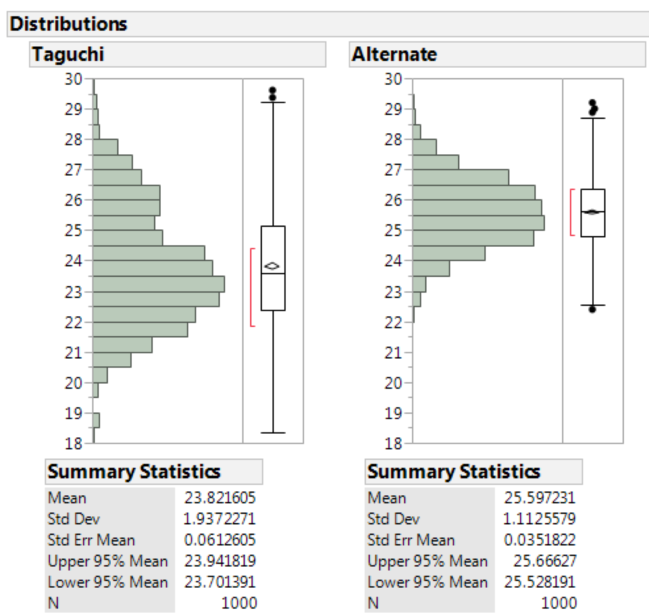
	Control Factor A	Control Factor B	Control Factor C	Control Factor D	Control Factor E	Control Factor F	Control Factor G	Control Factor H
Taguchi optimium factor selection	L1	L1	L2	L3	L1	L3	L1	L2
Alternate optimum factor selection	L1	L3	L2	L1	L1	L1	L1	L3

Comparison of 'most robust' control factor setting predictions

As you can see, the predictions <u>do not agree</u>. The differences are not trivial; from the S/N ratio graph, Control Factor D and Control Factor F are the most significant, and the predictions are different for both.

Is there a way to figure out which one is correct?

Using a simulator, and with the standard deviation calculation factor set at 5% of the model's nominal of 25.22, 1000 Monte Carlo simulations were run for each group; 250 for each of the four noise factor settings. These two columns of data were then compared to each other. See graphs below.



Note the fairly large difference between the standard deviation of the two populations. With this data set, the alternate JMP-based method clearly gave a significantly better prediction for where to set the control factors to achieve the lowest variation in the output.

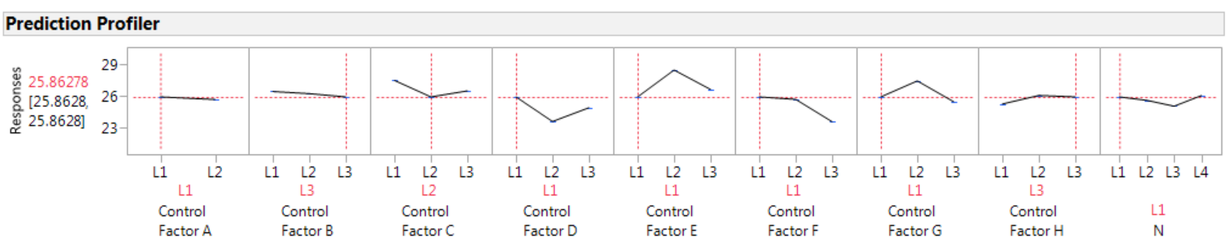
So – what's going on? A hint is to review the two definitions of what we're trying to accomplish with these experiments:

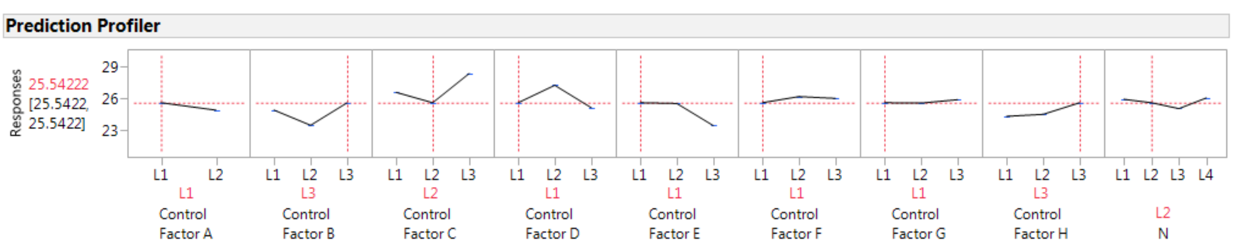
- In Taguchi language: We want to find settings of the control factors that minimize the effect of the noise factors on the output.
- In traditional DOE language: We want to discover where there are interactions between the control factors and noise factors, and set the control factors to minimize the effect of those interactions on the output.

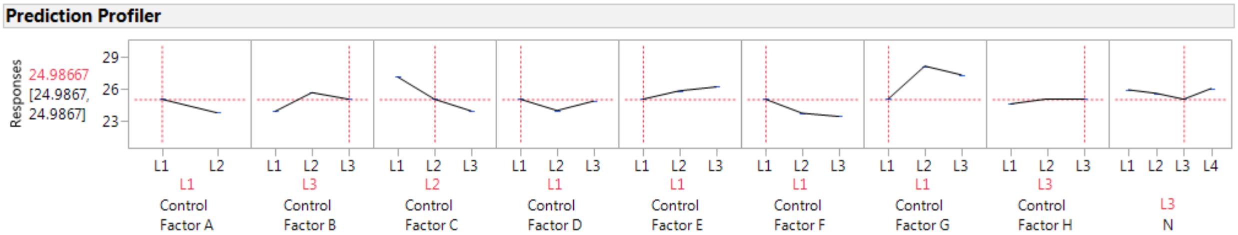
In the second definition, the inclusion of the word 'interactions' is significant. Despite the absence of the word in the first definition, it is clear we are looking for interactions in Taguchi DOEs; if there were no interactions between the control factors and noise factors, there would be no signals in the S/N ratio table.

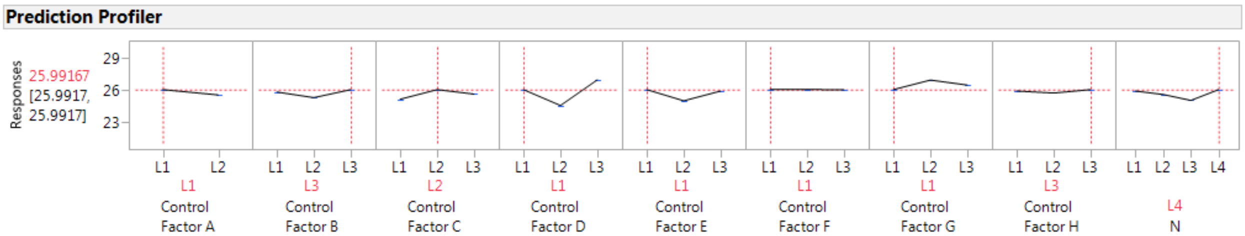
Funny thing about interactions, however. They are a two way street. If there is an interaction between a control factor and a noise factor, that effect goes both ways. The S/N ratio analysis seems to ignore this fact; it is only measuring the effect of varying the control factors on the output, given variation from the noise factors. It doesn't examine how variation of the noise factors might affect the behavior of the control factors themselves.

Going back to the profiler from the JMP-based alternate analysis: Let's look at what happens to the response and control factor profiles when we move the level of the noise factor across the four levels. Recall the S/N ratio analysis says L3 is optimum for Control Factor F, while the Profiler analysis says L1 is best. Leaving all the factors at the settings predicted by the Profiler method, we will slide the noise factor levels to the four different settings and record the response output. (The simulation model here has no common-cause variation.)



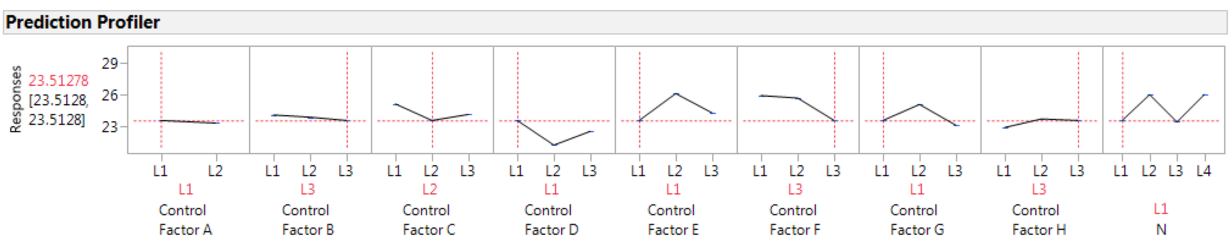


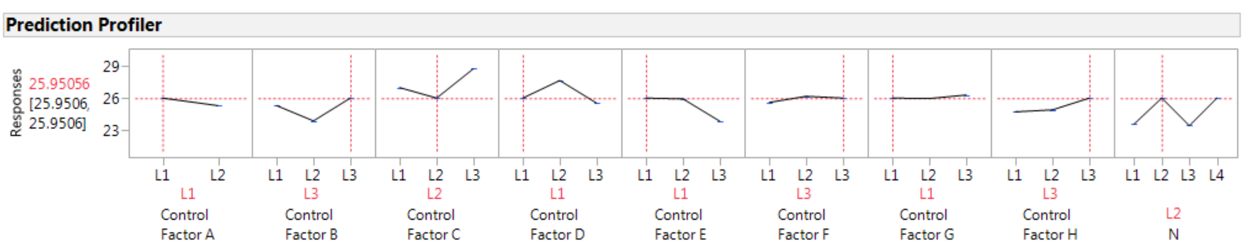


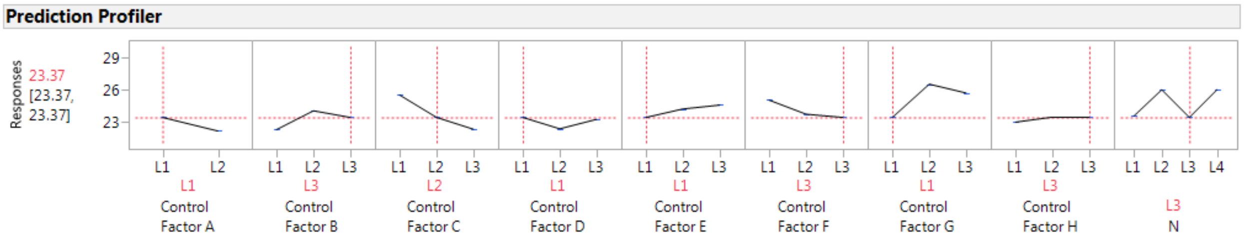


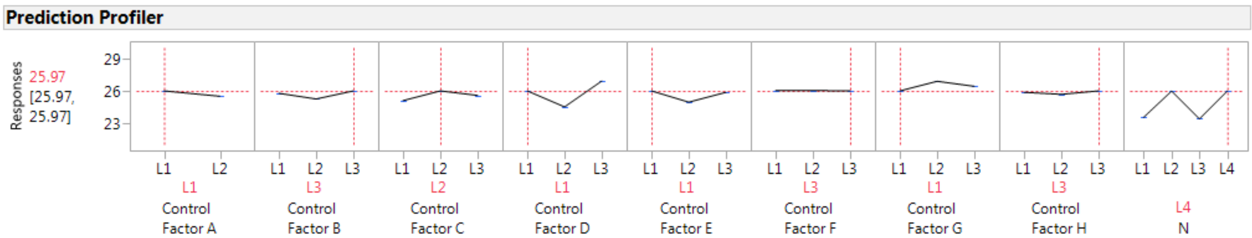
Note that at the four different levels of the noise factor (N), the shapes of the control factor profiles are changing (this shows how the control factor/noise factor interactions are affecting the control factors when the noise factor is changed). However, at these control factor settings, the response is holding relatively steady from 25-26.

Now, let's change one thing: set the level of Control Factor F from L1 (optimum predicted by the Profiler method) to L3 (optimum predicted by the S/N ratio method), and go through the same exercise.









Similar interaction effects are happening here; the shape and location of the control factor profiles are moving around as we slide through the different levels of the noise factor. However, at this setting, there is significantly more effect on the response. The results of the above exercise are summarized in the table below:

Factor level	Control Factor F, L1	Control Factor F, L3
Noise L1	25.86	23.51
Noise L2	25.54	25.95
Noise L3	24.99	23.37
Noise L4	25.99	25.97
Range (max vs min)	1.00	2.60

Given the paradigm of thinking about interactions, the above example demonstrates clearly why L1 is a better setting than L3. As noted above, the S/N ratio analysis method does not examine how interaction with the noise factors might affect the behavior of the control factors.

One final point. This simulation data set is admittedly ‘weird’. The question is whether it is completely unrealistic.

Recall the Autoliv example. Both the control factor and noise factors were categorical (we were testing two different technologies for robustness against lot-to-lot variation of four components). Since categorical factors can be quite different in kind (as the control factor in this example), it is not out of the question that one level of a control factor might behave quite differently than another level in regards to interactions with the noise factors. In fact, it is these differences we are attempting to find. Although this example is somewhat extreme, the type of noise-to-control factor interactions shown here are not out of the question for categorical factors.

Completing both types of analyses is easy using JMP. Given this example, it certainly seems that the Profiler analysis method should be included whenever a robust optimization experiment is performed as a ‘sanity’ check.