Outline

- Why Easy DOE? – Key Features
- Why DOE?
- 1st example use of Guided Easy DOE
- Review important concepts about factors and models in the *Guided Easy DOE* process
- 2nd example use of Guided Easy DOE

Why Easy DOE? - Key Features

JMP makes it easier for everyone to experiment

- End-to-end coverage of every step of experimentation.
- Streamlined experience through tailored elements in a new user interface.
- Guided mode for novice experimenters (default) and Flexible mode for more demanding situations.
- Comprehensive summary report is automatically written based on the current state of the experiment.
- Save your work at any time and return to the same point.
- Easily share experiments with others.

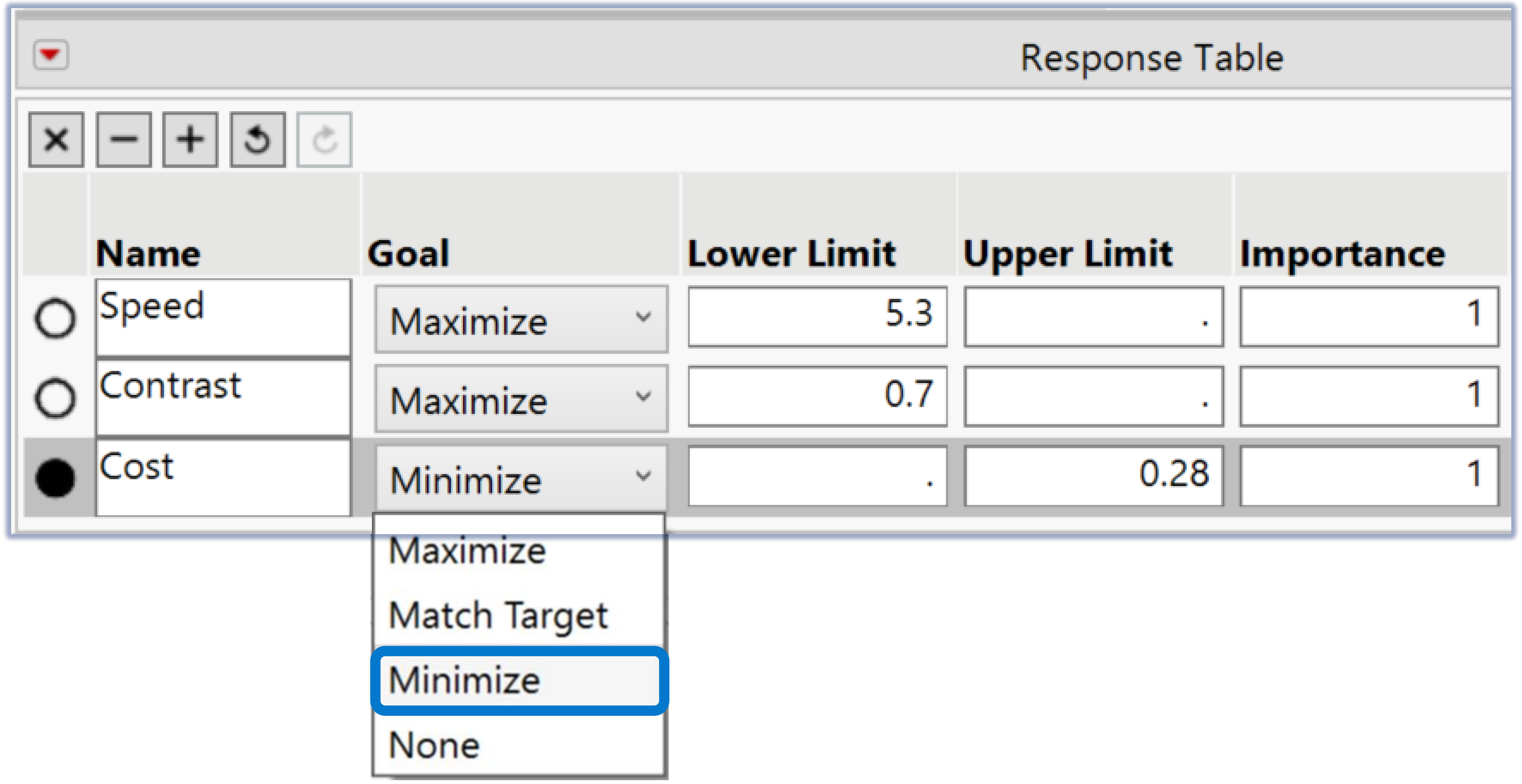
Developer Tutorial: Easy DOE – Expertly Guiding Users Through Designing an Experiment

Why use DOE?

LOWER COSTS,
QUICKER ANSWERS,
SOLVE BIGGER PROBLEMS,
MAKE BETTER-INFORMED DECISIONS

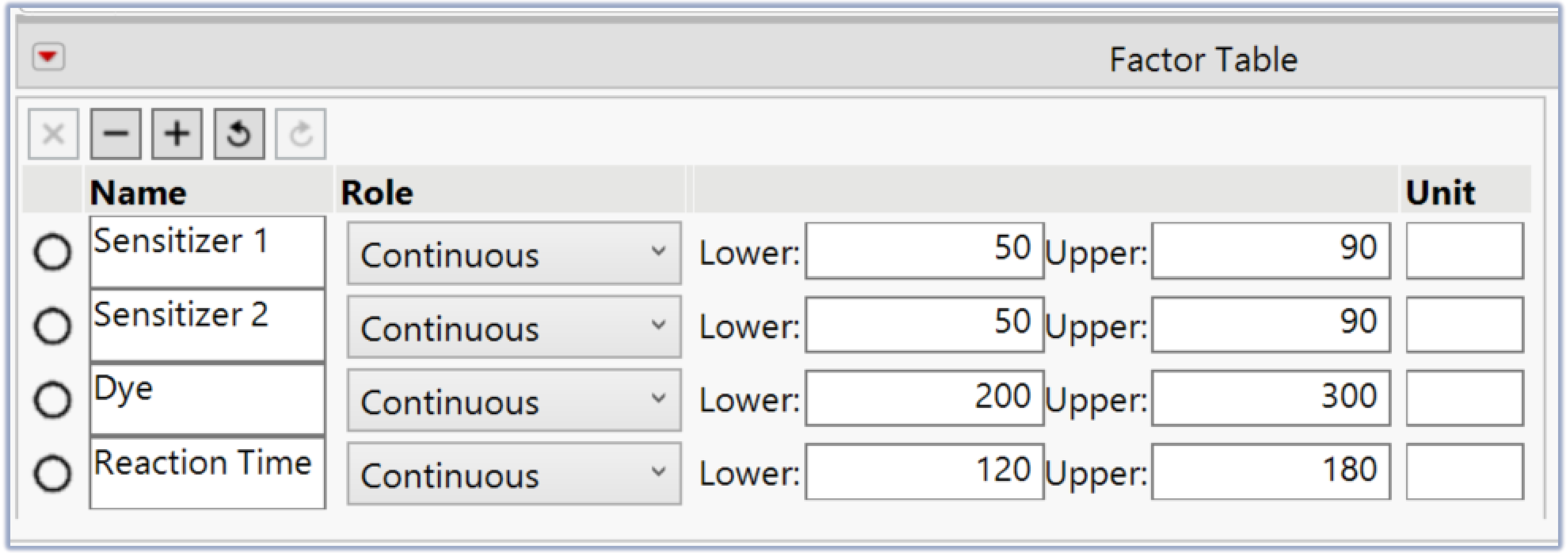
- More rapidly answer *"what if?"* questions
- *Identify important factors* when faced with many
- Do *sensitivity* and *trade-space* analysis
- *Optimize* across multiple responses
- By running efficient subsets of all possible combinations, one can – for the same resources and constraints – *solve bigger problems*
- By running sequences of designs one can be as *cost effective as possible* and *run no more trials than needed* to get a useful answer

Use Easy DOE



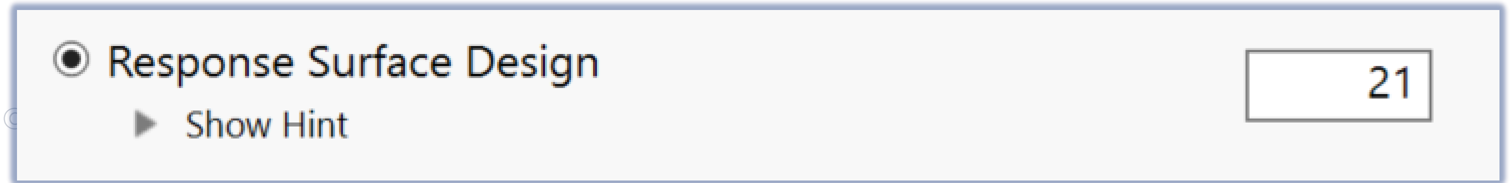
Response Table

	Name	Goal	Lower Limit	Upper Limit	Importance
○	Speed	Maximize	5.3	.	1
○	Contrast	Maximize	0.7	.	1
●	Cost	Minimize	.	0.28	1



Factor Table

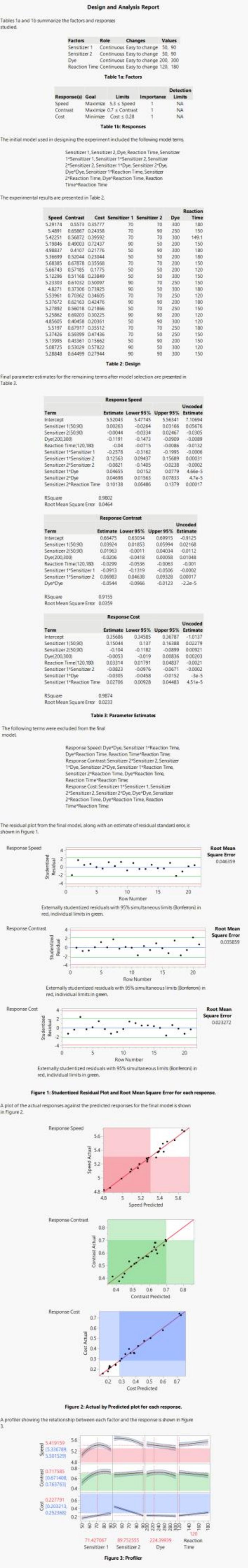
	Name	Role					Unit
○	Sensitizer 1	Continuous	Lower:	50	Upper:	90	
○	Sensitizer 2	Continuous	Lower:	50	Upper:	90	
○	Dye	Continuous	Lower:	200	Upper:	300	
○	Reaction Time	Continuous	Lower:	120	Upper:	180	

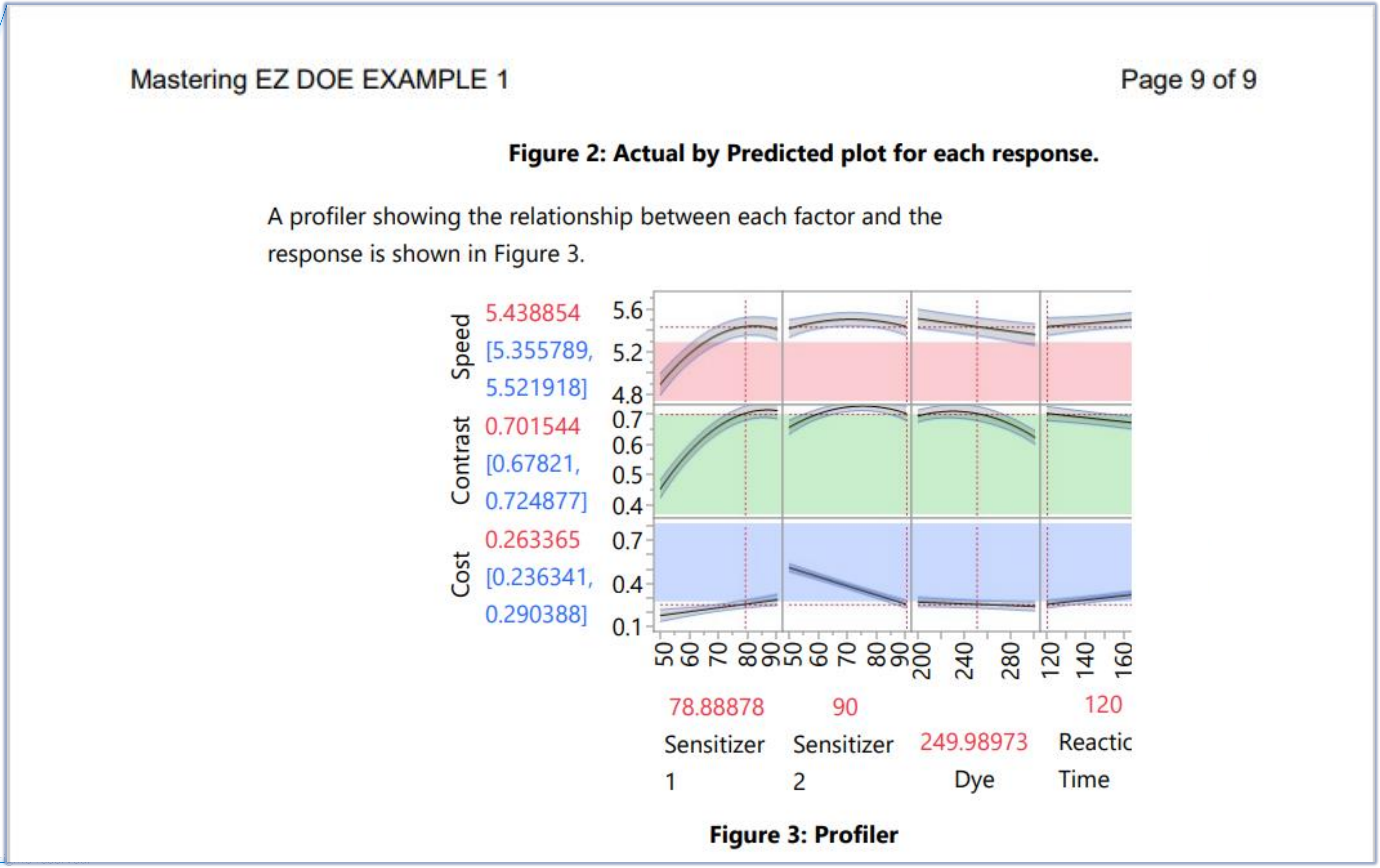


◉ Response Surface Design 21

3-response, 4-factor, trade-space analysis and optimization example

Last page of Report shows Prediction Profiler after pressing Optimize button & meeting all requirements





Mastering EZ DOE EXAMPLE 1

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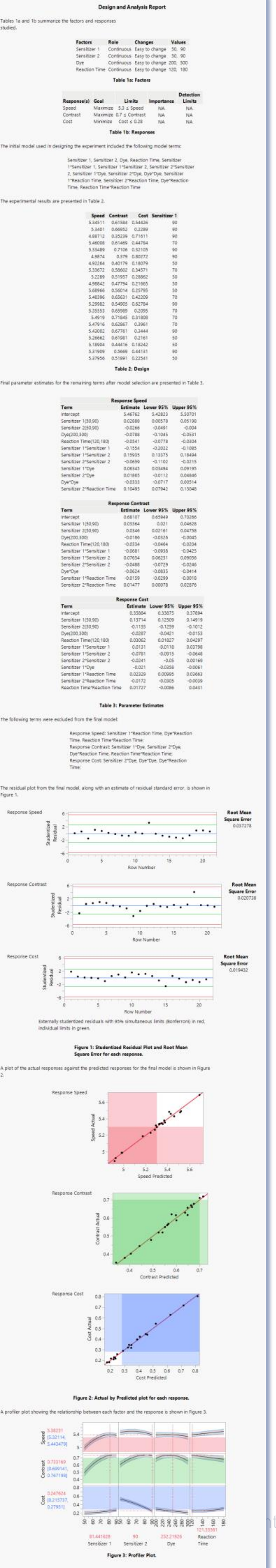
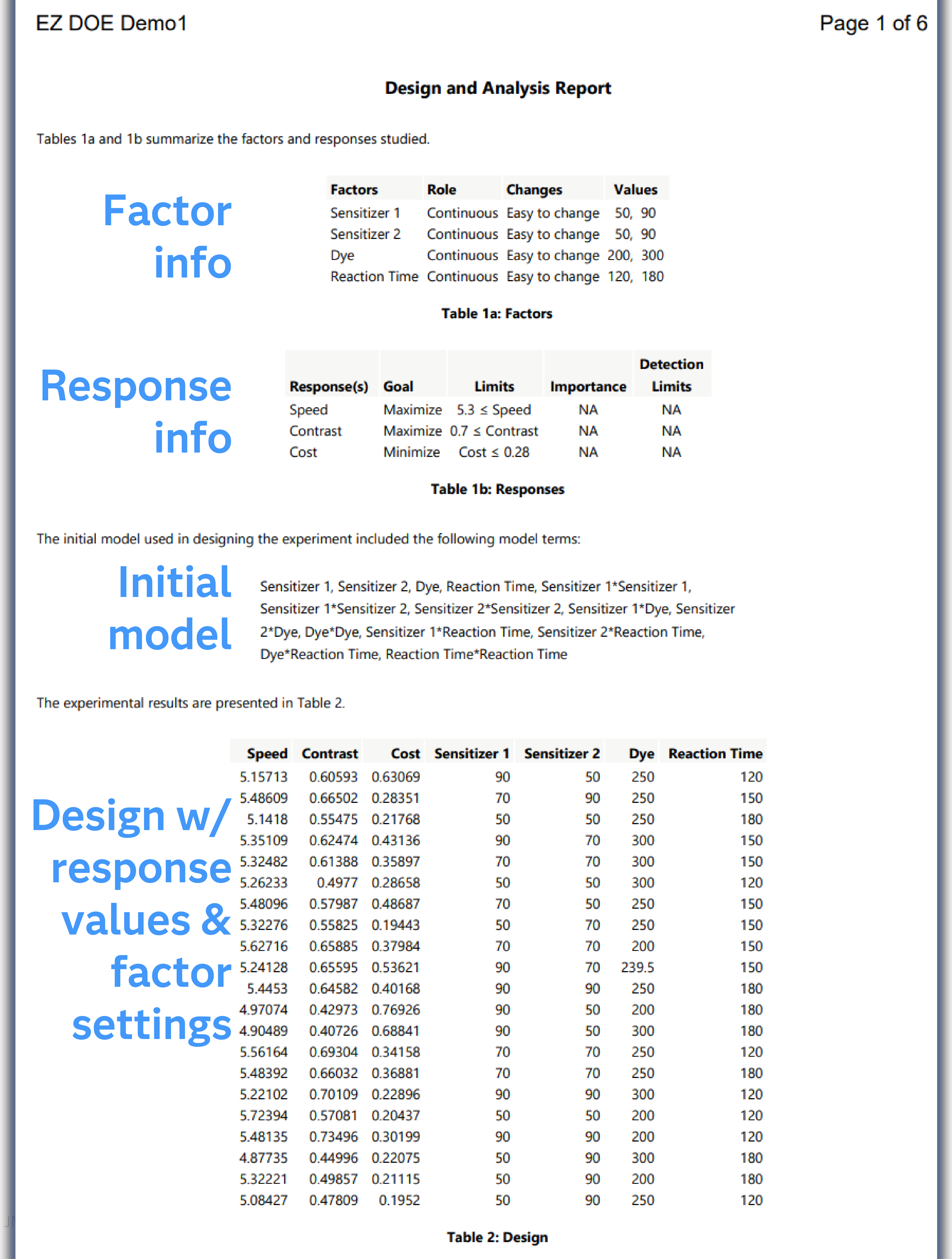
Figure 2: Actual by Predicted plot for each response.

A profiler showing the relationship between each factor and the response is shown in Figure 3.

Figure 3: Profiler





Design and Analysis Report

Tables 1a and 1b summarize the factors and responses studied.

Factor info

Factors	Role	Changes	Values
Sensitizer 1	Continuous	Easy to change	50, 90
Sensitizer 2	Continuous	Easy to change	50, 90
Dye	Continuous	Easy to change	200, 300
Reaction Time	Continuous	Easy to change	120, 180

Table 1a: Factors

Response info

Response(s)	Goal	Limits	Importance	Detection Limits
Speed	Maximize	5.3 ≤ Speed	NA	NA
Contrast	Maximize	0.7 ≤ Contrast	NA	NA
Cost	Minimize	Cost ≤ 0.28	NA	NA

Table 1b: Responses

The initial model used in designing the experiment included the following model terms:

Initial model

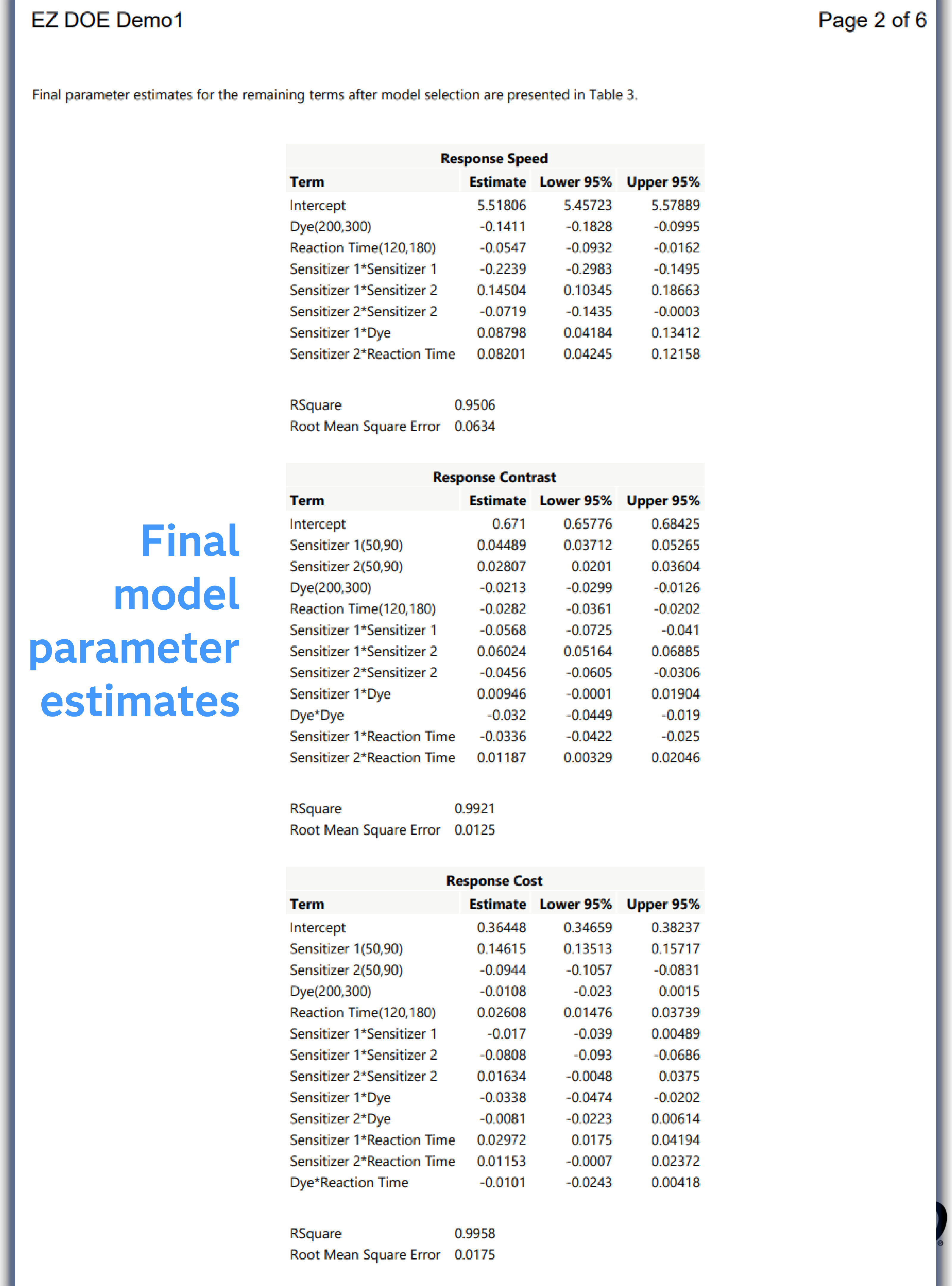
Sensitizer 1, Sensitizer 2, Dye, Reaction Time, Sensitizer 1*Sensitizer 1, Sensitizer 1*Sensitizer 2, Sensitizer 2*Sensitizer 2, Sensitizer 1*Dye, Sensitizer 2*Dye, Dye*Dye, Sensitizer 1*Reaction Time, Sensitizer 2*Reaction Time, Dye*Reaction Time, Reaction Time*Reaction Time

The experimental results are presented in Table 2.

Design w/ response values & factor settings

Speed	Contrast	Cost	Sensitizer 1	Sensitizer 2	Dye	Reaction Time
5.15713	0.60593	0.63069	90	50	250	120
5.48609	0.66502	0.28351	70	90	250	150
5.1418	0.55475	0.21768	50	50	250	180
5.35109	0.62474	0.43136	90	70	300	150
5.32482	0.61388	0.35897	70	70	300	150
5.26233	0.4977	0.28658	50	50	300	120
5.48096	0.57987	0.48687	70	50	250	150
5.32276	0.55825	0.19443	50	70	250	150
5.62716	0.65885	0.37984	70	70	200	150
5.24128	0.65595	0.53621	90	70	239.5	150
5.4453	0.64582	0.40168	90	90	250	180
4.97074	0.42973	0.76926	90	50	200	180
4.90489	0.40726	0.68841	90	50	300	180
5.56164	0.69304	0.34158	70	70	250	120
5.48392	0.66032	0.36881	70	70	250	180
5.22102	0.70109	0.22896	90	90	300	120
5.72394	0.57081	0.20437	50	50	200	120
5.48135	0.73496	0.30199	90	90	200	120
4.87735	0.44996	0.22075	50	90	300	180
5.32221	0.49857	0.21115	50	90	200	180
5.08427	0.47809	0.1952	50	90	250	120

Table 2: Design



Final parameter estimates for the remaining terms after model selection are presented in Table 3.

Final model parameter estimates

Response Speed

Term	Estimate	Lower 95%	Upper 95%
Intercept	5.51806	5.45723	5.57889
Dye(200,300)	-0.1411	-0.1828	-0.0995
Reaction Time(120,180)	-0.0547	-0.0932	-0.0162
Sensitizer 1*Sensitizer 1	-0.2239	-0.2983	-0.1495
Sensitizer 1*Sensitizer 2	0.14504	0.10345	0.18663
Sensitizer 2*Sensitizer 2	-0.0719	-0.1435	-0.0003
Sensitizer 1*Dye	0.08798	0.04184	0.13412
Sensitizer 2*Reaction Time	0.08201	0.04245	0.12158

RSquare	0.9506
Root Mean Square Error	0.0634

Response Contrast

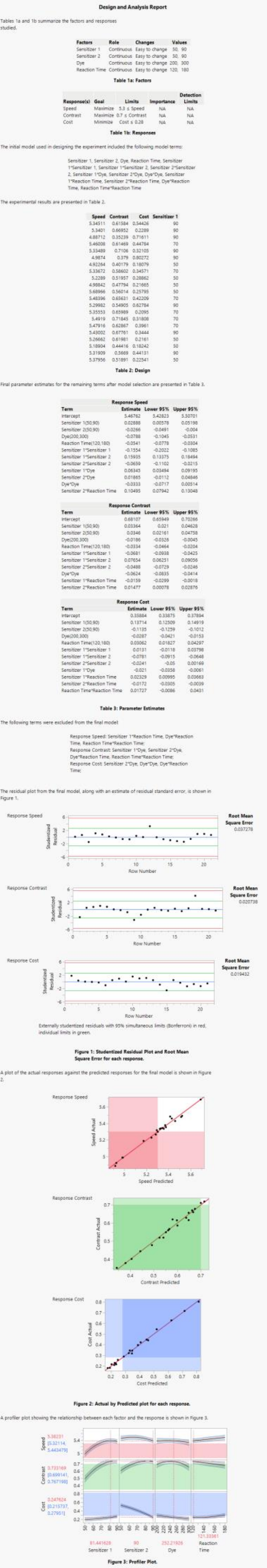
Term	Estimate	Lower 95%	Upper 95%
Intercept	0.671	0.65776	0.68425
Sensitizer 1(50,90)	0.04489	0.03712	0.05265
Sensitizer 2(50,90)	0.02807	0.0201	0.03604
Dye(200,300)	-0.0213	-0.0299	-0.0126
Reaction Time(120,180)	-0.0282	-0.0361	-0.0202
Sensitizer 1*Sensitizer 1	-0.0568	-0.0725	-0.041
Sensitizer 1*Sensitizer 2	0.06024	0.05164	0.06885
Sensitizer 2*Sensitizer 2	-0.0456	-0.0605	-0.0306
Sensitizer 1*Dye	0.00946	-0.0001	0.01904
Dye*Dye	-0.032	-0.0449	-0.019
Sensitizer 1*Reaction Time	-0.0336	-0.0422	-0.025
Sensitizer 2*Reaction Time	0.01187	0.00329	0.02046

RSquare	0.9921
Root Mean Square Error	0.0125

Response Cost

Term	Estimate	Lower 95%	Upper 95%
Intercept	0.36448	0.34659	0.38237
Sensitizer 1(50,90)	0.14615	0.13513	0.15717
Sensitizer 2(50,90)	-0.0944	-0.1057	-0.0831
Dye(200,300)	-0.0108	-0.023	0.0015
Reaction Time(120,180)	0.02608	0.01476	0.03739
Sensitizer 1*Sensitizer 1	-0.017	-0.039	0.00489
Sensitizer 1*Sensitizer 2	-0.0808	-0.093	-0.0686
Sensitizer 2*Sensitizer 2	0.01634	-0.0048	0.0375
Sensitizer 1*Dye	-0.0338	-0.0474	-0.0202
Sensitizer 2*Dye	-0.0081	-0.0223	0.00614
Sensitizer 1*Reaction Time	0.02972	0.0175	0.04194
Sensitizer 2*Reaction Time	0.01153	-0.0007	0.02372
Dye*Reaction Time	-0.0101	-0.0243	0.00418

RSquare	0.9958
Root Mean Square Error	0.0175



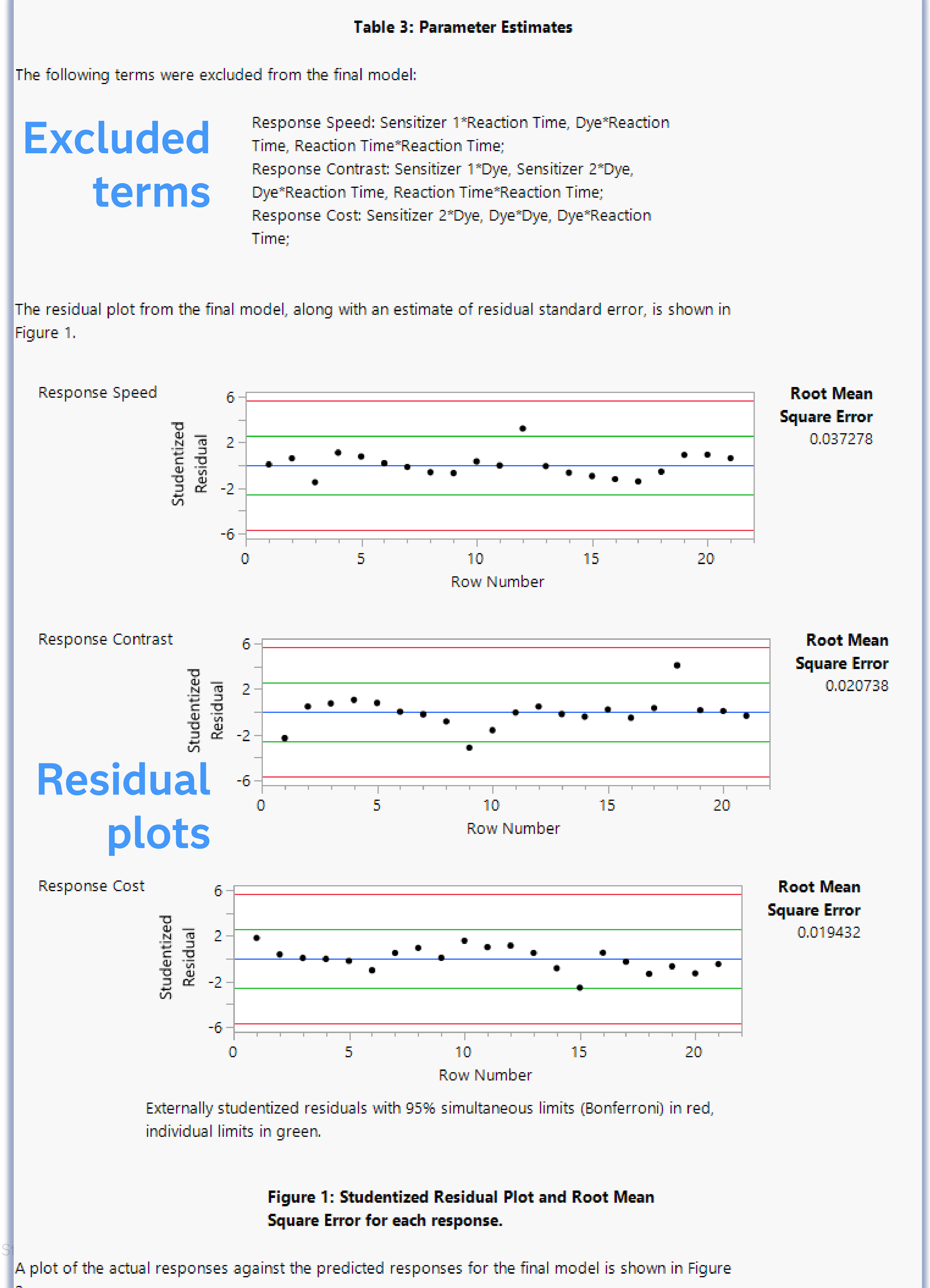


Table 3: Parameter Estimates

The following terms were excluded from the final model:

Excluded terms

Response Speed: Sensitizer 1*Reaction Time, Dye*Reaction Time, Reaction Time*Reaction Time;
Response Contrast: Sensitizer 1*Dye, Sensitizer 2*Dye, Dye*Reaction Time, Reaction Time*Reaction Time;
Response Cost: Sensitizer 2*Dye, Dye*Dye, Dye*Reaction Time;

The residual plot from the final model, along with an estimate of residual standard error, is shown in Figure 1.

Residual plots

Externally studentized residuals with 95% simultaneous limits (Bonferroni) in red, individual limits in green.

Figure 1: Studentized Residual Plot and Root Mean Square Error for each response.

A plot of the actual responses against the predicted responses for the final model is shown in Figure

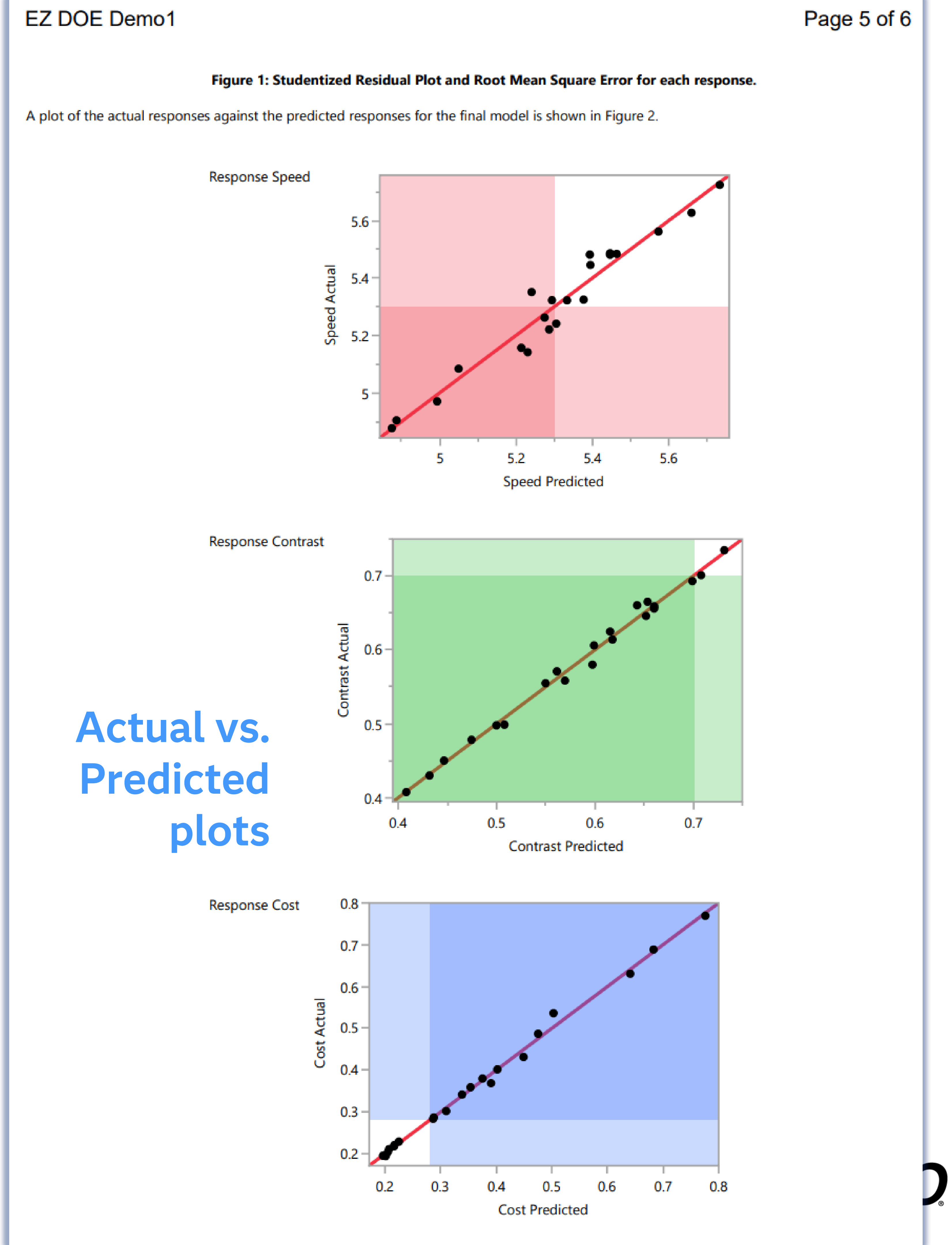
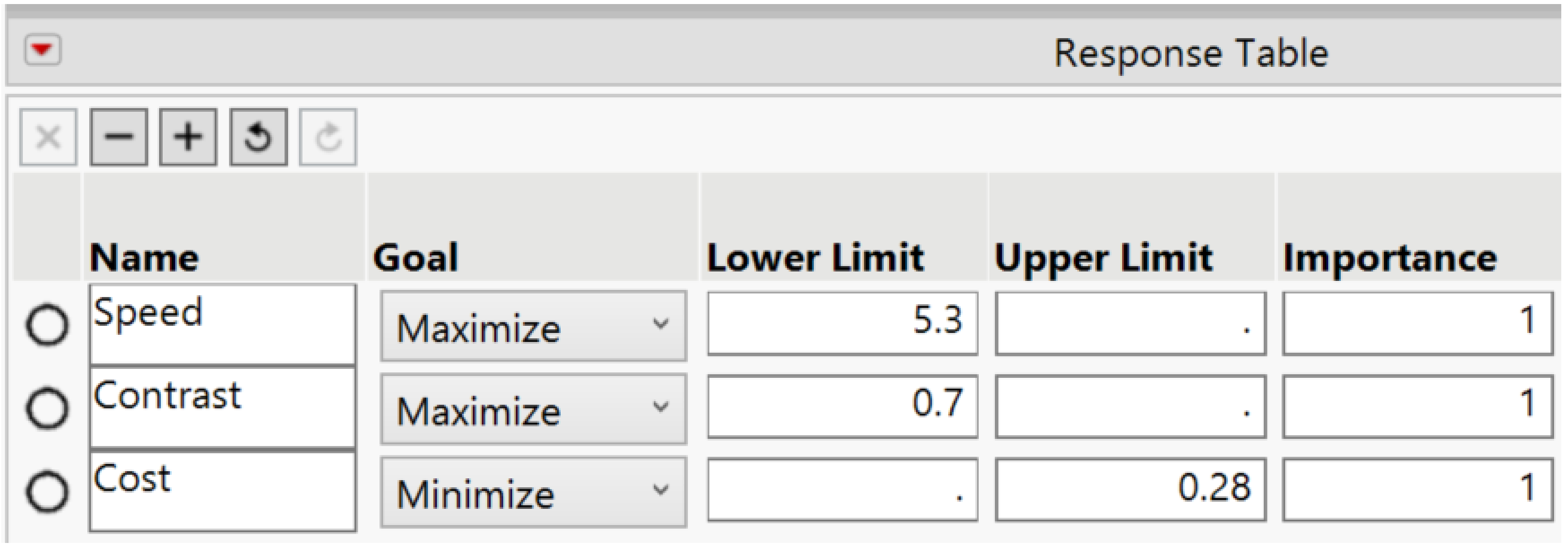


Figure 1: Studentized Residual Plot and Root Mean Square Error for each response.

A plot of the actual responses against the predicted responses for the final model is shown in Figure 2.

Actual vs. Predicted plots

Use Easy DOE



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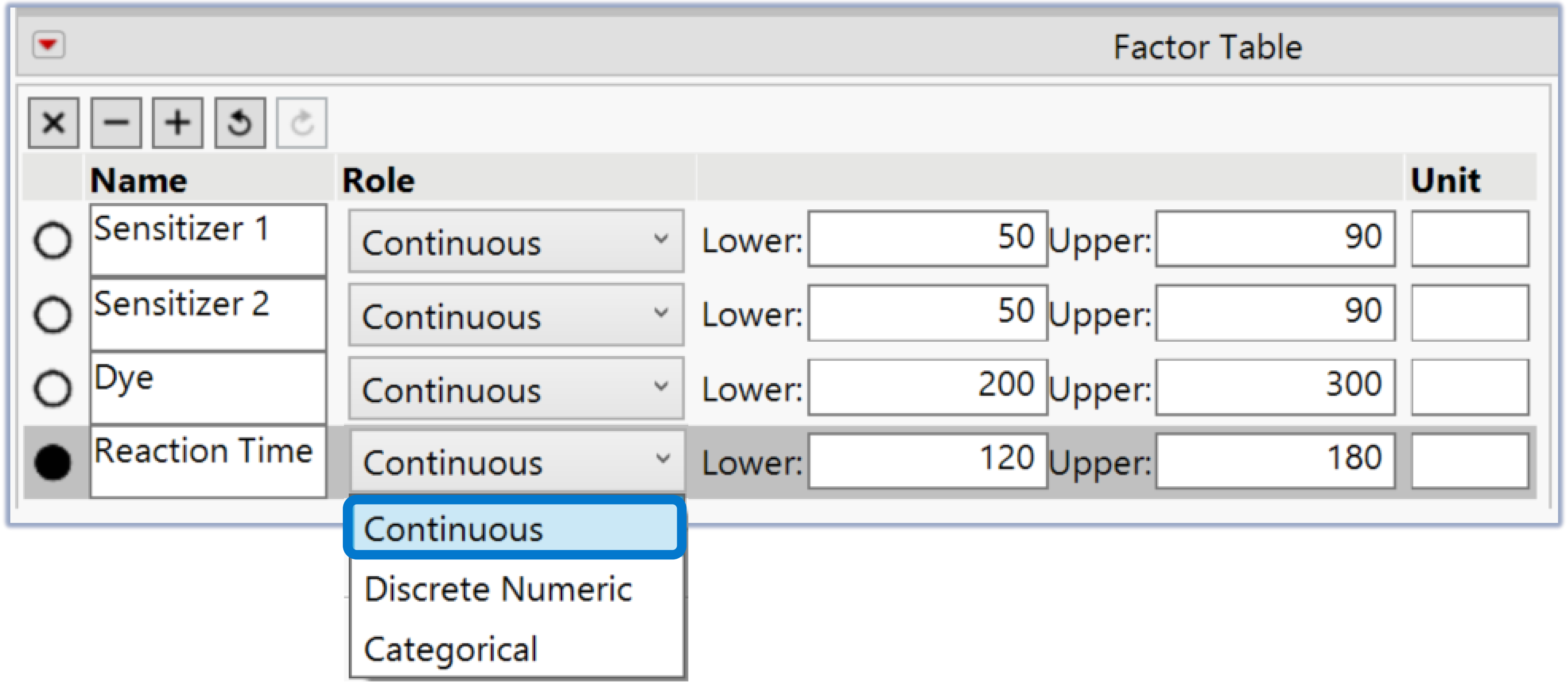

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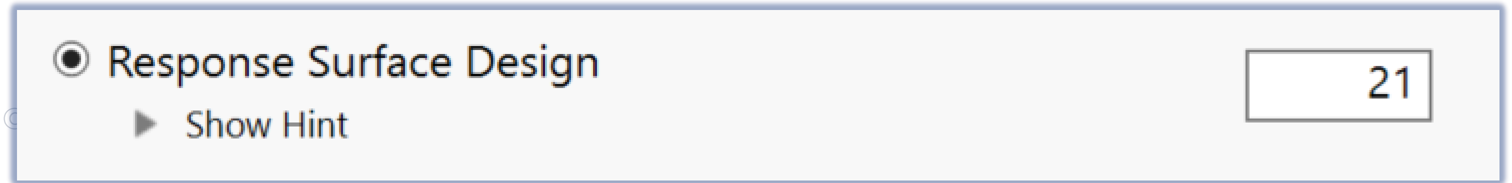


◉ Response Surface Design 21

▶ Show Hint

3-response, 4-factor, trade-space analysis and optimization example

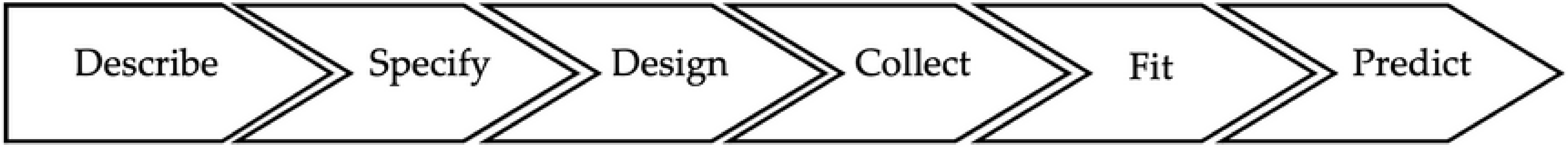
Go to JMP 18…

Easy DOE Demo

- ✓ Start with the end…presenting DOE results *interactively* to decision makers
- ✓ Recreate the "Why DOE?" example using Easy DOE platform
- Introduce the 6-step DOE Process implemented in the Easy DOE interface
- Review factor types supported and model choices
- Again, use Guided Easy DOE process for slightly more complex 3-response, 4-factor, trade-space/optimization example using new *.jmpdoe* file.
  1. Define
  2. Specify
  3. Design
  4. Data Entry
  5. Analyze
  6. Predict

     Report

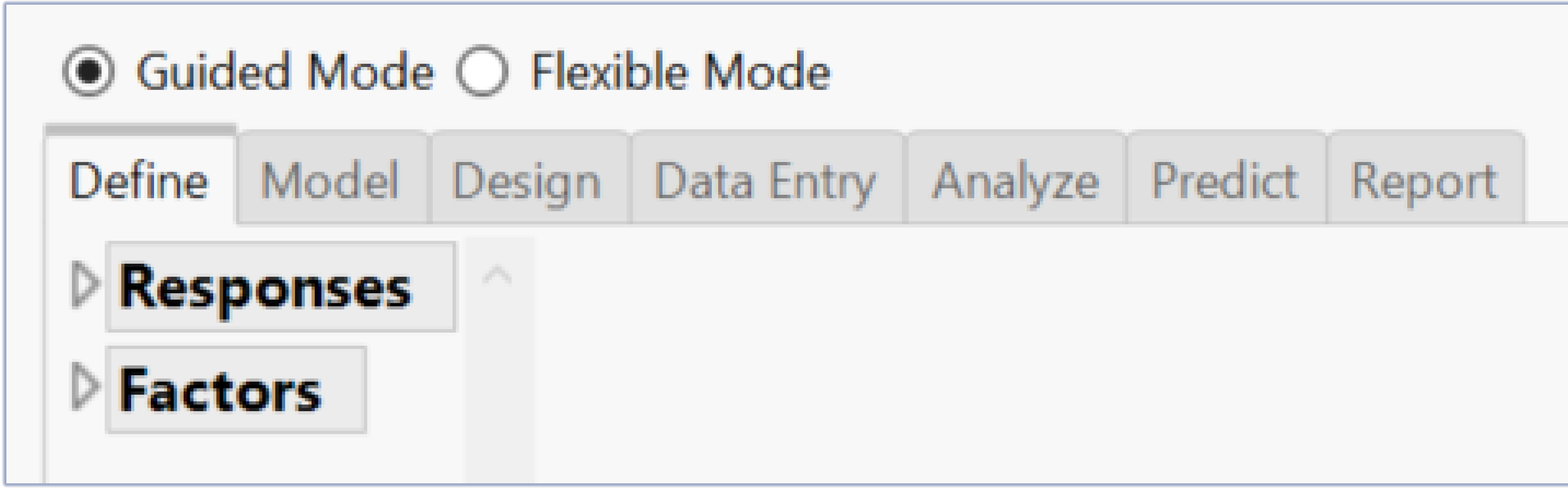
6-Step DOE Process



Describe	Specify	Design	Collect	Fit	Predict
Identify goal, responses, and factors. Ranges & specs require SME*	Identify effects for an assumed model. Propose 1st or 2nd order?	Generate a design and evaluate it for suitability.	Run trials using design settings. Measure response for each run.	Determine a model that best fits experimental data.	Use the model to optimize factor settings or to predict process performance.

Two Modes

Same 6 Steps plus a *Report*

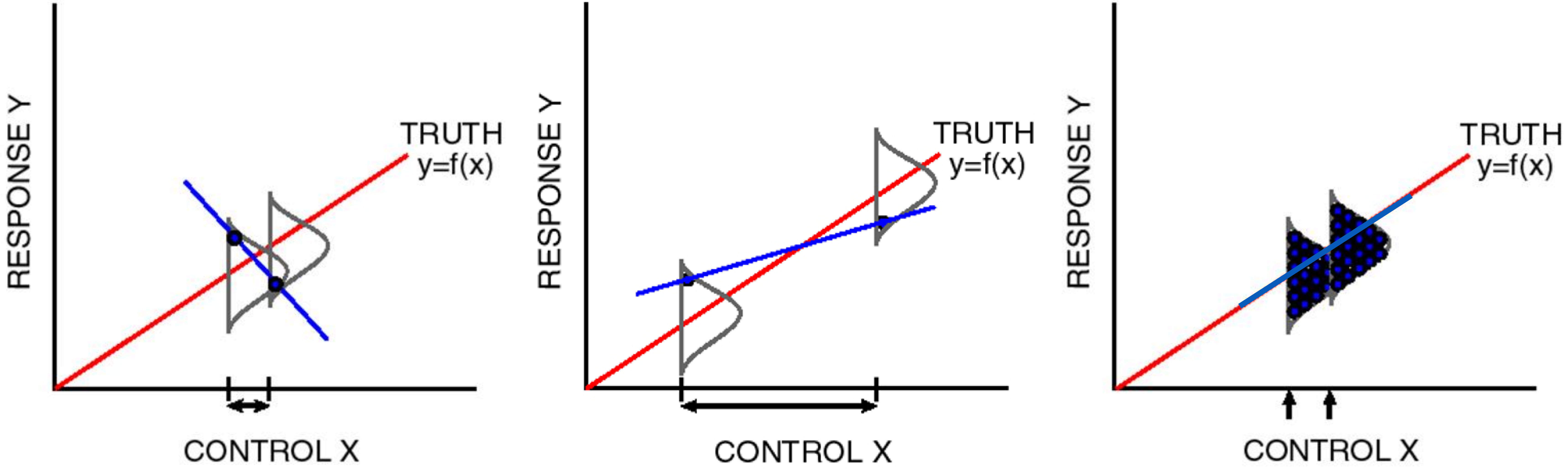


● Guided Mode ○ Flexible Mode

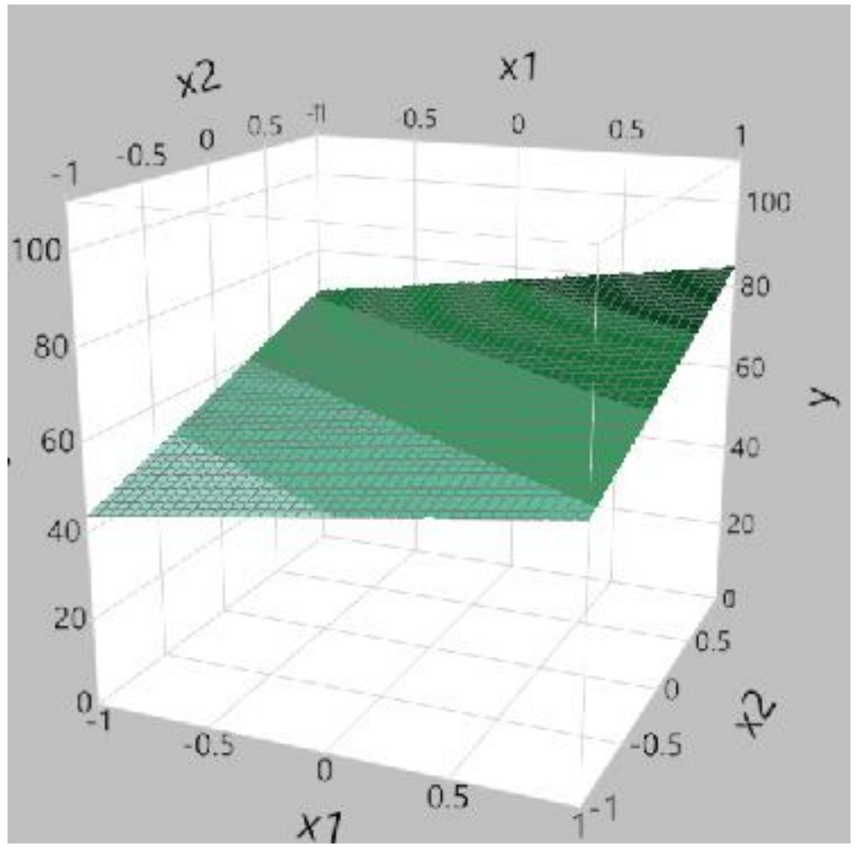
*Subject Matter Expert

Timid vs. Bold Range Settings

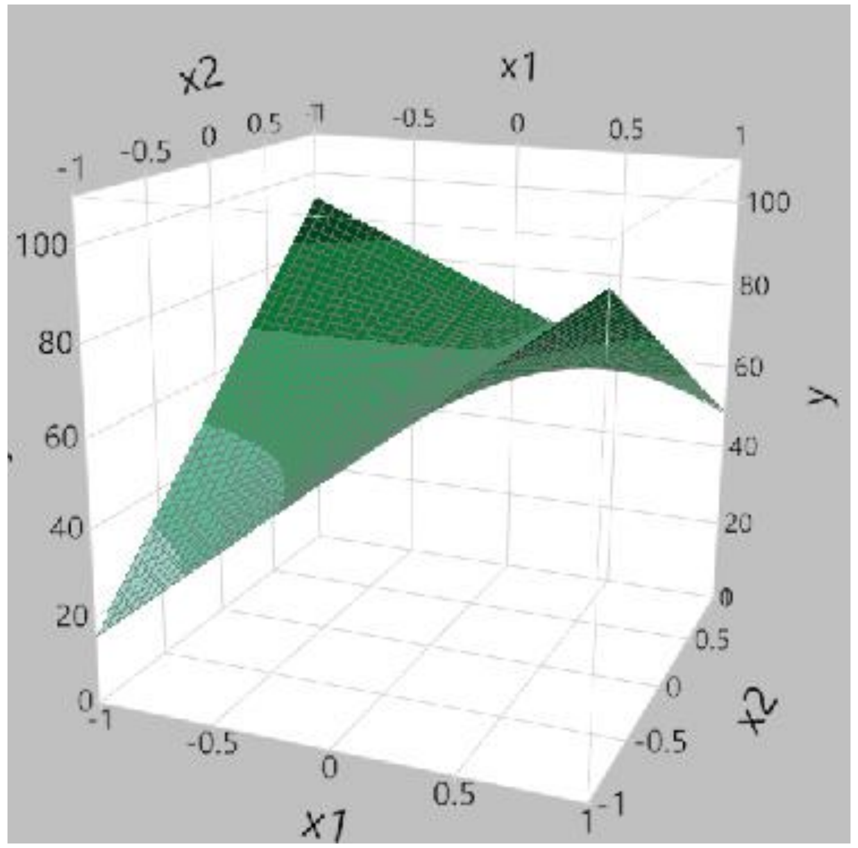
Boldness overcomes the need for large sample size



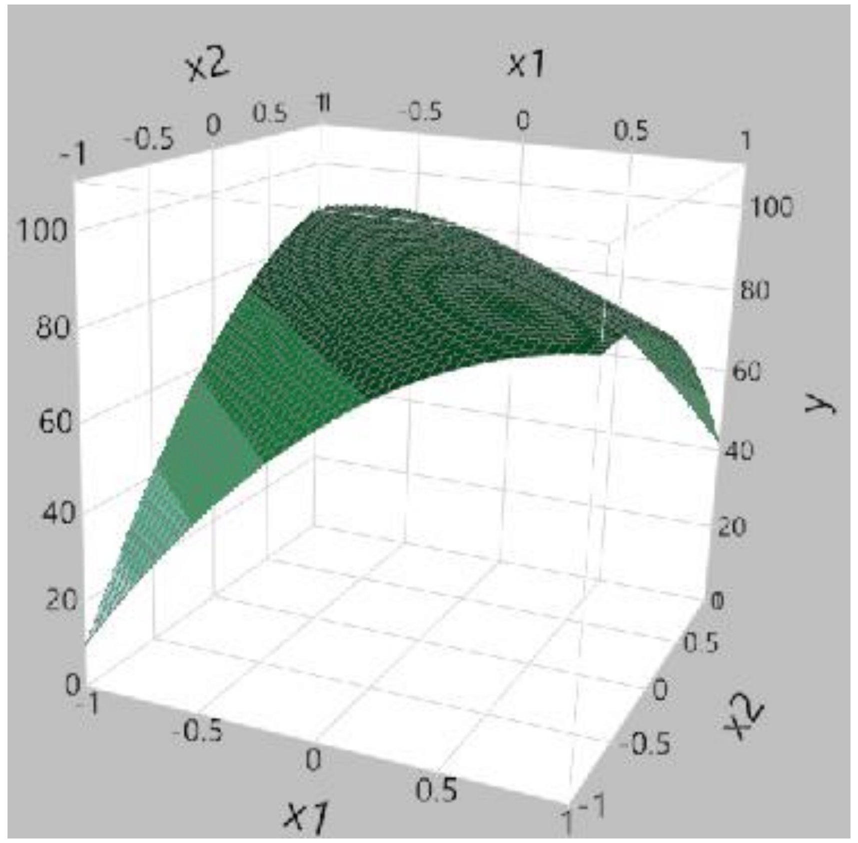
Quadratic model is not much bigger than *Interaction* model. If you have continuous factors, choose full 2^{nd} order, *Quadratic*.



1st Order



2nd Order



Full 2nd Order

$y = a_0 + a_1x_1 + a_2x_2$

For k factors there are
k main effects

3-factor Linear Model has 4 terms (8 corners)
6-factor Linear Model has 7 terms (64 corners)
10-factor Linear Model has 11 terms (1K corners)
20-factor Linear Model has 21 terms (1M corners)

$y = a_0 + a_1x_1 + a_2x_2$

$+ a_{12}x_1x_2$

For k factors there are
k(k-1)/2 interaction effects

3-f Interaction Model has 7 terms (2X ME)
6-f Interaction Model has 22 terms (3X ME)
10-f Interaction Model has 56 terms (5X ME)
20-f Interaction Model has 211 terms (10X ME)

$y = a_0 + a_1x_1 + a_2x_2$

$+ a_{12}x_1x_2$

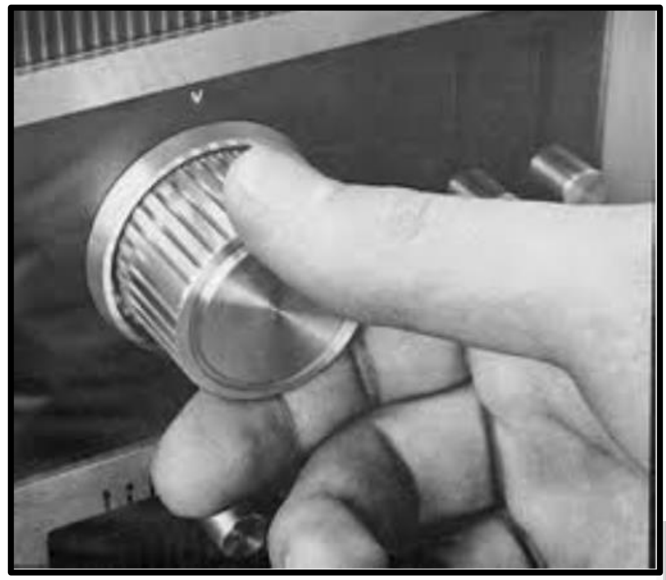
$+ a_{11}x_1^2 + a_{22}x_2^2$

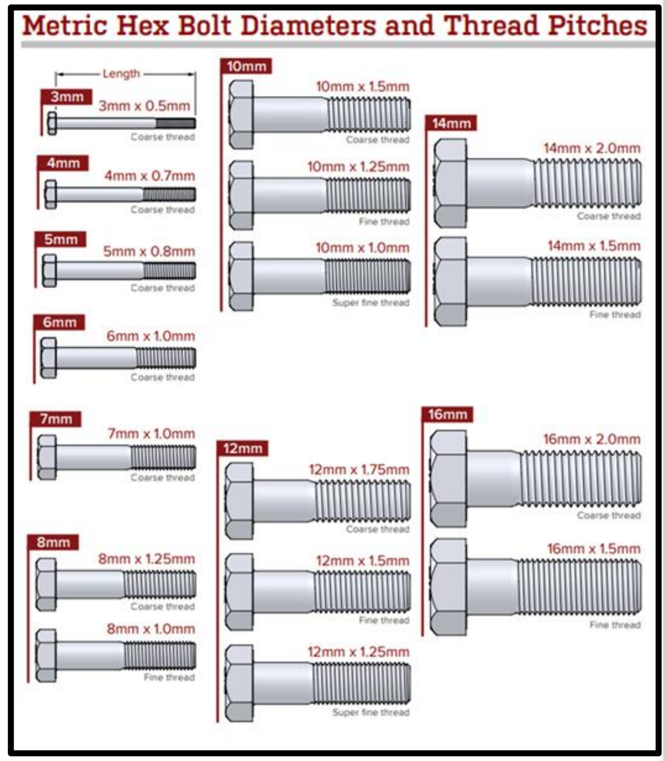
For k factors there are
k squared effects

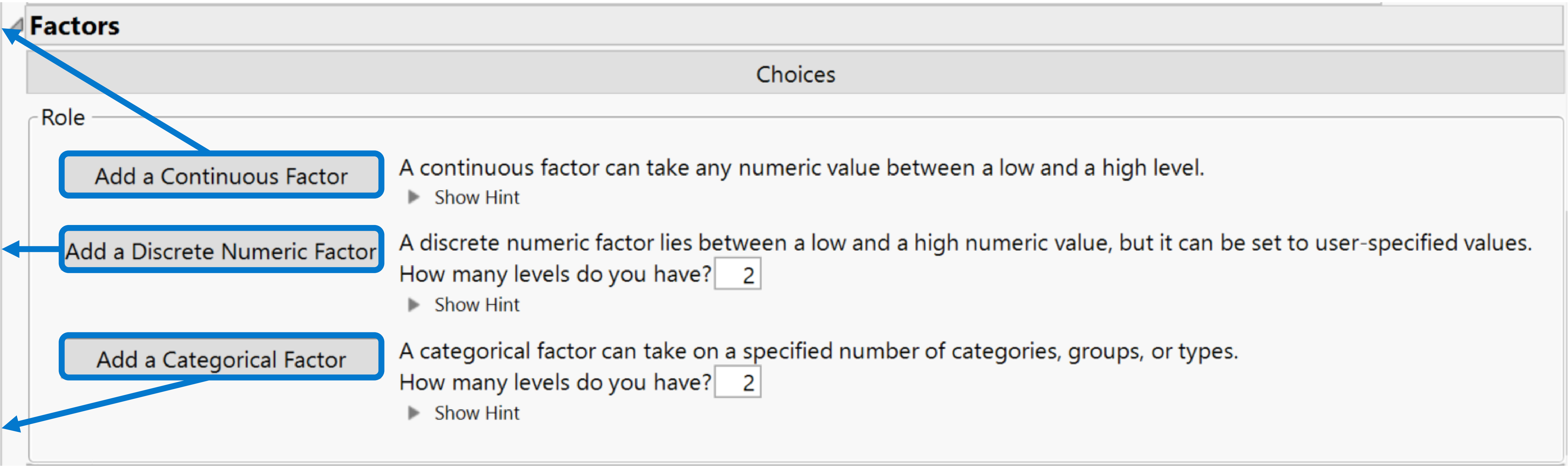
3-f Quadratic Model has 10 terms (2.5X ME)
6-f Quadratic Model has 28 terms (4X ME)
10-f Quadratic Model has 66 terms (6X ME)
20-f Quadratic Model has 231 terms (11X ME)

If no squared terms, then optimum can ONLY be a corner!

Three Types of Factors Supported







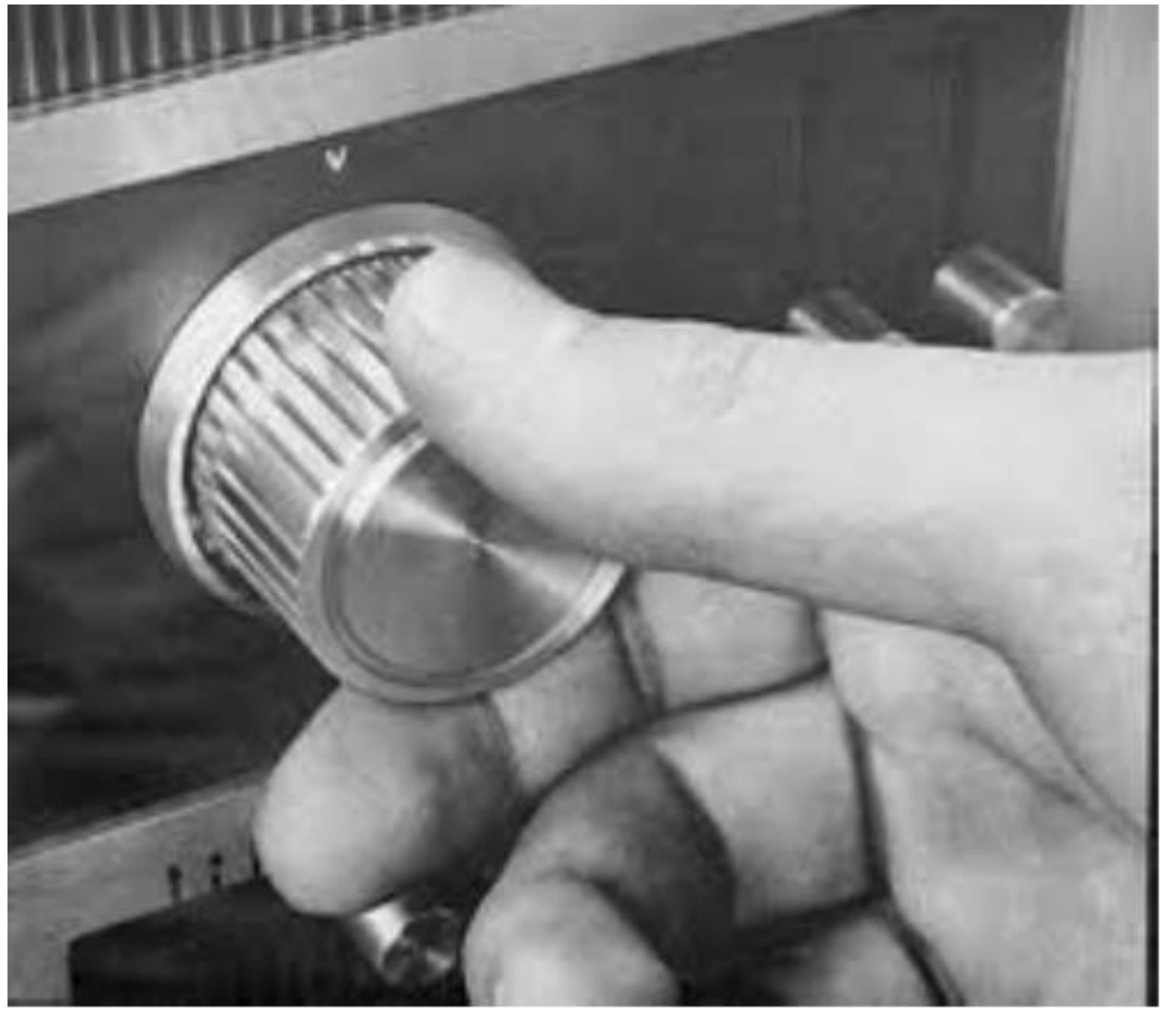
A continuous factor can take any numeric value between a low and a high level.

A discrete numeric factor lies between a low and a high numeric value, but it can be set to user-specified values.

How many levels do you have? 2

A categorical factor can take on a specified number of categories, groups, or types.

How many levels do you have? 2

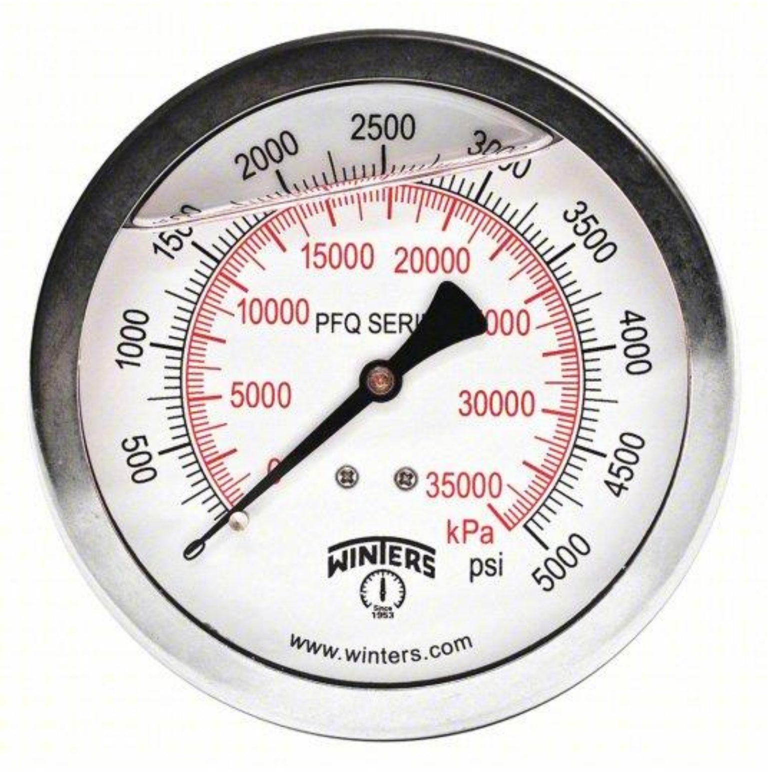


Continuous Factors are finely adjustable over a range.

Think, can I turn a control knob to adjust to any setting?

Examples (Clockwise) are

Time*, *Temperature*, *Speed*, *RPM*, and *Pressure



Categorical Factor: *Vendor*

Order doesn't matter.

Interpolation makes no sense.

L1 AA ANCHOR BOLT, INC.

L2 BMB Fasteners, Inc.

L3 CHAMPION BOLT & SUPPLY INC.

Categorical Factor: *Vendor*

Order doesn't matter.
Interpolation makes no sense.

L1 BMB Fasteners, Inc.

L2 CHAMPION BOLT & SUPPLY INC.

L3 AA ANCHOR BOLT, INC.

Categorical Factor: *Vendor*

Order doesn't matter.

Interpolation makes no sense.

L1 BMB Fasteners, Inc.

L2 CHAMPION BOLT & SUPPLY INC.

L3 AA ANCHOR BOLT, INC.

Categorical Factor: *Grade of Stainless Steel*

Order potentially matters.

Ordinal Ranking may make sense.

L1 304 Stainless Steel Pros and Cons

The main benefit is that 304 stainless steel is usually considered to be one of the strongest of the mild steels available on the market. It boasts a respectable level of corrosion resistance and is **much easier to mold** than its 316 stainless steel alternative. However, like 18-8 grade stainless steel it is vulnerable to corrosion when exposed to salt water. 304 stainless steel **costs more than 18-8 but less than 316 stainless steel**.

L2 18-8 Stainless Steel Pros and Cons

As already mentioned, 18-8 grade stainless steel is celebrated for its superior level of corrosion resistance. However, it is known to show signs of corrosion when exposed to chlorides, such as salt. Therefore, it is not the ideal stainless steel to use for marine applications. On the upside, 18-8 grade stainless steel properties include the fact that **it can be bent and molded** without it having an effect on its overall strength and durability. This type of stainless steel is also not only **extremely budget-friendly**, but it also requires little to no maintenance. 18-8 stainless steel yield strength is also impressive.

L3 316 Stainless Steel Pros and Cons

316 stainless steel boasts a higher strength and durability than 304 stainless steel. It also has a higher level of corrosion resistance, including when exposed to salt water. It performs well against pitting and is also resistant to caustic chemicals. As mentioned above, however, 316 stainless steel is **less malleable** than 304 stainless steel. It is also **substantially more expensive.**

Categorical Factor: *Vendor*

Order doesn't matter.

Interpolation makes no sense.

L1 BMB Fasteners, Inc.

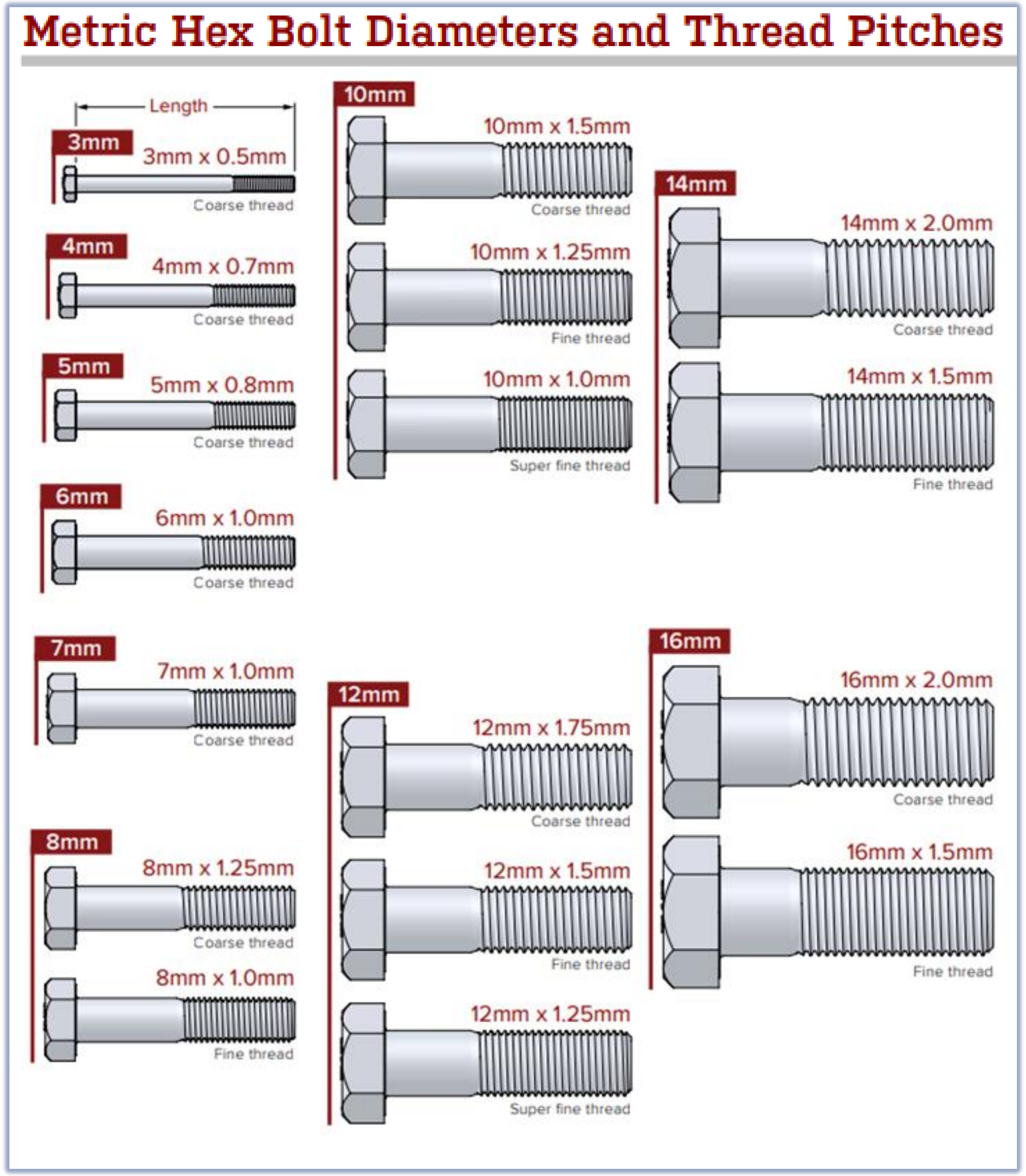
L2 CHAMPION BOLT & SUPPLY INC.

L3 AA ANCHOR BOLT, INC.

Discrete Numeric Factor: *Diameter*

Order does matter.

Interpolation makes sense.



Designs like a *categorical* factor, but models as *continuous*

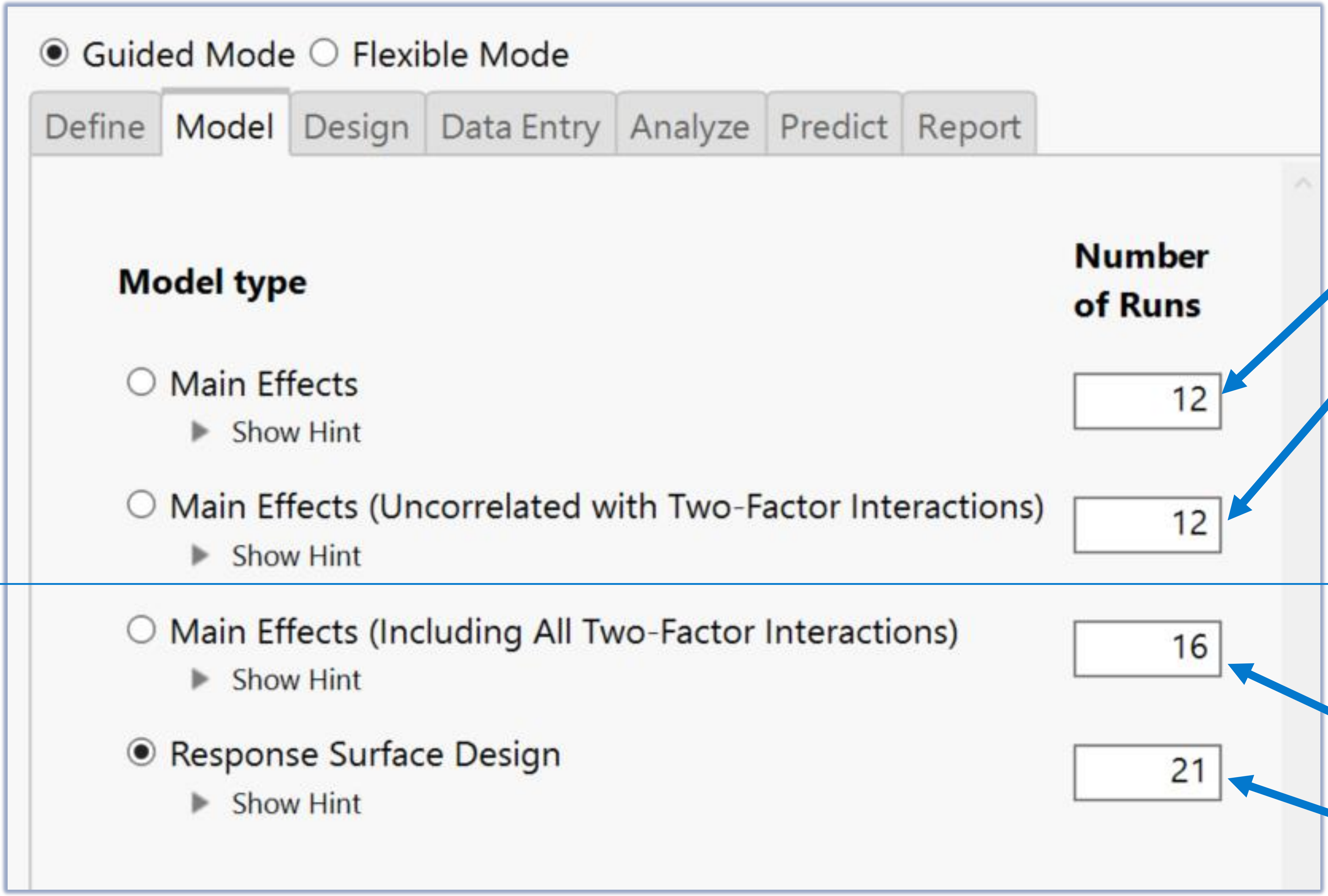
Bolt diameters are only available in whole millimeters between 3 & 16, with no choice of 9, 11, 13, & 15 mm.

For range of 7 to 10, mid point is ~~8.5~~. Only "mid" level is 8 mm which is unevenly spaced between ends.

For range of 10 to 16, mid point is ~~13~~. Only "mid" levels are evenly spaced, 12 & 14 mm.

Model Choices in Easy DOE

As complexity supported increases, so do the number of runs



● Guided Mode ○ Flexible Mode

Model type	**Number of Runs**
○ Main Effects ▶ Show Hint	12
○ Main Effects (Uncorrelated with Two-Factor Interactions) ▶ Show Hint	12
○ Main Effects (Including All Two-Factor Interactions) ▶ Show Hint	16
● Response Surface Design ▶ Show Hint	21

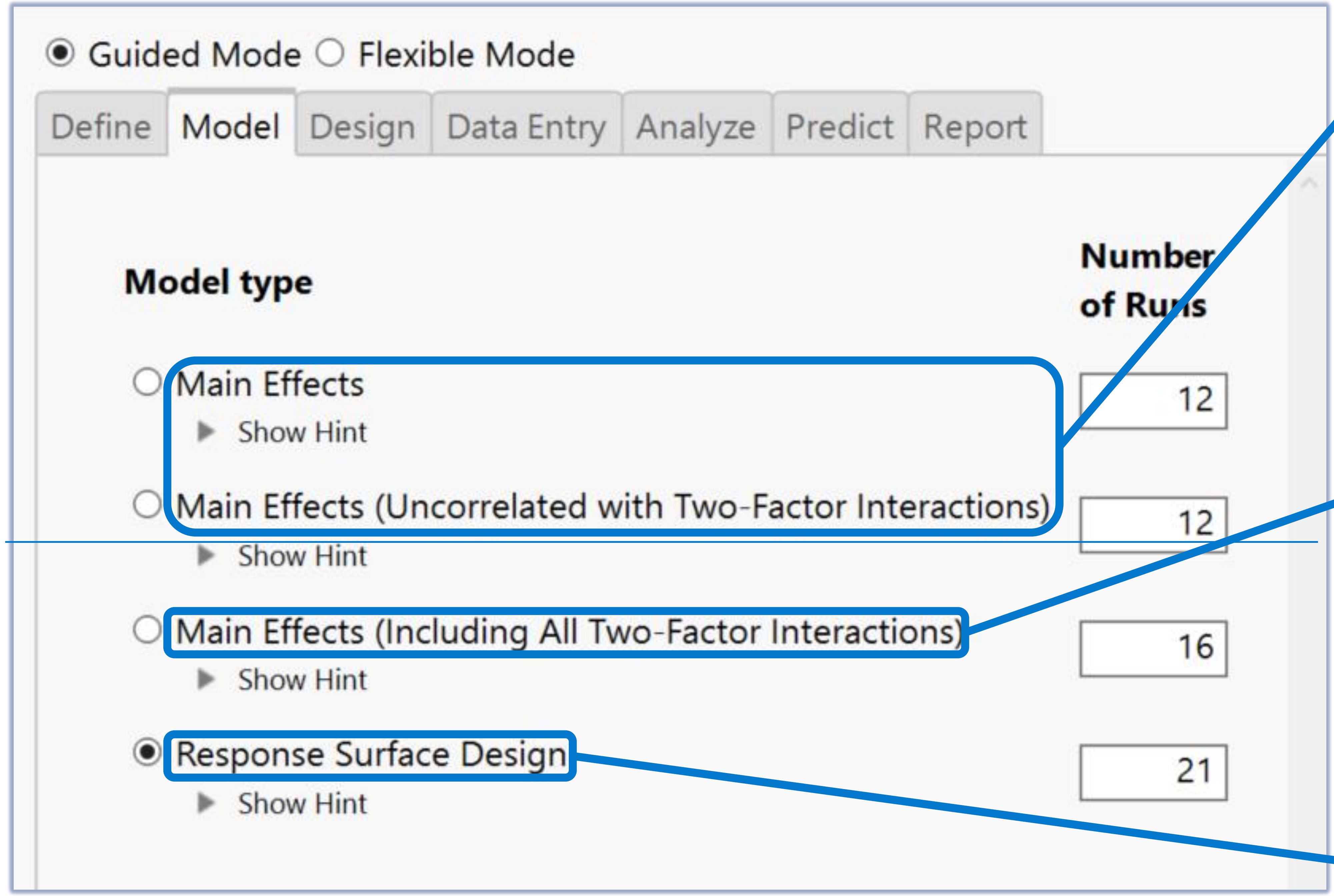
Screening

- Less complex (fewer runs)
- More robust (usually ≈1.5X runs)
  - *When conditions are appropriate* – designs for this choice include mid-levels for continuous factors

Prediction

- Less complex (fewer runs)
- More robust (usually ≈1.2X runs)
  - Design will have mid-levels for continuous factors supporting *optima NOT forced into corners!*

Model Choices in Easy DOE



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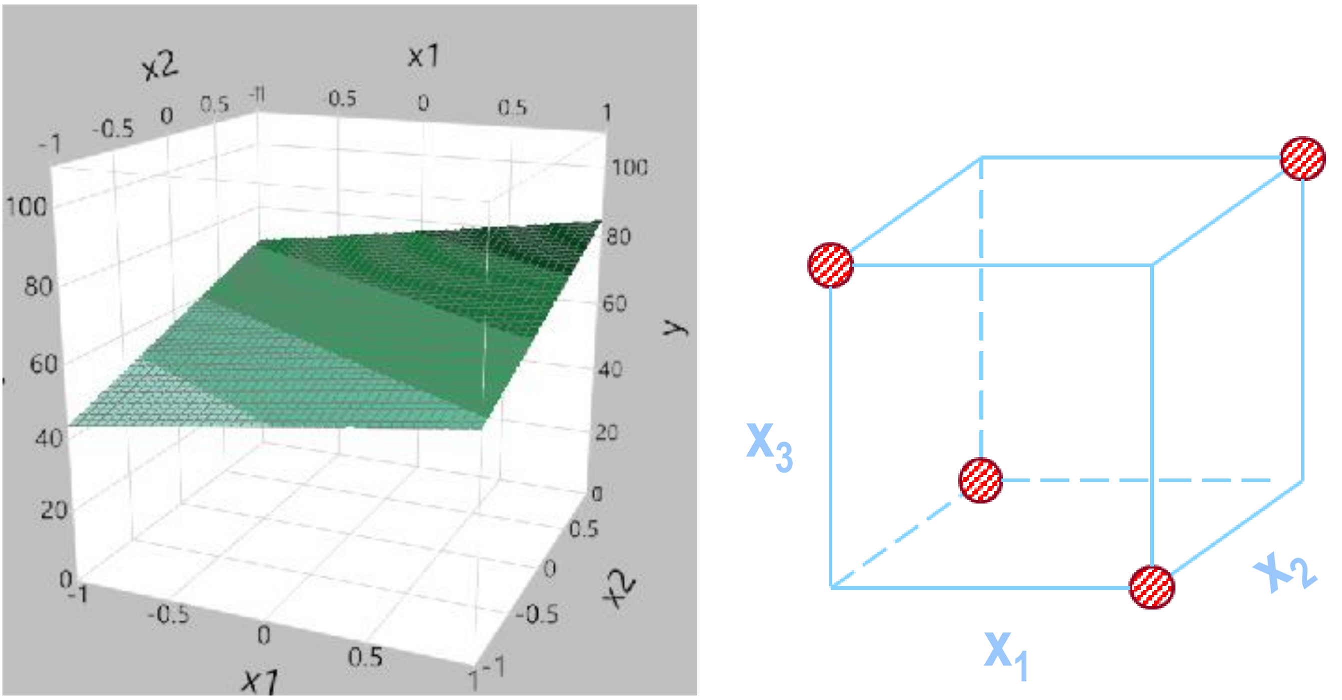
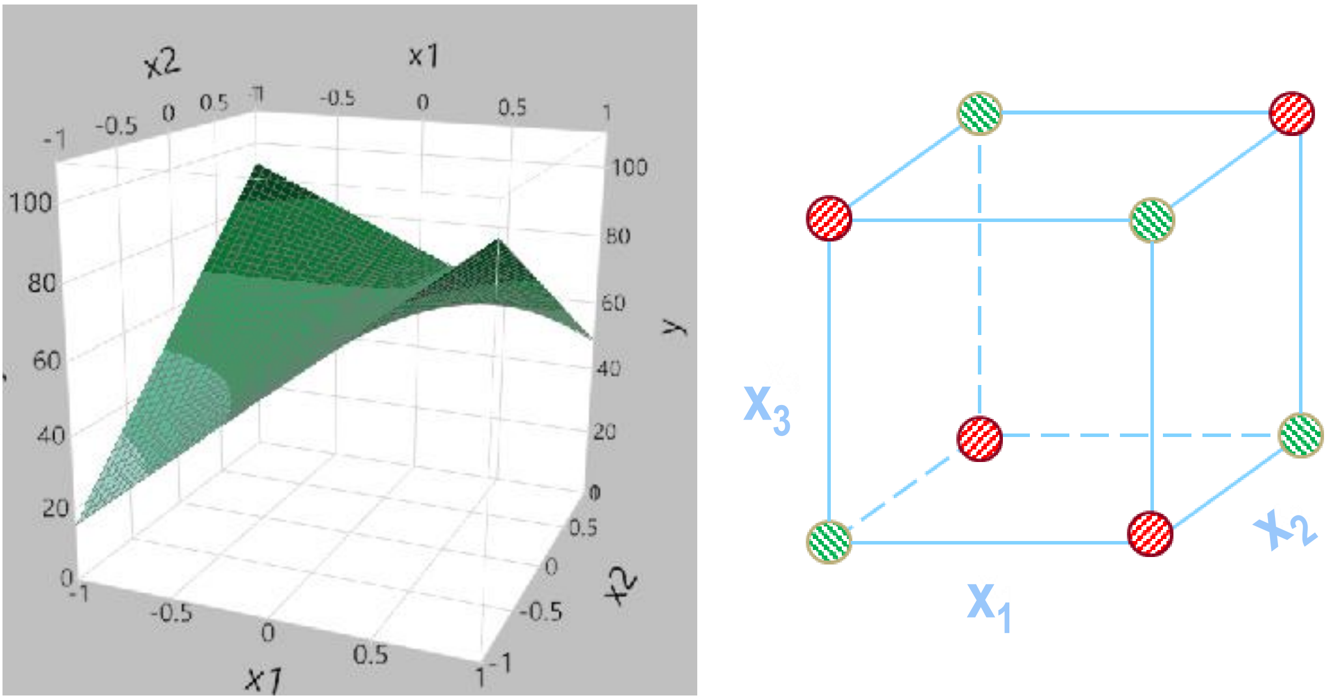
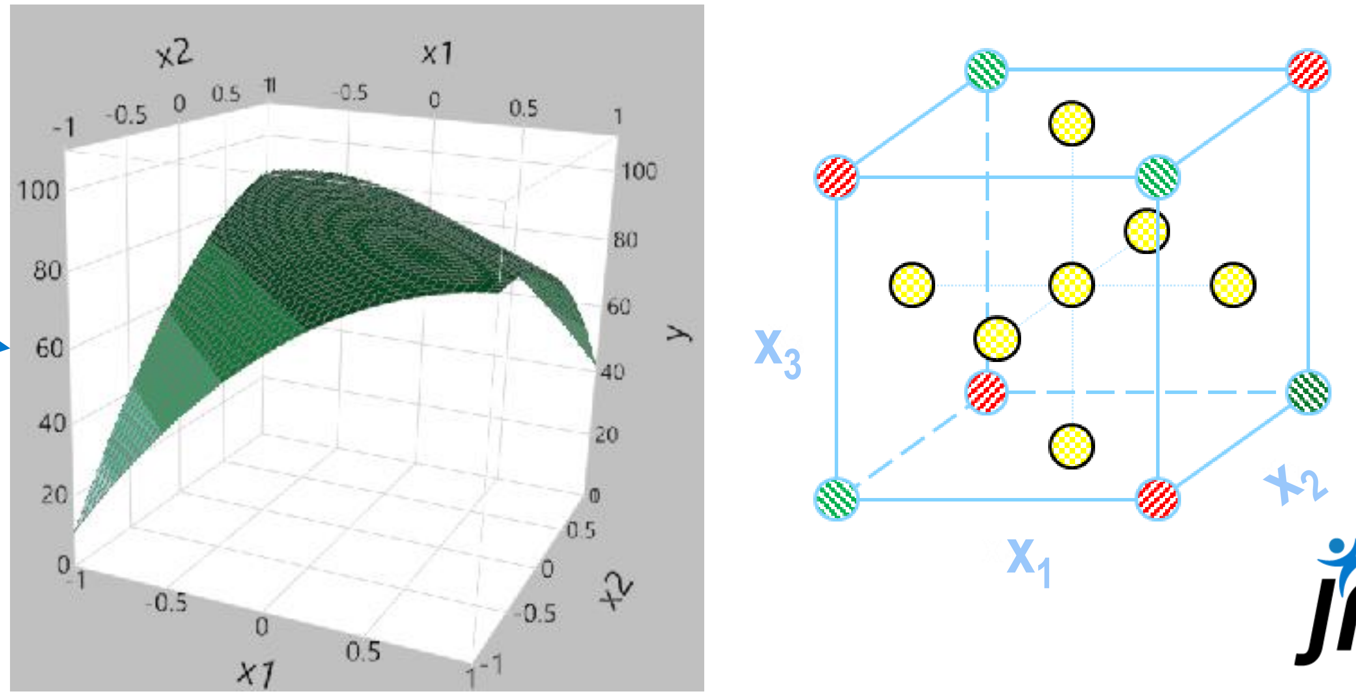


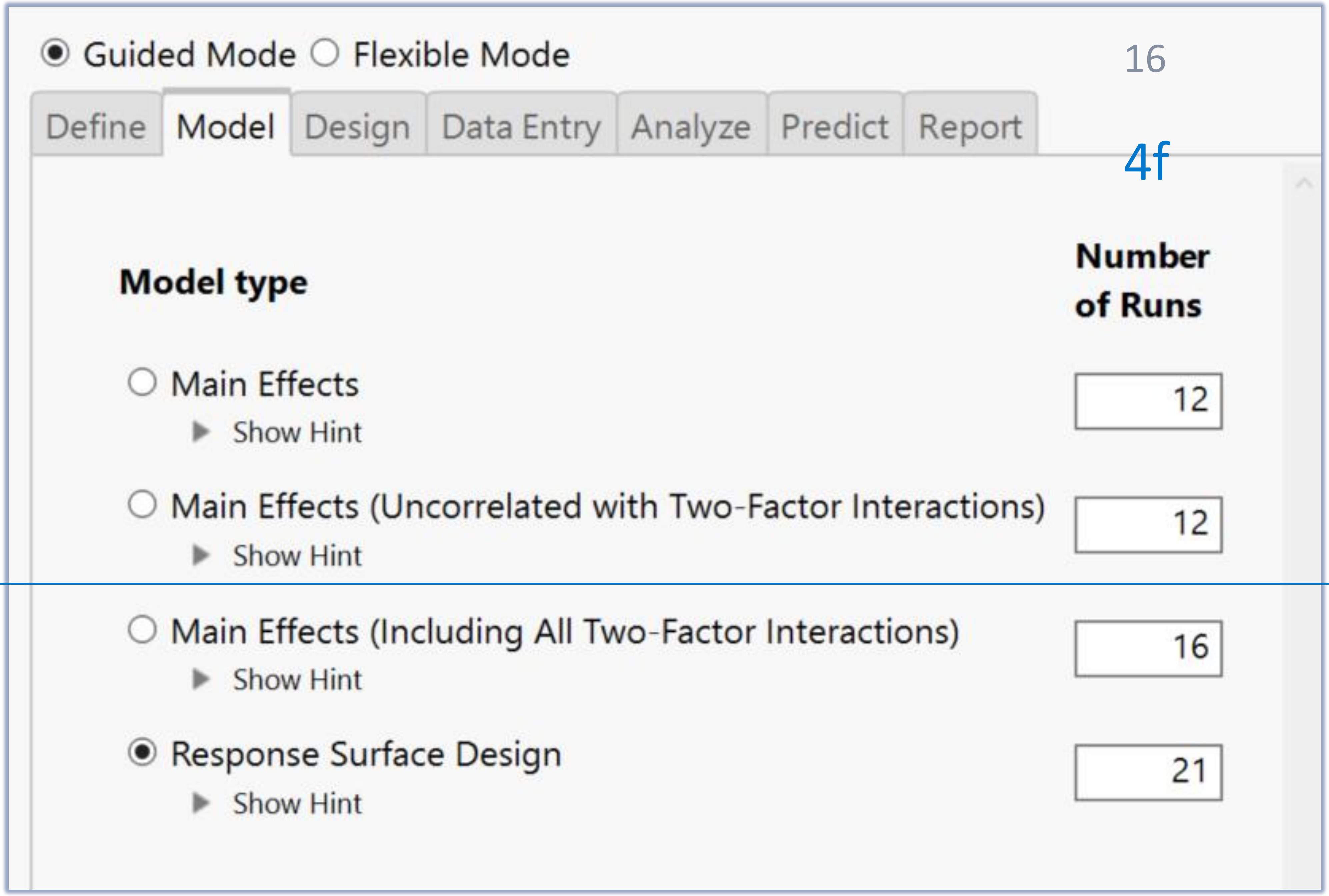




As complexity to be supported increases, so do the number of runs

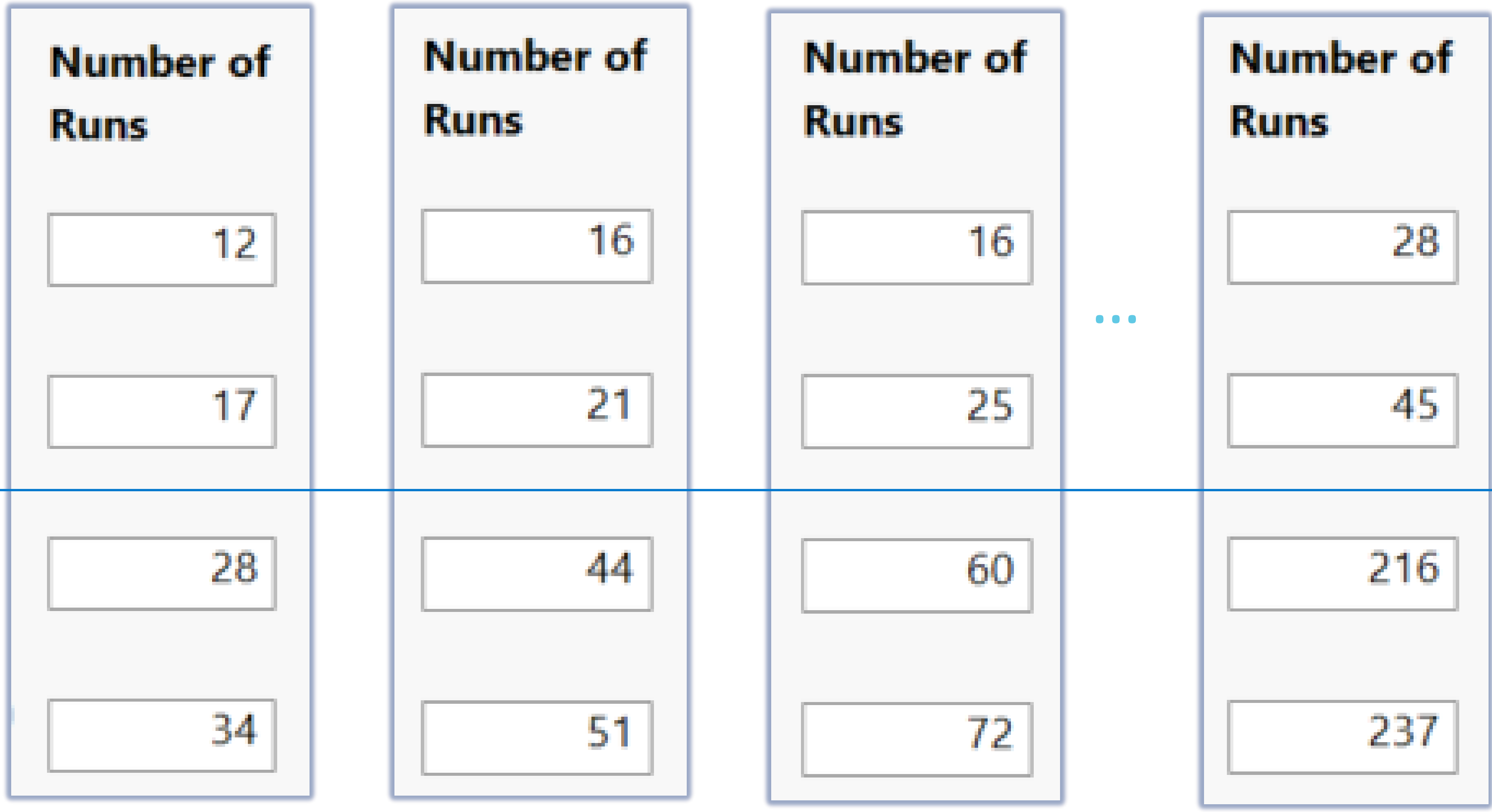
Model Choices in Easy DOE

Number of runs for increasing numbers of continuous factors



● Guided Mode ○ Flexible Mode

Model type	Number of Runs
○ Main Effects	12
○ Main Effects (Uncorrelated with Two-Factor Interactions)	12
○ Main Effects (Including All Two-Factor Interactions)	16
● Response Surface Design	21



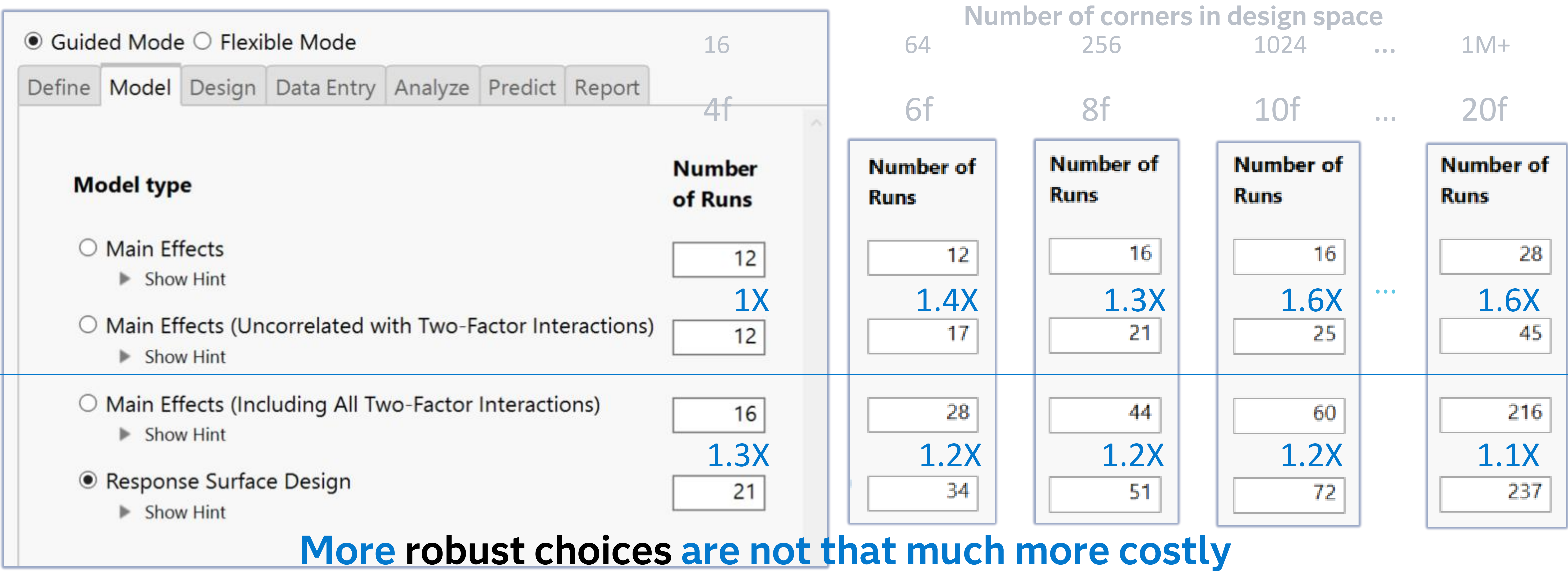
Number of corners in design space

	16	64	256	1024	…	1M+
	4f	6f	8f	10f	…	20f
	Number of Runs	Number of Runs	Number of Runs	Number of Runs		Number of Runs
Main Effects	12	12	16	16	…	28
Main Effects (Uncorrelated with Two-Factor Interactions)	12	17	21	25		45
Main Effects (Including All Two-Factor Interactions)	16	28	44	60		216
Response Surface Design	21	34	51	72		237

NOTE: Number of factors need not be even

Model Choices in Easy DOE

Number of runs for increasing numbers of continuous factors



● Guided Mode ○ Flexible Mode

Number of corners in design space

	16	64	256	1024	...	1M+
	4f	6f	8f	10f	...	20f
Model type	**Number of Runs**	**Number of Runs**	**Number of Runs**	**Number of Runs**		**Number of Runs**
○ Main Effects ▶ Show Hint	12	12	16	16		28
	1X	1.4X	1.3X	1.6X	...	1.6X
○ Main Effects (Uncorrelated with Two-Factor Interactions) ▶ Show Hint	12	17	21	25		45
○ Main Effects (Including All Two-Factor Interactions) ▶ Show Hint	16	28	44	60		216
	1.3X	1.2X	1.2X	1.2X		1.1X
● Response Surface Design ▶ Show Hint	21	34	51	72		237

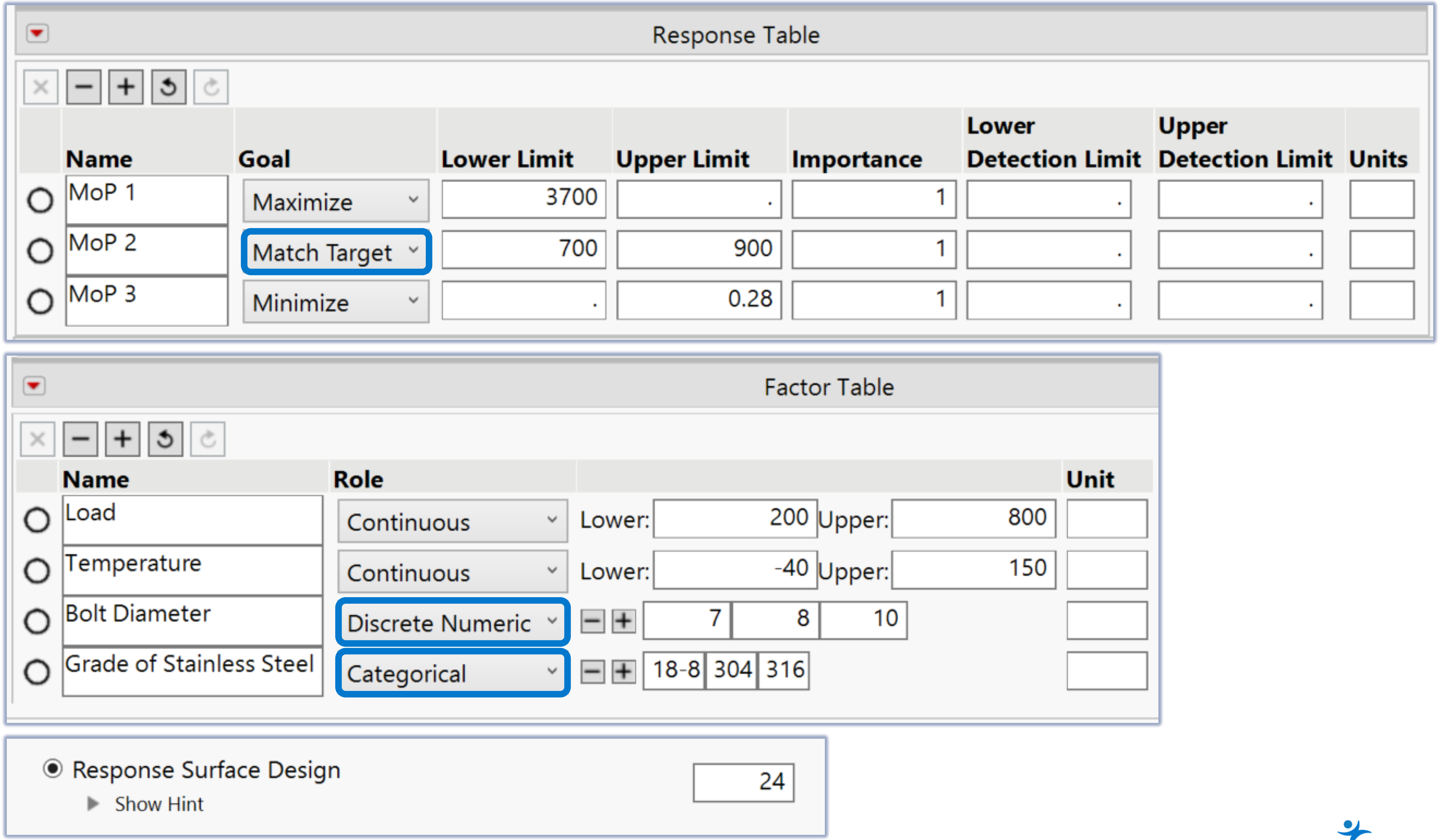
More robust choices are not that much more costly and can actually save development time by reducing the number of rounds of experimentation.

Use Easy DOE Second Time with a few Changes

3-response, 4-factor, trade-space analysis and optimization example

New type
of goal,
Match Target

New types of factors,
Discrete Numeric
& Categorical



Response Table

	Name	Goal	Lower Limit	Upper Limit	Importance	Lower Detection Limit	Upper Detection Limit	Units
○	MoP 1	Maximize	3700	.	1	.	.	
○	MoP 2	Match Target	700	900	1	.	.	
○	MoP 3	Minimize	.	0.28	1	.	.	

Factor Table

	Name	Role		Unit
○	Load	Continuous	Lower: 200 Upper: 800	
○	Temperature	Continuous	Lower: -40 Upper: 150	
○	Bolt Diameter	Discrete Numeric	7 8 10	
○	Grade of Stainless Steel	Categorical	18-8 304 316	

● Response Surface Design 24

▶ Show Hint

MoP = Measure of Performance

Go to JMP 18…

Why Easy DOE? - Key Features

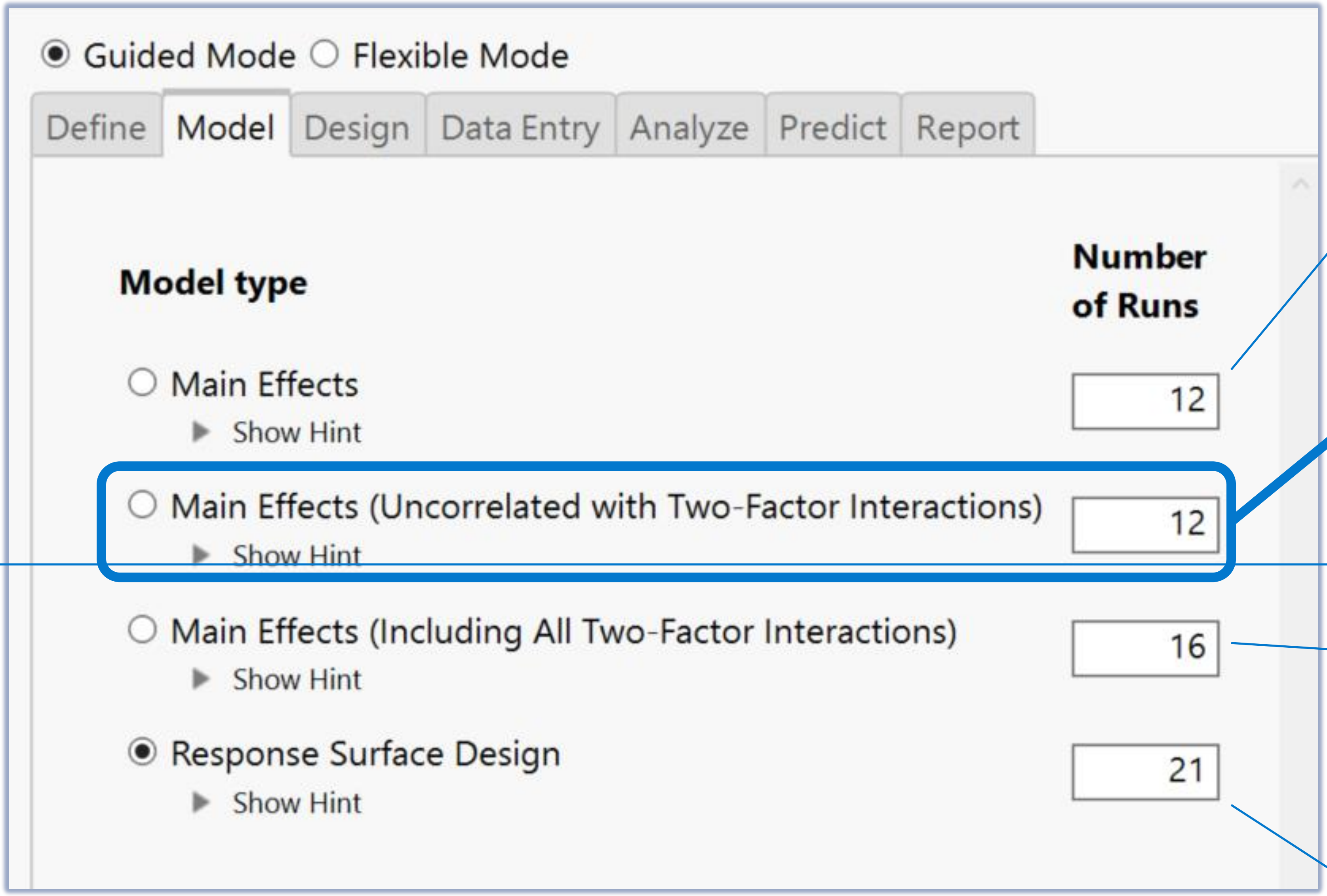
JMP makes it easier for everyone to experiment

- End-to-end coverage of every step of experimentation.
- Streamlined experience through tailored elements in a new user interface.
- Guided mode for novice experimenters (default) and Flexible mode for more demanding situations.
- Comprehensive summary report is automatically written based on the current state of the experiment.
- Save your work at any time and return to the same point.
- Easily share experiments with others.

Developer Tutorial: Easy DOE – Expertly Guiding Users Through Designing an Experiment

2nd Model Choice in Easy DOE

applies an algorithm to factor choices & generates a DSD *when appropriate**



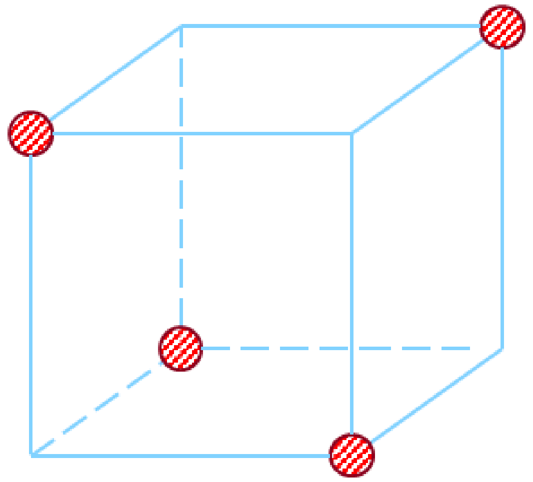
● Guided Mode ○ Flexible Mode

Define | Model | Design | Data Entry | Analyze | Predict | Report

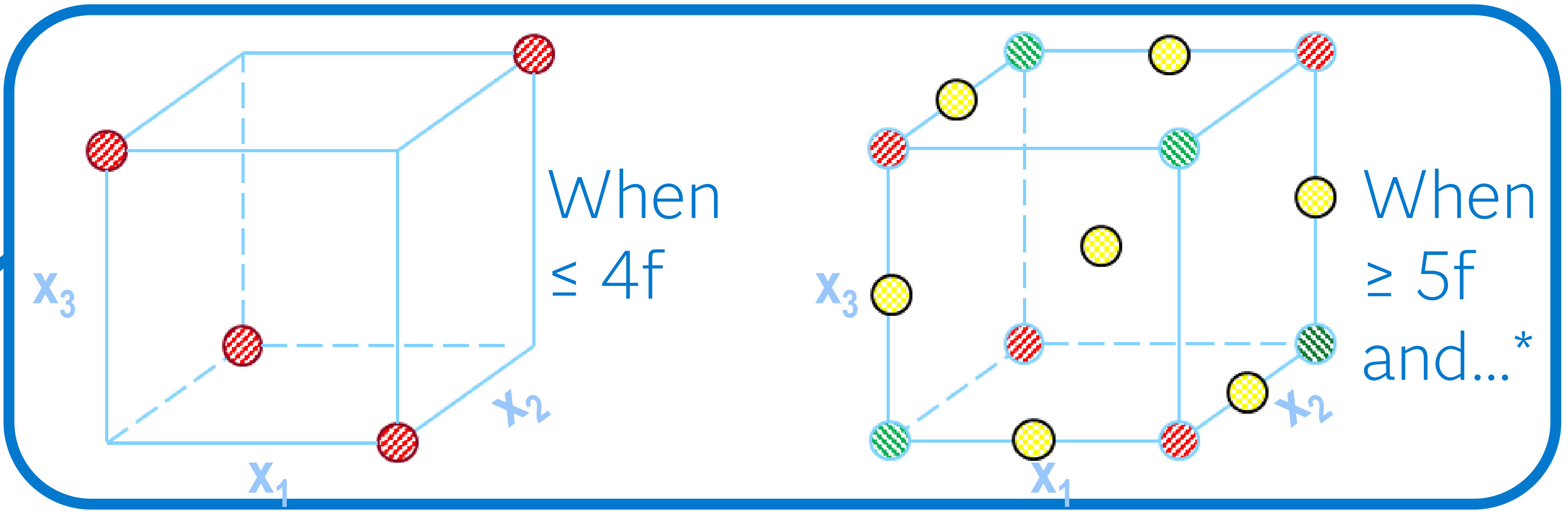
Model type	**Number of Runs**
○ Main Effects ▶ Show Hint	12
○ Main Effects (Uncorrelated with Two-Factor Interactions) ▶ Show Hint	12
○ Main Effects (Including All Two-Factor Interactions) ▶ Show Hint	16
● Response Surface Design ▶ Show Hint	21

*Definitive Screening Design (DSD) is created for as few as 5 factors, provided that at least 3 are continuous, and no more than 3 factors are categorical at 2-levels.

If a categorical factor at ≥ 3-levels, or a discrete numeric factor is used, then design will NOT be a DSD.

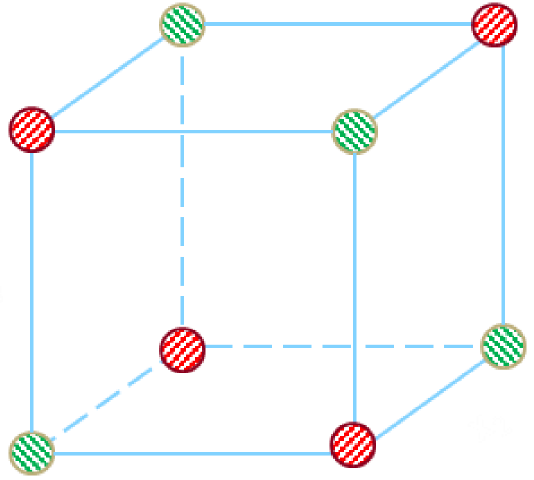


Projection of 5 or more factor DSD into 3 factors

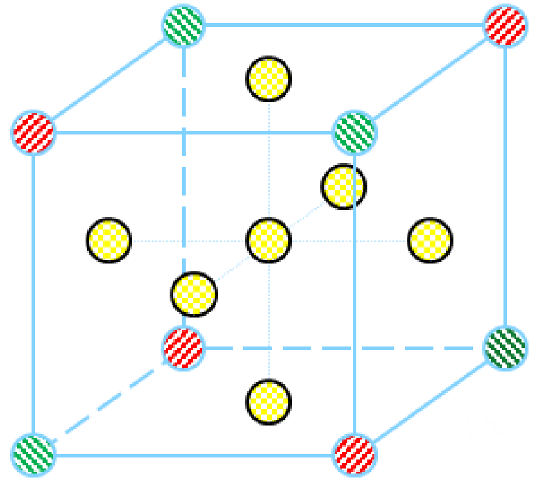


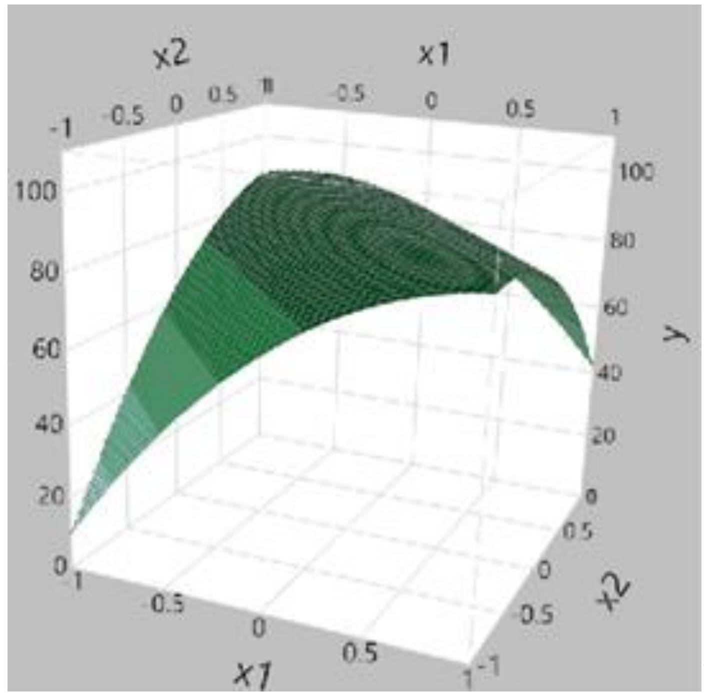
When ≤ 4f

When ≥ 5f and…*



DSD has *potential* to support a response surface model if only a few factors are important.





JMP® STATISTICAL DISCOVERY