

# The JMP® Design of Experiments Advantage

Fit the design to your problem, not your problem to the design

WHITE PAPER

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## Introduction

Successful organizations use structured experimentation to design new products and improve existing processes. JMP software's unique approach to the design of experiments (DOE) offers you a competitive edge, helping you explore and exploit the multifactor opportunities that exist in almost all real-world situations.

JMP offers state-of-the-art capabilities for design of experiments, integrating cutting-edge research so you can find the experiments that best answer your specific questions in your specific circumstances. JMP also offers a rich set of analyses tailored to your design in a form you can easily use, in an environment that harnesses the full power of JMP – graphics, scripting, journaling, interaction with other platforms, project collaboration, and trusted analytics.

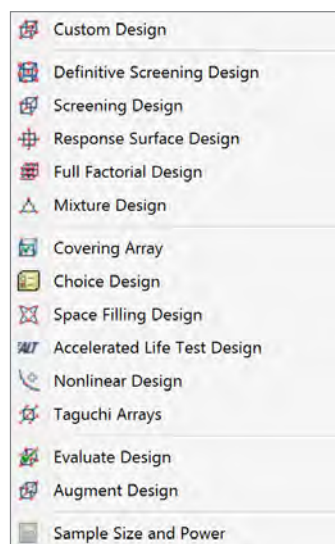
Rather than force a textbook design onto your problem, use JMP to tailor the design to your problem and resource limitations. The unique Custom Design platform constructs an optimal design to fit your individual needs, taking into account your ability to manipulate factors, constraints on factor settings, information from covariates, and other experimental conditions and resource restrictions.

Conducting an experiment almost always advances your knowledge, but often raises further questions. JMP lets you build on existing experimental results by augmenting your original design. The Augment platform lets you treat experimentation as an iterative process by leveraging your existing experimental data to gain more focused and detailed knowledge with only a small number of additional experimental runs. Coupled with a custom design, a definitive screening design, or any other design type, Augment delivers concrete results. You can even repair a broken design by adding new runs that don't fall in an unfeasible design region: The Augment platform lets you impose constraints on the design space.

Here are some of the DOE platforms and methods that you can use to meet your unique needs:

**Custom Design** – If a predefined standard design doesn't fit your problem, you can construct cost-effective, optimal designs that are custom-built for your specific experimental situation. The Custom Design platform creates a wide array of **design types** capable of addressing a wide range of experimental goals.

**Definitive Screening Design** – One of the most important classes of designs developed over the past 20 years, definitive screening designs provide sound information about main effects while allowing you to detect and identify factors causing strong nonlinear effects on the response. Depending on the number of active factors, you can potentially learn about dominant two-factor interactions. If few factors are active, the DSD can even support analysis of a



complete response surface model. Because the required number of runs only slightly exceeds twice the number of factors, you can use these designs to screen a large number of factors.

**Main Effects Screening Design** – If no standard screening design exists for your experimental situation, JMP provides *main effects screening designs*. Main effects screening designs are especially useful when you have categorical factors with three or more levels. These designs are excellent for estimating main effects when interactions are negligible.

**Space Filling Design** – These designs are primarily used with deterministic experiments, such as computer simulations, where standard experimental designs are not appropriate. JMP provides seven different space-filling design types, including optimally spaced Latin Hypercube designs, for use when all factors are continuous and there are no constraints on the design space. If you have restrictions on your design space or if you have categorical factors, JMP provides the Fast Flexible Filling method, based on clustering. This method generates a well-spaced design regardless of how irregular your design space is. If you need more detail than your initial design provided, you can use the Augment platform to augment your experiment with points that are spatially separated from the original points.

**Mixture Design** – If your factors are ingredients of a formulation whose proportions sum to a fixed total, you should use a mixture design. If you also have additional restrictions on the settings of your mixture design factors, JMP provides both optimal and space-filling methods to generate a mixture design that accommodates those restrictions. When you have nonmixture factors, the Custom Design platform provides the flexibility to generate mixture designs.

**JMP® PRO Covering Array** – If your goal is to determine if there are combinations of factor settings that cause failures in your deterministic (often software or communication) system, use JMP software's new Covering Array platform. Specify the size of the largest n-way combination of components that is likely to drive a failure – the desired strength of your design. JMP will find the smallest design that tests all possible combinations of this size. You can also exclude any combinations that are not permitted.

**Evaluate Design** – Assess the strengths and limitations of your existing experimental design with the Evaluate Design platform.

**Augment Design** – Once you've conducted your design and analyzed the results, if you find that additional runs are needed, or if you have pre-existing historical data you would like to leverage, use the Augment Design platform to add runs that are optimal for your design. If some of your original runs proved infeasible, keep the successful runs and augment them with new runs subject to restrictions that avoid the region where the process can't operate.

## Custom Design

Using the JMP Custom Design platform, you describe the process variables and constraints, make selections relating to your *a priori* model and design size and structure, and JMP constructs a design to match. The Custom Design window guides you through the process step by step:

1. **Define** responses, factors and factor constraints.
2. **Specify** the *a priori* model.
3. **Generate** the design.
4. **Review** and evaluate the design.
5. **Conduct** the experiment.
6. **Fit** a model and predict performance.

**Note:** Examples in the sections below use the Coffee Data.jmp sample data table.

### Define Responses, Factors and Factor Constraints

When you choose **DOE > Custom Design**, the Custom Design window appears with outlines to add your responses and factors.

The screenshot shows the JMP Custom Design window with three main sections:

- Responses:** Contains a table with columns: Response Name, Goal, Lower Limit, Upper Limit, and Importance. One response is listed: Strength (Goal: Match Target, Lower Limit: 1.2, Upper Limit: 1.4, Importance: .). Below the table is a text field labeled "optional item".
- Factors:** Contains a table with columns: Name, Role, Changes, and Values. Factors listed include Grind (Categorical, Easy, Coarse), Temperature (Continuous, Easy, 195), Time (Continuous, Easy, 3), Charge (Continuous, Easy, 1.6), and Station (Blocking, Easy, 1, 2, 3). The "Add N Factors" field is set to 1.
- Define Factor Constraints:** Contains radio buttons for: None (selected), Specify Linear Constraints, Use Disallowed Combinations Filter, and Use Disallowed Combinations Script.

1. Add one or more responses and their goals, limits and importance values.
2. Add different types of factors, their **Values**, and the degree of difficulty involved in changing their settings from one run to the next (**Changes**).

**Note:** Indicating that a factor is *hard* or *very hard* to change yields split-plot or split-split plot designs.

You can specify any combination of the following types of factors: continuous, discrete numeric, categorical, blocking, covariate, mixture, constant or uncontrolled.

3. Define constraints on factor settings, if appropriate.

## Specify the Model

In the Model outline, specify your *a priori model*, which is a model consisting of the effects that you want to estimate.

Name	Estimability
Intercept	Necessary
Grind	Necessary
Temperature	Necessary
Time	Necessary
Charge	Necessary
Station	Necessary

Add main effects, interactions, response surface model terms, crossed terms, powers, and mixture-specific terms. For each effect, indicate whether it is *Necessary* to estimate that effect, or if it is acceptable to only estimate the effect *If Possible*, given the run size and other requirements.

## Generate the Design

In the Design Generation outline, specify the size and structure of the design.

Number of Center Points:

Number of Replicate Runs:

**Number of Runs:**

☐ Minimum 6

☐ Default 12

☒ User Specified

1. Require additional center points and replicated runs, if desired. If there are no fixed blocks or hard-to-change factors, the Design Generation outline enables you to group runs into random blocks. If you have hard-to-change or very-hard-to-change factors, you can specify the numbers of whole plots and subplots, and whether they vary independently (if you have both hard- and very-hard-to-change factors).
2. Specify the number of runs. JMP gives you some guidance:
  - The Minimum number is the number of terms in the model and gives a saturated design.
  - The Default number is based on heuristics for creating a balanced design with at least four runs more than the number of terms. This allows for an estimate of model error that has at least four degrees of freedom.
3. Construct the design.

## Review and Evaluate the Design

After defining a custom design, but before you create the design table, you can preview the design and investigate details by looking at various plots and tables that serve as design diagnostic tools. [Learn more.](#)

**Design**

Run	Grind	Temperature	Time	Charge	Station
1	Medium	205	4	2.4	1
2	Coarse	195	3	1.6	1
3	Medium	205	3	1.6	1
4	Coarse	195	4	2.4	1
5	Coarse	205	4	1.6	2
6	Medium	195	4	2.4	2
7	Medium	195	3	1.6	2
8	Coarse	205	3	2.4	2
9	Coarse	205	4	1.6	3
10	Coarse	195	3	2.4	3
11	Medium	195	4	1.6	3
12	Medium	205	3	2.4	3

**Design Evaluation**

- Power Analysis
- Prediction Variance Profile
- Fraction of Design Space Plot
- Prediction Variance Surface
- Estimation Efficiency
- Alias Matrix
- Color Map On Correlations
- Design Diagnostics

Output Options

Run Order: Randomize within Blocks

Make Table

Back

Once you are satisfied with the design, click **Make Table** to create the design table.

## Conduct the Experiment

Run the experiment and add the results to the design table.

Custom Design

Design Custom Design

Criterion D Optimal

Model

DOE Dialog

Columns (6/0)

- Grind \*
- Temperature \*
- Time \*
- Charge \*
- Station \*
- Strength \*

	Grind	Temperature	Time	Charge	Station	Strength
1	Medium	205	4	2.4	1	
2	Coarse	195	3	1.6	1	
3	Medium	205	3	1.6	1	
4	Coarse	195	4	2.4	1	
5	Coarse	205	4	1.6	2	
6	Medium	195	4	2.4	2	
7	Medium	195	3	1.6	2	
8	Coarse	205	3	2.4	2	
9	Coarse	205	4	1.6	3	
10	Coarse	195	3	2.4	3	
11	Medium	195	4	1.6	3	
12	Medium	205	3	2.4	3	

In this example, add your results in the **Strength** column. Now you are ready to analyze your results. Notice the **Model** script, which makes running your analysis easy.

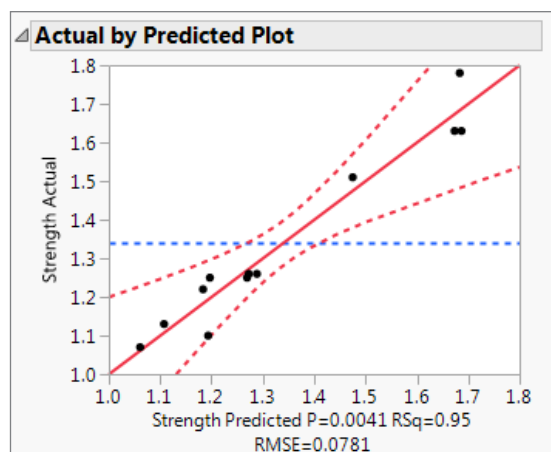
## Fit a Model and Predict Performance

The design table provides scripts that guide your analysis. The **Model** script adds the appropriate responses and model effects in the Fit Model launch window, so all you have to do is select the **Run Script** option and click **Run** to obtain the report. The analysis is for the original *a priori* model that the design was built to support.

*Note:* Screening designs have an additional script that automatically performs a screening analysis.

For example, here are a few things that you can do with the Fit Model report (launched from the **Model** script).

1. Examine the Actual by Predicted plot to assess your model's fit.



2. Use the Effect Summary report to determine a final model. Review the analysis.

Eliminate effects that appear inactive in order to simplify the model and add degrees of freedom to the error term. The entire report updates automatically. Note that adding effects to the model, which the design was not built to support, should be done with caution.

**Effect Summary**

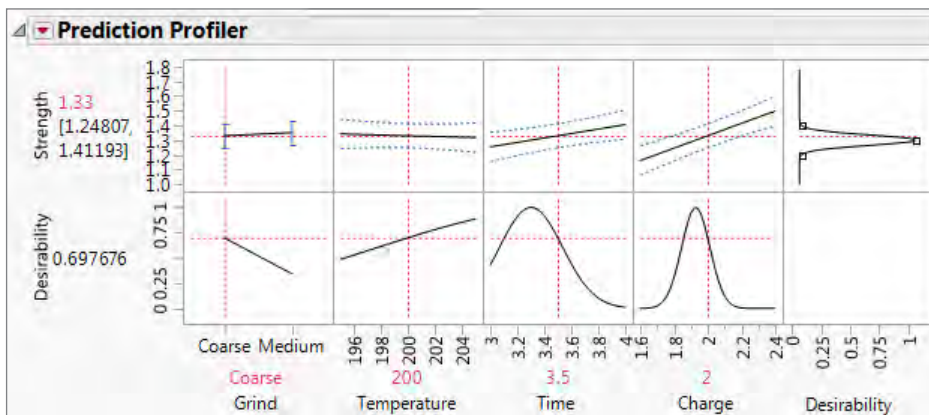
Source	LogWorth	PValue
Charge(1,6,2,4)	3.178	0.00066
Station	2.004	0.00991
Time(3,4)	1.699	0.02000
Temperature(195,205)	0.220	0.60303
Grind	0.186	0.65103

[Remove](#) [Add](#) [Edit](#) ☐ FDR



3. Take advantage of the Prediction Profiler's flexibility and interactivity to:

- See how your predicted response changes as you vary factor settings.
- Explore the effects of interactions.
- Find optimal settings for your factors.
- Gauge your model's sensitivity to changes in the factor settings.



## Custom Design Types

In the real world, a predefined standard design rarely provides an exact match for your unique experimental needs. You can construct a broad range of designs that are custom-built to your needs with the Custom Design platform.

### Factor screening with flexible fixed and random block sizes

In a standard screening design, block sizes are limited to powers of two. In a custom design, you can have blocks of any size. Blocks can be fixed or random effects.

- For a fixed block, add a blocking factor with any number of runs per block.
- For random blocks, define factors as hard-to-change or very-hard-to-change, or group your runs into random blocks of any size.

JMP constructs a design that is optimal for your specifications involving blocks. See an [example of a design with fixed blocks](#) and an [example of a split-plot design](#) on the JMP User Community.

### Supersaturated designs for factor screening

Identify the vital few factors that are driving process behavior with a supersaturated design. Factor screening relies on the principle of effect sparsity, which states that only a few of the many factors in a screening experiment are active. A supersaturated design can examine dozens of factors using fewer than half as many runs as factors. See an [example of a supersaturated design](#) on the JMP User Community.

## Response surface models with categorical factors

When you have categorical factors, standard response surface designs aren't feasible since they are limited to continuous and blocking factors. To include a categorical factor in a response surface experiment, you could replicate a standard response surface design for each level of the categorical factor, but this would require more runs than are necessary. Standard response surface designs also require fixed block sizes. The Custom Design platform can construct I-optimal response surface designs that include both categorical factors and blocks of arbitrary sizes. These designs involve substantially fewer runs, making them more cost-effective. See an [example of a response surface design with a categorical factor](#) and a [response surface design with flexible blocks](#) on the JMP User Community.

## Split-plot, split-split-plot, and two-way split-plot (strip-plot) designs

Many experimental situations involve process factors that are harder to change than other process factors. For example, oven temperature can be hard to change, while the finish applied to parts placed in the oven is easy to change. Randomizing all runs is difficult and perhaps impossible. In this situation, treat oven temperature as a whole-plot factor to acknowledge the restriction on randomization. Build the whole-plot factor into your design by designating oven temperature as a hard-to-change factor.

You can specify factors as hard-to-change or very-hard-to-change in the Custom Design platform. These factors result in random blocks of runs. The resulting types of designs are random block, split-plot, split-split-plot, and two-way split-plot (strip-plot) designs. The models for these designs have one or more random effects. The Custom Design platform can construct either D-optimal or I-optimal designs for these situations.

You can analyze the resulting experimental data using the Fit Model platform with the Standard Least Squares personality and the REML methodology, or, in JMP Pro, using the Mixed Model personality. The Model script adds the appropriate terms to the Model Effects list and selects the REML method by default. See an [example of a split-plot design](#) and an [example of a two-way split-plot design](#) on the JMP User Community.

## Mixture designs with process variables

The Mixture Design platform provides classic mixture designs. In these designs, all factors are required to be mixture components. But you might want to vary certain process settings along with the percentages of the mixture components. The Custom Design platform constructs optimal designs that include both mixture components and process variables so that you can study both types of factors in a single experiment. See an [example of a mixture design with process variables](#) on the JMP User Community.

## Mixture of mixtures designs

If your situation calls for experimentation with a mixture of mixtures, you can specify your design situation using linear constraints. The Custom Design platform will provide you with an optimal design. See an [example of a mixture of mixtures design](#) on the JMP User Community.

## Designing experiments with fixed covariate factors

You may have quantitative or qualitative data available for your experimental units prior to the start of an experiment. If these variables, called *covariates*, are likely to affect the experimental response, you should include them as design factors. However, unlike other factor types, a covariate factor cannot be set to an arbitrary value for the study. The Custom Design platform uses the available covariate values to create an optimal design, given your specified number of runs. The design table indicates which units to include in the study, based on their covariate values, and sets the levels of other specified factors so that the entire design is optimized. If you have a set of candidate design settings from which you want to select an optimal subset for a design, you can define all of your variables as covariates. See an [example of a design with fixed covariate factors](#) on the JMP User Community.

## Infeasible factor combinations

Sometimes it is impossible to vary factors independently over their entire experimental range. In these situations, you have factors whose levels are constrained. You can disallow particular combinations of factor levels in the Custom Design platform (and in several other DOE platforms). You can specify linear inequality constraints in equation form or use the intuitive Disallowed Combinations filter. See an [example of a design with factor constraints](#) on the JMP User Community.

## Optimize Custom Designs

Depending on your goals, select the type of optimization that is appropriate.

Goal	Optimization	Description
Inference	D-Optimal	Appropriate for screening experiments. Focus is on precise estimation of the effects to help indicate which effects are important, or active, and which are negligible.
Prediction	I-Optimal	Appropriate for response surface designs. Focus is on minimizing the average prediction variance inside the design region.
Minimize Aliasing	Alias Optimality	Focus is on minimizing the aliasing between effects that are in the <i>a priori</i> model, specified in the Model outline, and effects that are not in the model but are potentially active. Effects that are not in the model but are potentially active are called <i>alias effects</i> . You can specify these in the Alias Terms outline. By default, the Alias Terms list includes relevant two-factor interactions.

In JMP, the default and recommended criterion is set to D-optimal for all design types except response surface designs. If you add effects in the Model outline by pressing the RSM button, JMP automatically creates an I-optimal design. If you add those same effects without pressing the RSM button, JMP creates a D-optimal design. You can change the design criterion manually by selecting the Optimality Criterion option from the Custom Design red triangle menu.

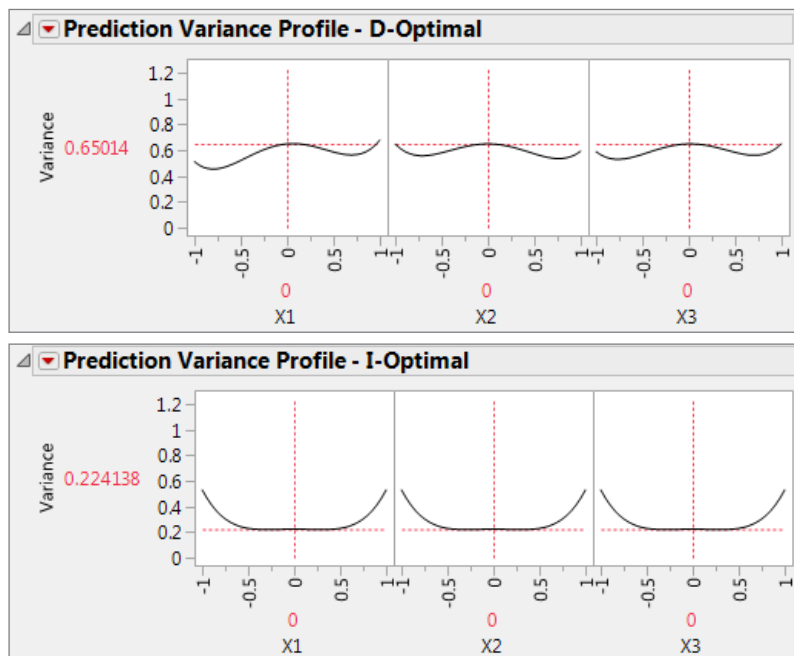
## I-Optimal Versus D-Optimal

I-optimal designs tend to place fewer runs at the extremes of the design region than D-optimal designs. Examples of D- and I-optimal 16-run designs are shown below. The D-optimal design has no center points, while the I-optimal design has two center points.

Design - D-Optimal			
Run	X1	X2	X3
1	0	-1	-0.12
2	-1	-1	1
3	1	0	-1
4	-1	0	-1
5	-1	-1	-1
6	1	1	0
7	-1	1	1
8	1	-1	1
9	1	1	1
10	0	0	1
11	-1	1	0
12	-1	0	0
13	1	-1	-1
14	0	1	-1
15	1	1	-1
16	-1	1	-1

Design - I-Optimal			
Run	X1	X2	X3
1	1	1	-1
2	0	0	0
3	-1	-1	-1
4	0	0	0
5	1	-1	1
6	1	-1	-1
7	1	1	1
8	0	0	1
9	-1	1	1
10	0	0	-1
11	-1	0	0
12	1	0	0
13	0	1	0
14	-1	-1	1
15	0	-1	0
16	-1	1	-1

Prediction Variance Profile plots compare both 16-run response surface designs in terms of prediction variance.



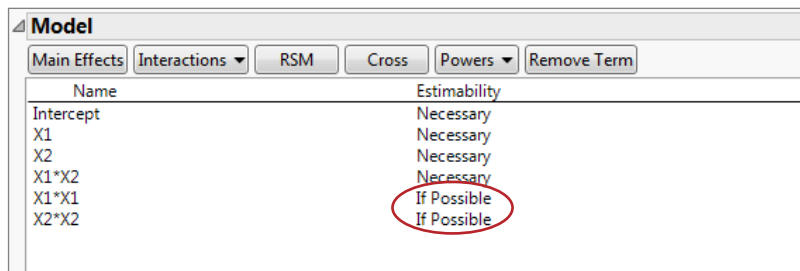
The D-optimal design's prediction variance at the center of the design region (0.650) is about three times the variance of the I-optimal design at the center of the region (0.224).

## Bayesian Optimality

In screening designs, experimenters often add center points and other replicated points to a design to help determine whether the *a priori* model is adequate. Although this is good practice, it is not guided by any theory. The Custom Design platform supplies a theoretical foundation for choosing a design that is robust to the modeling assumptions.

### How it works

In the Model outline, if you have terms whose estimability is set to If Possible instead of Necessary, then JMP uses Bayesian I-optimality or D-optimality.



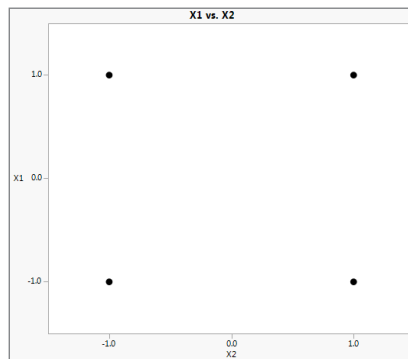
Name	Estimability
Intercept	Necessary
X1	Necessary
X2	Necessary
X1*X2	Necessary
X1*X1	If Possible
X2*X2	If Possible

This criterion results in a design that allows the precise estimation of all of the primary terms while providing omnibus detectability (and some estimability) for the potential terms.

### Example

Suppose you want to model a response as a function of two main effects and an interaction. You can afford five runs.

Suppose that the Model outline (see above) only consists of the four Necessary effects: the Intercept, the two main effects, and their interaction. Four runs are required to estimate these four effects, and the four runs are optimally placed on the vertices of the design space, as shown to the right. But you can afford an extra run, and you would like to use this run to check for curvature.

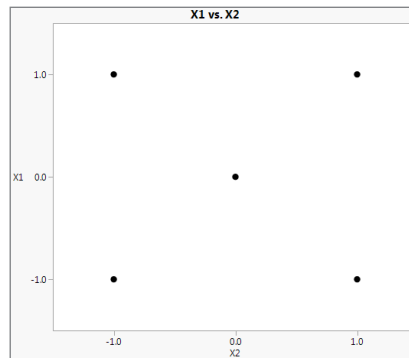


If you specify five runs instead of four in the Design Generation outline, the resulting design replicates one of the four vertices. This is because replicating a run is the D-optimal choice for improving the estimates of the terms in the model. But the resulting design does not address lack of fit.

To obtain a design that addresses lack of fit, in the Model outline, click **Powers** and select **2nd**. This adds the two quadratic terms to the model as Necessary, or *primary*, terms, meaning that they must be estimable. However, estimating these additional terms requires a minimum of six runs, whereas you only have five runs. Change the Estimability of the two quadratic terms to If Possible, which treats them as *potential* terms instead. This means that these terms are estimated to the extent possible given the number of runs.

The five-run design that is generated places a point at the center of the design region, as shown to the right. This center point allows you to check for curvature, which was your intent.

The design you generated is Bayesian D-optimal. When you have If Possible terms in the model, you can specify Bayesian D-optimality or Bayesian I-optimality by selecting Make D-Optimal Design or Make I-Optimal Design, respectively, under the Optimality Criterion option.



To take advantage of the benefits of this approach, the sample size should be larger than the number of primary terms but smaller than the total number of primary and potential terms. In this example, you have four necessary terms and two potential terms, and you can afford five runs. So the sample size (five) is larger than the number of primary terms (four) and smaller than the number of primary and potential terms (six).

For more information, see the [Custom Designs](#) documentation on JMP.com.

## Evaluate Design

How good is your design? Before you commit to a design, you can preview and evaluate it. Get a sense of how well your design will perform using the plots and reports in the Design Evaluation outline.

Most designs display these reports under the Design Evaluation outline:

- [Power Analysis](#)
- [Prediction Variance Profile](#)
- [Fraction of Design Space Plot](#)
- [Prediction Variance Surface](#)
- [Estimation Efficiency](#)
- [Alias Matrix](#)
- [Color Map on Correlations](#)
- [Design Diagnostics](#)

## Power Analysis

Use the Power Analysis outline to:

- Assess the ability of your design to detect effects of practical importance.
- Calculate the power of tests for parameters in your *a priori* model.

*Note:* This example is based on the design for Coffee Data.jmp.

**Power Analysis**

Significance Level 0.05  
Anticipated RMSE 0.1

Term	Anticipated Coefficient	Power
Intercept	1.4	1
Grind	0.05	0.291
Temperature	0.05	0.291
Time	0.05	0.291
Charge	0.05	0.291
Station 1	0.1	0.507
Station 2	0.1	0.507

Apply Changes to Anticipated Coefficients

**Effect Power**

Station 0.888

**Design and Anticipated Responses**

Anticipated Response	Grind	Temperature	Time	Charge	Station
1.4	Coarse	195	3	1.6	1
1.5	Medium	195	4	2.4	2
1.1	Medium	195	4	1.6	3
1.6	Medium	205	4	2.4	1
1.6	Coarse	205	3	2.4	2
1.2	Medium	205	3	2.4	3
1.4	Medium	205	3	1.6	1
1.6	Coarse	205	4	1.6	2
1.3	Coarse	205	4	1.6	3
1.6	Coarse	195	4	2.4	1
1.3	Medium	195	3	1.6	2
1.2	Coarse	195	3	2.4	3

Apply Changes to Anticipated Responses

Begin by specifying the significance level and an estimate of RMSE. All power calculations are based on these specifications. Then, within the Power Analysis outline, you can approach power calculations from two perspectives:

- For all model terms, specify Anticipated Coefficient values that reflect differences that you want to detect. Click **Apply Changes to Anticipated Coefficients** to see power calculations.
- For all design settings, specify Anticipated Response values that reflect differences you want to detect. Click **Apply Changes to Anticipated Responses** to calculate the corresponding anticipated coefficients and to see power calculations.

In either case, once you apply the changes, the power of the effects is computed at the specified values.

In the Coffee Data.jmp data table, Temperature is a continuous factor with coded levels of -1 and 1. Consider the test that Temperature has no effect on the response. This test is equivalent to a test of whether the Anticipated Coefficient for Temperature is 0. You are interested in how likely you are to detect a change of 0.10 units in the response.

In the Power Analysis report, you can specify the significance level of the tests and the Anticipated RMSE (root mean square error). Here the Anticipated RMSE is set to 0.1. The report indicates that, when the Anticipated Coefficient for Temperature is 0.05, the power of the test is 0.291. The coefficient, 0.05, corresponds to an effect size of 0.10 units (twice the coefficient of 0.05). Consequently, the power of this test to detect a difference of 0.10 units across the levels of Temperature is only 0.291.

In the example, the Anticipated Coefficients for Temperature and the other three continuous factors are set to one-half of the Anticipated RMSE. The power for each of the two terms associated with the categorical variable Station, whose coefficients are the same size as the Anticipated RMSE, is 0.507. If you want higher power of detecting the continuous or categorical effects, you may want to revise your design or relax your requirements.

## Prediction Variance Profile

The Prediction Variance Profile plot shows you the precision of your prediction at any combination of factor levels. The prediction variance for any factor setting is the product of the error variance and a quantity that depends on the design and the factor setting. The ratio of the prediction variance to the error variance, called the *relative prediction variance*, depends only on the design and not on the experimental data. Ideally, your design has small relative prediction variance throughout the region over which the factors vary.

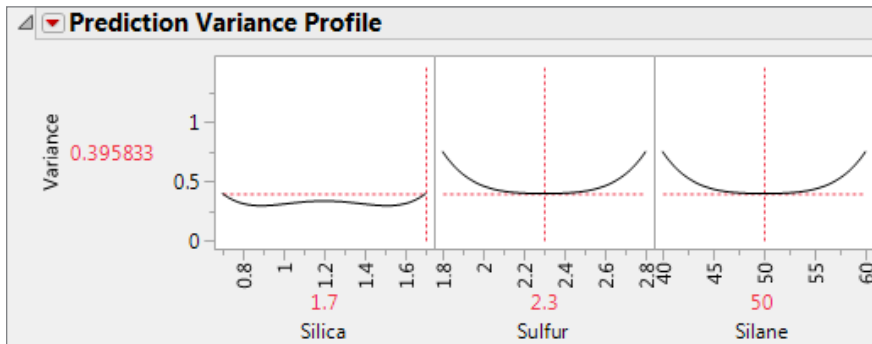
In the Prediction Variance Profile plot, you can:

- Explore values of the relative prediction variance by varying your factor settings.
- Compare designs by looking at their Prediction Variance Profile plots side by side.



- Find the maximum prediction variance for a design and factor settings where it occurs using the Maximize Desirability option.

*Note:* This example is based on the design for Bounce Data.jmp.

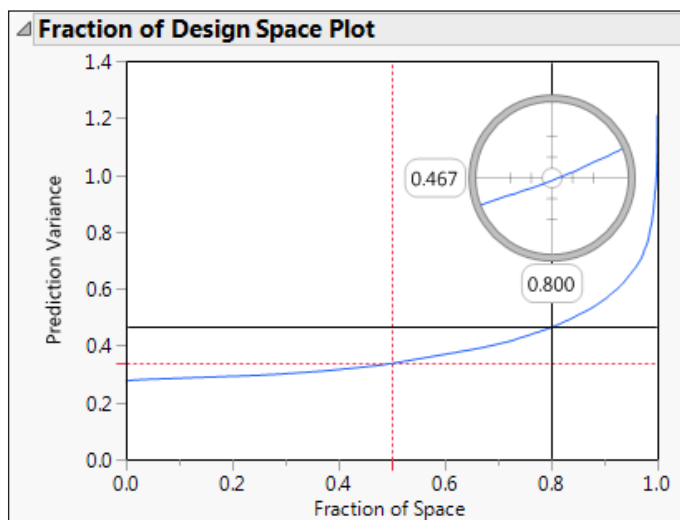


In this example, the plot shows that the relative prediction variance at the high level of Silica and the middle levels of Sulfur and Silane is 0.396.

### Fraction of Design Space Plot

If you are interested in prediction, then it is also useful to examine the Fraction of Design Space plot. This plot shows the proportion of the design space over which the relative prediction variance is less than a given value. Ideally, you would like the relative prediction variance to be small over most of the design space. You can compare designs based on their Fraction of Design Space plots.

*Note:* This example is based on the design for Bounce Data.jmp.

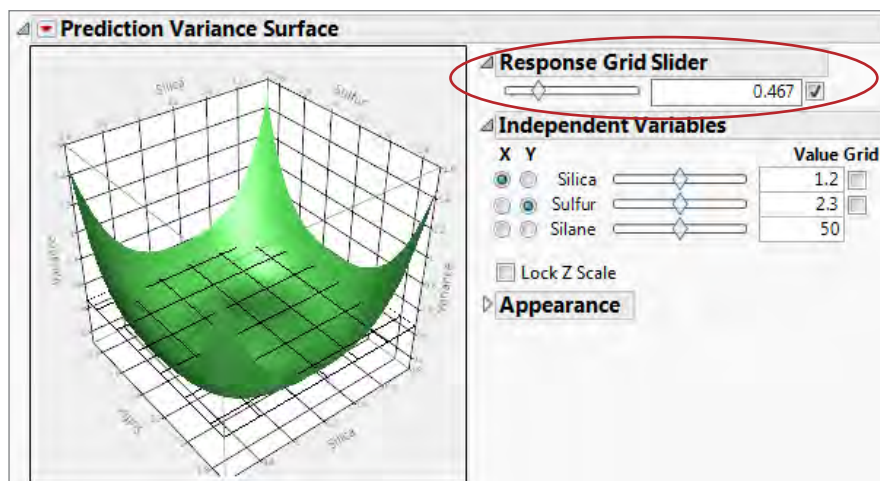


This plot shows that, for 80 percent of the design space, the relative prediction variance is below 0.467.

## Prediction Variance Surface

You can explore the precision of your predictions at settings of any two factors using the Prediction Variance Surface plot. The plot shows a surface that represents the relative prediction variance as a function of design factors. You can drag the plot to rotate it and change the perspective.

*Note:* This example is based on the design for Bounce Data.jmp.



This plot shows the relative prediction variance as a function of Sulfur and Silica. The grid is set at a relative prediction variance of 0.467. The plot shows the portion of the Sulfur and Silica design region where the relative prediction variance is below 0.467. You can see that this region comprises most of the Sulfur and Silica design settings. (And, from the Fraction of Design Space plot, you know that the design region for all *three* factors where the relative prediction variance is below 0.467 comprises 80 percent of the design space.)

## Estimation Efficiency

If you are interested in inference, you want to be able to estimate parameters with the greatest possible precision. The Estimation Efficiency report gives you a measure of precision called the *fractional increase in confidence interval (CI) length*. It also gives you the relative standard error for each parameter estimate in the model.

Note: This example is based on the design for Bounce Data.jmp.

Estimation Efficiency		
Term	Fractional Increase in CI Length	Relative Std Error of Estimate
Intercept	1.236	0.577
Silica	0.369	0.354
Silane	0.369	0.354
Sulfur	0.369	0.354
Silica*Silane	0.936	0.5
Silica*Sulfur	0.936	0.5
Sulfur*Silane	0.936	0.5
Silica*Silica	1.016	0.52
Silane*Silane	1.016	0.52
Sulfur*Sulfur	1.016	0.52

The Fractional Increase in CI Length compares the length of a parameter's confidence interval, as given by the current design, to the length of such an interval given by an *ideal* design. The ideal design is an orthogonal design, if one were to exist. In selecting a design, you would like the fractional increase in confidence interval length to be as small as possible. (Specifically, the Fractional Increase in CI Length is computed as follows: The length of the ideal confidence interval for the parameter is subtracted from the length of its actual confidence interval. This difference is then divided by the length of the ideal confidence interval.)

In this example, some parameters have fractional increases in confidence interval length around 1, which means that their confidence intervals are twice as long as the confidence intervals for the ideal design. Larger increases in the lengths of confidence intervals are typical in response surface designs. This is because the quadratic effects vary between 0 and 1, whereas for the "ideal" design, every column in the model matrix is assumed to have an equal number of +1 and -1 values. Consequently, for response surface designs, this metric is best used for design comparison, rather than interpreted as having an absolute meaning.

## Alias Matrix

If you suspect that there are potentially active effects that are not in your *a priori* model but that might bias the estimates of model terms, you should list them in the Alias Terms outline. Then, once you have generated your design, examine the Alias Matrix. Its entries represent the degree of bias imparted to model parameters by the non-negligible effects of the Alias Terms.

In evaluating your design, you ideally want one of two situations to occur relative to any entry in the Alias Matrix. Either the entry is small or, if it is not small, the effect of the alias term is small, so that the bias for the effect being estimated will be small. If you suspect that the alias term may have a substantial effect, then that term should be included in the model or you should consider an alias-optimal design.

Note: This example is based on the design for Coffee Data.jmp.

Alias Matrix							
Effect	Grind*Temperature	Grind*Time	Grind*Charge	Temperature*Time	Temperature*Charge	Time*Charge	
Intercept	0	0	0	0	0	0	0
Grind	0	0	0	0.333	-0.33	-0.33	
Temperature	0	0.333	-0.33	0	0	-0.33	
Time	0.333	0	-0.33	0	-0.33	0	
Charge	-0.33	-0.33	0	-0.33	0	0	
Station 1	-0.41	0	0	0	0	0.816	
Station 2	0.707	0	0	0	0	0	

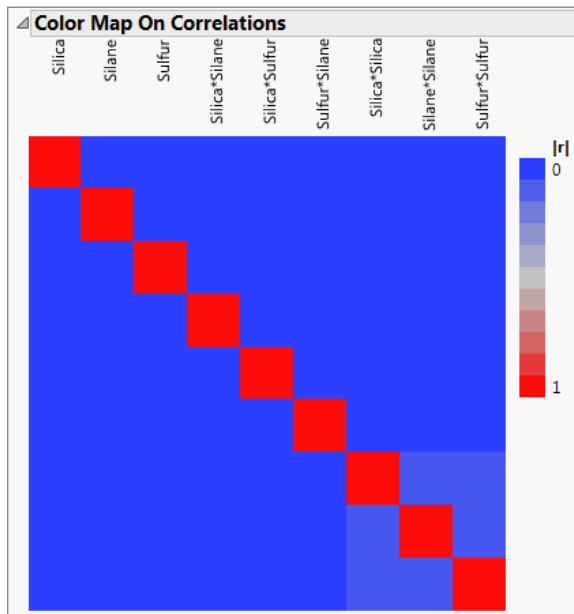
In this example, the *a priori* model, whose terms are listed in the Model outline, consists only of main effects. The Alias Terms outline contains all two-way interactions by default. The Alias Matrix shows the model terms in the first column and the alias terms across the top. For example, consider the model effect Temperature. If the Grind\*Time interaction is the only active two-way interaction, the estimate for the coefficient of Temperature is biased by 0.333 times the true value of the Grind\*Time effect. If other interactions are active, then the value in the Alias Matrix indicates the additional amount of bias incurred by the Temperature coefficient estimate.

## Color Map on Correlations

If you are interested in inference, you want to examine the Color Map on Correlations. Large correlations among effects inflate the standard errors of estimates, making it difficult to identify active effects. The Color Map on Correlations shows the absolute value of the correlation between any two effects that appear in either the Model or the Alias Terms outline. There is a cell for each effect in the Model outline and a cell for each effect in the Alias Terms outline.

By default, the absolute magnitudes of the correlations are represented by a blue-to-gray-to-red intensity color theme. In general terms, the color map for a good design shows a lot of blue off the diagonal, indicating orthogonality or small correlations between distinct terms.

Note: This example is based on the design for Bounce Data.jmp.



The deep red coloring indicates absolute correlations of one. As you would expect, there are red cells on the diagonal, showing correlations of model terms with themselves. All other cells are either deep blue or light blue. The light blue squares correspond to correlations between quadratic terms. From the perspective of correlation, this is a good design.

## Design Diagnostics

Use the Design Diagnostics outline to compare the efficiency of designs relative to three popular efficiency measures ( $D$ -,  $G$ -, and  $A$ -efficiency). For an ideal design, the various efficiency values are 100 percent. However, when there are quadratic effects in the model, inequality constraints, or disallowed combinations, then these efficiency measures are best used for comparing design alternatives rather than interpreting them as having an absolute meaning. The report also gives the average variance of prediction across the entire design region.

Note: This example is based on the design for Bounce Data.jmp.

Design Diagnostics	
D Efficiency	36.6429
G Efficiency	72.42729
A Efficiency	29.3578
Average Variance of Prediction	0.384722
Design Creation Time (seconds)	0

The design for Bounce Data.jmp is a Box-Behnken design whose goal is optimization. Not surprisingly, the D- and A-efficiencies, which reflect the precision of parameter estimates, are comparatively low. The G-efficiency, which reflects the maximum prediction variance, is relatively high.

However, keep in mind that these efficiency measures should not be interpreted on their own, but rather used to compare designs. The Design Diagnostics values below are for a 15-run RSM design with no center points created using the Custom Design platform.

<b>Design Diagnostics</b>	
I Optimal Design	
D Efficiency	44.71631
G Efficiency	91.44599
A Efficiency	31.29074
Average Variance of Prediction	0.367593
Design Creation Time (seconds)	11

The G-efficiency (91.45) is much higher than that of the Box-Behnken design (72.43). The D- and A- efficiencies are higher as well. The Average Variance of Prediction is only slightly smaller.

For more information, see the [Evaluate Designs](#) documentation on JMP.com.

## Augment Design

Are the results from the design you just ran inconclusive? Don't start again from scratch! Add new runs to your design with the Augment Design platform. Treat experimentation as an iterative process. Sometimes a single experiment fails to provide completely conclusive results or to optimize your process. In particular, screening experiments (often by design) can leave some ambiguities in terms of which main effects or interactions are active. You can resolve these ambiguities with the Augment Design platform.

Perhaps you were the victim of a broken design. Were you too bold in your initial selection of factor settings? Did your process break down for some of those settings? Did you run a design and find constraints you didn't know about? Leverage your successful runs by augmenting the design you actually ran with new runs that allow you to fit the model you had originally envisioned. The new runs are selected so that they optimize the overall design. You can group sets of experimental runs into separate blocks so you can account for changes between your initial runs and your augmented runs.

Adding runs can help you accomplish these objectives:

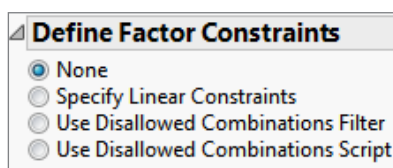
- Salvage experiments that resulted in runs that were infeasible, incorrect or simply overlooked.

- Check the assumption that the error variance is constant using **replication**. If your design has large process or measurement variability, replication can reduce the variability of the regression coefficients.
- Check for lack of fit or curvature with **center points**. Center points are replicated points at the design center that allow for an independent estimate of pure error, which is used in the lack-of-fit test. Center points also reduce the prediction error in the center of the design region.
- Resolve the confounding of two-factor interactions and main effects with a **fold-over design**. These designs are especially useful as a follow-up to a saturated or near-saturated fractional factorial or Plackett-Burman design.
- Transform a screening design into a powerful response surface design by adding **axial points**, together with center points. Then you can develop a sound prediction model and optimize your process.
- Add runs that are interior to the design for deterministic or spatial modeling using a **space-filling** design. These runs can satisfy linear constraints.
- **Augment** your design by adding more terms to your original model to estimate additional effects, test for curvature, or resolve ambiguities. The Augment button is the most flexible option. For example, by adding quadratic terms to your original linear model, you can construct a response surface design. You can designate additional model terms to be estimable *if possible*, given your experimental budget. You can also change your region of experimentation by defining factor constraints.

For more information, see the [Augment Designs](#) documentation on JMP.com.

## Define Factor Constraints

If your design has certain combinations of factor levels that could cause damage, or are not feasible due to equipment limitations, you can specify these constraints in most DOE platforms.



You can either:

- Specify your restriction as a linear inequality (Specify Linear Constraints).
- Specify constraints using a data filter approach (Use Disallowed Combinations Filter).
- Specify constraints using a script (Use Disallowed Combinations Script).

For example, the Disallowed Combinations Filter to the right shows the following:

- For Material A, values of Temperature that exceed 0.7 are not allowed.
- Combining Material A with Coating d is not allowed.

For more information on defining factor constraints, see the [Custom Designs](#) documentation on JMP.com.

## Definitive Screening Design

Use a *definitive screening design* (DSD) when screening is the goal, and where interaction and nonlinear effects are potentially active. These designs can screen many factors in very few runs. DSDs have clear advantages over standard screening designs: They avoid confounding of effects and can identify factors that have a nonlinear effect on the response. DSDs accommodate two-level categorical factors.

The design to the right is a DSD for seven continuous factors. Note that the design sets continuous factors at three levels. This is necessary in order to estimate nonlinear effects.

DSDs have the following advantages:

- The designs are small, requiring only a few more runs than twice the number of factors.
- Main effects are orthogonal.
- Main effects are uncorrelated with two-factor interactions and quadratic effects.
- Quadratic effects can be estimated.
- Two-factor interactions are not completely confounded with each other.
- For six or more factors, you can estimate all possible full quadratic models for any three factors. For 18 or more factors, you can estimate all possible full quadratic models in any four factors. For 24 or more factors, you can estimate all possible full quadratic models in any five factors.
- The designs can be blocked.

Design							
Run	X1	X2	X3	X4	X5	X6	X7
1	0	1	1	1	1	1	1
2	0	-1	-1	-1	-1	-1	-1
3	1	0	1	1	-1	1	-1
4	-1	0	-1	-1	1	-1	1
5	1	-1	0	1	1	-1	1
6	-1	1	0	-1	-1	1	-1
7	1	-1	-1	0	1	1	-1
8	-1	1	1	0	-1	-1	1
9	1	1	-1	-1	0	1	1
10	-1	-1	1	1	0	-1	-1
11	1	-1	1	-1	-1	0	1
12	-1	1	-1	1	1	0	-1
13	1	1	-1	1	-1	-1	0
14	-1	-1	1	-1	1	1	0
15	1	1	1	-1	1	-1	-1
16	-1	-1	-1	1	-1	1	1
17	0	0	0	0	0	0	0

In addition, you can use Augment to add trials to a definitive screening design. DSD followed by Augment is a powerful combination.



For example, suppose you have seven factors and your 17-run DSD indicates that there is a quadratic effect. With an additional 20 runs, you can augment the DSD so that the augmented design is capable of estimating and testing all quadratic terms and two-way interactions. The DSD plus the augmented design require a total of 37 runs. By comparison, a Central Composite design would require 80 runs, and a Box-Behnken design would require 62 runs.

For more information, see the [Definitive Screening Designs](#) documentation on JMP.com.

## Main Effects Screening Design

If your design includes multilevel categorical factors or discrete numeric factors, retrofitting a classical screening design can be difficult or impossible. For these situations, JMP provides *main effects screening designs*. These designs are orthogonal or nearly orthogonal. They can accommodate categorical factors and discrete numeric factors with any number of levels. Even in cases where a classical design does fit, main effects screening designs usually require fewer runs.

For more information on main effects screening designs, see the [Screening Designs](#) documentation on JMP.com.

## Classical Designs

JMP also provides many classical designs.

### Screening Designs

Screening designs can identify active factors and interactions. In the Screening Design platform, you can select a classical screening design from a list. The list includes designs that group the experimental runs into blocks of equal sizes where the size is a power of two.

You also have the option to construct a main effects screening design. If no classical design exists for your selection of factor types and levels, a main effects screening design is automatically provided.

For more information, see the [Screening Designs](#) documentation on JMP.com.

### Response Surface Designs

If you are interested in process optimization or sophisticated process modeling, you need the ability to include response surface terms in your model. The Response Surface Design platform offers standard response surface designs, including Box-Behnken designs and central composite designs, for a range of run sizes that accommodates various block sizes and numbers of center points.

For more information, see the [Response Surface Designs](#) documentation on JMP.com.

## Full Factorial Designs

To test all possible combinations of factor levels, use the Full Factorial Design platform. This platform constructs designs for continuous factors at two levels and categorical factors with an arbitrary number of levels. You can add center points or replicate the design.

For more information, see the [Full Factorial Designs](#) documentation on JMP.com.

## Mixture Designs

Suppose that your process involves components that sum to a fixed amount. For example, a process requires a solution of a given volume, but you can vary the volumes of the ingredients that constitute the solution. In this case, the factors are *mixture* components.

The Mixture Design platform provides various types of standard mixture designs: Simplex Centroid, Simplex Lattice, Extreme Vertices and ABCD designs.

The Mixture Design platform also offers a powerful recent design type called *Space Filling*, which spreads points evenly within the design space. Use the Space Filling, Optimal or Extreme Vertices methods to impose constraints on your design region. The Optimal design method constructs a Custom mixture design.

For more information, see the [Mixture Designs](#) documentation on JMP.com.

## Classical Design Options

**Center Points and Replicates:** Add center points to the design and specify a number of replicates in the screening, response surface, and full factorial designs. You can also specify a number of replicates in mixture designs. Note that, in classical designs, the term *number of replicates* refers to the number of *additional* duplications of the entire design.

**Viewing and Modifying the Design:** (applies to both classical and specialized designs) Preview the runs in the design. Use the Back button to make changes to your design or create a new design.

**Design Evaluation:** Assess the quality of your intended design in the Screening and Response Surface platforms using the versatile Design Evaluation option.

**Run Order:** (applies to both classical and specialized designs) Define the run order in the resulting design data table.

## Specialized Designs

JMP provides a variety of designs that address specific situations not addressed by classical designs.

### Covering Arrays

**JMP PRO** JMP software's covering arrays are a highly efficient way to test deterministic systems where failures occur as a result of interactions among components or subsystems. Most general-purpose statistical packages do not provide covering arrays. Compared to specialized packages that do offer covering arrays, JMP implementation is extremely efficient.

For example, covering arrays can be used in software, circuit and network design. In these systems, failures often occur as a result of a few specific factor-setting combinations that are unknown to the tester. The largest number of factors that drives a failure,  $n$ , is called the *strength*. The design goal is to reveal if any  $n$ -way combination of settings causes a failure in the system.

Covering arrays cover all combinations required by the specified strength of the design. The key is to construct a design that does this in a minimal number of runs. The designs constructed by the JMP Covering Array platform are often optimal in terms of size. When they are not optimal, you can manually continue the optimization process to find a smaller design. Diagnostic metrics help you determine the quality of your design.

If your design has restrictions, the Covering Array platform can accommodate these. Incompatible system settings often occur in software, circuit, and network systems. For example, you can't test Internet Explorer 10 on a Mac because it is not supported. In the Covering Array platform, you can specify disallowed combinations and obtain a covering array design that respects those restrictions.

The following example shows the factors and settings used in obtaining a five-factor covering array of strength 2. Notice that there are 320 possible combinations of settings ( $5 \times 4 \times 2 \times 4 \times 2$ ).

Factors					
Add Factor ▼		Remove	Add N Factors	1	Strength: t = 2 ▼
Name	Role	Values			
▼ Market	Categorical	USA	UK	Canada	France Mexico
▼ Near Phone	Categorical	ISDN	Bus	Coin	Res
▼ Near Interface	Categorical	A		B	
▼ Far Phone	Categorical	ISDN	Bus	Coin	Res
▼ Far Interface	Categorical	A		B	

You can check that all possible combinations of any of the 10 pairs of factors appear at least once in the 20-run covering array.

	Response	Market	Near Phone	Near Interface	Far Phone	Far Interface
1		• USA	ISDN	A	ISDN	A
2		• USA	Bus	B	Bus	B
3		• USA	Coin	A	Coin	A
4		• USA	Res	A	Res	A
5		• UK	Bus	A	ISDN	A
6		• UK	ISDN	A	Bus	A
7		• UK	Res	B	Coin	A
8		• UK	Coin	A	Res	B
9		• Canada	Coin	B	ISDN	A
10		• Canada	Res	A	Bus	A
11		• Canada	ISDN	A	Coin	B
12		• Canada	Bus	A	Res	A
13		• France	Res	A	ISDN	B
14		• France	Coin	A	Bus	A
15		• France	Bus	A	Coin	A
16		• France	ISDN	B	Res	A
17		• Mexico	ISDN	A	ISDN	A
18		• Mexico	Bus	B	Bus	B
19		• Mexico	Coin	A	Coin	A
20		• Mexico	Res	A	Res	A

For more information, see the [Covering Arrays](#) documentation on JMP.com.

## Choice Designs

Are you designing a new product or service? Use choice designs to prioritize customer preferences so that you can bring the right product to market. For example, suppose that you own a coffee shop and want to provide a brew that most people prefer. You want to find the best combination of grind, temperature, time and coffee amount.

A classical experiment would require that each respondent taste and rate or rank a large number of test brews. This is not a practical experimental strategy. A choice experiment allows respondents to indicate which of two or more product profiles they prefer.

	Choice Set	Choice ID	Grind	Temperature	Time	Amount
1	1	1	Coarse	200	3.5	2
2	1	2	Medium	195	3	2.4
3	2	1	Coarse	195	4	2
4	2	2	Medium	200	3.5	2.4
5	3	1	Medium	205	3	1.6
6	3	2	Coarse	195	4	2.4
7	4	1	Medium	195	4	1.6
8	4	2	Coarse	205	3	2.4
9	5	1	Coarse	200	3	1.6
10	5	2	Medium	205	3.5	2
11	6	1	Coarse	195	3.5	1.6
12	6	2	Medium	200	4	2
13	7	1	Coarse	205	4	1.6
14	7	2	Medium	195	3	2

The design above provides each respondent with seven choice sets. Each choice set consists of two product profiles, Choice ID 1 and Choice ID 2. Within each choice set, a respondent indicates the profile (Choice ID) for the brew he or she prefers.

If you have prior information about customer preferences, you can enter that into the Choice platform to construct even more sensitive designs.

For more information, see the [Discrete Choice Designs](#) documentation on JMP.com.

## Space-Filling Designs and the Fast Flexible Filling Method

Use space-filling designs to model systems that are deterministic or near-deterministic. For example, consider a computer simulation. The goal is to find a simpler and faster empirical model that adequately predicts the behavior of the system over limited ranges of the factors.

In deterministic systems, there is no variance. Your goal is to minimize *bias*, which is the difference between the approximating model and the true mathematical function. Space filling designs attempt to reduce the bias by:

- Spreading the design points as far from each other as possible consistent with staying inside the experimental boundaries.
- Spacing the points evenly over the region of interest.

To minimize bias, you can choose from several methods. The powerful Fast Flexible Filling method is an innovative cluster-based method for distributing design points evenly throughout the region of interest. Unlike standard space-filling design methods, you can use the Fast Flexible Filling method with categorical factors or if you have constraints on the design region. You can also choose between two optimality criteria, the Centroid criterion and MaxPro, which places some points very close to the edges of the design space.

The Space Filling Design platform also offers the following standard methods:

- **Sphere Packing** maximizes the minimum distance between pairs of design points.
- **Latin Hypercube** maximizes the minimum distance between design points, but requires even spacing of the levels of each factor.
- **Uniform** minimizes the discrepancy between the design points and a theoretical uniform distribution.
- **Minimum Potential** spreads points inside a sphere around the center.
- **Maximum Entropy** measures the amount of information contained in the distribution of a set of data.
- **Gaussian Process IMSE Optimal** creates a design that minimizes the integrated mean squared error of the Gaussian process over the experimental region.

For more information, see the [Space Filling Designs](#) documentation on JMP.com.

## Accelerated Life Test Design

When product reliability at normal use conditions is very high, use accelerated life testing to predict product performance at normal use levels. The Accelerated Life Test (ALT) Design platform enables you to construct a design to test your product under conditions that are more severe than normal use conditions. These severe conditions cause the product to degrade faster and fail more quickly. You can then use this accelerated failure data to predict product reliability at normal use conditions.

The ALT platform can create and evaluate designs for situations involving one or two accelerating factors. For two accelerating factors, you can include their interaction. Optimization choices for your design include D-optimality or two types of I-optimality criteria.

Use the ALT platform to design initial experiments or to augment existing designs. For example, you can augment an existing design with design points that target reducing the variance of specified estimates.

The design process requires initial estimates of acceleration model parameters. Since those parameters are usually unknown, you can specify a multivariate normal prior distribution to describe their uncertainty.

For more information, see the [Accelerated Life Test Designs](#) documentation on JMP.com.

## Nonlinear Design

In some design situations, the *a priori* model is known to be nonlinear in its parameters. This is often the case in modeling chemical reactions, metallurgic activity and mechanical effects. Use the Nonlinear Design platform to construct optimal designs and to optimally augment designs in these situations.

To construct a Nonlinear Design, your data table must contain a formula column that shows the functional relationship between the factor and the response. If you have prior information about the parameters, you can enter it when you construct your nonlinear design, or you can construct your nonlinear design with no prior information.

For more information, see the [Nonlinear Designs](#) documentation on JMP.com.

## Taguchi Arrays

Taguchi orthogonal arrays address the integration of noise factors into the experimental design. Factors are considered *signal* effects or *noise* effects. The signal factors are those that you can control in production. The noise factors must be controlled during the experiment, but are assumed to vary in production. Your goal is to find signal factor settings that minimize noise.

Taguchi arrays are classical two-, three-, and mixed-level fractional factorial designs for the signal effects. The design for the signal effects is called the *inner* array. An *outer* array controls the settings of the noise effects. The experiment includes all combinations of the inner and outer array settings. The mean and signal-to-noise ratio are calculated across the outer runs for each inner array setting. These two values are the responses for the inner array settings.

Because runs at all combinations of inner array settings and outer array settings are required, more efficient design strategies are based on using screening designs that include both the signal and noise factors. This methodology, known as the *combined array* approach, leverages knowledge about interactions between control and noise factors. (See Chapter 12 in Montgomery, Douglas C., *Design and Analysis of Experiments*. Eighth ed. Hoboken, NJ: Wiley Custom Learning Solutions, 2012.)

For more information, see the [Taguchi Designs](#) documentation on JMP.com.



## About SAS and JMP®

JMP is a software solution from SAS that was first launched in 1989. John Sall, SAS co-founder and Executive Vice President, is the chief architect of JMP. SAS is the leader in business analytics software and services, and the largest independent vendor in the business intelligence market. Through innovative solutions, SAS helps customers at more than 75,000 sites improve performance and deliver value by making better decisions faster. Since 1976 SAS has been giving customers around the world THE POWER TO KNOW®.



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