STATISTICAL DISCOVERY

WHITE PAPER

The JMP® Design of Experiments Advantage

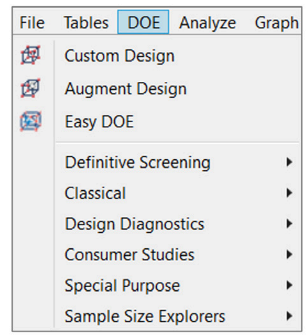
Fit the Design to Your Problem

Contents

Introduction

In today's fast-paced and highly competitive landscape, successful organizations leverage structured experimentation to drive innovation and optimize processes. JMP's advanced approach to design of experiments (DOE) provides you with a strategic edge, enabling you to explore and exploit the multifactor opportunities present in all real-world scenarios.

JMP offers state-of-the-art DOE capabilities, seamlessly integrating the latest research and methodologies to help you design experiments that precisely address your unique questions within your specific context. With JMP, you gain access to a comprehensive suite of analysis tools, all within a user-friendly environment that maximizes the power of JMP — from interactive, dynamic graphics and robust scripting to project collaboration and industry-leading analytics.



The Custom Design platform in JMP allows you to break free from the limitations of standard designs. Instead of forcing a generic design onto your problem, you can tailor an experiment to meet your specific challenges and resource constraints. This platform constructs an optimal design that considers your ability to control factors, set constraints, incorporate covariate information, and navigate other experimental conditions and resource limitations.

JMP provides a diverse array of DOE platforms and methods to meet your specific needs, helping you achieve optimal results across a wide range of experimental scenarios:

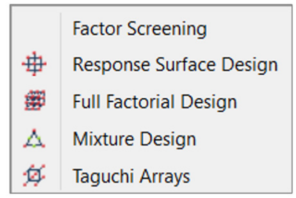
Custom Design: This platform empowers you to create cost-effective, optimal designs tailored to your experimental situation. Whether a standard design fails to fit your needs or you require a more customized approach, JMP enables you to construct a broad range of design types to achieve your experimental goals.

Augment Design: When your initial experiment results are inconclusive or if you have pre-existing data to leverage, this platform allows you to add optimal runs to your existing design. It is particularly valuable when original runs were infeasible or when further exploration is necessary.

Easy DOE: Ideal for users new to design of experiments, this platform simplifies the setup and execution of standard DOE designs, minimizing complexity while ensuring robust experimental outcomes.

Definitive Screening: This platform offers powerful screening designs that can identify main effects and detect nonlinear effects with fewer runs than traditional methods. definitive screening designs (DSDs) can also support the analysis of a full response surface model when few factors are active, making it a versatile tool in exploratory experiments.

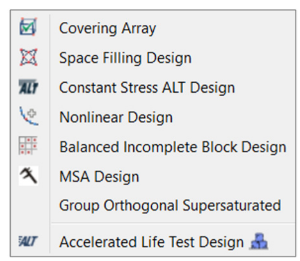
Classical Designs: For scenarios where traditional experimental designs are sufficient, this platform offers well-known designs such as full factorial, fractional factorial, and response surface designs, providing a reliable foundation for your experimentation.



Design Diagnostics: After creating a design, this platform enables you to evaluate its properties, such as power, prediction variance, and aliasing. These diagnostics ensure that your design is robust and capable of delivering reliable, reproducible results.

Consumer Studies: Tailored for experiments involving consumer preferences and choices, this platform supports such designs as choice modeling, enabling you to assess consumer preferences for various product features effectively.

Special Purpose Designs: This category includes specialized design types for unique experimental challenges. Options such as space filling designs, Taguchi arrays, or accelerated life test designs are available to address specific needs in complex experimental scenarios.



Sample Size Explorers: This tool helps you determine the appropriate sample size for your experiment, allowing you to explore the relationship between sample size, power, and effect size. It ensures that your design has sufficient power to detect significant effects.

And JMP continues to evolve, integrating cutting-edge enhancements and new capabilities to keep you at the forefront of experimental design and analysis. With these tools, you are equipped to push the boundaries of what is possible in your experiments, leading to innovative solutions and superior results.

Custom Design in JMP

Tailoring experimental designs to your needs

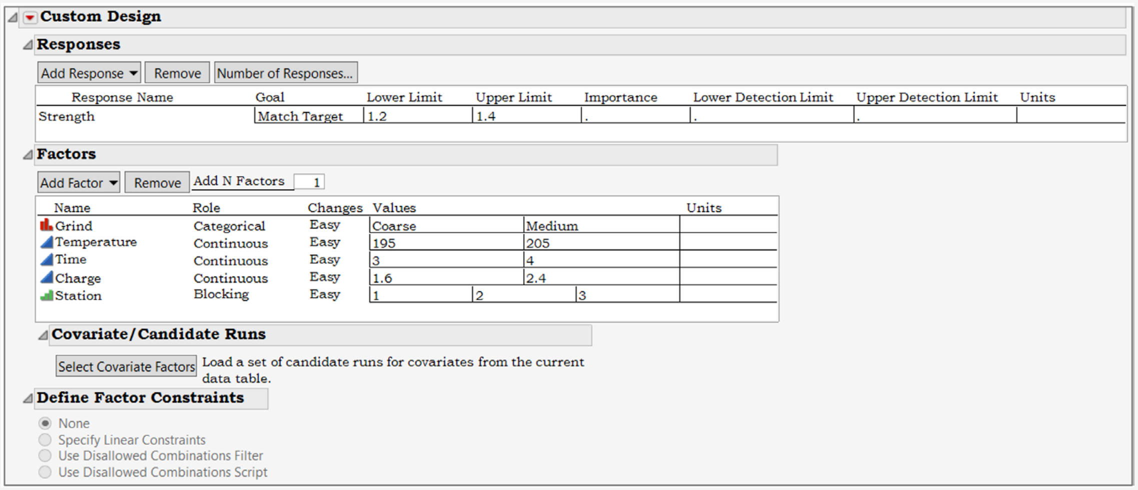
The Custom Design platform in JMP offers unparalleled flexibility for constructing experimental designs tailored to the specific demands of your research. Whether you are navigating complex constraints, managing multiple factors, or addressing unique model requirements, JMP Custom Design provides a guided and interactive process that ensures your design is optimal for your objectives. The workflow is streamlined into six essential steps, enhanced with interactive features that simplify the design process.

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

1

Define responses, factors, and factor constraints

Begin by defining the responses of your experiment, including their goals, limits, and importance values. You can add various types of factors, such as continuous, discrete numeric, categorical, and more. If your experiment requires it, you can also specify constraints on factor settings. JMP's intuitive interface guides you through these initial steps, making it easy to set up your experiment efficiently.

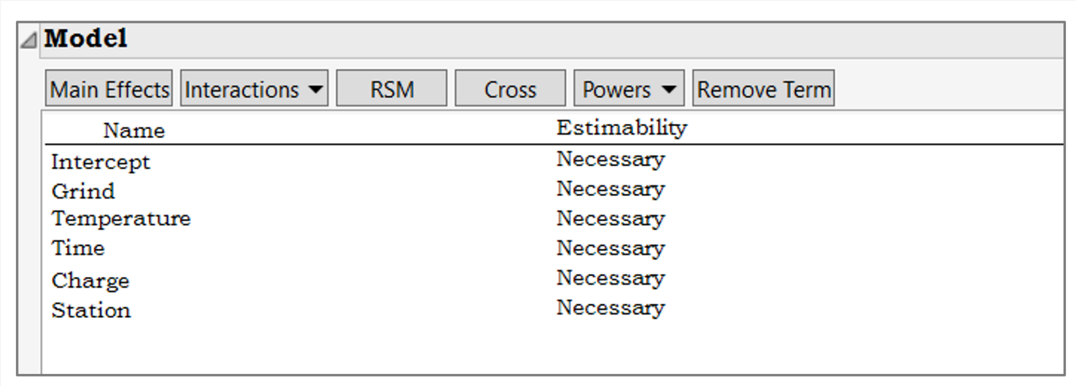


When you choose DOE > Custom Design, the Custom Design window appears with outlines to add your responses and factors. You can add one or more responses and their goals, limits, importance values, and detection limits; add different types of factors, their values, and the degree of difficulty involved in changing their settings from one run to the next (indicating that a factor is hard or very hard to change yields split-plot or split-split plot designs); specify any combination of the following types of factors: continuous, discrete numeric, categorical, blocking, covariate, mixture, constant, or uncontrolled; and define constraints on factor settings, if appropriate.

2

Specify the a priori model

Define the effects you intend to estimate, including main effects, interactions, and quadratic terms. The platform's enhanced interactivity allows you to see how changes in the model influence the design in real time. JMP helps you distinguish between effects that are critical to estimate and those that are desirable but not essential, allowing for more informed decision making.

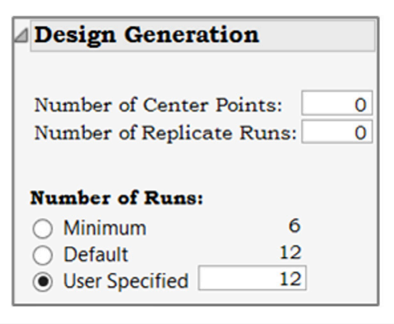


In the Model outline, specify your a priori model, including the effects you want to estimate, such as main effects, interactions, response surface model terms, crossed terms, powers, and mixture-specific terms. For each effect, indicate whether it is necessary to estimate or if it is acceptable to estimate only if possible, given the run size and other requirements

3

Generate the design

Customize the design's size and structure by specifying the number of runs, adding center points, and incorporating replicated runs if needed. The platform provides real-time feedback during design generation, enabling you to adjust on the fly to ensure your design is both robust and efficient.

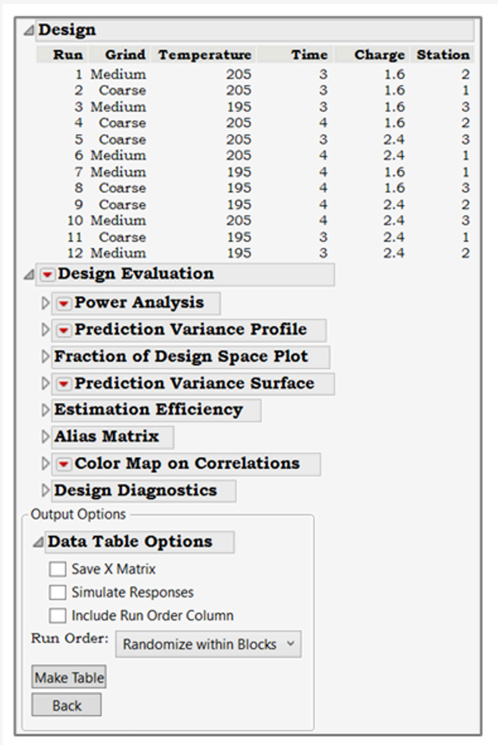


Require additional center points and replicated runs if desired; group runs into random blocks if there are no fixed blocks or hard-to-change factors; specify the numbers of whole plots and subplots if you have hard-to-change or very-hard-to-change factors; indicate whether they vary independently; specify the number of runs with JMP's guidance (minimum for a saturated design and default for a balanced design with at least four degrees of freedom); and construct the design.

4

Review and evaluate the design

Before committing to a design, you can preview it and evaluate its potential performance using a suite of diagnostic tools. These include power analysis, prediction variance profiles, and estimation efficiency reports. The platform's interactive evaluation tools offer immediate insights, allowing you to refine your design for optimal results.

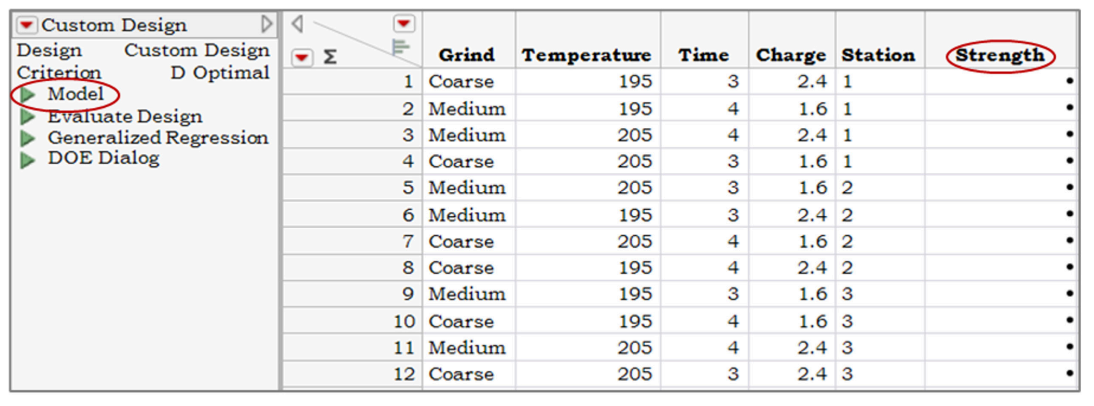


After defining a custom design — but before creating the design table — you can preview the design and investigate details using various plots and tables as design diagnostic tools. Once satisfied with the design, click Make Table to create the design table.

5

Conduct the experiment

Once the design is finalized, conduct the experiment and input the results into the design table. JMP's built-in Model script simplifies the analysis process, automatically setting up the appropriate responses and model effects. The platform's guided steps ensure accuracy and streamline the transition from data collection to analysis.



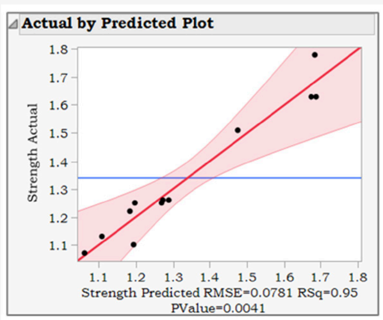
	Grind	Temperature	Time	Charge	Station	Strength
1	Coarse	195	3	2.4	1	•
2	Medium	195	4	1.6	1	•
3	Medium	205	4	2.4	1	•
4	Coarse	205	3	1.6	1	•
5	Medium	205	3	1.6	2	•
6	Medium	195	3	2.4	2	•
7	Coarse	205	4	1.6	2	•
8	Coarse	195	4	2.4	2	•
9	Medium	195	3	1.6	3	•
10	Coarse	195	4	1.6	3	•
11	Medium	205	4	2.4	3	•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

Run the experiment, add the results to the design table in the Strength column, and then analyze your results using the Model script, which simplifies running your analysis.

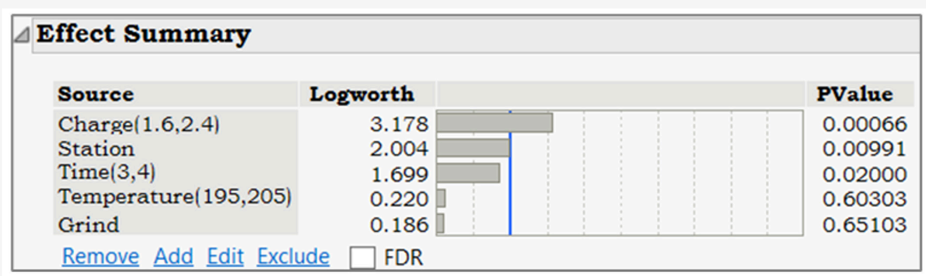
6

Fit a model and predict performance

Use the JMP Fit Model platform to analyze your experimental results. Interactive tools such as the Prediction Profiler enable you to explore the effects of varying factor settings, optimize factor levels, and assess model sensitivity. These tools are now more seamlessly integrated into the workflow, facilitating a smooth transition from design to analysis.



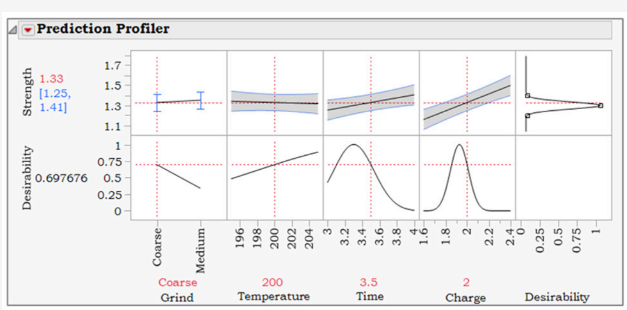
The design table provides scripts that guide your analysis, with the Model script adding the appropriate responses and model effects in the Fit Model launch window. You then simply select the Run Script option and click Run to obtain the report for the original a priori model that the design was built to support. For screening designs, an additional script automatically performs a screening analysis, enabling you to, for example, examine the Actual by Predicted plot to assess your model's fit.



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

Use the Effect Summary report to determine a final model, review the analysis, eliminate effects that appear inactive to simplify the model, and add degrees of freedom to the error term. The entire report updates automatically, but note that adding effects to the model, which the design was not built to support, should be done with caution.



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, and gauge your model's sensitivity to changes in the factor settings.

Types of custom designs in JMP

JMP expands the capabilities of the Custom Design platform by offering a variety of specialized design types tailored to real-world experimentation needs:

Factor screening with flexible fixed and random block sizes	Traditional designs usually limit block sizes to powers of two, but JMP allows you to create blocks of any size, whether fixed or random, giving you more flexibility.
Supersaturated designs for factor screening	When you need to evaluate many factors but want to keep the number of runs low, JMP's supersaturated designs are ideal, focusing on identifying key factors efficiently.
Response surface models with categorical factors	JMP provides I-optimal designs that can include both categorical factors and blocks of different sizes, useful when standard designs fall short.
Split-plot, split-split-plot, and two-way split-plot designs	For factors that are hard to change, JMP's split-plot designs include random effects, ensuring the design reflects real-world constraints.
Mixture designs with process variables	Design experiments considering both mixture components and process variables together, enabling comprehensive analysis in one experiment.
Mixture of mixtures designs	Handle complex experiments involving mixtures of mixtures with linear constraints, allowing you to manage intricate relationships effectively.
Fixed covariate factors	Optimize designs by including covariate factors – variables that affect the response but cannot be easily changed — ensuring a more robust design.
Infeasible factor combinations	Manage situations where certain factor combinations are not possible by setting constraints or using filters to create a feasible and optimized design.

Optimize custom designs

JMP offers multiple optimization criteria to ensure your design aligns with your experimental goals:

D-optimal	Focused on precise effect estimation, making it suitable for screening experiments where identifying active factors is crucial.
I-optimal	Best suited for response surface designs, minimizing prediction variance across the design space, making it ideal for optimization studies.
A-optimal	For minimizing the average variance of the estimated regression coefficients, which is particularly useful when the goal is to improve the precision of the estimates for model parameters.
Alias optimality	Reduces aliasing between effects in your model and those not included but potentially active, ensuring the model accurately reflects the true relationships between factors.

JMP defaults to D-optimal designs for most applications but automatically generates I-optimal designs when response surface model (RSM) terms are included. The platform also supports Bayesian D-optimality and I-optimality, providing robust design options even when certain model terms are only included if possible.

Evaluate Design

JMP's design evaluation tools offer a comprehensive analysis of your design's quality and performance:

- **Power analysis:** Evaluate your design's ability to detect significant effects, ensuring that your experiment has sufficient power.
- **Prediction variance profile and surface:** Visualize the precision of predictions across the design space, helping you understand how well your design will perform in different scenarios.
- **Fraction of design space plot:** Determine the proportion of the design space where prediction variance is acceptably low, providing insights into the reliability of your design.

- **Estimation efficiency:** Measure the precision of parameter estimates to assess the overall quality of your design.
- **Alias matrix and color map on correlations:** Evaluate potential confounding between factors and visualize correlations, ensuring that your design is as orthogonal as possible.
- **Design diagnostics:** Compare your design's efficiency with popular measures, including D-, G-, and A-efficiency, helping you refine your design for optimal performance.

By integrating these advanced features, JMP Custom Design ensures that your experimental designs are tailored to your specific needs while being optimized for accuracy, efficiency, and reliability.

Since D-optimal and I-optimal designs serve distinct purposes, choosing the right one depends on your research goals:

- **D-optimal designs** are ideal for precise parameter estimation. By maximizing the determinant of the information matrix, these designs ensure the most accurate estimation of model coefficients. They are particularly useful in screening experiments where the goal is to identify significant factors and interactions. D-optimal designs typically place experimental runs at the extremes of the design space to maximize the precision of estimates.
- **I-optimal designs** focus on minimizing the average prediction variance across the design space, making them perfect for studies aimed at accurate predictions, such as in response surface methodology and optimization studies. These designs distribute runs more evenly, including center points, to ensure reliable predictions throughout the experimental region.

Choosing the right design

- **D-optimal:** Best for precise estimation of model parameters, particularly in early-stage experiments focused on factor identification.
- **I-optimal:** Best for making accurate predictions across the entire experimental space, often used in optimization and response surface studies.

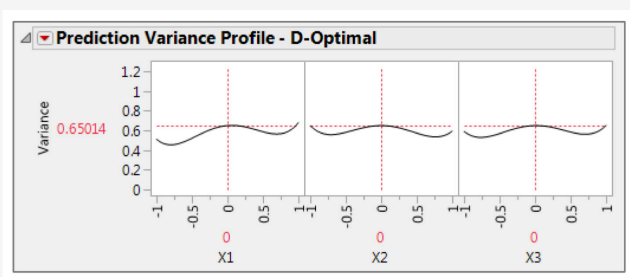
Design - D-Optimal

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

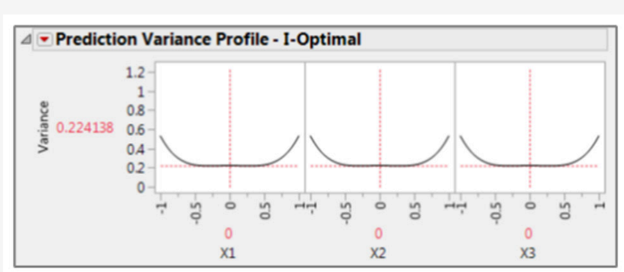
Design - I-Optimal

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

I-optimal designs tend to place fewer runs at the extremes of the design region than D-optimal designs. As this example illustrates, a D-optimal 16-run design has no center points, while an I-optimal design includes two center points.



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

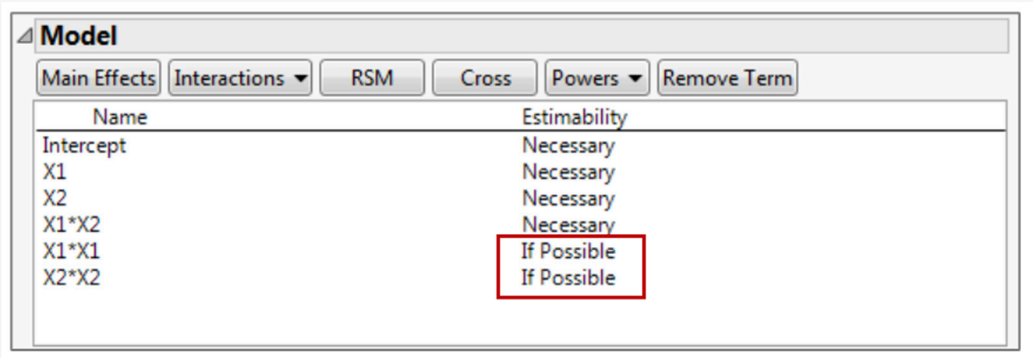


The D-optimal design's prediction variance at the center of the design region (0.650) is about three times the variance of the I-optimal design at the center of the region (0.224).

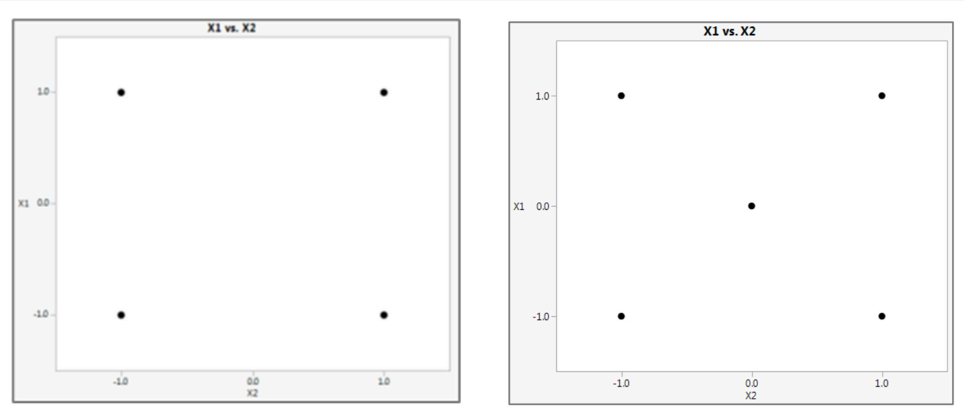
Bayesian optimality

The Custom Design platform in JMP incorporates Bayesian optimality to enhance the robustness and precision of experimental designs, especially when dealing with potentially active interactions or nonlinear effects. This criterion is particularly useful in situations where the number of experimental runs is constrained and must accommodate both necessary and possible effects.

In the Model outline, you can designate terms as either "Necessary" or "If Possible." Necessary terms are those that must be estimated with high precision, while If Possible terms represent effects that are desirable to estimate if resources permit. Bayesian D-optimality focuses on maximizing the precision of the Necessary terms, while also providing some estimability for the If Possible terms, even with a limited number of runs.



In screening designs, experimenters often add center points and other replicated points to determine whether the a priori model is adequate. This practice lacks theoretical guidance, whereas the Custom Design platform provides a theoretical foundation by using Bayesian I-optimality or D-optimality when terms in the Model outline are set to If Possible instead of Necessary. It results in a design that allows precise estimation of primary terms while offering detectability and some estimability for potential terms.



For example, if you want to model a response as a function of two main effects and an interaction with five runs, and the Model outline includes only the four Necessary effects (intercept, two main effects, and their interaction), four runs are optimally placed on the vertices of the design space. However, if you specify five runs, the design replicates one of the vertices, addressing D-optimality but not lack of fit. To address lack of fit, add two quadratic terms as potential terms by setting their estimability to If Possible, generating a Bayesian D-optimal design with a center point. Doing so allows for curvature checking, with the sample size larger than the number of primary terms but smaller than the total number of primary and potential terms.

Key features

1. **Bayesian D-optimality:** This criterion allows for precise estimation of the specified Necessary effects, while also attempting to estimate other potential effects as allowed by the design's constraints. It is particularly useful when there are potentially active interactions or nonlinear effects that need to be considered alongside the primary factors.

2. **Design flexibility:** The Bayesian D-optimal design can adjust to include extra runs that improve the estimation of the Necessary effects, without compromising the overall robustness of the design. This flexibility is essential for addressing possible model inadequacies or checking for lack of fit.

3. **Enhanced model detection:** By incorporating Bayesian principles, the design is more resilient to potential model inaccuracies, providing a theoretical foundation for choosing designs that are robust to the assumptions made during the modeling phase.

4. **Optimizing limited resources:** Bayesian optimality is most effective when the number of runs is larger than the number of Necessary terms but smaller than the sum of Necessary and If Possible terms. This approach ensures that critical effects are estimated precisely, while still allowing for some exploration of additional effects.

Bayesian optimality in JMP Custom Design enhances the robustness and flexibility of experimental designs, particularly when faced with limited experimental runs and the need to consider both primary and secondary effects. This approach ensures that designs are both efficient and theoretically sound, providing better results even in complex experimental scenarios.

Evaluating your design with JMP Custom Design

JMP Custom Design is equipped with an extensive array of tools designed to rigorously evaluate and enhance the quality of your experimental designs. These tools provide a detailed assessment of your design's robustness, precision, and efficiency, ensuring that your experiment is set up to deliver reliable and meaningful results.

Power analysis

Power analysis is essential for determining whether your design has the statistical power to detect significant effects. By calculating the probability that your experiment will identify a true effect of a given size, power analysis helps you ensure that your study is neither underpowered nor overpowered. This tool is vital for optimizing the number of runs in your experiment, balancing the need for precision with the constraints of time and resources.

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

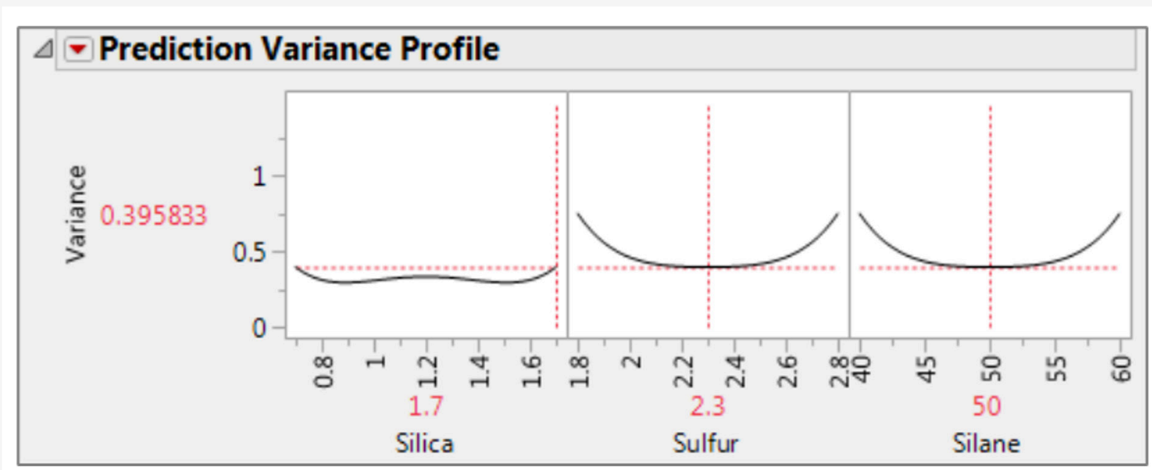
Anticipated Response	Grind	Temperature	Time	Charge	Station
1.4	Coarse	195	3	1.6	1
1.5	Medium	195	4	2.4	2
1.1	Medium	195	4	1.6	3
1.6	Medium	205	4	2.4	1
1.6	Coarse	205	3	2.4	2
1.2	Medium	205	3	2.4	3
1.4	Medium	205	3	1.6	1
1.6	Coarse	205	4	1.6	2
1.3	Coarse	205	4	1.6	3
1.6	Coarse	195	4	2.4	1
1.3	Medium	195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

Apply Changes to Anticipated Responses

Use power analysis to assess your design's ability to detect effects of practical importance and calculate the power of tests for parameters in your a priori model by specifying the significance level and an estimate of RMSE. Approach power calculations by either specifying Anticipated Coefficient values for all model terms or Anticipated Response values for all design settings, with the power computed at the specified values. As illustrated in the Coffee Data.jmp example, the Temperature's Anticipated Coefficient of 0.05 corresponds to an effect size of 0.10 units and a power of 0.291. The power for continuous and categorical factors suggests revising the design or relaxing requirements for higher power.

Prediction variance profile

The prediction variance profile provides a comprehensive look at how well your design can predict outcomes across different combinations of factor levels. By plotting the prediction variance, this tool allows you to identify areas within the design space where predictions might be less precise. Understanding these variances is crucial for ensuring that your design provides consistent accuracy across the entire experimental space, which is particularly important in response surface designs and optimization studies.



The prediction variance profile plot shows the precision of your prediction at any combination of factor levels, where the prediction variance, as the product of the error variance and a quantity dependent on the design and factor setting, yields the relative prediction variance that depends only on the design and not on the experimental data. In this plot, you can explore relative prediction variance by varying factor settings, compare designs side by side, and find the maximum prediction variance and its location using the Maximize Desirability option. As illustrated in the Bounce Data.jmp example, the relative prediction variance is 0.396 at the high level of Silica and the middle levels of Sulfur and Silane.

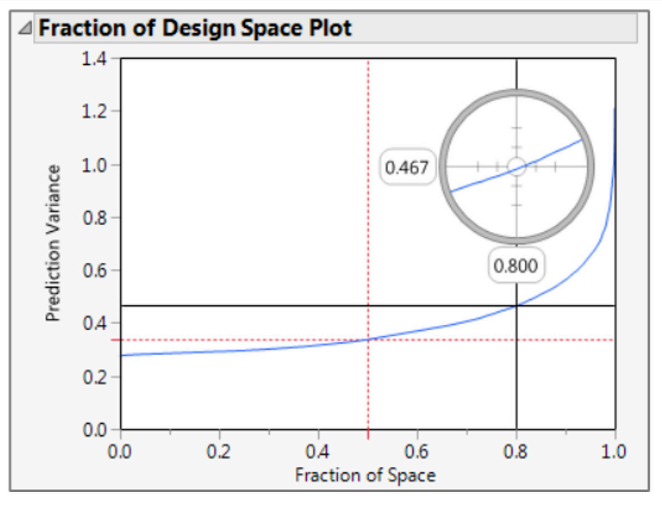
Design Diagnostics

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

Use the design diagnostics outline to compare the efficiency of designs relative to D-, G-, and A-efficiency, where ideal designs have efficiency values of 100 percent. However, when quadratic effects, inequality constraints, or disallowed combinations are present, these measures are better suited for comparing design alternatives rather than for absolute interpretation. As illustrated in the Bounce Data.jmp example, the G-efficiency (91.45) is significantly higher than that of the Box-Behnken design (72.43), with higher D- and A-efficiencies and a slightly smaller Average Variance of Prediction.

Fraction of design space plot

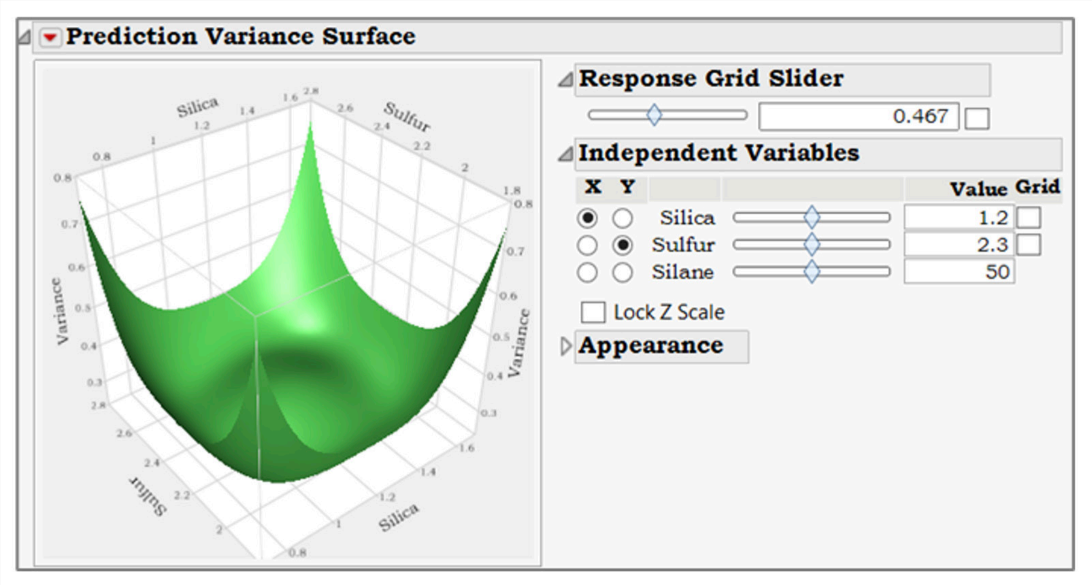
The fraction of design space plot is a powerful diagnostic tool that shows the proportion of the design space where the prediction variance is below a specified threshold. This plot is used for assessing the overall effectiveness of your design in minimizing prediction errors. A well-constructed design should ideally maintain a low prediction variance across most of the design space, ensuring reliable predictions regardless of where in the space the experiment operates.



If you are interested in prediction, it is useful to examine the fraction of design space plot, which shows the proportion of the design space where the relative prediction variance is less than a given value. Ideally, it is small over most of the design space, allowing for design comparisons. As shown in the Bounce Data.jmp example, the relative prediction variance is below 0.467 for 80 percent of the design space.

Prediction variance surface

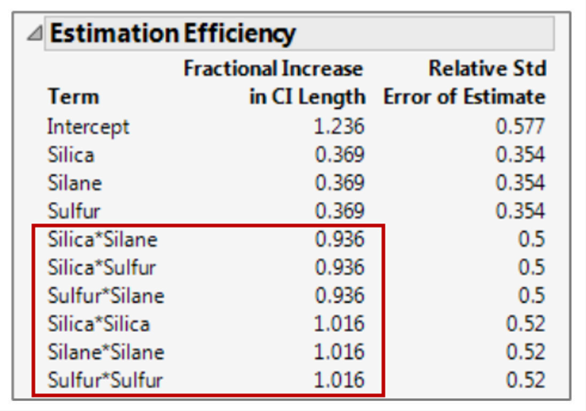
The prediction variance surface offers a three-dimensional view of prediction variance as a function of two design factors. This tool enables you to explore how prediction precision varies within specific regions of the design space, allowing you to make targeted adjustments to improve accuracy. The ability to visualize prediction variance in this way is particularly useful when optimizing multifactor experiments, as it highlights regions where the design may require refinement.



The prediction variance surface plot allows you to explore the precision of your predictions at settings of any two factors, showing a surface representing the relative prediction variance as a function of design factors. It can be rotated for different perspectives, as illustrated in the Bounce Data.jmp example, where the plot shows the relative prediction variance as a function of Sulfur and Silica. In this example, the grid is set at 0.467, highlighting that most of the Sulfur and Silica design region has a relative prediction variance below 0.467, which corresponds to 80 percent of the design space according to the fraction of design space plot.

Estimation efficiency

Estimation efficiency measures the precision with which your design estimates model parameters, relative to an ideal design. This metric provides insight into how effectively your design is at generating reliable parameter estimates. The estimation efficiency report details the fractional increase in confidence interval length compared to an ideal, orthogonal design, helping you understand the trade-offs in precision that your design may impose. This is especially important when dealing with complex models where interactions and nonlinearities are present.



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

If you are interested in inference and hope to estimate parameters with the greatest possible precision, the estimation efficiency report provides a measure of precision called the fractional increase in confidence interval (CI) length. It also includes the relative standard error for each parameter estimate in the model, where the Fractional Increase in CI Length compares the length of a parameter's confidence interval from the current design to that from an ideal orthogonal design, with a smaller fractional increase being preferable. Response surface designs often show larger increases due to varying quadratic effects, making this metric more suitable for design comparison than for absolute interpretation, as illustrated by parameters with fractional increases around 1, indicating confidence intervals twice as long as those for the ideal design.

Alias matrix

The alias matrix is critical for identifying potential confounding among model terms. Confounding occurs when the effects of two or more factors cannot be distinguished from one another, which can bias the estimates of your model parameters. The alias matrix reveals how non-modeled effects might influence your results, allowing you to refine your design to minimize these risks. This tool is essential for ensuring that your design accurately reflects the true relationships between factors, particularly in experiments involving complex interactions.

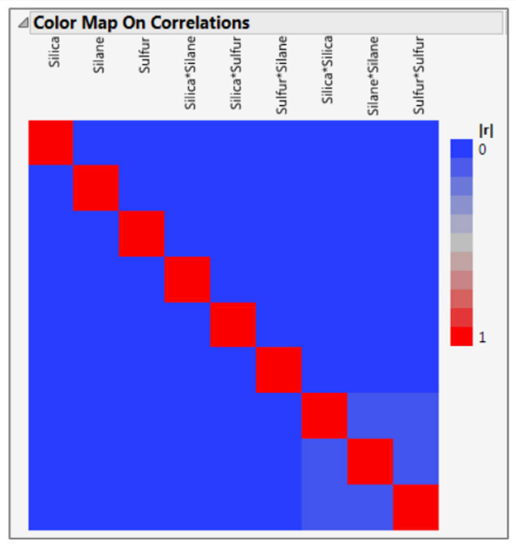
Alias Matrix

Effect	Grind*Temperature	Grind*Time	Grind*Charge	Temperature*Time	Temperature*Charge	Time*Charge
Intercept	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

If you suspect there are potentially active effects not included in your a priori model that might bias the estimates of model terms, list them in the Alias Terms outline. Next, after generating your design, examine the alias matrix, where the entries represent the degree of bias imparted to model parameters by the non-negligible effects of the Alias Terms. Ideally, you want either a small entry or a small effect of the alias term to minimize bias. However, if a substantial effect is suspected, consider including the term in the model or using an alias-optimal design. As illustrated in the Coffee Data.jmp example, the a priori model includes only main effects and the alias matrix shows that the estimate for the Temperature coefficient is biased by 0.333 times the true value of the active Grind*Time interaction.

Color map on correlations

The color map on correlations provides a visual representation of the correlations between different effects in your model. High correlations can inflate standard errors, making it more difficult to detect significant effects. This tool helps you assess the degree of orthogonality in your design, with the goal of minimizing correlations between effects. A well-designed experiment will show low correlations (depicted in blue) across the map, indicating that the effects can be estimated independently and precisely.



If you are interested in inference, examine the color map on correlations, as large correlations among effects inflate standard errors, making it difficult to identify active effects. The map shows the absolute value of correlations between any two effects in the Model or Alias Terms outline, where a good design typically displays blue off-diagonal cells indicating orthogonality or small correlations between distinct terms. Deep red on the diagonal represents absolute correlations of one; light blue squares correspond to correlations between quadratic terms, indicating a well-designed model from the perspective of correlation.

Design diagnostics

Design diagnostics offer a comparative analysis of your design's efficiency, focusing on key metrics such as D-efficiency, G-efficiency, and A-efficiency. D-efficiency measures the design's ability to minimize the variance of estimated parameters, G-efficiency assesses the maximum prediction variance, and A-efficiency considers the average variance of parameter estimates. By comparing these metrics, the design diagnostics tool helps you identify the most efficient design, ensuring that your experiment is optimized to deliver precise and reliable results with minimal resources.

Design Diagnostics

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

Use the design diagnostics outline to compare the efficiency of designs relative to D-, G-, and A-efficiency, where ideal designs have efficiency values of 100 percent. However, when quadratic effects, inequality constraints, or disallowed combinations are present, these measures are better suited for comparing design alternatives rather than for absolute interpretation. As illustrated in the Bounce Data.jmp example, the G-efficiency (91.45) is significantly higher than that of the Box-Behnken design (72.43), with higher D- and A-efficiencies and a slightly smaller Average Variance of Prediction.

Augment Design

Enhancing and refining your experimental process

In the fast-paced world of research and development, initial experiments do not always yield clear or optimal results. Instead of starting from scratch, the JMP Augment Design platform empowers you to refine and extend your existing experiments.

By adding new runs, you can treat experimentation as a dynamic, iterative process — one that adapts to emerging insights and challenges. This capability is especially valuable when screening experiments fail to answer questions about which main effects or interactions are truly significant.

If your initial design encountered setbacks — perhaps due to overly ambitious factor settings that led to failures, or unexpected constraints that appeared during the experiment — Augment Design allows you to recalibrate by introducing additional runs that optimize the overall design. Moreover, JMP enables you to group experimental runs into separate blocks, accounting for variations between initial and subsequent runs, ensuring the integrity and continuity of your research.

Benefits of augmenting your design

- **Rescue infeasible or flawed runs:** If initial runs were unfeasible, incorrect, or missed, augmenting your design with additional runs can help recover valuable data and insights.
- **Validate error variance assumptions:** Through replication, you can check the assumption of constant error variance, reinforcing the reliability of your experimental outcomes.
- **Test for fit and curvature:** Adding center points allows you to evaluate model fit and curvature, while also reducing prediction error at the center of your design space.
- **Address confounding issues:** Utilize a fold-over design to resolve confounding between two-factor interactions and main effects, which is particularly useful following a saturated or near-saturated fractional factorial or Plackett-Burman design.
- **Evolve screening designs:** Transform a screening design into a robust response surface design by adding axial and center points, enhancing your capacity for precise prediction modeling and process optimization.
- **Enhance spatial modeling:** Introduce interior runs using space-filling designs to meet linear constraints, ideal for deterministic or spatial modeling scenarios.
- **Expand and fine-tune your model:** The Augment button's flexibility allows you to incorporate additional terms into your model, estimate more effects, test for curvature, or clarify ambiguities — whether by adding quadratic terms or defining new factor constraints.

Defining factor constraints

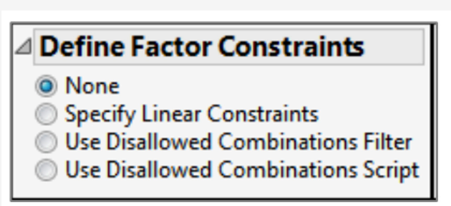
Ensuring feasibility in your design

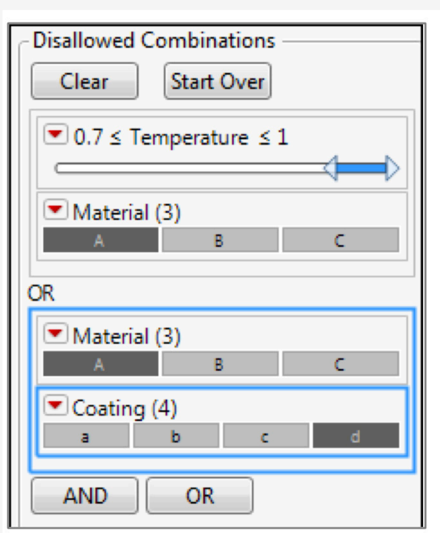
In experimental design, certain factor combinations may be impractical due to equipment limitations or potential risks.

DOE in JMP offers sophisticated tools to help you define and manage these constraints effectively:

- **Linear inequalities:** Set up restrictions as linear inequalities to keep factor levels within safe and feasible limits.
- **Disallowed combinations filter:** Employ a data filter to prevent specific factor combinations that are unworkable or unsafe. For example, you might restrict Material A from being used at Temperature levels above 0.7, or block the combination of Material A with Coating D.
- **Scripting constraints:** For more complex scenarios, scripting allows for advanced customization and precise control over your design.

By clearly defining and enforcing these constraints, you ensure that your experimental design remains both viable and safe, while still allowing you to thoroughly explore the possibilities within your design space.





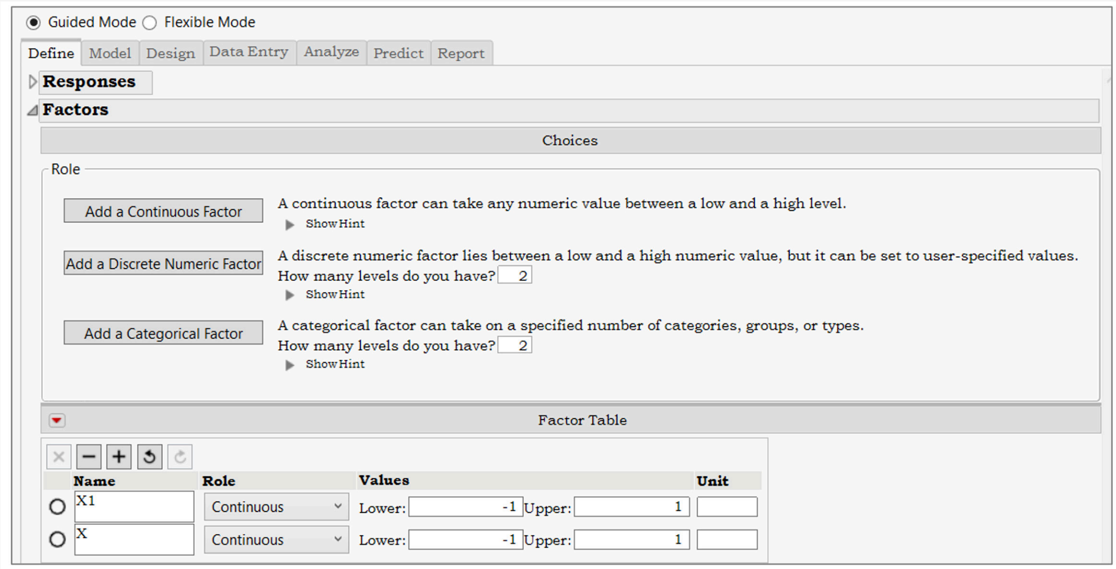
If your design includes factor level combinations that could cause damage or are not feasible due to equipment limitations, you can specify these constraints in most DOE platforms by using a linear inequality (Specify Linear Constraints), a data filter (Use Disallowed Combinations Filter), or a script (Use Disallowed Combinations Script). As illustrated in the example, the values of Temperature exceeding 0.7 are not allowed for Material A, and combining Material A with Coating D is also not allowed.

Easy DOE in JMP

Streamlining the design of experiments

JMP Easy DOE is designed to make the process of designing, executing, and analyzing experiments both simple and comprehensive.

Whatever your competencies may be, from a novice to a seasoned experimenter, Easy DOE provides a streamlined and intuitive experience, guiding you through each step with clear, user-friendly instructions.



Use Easy DOE for an end-to-end guided design of experiment solution, where you create definitions, enter data, and analyze an experiment within a single JMP platform. Using either option (the guided mode for assistance through design and analysis steps or the flexible mode to proceed independently) allows you to save your progress for later analysis or sharing, and then to export a report once the analysis is complete.

Modes of operation

- **Guided mode:** This mode provides a step-by-step workflow, offering guidance and suggestions at every stage of the experimental design process. It is perfect for users who are new to DOE or those who prefer a more structured approach to ensure they cover all necessary steps.

- **Flexible mode:** For more experienced users, this mode offers the flexibility to customize the design process using advanced features. It allows you to modify the design and analysis steps to meet the specific needs of your experiment, giving you greater control over the process.

Tabs and workflow

JMP Easy DOE is organized into a series of sequential tabs, each representing a critical step in the experimental design process. This structure ensures that users can follow a logical workflow from start to finish:

1. **Define:** In this tab, specify the inputs (factors) and outcomes (responses) for your experiment. Set goals for each response, such as maximizing, minimizing, or targeting a specific value, ensuring your design aligns with your objectives.

2. **Model:** Choose the model that best represents the relationship between factors and responses. The platform offers a variety of model types, including main effects, interactions, and quadratic terms, allowing you to tailor the model to your experiment's complexity.

3. **Design:** Review the generated experimental design. You can see the setup and make any necessary adjustments before proceeding, ensuring that the design is robust and aligned with your experimental goals.

4. **Data entry:** After conducting your experiment, enter your results. You can manually input data, paste it from another table, or load it from an existing data table, making it easy to integrate your findings into the analysis.

5. **Analyze:** Fit the specified model to your experimental data. You can evaluate the model's assumptions, identify the most significant effects, and refine your analysis as needed to ensure accuracy and relevance.

6. **Predict:** Optimize factor settings to achieve the desired outcomes. This tab helps you explore how changes in factor levels affect your responses, guiding you to the best possible settings for your objectives.

7. **Report:** The final tab allows you to generate a comprehensive, autogenerated report of your experiment, including all aspects from design to analysis and predictions. This feature is particularly beneficial for new users, as the interpretation is written for them, ensuring that the results are clearly communicated and easy to understand. The report can be easily exported for sharing with colleagues or for further review, ensuring transparency and reproducibility in your work.

End-to-end solution

Easy DOE integrates all these steps into a cohesive, end-to-end solution that streamlines the entire experimental process. The platform's design allows for easy navigation between steps, enabling you to adjust as needed without losing your progress. The ability to save your work and return to it later adds to the platform's flexibility, making it a powerful tool for effective and efficient experimentation.

With Easy DOE, JMP has created a solution that balances ease of use with powerful design capabilities. This makes it suitable for a wide range of experimental applications, from simple studies to more complex designs, ensuring that users at all levels can conduct their experiments with confidence and precision.

Definitive screening design

Efficient and comprehensive factor screening

When your primary objective is to screen a large number of factors — and when interactions or nonlinear effects may be present — definitive screening design (DSD) in JMP offers an efficient and powerful solution. DSDs are designed to minimize the number of experimental runs needed to identify key factors, while also providing the ability to detect curvilinear effects — something that standard screening designs often fail to achieve. Additionally, DSDs handle two-level categorical factors, making them highly versatile.

Advantages of DSDs

- **Small design size:** DSDs require only a few more runs than twice the number of factors, making them extremely efficient.
- **Orthogonal main effects:** The main effects in DSDs are orthogonal, meaning they are uncorrelated with other effects, enhancing the clarity of your results.
- **Uncorrelated two-factor interactions:** Main effects are uncorrelated with two-factor interactions and quadratic effects, reducing potential confounding.
- **Quadratic estimation:** DSDs allow for the estimation of quadratic effects, which is crucial for understanding complex relationships between factors.
- **Minimized confounding:** Unlike traditional designs, DSDs minimize confounding among two-factor interactions, providing more reliable insights.
- **Flexibility in estimation:** For six or more factors, DSDs can estimate all possible full quadratic models for any three factors. As the number of factors increases, DSDs can estimate full quadratic models for any four or five factors, making them highly adaptable.
- **Blocking capability:** DSDs can be blocked, adding flexibility to your experimental setup, especially when dealing with external factors or constraints.

Augmenting DSDs for enhanced capability

JMP Augment Design can further enhance DSDs by allowing additional trials, making this approach even more powerful. For example, if a 17-run DSD for seven factors indicates a quadratic effect, you can augment the design with 20 additional runs. This augmented design will then allow you to estimate and test all quadratic terms and two-way interactions with just 37 runs, compared to the 80 runs required for a central composite design or 62 runs for a Box-Behnken design.

Main effects screening design: Handling complex factor structures

When your design involves multilevel categorical factors or discrete numeric factors, classical screening designs may not be feasible. JMP addresses this challenge with main effects screening designs, which are either orthogonal or nearly orthogonal. These designs can accommodate categorical factors and discrete numeric factors with any number of levels, providing a robust solution even when traditional designs are not applicable. Additionally, main effects screening designs typically require fewer runs, offering efficiency without compromising on the quality of results.

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

When screening is the goal and interaction and nonlinear effects are potentially active, use a definitive screening design (DSD). DSDs can screen many factors in very few runs, avoiding confounding of effects and identifying nonlinear effects. It offers clear advantages, such as small design size, orthogonal main effects, uncorrelated main effects with two-factor interactions and quadratic effects, the ability to estimate quadratic effects, and the option to augment the design for further analysis. As illustrated, a seven-factor DSD can be augmented to estimate and test all quadratic terms and two-way interactions with 37 runs, compared to 80 runs for a central composite design or 62 runs for a Box-Behnken design.

Classical designs in JMP

Time-tested methods for robust experimentation

Classical designs are foundational tools in the world of experimental design, offering time-tested methodologies that are widely recognized across various disciplines. These methods are essential for researchers and practitioners who seek robust, reliable results in their experiments, providing a structured approach to understanding the factors that drive outcomes and optimizing processes.

Factor screening

When faced with numerous variables and limited resources, classical screening designs such as fractional factorial and Plackett-Burman are indispensable. These designs are tailored to identify the most critical factors influencing your experimental outcomes, focusing on main effects while assuming that interactions are minimal. This approach allows you to efficiently zero in on the variables that matter most, making the best use of your resources and time.

Response surface design

For those looking to model and optimize processes with multiple continuous factors, response surface designs (RSD) are a powerful option. RSDs, including central composite designs (CCD) and Box-Behnken designs, are particularly effective in identifying the optimal settings of factors to achieve desired outcomes. These designs allow for the fitting of quadratic models, capturing the nuances of curvature in the response, and providing the precision needed to fine-tune processes for peak performance.

Full factorial design

Full factorial designs represent the most exhaustive method of experimentation, where every possible combination of factor levels is tested. This approach yields comprehensive insights into all main effects and interactions, offering a complete understanding of the system under study. However, the exponential increase in required runs with additional factors can make this design impractical for large-scale experiments. Despite this, when feasible, full factorial designs provide unmatched detail and depth in experimental analysis.

Mixture design

In scenarios where your experiment involves mixtures — such as in pharmaceuticals, food science, or chemical formulations — mixture designs are the go-to method. These designs focus on the proportions of components within a mixture and how these proportions affect the response. JMP offers a range of mixture designs, including simplex centroid, simplex lattice, and extreme vertices designs, each tailored to explore and optimize the specific properties of mixtures, ensuring that you can achieve the best possible formulation.

Taguchi arrays

Taguchi designs are a robust method focused on improving quality by addressing variability. These designs use orthogonal arrays to study the effects of multiple factors on both the mean and variability of the response, making them particularly useful in quality control and manufacturing. By identifying factors that reduce variability, Taguchi designs help you ensure consistent performance, even in the presence of uncontrollable external influences, thus enhancing the overall reliability and quality of your products or processes.

Classical design options in JMP

- **Center points and replicates:** Easily add center points to detect curvature in your response surface and specify the number of replicates to improve the reliability of your results. Replicates help in accurately estimating experimental error by providing multiple observations for each factor combination.

- **Viewing and modifying the design:** Preview and modify your experimental design interactively, making adjustments to factors, levels, and settings before finalizing. This flexibility ensures that your design is optimized to meet your specific research objectives.

- **Design evaluation:** Evaluate your design's robustness and effectiveness using comprehensive tools as described in the custom design evaluation.

- **Run order:** Control the run order of your experiments to minimize the influence of lurking variables. You can randomize the order to avoid systematic bias or sequence runs according to practical constraints.

Design Diagnostics in JMP

Ensuring robust experimental designs

The Design Diagnostics platform in JMP offers powerful tools for evaluating and comparing experimental designs. This platform allows users to assess the quality and efficiency of their designs before conducting experiments, ensuring that the chosen design will meet the study's objectives and yield reliable results.

Evaluate design

The evaluate design feature provides a comprehensive analysis of a single experimental design, as described earlier in the Custom Design section.

Compare designs

The compare designs feature extends the capabilities of the evaluate design tool by allowing users to compare up to four designs simultaneously against a reference design. This comparison includes:

- **Relative efficiency measures:** Compares the efficiencies of different designs in estimating effects.
- **Prediction variance surface:** Visualizes how prediction variance differs across the design space for each design.
- **Alias matrix diagnostics:** Evaluates how different designs handle aliasing, providing insights into which design is most robust against confounding.
- **Power analysis:** Compares the power of different designs to detect specified effects, helping users choose the most powerful design for their needs.

By providing these detailed diagnostic tools, the Design Diagnostics platform in JMP 18 helps users ensure that their experimental designs are not only optimal for their specific needs but also robust and reliable, ultimately leading to more trustworthy and useable results in their experiments.

Consumer studies in JMP

Designing experiments for customer insights

In today's market, understanding consumer preferences is essential for successful product development. The JMP Consumer Studies platform offers powerful tools designed to capture and analyze these preferences, enabling companies to create products and services that align with consumer demand.

Choice design

Choice design supports the creation of discrete choice experiments (DCEs), where participants choose their preferred product profiles from sets varying in attributes. This method helps determine the relative importance of features and the trade-offs consumers are willing to make. The platform also supports Bayesian D-optimality, ensuring robust, optimized designs that yield insightful data on consumer preferences.

MaxDiff design

MaxDiff design (maximum difference scaling) asks respondents to select the most and least preferred items from a set, forcing a clear ranking of preferences. This method provides more definitive results than traditional scales and closely matches a balanced incomplete block design, ensuring accurate assessment of relative importance. MaxDiff helps organizations prioritize features and tailor their offerings to better meet customer needs.

	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

By using choice designs to prioritize customer preferences when designing a new product or service, you can bring the right product to market by presenting respondents with choice sets of product profiles to indicate their preference. In this example, respondents choose between different brews based on grind, temperature, time, and coffee amount. If prior information about customer preferences is available, it can be incorporated into the choice designs for constructing more sensitive designs.

Special purpose designs in JMP

Solutions for advanced experimental challenges

The Special Purpose platform in JMP includes a range of design types to address unique and complex experimental situations.

Space filling designs

Space filling designs are ideal for deterministic experiments, like computer simulations, where traditional designs fall short. These designs ensure uniform coverage of the design space, allowing for comprehensive exploration of complex systems. By evenly distributing design points, space filling designs represent all regions effectively, making them ideal for studying intricate or unknown relationships.

Constant stress ALT design

In reliability studies, particularly in accelerated life testing (ALT), the constant stress ALT design plays an important role. It tests products under consistent stress conditions to predict their lifespan under normal usage. This design helps understand product performance over time, offering insights into durability and identifying potential failure points before they occur in real-world use.

Nonlinear designs

When dealing with models known to be nonlinear in their parameters, nonlinear designs offer an optimal solution. This design is particularly useful in fields such as chemical engineering, metallurgy, and mechanical studies, where the relationships between variables are complex and nonlinear. By constructing designs tailored to these nonlinear relationships, this platform helps researchers gain more accurate and meaningful insights from their experiments.

Balanced incomplete block design

Balanced incomplete block design (BIBD) is ideal when it is not feasible to test all treatments together, often due to resource constraints. BIBD allows for a balanced comparison across incomplete blocks, ensuring that each treatment is tested an equal number of times across the experiment. This design is particularly useful when a full factorial design is impractical, providing a way to still obtain reliable comparative data.

Measurement systems analysis

Measurement systems analysis (MSA) designs are important for evaluating the accuracy and precision of measurement systems. MSA aids in designing experiments to assess variability within measurement systems, identifying sources of measurement error and ensuring the reliability of the data collected. MSA designs are particularly significant in quality control processes, where the integrity of measurements is crucial.

Group orthogonal supersaturated designs

In situations where the number of factors exceeds the number of experimental runs, group orthogonal supersaturated designs offer a solution. These designs are used to screen a large number of factors in fewer runs, helping to identify significant factors efficiently. This approach is particularly valuable in preliminary studies where resources are limited, but a broad exploration of potential factors is necessary.

Accelerated life test design

Similar to the constant stress ALT design, the accelerated life test design offers flexibility in stress levels and types. It is used to predict product reliability under normal usage conditions by subjecting products to accelerated stress. This design enables researchers to understand how products will perform over time and under various conditions, making it a useful tool in product development and quality assurance.

Covering array designs

Ensuring comprehensive testing with minimum runs

Exhaustively testing complex engineered systems is usually infeasible, if not impossible. Covering arrays (CAs) are designs that can be used to effectively test such systems at minimal cost. Such a testing strategy is known as combinatorial testing and is sometimes referred to as pseudo exhaustive testing.

Combinatorial testing is a testing strategy that is usually used for testing complex engineered systems when exhaustive testing is impossible, or impractical, and when it is critically important to uncover faults in a system. Empirical evidence shows that failures that occur during the operational phase of such systems are often due to faults that involve interactions between six or fewer inputs. CAs ensure that a combinatorial testing strategy will result in a suite of test cases that guarantees that all combinations of the values of any set of t inputs are included in the test suite. Furthermore, the test suite will accomplish this coverage at minimal cost. This coverage property of CAs makes them useful for a wide variety of applications, from software and hardware testing to network configuration and even biological experiments.

CAs are typically much smaller than their traditional Design of Experiments (DOE) counterparts since they do not guarantee balance, they only guarantee that each level combination occurs at least once, for some run of the design. JMP's Covering Array platform provides the familiar JMP DOE user interface for specifying factors (i.e., inputs) and levels and also allows for the specification of disallowed combinations. It also provides a way to specify the desired order of interactions to be covered (referred to as the strength). In addition, JMP provides an analysis tool to help identify the root cause(s) of failures, if they do occur. The good news is that if the system passes all test cases in the suite, then the test engineer can be confident that there are no faults due to t or fewer inputs.

Sample Size Explorers in JMP

Tailoring experiments for precision and power

Sample size explorers

The Sample Size Explorers platform in JMP 18 provides robust tools to calculate and evaluate sample sizes necessary for various types of studies, ensuring that your experiments are adequately powered to detect meaningful effects. These explorers guide users in balancing sample size, confidence intervals, reliability, and quality standards, making it easier to design experiments that are both efficient and statistically sound.

Power explorers

The power explorers help you determine the sample size required for hypothesis testing. They allow you to explore the relationship between sample size and the power of a hypothesis test to detect a specified difference. This tool is vital for ensuring that your study has a sufficient sample size to achieve reliable and meaningful results.

Confidence interval explorers

The confidence interval explorers assist in selecting the appropriate sample size to achieve a desired margin of error for various types of interval estimates, including confidence intervals, prediction intervals, and tolerance intervals. This tool helps ensure that your interval estimates have the precision required for your study's objectives.

Reliability explorers

The reliability explorers are specifically designed to determine sample sizes for reliability demonstrations and life testing. They allow you to explore trade-offs between factors such as test time, the number of failures allowed, and the sample size needed to demonstrate a specified level of reliability, even in nonparametric scenarios.

Quality explorers

The quality explorers focus on determining sample sizes for quality studies, particularly in relation to the Sigma Quality Level. This explorer helps you explore the relationship between the number of defects, the number of opportunities for defects, and the Sigma Quality Level, providing insights into process improvements and quality assurance.

These explorers provide a comprehensive suite of tools for tailoring your experimental design to meet your study's specific needs, ensuring precision, reliability, and efficiency in your research.