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Workshop Schedule

DOE Simplified

April 29: Minneapolis, MN

An overview of Design of Experiments (DOE) from A to Z, based on the popular book. \$295* (\$195 each, 3 or more)

Statistics for Technical Professionals

February 18–19: Minneapolis, MN June 15–16: Minneapolis, MN

Revitalize the statistical skills you need to stay competitive. \$995* (\$795 each, 3 or more)

Experiment Design Made Easy

January 20–22: San Jose, CA February 24–26: Minneapolis, MN March 30–April 1: Philadelphia, PA May 4–6: Minneapolis, MN

Study the practical aspects of DOE. Learn about simple, but powerful, two-level factorial designs. \$1495* (\$1195 each, 3 or more)

Response Surface Methods for Process Optimization

March 16–18: Minneapolis, MN June 22–24: Minneapolis, MN

Maximize profitability by discovering optimal process settings. \$1495* (\$1195 each, 3 or more)

Mixture Design for Optimal Formulations

February 3-5: Minneapolis, MN May 11-13: Minneapolis, MN

Find the ideal recipes for your mixtures with high-powered statistical tools. \$1495* (\$1195 each, 3 or more)

Robust Design: DOE Tools for Reducing Variability

April 13-15: Minneapolis, MN

Use DOE to create products and processes robust to varying conditions. A must for Six Sigma. Factorial and RSM proficiency are required. \$1495* (\$1195 each, 3 or more)

PreDOE: Basic Statistics for Experimenters

Six-hour web-based training. This course or the equivalent is a prerequisite for all workshops—www.statease.net. \$95

Attendance is limited to 20. Contact Sherry at 800.801.7191 x18 or sherry@statease.com.

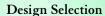
*Includes a \$95 student materials charge which is subject to state and local taxes.



ABOUT STAT-EASE SOFTWARE, TRAINING, AND CONSULTING FOR DOE Phone 612.378.9449 Fax 612.378.2152 E-mail info@statease.com Web Site www.statease.com

A DOE for the Sweet Tooth

Just in time for the holidays, I decided to embark on some kitchen recipe experimentation. Mark shouldn't be the only one around here allowed to play in the kitchen! Enough of the pound cake, a serious sweet tooth is prevalent in my household. The target—a recipe for chocolate-covered peanut butter balls.



This entire project was started by an unsuspecting group of employees at my husband's place of employment. One person brought a batch of peanut butter balls to work, and the others decided to try to improve on her recipe. The following days brought variations of the peanut butter ball recipe and a few of the treats made their way home for me to enjoy. Of course, the experimenter in me took over and I decided to try adding a bit of structure to the recipe exploration process.

First, I searched the internet and found many variations of the recipe. They



called for various types of peanut butter—creamy, chunky, etc. Then they added various types of "crispies." The chocolate coating was generally semi-sweet chocolate chips, but some recipes called for adding Hershey bars to the mix.

Often experimenters are unsure what type of design is appropriate for their problem. The answer to this is dependent on the objective of the experiment, the amount and type of information desired, the number of factors involved, and constraints on the number of runs that could practically be done. As I tried to decide what type of design to use, I realized that I would have to choose

Run	A: Peanut Butter	B: Crispies	C: Chocolate				
1	Chunky	Rice Krispies	Chips				
2	Chunky	Graham Crackers	Chips + Bar				
3	Creamy w/ Buttersc. Chips	Corn Flakes	Chips				
4	Creamy w/ Buttersc. Chips	Rice Krispies	Chips				
5	Creamy	Graham Crackers	Chips				
6	Creamy	Rice Krispies	Chips + Bar				
7	Creamy	Corn Flakes	Chips				
8	Chunky	Corn Flakes	Chips + Bar				
9	Creamy w/ Buttersc. Chips	Graham Crackers	Chips + Bar				
10	Creamy	Graham Crackers	Chips + Bar				
Table 1: D-optimal design							

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between doing a mixture design, in which I would vary the proportions of the ingredients, or a factorial design, in which I would vary the ingredients themselves. A combined design was possible, but I dismissed that thought because of the number of runs it would require. I realized that a constraint on the number of runs I could do was the number of peanut butter balls that people were willing to taste test. Here's what I decided:

Objective: To study the effects of different ingredients on overall taste.

Factors and Levels:

A: Peanut Butter—Creamy, Chunky, or Creamy with Butterscotch Chips added B: Crispies—Rice Krispies, Corn Flakes, or Graham Crackers

C: Chocolate Coating—Chocolate Chips or Chips with a Hershey Bar added

Amount and Type of Information: I was primarily interested in the main effects of each factor, and I suspected an interaction between the peanut butter and the type of crispies used. To keep runs to a minimum, I chose to assume there was not an interaction between the chocolate coating and either the peanut butter or the crispies.

Based on this subject matter knowledge, I created a D-optimal general factorial design with Design-Expert® 6 software. It was customized to only estimate the A, B, C, and AB effects. Since my factors had more than two levels each, a standard two-level factorial design wouldn't fit. If all possible combinations were run, this would be $3 \times 3 \times 2 = 18$ combinations. As much as people like chocolate and peanut butter, it was asking too much to test all 18 combinations. Plus, at ½ hour per run, that would mean 9+ hours in my kitchen just creating these concoctions! The D-optimal design, which is much like a fractional factorial, resulted in just 10 combinations (see Table 1).

The production of the peanut butter balls went fairly smoothly. I generally made two batches a day, being careful to clean the bowls between each batch. A standard design question to consider is, since the batches were being done on different days, should the design be blocked on day? Blocking is an important consideration. It is a technique used to eliminate the variation caused by an uncontrollable variable. Often, when a DOE is spread out over 2 or 3 days, it makes sense to block by day because the process may vary from one day to the next. For this situation, I did not feel that my batches would be affected by day-to-day variations. Furthermore, I would only be completing about 2 batches in a day. It is generally recommended that a block have at least 4 runs in it in order to make a valid comparison of the block-to-block differences.

Data Collection: Taste Testing

Collecting sensory data such as a taste rating is common in the food industry. First, a hedonic scale (see Figure 1 below) must be developed so panelists can rate the taste of the product. My husband felt that the descriptive words I used may have biased the ratings, and in retrospect, he is probably right. Another lesson learned.

Hedonic Scale

1 - lck!

2 -

3 - Too gooey, sticky

4 -

5 - Like it

6 -

7 - The best

Figure 1: Hedonic Scale

A second issue was how many chocolate-covered peanut butter balls any one person could be expected to evaluate. Many people would decide that eating 10 of these at once would be peanut butter (let alone fat) overload! So, it was

Analysis of variance table									
		Sum of		Mean	F				
Source		Squares	DF	Square	Value	Prob > F			
Block		48.99	17	2.88					
Model		73.28	8	9.16	6.14	< 0.0001			
	Α	27.35	2	13.67	9.16	0.0003			
	В	3.38	2	1.69	1.13	0.3283			
	C	6.77	1	6.77	4.53	0.0371			
	AB	26.18	3	8.73	5.85	0.0014			
Residual		95.52	64	1.49					
Cor Total		217.79	89						

Table 2: ANOVA (Ratings Model)

decided that each person would taste test 5 of the 10 recipes. I knew that I would be able to get at least 10 people to participate in the taste panel. The testing was set up so each run would be positioned 1st, 2nd, ..., 5th in taste order at least twice. This helps offset position bias in the ratings.

Half of the peanut butter balls were sent with my husband to his place of employment and half were brought to Stat-Ease, Inc. Productivity that day may have dropped a bit due to frequent snack breaks, or it may have increased due to sugar overload! The panelists discovered that some of the combinations were fairly gooey and stuck to the pan, while other combinations were drier and easier to handle. Some people encountered the added butterscotch chips and liked the additional sweetness, while others did not.

Data Analysis

The analysis of variance (Table 2)

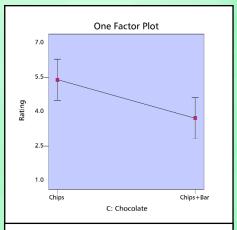


Figure 2: Plot of Coating Type

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More on Peanut Butter Balls...

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showed a significant model that included a strong AB interaction (peanut butter vs crispies) and a lesser, but still significant, main effect C (chocolate type).

As shown by Figure 2, the chocolate chips alone were favored (higher rating) over adding the Hershey bar into the chocolate coating. Some panelists commented that using the semi-sweet chocolate was a bit bitter, and one panelist had the idea that the butterscotch chips should have been added to the coating rather than to the peanut butter! There is always room for improvement!

Figure 3 shows the interaction graph of the type of peanut butter versus the type of crispy. The black line on the bottom is for creamy peanut butter. This produced a softer ball and was significantly less desirable than either the chunky peanut butter (red line) or the creamy with added butterscotch chips (green line).

The favorite combination appears to be the combination of chunky peanut butter and graham crackers. This average rating is higher than the others, although some of the least significant difference (LSD) bars overlap other bars. In order for there to have been a clear favorite combination, the best mean and its LSD bar should not overlap any others. If additional data were collected from more taste panelists, the means would become more exact and the LSD bars would shorten.

The end result of this DOE was a very tasty treat. I am convinced that additional experimentation is needed to optimize the exact amounts of each ingredient, so a mixture design may be

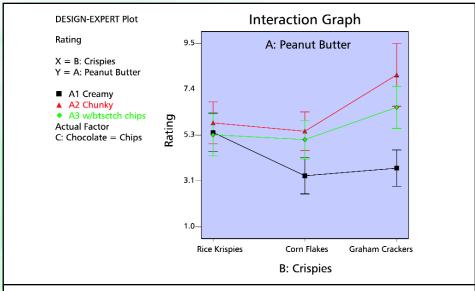


Figure 3: Interaction Graph

in the picture (after my taste panelists recuperate from their sugar high)! I thank the eager volunteers from both Life Fitness and Stat-Ease, Inc. for their help as taste testers.

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Lessons Learned:

- 1. Don't use your Kitchen Aid mixer above the "2" setting or flour flies all over.
- 2. Creamy peanut butter makes a gooey mess.
- 3. Try experimenting with the chocolate coating to make it sweeter.
- 4. Use waxed paper on cookie sheets to make clean-up easier.
- 5. Remove balls from the freezer one day prior to taste testing to minimize any effects caused by the thawing process.
- 6. Don't bias the hedonic scale with influential words.
- 7. Irish Water Spaniels love peanut butter balls. (I lost Run #3 to the dog before the chocolate coating was applied! See the culprit on page 1.)

Chocolate-Covered Peanut Butter Balls

(makes about 30)

1 c. chunky peanut butter ½ c. butter (softened) 1 c. powdered sugar

Cream together.

1 c. Graham Crackers (crushed)

Add to peanut butter mixture. Roll into balls.

½ bag chocolate chips

Melt in the microwave using the defrost setting. Add water as needed to thin.

Dip balls in chocolate and freeze.

Optimize your Formulations with Mixtures!

In design of experiments, mixture design methods are used to optimize product formulations and performance. Mixture designs help you define the precise formulations necessary to achieve your goals, and meet your customer's expectations. Stat-Ease's "Mixture Design for Optimal Formulations" (MIX) workshop provides hands-on knowledge of these powerful tools. This computerintensive, intermediate-level three-day class is recommended for anyone seeking a competitive edge. Knowledge of factorial designs is preferred and can be learned in the "Experiment Design Made Easy" (EDME) workshop.

The MIX workshop covers the in's and out's of Scheffe' modeling, simplex designs, and optimization. In this class, you will also look at D-optimal designs. Because D-optimal designs provide maximum design flexibility, they will be used

to illustrate common experimental problems such as how to add constraints on a design space. In addition, you will discover how to use the powerful design evaluation features in Design-Expert software to determine if a design will meet your needs, before you actually perform the runs.

Combining process factors with the mixture formulation can provide a powerful tool that leads to optimal process settings for various formulations. Analysis of mixture designs will be covered in detail, including how and when to use backward, forward and stepwise algorithmic model reduction. You will also learn how to create customized contour and 3D surface graphs that clearly illustrate the optimal formulation.

The MIX workshop covers numerical and graphical optimization routines that are favorites with experimenters. You'll discover how to maximize the information gained from these tools, plus a few tricks you probably haven't thought of yet!

Join us in Minneapolis, MN on Feb 3-5 for our next Mixture Design for Optimal Formulation workshop.

If you have at least 4-6 students who need to learn mixture designs, consider bringing the MIX workshop in-house. Contact Sherry Klick at 612.378.9449 x18 for a quotation.

Those of you working with processes should take a look at our Response Surface Methods for Process Optimization (RSM) workshop. This course is equivalent to the MIX workshop, but it explores designs for process factors and process constraints. Information on all workshops is available at http://www.statease.com/training.html.

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