STATeaser

ABOUT STAT-EASE® SOFTWARE, TRAINING, & CONSULTING FOR DOE

Workshop Schedule

Experiment Design Made Easy (EDME)
December 4-5, 2012: Minneapolis, MN
February 12-13, 2013: Minneapolis, MN*
March 11-12, 2013: San Diego, CA*
$1295 ($1095 each, 3 or more)

Response Surface Methods for Process Optimization (RSM)
March 13-14, 2013: San Diego, CA*
$1295 ($1095 each, 3 or more)

Mixture Design for Optimal Formulations (MIX)
October 23-24, 2012: Minneapolis, MN*
February 14-15, 2013: Minneapolis, MN*
$1295 ($1095 each, 3 or more)

Advanced Formulations: Combining Mixture & Process Variables (MIX2)
October 25-26, 2012: Minneapolis, MN*
May 16-17, 2013: Minneapolis, MN*
$1495 ($1195 each, 3 or more)

PreDOE: Basic Statistics for Experimenters Online Course
Free (a $95 value). Learn more at: http://www.statease.com/clas_pre.html.

*Attend the EDME/RSM, EDME/MIX, or MIX/MIX2 workshops in the same week and save $395 on tuition!

Free Webinar: Real-Life DOE
by Stat-Ease Consultant Mark Anderson, Wednesday, October 17 at 8:00 am CDT, with an encore presentation on Wednesday, November 14 at 12:00 pm CDT. Check the web site for details. www.statease.com/webinar.html.

Workshops limited to 16. Multiclass discounts are available. Contact Elicia Bechard at 612.746.2038 or workshops@statease.com.

The Optimal Recession Proof Recipe

Almost everyone reading this article has had the "opportunity" to go to college and live on a shoestring budget. It is a rite of passage for any engineer or scientist. Ramen noodles are a well-known staple of that limited-budget, college diet. Where else can you pay 20¢ for a meal packed with 380 calories and offered in such a flavorful array of varieties: chicken, creamy chicken, roast chicken, beef, pork, cheese, even shrimp…the possibilities are endless!

Figure 1: Ramen taste testers from L to R: Brooks Henderson, Joe Carriere, John Dennis, and Hank Anderson

John, a new programmer, recently joined our ranks here at Stat-Ease. Being just out of college he is still acquainted with this cost-effective diet. In fact, he still eats ramen noodles for lunch a couple times a week. Having recently taken all of our design of experiments (DOE) workshops, John was anxious to practice his new skills. What better way than to try to optimize the cooking of his weekly meals? Being an experimenter at heart, I jumped at the opportunity to lead some of our programmers through the process of brainstorming, setting up a DOE, and running the experiment. The result of this enjoyable effort was every college student's dream—the perfect ramen noodle recipe!

We started by brainstorming the factors that would affect the taste and cooking time of the ramen noodles. We knew we wanted to rate the taste and crunchiness (texture) of the noodles, using a panel of tasters, but we also wanted to come up with a quantitative, measurable, response to determine how well done the noodles were. After rejecting many possibilities, we finally came up with one. We would weigh the noodles before and after cooking to see how much water was absorbed. This turned out to be a very good response that correlated well with the crunchiness of noodles. We also learned something quite unexpected from this response, which we'll get to later.

As a result of brainstorming, we narrowed it down to four factors:

A. Water Amt.—240 to 720 grams
B. Cooking Time—60 to 300 seconds
C. Brand—Maruchan® vs. Top Ramen®
D. Flavor—Beef vs. Chicken

The responses were 1) Taste Rating, 2) Crunchiness Rating, and 3) Noodle

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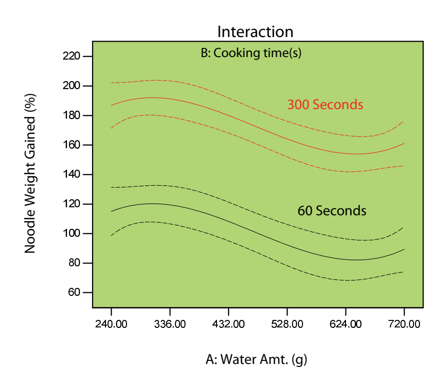


Figure 1: Interaction plot for Noodle Weight gained

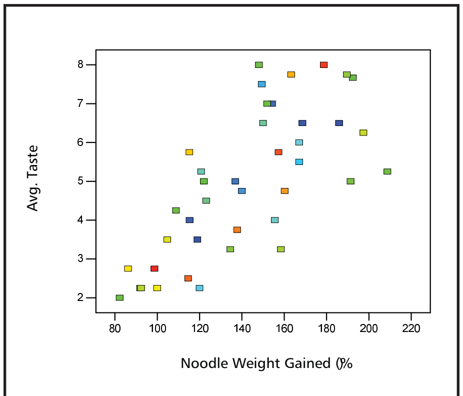


Figure 2: Scatterplot of Avg. Taste vs. Noodle Weight gained

weight gained (measured as a percentage of the original noodle weight). Because we had it narrowed down to the most influential factors, we decided to use an optimal response surface design (RSM). This a very flexible, custom design that can fit any design space or constraint. The optimal runs are chosen by the software to fit the model you choose.

In all RSM designs, you must ask yourself the question, what will the response surface look like? This determines which model to design for. In this case, we expected the taste and crunchiness responses to be a gentle sloping plane or perhaps rise to a peak and fall off at some point. Simple linear or quadratic models would suffice here, so we'd use the default quadratic setting (when in doubt, build it stout). However, the noodle weight gained would be a different story. If you think about how much water the noodles will absorb, it seems that more time in the microwave will cause the weight to rise, but only to a point. Eventually, the noodles will be saturated and the noodle weight gained will plateau. The same goes for the amount of water used. We expected that more water would hasten saturation and thus lead to a higher noodle weight gained. The simplest model that can approximate this plateau is a cubic polynomial. Therefore, when specifying the model for the optimal design build, we added the terms with A^3 and B^3 to the default quadratic model.

See Figure 1 for an interaction plot showing the water weight gained versus the amount of water and cooking time. We were correct about the cubic model being needed, but only A^3 turned out to be significant (not B^3). Figure 1 demonstrates that plateauing cubic model. The response rises to a plateau as you scan the plot from right to left. The negative slope was the opposite of what we expected.

Using less water actually caused the noodles to gain more weight, cooking more. Now, after actually collecting data, this makes sense. When more water is used, the microwave has more water molecules to heat up, so it takes longer to reach a boiling point. With less water, there is less mass to heat and everything cooks faster. This brought to mind the first time I made "quick nachos", by putting shredded cheese on chips and melting it in the microwave. The cheese burned in about 15 seconds, whereas most things need a lot longer to cook in the microwave. Less mass equals shorter cooking time. In our experiment, we always had excess water, so more water didn't increase noodle weight gained. This was an unforeseen result that only became apparent after experimentation.

It turns out that our taste ratings correlated quite closely with how well the noodles were cooked or undercooked. More cooking or noodle weight gained generally resulted in higher taste ratings. This can be seen in the often overlooked scatter plot available in the "graph columns" node of Design-Expert® software (see Figure 2). The correlation between these two responses was reported at 0.729, that is, as noodle weight is gained, the taste improves.

Knowing that the best tasting ramen noodles were those that were well-cooked, and that more water takes longer to cook, it's not a surprise that a low amount of water produced the best tasting ramen noodles. A longer cooking time was also desirable, but it peaked before the maximum. Our optimum recipe contained 367g of water (1.6 Cups) and was cooked in the microwave for 250 seconds.

Last, but not least, which brand and flavor was most desirable to our tasters? The chicken-flavored ramen fared better on average for our tasters. The two brands faired equally well with the chicken seasoning. With the beef flavor, however, one brand stood out. At the risk of upsetting the makers of this delectable cuisine, we'll keep that to ourselves. That way, you can choose your favorite brand via your own designed experiments. After this article, we know you just can't wait to crack open a case of ramen and take a trip down memory lane.

–Brooks Henderson, brooks@statease.com

DOE—How Do I Get Started?

Designed experiments require some up front planning to be successful. You need to decide on a number of things before you can even choose the right design. Start by gathering a small group of people together (4-6) who are knowledgeable about the process or product that you want to experiment on. The purpose of the gathering is to brainstorm. Work through the questions presented below. The answers will help you to choose the best design.

- What is your objective?
- What responses do you want to measure and how will you measure them?
- How much of a change in each response do you want to detect?
- What is the normal process variation for each response?
- Which factors do you want to study and at how many levels?
- What levels are wide enough apart to induce a change to the response, but still make a measurable result?
- How many runs are you willing to make? Does that provide enough power to estimate the effects you want to find?
- What will you do with factors that you're not studying?

Don't get too worried about this process. Just take it step by step and before you know it you'll be making significant improvements to your process or product!

Objectives and Design Options

What is the objective of the study? Here is a list of possible objectives and suggested designs:

A. Screen out insignificant factors and identify significant factors. Get some idea about the existence of interaction effects: Use a Factorial Design that is color-coded Yellow (Resolution IV). Also consider the Min Run Res IV designs.

B. Understand main effects and get complete information about two-factor interactions: Use a Factorial Design that is color-coded White or Green (Resolution V). Also consider the Min Run Res V designs.

C. Quickly trouble-shoot a process and get immediate results. You will have to go back later and do follow-up experimentation to understand why the conditions work: Use a Factorial Design that is color-coded Yellow (Res IV), or Red (Res III), or a Min Run Res IV design.

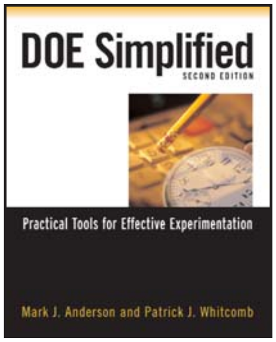
D. Characterize how the significant factors affect your responses (for optimization purposes): You already know the important factors. Now is the time to use a Response Surface Design. Use Central Composite designs to study each factor at 5 levels. Use Box-Behnken designs to study each factor at 3 levels. Optimal designs will create a custom design based on the type of factors you have and the polynomial that you want to fit.

E. Optimize a formulation. Your product is actually a mixture, or a formulation, such as a food product, a drug formulation, or a chemical composition: Use a Mixture design. These designs allow you to set a total amount for the mixture. Then each component range is constrained by the fact that as you increase the amount of one component, the other components must decrease in order to keep the total amount constant. Mixture optimal designs are most commonly used because they allow the most flexibility in your component ranges.

Responses and Factors

After deciding on the objective of the experiment, you need to determine what responses you are measuring. The power or precision of the design is calculated by estimating the signal-to-noise ratio. For more information on power and the signal-to-noise ratio, take a look at the PowerPoint slides from our May 2008 webinar on "The Difference Between Repeats and Replicates in DOE," which you will find starting on page 10 at http://www.statease.com/webinars/08-May_Replicates_vs_Repeats.pdf.

Factor settings are critical. If you set the low and high levels too close together, the response is unlikely to change more than the normal process variation. You will not find a significant factor effect unless you have a lot of replication. On the other hand, setting the low and high levels too far apart leads to combinations of factor settings that may produce immeasurable product. This is an opportunity for your team to make their best decisions! Remember that the DOE NEEDS to produce some "bad" product in order for you to figure out how to make the "good" product.



The topics discussed here have been covered in previous *Stat-Teaser* articles, and in the webinars that Stat-Ease regularly hosts. If you would like to find resources on these and other topics of interest, search our web site at http://www.statease.com/search.html. For further information on how to get started with your designed experiments, check out the texts *DOE Simplified* and *RSM Simplified* written by Mark Anderson and Pat Whitcomb. They may be purchased online at http://www.statease.com/prodbook.html.
—Shari Kraber, shari@statease.com

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Private Industry-Specific Workshops Offered

09/12

Get your whole team up-to-speed on the latest design of experiments (DOE) techniques with Stat-Ease private in-house training. Our highly rated instructors will help you sharpen the axes by learning how to optimize your products and processes for better quality, costs, satisfaction, etc.

Stat-Ease Trainers listed from left to right: Wayne Adams, Brooks Henderson, Pat Whitcomb, Shari Kraber, and Mark Anderson

In addition to our normal classes, Stat-Ease offers a number of industry-specific courses that are only available as private workshops. These include: Designed Experiments for Life Sciences (DELS), Designed Experiments for Pharma (DEPH), and Designed Experiments for Assay Optimization (DEAO). Also coming soon is Designed Experiments for Food Science (DEFsci). If you have food industry examples you would like to share with us, please let us know.

If you have 6 or more students to train, a private in-house workshop may be the most cost-effective route to go, not to mention convenient. For more information and complete descriptions of in-house courses please see the Stat-Ease web site at http://www.statease.com/clas_in.html. Contact Workshop Coordinator Elicia Bechard for a quote (workshops@statease.com). Plan now and get a Stat-Ease private workshop into your budget for 2013!

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