Modern DOE Doubles Medical-Device Production Rate at Half The Variation

By Mark J. Anderson, PE, CQE, Stat-Ease, Inc. (mark@statease.com)

(This updated case study[1] reveals new details withheld at the time to maintain competitive advantage for our client. Now that some years went by, we can tell the rest of the story. - Mark)

Introduction

Using response surface methods (RSM) for statistical design of experiments (DOE),[2,3] engineers at a multinational medical-device manufacturer successfully modeled a key process for their flagship product. The RSM model then became the foundation for development of robust specifications to ensure quality at six sigma levels. Furthermore, RSM optimization tools pinpointed potential for doubling the production rate while halving the variation in a critical attribute.

The DOE was led by a six-sigma trained process development engineer and his team. Their education on modern DOE, including RSM was provided by experts from Stat-Ease, Inc., of Minneapolis, Minnesota, who also provided consulting help for this project.

Details on the experiment design

The manufacturing team performed a 50-run, Box-Behnken design (BBD) on five critical process factors known to affect results for coating an implantable medical device. For proprietary reasons, the factors cannot be fully revealed, but they were selected from experiments that screened such things as pressures, speeds, distances, flows and environmental factors that influenced product performance. The BBD is a popular template for RSM because it requires only three-levels of each process factor and only a fraction of all the possible combinations. Details on RSM, and the BBD in particular, can be found in reference 3. Figure 1 shows a BBD on three factors.

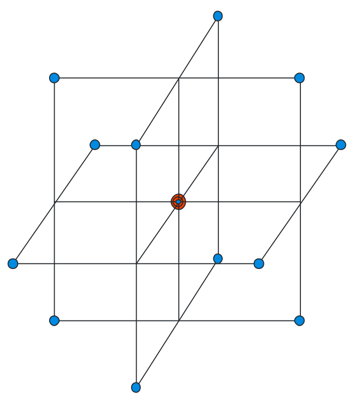

Figure 1: Box-Behnken design on three factors

The BBD is comprised of planes intersecting at a center point with outlying points at the extreme vertices in each of the factor dimensions. This selection of points suffices to fit a second-order polynomial equation, called a "quadratic model" in the parlance of RSM. The quadratic generally provides an adequate fit of data from experiments done for purposes of process optimization.

Analyzing the results and interpreting them

Six key responses, coded as “Y_i”, were measured on a number of parts made at each process setup dictated by the BBD template. They included measures of coating weight, application rates and visual integrity (quantified against established inspection criteria on a scale from 1 to 5).

Aided by statistical software,[4] the medical-device engineers modeled the averaged results. Mathematical transformations provided more precise and normal fits for some responses, for example, the square root for response Y_1. The model for this critical-to-quality attribute is spelled out below;

$$\mathrm{Sqrt}(Y_1) = 44.0 - 0.0067\,A + 3.19\,B - 3.76\,C + -0.304\,D + 0.880\,AB + -0.921\,BC - 0.431\,A^2 - 4.024\,B^2 + 0.372\,C^2$$

This predictive equation works for factors coded from -1 at the low to +1 to the high end of the ranges depicted in Figure 1 above. For example, to predict the result with factors all set high, plug in 1 for A, B, C and D:

$$\mathrm{Sqrt}(Y_1) = \beta_0 - \beta_1\,(1) + \beta_2\,(1) - \beta_3\,(1) - \beta_4\,(1) + \beta_{12}\,(1)(1) - \beta_{23}\,(1)(1) - \beta_{11}\,(1^2) - \beta_{22}\,(1^2) + \beta_3\,(1^2)$$

(Coefficients labeled generically with Greek betas—the intercept as β_0, the coefficient for the main effect A as β_1 and so forth). The resulting value must then be untransformed by squaring it, thus returning to the original units of measure. From this model, responses can be predicted over the entire experimental region and plotted.

To gain perspective on the models, it helps to view the perturbation of the predicted responses caused by changing only one factor at a time from the center point of the experimental region. For example, see from Figure 2 that the first response (untransformed) varies primarily as a function of factors B (highlighted) and C.

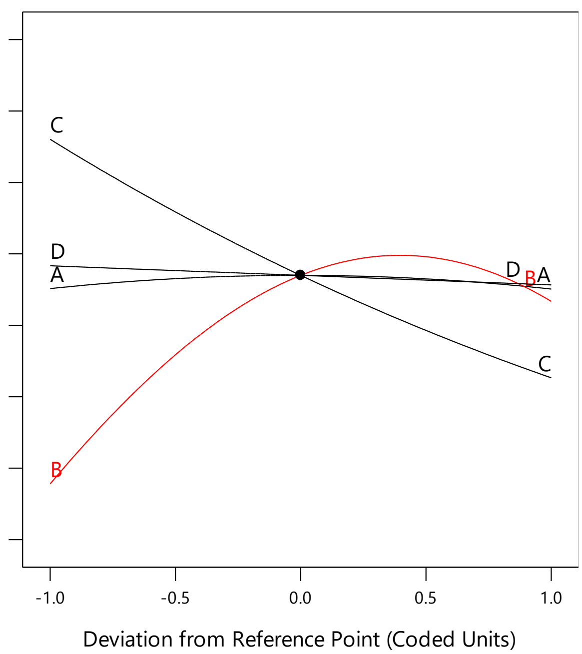

Figure 2: Perturbation plot for first response (Y_1)

As factor C increases, the response decreases in relatively linear fashion. However, as a result of its large coefficient on the squared term (4.024), factor B creates a nonlinear effect on Y_1—going up and then down.

Only two factors can be displayed on a plot and thus B and C become the best candidates for providing an informative picture of response Y_1 – see Figure 3 for a 3D display.

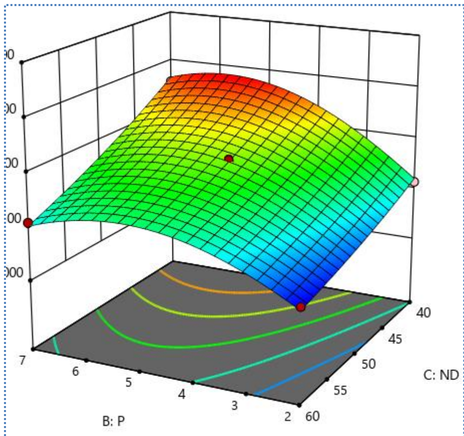

Figure 3: Response surface for Y_1 as a function of factors B and C

In similar fashion the other three responses were explored graphically. However, the real test came by overlaying the contour plots for all six responses with each of them controlled as tightly as possibly around their targeted values. Figure 4 reveals a "sweet spot" where all specifications can be achieved, for example at the flagged location in the space mapped by factors B and C (others set at center points for this 'slice' of the experimental space). Notice how only some specifications are limiting factors: Y1 upper and lower specification limits (USL and LSL), Y_5 LSL and Y_6 USL. This is good to know.

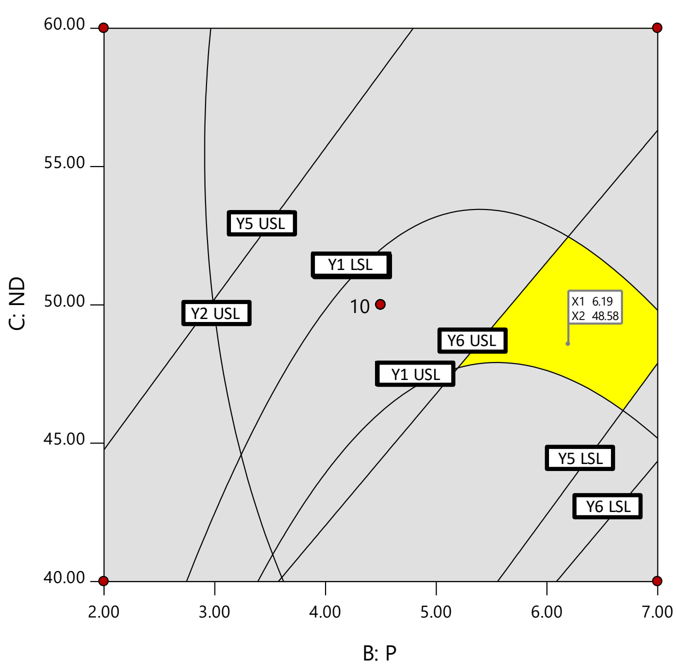

Figure 4: Overlay plot reveals window of operability

Numerical optimization provided by the statistical software pinpointed the most desirable combination of factors based on their predictive models.

RSM model predictions confirmed

The manufacturer's design for six sigma (DFSS) protocol mandated follow-up studies to confirm runs based on models derived from the experiments. The confirmation runs demonstrated that input parameters did indeed control critical outputs. The engineers then confirmed with a high level of statistical confidence that targeted performance could be achieved for optimum process with fast cycle time and high yield.

Ultimately the team, aided by modern DOE, doubled the medical-device production rate at half the variation in the most critical-to-quality attribute.

REFERENCES

1. Anderson, M.J., "Response Surface Methods (RSM) Achieve Design For Six Sigma (DFSS) Goals For Medical Device Manufacturing".

2. Anderson, M.J. & Whitcomb, P.W., *DOE Simplified, Practical Tools for Effective Experimentation*, *Second Edition*,3rd *Edition*, Productivity Press, New York, NY, 2015.

3. Anderson, M.J. &Whitcomb, P.W., *RSM Simplified, Optimizing Processes Using Response Surface Methods for Design of Experiments, 2nd Ed*, Productivity Press, New York, NY, 2016.

4. *Design-Expert® software*, Stat-Ease, Inc, Minneapolis, MN.