Design of Experiments Reduces Rubber Scrap by 90%

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Executive summary

Powerful interactions affect the performance of many rubber and plastics processes. Unfortunately, these critical effects cannot be revealed by the traditional scientific method, which dictates changing one factor at a time (OFAT). This case study provides inspiration to overcome the limitations of OFAT via a very simple design of experiment (DOE) called a two-level factorial.[1] By employing a multifactor approach the technical staff at a custom rubber molder uncovered a combination of material selection and manufacturing protocol that created unacceptable results. Armed with this process knowledge, they achieved a breakthrough quality improvements.

Robinson Rubber Products Company, a Minnesota-based custom molder, designs and manufactures components for original equipment manufacturers. They specialize in complex parts such as one involving an inner and outer steel sleeve with molded rubber bonded in between. This particular component had to meet very tough requirements for an automotive application, thus it experienced an intermittent scrap rate of up to 10%. The most common problem was that the part did not pass the company's tough metal-to-rubber bonding test, which requires that the rubber tears apart rather than pulling away from the metal.

Over the years, Robinson made many one-factor-at-a-time (OFAT) changes to the process but the problem continued to reoccur. Finally their Quality Assurance (QA) Manager, John Engler, performed a statistically-designed, multifactor experiment that modeled the effects of five key manufacturing variables. This led to significantly better settings that optimized the rubber-to-metal bond, resulting in scrap rates that consistently fell below 1%, with no recurrence of bond problems.

Tough rubber-to-metal bonding problem

The problematic part, similar to that pictured in Figure 1, uses two coats of a bonding agent applied to each of the metal inserts. The inserts are hand-loaded into a 16-cavity mold, the rubber is injected, and the parts dwell in the mold for a specified time, temperature and pressure. To verify the bonding, operators periodically perform a destructive test on product by pushing the inner steel insert out of an assembly and visually checking the rubber-to-metal bond.

Figure 1: Problematic rubber-to-metal bonding (after destructive peel-back)

Robinson periodically experienced a large number of rejects because of bond failure. Engineers and operators expressed differing opinions on the problem – achieving a consensus was nearly impossible due to so many variables and potential interactions. The injection speed, injection pressure, vulcanizing temperature, and dwell time of the injection molding machine can easily be adjusted. The thickness of the bonding agent and amount of time it is allowed to dry are other important variables. "Process changes would be made on the fly until the problem went away," Engler said. "Then after a period of time the problem would reappear and the trial and error process would start all over. When this happened three times in only two weeks, we knew that we needed to find a new method to find the root cause of the problem."

A major problem with the OFAT method is that it cannot detect the interactions of multiple factors. By varying an individual variable you can find the optimal value of each one with all the others held constant. However, when you combine the supposedly-optimized values of each variable the results are usually far less than optimal, often because of the ways that they interact with each other.

Design of experiments uncovers interaction of variables

"My past experience with similar problems suggested to me that the only way to really understand what was happening was to perform a designed experiment to find the critical factors that are required to achieve a robust rubber-to-metal bond," Engler said. "DOE provides a better approach that varies the values of all variables in parallel so it uncovers not just the main effects of each variable but also the interactions between the variables. This approach makes it possible to identify the optimal values for all variables in combination and also requires far fewer experimental runs than the OFAT approach."

Experimental designs are available with as little as k+1 runs where k equals the number of variables to be tested, for example: 7 factors in 8 runs. But more accurate results can be achieved by higher resolution designs which are capable of evaluating the main effects of each variable as well as the two-factor interactions.[1,2] For example, 16 runs suffice for a high-resolution design on 5 factors – only half of the 32 combinations of all these factors at two levels each.

After a brief training session on DOE, the Robinson Rubber technical staff worked together to select the factors that they thought were the most likely to cause the bond problems. Engler was chosen to coordinate and monitor each step of the experiment.

Experimental design

The five factors that were selected were:

A. Vulcanizing temperature (low versus high),
B. Bond material (two types),
C. Bond application thickness (one vs two coats),
D. Injection pressure (low vs high),
E. Bond settling time (low vs high).

With this information entered, a specialized DOE program[3] generated an ideal two-level design with 16 runs – a high-resolution half fraction of all possible combinations. Table 1 provides the test matrix – a standard template that works for any 5 factors at two levels each.

Table 1: Two-level factorial test matrix (half-fraction)

Std Order	A: Cure Temp deg C	B: Bond Material	C: Bond Coats	D: Inject Pressure psi	E: Settling time minutes
1	295	A	1	1000	120
2	325	A	1	1000	1
3	295	B	1	1000	1
4	325	B	1	1000	120
5	295	A	2	1000	1
6	325	A	2	1000	120
7	295	B	2	1000	120
8	325	B	2	1000	1
9	295	A	1	3000	1
10	325	A	1	3000	120
11	295	B	1	3000	120
12	325	B	1	3000	1
13	295	A	2	3000	120
14	325	A	2	3000	1
15	295	B	2	3000	1
16	325	B	2	3000	120

Robinson ran the experiment on the first shift over two days. The design blocked out the day-by-day impact. It included an additional six cures at the beginning, middle and end of each day with the same conditions to serve as controls to detect the effect of any variables besides those that were being measured in the experiment. The order of the cures was randomized as insurance against lurking variables such as machine wear. Slight modifications by Engler were introduced to simplify the temperature changes. Every cure was monitored in person by Engler to ensure that all the factors were correct for each cure.

The primary measures of performance were:

1. Bond – the amount of rubber bond coverage remaining on the steel sleeve measured on a scale of 1 to 10 with 1 being almost no bond and 10 being 90% to 100% bond remaining. A rating of 8 or better was considered to be an acceptable bond in accordance with the drawing specification.
2. Cure – the completeness of the cure was rated on a 1 to 5 scale with 1 being a very low state of cure and 5 being completely cured. A rating of 3 or better was considered acceptable.

Optimizing the values of each variable

Engler and his QA technician Tom Somers rated the parts together. They then calculated the fraction defect for bond and cure and entered this data into the software, which then generated reports that identified the significant factors for these two critical responses. The results showed that within the tested ranges neither the bond settling nor the injection pressure created any appreciable effect on performance of the part. That eliminated two suspected variables. However, higher temperature, factor A, provided a significant improvement – it created a main effect on cure failure. This is graphically illustrated by an ordered bar chart (see Figure 2), commonly known as a "Pareto" – an Italian economist who observed that a vital few individuals, say 20 percent, typically account for the bulk of the response, over 80 percent.

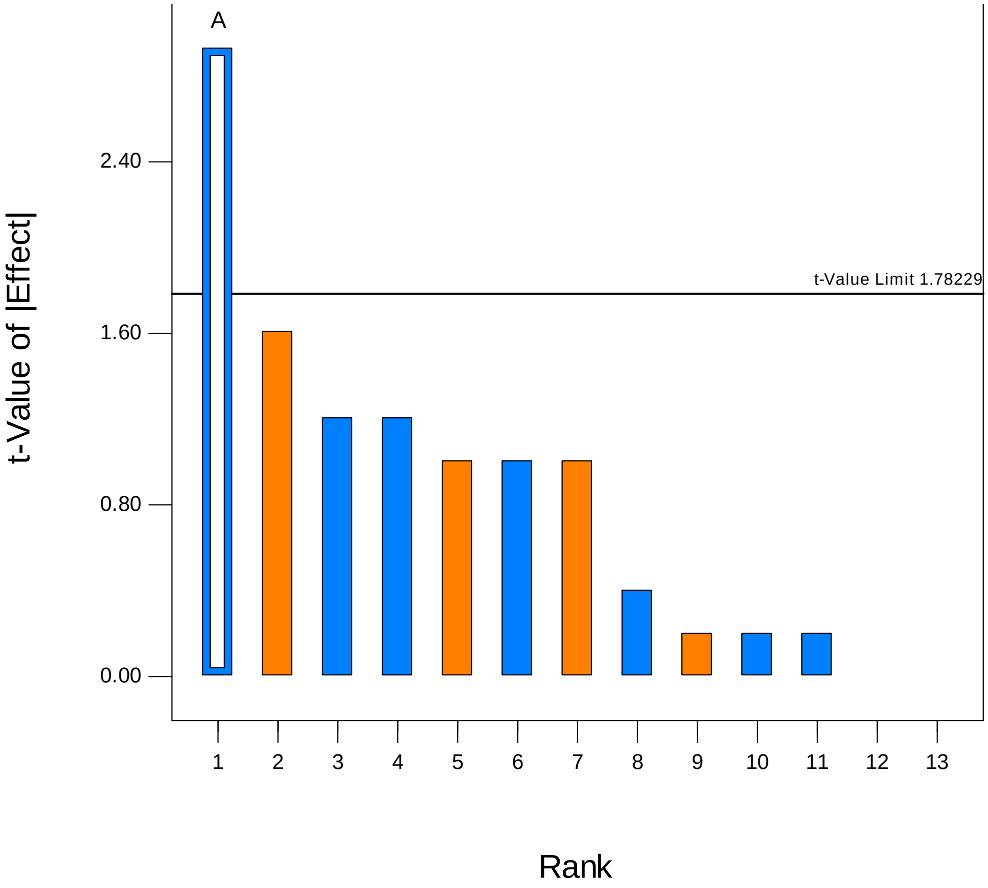

Figure 2: Pareto chart for effects on cure

Note that for statistical purposes this particular chart displays the t-value of the effect and features a threshold bar for significance at 95 percent confidence.

But what proved most interesting is the significant interaction of bonding agent with coating thickness illustrated in Figure 3. This plot provides statistical measuring sticks know as least significant difference (LSD) bars that are set for making comparisons with 95 percent confidence. The LSDs overlap at two coats of either bond agent, thus providing a robust operating condition if both materials must be used for purchasing leverage. However, if only one coat could be afforded, then only the B2 bonding agent would work reliably. The separation of the LSD bars at the left side of the interaction plot shows a significant increase in bond failure with only one coat of B1.

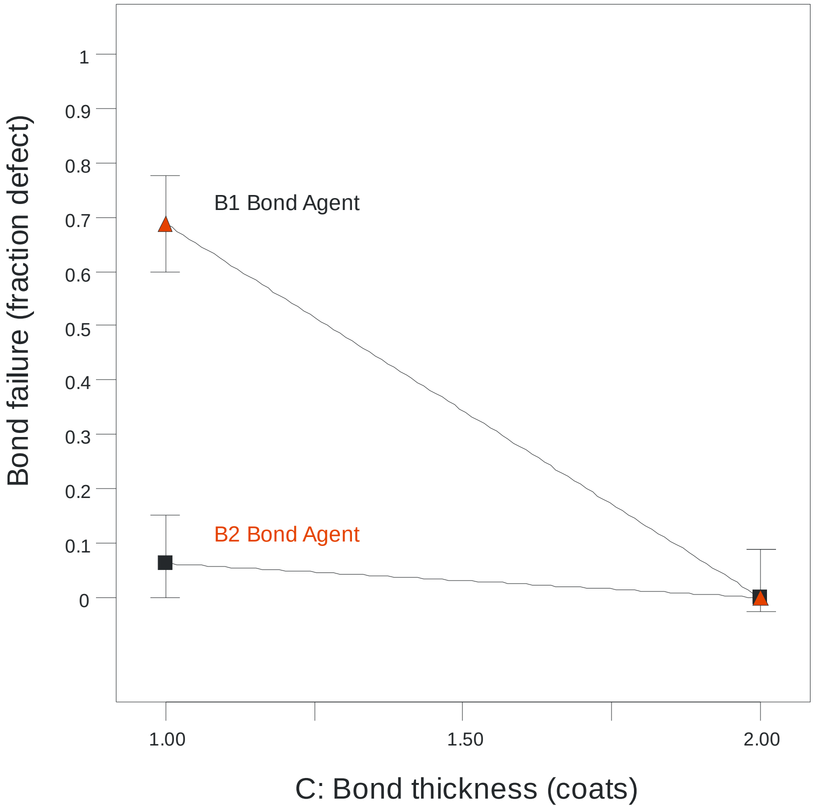

Figure 3: Interaction of bond agent with thickness of coating

Another way of spinning this story is that only the B2 bonding agent worked well either thin or thick (1 vs 2 coats; respectively). This would be important if operators varied in how much bond they applied per coat.

Results

Robinson Rubber began consistently producing the part under using this robust bonding agent at high temperature. The scrap rate immediately dropped to well below 1% and remained at that low level throughout subsequent production runs. “Design of experiments is clearly a useful tool that can help determine the root cause of and solution for difficult problems that might fester for years otherwise,” QA Manager Engler concluded.

References

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3. Vaughn, N. A., et al, *Design-Expert® Software*, Stat-Ease, Inc, Minneapolis, MN, 2007.