An Experimental Study to Reduce Shrinkage in the Injection Molding Process

Wyatt Clegg

Executive Summary

We determined the number of runs needed in a list of experiments to find a significant factor effect of 4.6 or greater with 0.95 power to be 12. We then used a 2^{7-3} fractional factorial design to create a list of experiments. Finding three main effects were significant, we augmented the design by reversing the sign on the holding pressure variable. All factors but screw speed contribute to shrinkage in injection molded parts, with low levels of mold temperature, moisture content, and booster pressure combined with high levels for holding pressure, cycle time, and gate size producing minimally shrunk parts with 7.62 percent shrinkage, on average.

1 Introduction

An injection molding process is used to form plastic into novel objects. As the plastic is cooled down after being ejected from the mold, the plastic shrinks. The shrinkage is not uniform, and we want to find the settings of our injection molding process that, on average, minimize the plastic shrinkage in the injection molded parts. We changed the 7 factor settings for our process in Table 1 for our planned experiments. Furthermore, we designed an experimental procedure and carried out a list of experiments to determine the optimal settings for our injection molding process. We identified by analysis of the data obtained in carrying out the list of experiments several main effects and their interaction that significantly change the shrinkage in our injection molding process.

2 Experiment Design

We recognized that experimental runs are costly in terms of the time, labor, and material needed to perform experiments. We therefore would like to determine the significant effects with as few experiments as possible. As we have 7 factors of interest, a full factorial design would consist of $2^7 = 128$ experimental runs. At maximum, we were able to perform 32 experimental runs. We determined previously that $N = 12$ experiments are needed to find a significant effect of 4.6 with 0.95 power. A full factorial design is therefore impossible, so we considered a fractional factorial design with at least $N = 12$ runs.

2.1 2^{7-3} Fractional Factorial Design

A fractional factorial design allows us to find many of the significant effects in the full factorial design without performing as many experimental runs. However, in a fractional factorial design some effects are completely confounded. We therefore design the list of experiments such that main effects can be estimated.

For our fractional factorial design, we selected the following generators: $x_5 = x_1x_2x_3$, $x_6 = x_1x_2x_4$, and $x_7 = x_1x_3x_4$. No blocks were included. We elected to perform 16 runs, because $16 \geq N = 12$ and a fractional factorial design of 16 allows us to augment the design, if necessary, and still be under our 32 run maximum. The defining relation is as follows:

$$I = x_1x_2x_3x_5 = x_1x_2x_4x_6 = x_1x_3x_4x_7 = x_1x_5x_6x_7 = x_3x_4x_5x_6 = x_2x_4x_5x_7 = x_2x_3x_6x_7. \quad (1)$$

Furthermore, the aliasing structure is shown in Equations (2) to (16), with aliasing included up to four interactions:

$$x_1 = x_2x_3x_5 = x_2x_4x_6 = x_3x_4x_7 = x_5x_6x_7 \quad (2)$$

Table 1: Experiment Variables

Variable	Factor Name	Levels
x_1	Mold Temperature (MT)	(High, Low)
x_2	Moisture Content (MC)	(High, Low)
x_3	Holding Pressure (HP)	(High, Low)
x_4	Screw Speed (SS)	(High, Low)
x_5	Booster Pressure (BP)	(High, Low)
x_6	Cycle Time (CT)	(High, Low)
x_7	Gate Size (GS)	(High, Low)

$$x_2 = x_1x_3x_5 = x_1x_4x_6 = x_3x_6x_7 = x_4x_5x_7 \tag{3}$$

$$x_3 = x_1x_4x_7 = x_2x_6x_7 = x_4x_5x_6 = x_1x_2x_5 \tag{4}$$

$$x_4 = x_1x_3x_7 = x_2x_5x_7 = x_3x_5x_6 = x_1x_2x_6 \tag{5}$$

$$x_5 = x_1x_6x_7 = x_2x_4x_7 = x_3x_4x_6 = x_1x_2x_3 \tag{6}$$

$$x_6 = x_1x_5x_7 = x_2x_3x_7 = x_3x_4x_5 = x_1x_2x_4 \tag{7}$$

$$x_7 = x_1x_3x_4 = x_1x_5x_6 = x_2x_3x_6 = x_2x_4x_5 \tag{8}$$

$$x_1x_2 = x_3x_5 = x_4x_6 \tag{9}$$

$$x_1x_3 = x_2x_5 = x_4x_7 \tag{10}$$

$$x_1x_4 = x_2x_6 = x_3x_7 \tag{11}$$

$$x_1x_5 = x_2x_3 = x_6x_7 \tag{12}$$

$$x_1x_6 = x_2x_4 = x_5x_7 \tag{13}$$

$$x_1x_7 = x_3x_4 = x_5x_6 \tag{14}$$

$$x_2x_7 = x_3x_6 = x_4x_5 \tag{15}$$

$$x_1x_2x_7 = x_1x_3x_6 = x_1x_4x_5 = x_2x_3x_4 = x_2x_5x_6 = x_3x_5x_7 = x_4x_6x_7 \tag{16}$$

Main effects are completely confounded with three-way interactions, and two-way interactions are completely confounded with one another. The results of the list of experiments will tell us which effects are significant. Furthermore, it will indicate if further experiments are needed to identify all significant effects affecting shrinkage in injection molded parts.

2.2 Foldover Design

A fractional factorial design allows for further testing after observing the results of some experiments. Should the design have a number of effects that are significant, the design is augmented with another list of experiments. The additional list of experiments will reduce confounding among factors of interest.

We will refrain from augmenting the design if only one main effect appears to be significant. The three-way interaction that a main effect is completely confounded with will likely not be significant without the other main effects involved in the three-way interaction being significant due to the hierarchical ordering principle. Therefore we can assume only the single main effect makes a significant difference in the shrinkage of the injection molding process and can optimize the injection molding process based on that one main effect.

Augmentation will also introduce a block into the design: the data we collected first will be in a different block than the data collected as part of the augmentation process. This block will be included in the model, regardless of which fixed effects are selected.

Table 2: Initial Fractional Factorial List of Experiments and Results

Experiment	x_1	x_2	x_3	x_4	x_5	x_6	x_7	Shrinkage
1	-1	-1	1	1	1	1	-1	15.82
2	1	-1	1	1	-1	-1	1	17.20
3	1	1	1	-1	1	-1	-1	16.79
4	-1	-1	-1	1	-1	1	1	19.95
5	-1	1	-1	1	1	-1	1	20.46
6	1	1	-1	-1	-1	-1	1	21.79
7	-1	1	1	-1	-1	1	1	12.08
8	1	-1	-1	-1	1	1	1	26.98
9	-1	1	1	1	-1	-1	-1	6.48
10	-1	1	-1	-1	1	1	-1	23.51
11	-1	-1	-1	-1	-1	-1	-1	10.85
12	1	-1	1	-1	-1	1	-1	16.08
13	1	1	-1	1	-1	1	-1	24.46
14	1	-1	-1	1	1	-1	-1	22.70
15	1	1	1	1	1	1	1	17.49
16	-1	-1	1	-1	1	-1	1	18.72

3 Results

3.1 2^{7-3} Fractional Factorial Design

We created an list of experiments according to the Table 2 described with defining relation in Equation 1. We found that the effects for x_3, x_1, and x_5 were the most significant after fitting an ANOVA model by examining the half-normal plot shown in Figure 1a.

From our aliasing structure, we see that x_1, x_3, and x_5 are completely confounded with other variables. We seek to reduce the amount of confounding in our model by augmenting the design. We reverse the sign on x_3 for our augmented design, such that the defining relation becomes

$$I = x_1x_2x_4x_6 = x_1x_5x_6x_7 = x_2x_4x_5x_7. \tag{17}$$

We then augment the design and evaluate the data with a new list of experiments shown in Table 4. The aliasing pattern is shown in Equations (18) to (31).

$$x_1 = x_2x_4x_6 = x_5x_6x_7 = x_1x_2x_4x_6 = x_1x_5x_6x_7 \tag{18}$$

$$x_2 = x_1x_4x_6 = x_4x_5x_7 = x_1x_2x_4x_6 = x_2x_4x_5x_7 \tag{19}$$

$$x_4 = x_1x_2x_6 = x_2x_5x_7 = x_1x_2x_4x_6 = x_2x_4x_5x_7 \tag{20}$$

$$x_5 = x_1x_6x_7 = x_2x_4x_7 = x_1x_5x_6x_7 = x_2x_4x_5x_7 \tag{21}$$

$$x_6 = x_1x_2x_4 = x_1x_4x_7 = x_1x_2x_4x_6 = x_1x_4x_6x_7 \tag{22}$$

$$x_7 = x_1x_5x_6 = x_2x_4x_5 = x_1x_5x_6x_7 = x_2x_4x_5x_7 \tag{23}$$

$$x_1x_2 = x_4x_6 = x_2x_4x_6x_7 = x_1x_4x_5x_7 = x_1x_4x_5x_7 = x_2x_5x_6x_7 \tag{24}$$

$$x_1x_4 = x_2x_6 = x_4x_5x_6x_7 = x_1x_2x_5x_7 = x_1x_2x_5x_7 = x_4x_5x_6x_7 \tag{25}$$

$$x_1x_6 = x_2x_4 = x_5x_7 \tag{26}$$

$$x_4x_6 = x_1x_2 = x_1x_4x_5x_7 = x_2x_5x_6x_7 = x_2x_5x_6x_7 = x_1x_4x_5x_7 \tag{27}$$

$$x_1x_5 = x_6x_7 = x_2x_4x_5x_6 = x_1x_2x_4x_7 = x_1x_2x_4x_7 = x_2x_4x_5x_6 \tag{28}$$

$$x_1x_7 = x_5x_6 = x_2x_4x_6x_7 = x_1x_2x_4x_5 = x_1x_2x_4x_5 = x_2x_4x_6x_7 \tag{29}$$

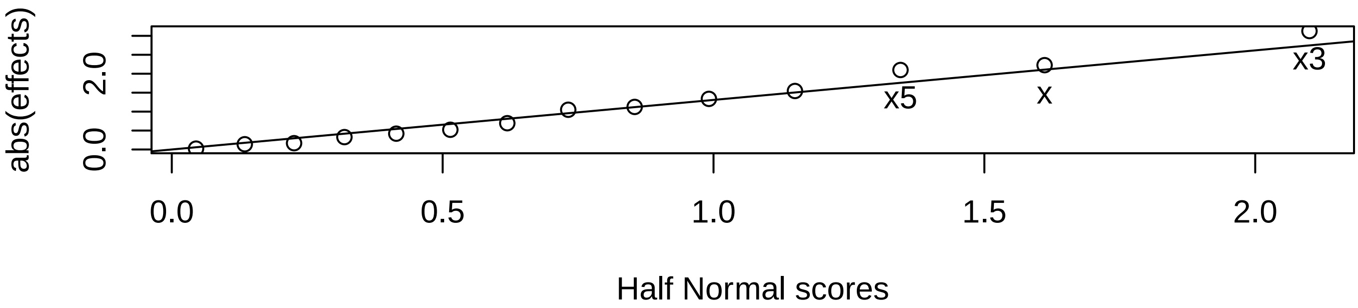
$$x_2x_7 = x_4x_5 = x_1x_2x_5x_6 = x_1x_4x_6x_7 = x_1x_2x_5x_6 \tag{30}$$

$$x_4x_7 = x_2x_5 = x_1x_4x_5x_6 = x_1x_2x_6x_7 = x_1x_5x_6x_7 = x_1x_2x_6x_7 \tag{31}$$

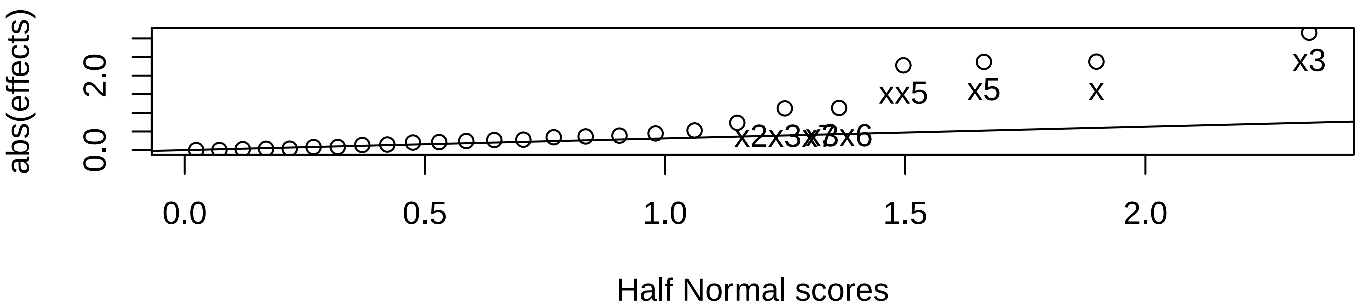
3.2 Foldover Design

Now that we have augmented the design, we evaluate the data with the new list of experiments by examining the half-normal plot in Figure 1b. x_3 is now independent of any factor effects of order less than 5.

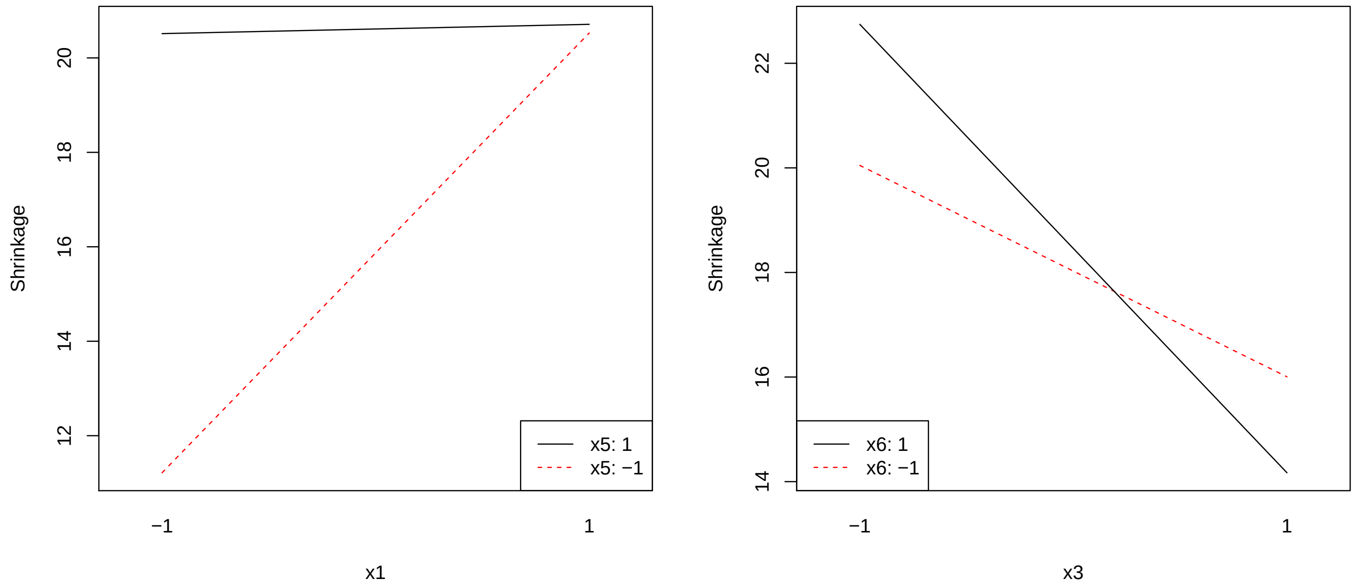
Figure 1b shows us that many of our factors and their interactions are significant. The main effects x_1, x_3, and x_5 are significant, along with the interactions x_1x_5, x_3x_6, and $x_2x_3x_7$. By the hierarchical ordering principle, the main effects x_2, x_6, and x_7 should be significant. Furthermore, the interaction x_2x_3 should be significant by the same principle.



(a) Halfnormal Plot for Factor Effects with x_1, x_5, and x_3 Significant



(b) Halfnormal Plot for Factor Effects with Augmentation, with x_3, x_1, x_5, x_1x_5, x_3x_6, and $x_2x_3x_7$ Significant



(a) Interaction Plot for x_1 and x_5 (b) Interaction Plot for x_3 and x_6

Figure 2: Interaction Plots for Two-Way Interactions

Figure 2 shows the interaction between x_1 and x_5 and the interaction between x_2 and x_3. Both interactions are significant and show us the true optimum value for our parameters. Figure 3 shows the behavior of x_2, x_3, and x_7. We see that the three-way interaction is significant and should be accounted for when choosing optimum values.

Examining the interaction plots in Figures 2 and 3 and the table of effects in Table 3, we conclude that the optimum settings to minimize shrinkage in our injection molded parts is $x_1 = x_2 = x_5 = -1$ and $x_3 = x_6 = x_7 = 1$. Changing the level of x_4 will not make a significant difference. Note that we had an experiment in Table 4 with similar settings that had 5.62 percent shrinkage. We estimate that, on average, a part molded at the aforementioned conditions will have 7.65 percent shrinkage.

We verified our assumptions by looking at the residuals. Residuals should follow a normal distribution. Both the QQ plot and histogram of residuals in Figure 4 appear to have some non-normal trends. However, this may be due to our low number of experimental runs. The distribution of the residuals appears normal enough to justify the analysis carried out above.

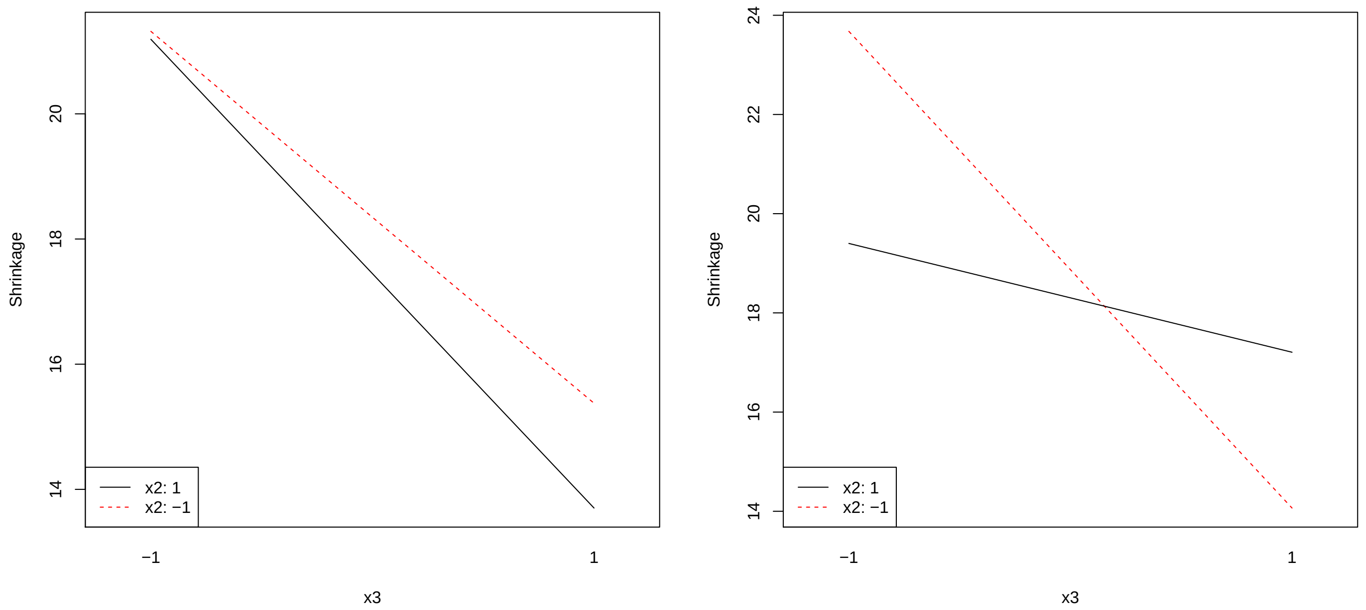
In literal terms, a molding procedure carried out with low levels for mold temperature, moisture content, and booster pressure, combined with high levels for holding pressure, cycle time, and gate size will minimize shrinkage in molded parts.

Table 3: Estimated Effect of Each Factor

Factor	Value
x_1	2.377
x_2	-0.367
x_3	-3.154
x_4	0.389
x_5	2.371
x_6	0.216
x_7	0.345
x_2x_3	0.734
$x_1x_3x_7$	-0.529
x_1x_5	-2.279
x_3x_6	-1.133

Table 4: Added Fractional Factorial List of Experiments and Results

Experiment	x_1	x_2	x_3	x_4	x_5	x_6	x_7	Shrinkage
1	-1	-1	-1	1	1	1	-1	26.11
2	1	-1	-1	1	-1	-1	1	24.25
3	1	1	-1	-1	1	-1	-1	21.75
4	-1	-1	1	1	-1	1	1	5.61
5	-1	1	1	1	1	-1	1	20.84
6	1	1	1	-1	-1	-1	1	18.41
7	-1	1	-1	-1	-1	1	1	10.45
8	1	-1	1	-1	1	1	1	14.73
9	-1	1	-1	1	-1	-1	-1	15.05
10	-1	1	1	-1	1	1	-1	15.13
11	-1	-1	1	-1	-1	-1	-1	9.25
12	1	-1	-1	-1	-1	1	-1	25.61
13	1	1	1	1	-1	1	-1	16.41
14	1	-1	1	1	1	-1	-1	20.35
15	1	1	-1	1	1	1	1	24.90
16	-1	-1	-1	-1	1	-1	1	23.52



(a) $x_7 = -1$ (b) $x_7 = 1$

Figure 3: Interaction Plots for Three-Way Interaction Between x_2, x_3, and x_7.

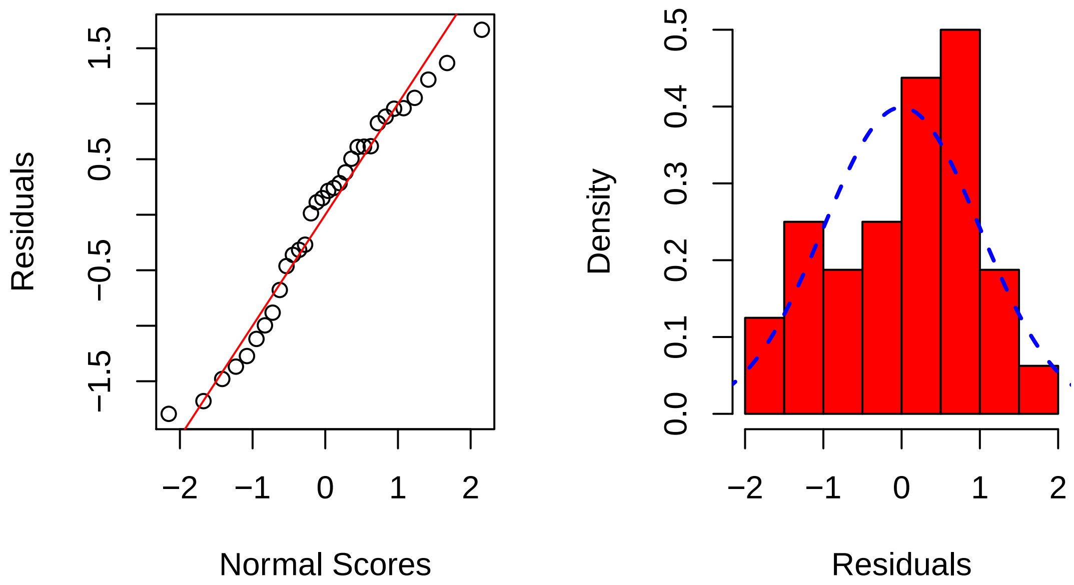


Figure 4: QQ Plot and Histogram of Residuals

4 Conclusions

We conclude that all factors but screw speed are important to the analysis, with low levels of mold temperature, moisture content, and booster pressure combined with high levels for holding pressure, cycle time, and gate size are the most significant factors when reducing shrinkage in our injection molding process. Further analysis could explore the exact relation between these factors and the shrinkage of injection molded parts.