Application Note

The Optimization of Injection Molding Processes Using Design of Experiments

PROBLEM

Manufacturers have three primary goals: 1) produce goods that meet customer specifications; 2) improve process efficiency in cycle times, labor cost and energy consumption; 3) increase process robustness by reducing sensitivity to small changes in process or material parameters. To meet these goals, manufacturers often employ one-variable-at-a-time investigations to construct models relating independent process parameters to product quality. The models are used to devise iterative process modifications that lead to a process having a reasonable trade-off between process efficiency and product quality. Unfortunately, this method of process development does not explicitly test the robustness of the process.

BACKGROUND

A manufacturing process must exhibit an adequate breadth of operating conditions, sometimes referred to as the process window [1]. Figure 1 shows the process window for an injection molding process in terms of the injection velocity and pack pressure. The size and shape of the process window is determined by certain constraining boundaries. Boundaries 1, 2 and 5 are defined by the machine's injection velocity and pack pressure limits; 3 defines the combined upper limits of injection velocity and pack pressure beyond which unacceptable levels of flash are produced; and 4 determines the lower limits of pack pressure and injection velocity beyond which undesirable short shots and sink marks occur. Viable production processes lie within the process window determined by these boundaries.

Process set-points that might be chosen by a plastics manufacturer are shown as circles within the process window. While the robustness of the process can be tested by changing one process variable, depending on the initial settings, such investigations can lead to different process limits. Such studies also ignore the possibility of interactions between the process variables which are common, and ignoring them can result in selecting process conditions too close to a process window boundary (denoted by *, Figure 1).

While such investigations may lead to operable processes, they do not necessarily lead to robust processes nor do they provide reliable, quantitative models of the process that can be used for yield prediction, process optimization and quality control [2, 3].

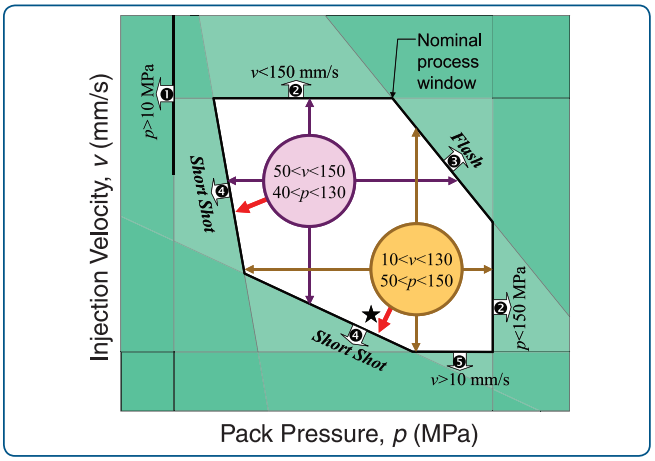

Figure 1 - Process window definition

The identification of robust process settings is best accomplished with Design of Experiments (DOE) approaches. DOE is a structured, efficient method that simultaneously investigates multiple process factors using a minimal number of experiments [4-6].

Consider: To treat n = 10 independent variables at m = 2 levels requires 2^{10} or 1024 experiments for a full high/low evaluation. The prospect of performing such a high number of experiments is daunting, especially in a manufacturing setting. The use of DOE drastically reduces the size of experimental matrices while retaining a balance in the points tested in parameter space. This balance permits valid statistical analyses of the results and determination of the main effects of process parameters.

A very useful DOE approach, D-optimal designs, can be generated using a numerical optimization technique that maximizes the "volume" of the investigated process parameter space (as measured by the determinant of the design matrix multiplied with its transpose) [6]:

$$D = \det(\mathbf{X}'\,\mathbf{X}) \qquad \textbf{(1)}$$

This application note will use injection molding production data to show how DOE can be used to determine process robustness and how it can be effective in identifying process window boundaries and their relation to process settings.

SOLUTION

Evaluating DOEs for Minimum Runs

In the DOE approach, a set of conditions for a stable injection molding process that produces acceptable molded parts with repeatable part weights and thicknesses is first determined. Then ranges are defined around these process settings to encompass the expected long term variation for, in this example, 10 important process factors (Table 1). These factors are the independent variables in the process model. The combination of minima and maxima of these different factors (coded -1 and +1) are used to set up the experimental designs.

#	Factor	Min	Max
1	Pack Time (s)	2	4
2	Material Blend (%)	0	40
3	Barrel Temperature (c)	195	205
4	Coolant Temperature (c)	25	35
5	Injection Velocity (mm/s)	60	80
6	Pack Pressure (MPa)	60	80
7	Shot Size (mm)	20.75	20.75
8	Back Pressure (MPa)	20	26
9	Cooling Time (s)	6	10
10	Screw Speed (RPM)	100	150

Table 1

Tables 2.1 – 2.4 show the four design approaches evaluated in this study. Note that the 6-run design in Table 2.4 is not normally used as all factors are confounded and such designs do not normally produce reasonable models. Occasionally, however, such designs can perform well, as is discussed below. MKS' SenseLink QM was used for data acquisition, analysis, and quality control.

The results of regression analysis are shown in Figure 2. The dark line in each graph is the best estimate of the main effects derived using an aggregation of all DOEs. Figure 2 shows that regression models for the fractional factorial design and the D-optimal design closely match the best estimate while those of the 6- and 8-run DOEs fail. This is because the 6- and 8-run DOEs suffer from confounded parameters, (pack time with pack pressure; material blend with shot size; back pressure with cooling time and screw RPM in the 6-run DOE). The

Run	1	2	3	4	5	6	7	8	9	10
1	-1	-1	-1	-1	-1	-1	-1	-1	1	1
2	-1	-1	-1	1	-1	1	1	1	-1	1
3	-1	-1	1	-1	1	1	1	-1	-1	1
4	-1	-1	1	1	1	-1	-1	1	1	1
5	-1	1	-1	-1	1	1	-1	1	-1	-1
6	-1	1	-1	1	1	-1	1	-1	1	-1
7	-1	1	1	-1	-1	-1	1	1	1	-1
8	-1	1	1	1	-1	1	-1	-1	-1	-1
9	1	-1	-1	-1	1	-1	1	1	-1	-1
10	1	-1	-1	1	1	1	-1	-1	1	-1
11	1	-1	1	-1	-1	1	-1	1	1	-1
12	1	-1	1	1	-1	1	-1	-1	-1	-1
13	1	1	-1	-1	-1	1	1	-1	1	1
14	1	1	-1	1	-1	-1	-1	1	-1	1
15	1	1	1	-1	1	-1	-1	-1	-1	1
16	1	1	1	1	1	1	1	1	1	1

Table 2.1 - 16 run, 2^{10-6} matrix

Run	1	2	3	4	5	6	7	8	9	10
1	1	-1	1	1	1	1	1	-1	1	1
2	-1	1	1	1	-1	1	-1	-1	-1	-1
3	-1	-1	-1	-1	1	1	1	-1	-1	1
4	1	1	-1	-1	-1	1	-1	-1	1	-1
5	1	-1	-1	1	1	-1	-1	1	-1	-1
6	-1	1	-1	1	1	1	1	1	1	-1
7	-1	-1	1	-1	-1	-1	-1	1	1	-1
8	-1	-1	-1	1	-1	1	-1	1	1	1
9	1	1	-1	1	-1	-1	1	-1	-1	1
10	1	1	1	-1	1	1	-1	1	-1	1
11	1	-1	1	-1	-1	1	1	1	-1	-1

Table 2.2 - 11 run, D-optimal matrix

Run	1	2	3	4	5	6	7	8	9	10
1	-1	-1	-1	-1	-1	-1	-1	-1	1	1
2	-1	-1	-1	1	-1	1	1	1	-1	1
3	-1	-1	1	-1	1	1	1	-1	-1	1
4	-1	-1	1	1	1	-1	-1	1	1	1
5	-1	1	-1	-1	1	1	1	1	1	1
6	1	1	1	1	1	1	-1	1	-1	-1
7	-1	1	1	-1	-1	-1	1	1	1	-1
8	-1	1	1	1	-1	1	-1	-1	-1	-1

Table 2.3 - 8 run, 2^{7-4} DOE

Run	1	2	3	4	5	6	7	8	9	10
1	1	-1	-1	1	-1	1	-1	-1	1	-1
2	1	1	-1	-1	-1	1	1	-1	-1	-1
3	-1	1	-1	1	-1	-1	1	-1	1	-1
4	-1	-1	1	-1	1	-1	-1	1	-1	1
5	1	1	1	1	-1	1	1	1	1	-1
6	1	1	-1	1	1	1	1	-1	1	1

Table 2.3 - 6 run, oversaturated DOE

8-run DOE provides a better estimation of the main effects, however, the effect of pack time, cool time, and screw pack time is not investigated and cool time and screw RPM are confounded with other factors.

These results demonstrate the need for extensive experimental designs for the estimation of main effects when using multiple regression techniques.

Multivariate analyses (MVA), on the other hand, can determine main effects from limited data. Principal Components Analysis (PCA) and Projection to Latent Structures (PLS) methods evaluate process behavior using Distance to the Model (DModX) and Hotelling t-squared (T2) scores [8]. Figures 3.1 to 3.4 show the loadings scatter plots derived using the DOEs in Table 2. Each loadings plot shows the amount of the observed process behavior modeled by the first two principal components due to each process state. Process states further from the origin have greater influence on the process behavior. The plot also indicates the correlation of each process state with respect to other process states. For example, the upper right quadrant of Figure 3.1 includes the weight, thickness, and other process states calculated from the machine process traces (i.e. M10, M11, M15, M17, and M40 correspond to screw velocity during packing, average pack pressure, injection energy, and integral of pressure during packing, respectively).

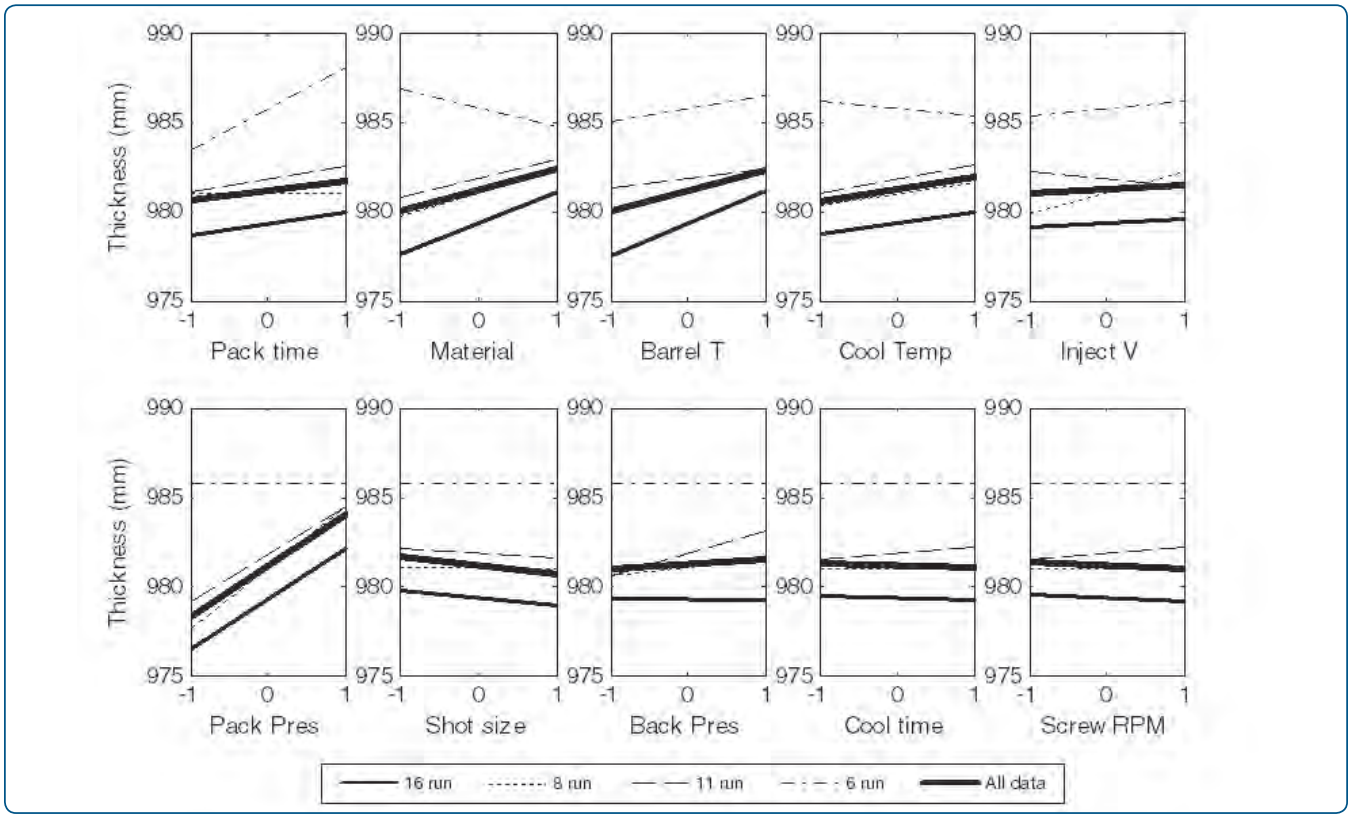

Figure 2 - DOE regression models

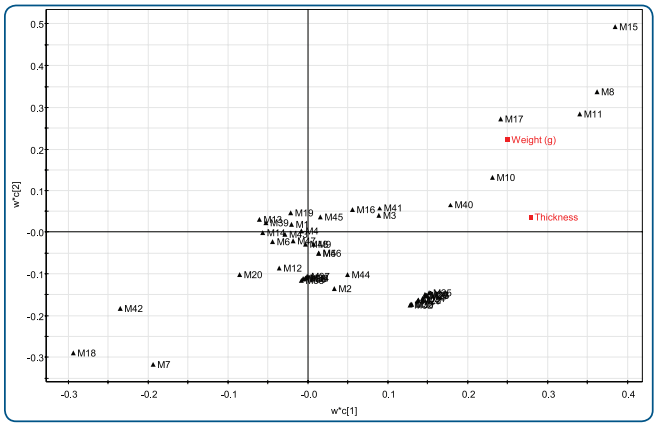

Figure 3:1 - 16-run DOE

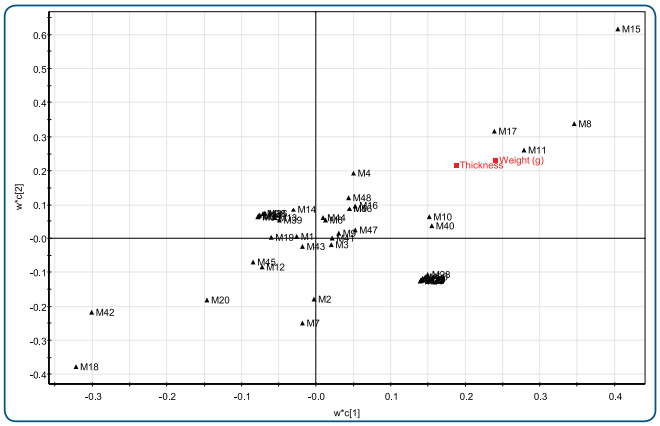

Figure 3:2 - D-optimized DOE

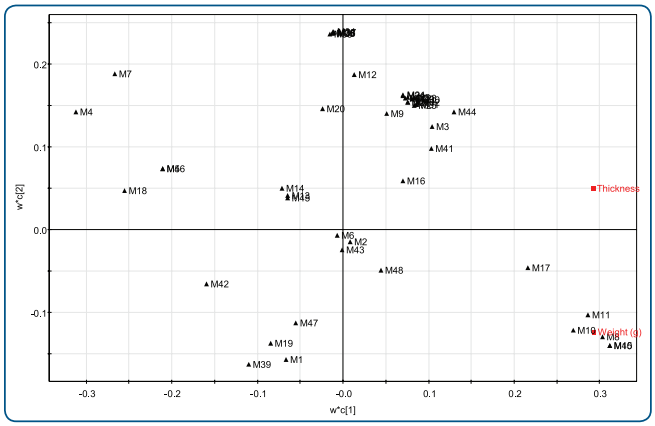

Figure 3:3 - 8-run DOE

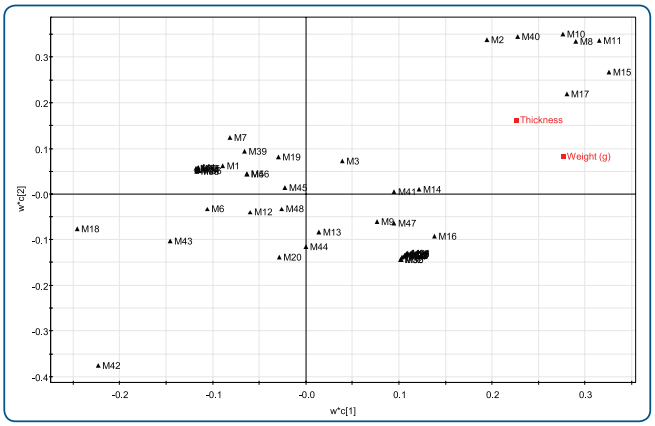

Figure 3:4 - 6-run DOE

Inspection of the loadings plots shows that the 11-run DOE (Figure 3.2) to be similar to the best estimate 16-run DOE (Figure 3.1) even though less data was used (thickness, weight, M2, M18, M15, and other states are similarly placed). The two models should therefore provide similar predictions. The loadings plot for the 8-run DOE (Figure 3.3) and the 6 run DOE (Figure 3.4) vary significantly from the best estimate. Specifically, the loadings plot for the 8 run DOE places M2, a process state for pack time, very close to the origin, and also clusters many other process states together. The 8-run DOE fails because the effect of pack time was not investigated.

Evaluating DOEs for Robustness

An 8 run, 3 factor full factorial design (Table 3) was used to investigate process robustness. Melt temperature, *T*, injection velocity, *v*, and pack pressure, *P* were chosen to test short shot behavior. Run number 8 in Table 3 is the standard process with all settings at their high value. Low values were chosen so short shots would occur when any two of the process factors were jointly operated at their lower settings. Several common process faults were imposed on the process in the validation DOE of Table 3. Figure 4 shows the distance from the process data to the models generated from the four experimental designs and a model generated from the aggregate data. Higher values of DModX indicate process deviation from the reference model. The results show that the 5 most critical faults were detected by the models for the 41-run aggregate dataset, the 16-run DOE, 11-run DOE, and 6-run DOE. The model for the 8-run DOE failed since: 1) all of the DModX values are

Run	Barrel Temp (C)	Injection Velocity (mm/s)	Pack Pressure (MPa)
1	172.5	15	15
2	172.5	15	70
3	172.5	70	15
4	172.5	70	70
5	200	15	15
6	200	15	70
7	200	70	15
8	200	70	70

Table 3

very high, and 2) the DModX only captured 3 of the 8 defects. The 6-run DOE performed surprisingly well, given that each of the ten process factors were confounded with one other process factor; the performance far surpassed that of the 8-run DOE despite fewer runs. The multivariate analysis was thus able to model the principal components effectively.

The factorial DOE developed to evaluate the robustness of multivariate models generated 80 observations for the part weight. These data were imported into a multivariate analysis program (SIMCA® P+ v. 11, Umetrics) and the main effects of the process settings on the part weight were calculated (Figure 5). The results showed that pack pressure, *P*, injection velocity, *v*, and melt temperature, *T*, were all significant.

However, the correlation coefficient for the model, R^2, was only 0.81, implying that 81% of the process behavior was accounted for by the model. This could be significantly improved.

The model was therefore expanded to include interaction terms. The analysis yielded the main and interaction effects shown in Figure 6, and the R^2 value for the model was 0.99. Thus this model is a much better estimate than the purely linear model. It should be noted that the addition of interaction terms significantly alters the model behavior. Specifically, the effect of injection velocity, which was strong in the purely linear model, becomes insignificant. Instead, the part weight is greatly reduced only when the injection velocity and melt temperature are changed in combination. Other interaction terms were also found to be significant. The impact of this change can be fully appreciated when one considers its implications for the definition of the acceptable process window.

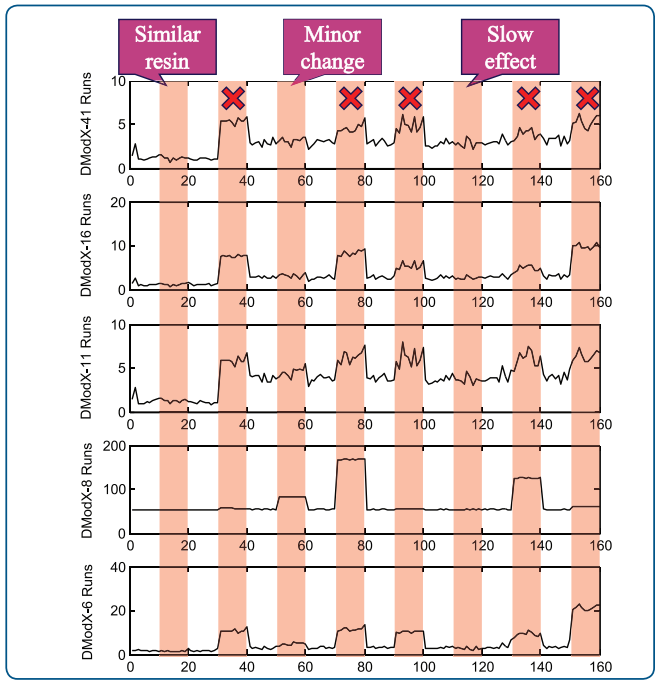

Figure 4 - Process fault diagnostics

Acceptable process windows were defined using multivariate analysis to build the model with interaction terms (Umetrics MODDE® v.7). The model predicted the product weight as two of the factors were varied over a specified range while holding the third factor constant (Figures 7.1-7.3). The calculated product weights greater than 0.21 grams were found not to produce a short shot. These were deemed to be within the acceptable process window. No upper limit was specified.

The behavior of the predicted product weights as the process strays from the set point (the lines emanating from the grey circles in Figure 7) is instructive. The predicted magnitude of displacement for a single process variable that shifts the process out of the acceptable window is significantly greater than the shift predicted for the simultaneous displacement of two variables. This implies that it is more likely that defects will occur through small changes in multiple process factors than through large changes in a single process factor. This likelihood can be quantified. If we define process limits as the number of standard deviations (σ) from set point before reaching the boundary of the defined process window:

$$n = \frac{x_{standard} - x_{boundary}}{\sigma} \qquad (2)$$

Tables 3.1 to 3.3 show values for n in the injection molding process in which the standard deviation values for the barrel temperature, injection velocity, and pack pressure were assumed to be 5°C, 20 mm/s, and 10 MPa, respectively. The probability of a short shot occurring can be estimated for the univariate analysis as:

$$\text{Prob} = 1 - \textit{normsdist}\ (n) \qquad (3)$$

where *normsdist* is the standard normal cumulative distribution function.

For the multivariate analysis, the number of standard deviations for each of the two process states, n_1 and n_2, were first calculated from the process settings along the bold arrows in Figures 7.1-7.3. Assuming mutual independence of the process factors, the joint probability of the short shot occurring in the multivariate analysis is then given by:

$$\text{Prob} = 1 - \textit{normsdist}\ (n_1) \cdot \textit{normsdist}\ (n_2) \qquad (4)$$

	Barrel Temp (C)		Inj Velocity (mm/s)		Probability
	Limit	# Std Dev	Limit	# Std Dev	
Univariate	200	0	10	3	0.135%
Univariate	170	6	70	0	0.000%
Multivariate	187	2.6	28	2.1	2.244%

Table 4.1 Temperature and Velocity Limits at P=70 MPa

	Barrel Temp (C)		Pack Pressure (MPa)		Probability
	Limit	# Std Dev	Limit	# Std Dev	
Univariate	200	0	18	5.2	0.000%
Univariate	170	6	70	0	0.000%
Multivariate	186	2.8	23	4.7	0.256%

Table 4.2 Temperature and Pressure Limits at V=70 mm/s

	Inj Velocity (mm/s)		Pack Pressure (MPa)		Probability
	Limit	# Std Dev	Limit	# Std Dev	
Univariate	10	3	70	0	0.135%
Univariate	70	0	22	4.8	0.000%
Multivariate	38	1.6	43	2.7	5.808%

Table 4.3 Velocity and Pressure Limits at T=200°C

The results in Tables 4.1-4.3 indicate a significant discrepancy between the predictions of univariate analysis compared to those of multivariate analyses. The univariate analyses indicate only one very small probability of producing short shots (0.135% for velocity violations of the process window boundary — Figs. 7.1 and 7.3); no short shots were predicted for any values of melt temperature or pack pressure. By comparison, the multivariate analyses predict a much higher probability of short shots: ~2.2% for combinations of lower barrel temperature and pack pressure; ~5.8% for combinations of lower injection velocity and pack pressure. If the constraints were tighter or the process variation was higher, then the likelihood of short shots would be significantly greater. The use of multivariate analyses shows that the process is far less robust than is indicated by the univariate analyses. The multivariate approach is therefore well suited as a means of measuring the robustness of a process within a defined process window.

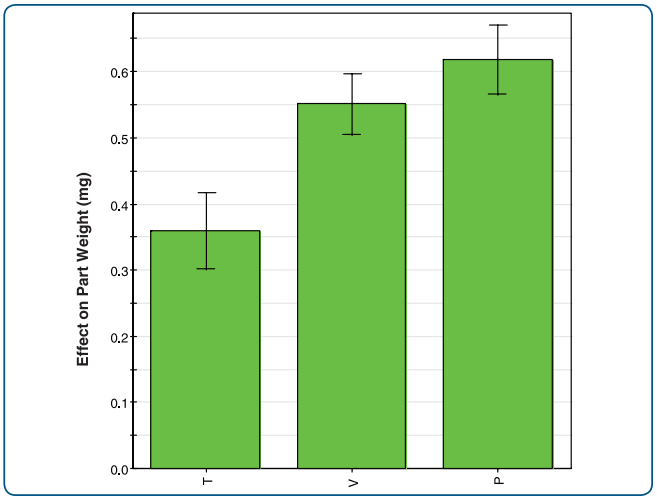

Figure 5 - The (scaled) main effects of the process settings on the part weight in the estimation of robustness

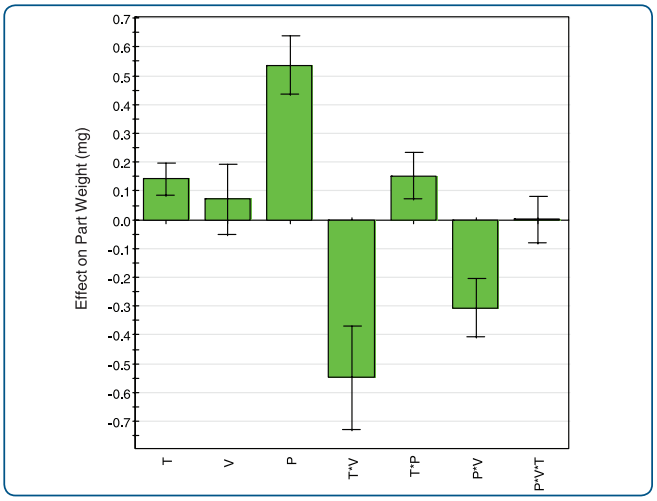

Figure 6 - The main and interactive effects of the process settings on the part weight in the estimation of robustness

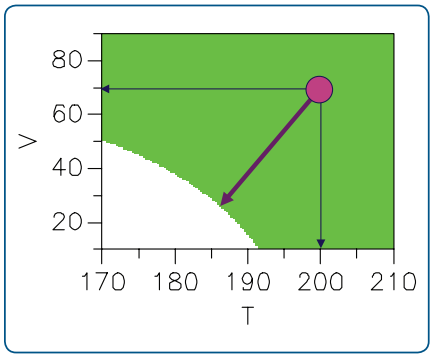

Figure 7:1 - Temperature-velocity window; P=70 MPa

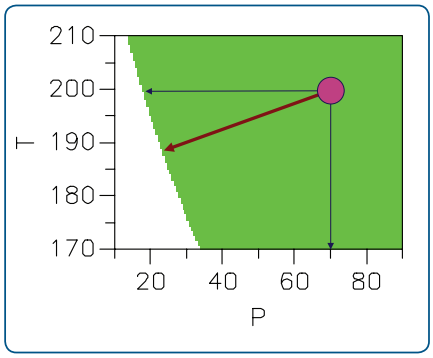

Figure 7:2 - Temperature-pressure window; V=70 mm/sec

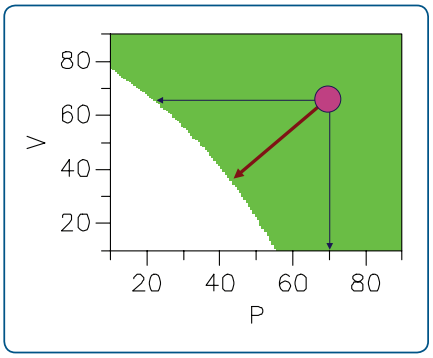

Figure 7:3 - Pressure-velocity window; T=200°C

CONCLUSION

The number of characterization experiments needed to develop reliable model-based process and quality control is a serious impediment to implementation in plastics manufacturing. This note shows how the effective use of Design of Experiments can facilitate the development of models through the use of robust approaches such as multivariate analyses. Principal Components Analysis and Projection to Latent Structure methods can employ data from oversaturated DOEs to effectively predict process faults and to characterize the variational effect of many process factors simultaneously. While such DOEs are inadequate for effective multivariate regression analysis, PCA models provide reasonable fidelity to setup the process and evaluate its robustness. The case study for plastics injection molding in this report shows how neglecting the interaction affects results in poor identification of the process boundaries and gross over estimations of the process robustness.

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