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Evaluating and controlling process variability in micro-injection moulding

U. M. Attia*[1] and J. R. Alcock[2]

*[1] *Building 56, Cranfield University, Wharley End, Cranfield, Bedfordshire, MK43 0AL, UK.* Phone: +44 (0) 1234750111 ext. 2408. E-mail: u.attia@cranfield.ac.uk

[2] *Building 61, Cranfield University, Wharley End, Cranfield, Bedfordshire, MK43 0AL, UK.* E-mail: j.r.alcock@cranfield.ac.uk

Abstract

Microsystem technologies require relatively strict quality requirements. This is because their functionalities are usually dependent on stringent requirements of dimensions, masses or tolerances. When mass-producing micro-components, e.g. replication of disposable microfluidic diagnostics devices, the consistency of the produced components could be significantly affected by process variability. The variability could be associated with a specific process parameter or could be a result of process noise.

This paper presents a methodology to assess and minimise process variability in micro-injection moulding, an example of well-established mass-production techniques for micro-components. A design-of-experiments approach was implemented, where five process parameters were investigated for possible effects on the process variability of two components. The variability was represented by the standard deviation of the replicated part mass. It was found that melt temperature was a significant source of variability in part mass for one of the components, whilst the other was affected by unsystematic variability. Optimisations tools such as response surfaces and desirability functions were implemented to minimize mass variability by more than 40%.

Keywords: micro-injection moulding, quality control, design-of-experiments, process variability, processing parameters.

1. Introduction

Micro-injection moulding (μIM), a key technology in high-volume micro-manufacturing of polymer-based components, requires accurate control of quality parameters to ensure the replication fidelity and consistency of produced components.

The design-of-experiments (DOE) approach has been used in the recent years to evaluate and control the effect of processing parameters on the replication quality of μIM [1]. DOE allows the correlation of process inputs and outputs whilst using less experiments compared to the conventional approach of changing one parameter at a time. It is also used to detect interactions between input factors.

Typical processing parameters (factors) include polymer-melt temperature, mould temperature, holding pressure, cooling time, injection velocity and metering volume. Quality parameters (responses) are usually associated with evaluating the replication fidelity of the processes by completely filling the mould cavity. Typical responses include filling quality of micro-sized channels [2], feature dimension [3-6], part mass [7-11], flow length [12,13], filling volume fraction [14], weld-line formation [15], demoulding forces [16] and minimising injection time, pressure and temperature distribution using a three-dimensional simulation package [17].

However, a processing aspect that is rarely addressed in the literature is the possible influence of process parameters on the *variability* of the response in micro-injection moulding. Process variability is particularly important for microsystem techniques, where tight tolerances are usually required for, e.g. dimensions or masses. Variation, in such cases, might affect the stability of the process quality outcome.

Variation occurs normally in industrial processes, which means that measuring a specific output value from the process will reveal differences in measurements between experimental runs even if the processing conditions are kept the same [18]. However, an important element of understanding the effect of processing conditions on the process output is to be able to distinguish between variations that are attributed to changes in factors and those that result from other causes. The former variations are usually referred to as the *signal* [19], or *systematic variability* [20], which is the change of response that the experimenter is seeking to detect. The latter is usually referred to as the *noise*, *scatter* or *unsystematic variability* of the response that occurs during standard operation conditions. Hence, a fairly high signal-to-noise ration, for example from 4 to 10 [18], is favourable, because it indicates that the effect of changing the factors can be distinguished from experimental noise.

A concept relevant to experimental signal and noise is the difference between *replicates* and *repeats*. *Replication* is the process of conducting experimental trials in a random order, such that factor combination is kept the same, while each experimental trial is done independently [18,19,21]. *Repetition*, on the other hand, is the process of running experimental trials under the same setup of machine parameters. Replicates are useful for improving the chance of detecting statistically significant factors (signals) from within the natural process variation (noise). The more replicates undertaken, the higher are the chances of accurately identifying signals from process noise.

This paper investigates controlling process variability in μIM. It compares the “natural” process variation to variations attributed to specific factors. Two micro-moulded Polymethyl Methacrylate (PMMA) components were experimentally tested to determine process variability and its effect on the produced part mass. Optimisation tools such as response curves and desirability functions are applied to minimize process variation.

2. Experiment

2.1. Component geometries

The two components, denoted as Part 1 and Part 2, were assembly elements of a microfluidic device for a medical diagnostics application (A detailed description of the device functionality and process chain is available in the literature [22]). The components were of the same radial dimension (10 mm) and both contained through-section micro-sized holes. However, the shape complexity and the dimensions of the micro-features varied between components. Part 1 consisted of simple cylindrical features with a relatively large surrounding space for polymer melt to freely fill the cavity. Part 2, on the other hand, contained more complex features that would pose relatively “challenging” flow paths for polymer flow. Figure 1 shows SEM micrographs of the aluminium mould inserts and corresponding PMMA replicates for both components.

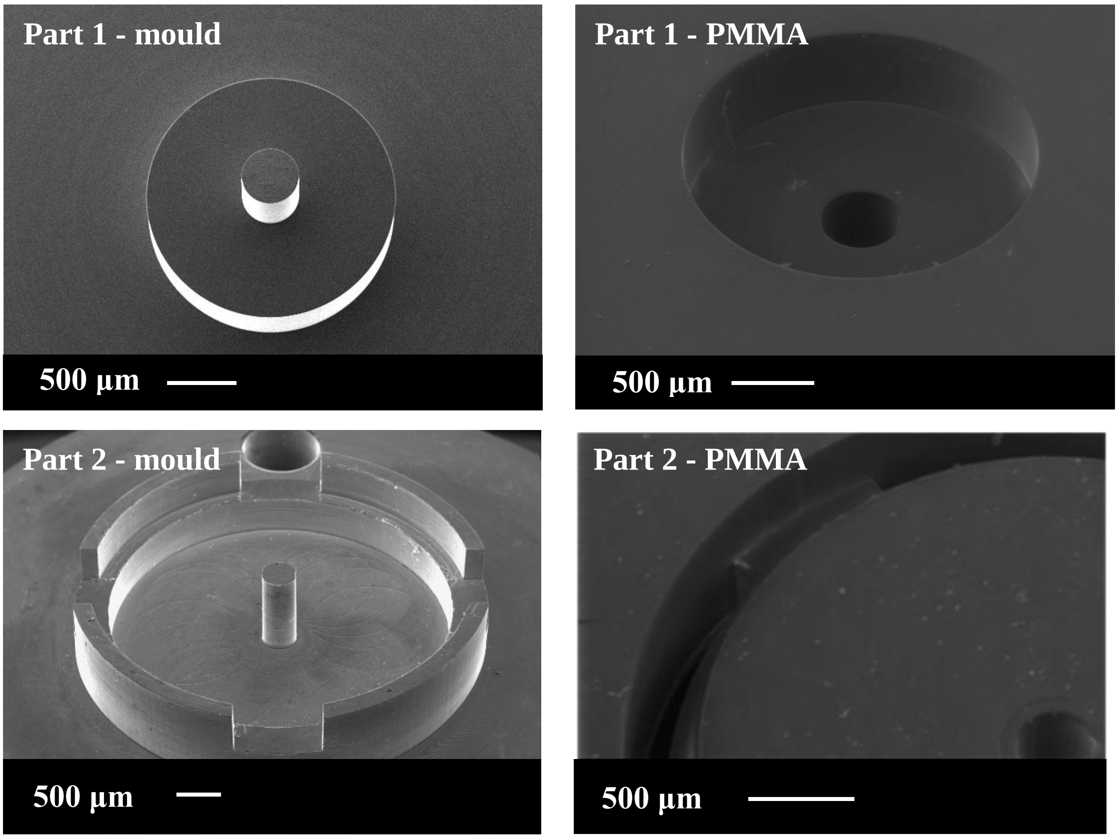


Fig 1 SEM micrographs of mould-inserts and replicated PMMA parts of the two tested components

2.2. Methodology and equipment

Five processing parameters were investigated: Polymer-melt temperature (T_p), mould temperature (T_m), holding pressure (P_h), Injection velocity (V_i) and cooling time (t_c). The data collected was the component mass (W).

A 2-level, half-factorial design of Resolution-V (2^{5-1}) was selected for this application. In this design the main effects are not confounded with other main effects or with second-order interactions, and the second-order interactions are not confounded with each other. This allowed for a relatively small number of experiments to be undertaken without significantly compromising the accuracy of the results.

The micro moulding machine used is a Battenfeld Microsystems 50. The PMMA grade was VS-UVT from Altuglas®. This particular grade was selected for its ease of flow (MFI = 24 g/10 min) and its optical transparency (light transmittance 92%). A sensitive weighing scale with a readability of 0.01 mg was used to weigh the parts. Data analysis and optimization was conducted with Minitab® 15 [23].

2.3. Experimentation design and procedure

Table 1 presents the levels of the five factors for the tested components.

Part	Metering Volume [mm^3]	T_p [°C]		T_m [°C]		V_i [mm/s]		P_h [bar]		t_c [s]	
		Low level (-)	High level (+)	Low level (-)	High level (+)	Low level (-)	High level (+)	Low level (-)	High level (+)	Low level (-)	High level (+)
1	179	240	255	70	81	200	300	250	500	4	7
2	177	230	250	72	84	200	300	100	300	3	6

Table 1. Higher and lower levels for the five factors for Part 1 and Part 2.

Procedures for selecting the levels for each factor are available in the literature [10]. Table 2 presents the half-factorial design in its standard order. All runs were performed in a randomised order using a built-in randomisation function in Minitab.

Standard Order	**T_p [°C]**	**T_m [°C]**	**P_h [bar]**	**V_i [mm/s]**	**t_c [s]**
1	-	-	-	-	+
2	+	-	-	-	-
3	-	+	-	-	-
4	+	+	-	-	+
5	-	-	+	-	-
6	+	-	+	-	+
7	-	+	+	-	+
8	+	+	+	-	-
9	-	-	-	+	-
10	+	-	-	+	+
11	-	+	-	+	+
12	+	+	-	+	-

13	-	-	+	+	+
14	+	-	+	+	-
15	-	+	+	+	-
16	+	+	+	+	+

Table 2. A half-factorial, two level 16-run (2^{5-1}) experimentation design.

For each run, the moulder was left to operate for 50 cycles to ensure process stability, and then 10 parts are collected to represent the samples of the process “repeats” for that particular run. An average mass (W) was obtained from 10 samples for each run. Each set of designed experiments was repeated 3 times, R1 to R3, where runs are conducted in a random order in each replicate, such that 3 “replicates” are obtained for each experimental run.

The purpose of the experiment was to detect potential influential process parameters that affect the *variability* in part mass rather than the mass of the part itself. Therefore, the response of the experiment design was required to be a parameter that reflects variability in mass rather than the mass magnitude. Standard deviation (SD) of the process replicates would be such a measure. However, as SD does not follow a normal distribution, an assumption in DOE, it could not be used as a direct response to the experiments. Hence, the natural logarithm of the SD was used as the experimental response [19,21]. Specifically, the response of the factorial design was set as *ln (SD)* of the 3 replicates. The possible influences of the processing parameters on the response were detected and analysed.

The experimental data is presented below in a series of Pareto charts, where the magnitude of each bar was calculated from the half the difference, i.e. $|\Delta/2|$, of the responses obtained for the average masses measured at the low and high levels of a specific factor (or interaction). Alpha represented a measurement of risk, the value of 0.05 indicating a confidence limit of 95%. The vertical line on each Pareto chart corresponded to the threshold beyond which factors become statistically significant, where the significance threshold was determined by the chosen value of alpha. The value of the line was determined from the t-distribution, where t is the 1-(alpha/2) quantile of the distribution [23].

2.4. Minimising process variability

As noted above, if the DOE design revealed no significant effect of any factor on the process variability, this would indicate that variation in part mass could be attributed to the “natural” noise of the process, and that none of the chosen input factors had played a role in this variation. If, on the other hand, one or more factors were shown to be statistically significant in process variation, this would indicate that a certain “signal” was detectable from particular factor(s). In this latter case there would be a possibility to minimise or at least decrease this variability using an optimization tool.

In this paper, two methods were used to provide guidance on minimising detected variability. Firstly, surface plots were used to visualise and minimize the effect of influential factors. Secondly, a desirability-function tool was also implemented to predict a combination of factor values that would render a target *T*, where that target was to minimise the response beyond a pre-set upper limit *U*.

For the example of one response being optimized, the individual desirability can be represented by the equation [21]:

$$f_i(y) = \begin{cases} 1 & y \prec L \\ \left(\dfrac{U-y}{U-T}\right)^r & T \le y \le U \\ 0 & y \succ U \end{cases} \qquad (1)$$

The response, *y*, varies over a range between 0 and 1, where 1 corresponds to achieving the target and 0 where the function is outside the pre-set limits. In Equation (1), the function weight, *r*, determines the shape of the function, which was set to be linear in this set of experiments, the simplest use of the function.

3. Results

3.1. Part mass data

Table 3 shows the measurements of mass obtained from the produced parts. R1 to R3 represent the three "replicates" of each experimental run. Each mass reported in the table was the average mass of 10 repeats. The table also presents the average of part mass for the 3 replicates of each run, W_1 and W_2 respectively, the standard deviation of the replicate masses and the ln (SD) of the replicate masses.

						Part 1					**Part 2**				
	T_p	**T_m**	**P_h**	**V_i**	**t_c**	**Average masses of replicates [mg]**			**W_1 [mg]**	**ln (SD)**	**Average masses of replicates [mg]**			**W_2 [mg]**	**ln (SD)**
						R1	**R2**	**R3**			**R1**	**R2**	**R3**		
1	-	-	-	-	+	91.1	91.2	91.3	91.2	-2.61	88.3	88.1	88.9	88.4	-0.78
2	+	-	-	-	-	91.3	91.8	92.7	91.9	-0.33	88.5	88.8	88.6	88.6	-2.76
3	-	+	-	-	-	92.0	92.2	92.4	92.2	-1.59	88.6	89.4	89.3	89.1	-1.68
4	+	+	-	-	+	91.2	92.0	92.8	92.0	-0.24	88.8	89.1	89.1	89.0	-2.49
5	-	-	+	-	-	92.6	94.1	95.2	93.9	-0.28	90.0	90.8	90.2	90.3	-1.67
6	+	-	+	-	+	93.5	93.4	94.9	94.0	-0.16	89.8	90.2	89.9	90.0	-2.53
7	-	+	+	-	+	93.7	94.2	95.2	94.4	-0.31	89.9	90.3	90.5	90.2	-2.11
8	+	+	+	-	-	93.9	94.1	94.5	94.2	-1.20	90.5	90.8	90.8	90.7	-2.62
9	-	-	-	+	-	90.7	91.6	92.2	91.5	-0.26	87.4	87.9	87.9	87.7	-2.02
10	+	-	-	+	+	90.5	90.7	91.1	90.8	-1.24	87.7	87.8	88.0	87.8	-2.71

11	-	+	-	+	+	90.8	91.5	91.3	91.2	-0.97	87.8	87.9	88.3	88.0	-2.11
12	+	+	-	+	-	91.4	91.6	92.6	91.9	-0.46	88.4	88.2	88.2	88.3	-2.83
13	-	-	+	+	+	92.9	94.3	93.6	93.6	-0.38	89.4	90.0	90.0	89.8	-1.86
14	+	-	+	+	-	93.4	93.5	95.0	93.9	-0.10	89.6	90.2	90.1	89.9	-2.06
15	-	+	+	+	-	93.3	94.1	95.2	94.2	-0.08	89.8	90.4	90.0	90.1	-2.05
16	+	+	+	+	+	93.1	93.6	94.0	93.6	-0.82	89.8	90.2	90.1	90.0	-2.29

Table 3. Average masses of measured repeats for each of the three replicates (R1 to R3).

Figures 2 and 3 plot graphically the data of table 3 for Part 1 and Part 2, respectively. The points represent the ten-part average part-mass data for each of the three replicates. The vertical lines represent the standard deviations of the corresponding 10 repeats.

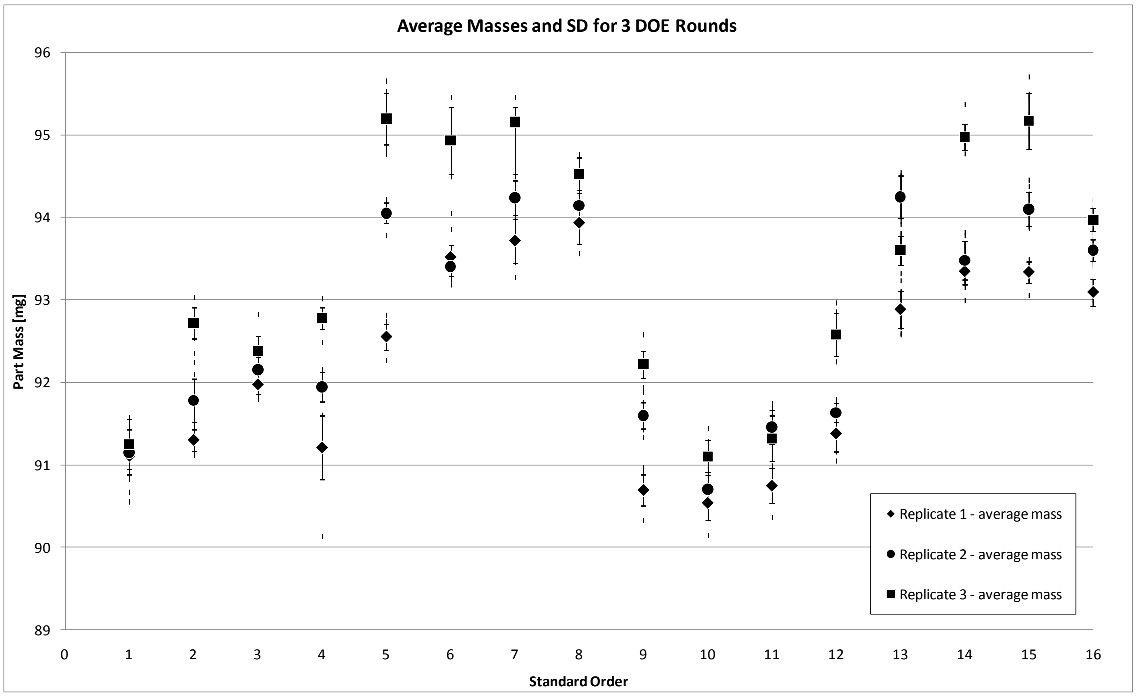


Fig 2 Part 1: Average masses of three replicates and their corresponding standard deviations

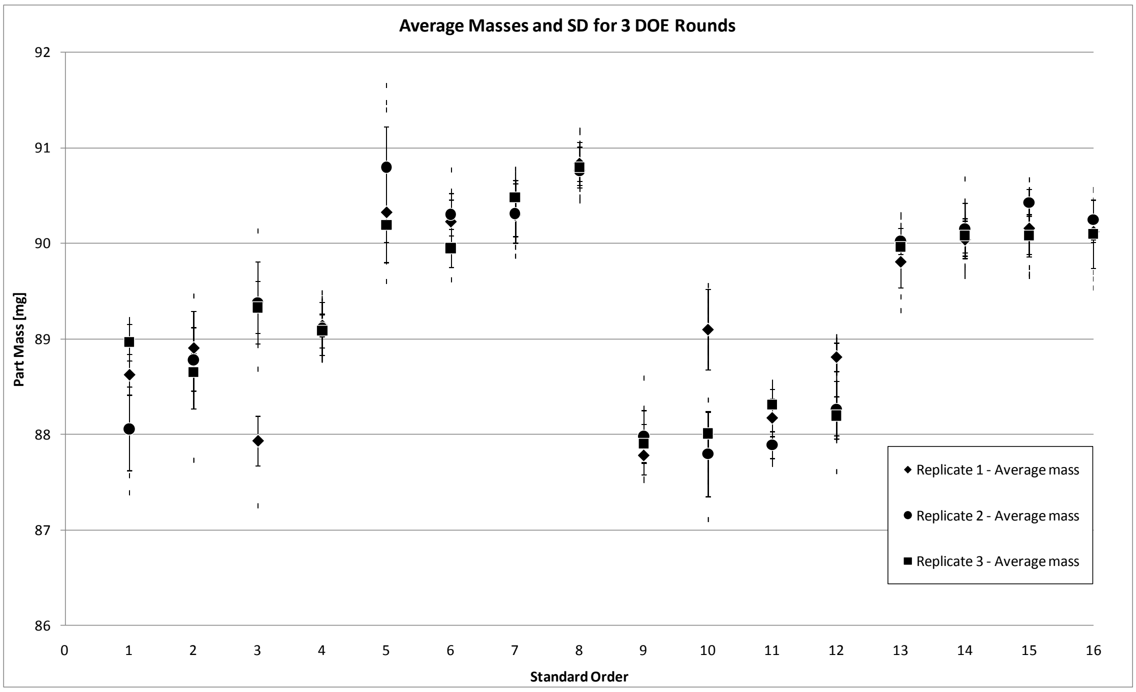
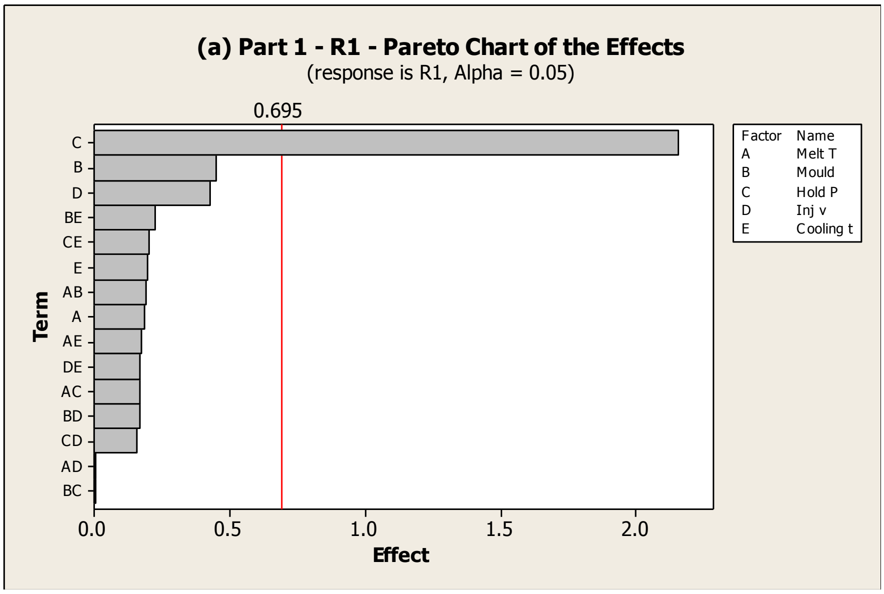


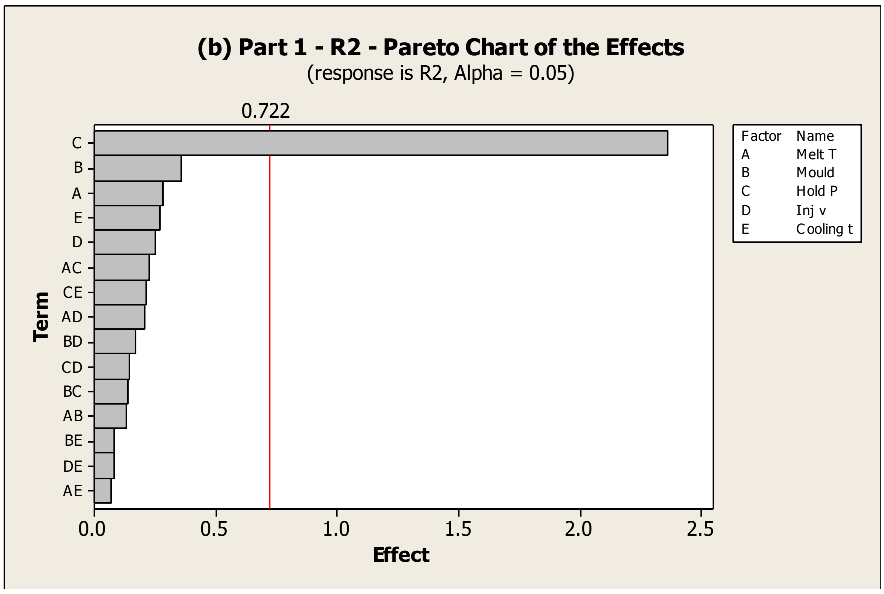
Fig 3 Part 2: Average masses of three replicates and their corresponding standard deviations

3.2 DOE analysis and results

3.2.1. Part 1

Figure 4 is a set of Pareto charts of the magnitude of the effect of a specific experimental factor, or of the interactions of such factors, on the output response, ln (SD). The factors were: polymer-melt temperature (A), mould temperature (B), holding pressure (C), injection speed (D) and cooling time (E). In Figure 4, plots (a), (b) and (c) correspond to individual experimental responses of R1, R2 and R3 respectively. Figure 5 presents a Pareto chart for the average weight of the three replicates (W_1).





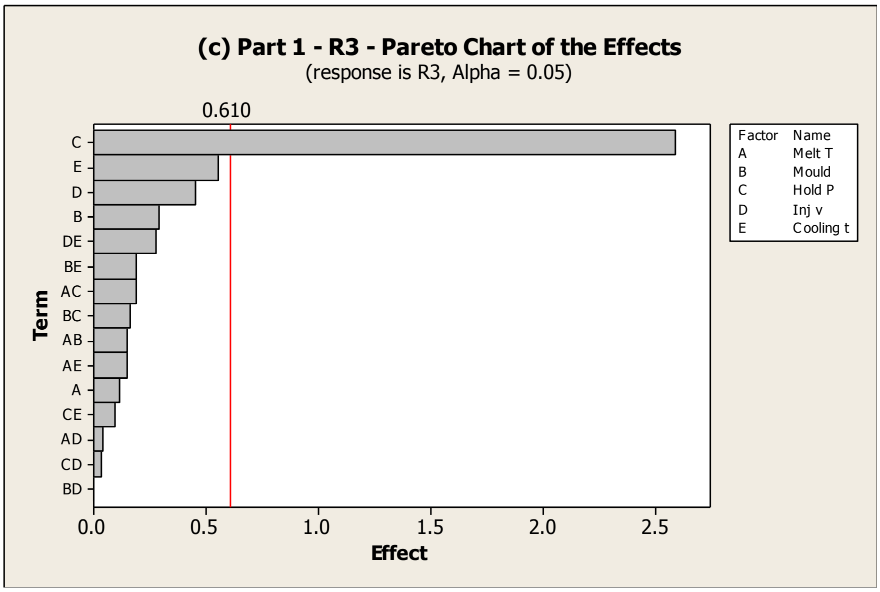


Fig 4 Pareto charts of effects for Part 1 of (a) Replicate 1, (b) Replicate 2 and (c) Replicate 3

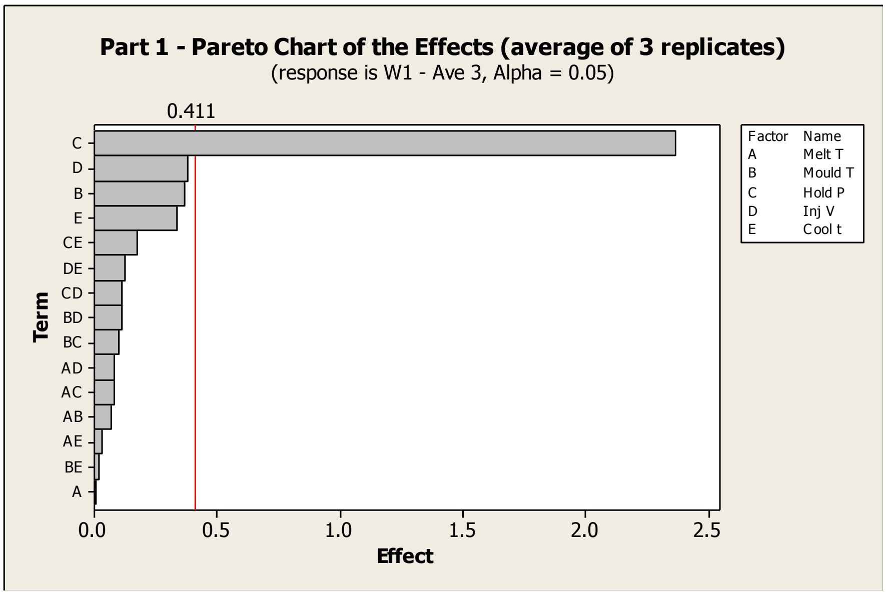


Fig 5 Pareto chart of effects for Part 1, where response is average mass W1

Figure 6 present the Pareto chart for variability in the mass of Part 1, where the response used to assess variability is ln (SD).

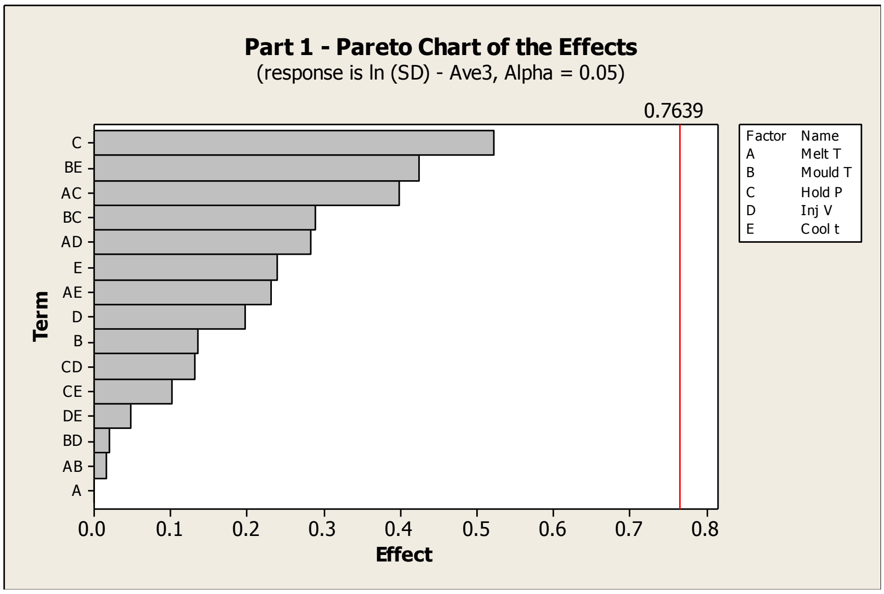


Fig 6 Pareto chart of effects for variability in mass for Part 1, where Response is ln (SD)

3.2.2. Part 2

Figure 7 presents the Pareto chart for part mass, where the three replicated experiments are analysed individually. As with Part 1, the factors were: polymer-melt temperature (A), mould temperature (B), holding pressure (C), injection speed (D) and cooling time (E).

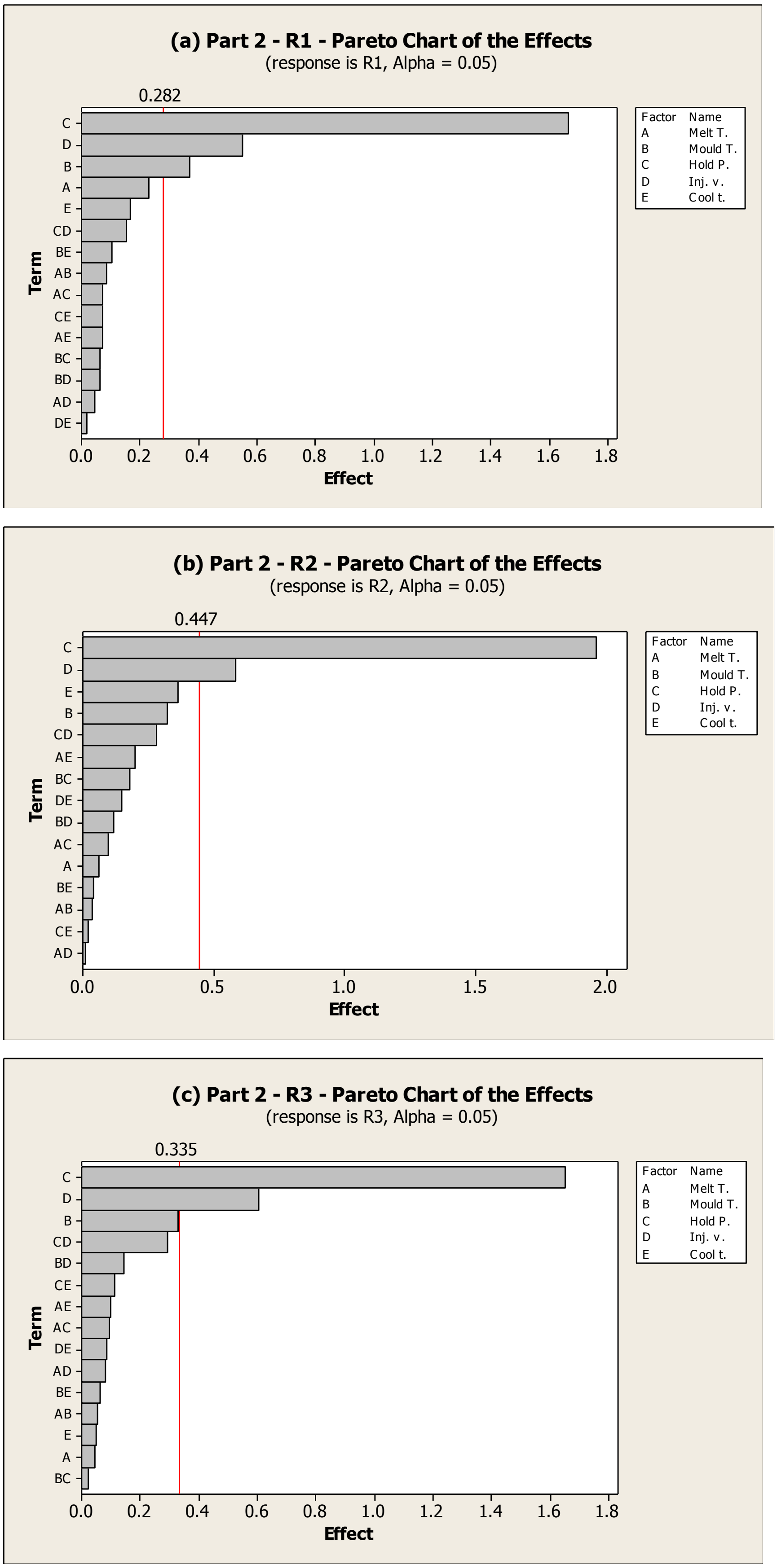


Fig 7 Pareto charts of effects for Part 2 of (a) Replicate 1, (b) Replicate 2 and (c) Replicate 3

Figure 8 presents the chart corresponding to the overall average of part masses (W_2) listed in Table 3.

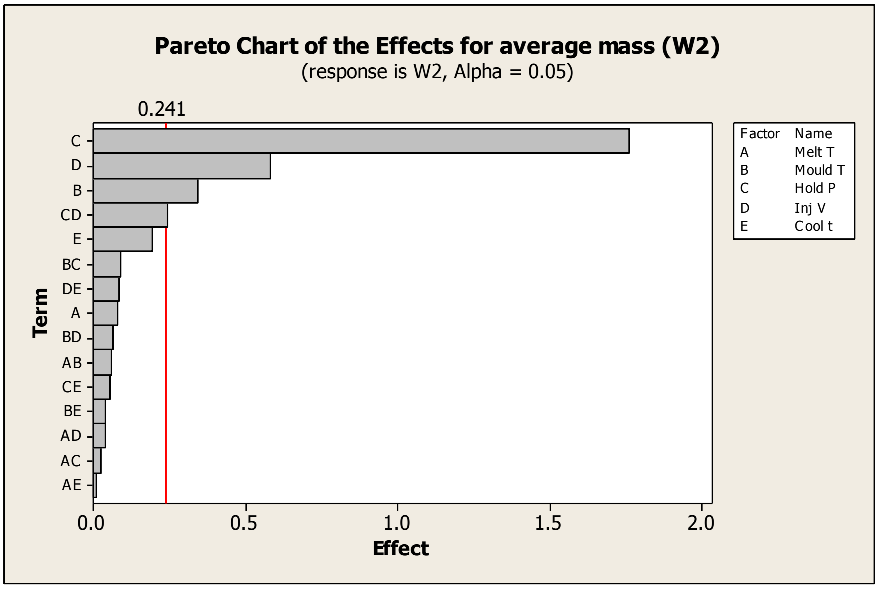


Fig 8 Pareto chart of effects for Part 2, where response is average mass W2

Figure 9 presents the Pareto chart for mass variability in Part 2.

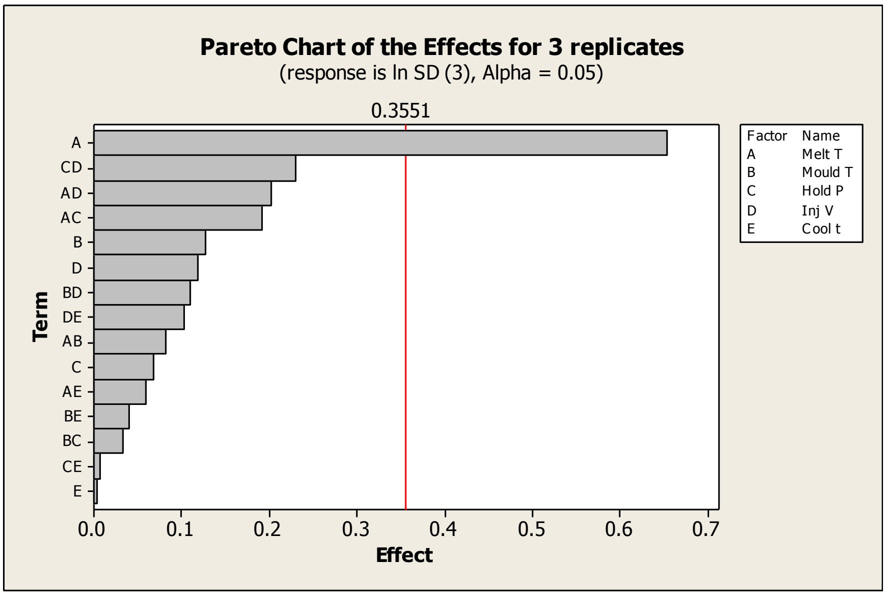


Fig 9 Pareto Chart for ln (SD) for average part mass of three replicates

4. Discussion

4.1. Replication

Figure 4 presents the three Pareto plots corresponding to R1, R2 and R3 as responses. The plots show that in each case holding pressure was identified as the most influential parameter on the mass of the part. The magnitude of the bar reveals that its effect is considerably larger than any other factor (or interaction between factors).

The order and magnitude of other factors differ from one plot to another, but they are not statistically significant, and their variation can be attributed to process noise. The similarity between the three plots of Figure 4 indicates that process replicability does not affect the mass, and hence the filling quality, of Part 1, which indicates that experimental results are reproducible. The half-factorial DOE design is also shown to be sufficient for rendering reproducible results. Figure 5, the Pareto chart of the average mass for Part 1 (W_1), shows that, again, holding pressure is the only statistically significant process parameter for part mass.

Figure 7 shows the effects of the individual replicates of Part 2. Where average masses in replicates R1 and R3 were the responses, the most influential parameters were, in order, holding pressure, injection velocity and mould temperature. However, when R2 was used as a response, holding pressure followed by injection velocity were influential parameters, whereas other factors were evaluated to be statistically insignificant. This discrepancy suggested that process variability was high enough that it affected the replication of the part.

The Pareto chart of the average mass (W_2) is plotted in Figure 8. Similar to the individual plots of R1 and R3 of Figure 7, holding pressure, injection velocity and mould temperature are highlighted as the main effects influencing part mass. However, a borderline effect of interaction between holding pressure and injection velocity is also detected. This "disturbance" in effects for the average-mass plot arises from the inconsistency in results for the individual replicates.

4.2. Evaluating parameters that influence variability

The individual plots of figure 4 and the average plot of figure 5 showed similar results for analysing individual replicated data and average data. This similarity suggests that the process replicability was not influenced by specific factors. The three plots of Figure 4 were similar in showing that holding pressure is a statistically significant factor. On the other hand, they showed discrepancies in the position of the threshold line and the significance and order of other factors and interactions. These variations may be attributed to the noise of the process that made the three replicates slightly different, without affecting the overall main output of the analysis. Hence, Figure 5, which combined the data points of all the three replicates, revealed the same significant factor.

In order to confirm the lack of influence of a specific factor on variability, process variability was investigated as the experimental response, represented by ln (SD). Figure 6 showed the Pareto chart for variability of Part 1. The main effects and interactions lie below the threshold of statistically significant effects. Changes between process replicates could not be attributed to any particular factor or interaction.

In contrast Figures 7 and 8 indicated process variability was high enough that it affected the replication of Part 2. Figure 9 showed the Pareto chart for variability of Part 2. It shows that melt temperature was the statistically significant source of variation between the three replicates.

The results in Figure 9 show an example of how DOE may be used to detect a specific source of variation in micro-injection moulding. They further show that the factor (or factors) that are significant for process variation may not necessarily the same as those that affect the part quality parameters. For Part 2, for example, *variation* in part mass was affected by melt temperature, whereas *part mass* itself was affected by holding pressure and injection velocity, as shown in Figures 7 and 8.

4.3. Minimizing variability

Detecting a particular source of variability makes it possible to control it, and hence minimise it, by studying the relation between the factor and the response.

Figure 10 comprises surface plots illustrating the behaviour of variability versus melt temperature and the other factors.

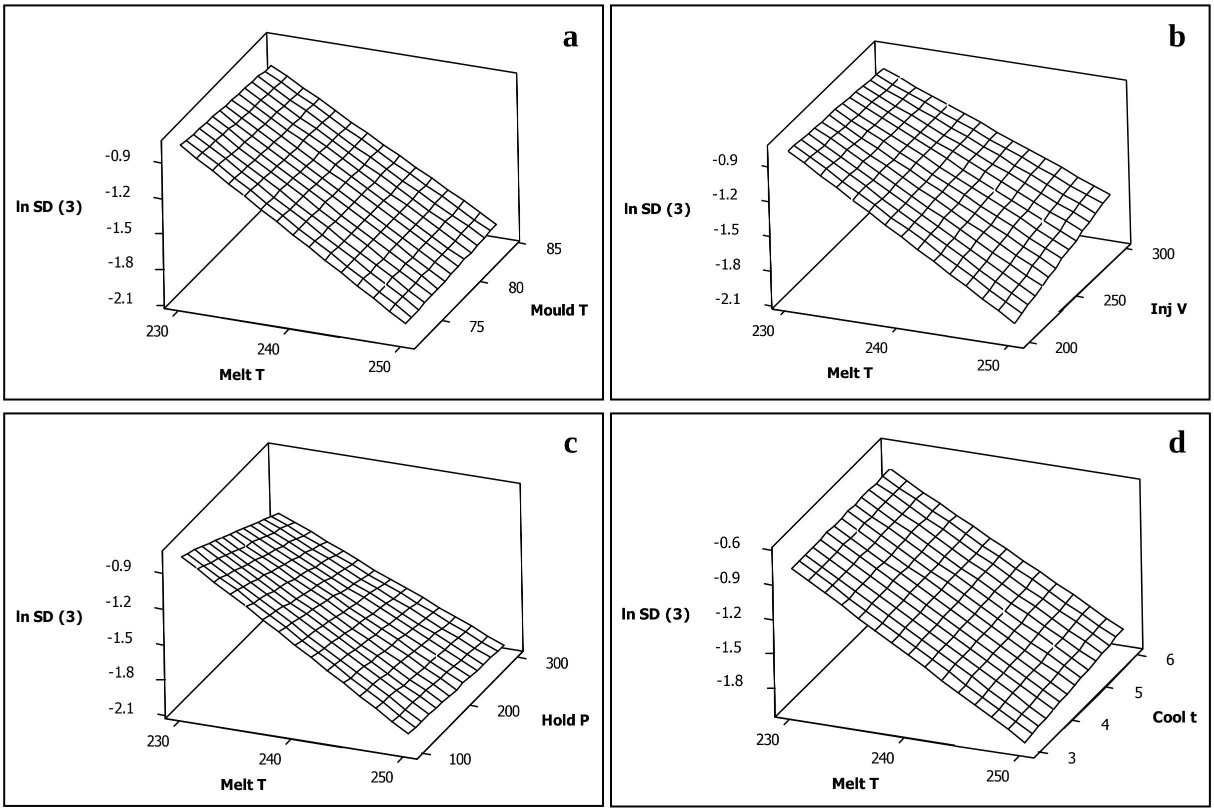


Fig 10 Surface plot of ln (SD) for three replicates versus melt temperature combined with (a) injection velocity (b) mould temperature (c) holding pressure and (d) cooling time

The four surface plots in Figure 10 show that decreasing the process variability would be achieved by increasing melt temperature. It should be noted that the surfaces are linear in shape, because of the preset assumption in the applied 2-level design that the relation between the factors and the responses followed a linear model. On average the plots in Figure 10 indicate that setting the melt temperature to its high level (250°C) would decrease ln (SD) to approximately -1.9, a standard deviation of approximately 0.15.

A more quantitative approach to control the relation between the standard deviation and process factors was applied by using a desirability function that, by iterating over Equation 1, suggested a combination of factor values to reach a pre-set target. The pre-set condition of the desirability function was to minimize ln (SD) with a maximum acceptable value of -1.9, as noted from Figure 10.

Table 4 lists the set of processing conditions suggested by the desirability function and the predicted value of the response.

Factors	Melt T [°C]	250
	Mould T [°C]	84
	Hold P [bar]	300
	Inj. V [mm/s]	200
	Cool t [°C]	3
Response	ln (SD)	-2.05

Table 4. Processing conditions and predicted response values by desirability function.

The values shown in Table 4 agree, in general, with the trends shown in Figure 10, where the statistically significant factor, melt temperature, is maximized to its upper level, and the other factors, although not statistically significant, are set to minimize the response following the trends calculated from the DOE analysis and presented in the plots of Figure 10. The predicted response of -2.05 corresponds to a standard deviation of 0.13.

A set of experiments was conducted to attempt to validate the recommendations of the desirability function. The process conditions in Table 4 were applied to produce parts for three replicates. The standard deviation of the three replicates was calculated and compared to the value of 0.13 predicted by the desirability function. The experimental value of ln (SD) following the setup recommended by the desirability function was -1.90 (SD of 0.15).

It should be noted, however, that the recommended factor values listed in Table 4 are limited by the original setup of the experimental design, which sets the upper limit of the melt temperature to 250°C. The trends shown in Figure 10 suggest that increasing the melt temperature beyond the upper limit of 250°C would render lower values of ln (SD) and, hence, less variability. Hence, the same set of experiments was repeated while increasing the melt temperature from 255°C to 270°C by increments of 5 degrees.

Figure 11 presents the standard deviation of the replicates at each value of melt temperature (where the datum at 250°C is from the conditions described in Table 4).

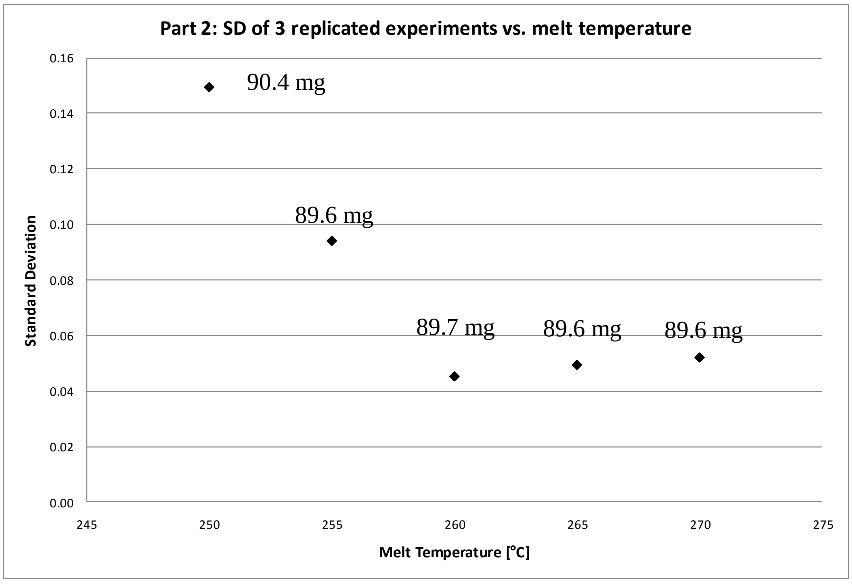


Fig 11 Standard deviation vs. melt temperature at recommended setup (mould T of 84°C, injection V of 200 mm/s, holding P of 300 bars and cooling t of 3 sec). Average mass noted for each data point

Figure 11 shows that increasing the melt temperature resulted in a significant decrease in standard deviation of the replicated runs from approximately 0.09 at 255°C down to approximately 0.04 at 260°C – a decrease in variability by approximately 44%. Above 260°C, increasing the melt temperature had little effect on the variation of the process. In addition, Figure 11 shows that altering the factors to decrease variability induced no significant change in average part mass, and hence filling quality.

It has been shown above that DOE can be used as an effective tool not just to quantify the influence of factors on part quality in micro-moulding, but to quantify the influence of factors on part reproducibility. Furthermore, with the addition of response surfaces and the use of a desirability function it has been shown that DOE can be used as a tool to minimise process variability in micro-moulding.

However, DOE cannot give information on causal mechanisms, i.e. why melt temperature affects process variability. In this respect, it can be noted that Parts 1 and 2 showed different responses to process variability, although the same experimental design, machine setup and material were used. This suggests a possibility that the complexity of the geometry plays a role in process variability in micro-injection moulding. The flow behaviour of molten polymer is highly influenced by the material viscosity, which changes with temperature. The variability observed in Part 2 could be associated with the flow resistance posed by the relatively complex cavity geometry. Increasing melt temperature may result in better flow behaviour and, hence, consistency in replicated parts.

5. Conclusion

This paper aimed at assessing and controlling process variability in a high-volume micro-system process. It investigated possible effects of processing parameters on process variability in micro-injection moulding. The design of experiments (DOE) approach was shown to be an effective tool to quantify the influence of factors on part reproducibility. DOE was used to analyse the effect of five processing parameters on the variability of part mass for two components. In one component no factor was identified as a source of variability, whilst for the other component melt temperature was identified as a statistically significant factor affecting the replicability of the process.

It was shown that a combination of DOE with response surfaces and a desirability function could be used as a tool to minimise process variability in micro-moulding. Response surfaces were used to illustrate the inverse relationship between standard deviation of part mass and melt temperature. Desirability functions were used to calculate a possible combination of factors that minimized standard deviation within the preset limits of the experimental design. The reduction in variation achieved experimentally displayed a close match with the prediction of the function

It was shown that increasing the melt temperature beyond the limits of the experimental design decreased standard deviation by more than 40%. These results suggested that the complexity of the moulded geometry may be related to the variability of the process.

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Attia, Usama M.

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