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Optimizing process conditions for multiple quality criteria 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

This paper presents a statistical technique to optimise process conditions for multiple quality criteria in micro-injection moulding. A sample hierarchical component with micro-features was replicated, where it was required to improve the process conditions for both complete mould filling and variability in mass. A design-of-experiments approach was used to investigate the effect of five processing parameters on both criteria. It was found that holding pressure, melt temperature and injection velocity were statistically significant for part mass, whereas injection velocity alone was significant for mass variation. Desirability functions were used to predict processing conditions that improved both requirements within pre-set conditions. The technique was validated by experiment and it was shown to be applicable for process parameters for multiple criteria.

Keywords: Micro-injection moulding, design-of-experiments, multiple criteria

1. Introduction

Micro-injection moulding (μIM) is a key technology in mass-producing micro-scaled components. High-volume production, replication fidelity and high precision are some of the features that promote the use of μIM for applications such as medical diagnostics and chemical analysis.

Quality parameters in μIM are usually associated with the ability to completely fill the micro-size cavities in the mould cavity during processing. Table 1 presents a number of designed experiments' methods (DOE) used to evaluate the effect of process parameters on different responses in micro-injection moulding.

Factors and DOE method	Response	Materials	Main results	Ref.
Melt temp., injection pressure, holding pressure, injection speed and mould temp.	Filling quality of micro-featured channels	PC, SBS, MABS, COC and PMMA	Melt temp. and mould temp. are most significant parameters.	[1]
Injection time, injection pressure, injection temp. and mould temp. DOE design: Level 9 orthogonal Taguchi design.	3D numerical simulation of part filling.	PS, PC and PMMA	The mould temp. is the most important parameter. It must be higher than material T_g.	[2]

Injection speed, holding pressure time, cooling time, metering size, melt temp. and mould temp. DOE design: 2-level half factorial (2^{5-1}) and 2-level fractional factorial design (2^{3-1}).	Part mass and dimensions	PC and POM	Metering size and holding pressure are most significant. The interaction between both is also important	[3,4]
Injection speed, injection pressure, mould temperature and injection time. DOE design: Level 9 orthogonal Taguchi design.	Part mass	POM	Mould temperature is the most significant parameter. High mould temperature, injection speed and injection pressure are recommended for filling.	[5]
Injection speed, mould temp., melt temp. and holding pressure. DOE design: 2-level full-factorial (2^4).	Complete filling of donut-shaped parts	PS and PC	Injection speed and holding pressure are the most influential, while melt temp. and mould temp. have less influence.	[6]
Melt temp., mould temp., injection speed, holding pressure, air evacuation and the size of features. DOE design: 2-level fractional factorial (2^{6-2}).	Complete filling of high-aspect-ratio rods.	PP, POM and ABS	Melt temp. and injection speed are key factors for PP and ABS. Mould temp. is also significant in case of POM.	[7]
Injection speed, shot size, vacuum, holding pressure, piston diameter. DOE design: 2-level full factorial (2^5).	Micro-feature height.	PC	The diameter of the piston, shot size, injection speed and mould temperature are significant parameters.	[8]
Melt temp., mould temp., injection speed and distance between micro-features. DOE design: 2-level full factorial designs (2^2) for PP and ABS and (2^3) for POM.	Complete filling of micro-structures.	PP, POM and ABS	Injection speed and melt temp. are influential in case of POM and ABS with some side effects. Mould temp. improves filling for some shapes. Distance between micro-features is not influential.	[9]
Melt temp., mould temp., injection speed and surface finish. DOE design: Level 9 orthogonal Taguchi design.	Flow length along a micro-channel into a flat cavity.	PP, ABS and PC	The high levels of all processing parameters result in better filling. Surface finish is related to level of turbulence in melt flow.	[10]
Melt temp., mould temp., injection speed and holding pressure. DOE design: 2-level full factorial designs (2^2).	Weld-line formation.	PS	Injection speed and mould temperature have the main effect on weld-line placement and orientation.	[11]
Melt temp., mould temp., cooling time and ejection delay time. These were combined with surface treatment. DOE design: Level 9 orthogonal Taguchi design.	Ejection forces.	ABS and PC	Surface treatment reduces ejection forces.	[12]
Injection pressure, melt temp., mould temp. and flow ratio. DOE design: Level 9 orthogonal Taguchi design.	Flow length	PP	Melt temp. and injection pressure are the most significant factors.	[13]

Holding pressure, filling flow rate and mould temperature. DOE design: Taguchi orthogonal design L_{18} (2^1 x 3^7).	Filled volume fraction of microfilters	COC	Flow rate found to be the most important processing parameter	[14]
Melt temp., mould temp., injection pressure, holding pressure, ejection temp. and injection speed. DOE design: Taguchi orthogonal design L_{18} (3^7).	Tensile strength of weld lines.	PP	High melt temperatures decrease weld line strength. Higher mould temperatures and injection speed increases strength.	[15]
Back pressure, mould temp., melt temp., hold pressure, holding time, injection speed, metering size and cooling time. DOE design: Taguchi orthogonal design L_{18}, followed by a robust parameter design using a 2-level full factorial design (2^3).	Multiple quality characteristics: gear outside diameter and tooth thickness.	POM	Significant parameters for diameter are mould temp., injection speed and pack pressure, whereas for tooth thickness they are holding pressure, cooling time and mould temperature. Mould temperature and holding pressure affects multiple quality characteristics.	[16]

Table 1: DOE methods and responses used to evaluate the effect of process parameters on Micro-injection moulding.

The work summarised above has focused on using design-of-experiment (DOE) approach to study the effect of a set of process parameters on a single response. However, micro-manufacturing processes such as µIM may often require a number of quality criteria to be met simultaneously. These could be, for example, a specific feature dimension and a maximum acceptable variability in part mass. In such cases, an optimisation process would be required to attempt to meet both requirements within the "process window" that was available.

Process variability, in this context, refers to variations that occur normally in industrial processes. Such variations are usually attributed to changes in process parameters (factors), i.e. those which can be varied in a controlled manner, and/or changes that result from other causes, which have not been or cannot be controlled. In experimental terms, the former variations are usually referred to as the *signal* [17], or *systematic variability* [18], 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.

This paper presents an example of a micro-injection moulded part, where DOE was used to investigate the effect of processing parameters on two quality criteria, namely complete mould filling, as represented by part mass and variability in part mass in replicated experiments. A desirability function approach was then used to attempt to optimise process conditions for both responses.

2. Experiments

2.1 Overview of statistical methodology

The aspect of variability that was investigated in this paper was that of replicability. *Replication*, in this context, is the process of running experimental trials in a random order, such that resetting is done after each experimental trial [17,19]. Hence, investigating variability using DOE requires that each set of DOE experiments is replicated as part of the experimental methodology. This is in contrast with *repetition*, which is the process of running experimental trials under the same combination of machine parameters during a single machine run [17].

DOE assumes that responses follow a normal probability distribution, which is not the case for standard deviation. Hence, variability was represented here using the natural logarithm of the standard deviation, ln (SD), which transforms the data closer to a normal distribution [17,20].

To improve both replicability and part quality a statistical tool was required to optimise factors for multiple responses [20,21]. Here, desirability functions were used to predict a combination of processing parameters that fulfilled the two requirements. Each response y_i is individually converted into a desirability function d_i that ranges between 0 and 1, where d_i=1 represents being at the target and d_i=0 lies outside the target range. The factors are calculated to maximise the overall desirability, D, where $D = (d_1.d_2. \ldots .d_m)^{1/m}$, and m is the number of responses.

Objectives of the desirability functions can be either to meet a target within specified range, to minimize or to maximize responses. In this paper, the target T was to produce parts within a specific mass range and to minimize variability in part mass. The individual functions for meeting a target and minimising the response are represented in Equations (1) and (2), respectively.

$$d_1 = \begin{cases} 0 & y \prec L \\ \left(\dfrac{y-L}{T-L}\right)^{r_1} & L \le y \le T \\ \left(\dfrac{U-y}{U-T}\right)^{r_2} & T \le y \le U \\ 0 & y \succ U \end{cases} \qquad (1)$$

$$d_2 = \begin{cases} 1 & y \prec T \\ \left(\dfrac{U-y}{U-T}\right)^{r} & T \le y \le U \\ 0 & y \succ U \end{cases} \qquad (2)$$

In both equations U and L are the upper and lower limits, respectively, and r-values are the function weight (liner or non-liner), which in this case are all set to be equal to 1.

For Equation (1) the target, upper and lower values were selected based on the filling quality of the produced samples. Briefly, after each set of experiments, samples of the 16 runs were inspected under the microscope to check their filling quality. The completely filled parts were weighed and their average mass was calculated and set as the “target” mass for the desirability function. The filled samples that had the smallest and the largest masses were also identified, and their weights were selected as the lower and upper limits, respectively.

A similar approach was followed for Equation (2), except that no lower limit existed, since the purpose of the function was to minimise the response (variability).

2.2 Component geometry

The component chosen for this study was a Polymethyl Methacrylate (PMMA) assembly element of a microfluidic device for use in medical diagnostics. As illustrated in Figure 1, the element is disc-shaped with a diameter of 10 mm and a thickness of 1 mm.

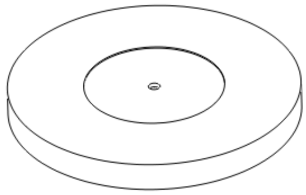


Fig 1 A CAD drawing of the test element.

More details about the manufacturing process-chain and device design are available in the literature [22,23]. The component possessed several micro-scale geometries, including a central, conically shaped through-hole that was 100 um to 150 μm in diameter, and a disk impression on the component surface, which had a depth of 50 μm. Figure 2 shows SEM micrographs of the mould insert and an example of a replicated PMMA part from a fully-filled moulding.

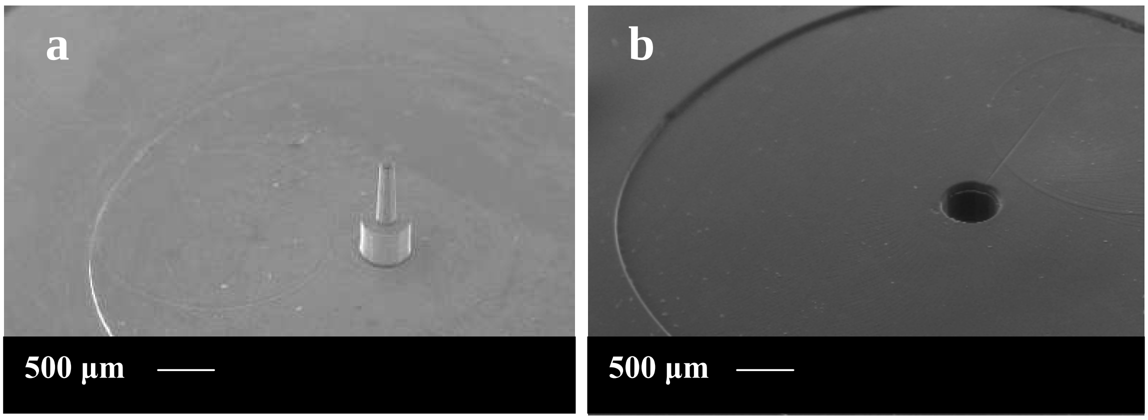


Fig 2 SEM micrographs of (a) mould insert and (b) replicated PMMA part.

2.3 Equipment and process parameters:

Five process parameters (factors) 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 micro moulding machine used was a Battenfeld Microsystems 50. The PMMA material 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%). The Vicat softening temperature of the material is 85°C. The minimum melt and mould temperatures recommended by the manufacturer were 195°C and 50°C, respectively. 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 [24].

2.4 Experimental design and procedure

A two-level, half-factorial (2^{5-1}) design was used to test the effect of process parameters on the two selected responses. The resolution-V design decreases the number of required experiments to half of that of a full-factorial one (16 runs per experiment instead of 32). In addition, in this particular design main effects are not confounded with second-order interactions, and second-order interactions are not confounded with each other. This allowed for fewer experimental runs without compromising the accuracy of the results.

Table 2 presents the levels of the five factors tested in the experimental design.

Metering Volume [mm^3]	T_p [°C]		T_m [°C]		V_i [mm/s]		P_h [MPa]		t_c [s]	
	Low level (-)	High level (+)	Low level (-)	High level (+)	Low level (-)	High level (+)	Low level (-)	High level (+)	Low level (-)	High level (+)
178	230	250	72	80	200	300	10	30	4	7

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

Table 3 presents the half-factorial design in its standard order. The experiments were performed following a randomised order of the runs using a built-in randomisation function in Minitab. For each run, the machine was left to finish 50 continuous cycles (repeats) and then 10 parts were collected for inspection. This was done to ensure that the process reached stability before sample collection. The experimentation setup shown in Table 3 was replicated three times in randomised run sequences.

Standard Order	**T_p [°C]**	**T_m [°C]**	**P_h [MPa]**	**V_i [mm/s]**	**t_c [s]**
1	-	-	-	-	+
2	+	-	-	-	-
3	-	+	-	-	-
4	+	+	-	-	+
5	-	-	+	-	-
6	+	-	+	-	+
7	-	+	+	-	+
8	+	+	+	-	-
9	-	-	-	+	-
10	+	-	-	+	+
11	-	+	-	+	+
12	+	+	-	+	-
13	-	-	+	+	+
14	+	-	+	+	-
15	-	+	+	+	-
16	+	+	+	+	+

Table 3. A half-factorial, two level 16-run (2^{5-1}) experimentation design.

Two outputs were evaluated: filling quality and process variability. The former response was represented by the average mass calculated from the three replicates (W), where producing a part that has a mass within a specific tolerance indicates that it is completely filled. Inspecting the replicated parts under the microscope showed that completely filled parts had average mass of 88.6 mg within a range of approximately ±0.5%. The latter response was represented by ln (SD), calculated from the standard deviation of the three replicates.

As outlined above, desirability functions were used to optimise factors for part mass and variability. The filled part mass tolerance was used to pre-set the conditions used in the desirability function to a target mass of 88.6 mg, a lower limit of 88.4 mg and an upper limit of 89 mg, based on the 0.5 percentage point limits. The target for process variability was set to minimise the value of ln (SD), such that its maximum value would not exceed -1.9, corresponding to SD of 0.15. This set the upper limit not to exceed the average of the SD found from the previous 16 runs of the DOE.

Table 4 presents the combination of factors calculated from Equations 1 and 2 to meet both these requirements. The responses show the expected values for both mass and variability. The values of d_1 and d_2 represent the individual desirabilities of each response from Equations (1) and (2). D represents the combined desirability, which is a measure of how the factors combination recommended by the function was able to meet both response requirements.

Factors	
Melt T [°C]	250
Mould T [°C]	80
Hold [MPa]	30
Inj. V [mm/s]	285
Cool t [sec]	4
Responses	
Part mass [mg]	88.5
d_1	0.72
ln (SD)	-2.0
d_2	0.97
D	0.83

Table 4. Factors combination suggested by desirability function for multiple responses.

3. Results

Table 5 lists the measured masses of the replicated parts for the three replicated experimental sets R1, R2 and R3. The average mass (W) of the three replicates and ln (SD) are listed as the first and second response of the DOE, respectively.

	T_p	T_m	P_h	V_i	t_c	Average mass [mg]			W [mg]	SD	ln (SD)
						R1	R2	R3			
1	-	-	-	-	+	87.7	86.5	86.2	86.8	0.77	-0.26
2	+	-	-	-	-	88.5	87.4	87.6	87.8	0.54	-0.61
3	-	+	-	-	-	88.6	87.9	87.4	88.0	0.58	-0.54
4	+	+	-	-	+	88.0	87.5	87.5	87.7	0.31	-1.18
5	-	-	+	-	-	88.9	88.5	88.0	88.5	0.44	-0.81
6	+	-	+	-	+	89.0	88.4	88.2	88.5	0.38	-0.98
7	-	+	+	-	+	88.8	88.4	87.9	88.4	0.49	-0.71
8	+	+	+	-	-	89.3	88.8	88.9	89.0	0.26	-1.34
9	-	-	-	+	-	86.7	86.7	86.4	86.6	0.17	-1.77
10	+	-	-	+	+	87.1	86.8	86.9	87.0	0.14	-1.94
11	-	+	-	+	+	86.6	86.6	86.4	86.6	0.09	-2.39
12	+	+	-	+	-	87.9	87.7	87.5	87.7	0.23	-1.47
13	-	-	+	+	+	87.8	88.3	88.0	88.0	0.24	-1.41
14	+	-	+	+	-	88.6	88.3	88.5	88.5	0.13	-2.04
15	-	+	+	+	-	88.8	88.1	88.3	88.4	0.35	-1.04
16	+	+	+	+	+	89.1	88.7	88.1	88.6	0.48	-0.74

Table 5. Average masses of measured repeats for each of the three replicates (R1 to R3).

Figure 3 plots the average masses listed in Table 5 in addition to interval lines that represent the standard deviation of the repeated cycles for each of the 16 runs. The interval lines represent the *repeatability* of the process whilst the three average-mass points represent the *replicability* of the process.

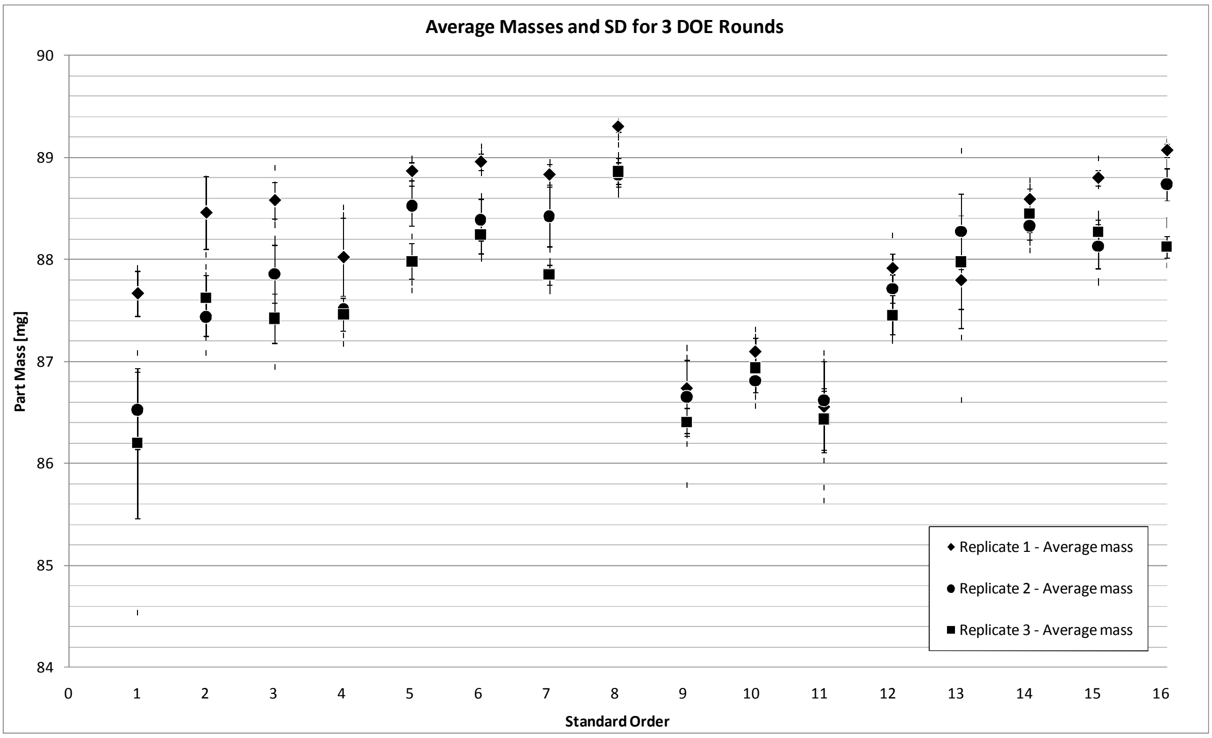


Fig 3 Average masses of three replicates and corresponding SD interval lines.

The results of the experimental design are presented in the form of main-effect charts and Pareto Charts. The former correlates the factors to the response by taking the average response values for each factor at its high and low levels. The difference, denoted as Δ, is then plotted as a line (linear for 2-level designs) for each factor, where the slope represents the significance of the factor effect. The bars of the Pareto charts represent a factor, or interaction between factors, with the bar length reflecting its effect on the response. The effects are calculated by taking the absolute value of half the difference between averages, i.e. |Δ/2|.

Figures 4 and 5 show the main-effect charts and the Pareto Charts for mass and variability, respectively. The five tested factors are denoted by letters: polymer-melt temperature (A), mould temperature (B), holding pressure (C), injection speed (D) and cooling time (E).

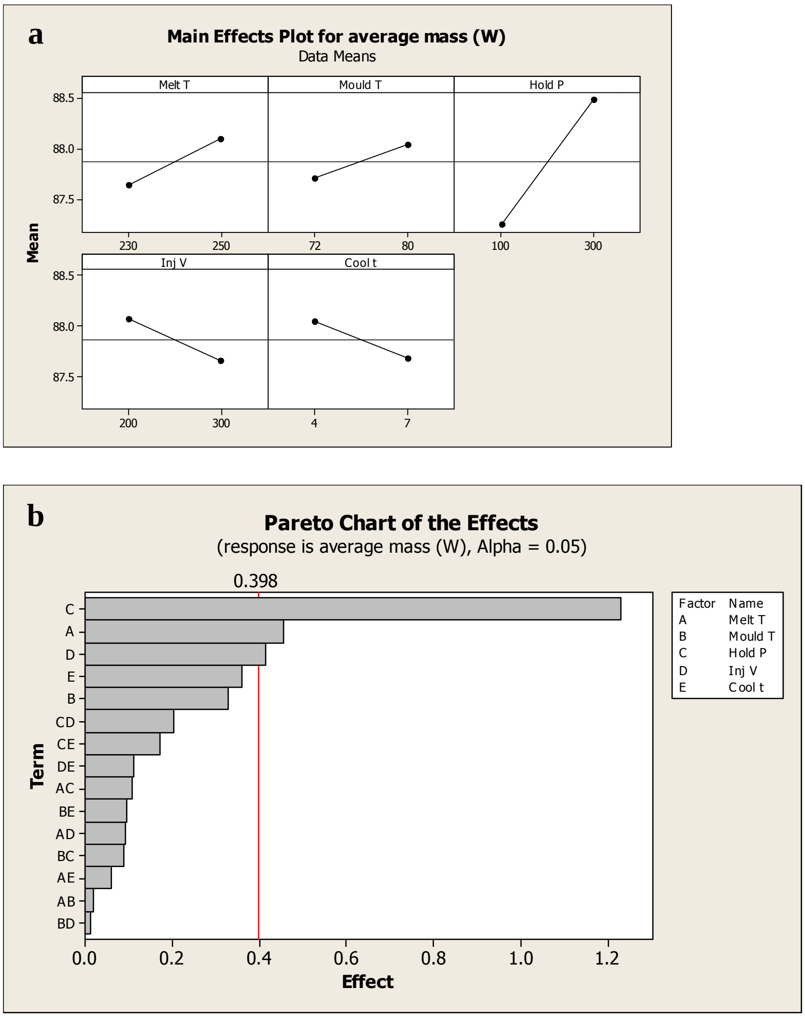
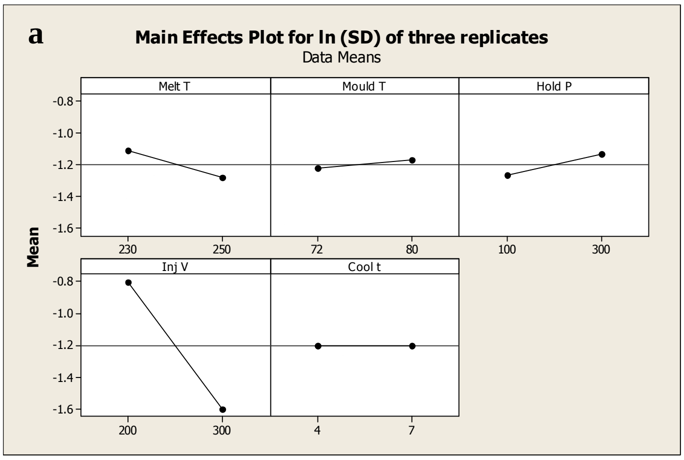


Fig 4 Analysis result for average part mass (W) (a) Main effect chart and (b) Pareto chart.



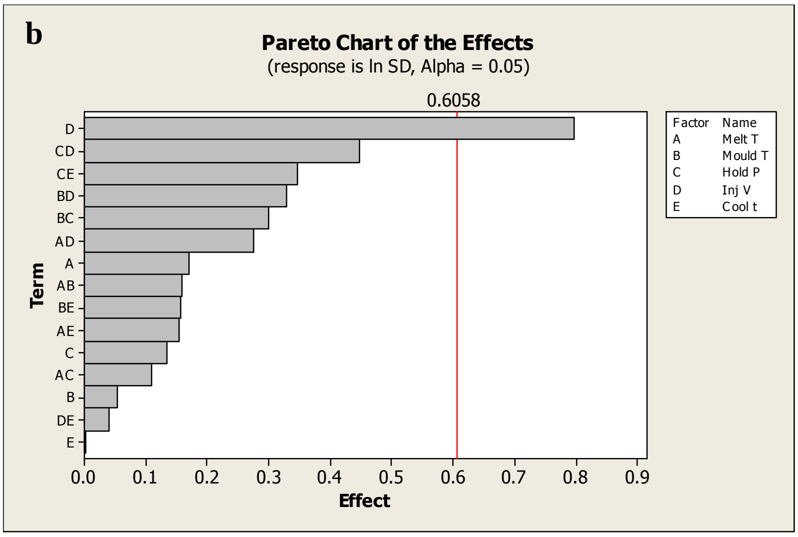


Fig 5 Analysis result for variability (ln SD) (a) Main effect chart and (b) Pareto chart.

In Figures 4(b) and 5(b) the alpha value represents the risk of finding an effect that does not actually exists, where an alpha value of 0.05 means confidence limit of 95%. The vertical lines represent the threshold value beyond which the effect becomes statistically significant within the pre-set confidence limit of alpha. The position of the line is determined from the t-distribution, where t is the 1-(alpha/2) quantile of the distribution [24].

Polymer parts were replicated following the factor values shown in Table 4. Table 6 presents the data for the replicated experiments. Each replicated value (R_1, R_2 and R_3) represents the average from 10 repeats. The standard deviation is calculated for the three replicates.

Part mass [mg]			Average [mg]	SD	Ln (SD)
R1	R2	R3			
88.9	89.0	88.8	88.9	0.10	-2.33

Table 6. Results of validation experiments for the desirability function.

4. Discussion

The plots in Figure 4 showed that three influential parameters affect the *magnitude* of the part mass, namely holding pressure followed by melt temperature and injection velocity. No significant interactions were detected

Concerning part-mass *variability*, Figure 5 indicated that a single experimental factor was a significant source of mass variation in replicated parts, in this case the injection velocity. Hence, the main significant factor that affected the mass *magnitude* (holding pressure) was not the same as the one that affected mass *variation* (injection velocity).

Concerning sample magnitude, the effect of holding pressure on part mass was expected, since increasing the holding pressure allowed for more material to fill the mould cavity before complete freezing and, hence, increasing its mass. The effect of holding pressure on quality filling in Micro-injection moulding was also evident in earlier experiments involving different geometries and polymers [3,4,6]. Increasing melt temperature also affects the filling of the mould cavity, because the viscosity of the polymeric melt decreases with increasing its temperature allowing for better filling of micro-scaled features. This effect of melt temperature also agrees with earlier experiments involving filling microstructures by micro-injection moulding [7,9].

Concerning mass variability, increased injection velocity was shown to be a source of decreased variance in the obtained data. This may lie in the fact that increasing velocity leads to an increase in shear rate, which in turn decreases the viscosity of the polymer and allows for better flow inside the mould cavity. This improved flow would result in consistent filling performance from one cycle to another. Previous experiments showed that increasing the injection velocity results in better mould cavity filling for micro-injection moulding [6-9].

Figure 5a indicated that increasing injection velocity, the identified significant effect, leads to a decrease in ln (SD), i.e. a decrease in process *variation*. On the other hand, Figure 4a showed that increasing injection velocity led to a decrease in part mass. This indicates that if a combination of factors is to be found to fulfil both response requirements, i.e. a decrease in variability and an increase in part mass, a compromise would be necessary for the value of injection velocity.

The values shown in Table 4 indicate how the desirability function took into consideration the trends discussed above. The holding pressure and melt temperature were set to their upper limits to satisfy the part-mass requirement. For the injection velocity, the selected value was at a point closer to the upper limit (to satisfy variability requirement) but not at the upper limit in order not to violate the velocity requirement for part mass.

This compromise in injection velocity affected the predicted responses, as shown in Table 4. The predicted part mass was 88.5 which was slightly lower than the target mass of 88.6 but still within the pre-set tolerance of ±0.4 mg. The predicted ln (SD) was -2.0 (corresponding to SD of 0.14) which was lower than the upper limit set to -1.9.

Since a compromise had to be made between two responses, the individual desirability d_1 and d_2 of mass and mass-variability, respectively, are less than 1. The overall desirability, D, is therefore calculated to be 0.83.

Table 6 presents the results of the validation experiments, where average mass was 88.9 mg and SD was shown to be 0.10. Hence, the average part mass was higher than predicted by approximately 0.3%, although it still lay within the pre-set tolerance of ±0.4 mg, whereas the standard deviation obtained was lower than predicted by the desirability function. Comparing the obtained SD of 0.1 to the original run standard deviations listed in Table 5 shows that it was possible to achieve variability, when optimising for both mass magnitude and mass variability, that fell within the lowest quarter of the original experimental data.

The presented experiment showed that designed experiments could be used to optimise process conditions for multiple quality criteria. This is particularly important for industrial environments where quality requirements involve a number of criteria to be met simultaneously. In addition, process variability resulting from process replication was discussed. This is also an important issue in industrial environments, where changing in, e.g. processing shifts, might affect the consistency of the produced parts. The presented statistical technique was implemented to detect the source of such variability, if any, and minimise it.

On the other hand, the methodology used has some limitations that need to be taken into consideration when applied. Firstly, the 2-level experimental design assumed the linearity of the factors with respect to the responses. This could not be verified until further experiments involving, for example, 3-level designs could be done, which might require extra time and resources. Secondly, the accuracy of the obtained results depended on the resolution of the selected experimentation design. In the presented case, a fractional factorial design was adequate for the selected responses. In other applications, were more strict measurements and tolerances are required, a higher resolution design might be required. Finally, it should be noted that the desirability function suggests optimised process conditions within the initially specified upper and lower levels of the tested factors. Investigating process performance outside these limits would require extending the experimentation “window” for the required factors beyond the initial values.

Future work might focus on using the same technique for more than two responses, including extra responses, such as feature dimensions. In addition, more factors would be included in the experimentation design to investigate other sources of process variability.

5. Conclusion

This paper aimed at presenting a methodology for optimising process conditions for multiple quality criteria in µIM. Five processing parameters were investigated for their effect on part mass and mass variation. It was found that holding pressure followed by melt temperature and velocity were significant for part mass, whilst injection velocity alone was significant for mass variation. Hence the main significant effect differed between part mass and mass variation. Further, injection velocity was found to be a parameter of a different effect on the two responses, its effect proportional to mass variation but inversely related to part mass. Hence, for some micro-moulded components, attempting process optimization for part quality alone may lead to an unintended consequence of increases in mass variation.

Desirability functions were used to find a combination of factors to meet a specific mass requirement and to minimise variability simultaneously. The function produced a set of values that took into consideration the contradicting effect of injection velocity on both criteria. The suggested conditions were tested, where the average mass deviated by only 0.3% and the variability was better than what was predicted by the functions. Both responses were within the pre-set requirements and the method was shown to be useful in optimising multiple quality criteria.

References

[1] Mönkkönen K, Hietala J, Pääkkönen P, Pääkkönen EJ, Kaikuranta T, Pakkanen TT and Jääskeläinen T (2002) Replication of sub-micron features using amorphous thermoplastics. Polym Eng Sci 42: 1600-1608

[2] Shen YK, Yeh SL, Chen SH (2002) Three-dimensional non-Newtonian computations of micro-injection molding with the finite element method. Int Commun Heat Mass 29:643-652

[3] Zhao J, Mayes R, Chen G, Xie H, Chan P (2003) Effects of process parameters on the micro molding process. Polym Eng Sci 43:1542-1554

[4] Zhao J, Mayes R, Chen G, Chan PS, Xiong ZJ (2003) Polymer micromould design and micromoulding process. Plast Rubber Compos 32:240-247

[5] Ong NS, Koh YH (2005) Experimental investigation into micro injection molding of plastic parts. Mater Manuf Process 20:245-253

[6] Aufiero R (2005) The effect of process conditions on part quality in microinjection molding. ANTEC: Proc Annual Technical Conf (Boston, MA, 1-5 May 2005):36-40

[7] Sha B, Dimov S, Griffiths C, Packianather MS (2007) Micro-injection moulding: factors affecting the achievable aspect ratios. Int J Adv Manuf Technol 33:147-156

[8] Pirskanen J, Immonen J, Kalima V, Pietarinen J, Siitonen S, Kuittinen M, Mönkkönen K, Pakkanen T, Suvanto M, Pääkkönen EJ (2005) Replication of sub-micrometre features using microsystems technology. Plast Rubber Compos 34:222-226

[9] Sha B, Dimov S, Griffiths C, Packianather MS (2007) Investigation of micro-injection moulding: factors affecting the replication quality. J Mater Process Technol 183:284-296

[10] Griffiths C, Dimov S, Brousseau EB, Hoyle RT (2007) The effects of tool surface quality in micro-injection moulding. J Mater Process Tech 189:418-27

[11] Tosello G, Gava A, Hansen HN, Lucchetta G (2007) Influence of process parameters on the weld lines of a micro injection molded component. ANTEC: Proc Annual Technical Conf (Cincinnati, OH, 6-11 May 2007):2002-2006

[12] Dimov S, Menz W (ed.) (2008) Micro-injection moulding: surface treatment effects on part demoulding. 4M2008 Proc. 9th - 11th Sept. UK: Whittles Publishing.

[13] Jung W-C, Heo Y-M, Shin K-H, Yoon G-S, Chang S-H (2007) An experimatal study on micro injection paramaters. ANTEC: Proc Annual Technical Conf (Cincinnati, OH, 6-11 May 2007): 638-642

[14] Lee B-K, Hwang CJ, Kim DS, Kwon TH (2008) Replication quality of flow-through microfilters in microfluidic lab-on-a-chip for blood typing by microinjection molding. J Manuf Sci E-T ASME 130:0210101-0210108

[15] Xie L, Ziegmann G (2009) Influence of processing parameters on micro injection molded weld line mechanical properties of polypropylene (PP). Microsyst Technol 15:1427-1435

[16] Huang M-S, Li C-J, Yu J-C, Huang Y-M, Hsieh L-C (2009) Robust parameter design of micro-injection molded gears using a LIGA-like fabricated mold insert. J Mater Process Technol 209:5690-5701

[17] Antony J (2003) Design of experiments for engineers and scientists. Butterworth-Heinemann: Oxford

[18] Eriksson L, Johansson N, Kettaneh-Wold N, Wikstrom C, Wold S (2008) Design of experiments: principles and applications, 3rd edn. Umetrics, Umeå

[19] Del Vecchio RJ (1997) Understanding design of experiments: a primer for technologists. Hanser/Gardner Publications, Cincinnati

[20] Montgomery DC (2005) Design and analysis of experiments, 6th edn. Wiley, Hoboken, Great Britain

[21] Lahey JP, Launsby RG (1998) Experimental Design for Injection Molding. Launsby Consulting, Colorado Springs, CO

[22] Marson S, Attia UM, Allen DM, Tipler P, Jin T, Hedge J and Alcock JR (2009) Reconfigurable micro-mould for the manufacture of truly 3D polymer microfluidic devices. Proc CIRP Design Conf (Cranfield, UK, 30-31 March 2009):343-346

[23] Attia UM, Alcock JR (2009) An evaluation of process-parameter and part-geometry effects on the quality of filling in micro-injection moulding. Microsys Technol. Doi: 10.1007/s00542-009-0923-1

[24] Minitab Inc. Available at: www.minitab.com. Accessed 2009

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Attia, Usama M.

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