Multi-Objective Optimisation of Plastic Injection Moulding Process using Mould Flow Analysis and Response Surface Methodology

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Abstract
In the production of plastic components using injection moulding, concurrently maintaining a stable part weight and a high production rate remains a challenge. As a statistical tool, the response surface methodology was used in the present study to examine the effects of process parameters on part weight and production rate as responses of the production process. This was done in a bid to optimise the process parameters and obtain weight stability at high rates of production. The study took advantage of a validated numerical simulation using MoldFlow Insight to generate the input data required in the statistical analysis (response surface method). The influence of process parameters such as the mould temperature, the melt temperature, the packing time, and the packing pressure was studied using an analysis of variance. Results indicated that the packing time has an antagonistic impact on both responses, where an increase in packing time resulted in a high part stability, but a low production rate. The analysis of variance revealed that the part weight was more greatly affected by the packing time and packing pressure, but less so by the melt temperature and mould temperature. Real-scale injection testing using the optimal parameters producing the best trade-off between the part weight and production rate was performed to validate the efficiency of the optimisation procedure proposed in this work. The part weight and production rate predicted by the response surface methodology were in good agreement with the experimental observations, with relative errors less than 2.5%.

Keywords: Plastic injection moulding, Numerical simulation, Moldflow, Analysis of variance, Part weight, Production rate.

1- Introduction

Nowadays, competition in the fabrication of plastic products requires to produce high quality components in the shortest processing lead time. Injection moulding is considered as an efficient mass production technology, with the capacity to produce complex shape parts at high production rates with minimal resulting waste material. However, high production rates are generally detrimental to the quality of the product, which is dependent on several factors, including part geometry, material properties, mould characteristics, and process parameters (Meiabadi et al., 2013). Several research groups have developed and employed different approaches to meet geometrical and dimensional requirements, while minimizing defects in plastic products.

Computer-aided engineering (CAE) has been successfully used to numerically simulate the injection moulding stage while avoiding defects such as sinks, voids, dead zones, warpage, cracks, and weldlines (Meiabadi et al., 2017) . The analysis of variance (ANOVA) has also been used to quantify the weight of each process parameter on the quality of injected parts (Marwah et al., 2017). Recently, hybrid metaheuristic/numerical methods consisting of a combination of evolutionary algorithms, neural networks, and numerical simulation were used to optimise the process parameters in order to produce high quality injected parts with reduced defects such as shrinkage, warpage, and weldline. Spinal (2006) and Changyu et al. (2007) used a hybrid method integrating numerical simulation, neural networks, and evolutionary algorithms to reduce volumetric shrinkage. Chen et al. (2014, 2106) utilized a systematic optimisation method consisting of design of experiment methods, back propagation a neural network, a genetic algorithm, and a combination of particle swarm optimisation and genetic algorithms for multi-objective optimisation of warpage and part length. Chen et al. (2008) also employed another hybrid method combining the Taguchi method, the Davidon-Fletcher-Powell method, and back-propagation neural networks to optimise the quality of a product while weight was selected as the only product quality metric. Kurtaran et al. (2005) specifically proposed an optimisation method exploiting Moldflow, an artificial neural network, and a genetic algorithm to reduce warpage of a plastic bus ceiling lamp. In this study, the influence of mould temperature, melt temperature, packing pressure, pressure time, and cooling time on component warpage was simulated using Moldflow and validated by CMM measurements. These data were then implemented into a neural network which was combined with a genetic algorithm to define the optimum setting producing minimum warpage. Ozcelik et al. (2006) proposed a similar approach to minimize warpage in a thin shell plastic part. The impact of mould temperature, melt temperature, packing pressure, packing time, cooling time, runner type, and gate location on warpage was quantified using the Moldflow software, and the values were used as input factors in the Taguchi method for highlighting the critical process parameters. In this approach, a warpage model was built using a neural network (i.e., it was trained by the warpage data predicted via Moldflow simulations) as a prediction tool, and combined with a genetic algorithm to define the best process setting reducing the component warpage. The Design-Expert software was also successfully used by Rajalingam et al. (2011) to optimise injection moulding parameters, such as mould temperature, injection pressure, and screw rotation speed, to improve the dimensional accuracy of a plastic part. Martowibowo et al. (2017) focused on the initial setting of the injection press to define the optimised parameters producing the minimum cycle time, using a hybrid approach combining numerical simulation (Moldflow) with a genetic algorithm. Chen et al. (2013) combined numerical simulation and statistical approaches to minimize the warpage and shrinkage occurring during solidification of the part as well as volumetric shrinkage occurring at the ejection stage of the process, using the MoldFlow software and Taguchi method. A similar finite element model (using Moldflow) was used by Faiz et al. (2017) to simulate the plastic injection process and optimise the warpage value. Using the Taguchi method, Mehat and Kamaruddin (2011) demonstrated that injection time and melt temperature were the key parameters influencing the mechanical properties of injected products. Tutar and Karakus (2010) proposed an advanced numerical scheme combining a volume of fluid method with the finite volume method for the simulation of mould filling, using a single-cavity and a multi-cavity mould. The flow front advancement predicted with this approach was in good agreement with those obtained by Moldflow simulations and experimental tests for all mould cavities. In another vein, Abohashima et al. (2015) confirmed that the most common defects appearing in thin-walled containers (i.e., inverted label and incomplete plastic filling, which are specific to food packaging) could be minimized using the proper process parameters obtained by the Taguchi approach. Other works also focused on decreasing the weldline in injected parts, using different strategies. In this respect, Sedighi et al. (2017) determined the best gate position leading to the minimum weldline length via a neural network trained by Moldflow simulation results and a genetic algorithm. Also, Shayfull et al.

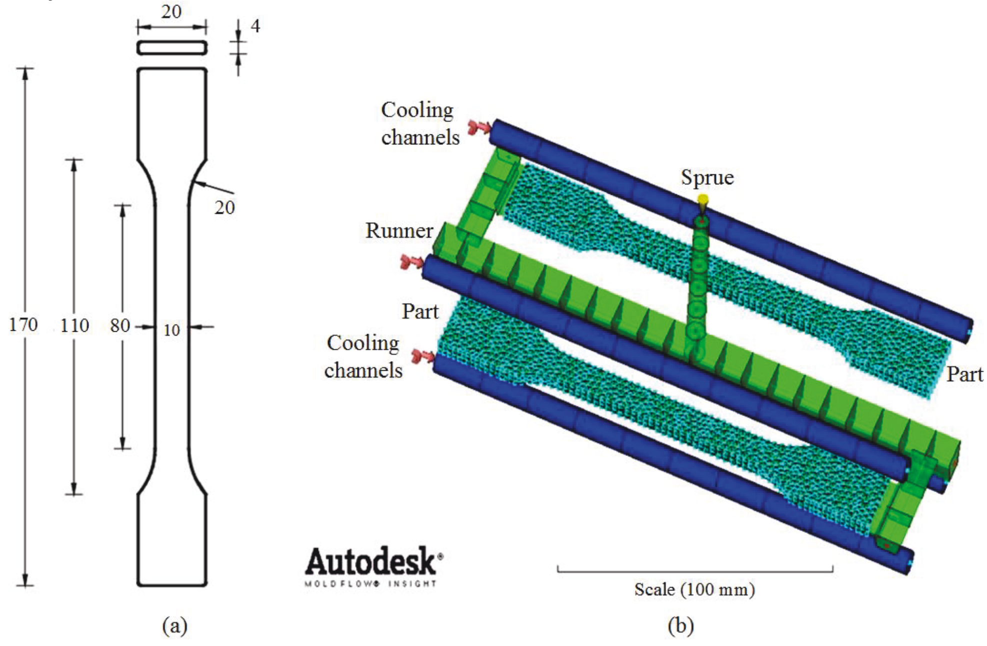
(2011) used the Taguchi method to highlight that melt temperature followed by cavity temperature, packing pressure, packing time, core temperature and filling time are respectively the most significant parameters affecting the weldline length.
Although the effectiveness of these approaches has been demonstrated for optimising injection moulding process parameters, most of the studies analysed only one output characteristic at a time (minimizing one or several defects separately). Therefore, the interaction of process parameters on the properties of the final product (i.e., multi-objective optimisation) has received very little attention in the literature. This work aims to optimise the process parameters of the plastic injection moulding process, using a response surface methodology and validated numerical simulation combination to determine the best trade-off between the nominal part weight and a high production rate.

2- Methodology

2.1 Numerical simulation of the injection process and model validation

Numerical simulations were performed using Moldflow Insight (Autodesk Inc.). The rectangular dogbone shape specimen illustrated in Fig. 1a was designed using CATIA software, and imported into Moldflow as a double-cavity mould with a rectangular gate and trapezoidal runner. The parts were meshed using a midplane mesh, as illustrated in Fig. 1b, where a sprue, runner, and cooling system are also visible. Each specimen contains 141,875 triangular elements with an edge length of 0.8 mm.

Figure 1 (a) Rectangular dogbone specimens, all dimension in mm; (b) general view of the double-cavity mould meshed in MoldFlow



The flow of the molten polymer inside the mould cavity is described by the conservation of momentum, mass, and energy (Eq. (1), (2), and (3)), which are discretized into finite elements and solved in Moldflow by the standard finite element method:

$$\frac{\delta \rho}{\delta t} + \nabla.(\rho V) = 0 \quad (1)$$

$$\rho \frac{DV}{Dt} = -\nabla P + \nabla.\tau + \rho g \quad (2)$$

$$\rho C_P \frac{DT}{Dt} = \nabla.(k\nabla T) + \tau{:}\nabla V + \beta T \frac{DP}{Dt} \tag{3}$$

where ρ, t, V, P, τ, g, k, C_p, β, and T are the fluid density, time, velocity vector, pressure, viscous stress tensor, gravitational acceleration vector, thermal conductivity, specific heat capacity, expansivity, and temperature, respectively. The plastic material in this study was PP 512MN10 provided by SABIC (Saudi Arabia). The polypropylene provides excellent flow properties during injection moulding, as well as a good combination of high impact strength and stiffness during service. It is widely used in vacuum cleaner housings, large size flower pots, foodstuff containers and ice cream containers, where good processability, high toughness, and low warpage are required. The properties of this polymer are listed in Table 1.

Table 1 PP 512MN10 material properties

Melt temperature	160°C
Specific heat	2.753 J/kg·°C
Thermal conductivity	0.18 W/m·°C
Melt density	0.90 g/cm^3
Solid density	1.089 g/cm^3
Shear modulus	640 MPa
Elastic modulus	2.034 MPa

Numerical simulation results were validated with real-scale injections, using a Krauss Maffei 150 C2 injection press and the moveable half of the mould illustrated in Fig. 2. The process parameters representing the typical values for the injection moulding of this material (reported in Table 2) were used in both numerical simulations and experimental testing (Meiabadi et al., 2013). The target part weight calculated by Moldflow was assessed at 17.71 g (i.e., calculated from the volume of the CAD model and the solid density of the material). Results presented in Table 2 confirm that the part weight and total cycle time obtained by simulation and experimentally are similar, with a relative difference below 4%, confirming that Moldflow can be used effectively to generate a database being implemented into Design-Expert V8 software for an analysis of variance.

Table 2 Validation of simulation results using typical process parameters

Process parameters						Outputs	Experimental results (real-scale injection)	Simulation results (Moldflow)	Relative difference
Melt temperature (°C)	Mould wall temperature (°C)	Packing time (s)	Packing pressure (MPa)	Injection speed (mm/s)	Cooling time (s)				
233	23	16.5	10	20	15	Part weight (g)	16.34	16.15	3.8%
						Total cycle time (s)	32.80	31.60	1.2%

Figure 2 Moveable half of the mould used for the validation of the numerical simulations

2.2- Response surface methodology

The Response surface methodology (RSM) was used to determine the relationships between the input variables and output responses of the injection moulding process. This approach aims to quantify the relationship between the input variables and output responses by using a minimum error (i.e., residual error) in the form of a mathematical model relating a response η with the *k* levels of controlled variables, as reported in Eq. (4) (Moradi et al., 2017):

$$\eta = f(x1, x2, \ldots, xk) + \mathcal{E} \quad (4)$$

where x is a control variable and $\mathcal{E}$ represents the random experimental error due to some unknown or uncontrollable variables. Formally, the response variable is defined by a second-order polynomial equation (Eq. (5)) as the response η is stated according to the input parameters (Moradi and Mohazabpak, 2017):

$$\eta = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i,j=1} \sum_{i<j} \beta_{ij} x_i x_j$$

(5)

where β_0 is a constant, β_i is a linear coefficient, β_{ii} is a quadratic coefficient, and β_{ij} is an interaction coefficient. In this work, the part weight and total cycle time are considered as the response variables (i.e., output responses), while the melt temperature, mould wall temperature, packing time, and packing pressure are selected as the independent variables (i.e., input variables). The total cycle time is an indication of the production rate (inversely proportional relation), calculated by the sum of the filling time, packing time, and cooling time during the plastic injection moulding stage. The part weight quantifies the stability of the process from part-to-part, and is simply measured using a precision balance. The response surface design is based on a central composite design full replication with four factors and three levels. In this approach, the coefficient for a given term represents the change in the mean response associated with a change in that specific term, while the other terms in the model are constant. The sign of the coefficient indicates the direction of the relationship between the term and the response. The size of the coefficient is usually used to assess the practical significance of the effect of that term on the response variable. The statistical significance of a given term is finally determined using the p-value (as reported in Table 5). Table 3 shows the values used for the three levels of independent variables, which were selected as low (-1), moderate (0), and high (1) values of process parameters implemented in designing the experiments. The specific values corresponding to each level were set based on the processing parameters recommended by Moldflow for the PP 512MN10.

Table 3 Levels of independent variables

Variables	Sign	-1 (low)	0 (medium)	1 (high)
Melt temperature (°C)	A	215	225	235
Mould wall temperature (°C)	B	20	35	50
Packing time (s)	C	10	25	40
Packing pressure (MPa)	D	10	25	40

3- Results and discussion

3.1 Results

The evolution of the part weight and total cycle time for 30 simulation runs (i.e., 30 different moulding conditions) is presented in Table 4. Based on the real-scale injection results, the filling time used for the numerical simulations was set at 0.1 s. Since the filling time is very small (i.e., can be neglected) and the cooling time is constant, the variation of the total cycle time (i.e., sum of filling, packing, and cooling times), depends only on the packing time, with no need for an analysis of variance since it depends only on one parameter.

Table 4 Design of experiments variables and numerical simulation results

	Independent variables (input)				Response variables (output)	
Run	Melt temperature (°C)	Mould wall temperature (°C)	Packing time (s)	Packing pressure (MPa)	Part weight (g)	Total cycle time (s)
1	215	50	10	10	15.62	25.0
2	215	20	10	40	15.87	25.0
3	235	20	10	10	15.62	25.0
4	225	35	25	40	16.47	40.0
5	225	35	25	25	16.32	40.0
6	225	35	25	10	16.15	40.0
7	235	50	40	10	16.12	55.0
8	235	50	10	10	15.43	25.0
9	215	20	40	40	16.50	55.0
10	235	20	40	40	16.50	55.0
11	225	35	25	25	16.32	40.0
12	225	35	10	25	15.64	25.0
13	215	35	25	25	16.32	40.0
14	215	50	10	40	15.66	25.0
15	225	35	25	25	16.32	40.0
16	225	35	25	25	16.32	40.0
17	215	50	40	10	16.12	55.0
18	225	50	25	25	16.28	40.0
19	235	20	10	40	15.66	25.0
20	225	35	25	25	16.32	40.0
21	215	20	40	10	16.19	55.1
22	235	35	25	25	16.32	40.1
23	225	35	40	25	16.32	55.1
24	235	50	10	40	15.47	25.0
25	235	20	40	10	16.19	55.0
26	235	50	40	40	16.44	55.1
27	225	35	25	25	16.32	40.1
28	215	20	10	10	15.82	25.1
29	225	20	25	25	16.35	40.1
30	215	50	40	40	16.44	55.0

The independent and response variables reported in Table 4 were then implemented into the Design-Expert V8 software (Stat-Ease Inc.) to perform an analysis of variance and highlight the parameters producing the most significant effects on the part weight. This statistical analysis was done on the assumption that the factors are fixed, not random, while the design is crossed, and not nested.

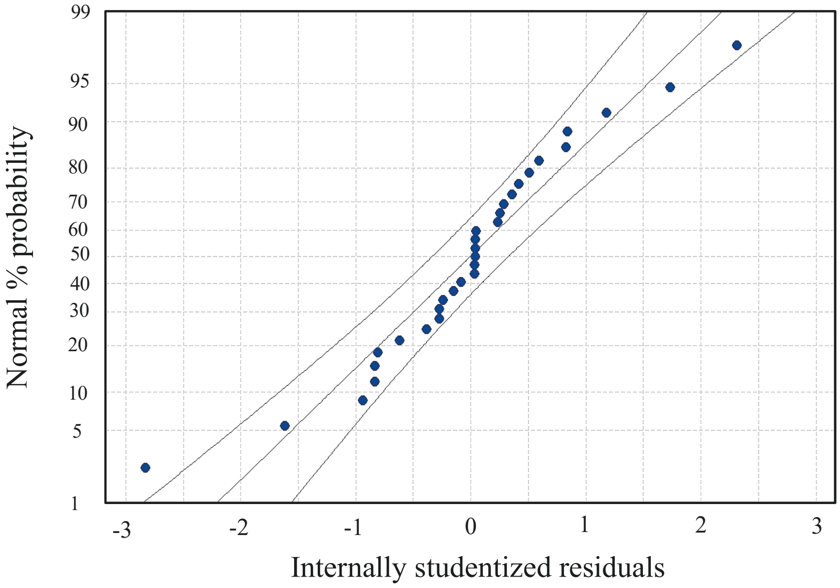
Table 5 presents the analysis of variance (ANOVA) for part weight. The first row (Model row) shows how much variations in the response are explained by the model, along with the overall model test for significance. The model is separated into individual terms in the next rows and tested independently. The Residual row shows how much variation in the response is still unexplained. Lack of Fit is the amount by which the model predictions deviate from observations. Pure Error is the difference between replicate runs. The Source column presents a meaningful name for the rows. The sum of the squared differences between the overall average and the amount of variation is explained by each row's source. Degrees of Freedom is the number of estimated parameters used to compute the source's sum of squares. Mean Square determines the sum of squares divided by the degrees of freedom. F Value compares the source's mean square to the residual mean square. The p-value is a probability that measures the evidence against the null hypothesis. Lower probabilities provide stronger evidence against the null hypothesis. If the p-value is very small (less than 0.05 by default), then the source is significant. Significant model terms probably have a real effect on the response. In this work, the p-values for all model terms are lower than 0.05, indicating that all of them are significant and must be used to derive the regression equation. Results reported in Table 5 also propose that the packing time with a 2905.93 F-Value and a packing pressure with a 257.14 F-Value are the two most significant variables controlling the part weight, while the melt temperature and the mould temperature produce no significant impact on this response variable.

Table 5 Analysis of variance (ANOVA) for part weight

Source	**Sum of Squares**	**Degrees of freedom**	**Mean Square**	**F Value**	**p-value**
Model	1.915E+006	8	2.393E+005	582.96	< 0.0001
A (Melt temperature)	18552.96	1	18552.96	45.19	< 0.0001
B (Mould temperature)	40734.71	1	40734.71	99.22	< 0.0001
C (Packing time)	1.193E+006	1	1.193E+006	2905.93	< 0.0001
D (Packing pressure)	1.056E+005	1	1.056E+005	257.14	< 0.0001
AC	20473.76	1	20473.76	49.87	< 0.0001
BC	7921.43	1	7921.43	19.29	0.0003
CD	47894.73	1	47894.73	116.66	< 0.0001
C^2	4.805E+005	1	4.805E+005	1170.39	< 0.0001
Residual	8621.84	21	410.56		
Lack of Fit	8621.84	16	538.87		
Pure Error	0.000	5	0.000		

Fig. 3 presents the normal probability plot of the residuals displaying the residuals versus their expected values, assuming that the distribution is normal. Because the points are close to the expected values (i.e., straight line), this plot confirms the assumption that the residuals are normally distributed. So, it is reasonable to assume that the error terms are normally distributed, which is a regression model condition.

Figure 3 Normal probability plot of the residuals

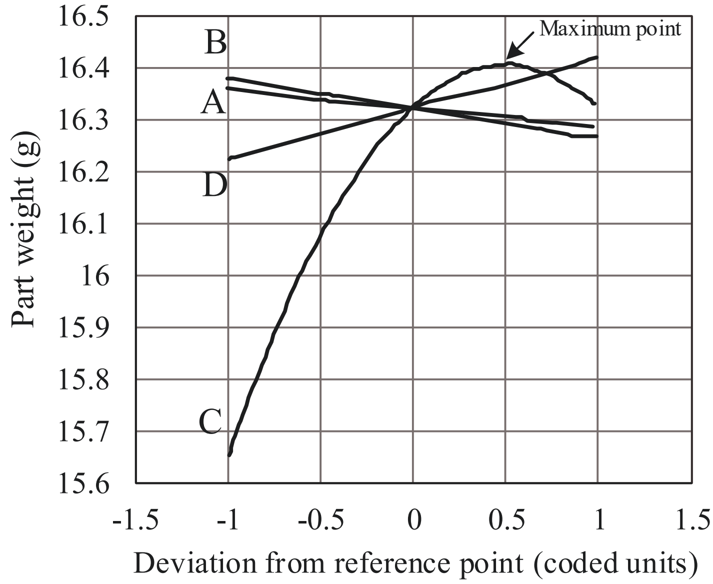


Of all the different transformations on the responses available in Design-Expert, the power transformation is the one that allows transformation to any power in the –3 to +3 range. However, a Box-Cox plot can propose an adequate power transformation to apply to response data. The regression equation drawn from this analysis of variance and reported in Eq. (6) was used to predict the part weight according to each independent variable:

$$(Part\ weight)^3 = 4347.9 - 32.1A - 47.6B + 257.5C + 76.6D + 35.8AC + 22.3BC + 54.7CD - 258.4C^2 \quad (6)$$

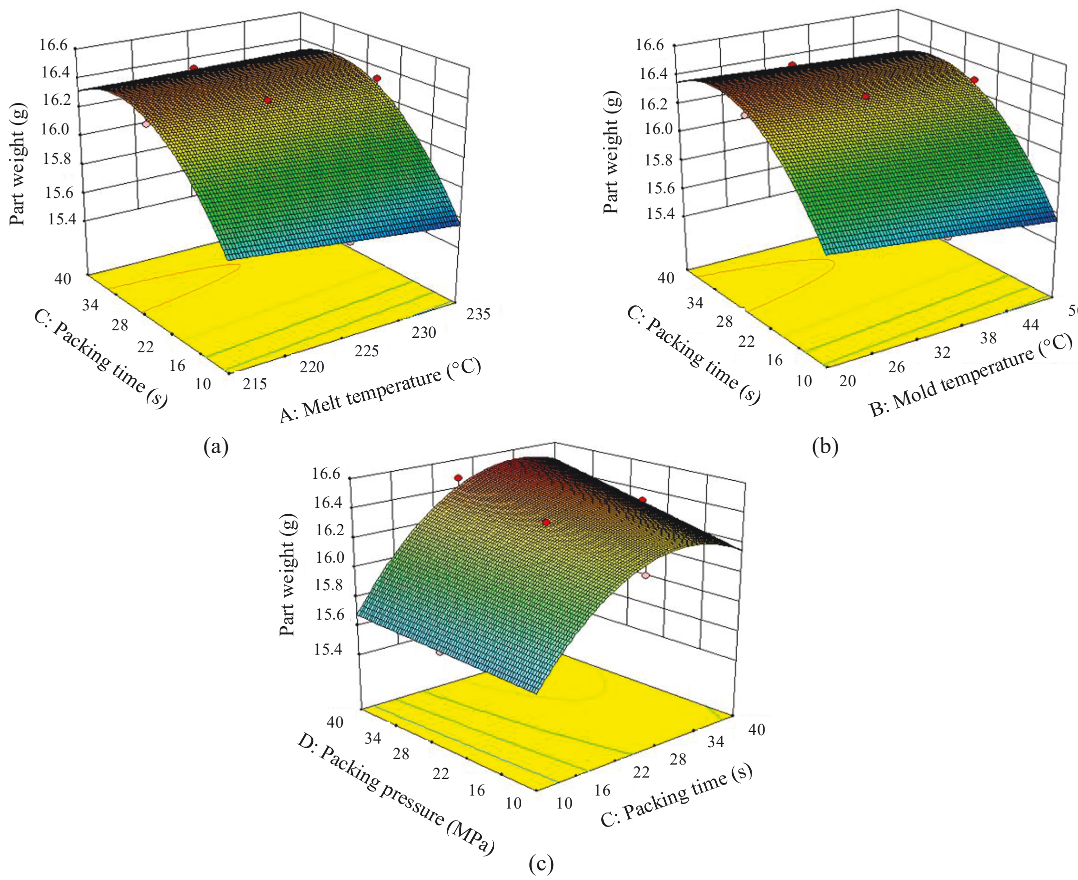
where A is the melt temperature, B is the mould wall temperature, C is the packing time, and D is the packing pressure. As stated above, the high values of the coefficients C and D in Eq. (6) produce significant changes on the part weight, and can be thus considered as the most significant control variables. For better clarity, the sensitivity of the part weight according to the four input variables was plotted in a perturbation plot (Fig 4) to visualize the effect of each factor on the output variable when other factors are kept constant. An increase in the packing time up to 0.5 coded unit (i.e., between 0 and 1 levels, corresponding in fact to 32 s) produces a significant change in the part weight when the other process parameters are set at the central point (melt temperature = 225°C, mould wall temperature = 35°C, and packing pressure = 25 MPa). Above this local maximum point indicated by a black arrow in Fig. 4, a further increase in packing time produces a slight decrease in part weight. Furthermore, line D corresponding to the packing pressure shows that an increase in packing pressure (when other process parameters are constant at the central point) also produces an increase in part weight, probably due to compression of an extra material into the mould with a higher packing pressure. Lines A and B depict a slight decrease in part weight with an increase in melt or mould temperature when other parameters are on central point values.

Figure 4 Perturbation plot of part weight (A-Melt temperature, B-Mould temperature, C-Packing time, D-Packing pressure)



Because the perturbation plot can only be used to quantify the effect of each variable, one at the time, the interaction of the process parameters on the part weight was quantified using the 3D surface plots illustrated in Fig. 5. Due to the high significance of the packing time depicted during the previous perturbation analysis, this input variable was combined with the three other process parameters to assess the interaction of parameters on the part weight. As predicted by the analysis of variance and the regression equation (low magnitude of the F-value and the coefficient for the parameters AC in Table 5 and Eq.(6)) the results reported in Fig. 5a confirm that an increase in packing time leads to a higher part weight regardless of the melt temperature. In this respect, a higher packing time in fact corresponds to the hydraulic pressure being maintained for a longer period, resulting in small changes in the pressure curve and no significant fluctuations in the part weight. The 3D surface plot presented in Fig. 5b confirms that the part weight is significantly affected by the packing time regardless of the mould temperature. This confirms that as long as the polymer is in molten state (i.e., $T > 160°C$), the mould temperature is not a competitive parameter driving the part weight, but could be taken into account for the optimisation of the cycle time, where a higher mould temperature may lead to a decrease in the production rate. Finally, and as expected by the ANOVA (see F-value and coefficient of CD parameters in Table 5 and Eq. (6)), a simultaneous increase in packing time and packing pressure leads to a higher part weight, as reported in Fig. 5c.

Figure 5 Surface plots showing the interaction of (a) packing time and melt temperature, (b) packing time and mould temperature, and (c) packing time and packing pressure on part weight



4- Multi-objective optimisation

It is well accepted that the part weight and production rate (closely related to total cycle time) are two relevant quality indexes in plastic injection moulding, where the objective is to attain the desired part weight in the shortest total cycle time. Since the total cycle time is calculated as the sum of the packing time (variable), cooling time (constant), and filling time (very low, therefore negligible), minimizing this process parameter corresponds ultimately in minimizing the packing time. However, and as demonstrated above by the analysis of variance, the packing time is the main process parameter influencing the part weight. Therefore, it seems that it is not possible to achieve the desired weight in the shortest packing time. This challenge can be overcome using a higher packing pressure to counterbalance the consequences of minimizing the packing time. Before performing the statistical optimisation using the Design-Expert software (i.e., obtaining an optimal point and desired objectives), the range of input parameters was defined according to the values reported in Table 6, where the target part weight (17.71 g) should be reached within the minimum packing time. The influence of the packing time on the part weight illustrated in Fig. 5 was compensated by an increase in the packing pressure up to 100 MPa in the optimisation criteria. The optimised process parameters producing the desired part weight while reducing the total cycle time are reported in Table 7. The part weight and cycle time predicted by the response surface methodology (RSM) approach were validated with real-scale injections using the process parameters reported in Table 7 and the same Krauss

Maffei 150 C2 injection press and the mould illustrated in Fig 2. RSM predictions and experimental results reported in Table 7 are similar (with a relative difference below 2.3%), confirming that the regression equation is accurate, the optimisation procedure is viable, and the numerical simulations are reliable.

Table 6 Range of optimisation criteria

Parameters	Name	Goal	Lower limit	Upper limit
Input parameters	Melt temperature	within the range*	215	275
	Mould temperature	within the range*	20	50
	Packing time	minimize	40	60
	Packing pressure	within the range*	10	100
Output parameters	Part weight	is target = 17.71	15.493	17.713

*: i.e., range based on practical recommendations for this polymer

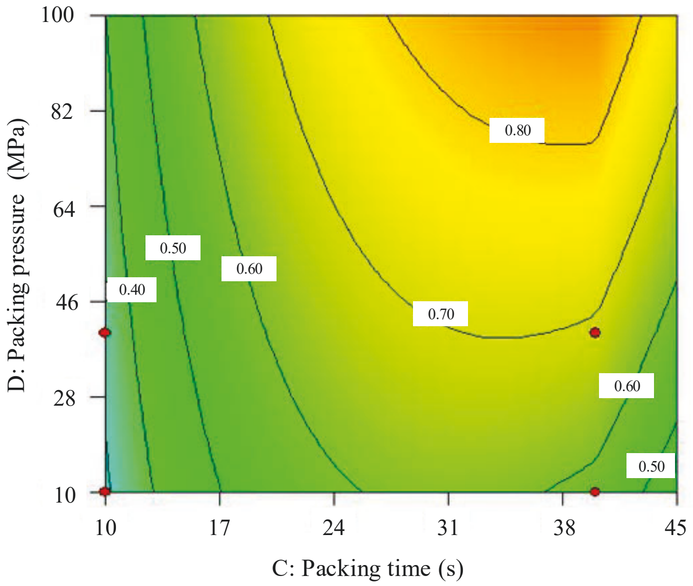
Table 7 Validation of the RSM predictions using real-scale injection

Optimised process parameters				Output parameters	RSM prediction	Real-scale injection	Relative difference
Melt temperature (°C)	Mould wall temperature (°C)	Packing time (s)	Packing pressure (MPa)				
273	20	40	100	Part weight (g)	17.15	17.52	2.1%
				Total cycle time (s)	50.04	51.20	2.3%

Fig. 6 demonstrates a desirability plot quantifying how the packing time and packing pressure influence the optimisation criteria (achieving the target part weight while reducing total cycle time concurrently). The envelop demonstrating the higher desirability at 80% (dark orange zone in Fig. 6) is obtained for a packing pressure ranging from 90 to 100 MPa and a packing time of 30 to 40 s.

3.1 Discussion

Figure 6 Effects of packing time and packing pressure on desirability



5- Conclusions

In the present research, a numerical simulation and a statistical analysis were combined to concurrently achieve part weight stability and increase the production rate of a PP 512MN10 part obtained by the injection moulding process. Following a first validation step using real-scale injections, Moldflow software was used to simulate the part weight and the cycle time for different process parameters, such as the mould temperature, the melt temperature, the packing time, and the packing pressure, based on a design of experiments obtained by a response surface methodology (simulating 30 moulding conditions). This database was then implemented into the Design-Expert software to perform an analysis of variance and propose a regression model to highlight the process parameters producing the most significant effect on the part weight.

Results demonstrated that the packing time is the most significant process parameter influencing both part weight and total cycle time. Simulation results also confirmed that the total cycle time could be accurately assessed by taking into account only the packing time and the cooling time (where cooling time was set constant for all tests). Therefore, a higher packing pressure and, to some extent, a longer packing time, could be used to attain the desired part weight in a reasonable total cycle time. The response surface methodology was used successfully to determine the optimal process parameters producing the desired part weight and lower cycle time. A second validation step using real-scale injections confirmed that the two output variables predicted by the response surface methodology were similar to those obtained by experiments, with a relative difference below 2.3%. This work confirms that the optimisation of process parameters can be realized at low cost and at reduced time using a combined approach involving numerical simulation, statistical analysis, and only few experimental validations.

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