MECHANICAL ENGINEERING | RESEARCH ARTICLE

Multi response optimization of injection moulding process parameters of polystyrene and polypropylene to minimize surface roughness and shrinkage’s using integrated approach of S/N ratio and composite desirability function

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Abstract: The present study is intended to optimize and develop a prediction model for horizontal injection moulding process parameters. The processing materials are polystyrene (PS) and polypropylene (PP), while the final products are cups. The mould material used is aluminum alloy 6061-T651. The process parameters investigated are injection temperature, injection pressure, injection speed and mould temperature while the response variables are surface roughness, shrinkage inflow and cross-flow directions. Taguchi orthogonal array L9 is designed for experimental runs, while the levels are defined based on screening experiments. For optimization of process parameters, an integrated approach of signal to noise (S/N) ratio and composite desirability function is applied. The results show that injection temperature has a significant effect on surface roughness, shrinkage inflow and cross-flow directions for both polystyrene and polypropylene. Injection pressure has

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PUBLIC INTEREST STATEMENT

Injection moulding is a process mostly used for making similar polymer parts in the mould. In this process, the molten polymer is injected in the mould with certain pressure and speed to adopt the shape of the mould. Both materials and process parameters play an essential role in making high-quality products. In this study, the process parameters of two materials, namely Polystyrene (PS) and Polypropylene (PP), are optimized using an integrated approach for a mould made of aluminum alloy. The relationship between the process parameters and responses are studied through surface plots. The results show that injection temperature has a significant effect on surface roughness, shrinkage inflow and cross-flow directions for both materials. The results provide useful technical information on how the injection temperature and pressure has a significant effect on surface roughness and shrinkage in parallel flow and cross-flow direction of the manufactured parts. This study can be used as a guide to the different injection moulding process industries.
a significant effect on surface roughness and shrinkage in parallel flow direction for PS, while for polypropylene PP it has a significant effect on surface roughness and shrinkage in cross-flow direction. The optimal process parameters identified for PS are injection temperature at 533.15 K, injection pressure at 60 MPa, injection speed at 80 mm/s and mould temperature at 313.15 K. While for PP the optimal process parameters are injection temperature at 513.15 K, injection pressure at 60 MPa, injection speed at 70 MPa, mould temperature at 313.15 K. The novelty of this paper lies by optimizing injection moulding process parameters to minimize surface roughness and shrinkages using proposed integrated approach for the said mould.

Subjects: Industrial Engineering & Manufacturing; Mechanical Engineering; Materials Science

Keywords: Injection moulding; polystyrene; polypropylene; process parameters optimization; signal to noise ratio; composite desirability function

1. Introduction
Injection moulding is a process mostly used for making similar polymer parts from the mould. In this process, the molten polymer is injected in the mould with certain pressure and speed to adopt the shape of the mould (Singh & Verma, 2017).

Both the material used for making the mould and process parameters play an important role in making high-quality products. In order to produce high-quality product within no time, the process parameters need to be optimized (Kashyap & Datta, 2015). The quality of the product is based on strength, warpage, durability, surface roughness, aesthetics etc. which is influenced by the process conditions. In injection moulding, the process conditions include injection pressure, holding pressure, cooling time, injection speed, injection temperature and mould temperature etc. (Zhil’tsova et al., 2009).

Optimized process parameters produce high-quality products in less time. But getting optimized parameters is a difficult task that depends on the experience of an operator (Khosravani & Nasiri, 2019). The products are made from polymers that have different behaviours depending on the type of monomer. Usually, the conditions for producing the polymers are selected based on a literature study, and then some of the conditions are chosen on the trial and error method. But the trial and error method takes a long time and is costly. For the analytical approach of finding optimized process parameters, many equations were developed, but they could not give a reliable solution because of the complexity of the injection moulding process. That is why researchers have tried hard to introduce different optimization techniques (Fan et al., 2003). The literature discussed in the following section will summarize the previous work done by researchers on the optimization of process parameters for injection moulding using different materials.

Prathabrao et al. (2019) have optimized the injection moulding parameters for cemented tungsten carbide and tantalum carbide on the basis of shrinkage and warpage. The parameters considered during the research were grain growth inhibitor, injection speed, injection temperature and injection pressure. The optimum level obtained was 0.8 wt.% and 1.2 wt.% grain growth inhibitor, 145 °C injection temperature, 45 % and 55 % injection pressure and 40 % injection speed for minimum shrinkage and warpage. Miranda & Nogueira (2019) have developed a simulation system to study the impact of different moulds on the efficiency of injection moulding of polystyrene polymer. In one mould, vents were added while the other mould was left without a venting system. The simulation results showed that the process efficiency was greatly increased when the venting system was included by reducing the time by about 35 %, and waste generation was reduced from 65 % to 1 %. Feng & Zhou (2019) have designed an automated system based on
hybrid RBF and MOGA to achieve a reduction in shrinkage, warpage and weld line. The process parameters considered for optimization in this research were cooling time, melt temperature, mould temperature, packing time and pressure. The designed system was then implemented to injection moulding process of a thin walled automobile air conditioner. The results showed accuracy in providing the optimal solution, and due to automation, the dependencies on engineers and experts were decreased in optimal design.

Maged et al. (2019) have implemented a methodology of six sigma called DMAIC to injection moulding process in order to eliminate the factors affecting the quality of the product. As a result, the cost of rejection has been reduced by 45 %, while the quality or acceptance has been increased from 4.06 to 4.5 sigma level. Rathore et al. (2019) have optimized the process parameters for the microinjection moulding process by considering the number of pores and shrinkage as response variables in making a V-shaped medical component. The parameters studied in this research were Injection speed, packing pressure, mould and melt temperature. The objective of the research was to reduce the shrinkage and number of pores. The results have shown that with the increase in packing pressure, the number of pores has been reduced by 10 %, and ~4.8 % reduction has been achieved with the increase in melt temperature. The optimum level obtained was 1000 bar packing pressure and 210 °C melting temperature. Park et al. (2019) have presented a case study to reduce the cooling time and cycle time in the injection moulding process. They compared the traditional way of cooling using straight drilled cooling channels with the new cooling channels developed using 3D printing. As a result, a 50 % reduction has been achieved with the use of newly developed cooling channels. Alvarado-Iniesta et al. (2019) have proposed, for the first time, a multi-objective and many-objective optimized model for the injection moulding process. To achieve this objective Pareto Explorer method was implemented on a model with seven objectives to support decision making in selecting plastic gear. The complete model was studied with four different scenarios, and each scenario gave a better result than the previous one. Li et al. (2019) have used a combination of Taguchi, response surface methodology and NSGA II for the optimization of injection moulding process parameters for composites in a multi-objective optimization problem. The objectives were to reduce the warpage, shrinkage and residual stresses considering fibre content and fibre aspect ratio along with injection parameters cooling time, melting temperature and injection pressure. The results showed that fibres parameters have a great impact on the warpage and residual stress. The optimum level obtained was 20% fibre content, 30 fibre aspect ratio, 240 °C melting temperature, 70 MPa injection pressure and 25 s cooling time. Ogorodnyk et al. (2019) have used two statistical methods named Information gain and relief to choose significant parameters in thermoplastic injection moulding. A total of 47 parameters were considered for the study. As a result of the study, the parameters got high marks in both the methods are cushion size after holding pressure followed by the smallest size of the cushion, average cushion value, tool and barrel temperature and holding & backpressure. Mukras et al. (2019) have worked on the optimization of process parameters of injection moulding using a genetic algorithm. Seven parameters were optimized on the basis of shrinkage and warpage, which include injection pressure, mould and melt temperature, injection speed, packing pressure, packing and cooling time. Two relationships were made from the objective functions and process parameters. The results showed a worthy trade-off between shrinkage and warpage. The optimum level obtained was 200 °C melt temperature, 15 °C mould temperature, 60 mm/s, 800 bar injection pressure, 400 bar packing pressure, 30 s cooling time, 9 s holding time. Wang et al. (2019) have used Taguchi design for the optimization of micro injection moulding parameters for double concave structures to reduce shrinkage. The parameters considered were melt temperature, injection speed and mould temperature. The results showed that melt temperature has the highest effect on the shrinkage, followed by injection speed and mould temperature, respectively. The optimal level obtained was 240 °C melt temperature, 90 °C mould temperature, 30 mm/s injection speed.

Song et al. (2018) have investigated the impact of the process parameters of injection moulding during the fabrication of polymer microfluid chip made of a porous array. The parameters considered during the process were mould temperature, cooling time, melt temperature, packing pressure, injection speed and injection pressure. They have used a single factor
experiment during the process to study the uniform dimensions. The results showed that mould temperature and injection pressure have a high effect as compared to other parameters. With the increase in melt temperature, the thickness between the movable and fixed template is decreased, which shows improvement in uniformity. Han et al. (2018) have used Taguchi design to optimize the injection moulding process parameters during the manufacturing of automobile plastic airbag housing. The objective was to reduce the weight by replacing steel housing with plastic housing. The optimal process parameters considered for this process were injection time 3.2 s, holding pressure 90 MPa, holding time 8 s, cooling time 35 s, melt temperature 245 °C, cavity plate cooling temperature 20 °C and core plate coolant temperature 35 °C. The results showed that the melt temperature has the highest impact on the deformation, which is reduced to 0.2 mm and got a 23% reduction in weight. Abbas-Abadi (2020) investigated the mechanism of degradation, the share of each mechanism and the needed activation energy for different polymers to reduce the polymeric wastes sent to landfills. Malewska & Prociak (2020) analyzed the formation of Porous polyurethane (PUR) and polystyrene (PS) composites by the co-expansion process.

Table 1 shows the parameters and response variables considered by various authors during the optimization of injection moulding process parameters (Bensingh et al., 2019; Chen et al., 2016; Gao et al., 2018; Khamsi et al., 2019; Kitayama et al., 2019; Kumar et al., 2016; López et al., 2016; Oliaei et al., 2016; Sánchez-Sánchez et al., 2018; Singh et al., 2018; Zhang et al., 2016; Zhao et al., 2015). It is clear from the table that certain parameters like filling time, back pressure, holding time, and holding pressures are not important parameters and are not considered. Different materials and techniques are considered by various authors in their research. In this research work, the Taguchi optimization technique and ANOVA are used to study the surface roughness quality of polystyrene and polypropylene material.

The current study deals with the multi-response optimization of injection moulding process parameters for polystyrene (PS) and polypropylene (PP) using the proposed integrated approach of S/N ratio and composite desirability function. The process parameters investigated are injection temperature, injection pressure, injection speed and mould temperature while the response variables are surface roughness, shrinkage inflow and cross-flow directions. From the literature review, it is concluded that such responses are not optimized simultaneously for such a combination of process parameters for the mould of aluminum alloy 6061-T651. Therefore, the present study concentrates on the optimal selection of process parameters to minimize the surface roughness and shrinkages in parallel and cross-flow directions during injection moulding of PS and PP parts. Prediction models are developed for both PS and PP based on modelled parameters using best subset regression analysis, i.e. coefficient of determination (R²), adjusted R², predicted R², and Mallows Cp. The prediction model is validated using confirmation tests. The results show that the prediction models developed in the present study are reliable in performance and provided a better estimation of responses. Finally, surface plots are plotted for modelled parameters to study their effect on surface roughness, shrinkage in parallel flow and cross-flow direction.

The rest of this paper is organized as follows: Section 2 describes the materials and methods used in the study that includes the experimental setup, experimental design, optimization methodology and Taguchi orthogonal array design. Section 3 describes the results obtained by applying various approaches. In this section, the optimization of injection moulding process parameters is discussed. In addition to that, the effect of process parameters on responses, development of prediction model and the relationship among responses and modelled process parameters are also studied through surface plots. These surface plots are for surface roughness, shrinkage in flow direction and shrinkage in cross-flow direction. Finally, Section 5 summarizes and concludes the paper.

2. Materials and methods
This section presents the material and methodology used throughout the process.
Table 1. Contribution towards optimization of injection moulding process parameters

| Parameters considered | Authors               | A | B | C | D | E | F | G |
|-----------------------|-----------------------|---|---|---|---|---|---|---|
|                       | Joseph et al. [21]    |   |   |   | ● |   |   |   |
|                       | Kumar et al. [22]     |   |   |   |   | ● |   |   |
|                       | Oliaei et al. [23]    |   |   |   |   |   |   | ● |
|                       | Sanchez & Avila [24]  |   |   |   |   |   |   |   |
|                       | Singh & Verma [25]    |   |   |   |   |   | ● |   |
|                       | Chen et al. [26]      |   |   |   |   |   | ● |   |
|                       | Gao et al. [27]       |   |   |   |   | ● |   |   |
|                       | Khamis et al. [28]    |   |   |   |   | ● |   |   |
|                       | Kitayama et al. [29]  |   |   |   |   |   |   | ● |
|                       | Zhang et al. [30]     |   |   |   |   |   |   |   |
|                       | Zhao et al. [31]      |   |   |   |   | ● |   |   |
|                       | Lopez et al. [32]     |   |   |   |   |   |   |   |
|                       | Present research study| ● |   |   |   |   |   |   |

| Parameters considered | Authors               | H | I | J | K | L | M | Applied methods                                      | Response studied                      |
|-----------------------|-----------------------|---|---|---|---|---|---|------------------------------------------------------|---------------------------------------|
|                       | Joseph et al. [21]    |   |   |   | ● |   |   | Hybrid artificial neural networks and particle swarm optimization | Radius of curvature, Waviness, Surface roughness |
|                       | Kumar et al. [22]     | ● |   |   |   |   |   | Pilot study, theoretical model                       | Fracture                              |

(Continued)
Table 1. (Continued)

| Authors                  | Parameters considered | Applied methods                  | Response studied            |
|--------------------------|-----------------------|-----------------------------------|-----------------------------|
| Oliaei et al. [23]       | ●                     | Taguchi, ANOVA and Artificial Neural Network | Warpage and Shrinkage       |
| Sanchez & Avilaa [24]    | ●                     | Taguchi method                    | Tensile strength            |
| Singh & Verma [25]       | ●                     | Taguchi and desirability function hybridization | Cycle time and warpage      |
| Chen et al. [26]         | ●                     | Taguchi method, RSM, and hybrid GA-PSO | Length and Warpage          |
| Gao et al. [27]          | ●                     | novel optimization method          | Mobile phone shell          |
| Khamis et al. [28]       | ●                     | Taguchi method                    | Strength                     |
| Kitayama et al. [29]     | ●                     | Multi objective design optimization | Weld line reduction and short cycle time |
| Zhang et al. [30]        | ●                     | ANOVA, Neural Network, Particle Swarm optimization | Warpage and clamping force |

(Continued)
| Authors          | H | I | J | K | L | M | Applied methods                                                                 | Response studied                |
|------------------|---|---|---|---|---|---|---------------------------------------------------------------------------------|--------------------------------|
| Zhao et al. [31] |   | ● |   |   | ● | ● | Improved efficient global optimization (IEGO) algorithm, Non dominated sorting based genetic algorithm II (SNGA – II) | Warp, shrinkage, sink marks     |
| Lopez et al.[32] | ● | ● |   |   |   |   | ANOVA                                                                            | Weight and Pressure             |
| Present research study | ● |   |   |   |   |   | Proposed Integrated approach of S/N ratio and composite desirability function | Surface roughness, shrinkage in parallel flow and cross-flow direction |

● Represents various parameters considered,
A-Filling time, B-Injection Pressure, C-Injection Speed, D-Back Pressure, E-Holding Pressure, F-Holding Time, G-Cooling Time, H-Injection Temperature, I-Packing Pressure, J-Screw Rotation Speed, K-Mould Temperature, L-Packing Time, M-Melt Temperature.
2.1. Experimental setup

The experiments were conducted on a horizontal injection moulding machine, and mould was fabricated from aluminum alloy 6061-T651. The schematic and actual moulds are shown in Figures 1 and 2, respectively. The processing material in injection moulding is polystyrene (PS) and polypropylene (PP).

The horizontal type of injection moulding machine (NINGBO JETEL, JTL 900), as shown in Figure 3 was used for the production of cups. All the experiments and parametric study was performed on a horizontal injection moulding machine.
Figure 4 shows the cups produced from polystyrene and polypropylene by injection moulding. In a parametric study, the response variables such as surface roughness and shrinkages are obtained from these cups.

For this study, four process parameters, namely injection temperature, injection pressure, injection speed, and mould temperature, are selected for PS and PP. The response variables are surface roughness, flow and x-flow shrinkage.
2.2. Optimization methodology

For optimization, an integrated approach of the Taguchi signal to noise (S/N) ratio and composite desirability function is applied in the present study. Taguchi based S/N ratio enables to identify the optimal levels of injection moulding process parameters for the responses separately. However, simultaneous optimizations of process parameters are highly desirable in practice. Therefore, S/N ratio for measured responses is integrated with the composite desirability function to optimize the process parameters. This technique is selected because, compared to other optimization techniques, this optimization technique doesn’t allow response clashing (Gupta et al., 2020). Figure 5 shows the methodology followed for the optimization of process parameters of injection moulding.

During the first stage of optimization S/N ratios of individual responses are calculated. S/N ratio reduces variability in the process by minimizing the effect of noise factors (uncontrollable factors) (Fan et al., 2003; Feng & Zhou, 2019; Singh et al., 2016). It measures the quality characteristics of the responses that deviate from the desired value (Fan et al., 2003; Feng & Zhou, 2019; Singh et al., 2016). For optimal levels of process parameters, higher values of S/N ratio are always selected. As the present study is concerned with minimization of responses, i.e. to reduce surface roughness, shrinkages in parallel flow and cross-flow direction, thus, the smaller-the-better quality
characteristic of S/N ratio is applied. The smaller-the-better quality characteristic of the S/N ratio is calculated using Equation (1).

\[
\frac{S}{N} = -10 \log_{10} \left[ \frac{1}{r} \left( \sum_{i=1}^{r} y_i^2 \right) \right]
\]  

(1)

Where \( y_i \) is the measured value of the ith response, \( r \) is the number of times the ith experiment is repeated (in the present study is \( r = 1 \)).

The second stage starts with a desirability function analysis of S/N ratios. The main purpose is to convert the multi-response problems into a single response problem (Singh et al., 2017), and therefore, it is termed as composite desirability function (Zhao et al., 2015). As higher values of S/N ratio are desirable; therefore, the-larger-the better desirability function is applied (Singh et al., 2017). The-larger-the better desirability function desirability is expressed in Equation (2).

\[
d_i = \begin{cases} 
0, & y_i \leq y_{\min} \\
\left( \frac{y_i - y_{\min}}{y_{\max} - y_{\min}} \right)^t, & y_{\min} \leq y_i \leq y_{\max}, t \geq 0 \\
1, & y_i \geq y_{\max} 
\end{cases}
\]

(2)

Where \( d_i \) is the individual desirability value of the response, and \( t \) is the weight assigned to desirability value, which is usually user-defined. It ranges from 0.1 to 10. Larger values of \( t \) are specified if it is highly desirable \( y_i \) to increase abruptly above \( y_{\min} \). Therefore, in the present study, “\( t \)” is assigned a value of 1.

In the third stage, the individual desirability values of S/N ratios are combined using the geometric mean, as expressed in Equation (3).

\[
D = (d_1 \times d_2 \times d_3 \times \ldots \times d_n)^\frac{1}{n}
\]

(3)

The range for \( D \) is between 0 and 1, and higher values of \( D \) are more favourable. The purpose of the geometric mean is that, if any of the responses have individual desirability value of zero (means the response variable is unacceptable) thus, it makes the composite desirability zero (\( D = 0 \)), i.e. the overall product is unacceptable (Derringer & Suich, 1980).

Finally, the optimal process parameters for the combined responses are obtained based on mean composite desirability values determined for S/N ratios at each level for individual factors. The optimal levels obtained are validated by experimental runs, and the performance is evaluated based on predicted values of composite desirability values using Equation (4).

\[
\mu_{\text{optimal}} = \mu_{\text{mean}} + \frac{8}{9} \sum_{i=1}^{p} (\mu_i - \mu_{\text{mean}})
\]

(4)

Where \( \mu_{\text{mean}} \) is the overall mean of composite desirability, \( p \) is a number of process parameters, \( \mu_i \) is the mean values of composite desirability at optimal levels.

### 2.3. Taguchi orthogonal array design

To design a matrix for experimental runs, it is important to set levels for process parameters. Therefore, the levels are identified based on screening experiments and are tabulated in Table 2 for PS and in Table 3 for PP. Experimental runs are designed based on Taguchi orthogonal array design. Taguchi orthogonal array of L9 is selected for PS and PP, as shown in Table 4. The main purpose of choosing this design is to reduce experimental runs and the cost of experimentation.
Surface roughness is measured with Mitutoyo profilometer surface roughness tester SJ-201, as shown in Figure 6.

Shrinkage is measured based on ISO-294-4 standard. Shrinkage of injection moulded parts is defined in Figure 7. It is the relative difference between the final part dimensions and the mould dimensions. It varies with material type, a direction in which the molten materials exit the gates and enters the mould and cross-flow (transverse) direction. Shrinkage inflow (parallel) direction can be calculated by Equation (5).

\[ S_f = \frac{L_m - L_p}{L_m} \]  

(5)

Where \( L_m \) is mould cavity length, \( L_p \) is the length of a part after cooling.

In cross-flow (x-flow) direction the mould shrinkage can be calculated by Equation (6)

\[ S_t = \frac{W_m - W_p}{W_m} \]  

(6)

Where \( W_m \) is mould cavity width, \( W_p \) is the width of the part after cooling.

The surface roughness and shrinkage (flow and x-flow) values obtained for each experimental runs are shown in Table 4. Analysis of variance (ANOVA) is performed to evaluate significant control parameters. A prediction model is developed using Taguchi based regression model for PS and PP. The model is assessed using ANOVA. Finally, by experimental tests, the model is validated.

| Table 2. Parameters and their levels considered for Polystyrene (PS) |
| --- |
| **Levels** | **Symbols** | **Level 1** | **Level 2** | **Level 3** |
| Parameters |  |  |  |  |
| Injection Temperature (K) | T | 513.15 | 523.15 | 533.15 |
| Injection Pressure (MPa) | P | 40 | 50 | 60 |
| Injection Speed (mm/s) | S | 70 | 80 | 90 |
| Mould Temperature (K) | M | 313.15 | 318.15 | 323.15 |

| Table 3. Parameters and their Levels considered for Polypropylene (PP) |
| --- |
| **Levels** | **Symbols** | **Level 1** | **Level 2** | **Level 3** |
| Parameters |  |  |  |  |
| Injection Temperature (K) | T | 493.15 | 503.15 | 513.15 |
| Injection Pressure (MPa) | P | 40 | 50 | 60 |
| Injection Speed (mm/s) | S | 70 | 80 | 90 |
| Mould Temperature (K) | M | 313.15 | 318.15 | 323.15 |
Table 4. Taguchi orthogonal array L9 design with measured responses for both polystyrene and polypropylene

| Exp runs | T (K) | P (MPa) | S (mm/s) | M (K) | PS | PP | PS | PP | PS | PP |
|----------|-------|---------|----------|-------|----|----|----|----|----|----|
|          |       |         |          |       | Ra (μm) | S.F(%) [cm/cm] | S.XF (%) [cm/cm] |       |     |     |     |
| 1        | 1     | 1       | 1        | 1     | 0.541 | 0.775 | 0.857 | 0.952 | 1.231 | 1.211 |
| 2        | 1     | 2       | 2        | 2     | 0.435 | 0.651 | 0.702 | 0.823 | 1.175 | 1.155 |
| 3        | 1     | 3       | 3        | 3     | 0.373 | 0.542 | 0.634 | 0.612 | 1.094 | 1.074 |
| 4        | 2     | 1       | 2        | 3     | 0.312 | 0.485 | 0.514 | 0.444 | 1.012 | 0.992 |
| 5        | 2     | 2       | 3        | 1     | 0.242 | 0.318 | 0.407 | 0.337 | 0.975 | 0.955 |
| 6        | 2     | 3       | 1        | 2     | 0.211 | 0.285 | 0.355 | 0.268 | 0.915 | 0.861 |
| 7        | 3     | 1       | 3        | 2     | 0.141 | 0.188 | 0.313 | 0.142 | 0.723 | 0.782 |
| 8        | 3     | 2       | 1        | 3     | 0.085 | 0.076 | 0.191 | 0.168 | 0.867 | 0.584 |
| 9        | 3     | 3       | 2        | 1     | 0.012 | 0.023 | 0.251 | 0.212 | 0.804 | 0.677 |

Ra (Surface roughness), S.F (shrinkage in flow direction), S.XF (shrinkage in cross-flow direction)
3. Results and analysis

This section presents the material and methodology used throughout the process.

3.1. Optimization of injection moulding process parameters

The process parameters of injection moulding for PS and PP are optimized using an integrated approach based on Taguchi S/N ratios and composite desirability functions, as discussed in the material and methods section. The S/N ratios are calculated using Equation (1) for an individual response, as tabulated in Table 5. It shows that the highest S/N ratios observed for surface roughness of PS injection moulded part is 38.416 at experimental run 9, while for shrinkage in parallel flow direction is 14.379 at experimental run 8, and for shrinkage in cross-flow direction...
Similarly, for responses of PP the highest S/N ratio calculated for Ra is 32.765, for S.F is 16.954, for S.XF is 4.672 at experimental run 9, 7, 8, respectively. As the S/N ratios fail to provide simultaneous optimization of responses, therefore, the S/N ratios of individual responses are transformed to desirability values based on transformation function using Equation (2) as tabulated in Table 6. Then the individual desirability of S/N ratios is converted to composite desirability based on geometric mean using Equation (3) as shown in Table 7. It shows that higher composite desirability values of S/N ratios for PS and PP are obtained at experimental run 9, i.e. 0.218 for PS and 0.210 for PP. The combination of levels for process parameters at experimental run 9 are injection temperature at level 3, injection pressure at level 3, injection speed at level 2, and mould temperature at level 1. However, to obtain the optimal process parameters, the mean values of composite desirability are calculated as tabulated in Table 8 for PS and Table 9 for PP. Higher mean values of composite desirability will correspond to better performance of process parameters of injection moulding. Thus, the optimal process parameters for PS are injection temperature and injection pressure at level 3, while injection speed and mould temperature at level 1, as shown in Table 5.

The optimal process parameters obtained are validated experimentally by performing confirmation tests. The experiments are repeated three times for PS and PP and the results are shown in

| Exp. Runs | Ra      | S.F | S.XF   | Ra      | S.F | S.XF   |
|-----------|---------|-----|--------|---------|-----|--------|
| 1         | 5.336   | 1.340 | -1.805 | 2.214   | 0.427 | -1.663 |
| 2         | 7.230   | 3.073 | -1.401 | 3.728   | 1.692 | -1.252 |
| 3         | 8.566   | 3.958 | -0.780 | 5.320   | 4.265 | -0.620 |
| 4         | 10.117  | 5.781 | -0.104 | 6.285   | 7.052 | 0.070  |
| 5         | 12.324  | 7.808 | 0.220  | 9.951   | 9.447 | 0.400  |
| 6         | 13.514  | 8.995 | 0.772  | 10.903  | 11.437 | 1.300  |
| 7         | 17.016  | 10.089 | 2.817 | 14.517  | 16.954 | 2.136  |
| 8         | 21.412  | 14.379 | 1.240 | 22.384  | 15.494 | 4.672  |
| 9         | 38.416  | 12.007 | 1.895 | 32.765  | 13.473 | 3.388  |

Table 5. S/N ratios of responses for PS and PP

| Exp. Runs | Desirability values for PS | Desirability values for PP |
|-----------|---------------------------|---------------------------|
|           | Ra | S.F | S.XF | Ra | S.F | S.XF |
| 1         | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 2         | 0.057 | 0.133 | 0.087 | 0.050 | 0.077 | 0.065 |
| 3         | 0.098 | 0.201 | 0.222 | 0.102 | 0.232 | 0.165 |
| 4         | 0.145 | 0.341 | 0.368 | 0.133 | 0.401 | 0.274 |
| 5         | 0.211 | 0.496 | 0.438 | 0.253 | 0.546 | 0.326 |
| 6         | 0.247 | 0.587 | 0.557 | 0.284 | 0.666 | 0.468 |
| 7         | 0.353 | 0.671 | 1.000 | 0.403 | 1.000 | 0.600 |
| 8         | 0.486 | 1.000 | 0.659 | 0.660 | 0.912 | 1.000 |
| 9         | 1.000 | 0.818 | 0.800 | 1.000 | 0.789 | 0.797 |

Table 6. Desirability values of S/N ratios for PS and PP

2.817 for experimental run 7. Similarly, for responses of PP the highest S/N ratio calculated for Ra is 32.765, for S.F is 16.954, for S.XF is 4.672 at experimental run 9, 7, 8, respectively. As the S/N ratios fail to provide simultaneous optimization of responses, therefore, the S/N ratios of individual responses are transformed to desirability values based on transformation function using Equation (2) as tabulated in Table 6. Then the individual desirability of S/N ratios is converted to composite desirability based on geometric mean using Equation (3) as shown in Table 7. It shows that higher composite desirability values of S/N ratios for PS and PP are obtained at experimental run 9, i.e. 0.218 for PS and 0.210 for PP. The combination of levels for process parameters at experimental run 9 are injection temperature at level 3, injection pressure at level 3, injection speed at level 2, and mould temperature at level 1. However, to obtain the optimal process parameters, the mean values of composite desirability are calculated as tabulated in Table 8 for PS and Table 9 for PP. Higher mean values of composite desirability will correspond to better performance of process parameters of injection moulding. Thus, the optimal process parameters for PS are injection temperature and injection pressure at level 3, while injection speed and mould temperature at level 1, as shown in Table 5.

The optimal process parameters obtained are validated experimentally by performing confirmation tests. The experiments are repeated three times for PS and PP and the results are shown in
| Exp Runs | Composite desirability values for PS | Rank | Composite desirability values for PS | Rank |
|----------|-------------------------------------|------|-------------------------------------|------|
| 1        | 0.000                               | 9    | 0.000                               | 9    |
| 2        | 0.000                               | 8    | 0.000                               | 8    |
| 3        | 0.001                               | 7    | 0.001                               | 7    |
| 4        | 0.006                               | 6    | 0.005                               | 6    |
| 5        | 0.015                               | 5    | 0.015                               | 5    |
| 6        | 0.027                               | 4    | 0.030                               | 4    |
| 7        | 0.079                               | 3    | 0.080                               | 3    |
| 8        | 0.107                               | 2    | 0.201                               | 2    |
| 9        | 0.218                               | 1    | 0.210                               | 1    |
Table 10. For PS and PP there is good improvement in the performance of responses at optimal levels as the composite desirability value improves by about 17.6% from initial control parameters for PS and 16.6% for PP.

3.2. Effect of process parameters on response

To study the effect of process parameters on responses for PS and PP, analysis of variance (ANOVA) is performed at a 95% confidence interval. The ANOVA results are summarized in Tables 11, and 12. P-value less than 0.05 shows a significant effect of process parameters on response. The ANOVA results for both PS and PP show that injection temperature has a significant effect on surface roughness, shrinkage in parallel flow and cross-flow direction as their P-value is less than 0.05, as shown in Tables 11 and 12. For PS, injection pressure has significant effect on surface roughness and shrinkage in parallel flow direction, while for PP it has significant effect on surface roughness and shrinkage in cross-flow direction. The other parameters, such as injection speed, and mould temperature, are found insignificant for both PS and PP.

The adequacy of ANOVA for PS and PP are analyzed using residual plots for normality and homogeneity (constant variance). As shown in Figure 8(a-c), for PS, and Figure 9(a-c) for PP the residuals of surface roughness, shrinkage in parallel flow and cross-flow direction are near to the fitted line, and also the P-value for the Anderson Darling normality test is greater than 0.05; therefore, it is concluded that the residuals are normally distributed for both polymers. The homogeneity of residuals is analyzed through versus fits plots as shown in Figure 8(d-f) for PS and for PP in Figure 9(d-f). The plots show that the residuals are randomly distributed and depict no specific pattern shapes; therefore, it shows that the residuals are homogenous (have a constant variance). Thus, it is concluded that ANOVA provides reliable results, and it can be used further for the development of the regression model.

3.3. Development of prediction model

To develop a prediction model for PS and PP best subset regression analysis is performed to obtain the best subset of process parameters that can provide the precise estimation of responses. The precision and fitness of the prediction model are assessed using the coefficient of determination ($R^2$), adjusted $R^2$, predicted $R^2$, and Mallows Cp. $R^2$ determines the percentage variation in responses explained by the model or, in other words, it determines how well the data fit the model. It varies between 0 % and 100 %, and for the best fit model, $R^2$ needs to be higher. Adjusted $R^2$ adjusts the number of control variables (process parameters) in the regression model to determine a more suitable model. Predicted $R^2$ determines the predictive ability of the model.
|       | Initial control levels | Optimal Levels | Predicted | 1  | 2  | 3  |
|-------|------------------------|----------------|-----------|----|----|----|
| PS    | Levels                 |                |           |    |    |    |
|       | 3-1-2-2                | 3-3-2-1        |           |    |    |    |
| Ra    | 0.752                  | 0.011          | 0.023     | 0.018 | 0.015 |
| S.F   | 0.586                  | 0.191          | 0.205     | 0.216 | 0.197 |
| S.XF  | 1.055                  | 0.732          | 0.762     | 0.743 | 0.751 |
| D     | 0.018                  | 0.212          | 0.187     | 0.202 | 0.193 |
| % Improvement in D |                  |                | 17        | 18   | 18  |
| PP    | Levels                 |                |           |    |    |    |
|       | 3-2-2-2                | 3-3-1-1        |           |    |    |    |
| Ra    | 0.515                  | 0.021          | 0.034     | 0.028 | 0.039 |
| S.F   | 0.431                  | 0.153          | 0.168     | 0.157 | 0.164 |
| S.XF  | 0.943                  | 0.585          | 0.612     | 0.592 | 0.602 |
| D     | 0.045                  | 0.235          | 0.195     | 0.225 | 0.211 |
| % Improvement in D |                  |                | 15        | 18   | 17  |
### Table 11. Analysis of variance for PS

#### ANOVA for Surface roughness

| Factors            | DF | Adj SS   | Adj MS   | F-Value | P-Value |
|--------------------|----|----------|----------|---------|---------|
| Injection Temperature (K) | 1  | 0.20572  | 0.20572  | 1112.75 | 0.001*  |
| Injection Pressure (MPa)    | 1  | 0.026401 | 0.026401 | 142.8   | 0.001*  |
| Injection Speed (mm/s)      | 1  | 0.001094 | 0.001094 | 5.91    | 0.072   |
| Mould Temperature (K)       | 1  | 0.000104 | 0.000104 | 0.56    | 0.495   |
| Error                   | 4  | 0.000739 | 0.000185 |         |         |

#### ANOVA for shrinkage in flow direction

| Factors            | DF | Adj SS      | Adj MS      | F-Value | P-Value |
|--------------------|----|-------------|-------------|---------|---------|
| Injection Temperature (K) | 1  | 0.344641    | 0.344641    | 81.06   | 0.001*  |
| Injection Pressure (MPa)    | 1  | 0.032856    | 0.032856    | 7.73    | 0.048*  |
| Injection Speed (mm/s)      | 1  | 0.0004      | 0.0004      | 0.09    | 0.774   |
| Mould Temperature (K)       | 1  | 0.005163    | 0.00452     | 1.21    | 0.332   |
| Error                   | 4  | 0.017007    | 0.004252    |         |         |

#### ANOVA for shrinkage in the cross-flow direction

| Factors            | DF | Adj SS      | Adj MS      | F-Value | P-Value |
|--------------------|----|-------------|-------------|---------|---------|
| Injection Temperature (K) | 1  | 0.203873    | 0.203873    | 63.3    | 0.001*  |
| Injection Pressure (MPa)    | 1  | 0.003901    | 0.003901    | 1.21    | 0.333   |
| Injection Speed (mm/s)      | 1  | 0.00814     | 0.00814     | 2.53    | 0.187   |
| Mould Temperature (K)       | 1  | 0.000228    | 0.000228    | 0.07    | 0.803   |
| Error                   | 4  | 0.012883    | 0.003221    |         |         |

*significant
for the new set of observations. Mallow Cp compares the full regression models with the best subset of process parameters (Gilmour, 1996). The value of Mallow Cp closer to the number of predictors plus constant term provides relatively precise estimates of response (Gilmour, 1996). Table 13 shows the summarized results of Mallow Cp. The results show that as the number of variables in each model increases, the $R^2$ value also increases; therefore, it does not justify the improvement in the model; in this regard, adjusted $R^2$ is used for comparison of a different model by incorporating the best subset of process parameters. For surface roughness, the most suitable model has three process parameters, i.e. injection temperature, injection pressure, and injection speed having high adjusted $R^2$ value of 99.4 % with a good predicted $R^2$ value of 98.5 % and Mallow Cp of 3.6 which is much closer to a number of process parameters incorporated in the model. Subsequently, by adding the mould temperature to the model increases $R^2$ but not Adjusted $R^2$. These results show that mould temperature does not improve the surface roughness; therefore, it can be removed from the model. Similar results are obtained for surface roughness of PP, as shown in Table 14, with an adjusted $R^2$ value of 98.9 % and predicted $R^2$ value of 98 %. In Table 13 for shrinkage in parallel flow, the suitable model obtained has three process parameters, i.e. injection temperature, injection pressure, and mould temperature having an adjusted $R^2$ value of 93 % with Mallow Cp of 3.1. For shrinkage in parallel flow for PP as shown in Table 14, the suitable model incorporates three process parameters, i.e. injection temperature, injection pressure, and injection speed. The adjusted and predicted $R^2$ obtained are 84.8 % and 71.6 % having

| Factors                              | DF | Adj SS   | Adj MS   | F-Value | P-Value |
|--------------------------------------|----|----------|----------|---------|---------|
| Injection Temperature (K)            | 1  | 0.47096  | 0.47096  | 496.46  | 0.001*  |
| Injection Pressure (MPa)             | 1  | 0.059601 | 0.059601 | 62.83   | 0.001*  |
| Injection Speed (mm/s)               | 1  | 0.001291 | 0.001291 | 1.36    | 0.308   |
| Mould Temperature (K)                | 4  | 0.000028 | 0.000028 | 0.03    | 0.872   |

| ANOVA for shrinkage in flow direction |
|---------------------------------------|
| Injection Temperature (K)             | 1  | 0.5797   | 0.5797   | 43.71   | 0.003*  |
| Injection Pressure (MPa)              | 1  | 0.03315  | 0.03315  | 2.5     | 0.189   |
| Injection Speed (mm/s)                | 1  | 0.0147   | 0.0147   | 1.11    | 0.352   |
| Mould Temperature (K)                 | 4  | 0.01279  | 0.05305  | 0.96    | 0.382   |

| ANOVA for shrinkage in cross-flow direction |
|---------------------------------------------|
| Injection Temperature (° C)                | 1  | 0.325268 | 0.325268 | 223.59  | 0.001*  |
| Injection Pressure (MPa)                   | 1  | 0.023188 | 0.023188 | 15.94   | 0.016*  |
| Injection Speed (mm/s)                     | 1  | 0.004004 | 0.004004 | 2.75    | 0.172   |
| Mould Temperature (K)                      | 4  | 0.006208 | 0.005819 | 4.27    | 0.108   |

*significant

Table 12. Analysis of variance for PP

ANOVA for Surface roughness

| Factors                              | DF | Adj SS   | Adj MS   | F-Value | P-Value |
|--------------------------------------|----|----------|----------|---------|---------|
| Injection Temperature (K)            | 1  | 0.47096  | 0.47096  | 496.46  | 0.001*  |
| Injection Pressure (MPa)             | 1  | 0.059601 | 0.059601 | 62.83   | 0.001*  |
| Injection Speed (mm/s)               | 1  | 0.001291 | 0.001291 | 1.36    | 0.308   |
| Mould Temperature (K)                | 4  | 0.000028 | 0.000028 | 0.03    | 0.872   |

| ANOVA for shrinkage in flow direction |
|---------------------------------------|
| Injection Temperature (K)             | 1  | 0.5797   | 0.5797   | 43.71   | 0.003*  |
| Injection Pressure (MPa)              | 1  | 0.03315  | 0.03315  | 2.5     | 0.189   |
| Injection Speed (mm/s)                | 1  | 0.0147   | 0.0147   | 1.11    | 0.352   |
| Mould Temperature (K)                 | 4  | 0.01279  | 0.05305  | 0.96    | 0.382   |

| ANOVA for shrinkage in cross-flow direction |
|---------------------------------------------|
| Injection Temperature (° C)                | 1  | 0.325268 | 0.325268 | 223.59  | 0.001*  |
| Injection Pressure (MPa)                   | 1  | 0.023188 | 0.023188 | 15.94   | 0.016*  |
| Injection Speed (mm/s)                     | 1  | 0.004004 | 0.004004 | 2.75    | 0.172   |
| Mould Temperature (K)                      | 4  | 0.006208 | 0.005819 | 4.27    | 0.108   |

*significant
As shown in Table 13, shrinkage in cross-flow, the appropriate model has three process parameters, i.e. injection temperature, injection pressure, and injection speed with adjusted and predicted $R^2$ value of 90.8% and 77.1%. For shrinkage in cross-flow for PP as shown in Table 14, the appropriate model four process parameters, i.e. injection temperature, injection pressure, injection speed and mould temperature. The adjusted and predicted $R^2$ achieved are 98.4% and 91.2% having Mallow Cp of 5. Based on this analysis, the precise regression models (uncoded) obtained are shown in Table 15.

To validate the performance of prediction models for polystyrene and polypropylene, experiments were performed for other combinations of process parameters. As shown in Figure 10(a-f), there is good agreement between predicted values and experimental values of all the responses.
Table 13. Best subset regression for PS

| Surface roughness       | No of Vars | R²    | Adjusted R² | Predicted R² | Mallows Cp | T   | P   | S   | M   |
|-------------------------|------------|-------|-------------|--------------|------------|-----|-----|-----|-----|
|                         |            | 1     | 87.9        | 86.2         | 78.3       | 148.3| X   |     |     |
|                         |            | 2     | 99.2        | 98.9         | 98         | 7.5  | X   | X   |     |
|                         |            | 3     | 99.6        | 99.4         | 98.5       | 3.6  | X   | X   | X   |
|                         |            | 4     | 99.7        | 99.4         | 97.2       | 5    | X   | X   | X   |
| Shrinkage (flow)        |            | 1     | 86.1        | 84.2         | 76.5       | 8    | X   |     |     |
|                         |            | 2     | 94.4        | 92.5         | 85         | 2.3  | X   | X   |     |
|                         |            | 3     | 95.6        | 93           | 83.2       | 3.1  | X   | X   | X   |
|                         |            | 4     | 95.7        | 91.5         | 70.7       | 5    | X   | X   | X   |
| Shrinkage (X-flow)      |            | 1     | 89          | 87.4         | 80.4       | 2.8  | X   |     |     |
|                         |            | 2     | 92.6        | 90.1         | 83.5       | 2.3  | X   |     | X   |
|                         |            | 3     | 94.3        | 90.8         | 77.1       | 3.1  | X   |     | X   |
|                         |            | 4     | 94.4        | 88.7         | 72.7       | 5    | X   |     | X   |
| No of Vars | R²     | Adjusted R² | Predicted R² | Mallows Cp | T  | P  | S  | M  |
|-----------|--------|-------------|--------------|------------|----|----|----|----|
| 1         | 87.9   | 86.2        | 79.7         | 63.2       | X  | X  | X  | X  |
| 2         | 99     | 98.7        | 98.1         | 2.4        | X  | X  | X  | X  |
| 3         | 99.3   | 98.9        | 98           | 3          | X  | X  | X  | X  |
| 4         | 99.3   | 98.6        | 96.3         | 5          | X  | X  | X  | X  |

**Shrinkage (flow)**

| No of Vars | R²     | Adjusted R² | Predicted R² | Mallows Cp | T  | P  | S  | M  |
|-----------|--------|-------------|--------------|------------|----|----|----|----|
| 1         | 83.6   | 81.3        | 72.3         | 3.6        | X  | X  | X  | X  |
| 2         | 88.4   | 84.5        | 69.4         | 3.1        | X  | X  | X  | X  |
| 3         | 90.5   | 84.8        | 71.6         | 4          | X  | X  | X  | X  |
| 4         | 92.3   | 84.7        | 64.7         | 5          | X  | X  | X  | X  |

**Shrinkage (X-flow)**

| No of Vars | R²     | Adjusted R² | Predicted R² | Mallows Cp | T  | P  | S  | M  |
|-----------|--------|-------------|--------------|------------|----|----|----|----|
| 1         | 89.2   | 87.7        | 81.1         | 22         | X  | X  | X  | X  |
| 2         | 95.6   | 94.1        | 90.4         | 8          | X  | X  | X  | X  |
| 3         | 97.3   | 95.7        | 89.5         | 5.8        | X  | X  | X  | X  |
| 4         | 98.4   | 96.8        | 91.2         | 5          | X  | X  | X  | X  |
i.e. surface roughness, shrinkage in parallel flow and cross-flow directions for polystyrene and polypropylene. Hence it is concluded that the prediction models developed in the present study are reliable in performance and provide a good estimation of responses for the new observations that are not included in the experimental design as presented in Table 4, but are within defined levels as shown in Tables 2, and 3.

### Table 15. Prediction models for polystyrene and polypropylene

| Prediction models | Equation Number |
|-------------------|-----------------|
| **Polystyrene**   |                 |
| \(Ra = 5.3 - 0.02T - 0.007P - 0.002S\) | (7) |
| \(S.F = 7.1 - 0.02T - 0.007P - 0.006M\) | (8) |
| \(S.XF = 6 - 0.02T - 0.003P - 0.004S\) | (9) |
| **Polypropylene** |                 |
| \(Ra = 7.43 - 0.028T - 0.01P - 0.002M\) | (10) |
| \(S.F = 8.36 - 0.03T - 0.007P - 0.005S\) | (11) |
| \(S.XF = 6.67 - 0.02T - 0.006P + 0.003S - 0.007M\) | (12) |

Figure 10. Predicted values vs experimental values, a surface roughness for polystyrene, b surface roughness for polypropylene, c shrinkage in parallel flow for polystyrene, d shrinkage in parallel flow for polypropylene, e shrinkage in cross-flow for polystyrene, f shrinkage in cross-flow for polypropylene.
3.4. Relationship among responses and process parameter

The relationship between responses and modelled process parameters is studied through surface plots. The surface plot shows the simultaneous effect of two process parameters on the response while keeping the other parameters constant.

3.4.1. Surface plots for surface roughness

The surface plots for surface roughness of polystyrene are shown in Figure 11(a). There are three modelled parameters for surface roughness of polystyrene, i.e. injection temperature, injection pressure and injection speed. The plots show that by holding injection speed constant, i.e. at 80 mm/s, the surface roughness decreases significantly with an increase in injection temperature from 515 to 530 K and for an increase in injection pressure from 40 to 60 MPa the reduction in surface roughness is less effective. Holding the injection pressure constant at 50 MPa, the increase in temperature decreases the surface roughness, but the injection speed has no effect on the surface roughness as the line is constant. By holding the injection temperature constant at 513.15 K, surface roughness decreases with an increase in injection pressure; however, for an increase in injection speed, the decreasing trend of surface roughness is insignificant. Figure 11(b) shows surface plots of surface roughness for polypropylene. The modelled parameters are injection temperature, injection pressure and mould temperature. The plots depict that by holding the mould temperature at 318.15 K, an increase in injection temperature from 493.15 to 513.15 K decreases the surface roughness expressively, and for an increase in pressure from 40 to 60 MPa, the effect of decreasing surface roughness is bland. Holding the injection pressure at 50 MPa and injection temperature at 503.15 K, the mould temperature has almost no effect on surface roughness as the slope of the curve is constant, while increasing injection temperature and injection pressure reduces the surface roughness significantly as the slopes of the curves for both parameters are steeper.

3.4.2. Surface plots for shrinkage in flow direction

For polystyrene surface plots for shrinkage in the flow, the direction as shown in Figure 12(a). This surface plot is based on three parameters, i.e. injection speed, injection temperature and injection pressure. Holding the mould temperature constant at 318.15 K, the shrinkage has been greatly reduced with an increase in injection temperature from 515 K to 530 K. While there is a slight decrease in shrinkage with an increase in injection pressure from 40 MPa to 60 MPa. Similarly, by holding the injection pressure at 50 MPa, the shrinkage in flow direction has been effectively decreased by...
changing injection temperature from 515 K to 530 K. There is almost no change in shrinkage with a change in mould temperature from 315 K to 322.5 K. Shrinkage is decreased with increase in injection pressure from 40 MPa to 60 MPa, keeping the injection temperature at 523.15 K. The increase in mould temperature has little effect on shrinkage in the flow direction. Figure 12(b) shows surface plots for shrinkage in flow direction for polypropylene. Holding the injection speed at 80 mm/s and injection pressure at 50 MPa, the shrinkage is greatly reduced with an increase in injection temperature from 493.15 to 513.15 K. Changing the injection pressure and injection speed has a very small effect on shrinkage in the flow direction. Holding the injection temperature at 503.15 K, there is much decrease in shrinkage with an increase in injection pressure. Small change is observed in shrinkage with an increase in injection speed from 70 mm/s to 90 mm/s.

3.4.3. Surface plots for shrinkage in cross-flow direction
For polystyrene, the surface plots for shrinkage in the X-flow direction have shown in Figure 13(a). The process parameters are the same as those considered for shrinkage in the flow direction. Shrinkage is highly reduced with the increase in injection temperature from 515 K to 530 K while keeping the injection speed constant at 80 mm/s. There is a small reduction in shrinkage in X-flow direction with an increase in injection pressure from 40 MPa to 60 MPa. Similarly, holding the injection pressure constant at 50 MPa, the shrinkage has been effectively reduced with the increase in injection temperature from 515 K to 530 K. Slight reduction has been observed in shrinkage with the increase in injection speed from 70 mm/s to 90 mm/s. Holding the injection temperature constant at 523.15 K, the shrinkage is slightly reduced with the increase in injection pressure and speed both. Figure 13(b) shows the polypropylene surface plots for shrinkage in the X-flow direction. Holding the injection speed at 80 mm/s and mould temperature at 318.15 K, the shrinkage in X-flow has been significantly decreased with an increase in injection temperature from 493.15 to 513.15 K while a small reduction in shrinkage is observed with increase in injection pressure. Holding the injection pressure at 50 MPa and Mould temperature at 318.15 K, the shrinkage has been highly reduced with an increase in injection temperature but is slightly increased with an increase in injection speed from 70 mm/s to 90 mm/s. Similarly, shrinkage has been effectively reduced with an increase in injection temperature while keeping constant the injection pressure at 50 MPa and mould temperature at 318.15 K but is slightly increased with an increase in injection speed. Holding the injection temperature constant at 503.15 K and injection speed at 80 mm/s, the shrinkage in X-flow direction has been reduced with an increase.
injection pressure and also slightly decreases with an increase in mould temperature from 315 K to 322.5 K.

4. Conclusion
In the present study, Taguchi based S/N ratios were successfully integrated with composite desirability function to optimize the process parameters of horizontal injection moulding of cups for polystyrene (PS) and polypropylene (PP) using mould fabricated from aluminum alloy 6061-T651. The process parameters investigated were injection temperature, injection pressure, injection speed and mould temperature while the response variables were surface roughness, shrinkage inflow and cross-flow directions. Taguchi orthogonal array L9 was designed for experimental runs for both polystyrene and polypropylene. Following conclusions can be drawn from the present study:

- Taguchi orthogonal array design is found effective for the reduction of experimental cost as well as resources and time of experimentation.
- The optimal process parameters identified for PS were injection temperature at 533.15 K (level 3), injection pressure at 60 MPa (level 3), injection speed at 80 mm/s (level 2) and mould temperature at 313.15 K (level 1).
- For PP the optimal process parameters were injection temperature at 513.15 K (level 3), injection pressure at 60 MPa (level 3), injection speed at 70 MPa (level 1), mould temperature at 313.15 K (level 1). The optimal levels for both PS and PP were validated by confirmation tests, and the results showed that the composite desirability values improved by 17.6 % for PS and 16.6 % for PP from initial control parameters to optimal control parameters.
- Confirmation tests for optimized parameters showed that the proposed integrated approach of S/N ratios and composite desirability provide promising and improved results.
- The ANOVA results revealed that injection temperature has a significant effect on all the response variables for both PS and PP. Injection pressure has a significant effect on surface roughness and shrinkage in parallel flow direction for PS, while PP has a significant effect on surface roughness and shrinkage in cross-flow direction. The other parameters were found insignificant for both polymers.
The performance of prediction models was validated by performing experimental runs for other combinations of process parameters. Hence it was demonstrated that the optimal parameters and predication models developed in the present study are reliable in performance and provided a good estimation of responses.

For PS and PP, the surface roughness decreases with an increase in injection temperature and injection pressure, while keeping the injection speed constant. For PS, surface roughness decreases with the increase in injection pressure and injection speed at constant injection pressure, whereas for PP keeping mould temperature, constant surface roughness decreases with an increase in injection temperature and injection pressure.

Shrinkage in flow direction for PS decreases with an increase in injection temperature and injection pressure at a constant mould temperature. For constant injection pressure and injection temperature a slight decrease in shrinkage is observed for the increase in mould temperature. For PP keeping the injection speed constant, shrinkage in flow direction decreases with an increase in injection temperature and injection pressure.

Shrinkage in cross-flow direction for PS decreases with an increase in injection temperature and injection speed at constant injection pressure, while for PP keeping the injection pressure and mould temperature at constant shrinkage in cross-flow direction decreases with an increase in injection temperature, and decrease in injection speed.
Gupta, M. K., Mia, M., Pruncu, C. I., Khan, A. M., Rahman, M. A., Jamil, M., & Sharma, V. S. (2020). Modeling and performance evaluation of Al2O3, MoS2 and graphite nanoparticle-assisted MQL in turning titanium alloy: An intelligent approach. Journal of the Brazilian Society of Mechanical Sciences and Engineering, 42(4), 1-21. https://doi.org/10.1007/s40430-020-2256-z

Han, S. R., Park, J. I., & Cho, J. R. (2018). Development of plastic passenger air bag (PAB) housing for replacing the steel PAB housing and reducing the automobile weight. Journal of the Brazilian Society of Mechanical Sciences and Engineering, 40(4), 224. https://doi.org/10.1007/s40430-018-1060-9

Kashyap, S., & Datto, D. (2015). Process parameter optimization of plastic injection molding: A review. International Journal of Plastics Technology, 19(1), 1-18. https://doi.org/10.1057/s12588-015-9115-2

Khamis, S. Z., Othman, M. H., Hasan, S., Main, N. M., Masrol, S. R., Shaari, M. F., & Salim, S. (2019). Multiple responses optimisation in injection moulding parameter for polypropylene-nanoclay-gigantochloa scortechinii via taguchi method. Journal of Physics: Conference Series, 1150(1), 012062. IOP Publishing. http://doi.org/10.1088/1742-6596/1150/1/012062

Khosravani, M. R., & Nasiri, S. (2019). Injection moulding manufacturing process: Review of case-based reasoning applications. Journal of Intelligent Manufacturing, 1-18. https://doi.org/10.1007/s10845-019-01481-0

Kitoyama, S., Ishizuki, R., Takano, M., Kubo, Y., & Aiba, S. (2019). Optimization of mold temperature profile and process parameters for weld line reduction and short cycle time in rapid heat cycle molding. The International Journal of Advanced Manufacturing Technology, 103(5–8), 1735–1744. https://doi.org/10.1007/s12588-019-03685-3

Kumar, B. B., Deddamani, M., Zeitmann, S. E., Gupta, N., Ramesh, M. R., & Ramakrishna, S. (2016). Processing of cenosphere/HDPE syntactic foams using an industrial scale polymer injection molding machine. Materials & Design, 92, 414–423. http://dx.doi.org/10.1016/j.matdes.2015.12.052

Li, K., Yan, S., Zhong, Y., Pan, W., & Zhao, G. (2019). Multi-objective optimization of the fiber-reinforced composite injection molding process using Taguchi method, RSM, and NSGA-II. Simulation Modelling Practice and Theory, 91, 69–82. https://doi.org/10.1016/j.simpat.2018.09.003

López, A., Alsa, J., Martínez, A., & Mercado, D. (2016). Injection moulding parameters influence on weight quality of complex parts by means of DOE application: Case study. Measurement, 90, 349–356. http://dx.doi.org/10.1016/j.measurement.2016.04.072

Maged, A., Haridy, S., Kaybay, S., & Bhiuian, N. (2019). Continuous improvement of injection molding using Six sigma: Case study. International Journal of Industrial and Systems Engineering, 32(2), 243. https://doi.org/10.1504/IJISE.2019.100165

Malewski, E., & Procik, A. (2020). Porous polyurethane-poly styrene composites produced in a co-expansion process. Arabian Journal of Chemistry, 13(1), 37–44. https://doi.org/10.1016/arabjc.2017.01.014

Miranda, D. A. D., & Nogueira, A. L. (2019). Simulation of an injection process using a CAE tool: Assessment of operational conditions and mold design on the process efficiency. Materials Research, 22(2), https://doi.org/10.1590/1980-5373-mr-2018-0564

Mukras, S. M., Omar, H. M., & al-Mufadi, F. A. (2019). Experimental-based multi-objective optimization of injection molding process parameters. Arabian Journal for Science and Engineering, 44(9), 7653–7665. https://doi.org/10.1007/s13369-019-03855-1

Ogorodnyk, O., Lyngstad, O. V., Larsen, M., & Martinsen, K. (2019). Application of feature selection methods for defining critical parameters in thermoplastics injection molding. ELSEVIER 52nd CIRP Conference on Manufacturing Systems. http://doi.org/10.1016/j.procir.2019.03.020

Olliea, E., Heidari, B. S., Davachi, S. M., Bahrami, M., Davoodi, S., Hejazi, I., & Seyf, J. (2016). Warpage and shrinkage optimization of injection-molded plastic spoon parts for biodegradable polymers using taguchi, ANOVA and artificial neural network methods. Journal of Materials Science & Technology, 32(8), 710–720. http://dx.doi.org/10.1016/j.jmst.2016.05.010

Park, H. S., Dang, X. P., Nguyen, D. S., & Kumar, S. (2019). Design of advanced injection mold to increase cooling efficiency. International Journal of Precision Engineering and Manufacturing-Green Technology, 7(2), 319–328. https://doi.org/10.4068-s19-00041-4

Prathabroo, M., Amin, S. Y. M., Ibrahim, M. H. I., Othman, M. H., & Shohbudin, S. N. A. (2019). Optimization of injection molding parameters for WC-TaC-6Co. International Journal of Enginee ring & Technology WC-TaC-6Co, 8, 1-5. http://eprints.uthm.edu.my/id/eprint/11975

Rathore, J. S., Luccietta, G., & Cormignato, S. (2019). Towards optimization of µ-injection molding process for a new V-shaped geometrical component using X-ray CT-based quality characterization. Journal of Manufacturing and Materials Processing, 3(1), 13. https://doi.org/10.3390/jmmp3010013

Sánchez-Sánchez, X., Elias-Zúñiga, A., & Hernández-Avila, M. (2018). Processing of ultra-high molecular weight polyethylene/graphite composites by ultrasonic injection moulding: Taguchi optimization. Ultrasonics Sonochemistry, 44, 350–358. https://doi.org/10.1016/j.ulsone.2018.02.042

Singh, G., Jain, V., & Gupta, D. (2017). Multi-objective performance investigation of orthopaedic bone drilling using Taguchi membership function. Proceedings of the Institution of Mechanical Engineers. Part H, Journal of Engineering in Medicine, 231(12), 1133–1139. https://doi.org/10.1177/0954411917735129

Singh, G., Jain, V., Gupta, D., & Ghai, A. (2016). Optimization of process parameters for drilled hole quality characteristics during cortical bone drilling using Taguchi method. Journal of the Mechanical Behavior of Biomedical Materials, 62, 355–365. https://doi.org/10.1016/j.jmbbm.2016.05.015

Singh, G., Pradhan, M. K., & Verma, A. (2018). Multi response optimization of injection moulding process parameters to reduce cycle time and warpage. Materials Today: Proceedings, 5(2), 8398-8405. https://doi.org/10.1016/j.matpr.2017.11.534

Singh, G., & Verma, A. (2017). A Brief Review on injection moulding manufacturing process. Materials Today: Proceedings, 4(2), 1423-1433. https://doi.org/10.1016/j.matpr.2017.01.164

Song, M. C., Wang, X. L., Hou, S. J., Liu, Y., & Liu, J. S. (2018). Investigation of injection moulding parameters on the uniformity of porous array of polymer microfluidic chip. Journal of the Brazilian Society of Mechanical Sciences and Engineering, 40(3), 131. https://doi.org/10.1007/s40430-018-1053-4

Wang, M. W., Arifin, F., & Huang, J. Y. (2019). Optimization of the micro molding of a biconcave structure. International Journal of Technology, 10(2), 269. https://doi.org/10.14716/ijtech.v10i2.2375
Zhang, J., Wang, J., Lin, J., Guo, Q., Chen, K., & Ma, L. (2016). Multi-objective optimization of injection molding process parameters based on Opt LHD, EBFNN, and MOPSO. The International Journal of Advanced Manufacturing Technology, 85(9-12), 2857-2872. http://doi.org/10.1007/s00170-015-8100-4

Zhao, J., Cheng, G., Ruan, S., & Li, Z. (2015). Multi-objective optimization design of injection molding process parameters based on the improved efficient global optimization algorithm and non-dominated sorting-based genetic algorithm. The International Journal of Advanced Manufacturing Technology, 78(9-12), 1813-1826. https://doi.org/10.1007/s00170-014-6770-y

Zhil'tsova, T. V., Oliveira, M. S. A., & Ferreira, J. A. F. (2009). Relative influence of injection molding processing conditions on HDPE acetabular cups dimensional stability. Journal of Materials Processing Technology, 209(8), 3894–3904. https://doi.org/10.1016/j.jmatprotec.2008.09.018