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Study on the influence of injection molding parameters on the warpage using simulation and Taguchi method

V. L. Trinh[a*], Dung Hoang Tien[a] and N. S. Dinh[a]

[a]*School of Mechanical and Automotive Engineering, Hanoi University of Industry, 298 Caudien Street, Hanoi 10000, Vietnam*

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A B S T R A C T

Injection moulding (IM) is a processing technique produced from polymeric products. Warpage defect (WD) is the defect that generally occurs during the IM process due to the inappropriate processing parameters of the melt temperature, mould surface temperature, packing pressure, injection pressure, and packing pressure time. This paper investigates the IM parameters that influence product warpage by combining the simulation, analysis of variance, signal-to-noise analysis, and Taguchi method. The simulation process was performed by Moldflow software. The product material is high-density polyethylene. The WD has been predicted and optimized to enhance product quality. Melt temperature and packing pressure time are the factors that acrimoniously influenced the warpage of the product. The results show that the packing pressure time and melt temperature have the highest effects on the WD by the contributions of 48.94% and 37.48%, respectively. The optimal IM parameters are scanned again with the WD abated at about 1.2%. The mathematical formula has been constructed to predict the WD with the reflection of acceptable values of 86.29%. The research hopes that the results have been applied to designing and fabricating the plastic product in the near future.

1. Introduction

Injection moulding (IM) is a mass fabricating method of polymer products. This technology produces plastic parts for almost all areas of automotive, medical, consumer, electronics, and industrial products (Kumar et al., 2016; Low and Lee, 2008). Many researches have been developed IM products for practice applications, such as developing IM products for drug delivery medium (Zema et al., 2012), injecting a big LCD panel (Wang et al., 2009), producing the thin parts (Nian et al., 2015), developing the complex parts (López et al., 2016), fabricating the complex slender parts (Torres-Alba et al., 2023), and manufacturing the plastic gears (Solanki et al., 2022). High-density polyethylene (HDPE) has good characteristics of low cost, toughness, impact resistance, abrasion resistance, water absorption resistance, and recycle processing ability (Amjadi and Fatemi, 2020). HDPE has advantages in manufacturing as high production rate and moldability in complex shapes (Amjadi and Fatemi, 2021). IM consists of a series steps of filling melt material into the cavity, packing stage, cooling melt material down to ejection temperature, and ejecting molded part out of the mold (Khosravani and Nasiri, 2020). The sample quality generally depends on factors including design criteria of product and mold, IM machine characters, polymer features, and environmental condition (Nian et al., 2019). Defects often occur during the IM process, such as warpage, shrinkage, short shot, flash, and weld lines. Warpage defect (WD) is a sore problem in the final product, such as quality decrease, assembly dwindling, and joint mistake (Guo et al., 2002). Some other reasons causes warpage are distortion phenomena of material (Zheng et al., 2011), residual stresses during cooling stage, and shrinkage (Lee et al., 2019). These defects have been eliminated by selecting a group of the proper IM parameters. It is not easy to gain the optimal IM factors to guarantee the quality by technical handbook or actual experience. Many research groups have been focused on the technology and methods to enhance the IM process and reduce defects, such as using an intelligent solution for improving IM process (Khosravani et

* Corresponding author.
E-mail addresses: longtv@haui.edu.vn (V. L. Trinh)

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al., 2022), optimizing the process factors to minimize the weld lines by using the numerical technique (Kitayama et al., 2018), using GRA method to optimize the IM process parameters for improving the quality of product (Kumar et al., 2019), applying artificial neural network (ANN) to optimize the warpage and shrinkage in the IM process (Oliaei et al., 2016), improving the accuracy of gear geometry via using technique of controlling the IM parameter during injection molding process (Dhaduti et al., 2020), controlling the plastic flow by using deep neural network method to enhance the efficiency of production process (Xu et al., 2023), and using sensors to measure the mechanical characteristics of IM products (Ageyeva et al., 2019).

Lots of groups have been spent on methodologies and tools to seek the processing factors for IM process to eliminate warpage and other defects, such as using warpage optimization technique by using Taguchi method (Tang et al., 2007), studying the influence of the mold temperature on the warpage (Karagöz, 2021), finding processing factors affected on warpage (Martowibowo and Khloeun, 2019), reducing warpage with the neural network method (Yin et al., 2011), genetic algorithm method (Ozcelik and Erzurumlu, 2006), and using the signal-to-noise (S/N) analysis to find out the impact of IM parameters on the product quality (Altan, 2010). The higher S/N is the more robust of the system's function such as the injection molding system (Jugulum and Singh, 2008; Nasir et al., 2014) and the turning system (Sivaiah and Chakradhar, 2019).

Taguchi method has generally applied to design complicated experiments with the ability of optimizing processes and minimizing experiments (Fei et al., 2013). Taguchi method is cost effective and time saving by producing a lot of information while using small experiments (Zhao et al., 2022). Some successful goals are solved by Taguchi method, such as handling the compression strength problem (Wang et al., 2014), reducing the shear stress with controlling the filling phenomena (Hentati et al., 2019), controlling the flexural modulus with processing factors (Mehat and Kamaruddin, 2011), minimizing the product warpage (Wang et al., 2021; Zheng et al., 2015).

This paper demonstrates the effect of processing parameters (PP) on WD during the IM process to enhance the product quality. Some technical tools are used in the study to examine the IM factors that affect warpage, including the simulation, analysis of variance (ANOVA), signal-to-noise (S/N) ratio analysis, and Taguchi method. The WD is predicted and minimized via controlling the mixture of PP during manufacturing procedure, including the filling time, melt temperature, melt surface temperature, injection pressure, packing pressure, packing time, coolant inlet temperature, cooling time, and mold open time. The experiments were executed by using Moldflow software. The results show that the packing pressure time is highest on the warpage with 48.94%, the melt temperature is second position with 37.48%. The optimal PP set is re-scanned with WD decrease of about 1.2% after optimization. The mathematical formula has been constructed to predict and control the WD during the IM process with the acceptable value of 86.29%. The results are well provided for the IM designing and manufacturing processes.

2. Experimental design

2.1 Mold design and material

A tensile test specimen D638 was selected for the test as shown in **Fig. 1** (García-Domínguez et al., 2020). The specimen has the detail dimensions including 185 mm of the total length, 19 mm of the large width, 115 mm of the gripping distance, 57 mm of the small section length, 13 mm of the small section width, 76 mm of the fillet radii, and 3.2 mm of the thickness.

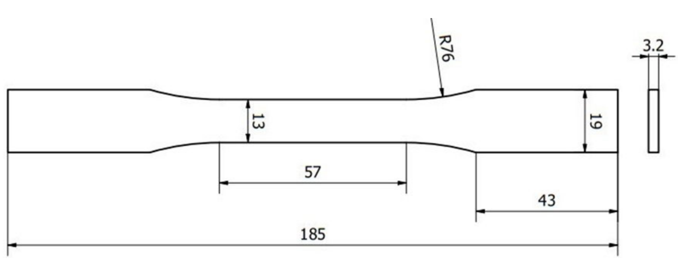


Fig. 1. The design of the product

The product is shaped by using a two-plate mold. The resin is selected to fill in the cavity as high density polyethylene (HDPE; coded 7070-Formosa Plastic). **Table 1** figures the material properties with melt density of 0.73817 g/cm³, elastic modulus of 911 MPa, solid density of 0.95121 g/cm³, specific heat capacity of 3000 J/(kg-C), thermal conductivity of 0.27 W/(m-C), and Poisson's ratio of 0.426. The IM machine is a SE180EV-A model with type C450M from Sumitomo (SHI) Demag, Japan. The basic parameters require for simulation procedure such as maximal injection stroke (450 mm), highest injection rate (356 cm³/s), screw diameter (36 mm), the maximum injection pressure (259 MPa), and maximal clamp force (183.5 Tonne) (Sumitomo-shi-DEMAG.us/, 2022). **Fig. 2** shows the product arrangement and cooling channel in the mold cavity. The cooling channel parameters include the cooling channel diameter of 8 mm, the distance between two closed cooling lines in the same plate of 50 mm, the distance from the cooling channel center on the cavity plate to the part surface of 14 mm, the distance from the cooling channel center on the core plate to the part surface of 12.8 mm, and the distance between two symmetrical cooling lines via parting line of 30 mm. **Fig. 3** shows the configuration of the mesh. The mesh is three dimensional tetrahedral type with the thickness of 0.8 mm. The total elements is 399018.

Table 1. The material properties of HDPE

Properties	Value	Unit
Melt density	0.73817	g/cm^3
Solid density	0.95121	g/cm^3
Transition temperature	112	^{o}C
Specific heat capacity	3000	J/(kg-C)
Elastic modulus	911	MPa
Poisson's ratio (υ)	0.426	

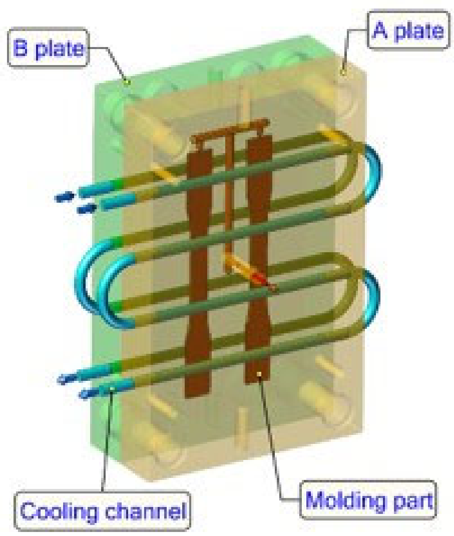


Fig. 2. The product arrangement and cooling channel design in the mold

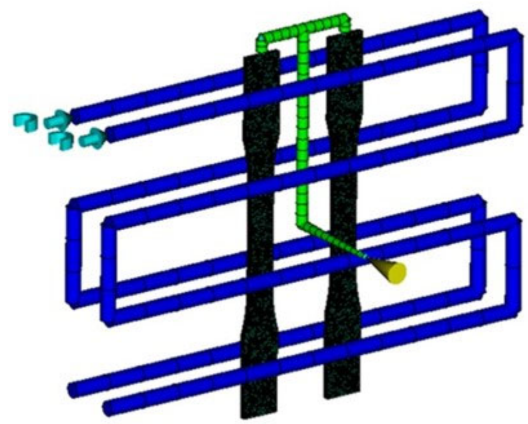


Fig. 3. The mesh configuration

2.2 Experiment set-up

Taguchi method was applied to design and conduct the purpose of the work. The crucial factors used to investigate the influence of the IM parameters on the WD include melt temperature (A), mold surface temperature (B), injection pressure (C), packing pressure (D), and packing pressure time (E). These parameters have been consulted by using the IM handbooks, practical experiments, and previous studies (Li et al., 2008).The D factor has been calculated by following formula:

$$D = x_i \tag{1}$$

where:

D is the packing pressure (MPa)
x_i is the percentage of injection pressure in the i_{th} level.
The E factor is estimated by the following formula (Kazmer, 2016):

$$t_s = \frac{h^2}{\pi^2.\alpha} \ln\left(\frac{4}{\pi} \times \frac{T_{melt} - T_{coolant}}{T_{no\_flow} - T_{coolant}}\right) \tag{2}$$

where:

t_s is the packing pressure time (s).
h is nominal cavity wall thickness (m).
T_{melt} is melt temperate (for specific heat is 3000 J/(kg-C)).
T_{no_flow} is the temperature where the plastic flow desists inside the cavity after injection.
$T_{coolant}$ is the coolant temperature.

α is thermal diffusivity (m^2/s).

$$a = \frac{k}{\rho * c_p} \tag{3}$$

where

k is thermal conductivity (W/(mK)).
ρ is specific heat capacity (J/(kgK)).
c_p is density (kg/m^3).

Table 2 shows the five levels of the IM parameters. The IM factors were set for the study including A (with 190 °C, 210 °C, 230 °C, 250 °C, and 270 °C), B (with 24 °C, 40 °C, 55 °C, 70 °C, and 85 °C), C (with 70 MPa, 78 MPa, 86 MPa, 94 MPa, and 102 MPa), D (with 60 %, 70 %, 80 %, 90 %, and 100 % of the corresponding injection pressure levels), and E (with 4s, 6s, 8s, 10s, and 12s).

Table 2. Five levels of effective factors

IM parameters	Interpret	Action area	Level 1	Level 2	Level 3	Level 4	Level 5
Melt Temperature(°C)	A	180-280	190	210	230	250	270
Mold Surface Temperature(°C)	B	20-95	25	40	55	70	85
Injection Pressure (MPa)	C	70-105	70	78	86	94	102
Packing pressure (%)	D	100%	60	70	80	90	100
Packing pressure time	E	8	4	6	8	10	12

Table 3 shows the L_{25} orthogonal array of 25 experiments for the IM process with above processing parameters. **Table 4** shows the codes represented for processing parameters in L25 orthogonal array.

Table 3. The layout of the L25 orthogonal array with the actual parameter

Run	Melt	Mold	Injection	Packing	Packing
1	190	25	70	60	4
2	190	40	78	70	6
3	190	55	86	80	8
4	190	70	94	90	10
5	190	85	102	100	12
6	210	25	78	80	10
7	210	40	86	90	12
8	210	55	94	100	4
9	210	70	102	60	6
10	210	85	70	70	8
11	230	25	86	100	6
12	230	40	94	60	8
13	230	55	102	70	10
14	230	70	70	80	12
15	230	85	78	90	4
16	250	25	94	70	12
17	250	40	102	80	4
18	250	55	70	90	6
19	250	70	78	100	8
20	250	85	86	60	10
21	270	25	102	90	8
22	270	40	70	100	10
23	270	55	78	60	12
24	270	70	86	70	4
25	270	85	94	80	6

Table 4. The parameter codes in L25 orthogonal array

Run	A (°C)	B (°C)	C (MPa)	D (%)	E (s)
1	1	1	1	1	1
2	1	2	2	2	2
3	1	3	3	3	3
4	1	4	4	4	4
5	1	5	5	5	5
6	2	1	2	3	4
7	2	2	3	4	5
8	2	3	4	5	1
9	2	4	5	1	2
10	2	5	1	2	3
11	3	1	3	5	2
12	3	2	4	1	3
13	3	3	5	2	4
14	3	4	1	3	5
15	3	5	2	4	1
16	4	1	4	2	5
17	4	2	5	3	1
18	4	3	1	4	2
19	4	4	2	5	3
20	4	5	3	1	4
21	5	1	5	4	3
22	5	2	1	5	4
23	5	3	2	1	5
24	5	4	3	2	1
25	5	5	4	3	2

3. Results and Discussion

3.1 Taguchi analysis

Table 5 shows the WD values performed by the digital experimental process. Taguchi method is applied to determine the influence of IM parameters on the WD. The IM process is simulated and analyzed by Moldflow. The signal-to-noise (S/N) analysis is conducted by Minitab to determine the impact of factors on the quality criterion related to the WD. With minimizing the WD, the smaller WD is the better quality, corresponding to the product quality increase as the warpage decreases. The minimum WD is determined by selecting the highest peaks from response factors via analyzing the S/N ratio.

Table 5. The warpage deformation values

Run	A (°C)	B (°C)	C (MPa)	D (%)	E (s)	WD (mm)
1	1	1	1	1	1	1.956
2	1	2	2	2	2	1.694
3	1	3	3	3	3	1.636
4	1	4	4	4	4	1.541
5	1	5	5	5	5	1.496
6	2	1	2	3	4	1.679
7	2	2	3	4	5	1.643
8	2	3	4	5	1	1.874
9	2	4	5	1	2	1.845
10	2	5	1	2	3	1.772
11	3	1	3	5	2	1.785
12	3	2	4	1	3	1.822
13	3	3	5	2	4	1.783
14	3	4	1	3	5	1.756
15	3	5	2	4	1	2.016
16	4	1	4	2	5	1.846
17	4	2	5	3	1	2.174
18	4	3	1	4	2	1.955
19	4	4	2	5	3	1.746
20	4	5	3	1	4	1.901
21	5	1	5	4	3	1.843
22	5	2	1	5	4	1.713
23	5	3	2	1	5	1.903
24	5	4	3	2	1	2.335
25	5	5	4	3	2	2.059

Fig. 4 shows the warpage distribution map of the first experimental analyis with the maximum WD value of 1.956 mm.

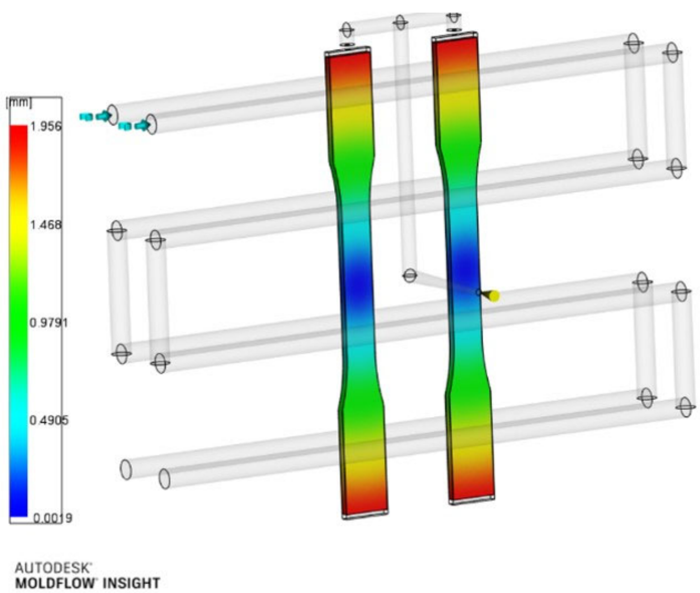


Fig. 4. Warpage deformation of the experiment of Run 1.

The S/N with the feature of the higher as the more stable function that is calculated to meet the WD minimum. The S/N ratio model is determined by the mean of "smaller the bester" by following equation (4)(Jugulum and Singh, 2008; Nasir et al., 2014):

$$S/N = -10\log\left(\sum (y^2)/n\right) \tag{4}$$

where, n = The number of observations
y = The result of each response

Table 6 shows the S/N ratio values and its mean marks of all experimental studies.

Table 6. the S/N ratio values and its mean marks

Run	A (°C)	B (°C)	C (MPa)	D (%)	E (s)	WD (mm)	S/N ratios	Mean values
1	1	1	1	1	1	1.956	-5.82738	1.956
2	1	2	2	2	2	1.694	-4.57827	1.694
3	1	3	3	3	3	1.636	-4.27567	1.636
4	1	4	4	4	4	1.541	-3.75605	1.541
5	1	5	5	5	5	1.496	-3.49863	1.496
6	2	1	2	3	4	1.679	-4.50101	1.679
7	2	2	3	4	5	1.643	-4.31275	1.643
8	2	3	4	5	1	1.874	-5.45539	1.874
9	2	4	5	1	2	1.845	-5.31993	1.845
10	2	5	1	2	3	1.772	-4.96927	1.772
11	3	1	3	5	2	1.785	-5.03276	1.785
12	3	2	4	1	3	1.822	-5.21097	1.822
13	3	3	5	2	4	1.783	-5.02303	1.783
14	3	4	1	3	5	1.756	-4.89049	1.756
15	3	5	2	4	1	2.016	-6.08981	2.016
16	4	1	4	2	5	1.846	-5.32463	1.846
17	4	2	5	3	1	2.174	-6.74519	2.174
18	4	3	1	4	2	1.955	-5.82294	1.955
19	4	4	2	5	3	1.746	-4.84088	1.746
20	4	5	3	1	4	1.901	-5.57964	1.901
21	5	1	5	4	3	1.843	-5.31051	1.843
22	5	2	1	5	4	1.713	-4.67515	1.713
23	5	3	2	1	5	1.903	-5.58878	1.903
24	5	4	3	2	1	2.335	-7.36574	2.335
25	5	5	4	3	2	2.059	-6.27313	2.059

Table 7 shows the levels of mean values for the IM parameters filled in the response table for mean. The Delta value is calculated by following formula:

$$\text{Delta} = \left|\text{Level}_{max} - \text{Level}_{min}\right| \qquad (5)$$

Table 7. The response table for mean

Level	A	B	C	D	E
1	1.665	1.822	1.830	1.885	2.071
2	1.763	1.809	1.808	1.886	1.868
3	1.832	1.830	1.860	1.861	1.764
4	1.924	1.845	1.828	1.800	1.723
5	1.971	1.849	1.828	1.723	1.729

Table 8 shows the ranks of the significant levels of the IM parameters to the response. The influencing rank is queued as E-A-D-C-B. The results show that the E and A factors are the two main parameters affecting on the WD because of its high delta signal values.

Table 8. The response table of S/N ratios

Level	A	B	C	D	E
1	-4.387	-5.199	-5.237	-5.505	-6.297
2	-4.912	-5.104	-5.120	-5.452	-5.405
3	-5.249	-5.233	-5.313	-5.337	-4.921
4	-5.663	-5.235	-5.204	-5.058	-4.707
5	-5.843	-5.282	-5.179	-4.701	-4.723
Delta	1.455	0.178	0.194	0.805	1.590
Rank	2	5	4	3	1

With minimizing the WD, the highest peaks are chosen for each IM parameter based on the S/N ratio to prove the optimal processing parameters for the purpose of the WD minimum. **Fig. 5** shows the best combination of the IM parameters picked up from the response table of S/N ratio values as A1-B2-C2-D5-E4. **Fig. 6** shows the effect of IM factors on the WD. **Fig. 6(a)** shows the dominant effect of IM parameters on the WD for means. It revealed that the A factor increases, the WD increases. This phenomenon is caused by physical behavior of HDPE material. The maximum WD occurred at 85°C and minimum WD at 25°C with the B factor. The highest WD gets at 86MPa, and the smallest WD at 78 MPa with the C factor. The minimum WD is at 100% with the D factor. It revealed that the WD tends to decrease with the increasing the percentage of the packing pressure. The WD changes rapidly as changing the E factor, and the minimum WD occurs at 10s. **Fig. 6(b)** shows the crucial effects for S/N ratios on WD. The tip mean S/N ratios are A at 190°C, B at 40°C, C at 78 MPa, D at 100%, and E factor at 10s. The optimal IM parameters combination is A1-B2-C2-D5-E4.

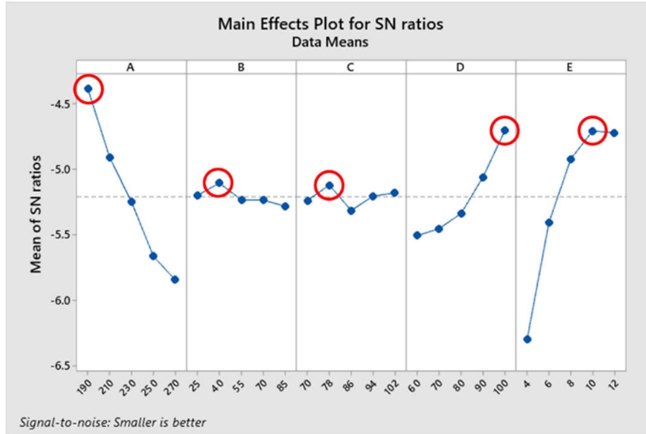
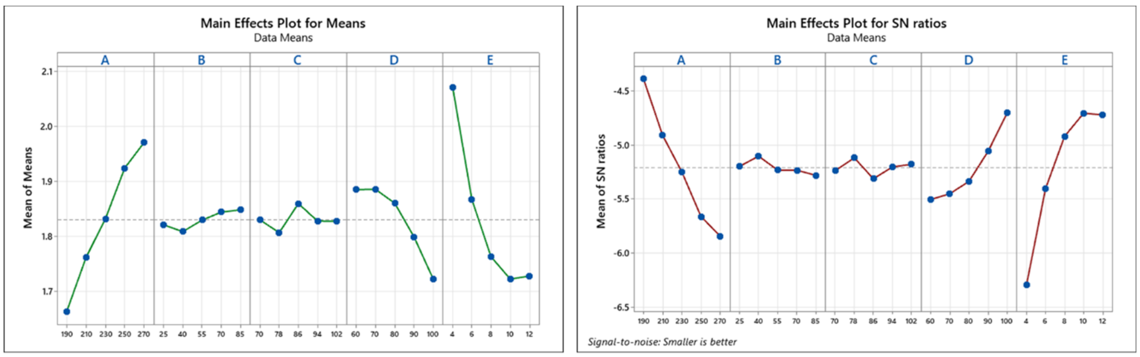


Fig. 5. The best combination of IM parameters



(a) (b)

Fig. 6. The effect of process parameters on WD; (a) Main effect of process parameters for means; (b) Main effects for S/N ratios on warpage

3.2 Analysis of variance (ANOVA)

Analysis of variance (ANOVA) technique is used to make the decision for selecting or detecting the parameters that have effect on the desired performance of a working technological system such as the IM system. ANOVA contains tools to test all of the factors and their interactions during the manufacturing process via comparison of the mean squares with the experimental errors estimated at the particular confidence levels. The calculation values include the degrees of freedom (DF), sequential sums of squares (Seq SS), adjusted sums of squares (Adj SS), adjusted mean squares (Adj MS), F-value (F), P-Value, and the percentage of contribution (%).

Table 9 shows the results conducted by ANOVA analysis. The E factor is the biggest influencing parameter with the contribution of 48.94%. The second position is the A factor with 37.48%. The third position is the D factor with 12.14%. The effect of B and C factors are negligible.

Table 9. ANOVA analysis Results

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
A	4	6.8635	37.48%	6.86354	1.71588	94.29	0
B	4	0.088	0.48%	0.08795	0.02199	1.21	0.429
C	4	0.1026	0.56%	0.10258	0.02564	1.41	0.374
D	4	2.2227	12.14%	2.22268	0.55567	30.54	0.003
E	4	8.9625	48.94%	8.96251	2.24063	123.13	0
Error	4	0.0728	0.40%	0.07279	0.0182		
Total	24	18.312	100.00%				

3.3 Optimal monitoring

The results show that the optimal composed set of the IM parameters (SoP) for minimization of warpage is A1-B2-C2-D5-E4. To guarantee, the SoP was tested again by Moldflow. **Table 10** shows the results of the WD before and after optimization procedure. The minimum WD is 1.496 mm after 25 experiments. The minimum WD is 1.478 mm after testing with the optimal factors set corresponding to reduction of about 1.20%. The results confirmed that the study is effectiveness in determining the optimal factors to achieve the minimum WD of the plastic product during the IM process.

Table 10. Results of warpage after optimization

Parametter	Value
Melt Temperature (°C)	190
Mold Surface Temperature (°C)	40
Injection Pressure (Mpa)	78
Packing pressure (%)	100
Packing pressure time (s)	10
WD after optimize (mm)	**1.478**
Minimal WD before optimize (mm)	1.496

3.4 Predictive mathematical modeling

The linear regression analysis is applied to construct the predictive mathematical form of the WD as a function of A, B, C, D, and E factors. **Table 11** shows the predictive model and the acceptable value (R-square) obtained through the regression analysis. The R-square is 86.29%. This guarantees that the mathematical model fits the data.

Table 11. The fit regression models and the R^2 values

Regression model (mm)	R^2
Warpage deflection one gate = 1.551 + 0.003869 A + 0.000596 B + 0.00020 C - 0.00412 D - 0.04143 E	86.29%

Fig. 7 shows the probability plot of the WD. It revealed that the residuals were arranged near the straight line for the WD. The regression line follows the rule of the normal distribution region with features appearing in the middle of the data marks. It reveals that the regression line is a good fit model. Hence, the regression equation is a suitable model.

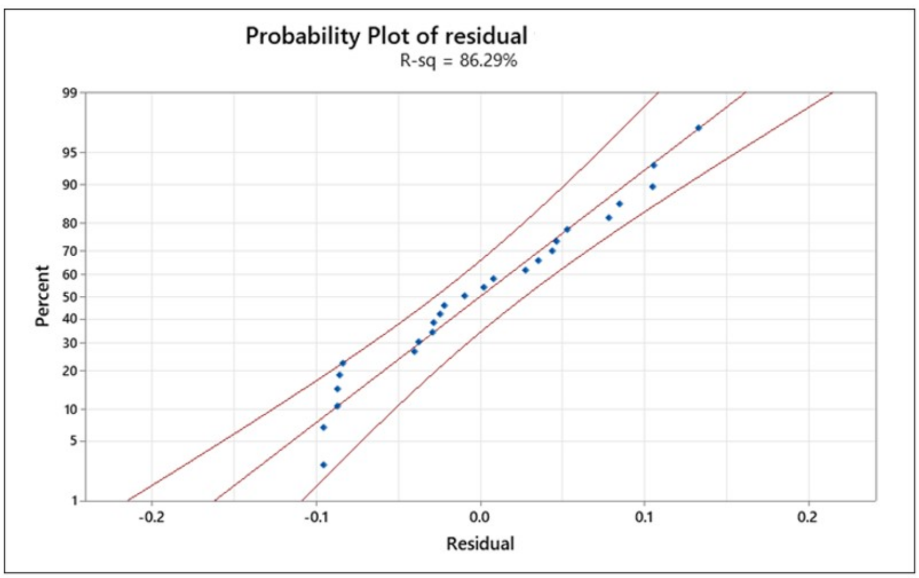


Fig. 7. Normal probability plot of the residuals

4. Conclusions

Taguchi and simulation methods are successfully used in a combination way to study the influence of IM parameters such as the melt temperature, the mould surface temperature, the injection pressure, the packing pressure, and the packing pressure time on the warpage. The signal-to-noise ratio (S/N) is applied to find the best combination of the IM parameters with the purpose of minimization of the WD. The ANOVA method is used to seek the factor that has the strongest influence on the WD during the IM process. The results show that the E and A factors have the greatest influences on the WD with the contributions of 48.94% and 37.48%, respectively. The mathematical model is constructed to predict the WD during the IM process. The normal probability plot is drawn to check the fitting of the regression model with input data. The regression model is reasonable and has no outliers. The optimal factors set is re-inspected with WD abated slightly by an amount of about 1.2% after optimization. The predictive mathematical model is really good for the set of IM parameters in producing plastic products with the representation data of acceptable values of 86.29%. The results have been applied to the design, fabricating, and production stages of injection moulding.

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