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Injection Molding Parameter Optimization Using Taguchi and Moldflow

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Short shot defect;
Moldflow Analysis;
Taguchi method;
Cycle Time;

ABSTRACT
Geopolitical tensions in the Middle East have increased uncertainty in petrochemical and polypropylene supply, reducing plastic raw material availability and forcing plastic injection companies to improve process efficiency, minimize scrap, and reduce production losses. In automotive component manufacturing, the Cover Defroster product still faces short shot defects caused by incomplete molten plastic flow into the mold cavity. Many injection molding companies also still rely on trial-and-error machine settings, which increases material waste, setting time, and production cost. This study aims to optimize injection molding parameters using the Taguchi method and Moldflow simulation to eliminate short shot defects and minimize cycle time. This research used a computer simulation-based experimental design. The product studied was a polypropylene type LA880T. Four process parameters were tested using an Orthogonal Array L16, namely injection pressure, mold temperature, melt temperature, and injection time. Moldflow Insight was used to simulate material flow, while ANOVA, Tukey test, and Signal-to-Noise Ratio with the Smaller-the-Better approach were used to analyze cycle time performance. The simulation showed that trials 1 to 4 produced short shot defects and were rejected. ANOVA results showed that injection time had a significant effect on cycle time, while injection pressure, mold temperature, and melt temperature had no significant effect. The best parameter combinations were trials 6, 12, and 15, which produced good products without short shot defects and achieved the shortest cycle time of 24.12 seconds. The integration of Taguchi and Moldflow effectively supports parameter optimization, reduces defect risk, and improves injection molding process efficiency.

INTRODUCTION

Plastic materials are currently widely used in the manufacture of various products. Polypropylene plastic is used in more than half of the components of automobiles (Nashiro et al., 2022). The processing process of plastic materials can be carried out by several methods, namely Injection Molding, Extrusion, Blow Molding, and Thermofirming. Injection Molding as a technique to inject molten plastic into molds to form products according to the desired design thermoforming (Bryce, 1998; Beaumont et al., 2002). In the field of plastic injection in the automotive component manufacturing industry (Çalışkan, Koca, et al., 2023; Çalışkan, Özer, et al., 2023; Ghimp, 2025; Hsiao et al., 2023; Slama et al., 2023; Yang et al., 2022). One of the main problems in the plastic injection process is the defective short shot product (Aribowo & Dani, 2023; López-Adrio & Álvarez, 2024; Tang, 2025; Yasin, 2022; Zhou et al., 2023). This happens due to an imperfect flow of material entering the mold cavity, so the product cannot be delivered to the customer.

Currently, there are still many plastic injection industries whose machine setting process applies a trial-and-error method to be able to produce products that meet quality standards. That would cost a lot of money, including wasted material costs, machine setting time, and operator costs. Before the injection process, modeling simulations are carried out using Moldflow insight software to predict the flow of molten plastic into the mold and help identify process problems before production begins (Arrk, 2024; Zhou et al., 2023; Szabó et al., 2021). By using Moldflow software to conduct simulations, engine setting parameters can be optimized to avoid short shot defects and material disposal used for trial and error activities. Research by Chen et al. (2023) shows that the use of the Taguchi method and Moldflow analysis can reduce short shot defects in plastic products produced through injection molding. So that the Company can save the cost of setting the machine at the beginning of production.

The research gap addressed by this study is fourfold. First, no previous study has simultaneously optimized four injection molding parameters (injection pressure, mold temperature, melt temperature, injection time) for the specific product (Cover Defroster from polypropylene) using both Moldflow simulation and Taguchi L16 orthogonal array. Second, previous research has focused either on eliminating short shot defects or minimizing cycle time separately, with limited attention to optimizing both objectives simultaneously. Third, most studies have used physical experiments which are resource-intensive, whereas this study uses Moldflow simulation that allows rapid, cost-effective experimentation across 16 parameter combinations. Fourth, the specific context of polypropylene injection molding for automotive interior components has not been extensively studied using the combined methodology. The urgency of this research is driven by several factors. First, short shot defects directly impact production yield, with experiments 1-4 showing complete product rejection, representing a 25% defect rate across initial parameter combinations. Second, cycle time inefficiency directly affects production throughput and operational costs, with injection time varying from 1.0 to 1.7 seconds, a 70% difference. Third, the trial-and-error method currently used by many plastic injection industries is wasteful, consuming material, time, and labor costs (Wibowo et al., 2020). Fourth, Moldflow simulation can reduce the need for physical trials, saving approximately 60-80% of typical setup costs. Fifth, the global push for manufacturing efficiency and reduced waste aligns with optimizing injection molding parameters. Sixth, as the automotive industry increasingly demands high-quality plastic components at lower costs, parameter optimization becomes a competitive necessity. Seventh, the Indonesian government's "Making Indonesia 4.0" roadmap prioritizes manufacturing efficiency improvements, making this research nationally relevant.

The novelty of this study lies in several aspects. First, it combines Moldflow simulation with the Taguchi method (L16 orthogonal array) to simultaneously address short shot elimination and cycle time minimization, an integrated approach not widely documented for polypropylene Cover Defroster products. Second, it identifies that injection time is the only statistically significant parameter affecting cycle time ($p = 0.000$), while injection pressure, mold temperature, and melt temperature show no significant effects, providing specific guidance for process optimization. Third, it identifies the critical threshold for injection pressure (minimum 30 MPa required to avoid short shots, with 25 MPa producing defects), establishing a practical process window. Fourth, it successfully identifies three optimal parameter combinations (trials 6, 12, and 15) all achieving 24.12-second cycle time without defects, providing flexibility for manufacturers. The purpose of this study is to optimize injection molding process parameters to eliminate short shot defects while minimizing production cycle time for a polypropylene Cover Defroster product. The contribution of this research is to provide an integrated methodology combining Moldflow simulation and Taguchi optimization that can be applied to similar injection molding applications, and to provide empirical data on the effects of injection pressure, mold temperature, melt temperature, and injection time on short shot defects and cycle time. The benefits include: first, reducing production costs by eliminating trial-and-error setup; second, improving product quality by preventing short shot defects; third, increasing production efficiency by minimizing cycle time; fourth, providing a reference framework for other injection molding applications; and fifth, contributing to the body of knowledge on polypropylene injection molding optimization.

METHOD

1. Description Part

Product Cover Defroster based on 3D data design from customer, the product has dimensions of 319mm x 66mm x 30mm, and the product weight is 50 grams, the part is shown in Figure 1.

Figure 1. Cover Defroster

2. Research Design

The research employs a combined experimental and simulation approach to optimize injection molding parameters while minimizing short-shot defects as shown in Figure 2 and cycle time. The methodology integrates the Taguchi design of experiments with Moldflow Insight simulation in Cover Defroster products.

Figure 2. Defect Short shot
Source: Documentation (2025)

The plastic material used for the manufacture of the product is Polypropylene type LA880T. Polypropylene (PP) was selected as the molding material due to its widespread automotive application, mechanical performance, and melt flow characteristics. Key properties used in the simulation are listed in Table 2, including specific gravity, melt flow rate, tensile strength, and recommended processing temperature. Accurate material characterization is critical to ensure that the simulation predicts realistic melt behavior, solidification, and viscosity effects. The material characteristics of Polypropylene are shown in Table 2.

Table 2. Characteristic properties of polypropylene LA880T

Test Item	Unit	Result
Specific Gravity	-	1.05
Melt Flow Rate	g/10min	21
Tensile Yield strength (23°C)	Mpa	22
Tensile Modulus (23°C)	Mpa	2204
Recommended Processing Temperature	°C	190 - 230

Source : The Polyolefin Company Pte. Ltd (2025)

The method used is an experiment with a computer simulation approach and experimental design. The Moldflow Insight simulation will be used to model the flow of material in the mold depicted in Figure 3.

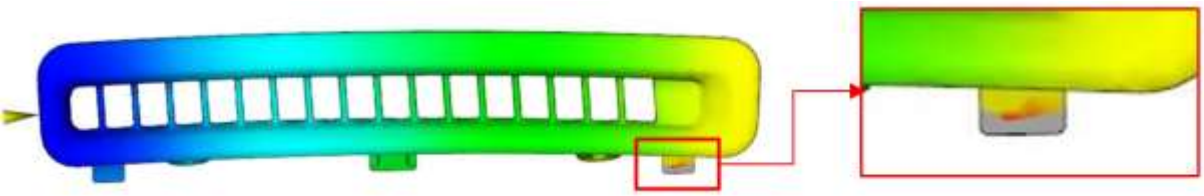

Figure 3. Simulation Defect Short Shot

The stages in this research methodology can be seen in Figure 4.

Problems

Inefficient Short Shot & Cycle Time in the plastic injection process.

↓

Theoretical Foundations

1. Plastic Injection Process
2. Simulated Moldflow Analysis to analyze the parameters of plastic injection
3. The Taguchi method for parameter optimization (Orthogonal Array L16).
4. Analysis S/N Ratio (Smaller the Better)

↓

Research Methodology

1. Experimental Design with the Taguchi method
2. Simulated Moldflow Analysis with 16 parameter combinations
3. Analysis S/N Ratio (Smaller the Better)

↓

Results

Optimal combination of parameters for short shot defect minimization and cycle *time*

Figure 4. Frame of Mind

3.2 Orthogonal Array L16

In this study, the Orthogonal Array L6 (4^4) was used to test four factors: injection pressure, mold temperature, melt temperature, and injection time. These factors are tested in four levels, each shown in Table 3. This allows experiments to be carried out with a low number of experiments (16 experiments), as shown in Table 4.

Table 3. Parameter and Level Factors

		Factor			
		Injection Pressure	Mold Temperature	Melt Temperature	Injection Time
		(Mpa)	(°C)	(°C)	(s)
Level	1	25	35	200	1
	2	30	40	210	1.3
	3	35	45	220	1.5
	4	40	50	230	1.7

Table 4. Orthogonal Array L16

Trial	Factor			
	Injection Pressure	Mold Temperature	Melt Temperature	Injection Time
	(Mpa)	(°C)	(°C)	(s)
1	25	35	200	1.0
2	25	35	210	1.3
3	25	40	220	1.5
4	25	45	230	1.7
5	30	35	220	1.7
6	30	40	230	1.0
7	30	45	200	1.3
8	30	50	210	1.5
9	35	35	230	1.3
10	35	40	200	1.5
11	35	45	210	1.7
12	35	50	220	1.0
13	40	35	210	1.5
14	40	40	220	1.7
15	40	45	230	1.0
16	40	50	200	1.3

This methodology allows pre-production optimization of injection parameters, reducing trial-and-error material waste and machine setup time. It also provides insight into the sensitivity of cycle time and defect formation to each process factor, ensuring both quality and productivity are addressed before physical trials.

RESULT AND DISCUSSION

Experiments were carried out with 16 moldflow analysis simulations by examining the defect short shot and cycle time factors. Where the simulation results are presented in Table 5.

Table 5. Results of the Moldflow Simulation Experiment

Trial	Factor				Experimental Results		
	Injection Pressure	Mold Temperature	Melt Temperature	Injection Time	Short shot		cycle time
	(Mpa)	(°C)	(°C)	(s)	Yes/No	Status	(s)
1	25	35	200	1.0	Yes	Reject	24.12

2	25	35	210	1.3	Yes	Reject	24.47
3	25	40	220	1.5	Yes	Reject	24.70
4	25	45	230	1.7	Yes	Reject	24.90
5	30	35	220	1.7	No	Good	24.93
6	30	40	230	1.0	No	Good	24.12
7	30	45	200	1.3	No	Good	24.46
8	30	50	210	1.5	No	Good	24.70
9	35	35	230	1.3	No	Good	24.47
10	35	40	200	1.5	No	Good	24.70
11	35	45	210	1.7	No	Good	24.92
12	35	50	220	1.0	No	Good	24.12
13	40	35	210	1.5	No	Good	24.70
14	40	40	220	1.7	No	Good	24.93
15	40	45	230	1.0	No	Good	24.12
16	40	50	200	1.3	No	Good	24.46

Source: Documentation (2025)

The results of the Moldflow Analysis simulation showed that experiments 1 to 4 detected defects short shots. So that experiments 1 to 4 have a reject status and must be eliminated.

4.1 *Analysis of Variance* (ANOVA)

The analysis used in this experiment is Analysis of Variance (ANOVA) one way to determine the results of the difference from cycle time based on 4 factors, namely Injection Pressure, Mold Temperature, Melt Temperature, and Injection Time.

Table 6. ANOVA Test Results ($\alpha = 0.05$)

Variabel	DF	SS WO	Adj MS	F-Value	P-Value
Injection Pressure (MPa)	3	0.000147	0.000049	1.20	0.443
Mold Temperature (°C)	3	0.000261	0.000087	2.13	0.276
Melt Temperature (°C)	3	0.000148	0.000049	1.21	0.440
Injection Time (s)	3	0.916413	0.305471	7471.25	0.000*
Error	3	0.000123	0.000041		
Total	15				

significant

The results of the ANOVA test analysis in Table 6 show that the Injection Pressure (Mpa) has a P-Value (0.443) > 0.05, so there is no significant or meaningful difference from the four groups of Injection Pressure (25, 30, 35, 40) to the change Cycle Time. Variabel Mold Temperatue has a P-Value (0.276) > 0.05, so there is no significant or meaningful difference between the four groups Mold Temperatue (35, 40, 45, 50) to the change Cycle Time. Test results on variables Melt Temperatue also had a P-value of (0.440) > 0.05 which means there was no significant difference from the four groups Melt Temperature (200, 210, 220, 230) to change cycle time.

However, on the Injection Time showed an effect with a P-value (0.000) < 0.05 which means that there was a significant or significant difference from the four groups Injection Time against change cycle time. Overall, the results of the ANOVA test showed that of the four research variables, there was 1 variable that had a significant effect on cycle time i.e. Injectiom Time. While the other three variables are Injection Pressure, Mold Temperature, and Melt

Temperature have results that do not have a significant effect on Cycle Time. Due to the significant influence of Injection Time, then to measure the differences of each category, it will be followed by an analysis Post Hoc Test Using the test Tukey.

Table 7. ***R-Square***

S	R-sq	R-sq(adj)	R-sq(before)
0.0063942	99.99%	99.96%	99.73%

Table 7 shows the results of the R-Square Adjusted shows that of the 4 variables used, namely Injection Pressure, Mold Temperature, Melt Temperature and Injection Time able to explain Cycle Time of 99.96%, while the other 0.04% is explained by other variables besides these 4 variables.

Tabel 8. ***Coefficient***

Term	*Mean*	Coef	T-Value	P-Value
Constant	-	24.5506	15043.15	0.000
Injection Pressure (MPa)				
25	24.54	-0.00557	-1.90	0.154
30	24.55	0.00186	0.67	0.553
35	24.55	0.00186	0.67	0.553
40	24.55	0.00186	0.67	0.553
Mold Temperature (°C)				
35	24.56	0.00458	1.58	0.212
40	24.55	0.00424	1.20	0.318
45	24.55	-0.00367	-0.99	0.395
50	24.55	-0.00515	-1.40	0.257
Melt Temperature (°C)				
200	24.55	-0.00291	-0.93	0.423
210	24.55	0.00332	0.93	0.420
220	24.56	0.00465	1.27	0.295
230	24.55	-0.00505	-1.48	0.235
Injection Time (s)				
1.0	24.12	-0.42855	-135.14	0.000
1.3	24.70	-0.08384	-25.12	0.000
1.5	24.70	0.14529	40.26	0.000
1.7	24.92	0.36710	100.32	0.000

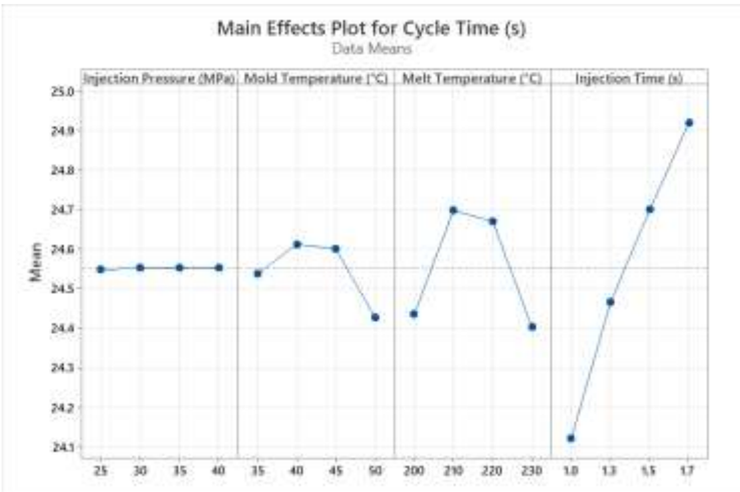

Figure 5. Red Plot

The results of the analysis in Table 8 and Figure 5 show that the Injection Pressure variable of 25 Mpa has the lowest average cycle time of 24.55, while Injection Pressure of 30, 35, and 40 Mpa has the highest average cycle time of 24.55. Mold Temperature of 40, 45, and 50°C has the lowest average cycle time of 25.55, while Mold Temperature of 35°C has the highest average cycle time of 24.56.

Melt Temperature of 200, 210, and 230 Mpa have an average cycle time lowest of 24.55, while Melt Temperature by 220°C has an average cycle time the highest of 24.56. On Injection Time by 1.0 seconds has an average cycle time lowest of 24.12, while Injection Time of 1.7 seconds has an average value cycle time the highest of 24.92.

Table 9. Test Tukey Injection Time

Injection Time	N	Mean	Grouping
1.7	4	24.9177	A
1.5	4	24.6959	B
1.3	4	24.4668	C
1.0	4	24.1221	D

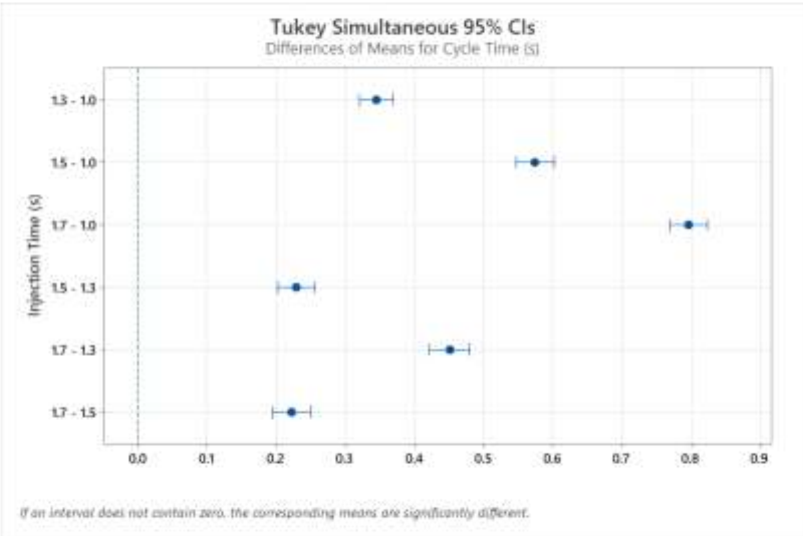

Figure 6. Test Tukey Injection Time

The results of the Post Hoc test using the Tukey test showed that the Injection Time of 1.0 seconds resulted in the shortest cycle time with an average of 24.12 and was significantly different from the other groups. The second best injection time was 1.3 seconds which resulted in an average cycle time of 24.47 and was significantly different from the rest of the group. In third place is injection time for 1.3 seconds and 1.7 seconds, both of which result in longer cycle times and are significantly different from all groups.

4.2 S/N Ratio Analysis

This study focuses on minimizing short shot defects and cycle time and then applying Smaller the Better which means that a higher S/N Ratio value (closer to 0 or more positive) shows better results, which means a shorter cycle time (smaller is better in this case). Where the formula of the S/N Ratio STB approach is

$$sn_{STB} = -10 \text{ Log} \left[\frac{1}{n} \sum_{i=1}^{n} y^2\right]$$

Where:

a. n is the number of attempts.

b. y_i is the value of the observation response (cycle time).

Based on the results of the calculation of the S/N ratio of STB, the response value of each experiment is presented in Table 6.

Table 6. S/N Ratio Response Value

Trial	Experimental Results		
	Cycle time (s)	*Cycle time kuadrat* (s^2)	*S/N Ratio (STB)*
1	24.12	581.77	-27.64
2	24.47	598.78	-27.77
3	24.70	610.09	-27.85
4	24.90	620.00	-27.92
5	24.93	621.50	-27.93
6	24.12	581.77	-27.64
7	24.46	598.29	-27.77
8	24.70	610.09	-27.85
9	24.47	598.78	-27.77
10	24.70	610.09	-27.85
11	24.92	621.00	-27.93
12	24.12	581.77	-27.64
13	24.70	610.09	-27.85
14	24.93	621.50	-27.93
15	24.12	581.77	-27.64
16	24.46	598.29	-27.77

From the results of the S/N Ratio response value, experiments 1, 6, 12 and 15 had the lowest noise value of -27.64. However, because of experiment 1 there was a short shot defect so it had to be eliminated. This means that the best experiments to get product results that are not short shots and the shortest cycle time are experiments 6, 12, and 15.

CONCLUSION

The conclusions obtained from the study on optimizing process parameters for short shot elimination to minimize cycle time are as follows: The injection pressure factor with a level of 25 Mpa shows the product quality results detected in short shot defects as shown in experiments 1, 2, 3 and 4. So that the four experiments must be eliminated because they will produce rejected products. The best parameters to get a product with good quality and the shortest cycle time are trials 6, 12 and 15. With results showing that all three produced the same production cycle time of 24.12 seconds. These three parameters can be used because they produce good quality product output.

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