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Defect Optimization in Injection Molded Parts Using Metal Epoxy Composite (MEC) as a Hybrid Mold by Taguchi Method

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ABSTRACT

Injection molding with alternative mold materials, such as metal epoxy composite (MEC), offers potential cost reductions and manufacturing flexibility; however, their lower thermal conductivity increases susceptibility to dimensional defects. This study aims to optimize injection molding process parameters to minimize warpage and shrinkage defects in molded parts produced using MEC as a hybrid mold insert. A simulation-based approach was adopted using Autodesk Moldflow, integrated with the Taguchi method for systematic process optimization. Six key process parameters were selected and arranged using an orthogonal array, while signal-to-noise ratio analysis and analysis of variance were applied to identify statistically significant factors. The results indicate that warpage is predominantly influenced by packing pressure and mold temperature, whereas shrinkage is mainly governed by melt temperature. Confirmation tests demonstrated strong agreement between predicted and simulated results, with error margins of 1.12% for warpage and 0.44% for shrinkage, confirming the reliability of the optimization model. Overall, the findings demonstrate that MEC hybrid molds can achieve acceptable dimensional stability when supported by appropriate parameter optimization, thereby providing a cost-effective alternative for small to medium-scale injection molding applications.

Keywords: Autodesk Moldflow Insight, Injection Molding, Metal Epoxy Composite (MEC), Shrinkage, Taguchi Method, Warpage.

1. INTRODUCTION

Injection molding is one of the most widely applied manufacturing processes for producing plastic components with complex geometry and high dimensional accuracy. Its extensive application in automotive, electronics, aerospace, and medical industries is attributed to its high productivity, repeatability, and precision [1, 2]. Despite these advantages, molded part quality is highly sensitive to mold material selection and process parameter control, as improper settings may lead to defects such as warpage, shrinkage, sink marks, and weld lines [3, 4]. Conventional injection molds are commonly fabricated from hardened steel or aluminum alloys due to their superior mechanical strength and thermal conductivity. However, these materials involve high tooling costs and long fabrication times, which are less suitable for rapid prototyping and low to medium-volume production [5, 6]. Consequently, alternative mold materials such as metal epoxy composite have been introduced as hybrid mold inserts to overcome these limitations. Metal epoxy composite molds are typically produced by reinforcing epoxy resin with metal fillers such as copper or brass. This approach enhances thermal conductivity and mechanical strength compared to pure epoxy molds while maintaining low manufacturing cost and short lead time [7–9]. Previous studies have reported that MEC based hybrid molds are suitable for short production

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runs and functional prototypes [10, 11]. Nevertheless, the relatively low thermal conductivity of MEC compared to steel results in non-uniform heat dissipation during molding, leading to residual stress development and dimensional instability [12]. Warpage and shrinkage are among the most critical defects in injection-molded parts, particularly when alternative mold materials are used. These defects are strongly influenced by processing conditions such as melt temperature, mold temperature, packing pressure, and cooling parameters [13–15]. Therefore, systematic optimization of injection molding parameters is essential to ensure acceptable part quality when MEC hybrid molds are employed. The Taguchi method has been widely adopted as a robust statistical optimization technique in injection molding due to its ability to efficiently evaluate multiple parameters using fewer experimental trials [16, 17]. When combined with numerical simulation tools such as Autodesk Moldflow Insight, the Taguchi method enables accurate prediction of defect behavior while minimizing experimental cost and time [18, 19]. However, few studies have focused specifically on process optimization for MEC-based hybrid molds. This study addresses this gap by investigating the influence of key process parameters on warpage and shrinkage defects using a Taguchi-based simulation approach.

2. MATERIAL AND METHODS

The overview of the entire research methodology and operational steps shown in Figure 1 is important to achieving the objectives of this project.

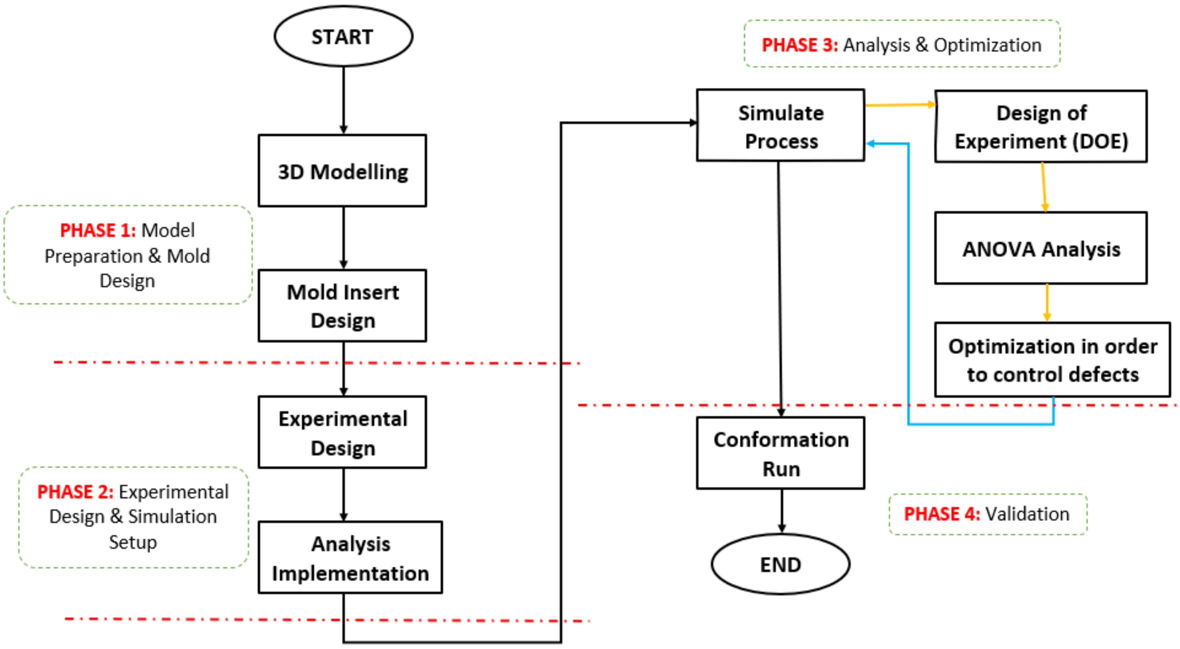
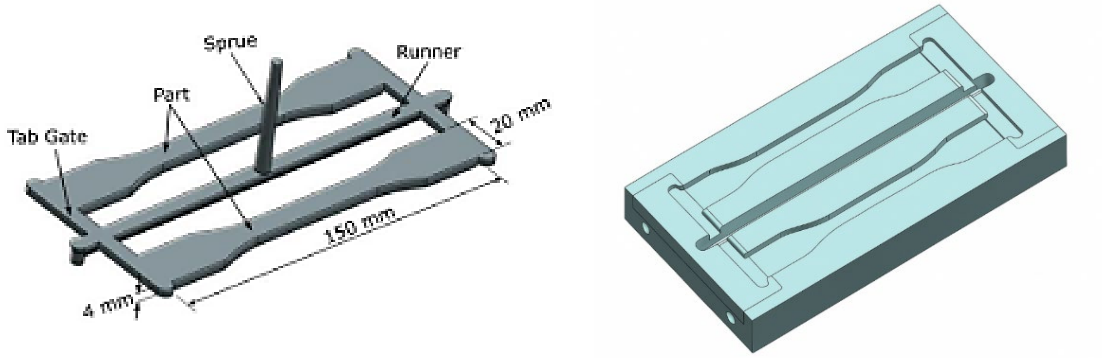


Figure 1: The overall research methodology.

2.1 Model and Mold Design

A standard thick, flat plastic specimen, based on ISO 3167, was designed in SolidWorks to represent a geometry susceptible to warpage and shrinkage. The mold system was configured as a hybrid design, combining a conventional steel mold base with MEC inserts for the core and cavity regions. This design approach (Figure 2) ensures adequate structural rigidity while allowing evaluation of the thermal behavior of MEC during the injection molding cycle [8, 10].



(a) (b)

Figure 2: Illustration of the CAD model of the test specimen and the MEC hybrid mold configuration used in this study. (a) CAD model of ISO 3167 thick flat specimen and (b) MEC hybrid mold insert configuration [8].

2.2 Injection Molding Simulation Setup

The injection molding process was simulated using Autodesk Moldflow Insight (Figure 3). Acrylonitrile Butadiene Styrene (ABS) was selected as the molding material due to its widespread industrial use. The simulation sequence included filling, packing, cooling, and warpage analysis. A three-dimensional fusion mesh was employed to ensure accurate prediction of temperature distribution and residual stresses. Cooling channels were uniformly arranged within the mold insert, and water was used as the cooling medium.

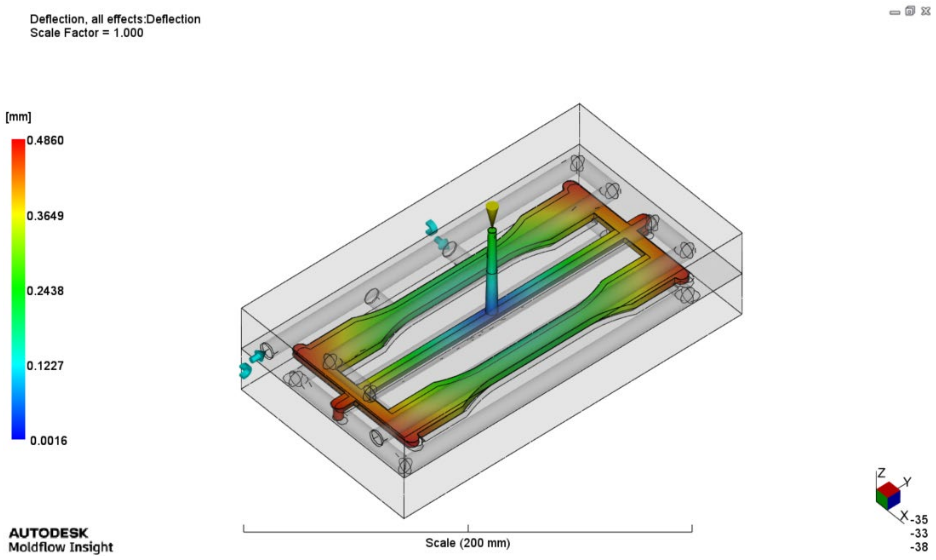


Figure 3: Example of the analysis process using Autodesk Moldflow Insight.

2.2.1 Refine Mesh Density

The discretization of the geometric model into a finite element structure is governed by the global edge length and merge tolerance settings, with the total computational time directly proportional to the level of refinement and the part scale. However, the accuracy of the numerical analysis depends more significantly on the strategic application of mesh density refinement within the part and the mold bodies. Specifically, the molded part requires a higher mesh density in thin-walled sections to precisely resolve the volumetric shrinkage and internal stress distributions that contribute to warpage during the packing and solidification phases. Furthermore, the mesh for the mold is refined at the contact interfaces and around the cooling channels to accurately simulate heat dissipation through the Metal Epoxy Composite (Figure 4). This localized refinement is vital because the hybrid material's unique thermal conductivity requires a high-resolution mesh to effectively capture thermal exchange between the polymer melt and the mold cavity. Consequently, this targeted refinement strategy ensures that the simulation reliably predicts manufacturing defects while maintaining computational efficiency.

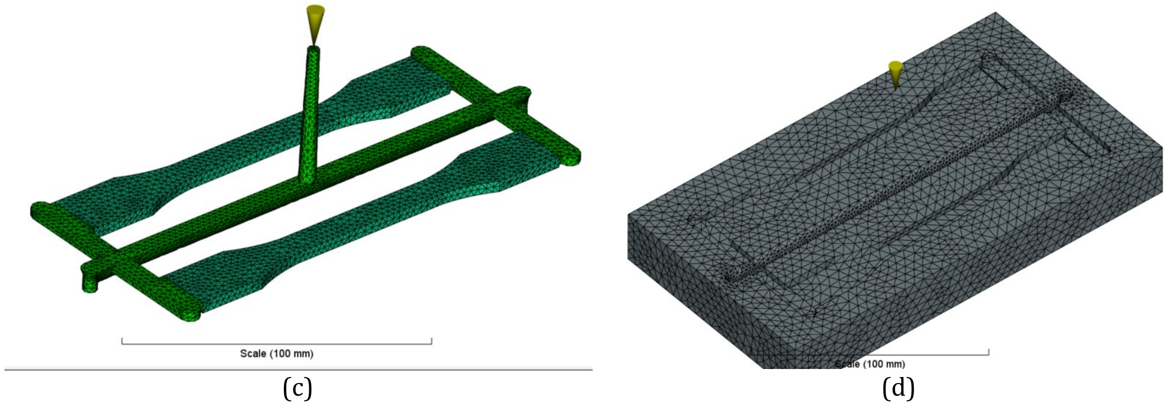


Figure 4: Meshing Process. (c) Thick flat part after the meshing process, and (d) Mold insert after the meshing process.

2.2.2 Gate Location

Gate location analysis is performed using Moldflow Insight to identify the optimal injection point for uniform material distribution within the mold cavity. This evaluation employs a scoring system in which blue regions indicate highly suitable areas and red regions indicate unfavorable locations for gate placement. As illustrated in Figure 5, the most favorable gate positions are typically located centrally and symmetrically with respect to the part geometry because this configuration promotes balanced filling throughout the cavity. In contrast, the edges of the part are identified as the least suitable areas for gate positioning. Consequently, this analysis facilitates selecting a gate location that minimizes filling imbalances and reduces the risk of subsequent molding defects.

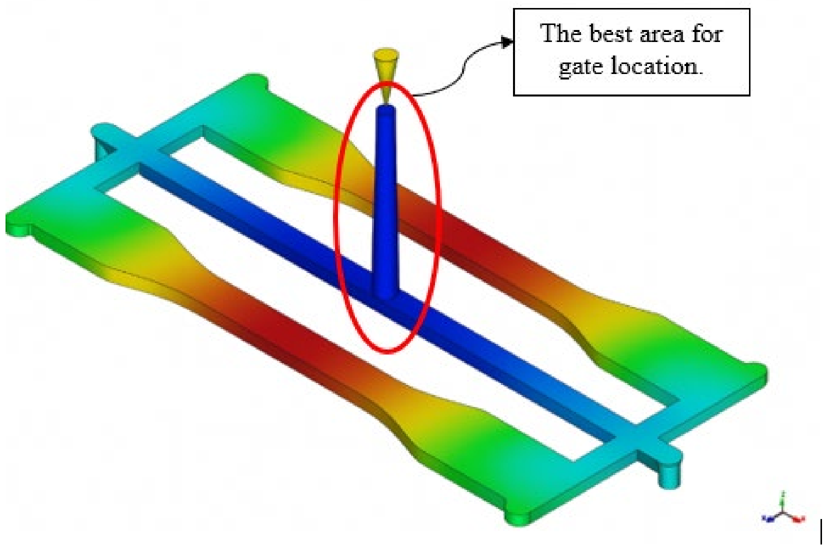


Figure 5: Gating suitability that suggest by Moldflow.

2.2.3 Design Cooling Systems

An optimized cooling system was engineered to facilitate reaching the target ejection temperature by incorporating cooling channels with a diameter of 80 millimeters. This configuration (Figure 6) uses water as the primary heat-transfer medium because it effectively extracts thermal energy from the mold cavities to ensuring thermal stability throughout the production cycle (Table 1) [8]. The implementation of this cooling strategy maintains consistent solidification rates and supports the overall efficiency of the hybrid mold system.

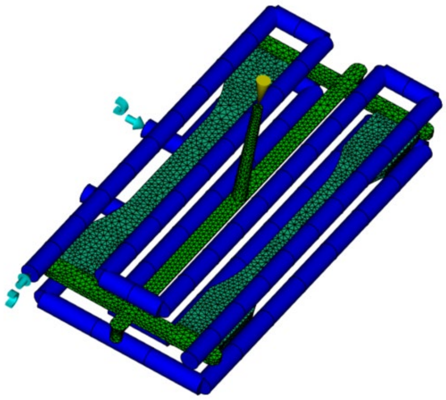


Figure 6: Design of cooling systems [8].

Table 1: Coolant properties [8].

Coolant Material	Formulation	Density	Specific Heat (J/kg°C)	Thermal Conductivity (W/m°C)	Thermal diffusivity (m^2/s)
Water	100% H_2O	1,000	4,200	0.6	1.43×10^{-7}

2.3 Experimental Design

Design of Experiments is a systematic methodology for identifying optimal, statistically significant parameters by analyzing the influence of variables during experimental trials. This strategy effectively accommodates both precisely controlled factors and uncontrollable elements categorized as noise. Specifically, quantitative parameters are defined by measurable ranges and control levels, while qualitative factors are determined independently. As illustrated in Figure 7, the selection of noise factors and control variables is central to the Taguchi parameter design because it integrates uncontrollable components into the analytical framework. This approach enables a more robust evaluation of the injection molding process by accounting for variability that is typically difficult to control.

2.3.1 Process Parameters and Noise Factors

Process parameters serve as adjustable inputs that enable precise regulation of a manufacturing system to meet specific quality standards. These controllable settings are systematically varied across multiple levels to identify the most efficient operating conditions for the mold. In contrast, noise factors represent the external or internal variables that are typically difficult or expensive to manage during standard production cycles. Taguchi experimental designs incorporate sources of variability, such as material inconsistencies or fluctuating room temperatures, to ensure the process remains stable despite these interferences. The goal is to maximize the signal-to-noise ratio because a higher value indicates that the influence of the controlled parameters is significantly stronger than the impact of unpredictable noise. The data for this investigation are presented in Tables 2 and 3 to define six primary control factors, alongside noise variables such as different material manufacturers and variations in ambient temperature.

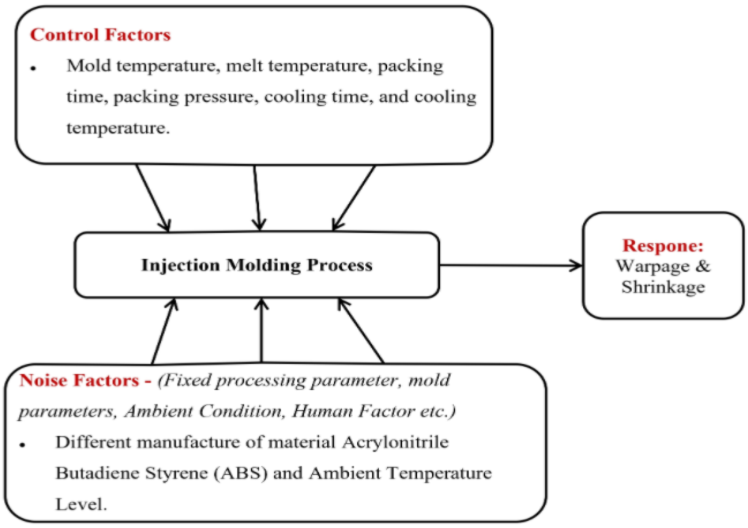


Figure 7: Selection of noise factors and control factors in the injection molding process.

Table 2: The process parameters and their levels.

Experimental Factors	Experimental Level		
	1	**2**	**3**
A: Mold Temperature (°C)	50	55	60
B: Melt Temperature (°C)	230	235	240
C: Packing Time (s)	13	16	19
D: Packing Pressure (MPa)	50	70	90
E: Cooling Time (s)	15	19	23
F: Cooling Temperature (°C)	20	22	24

Table 3: Noise factors and their levels.

Noise Factors	Levels	
	1	**2**
X: Group Manufacture	Chi Mei Corporation	Monsanto Kasei
Y: Ambient Temperature Level	20°C	25°C

2.3.2 Taguchi Orthogonal Array (L18)

The Taguchi method utilizes orthogonal arrays as a specialized experimental design to study multiple decision variables with a minimum number of trials. These arrays are mathematically balanced because each level of every factor appears an equal number of times across the experimental runs, ensuring that the effect of one factor can be independently separated from the others without a full factorial approach. In this project, the L18 orthogonal array is used to evaluate six primary injection molding parameters: mold temperature, melt temperature, packing time, packing pressure, cooling time, and cooling temperature. Each factor is examined at three distinct levels to capture nonlinear relationships while maintaining a superior balance that effectively manages potential interactions between variables. This configuration is particularly advantageous compared to smaller arrays because it provides sufficient degrees of freedom to enable robust analysis of the hybrid mold system.

To quantify the success of these experimental trials, the signal-to-noise ratio is employed as the primary analytical tool to identify quality characteristics that deviate from the target value (Table 4). This ratio serves as a performance measure to determine the most robust parameter settings by filtering out environmental variability and minimizing the sensitivity of the system to uncontrollable noise. Since the primary objective of this study is to minimize defects such as warpage and shrinkage to the ABS part, the "Smaller the better" criterion is applied. This systematic methodology enables the identification of optimal configurations, such as specific pressure and temperature levels that ensure maximum dimensional accuracy. The integration of the L18 array with the signal-to-noise ratio provides a reliable framework for achieving high-quality production results with maximum efficiency in the Metal Epoxy Composite hybrid mold process.

Table 4: Combination parameter for the control factor.

RUN	PARAMETERS					
	Mold Temperature °C	Melt Temperature °C	Packing Time (s)	Packing Pressure (MPa)	Cooling Time (s)	Cooling Temperature °C
1	50	230	13	50	15	20
2	50	235	16	70	19	22
3	50	240	19	90	23	24
4	55	230	13	70	19	24
5	55	235	16	90	23	20
6	55	240	19	50	15	22
7	60	230	16	50	23	22
8	60	235	19	70	15	24
9	60	240	13	90	19	20
10	50	230	19	90	19	22
11	50	235	13	50	23	24
12	50	240	16	70	15	20
13	55	230	16	90	15	24
14	55	235	19	50	19	20
15	55	240	13	70	23	22
16	60	230	19	70	23	20
17	60	235	13	90	15	22
18	60	240	16	50	19	24

2.4 Statistical Tools

The implementation of statistical tools such as the signal-to-noise ratio and the Analysis of Variance is essential for evaluating the performance and stability of the injection molding process. These methodologies enable a structured assessment of how various control factors affect the quality of the final product while accounting for the inherent variability in manufacturing environments.

2.4.1 Signal to Noise Ratio Analysis

The signal-to-noise ratio is a performance measure used in the Taguchi method to quantify the effect of noise on the response variable. In this study, the "Smaller the Better" quality characteristic is used because the primary goal is to minimize defect magnitudes, such as warpage and shrinkage. Transforming the experimental results to a logarithmic scale, this ratio provides a clear indication of which parameter settings maximize the process's robustness. A higher signal-to-noise ratio is consistently sought because it signifies that the experimental signal is dominant over the unwanted noise fluctuations. The optimal levels for each injection molding parameter are selected from the points that yield the highest signal-to-noise ratio values in the response diagrams. The signal S/N Ratio for "Smaller the Better" is calculated using this formula (Eq. 1):

$$SN = -10\log(MSD) \quad (1)$$

2.4.2 Analysis of Variance (ANOVA)

The signal-to-noise ratio identifies the optimal parameter levels. The Analysis of Variance is then performed to determine the statistical significance of each factor and its percentage contribution to the total variance (Table 5). This technique involves partitioning the total variability of the experimental data into components attributable to individual factors and the experimental error. By applying a 95% confidence level, the method uses the F-test to evaluate whether the variance of a specific parameter is significantly larger than the error variance. Specifically, a factor is deemed statistically significant if its calculated F value exceeds the critical F value obtained from statistical distribution tables. Additionally, the percentage contribution highlights which parameters exert the greatest influence on the quality characteristics, enabling targeted process control.

Table 5: ANOVA formula.

Source of variation	Sum of squares, SS	Degree of freedom, df	Mean Square, MS	F Value
Between treatment	$SSB = \sum n_j(\ddot{X}_j - \ddot{X})^2$	$k-1$	$MSB = \frac{SSB}{k-1}$	$F = \frac{MSB}{MSE}$
Error / residual	$SSE = \sum\sum n_j(X - \ddot{X}_j)^2$	$N-k$	$MSE = \frac{SSE}{N-k}$	
Total	$SST = \sum\sum n_j(X - \ddot{X})^2$	$N-1$		

2.4.3 Integration of Statistical Findings

The combined use of these statistical techniques provides a comprehensive framework for process optimization. The signal-to-noise ratio is the primary tool for determining the optimal configuration of levels, such as temperature and pressure settings, to achieve the target quality. Simultaneously, the Analysis of Variance provides a quantitative validation of these findings by ranking the importance of each variable. This integrated approach ensures that the optimization process is not only based on observed trends but is also supported by reliable statistical evidence. Therefore, the final results lead to a well-defined set of operating conditions that guarantee minimal dimensional deviation and enhanced consistency in the production of hybrid molded parts.

3. RESULTS AND DISCUSSION

3.1 Analysis Results

3.1.1 Warpage & Shrinkage Analysis

i. S/N Ratio for Warpage

The analysis of the signal-to-noise ratio for the warpage defect identifies the optimal process parameters required to minimize dimensional inaccuracy in parts produced with the MEC hybrid mold. According to the response diagram for warpage illustrated in Figure 8, the main effects plot shows that Packing Pressure (Factor D) is the most significant parameter, as it has the highest rank and the largest delta value. The graph shows a steep upward slope, with the signal-to-noise ratio increasing substantially as the pressure rises to level 3. This observation is supported by statistical findings indicating that Packing Pressure accounts for 47.66% to the total variation, as it effectively counteracts volumetric shrinkage within the mold cavity. Furthermore, Mold Temperature (Factor A) is statistically significant because it ranks second-highest in the response table. Its higher setting at level 3 maintains the thermal gradients and material flow during solidification more effectively than lower temperatures. In contrast, Factor C, which refers to Packing Time, shows a distinct negative correlation: the highest signal-to-noise ratio is achieved at the lowest setting (level 1), suggesting that excessive packing time may introduce detrimental residual stresses. Moreover, Cooling Temperature (Factor F) contributes a negative trend starting at level 1. Consequently, by selecting the highest points from each plot in the response diagram, the optimal parameter combination to reduce warpage is determined to be **A3, B2, C1, D3, E1, and F1,** which maximizes process robustness and ensures the dimensional accuracy of the final product.

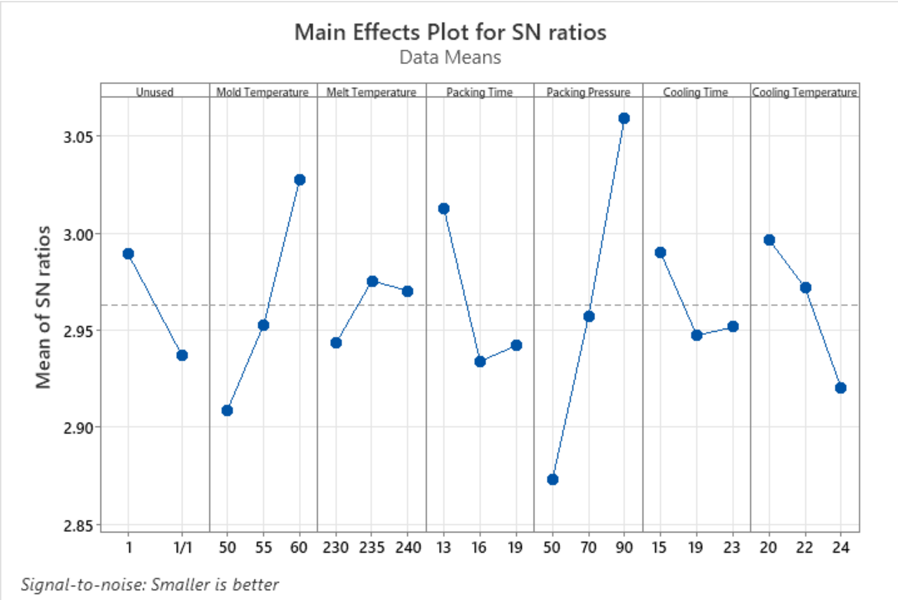


Figure 8: Response diagram of S/N Ratio for warpage.

ii. S/N Ratio for Shrinkage

The analysis of the signal-to-noise ratio for the shrinkage defect demonstrates that melt temperature is the most influential factor in determining the dimensional stability of the parts produced (Figure 9). According to the response table and the corresponding main effects plot, melt temperature (Factor B) ranks highest because it exhibits the largest delta value among all process parameters. Specifically, the signal-to-noise ratio is maximized at level 1, which corresponds to a temperature of 230°C. This result suggests that a lower melt temperature is highly effective in minimizing shrinkage because it reduces the polymer's initial thermal expansion and limits the total volume change during cooling. Furthermore, packing pressure (Factor D) also plays a significant role in controlling this defect. The graph shows a positive correlation: the signal-to-noise ratio increases as pressure is raised to level 3 at 90 MPa. Higher packing pressure ensures that more material is compressed into the mold cavity to compensate for the plastic's volumetric contraction as it solidifies. Additionally, mold temperature (Factor A) reaches optimal performance at level 3 (60 °C). This setting helps maintain a stable thermal gradient, which contributes to more uniform solidification across the part geometry. In parallel with these primary factors, packing time (Factor C) is most effective at level 1 with a duration of 13 seconds. Regarding the cooling parameters, the analysis indicates that level 2 for cooling time (19 seconds) and level 3 for cooling temperature (24°C) are the optimal settings for this specific mold configuration. The comprehensive optimization identifies the best parameter combination to reduce shrinkage as **A3, B1, C1, D3, E2, and F3**. By prioritizing the melt temperature as the most critical variable, the process can be fine-tuned to achieve maximum dimensional accuracy and minimize manufacturing defects.

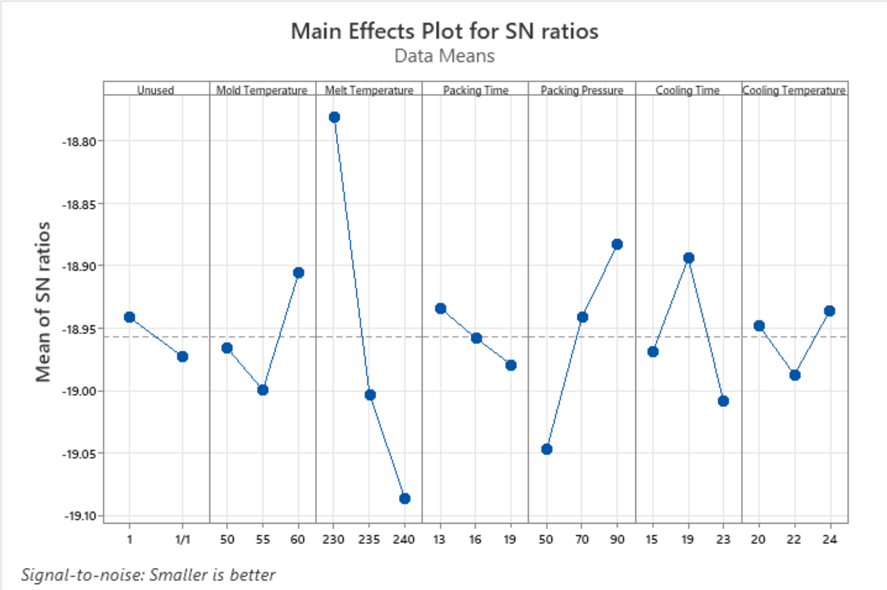


Figure 9: Response diagram of S/N Ratio for shrinkage.

3.1.2 ANOVA Analysis

Analysis of Variance (ANOVA) is a robust statistical technique used to assess whether differences among the means of multiple groups are statistically significant or merely due to random variation. To achieve this, the method divides the total variability found in the data into two primary sources. Specifically, it distinguishes between the variance across the groups, which represents the actual effect of the experimental factors, and the variance within each group, which reflects the inherent experimental error or noise. The fundamental metric used in this process is the F statistic. This value is determined by calculating the ratio of the mean square of the factor to the mean square of the error. Consequently, a high F statistic suggests that the factor being tested has a substantial influence that outweighs the background noise. Furthermore, the analysis provides a P value to represent the probability that the results occurred by chance. If this value is lower than the chosen significance level of 0.05, the factor is considered statistically significant. Ultimately, in technical research, ANOVA is indispensable because it enables the calculation of the percentage contribution of each variable. This ensures that researchers can identify which specific parameters, such as packing pressure or mold temperature, exert the greatest control over a product's final quality.

3.1.2.1 ANOVA for Warpage

Table 6: ANOVA results for warpage.

Source of Variance	***Degree of Freedom***	***Sum of Square***	***Mean Square***	***F-Statistic***	***P-Value***	***Percentage***
A	2	0.043484	0.021742	11.86	0.021	19.95 %
B	2	0.003595	0.001798	0.98	0.450	1.65 %
C	2	0.022628	0.011314	6.17	0.060	10.38 %
D	2	0.103867	0.051933	28.34	0.004	47.66 %
E	2	0.006660	0.003330	1.82	0.275	3.06 %
F	2	0.018053	0.009026	4.92	0.083	8.28 %
Residual Error	4	0.007331	0.001833			
Total	17	0.217916				

The ANOVA results for warpage are summarized in Table 6. The ANOVA confirms that packing pressure (D) and mold temperature (A) are the only statistically significant factors influencing warpage at the 95% confidence level ($p < 0.05$), while melt temperature, packing time, cooling time, and cooling temperature exhibit minor influence within the studied range. Packing pressure exerted the greatest impact, accounting for 47.66% of the total effect ($F = 28.34$). Although packing time and cooling temperature showed moderate F-values, they did not meet the significance threshold ($p > 0.05$). Melt temperature and cooling time were found to have a negligible effect on warpage deformation within the tested parameters. These findings are consistent with previous studies on hybrid mold behavior and the dominance of the packing phase in warpage control [14,15,20,21].

3.1.2.2 ANOVA for Shrinkage

ANOVA results from Table 7 indicate that melt temperature (B) is the primary factor influencing shrinkage because it accounts for 60.27% of the total variance. Specifically, this parameter is statistically significant, with an F statistic of 22.16 and a P value of 0.007, both well within the required thresholds relative to the critical F value of 3.37. In contrast, packing pressure (D) shows a noticeable but statistically insignificant effect at the 95% confidence level. Although its F statistic of 6.19 exceeds the critical value, its P value of 0.060 remains slightly above the 0.05 significance level. Furthermore, factors such as mold temperature (A), packing time (C), cooling time (E), and cooling temperature (F) have negligible effects on shrinkage within the studied range. These variables yielded F-statistics below the critical value and P values greater than 0.05. Consequently, the analysis confirms that melt temperature control is the most critical requirement for ensuring dimensional stability and minimizing material contraction during the injection molding process.

Table 7: ANOVA results for shrinkage.

Source of Variance	***Degree of Freedom***	***Sum of Square***	***Mean Square***	***F-Statistic***	***P-Value***	***Percentage***
A	2	0.027059	0.013529	2.00	0.249	5.45 %
B	2	0.299143	0.149572	22.16	0.007	60.27 %
C	2	0.006173	0.003086	0.46	0.662	1.24 %
D	2	0.083513	0.041757	6.19	0.060	16.83 %
E	2	0.040384	0.020192	2.99	0.161	8.14 %
F	2	0.008646	0.004323	0.64	0.574	1.74 %
Residual Error	4	0.027004	0.006751			
Total	17	0.496329				

3.2 Optimization and Confirmation Test

The optimal parameter combination for warpage reduction was identified as mold temperature 60 °C, melt temperature 235 °C, packing time 13 s, packing pressure 90 MPa, cooling time 15 s, and cooling temperature 20 °C. For shrinkage minimization, the optimal settings were mold temperature 60 °C, melt temperature 230 °C, packing time 13 s, packing pressure 90 MPa, cooling time 19 s, and cooling temperature 24 °C. This data can be seen in Table 8 below.

Table 8: Recommended settings for Warpage and Shrinkage.

Factors	Recommended Setting & Level (Warpage)	Recommended Setting & Level (Shrinkage)
Mold Temperature (A)	60°C *(Level 3)*	60°C *(Level 3)*
Melt Temperature (B)	235°C *(Level 2)*	230°C *(Level 1)*
Packing Time (C)	13 sec *(Level 1)*	13 sec *(Level 1)*
Packing Pressure (D)	90 MPa *(Level 3)*	90 MPa *(Level 3)*
Cooling Time (E)	15 sec *(Level 1)*	19 sec *(Level 2)*
Cooling Temperature (F)	20°C *(Level 1)*	24°C *(Level 3)*

Confirmation tests were conducted using these optimal settings. Table 9 compares the predicted values from the Taguchi analysis in Minitab with the Moldflow simulation results. The percentage error was calculated to evaluate prediction accuracy.

$$Margin\ Error\ (\%) = \left[\frac{(Confirmation\ Test\ Result - Predicted\ Result)}{Predicted\ Result}\right] \times 100\% \tag{2}$$

Table 9: Comparison between predicted and confirmation test results.

Response	Prediction (Minitab)	Simulation Moldflow (Confirmation Test)	Error Margin (%)
Warpage	0.664712	0.67215	1.12%
Shrinkage	8.41989	8.3825	0.44%

A margin of error analysis reveals that the Minitab predictions align closely with the Moldflow simulation results. Specifically, the calculated errors for shrinkage and warpage are 0.44% and 1.12%, respectively, which are significantly below the standard 5% engineering threshold for process validation. These minimal discrepancies demonstrate that the Taguchi-based prediction model accurately reflects the injection molding responses and remains consistent with the confirmation tests. Consequently, the results indicate that the optimized process parameters are stable and effective for controlling part deformation. Furthermore, the strong agreement between the data sets validates the reliability of the hybrid mold system and the overall optimization strategy.

4. CONCLUSION

This study concludes that the primary research objectives have been met through a comprehensive investigation into optimizing injection-molded defects using Metal Epoxy Composite hybrid molds. Regarding the first objective, the research effectively determined the optimal injection molding parameters by utilizing the Taguchi method to evaluate the performance of MEC as a mold insert material. Specifically, the analysis identified packing pressure and mold temperature as the most critical factors for warpage, while melt temperature was the dominant variable for managing shrinkage. The identification of these specific operating conditions provides a clear and robust framework for manufacturers seeking to utilize MEC as a cost-effective alternative to traditional steel tooling.

In relation to the second objective, the optimization of injection molding defects was achieved through a structured methodology involving Autodesk Moldflow Insight and statistical analysis. The study utilized signal-to-noise ratio calculations and Analysis of Variance to isolate the primary influences on dimensional instability. Furthermore, the effectiveness of this optimization strategy was confirmed by comparing Minitab's predicted values with the actual results from confirmation simulations. The results demonstrated exceptional precision, with calculated error margins of only 1.12% for warpage and 0.44% for shrinkage. Because these discrepancies are significantly lower than the standard 5% engineering validation threshold, the reliability of the Taguchi-based optimization model is statistically verified.

Ultimately, the synthesis of these findings proves that Metal Epoxy Composite hybrid molds are a viable and reliable choice for small to medium-scale manufacturing applications. Although MEC has lower thermal conductivity than conventional mold materials, a systematic optimization approach can mitigate defects such as warpage and shrinkage. Therefore, the achievement of both research objectives demonstrates that MEC hybrid molds can be used to produce high-quality parts while maintaining dimensional stability and reducing overall tooling costs.

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