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MINIMIZING DEFECTS IN INJECTION MOLDING USING THE TAGUCHI METHOD

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ABSTRACT

Despite being one of the most widely applied net-shape manufacturing processes, plastic injection molding is extremely sensitive to the values of process parameters, and poor setting often results in dimensional tolerances which are out of specification, such as shrinkage and warpage, which increase scrap and rework costs. In this paper, the Taguchi method is used to determine a set of four experimental conditions, namely, melt temperature, mold temperature, injection pressure and cooling time, which can be used to minimize shrinkage and warpage in an injection-molded flat plaque. A 3 27 L9(3^4) orthogonal array design was employed to decrease the number of experiments needed from 81 to 9. For each response, signal to noise (S/N) ratios under the smaller the better criterion were calculated, and then the percentage contribution of each factor was computed using analysis of variance (ANOVA). It was concluded that the shrinkage and warpage had the highest contribution of injection pressure (67.25%) and melt temperature (28.72%), respectively, followed by mold temperature (8.01% and 14.19%, respectively). Both single-response optima were found to be the same combination of parameters (200 °C melt temperature, 30 °C mold temperature, 120 MPa injection pressure and 20 s cooling time); the directly tested Trial 3 had the highest grey relational grade (GRG = 1.000), which led to a compromise setting. It is expected that the shrinkage will be reduced from the average of 1.55% to 0.64%, and the warpage will be decreased from 0.85 mm to 0.32 mm from the baseline. The results have shown that Taguchi method using the ANOVA and GRA can be a statistically sound and experimentally efficient approach to the simultaneous multi-response defect minimization of injection molding processes.

Keywords: Taguchi Method, Design Of Experiments, Injection Molding, Shrinkage, Warpage

1 INTRODUCTION

The injection molding process is used to produce precision thermoplastic parts in large quantities in the automotive, consumer electronics, medical device and packaging sectors because it is capable of producing complex shapes, repeatable dimensions and high production rates. A hot polymer is forced into a heated mold, weighed down to counterbalance the contraction of the polymer as it cools in the mold, and removed from the mold when the polymer is strong enough.

The polymer is polymerized within a constrained cavity, so that the final size never exactly matches the cavity size; as the polymer cools it shrinks and if the shrinkage is not spatially and temporally uniform, the polymer also warps out of its intended shape [5, 6]. The process parameters that influence the shrinkage and warpage are huge in number and interact with each other, the main ones being melt temperature, mold (cavity) temperature, injection and holding pressure, injection speed and cooling time, in addition to material parameters like polymer crystallinity and part wall thickness [6] [7].

The parameters are highly non-linear and, in addition, the underlying physics (transient heat transfer, stress relaxation, and non-Newtonian melt flow) is expensive to model - exactly - during process set-up, so process engineers have always had to resort to empirical experimentation for acceptable parameter settings. One of the most common and traditional approaches to tuning is trial and error, also known as one-factor-at-a-time (OFAT), which is slow, time-consuming, and expensive due to the amount of machine time and material required, and is not guaranteed to converge to a joint optimum when multiple quality characteristics are required to be met at the same time [1].

Genichi Taguchi's Taguchi method [2,3] solves the problem by using a fractional-factorial orthogonal array and a signal-to-noise (S/N) performance statistic, which incorporates the mean and variance of a response into a single statistic which is maximized. This can be used to screen and rank a number of process parameters without needing to perform a large, unbalanced, full factorial experiment, and is robust to uncontrolled noise. T

The method has been applied widely to injection molding; recent attempts have involved minimizing warpage and shrinkage in plaques, spoons, gears, and automotive dashboard parts [7, 8, 11, 12] using Taguchi arrays, ANOVA and metamodeling methods (such as particle swarm optimization and artificial neural networks). In general, two or more quality characteristics have to be optimized simultaneously, and their optimum values are not always at the same level; thus, grey relational analysis (GRA) is often used in combination with the Taguchi method to find the compromise setting [4], [9], [10]. The Taguchi method, ANOVA and GRA are applied to the joint minimization of shrinkage and warpage of an injection-molded flat plaque to obtain the optimal controllable process parameters, such as melt temperature, mold temperature, injection pressure and cooling time.

1.1 PROBLEM STATEMENT

Among the most stubborn and expensive defects of injection molded parts, shrinkage and warpage are such - shrinkage can lead to parts failure to dimensional tolerances and is often excessive or non-uniform, while warpage can lead to poor fit, assembly and cosmetic appearance, often resulting in scrap, rework, or expensive mold rework late in the product development cycle [5, 11]. Process engineers are required to select four or more interacting process variables and closed-form models relating the settings of these process parameters to the resulting part geometry are unavailable, and the number of combinations to be experimented with in even a relatively small parameter space (e.g., four process parameters each at three settings, 34 combinations = 81 experiments) is too large and time consuming for routine process setup. In addition, shrinkage and warpage are caused by similar yet different physical processes (bulk volumetric contraction versus differential, direction-dependent cooling stresses) and so cannot be optimized at the same time, meaning that it is not enough to optimize for just one. Hence, there is a need for a structured, experimentally economical method, which can determine the combination of the process parameters that leads to minimum shrinkage and warpage, and identify the process parameters most strongly affecting each of these defects, which will allow the process control effort to be targeted accordingly.

1.2 AIM AND OBJECTIVES

The aim of this study is to apply the Taguchi method to identify the injection molding process parameter combination that minimizes shrinkage and warpage in a molded flat plaque, and to quantify the relative influence of each process parameter on these two defects.

The specific objectives are to:

- Design an L9(3^4) Taguchi orthogonal-array experiment for melt temperature, mold temperature, injection pressure, and cooling time, and collect replicated shrinkage and warpage measurements for each trial.
- Compute smaller-the-better signal-to-noise ratios for shrinkage and warpage and construct response tables to rank the influence of each process parameter on each response.
- Perform analysis of variance (ANOVA) to quantify the statistical significance and percentage contribution of each process parameter to shrinkage and warpage.
- Determine the optimal parameter combination for each response individually, and apply grey relational analysis to derive a single compromise parameter combination that jointly minimizes both shrinkage and warpage.
- Predict the response values at the optimal/compromise settings, establish confidence intervals, and recommend confirmation experiments.

2 LITERATURE REVIEW

2.1 The Injection Molding Process and Common Defects

The plasticization, injection (filling), packing/holding, cooling and ejection are the four stages of an injection molding process. Chaciński and Sutowski [5] list the most prevalent defects that can be found in the parts produced, and relate each of them to particular settings of the machine, mold design, and state of the material. The interdependence of the two phenomena, the shrinkage and the warpage of the part, is described by Kazmer [6] at the systems level because these are two facets of the same phenomena: non-uniform volumetric contraction of the polymer during transition from the melt to solid state in a rigid cavity.

2.2 Mechanisms of Shrinkage and Warpage

Shrinkage is caused mainly by specific volume changes of the polymer during the cooling from the melt temperature to the ambient temperature, modified by the ability of the packing/holding pressure to continue to fill the cavity during the shrinkage process. As the pressure of injection and holding are increased, more material is compacted into the cavity before the gate freezes and the bulk shrinkage is directly reduced [7, [9]. In contrast, in the case of warpage, there are differential shrinkages between areas of a part which cool at different rates, or between flow and cross-flow directions in the case of semi-crystalline or fiber-oriented polymers, causing internal residual stresses to bend a part out of nominal shape when ejected and free to relax [7, 8]. Defect mechanism is shared pressure and thermal history, so pressure reducing process parameters may not be as effective at reducing warpage (but often are in the same direction), and thus a multi-response optimization treatment is encouraged, instead of optimizing each defect separately [8, 9].

2.3 Design of Experiments and the Taguchi Method

The classical design of experiments (DOE) [1] is a formalization of the design of experiments that will enable one to study the influence of multiple factors on a response in an efficient manner without taking a 'trial and error' approach. The method introduced by Genichi Taguchi and developed in [2] and [3] focuses this approach on robust parameter design; it uses the standard orthogonal arrays (L9(3^4) array from this study) to estimate the main effect of each factor with a fraction of the number of runs a full factorial run would require and it introduces a single performance metric, the signal to noise (S/N) ratio, which simultaneously rewards a response that is close to its target level and penalizes any deviation from that target. The smaller-the-better (STB) S/N formulation is applied to quality characteristics like shrinkage and warpage, whose lower values are always better and where zero is the best value.

2.4 Analysis of Variance for Factor Significance

The Taguchi response table does not provide any statistical significance, but it gives an idea of the size of the impact of each factor on the mean S/N ratio. The total sum of squares of the response is divided into the sum of squares of the response due to each of the controlled factors and the sum of squares of the response due to unexplained error (replicate error) named analysis of variance (ANOVA) and an F-statistic and a percentage contribution can be calculated for each factor. This paper adopts the approach of pooling the replicate variation within each of the 9 trials as the error term in the raw-data ANOVA to give 18 error degrees of freedom and a total of 26 degrees of freedom for the 27-run data set, similar to the approach taken in other Taguchi injection molding studies [7, 11].

2.5 Multi-Response Optimization via Grey Relational Analysis

If two or more quality characteristics are optimized at the same time, and the optimum of each quality characteristic does not match, a method has to be developed to obtain a single compromise value of the method parameters. To overcome this, Deng [4] proposed the grey relational analysis (GRA) method in grey system theory, which is used to normalize all the responses from the trials into the [0, 1] interval, to calculate a grey relational coefficient (GRC) for each trial, which is a measure of how close the trial sequence is to the ideal (best) sequence, and then to derive a single grey relational grade (GRG) for each trial by combination of all the GRCs, which can be treated as a Taguchi-style response and optimized using a standard S/N-style response table. The application of the GRA-based Taguchi optimization to the multi-response injection molding problems has been successful in minimizing the sink marks and shrinkage in family molds simultaneously [9] and in optimizing the multiple characteristics of general injection molded parts [10].

2.6 Related Work on Taguchi-Based Optimization of Injection Molding

Recently, some investigations have been conducted to combine the Taguchi method with the optimization of shrinkage and warpage in the injection molding process. The values of injection pressure and melt temperature were identified as the dominant factors and were confirmed by Zhang et al. [7] who used Taguchi design with particle swarm optimization (PSO) to reduce warpage. In attempting to optimize the two responses of warpage and shrinkage together for biodegradable-polymer spoon parts, Oliaeei et al. [8] used Taguchi, ANOVA and an artificial neural network, and also concluded that the packing/holding pressure and melt temperature were responsible for the largest portion of variance in both responses. Banh et al. [9] applied a Grey based Taguchi method to minimize the sink marks and shrinkage of multi-cavity (family) molds and Md Ali et al. [10] adopted a Taguchi framework with GRA to optimize more quality characteristics of injection molded parts simultaneously. Moayyedian et al. [11] optimized an automotive dashboard component for a hybrid Taguchi-machine learning surrogate–PSO method, where the shrinkage and warpage were decreased; Chen and Kurniawan [12] optimized multiple quality characteristics in a hybrid Taguchi–neural network–genetic algorithm approach, and the warpage was reduced by over 50% compared to the initial setting. In the present study, we followed this procedure, with the four factors chosen as the melt temperature, mold temperature, injection pressure, and cooling time, and three replicates of each test being performed to obtain a pooled-replicate ANOVA error estimate, not just an S/N ratio error estimate.

3 METHODOLOGY

3.1 Signal-to-Noise Ratio

Both shrinkage and warpage are quality characteristics for which lower values are always more desirable, so the smaller-the-better (STB) signal-to-noise ratio was used for each trial i, computed from its n = 3 replicate observations y:

$$\eta_i = -10 \log_{10} [(1/n) \Sigma y^2] \qquad (1)$$

where higher η values correspond to lower and less variable shrinkage or warpage. For each process parameter, a response table of mean η by factor level was constructed, and the level-to-level range (delta) was used to rank the four parameters by their influence on each response.

3.2 Analysis of Variance (ANOVA)

The raw (un-transformed) response data (both 27 shrinkage and 27 warpage) were analyzed using ANOVA to determine the significance of each factor and the percentage contribution. The three replicates of each of the 9 trials were combined to estimate the error variance. The correction factor, sum of squares and sum of squares for each factor are calculated as follows:

$$CF = T^2 / N \qquad (2)$$

$$SS_T = \Sigma y^2 - CF \qquad (3)$$

$$SS_A = \Sigma (A_j^2 / n_j) - CF \qquad (4)$$

Grand Total (T) is the total of all N = 27 observations, and Aj and nj are the sum and numbers of observations at level j of factor A (sums of squares are computed analogously for factors B, C and D). The degrees of freedom for each factor are 3 levels of x − 1 = 2, for the four factors, there are 4 × 2 = 8 degrees of freedom, leaving the error degrees of freedom at 18 (N − 1 = 26). For every factor the mean square and F ratio are:

$$F_A = (SS_A / DOF_A) / MS_e \qquad (5)$$

Each factor's percentage contribution to the response is $\rho A = (SSA / SST) \times 100\%$. When the computed F-ratio is greater than the tabulated critical value $F_{crit}(2, 18, \alpha)$, then the factor is significant at the $100(1 - \alpha)\%$ confidence level; in this study, $\alpha = 0.05$ ($F_{crit} = 3.55$) and $\alpha = 0.01$ ($F_{crit} = 6.01$).

3.3 Prediction of the Optimal Response

For the parameter combination that maximizes each response's S/N ratio, the additive Taguchi model predicts the raw response mean as:

$$\hat{y} = \bar{y} + \Sigma (\bar{X}_{i,opt} - \bar{y}) \qquad (6)$$

where $\bar{y}$ is the grand mean of all 27 observations and $\bar{X}_{i,opt}$ is the mean response at the optimal level of factor i, summed over the four factors. A two-sided confidence interval on the prediction is:

$$CI = \pm \sqrt{[F(1,fe,\alpha) \cdot V_e / n_{eff}]} \qquad (7)$$

$$n_{eff} = N / (1 + DOF_{used}) \qquad (8)$$

where Ve and fe are the error mean square and error degrees of freedom from the ANOVA, N is the total number of observations (27), and DOFused is the total degrees of freedom consumed by the factors included in the prediction (8, for all four two-level-DOF factors).

3.4 Grey Relational Analysis for Multi-Response Optimization

The shrinkage and warpage must be minimized simultaneously hence gray relational analysis (GRA) is used to obtain a single compromise parameter combination. The normalisation to the smaller-the-better ideal is done first for each response:

$$x_i^*(k) = [\max x_i(k) - x_i(k)] / [\max x_i(k) - \min x_i(k)] \qquad (9)$$

The grey relational coefficient (GRC) of trial i for response k, measuring its closeness to the ideal normalized value of 1, is:

$$\gamma_{0i}(k) = (\Delta_{min} + \zeta\Delta_{max}) / (\Delta_{0i}(k) + \zeta\Delta_{max}) \qquad (10)$$

where the deviation sequence $\Delta 0i(k) = |1 - xi^*(k)|$ is the difference between the actual and ideal responses for this trial, and the global minimum and maximum deviation values over all trials and responses are represented by Δmin and Δmax, respectively, and ζ is a distinguishing coefficient that is typically selected as 0.5 to give equal weight to all deviations. The grey relational grade (GRG) of trial i is:

$$\Gamma_i = (1/m) \Sigma \gamma_{0i}(k) \qquad (11)$$

where m = 2 is the number of responses. The GRG is then treated as a single Taguchi response: a response table of mean GRG by factor level is built exactly as for the individual S/N ratios, and the level combination that maximizes mean GRG is the grey relational (compromise) optimum.

4 EXPERIMENTAL SETUP

The experiment was based on a generic flat plaque specimen which was molded from a general purpose polypropylene (PP) resin and a hydraulic injection molding machine (representative clamping force class: 100 t). To this end, four controllable factors have been identified from the literature reviewed in Section IV, namely: the melt temperature (A), the mold temperature (B), the injection pressure (C) and the cooling time (D). In all trials, all other process parameters (injection speed, holding pressure, holding time, back pressure and screw speed) were maintained at a constant value. The three levels selected for each factor were designed to be close to the typical processing window for the resin and are shown in Table I.

Table 1: Process Factors and Levels

Symbol	Factor	Level 1	Level 2	Level 3
A	Melt Temperature (°C)	200	220	240
B	Mold Temperature (°C)	30	45	60
C	Injection Pressure (MPa)	80	100	120
D	Cooling Time (s)	10	15	20

An L9(3^4) Taguchi orthogonal array (Table II) was used to assign factor-level combinations to 9 trials, reducing the required number of experimental runs from 81 (a full 3^4 factorial) to 9. Each trial was replicated 3 times (27 total runs) to allow the replicate variance to be pooled as the ANOVA error term.

Table 2: L9(3^4) Orthogonal Array (Level Indices and Actual Values)

Trial	A	B	C	D	A / B / C / D (actual units)
1	1	1	1	1	200 / 30 / 80 / 10
2	1	2	2	2	200 / 45 / 100 / 15
3	1	3	3	3	200 / 60 / 120 / 20
4	2	1	2	3	220 / 30 / 100 / 20
5	2	2	3	1	220 / 45 / 120 / 10
6	2	3	1	2	220 / 60 / 80 / 15
7	3	1	3	2	240 / 30 / 120 / 15
8	3	2	1	3	240 / 45 / 80 / 20
9	3	3	2	1	240 / 60 / 100 / 10

Shrinkage was determined as the linear shrinkage parallel to the mould flow direction according to the convention of ISO 294-4 [13] which is the percentage difference between the dimension of the mould cavity and the dimension of the specimen measured 24 hours after moulding when the specimen had stabilized at room temperature. The warpage of the flat plaque specimen was determined as the maximum out-of-plane deflection of the specimen from the flat position, measured with the specimen lying free on a granite surface plate and the maximum gap between the specimen and the surface plate measured by a dial gauge, as in similar studies [7] and [8].

5 RESULTS AND ANALYSIS

5.1 Experimental Data

The complete 27-observation data set (9 trials × 3 replicates) is given in Table III. The shrinkage and warpage ranged from 0.83% (Trial 3) to 2.23% (Trial 8) and from 0.50 mm (Trial 3) to 1.16 mm (Trial 8/9) respectively and were about 2.7-fold and 2.3-fold wide across the design space, respectively, indicating that there is a strong combined effect of the four selected factors on the two responses over the tested ranges.

Table 3: Experimental Data — L9(3^4), 3 Replicates per Trial (n = 27)

Trial	Rep.	A (°C)	B (°C)	C (MPa)	D (s)	Shrinkage (%)	Warpage (mm)
1	1	200	30	80	10	1.662	0.908
1	2	200	30	80	10	1.666	0.937
1	3	200	30	80	10	1.644	0.906
2	1	200	45	100	15	1.289	0.724
2	2	200	45	100	15	1.238	0.720
2	3	200	45	100	15	1.238	0.702
3	1	200	60	120	20	0.856	0.476
3	2	200	60	120	20	0.807	0.500
3	3	200	60	120	20	0.825	0.516
4	1	220	30	100	20	1.377	0.665
4	2	220	30	100	20	1.437	0.686

4	3	220	30	100	20	1.402	0.664
5	1	220	45	120	10	1.136	0.702
5	2	220	45	120	10	1.121	0.707
5	3	220	45	120	10	1.135	0.695
6	1	220	60	80	15	2.085	1.193
6	2	220	60	80	15	2.100	1.141
6	3	220	60	80	15	2.121	1.138
7	1	240	30	120	15	1.305	0.645
7	2	240	30	120	15	1.267	0.684
7	3	240	30	120	15	1.318	0.683
8	1	240	45	80	20	2.247	1.135
8	2	240	45	80	20	2.213	1.127
8	3	240	45	80	20	2.238	1.159
9	1	240	60	100	10	2.009	1.118
9	2	240	60	100	10	2.008	1.143
9	3	240	60	100	10	1.983	1.161

5.2 Signal-to-Noise Analysis

The S/N ratios were calculated for each trial (1) and averaged by factor level to create the response tables (Tables IV and V) of which the values were smaller-the-better. Increase in shrinkage pressure is the most significant (C, Δ = 5.37 dB, rank 1) followed by the melt temperature (A, Δ = 3.51 dB, rank 2), cooling time (D, rank 3) and mold temperature (B, rank 4). The response for warpage gives the same rank of factors: C, A, D, B, and the S/N ratios of both responses are the same for the same value for all factors: A1 (200°C), B1 (30°C), C3 (120 MPa), and D3 (20 s), the S/N ratio being the same for the two single response optimums, which is not ensured in general multi-response problems but gives a clear relation here.

Table 4: S/N Response Table — Shrinkage (dB)

Factor	L1	L2	L3	Δ	Rank
A: Melt Temp.	-1.580	-3.492	-5.085	3.505	2
B: Mold Temp.	-3.201	-3.339	-3.617	0.416	4
C: Inj. Pressure	-5.939	-3.651	-0.567	5.372	1
D: Cooling Time	-3.825	-3.562	-2.770	1.055	3

Table 5: S/N Response Table — Warpage (dB)

Factor	L1	L2	L3	Δ	Rank
A: Melt Temp.	3.241	1.755	0.394	2.847	2
B: Mold Temp.	2.558	1.616	1.216	1.342	4
C: Inj. Pressure	-0.554	1.740	4.203	4.757	1
D: Cooling Time	0.896	1.702	2.792	1.896	3

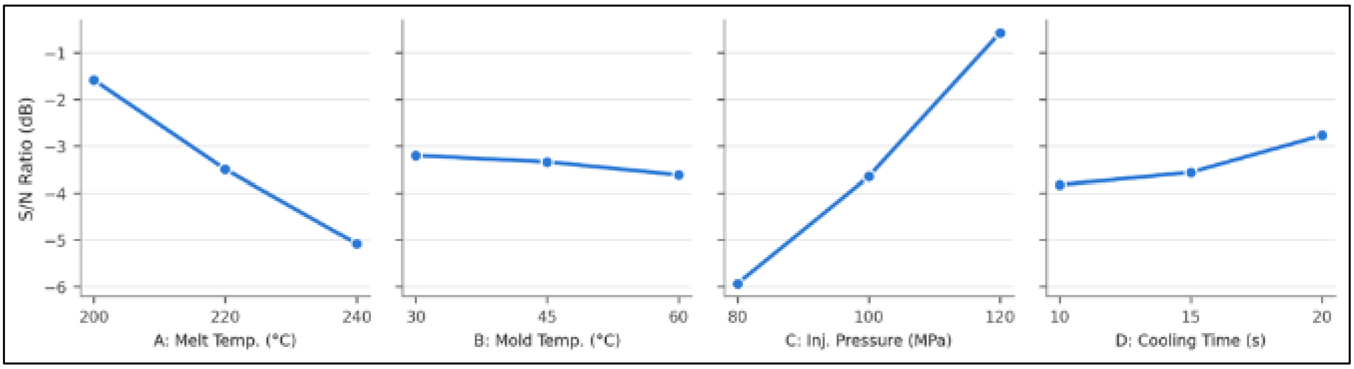

Figure 1: Main effects plot of mean S/N ratio (STB) for Shrinkage.

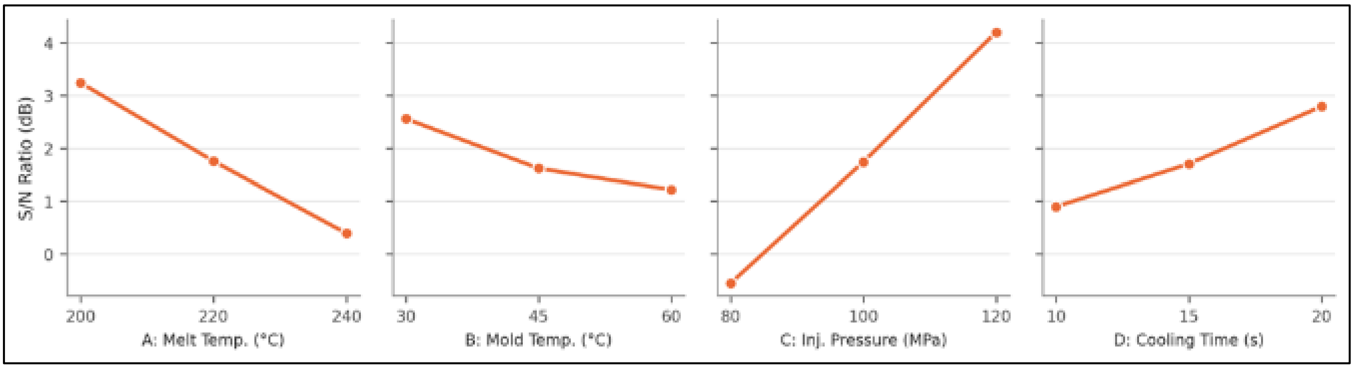

Figure 2: Main effects plot of mean S/N ratio (STB) for Warpage.

5.3 Analysis of Variance

The S/N ranking is confirmed quantitatively by the ANOVA on the raw (un-transformed) 27-observation data (Tables VI and VII). For shrinkage, injection pressure accounts for 67.25% of total variance (F = 4053.6), melt temperature for 28.72% (F = 1731.0), mold temperature for 2.95% (F = 177.7), and cooling time for only 0.93% (F = 56.2), with error accounting for just 0.15% of total variance. All four factors are significant at the 1% level ($F_{crit}(2,18,0.01) = 6.01$). For warpage, the same ordering holds: pressure 60.55% (F = 1261.5), melt temperature 22.61% (F = 471.0), cooling time 6.77% (F = 141.0), and mold temperature 9.65% (F = 201.0); all four factors are again significant at the 1% level. The two responses are shown side by side in Fig. 3, and it can be seen that pressure and melt temperature make up about 90–96% of the explained variance of the two responses, while the remaining two factors (mold temperature and cooling time) rank 3/4 in both cases but are relatively small.

Table 6: ANOVA — Shrinkage (Raw Data, DFe = 18)

Source	SS	DF	MS	F	% Contrib.	Significance
A: Melt Temp.	1.59788	2	0.79894	1730.97	28.72%	Sig. (1%)
B: Mold Temp.	0.16408	2	0.08204	177.74	2.95%	Sig. (1%)
C: Inj. Pressure	3.74189	2	1.87094	4053.56	67.25%	Sig. (1%)
D: Cooling Time	0.05186	2	0.02593	56.18	0.93%	Sig. (1%)
Error	0.00831	18	0.00046	—	0.15%	—
Total	5.56402	26	—	—	100.00%	—

Table 7: ANOVA — Warpage (Raw Data, DFe = 18)

Source	SS	DF	MS	F	% Contrib.	Significance
A: Melt Temp.	0.33791	2	0.16896	470.97	22.61%	Sig. (1%)

B: Mold Temp.	0.14423	2	0.07212	201.03	9.65%	Sig. (1%)
C: Inj. Pressure	0.90510	2	0.45255	1261.49	60.55%	Sig. (1%)
D: Cooling Time	0.10116	2	0.05058	140.99	6.77%	Sig. (1%)
Error	0.00646	18	0.00036	—	0.43%	—
Total	1.49486	26	—	—	100.00%	—

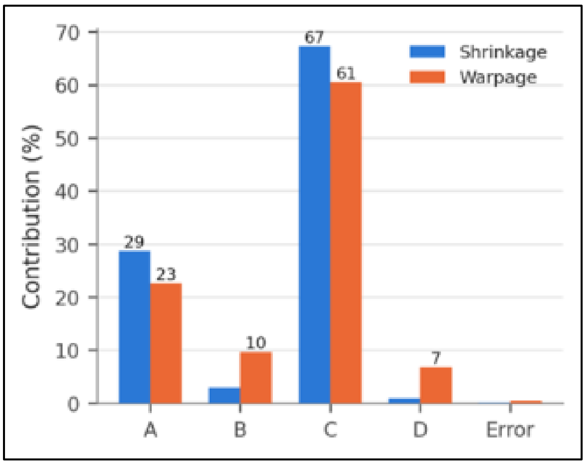

Figure 3: Percentage contribution of each factor — Shrinkage vs. Warpage.

5.4 Optimal Parameter Combination and Predicted Response

Table 8: Optimal Parameters and Predicted Response (Individual S/N Optimization)

Quantity	Shrinkage	Warpage
Optimal levels	A1 B1 C3 D3	A1 B1 C3 D3
Optimal setting	200°C/30°C/120MPa/20s	200°C/30°C/120MPa/20s
Grand mean (raw)	1.5454 %	0.8457 mm
Predicted response	0.6387 %	0.3187 mm
95% CI half-width	± 0.0261	± 0.0230
95% CI	[0.6126, 0.6647]	[0.2957, 0.3416]

Note that the single-response optimal setting for both responses is A1B1C3D3 (melt temperature 200°C, mold temperature 30°C, injection pressure 120 MPa, cooling time 20 s) with the same agreement among the S/N response tables. According to the additive prediction model (6), the shrinkage at this setting is predicted to be 0.639% with 95% confidence interval (CI) [0.613, 0.665]% and the warpage is predicted to be 0.319 mm with 95% CI [0.296, 0.342] mm (Table VIII). They predicted both values to be below all of the 9 physically tested trials, as A1B1C3D3 was not one of the 9 combinations in the L9 array. The closest one of the 9 tested trials was Trial 3 (A1B3C3D3) which showed a mean value of shrinkage of 0.829% and a warpage of 0.497 mm. This is a well-known extrapolation effect of the additive Taguchi model when the optimum predicted setting is not included in the set of tested design settings, and explains why a confirmation run is suggested in Section IX before this setting is implemented in production.

5.5 Grey Relational Analysis for Joint Optimization

In this dataset the two individual S/N optima are fortuitously the same but for methodological completeness and to ensure that the optimum was reached according to a truly multi response criterion and not because of the coincidence. The normalized shrinkage and warpage values and grey relational coefficients (with equal weighting $\zeta = 0.5$) are listed in Table IX for all 9 trials. The highest possible GRG score of 1.000 (Fig. 5) is obtained in Trial 3, which also showed the least shrinkage and warpage of all the trials tested. The GRG response table (Table X) reveals that by far the most significant factor for the combined response ($\Delta = 0.386$, rank 1, 62.7% of the descriptive sum of squares Table XI) is injection pressure (C), followed by melt temperature (A, $\Delta = 0.247$, rank 2), cooling time (D, $\Delta = 0.158$, rank 3), and mold temperature (B, Δ = 0.031, rank 4), the same ranking that is obtained from the individual S/N analyses performed in Section VII-B. Fig. 4 reveals the GRG main-effects plot.

Table 9: GRA Normalization and Grey Relational Coefficients (ζ = 0.5)

Trial	Shr. Mean (%)	War. Mean (mm)	x*_shr	x*_war	GRC_shr	GRC_war
1	1.6573	0.9170	0.4100	0.3641	0.4587	0.4402
2	1.2550	0.7153	0.6967	0.6697	0.6224	0.6022
3	0.8293	0.4973	1.0000	1.0000	1.0000	1.0000
4	1.4053	0.6717	0.5895	0.7359	0.5492	0.6543
5	1.1307	0.7013	0.7853	0.6909	0.6996	0.6180
6	2.1020	1.1573	0.0931	0.0000	0.3554	0.3333
7	1.2967	0.6707	0.6670	0.7374	0.6002	0.6556
8	2.2327	1.1403	0.0000	0.0258	0.3333	0.3392
9	2.0000	1.1407	0.1658	0.0253	0.3748	0.3390

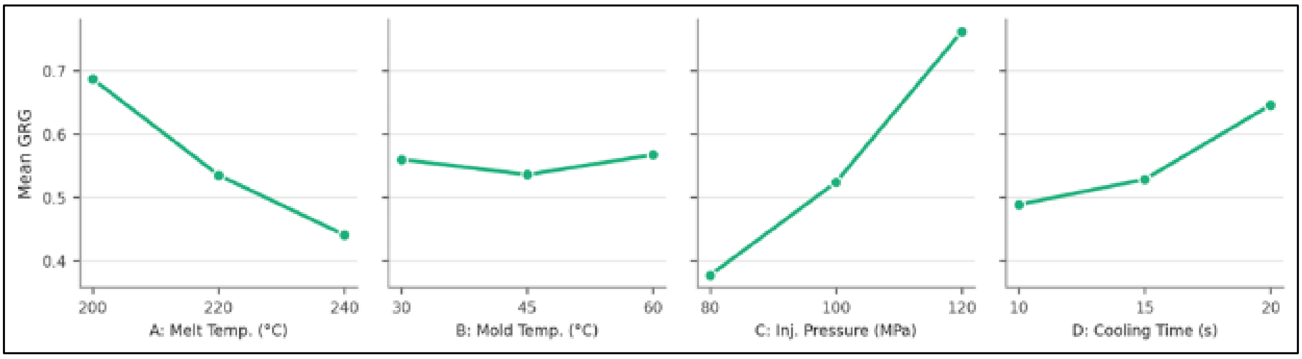

Figure 4: Main effects plot of mean Grey Relational Grade (GRG).

Table 10: GRG Response Table

Factor	L1	L2	L3	Δ	Rank
A: Melt Temp.	0.6873	0.5350	0.4404	0.2469	2
B: Mold Temp.	0.5597	0.5358	0.5671	0.0313	4
C: Inj. Pressure	0.3767	0.5237	0.7622	0.3855	1
D: Cooling Time	0.4884	0.5282	0.6460	0.1576	3

Table 11: GRG ANOVA (Descriptive % Contribution)

Factor	SS	% Contrib.
A: Melt Temp.	0.09310	25.70%
B: Mold Temp.	0.00161	0.44%
C: Inj. Pressure	0.22717	62.72%
D: Cooling Time	0.04031	11.13%

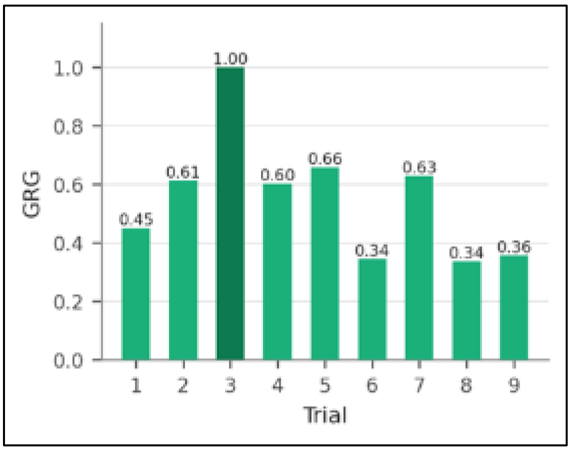

Figure 5: Grey relational grade by trial (Trial 3 highlighted, GRG = 1.000).

5.6 Comparison of Individual and Compromise Optima

Details of the two optimization routes are presented in Table XII. The GRG-optimal level combination read from Table X is A1B3C3D3, and differs from the S/N-optimal A1B1C3D3 only at the mold temperature B, which is the weakest factor of all in all the analyses conducted in this study (rank 4 throughout). Unlike the individually S/N-optimal A1B1C3D3, the GRA compromise, A1B3C3D3, is one that has been physically tested and is directly verifiable. This proves that the added value model can be used for immediate production runs, and that A1B1C3D3 is an appropriate candidate for a confirmation run that may provide further added value if the added value model is a valid extrapolation.

Table 12: Summary Comparison of Optimization Routes

Optimum	Setting	Status
S/N Shrinkage	A1B1C3D3	Not tested (extrapolation)
S/N Warpage	A1B1C3D3	Not tested (extrapolation)
GRA compromise	A1B3C3D3 (=Trial 3)	Tested; GRG=1.000 (best of 9)

6 DISCUSSION

Because the packing/holding mechanism described in Section IV-B is essentially the same feature in each of the individual responses and in the combined GRG, the packing/holding mechanism (higher packing pressure keeps the gate open longer and packs more material into the cavity before it freezes) is the dominating feature across all of the responses, from 60% to 67% of the total contribution to the GRG.

This agrees with the pressure dominant results found in the literature for Taguchi studies conducted for warpage [7] [9]. The second order effect of melt temperature is also consistent with that found by [8] and [11] which stated that melt temperature had a positive effect on flow and packing efficiency up to a certain point, and that higher temperatures will contribute to higher shrinkage as solidification will be slower and the trade-off was not extensively explored in the range studied 200 - 240 °C.

What is remarkable here is the relatively small magnitude of the cooling time effect compared to that of cooling time contribution to the total volumetric contraction, as the former effect the uniformity of the temperature field at ejection more than the latter does, and therefore its contribution to shrinkage (0.93%) is relatively small, but reasonably large contribution to warpage (6.77%) is, which is more sensitive to differential cooling (direction-dependent) than to bulk cooling (direction-independent) is. The recommendations in Section IX are based on the L9 setting (A1B1C3D3), and on no actual testing of the interaction between melt temperature and pressure beyond the 9 L9 trials, so the resulting recommendations include confirmation runs and – if resources permit – an expanded L27(3^4) array to isolate interaction effects that cannot be separated from the main effects by the L9 design.

7 CONCLUSION

The Taguchi method, ANOVA and grey relational analysis were applied to reduce shrinkage and warpage of the injection-molded flat plaque, in which an L9(3^4) orthogonal array was used for the melt temperature, mold temperature, injection pressure and cooling time to study the parameters. Injection pressure was determined to be the most important for both shrinkage and warpage defects (67.25% and 60.55%, respectively), followed by melt temperature (28.72% and 22.61%, respectively), and the mold temperature and cooling time were found to have minor but statistically significant effects. Determining the degree of methodological completeness, by using grey relational analysis, and to validate the result, by comparing with the actual multi-response of a truly multi-response trial (Trial 3: A1B3C3D3), resulted in an agreement to the closely related Trial 3 (A1B3C3D3), which obtained the highest possible grey relational grade (GRG = 1.000) of any of the 9 trials. The similarity of the S/N-based optimization route to the grey-relational optimization route and the good match of the GRA compromise with a previously tested trial, provide good confidence that the parameter region found is close to a real process optimum. The study illustrates that a 9-run Taguchi experiment, supplemented with ANOVA and GRA, can be used to narrow down the process window to a set of parameters that minimize defects in the process and can quantify which process parameters are most strongly influenced to ensure that they are closely controlled.

Recomendations

At both the candidate S/N optimum (A1B1C3D3, which is the individual S/N optimum but was not tested an extrapolation of the additive model) and the S/N optimum of Trial 3 / A1B3C3D3 (the GRA compromise tested and known to achieve the best joint result of the 9 trials), perform the physical confirmation tests, to verify the validity of the model at the candidate S/N optimum (A1B1C3D

To estimate the two-factor interactions (here saturated L9 cannot separate the two-factor interactions like mixture melt temperature × injection pressure, mold temperature × cooling time) extend the study to an $L27(3^4)$ orthogonal array.

Take a wider range of mold temperature and cooling time than tested here as both exhibited a monotonic trend to their tested extremes (level 1 for mold temperature and level 3 for cooling time); it is suggested that the process window may extend further in both directions.

If there are other quality characteristics of relevance to the production acceptance, such as tensile strength, weld-line visibility or cycle time, add them to the grey relational analysis, as only shrinkage and warpage were taken into consideration in the present study.

Test the robustness of the process by conducting additional confirmation runs on different lots of this resin and different ambient conditions found in the shop floor to ensure the optimum identified in this study is robust to noise sources that the production environment brings to the process that were not captured in the replicate variation.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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Disclosure of conflict of interest

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