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Performance Evaluation And Optimization Of Injection Molding Using Hybrid Conformal Cooling Channels

Prof. Pankaj Dhoble [1], Dr. R. R. Deshmukh [2], Md. Azar Nisar Bargir [3]
Assistant Professor & Head, Innovation Incubation & Research Centre, Jawaharlal Nehru Engineering College, MGM University, Chh. Sambhajinagar, MH, India.
Professor, Department Of Mechanical Engineering, Jawaharlal Nehru Engineering College, MGM University, Chh. Sambhajinagar, MH, India.
Assistant Professor, Department Of Mechanical Engineering, Jawaharlal Nehru Engineering College, MGM University, Chh. Sambhajinagar, MH, India.

Abstract:
Background*: Injection molding performance is strongly influenced by part shrinkage and cycle time, which directly affect product quality and manufacturing efficiency. Optimizing these outcomes requires careful control of processing parameters and effective cooling channel design. Multi-objective optimization techniques provide a systematic approach to improving molding performance.*
Materials and Methods*: This study applied a Taguchi-based Grey Relational Analysis (GRA) technique to optimize injection molding parameters. Experiments were conducted on a 100-ton Electronica injection molding machine using LDPE material to manufacture components with a diameter of 30 mm. Three cooling approaches were evaluated: traditional cooling channels, porous conformal cooling channels, and hybrid conformal cooling channels. Injection pressure, injection temperature, and coolant flow rate were selected as input parameters. Shrinkage and cycle time were considered as performance responses.*
Results*: The analysis showed that the hybrid conformal cooling channel design achieved the highest Grey Relational Grade, indicating superior overall performance compared to the other cooling strategies. Optimal parameter combinations were identified for each cooling method. The results also revealed that cooling channel design and injection pressure had a significant influence on both shrinkage reduction and cycle time improvement.*
Conclusion: *The study confirms that the Taguchi-GRA approach is effective for simultaneous optimization of multiple quality characteristics in injection molding. Hybrid conformal cooling channels provide notable advantages in reducing shrinkage and cycle time. The findings offer practical guidance for mold design improvement and enhanced process control in industrial injection molding applications.*
Key Word: *Injection Molding, Grey Relational Analysis, Conformal Cooling Channels, Process Optimization, Shrinkage, Cycle Time Reduction.*

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I. Introduction

Background and Motivation

Injection molding is one of the most widely used manufacturing processes for producing plastic components with complex shapes and high dimensional accuracy. Despite its advantages, maintaining consistent product quality and achieving efficient production remain challenging because the process involves many interacting parameters. Among these, part shrinkage and cycle time are two critical performance measures. Shrinkage affects dimensional stability and product fit, while cycle time directly influences productivity and manufacturing cost. Optimizing these two responses simultaneously is difficult, as improvements in one may adversely impact the other.

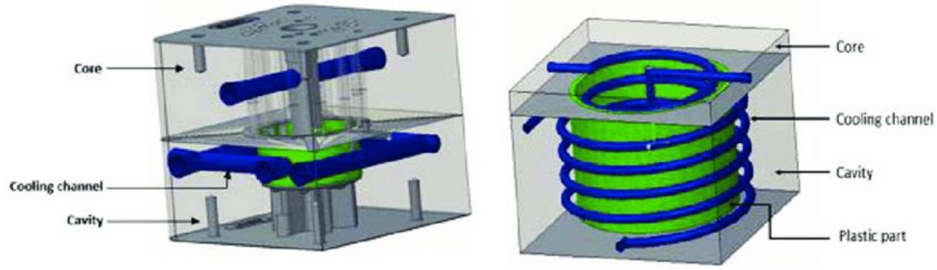

Fig.1 Compression between traditional & conformal Cooling system [9]

Conventional statistical approaches, such as regression-based methods, generally require large datasets, normally distributed data, and independent variables. These assumptions are often not satisfied in practical injection molding operations, where experimental data are limited and parameter interactions are complex. In many cases, the relationships between process variables and quality outcomes are uncertain or partially known. This uncertainty highlights the need for flexible optimization techniques that can handle limited data and multiple performance objectives.

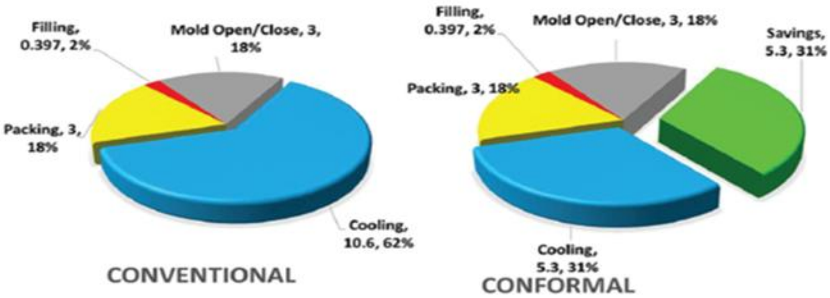

Fig. 2 The main steps of injection molding considering conformal & Conventional cooling.

Reducing cycle time contributes to higher production rates and lower operational costs, whereas minimizing shrinkage improves dimensional accuracy, surface quality, and material utilization. Achieving an optimal balance between these two factors enhances product reliability and strengthens competitiveness in manufacturing applications.

Fig.2 During Experimentation & calibration [9]

Design of Experiments and Taguchi Method

Design of Experiments (DOE) provides a systematic way to study the influence of process variables on performance characteristics. Among various DOE techniques, the Taguchi method is widely used due to its efficiency and simplicity. It employs orthogonal arrays to reduce the number of experimental runs while still capturing the essential effects of input parameters.

An important element of the Taguchi method is the Signal-to-Noise (S/N) ratio, which evaluates both the mean performance and variability of a response. A higher S/N ratio indicates that the process is more robust and less sensitive to external disturbances. This approach enables the identification of parameter settings that consistently deliver improved performance under varying operating conditions.

Grey Relational Analysis for Multi-Response Optimization

Grey System Theory was developed to analyze systems characterized by incomplete or uncertain information. Grey Relational Analysis (GRA), a key tool within this theory, is particularly effective for multi-objective optimization problems. GRA transforms multiple performance responses into a single indicator known as the Grey Relational Grade (GRG), which represents the overall quality of a given experimental condition. A higher GRG signifies closer agreement with the ideal performance.

One of the main advantages of GRA is its ability to work with small datasets without requiring assumptions about data distribution. This makes it well suited for manufacturing studies where experiments are costly or time-consuming. In injection molding, where multiple quality characteristics must be optimized simultaneously, GRA provides a practical and reliable solution.

Integrating the Taguchi method with GRA combines structured experimental design with effective multi-response evaluation. The Taguchi method determines optimal factor levels using S/N ratios, while GRA aggregates the multiple outcomes into a single performance index. This hybrid approach simplifies decision-making and is highly effective for addressing trade-offs between competing objectives.

Research Objectives And Contributions

The main objectives of this study are:

- To optimize key injection molding parameters, namely injection pressure, injection temperature, and coolant flow rate, using a Taguchi-based Grey Relational Analysis approach, with the aim of simultaneously reducing part shrinkage and cycle time.
- To evaluate and compare the performance of three cooling strategies: conventional cooling channels, porous conformal cooling channels, and hybrid conformal cooling channels.

This research offers practical guidance for selecting suitable cooling channel designs and process parameter combinations. The proposed optimization framework supports improvements in product quality, energy efficiency, and material utilization. Additionally, the study provides a structured methodology for multi-objective optimization that can be applied to a wide range of industrial injection molding applications.

II. Methodology

Selection of Process Parameters and Levels

Three important injection molding parameters were selected for this study: Injection Pressure, Injection Temperature, and Coolant Flow Rate. Each parameter was evaluated at three different levels, as shown in Table 1. These factors were chosen based on prior studies and practical relevance to product quality and process efficiency [10][11].

Table 1. Process Parameters and Their Levels for Injection Molding

Sr. No.	Parameter	Level 1	Level 2	Level 3
A	Injection Pressure (MPa)	45	55	65
B	Injection Temperature (°C)	200	210	220
C	Coolant Flow Rate (%)	60	80	100

Experimental Design

An L27 orthogonal array (OA) was selected from the Taguchi design to structure the experiments efficiently. This OA allows for studying the influence of three parameters at three levels using just nine experimental runs per cooling strategy. To improve reliability, each experiment was repeated five times and the results were averaged to minimize the effects of random variation [12].

Measurement of Response Characteristics

Two main outputs were measured:

• Cycle Time: Recorded directly from the machine's control panel during each trial.

• Part Shrinkage (Diameter): Measured using a calibrated Video Measuring Machine (VMM) in a NABL-accredited lab. Measurements were taken at three different positions on the part and averaged to ensure accuracy and consistency [13].

Calculation of Signal-to-Noise (S/N) Ratio

To optimize the process with respect to both response variables (shrinkage and cycle time), a combination of the Taguchi method and Grey Relational Analysis (GRA) was used. This integrated approach simplifies multi-objective optimization by converting it into a single-response problem [14].

The following six steps outline the GRA procedure used:

Calculation of Signal-to-Noise (S/N) Ratio

For both response characteristics, the "Lower-the-Better" (LB) criterion was applied, since lower values are desirable for quality and efficiency. The S/N ratio for the LB criterion is calculated using:

$$\frac{S}{N} = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_{ij}^2\right) \tag{1}$$

Where:

Yij = Measured value of the j-th response in the i-th experiment

n = Number of repetitions per experiment

Normalization of S/N Ratios

To bring all values to a common scale (0 to 1), normalization was done using:

$$Z_{ij} = \frac{\max(y_{ij}) - y_{ij}}{\max(y_{ij}) - \min(y_{ij})} \tag{2}$$

Where:
y_{ij} = S/N ratio
$max(y_{ij})$, $min(y_{ij})$ = Maximum and minimum S/N values across experiments

Calculation of Deviation Sequences
The absolute deviation from the ideal value (1) was computed:

$$\Delta_{oi}(k) = |x_o(k) - x_i(k)| \quad (3)$$

Where:
$x_0(k)$x= Ideal normalized value (1)
$x_i(k)$ = Actual normalized value for the i-th experiment and k-th response

Grey Relational Coefficient (GRC)
The GRC measures the closeness between each experiment and the ideal solution:

$$\xi_i(k) = \frac{\Delta_{Min} + \zeta\Delta_{\max.}}{\Delta_{oi}\,(k) + \zeta\Delta_{\max.}} \quad (4)$$

Where:
ζ = Distinguishing coefficient (set to 0.5)
Δ_{min}\ Δ_{max} = Minimum and maximum values of the deviation sequence

Grey Relational Grade (GRG)
The GRG is the average of the GRCs across all responses and serves as a single score for overall performance:

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k) \quad (5)$$

A higher GRG indicates a better overall outcome for that experimental run.

Identification of Optimal Parameters
To determine the best settings, the average GRG was calculated for each level of each parameter. The parameter level with the highest average GRG was considered optimal for enhancing both shrinkage and cycle time performance [15].

III. Results & Discussion

Experimental Results for Traditional, Porous Conformal, and Hybrid CCC
This section presents an integrated interpretation of the experimental data for the Hybrid Conformal Cooling Channel across the sequential stages of Grey Relational Analysis (GRA). The consolidated presentation enables a clear comparison of performance at each step of the optimization procedure and highlights the progression from raw experimental observations to final multi-objective evaluation.

The experimental results obtained from the 27 trials using the Hybrid Conformal Cooling Channel are first reported. These results include measured values of part shrinkage (mm), cycle time (s), and cooling time (s). This dataset represents the primary experimental evidence and forms the foundation for all subsequent analyses. Presenting the raw measurements ensures transparency and supports reproducibility by allowing direct verification of the experimental outcomes.

Subsequently, the Signal-to-Noise (S/N) ratios corresponding to shrinkage and cycle time are calculated using the lower-the-better criterion. These S/N ratios provide an initial assessment of process robustness by accounting for both the magnitude and variability of the responses under different experimental conditions.

The normalized S/N ratios are then determined to bring all response variables onto a common, dimensionless scale. This normalization step is essential to eliminate the influence of differing units and magnitudes, ensuring that each performance characteristic contributes equally to the Grey Relational Analysis.

Following normalization, deviation sequences are computed for each response. These values represent the absolute difference between the ideal normalized condition and the experimentally obtained normalized values. The deviation sequences quantify how far each trial deviates from the desired optimal performance.

Based on the deviation sequences, Grey Relational Coefficients (GRCs) are calculated for the Hybrid Conformal Cooling Channel. The GRCs indicate the degree of similarity between the actual performance and the ideal reference condition for each response characteristic, providing a standardized measure of individual response performance.

Finally, the Grey Relational Grades (GRGs) are obtained by aggregating the GRCs into a single performance index, and the corresponding ranks are assigned. The GRG converts the multi-response optimization problem into a single comparative metric, enabling direct ranking of experimental runs according to their overall performance. This approach facilitates clear identification of optimal process conditions for the Hybrid Conformal Cooling Channel.

Run No.	PARAMETERS			RESPONSE VALUE			S/N RATIO		NOR. S/N RATIO		DEVIATION SEQUENCE		G.R. COEFFICIENT		GREY RELATIONAL GRADE	RANK
	Injection Pressure (MPa)	Injection Temp. (°C)	Coolent Flow Rate (%)	Srinkage (mm)	Cycle Time (Sec.)	Cooling Time (Sec.)	Srinkage (LB)	Cycle Time (LB)	Srinkage (LB)	Cycle Time (LB)	Srinkage (LB)	Cycle Time (LB)	Srinkage (LB)	Cycle Time (LB)		
1	45	200	60	30.719	22.87	10	29.75	27.19	0.84	0.48	0.16	0.5	0.75	0.5	0.42	12
2	45	200	60	30.739	22.84	10	29.75	27.17	0.72	0.50	0.28	0.5	0.64	0.5	0.38	16
3	45	200	60	30.861	22.89	10	29.79	27.19	0.04	0.47	0.96	0.5	0.34	0.5	0.28	25
4	45	210	80	30.871	22.08	10	29.79	26.88	-0.02	1.00	1.02	0.0	0.33	1.0	0.44	9
5	45	210	80	30.786	22.41	10	29.77	27.01	0.46	0.78	0.54	0.2	0.48	0.7	0.39	14
6	45	210	80	30.702	22.07	10	29.74	26.88	0.93	1.01	0.07	0.0	0.88	1.0	0.63	2
7	45	220	100	30.747	23.09	10	29.76	27.27	0.68	0.34	0.32	0.66	0.61	0.43	0.35	21
8	45	220	100	30.835	22.72	10	29.78	27.13	0.18	0.58	0.82	0.4	0.38	0.5	0.31	24
9	45	220	100	30.799	23.63	10	29.77	27.47	0.39	0.00	0.61	1.0	0.45	0.3	0.26	26
10	55	200	80	30.749	22.43	10	29.76	27.02	0.67	0.77	0.33	0.2	0.60	0.7	0.43	11
11	55	200	80	30.751	22.77	10	29.76	27.15	0.66	0.55	0.34	0.5	0.59	0.5	0.37	18
12	55	200	80	30.841	23.32	10	29.78	27.35	0.15	0.20	0.85	0.8	0.37	0.4	0.25	27
13	55	210	100	30.762	22.96	10	29.76	27.22	0.59	0.42	0.41	0.6	0.55	0.5	0.34	23
14	55	210	100	30.796	22.38	10	29.77	27.00	0.40	0.80	0.60	0.2	0.46	0.7	0.39	15
15	55	210	100	30.702	22.39	10	29.74	27.00	0.93	0.79	0.07	0.2	0.88	0.7	0.53	3
16	55	220	60	30.791	22.45	10	29.77	27.02	0.43	0.76	0.57	0.24	0.47	0.67	0.38	17
17	55	220	60	30.701	22.87	10	29.74	27.19	0.94	0.48	0.06	0.5	0.89	0.5	0.46	6
18	55	220	60	30.753	22.81	10	29.76	27.16	0.65	0.52	0.35	0.5	0.58	0.5	0.37	19
19	65	200	100	30.698	23.11	10	29.74	27.28	0.96	0.33	0.04	0.7	0.92	0.4	0.45	8
20	65	200	100	30.693	23.07	10	29.74	27.26	0.98	0.35	0.02	0.6	0.97	0.4	0.47	5
21	65	200	100	30.692	23.25	10	29.74	27.33	0.99	0.24	0.01	0.8	0.98	0.4	0.46	7
22	65	210	60	30.765	22.51	10	29.76	27.05	0.58	0.72	0.42	0.3	0.54	0.6	0.39	13
23	65	210	60	30.743	23.21	10	29.75	27.31	0.70	0.27	0.30	0.7	0.63	0.4	0.34	22
24	65	210	60	30.699	23.21	10	29.74	27.31	0.95	0.27	0.05	0.7	0.91	0.4	0.44	10
25	65	220	80	30.645	22.43	10	29.73	27.02	1.26	0.77	-0.26	0.23	2.05	0.68	0.91	1
26	65	220	80	30.702	22.54	10	29.74	27.06	0.93	0.70	0.07	0.3	0.88	0.6	0.50	4
27	65	220	80	30.755	22.81	10	29.76	27.16	0.63	0.52	0.37	0.5	0.58	0.5	0.36	20

Fig.2 Design Matrix For Hybrid Conformal Cooling Channel

The plot shows the Grey Relational Grade for each Run Number across the three cooling channel types. A higher Grey Relational Grade indicates a better overall performance. As shown in the chart, the Hybrid CCC generally performs the best.

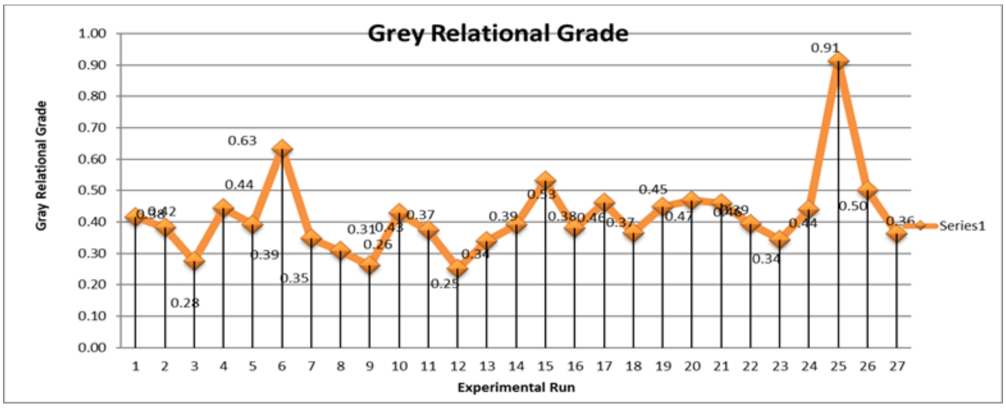

Fig.3 Grey Relational Grade by Cooling Type

The optimal parameter combination for the Hybrid Conformal Cooling Channel is identified as A2B3C1 (Injection Pressure 55 MPa, Injection Temp. 220 °C, Coolant Flow Rate 60%), yielding the highest Grey Relational Grade in Run 6 (0.6319). The analysis of main effects indicates that Coolant Flow Rate is the most influential parameter (Rank 1), followed by Injection Pressure (Rank 2), and Injection Temperature (Rank 3). This suggests that precise control over coolant flow is paramount for maximizing the benefits of this advanced design.

Confirmation Experiment

A confirmation experiment is a vital step in validating the predicted optimal settings derived from Taguchi-based optimization. While essential, specific data for a confirmation experiment related to this injection molding study was not provided within the supplied research materials. This represents a limitation, and empirical verification is suggested for future work.

IV. Conclusion

This research successfully demonstrated the application of a Taguchi-based Grey Relational Analysis for the multi-objective optimization of injection molding parameters, aiming to simultaneously minimize part shrinkage and cycle time. The study systematically investigated the influence of Injection Pressure, Injection Temperature, and Coolant Flow Rate across three distinct cooling channel designs: Traditional Cooling, Porous Conformal Cooling Channels, and Hybrid Conformal Cooling Channels.

The analysis identified specific optimal parameter combinations for each cooling strategy:

For Hybrid Conformal Cooling Channels, the optimal settings were 55 MPa Injection Pressure, 220 °C Injection Temperature, and 60% Coolant Flow Rate, achieving the highest Grey Relational Grade of 0.6319. Coolant Flow Rate was determined to be the most influential factor.

The comparative analysis unequivocally establishes the superior overall performance of the Hybrid Conformal Cooling Channel, as evidenced by its highest Grey Relational Grade. This finding highlights the significant advantages of advanced cooling channel designs in achieving enhanced product quality and manufacturing efficiency. The observed shift in the most influential process parameter across different cooling strategies provides a deeper understanding of how mold design fundamentally alters process sensitivity, offering crucial guidance for targeted process control and future mold design improvements.

In conclusion, this study not only provides precise optimal process parameters for various cooling configurations but also offers a robust, data-driven justification for the adoption of advanced cooling channel designs, particularly the Hybrid Conformal Cooling Channel, in injection molding. These findings demonstrate a clear and quantifiable pathway for technological advancement and competitive advantage within the manufacturing industry, enabling significant improvements in part quality (reduced shrinkage) and manufacturing efficiency (reduced cycle time) in industrial settings.

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