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Multi-Objective Optimization of Injection-Molded Car Door Handles Using Taguchi Method and Grey Relational Analysis

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ABSTRACT

Injection-molded automotive components, such as exterior car door handles, often suffer from defects like volumetric shrinkage, residual stress, and deflection, impacting their structural integrity and aesthetic quality. Traditional optimization methods struggle to balance the multiple conflicting objectives involved in material selection, mold design, and process parameters. This study addresses these challenges by integrating the Taguchi method and Grey Relational Analysis (GRA) for multi-objective optimization in Moldflow simulations. Key process parameters, including melt temperature, injection pressure, and cooling time, were systematically analyzed and optimized to reduce defects. Simulation trials using Acrylonitrile Butadiene Styrene (ABS), Polypropylene (PP), and Polycarbonate (PC) demonstrated notable improvements, achieving a 56.4% reduction in weld-line width and a 68.9% decrease in sink-mark depth. These results highlight the effectiveness of the combined Taguchi-GRA approach in enhancing injection molding efficiency, improving product quality, and ensuring component longevity. The study establishes a robust foundation for further research on optimizing complex injection-molded automotive parts and exploring advanced material formulations to meet stringent industry standards.

Keywords: Injection Molding, Moldflow Simulation, Multi-Objective Optimization, Taguchi Method, Grey Relational Analysis.

1. INTRODUCTION

Injection molding is a pivotal manufacturing process extensively utilized in the production of high-precision plastic components, particularly within the automotive sector. This method is favored for its cost efficiency, high production rates, and capability to create complex geometries with consistent quality. However, the pursuit of optimal performance in injection-molded components is fraught with challenges, primarily due to various defects such as volumetric shrinkage, residual stress, deflection, weld lines, and sink marks. These defects not only detract from the aesthetic and functional attributes of the final products but also lead to material wastage, elevated production costs, and diminished durability of automotive parts [1], [2]. The complexities associated with injection molding defects arise from the intricate interplay of processing parameters and material characteristics. For instance, residual stresses can significantly affect the mechanical properties of molded parts, as highlighted by [1], who noted that low mold temperatures in HDPE components resulted in high residual stresses, thereby reducing impact strength. Furthermore, the influence of mold temperature on the adhesion strength in two-component injection molding has been documented, indicating that temperature

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variations can drastically affect the interfacial properties of the materials involved [3]. Such findings underscore the necessity for meticulous control over processing conditions to mitigate defects and enhance the overall quality of injection-molded components.

To address the challenges in producing good quality products by injection molding, Moldflow simulation has emerged as a critical tool in the injection molding process. This software enables manufacturers to predict potential defects and optimize design parameters before the actual production begins. For instance, [4] demonstrated that computer simulation can effectively identify issues such as air traps and weld line positions, allowing for necessary design modifications without incurring excessive costs. Furthermore, the integration of Moldflow simulations facilitates a comprehensive understanding of the thermal and mechanical behavior of the materials involved, which is essential for optimizing process parameters such as melt temperature and cooling time [5]. The predictive capabilities of Moldflow simulation extend to the analysis of mold filling and cooling processes, which are crucial for ensuring the quality of the final product. By simulating the flow of the polymer melt within the mold, manufacturers can identify potential filling imbalances and adjust the design of the runner system accordingly [6]. This capability not only enhances the efficiency of the production process but also significantly reduces the likelihood of defects in the molded components. Additionally, studies have shown that utilizing Moldflow simulations can lead to substantial reductions in cooling times, thereby improving overall production efficiency [5]. By leveraging the predictive capabilities of this software, the industry can enhance the quality, efficiency, and durability of injection-molded components, thereby addressing the challenges posed by traditional manufacturing methods [7].

Using a trial-and-error approach alone in conducting simulations for injection molding can be time-consuming and inefficient, particularly for complex automotive components like exterior car door handles. The intricacies involved in the design and manufacturing of these components necessitate a systematic optimization process to ensure that the best process parameters are identified without excessive computational costs and delays in production. Without such optimization, manufacturers may find themselves engaging in multiple simulation iterations, which not only prolongs the time-to-market but also elevates material wastage and operational expenses [8]. To address these challenges effectively, this study proposes integrating advanced optimization techniques within the simulation phase of the injection molding process. By leveraging the Taguchi method for robust experimental design and Grey Relational Analysis (GRA) for multi-objective optimization, this approach systematically refines process parameters before actual manufacturing begins. This integration enhances the efficiency of simulation trials, reducing reliance on time-consuming trial-and-error methods while ensuring optimal material selection, mold design, and processing conditions.

1.1 Multi-Objective Optimization in Injection Molding Simulation

Injection molding is a highly complex process influenced by multiple interdependent variables, including material properties, mold design, and process parameters such as melt temperature, injection pressure, packing pressure, and cooling time. These factors must be carefully controlled to minimize defects such as warpage, shrinkage, residual stress, and weld lines while ensuring optimal production efficiency and product durability. Achieving an ideal balance among these conflicting objectives is challenging, requiring a multi-objective optimization approach to systematically improve overall product quality and manufacturing efficiency [4], [9]. Multi-objective optimization in injection molding simulation aims to simultaneously enhance multiple performance criteria by integrating advanced computational techniques into the design and manufacturing process. Unlike conventional optimization approaches focusing on a single performance measure, multi-objective optimization enables manufacturers to evaluate trade-offs between conflicting parameters, ensuring that critical quality aspects are addressed without compromising other essential factors [10], [11]. For instance, the integration of techniques such as the Taguchi method and Grey Relational Analysis (GRA) into Moldflow simulations allows for a comprehensive assessment of how various process parameters interact, leading to improved outcomes in terms of defect reduction and overall product quality [12], [13].

The importance of optimization in injection molding is particularly evident in the production of complex automotive components, such as exterior car door handles. These components require not only aesthetic appeal but also mechanical strength and durability. By employing multi-objective optimization, manufacturers can systematically determine the optimal combination of material selection, mold design, and process parameters before real manufacturing begins. This proactive approach minimizes defects such as volumetric shrinkage, residual stress, weld lines, and sink marks, ensuring higher-quality car door handles with improved mechanical strength, surface finish, and dimensional accuracy [14], [15]. Furthermore, the application of optimization techniques can lead to significant cost savings and reduced material wastage. By minimizing the number of trial iterations required to achieve optimal production conditions, manufacturers can enhance production efficiency and shorten development cycles. This is particularly crucial in the competitive automotive industry, where time-to-market is a critical factor [16], [17]. Ultimately, integrating optimization into simulation experiments enhances reliability, improves product consistency, and reduces production risks before full-scale manufacturing, thereby contributing to the overall success of the injection molding process [16].

In this study, the Taguchi method is employed for experimental design and parameter screening to identify the most influential factors affecting injection molding quality. The Taguchi method is a robust statistical approach that focuses on improving product quality by minimizing variability and defects through systematic experimentation. By utilizing orthogonal arrays, the Taguchi method allows for efficient testing of multiple factors simultaneously, significantly reducing the number of experiments required compared to traditional methods [18]. This efficiency is particularly beneficial in the context of injection molding, where numerous variables can impact the final product’s quality. Following the identification of key parameters, Grey Relational Analysis (GRA) is applied to perform multi-objective decision-making. GRA facilitates the transformation of multiple performance attributes into a single optimization index, enabling manufacturers to evaluate trade-offs between conflicting objectives, such as minimizing defects while maximizing strength and durability [19]. This integration provides a systematic framework for selecting optimal process parameters that minimize defects such as volumetric shrinkage and residual stress while improving dimensional accuracy and structural integrity.

By incorporating multi-objective optimization within Moldflow simulations, this approach reduces the need for excessive trial-and-error experiments, leading to significant time and cost savings in the product development phase. The optimized parameters identified in the simulation phase can then be directly implemented in the actual manufacturing process, ensuring that high-quality automotive components, such as exterior car door handles, are produced efficiently and consistently. This methodology not only improves product reliability but also enhances overall production sustainability by reducing material wastage and energy consumption [20]. The application of the Taguchi method in conjunction with GRA has been shown to yield substantial improvements in the injection molding process. For instance, [21] demonstrated that this combined approach effectively optimized the injection molding parameters for automotive components, resulting in enhanced mechanical properties and reduced defect rates. Similarly, studies have indicated that the Taguchi method can significantly improve the quality of molded parts by systematically addressing the factors that contribute to defects, thereby ensuring that the final products meet stringent industry standards [22]. Recognizing this, the present study aims to develop an optimized injection molding process for exterior car door handles by integrating the Taguchi method and Grey Relational Analysis (GRA) within Moldflow simulations. Additionally, this study seeks to identify the critical process parameters that significantly impact the quality of exterior car door handles. By integrating these optimization techniques, the research aims not only to improve product reliability but also to enhance overall production sustainability by minimizing material wastage and energy consumption.

2. EXPERIMENTAL PROCEDURE

2.1 Modelling of exterior car door handle

An exterior car door handle was designed using SolidWorks (Figure 1) and utilized as the reference model for this study. To conduct the simulation, Moldflow Plastic Insight (MPI) was employed, applying a fusion mesh type with a maximum aspect ratio of 7.79, a match percentage of 94.6%, and a reciprocal percentage of 95.6%. The fusion-meshed model of the exterior car door handle is illustrated in Figure 2.

Figure 1: 3D-rendered model of an exterior car door handle created using SolidWorks.

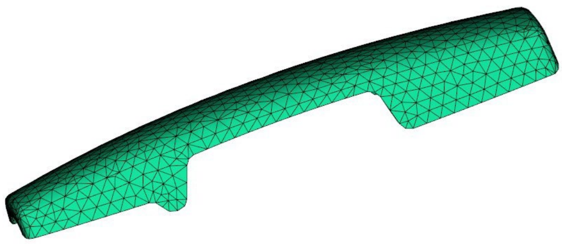

Figure 2: Exterior car door handle with a fusion mesh structure.

2.2 Determination of Quality Characteristics

The analysis of the exterior car door handle in this study focused on three key quality characteristics: volumetric shrinkage, residual stress, and deflection. These factors play a crucial role in determining the structural integrity, durability, and aesthetic appeal of the final product. If not properly controlled, they can lead to defects that compromise the component's performance, reliability, and customer satisfaction. Volumetric shrinkage refers to the percentage increase in density as the molded component cools from the packing phase to room temperature. Excessive or uneven shrinkage can result in dimensional inaccuracies, leading to surface defects such as sink marks and warping. These defects not only affect the visual appearance of the exterior car door handle but also compromise its structural stability. If volumetric shrinkage is not properly managed, the final product may suffer from poor fitting and reduced mechanical strength. Residual stress is another critical factor that impacts the mechanical properties and long-term reliability of the exterior car door handle. These stresses arise due to non-uniform cooling and plastic deformation during the molding process, impacting the mechanical properties of the exterior car door handle, including its strength, fatigue resistance, and dimensional stability. Excessive residual stress can lead to premature failure or cracking under load, compromising both safety and longevity, especially when exposed to external forces or environmental changes. Meanwhile, deflection refers to the deviation of the plastic component from its intended shape due to clamping and cavity pressures during the molding process. This distortion can significantly affect both the performance and aesthetic quality of the component. Excessive deflection may result in misalignment or improper fitting of the car door handle, leading to operational inefficiencies.

2.3 Selection of Influence Factors

Several control factors were selected for this study, including material selection and key injection molding process parameters. The process parameters considered in this research include melting temperature, filling pressure, filling time, injection time, cooling time, and injection pressure. The chosen control factors and their corresponding levels are presented in Table 1.

Table 1: Simulation Control Factor Levels.

Column	Factor	Level 1	Level 2	Level 3
A	Material Selection	ABS	PP	PC
B	Melting Temperature (°C)	220	240	260
C	Filling Pressure (%)	60	80	100
D	Filling Time (s)	1.0	2.0	3.0
E	Injection time (s)	1	1.5	2
F	Cooling Time (s)	25	30	35
G	Injection Pressure (MPa)	60	70	80

Referring to Table 1, this study examines the influence of seven key control factors on the injection molding process for exterior car door handles, with each factor analyzed at three different levels to assess its impact on product quality. These factors were carefully selected due to their significant effects on volumetric shrinkage, residual stress, and deflection, which are critical in ensuring the structural integrity, mechanical performance, and dimensional precision of the final product. Among these factors, material selection plays a fundamental role, with Acrylonitrile Butadiene Styrene (ABS), Polypropylene (PP), and Polycarbonate (PC) chosen due to their distinct mechanical properties, shrinkage behavior, and thermal resistance. These material characteristics directly affect the strength, durability, and stability of the molded component. Additionally, melting temperature, set at 220°C, 240°C, and 260°C, is a crucial parameter as it governs the fluidity of the molten plastic, ensuring optimal mold filling and reducing defects.

Equally important, filling pressure, varied at 60%, 80%, and 100%, regulates the flow of material into the mold cavity, preventing short shots or excessive flash formation. In conjunction with this, filling time, ranging from 1.0s to 3.0s, determines the speed of material injection, ensuring uniform flow and minimizing defects like weld lines. Likewise, injection time, tested at 1s, 1.5s, and 2s, controls the duration of plastic flow into the cavity, influencing packing efficiency and internal stress distribution. Furthermore, cooling time, set at 25s, 30s, and 35s, is critical in ensuring dimensional stability by allowing the part to solidify properly. Inadequate cooling may result in warping and residual stress accumulation, while excessive cooling prolongs cycle time, reducing overall production efficiency. Lastly, injection pressure, examined at 60 MPa, 70 MPa, and 80 MPa, significantly affects part density and defect formation, playing a key role in achieving high-quality, mechanically robust components.

2.4 Selection of Orthogonal Array (OA)

This study considers a total of seven control factors, each evaluated at three levels. Since each three-level factor contributes two degrees of freedom (DOF) (DOF = number of levels - 1), the total DOF required for the analysis amounts to 14. In the Taguchi method, the chosen orthogonal array (OA) must have a total DOF that is at least equal to or greater than the total DOF of the studied factors. Consequently, an L18 OA was selected to conduct the simulation, as detailed in Table 2.

Table 2: OA L18 of simulation runs.

Trial Number	1 A	2 B	3 C	4 D	5 E	6 F	7 G
1	1	1	1	1	1	1	1
2	1	2	2	2	2	2	2
3	1	3	3	3	3	3	3
4	2	1	1	2	2	3	3
5	2	2	2	3	3	1	1
6	2	3	3	1	1	2	2
7	3	1	2	1	3	2	3
8	3	2	3	2	1	3	1
9	3	3	1	3	2	1	2
10	1	1	3	3	2	2	1
11	1	2	1	1	3	3	2
12	1	3	2	2	1	1	3
13	2	1	2	3	1	3	2
14	2	2	3	1	2	1	3
15	2	3	1	2	3	2	1
16	3	1	3	2	3	1	2
17	3	2	1	3	1	2	3
18	3	3	2	1	2	3	1

3 RESULTS AND DISCUSSION

3.1 Analysis of the experimental results via Grey relational analysis (GRA)

Grey Relational Analysis (GRA) is a fundamental component of Grey System Theory (GST), which was first introduced by Professor Julong Deng in 1982 at Huazhong University of Science and Technology, China. The theory was developed to address decision-making challenges in situations where information is insufficient, uncertain, or incomplete [23]. Unlike traditional statistical methods, which require large datasets and strict probability distributions, GST allows analysis in scenarios with limited data. Among its various techniques, GRA is particularly useful for multi-objective optimization, enabling researchers and engineers to analyze systems with multiple interdependent variables and select the best-performing parameter combinations [24]. GRA works by quantifying the relationships between different factors through a normalization and ranking process. It is particularly beneficial in cases where multiple performance indicators need to be optimized simultaneously. The process begins with data normalization, which ensures consistency across different units of measurement. Then, the grey relational coefficient (GRC) is calculated to determine how closely each experimental condition aligns with the ideal target. Finally, the grey relational grade (GRG) is derived by averaging the GRC values, providing a comprehensive ranking of the various parameter settings [25]. This systematic approach allows engineers to identify optimal conditions efficiently, even when dealing with complex industrial processes. One of the greatest advantages of GRA is its effectiveness in multi-objective optimization, particularly in manufacturing and engineering applications. It enables the simultaneous optimization of multiple conflicting objectives, ensuring that different quality parameters are balanced appropriately [26]. Additionally, GRA is highly efficient even with limited data, making it suitable for small-sample experimental studies where gathering extensive datasets may not be feasible. Its computational simplicity allows for faster decision-making compared to more complex models like machine learning or artificial intelligence [27].

3.1.1 Grey Generation of Raw Data

GRA technique begins with a pre-processing stage, where the initial data sequences are organized and prepared for further analysis. This stage involves standardizing, rescaling, and structuring the data into a comparable format. To ensure consistency in evaluating quality characteristics such as volumetric shrinkage, warpage, and residual stress, the data must be normalized within a range of 0 to 1. The normalization process depends on the nature of the data, which can be classified into three categories: “the higher - the better," “the lower- the better,” and “the nominal value is the best.” By applying appropriate normalization methods, variations in different performance measures are effectively adjusted, ensuring a fair and balanced comparison for optimization. In this study, the “the lower - the better” criterion, as defined by Equation 1, is applied to evaluate volumetric shrinkage, warpage, and residual stress in the exterior car door handle. This approach ensures that minimizing these factors leads to improved dimensional accuracy, structural integrity, and overall product quality. Table 3 presents the normalized values for volumetric shrinkage, warpage, and residual stress.

$$x_i^* (k) = \frac{max\, x_i^0 (k) - x_i^0(k)}{max\, x_i^0 (k) - min\, x_i^0 (k)} \quad (1)$$

Table 3: The normalized values for volumetric shrinkage, warpage, and residual stress.

Trial Number	Volumetric Shrinkage	Residual Stress	Deflection
1	1.000	0.695	0.847
2	0.918	0.854	0.898
3	0.846	0.924	0.930
4	0.208	0.723	0.262
5	0.108	0.774	0.300
6	0.000	0.834	0.000
7	0.989	0.206	0.732
8	0.861	0.425	0.918
9	0.750	0.426	0.891
10	0.962	1.000	1.000
11	0.926	0.701	0.832
12	0.836	0.760	0.818
13	0.197	0.706	0.319
14	0.099	0.776	0.140
15	0.022	0.829	0.190
16	0.999	0.424	0.771
17	0.856	0.308	0.906
18	0.753	0.000	0.740

3.1.2 Determination of deviation sequence

The deviation sequence $\Delta 0_i\ (k)$ is the absolute difference between the reference sequence $x_0{}^*\ (k)$ and the comparability sequence $x_i{}^*\ (k)$ after normalization. The deviation sequence is listed in Table 4.

Table 4: Deviation Sequence.

Trial Number	Volumetric Shrinkage	Residual Stress	Deflection
1	0.000	0.306	0.153
2	0.082	0.146	0.102
3	0.155	0.076	0.070
4	0.792	0.277	0.738
5	0.892	0.226	0.700
6	1.000	0.166	1.000
7	0.012	0.794	0.268
8	0.139	0.575	0.082
9	0.250	0.574	0.109
10	0.038	0.000	0.000
11	0.074	0.299	0.168
12	0.164	0.240	0.183
13	0.803	0.294	0.681
14	0.900	0.224	0.860
15	0.979	0.171	0.810
16	0.001	0.576	0.229
17	0.144	0.692	0.094
18	0.250	1.000	0.026

3.1.3 Determination of Grey Relational Coefficient (GRC) and Grey Relational Grade (GRG)

The relationship between the ideal (optimal) and actual normalized volumetric shrinkage, warpage, and residual stress is expressed by GRC for all sequences. If the two sequences agree at all points, then their GRC is 1. The GRC $\gamma\big(x_0(k), x_i(k)\big)$ as expressed by Equation 2.

$$\gamma\big(x_0(k), x_i(k)\big) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{0i}\ (k) + \zeta\Delta_{max}} \tag{2}$$

where, Δ_{min} is the smallest value of $\Delta 0_i\ (k) = min\ _i\ min_k\ |x_0^*\ (k) - x_1^*\ (k)|$ and Δ_{max} is the largest value of $\Delta 0_i\ (k) = max\ _i\ max_k\ |x_0^*\ (k) - x_1^*\ (k)|$, $x_0^*\ (k)$ is the ideal normalized volumetric shrinkage, warpage, and residual stress, $x_1^*\ (k)$ is the normalized comparability sequence, and ζ is the distinguishing coefficient. The value of ζ can be adjusted with the systematic actual need and defined in the range between 0 and 1; here it is chosen as 0.5.

The GRG provides the foundation for the overall assessment of the many performance aspects. The GRG, which is defined as the average of the GRC, is shown in Equation 3. Table 5 shows the results of GRC and GRG.

$$\gamma\ \big(x_{0,}x_i\big) = \frac{1}{m}\sum_{i=1}^{m} \gamma\big(x_0(k), x_i(k)\big) \tag{3}$$

Table 5: Grey Relational Coefficient (GRC) and Grey Relational Grade (GRG).

Trial Number	Volumetric Shrinkage	Residual Stress	Deflection	GRG
1	1.000	0.621	0.765	0.795
2	0.860	0.774	0.830	0.821
3	0.764	0.868	0.877	0.837
4	0.387	0.643	0.404	0.478
5	0.359	0.689	0.417	0.488
6	0.333	0.751	0.333	0.472
7	0.979	0.386	0.651	0.672
8	0.782	0.465	0.859	0.702
9	0.667	0.466	0.821	0.651
10	0.929	1.000	1.000	0.976
11	0.871	0.626	0.749	0.749
12	0.753	0.676	0.733	0.721
13	0.384	0.630	0.423	0.479
14	0.357	0.691	0.368	0.472
15	0.338	0.745	0.382	0.488
16	0.999	0.465	0.686	0.717
17	0.777	0.420	0.824	0.680
18	0.667	0.333	0.658	0.553

3.2 Determination of optimal factors via main effect analysis

The main effect analysis is a crucial step in identifying the most influential factors in an injection molding process. This method evaluates the impact of each control factor on key quality characteristics, such as volumetric shrinkage, warpage, and residual stress, to determine the optimal process parameters. By analyzing the variation in performance across different factor levels, the most effective combination of parameters can be selected to minimize defects and enhance product quality. In this study, the main effect analysis was used to examine how factors such as material selection, melting temperature, filling pressure, injection time, cooling time, and injection pressure influence the molding outcomes. The results provided insights into which levels of these parameters contribute to the lowest defect rates, ensuring better dimensional accuracy, mechanical performance, and overall durability of the exterior car door handle. By selecting the optimal factor levels, manufacturers can enhance production efficiency while reducing material waste and defect rates. Table 6 displays the results of the main effect analysis.

Table 6: Main Effect Analysis.

Factors	Symbol	Level 1	Level 2	Level 3	Max - Min	Rank
Material Selection	A	0.816	0.480	0.662	0.336	1
Melting Temperature (°C)	B	0.686	0.652	0.620	0.066	4
Filling Pressure (%)	C	0.640	0.622	0.696	0.074	2
Filling Time (s)	D	0.618	0.655	0.685	0.067	3
Injection Time (s)	E	0.642	0.659	0.658	0.017	7
Cooling Time (s)	F	0.641	0.685	0.633	0.052	5
Injection Pressure (MPa)	G	0.667	0.648	0.643	0.024	6

Referring to Table 6, the analysis of key factors influencing the injection molding process revealed that material selection (Factor A) had the most significant impact on the quality of the exterior car door handle, with the highest Max - Min difference of 0.336, ranking it as the most critical factor. Filling pressure (Factor C) and filling time (Factor D) followed, with differences of 0.074 and 0.067, respectively, indicating their substantial effect on the molding outcomes. Melting temperature (Factor B), cooling time (Factor F), and injection pressure (Factor G) showed moderate influence, with variations of 0.066, 0.052, and 0.024, respectively. These parameters still contribute to product quality but to a lesser extent compared to material selection and filling-related factors. The least impactful factor was injection time (Factor E), with a Max - Min difference of only 0.017, suggesting minimal influence on defect reduction and overall product performance. This ranking highlight that optimizing material selection, filling pressure, and filling time is crucial for improving dimensional accuracy, reducing defects, and enhancing the mechanical properties of injection-molded exterior car door handles. To enhance the comprehension of the main effect analysis, Figure 3 is generated based on the results presented in Table 6.

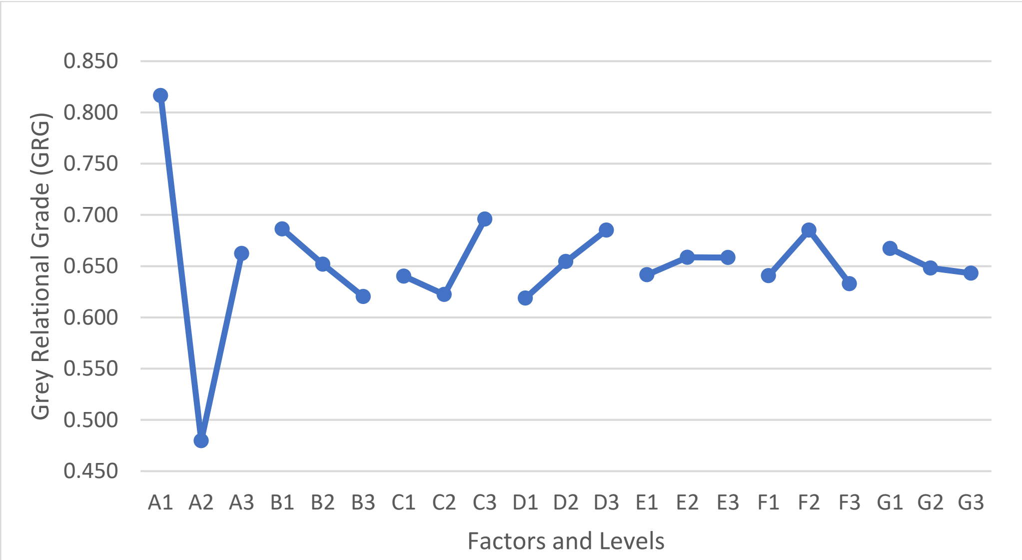

Figure 3: Main effects graph.

The main effect graph in Figure 3 illustrates the influence of different material selection and variation in injection molding processing parameters on the Grey Relational Grade (GRG), which represents the overall quality performance of the injection-molded exterior car door handle. Each factor is analyzed at three different levels to determine its contribution to optimizing the molding process.

From the graph, material selection (Factor A) shows the most significant variation, with a sharp drop at Level 2 (A2) compared to Levels 1 (A1) and 3 (A3). This indicates that the choice of material has the highest impact on the molding process, affecting volumetric shrinkage, residual stress, and deflection. A suitable material selection is crucial in ensuring dimensional stability and mechanical integrity. Different materials exhibit varying degrees of shrinkage during cooling, which directly impacts the dimensional accuracy of the final component. Materials with high shrinkage rates, such as polypropylene (PP), may cause warping or dimensional inconsistencies, leading to misalignment issues when assembling components. In contrast, materials like polycarbonate (PC) and acrylonitrile butadiene styrene (ABS) have lower shrinkage rates, making them more suitable for applications requiring precise dimensional control [28], [29]. Research has shown that the selection of materials significantly influences the mechanical properties and performance of injection-molded parts. For instance, Khosravani and Nasiri highlighted the importance of material properties in the injection molding manufacturing process, emphasizing that different materials can lead to varying outcomes in terms of quality and performance [30]. Additionally, the study by [28] demonstrated how the type of polypropylene used and the length of the flow path can affect the structure and properties of injection-molded parts, particularly concerning weld lines and overall integrity. Moreover, the work by [30] focused on controlling residual stress in PC molding, underscoring the material's significance in achieving optimal performance and minimizing defects during the injection process. This aligns with findings from [31], who explored the creation of material data for thermoset injection molding simulations, further illustrating the critical role of material selection in ensuring successful molding outcomes.

On the other hand, melting temperature (Factor B) exhibits a relatively stable trend with minor variations across the three levels, suggesting that its impact is less pronounced compared to material selection. This can be attributed to several key factors. First, the influence of material properties plays a crucial role. Each material, whether ABS, PP, or PC, has its own optimal melting temperature range. As long as the temperature remains within this range, the polymer can flow properly into the mold without causing significant defects. Unlike material selection, which directly determines fundamental mechanical properties and shrinkage behavior, small changes in melting temperature do not drastically alter the final product's quality [32]. Another factor to consider is the thermal stability of the selected materials. ABS, PP, and PC are thermoplastics known for their ability to tolerate minor fluctuations in melting temperature without exhibiting drastic changes in mechanical performance or dimensional stability [32]. Therefore, while melting temperature plays a role in ensuring proper mold filling and material flow, its overall impact remains relatively stable. In contrast, material selection exerts a more significant influence, as it directly determines the structural properties and shrinkage behavior of the component [33]. Similarly, the study by Muthukumar highlighted how the melting temperature of polymers can influence their processing behavior and final properties, reinforcing the notion that while melting temperature is important, material selection is paramount [34].

Meanwhile, filling pressure (Factor C) and filling time (Factor D) display a moderate increasing trend, indicating that adjustments to these parameters can contribute to improving product quality. Higher filling pressure ensures better material distribution, reducing the risk of short shots and voids, while an optimized filling time allows for complete mold filling without introducing excessive stress [35]. Research has shown that the optimization of filling pressure is crucial for achieving uniform filling and minimizing defects in injection-molded parts [36]. In contrast, injection time (Factor E) shows minimal variation, implying that changes in injection duration have a relatively low impact on the final product. Injection time primarily determines the duration of material injection but does not significantly influence other quality attributes once an optimal threshold is met [37]. This is supported by findings from [38], who noted that while filling time is important for ensuring proper mold filling, its effect diminishes once the optimal conditions are established.

Cooling time (Factor F), however, plays a crucial role in controlling shrinkage and residual stresses, leading to noticeable fluctuations in its effect. A well-optimized cooling time ensures uniform solidification, preventing warpage and internal stress accumulation. If cooling is too rapid, it can result in uneven shrinkage, whereas excessive cooling time can reduce production efficiency without providing additional quality benefits. On the other hand, injection pressure (Factor G) remains relatively stable, suggesting that while it is essential for proper mold filling, slight variations in pressure do not drastically impact the final component's quality. As long as the pressure is sufficient to push the molten material into the mold, other factors, such as material selection, filling pressure, and cooling conditions, play a more significant role in determining the structural integrity and dimensional accuracy of the exterior car door handle.

Overall, the analysis confirms that material selection is the most influential factor, followed by filling pressure, filling time, and cooling time. These findings emphasize the need for precise control of these parameters to enhance product reliability and minimize defects in injection-molded automotive components. In this case, the best combination of influential factors and levels can easily be obtained from the main effect analysis by selecting the level of each factor with the highest GRG. Table 7 listed the optimal factors for the exterior car door handle in this study.

Table 7: Optimal factors.

	Factor	Level	Description
A	Material Selection	1	Acrylonitrile Butadiene Styrene (ABS)
B	Melting Temperature (°C)	1	220
C	Filling Pressure (%)	3	100
D	Filling Time (s)	3	3
E	Injection Time (s)	2	1.5
F	Cooling Time (s)	2	30
G	Injection Pressure (MPa)	1	60

3.3 Analysis of Variance (ANOVA)

Conducting Analysis of Variance (ANOVA) in this study is essential to statistically determine the significance of each control factor in influencing the quality of the exterior car door handle. While the main effect analysis provides a general understanding of how different factors affect volumetric shrinkage, residual stress, and deflection, ANOVA quantifies the contribution of each parameter and identifies which factors have the most substantial impact on the overall optimization process. ANOVA helps to differentiate between real effects and variations caused by random experimental noise. By calculating the percentage contribution of each factor, it allows researchers to prioritize key parameters that significantly affect product quality, ensuring that optimization efforts focus on the most influential variables. Furthermore, ANOVA provides a statistical validation of the experimental results, reducing the risk of making conclusions based on trends that may not be statistically significant. This ensures that any recommendations made for process improvements are backed by strong data, leading to a more robust and reliable injection molding process for manufacturing high-quality car door handles. The computed quantity of degrees of freedom (DOF), sum of square, variance, F-ratio and percentage contribution (%) are presented in Table 8.

Table 8: Analysis of Variance (ANOVA).

	Factor	DOF	Sum Of Square	Variance	F-Ratio	Percentage
A	Material Selection	2	0.341	0.171	519.80	85.561
B	Melting Temperature (°C)	2	0.013	0.007	19.883	3.273
C	Filling Pressure (%)	2	0.018	0.009	26.961	4.438
D	Filling Time (s)	2	0.013	0.007	20.146	3.316
E	Injection Time (s)	2	0.001	0.001	1.762	0.290
F	Cooling Time (s)	2	0.010	0.005	14.514	2.389
G	Injection Pressure (MPa)	2	0.002	0.001	2.952	0.486
	Error	3	0.001	0.000	-	0.247
	Total	17	0.399	-	-	100.00

The results of the ANOVA presented in the Table 8 shows a detailed breakdown of the significance of each control factor in influencing the quality characteristics of the exterior car door handle. The analysis identifies material selection (Factor A) as the most dominant parameter, contributing 85.561% to the total percentage. With the highest F-ratio of 519.805, it is evident that material selection plays a crucial role in determining the final product's quality, affecting its mechanical performance, shrinkage behavior, and dimensional stability. This underscores the importance of selecting an appropriate material to optimize the injection molding process.

Among the remaining factors, filling pressure (Factor C) and melting temperature (Factor B) exhibit moderate contributions of 4.438% and 3.273%, respectively. Their relatively lower F-ratios (26.961 for filling pressure and 19.883 for melting temperature) suggest that while these parameters do have an impact on the molding process, their influence is not as significant as material selection. Similarly, filling time (Factor D) contributes 3.316%, with an F-ratio of 20.146, indicating that optimizing this parameter can help improve product consistency and reduce defects. Cooling time (Factor F) accounts for 2.389% of the percentage of contribution, with an F-ratio of 14.514, emphasizing its role in controlling shrinkage and residual stress. Although cooling time is an important parameter, its effect is less pronounced than the previously mentioned factors. Injection time (Factor E) and injection pressure (Factor G) exhibit minimal impact, contributing only 0.290% and 0.486%**, respectively. Their low F-ratios (1.762 for injection time and 2.952 for injection pressure) indicate that variations in these parameters do not significantly affect the final product.

The error contribution is 0.247%, which is relatively low, confirming the reliability of the experimental results and the effectiveness of the selected control factors. Since material selection dominates the variance, it should be given top priority in process optimization. Other parameters such as filling pressure, melting temperature, and filling time should also be carefully adjusted to further enhance the quality of the exterior car door handle.

4 CONCLUSION

In conclusion, the integration of the Taguchi method and GRA in this study provides a robust optimization framework for improving the injection molding process of exterior car door handles. The Taguchi method identifies key control factors and their most effective levels, while GRA refines these findings by addressing multiple quality criteria simultaneously. From the main effect analysis, the results indicate that the most suitable material selection is ABS (Level 1), as it provides superior dimensional stability and mechanical strength. The optimal melting temperature is 220°C (Level 1), which ensures proper material flow while minimizing thermal degradation. A filling pressure of 100% (Level 3) and a filling time of 3.0 seconds (Level 3) are ideal for achieving uniform mold filling and reducing voids or defects. Additionally, an injection time of 1.5 seconds (Level 2) helps balance material flow and injection stability, while a cooling time of 30 seconds (Level 2) is essential for reducing residual stress and ensuring dimensional accuracy. Lastly, an injection pressure of 60 MPa (Level 1) is optimal for maintaining part consistency without inducing excessive internal stresses. This optimized parameter combination is expected to improve the overall quality, durability, and performance of the exterior car door handle while minimizing defects such as shrinkage, warpage, and residual stress.

From ANOVA, the results indicate that material selection emerged as the most significant factor, contributing 85.561% to the overall percentage of contribution. This underscores the necessity of choosing the appropriate material, as it directly impacts the mechanical properties, shrinkage behavior, and dimensional stability of the final product. Factors such as filling pressure, melting temperature, and filling time also play notable roles in optimizing the molding process, albeit to a lesser extent. Additionally, the results also indicate that parameters like cooling time, injection time, and injection pressure have a comparatively lower influence on the final component's quality. However, their effects should not be overlooked, as they contribute to reducing defects such as warpage and residual stress. The low error percentage (0.247%) further validates the reliability of the findings, reinforcing the effectiveness of the selected factors in achieving optimal product quality.

The integration of the Taguchi method and Grey Relational Analysis (GRA) provides a structured and effective approach to process optimization. This combined methodology enhances the injection molding process by systematically identifying optimal parameter settings, resulting in superior product quality, minimized defects, and increased manufacturing efficiency. By adopting this approach, manufacturers can achieve greater consistency in production, improve cost-effectiveness, and promote sustainability, particularly in multi-objective optimization scenarios where multiple performance criteria must be simultaneously optimized.

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