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Review: Optimizing Plastic Injection Processes for Enhanced Quality and Sustainable Manufacturing

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Abstract

In the automotive world, plastic products are components that cannot be separated. Almost all automotive products use plastic because it is easy to produce, and the price is relatively cheap compared to other materials. For applications such as covers, the demand for plastic surface quality is higher than for different uses. Therefore, a lot of costs are incurred to achieve this quality. However, ongoing efforts have decreased the time and expense of developing plastic molds. This Review reports many researchers have conducted studies to improve the quality of these products. This review consolidates several research articles on optimizing plastic injection processes to reduce defects and improve product quality. Techniques such as Taguchi Method, Response Surface Methodology (RSM), Artificial Neural Networks (ANN), and Finite Element Method (FEM) were evaluated in this research. This review highlights the importance of process parameters such as melting temperature, injection pressure, and cooling time, as well as the role of digital simulation in designing efficient and sustainable molds. The results of the study show that in several studies, defects often occur in the product without carrying out the optimization process. Still, the Taguchi and ANOVA methods can reduce the weld line and sink after optimizing the process parameters, such as melting temperature, injection pressure, cooling time, and injection speed. Mark up to 30%. These findings highlight the potential of these techniques to significantly improve product quality and support more sustainable manufacturing practices in the plastic injection molding industry.

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1. Introduction

Injection molding is a widely used manufacturing process for producing plastic products with high precision and efficiency [1]. This process involves injecting molten plastic into a mold to form the desired product [2]. However, it often encounters defects such as shrinkage, warpage, and sink marks, as illustrated in Figure 1.

(a) (b) (c)

Figure 1. (a) Shrinkage, (b) Warpage, (c) Sinkmark

These defects can significantly affect the final product's quality and dimensional accuracy, which is critical in automotive, electronics, and medical devices. Consequently, extensive research has been conducted to address these issues in the injection molding process.

Rizwan Mohd Khan and Gaurav Acharya (2016) concluded that sink marks can be mitigated by optimizing process parameters such as melt temperature, injection pressure, cooling time, and holding pressure [3]. Additionally, Mathivanan et al. found that the rib-to-gate distance also influences

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sink mark severity, where greater distances increase the intensity of the defect [4]. Meanwhile, Masatomo Inui (2018) identified product thickness variations as a primary cause of sink marks and suggested improved rib designs to address this issue [5]. Warpage defects are another primary concern in injection molding. S.Q. Ch'ng et al. (2018) noted that packing pressure, packing time, cooling time, and melt temperature are four key parameters influencing warpage. Optimizing these parameters can effectively reduce warpage defects [6]. A similar approach was suggested by Chiwapon Nitnara et al., who added that filling time is also a critical factor in minimizing warpage [7]. Additionally, several studies highlight the impact of gate design on product quality. According to Naveen Reddy Pothula (2019), using a single gate is more effective than two or three gates in reducing sink mark severity [8]. New technologies, such as External Gas-Assisted Injection Molding (EGAIM), have also been introduced to significantly reduce sink marks, as reported by Shaofei Jiang et al. (2020) and Yen-Chih Chen et al. (2020) [9], [10]. Cooling efficiency in the injection molding process is crucial in reducing shrinkage defects. G. Gumono et al. (2023) demonstrated that efficient cooling improves product quality [11]. Furthermore, Zhiguo Ma et al. (2021) recommended using diamond-shaped inserts in runners made from beryllium copper as a simple and effective solution for reducing sink marks near the gate area [12]. Indra Mawardi et al. (2019) emphasized that injection temperature is a critical parameter in the injection molding process. Higher temperatures above the material's melting point can reduce defects such as short shots and shrinkage. However, other parameters like injection pressure and cooling time must also be optimized to address defects such as flashing and sink marks [13]. On the other hand, defects such as spots are often found in plastic products. One cause is corrosion in molds made of metal. Corrosion in metal molds, such as stainless steel or carbon steel, can be accelerated by high humidity or exposure to aggressive chemicals often found in injection molding. According to I Gusti Ayu Arwati et al. (2022), corrosion-resistant materials and protective coating methods are essential to prevent this damage [14]. In addition, the use of natural inhibitors, such as chitosan, has proven effective in reducing metal corrosion rates in various industrial environments [15].

Given the numerous methods developed to address defects in the injection molding process, a comprehensive literature review is necessary to summarize these findings. Such a review aims to provide better guidance for optimally producing high-quality plastic products.

2. Optimization Methods for Plastic Injection Process

This method includes various methodologies, including the Taguchi method, Response Surface Methodology (RSM), Artificial Neural Networks (ANN), and Finite Element Method (FEM). Each article reviewed was selected based on its relevance and contribution to improving product quality and process efficiency in the plastic injection industry.

This approach enables the identification of critical process parameters and the development of models that can predict and reduce defects such as shrinkage, warpage and sink marks, short shots, jetting, flash, and bubbles. Using various optimization and simulation techniques, these studies provide practical guidance for optimizing process parameters and improving product quality. These diverse methodologies include variance analysis to determine key factors, numerical modeling to predict defects, and the application of machine learning algorithms to automate process optimization.

The implementation of findings from these studies provides significant benefits, including reduced defect rates and enhanced production efficiency.

Optimization methods commonly used in optimizing plastic injection process parameters are Taguchi Method, Response Surface Methodology (RSM), Artificial Neural Networks (ANN), and Finite Element Method (FEM).

2.1. Taguchi method

Taguchi Method is a statistical approach developed by Dr. Genichi Taguchi to improve product quality and manufacturing processes. That method uses signal-to-noise (S/N) ratio and analysis of variance (ANOVA) analysis techniques to identify process parameters that influence the quality of the final product, both qualitatively and quantitatively.

Ramakrishnan and Mao (2017) applied that method to minimize shrinkage in the polymer gear injection process. Their study used five control parameters varied in five different levels as shown in Table 1.

Table 1. Experiment parameters and levels

Control Factors	Levels				
	1	2	3	4	5
Melt temperature (^{0}C)	205	210	215	220	225
Mold temperature (^{0}C)	80	85	90	95	100
Packing time (s)	10	20	30	40	50
Packing pressure (MPa)	80	85	90	95	100
Cooling time (s)	50	60	70	80	90

Based on ANOVA analysis, melting temperature contributed 95.12%, while packing pressure contributed 3.33%. Other parameters, such as mold temperature, packing time, and cooling time, do not significantly influence shrinkage [16]. Sreedharan and Jeevanantham (2018) identified that of 27 experiments to minimize shrinkage in ABS products for automotive applications, melting temperature had the most significant influence (95%). Meanwhile, injection pressure, packing pressure, and cooling time are insignificant [17]. Shuai Li et al. (2016) used six control parameters varied in three levels to minimize sink marks in the microcellular injection molding (MIM) process. From 18 experiments, mold temperature was identified as the most influential parameter, while injection rate and melting temperature were insignificant [18]. N.M. Mehat et al. (2017) optimized shrinkage on plastic gear products using seven control parameters with three levels. From 18 experiments, injection pressure, cooling time, and melting temperature were the parameters confirmed as the most influential, while packing time and injection time were not significant [19]. Qazi Muhammad Usman Jan et al. (2020) stated that of nine experiments carried out using four control parameters with three levels, injection pressure had the most significant influence on shrinkage, while injection speed and mold temperature were insignificant [20]. Fatma Hentati et al. (2019) studied the effect of four control parameters with three levels to minimize shear stress. From nine experiments, injection pressure was identified as the most significant parameter, while material and mold temperature had no significant effect [21]. E. Farotti and M. Natalini (2018) reported that mold temperature was the most significant parameter of 25 experiments using four control parameters with two levels to increase the mechanical strength of PP plastic products [22]. S.M. Nasir et al. (2021) observed that packing pressure is the most significant parameter in minimizing sink marks based on experimental results with four control parameters at two levels [23]. Umer Abid et al. (2020) use four control parameters with three levels to minimize sink marks and warpages. Of the nine experiments, melting temperature had the most significant influence, while injection time was insignificant [24]. R. Jaafar et al. (2020) found that from 18 experiments with three control parameters at two levels, melting temperature had the highest influence of up to 86%, while injection pressure was insignificant [25]. D. Mathivanan et al. (2010) identified that from 27 experiments using six control parameters with three levels to minimize sink marks, the most influential factors were rib distance, rib-to-wall ratio, and melting temperature [4]. Padmakar Pachorkar et al. (2023) and Eko Ari Wibowo et al. (2022) concluded that from 27 experiments using five control parameters with three levels, melting temperature was the most significant parameter in minimizing shrinkage and sink marks [26], [27]. V.L. Trinh et al. (2023) reported that of 27 experiments using seven control parameters with three levels to minimize warpage and shrinkage in hot runner system molds, melting temperature was the most influential parameter while filling and cooling times were insignificant [28]. From the various studies above, the Taguchi combination method and statistical analysis are very effective for identifying and optimizing critical process parameters in injection molding. Melting temperature is often the dominant parameter in minimizing defects such as shrinkage, sink marks, and warpage.

Meanwhile, other parameters, such as injection pressure, cooling time, and packing pressure, have varying contributions depending on the material used and the type of research. Optimization of these parameters plays a vital role in improving the quality of the final product and the efficiency of the manufacturing process. Complete optimization results using the Taguchi Method and ANOVA from several authors can be seen in Table 2.

2.2. Response Surface Methodology (RSM)

Response Surface Methodology (RSM) is a mathematical and statistical method used to analyze and optimize the relationship between process parameters (input variables) and responses (output variables). That method helps identify optimal parameter combinations by modeling the response as hyperbolic, linear, or quadratic surfaces.

Table 2. Optimization results using the Taguchi Method from several authors

No	Author	Optimized parameters	Key results
1	Mathivanan et al. (2010) [4]	Melt temperature, Mold temperature	The optimal melt temperature of 240 °C and mold temperature of 60 °C minimized sink depth to 0.91 mm.
2	Ramakrishnan, Mao (2017) [16]	Melt temperature, Mold temperature	The optimal mold temperature of 100 °C minimized volumetric shrinkage to 1.9%.
3	Sreedharan, Jeevanan-tham (2018) [15]	Melt temperature, Injection pressure,	Optimal melt temperature of 240 °C reduced shrink-age by 14%.
4	Shuai Li et al. (2016) [16]	Mold temperature, Melt temperature, Injection rate	Optimized parameters reduced sink mark depth by 46.2%, from 4.87 mm to 2.62 mm.
5	Mehat N et al. (2017)[19]	Melting temperature, Mould tempera-ture, Injection pressure	Injection pressure significantly influenced shrinkage. Mold temperature (37.38%) and melting temperature (22.95%) most impacted tensile strength.
6	Usman Jan QM et al. (2020) [20]	Injection pressure, Mould temperature	For PP: Injection pressure 60 MPa.
7	Fatma Hentati et al. (2019) [21]	Melt temperature, Injection pressure, Mold temperature	Optimal shear stress achieved at melt temp. of 260 °C, injection pressure of 50 bar, and mold temp. of 60 °C.
8	E. Farotti, M. Natalini (2018) [22]	Melt temperature, Mold temperature	Mold temperature significantly improved tensile strength by 15%.
9	S. M. Nasir et al. (2021) [23]	Injection pressure, Mould temperature, Melting temperature	Injection pressure contributed the most (31.89% and 30.69%
10	Umer Abid et al. (2020) [24]	Melt temperature, Mold temperature, Injection pressure	Mold temperature contributed 85.37% and melt tem-perature contributed 52.54% in the warpage and Sink mark part
11	R. Jaafar et al. (2020) [25]	Melt temperature, Mold temperature, Injection pressure	Volumetric shrinkage was minimized to 0.956% using optimal melt and mold temperatures.
12	Padmakar Pachorkar et al. (2022)[26]	Melt temperature, Mold temperature,	Optimal melt temperature and mold temperature re-duced sink mark depth by 11%, and improved cycle time by 9%.
13	Eko Ari Wibowo et al. (2023) [27]	Injection pressure	Injection Pressure 135.4 MPa, Sinkmark Index 0.6933%.
14	V. L. Trinh et al. (2023) [28]	Melt temperature, Injection pressure	Optimal melt temperature reduced warpage by 16.6% and shrinkage by 2.45%. Main factors: Melt tempera-ture (66.67%)

Adel et al. (2024) minimized shrinkage on flat parts using the RSM approach. That research analyzes four process parameters, namely packing pressure, cooling time, packing time, and melting temperature, with a range of parameter values obtained through simulation analysis, as shown in Table 3.

Shrinkage values for melt flow direction and parallel melt flow direction were obtained from simulation analysis of the data generated by DOE. The results were tabulated with the shrinkage values for each run with the specified variable parameters obtained from the DOE. The specified variables parameters conditions were set and simulated in the AMI software. ANOVA was conducted to study the effect of process parameters on shrinkage and determine the significance contribution percentage as shown in Table 4.

Table 3. Recommended values of process parameters and their range

Process parameter	Units	Recommended value	Range of parameters	
			Minimum	Maximum
Packing pressure (A)	(MPa)	49,15	40,09	60,62
Cooling time (B)	(s)	12,68	9,208	17,43
Packing time (C)	(s)	10,92	8,34	14,4
Melt temperature (D)	(° C)	230	220	240

Table 4. Processing parameters contribution percentage on shrinkage

Process parameters	Shrinkage in melt flow direction	Shrinkage in melt flow direction
Packing pressure (A)	90,97%	90.92%
Cooling time (B)	0.10%	0.01%
Packing time (C)	0.04%	0.01%
Melt temperature (D)	1.62%	6.63%

In the research, the mathematical model has been gained by conducting the second-order polynomial regression model. The polynomial regression model, which related to the shrinkage in melt flow direction and parallel melt flow direction with all input parameters, which are packing pressure (A), cooling time (B), packing time (C), and melt temperature(D) was established by Design Expert software and represented in Equation 1. and Equation 2, respectively. Equations 1 and 2 were applied to calculate the prediction shrinkage values of the polynomial models in melt flow direction and parallel melt flow direction. Figures 2 and 3 show the comparison between the simulation result and the predicted result of shrinkage in the melt flow direction, respectively.

$$\text{Shrinkage in melt flow direction} = 1.71024 - 169.36 \times 10^{-4}\, A - 48.52 \times 10^{-4}\, D + 1.1 \times 10^{-4} AD - 1.3 \times 10^{-4} \mathrm{A}^2 \tag{1}$$

$$\text{Shrinkage in parallel melt flow direction} = 1.39834 - 208.07 \times 10^{-4} A - 141.26 \times 10^{-4}\, B + 129.44 \times 10^{-4}\, C - 24.63 \times 10^{-4} BD - 0.53 \times 10^{-4} CD + 0.28 \times 10^{-4} A^2 \tag{2}$$

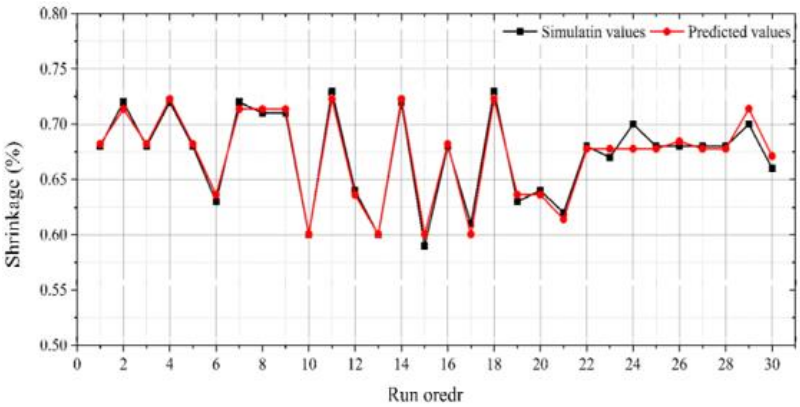

Figure 2. Simulation and predicted shrinkage results in a melt flow direction

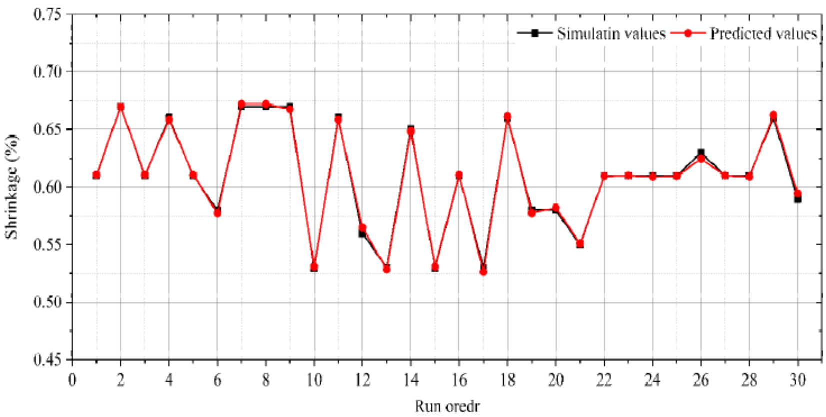

Figure 3. Simulation and predicted shrinkage results in a parallel melt flow direction

It was concluded that packing pressure was the most significant parameter influence in shrinkage for both melt flow direction and parallel melt flow direction, with 90.97% and 90.92 % contribution, respectively [29]. Mohd Amran Md Ali et al. (2020) analyzed the effect of melting temperature, mold temperature, injection time, and number of gates on filling time using RSM. From 27 experiments, it was concluded that the parameter that had the most influence on filling time was injection time, with a contribution reaching 99% [30]. M.U. Rosli et al. (2019) studied the effect of melting temperature, cooling time, and injection pressure on shrinkage and warpage using RSM. From 20 experiments carried out, it was concluded that these three parameters had a significant influence in minimizing shrinkage and warpage defects [31] Ashish Goyal et al. (2020) and their team analyzed the effect of melting temperature, packing pressure, and injection pressure on tensile modulus and product elongation using RSM. From 20 experiments, they concluded that melting temperature and packing pressure significantly influenced elongation, while tensile modulus was mainly influenced by melting temperature [32]. Huei Ruey Ong et al. (2020) and their research group analyzed the effect of mold temperature, melting temperature, and injection pressure on the rejection rate using RSM. From 17 experiments, they concluded that these three parameters had a significant influence in minimizing the rejection rate, with the optimal settings being a mold temperature of 70 °C, melting temperature of 220 °C, and injection pressure of 98 MPa [33]. S.Q. Ch'ng et al. (2018) and their team studied the effect of packing pressure, packing time, cooling time, and melting temperature on warpage using RSM. From 30 experiments, they concluded that these four parameters significantly influenced minimizing warpage up to 14.27% [6]. Sreedharan J. and A.K. Jeevanantham (2018) and their collaborative group analyzed the effect of injection time, holding time, filling time, and mold closing time on cycle time using RSM. From 31 experiments, they found that injection time was the most significant parameter, contributing to 86.46% in minimizing cycle time [34]. Trifenaus Prabu Hidayat et al. (2024) and their team optimized melt temperature, holding pressure, and injection pressure using RSM. From 15 experiments, they concluded that the optimal settings in the form of a melting temperature of 260 °C, holding pressure of 30 Bar, and injection pressure of 62 Bar were able to reduce rejects to almost zero [35].

Table 5. Optimization results using Response Surface Methodology (RSM) from several authors

No	Author	Optimized parameters	Key results
1	S Q Ch'ng et al. (2018) [6]	Melt temperature, mold temperature, injection time	Warpage reduced by optimizing parameters; results validated through ANOVA.
2	Adel et al. (2024) [29]	Melt temperature	Reduced shrinkage from 0.68% to 0.60% (parallel flow direction) and from 0.60% to 0.53% (normal flow direction).
3	Md Ali et al. (2021)[30]	Melt temperature, mold temperature	The optimal mold temperature of 60 °C improved fill time to 4.281 seconds.
4	M.U. Rosli, et al. (2019) [31]	Melt temperature, injection pressure	The optimal melt temperature of 315.98 °C and injection pressure of 62 MPa resulted in a volumetric shrinkage error of 0.27% and a warpage error of 0.19%.
5	Ashish Goyal et al. (2020)[32]	Melt temperature, injection pressure	Elongation is affected by melt temperature (87.04%) and tensile modulus by melt temperature (85.35%).
6	Huei Ruey Ong et al. (2020) [33]	Melt temperature, mould temperature, injection pressure	Optimal settings: Melt temperature 220 °C, Mould temperature 70 °C, Injection pressure 98%. Reduced rejection rate to 0%
8	Trifenaus Prabu Hidayat et al. (2024) [34]	Melting temperature, injection pressure	Optimized settings: Melting temperature 260 °C, Injection pressure 62 bar. Reduced defective products.
9	M. Hikam Muddin , M. Mas'ud (2023) [35]	Melt temperature	Optimized parameters: Melt temperature 285 °C, Short shot defects reduced to -0.0128 with desirability of 1.0.
10	Yenny Sari et al. (2023)[36]	Injection pressure	Optimum settings: Injection pressure 35 bar, Increased sigma level from 3.64 to 3.90
11	Asif, Muhammad (2022) [37]	Injection pressure, melt temperature	Reduced defects (flow marks, air bubbles) and improved efficiency by 50%; rejection rate reduced from 35% to 16%.

M. Hikam Muddin and M. Mas'ud (2023) discovered novel ways to optimize melting temperature, holding pressure, and cooling time using RSM. From 15 experiments, it was concluded that the optimal settings in the form of a melting temperature of 282.5 °C, holding pressure of 70 Bar, and cooling time of 1.8 seconds significantly reduced short shot defects by up to 61.47% [36]. Yenny Sari et al. (2023) also uncovered new insights by optimizing barrel temperature, injection pressure, and injection speed using RSM. From the analysis of product defect data, it was concluded that the optimal settings in the form of a barrel temperature of 180 °C, injection pressure of 35 Bar, and injection speed of 41% resulted in optimal product quality [37]. Asif Muhammad (2022) optimized melt temperature, injection pressure, injection speed, screw speed, flow rate, and viscosity using RSM. From 16 experiments, it was concluded that melting temperature had the greatest influence, namely 20.45%, in reducing defects such as flow marks, air bubbles, black dots, and hard fittings [38].

Each process parameter significantly influences certain types of defects or quality in the injection molding process. Parameters such as packing pressure, melting temperature, and injection time are often the dominant factors in minimizing defects such as shrinkage, sink marks, warpage, and others. Optimization with RSM proved effective in identifying optimal parameter settings, which contributed to increasing production efficiency and product quality. Complete optimization results with RSM from several authors can be seen in Table 5.

2.3. Artificial Neural Networks (ANN)

Artificial Neural Network (ANN) is a computational model inspired by biological neural networks. It is designed to recognize patterns and relationships in data. ANNs consist of layers of interconnected artificial neurons, enabling parallel and adaptive information processing.

Junhan Lee et al. (2023) used the ANN method in their research, with 6 optimized parameters, such as melting temperature, mold temperature, injection speed, packing pressure, packing time, and cooling time, and 3 levels, which were compared as in Table 6.

Table 6. Process conditions and levels for the injection-molding experiment

Conditions	Level 1	Level 2	Level 3
Melt temperature (∘C)	200	220	240
Mold temperature (∘C)	40	50	60
Injection speed (mm/s)	40	70	100
Packing pressure (bar)	150	200	250
Packing time (s)	6.0	12.0	18.0
Cooling time (s)	38	48	58

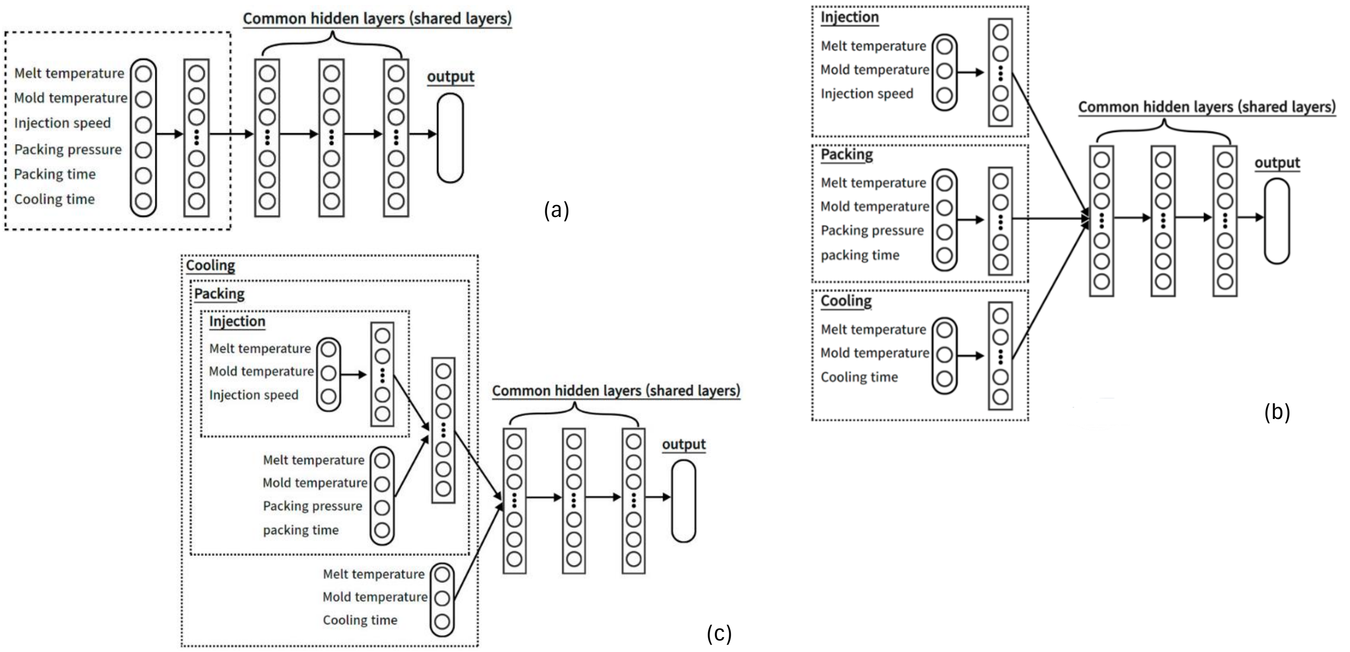

Figure 4. (a) Network #1: structure in which the input parameters are connected into a single layer. (b) Network #2: structure where input parameters are simultaneously applied through layers that are differentiated according to the injection-molding process stages. (c) Network #3: structure where input parameters are differentiated according to the injection- molding process stages and described through continuous sequence layers

The experiment was carried out with 50 conditions, consisting of 27 experiments using the L27 orthogonal array and 23 random experiments. Next, three network models were built to link process parameters with product quality, as shown in Figure 4.

The data processing process shows that Figure 3 provides the most accurate prediction results, with packing time as the most influential parameter [38]. Chihun Lee et al. (2020) used an Artificial Neural Network (ANN) to recommend optimal process parameters based on product geometry in injection molding. Research data was obtained from 3600 simulations (36 molds) and 476 experiments (11 molds). The five process parameters used include filling time, melting temperature, mold temperature, packing pressure, and packing time. In addition, 15 geometric features are used as input, including the number of cavities, number of gates, overall volume, cavity volume, overall surface area, cavity surface area, XY plane projection area, YZ plane projection area, ZX plane projection area, maximum thickness, thickness average, standard thickness deviation, maximum flow length, maximum flow length to thickness ratio, and minimum diameter of the hydraulic gate. The data was processed using the min-max normalization method to equalize the scale between parameters, then divided into three groups: training set (80%), validation set (10%), and test set (10%). The ANN model is designed with hyper-parameter tuning using a random search method to determine the optimal structure, including the number of layers, nodes, learning rate, and dropout rate. In addition, a transfer learning approach is applied, where the model is first trained with simulated data and then continues with experimental data to improve prediction accuracy. The research results show a low average relative error (RE): 0.63% for experimental data and 0.73% for simulated data. It was concluded that geometric features' volume and surface area are the parameters that most influence product weight. At the same time, process parameters such as melting temperature and packing pressure are also significant in influencing final product quality [39]. H. Lee et al. (2018) used ANN to optimally set process parameters based on actual data from machines and molds to reduce production defects such as warpage and shrinkage. Mold temperature data is obtained using a mold sensor, while product defects such as warpage and shrinkage are analyzed via a vision sensor. Controlled parameters include melting temperature, packing pressure, and cooling time. The ANN model was built using the Backpropagation Neural Network (BPNN) approach and trained with actual production data to study the relationship between process parameters and product quality. That system also uses real-time data to adjust process parameters during production, thereby preventing defects and improving product quality. As a result, ANN successfully predicted warpage defects (in mm) and shrinkage (in %) with high accuracy, reducing product defects significantly. That approach allows fast and adaptive decision-making regarding production conditions, making it an innovation compared to conventional optimization methods only applied before production [40]. J. Lee et al. (2022) used ANN to predict the relationship between process parameters and product quality in injection molding, especially for bowl-shaped products. Experimental data was obtained with polypropylene (PP) material over a specific range of process parameters, such as melting temperature, mold temperature, packing time, and cooling time. The data are divided into linear relationships (packing time 6-18 seconds) and non-linear relationships (packing time extended to 39 seconds). An ANN model with a Multi-Input Multi-Output (MIMO) structure is used to map the relationship between process parameters (input) and product quality attributes (mass, diameter, height). Hyper-parameter optimization uses hyper-band techniques, including setting the number of hidden layers, learning rate, and activation function. The data is divided into training, validation, and test sets. To evaluate performance, the ANN model was compared with linear and polynomial regression using Root Mean Square Error (RMSE) values . Research results show that ANN can handle complex (non-linear) relationships better, making it a superior method for injection molding with a wide variation of parameters [41].

Table 7. Optimization results using Artificial Neural Network (ANN) from several authors

No	Author	Optimized parameters	Key results
1	Junhan Lee et al. (2023) [38]	Melt temperature, Mold temperature.	Multi-task learning architecture improved prediction accuracy by two orders of magnitude.
2	Chihun Lee, et al. (2020)[39]	Melt temperature, Mold temperature	Root mean square error (RMSE) was reduced to 0.846 using ANN; weight prediction error was reduced to 0.662%.
3	H Lee et al. (2018) [40]	Melting temperature	Proposed a smart injection molding framework; real-time data reduced defects and improved system reliability.
4	J. Lee et al. (2022) [41]	Melt temperature, Mold temperature	ANN prediction accuracy surpassed linear and polynomial regression for both linear and nonlinear datasets.

Artificial Neural Network (ANN) has proven to be an effective method for optimizing injection molding processes. Its accurate prediction capabilities, adaptability to real-time production conditions, and proficiency in handling complex data relationships make it a valuable asset. By leveraging ANN, product quality can be improved, production defects minimized, and overall injection molding process efficiency achieved. The comprehensive optimization results using the ANN method from various authors are detailed in Table 7.

2.4. Finite Element Method (FEM)

Finite Element Method (FEM) is a highly precise numerical method used to solve engineering and physics problems, especially those involving partial differential equations (PDE). That method works by dividing the problem domain into small elements (finite elements) so that calculations are carried out on these elements to produce an accurate solution.

L. Chen et al. (2022) conducted research utilizing a three-dimensional transient finite element method (FEM) to simulate the cooling process in injection molding molds. The research primarily aimed at optimizing the mold cooling system to reduce cycle times and enhance product quality by minimizing defects such as warpages and sink marks. The researchers conducted experimental validation by comparing simulation results to real injection molding trials at initial melt temperatures of 320 °C, 305 °C, and 290 °C. The results demonstrated high accuracy, with a maximum error of less than 4% and an average error below 1%, affirming the reliability of the simulation method, as shown in Table 8.

Table 8. Simulation accuracy for initial melt temperatures 320, 305, and 290 degrees.

Initial melt temperature (°C)	Maximum error (%)	Average error (%)
320	3.79	0.95
305	3.64	0.91
290	3.22	0.84

The simulation employed realistic boundary conditions, including mold-polymer (2500 W/m^2K), mold-mold (30,000 W/m^2K), mold-air (10 W/m^2K), and mold-coolant (calculated using Reynolds and Prandtl numbers). Figures 5 and 6 illustrate the measurement points and the temperature differences at these interfaces during the injection cycle, showing the influence of different heat transfer coefficients on temperature distribution.

The mold geometry, initially comprising 142 components, was simplified into 12 key components for efficient meshing and analysis, using a three-dimensional tetrahedral mesh as shown in Figure 7.

Material properties considered included the plastic material (SABIC Polycarbonate OQ2720) with a specific heat of 1880 J/kg·K and thermal conductivity ranging from 0.22–0.27 W/m·K, and the mold material characterized by a specific heat of 460 J/kg·K, thermal conductivity of 29 W/m·K, and density of 7800 kg/m^3. Several assumptions were applied in this simulation, including neglecting the filling stage due to its significantly shorter duration compared to the cooling phase, thus ignoring convective heat transfer during filling. Imperfect thermal contact was also assumed at mold-mold interfaces, considering potential gaps or insulation effects. Moreover, the transient (unsteady-state) analysis method was employed instead of a steady-state analysis to accurately capture dynamic temperature variations throughout injection cycles. The transient FEM simulation provided superior accuracy compared to traditional steady-state methods, particularly for complex geometries and dynamic temperature conditions. This approach effectively improved mold cooling efficiency, product quality, and reduced production cycle times [42]. R. Achmaed Pratama et al. (2021) used FEM to analyze the effect of coolant temperature and injection time on product quality. The research was carried out with three variations of coolant temperature (18 °C, 22 °C, and 24 °C) and three variations of injection time (1.4 seconds, 1.6 seconds, and 1.8 seconds). Mesh was made in the cavity, and thermal conditions were analyzed using ANSYS software, while product quality was analyzed using Autodesk Moldflow Adviser R2 2017. It was concluded that coolant temperature had the most significant influence in reducing shrinkage and bubbles, while injection times that were not optimal could cause defects such as short shots. The combination of a cooling temperature of 24 °C and an injection time of 1.4 seconds produces the best product quality, with a quality level of 79.5% and a product weight of 0.415 grams [43]. Florian Zwicke et al. (2017) used FEM to predict shrinkage and warpage in the injection molding process and developed a cavity mold shape optimization method. The material is treated as viscoelastic in the liquid phase and elastic during solidification. The simulation uses the laws of non-linear elasticity and thermodynamics to describe changes in temperature and density during solidification to create a mold design that automatically produces a suitable final product after cooling. The simulation is carried out in two stages: calculating material changes during cooling and analyzing the final condition of the product. The results show that uneven temperature distribution during cooling causes significant shrinkage and warpage. The final product shows shape deviations due to different temperature distributions in other mold parts. The use of FEM allows automatic optimization of mold cavity shapes, improving shrinkage and warpage predictions [44].

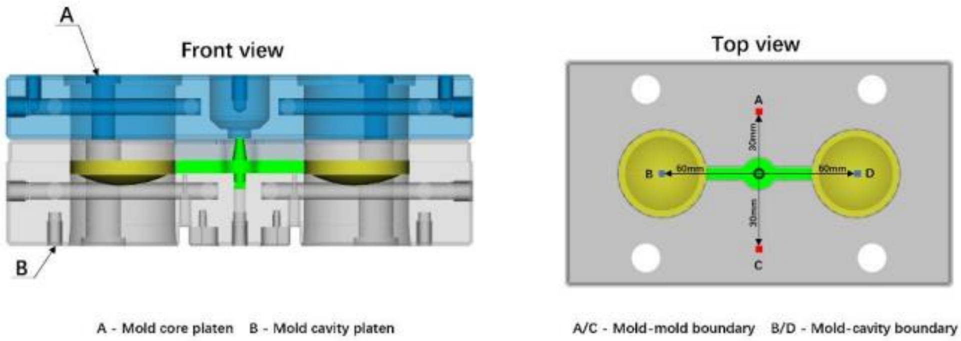

Figure 5. Mold-mold/mold-polymer temperature difference check points

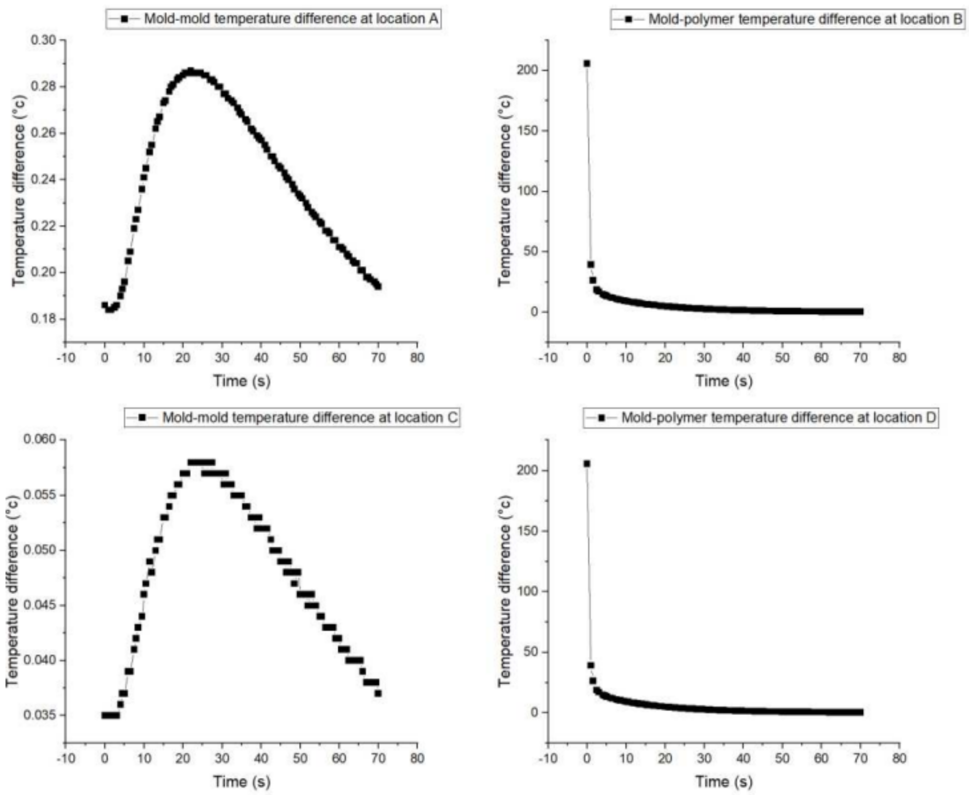

Figure 6. Mold-mold/mold-polymer temperature difference plot

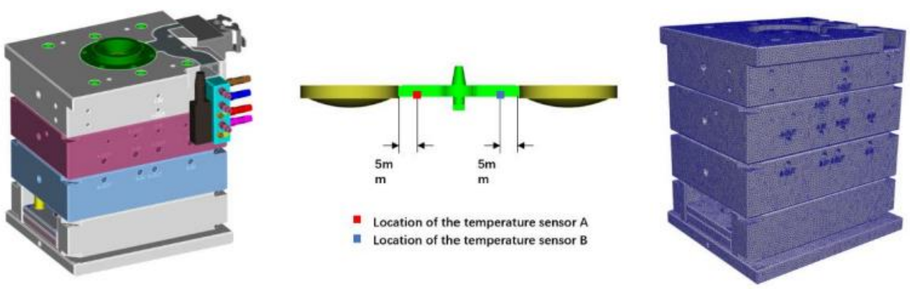

Figure 7. The model of the validation mold

X. Sun et al. (2019) developed a procedure to predict sink marks on thermoplastic products using FEM via Abaqus software, with pressure and temperature data from Moldflow as input. Two subroutines, UEXPAN (for thermal expansion) and UMAT (for constitutive relations) are implemented in Abaqus to improve the accuracy of the simulation. The simulation results were compared with experimental data using a Coordinate Measuring Machine (CMM) to measure the depth of sink marks. The simulation predicts a sink mark depth of 0.07 mm, lower than the experimental result of 0.22 mm, but still shows a significant increase in accuracy compared to Moldflow. Abaqus can also predict sink marks in areas with complex geometric designs, such as bosses and ribs. That procedure increased the accuracy of predicting sink marks in injection molding [45]. Hani Mizhir Magid et al. (2021) used FEM to analyze the main factors influencing mass production in the injection molding process. The research focuses on the distribution of pressure, temperature, and stress within the mold to improve product quality and process efficiency. The mold model with 20 cavities was designed using CATIA V5R20 software, with PVC as the polymer material. Simulations were performed using ABAQUS/CAE to predict the mechanical and thermal behavior of the mold during the filling, holding, and product release processes. The mesh uses medial axis elements in the cavity and ejector areas to model pressure and temperature distribution well. The simulation results show uneven pressure distribution in several cavities, especially those far from the injection center. Adjustment of runner and gate dimensions is recommended to reduce thermal stress. That research highlights the importance of balanced mold design, including optimization of runners, gates, and cooling systems to improve product efficiency and quality [46]. Bikram Singh Solanki et al. (2022) used FEM to evaluate the effect of injection molding process parameters on shrinkage and sink marks on gears made from polypropylene (PP). That research uses three control parameters, which vary at five levels. The mesh is created on the gear, with the number of elements reaching 162,415. It was concluded that packing pressure and packing time were the most significant parameters in reducing shrinkage and sink marks on gear. Melting temperature also affects shrinkage, but its contribution is lower [47].

Research shows that the Finite Element Method (FEM) is an efficient approach to analyzing and optimizing various aspects of the injection molding process, including temperature distribution, pressure, mold cavity design, and other process parameters. That method has been proven to increase the accuracy of predictions of defects such as shrinkage, sink marks, and warpage, which are significant challenges in production. With the application of FEM, not only the quality of the final product can be improved, but also production efficiency, making it an essential tool in the modern manufacturing industry. Complete optimization results using the FEM method from several authors can be seen in Table 9.

Table 9. Optimization results using Finite Element Method (FEM) from several authors

No	Author	Optimized parameters	Key results
1	L. Chen et al. (2022)[42]	Mold temperature	Reduced cycle time by 15%; maximum temperature error <4%.
2	R. Achmaed Pratama, et al. (2021)[43]	Mold temperature	Best product quality at 24 °C mold temperature and 1.4 s injection time with 79% quality prediction.
3	Zwicke F et al. (2017)[44]	Mold temperature	Automated cavity shape optimization reduced warpage by 12%.
4	X Sun et al. (2019) [45]	Melt temperature, Mold temperature	Sink mark depth was reduced by 33% using optimized conditions.
5	Hani Mizhir Magid et al. (2021)[46]	Mold temperature	Optimal mold temperature: 55-65 °C, Reduced stress and improved product quality.
6	Bikram Singh Solanki et al. (2022)[47]	Melt temperature	Minimum diametric shrinkage of 0.562% in numerical analysis; sink marks reduced by optimizing parameters.

2.5. Combined Method

The combined method is an approach to optimizing process parameters by combining two methods: Taguchi and Artificial Neural Network (ANN). Abdul R. et al. (2020) analyzed the prediction and optimization of shrinkage in products made from High-Density Polyethylene (HDPE) produced through injection molding using a combination of the Taguchi and ANN methods. That research tested three main parameters, namely injection speed, holding time, and cooling time, which were varied in three levels. Taguchi's experimental data was used to train, test, and validate the ANN model using MATLAB. The ANN model was trained using the backpropagation method, and its performance was evaluated using the Root Mean Square Error (RMSE) value. The ANN prediction results are compared with experimental results to ensure model accuracy. Compared to initial conditions (baseline), length shrinkage was reduced by 5.06%, and width shrinkage was decreased by 20.4% [48]. Mehdi Moayyedian et al. (2021) analyzed the optimization of the injection molding process for thin-walled products made from polypropylene (PP) using a combination of Taguchi and ANN methods. That research tested five main parameters, namely gate design, filling time, cooling time, pressure holding time, and melting temperature, which varied in three levels. Simulations were carried out on circular products (diameter 100 mm, thickness 1 mm) to measure defects such as short shots, shrinkage, and warpage. The ANN model uses a backpropagation algorithm to predict the relationship between process parameters and defects. The ANN was trained with Taguchi's experimental data and used for further optimization. Based on the ANN results, the best combination of parameters is: Filling time: 1 second, Cooling time: 3 seconds, pressure holding time: 3 seconds, Melting temperature: 230 °C. That combination produces the lowest defect values for short shot, shrinkage, and warpage [49]. Kefan Yang et al. (2022) analyzed the optimization of injection molding process parameters for polypropylene (PP) car door panels using a combined Taguchi and ANN method. The five main parameters tested were mold temperature, melt temperature, cooling time, holding pressure, and holding time, which varied in four levels. Simulations are carried out for each parameter combination to calculate shrinkage and warpage. A three-layer ANN model was developed to map the relationship between process parameters (input) and shrinkage/warpage (output). The model is trained using experimental data and verified to ensure prediction accuracy. The optimal parameter combination is: Mold temperature: 76 °C, Melting temperature: 205 °C, Cooling time: 23.8 seconds, Holding pressure: 54.7 MPa, Holding time: 22.1 seconds, which results in a shrinkage of 13.32 % and warpage of 4.315 mm [50]. Mohamed ELGhadoui et al. (2023) developed a hybrid optimization approach for plastic injection molding using a combined Taguchi and ANN method. That research tested seven process parameters, namely melting temperature, injection speed, injection pressure, cooling time, holding time, holding pressure, and displacement position, which were varied in three levels. Data from experiments are trained on an ANN model to map the relationship between process parameters and product quality, such as weight, cycle time, dimensional deviation, and energy consumption. As a result, the ANN approach can Reduce raw material consumption by up to 2%, Reduce cycle time by up to 12%, and Reduce energy consumption by up to 16% while maintaining product quality according to customer standards [51].

The combined Taguchi and Artificial Neural Network (ANN) method has proven effective for optimizing injection molding. By combining the Taguchi method's systematic experimental approach with the ANN's predictive capabilities, the research succeeded in improving product quality, reducing defects, and significantly increasing process efficiency. The results show that that approach provides better results than traditional methods, making it a handy tool for the modern manufacturing industry. Complete optimization results using a combined method from several authors can be seen in Table 10.

Table 10. Optimization results using Combined Method from several authors

No	Author	Optimized parameters	Key results
1	Abdul R. et al. (2020) [48]	Injection speed, holding time, cooling time	Achieved minimum shrinkage of 1.25% in the flow direction and 1.37% in the cross-flow direction.
2	Mehdi Moayyedian et al. (2019) [49]	Melt temperature	Optimal conditions: melt temperature 230 °c. improved product quality with a margin of error of 1.5%.
3	Kefan Yang et al. (2022) [50]	Mold temperature, melt temperature	Volume shrinkage: 13.32%, warpage deformation: 4.315 mm. Optimized mold temperature: 76 °C.
4	Mohamed ELGhadoui et al. (2023) [51]	Melt temperature, injection pressure	Reduced raw material consumption by 2%, cycle time by 12%, and energy consumption by 16%.

3. Conclusions

Optimizing parameters in the plastic injection process is crucial to improve product quality and reduce defects, such as shrinkage, warpage, and sink marks. This study highlights the effectiveness of modern approaches, such as Taguchi, Response Surface Methodology (RSM), Artificial Neural

Networks (ANN), and Finite Element Method (FEM), in minimizing defects by controlling key parameters, such as melt temperature, injection pressure, cooling time, and injection speed. These approaches improve product quality and support process efficiency and resource savings. In particular, the combination of Taguchi and ANN methods shows excellent potential in dealing with complex non-linear relationships between process parameters. This provides a more accurate and adaptive solution than conventional methods, making it a highly relevant tool for modern industries prioritizing precision and efficiency. Beyond the technical benefits, the use of digital simulation methods and mathematical modeling also significantly contributes to industrial sustainability. By supporting energy savings, raw material reduction, and minimizing environmental footprint, this approach is relevant for automotive, electronics, medical, and other manufacturing sectors that prioritize sustainability. Future research must integrate advanced technologies, such as machine learning, big data analytics, and the Internet of Things (IoT), to encourage automation and intelligence in optimization. In addition, exploring the use of recycled materials and developing more environmentally friendly production methods can strengthen the plastic manufacturing industry's contribution to global sustainability. By combining experimental approaches, digital simulation, and technological innovation, plastic injection processes can be continuously improved, creating high-quality products that meet market demands while significantly reducing environmental impact.

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