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Optimization of Filling Time and Volumetric Shrinkage Rate in Simulation of Plastic Product Injection Molding Process Using RSM and NSGA-II

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Abstract

Filling time (T_d) and volumetric shrinkage rate (Vs) are critical indicators in plastic injection molding. However, these two indicators often conflict, making it essential to optimize both simultaneously. This study aimed to optimize the td and Vs in simulating a plastic electrical socket product injection molding process. Four process parameters were investigated: melt temperature (T_{nc}), mold temperature (T_k), injection pressure (A_p), and pressure holding time (T_a). The Box-Behnken design method was used to determine the number of simulation samples, and the Response Surface Methodology (RSM) was employed to develop predictive models for t_d and V_s. The Non-dominated Sorting Genetic Algorithm (NSGA-II) technique was then applied for multi-objective optimization. The results showed that the RSM-based regression models for T_d and V_s had high coefficients of determination (R^2) of 0.946 and 0.990, respectively, indicating the significance of the developed models. The NSGA-II optimization generated 21 Pareto solutions, with T_{nc} ranging from 215.0 to 215.4 °C, T_k from 50 to 60 °C, A_p from 67.09 to 76.53 MPa, and t_a from 2.097 to 2.5 s. These parameter values corresponded to t_d values from 1.260 to 1.389 s and V_s values from 4.810 to 5.497%. To verify the accuracy of the optimization method, the solutions with the smallest t_d and V_s values were selected for re-simulation, and the results showed a difference of less than 2.03% between the predicted and re-simulated values. These results confirmed the effectiveness of the proposed approach in solving the multi-objective optimization problem for the plastic injection molding process, thereby enhancing both the efficiency and quality of the products.

Keywords: Optimization; filling time; volumetric shrinkage rate; injection molding process; Response surface methodology; NSGA-II.

1. Introduction

The demand for plastic products has witnessed a significant surge across diverse industries owing to their versatility, durability, and cost-effectiveness. Injection molding, a manufacturing process involving the injection of molten plastic into a mold, is a highly productive method widely adopted in industry[1, 2]. Chen and Turng [3]highlighted the versatility of injection molding in producing plastic products at higher rates compared to alternative methods such as compression molding, extrusion, and blow molding. However, the complexity of the injection molding process often results in undesirable defects. Amran et al. [4] underscored the challenges associated with producing complex plastic products with precise dimensions, attributing these challenges to the need for both advanced technology and precise control of process parameters. Suboptimal parameter settings can lead to defects like shrinkage, warping, and cracking, compromising product quality. Chen et al. [5] delved into the specific challenges of processing PET, emphasizing the difficulty in establishing optimal process parameters due to the unique characteristics and varying responses of different plastics to injection molding conditions. Several other studies have also been published regarding the problem of defects [6-9].

Traditionally, the optimization of injection molding parameters has been a time-consuming and costly endeavor [10, 11]. However, advanced computational tools and simulation software, including NX, Moldex3D, Moldflow, and others, have revolutionized this process [12, 13]. Computer-aided engineering (CAE) enables engineers to simulate and predict potential defects, facilitating fine-tuning process parameters for optimal product quality. However, applying these simulation tools is also complex, as obtaining optimal results requires carefully selecting and setting up various factors, including filling time, pressure, temperature, material properties, and specific product requirements.

Recent studies have explored the application of multi-objective optimization techniques to address engineering goals, such as Grey Relational Analysis (GRA)[14], Artificial Neural Network (ANN) [15, 16], Genetic

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Algorithm (GA)[17], Simulated Annealing (SA) [18], Adaptive Neuro-Fuzzy Inference System (ANFIS) [19, 20], Response Surface Methodology (RSM) [21-23] , and others. In the field of plastic injection molding, many studies have also applied multi-objective optimization techniques to achieve goals such as minimizing cycle time and maximizing product quality[10]. Zhou et al. [24] developed a Differential Sensitivity Fusion Method (DSFM) to perform the multi-objective optimization of process parameters in plastic injection molding. Their results showed that the DSFM-based metamodeling approach had better prediction accuracy and performance compared to some classical methods, such as response surface models and Kriging models. Cao et al. [25] conducted an experimental study to develop a regression model for warpage and volume shrinkage using the Random Forest (RF) algorithm. After establishing the RF regression model, a genetic algorithm was used to search for the optimal process parameter settings that would minimize the regression model's output. Another study investigated the optimization of injection molding parameters to minimize weld line width and sink mark depth in commercial-grade transparent Polymethyl Methacrylate (PMMA) components. The study employed a Taguchi-based Weighted Aggregated Sum Product Assessment (WASPAS) method, an Ant Lion optimization algorithm, and analysis of variance to optimize eight critical injection molding parameters [26]. In addition, many other optimization methods have also been applied recently in this field [13, 27-30].

Evolutionary algorithms, particularly genetic algorithms (GAs) and their variants such as NSGA-II, have emerged as powerful tools for addressing multi-objective optimization challenges in manufacturing processes. The NSGA-II has been extensively applied to find the Pareto-optimal solutions for injection molding processes [31-34]. This method approach evolves a population of candidate solutions by applying genetic operators like selection, crossover, and mutation. By evaluating and comparing the fitness of these candidate solutions based on the conflicting objectives, the evolutionary algorithm can efficiently explore the solution space and identify a diverse set of trade-off solutions[35]. Zhai et al. [36] combined an optimization algorithm with inverse-deformation design to enhance the injection quality of box-shaped parts using six different optimization algorithms. They concluded that the combination of the BP neural network, Box-Behnken design, and NSGA-II method yielded the best prediction results.

In the injection molding process, many performance indicators are significantly affected by the molding parameters that directly influence the productivity and quality of the product. Among these, filling time is a crucial indicator of the efficiency and effectiveness of the injection molding process [37, 38]. It is also typically considered an input parameter that can be controlled. Therefore, analyzing filling time as an output can provide a better evaluation of how various input parameters affect the system's overall performance. On the other hand, excessive volumetric shrinkage can result in deformation and residual stresses within the molded component [10, 39]. This indicator is closely related to the molded part's final dimensional stability and quality. Understanding shrinkage helps predict potential defects and ensures required tolerances. As a result, it is essential to optimize both filling time and volumetric shrinkage simultaneously. Reducing filling time can enhance productivity while minimizing volumetric shrinkage, improving dimensional accuracy, and decreasing defects. However, these two objectives often conflict, as strategies to reduce filling time may inadvertently increase volumetric shrinkage and vice versa.

Despite the numerous studies on the multi-objective optimization of injection molding processes, significant limitations remain in optimizing conflicting objectives and applying advanced algorithms to specific products. Therefore, this research focuses on optimizing the injection molding process for electrical socket production by identifying optimal process parameters to minimize filling time and volumetric shrinkage. A simulation-based approach is employed, utilizing the Box-Behnken design to generate experimental data. RSM is then applied to develop predictive models for the target metrics. Subsequently, the NSGA-II is implemented to determine Pareto-optimal solutions, balancing the trade-off between filling time and volumetric shrinkage. The results of this study contribute to the advancement of injection molding processes by providing insights into parameter optimization and enhancing quality and efficiency in electrical socket production.

2. Materials and Methods

2.1. 3D model of electrical socket

Based on the standard dimensions of a real product, a three-dimensional model of the electrical socket is created using SolidWorks software, as shown in Figure 3. The material for the model is set to ABS (Acrylonitrile Butadiene Styrene) from the SolidWorks material library. The volume of the 3D model is calculated to be 19.33 cm^3, and the weight of the preform is estimated by the software to be 19.72 g. This detailed 3D model developed in SolidWorks provides an accurate representation of the actual product dimensions and material properties, which can be used for further analysis and simulations. The use of standard product dimensions and commercially available modeling software ensures that the digital model closely matches the physical characteristics of the real-world electrical socket component.

ABS plastic material was selected in this study due to its superior properties, including high impact strength, good heat resistance, and excellent processability. Specifically, ABS is well-suited for applications requiring high mechanical strength and a good surface finish. The detailed technical specifications of the ABS resin used in this study are presented in Table 1, which includes melt temperature, thermal Conductivity, and other relevant processing parameters.

2.2. Methods

This research investigates the optimization of filling time (t_d) and volumetric shrinkage rate (V_s) during the injection molding of plastic products. A Box-Behnken design was employed to establish experimental conditions for four process parameters: melt temperature (T_{nc}), mold temperature (T_k), injection pressure (A_p), and pressure holding time (t_a). RSM method was subsequently applied to develop predictive models for filling time and volumetric shrinkage. The NSGA-II was then utilized to identify optimal parameter combinations that minimize both objectives simultaneously. The research methodology is visually represented in Figure 2.

Table 1. Primary properties of ABS plastic material

N. o	Properties	Unit	Value
1	Max melt temperature	ºC	280
2	Min melt temperature	ºC	200
3	Specific heat capacity	J/(Kg-K)	2700
4	Young Modulus	MPa	2250
5	Thermal Conductivity	W/(m-K)	0.18
6	Max shear stress	MPa	0.3
7	Poisson's Ratio		0.39

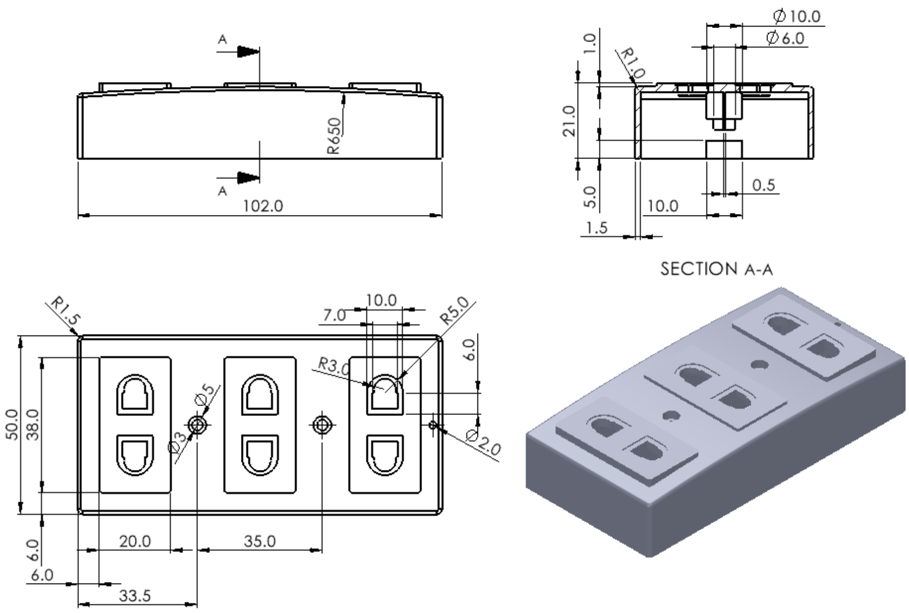

Figure 1. 3D model of electrical socket

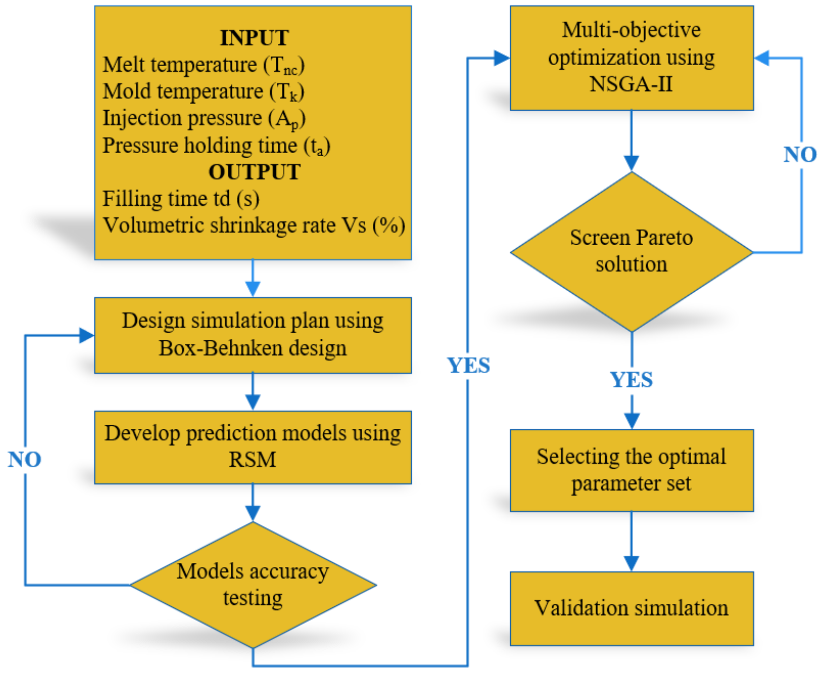

Figure 2. Flowchart of the study methodology

2.2.1. Process Parameter Selection

This research employs the Box-Behnken design method to determine the number of simulation samples. Three levels for each parameter were selected based on material properties and previous related studies (Table 2). Filling time t_d (s) and volumetric shrinkage rate V_s (%) were chosen as the output parameters of interest. This research employs the Box-Behnken design method to determine the number of simulation samples. Three levels for each parameter were selected based on material properties and previous related studies (see Table 2). Specifically, for ABS material, the recommended melt temperature ranges from 200 to 280 °C, and the mold temperature ranges from 25 to 80 °C. The injection pressure and pressure-holding time were selected based on various research studies and actual production practices at the factory [40, 41]. Other parameters were set as constants to isolate the effects of the varying parameters on the outcomes. This approach simplifies the analysis and focuses on the specific interactions being investigated.

Flow analysis was conducted using the SolidWorks Plastics module of SolidWorks software. Besides the parameters under investigation, other settings were kept constant as shown in Table 3. A thin-walled mesh method was employed, resulting in a total of 21,347 nodes and 42,786 elements.

Table 2. Coded and Actual Values of Processing Parameters

N.o	Processing parameter	Unit	Low	Center	High
			-1	0	+1
1	Melt temperature (T_{nc})	ºC	215	220	225
2	Mold temperature (T_k)	ºC	50	55	60
3	Injection pressure (A_p)	MPa	60	70	80
4	Pressure holding time (t_a)	s	1.5	2.0	2.5

Table 3. Some main setting parameters

N.o	Parameter setting	Value
1	Cooling time	10 s
2	Ambient temperature	30 ºC
3	Filling time	Auto
4	Flow/pack switch point in filled volume	99%
5	Nozzle diameter	2 mm
6	Sprue diameter, runner diameter, and branch diameter	6mm

2.2.2. RSM model

This study employs the statistical design method of RSM to investigate the interactions between injection molding process parameters and output responses. This method allows for the construction of a mathematical model describing the relationship between process parameters and output responses, thereby identifying the optimal point of the injection molding process. The full mathematical model is described in Equation (1)

$$Y=\alpha_0+\sum_{i=1}^{k}\alpha_i X_i+\sum_{i=1}^{k}\alpha_{ii}X_i^2+\sum_{ij}^{k}\alpha_{ij}X_iX_j+\varepsilon \qquad (1)$$

In which:

Y - Objective function corresponding to t_d and V_s;

X_i, X_j - Injection molding process parameters affecting the corresponding objective function;

α_i - First-order regression coefficient, describing the influence of factors X_i on the Y;

α_{ij}- First-order regression coefficient, describing the simultaneous influence of 2 factors X_i and X_j;

α_{ii}- Second-order regression coefficient, describing the second-order influence of factor X_i on the objective function Y;

α_0- Free coefficient in the model;

ε - Statistical error related to the mean value.

2.2.3. NSGA- II method

This study combines the NSGA-II algorithm with the RSM approach to optimize machining quality with respect to the input parameters. The NSGA-II algorithm differs from the simple genetic algorithm in applying a ranking step before performing the selection operator. This ranking process is based on Pareto dominance between individuals, allowing the algorithm to identify and prioritize individuals with better characteristics [42-44]. Based on non-dominated sorting, NSGA-II ensures that the individuals with the best fitness values across multiple objectives have a higher probability of progressing to the next generation. This hierarchical approach organizes the individuals into different fronts based on their dominance relationships, with individuals in the higher fronts being given higher priority for selection. Additionally, NSGA-II employs an elitist strategy, which involves merging the parent and offspring populations. This allows for cooperative competition between individuals from different populations, leading to the creation of a more effective next generation. This cooperation helps to prevent the loss of valuable solutions and promotes the exploration of diverse regions in the search space.

3. Results and Discussion

3.1. Simulation analysis results

The simulated results for 27 different conditions and their corresponding t_d and V_s are presented in Table 4. Figure 3 specifically illustrates the analysis results for model 01 (T_{nc} = 220ºC; T_k = 55ºC; A_p= 70 MPa and t_a = 2s). The simulation analysis results show that the mold is filled after 1.305 s, with a volume shrinkage of 5.679%.

3.2. RSM model

Predictive mathematical models for t_d and V_s parameters were developed using RSM, as presented in Equations 2 and 3. The accuracy of the models was assessed using the coefficient of determination (R^2), a measure of the goodness of fit between the predicted and observed values. The regression analysis revealed that the predictive equations for t_d and V_s had R^2 values of 0.946 and 0.990, respectively, indicating a high degree of accuracy and the ability to accurately describe the relationship between input and output parameters. These findings align with previous studies that emphasize the importance of accurate modeling in optimizing injection molding processes using RSM [45, 46].

Figure 4 illustrates the good agreement between the predicted and observed values of t_d and V_s, with the residuals being nearly collinear, further confirming the efficacy of the developed models. The relationship between simulated and predicted results for t_d and V_s is depicted in Figure 5.

Table 4. Process parameters and corresponding t_d and V_s results

N. o	T_{nc} (°C)	T_k (°C)	A_p (Mpa)	t_a (s)	t_d (s)	V_s (%)
1	220	55	70	2	1.305	5.679
2	225	55	70	1.5	1.292	6.066
3	225	60	70	2	1.267	6.028
4	215	55	60	2	1.509	5.612
5	225	55	70	2.5	1.292	5.811
6	220	60	80	2	1.273	5.792
7	220	55	80	1.5	1.305	5.756
8	215	55	80	2	1.290	5.360
9	215	60	70	2	1.285	5.548
10	220	60	70	1.5	1.273	5.843
11	220	50	70	1.5	1.322	5.659
12	220	55	80	2.5	1.300	5.548
13	220	60	60	2	1.302	5.954
14	215	55	70	1.5	1.312	5.501
15	220	55	70	2	1.300	5.686
16	225	50	70	2	1.300	5.893
17	215	55	70	2.5	1.312	5.095
18	220	55	60	1.5	1.390	5.988
19	225	55	60	2	1.312	6.065
20	220	60	70	2.5	1.273	5.650
21	225	55	80	2	1.293	5.989
22	220	50	60	2	1.458	5.551
23	220	55	60	2.5	1.400	5.413
24	220	50	80	2	1.314	5.543
25	215	50	70	2	1.352	5.195
26	220	50	70	2.5	1.322	5.194
27	220	55	70	2	1.305	5.679

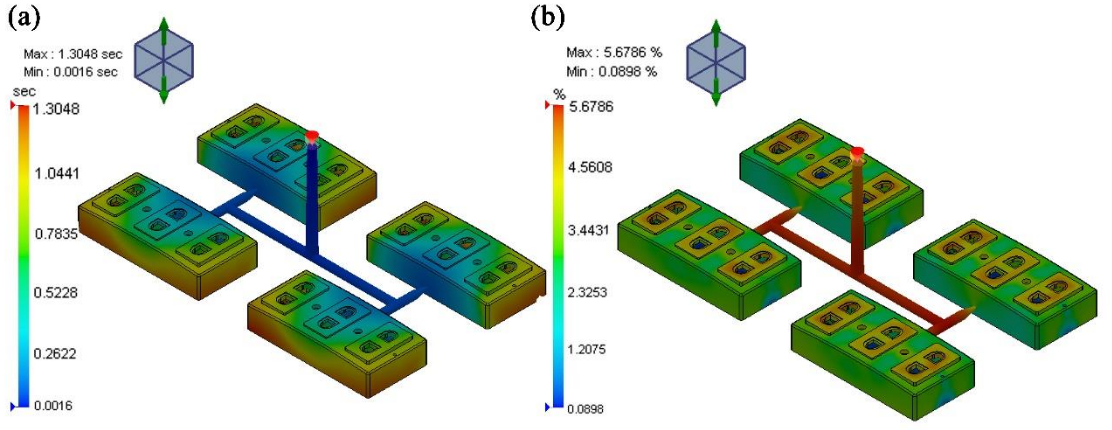

Figure 3. Filling time (a) and volumetric shrinkage rate (b) of model 01

$$t_d = 6.74957 + 0.04656\times T_{nc} - 0.11207 \times T_k - 0.193695 \times A_p - 0.0107 \times t_a + 0.000351 \times T_{nc} \times T_k + 0.0004975 \times T_{nc} \times A_p + 0.0005775 \times T_k \times A_p - 0.00069 \times A_p \times t_a - 0.0002365 \times T_{nc}^2 - 0.0001105 \times T_k^2 + 0.000355125 \times A_p^2 + 0.01495 \times t_a^2 \quad (2)$$

$$V_s = 7.96045 + -0.10321 \times T_{nc} + 0.63409 \times T_k - 0.279765 \times A_p - 5.35497 \times t_a - 0.002187 \times T_{nc} \times T_k + 0.000879 \times T_{nc} \times A_p + 0.01512 \times T_{nc} \times t_a - 0.000768 \times T_k \times A_p + 0.0272 \times T_k \times t_a + 0.018345 \times A_p \times t_a + 0.0004335 \times T_{nc}^2 - 0.0011265 \times T_k^2 + 0.000621125 \times A_p^2 - 0.27555 \times t_a^2 \quad (3)$$

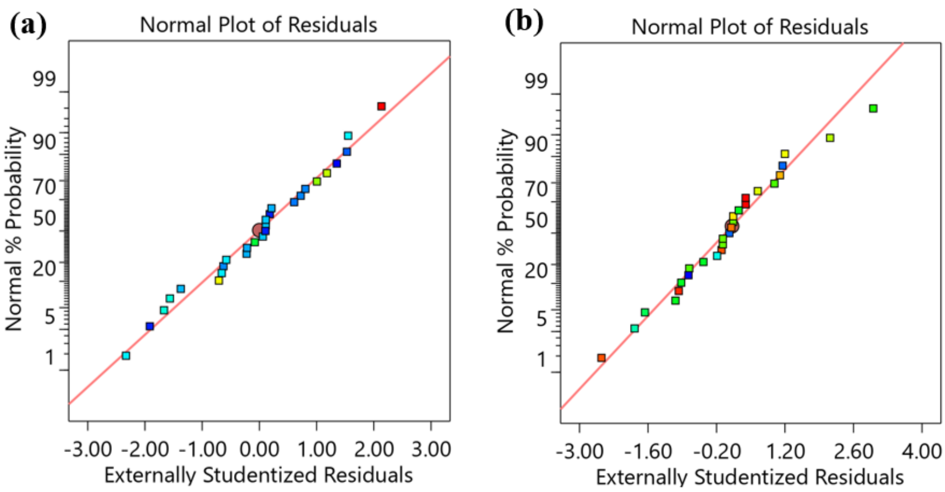

Figure 4. Normal Plot of Residuals for t_d (a) and V_s (b)

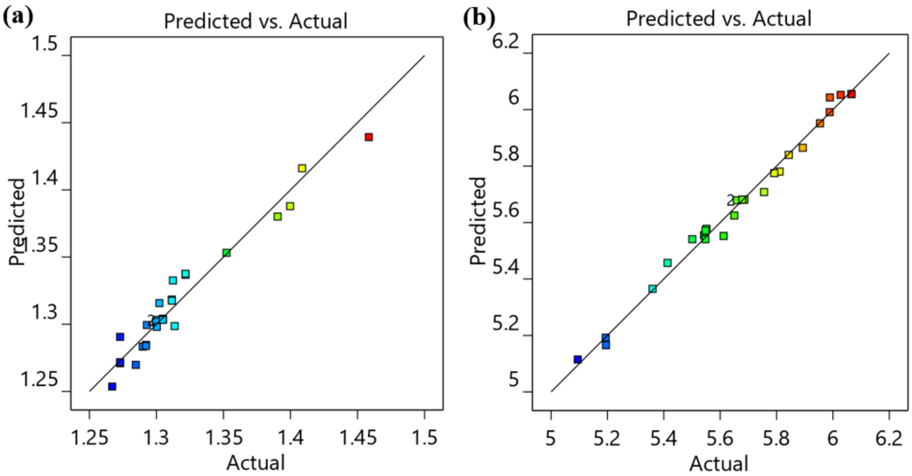

Figure 5. Comparison between simulation and prediction results for t_d (a) and V_s (b)

Table 5. ANOVA analysis results of t_d

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Model	14	0.052	94.59%	0.052	0.004	15.00	0.000
Linear	4	0.037	66.72%	0.037	0.009	37.03	0.000
T_{nc}	1	0.003	6.14%	0.003	0.003	13.63	0.003
T_k	1	0.013	23.41%	0.013	0.013	51.98	0.000
A_p	1	0.021	37.17%	0.021	0.021	82.50	0.000
t_a	1	0.000	0.00%	0.000	0.000	0.01	0.932
Square	4	0.009	16.76%	0.009	0.002	9.30	0.001
$T_{nc}*T_{nc}$	1	0.001	2.10%	0.000	0.000	0.75	0.405
T_k*T_k	1	0.001	1.82%	0.000	0.000	0.16	0.694
A_p*A_p	1	0.007	12.70%	0.007	0.007	26.91	0.000
t_a*t_a	1	0.000	0.13%	0.000	0.000	0.30	0.595
2-Way Interaction	6	0.006	11.11%	0.006	0.001	4.11	0.018
$T_{nc}*T_k$	1	0.000	0.56%	0.000	0.000	1.23	0.289
$T_{nc}*A_p$	1	0.002	4.46%	0.002	0.002	9.90	0.008
$T_{nc}*t_a$	1	0.000	0.00%	0.000	0.000	0.00	1.000
T_k*A_p	1	0.003	6.01%	0.003	0.003	13.35	0.003
T_k*t_a	1	0.000	0.00%	0.000	0.000	0.00	1.000
A_p*t_a	1	0.000	0.09%	0.000	0.000	0.19	0.670
Error	12	0.003	5.41%	0.003	0.000		
Lack-of-Fit	10	0.003	5.38%	0.003	0.000	44.23	0.022
Pure Error	2	0.000	0.02%	0.000	0.000		
Total	26	0.055	100.00%				

ANOVA was performed to verify the adequacy of the RSM models in capturing the statistical relationships between the two responses and the processing parameters. The results, summarized in Tables 5 and 6, indicate that both response surface models are highly significant (P< 0.05), confirming the models' validity.Furthermore, the ANOVA results revealed that three process parameters (T_{nc}, T_k, and A_p) have a significant impact on t_d, with P-values less than 0.01, however, t_a was not significant for the t_d. This may be because t_d primarily reflects the initial stage of the injection process, where the material is rapidly injected into the mold cavity. While holding pressure time is important for ensuring the part maintains its shape and compensates for shrinkage after filling, it does not directly influence the filling time itself. The analysis also quantified the contribution of each factor to the variation in t_d, with A_p being the most influential factor (37.17%), followed by T_k (23.41%) and T_{nc} (6.14%). For V_s, all four process parameters were found to be significant based on the ANOVA results in Table 5. The relative contributions of these factors to the variation in Vs were determined to be 55.42% for T_{nc}, 19.56% for t_a, 14.01% for T_k, and 1.58% for A_p.

Figure 6 shows the relationship between the processing parameters and the t_d value. Increasing the injection pressure results in a greater pushing force, helping the material to flow into the mold more quickly, thereby significantly reducing the time required to complete the mold filling process[47]. Higher mold temperature will reduce the viscosity of the material, making it easier to flow into the mold. Meanwhile, the melting temperature determines the flowability of the molten plastic before it is injected into the mold. Therefore, higher melting temperature can also increase the flowability of the material, thereby improving the mold filling process[48]. However, in this study, the pressure holding time ta has no significant effect on the mold filling time. This is because this parameter is mainly related to the control of shrinkage and the improvement of product quality after the mold cavity has been filled.

Melt temperature has a direct impact on volumetric shrinkage (Figure 7). Excessive temperature can lead to material degradation or loss of mechanical properties, resulting in increased shrinkage upon cooling. Prolonged pressure holding time allows the plastic to remain under pressure for longer as it cools and solidifies, compensating for shrinkage and improving final product quality [49]. Generally, higher mold temperatures slow down the solidification process, allowing for better molecular alignment and reducing shrinkage. However, increasing mold temperature in this study resulted in increased volumetric shrinkage. This may be attributed to the complex geometry and design of the electrical outlet, where high mold temperatures can induce internal thermal stresses during cooling, leading to non-uniform deformation and increased overall shrinkage. Injection pressure, while significantly impacting filling time, has a relatively smaller effect on volumetric shrinkage, as most shrinkage occurs during the cooling and pressure-holding phases[10, 50].

Table 6. ANOVA analysis results of V_s

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Model	14	1.866	99.00%	1.866	0.133	84.74	0.000
Linear	4	1.708	90.58%	1.708	0.427	271.35	0.000
T_{nc}	1	1.045	55.42%	1.045	1.045	664.14	0.000
T_k	1	0.264	14.01%	0.264	0.264	167.93	0.000
A_p	1	0.030	1.58%	0.030	0.030	18.90	0.001
t_a	1	0.369	19.56%	0.369	0.369	234.42	0.000
Square	4	0.075	4.00%	0.075	0.019	11.97	0.000
T_{nc}*T_{nc}	1	0.002	0.11%	0.001	0.001	0.40	0.540
T_k*T_k	1	0.004	0.24%	0.004	0.004	2.69	0.127
A_p*A_p	1	0.043	2.30%	0.021	0.021	13.08	0.004
t_a* t_a	1	0.025	1.34%	0.025	0.025	16.09	0.002
2-Way Interaction	6	0.083	4.43%	0.083	0.014	8.84	0.001
T_{nc}*T_k	1	0.012	0.63%	0.012	0.012	7.60	0.017
T_{nc}*A_p	1	0.008	0.41%	0.008	0.008	4.91	0.047
T_{nc}* t_a	1	0.006	0.30%	0.006	0.006	3.63	0.081
T_k*A_p	1	0.006	0.31%	0.006	0.006	3.75	0.077
T_k* t_a	1	0.018	0.98%	0.018	0.018	11.76	0.005
A_p* t_a	1	0.034	1.79%	0.034	0.034	21.39	0.001
Error	12	0.019	1.00%	0.019	0.002		
Lack-of-Fit	10	0.019	1.00%	0.019	0.002	112.15	0.009
Pure Error	2	0.000	0.00%	0.000	0.000		
Total	26	1.885	100.00%				

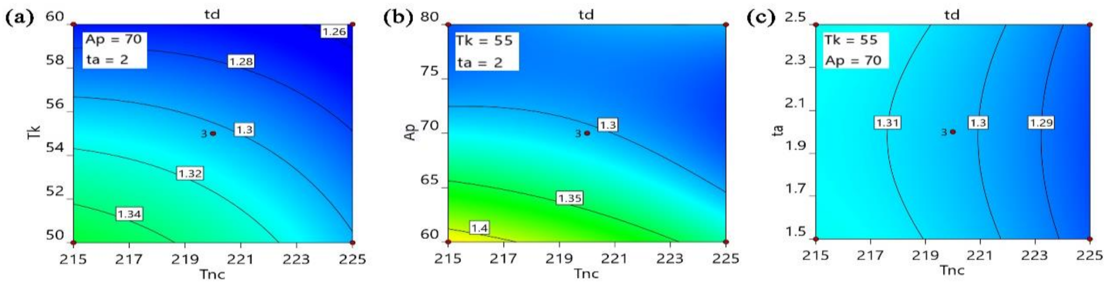

Figure 6. Contour plot for the influence of process parameters on t_d

3.3. Multi-objective optimization using NSGA-II

This study employs a multi-objective optimization model using the NSGA-II algorithm to minimize both filling time (t_d) and volume shrinkage rate (V_s) while adjusting processing parameters (T_{nc}, T_k, A_p, and t_a). The relationships between these parameters and the objectives are established using RSM. The goal is to find the optimal combination of processing parameters within specified constraints. Table 7 presents the details and values associated with the input parameters and objectives. For this specific study, the population size, mutation rate, crossover rate, and maximum generations were set to 60, 0.25, 0.8, and 500, respectively. These settings were chosen to ensure a reasonable convergence rate for the optimization process.

The results of the NSGA-II optimization analysis are presented in Figure 8 with 21 Pareto solutions (Table 8). For the objective function t_d, the range is from 1.260 to 1.389 s, and for the objective function V_s, it varies from 4.810 to 5.497%. The corresponding processing parameters T_{nc} range from 215.0 to 215.4 ºC, T_k from 50 to 60 ºC, A_p from 67.09 to 76.53 Mpa, and t_a from 2.097 to 2.5s. The NSGA-II method is highly flexible as it provides 21 Pareto solutions, allowing manufacturers to select the most suitable parameters based on their priorities, such as prioritizing efficiency by choosing a shorter filling time or prioritizing quality by selecting a lower volumetric shrinkage rate.

Table 7. Processing parameters and optimization objectives

Pocessing parameters	Level		Objectives	
	Low	High		
Melt temperature (T_{nc})	215	225	Filling time (t_d, s)	Minimum
Mold temperature (T_k)	50	60	Volume shrinkage (V_s, %)	Minimum
Injection pressure (A_p)	60	80		
Pressure holding time (t_a)	1.5	2.5		

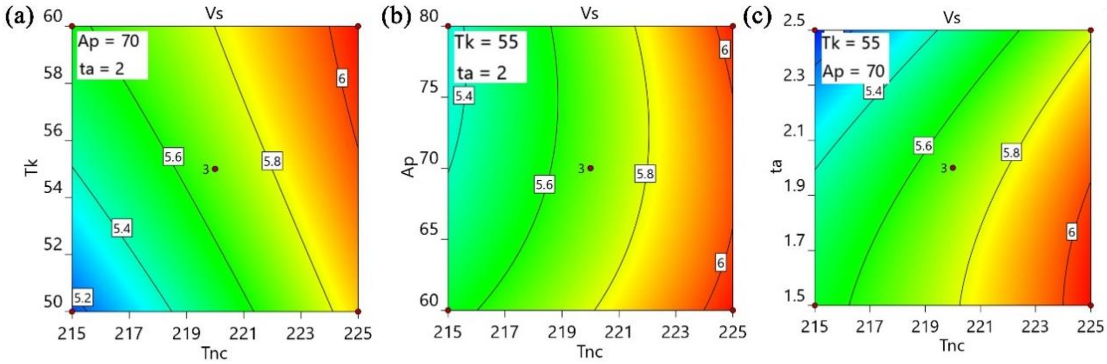

Figure 7. Contour plot for the influence of process parameters on V_s

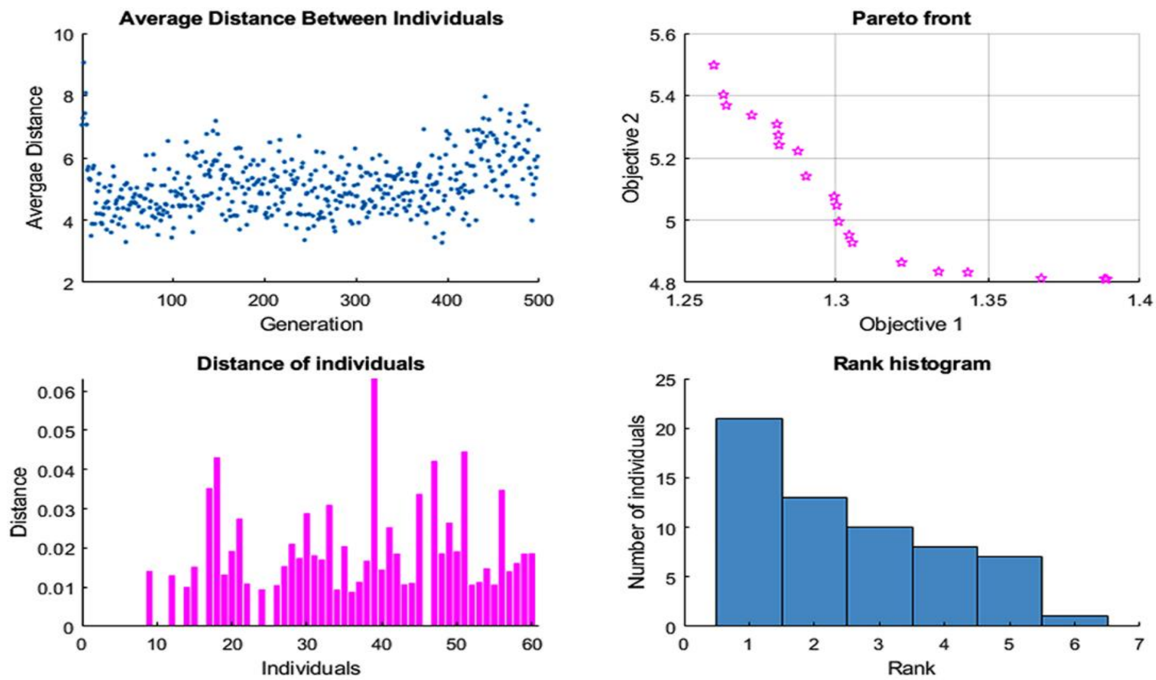

Figure 8. Multi-objective optimization results using NSGA-II

To validate the results of the optimization process using the NSGA-II method, the study conducted simulation analyses for two cases corresponding to the smallest values of the objective functions t_d and V_s. The results of the simulation analysis and comparison with the optimal values obtained by the NSGA-II method are presented in Table 9. The results indicate that the difference between the predicted and observed values is less than 2.03%, confirming the accuracy of the method used to solve the multi-objective optimization problem related to plastic flow during the injection molding process. This finding is consistent with other studies that have employed NSGA-II and similar modeling techniques. For example, Li et al. [31] combined Kriging with NSGA-II to optimize the quality of plastic parts, achieving an accuracy of 4.6%. Similarly, Lu and Huang [51] integrated the Ellipsoidal Basis Function Neural Network (EBFNN) model with the NSGA-II algorithm, reporting a maximum error of 15.767% for the volumetric shrinkage ratio and 9.952% for warpage deformation.

Despite the significant findings of this study, several limitations warrant further investigation. The scope of the study was confined to four primary processing parameters in the injection molding of electrical outlets, while numerous other factors influence the process. Future research should broaden its scope to encompass a wider range of processing parameters. Additionally, the proposed method's validation was solely based on simulations, necessitating experimental verification. Furthermore, a comparative analysis with other optimization algorithms could provide insights into the method's relative performance. By addressing these limitations and conducting comprehensive comparisons, future studies can offer a more holistic understanding of plastic injection molding and contribute to enhanced manufacturing efficiency.

Table 8. Results of 21 optimal solutions corresponding to processing parameters

N.o	T_{nc} (ºC)	T_k (ºC)	A_p (Mpa)	t_a (s)	t_d (s)	V_s (%)
1	215.00	50.00	67.09	2.500	1.389	4.810
2	215.01	50.03	72.61	2.497	1.334	4.835
3	215.02	52.69	75.83	2.450	1.300	5.047
4	215.00	60.00	75.37	2.097	1.260	5.497
5	215.04	51.88	76.53	2.475	1.301	4.995
6	215.00	50.01	68.99	2.500	1.368	4.813
7	215.01	55.60	75.16	2.391	1.287	5.222
8	215.02	54.93	75.78	2.486	1.290	5.141
9	215.03	50.73	76.50	2.478	1.305	4.927
10	215.00	50.01	67.13	2.500	1.388	4.812
11	215.00	60.00	75.37	2.097	1.260	5.497
12	215.01	56.47	75.81	2.294	1.281	5.308
13	215.00	50.09	71.42	2.496	1.343	4.832
14	215.00	59.61	75.62	2.437	1.264	5.368
15	215.00	59.65	75.55	2.357	1.263	5.403
16	215.04	51.44	76.20	2.497	1.304	4.952
17	215.01	50.33	74.04	2.496	1.322	4.864
18	215.03	56.60	75.70	2.446	1.281	5.241
19	215.02	58.21	75.25	2.386	1.272	5.337
20	215.01	56.52	75.68	2.374	1.281	5.273
21	215.04	53.46	75.18	2.465	1.299	5.076

Table 9. Simulation validation results of t_d and V_s compared to optimized values

Processing parameters				**Optimization results**		**Test results**		**Deviation (%)**	
T_{nc} (ºC)	T_k (ºC)	A_p (Mpa)	t_a (s)	t_d (s)	V_s (%)	t_d (s)	V_s (%)	t_d (s)	**V_s (%)**
215.0	50.0	67.09	2.5	1.389	4.810	1.378	4.902	0.77	1.90
215.0	60.0	75.37	2.1	1.260	5.497	1.285	5.409	2.03	1.61

4. Conclusion

This study successfully demonstrated the application of Response Surface Methodology (RSM) and the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) for optimizing filling time (t_d) and volumetric shrinkage rate (V_s) in the injection molding of plastic electrical sockets. Four process parameters, including melt temperature (T_{nc}), mold temperature (T_k), injection pressure (A_p), and pressure holding time (t_a), were used. By establishing predictive models for these critical quality characteristics and employing a multi-objective optimization approach, the research identified Pareto-optimal solutions that effectively balanced conflicting objectives. The results indicate that the predictive models for t_d and V_s were developed, exhibiting high coefficients of determination with R^2 values of 0.946 and 0.990, respectively. Applying NSGA-II for multi-objective optimization generated 21 Pareto solutions, with T_{nc} ranging from 215.0 to 215.4 °C, T_k ranging from 50 to 60 °C, A_p ranging from 67.09 to 76.53 MPa, and t_a ranging from 2.097 to 2.5 s. These values corresponded to t_d values ranging from 1.260 to 1.389 s and V_s values ranging from 4.810 to 5.497%. Finally, verification through re-simulation of the solutions confirmed the method's accuracy, with differences less than 2.03%. The findings of this study provide valuable insights into the complex interplay between process parameters and product quality in injection molding. The methodology presented can be adapted to optimize other product attributes and applied to a broader range of materials and product geometries.

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