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Optimizing Injection Molding for Propellers with Soft Computing, Fuzzy Evaluation, and Taguchi Method

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Abstract

This research explores multi-objective optimization in injection molding with a focus on identifying the optimal configuration for the moldability index in aviation propeller manufacturing. The study employs the Taguchi method and fuzzy analytic hierarchy process (FAHP) combined with the Technique for the Order Performance by Similarity to the Ideal Solution (TOPSIS) to systematically evaluate diverse objectives. The investigation specifically addresses two prevalent defects—shrinkage rate and sink mark—that impact the final quality of injection-molded components. Polypropylene is chosen as the injection material, and critical process parameters encompass melt temperature, mold temperature, filling time, cooling time, and pressure holding time. The Taguchi L25 orthogonal array is selected, considering the number of levels and parameters, and Finite Element Analysis (FEA) is applied to enhance precision in results. To validate both simulation outcomes and the proposed optimization methodology, Artificial Neural Network (ANN) analysis is conducted for the chosen component. The Fuzzy-TOPSIS method, in conjunction with ANN, is employed to ascertain the optimal levels of the selected parameters. The margin of error between the chosen optimization methods is found to be less than one percent, underscoring their suitability for injection molding optimization. The efficacy of the selected optimization method has been corroborated in prior research. Ultimately, employing the fuzzy-TOPSIS optimization method yields a minimum shrinkage value of 16.34% and a sink mark value of 0.0516 mm. Similarly, utilizing the ANN optimization method results in minimum values of 16.42% for shrinkage and 0.0519 mm for the sink mark.

Keywords:
Injection Molding;
Shrinkage;
Sink Mark;
Soft Computing;
FAHP;
TOPSIS;
Taguchi.

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1- Introduction

Injection molding of plastics is a sophisticated and broadly adopted process renowned for its exceptional efficiency in the mass production of plastic items. This technique is particularly effective in meeting high production demands while maintaining tight tolerances, rendering it a cost-effective manufacturing method for products with diverse forms and intricate geometries [1]. Nevertheless, the complexity inherent in injection molding necessitates meticulous engineering tasks. These tasks include designing part and mold geometry, precision machining and polishing of surfaces, assembling mold components, and conducting prototype tests with careful material and processing parameter selection. The final quality of molded parts depends on various factors, including the type of plastic material used, the geometry of the part, the design of the mold, and the conditions of the molding process [2, 3].

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Despite these advantages, producing injection-molded polymeric parts with the anticipated properties is an expensive and iterative process, often necessitating tooling adjustments. Designing molds, particularly when integrating unique additional geometries, becomes increasingly complex due to the presence of depressions and projections [4]. Defects such as warpage, shrinkage, sink marks, and residual stress significantly compromise product quality and precision, highlighting the need for proficient management of influencing factors throughout the molding process [5]. Residual stresses often develop within injection-molded products due to the deformation forced on the distorted geometry in assembly. Notably, the residual stresses induced by warpage significantly affect the mechanical properties of the product and are closely linked to molding process parameters. Thus, it is essential to consider the influence of the molding process when describing the mechanical behavior of the finished product [6-8].

Part and mold designs are typically determined early in product development and are not easily altered later. As a result, optimizing process parameters emerges as a more feasible and practical approach. Additionally, alongside warpage, shrinkage is a significant quality concern for thin-shell thermoplastic parts during injection molding. The degree of warpage and shrinkage is strongly influenced by the machining parameters of the injection molding process [9, 10].

Taguchi's factorial experimental design is centered on minimizing variation in the existence of external factors. Those trials are structured using orthogonal arrays, which integrate the impacts of each external factor and compute a signal-to-noise ratio (S/N ratio) for each trial [11-15]. The Fuzzy Logic method, which employs automated parameter adjustment, reduces defects such as welding lines, thereby improving part quality [16, 17]. Multi-objective optimization in injection molding necessitates the use of various optimization methods. By employing Taguchi methods, the fuzzy analytic hierarchy process (FAHP), and the technique for order performance by similarity to the ideal solution (TOPSIS), the study assesses various objectives and examines common defects such as short shot potential, warpage, and shrinkage rate. Polypropylene is selected as the injection material, and experiments validate simulation results using Finite Element Analysis (FEA). The suggested approach enhances the variety of choices with a high moldability index, providing robustness in quality evaluation for injection-molded parts. Further research could extend the scope to include additional quality criteria and parameters in injection molding processes [18].

Previous studies have focused on optimizing parameters of the process for horizontal injection molding of polypropylene (PP) and polystyrene (PS) to produce cups. An integrated approach revealed significant effects of injection pressure and temperature on roughness of surface and shrinkage, leading to the determination of optimal parameters for both materials and resulting in minimized roughness of surface and shrinkage in the molded cups [19]. Other reviews have explored efforts to optimize parameters of process to minimize shrinkage deformations and warpage in plastic injection molding (PIM). These reviews outlined the manufacturing process and factors contributing to these defects, followed by recent advancements in optimization methods such as artificial neural networks and genetic algorithms, and future aspects on quality assurance in injection molding machines were also considered [20]. Additionally, studies have examined factors influencing residual stresses and dimensional changes in injection-molded polypropylene. Through computer simulations and mechanical, thermal, and chemical evaluations, it was found that part geometry and holding pressure significantly affect warpage, while post-molding conditions have less influence. Ribbed specimens and lower holding pressures exhibited higher warpage, while annealing improved warpage and impact strength. Shrinkage values were unaffected by the parameters assessed [21].

Although Artificial Neural Network (ANN) models have demonstrated effectiveness in predicting nonlinear responses and facilitating process parameter optimization based on quality criteria, current methods for evaluating injection molding quality have limitations. This has led to the introduction of a novel approach that combines Taguchi with FAHP, TOPSIS, and ANN. This method aims to minimize the number of experiments required to determine optimal parameter levels, focusing on analyzing sink marks and shrinkage rates in plastic products. For example, Fonseca et al. (2024) demonstrated an integrated finite element/artificial neural network approach to enhance the strength and manufacturability of composite automotive components [22]. Similarly, Panchal & Sheth (2023) critically reviewed the application of artificial neural networks in optimizing injection molding process parameters [23]. Kengpol & Tabkosai (2024) proposed a hybrid deep learning model combining TSA with ANN for cost evaluation in the plastic injection industry [24]. EL Ghadoui et al. (2023) introduced a hybrid optimization method utilizing artificial neural networks and genetic algorithms for intelligent manufacturing in plastic injection molding [25]. Hermann et al. (2024) explored the use of neural networks to predict fiber orientation and geometry influence in injection molded components [26]. Furthermore, Ez-Zahraouy & Kamach (2024) investigated machine learning methods for quality prediction in injection molding processes [27]. Lastly, Seifert et al. (2024) examined the applicability of invertible neural networks in the injection molding process [28].

Identifying the optimal set of process parameters to mitigate defects is essential. This study aims to determine the best parameter combination to eliminate sink marks and minimize shrinkage rates. The parameters under examination include filling time, part cooling time, pressure holding time, melt temperature, and mold temperature. These parameters significantly influence the cooling and solidification process of the molten plastic inside the mold.

1-1- Gaps in Literature and Proposed Approach

Despite significant advancements in optimizing injection molding processes, gaps remain in effectively integrating multiple optimization methods and evaluating their combined impact on reducing defects. Previous studies have primarily focused on individual methods such as Taguchi, Fuzzy Logic, or ANN models. There is a need for a comprehensive approach that combines these methods to enhance the overall quality and efficiency of the injection molding process.

This study proposes an integrated approach combining Taguchi, FAHP, TOPSIS, and ANN to optimize injection molding process parameters. By evaluating multiple objectives and analyzing common defects like short shot possibility, shrinkage rate, and warpage, this approach aims to improve the moldability index and robustness in quality evaluation for injection-molded parts. This method will be validated using Finite Element Analysis (FEA) and experimental results, providing a more holistic and effective optimization strategy for the injection molding industry.

This article systematically explores the optimization of parameters in the injection molding process. It begins with an Introduction that outlines the importance and complexity of the plastic injection molding process, highlighting the need for meticulous design and parameter optimization to reduce defects such as shrinkage and warpage. The Material and Method section follows, presenting a comprehensive methodology that integrates FAHP, TOPSIS, and Taguchi to enhance moldability, including steps for problem description, parameter evaluation, optimization, and validation using ANN. The Problem Description elaborates on the key defects (shrinkage and sink marks) and their assessment using fuzzy evaluation and variable weighting. The Taguchi Orthogonal Array and TOPSIS sections detail the experimental design and prioritization of trials based on defect severity. The Results and Discussion section analyses the outcomes, highlighting the implications for propeller design in micro aircraft. The integration of ANN with Genetic Algorithm is explained to further optimize process parameters. Finally, the Conclusion summarizes the effectiveness of the proposed integrated approach and suggests directions for future research to enhance quality evaluation in injection molding.

2- Material and Methods

This study presents an extensive approach that combines FAHP, TOPSIS, and Taguchi methods to enhance multi-objective optimization in injection molding processes. The primary objective is to identify the most favorable alternatives with enhanced moldability. The proposed approach encompasses four distinct phases as shown in Figure 1.

1. Problem description: This phase involves defining two distinct plastic defects as the basis for quality evaluation in the injection molding process.
2. Application of FAHP with Taguchi: In this stage, significant parameters are evaluated and weighted using FAHP in conjunction with Taguchi. This process aims to expand the pool of alternatives within the injection molding process.
3. TOPSIS: The TOPSIS method is employed to calculate varied weights for optimization purposes, contributing to the selection of alternatives with superior moldability.
4. Analysis of the results: This phase involves assessing the outcomes to identify various alternatives in injection molding characterized by a high Moldability Index.
5. Validation using ANN: The final step involves validating the obtained results through the application of Artificial Neural Networks (ANN), ensuring the robustness and reliability of the proposed methodology.

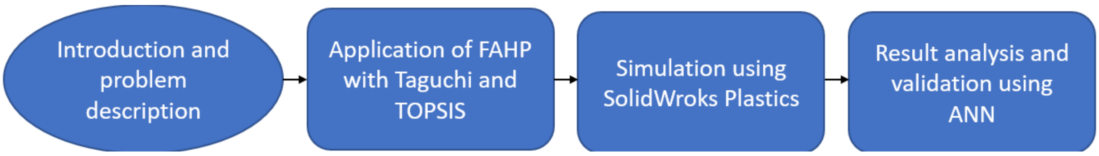


Figure 1. Flowchart of the proposed methodology

By employing a combination of advanced optimization techniques such as the Taguchi method, FAHP, TOPSIS, and ANN, this research offers a systematic approach to evaluating diverse objectives and identifying the optimal configuration for the moldability index. This integrated methodology enables researchers and manufacturers to effectively address multiple objectives simultaneously, considering critical factors like shrinkage rates and sink marks that directly impact component quality.

Furthermore, the validation of simulation results through Finite Element Analysis (FEA) and ANN adds credibility to the proposed optimization methodology, ensuring that the findings are robust and applicable in real-world manufacturing settings. The negligible margin of error observed in optimization methods underscores the accuracy and reliability of the proposed approach, further reinforcing its necessity and relevance in the field of injection molding for aviation propeller manufacturing.

The integration of FAHP, TOPSIS, and the Taguchi method creates a comprehensive and robust optimization framework. FAHP addresses uncertainty in parameter weighting, the Taguchi method systematically explores parameter effects, and TOPSIS effectively ranks alternatives. This synergistic approach ensures that the most effective process parameters are identified for injection molding optimization, enhancing the overall quality and performance of aviation propeller manufacturing.

2-1- Problem Description

The assessment of the quantity of external and internal defects in injected components serves as a crucial determinant of their overall quality. Among the prevalent defects adversely affecting the quality of parts produced through injection molding are the shrinkage rate and sink marks, illustrated in Figure 2. Both of these defects are intricately linked to geometric and process parameters. Shrinkage occurs during the packing/holding stage and cooling stage, while sink marks manifest during the cooling stage, stemming from non-uniformity of shrinkage.

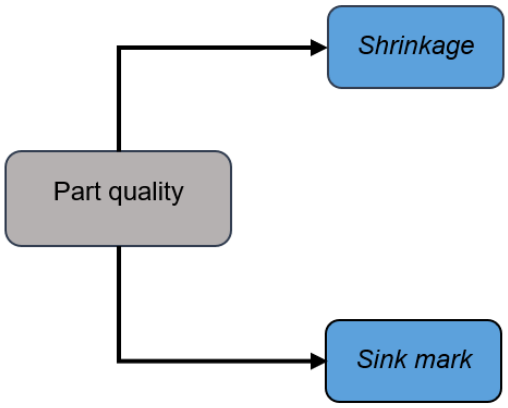


Figure 2. **Criteria for quality evaluation**

To assess the severity of each defect in the injected part, a fuzzy evaluation is employed, categorizing them into five distinct levels denoted as $\tilde{\alpha}_1$, $\tilde{\alpha}_2$, $\tilde{\alpha}_3$, $\tilde{\alpha}_4$, *and* $\tilde{\alpha}_5$. The gravity of each defect is established through the application of linguistic terms such as very low, low, medium, high, and very high, as depicted in Figure 2. Additionally, for rating the severity of defects, triangular membership functions are utilized, with corresponding triplet descriptions presented in both Figure 3 and Table 1 [16, 21, 29, 30].

In the fuzzy evaluation process, membership functions (such as triangular, trapezoidal, or Gaussian) represent the degree to which a defect like shrinkage or sink marks belongs to a fuzzy set, mapping severity to a value between 0 and 1. This process involves defining membership functions based on expert knowledge and historical data, assigning weights via the FAHP process, and integrating these elements using the Fuzzy-TOPSIS method. This comprehensive approach ensures a robust assessment of defect severity and helps identify optimal injection molding parameters.

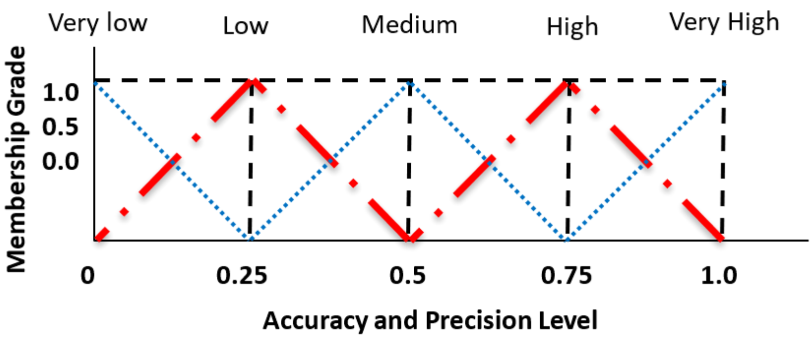


Figure 3. **Triangular membership function representing the severity of both shrinkage rate and sink mark**

Table 1. **Triplet characterization of linguistic variables used to assess the severity of defect weightiness**

Linguistic variables	Fuzzy rating	Triple description
Very High	a_5	(0.75, 1, 1)
High	a_4	(0.5, 0.75, 1)
Medium	a_3	(0.25, 0.5, 0.75)
low	a_2	(0, 0.25, 0.5)
Very low	a_1	(0, 0, 0.25)

2-2- Computation of the Weights for State Variables

To assign weights to variables, a variable weight profit vector is employed to modify the weights of chosen parameters, influencing the determination of product quality. This approach involves penalizing significant defects by adjusting negative parameters, while minor defects are incentivized through adjustments to positive factors. The introduction of corresponding adjustment parameters allows for the controlled modulation of punishment and reward levels [21, 30].

The vector $\mathbf{S}(\mathbf{X_j}) = \{s_1(x_j), s_2(x_j), \dots, s_p(x_j)\}$ is referred to as a p-dimensional variable weight profit vector.

$$s_j(x_j) = \begin{cases} \lambda_1 \alpha & x_j = \tilde{\alpha}_1 \\ \alpha & x_j = \tilde{\alpha}_2 \\ 1 & x_j = \tilde{\alpha}_3 \\ \beta & x_j = \tilde{\alpha}_4 \\ \lambda_2 \alpha & x_j = \tilde{\alpha}_5 \end{cases} \tag{1}$$

where $j \in \{1, \ 2 \dots, n\}$.$\alpha, \beta$ and λ are regarded as positive factor, negative factor, and regulative factor respectively [18].

2-3- Description and Application of Variable Weighting

The preliminary weights for each parameter are assigned using the Analytic Hierarchy Process (AHP). Initially, the weight for each parameter is determined by considering the relationships among defects (as illustrated in Figure 1) and the significance of defects relative to each other. The variable weight vector W is obtained as the normalized product of the constant weight factor w and the variable weight state vector s, as indicated in Equation 2 [18].

$$W_j(x_j) = \frac{w_j s_j(x_j)}{\sum_{k=1}^{n} w_k \, s_k(x_j)} \tag{2}$$

2-4- Taguchi-Designed Matrix for Experimental Design

This study incorporates a synergistic approach, combining Taguchi methodology with other optimization tools to evaluate the moldability indices of injected parts. All process parameters (five), each spanning five different levels as detailed in Table 2, are selected based on the Triangular membership function of Fuzzy. Furthermore, the choice of these parameters is guided by an extensive literature review, highlighting their significant impact on the injection process for evaluating three specific plastic defects. Furthermore, the choice of the L25 orthogonal array, as depicted in Table 3, is guided by the requisite number of parameters and levels for the study.

Table 2. Process parameters at five different levels

Parameters	L1	L2	L3	L4	L5
Melt Temp (P1) (°C)	200	215	230	255	280
Mold Temp (P2) (°C)	20	35	50	65	80
Filling Time (P3) (sec)	0.5	0.75	1	1.25	1.5
Pressure Holding Time (P4) (sec)	0.5	1	2	4	6
Pure Cooling Time (P5) (sec)	2	3	4	5	6

2-5- TOPSIS

This work involves m trial experiments and evaluates n distinct injection defects for quality assessment. The initial step entails assessing the initial weights of selected defects through the AHP (Analytic Hierarchy Process). Subsequently, a fuzzy relative matrix is considered based on the severity of potential plastic defects which $\widetilde{\mathbf{R}} = [\tilde{r}_{ij}]_{m \times n}$. Subsequently, the diverse weight for each criterion can be determined using Equations 1 and 2. Finally, Equation 3 is employed to represent the resulting varied weighted fuzzy evaluation matrix [18].

$$\widetilde{\mathbf{V}} = [\tilde{v}_{ij}]_{m \times n} \qquad i = 1, 2, \dots, m \qquad j = 1, 2, \dots, n \tag{3}$$

where: $\tilde{v}_{ij} = \tilde{r}_{ij} \times W_j = (r_{ij1} W_j, \quad r_{ij2} W_j, \quad r_{ij3} W_j)$

Here's a paraphrased and corrected version:

The TOPSIS method is used to rank 25 experiments by maximizing their distance from the negative ideal solution and minimizing their distance from the positive ideal solution. Derived from the weighted normalized fuzzy decision matrix, it is evident that the elements $\tilde{\mathbf{v}}_{ij}$ of normalized positive triangular numbers and their range fall within the closed interval [0, 1]. Consequently, the definition for the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) is as follows [18]:

$$\mathbf{A}^{+} = \{\tilde{v}_1^{+}\ \tilde{v}_2^{+}\ \ldots\ \ \tilde{v}_n^{+}\} \tag{4}$$

$$\mathbf{A}^{-} = \{\tilde{v}_1^{-}\ \tilde{v}_2^{-}\ \ldots\ \ \tilde{v}_n^{-}\} \tag{5}$$

Where: $\tilde{\mathbf{v}}_{\mathbf{j}}^{+} = (v_j^{+}, v_j^{+}, v_j^{+})$, $\mathbf{v}_{\mathbf{j}}^{+} = \max(v_{ij}^{+})$,$\tilde{\mathbf{v}}_{\mathbf{j}}^{-} = (v_j^{-}, v_j^{-}, v_j^{-})$ & $\mathbf{v}_{\mathbf{j}}^{-} = \min(v_{ij}^{-})$

Table 3. **L25 orthogonal array**

Experiment	P_1	P_2	P_3	P_4	P_5
1	1	1	1	1	1
2	1	2	2	2	2
3	1	3	3	3	3
4	1	4	4	4	4
5	1	5	5	5	5
6	2	1	2	3	4
7	2	2	3	4	5
8	2	3	4	5	1
9	2	4	5	1	2
10	2	5	1	2	3
11	3	1	3	5	2
12	3	2	4	1	3
13	3	3	5	2	4
14	3	4	1	3	5
15	3	5	2	4	1
16	4	1	4	2	5
17	4	2	5	3	1
18	4	3	1	4	2
19	4	4	2	5	3
20	4	5	3	1	4
21	5	1	5	4	3
22	5	2	1	5	4
23	5	3	2	1	5
24	5	4	3	2	1
25	5	5	4	3	2

The computation of the distance for each alternative or experiment, as per the orthogonal array, can be determined by [18]:

$$d_i^{\ +} = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^{\ +}), \forall i = 1,2,\ldots,m \tag{6}$$

$$d_i^{\ -} = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^{\ -}), \forall i = 1,2,\ldots,m \tag{7}$$

Where; $d(\tilde{v}_{ij}, \tilde{v}_j^{\ \pm}) = [1/3((v_{ij1} - v_{11}^{\ \pm})^2 + (v_{ij2} - v_{12}^{\ \pm})^2 + (v_{ij3} - v_{13}^{\ \pm})^2))]^{0.5}$.

Ultimately, the Moldability Index (MI) is computed as the quality index for the n choices. The MI serves as an indicator of the molding capability, influenced by the chosen parameters in the injection process. A higher Moldability Index signifies superior outcomes with minimized scrap during the process [18].

$$MI_i = \frac{d_i^{\ +}}{d_i^{\ +} + d_i^{\ -}}; \quad i = 1,2,\ldots,m. \tag{8}$$

3- Results and Discussion

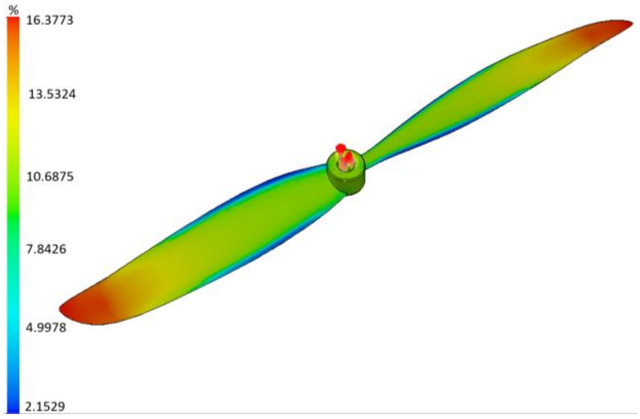
The plastic propeller designed for micro aircraft plays a crucial role in improving both efficiency and weight considerations as shown in Figure 4. Typically crafted from lightweight and durable materials such as nylon or composite plastics, these propellers contribute to the overall agility and maneuverability of micro aircraft. The design intricacies focus on aerodynamic efficiency, balancing thrust generation and energy conservation. Plastic propellers are particularly advantageous for micro aircraft due to their low weight, which is critical for maintaining desired performance characteristics. Additionally, their resistance to corrosion and affordability makes them a practical choice for small-scale aerial vehicles. The application of plastic propellers in micro aircraft underscores the importance of precision engineering to achieve optimal flight performance and stability in this specialized domain.

Shrinkage and sink marks are crucial aspects to consider during the injection molding process for components such as propellers, given their potential to affect the structural strength, surface finish, and overall functionality of the part. These defects arise due to the complex interactions between material properties, part geometry, and process parameters during molding. In this study, a comprehensive examination of shrinkage and sink marks was conducted using SolidWorks Plastics. The analysis focused on a propeller designed for micro aircraft, which measures 333 mm in length with a mounting point diameter of 19 mm. The injection molding process was simulated with three designated gates to evaluate the accuracy of the results using Finite Element Analysis (FEA). A shell (triangle) mesh with a size of 5 mm for the thicker part and 3 mm for the thinner sections resulted in a total of 14,399 triangles. Polypropylene (PP) was chosen as the material for the injected component, utilizing a surface mesh with an element thickness of 1 mm.

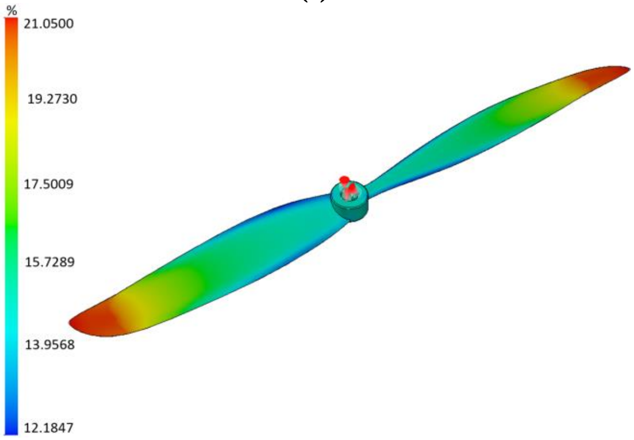
SolidWorks Plastics was employed to conduct a comprehensive examination of shrinkage and sink marks. In the realm of injection molding, the occurrences of shrinkage and sink marks are prevalent phenomena encountered during the cooling and solidification phases of the molded component. Shrinkage refers to the reduction in size or volume of a molded part as it cools from its molten state to a solid state. If not properly accounted for in the design and processing parameters, shrinkage can result in the final part dimensions being smaller than intended. The relationship between shrinkage and warpage lies in the uneven distribution of shrinkage within the part. Variations in cooling rates, material properties, and part geometry can lead to differential shrinkage across different regions of the part. This non-uniform shrinkage generates internal stresses, which, in turn, contribute to warpage [31]. Therefore, in the context of propeller applications within the aviation industry, a thorough analysis of the identified defects holds considerable significance. Employing the chosen orthogonal array based on Taguchi methodology, 25 trials are simulated. It is noteworthy that the minimum shrinkage is associated with trials 4 and 5, as depicted in Figure 5a, while the maximum shrinkage corresponds to trial number 22, as illustrated in Figure 5b. Thinner parts tend to experience more significant shrinkage in injection molding due to several factors, namely cooling rate, thermal contraction, material flow, and residual stress [31].

Another consideration in this research is the analysis of sink mark. Sink marks are depressions or dimples on the surface of a molded part caused by uneven cooling and solidification of the material. Sink marks can affect the cosmetic appearance of the part, and in some cases, they may compromise its structural integrity. They are typically more pronounced in areas with thicker cross-sections. Illustrated in Figures 6a and 6b, the least pronounced sink marks in the injected components are linked to trials 2 and 3, while the highest magnitude is associated with trial number 22.

Figure 4. 3D design of plastic propeller with three gates location

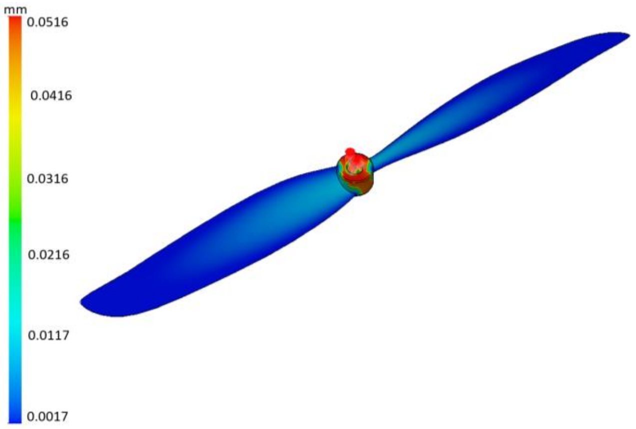


(a)

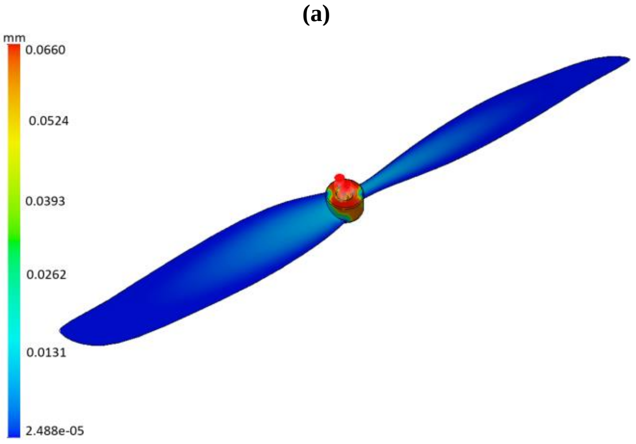


(b)

Figure 5. (a) Minimum shrinkage (b) Maximum shrinkage



(a)



(b)

Figure 6. (a) Minimum sink mark and (b) Maximum sink mark

SolidWorks Plastics is utilized to assess the results of injection molding across 25 experiments, employing the Taguchi method and a chosen L25 orthogonal array. The evaluation focuses on two plastic defects, namely shrinkage and sink marks, aiming to identify the optimal trial number associated with the minimal occurrence of defects in the injected parts. The initial weighting of each plastic defect is determined through the Analytic Hierarchy Process (AHP), as presented in Table 4, utilizing a classification outlined in Figure 2.

Table 4. **Calculation of initial weights**

	S1	S2	Initial weight
Step weight	0.7	0.3	
Shrinkage	1		0.7
Sink mark		1	0.3

The assessment of fuzzy ratings for two distinct defects identified in flow analysis through SolidWorks Plastics is executed across 25 trial numbers. Varying levels of fuzzy ratings are assigned based on the severity of these defects, represented as triangular fuzzy numbers, as delineated in Table 5.

In accordance with expert knowledge, assuming α=β=1.25 and λ_1 =λ_2 =1.5, the diverse weights for each defect are computed in Table 6 utilizing Equations 1 and 2. Subsequently, fuzzy logic is employed to assess the outcomes of the 25 trials across three distinct defects, as illustrated in Table 7, following the principles outlined in Equation 3.

Ultimately, the moldability index is computed for the 25 trial numbers, as demonstrated in Table 8, utilizing Equation 8. Therefore, trial numbers 1 to 5 exhibit the highest moldability index. The integration of Taguchi with the fuzzy logic method and TOPSIS provides a notable advantage in expanding the array of moldability index alternatives. These high moldability index trials (1 to 5) can be a viable option when configuring parameters for the initial five trials proves challenging in terms of factors such as injected parts, material, variable cost, and injection machine. Importantly, the evaluation of defects for each trial number encompasses a holistic consideration of both plastic defects, as opposed to individual assessments.

Table 5. **Fuzzy ratings for 25 trial numbers considering two plastic defects**

Trial number	Shrinkage	Sink mark
1	$\tilde{\alpha}_1$ (0,0,0.25)	$\tilde{\alpha}_1$ (0,0,0.25)
2	$\tilde{\alpha}_1$ (0,0,0.25)	$\tilde{\alpha}_1$ (0,0,0.25)
3	$\tilde{\alpha}_1$ (0,0,0.25)	$\tilde{\alpha}_1$ (0,0,0.25)
4	$\tilde{\alpha}_1$ (0,0,0.25))	$\tilde{\alpha}_1$ (0,0,0.25))
5	$\tilde{\alpha}_1$ (0,0,0.25))	$\tilde{\alpha}_1$ (0,0,0.25))
6	$\tilde{\alpha}_2$ (0,0.25,0.5)	$\tilde{\alpha}_2$ (0,0.25,0.5)
7	$\tilde{\alpha}_2$ (0,0.25,0.5)	$\tilde{\alpha}_2$ (0,0.25,0.5)
8	$\tilde{\alpha}_2$ (0,0.25,0.5)	$\tilde{\alpha}_2$ (0,0.25,0.5)
9	$\tilde{\alpha}_2$ (0,0.25,0.5)	$\tilde{\alpha}_2$ (0,0.25,0.5)
10	$\tilde{\alpha}_2$ (0,0.25,0.5)	$\tilde{\alpha}_2$ (0,0.25,0.5)
11	$\tilde{\alpha}_3$ (0.25,0.5,0.75)	$\tilde{\alpha}_3$ (0.25,0.5,0.75)
12	$\tilde{\alpha}_3$ (0.25,0.5,0.75)	$\tilde{\alpha}_3$ (0.25,0.5,0.75)
13	$\tilde{\alpha}_3$ (0.25,0.5,0.75)	$\tilde{\alpha}_3$ (0.25,0.5,0.75)
14	$\tilde{\alpha}_3$ (0.25,0.5,0.75)	$\tilde{\alpha}_3$ (0.25,0.5,0.75)
15	$\tilde{\alpha}_3$ (0.25,0.5,0.75)	$\tilde{\alpha}_3$ (0.25,0.5,0.75)
16	$\tilde{\alpha}_4$ (0.5,0.75,1)	$\tilde{\alpha}_4$ (0.5,0.75,1)
17	$\tilde{\alpha}_4$ (0.5,0.75,1)	$\tilde{\alpha}_4$ (0.5,0.75,1)
18	$\tilde{\alpha}_4$ (0.5,0.75,1)	$\tilde{\alpha}_4$ (0.5,0.75,1)
19	$\tilde{\alpha}_4$ (0.5,0.75,1)	$\tilde{\alpha}_4$ (0.5,0.75,1)
20	$\tilde{\alpha}_4$ (0.5,0.75,1)	$\tilde{\alpha}_4$ (0.5,0.75,1)
21	$\tilde{\alpha}_5$ (0.75,1,1)	$\tilde{\alpha}_4$ (0.5,0.75,1)
22	$\tilde{\alpha}_5$ (0.75,1,1)	$\tilde{\alpha}_5$ (0.75,1,1)
23	$\tilde{\alpha}_5$ (0.75,1,1)	$\tilde{\alpha}_5$ (0.75,1,1)
24	$\tilde{\alpha}_5$ (0.75,1,1)	$\tilde{\alpha}_5$ (0.75,1,1)
25	$\tilde{\alpha}_5$ (0.75,1,1)	$\tilde{\alpha}_4$ (0.5,0.75,1)

Following the computation of the Moldability Index as per Table 8, the subsequent stage involves calculating the Signal-to-Noise ratio, as presented in the same table, to establish the response table for Taguchi. The Response Table of Taguchi, as delineated in Table 9, will ascertain the optimal levels for each selected parameter, aiming to achieve minimal defects coupled with the highest moldability index. As indicated in Table 9, the optimal settings for the selected parameters are as follows: melt temperature at level 1, mold temperature at level 1, filling time at level 5, pressure holding time at level 4, and pure cooling time at level 3.

Once the optimal level has been identified, it is imperative to execute a simulation to verify that the defect values are significantly lower when compared to the minimum values of shrinkage and sink marks, as indicated in Figures 5 and 6. Consequently, the minimum values of shrinkage and sink marks corresponding to the optimal levels of the selected parameters are detailed in Figure 7.

Table 6. Computation of diverse weights utilizing the variable weight profit factor

Trial number	Shrinkage			Sink mark		
	X_j	$S_j(X_j)$	$w_j(X_j)$	X_j	$S_j(X_j)$	$w_j(X_j)$
1	$\tilde{\alpha}_1$	1.875	1.56	$\tilde{\alpha}_1$	1.875	3.93
2	$\tilde{\alpha}_1$	1.875	1.56	$\tilde{\alpha}_1$	1.875	3.93
3	$\tilde{\alpha}_1$	1.875	1.56	$\tilde{\alpha}_1$	1.875	3.93
4	$\tilde{\alpha}_1$	1.875	1.56	$\tilde{\alpha}_1$	1.875	3.93
5	$\tilde{\alpha}_1$	1.875	1.56	$\tilde{\alpha}_1$	1.875	3.93
6	$\tilde{\alpha}_2$	1.25	1.38	$\tilde{\alpha}_2$	1.25	2.72
7	$\tilde{\alpha}_2$	1.25	1.38	$\tilde{\alpha}_2$	1.25	2.72
8	$\tilde{\alpha}_2$	1.25	1.38	$\tilde{\alpha}_2$	1.25	2.72
9	$\tilde{\alpha}_2$	1.25	1.38	$\tilde{\alpha}_2$	1.25	2.72
10	$\tilde{\alpha}_2$	1.25	1.38	$\tilde{\alpha}_2$	1.25	2.72
11	$\tilde{\alpha}_3$	1	1.30	$\tilde{\alpha}_3$	1	2.30
12	$\tilde{\alpha}_3$	1	1.30	$\tilde{\alpha}_3$	1	2.30
13	$\tilde{\alpha}_3$	1	1.30	$\tilde{\alpha}_3$	1	2.30
14	$\tilde{\alpha}_3$	1	1.30	$\tilde{\alpha}_3$	1	2.30
15	$\tilde{\alpha}_3$	1	1.30	$\tilde{\alpha}_3$	1	2.30
16	$\tilde{\alpha}_4$	1.25	1.38	$\tilde{\alpha}_4$	1.25	2.72
17	$\tilde{\alpha}_4$	1.25	1.38	$\tilde{\alpha}_4$	1.25	2.72
18	$\tilde{\alpha}_4$	1.25	1.38	$\tilde{\alpha}_4$	1.25	2.72
19	$\tilde{\alpha}_4$	1.25	1.38	$\tilde{\alpha}_4$	1.25	2.72
20	$\tilde{\alpha}_4$	1.25	1.38	$\tilde{\alpha}_4$	1.25	2.72
21	$\tilde{\alpha}_5$	1.875	1.38	$\tilde{\alpha}_4$	1.25	3.58
22	$\tilde{\alpha}_5$	1.875	1.56	$\tilde{\alpha}_5$	1.875	3.93
23	$\tilde{\alpha}_5$	1.875	1.56	$\tilde{\alpha}_5$	1.875	3.93
24	$\tilde{\alpha}_5$	1.875	1.56	$\tilde{\alpha}_5$	1.875	3.93
25	$\tilde{\alpha}_5$	1.875	1.38	$\tilde{\alpha}_4$	1.25	3.58

A comprehensive sensitivity analysis assessed the influence of process parameters on defects like shrinkage rate and sink mark by systematically varying parameters such as melt temperature, mold temperature, filling time, cooling time, and pressure holding time. The FAHP method was used to weigh the significance of each parameter, which was then integrated with the Taguchi method's L25 orthogonal array for a thorough examination of parameter interactions and their sensitivity. The TOPSIS method ranked parameter combinations based on performance, identifying the most robust settings. Validation with ANN provided a predictive model, confirming that the optimal settings were robust with minimal deviation in defect rates under varied conditions.

Table 7. Fuzzy evaluation of results from 25 mold schemes through simulation

Trial number	Shrinkage	Sink mark
1	(0, 0, 0.39)	(0, 0, 0.98)
2	(0, 0, 0.39)	(0, 0, 0.98)
3	(0, 0, 0.39)	(0, 0, 0.98)
4	(0, 0, 0.39)	(0, 0, 0.98)
5	(0, 0, 0.39)	(0, 0, 0.98)
6	(0, 0.34, 0.69)	(0, 0.68, 1.36)
7	(0, 0.34, 0.69)	(0, 0.68, 1.36)
8	(0, 0.34, 0.69)	(0, 0.68, 1.36)
9	(0, 0.34, 0.69)	(0, 0.68, 1.36)
10	(0, 0.34, 0.69)	(0, 0.68, 1.36)
11	(0.32, 0.65, 0.97)	(0.57, 1.15, 1.72)
12	(0.32, 0.65, 0.97)	(0.57, 1.15, 1.72)
13	(0.32, 0.65, 0.97)	(0.57, 1.15, 1.72)
14	(0.32, 0.65, 0.97)	(0.57, 1.15, 1.72)
15	(0.32, 0.65, 0.97)	(0.57, 1.15, 1.72)
16	(0.69, 1.03, 0.13)	(1.36, 2.04, 0.27)
17	(0.69, 1.03, 0.13)	(1.36, 2.04, 0.27)
18	(0.69, 1.03, 0.13)	(1.36, 2.04, 0.27)
19	(0.69, 1.03, 0.13)	(1.36, 2.04, 0.27)
20	(0.69, 1.03, 0.13)	(1.36, 2.04, 0.27)
21	(1.03, 1.38, 1.72)	(1.79, 2.68, 3.58)
22	(1.17, 1.56, 1.95)	(2.94, 3.93, 4.91)
23	(1.17, 1.56, 1.95)	(2.94, 3.93, 4.91)
24	(1.17, 1.56, 1.95)	(2.94, 3.93, 4.91)
25	(1.17, 1.56, 1.95)	(1.79, 2.68, 3.58)

Table 8. Moldability indices for 25 mold schemes derived from simulation

Trial number	d_i^+	d_i^-	$d_i^+ + d_i^-$	MI_i	S/N
1	5.073	0.7924	5.8663	0.8649	-1.260
2	5.073	0.7924	5.8663	0.8649	-1.260
3	5.073	0.7924	5.8663	0.8649	-1.260
4	5.073	0.7924	5.8663	0.8649	-1.260
5	5.073	0.7924	5.8663	0.8649	-1.260
6	4.544	1.3232	5.8675	0.7744	-2.219
7	4.544	1.3232	5.8675	0.7744	-2.219
8	4.544	1.3232	5.8675	0.7744	-2.219
9	4.544	1.3232	5.8675	0.7744	-2.219
10	4.54431	1.3232	5.8675	0.7744	-2.219
11	3.7672	1.9442	5.7114	0.6595	-3.614
12	3.7672	1.9442	5.7114	0.6595	-3.614
13	3.7672	1.9442	5.7114	0.6595	-3.614
14	3.7672	1.9442	5.7114	0.6595	-3.614
15	3.7672	1.9442	5.7114	0.6595	-3.614
16	3.8113	2.1467	5.9581	0.6396	-3.880
17	3.8113	2.1467	5.9581	0.6396	-3.880
18	3.8113	2.1467	5.9581	0.6396	-3.880
19	3.8113	2.1467	5.9581	0.6396	-3.880
20	3.8113	2.1467	5.9581	0.6396	-3.880
21	1.7779	4.1911	5.9690	0.2978	-10.519
22	1.1206	5.6032	6.7238	0.1666	-15.563
23	1.1206	5.6032	6.7238	0.1666	-15.563
24	1.1206	5.6032	6.7238	0.1666	-15.563
25	1.7620	4.3748	6.1368	0.2871	-10.838

Table 9. Response Table of Taguchi for the optimum level

Parameters	L1	L2	L3	L4	L5
Melt Temp (P1) (°C)	**-1.2604**	**-2.2198**	-3.6144	**-3.8806**	-13.6095
Mold Temp (P2) (°C)	-4.2990	-5.3076	-5.3076	-5.3076	-4.3628
Filling Time (P3) (sec)	-5.3076	-5.3076	-5.3076	-4.3628	**-4.2990**
Pressure Holding Time (P4) (sec)	-5.3076	-5.3076	-4.3628	-4.2990	-5.3076
Pure Cooling Time (P5) (sec)	-5.3076	-4.3627	**-4.2990**	-5.3076	-5.3076

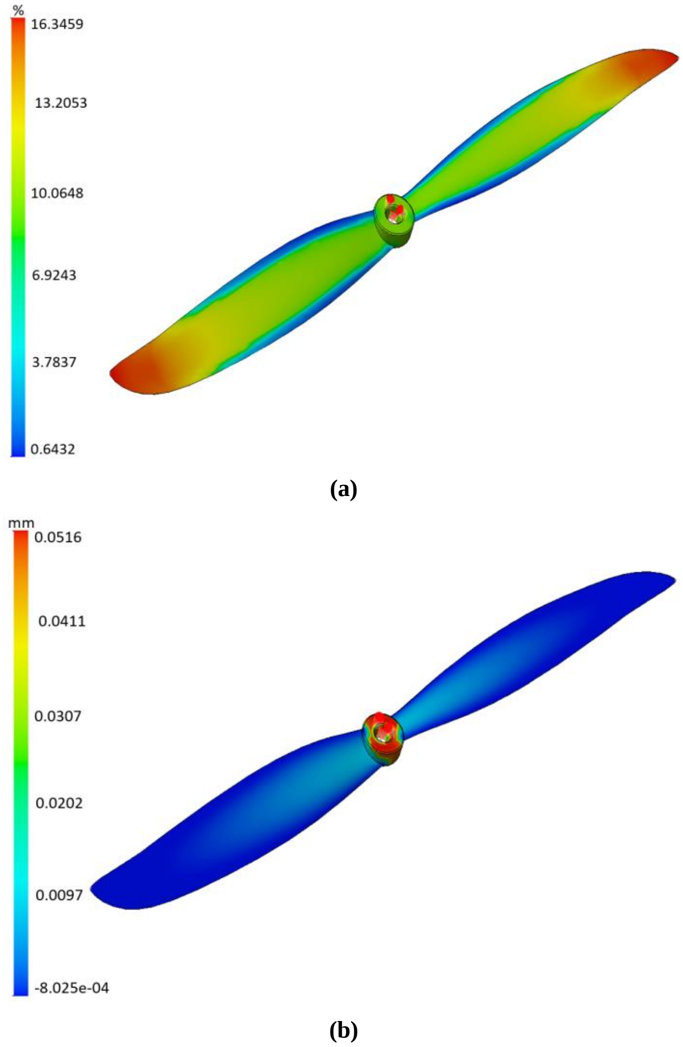


Figure 7. (a) Optimum shrinkage and (b) Optimum sink mark

Quantifying and Measuring Shrinkage and Sink Marks Shrinkage in the study is quantified and measured using SolidWorks Plastics, a simulation tool that predicts the behavior of plastics during the injection molding process. The shrinkage rate is determined by comparing the dimensions of the part in its molten state with its final dimensions after cooling. This comparison is made using precise measurements obtained from the simulation results, which account for the material properties, mold design, and process parameters.

Sink marks are also quantified using SolidWorks Plastics. The tool simulates the cooling and solidification process to predict areas where sink marks are likely to occur. The depth and distribution of sink marks are measured using the software's analysis features, which provide detailed surface topology data. This information helps in identifying and quantifying the severity of sink marks on the molded part.

By expanding the scope of the study to include these additional defects, a more comprehensive understanding of the factors influencing injection molding quality can be achieved. Future research could employ similar multi-objective optimization techniques to address these issues, further improving the overall quality of molded components.

3-1- Artificial Neural Network with Genetic Algorithm

The Artificial Neural Network (ANN) emerges as a powerful modeling tool, showcasing a unique capability to learn and produce functions by training data. ANNs create relations between input and output variables through the use of specific transfer functions. Comprising neurons, these small, interconnected processors communicate through weighted linkages, enabling the transmission of messages between them. In a sequence of training operations, biases and weights are adjusted to refine the network's performance [32, 33]. The backpropagation learning algorithm, a widely employed technique in engineering applications, was selected for this study, with the Levenberg–Marquardt variant chosen for training. The ANN modeling process involves two crucial phases: training and testing. During training, the network learns from a dataset, adjusting connection weights to minimize errors when comparing generated outputs with training patterns. The network iterates through the dataset until errors fall within acceptable tolerance levels [34]. The general step of ANN is given as below:

1. Data Collection and Preprocessing

- Gather and clean data.
- Normalize the data to a standard range.

2. Define the Neural Network Architecture

- Specify input neurons matching the features.
- Determine the number of hidden layers and neurons.
- Define output neurons based on the task.

3. Initialize Weights and Biases

- Randomly initialize weights and biases.

4. Choose Activation Functions

- Select activation functions for each layer (e.g., sigmoid, tanh, ReLU).

5. Forward Propagation

- Compute weighted sums and apply activation functions layer by layer to generate predictions.

6. Compute the Loss Function

- Calculate the error by comparing predictions with actual targets using a suitable loss function.

7. Backpropagation

- Calculate gradients of the loss with respect to weights and biases.
- Update weights and biases using gradient descent.

8. Training the Network

- Iterate forward propagation, loss computation, and backpropagation for multiple epochs.
- Use a validation dataset to monitor performance and avoid overfitting.

9. Model Evaluation

- Evaluate the trained model on a test dataset using relevant metrics.

10. Hyperparameter Tuning

- Optimize the model's performance by experimenting with different hyperparameters (e.g., learning rate, batch size).

11. Deployment and Inference

- Deploy the trained model for real-world data predictions.
- Continuously monitor and update the model as needed.

This framework outlines the key steps for developing, training, and deploying an Artificial Neural Network (ANN).

The Artificial Neural Network (ANN) used for validation was configured with the following considerations:

- ***Architecture***: The network typically included an input layer, one or more hidden layers, and an output layer. The number of neurons in each layer and the number of hidden layers were chosen based on the complexity of the data and the problem.

- ***Training Process***: The ANN was trained using a dataset divided into training, validation, and testing sets. Training involved adjusting weights and biases through backpropagation and optimization algorithms such as gradient descent. The network was evaluated based on performance metrics like accuracy, loss, or mean squared error.

- ***Factors Considered***:

- Network Depth: More layers can capture complex patterns but may require more data and computation.
- Number of Neurons: Sufficient neurons were included to balance model capacity and overfitting.
- Activation Functions: Functions like ReLU or sigmoid were selected based on the type of problem.
- Learning Rate: Tuned to ensure stable and effective training.
- Regularization Techniques: Applied to prevent overfitting and enhance generalization, such as dropout or weight decay.

The ANN in this study utilized five inputs which are pressure-holding time, cooling time, filling time, mold temperature and melt temperature. ANN model is used to predict a combined value for three outputs (moldability index, shrinkage rate and sink mark). In the ANN model, combined objective output is the summation of moldability index with 20% importance, shrinkage rate 50% importance and sink mark 30% importance respectively. Therefore, the objective output was a combination of those parameters with mentioned importance percentages.

Utilizing the backpropagation (BP) training technique, the neural network was constructed with an optimal configuration of layers and neurons to minimize error. Figure 8 illustrates the resulting neural network model. It shows that five input parameters were used with ten hidden layers. There is one combined objective output (the summation of 20% of moldability index, 50% of shrinkage rate and 30% of sink mark) in the model as shown in Figure 8.

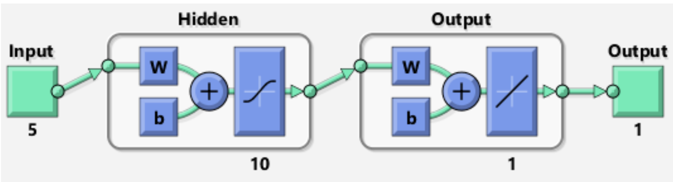


Figure 8. Neural Network. illustrating input, layer and output numbers

For the constructed ANN model, the regression analysis of the model was obtained and is depicted in Figure 9. It shows that all regression values are above 93%. Error histogram was also obtained, and it is given in Figure 10. Errors are the differences between targets and outputs.

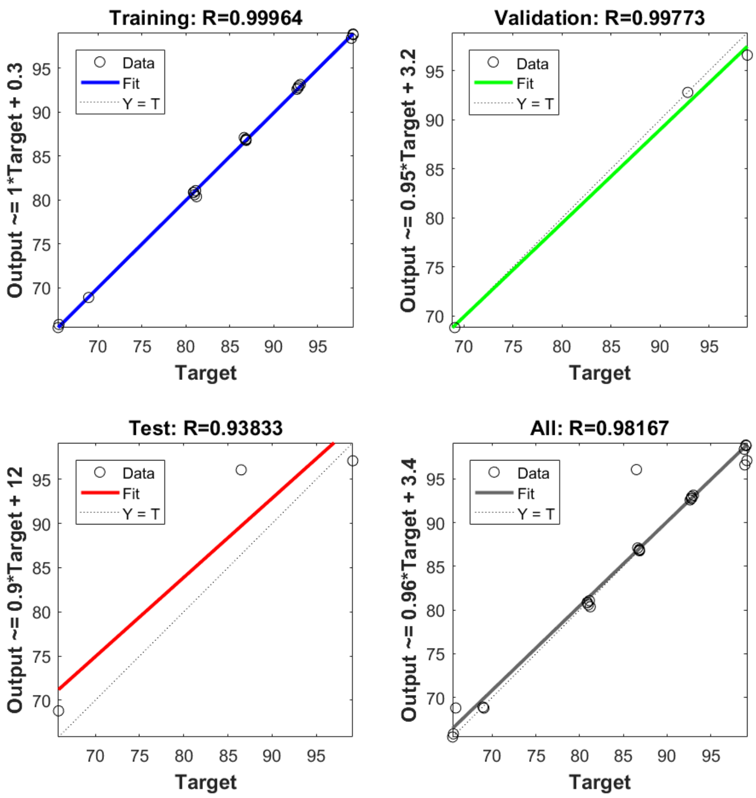


Figure 9. Regression of the ANN model

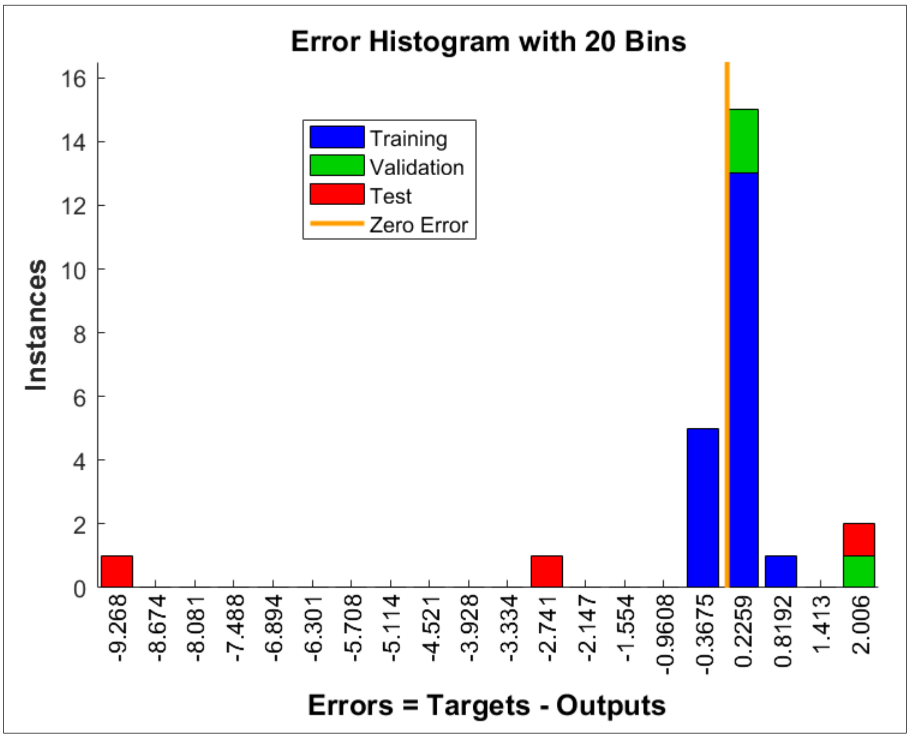


Figure 10. **Error Histogram**

After deriving the Artificial Neural Network (ANN) model, it was integrated with an algorithm of optimization within the computer program. In this investigation, the Genetic Algorithm (GA) method, commonly recognized in the field of evolutionary computations, was employed. Generally, GAs strives to construct numerical models that mirror natural evolution process, aiming to create a model capable of evolving towards the best possible solution for a specific problem. Holland [35] was the pioneer to introduce the idea of employing evolutionary principles in addressing optimization problems.

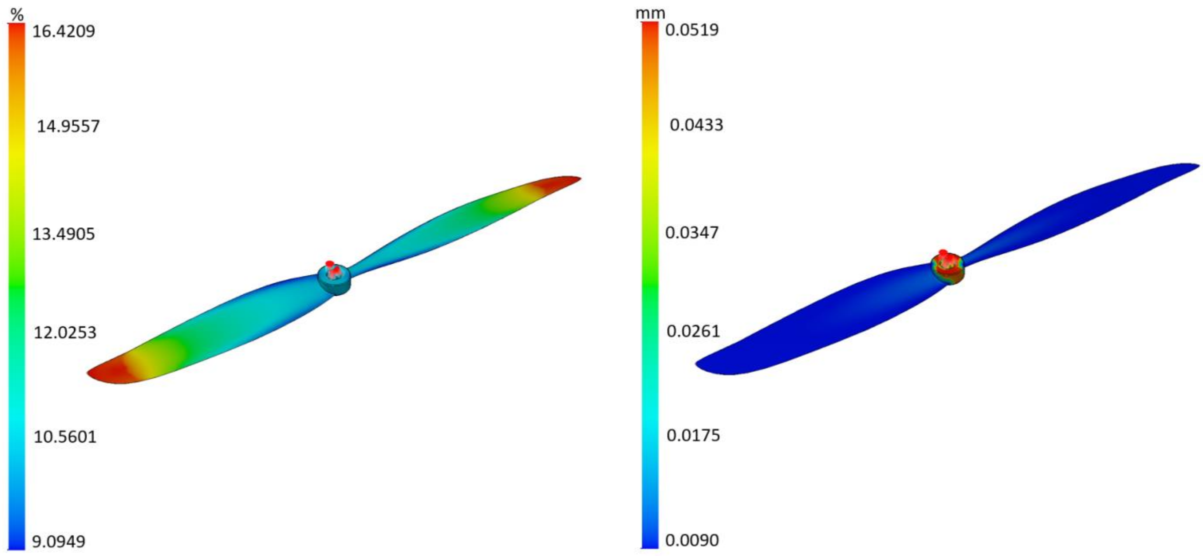
Genetic algorithms (GAs) stand out as a prominent example, mimicking the evolutionary process of chromosomes in live organisms. GAs aims to quest for the best possible value that the function can achieve across its entire domain. GA introduces the principles of automatic calculation steps and model-based optimization to imitate evolutionary characteristics.

GA can operate on strings of codes, functions, and numbers, making it more adept at solving complex problems [36]. The GA calculations involve several steps:

1. An initial population is generated by randomly selecting genomes with different lengths.
2. Each genome undergoes the estimation of a fitness function.
3. The genomes in the initial population are organized in accordance with their fitness functions.
4. Selection of the subsequent generation's genome is performed based on achieving the specified target objective function prescribed value.
5. The calculation of the new generation involves utilizing the chosen genomes and the likelihoods associated with the GA.
6. Termination criteria are assessed, with unsatisfied conditions prompting a return to step 2, and fulfilled criteria enabling the assessment of subsequent iterations.

As a GA model parameter, an initial population of 300 was chosen similar to Goldberg's research [37], establishing a population at the start up for typical optimization studies [38]. Cross-over probability was set at 0.85 and mutation probability was 0.05 which can be considered as typical values. The algorithm was executed for 100-150 generations, a duration deemed sufficient for addressing these types of problems. Upon the successful convergence of the optimization process, the optimal configuration for the input parameters was determined.

Subsequently, the validation of simulation outcomes through Fuzzy TOPSIS and Taguchi is essential, employing Artificial Neural Network (ANN) to ascertain the margin of error between these distinct optimization methodologies. The outcomes obtained through the ANN approach for the minimum shrinkage and sink mark are delineated as follows as shown in Figure 11:



(a) **(b)**

Figure 11. (a) Optimum shrinkage and (b) Optimum sink mark based on ANN optimization method

Therefore, the optimal settings for individual parameters using the ANN method are as follows: melt temperature set at level 1, mold temperature at level 5, filling time at level 1, pressure holding time at level 1, and pure cooling time at level 1.

In previous study by Moayyedian et al. [39] process parameters in the injection molding of polypropylene parts were optimized, aiming to minimize defects such as short shot, shrinkage, and warpage using Artificial Neural Network (ANN) and Taguchi techniques. Both studies demonstrate effective optimization of the injection molding process using advanced techniques. The present study provides a more focused approach on specific defects in aviation propeller manufacturing, employing a combination of FAHP, fuzzy-TOPSIS, and ANN to achieve highly precise results. The previous study, while broader in scope, effectively identifies optimal parameters for minimizing multiple defects in plastic parts. The methodologies and results of both studies highlight the importance of advanced optimization techniques in improving the quality and efficiency of injection-molded products.

In conclusion, it is crucial to ascertain the margin of error between two discrete optimization methodologies. Utilizing Equation 9, as presented below, the margin of error for shrinkage is calculated to be 0.42%, and for the sink mark, it is 0.58%, both of which are negligible. Consequently, it is evident that the amalgamation of Fuzzy TOPSIS with Taguchi and ANN stands as an acceptable combination for optimizing the injection molding process.

$$\text{Margin of Error}=\left\|\text{Value 1}/\text{Value 1}-\text{Value 2}\right\|\times 100\% \tag{9}$$

4- Conclusions

The integration of Taguchi and FAHP with TOPSIS proposes an effective method for evaluating diverse objectives and identifying the optimal alternative with the best moldability index in injection molding for specific parts. Taguchi methodology examines two common defects as criteria for assessing moldability across five process parameters at three levels each. A fuzzy evaluation, defining five levels, assesses the severity of each defect, with initial weight allocation determined via the analytic hierarchy process (AHP). The L25 orthogonal array of the Taguchi method assesses various alternatives for quality evaluation, while the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is used to rank the 25 experimental setups. Numerical analysis, considering two distinct plastic defects, is conducted for these trials, with precision ensured through Finite Element Analysis (FEA). Validation of simulation results is carried out using Artificial Neural Network (ANN). Based on various optimization methods and simulation outcomes:

- The moldability index obtained from both methods is highly similar, indicating the robustness of the approach.
- Minimum shrinkage and sink mark values were found to be 16.37% and 0.066mm, respectively, in the Fuzzy-TOPSIS and Taguchi methods, and 16.42% and 0.0519mm in the ANN method, with negligible margin of error.
- While the proposed approach addresses quality evaluation comprehensively, its scope is limited to selected objectives. Future research could expand on critical criteria and parameters in injection molding for more comprehensive guidelines.

5- Declarations

5-1- Author Contributions

Conceptualization, M.M.; methodology, M.M., A.D., and M.H.D.; software, M.M., A.D., and M.H.D.; validation, A.D.; formal analysis, M.M., A.D., and M.H.D.; investigation, M.M., M.H.D., M.A., and A.A.; resources, M.M., M.H.D., M.A., A.S., and A.A.; data curation, M.M., A.D., and M.H.D.; writing—original draft preparation, M.M., A.D., and M.H.D.; writing—review and editing, M.A., A.S., and A.A.; visualization, M.A., A.S., and A.A.; supervision, M.M., A.D., and M.A.; project administration, M.M. and A.A.; funding acquisition, M.A., A.S., and A.A. All authors have read and agreed to the published version of the manuscript.

5-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

5-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

5-4- Institutional Review Board Statement

Not applicable.

5-5- Informed Consent Statement

Not applicable.

5-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

6- References

[1] Min, B. H. (2003). A study on quality monitoring of injection-molded parts. Journal of Materials Processing Technology, 136(1–3), 1–6. doi:10.1016/S0924-0136(02)00445-4.

[2] Tang, S. H., Kong, Y. M., Sapuan, S. M., Samin, R., & Sulaiman, S. (2006). Design and thermal analysis of plastic injection mould. Journal of Materials Processing Technology, 171(2), 259-267. doi:10.1016/j.jmatprotec.2005.06.075.

[3] Crawford, R. J. (1987). Rubber and plastic engineering design and application. Mechanical Engineering Pubns Ltd., London, United States.

[4] Cutkosky, M. R., & Tenenbaum, J. M. (1987). CAD/CAM Integration through Concurrent Process and Product Design. American Society of Mechanical Engineers, Production Engineering Division (Publication) PED, 25, 1–10.

[5] Hassan, H., Regnier, N., Le Bot, C., & Defaye, G. (2010). 3D study of cooling system effect on the heat transfer during polymer injection molding. International Journal of Thermal Sciences, 49(1), 161–169. doi:10.1016/j.ijthermalsci.2009.07.006.

[6] Gu, Y., Li, H., & Shen, C. (2001). Numerical simulation of thermally induced stress and warpage in injection-molded thermoplastics. Advances in Polymer Technology, 20(1), 14–21. doi:10.1002/1098-2329(200121)20:1<14::AID-ADV1001>3.0.CO;2-S.

[7] Liu, S. J. (1996). Modeling and simulation of thermally induced stress and warpage in injection molded thermoplastics. Polymer Engineering & Science, 36(6), 807-818. doi:10.1002/pen.10468.

[8] Amer, Y., Moayyedian, M., Hajiabolhasani, Z., & Moayyedian, L. (2012). Reducing warpage in injection moulding processes using taguchi method approach: ANOVA. Proceedings of the IASTED International Conference on Engineering and Applied Science, EAS 2012, 227–233. doi:10.2316/P.2012.785-089.

[9] Jacques, M. S. (1982). An analysis of thermal warpage in injection molded flat parts due to unbalanced cooling. Polymer Engineering & Science, 22(4), 241–247. doi:10.1002/pen.760220405.

[10] Leo, V., & Cuvelliez, C. (1996). The effect of the packing parameters, gate geometry, and mold elasticity on the final dimensions of a molded part. Polymer Engineering and Science, 36(15), 1961–1971. doi:10.1002/pen.10592.

[11] Tarng, Y. S., & Yang, W. H. (1998). Application of the Taguchi method to the optimization of the submerged arc welding process. Materials and Manufacturing Processes, 13(3), 455–467. doi:10.1080/10426919808935262.

[12] Connor, A. M. (1999). Parameter sizing for fluid power circuits using Taguchi methods. Journal of Engineering Design, 10(4), 377–390. doi:10.1080/095448299261263.

[13] Liu, S. J., & Chang, C. Y. (2003). The influence of processing parameters on thin-wall gas assisted injection molding of thermoplastic materials. Journal of Reinforced Plastics and Composites, 22(8), 711–731. doi:10.1177/0731684403022008003.

[14] Lin, C. L. (2004). Use of the Taguchi method and grey relational analysis to optimize turning operations with multiple performance characteristics. Materials and Manufacturing Processes, 19(2), 209–220. doi:10.1081/AMP-120029852.

[15] Moayyedian, M., Qazani, M. R. C., & Pourmostaghimi, V. (2023). Optimized injection-molding process for thin-walled polypropylene part using genetic programming and interior point solver. International Journal of Advanced Manufacturing Technology, 124(1–2), 297–313. doi:10.1007/s00170-022-10551-2.

[16] He, W., Zhang, Y. F., Lee, K. S., Fuh, J. Y. H., & Nee, A. Y. C. (1998). Automated process parameter resetting for injection moulding: A fuzzy-neuro approach. Journal of Intelligent Manufacturing, 9(1), 17–27. doi:10.1023/A:1008843207417.

[17] Chen, M. Y., Tzeng, H. W., Chen, Y. C., & Chen, S. C. (2008). The application of fuzzy theory for the control of weld line positions in injection-molded part. ISA Transactions, 47(1), 119–126. doi:10.1016/j.isatra.2007.07.001.

[18] Moayyedian, M., Derakhshandeh, J. F., & Lee, S. H. (2019). Optimization of strain measurement procedure based on fuzzy quality evaluation and Taguchi experimental design. SN Applied Sciences, 1(11), 150–160. doi:10.1007/s42452-019-1428-x.

[19] Usman Jan, Q. M., Habib, T., Noor, S., Abas, M., Azim, S., & Yaseen, Q. M. (2020). Multi response optimization of injection moulding process parameters of polystyrene and polypropylene to minimize surface roughness and shrinkage's using integrated approach of S/N ratio and composite desirability function. Cogent Engineering, 7(1), 1781424. doi:10.1080/23311916.2020.1781424.

[20] Zhao, N. yang, Lian, J. yuan, Wang, P. fei, & Xu, Z. bin. (2022). Recent progress in minimizing the warpage and shrinkage deformations by the optimization of process parameters in plastic injection molding: a review. International Journal of Advanced Manufacturing Technology, 120(1–2), 85–101. doi:10.1007/s00170-022-08859-0.

[21] Guerra, N. B., Reis, T. M., Scopel, T., de Lima, M. S., Figueroa, C. A., & Michels, A. F. (2023). Influence of process parameters and post-molding condition on shrinkage and warpage of injection-molded plastic parts with complex geometry. International Journal of Advanced Manufacturing Technology, 128(1–2), 479–490. doi:10.1007/s00170-023-11782-7.

[22] Fonseca, J. H., Jang, W., Han, D., Kim, N., & Lee, H. (2024). Strength and manufacturability enhancement of a composite automotive component via an integrated finite element/artificial neural network multi-objective optimization approach. Composite Structures, 327, 117694. doi:10.1016/j.compstruct.2023.117694.

[23] Panchal, A., & Sheth, S. (2023). Optimization for Injection Molding Process Parameters Using Artificial Neural Network: A Critical Review. AIP Conference Proceedings, 2855(1), 090009. doi:10.1063/5.0168228.

[24] Kengpol, A., & Tabkosai, P. (2024). Design of hybrid deep learning using TSA with ANN for cost evaluation in the plastic injection industry. Frontiers in Mechanical Engineering, 10, 1336828. doi:10.3389/fmech.2024.1336828.

[25] EL Ghadoui, M., Mouchtachi, A., & Majdoul, R. (2023). A hybrid optimization approach for intelligent manufacturing in plastic injection molding by using artificial neural network and genetic algorithm. Scientific Reports, 13(1), 48679. doi:10.1038/s41598-023-48679-0.

[26] Hermann, T., Niedziela, D., Salimova, D., & Schweiger, T. (2024). Predicting the fiber orientation of injection molded components and the geometry influence with neural networks. Journal of Composite Materials, 58(15), 1801–1811. doi:10.1177/00219983241248216.

[27] Ez-Zahraouy, O., & Kamach, O. (2024). Quality Prediction in Injection Molding Using Machine Learning Methods. IEEE 15th International Colloquium of Logistics and Supply Chain Management, LOGISTIQUA 2024, 1–6. doi:10.1109/LOGISTIQUA61063.2024.10571516.

[28] Seifert, L., Lockner, Y., & Hopmann, C. (2024). Investigations on the applicability of invertible neural networks (INN) in the injection moulding process. AIP Conference Proceedings, 3012(1), 020001. doi:10.1063/5.0193494.

[29] Volke, J., & Heim, H. P. (2023). Evaluation of the injection molding process behavior during start-up and after parameter changes using dynamic time warping correspondences. Journal of Manufacturing Processes, 95, 183-203. doi:10.1016/j.jmapro.2023.03.076.

[30] Cheng, J., Feng, Y., Tan, J., & Wei, W. (2008). Optimization of injection mold based on fuzzy moldability evaluation. Journal of Materials Processing Technology, 208(1–3), 222–228. doi:10.1016/j.jmatprotec.2007.12.114.

[31] Goodship, V. (2004). Troubleshooting Injection Moulding. Smithers Rapra Technology, Shrewsbury, Shropshire, United Kingdom.

[32] Chow, T. T., Zhang, G. Q., Lin, Z., & Song, C. L. (2002). Global optimization of absorption chiller system by genetic algorithm and neural network. Energy and Buildings, 34(1), 103–109. doi:10.1016/S0378-7788(01)00085-8.

[33] Abidoye, L. K., & Das, D. B. (2015). Artificial neural network modeling of scale-dependent dynamic capillary pressure effects in two-phase flow in porous media. Journal of Hydroinformatics, 17(3), 446–461. doi:10.2166/hydro.2014.079.

[34] Kalogirou, S. A. (1999). Applications of artificial neural networks in energy systems. A review. Energy Conversion and Management, 40(10), 1073–1087. doi:10.1016/S0196-8904(99)00012-6.

[35] Holland, J. H. (1992). Adaptation in natural and artificial systems : an introductory analysis with applications to biology, control, and artificial intelligence. The University of Michigan Press, Michigan, United States.

[36] Dinc, A., & Mamedov, A. (2022). Optimization of surface quality and machining time in micro-milling of glass. Aircraft Engineering and Aerospace Technology, 94(5), 676–686. doi:10.1108/AEAT-06-2021-0187.

[37] Goldberg, D. E. (1989). Sizing Populations for Serial and Parallel Genetic Algorithms. In Proceedings of the Third International Conference on Genetic Algorithms. Proceedings of 3rd International Conference on Genetic Algorithms, 70-79. doi:10.5555/645512.657266.

[38] Dinc, A., & Otkur, M. (2020). Emissions prediction of an aero-piston gasoline engine during surveillance flight of an unmanned aerial vehicle. Aircraft Engineering and Aerospace Technology, 93(3), 462–472. doi:10.1108/AEAT-09-2020-0196.

[39] Moayyedian, M., Dinc, A., & Mamedov, A. (2021). Optimization of injection-molding process for thin-walled polypropylene part using artificial neural network and Taguchi techniques. Polymers, 13(23), 4158. doi:10.3390/polym13234158.