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Simulation-Based Optimization of Injection Molding Process Parameters for Minimizing Warpage by ANN and GA

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Abstract. Plastic injection molding is one of the most used methods for producing plastic products because it can be produced at a high production rate, low cost, and ease in manufacturing. However, one defect that affects product quality is namely warpage. To reduce plastic product warpage, the injection molding process is required optimal process control to increase plastic product quality. The objective of this paper is to optimize injection molding process parameters for minimizing the warpage of plastic glass. The optimization process is divided into two phases. The Finite Element Method (FEM) was employed in the first phase to simulate 32 experiments under various parameters. The parameters of this process consist of melt temperature ranging from 180 to 230 °C, mold temperature in the range of 20 – 45 °C, filling time from 0.82 to 0.92 s, packing time ranging from 5.88 to 7 s and cooling time of 14 to 18 s. In the second phase, Artificial Neural Network (ANN) combined Genetic Algorithm (GA) was developed to predict the warpage and solve the optimization process to find optimal parameters. Combining the intelligent method shows that ANN and GA effectively find the optimal process parameters that can reduce the warpage of the product by 35.73% from the maximum value.

Keywords: Artificial Neural Network (ANN); Finite Element Method (FEM); Genetic Algorithm (GA); Optimization; Plastic injection molding

1. Introduction

Plastic injection molding is the most popular process for producing plastic packaging, medical equipment, automotive parts, and electronics. In the plastic injection molding process, the plastic pellets are melted at high temperatures by a heater of the injection machine. Subsequently, melted plastic is injected into the mold cavity and core with specific injection pressure and packed by packing pressure. Finally, the melted plastic is cooled down to transform into a plastic product (Kitayama *et al.*, 2020; Cheng and Liu, 2018; Hasnan *et al.*, 2017). However, the process parameters, such as the melt temperature of the plastic, injection pressure, packing pressure, packing time, and cooling time, affect the resulting product's properties. The properties of plastic products from the injection molding process are required a high strength-to-weight ratio and durability. Controlling the process parameters is necessary for obtaining the best plastic product property.

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Traditionally, the conventional practice of determining injection molding process parameters is adjusted through trial and error by experienced engineers (Guo *et al.*, 2019). However, this method cannot precisely determine the optimal process parameters, resulting in time-consuming, repetitive testing and easy occurring defect. The most common type of defect that occurs in the plastic injection molding process is called warpage which affects the quality of the product (Huang *et al.*, 2021; Gao and Wang, 2008; Kurtaran and Erzurumlu, 2006; Hakimian and Sulong, 2012). The warpage of the product continues occurring because several related process parameters and independent process parameters intervene with the plastic injection molding process.

Computer-aided engineering (CAE) was a technology for numerical simulation of the plastic injection molding process (Hentati *et al.*, 2019). The advantage of CAE was less cost and faster experimenting virtually. Additionally, CAE serves as a tool for predicting the behavior of defects that may impact the product's quality, as well as for the validation and optimization of the product's design. At present, the intelligent method is widely used in combination with CAE to optimize the plastic injection molding process for reducing defects such as artificial neural networks, genetic algorithms, support vector machine, Etc (Zhao *et al.*, 2020).

Several studies have investigated the optimization of the injection molding process by different techniques. Shi, Xie, and Wang (2013) optimized plastic injection process parameters to reduce warpage by using the Kriging surrogate model. Erzurumlu and Ozcelik (2006) minimized warpage and sink marks of plastic parts under different design rib cross-section types and rib layout angles by using Taguchi optimization. Oliaei *et al.* (2016) optimized plastic injection process parameters by Taguchi's orthogonal array, and ANN was selected as the optimal parameter. Zhang *et al.* (2016) presented particle swarm optimization on the oil cooler cover cooling and a cooling channel to reduce warpage. Zhou, Turng, and Kramschuster (2006) used SVR and GA to optimize the process parameters. Dang (2014) used direct and metamodel-based methods as optimization injection molding process parameters. Farshi, Gheshmi, and Miandoabchi (2011) presented the Evolutionary Operation (EVOP) method used to minimize the warpage and shrinkage defects of plastic parts. Lockner and Hopmann (2021) used network-based transfer learning to reduce data of artificial neural network training for optimizing injection machine parameters.

The objective of this paper is to find the optimal injection molding process parameters for reducing warpage by determining the injection molding process parameters of plastic glass. we conducted experiments using a simulation method to assess warpage under various process parameters, including melt temperature, mold temperature, filling time, packing time, and cooling time. To further refine our results, we used artificial neural networks (ANN) to predict warpage based on simulation data and developed a Fitness Function Equation. Finally, we utilized the GA method to identify the optimal injection molding process parameters that will reduce warpage in plastic glass.

2. Methods

2.1. Sample Part

In this experiment, the part is a plastic glass used for an experimental simulation. The dimensions have a diameter of 97 mm, height of 70 mm, and thickness of 2 mm. Plastic glass is made of polystyrene (PS), which is widely used in consumer goods and commercial packaging. The general view of the part is presented in (Figure 1).

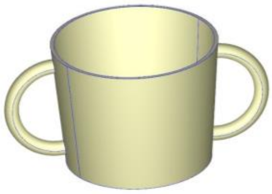


Figure 1 Plastic Glass

2.2. Experiment

The Finite Element Method (FEM) was developed to simulate the behavior of plastic material (Hashash, Jung, and Ghaboussi, 2004; Hung, Chen, and Lin, 2002). In addition, the FEM capability can help improve the defects that may occur before actual production (Irsyad *et al.*, 2020). A MOLDEX 3D software was used to simulate the plastic injection molding process to determine the defect of the sample part. This software uses the Finite Element Method to analyze the plastic behavior of the injection molding process by a mathematical function. In this simulation, various parameters are adjusted to determine the minimum warpage value.

The experiment simulation was created by the design of the experiment (DOE) method with 32 experiments. The process parameters of injection molding experiments consist of the melt temperature, mold temperature, filling time, packing time, and cooling time were chosen as input parameters as shown in Table 1.

Table 1 Process parameters

Process parameters	Level	
	Low	High
Melt temperature (degree)	180	230
Mold Temperature (degree)	20	45
Filling Time (mm/s)	0.82	0.94
Packing Time (s)	5.88	7
Cooling Time (s)	14	18

2.3. Warpage

The warpage is a distortion of the dimension part on 3 axes consisting of x, y, and z from the actual dimension of the part. Adjusting suitable injection molding process parameters is essential to decrease the warpage of parts, which is the main purpose of this paper. The warpage was measured as the total displacements on 3 axes of the product. An equation for the warpage is (Mukras, Omar, and al-Mufadi, 2019):

$$TW_{sum} = \Sigma\, y_{max}{}^{i} \qquad (1)$$
$$i = 1, 2, 3$$

where $y_{max}{}^{i}$ is the displacement on one axis of the product.

3. Results and Discussion

This paper consists of two phases: First, a simulation of injection molding process experiments. It has 32 experiments under different parameter setting values to determine the warpage value. Second, ANN has conducted predicted warpage from the simulation result of the experiment. The result from predicting the warpage value of ANN has created a mathematical model by coefficient value for fitness function of GA. Optimization by the GA method was performed to find the optimal injection molding parameter using a mathematical model from the ANN method, which results in the lowest warpage. (Figure 2) shows the process of this paper.

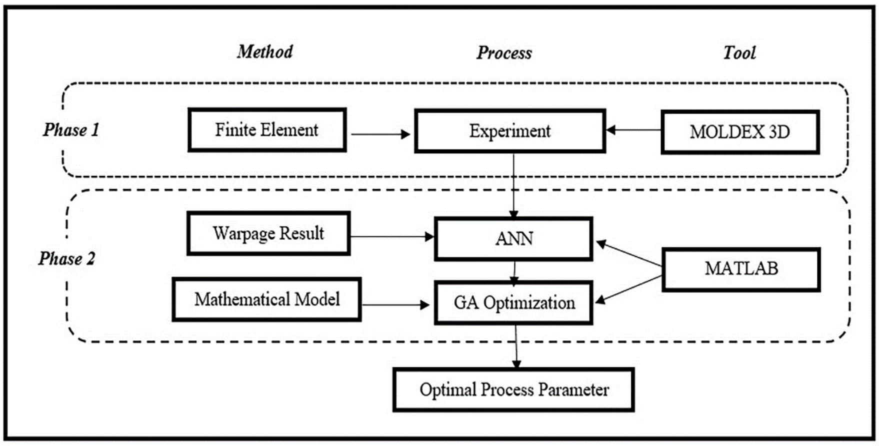


Figure 2 Process of paper

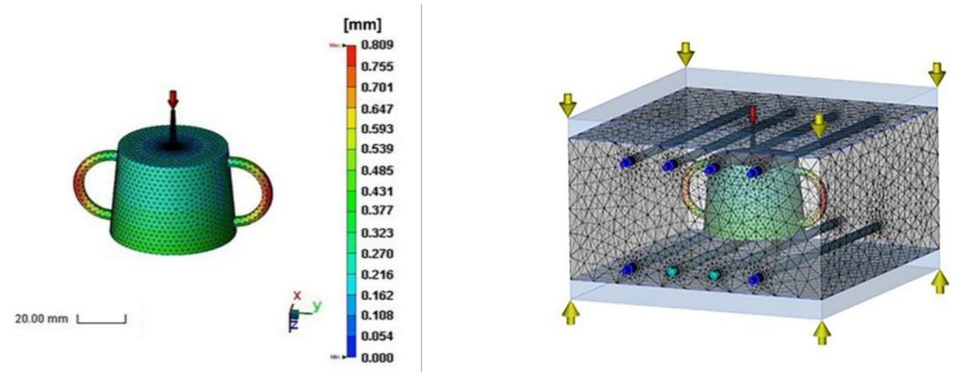
3.1. Simulation

Moldex3D software was used in this experiment to simulate the injection molding process (Sun *et al.*, 2021; Quintana and Frontini, 2020; Tseng, Chang, and Hsu, 2017) with 32 experiments in order to find out the warpage value. Table 2 shows results gained from the simulation, and mold base for analysis were used for the ANN method. (Figure 3) depicts the maximum warpage result that occurs on the red color area of the example plastic glass in experiment No. 1, which is 0.809 mm after the experiment simulation was conducted, and the mold base for analysis has 8 cooling channels used to heat transfer.

Table 2 Results of experiments simulation

No.	Melt Temperature	Mold Temperature	Filling Time	Packing Time	Cooling Time	Warpage
1	180	20	0.82	5.88	14	0.809
2	230	20	0.82	5.88	14	1.119
3	180	45	0.82	5.88	14	0.848
4	230	45	0.82	5.88	14	1.205
5	180	20	0.94	5.88	14	0.823
6	230	20	0.94	5.88	14	1.122
7	180	45	0.94	5.88	14	0.854
8	230	45	0.94	5.88	14	1.198
9	180	20	0.82	7	14	0.801
10	230	20	0.82	7	14	1.09
11	180	45	0.82	7	14	0.842
12	230	45	0.82	7	14	1.154
13	180	20	0.94	7	14	0.828
14	230	20	0.94	7	14	1.124
15	180	45	0.94	7	14	0.84
16	230	45	0.94	7	14	1.165
17	180	20	0.82	5.88	18	0.8
18	230	20	0.82	5.88	18	1.096
19	180	45	0.82	5.88	18	0.843
20	230	45	0.82	5.88	18	1.176
21	180	20	0.94	5.88	18	0.815
22	230	20	0.94	5.88	18	1.09

No.	Melt Temperature	Mold Temperature	Filling Time	Packing Time	Cooling Time	Warpage
23	180	45	0.94	5.88	18	0.845
24	230	45	0.94	5.88	18	1.162
25	180	20	0.82	7	18	0.795
26	230	20	0.82	7	18	1.076
27	180	45	0.82	7	18	0.834
28	230	45	0.82	7	18	1.115
29	180	20	0.94	7	18	0.812
30	230	20	0.94	7	18	1.097
31	180	45	0.94	7	18	0.835
32	230	45	0.94	7	18	1.129



(a) (b)

Figure 3 Simulation Analysis: (a) Warpage; and (b) Mold base

3.2. Artificial Neural Network (ANN)

ANN is widely used in engineering because ANN ability can analyze information by detecting data patterns and relationships through learning. It is easier to analyze and improve engineering processes (Hemmati *et al.*, 2020; Alas and Ali, 2019; Rafiq, Bugmann, and Easterbrook, 2001).

This section uses the ANN to predict the warpage results from the experiment simulation by MATLAB software. The experimental parameters are an input of ANN, consisting of melt temperature, mold temperature, filling time, packing time, and cooling time. During the network training, the weight (w) of the network is calculated by minimizing the error value between the predicted warpage value, which is called the output of ANN, and the actual warpage value (Chen *et al.*, 2008; Lee and Lin, 2006; Sadeghi, 2000). (Figure 4) shows the ANN model consists of five inputs, the transfer function is sigmoid, ten hidden layers, and one output. A Backpropagation network (BPN) has been adopted because it has the ability of fast responsiveness and high accuracy (Asmael *et al.*, 2022).

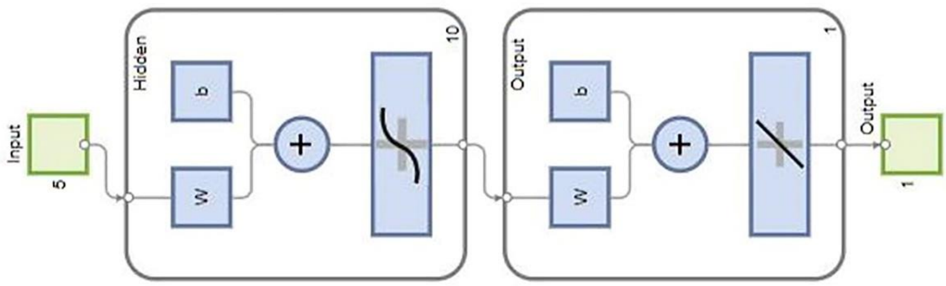


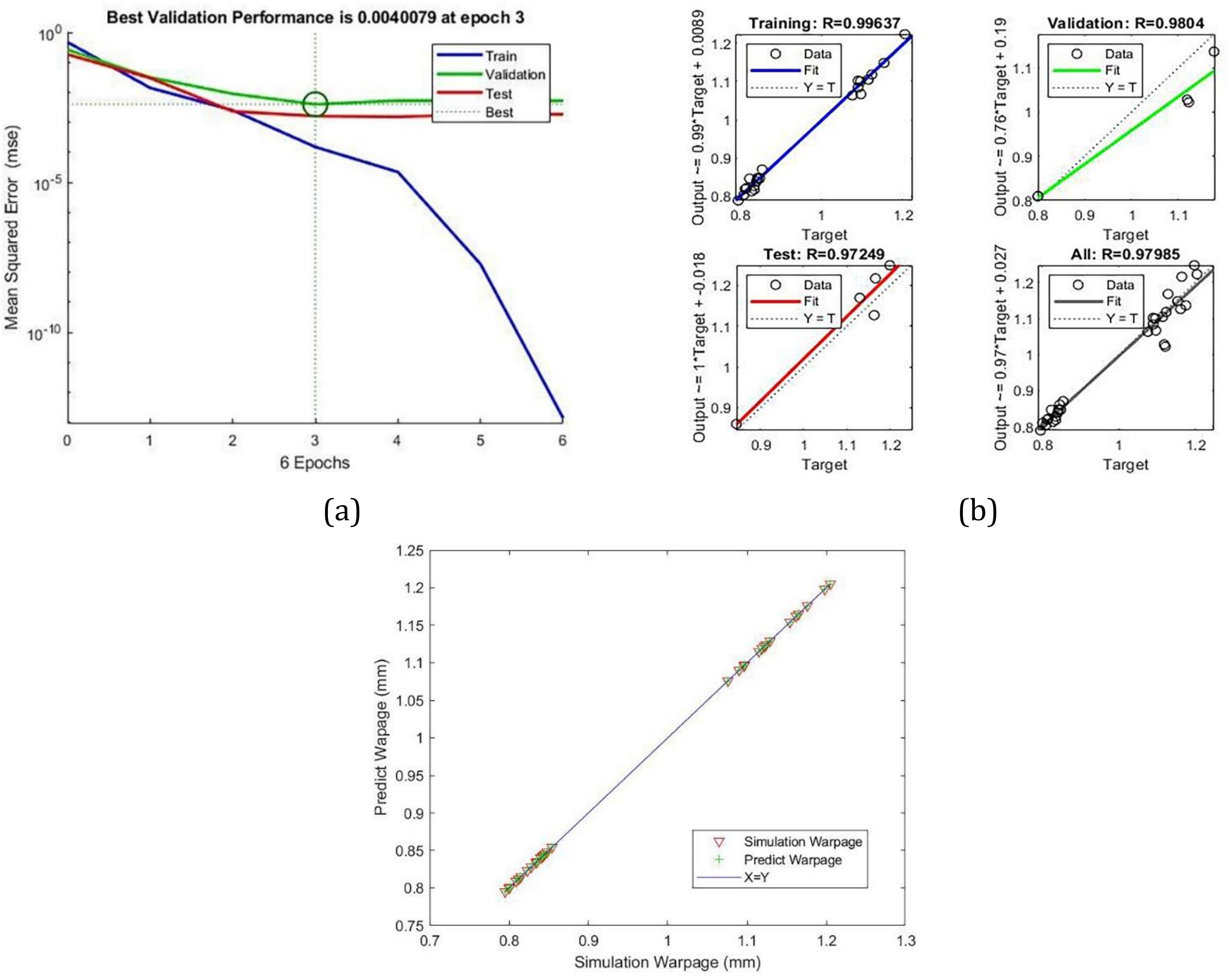
Figure 4 ANN Model

Using the warpage results obtained by the simulation experiment to predict by ANN, Table 3 shows the resulting warpage of ANN compared with the finite element method analysis of the experiment.

Table 3 Results of ANN prediction

No.	Melt Temperature	Mold Temperature	Filling Time	Packing Time	Cooling Time	Warpage	ANN Warpage
1	180	20	0.82	5.88	14	0.809	0.804
2	230	20	0.82	5.88	14	1.119	1.028
3	180	45	0.82	5.88	14	0.848	0.847
4	230	45	0.82	5.88	14	1.205	1.223
5	180	20	0.94	5.88	14	0.823	0.846
6	230	20	0.94	5.88	14	1.122	1.022
7	180	45	0.94	5.88	14	0.854	0.87
8	230	45	0.94	5.88	14	1.198	1.248
9	180	20	0.82	7	14	0.801	0.81
10	230	20	0.82	7	14	1.09	1.102
11	180	45	0.82	7	14	0.842	0.847
12	230	45	0.82	7	14	1.154	1.148
13	180	20	0.94	7	14	0.828	0.813
14	230	20	0.94	7	14	1.124	1.118
15	180	45	0.94	7	14	0.84	0.838
16	230	45	0.94	7	14	1.165	1.216
17	180	20	0.82	5.88	18	0.8	0.809
18	230	20	0.82	5.88	18	1.096	1.1
19	180	45	0.82	5.88	18	0.843	0.846
20	230	45	0.82	5.88	18	1.176	1.137
21	180	20	0.94	5.88	18	0.815	0.821
22	230	20	0.94	5.88	18	1.09	1.084
23	180	45	0.94	5.88	18	0.845	0.86
24	230	45	0.94	5.88	18	1.162	1.126
25	180	20	0.82	7	18	0.795	0.789
26	230	20	0.82	7	18	1.076	1.063
27	180	45	0.82	7	18	0.834	0.827
28	230	45	0.82	7	18	1.115	1.105
29	180	20	0.94	7	18	0.812	0.819
30	230	20	0.94	7	18	1.097	1.066
31	180	45	0.94	7	18	0.835	0.818
32	230	45	0.94	7	18	1.129	1.168

The results showed that the mean square error (MSE) of validation is 0.004, and the overall R-square value is 0.97985. The mean square error (MSE) of ANN has a value of close to 0, and the R-square is near 1. The average prediction error % of the ANN model was 1.97%. It clearly shows that the ANN has a high performance in predicting the result of the warpage as shown in (Figure 5).



(a) (b)

(c)

Figure 5 ANN Model performance: (a) Validation; (b) Overall data; and (c) Cross plot data

In this section, MATLAB software was used to analyze coefficients of the multiple linear regression equation for the objective function of GA. To create the mathematical model, a multiple linear regression equation was established to show the relationship of the injection molding processing parameters on the warpage by Equation 2 (Ozcelik and Sonat, 2009).

$$y_i = \beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_n x_n \tag{2}$$

where y is the value of the warpage, β_0 is intercept, β_1, β_2, ..., β_n are coefficients values obtained from MATLAB software, x_1, x_2, …, x_n are process parameters factors.

3.3. Genetic Algorithm (GA) Optimization

GA is an optimization technique that uses a randomized search method to achieve optimal values. It is based on a model of a natural genetic selection mechanism that has the ability to survive and pass on to the next generation (Eusuff, Lansey, and Pasha, 2006).

The optimization injection molding process parameters problem in Equation 3 was solved by a GA created by the MATLAB Optimization toolbox. The parameter value used for the GA is 100 for the population size, 0.6 for the crossover rate, and 0.05 for the mutation rate. The roulette wheel method was used to select the next generation. (Figure 6) shows the GA optimization terminates at generation no. 140 from 500 generations, which are the results of the objective function.

Minimize Warpage (Z). Z = (Melt Temperature, Mold Temperature, Filling Time, Packing Time, Cooling Time);
Subject to

$$\begin{gathered} 180 \leq \text{Melt Temperature} \leq 230\,^{\circ}\mathrm{C} \\ 20 \leq \text{Mold Temperature} \leq 45\,^{\circ}\mathrm{C} \\ 0.82 \leq \text{Filling Time} \leq 0.94 \text{ mm/s} \\ 5.88 \leq \text{Packing Time} \leq 7 \text{ mm/s} \\ 14 \leq \text{Cooling Time} \leq 18 \text{ s} \end{gathered} \tag{3}$$

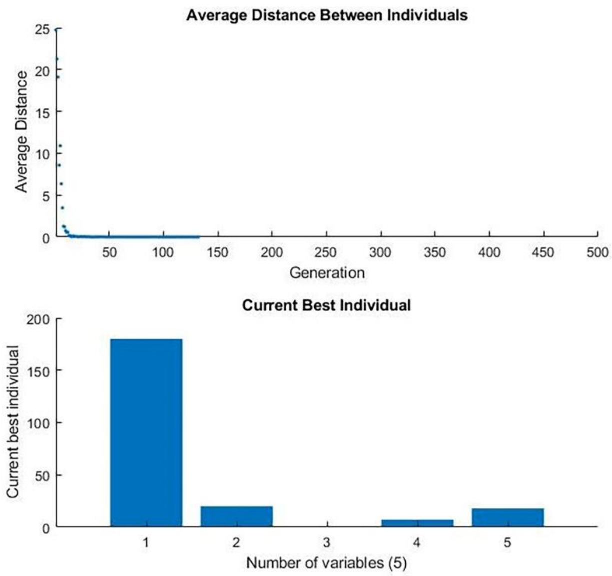


Figure 6 Result of GA optimization process parameter

From (Figure 6), the GA optimization process parameters result include melt temperature of 192 ∘ C, mold temperature of 23 ∘ C, filling time of 0.865 mm/s, packing time of 6.72 mm/s, and cooling time is 16 s which affects warpage that is 0.770 mm. The process parameters of experiment simulation no.8 consist of a melt temperature of 230 ∘ C, mold temperature of 45 ∘ C, filling time of 0.940 mm/s, packing time of 5.88 mm/s, and cooling time is 14 s have a maximum warpage value of 1.198 mm compare with the result of GA as shown in Table 4.

Table 4 Process parameter of experiment simulation and GA

	Melt Temperature	Mold Temperature	Filling Time	Packing Time	Cooling Time	Warpage
Experiment Simulation	230	45	0.940	5.88	14	1.198
GA	192	23	0.865	6.72	16	0.770

To confirm the result of this method, the optimal plastic injection molding process of GA consists of a melt temperature of 192 ∘ C, mold temperature of 23 ∘ C, filling time of 0.865 mm/s, packing time of 6.72 mm/s, and cooling time is 16 s were simulated by MOLDEX3D software as shown in (Figure 7).

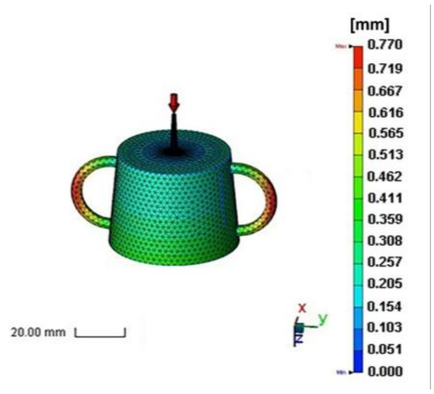


Figure 7 Confirmation optimal process parameters

The confirmation result shows that the warpage of the simulation is 0.770 mm, which equal to the results of GA. When the maximum warpage of the experiment simulation is considered, it depicts the maximum warpage on a plastic glass of experiment simulation, which is 1.198 mm before the optimization. After optimization, it was found that the warpage is reduced to 0.770 mm, which is about 35.73% of the maximum warpage. (Figure 8) shows a comparison of the warpage experiment simulation with GA.

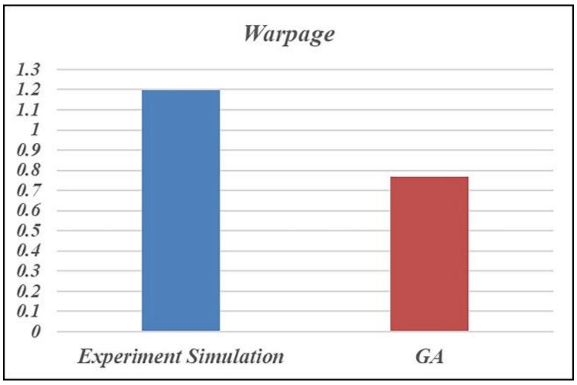


Figure 8 Result of GA optimization process parameter

4. Conclusions

The objective of this paper was to determine the optimal injection molding process parameters for minimized plastic glass warpage through a Finite Element, ANN and GA. The finite element method simulated five process parameters (melt temperature, mold temperature, filling time, packing time, and cooling time) for finding warpage under various parameters. The results of the experiment simulation were used for predictive models were established using ANN. The average prediction error of the ANN was 1.97%, with a mean square error (MSE) of 0.004. It shows that obtained results showed good prediction accuracy. After the prediction warpage by ANN, A mathematical was created for a Fitness Function of GA. In the optimization process, GA was utilized for the optimal selection of the plastic injection molding process parameters that reduced the warpage of the product by 35.73% from the maximum warpage of the simulation. It clearly shows that GA has high efficiency in finding the optimal injection molding process parameters. Moreover, it is a guideline for optimizing the process parameters of another plastic part with speed and accuracy. However, this simulation with the finite element method is prediction the behaviour of defects in the pre-production process where the simulation process parameters are stable and independent from interference complications. On the other hand, a higher defect value may occur in the experiment as other factors such as machinery deterioration, air humidity, and air temperature can easily intervene in the plastic injection molding process. Moreover, the current simulation did not include optimization of the injection and packing pressures by setting pressure following plastic melt flow behavior fill to the mold impression in the setting pressure process of the injection machine. The pressure values used in the simulation were based on the material profile within the simulation software. Thus, determining appropriate pressure values following plastic melt flow behavior may further enhance the efficiency of reducing product warpage.

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