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# Process Parameters Optimization for Multiple Quality Characteristics in Plastic Injection Molding using Taguchi Method, BPNN, GA, and Hybrid PSO-GA

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*This paper presents a two stage optimization system to find optimal process parameters of multiple quality characteristics in plastic injection molding. Taguchi method, Back-Propagation Neural Network (BPNN), Genetic Algorithm (GA), and combination of Particle Swarm Optimization and Genetic Algorithm (PSO-GA) are used in this study to find optimum parameter settings. Melt temperature, injection velocity, packing pressure, packing time, and cooling time are selected as initial process parameters in the experiment. First, experimental work is conducted using Taguchi orthogonal array. According to the result from the Taguchi experiment, S/N ratio is calculated to find the best combination settings for product quality. Then, ANOVA is used to determine significant factors of the control parameters. Moreover, the S/N ratio predictor and quality predictor are constructed using BPNN. In the first stage optimization, S/N ratio predictor and GA are used to reduce variance of quality characteristic. In the second stage optimization, the S/N ratio predictor and quality predictor with hybrid PSO-GA are used to find optimal parameter settings for quality characteristic and stability of the process. Finally, three confirmation experiments are conducted to assess the effectiveness of the proposed system. Upon optimization, it is seen that the proposed system not only improves the quality of plastic parts, but also reduces variability of the process effectively.*

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## 1. Introduction

Injection molding is commonly used to produce plastic products, because it can produce a large amount of product in a very short time with low production costs. Moreover, several advantages, such as short cycle time production, light weight of products, and high surface quality, make Plastic Injection Molding (PIM) work as a solution for industries to survive in the competitive world. Besides these advantages, PIM is a more complex process than it is previously thought. Inappropriate mold design, material, and parameter settings will produce defects in the plastic parts. Many researchers investigate defects in PIM, such as warpage, shrinkage, sink marks, short shot and so on.[1-7] A well-controlled parameter setting is one of the solutions to avoid or to reduce these defects. Previously, process parameters in PIM process relied on the technician's experience using trial-and-error approach. However, this approach is not effective and unsuitable for complex manufacturing processes. Then, many studies used the Taguchi method to determine the best combination of process parameters for improving product quality.[8-13] However, the Taguchi method is not suitable to find the optimal parameter settings for continuous value, and it has difficulties when it is used for multiple response process parameters design problem.[14-16]

In the previous study, several methods such as Back-Propagation Neural Network (BPNN), Response Surface Methodology (RSM), Design of Experiment (DOE), Genetic Algorithm (GA), Particle Swarm Optimization (PSO) were applied to optimize parameter settings in plastic injection molding.[17-22] In Ozcelik and Erzurumlu[23] research, warpage of a thin shell plastic part was successfully reduced over 40% using a combination of DOE, RSM, FEA and GA. Yin et al.[24] presented reduction of warpage value by 32.9% using the BPNN and Finite Element Analysis (FEA). In their study, they stated that process parameters can be optimized with the help of a prediction system, where BPNN was used to predict the relationship between parameter settings and warpage value. Chen et al.[25] presented the investigation of reducing shrinkage using RSM. Four process parameters were used (injection velocity, packing pressure, mold temperature, and melt temperature). The result from confirmation experiment found that the error of experimental data and predicted values were relatively small, around 9.8% and 1.8% for dx and dy variation, respectively.

Recently, many studies investigate a combination of optimization methods in improving product quality of plastic parts. The combination of several optimization systems is called hybrid optimization system and it is believed that it offers a better solution.[26-30] Since each optimization, has its own strengths and weaknesses, then a hybrid system is a good solution to solve problems by empowering each method and abandoning their weaknesses. Chen et al.[31] used BPNN, Simulated Annealing (SA) and PSO to obtain the best combination of parameter settings for precise product length and minimized warpage. Kurtaran and Erzurumlu[32] presented the combination of RSM and GA to minimize warpage of thin shell parts. In their study, mold temperature, melt temperature, packing pressure, packing time, and cooling time were considered as initial process parameters. Moreover, the RSM model was combined with GA to find optimum process parameter values. The combination system successfully reduced warpage by about 46%. Reséndiz and Rull-Flores,[33] determined the optimal variable selection using combinational Mahalanobis-Taguchi System (MTS), Binary PSO (BPSO), Binary Ant Colony Optimization (NBACO), and Gompertz Binary PSO (GBPSO) in application of automotive pedals components. In Wang et al.[34] study, they developed a combination of BPNN and PSO to find the optimal setting and to estimate the production cost of plastic parts in injection molding manufacturing. They successfully reduced the number of variables and they found that GBPSO is the fastest computational method compared to BPSO and NBACO algorithm.

According to previous studies, many researchers only focused on optimizing the process parameters to improve quality in PIM using various methods, but they did not asses the stability of the process. Therefore, besides improving the quality of plastic parts, this study also gives attention to the stability of the process. A systematic technique using Taguchi method, ANOVA, BPNN, GA, and hybrid PSO-GA are used to optimize length and warpage of plastic parts. Melt temperature, injection velocity, packing pressure, packing time, and cooling time are used as initial control factors in the real experimental work. There are three approaches of the proposed system. First, the Taguchi method is used to find the best combination of initial parameter settings for product length and warpage. The experimental data is used to construct S/N ratio predictor and quality predictor in the next stages. In the first stage optimization, combination of S/N ratio predictor and GA is used to reduce the variability of the process and consistency of product quality. Integration of the S/N ratio predictor and quality predictor with PSO-GA is used in the second stage optimization. The objective of the second stage is to find the optimal settings for quality characteristic and stability of the process. Finally, three confirmation experiments using the Taguchi method, the first stage optimization and the second stage optimization are performed to justify the effectiveness of the proposed system in this study.

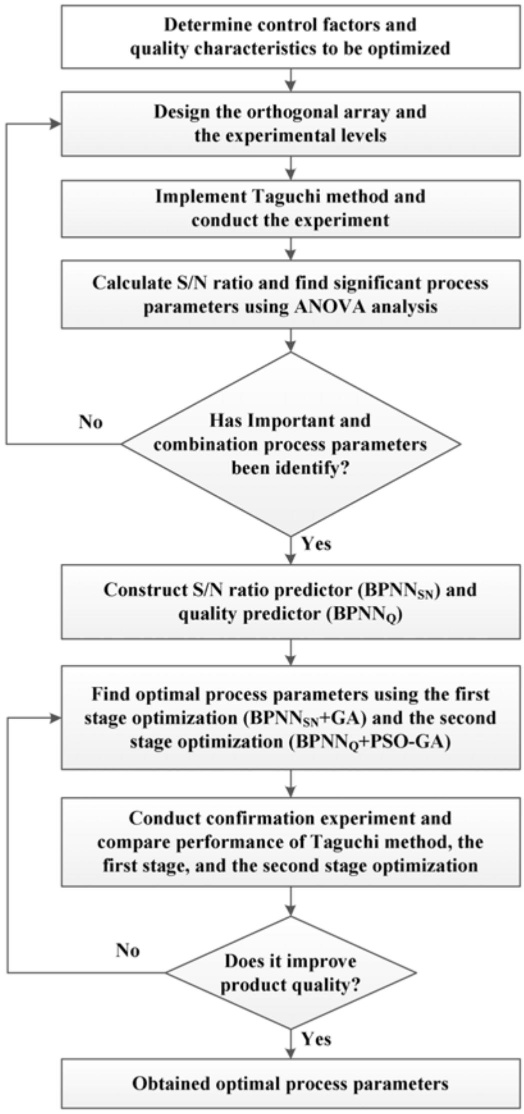


Fig. 1 Flowchart of the proposed research

## 2. Design of proposed system

This study proposes a multiple-stage optimization system for multiple-input multiple-output (MIMO) in plastic injection molding. Taguchi method, BPNN, GA and hybrid PSO-GA are applied to optimize the quality of plastic parts in the real experimental work. The flowchart of the proposed system is shown in Fig. 1.

Firstly, the Taguchi method is used to determine the best combination of parameter settings by calculating the signal-to-noise (S/N) ratio from the experimental data. The highest S/N ratio value is used to decide the best settings for quality responses. Significant factors are determined in this stage using Analysis of Variance (ANOVA). The S/N ratio prediction ($BPNN_{SN}$) and quality prediction ($BPNN_Q$) are constructed using BPNN. In the first stage optimization, $BPNN_{SN}$ is coupled with GA in order to minimize the variations of the process. In the second stage optimization, the optimal parameter settings are obtained using a combination of $BPNN_{SN}$, $BPNN_Q$ and hybrid PSO-GA. Finally, three confirmation experiments using the Taguchi method, the first stage and

Table 1 The range for parameter settings

| Control factor | Setting range |
|---|---|
| Melt temperature (°C) | 249~261 |
| Injection velocity (mm/s) | 30~46 |
| Packing pressure (MPa) | 27~43 |
| Packing time (s) | 0.9~2.1 |
| Cooling time (s) | 11~23 |

the second stage optimization are conducted to assess the effectiveness of these approaches.

### 2.1 Taguchi method

Firstly, quality characteristics, control factors, and the level of experiments should be determined. Melt temperature, injection velocity, packing pressure, packing time, and cooling time are selected as initial control factors in this study. Product length and warpage are used as quality characteristics of a plastic product. The length of a plastic part is very important to ensure that the product has correct length to the design. Target length for product length is 170.5 mm and minimal warpage values are the objective of the product quality in this study. Determination of the value ranges of process parameters are selected using expert recommendation in this study. Polybutylene terephthalate (PBT) is selected as the plastic material and the product is a printer's rear cover. In this study, expert's experience and brainstorming are used to find initial control settings in plastic injection molding. The control factors and their ranges are shown in Table 1.

The Taguchi method uses orthogonal array for the experiment and signal-to-noise (S/N) ratio to represent the quality variation. The experiments consist of multiple quality characteristics, which means different S/N ratio for quality characteristics. In this study, specific product length and warpage are used as quality characteristics. Therefore, nominal-the-best and smaller-the-better are selected to calculate S/N ratio for length and warpage, respectively. The formulation of S/N ratio for nominal-the-best and smaller-the-better are shown in Eqs. (1) and (2).

Nominal-the-best:

$$S/N = -10 \cdot \log[(\bar{y}-m)^2 + \bar{S}^2] \quad (1)$$

Smaller-the-better:

$$S/N = -10 \cdot \log\left(\frac{1}{n}\Sigma_{i=1}^{n} y_i^2\right) \quad (2)$$

where $y_i$ is the response value of a specific treatment under $i$ replications, m is the target value, $n$ is the number of replications, $\bar{y}$ is the average of all $y_i$ values, and $\bar{S}$ is the standard deviation of all $y_i$ values.

### 2.2 S/N ratio predictor and quality predictor

As mentioned earlier, after the S/N ratio for length and warpage is obtained, the BPNN is employed to construct S/N ratio predictor ($BPNN_{SN}$) and quality predictor ($BPNN_Q$). BPNN is used to map the relationship between process parameters (input factors) and quality characteristics (output responses). In this research, the scaled conjugate gradient method is used as training algorithm in BPNN to perform fast and stable results. In addition, the activation function is a sigmoid function. Twenty-five experimental data from the Taguchi orthogonal table are taken as training data of BPNN. Another five combinations of parameters within the levels are selected as the testing data for BPNN. Melt temperature, injection velocity, packing pressure, packing time, and cooling time are used as input for BPNN, while product length and warpage are used as output of BPNN. One hidden layer with nine neurons is used in the BPNN. The architecture of BPNN is shown in Fig. 2.

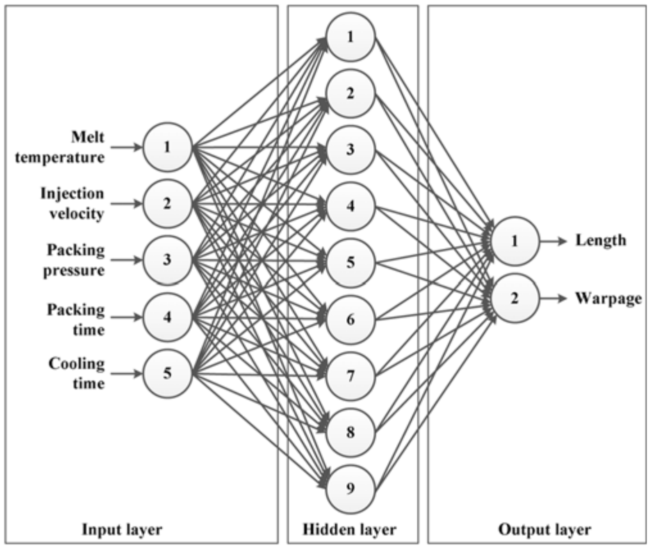


Fig. 2 Architecture of BPNN for the proposed system

### 2.3 The first stage optimization

In the first stage parameter settings of optimization, the S/N ratio predictor is integrated with Genetic Algorithms (GA). The objective of the first stage optimization is to reduce variations in plastic injection molding process. The fitness function for optimal process parameters is defined as follows:

$$Min\ F(X) = (Y_l - SN_l)^2 + (Y_w - SN_w)^2 \quad (3)$$

s.t.

$$LSR_m \le x_m \le USR_m; \quad m = 1, 2, \ldots, M$$

where $F(X)$ is the objective function; $Y_l$ is the predicted value of S/N ratio for length; $SN_l$ is the highest S/N ratio of length; $Y_w$ is the predicted value of S/N ratio for warpage; $SN_w$ is the highest S/N ratio of warpage; $x_m$ is the process control parameter; $LSR_m$ and $USR_m$ are the lower search bound and the upper search bound for parameter m, respectively.

### 2.4 The second stage optimization

In the second stage optimization, the S/N ratio predictor and the quality predictor with hybrid PSO-GA are used to find optimal parameter settings for quality characteristic and stability of the process. The objective of this stage is to get optimal parameter settings for high product quality and to improve the stability of injection molding process. The objective function of the second stage optimization is

Fig. 3 Illustrative of proposed plastic part


Fig. 4 The measurement method for the warpage

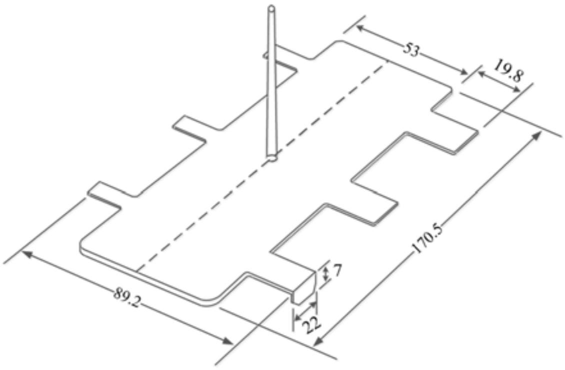


Fig. 5 The measurement method for the length

defined as follows:

$$\begin{aligned} &Min\ (Q_l - T_l)^2 + (Y_l - SN_1)^2 + (Y_w - SN_w)^2 \\ &Min\ Q_w \end{aligned} \tag{4}$$

s.t.

$$LSR_m \le x_m \le USR_m; \quad m = 1, 2, \ldots, M$$

where $Q_l$ is the predicted value for length; $Q_w$ is the predicted value for warpage; $T_l$ is the target value for length; $Y_l$ is the predicted value of S/N ratio for length; $SN_l$ is the highest S/N ratio of length; $Y_w$ is the predicted value of S/N ratio for warpage; $SN_w$ is the highest S/N ratio of warpage; $LSR_m$ and $USR_m$ are the lower search bound and the upper search bound for parameter m, respectively. $x_m$ is the process control parameter. M is the total control parameter.

## 3. Experimental Result and Analysis

This section presents an illustrative sequence of implementation of experimental work for process parameters optimization under five parameter settings and two quality responses. The proposed plastic product is a rear cover of a printer part, as shown in Fig. 3. The target value of quality responses are 170.5 mm for length and lower value for warpage. The illustration of measurement position for product warpage and length are shown in Figs. 4 and 5, respectively. Warpage value is recorded using laser measurement along the middle side of the parts (at the same side as measuring the length). The values of warpage are measured as the difference between upper and lower points on the

Table 2 Specifications of the VS-80 PIM machine

| Items | Contents |
|---|---|
| Type | VS-80 |
| Machine system | Half closed loop leak-free hydraulic system |
| Controller | VICTOR-8000 |
| Clamping force | 100 (ton) |
| Screw diameter | 28/32/36 (mm) |
| Injection pressure | 700-1100 (kg/cm$^2$) |
| Mold temperature | 40-80 (°C) |

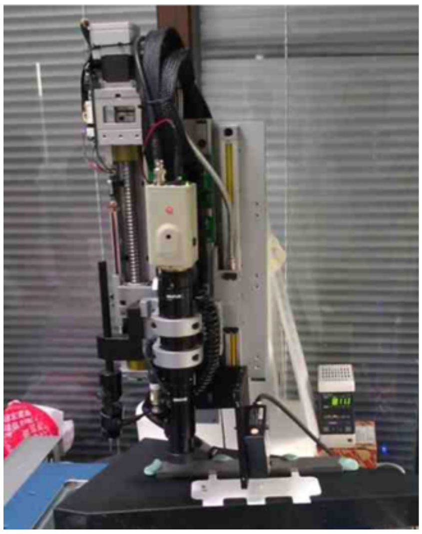

Fig. 6 A laser measurement device for warpage

Fig. 7 Mitutoyo digital slide caliper for length measurement

Table 3 Taguchi orthogonal array $L_{25}(5^6)$

| Parameter | Variable | Levels | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| Melt temperature (°C) | $x_1$ | 249 | 252 | 255 | 258 | 261 |
| Injection velocity (mm/s) | $x_2$ | 30 | 34 | 38 | 42 | 46 |
| Packing pressure (MPa) | $x_3$ | 27 | 31 | 35 | 39 | 43 |
| Packing time (s) | $x_4$ | 0.9 | 1.2 | 1.5 | 1.8 | 2.1 |
| Cooling time (s) | $x_5$ | 11 | 14 | 17 | 20 | 23 |

Table 4 Experimental treatments, response statistics, and S/N ratio (length)

| Treatment | Control factor | | | | | Length (mm) | | | | | Average (mm) | Standard deviation | S/N ratio |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $x_1$ | $x_2$ | $x_3$ | $x_4$ | $x_5$ | 1 | 2 | 3 | 4 | 5 | | | |
| 1 | 249 | 30 | 27 | 0.9 | 11 | 170.06 | 170.02 | 170.01 | 169.94 | 170.00 | 170.01 | 0.0434 | 6.092 |
| 2 | 249 | 34 | 31 | 1.2 | 14 | 170.16 | 170.31 | 170.22 | 170.24 | 170.20 | 170.23 | 0.0555 | 11.070 |
| 3 | 249 | 38 | 35 | 1.5 | 17 | 170.36 | 170.33 | 170.34 | 170.33 | 170.32 | 170.34 | 0.0152 | 15.666 |
| 4 | 249 | 42 | 39 | 1.8 | 20 | 170.52 | 170.51 | 170.50 | 170.51 | 170.52 | 170.51 | 0.0084 | 36.696 |
| 5 | 249 | 46 | 43 | 2.1 | 23 | 170.76 | 170.74 | 170.73 | 170.71 | 170.72 | 170.73 | 0.0192 | 12.660 |
| 6 | 252 | 30 | 31 | 1.5 | 20 | 170.32 | 170.31 | 170.30 | 170.31 | 170.31 | 170.31 | 0.0071 | 14.419 |
| 7 | 252 | 34 | 35 | 1.8 | 23 | 170.41 | 170.42 | 170.42 | 170.44 | 170.43 | 170.42 | 0.0114 | 22.287 |
| 8 | 252 | 38 | 39 | 2.1 | 11 | 170.31 | 170.30 | 170.30 | 170.29 | 170.29 | 170.30 | 0.0084 | 13.886 |
| 9 | 252 | 42 | 43 | 0.9 | 14 | 170.16 | 170.12 | 170.13 | 170.14 | 170.18 | 170.15 | 0.0241 | 9.000 |
| 10 | 252 | 46 | 27 | 1.2 | 17 | 170.23 | 170.19 | 170.19 | 170.18 | 170.20 | 170.20 | 0.0192 | 10.382 |
| 11 | 255 | 30 | 35 | 2.1 | 14 | 170.34 | 170.33 | 170.32 | 170.32 | 170.34 | 170.33 | 0.0100 | 15.376 |
| 12 | 255 | 34 | 39 | 0.9 | 17 | 170.14 | 170.14 | 170.13 | 170.12 | 170.14 | 170.13 | 0.0089 | 8.728 |
| 13 | 255 | 38 | 43 | 1.2 | 20 | 170.37 | 170.36 | 170.35 | 170.37 | 170.36 | 170.36 | 0.0084 | 17.186 |
| 14 | 255 | 42 | 27 | 1.5 | 23 | 170.40 | 170.36 | 170.35 | 170.35 | 170.36 | 170.36 | 0.0207 | 17.229 |
| 15 | 255 | 46 | 31 | 1.8 | 11 | 170.24 | 170.23 | 170.20 | 170.17 | 170.18 | 170.20 | 0.0305 | 10.528 |
| 16 | 258 | 30 | 39 | 1.2 | 23 | 170.31 | 170.33 | 170.34 | 170.33 | 170.34 | 170.33 | 0.0122 | 15.369 |
| 17 | 258 | 34 | 43 | 1.5 | 11 | 170.16 | 170.12 | 170.10 | 170.11 | 170.12 | 170.12 | 0.0228 | 8.434 |
| 18 | 258 | 38 | 27 | 1.8 | 14 | 170.20 | 170.18 | 170.20 | 170.18 | 170.18 | 170.19 | 0.0110 | 10.112 |
| 19 | 258 | 42 | 31 | 2.1 | 17 | 170.41 | 170.40 | 170.41 | 170.38 | 170.39 | 170.40 | 0.0130 | 19.758 |
| 20 | 258 | 46 | 35 | 0.9 | 20 | 170.27 | 170.26 | 170.24 | 170.23 | 170.22 | 170.24 | 0.0207 | 11.807 |
| 21 | 261 | 30 | 43 | 1.8 | 17 | 170.53 | 170.52 | 170.52 | 170.50 | 170.50 | 170.51 | 0.0134 | 34.248 |
| 22 | 261 | 34 | 27 | 2.1 | 20 | 170.39 | 170.38 | 170.37 | 170.39 | 170.34 | 170.37 | 0.0207 | 17.877 |
| 23 | 261 | 38 | 31 | 0.9 | 23 | 170.25 | 170.24 | 170.23 | 170.23 | 170.21 | 170.23 | 0.0148 | 11.424 |
| 24 | 261 | 42 | 35 | 1.2 | 11 | 170.07 | 170.04 | 170.03 | 170.00 | 169.99 | 170.03 | 0.0321 | 6.465 |
| 25 | 261 | 46 | 39 | 1.5 | 14 | 170.24 | 170.24 | 170.23 | 170.23 | 170.23 | 170.23 | 0.0055 | 11.501 |
| Testing data | | | | | | | | | | | | | |
| 26 | 250 | 43 | 39 | 1.4 | 18 | 170.44 | 170.42 | 170.42 | 170.41 | 170.41 | 170.42 | 0.01225 | 21.838 |
| 27 | 253 | 32 | 42 | 1.9 | 12 | 170.47 | 170.43 | 170.43 | 170.41 | 170.41 | 170.43 | 0.02449 | 22.596 |
| 28 | 254 | 35 | 28 | 2.0 | 16 | 170.36 | 170.34 | 170.32 | 170.33 | 170.31 | 170.33 | 0.01924 | 15.437 |
| 29 | 259 | 38 | 30 | 0.9 | 22 | 170.27 | 170.22 | 170.25 | 170.22 | 170.22 | 170.24 | 0.02302 | 11.535 |
| 30 | 260 | 41 | 36 | 1.2 | 21 | 170.36 | 170.37 | 170.33 | 170.33 | 170.34 | 170.35 | 0.01817 | 16.190 |

plastic part surface, as shown in Fig. 4, while the measurement position for the length is along the middle of the part (dotted line in Fig. 5). All dimensions are in mm.

### 3.1 Experimental apparatus

Plastic products are produced using Victor Taichung VS-80 plastic injection molding machine. The specifications of this machine are recorded in Table 2. The experimental data is collected using Mitutoyo digital slide caliper and NV300T laser measurement machine for length and warpage, respectively. The apparatus to measure warpage and the length of plastic products are shown in Figs. 6 and 7. Five injection shots for each treatment are made before collecting the data to make sure the previous setting would not affect the current setting of the injection molding machine and make the process more stable.

### 3.2 Taguchi experimentation and ANOVA analysis

First, the Taguchi orthogonal array $L_{25}(5^6)$ is selected in this study. The control factors and their levels are shown in Table 3. According to the design, melt temperature ($x_1$), injection velocity ($x_2$), packing pressure ($x_3$), packing time ($x_4$), and cooling time ($x_5$) are selected as control factors. There are 25 treatments for all combinations for five factors and five levels. Five replications are used for each setting to increase the sensitivity of statistical analysis. Therefore, a total of 125 sample data is collected for the $L_{25}(5^6)$ design. In addition, another five treatments for different settings are selected in this experiment and later will be used as testing data for BPNN.

The results of experiments are recorded in Table 4 and 5 for product length and warpage, respectively. Nominal-the-best and smaller-the-better are used as the formula to calculate S/N ratio of product length and warpage, respectively. The calculation for average, standard deviation and S/N ratio are recorded in Table 4 and 5. The highest value of S/N ratio is determined as optimal initial parameter setting. Therefore, the treatment no. 4 in Table 4 is selected as initial parameter for product length, since it has the highest value of S/N ratio (36.696) for product length. In addition, the treatment no. 22 in Table 5 (26.313) is selected as the optimal initial parameter setting for warpage. The initial parameter settings for highest S/N ratio for product length and warpage are shown in Table 6.

The purpose of ANOVA analysis is to determine the significant factors affecting product's length and warpage. The result of ANOVA analysis for product length and warpage is shown in Table 7 and 8, respectively. The significance factors are identified by F-test with a= 0.05. From Table 7, it is apparent that cooling time ($x_5$) and packing time ($x_4$) are significant factors for length, because their p-value is less than 0.05. On the contrary, factors like melt temperature ($x_1$), injection velocity ($x_2$), and packing pressure ($x_3$) are not significant since p-values

Table 5 Experimental treatments, response statistics, and S/N ratio (warpage)

| Treatment | Control factor | | | | | Warpage (mm) | | | | | Average (mm) | Standard deviation | S/N ratio |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $x_1$ | $x_2$ | $x_3$ | $x_4$ | $x_5$ | 1 | 2 | 3 | 4 | 5 | | | |
| 1 | 249 | 30 | 27 | 0.9 | 11 | 2.066 | 2.440 | 2.682 | 0.569 | 1.618 | 1.875 | 0.8335 | -6.097 |
| 2 | 249 | 34 | 31 | 1.2 | 14 | 1.600 | 0.327 | 0.614 | 0.669 | 0.974 | 0.837 | 0.4845 | 0.516 |
| 3 | 249 | 38 | 35 | 1.5 | 17 | 0.074 | 0.098 | 0.076 | 0.081 | 0.062 | 0.078 | 0.0131 | 22.040 |
| 4 | 249 | 42 | 39 | 1.8 | 20 | 0.124 | 0.094 | 0.159 | 0.101 | 0.073 | 0.110 | 0.0328 | 18.859 |
| 5 | 249 | 46 | 43 | 2.1 | 23 | 0.098 | 0.122 | 0.086 | 0.108 | 0.134 | 0.110 | 0.0190 | 19.101 |
| 6 | 252 | 30 | 31 | 1.5 | 20 | 0.158 | 0.203 | 0.116 | 0.100 | 0.136 | 0.143 | 0.0402 | 16.650 |
| 7 | 252 | 34 | 35 | 1.8 | 23 | 0.093 | 0.124 | 0.145 | 0.113 | 0.108 | 0.117 | 0.0194 | 18.571 |
| 8 | 252 | 38 | 39 | 2.1 | 11 | 0.255 | 0.261 | 0.251 | 0.243 | 0.278 | 0.258 | 0.0131 | 11.772 |
| 9 | 252 | 42 | 43 | 0.9 | 14 | 1.342 | 1.584 | 1.368 | 0.532 | 1.480 | 1.261 | 0.4188 | -2.383 |
| 10 | 252 | 46 | 27 | 1.2 | 17 | 0.544 | 0.702 | 0.684 | 0.658 | 0.451 | 0.608 | 0.1071 | 4.218 |
| 11 | 255 | 30 | 35 | 2.1 | 14 | 0.160 | 0.397 | 0.188 | 0.115 | 0.171 | 0.206 | 0.1100 | 12.823 |
| 12 | 255 | 34 | 39 | 0.9 | 17 | 0.166 | 0.849 | 0.884 | 0.136 | 0.801 | 0.567 | 0.3812 | 3.585 |
| 13 | 255 | 38 | 43 | 1.2 | 20 | 0.105 | 0.118 | 0.134 | 0.176 | 0.153 | 0.137 | 0.0282 | 17.109 |
| 14 | 255 | 42 | 27 | 1.5 | 23 | 0.175 | 0.069 | 0.170 | 0.212 | 0.239 | 0.173 | 0.0646 | 14.779 |
| 15 | 255 | 46 | 31 | 1.8 | 11 | 0.232 | 0.144 | 0.104 | 0.292 | 0.291 | 0.213 | 0.0856 | 12.919 |
| 16 | 258 | 30 | 39 | 1.2 | 23 | 0.137 | 0.079 | 0.076 | 0.105 | 0.082 | 0.096 | 0.0257 | 20.129 |
| 17 | 258 | 34 | 43 | 1.5 | 11 | 0.378 | 0.393 | 0.386 | 0.399 | 0.282 | 0.368 | 0.0485 | 8.633 |
| 18 | 258 | 38 | 27 | 1.8 | 14 | 0.424 | 0.422 | 0.348 | 0.424 | 0.370 | 0.398 | 0.0361 | 7.983 |
| 19 | 258 | 42 | 31 | 2.1 | 17 | 0.117 | 0.081 | 0.158 | 0.128 | 0.072 | 0.111 | 0.0352 | 18.743 |
| 20 | 258 | 46 | 35 | 0.9 | 20 | 0.279 | 0.262 | 0.229 | 0.174 | 0.249 | 0.239 | 0.0405 | 12.348 |
| 21 | 261 | 30 | 43 | 1.8 | 17 | 0.137 | 0.188 | 0.162 | 0.131 | 0.110 | 0.146 | 0.0301 | 16.591 |
| 22 | 261 | 34 | 27 | 2.1 | 20 | 0.037 | 0.043 | 0.049 | 0.058 | 0.052 | 0.048 | 0.0081 | 26.313 |
| 23 | 261 | 38 | 31 | 0.9 | 23 | 0.244 | 0.366 | 0.248 | 0.139 | 0.397 | 0.279 | 0.1040 | 10.636 |
| 24 | 261 | 42 | 35 | 1.2 | 11 | 0.352 | 0.268 | 0.271 | 0.302 | 0.252 | 0.289 | 0.0396 | 10.717 |
| 25 | 261 | 46 | 39 | 1.5 | 14 | 0.207 | 0.206 | 0.216 | 0.102 | 0.221 | 0.190 | 0.0498 | 14.175 |
| Testing data | | | | | | | | | | | | | |
| 26 | 250 | 43 | 39 | 1.4 | 18 | 0.144 | 0.197 | 0.148 | 0.068 | 0.110 | 0.1334 | 0.04795 | 17.070 |
| 27 | 253 | 32 | 42 | 1.9 | 12 | 0.131 | 0.148 | 0.150 | 0.203 | 0.331 | 0.1926 | 0.08195 | 13.720 |
| 28 | 254 | 35 | 28 | 2.0 | 16 | 0.153 | 0.151 | 0.094 | 0.049 | 0.131 | 0.1156 | 0.04413 | 18.262 |
| 29 | 259 | 38 | 30 | 0.9 | 22 | 0.260 | 0.427 | 0.370 | 0.350 | 0.452 | 0.3718 | 0.07493 | 8.455 |
| 30 | 260 | 41 | 36 | 1.2 | 21 | 0.164 | 0.063 | 0.143 | 0.077 | 0.170 | 0.1234 | 0.05001 | 17.638 |

Table 6 Initial parameter settings for highest S/N ratio for length and warpage

| Parameter variable | $x_1$ | $x_2$ | $x_3$ | $x_4$ | $x_5$ | Highest S/N ratio for length | Highest S/N ratio for warpage |
|---|---|---|---|---|---|---|---|
| Parameter combination | 249 | 42 | 39 | 1.8 | 20 | 36.696 | |
| | 261 | 34 | 27 | 2.1 | 20 | | 26.313 |

Table 7 ANOVA analysis for length

| Source of variance | DF | Seq SS | Adj SS | Adj MS | F | p-value | Percentage of contribution |
|---|---|---|---|---|---|---|---|
| $x_1$ | 4 | 0.034555 | 0.034555 | 0.008639 | 3.50 | 0.126 | 5.66 |
| $x_2$ | 4 | 0.011582 | 0.011582 | 0.002895 | 1.17 | 0.441 | 1.90 |
| $x_3$ | 4 | 0.060347 | 0.060347 | 0.015087 | 6.11 | 0.054 | 9.88 |
| $x_4$ | 4 | 0.238809 | 0.238809 | 0.059702 | 24.16 | 0.005 | 39.11 |
| $x_5$ | 4 | 0.255387 | 0.255387 | 0.063847 | 25.84 | 0.004 | 41.83 |
| Error | 4 | 0.009884 | 0.009884 | 0.002471 | | | 1.62 |
| Total | 24 | 0.610563 | | | | | 100 |

are greater than 0.05. The cooling time is the most influential factor with a contribution of 41.83%, followed by packing time at 39.11%, packing pressure at 9.88%, melt temperature at 5.66%, and injection velocity at 1.90%. According to p-value of ANOVA analysis in Table 8, the significant factors for warpage are packing time and cooling time. Vice versa, melt temperature, injection velocity, and packing pressure are considered as insignificant. Packing time is the most significant factors for warpage with a contribution of 39.85%, followed by cooling time at 23.84%, melt temperature at 14.80%, packing pressure at 13.64%, and injection velocity at 5.19%. Moreover, the coefficient $R^2$ for length and warpage are 98.38% and 97.32%, respectively.

### 3.3 The first stage optimization

In the first stage optimization, S/N ratio predictor ($BPNN_{SN}$) and GA

Table 8 ANOVA analysis for warpage

| Source of variance | DF | Seq SS | Adj SS | Adj MS | F | p-value | Percentage of contribution |
|---|---|---|---|---|---|---|---|
| $x_1$ | 4 | 0.62466 | 0.62466 | 0.15616 | 5.53 | 0.063 | 14.80 |
| $x_2$ | 4 | 0.21908 | 0.21908 | 0.05477 | 1.94 | 0.269 | 5.19 |
| $x_3$ | 4 | 0.57593 | 0.57593 | 0.14398 | 5.1 | 0.072 | 13.64 |
| $x_4$ | 4 | 1.68223 | 1.68223 | 0.42056 | 14.88 | 0.011 | 39.85 |
| $x_5$ | 4 | 1.00653 | 1.00653 | 0.25163 | 8.91 | 0.029 | 23.84 |
| Error | 4 | 0.11303 | 0.11303 | 0.02826 | | | 2.68 |
| Total | 24 | 4.22145 | | | | | 100 |

Table 9 Search values and setting values for verification experiment

| Method | Melt temperature (°C) | Injection velocity (mm/s) | Packing pressure (MPa) | Packing time (s) | Cooling time (s) |
|---|---|---|---|---|---|
| Taguchi method | 255 | 38 | 33 | 1.95 | 20 |
| Machine settings | 255 | 38 | 33 | 2 | 20 |
| First stage | 257.43 | 40.60 | 41.65 | 1.96 | 18.45 |
| Machine settings | 257 | 41 | 42 | 2 | 18.5 |
| Proposed system | 255 | 38 | 42.07 | 2.03 | 17.85 |
| Machine settings | 255 | 38 | 42 | 2 | 17.9 |

are employed. Twenty-five treatments from the Taguchi experiment are used as training data and the rest is used as testing data for $BPNN_{SN}$. A program writting in MATLAB 2007 software is used to train and test the network. Five control factors (melt temperature, injection velocity, packing pressure, packing time, and cooling time) are used as input responses of BPNN. S/N ratio for product length and warpage are used as output responses of BPNN. BPNN has a hidden layer and contains 7 neurons. The range of normalization is from 0.1 to 0.9. Moreover, sigmoid function is used for the activation function.

The training performance (RMSE) of $BPNN_{SN}$ training is 0.0032 and 0.0708 for testing. Then, GA is associated with S/N ratio predictor. The objective of this stage is to reduce the variation during the injection molding process. The fitness function for the first stage optimization is shown as follows:

$$Min\ F(X) = (Y_l - 36.696)^2 + (Y_w - 26.313)^2 \tag{5}$$

s.t.

$$249 \le x_1 \le 261; \quad 32 \le x_2 \le 44; \quad 27 \le x_3 \le 41;$$
$$1.65 \le x_4 \le 2.1; \quad 17 \le x_5 \le 23$$

where $F(X)$ is the fitness function; $Y_l$ and $Y_w$ are predicted S/N ratios for length and warpage, respectively; $x_1$ is melt temperature; $x_2$ is injection velocity; $x_3$ is packing pressure; $x_4$ is packing time; and $x_5$ is cooling time.

### 3.4 The second stage optimization

The optimal parameter settings in the first stage is taken as the initial values for the second stage. Using the same settings with S/N ratio predictor, then the RMSE of $BPNN_Q$ are 0.0032 and 0.0634 for training and testing, respectively. Then, the $BPNN_{SN}$ and $BPNN_Q$ are combined with hybrid PSO-GA to search for the optimal parameter settings. The objective of second stage optimization is to find the target of quality and to obtain the most stabilized parameter settings for multiple quality characteristics. The fitness function for the second stage optimization is shown as follows:

$$\begin{aligned} &Min\ G(X) = (Q_l - 170.5)^2 + (Y_l - 36.696)^2 + (Y_w - 26.313)^2 \\ &Min\ Q_w \end{aligned} \tag{6}$$

s.t.

$$1.65 \le x_4 \le 2.1; \quad 17 \le x_5 \le 23$$

where $G(X)$ is the fitness function for second stage optimization; $Q_l$ and $Q_w$ are the predicted values for length and warpage, respectively; $Y_l$ and $Y_w$ are predicted S/N ratio for length and warpage, respectively; $x_4$ and $x_5$ are the control factors.

### 3.5 Result and discussion

There are three confirmation experiments conducted in this study to assess the reliability of the proposed system. The first confirmation experiment is using initial parameter settings from the Taguchi method. The best parameter settings using the Taguchi method can be determined using combination settings of the highest S/N ratio for quality characteristic that is calculated in section 3.2. Then, the second experiment is utilized using the first stage optimization, and the final parameter settings are taken from the second stage optimization. The values in machine settings are slightly different from the search approach; therefore, the digit after the decimal point needs to round up. The search values and machine settings for the Taguchi method, the first stage and the second stage are shown in Table 9. Each experiment produced 25 sample products. The result of confirmation experiment for all approaches is shown in Table 10.

Comparison of the average, standard deviation and process capability index for product length and warpage, are shown in Tables 11 and 12, respectively. According to the experimental result, the standard deviation of the Taguchi method for length is 0.0161. This value is higher than the first stage (0.0150) and the second stage (0.0138). In addition, the standard deviation of the Taguchi method for warpage is 0.0462, which is almost two times of standard deviation of the first stage (0.0258) and three times higher than the second stage (0.0151).

The process capability index ($C_{pk}$) is applied to determine how far

Table 10 Result of confirmation experiment for product length and warpage

| Sample | Length Taguchi method (mm) | Length First stage (mm) | Length Proposed system (mm) | Sample | Warpage Taguchi method (mm) | Warpage First stage (mm) | Warpage Proposed system (mm) |
|---|---|---|---|---|---|---|---|
| 1 | 170.46 | 170.62 | 170.52 | 1 | 0.197 | 0.128 | 0.095 |
| 2 | 170.44 | 170.60 | 170.48 | 2 | 0.201 | 0.114 | 0.078 |
| 3 | 170.43 | 170.59 | 170.47 | 3 | 0.179 | 0.078 | 0.102 |
| 4 | 170.42 | 170.58 | 170.47 | 4 | 0.268 | 0.078 | 0.075 |
| 5 | 170.42 | 170.59 | 170.47 | 5 | 0.306 | 0.131 | 0.110 |
| 6 | 170.43 | 170.58 | 170.48 | 6 | 0.201 | 0.105 | 0.067 |
| 7 | 170.45 | 170.58 | 170.46 | 7 | 0.220 | 0.109 | 0.108 |
| 8 | 170.43 | 170.57 | 170.46 | 8 | 0.144 | 0.149 | 0.073 |
| 9 | 170.42 | 170.57 | 170.47 | 9 | 0.219 | 0.165 | 0.107 |
| 10 | 170.41 | 170.57 | 170.46 | 10 | 0.183 | 0.153 | 0.092 |
| 11 | 170.41 | 170.60 | 170.48 | 11 | 0.128 | 0.113 | 0.098 |
| 12 | 170.40 | 170.57 | 170.47 | 12 | 0.138 | 0.119 | 0.067 |
| 13 | 170.40 | 170.57 | 170.46 | 13 | 0.184 | 0.139 | 0.100 |
| 14 | 170.41 | 170.57 | 170.46 | 14 | 0.210 | 0.173 | 0.086 |
| 15 | 170.41 | 170.57 | 170.47 | 15 | 0.277 | 0.126 | 0.114 |
| 16 | 170.41 | 170.56 | 170.46 | 16 | 0.267 | 0.111 | 0.109 |
| 17 | 170.40 | 170.57 | 170.45 | 17 | 0.204 | 0.152 | 0.088 |
| 18 | 170.41 | 170.57 | 170.46 | 18 | 0.182 | 0.175 | 0.105 |
| 19 | 170.41 | 170.56 | 170.45 | 19 | 0.191 | 0.133 | 0.109 |
| 20 | 170.40 | 170.57 | 170.46 | 20 | 0.136 | 0.123 | 0.082 |
| 21 | 170.41 | 170.58 | 170.46 | 21 | 0.174 | 0.140 | 0.099 |
| 22 | 170.41 | 170.56 | 170.46 | 22 | 0.170 | 0.168 | 0.121 |
| 23 | 170.40 | 170.56 | 170.47 | 23 | 0.154 | 0.140 | 0.107 |
| 24 | 170.40 | 170.56 | 170.47 | 24 | 0.169 | 0.140 | 0.106 |
| 25 | 170.41 | 170.56 | 170.48 | 25 | 0.243 | 0.145 | 0.098 |

Table 11 Comparison of length quality statistics

| | Average (mm) | Standard deviation | $C_{pk}$ |
|---|---|---|---|
| Taguchi method | 170.42 | 0.0161 | 2.41 |
| First stage | 170.58 | 0.0150 | 2.77 |
| Proposed system | 170.47 | 0.0138 | 4.05 |

Table 12 Comparison of warpage quality statistics

| | Average (mm) | Standard deviation |
|---|---|---|
| Taguchi method | 0.198 | 0.0462 |
| First stage | 0.132 | 0.0258 |
| Proposed system | 0.096 | 0.0151 |

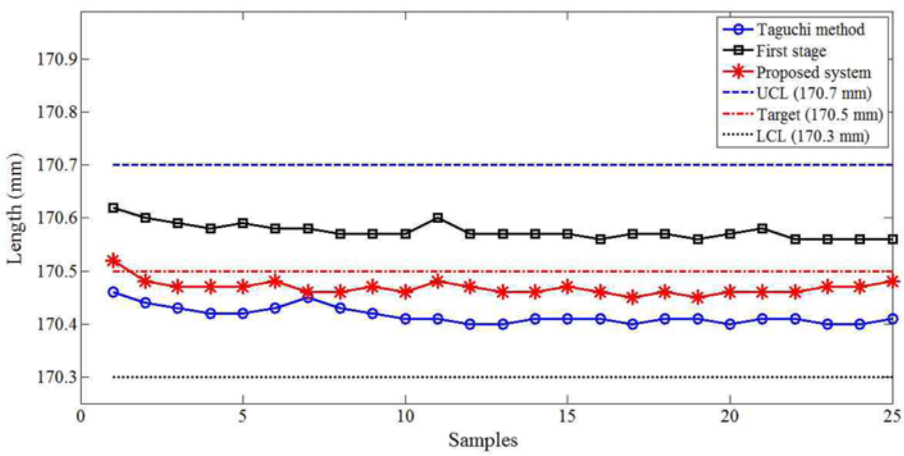


Fig. 8 Comparison of lengths between Taguchi method, first stage and proposed system

the process would fit the specification limits. In many applications, minimum value of the $C_{pk}$ is at least 1.33 and higher $C_{pk}$ value indicates good performance with small spread relative to the tolerance width. On the contrary, if $C_{pk}$ is less than 1.33, then the process may not achieve a good result and is inappropriate for a product. The $C_{pk}$ value of all methods is more than 1.33, which indicates all approaches achieve high yield rate and meet the specification. The $C_{pk}$ value of the Taguchi approach is 2.41, the first stage approach 2.77, and the second stage

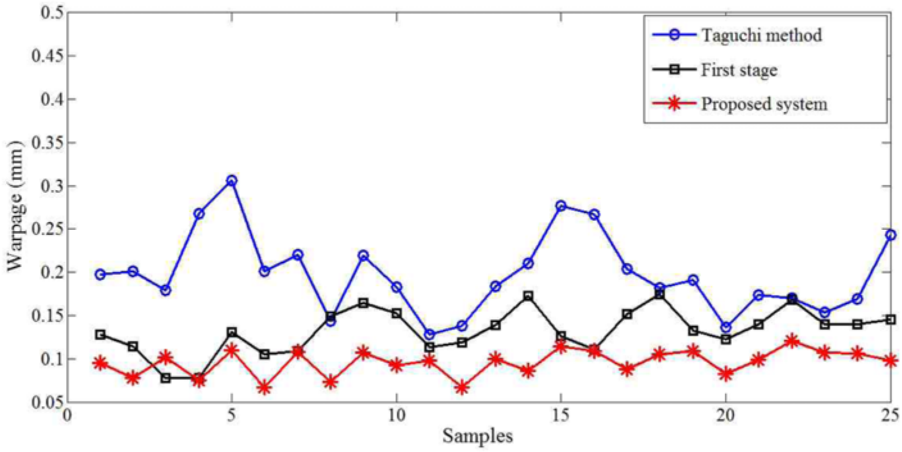


Fig. 9 Comparison of warpage between Taguchi method, first stage and proposed system

4.05. Thus, it can be concluded that the optimal process parameters of the first stage and the second stage are better than the Taguchi method. Since the second stage has the highest value of $C_{pk}$ and the best quality product, then the optimal process parameters of this approach definitely produce better performance than the Taguchi method and the first stage approach. In addition, the result of the second stage is closer to the target value and it is the most stabilized process for length and warpage, as shown in Figs. 8 and 9, respectively. Even though the result of the first stage approach does not do as well as the second stage result, this approach has better performance than the Taguchi method.

Comparing with the research of the cited literature Chen et al.,[32] the $C_{pk}$ value of the proposed system is 4.05, which is higher than Chen et al.[32] (2.913). In addition, the average warpage of the proposed system is 0.096, which is less than Chen et al.[32] (0.1351). Therefore, the proposed system successfully improves product quality and has more stable performance in the plastic injection molding process.

## 4. Conclusions

The objective of this study is to optimize process parameter settings for multiple quality characteristics using Taguchi method, BPNN, GA, and hybrid PSO-GA. The following conclusions are drawn:

(1) According to ANOVA analysis, packing time and cooling time are found as the most significant factors for length and warpage, respectively.

(2) The S/N ratio predictor and quality predictor successfully constructed using BPNN using data from the experiment. The first stage optimization combines S/N ratio predictor and GA to stabilize the process. In the second stage optimization, quality predictor and S/N ratio predictor were integrated with PSO-GA to find more stable and consistent combination of quality characteristics.

(3) Three confirmation experiments were conducted to assess the effectiveness of these methods. According to the result from 25 product samples, the second stage optimization has the most stable performance for length and warpage.

(4) The process capability index ($C_{pk}$) value of the second stage is the highest value (4.05), followed by the first stage (2.77) and the Taguchi method (2.41).

(5) The proposed optimization system successfully finds optimal parameter settings for getting closer to the target length and reduces warpage from 0.198 mm to 0.096 mm. Therefore, the proposed system is very effective to improve the quality of plastic parts and to stabilize variability in injection molding manufacturing industry.

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