Particle Swarm Optimization for Optimal Process Parameters in Injection Molding

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Abstract

Injection molding is a manufacturing process where the products or parts are made from plastic, glasses or other materials. In simple word, this process is involved with melting the required materials and injected it into the mold to produce a product or part. One of the biggest problems in manufacturing is to minimize the cost of producing a product without affecting their final product quality. To produce a high quality product using injection molding process, it is important to control efficiently the parameters involved in this manufacturing process. When one of these parameters has not been controlled efficiently, the quality of the final product can be affected. Soft computing technique can offer an option to evaluate this process efficiently at low cost before being applied by factory in creating and producing high quality product. This study focused on finding the optimal parameters’ combination to produce high quality product using Particle Swarm Optimization (PSO). Based on the previous researches, PSO have been known as reliable soft computing techniques in optimization problems. The results found that PSO improved the minimum warpage value by 1.2111% compared to observed data.

Keywords: Optimization, Particle Swarm Optimization, Injection molding, Soft computing, Warpage

1. Introduction

The nature of market today is very competitive, in order to survive in this nature, manufacturers must produce high quality product. Without any doubt, quality has become a crucial competitive factor (Zaklouta, 2011). Product quality is the main factor in this competition, cost to manufacture this high quality product also become one of the factors involved in this competitive market nature. This statement has been introduced by Ishikawa (1982) and supported by Ryan (2011), there are four common causes lead to affect quality as shown in Fig. 1.

Fig. 1 shows there are four major factors affect the quality in manufacturing industry according to Ishikawa Diagram. These four factors are materials, processes, equipment and measurement.

There are many different types of industries in the manufacturing industry, which is fabricated metal industry, food and kindred industry, rubber and miscellaneous plastic industry and various other industries. Apart from a wide range of industries, manufacturing industries also have a variety of techniques to produce a variety of products, one popular technique is the injection molding.

Injection molding is a manufacturing process where the products or parts are made from plastic, glasses or other materials (Todd et al., 1994). In simple word, this process is involved with melting the required materials and injected it into the mold to produce a product or part.

One of the main problems in manufacturing is to minimize the cost of producing a product without affecting their final product quality. To produce a high quality product using injection molding process, we have to control efficiently the parameters involved in this manufacturing process such as cooling temperature, mold temperature, injection time, Velocity/Pressure (V/P) switch over, cooling time and others. When one of these parameters has not been controlled efficiently, the quality of the final product can be affected.
To create or produce high quality product this process must be evaluated first before it being applied by factory, with soft computing technique this process can be evaluated efficiently at low cost.

One of the main issues in injection molding manufacturing is to determine the optimal combination value of control parameters to produce a high quality product. Until this day, there is no specific method to obtain the optimal combination values for injection molding control parameters without try-and-error method. This try-and-error method will increase the cost of manufacturing process undoubtedly (Lahoti et al., 2013). Based on nature offered by soft computing technique, this technique can be applied into this study.

In this study, the injection molding process has been evaluated using soft computing technique, PSO. This study focused on optimizing or minimizing the warpage value by finding the optimal combination values for involved parameters. Hence the objectives of this study are:

i. To estimate minimum warpage value in injection molding using PSO.
ii. To obtain the combination of parameters’ value that contributes to minimum warpage value.

1.1 PSO

PSO is one of the artificial intelligence techniques that solve optimization problem with repeatedly update or modify the possible solution to obtain the optimum solution (Kennedy, 2010). In PSO the problem will optimize with populations of candidate solutions also known as particle, these candidate solutions moving in search space according to simple formula of mathematic based on their position and velocity. Each particles move according to locally best known location and the particles also are guided toward to the known best location in the search space. The particles also being updated frequently with the better locations found by other particles. With this method of optimization, the solution or particle expected to move toward the best solution.

PSO is inspired by the movement pattern of living organisms such in a fish school or bird flock. PSO the first intended is to simulate the social behaviour (Kennedy, 1997) and it originally attributed to Kennedy, Shi and Eberhart (Kennedy and Eberhart, 1995; Shi. and Eberhart, 1998).

As stated by Kennedy and Eberhart (1995), PSO has its advantages such as does not requires derivatives that makes this technique more stable compare to other technique, smaller time steps are possible with PSO, easily parallelizable, lower computational cost, fewer parameters to adjust and simple to understand.

In other hand, this techniques also suffers due to several disadvantages such as not able to solve non-coordinate system problem, easy to suffer from the effect of partial optimism and does not has mutation and overlapping operator.

1.2 Injection Molding

The injection molding process can be explained as follows. Material is fed into high temperature barrel to melt the material granules and mixed them. After these granules has been melted and mixed, the machine will force the material into a mold cavity (Todd et al., 1994). In this mold cavity the material will be harden to produce a product or part according to mold. Fig. 2 shows the basic injection molding machine.

![Injection molding machine](image)

Fig. 2. Injection molding machine (Drobny, 2014).

Normally, engineer or industrial designer is the one who make the product’s design. The moldmaker is the creator of the mold, the mold usually made from metal based on product designed earlier. Injection molding is very popular for producing a variety of parts and products.

There are six steps in injection molding manufacturing process. The steps as follows:

i. Beginning of plastication
   In this step, screw transports the melted plastic to the barrel where the material is heated.
ii. End of plastication
   The screw stops after the barrel is filled with the melted plastic.
iii. Mold closing
   Clamping unit close the mold and ready to receive the melted material.
iv. Beginning of injection
   The screw move in axial motion to push the melted plastic into the mold until it is filled.
v. End of injection and mold cooling
   In this step, the mold begins to cool. Additional melted plastic is injected to fill the spaces produced by shrinkage.
vi. Ejection
   The produced product or part is ejected and the screw retract ready for next cycle.

1.3 Initial Data

The initial data used in this study is based on experimental data by Guo et al. (2012). The data in that study was obtained by using Moldflow. The objective of the study is to find combination of the parameters’ values that could lead to minimum warpage. Warpage can be described as dimensional distortion in a molded part or product that produced by injection molding (Rosato & Rosato, 2012). Fig. 3 shows the example of product
affected by warpage.

The researchers has chosen automotive interior trim product as the case study. Fig. 4 shows the shape of the automotive interior trim product.

The dimensions of this product are 260mm x 450mm x 70mm and the material of this product is polypropylene copolymer.

There are 4 parameters has been chosen in study by Guo et al. (2012), injection time (t_inject), cooling temperature (T_cool), mold temperature (T_mold) and V/P switch over (V/P). The cooling temperature is the temperature of coolant, injection time is the amount of time set to fill the mold, V/P switch over is switch-over from filling to packing/holding, or at the specified packing/holding pressure and mold temperature is mold temperature when the injection molding process takes place (Rosato & Rosato, 2012). The upper boundary, lower boundary and level for each parameter have been set as shown in Table 1.

The researchers have conducted 25 trials and result from the trials shown in Table 2.

### Table 1
The upper boundary, lower boundary and level of parameters.

<table>
<thead>
<tr>
<th>Code</th>
<th>Level</th>
<th>T_cool (°C)</th>
<th>t_inject (s)</th>
<th>V/P (%)</th>
<th>T_mold (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1</td>
<td>20</td>
<td>20</td>
<td>1.8</td>
<td>97</td>
<td>20</td>
</tr>
<tr>
<td>-0.5</td>
<td>25</td>
<td>25</td>
<td>1.9</td>
<td>97.5</td>
<td>25</td>
</tr>
<tr>
<td>0</td>
<td>30</td>
<td>30</td>
<td>2.0</td>
<td>98</td>
<td>30</td>
</tr>
<tr>
<td>0.5</td>
<td>35</td>
<td>35</td>
<td>2.1</td>
<td>98.5</td>
<td>35</td>
</tr>
<tr>
<td>1</td>
<td>40</td>
<td>40</td>
<td>2.2</td>
<td>99</td>
<td>40</td>
</tr>
</tbody>
</table>

### Table 2
Trial results.

<table>
<thead>
<tr>
<th>No.</th>
<th>T_cool (°C)</th>
<th>t_inject (s)</th>
<th>V/P (%)</th>
<th>T_mold (°C)</th>
<th>Warpage (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>25/0.5</td>
<td>2.1/0.5</td>
<td>98.5/0.5</td>
<td>25/0.5</td>
<td>4.102</td>
</tr>
<tr>
<td>2</td>
<td>35/0.5</td>
<td>1.9/0.5</td>
<td>98.5/0.5</td>
<td>35/0.5</td>
<td>4.101</td>
</tr>
<tr>
<td>3</td>
<td>35/0.5</td>
<td>2.1/0.5</td>
<td>98.5/0.5</td>
<td>25/0.5</td>
<td>3.959</td>
</tr>
<tr>
<td>4</td>
<td>25/0.5</td>
<td>1.9/0.5</td>
<td>97.5/0.5</td>
<td>25/0.5</td>
<td>4.198</td>
</tr>
<tr>
<td>5</td>
<td>35/0.5</td>
<td>1.9/0.5</td>
<td>97.5/0.5</td>
<td>25/0.5</td>
<td>4.103</td>
</tr>
<tr>
<td>6</td>
<td>35/0.5</td>
<td>1.9/0.5</td>
<td>98.5/0.5</td>
<td>25/0.5</td>
<td>4.115</td>
</tr>
<tr>
<td>7</td>
<td>25/0.5</td>
<td>2.1/0.5</td>
<td>97.5/0.5</td>
<td>35/0.5</td>
<td>4.098</td>
</tr>
<tr>
<td>8</td>
<td>30/0</td>
<td>2.0/0</td>
<td>98/0</td>
<td>30/0</td>
<td>4.097</td>
</tr>
<tr>
<td>9</td>
<td>35/0.5</td>
<td>1.9/0.5</td>
<td>97.5/0.5</td>
<td>35/0.5</td>
<td>4.091</td>
</tr>
<tr>
<td>10</td>
<td>25/0.5</td>
<td>1.9/0.5</td>
<td>97.5/0.5</td>
<td>35/0.5</td>
<td>4.185</td>
</tr>
<tr>
<td>11</td>
<td>35/0.5</td>
<td>1.9/0.5</td>
<td>98.5/0.5</td>
<td>35/0.5</td>
<td>4.199</td>
</tr>
<tr>
<td>12</td>
<td>25/0.5</td>
<td>2.1/0.5</td>
<td>98.5/0.5</td>
<td>35/0.5</td>
<td>4.088</td>
</tr>
<tr>
<td>13</td>
<td>25/0.5</td>
<td>1.9/0.5</td>
<td>98.5/0.5</td>
<td>35/0.5</td>
<td>4.189</td>
</tr>
<tr>
<td>14</td>
<td>35/0.5</td>
<td>2.1/0.5</td>
<td>97.5/0.5</td>
<td>25/0.5</td>
<td>3.929</td>
</tr>
<tr>
<td>15</td>
<td>35/0.5</td>
<td>2.1/0.5</td>
<td>98.5/0.5</td>
<td>35/0.5</td>
<td>3.961</td>
</tr>
<tr>
<td>16</td>
<td>35/0.5</td>
<td>2.1/0.5</td>
<td>97.5/0.5</td>
<td>35/0.5</td>
<td>3.952</td>
</tr>
<tr>
<td>17</td>
<td>25/0.5</td>
<td>2.1/0.5</td>
<td>97.5/0.5</td>
<td>25/0.5</td>
<td>4.079</td>
</tr>
<tr>
<td>18</td>
<td>30/0</td>
<td>2.0/0</td>
<td>99/1</td>
<td>30/0</td>
<td>4.077</td>
</tr>
<tr>
<td>19</td>
<td>30/0</td>
<td>2.0/0</td>
<td>98/0</td>
<td>40/1</td>
<td>4.059</td>
</tr>
<tr>
<td>20</td>
<td>30/0</td>
<td>2.2/1</td>
<td>98/0</td>
<td>30/0</td>
<td>3.841</td>
</tr>
<tr>
<td>21</td>
<td>20/-1</td>
<td>2.0/0</td>
<td>98/0</td>
<td>30/0</td>
<td>4.229</td>
</tr>
<tr>
<td>22</td>
<td>30/0</td>
<td>2.0/0</td>
<td>97/1</td>
<td>30/0</td>
<td>4.021</td>
</tr>
<tr>
<td>23</td>
<td>40/1</td>
<td>2.0/0</td>
<td>98/0</td>
<td>30/0</td>
<td>3.776</td>
</tr>
<tr>
<td>24</td>
<td>30/0</td>
<td>2.0/0</td>
<td>98/0</td>
<td>20/-1</td>
<td>4.083</td>
</tr>
<tr>
<td>25</td>
<td>30/0</td>
<td>1.8/-1</td>
<td>98/0</td>
<td>30/0</td>
<td>4.311</td>
</tr>
</tbody>
</table>

Min. 3.776

2. Development of Fitness Function

The mathematical equation is based on polynomial Eq. (1) obtained using Minitab software by Guo et al. (2012). This mathematical model simplified the relationship between involved parameters and warpage to describe and mimic the actual problem in this case study.

\[
W = B_0 + \sum_{i=1}^{4} B_i X_i + \sum_{i=j}^{4} B_{ij} X_i X_j + \sum_{i=1}^{4} B_i X_i^2
\]

(1)

where:

- \( W, B_0, B_i, B_{ij} \) = coefficients
- \( X_i, X_j \) = parameters

Based on obtained equation in Eq. (1), the regression model can be written as follows:

\[
W = 4.09888 - (0.11621) T_{cool} - (0.12179) t_{inject} + (0.00587) V/P - (0.00038) T_{mold} - (0.02497) T_{cool}^2 - (0.00509) t_{inject}^2 - (0.01734) V/P^2 - (0.00772) T_{mold}^2 - (0.04706) T_{cool} t_{inject} + (0.000419) T_{cool} V/P - (0.000106) T_{cool}^2 + (0.01294) t_{injected} V/P - (0.00106) t_{injected} T_{mold} - (0.00056) V/P T_{mold}
\]

(2)

where:

- \( T_{cool} \) = cooling temperature
- \( V/P = V/P \) switch over
- \( t_{inject} = injection time \)
- \( T_{mold} = mold temperature \)

2.1 Fitness Function Validation

Eq. (2) has been used to predict the warpage value to validate and verify this regression model to be used as
simulation for the problem. Predicted warpage values shown in Table 3.

Table 3
Predicted warpage values using regression model.

<table>
<thead>
<tr>
<th>No.</th>
<th>T\textsubscript{cool} (°C)</th>
<th>T\textsubscript{inject} (s)</th>
<th>V/P (%)</th>
<th>T\textsubscript{mold} (°C)</th>
<th>Predicted Warpage Values(mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>-0.5</td>
<td>4.1012725</td>
</tr>
<tr>
<td>2</td>
<td>0.5</td>
<td>-0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>4.0983275</td>
</tr>
<tr>
<td>3</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>-0.5</td>
<td>3.9641575</td>
</tr>
<tr>
<td>4</td>
<td>-0.5</td>
<td>-0.5</td>
<td>0.5</td>
<td>-0.5</td>
<td>4.1949475</td>
</tr>
<tr>
<td>5</td>
<td>0.5</td>
<td>-0.5</td>
<td>-0.5</td>
<td>0.5</td>
<td>4.1007025</td>
</tr>
<tr>
<td>6</td>
<td>0.5</td>
<td>-0.5</td>
<td>0.5</td>
<td>-0.5</td>
<td>4.1024775</td>
</tr>
<tr>
<td>7</td>
<td>-0.5</td>
<td>-0.5</td>
<td>0.5</td>
<td>-0.5</td>
<td>4.0871575</td>
</tr>
<tr>
<td>8</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.5</td>
<td>4.0988800</td>
</tr>
<tr>
<td>9</td>
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<td>0.5</td>
<td>0.5</td>
<td>4.0971125</td>
</tr>
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<td>10</td>
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<td>4.1924175</td>
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<tr>
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<td>-0.5</td>
<td>4.1894425</td>
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<tr>
<td>12</td>
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<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>4.0971225</td>
</tr>
<tr>
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<td>0.5</td>
<td>-0.5</td>
<td>4.1925325</td>
</tr>
<tr>
<td>14</td>
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<td>-0.5</td>
<td>3.9494425</td>
</tr>
<tr>
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<td>3.9589475</td>
</tr>
<tr>
<td>16</td>
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<td>3.9447925</td>
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<td>17</td>
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<td>-0.5</td>
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</tr>
<tr>
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<td>1</td>
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<td>0</td>
<td>3.9577000</td>
</tr>
<tr>
<td>24</td>
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<td>0</td>
<td>0</td>
<td>-1</td>
<td>4.0950300</td>
</tr>
<tr>
<td>25</td>
<td>0</td>
<td>-1</td>
<td>0</td>
<td>0</td>
<td>4.2155800</td>
</tr>
</tbody>
</table>

Fig. 5 shows line graph of comparison between warpage values from experiment data and predicted warpage values using regression model in Eq. (2).

The line pattern of warpage values between experiment and regression model are quite similar to each other as shown in Fig. 5. From this pattern, the regression model gives a close prediction to experiment warpage values. Therefore, the assumption could be withdrawn that the used regression model is good to predict the warpage value.

The assumption based on line pattern alone is not enough to verify and validate the regression model as a simulation to the problem. The paired t-test between experiment data and predicted regression model has been done to prove this assumption scientifically and indirectly verify and validate the regression model to be used as a picture of this problem.

Table 4, Table 5 and Table 6 show the result of paired t-test between experiment data and predicted regression model. This test has been done using SPSS software by IBM.

Table 4
Paired samples statistics between experiment data and predicted regression model.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>N</th>
<th>Std. Deviation</th>
<th>Std. Error Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experiment</td>
<td>4.073720</td>
<td>25</td>
<td>0.120849</td>
<td>0.024170</td>
</tr>
<tr>
<td>Regression</td>
<td>4.085651</td>
<td>25</td>
<td>0.0850016587</td>
<td>0.017000</td>
</tr>
</tbody>
</table>

Table 4 shows the mean, standard deviation and standard error mean for both variables is not significantly different from each other, all 25 data are valid to the test.

Table 5
Paired samples correlations between experiment data and predicted regression model.

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Correlation</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experiment</td>
<td>25</td>
<td>0.935805</td>
<td>0.000</td>
</tr>
<tr>
<td>Regression</td>
<td>25</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5 shows that the variables are positively correlated to each other with high value, 0.935805 which is close to 1.0. This indicates the experiment data and predicted regression model are close to perfect correlation.

Table 6
Paired samples test between experiment data and predicted regression model.

<table>
<thead>
<tr>
<th>Mean std Dev.</th>
<th>Std Error Mean</th>
<th>95% Confidence Interval of the Diff.</th>
<th>t</th>
<th>df</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.0119</td>
<td>0.05103</td>
<td>0.0102</td>
<td>-0.0330</td>
<td>0.0091</td>
<td>1.1691</td>
</tr>
</tbody>
</table>

The mean difference, standard deviation difference and standard error mean difference are shown in Table 4.4 for these two variables. This table also shows the 95% confidence interval ranges from -0.032995 to 0.009132, t(24) equals to -1.169069 and significance p equals to 0.253857.

In a nutshell, based on the similarity line pattern in line graph in Fig. 5 and supported scientifically by results shown in Table 3, Table 4, Table 5 and Table 6, the regression model is valid to be use to simulate the problem and suitable to be use as fitness function for this study.

3. PSO Optimization

The PSO optimization is conducted by using Matlab. The fitness function used in this optimization is based on regression model that obtained earlier as discussed in section 3. The lower and upper boundary for each parameter is set based on level in Table 1 and can be written as in Eq. (3), Eq. (4), Eq. (5) and Eq. (6). The default PSO operator setting has been set as shown in Table 7.

\[ \begin{align*}
-1 & \leq T_{cool} \leq 1 \\
-1 & \leq t_{inject} \leq 1 \\
-1 & \leq V/P \leq 1 \\
-1 & \leq T_{mold} \leq 1
\end{align*} \]
50 runs have been conducted using these setting. Table 9

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>T&lt;sub&gt;cool&lt;/sub&gt; (°C)</td>
<td>40</td>
</tr>
<tr>
<td>T&lt;sub&gt;inj&lt;/sub&gt; (s)</td>
<td>3.73027</td>
</tr>
<tr>
<td>V/P (%)</td>
<td>3.73027</td>
</tr>
<tr>
<td>T&lt;sub&gt;switch&lt;/sub&gt; (°C)</td>
<td>3.73027</td>
</tr>
<tr>
<td>Warpage (mm)</td>
<td>3.73027</td>
</tr>
</tbody>
</table>

Table 8: Warpage value of PSO optimization.

As shown in Table 8 the minimum warpage value is 3.73027 and the range of minimum warpage value is 3.73027 to 3.74113.

As shown in Table 8, the optimal solution value obtained by PSO optimization is 3.73207 when using combination of parameters’ value as shown in Table 9.

### Table 9: PSO operators setting.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coolant Temperature (°C)</td>
<td>40</td>
</tr>
<tr>
<td>Injection Time (s)</td>
<td>2.2</td>
</tr>
<tr>
<td>V/P Switch Over</td>
<td>97%</td>
</tr>
<tr>
<td>Mold Temperature (°C)</td>
<td>40</td>
</tr>
<tr>
<td>Warpage (mm)</td>
<td>3.73027</td>
</tr>
</tbody>
</table>

Fig. 6 shows the snapshots of the PSO optimization using Matlab.

The PSO operators setting as shown in Table 7 have been used in finding the minimal warpage value. A total of 50 runs have been conducted using these setting. Table 9 shows the warpage values of PSO optimization.

As shown in Table 8 the minimum warpage value is 3.73027 and the range of minimum warpage value is 3.73027 to 3.74113.

As shown in Table 8, the optimal solution value obtained by PSO optimization is 3.73207 when using combination of parameters’ value as shown in Table 9.

Based on Table 9, the minimum value of warpage is obtained when the coolant temperature is set at 40°C,
injection time is set at 2.2s, V/P switch over is set at 97% and mold temperature is set at 40°C. The warpage value is 3.73027 when these parameters set as discussed earlier.

4. Conclusion

The objective of the PSO optimization in this study is to determine the optimal process parameters in injection molding that could lead to the minimum warpage value. The minimum warpage value obtained from initial data is 3.776, while the minimum warpage value from PSO is 3.73027. Based on the facts and findings discussed earlier the PSO is capable of optimizing the warpage value, PSO has reduced the warpage value by 1.2111%. Therefore, PSO has been the effective technique in estimating the minimum warpage value compared to technique used by initial data.

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References