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Warpage Optimisation on the Moulded Part using Response Surface Methodology (RSM) and Glowworm Swarm Optimisation (GSO)

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Abstract. Nowadays, there are various of optimisation methods that have been explored by many researchers to find the appropriate processing parameters setting for the injection moulding process. From the previous researches, it was reported that the optimisation work has improved the moulded part quality. In this study, the application of optimisation work to improve warpage of the front panel housing have been explored. By selecting cooling time, coolant temperature, packing pressure and melt temperature as the variable parameters, design of experiment (DOE) have been constructed by using the rotatable central composite design (CCD) approach. Response Surface Methodology (RSM) was performed to obtain the mathematical model. This mathematical model then will be used in Glowworm Swarm Optimisation (GSO) method in order to determine the optimal processing parameters setting which will optimise the warpage condition. Based on the results, melt temperature is the most significant factor contribute to the warpage condition and warpage have optimised by 39.1% after optimisation. The finding shows that the application of optimisation work offers the best quality of moulded part produced.

1 Introduction

Injection moulding process consists into four main stages which are filling, packing, cooling and ejecting processes [1, 2]. Due to the complexity of injection moulding process, it is difficult for injection moulding industries in order to produce the best quality of the moulded part. Most common defects in injection moulding is a warpage [3]. Warpage is difficult to prevent due to design complexity and numerous influencing factors which affected the assembly process because of uneven clearance or interference problems. With an appropriate

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setting of injection moulding processing parameters, warpage condition can be reduced [4]. Previously, most of injection moulding industries have used try-and-error approach in order to obtain an appropriate processing parameters setting which consume time and production cost [5]. Today with the advancement of computer technology, an appropriate combination of processing parameters can be obtained by simulation analysis software with an aid of optimisation approach which is highly accurate, shorter time, and much more cheaper [3]. These days, many researchers come with various proposals of optimisation approaches to determine an optimal processing parameters in order to optimise the quality of injection moulded parts.

For instances, Annicchiarico et al. [6], proposed the half fractional factorial design of experiment optimisation method to investigate the processing parameter influence on the shrinkage in order to improve part quality. Squared specimen made from polyoxymethylene (POM) was used in this research. The preliminary screening was performed to identify high and low values for each selected parameter. Then, the significant factors have determined by conducting statistical analysis. The result shown that mould temperature are the most critical factor influenced the shrinkage for parallel and normal flow direction.

Yin et al. [7], explored Taguchi's method with multi-objectives optimisation approach to find an optimal processing parameters in order to reduce warpage and birefringence. An optical lens made of PMMA material was used in this research. At first, Taguchi's orthogonal array with three level was created to evaluate the initial process condition. S/N ratio was calculated and analysis of mean (ANOM) was performed as a multi-objectives optimisation approach in order to obtain an optimal processing parameter setting and to determine the most critical factor to warpage and birefringence. Experimental verification was conducted in this research by using optimal processing parameters that obtained from the optimisation work. The results show that the birefringence and warpage have reduced, which were smaller than minimal value obtained from the Taguchi's method. Melt temperature was found as the most significant factor to give effect to both warpage and birefringence.

Chen et al. [8], explored the optimisation work using Taguchi method, response surface methodology (RSM) and hybrid of genetic algorithm-particle swarm optimisation (GA-PSO) in order to find an optimum length and to reduce warpage. In this research, printer rear cover was used as specimen which made from PBT-2100 material. At first, Taguchi's method was conducted to investigate the initial processing parameters. By implementing ANOVA, the significant factors have been determined which are packing time and cooling time. Next, the RSM was conducted to generate mathematical models and the combination of RSM-GA was performed to determine an optimal processing parameters. This first stage optimal processing parameters will be optimised again by using hybrid GA-PSO method. The results of the second stage optimisation show that the optimum length achieved was 170.483mm which was claimed to be the closest target value (170.5mm) and warpage was reduced from 0.092 to 0.025mm.

In other research, Chen et al. [9], proposed the sequence of optimisation methods which consist of Taguchi's method, back-propagation neural network (BPNN), genetic algorithm (GA) and hybrid particle swarm optimisation and genetic algorithm (PSO-GA) to get an optimum length and to reduce warpage. The same printer rear cover made from PBT-2100 material was used as research specimens. For initial, Taguchi's method was performed to obtain the best combination of processing parameters. Next, ANOVA was carried out to identify the significant factors contributed to the responses and the result are the packing time and cooling time. Afterward, BPNN was conducted to plot the relationship between variables and responses. Then, the first stage optimisation was employed by using GA to obtain the initial optimal processing parameters. Next, the second stage optimisation which used hybrid PSO-GA approach to determine an optimal processing parameters setting was performed.

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The results show that the optimal length achieve was 170.52mm from the target length which was 170.5mm and warpage was reduced from 0.198mm to 0.096mm.

Based on the literatures, moulded part qualities can be enhanced by the application of optimisation work. Therefore, in this study an alternative optimisation approach has been introduced to improve warpage on front panel housing part made of Acrylonitrile-Butadiene -Styrene (ABS). Based on input processing parameters design of experiment (DOE) will be generated by using full factorial Design (FFD) with an aid of rotatable central composite design of experiment (CCD). Then AMI 2013 software will be used to analyse warpage condition for each run. Response surface methodology (RSM) will be performed in order to obtain the mathematical model function and analysis of variance (ANOVA) will be used to define the significant factors influencing on the warpage condition. The mathematical model obtained from RSM will be used in glowworm swarm optimisation (GSO) method as an objective function to determine the optimal processing parameters which will optimise warpage of the moulded part.

2 Response surface methodology

Response surface methodology (RSM) is a classical optimisation approach. It was used to demonstrate the relationship between variable parameters which influence the response condition in two or three-dimensional hyperbolic surface[10]. The mathematical model function will be obtained by using the second-order polynomial regression model in this study which will be used as the objective function in GSO. The necessary information to construct the response model are generally accumulated by the simulation works [11, 12]. Figure 1 shows the RSM flowchart in this study.

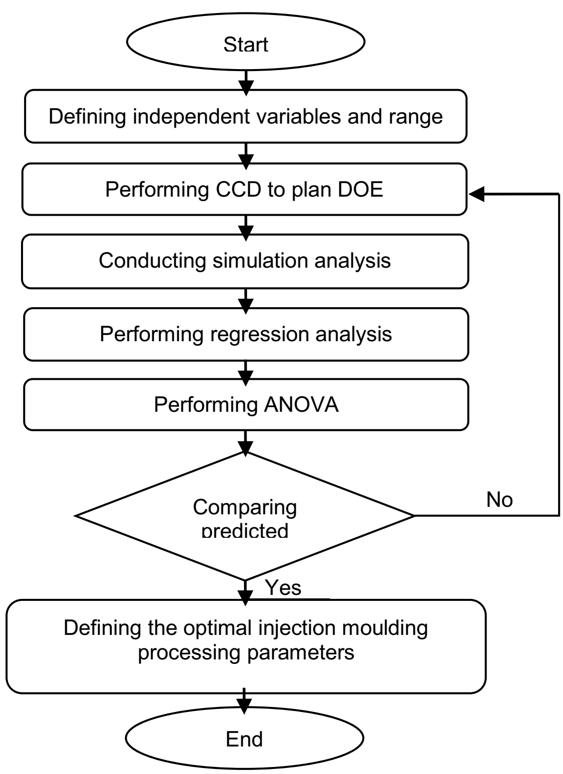

Fig. 1. Response Surface Methodology (RSM) flowchart

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2.1 Design of Experiment Setup

In this study, coolant inlet temperature, melting temperature, packing pressure and cooling time have been selected as variable parameters and the range of each parameter as shown in Table 1. At first, full factorial design (FFD) with four centre points was selected as an experimental design to evaluate the model and main effects contribute to the warpage condition by using Design Expert 7.0 software. In order to obtain the significant curvature which is important in the RSM regression analysis, the augment of rotatable central composite design (CCD) was performed. Therefore, 30 runs of specified condition have been generated and each run will be set in AMI 2013 simulation software to evaluate the warpage condition of the moulded part.

Table 1. Variable parameters and levels

Factors	Level	
	Minimum	**Maximum**
Coolant inlet temperature, A (°C)	25	65
Melt temperature, B (°C)	220	260
Packing pressure, C (MPa)	46.74	56.74
Cooling time, D (s)	20	35

2.2 Finite element analysis setup

The CAE software, Autodesk Moldflow Insight (AMI) 2013 have been used to simulate the injection moulding process and to evaluate the warpage condition of front panel housing moulded part which has 2.5mm of average thickness and made from ABS material with trade name as Toray/Toyolac 700-314 as shown in Fig. 2. The moulded part, gating system and cooling channels 3D data was created and imported into the software for meshing process. In order to obtain more precise results, the mould insert material made of P20 steel and Nissei NEX1000, 80 tonne injection moulding machine specification have been set in the AMI software. Then, the Cool (FEM)+Fill+Pack+Warp analysis has been performed to evaluate warpage condition for each run which have been generated by DOE.

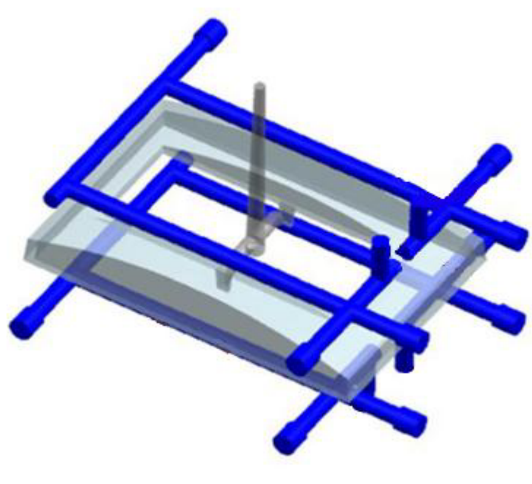

Fig. 2. Front panel housing with straight drilled cooling channels

2.3 RSM Regression Analysis

The warpage results for each run which obtained from the simulation analysis will be used in the RSM regression analysis. By using Design Expert 7.0 software the regression analysis was performed with the backward quadratic model in order to obtain the mathematical model function which representing the relationship between variable parameters and response. The software will calculate using second-order polynomial regression model in a statistical manner and the results will be verified with ANOVA.

2.4 Analysis of Variance (ANOVA)

The result of the quadratic model obtained from the RSM regression analysis will be verified by analysis of variance (ANOVA) to determine either the mathematical model was statistically significant or otherwise. In the same manner, the significant factors that contribute to the warpage condition will be defined.

3 Glowworm swarm optimisation

The operators in GSO are recognised as glowworms [13] that carry a luminescent amount which has been called as luciferin [14]. Every glowworm utilises an artificial proportional luciferin to transmit the fitness of its current location and evaluate based on the objective model function to its neighbours. The glowworms rely on the variable of their neighbourhood which is based on the radial sensor range boundary in order to identify their neighbours and evaluate their movements. Each glowworm using the probabilistic mechanism by selecting a neighbour that contain the higher luciferin amount than its own and moves toward it. In other words, it will be attracted to the neighbours which are glowing brighter. Finally, the movement of the glowworms will be based on the local information and particular neighbour interactions which empower the majority swarm to form multiple optima of a given multimodal function.

In this study, GSO method will be carried out to obtain the optimised processing parameters of injection moulding process based RSM mathematical model function. MATLAB R2014a software will be used to conduct GSO analysis. Figure 3 shows the flowchart of GSO for this study.

3.1 Defining mathematical model function

The objective function used in GSO is the mathematical model function which has been obtained from the RSM regression analysis. The formulated objective function has been taken in this study is a warpage function.

3.2 Initialisation of glowworms' parameters

The initial glowworms' parameters were set based on the selected injection moulding variable parameters limit in this study to create the solution space. Then, the GSO agents will be deployed randomly in the solution space by setting the initial glowworms population size and maximum iteration based on the research requirement. In this study 30 numbers of glowworms and 40 iterations have been set.

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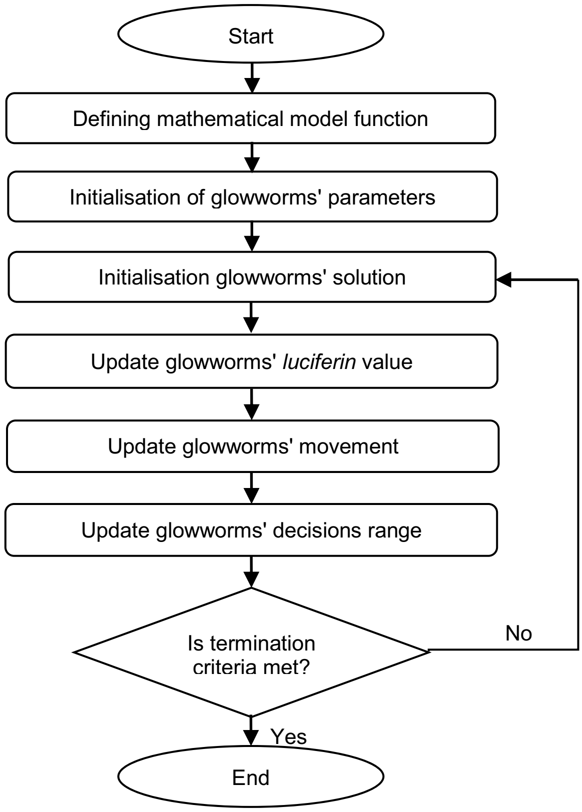

Fig. 3. Flowchart of Glowworm Swarm Optimisation (GSO)

3.3 Initialisation glowworms' solution

The initial solution of initial *luciferin* value (l_o), *luciferin* decay constant (ρ), *luciferin* enhancement constant (γ), beta (β), step size (s), neighbourhood range $r_d^i(t)$ and parameter used to control the number of neighbours (n_t) was set based on the research requirement where each glowworm contained the same *luciferin* value and sensor range in this phase. In this study, GSO control parameters optimal setting are: $\beta = 0.08, \rho = 0.4, \gamma = 0.6$ and $r_d^i(t) = 3$.

3.4 Update glowworms' luciferin value

At the beginning, each glowworm contains the same *luciferin* value. Influenced by the objective function value of their current location, the *luciferin* value will be changed. The rule of *luciferin* update was given by standard Equation (1) where $li(t)$ is the *luciferin* level for glowworm i at time t, ρ is the *luciferin* decay constant ($0 < \rho < 1$), and $Ji(t)$ indicates the objective function at agent i's location at time t.

$$li(t+1) = (1-\rho)li(t) + \gamma Ji(t+1) \quad (1)$$

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3.5 Update glowworms' movement

In the movement-update phase, each glowworm will move toward neighbour that contained the higher *luciferin* value than its own using a probabilistic mechanism. The probability of agent i move to agent j was given by a standard Equation (2) where $l_i(t)$ is the *luciferin* value for glowworm i, $d(i,j)$ is the Euclidean distance between agent i and j.

$$P_{ij}(t) = \frac{l_j(t)-l_i(t)}{\sum_{k\in N_i(t)} l_k(t)-l_i(t)} \tag{2}$$

Then, the glowworm i movement can be expressed by Equation (3) where s is the step size.

$$x_i(t+1) = x_i(t) + s\left[\frac{x_j(t)-x_i(t)}{\|x_j(t)-x_i(t)\|}\right] \tag{3}$$

3.6 Update glowworms' local decisions range

Local decision range update phase will be used to determine multiple peaks in a multimodal functional landscape in order to obtain the optimal variable parameters which optimise warpage value effectively. When the number of neighbours changed, the local decision domain needs to update in each of iteration. The rule is given by Equation (4) where $r_d^i(t+1)$ is the local decision domain of glowworm i in the $t+1$ iteration, β is the constant parameter that affected the rate of change of the neighbour domain and n_t is the threshold used to control the number of neighbours.

$$r_d^i(t+1) = \min\{r_s, \max\left\{0, r_d^i(t) + \beta(n_t - |N_i(t)|)\}\right\} \tag{4}$$

4 Results and discussions

4.1 Injection moulding process simulation

Warpage value obtained from simulation analysis was shown in Table 2. The results tabulate the warpage value for each run with the specified variable parameters condition which obtained from the DOE. The specified variable parameters condition was set and simulated in the AMI 2013 software.

4.2 Response surface methodology (RSM) regression analysis

From regression analysis, the determination coefficient, R^2 that fitted the model is 0.9710. The adjusted determination is 0.9618, which indicated that the regression model is significant with an adequate precision is more than 4, which is 37.564. The model is more significant if R^2 value is closer to 1 [15]. The standard deviation for this model is 8.807×10-3 and this value indicated that it is relatively lower than 0.05 which is better for precision and reliability of the experiment [16]. The polynomial regression model which relates to the warpage with all input parameters (coolant inlet temperature (A), melt temperature (B), packing pressure (C) and cooling time (D) is established by Design Expert 7 software and represented in Equation 5. This mathematical model function will be used in GSO as an objective function.

$$\begin{aligned} Warpage = &-0.251 + (3.43\times10^{-3}A) + (2.212\times10^{-3}B) + (7.917\times10^{-4}C) \\ &-(2.806\times10^{-3}D) - (1.328\times10^{-5}AB) - (1.832\times10^{-5}D^2) \end{aligned} \tag{5}$$

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Table 2. Injection moulding process simulation results.

Standard Order	Data Source	Variable parameters for injection moulding simulation				Response
		Coolant temperature (°C)	Melt temperature (°C)	Packing Pressure (MPa)	Cooling time (s)	Warpage (mm)
1	DOE	25	220	46.74	20	0.220
2		65	220	46.74	20	0.155
3		25	260	46.74	20	0.305
4		65	260	46.74	20	0.225
5		25	220	56.74	20	0.215
6		65	220	56.74	20	0.170
7		25	260	56.74	20	0.310
8		65	260	56.74	20	0.235
9		25	220	46.74	35	0.175
10		65	220	46.74	35	0.130
11		25	260	46.74	35	0.255
12		65	260	46.74	35	0.185
13		25	220	56.74	35	0.175
14		65	220	56.74	35	0.135
15		25	260	56.74	35	0.245
16		65	260	56.74	35	0.190
17	Centre	45	240	51.74	27.5	0.215
18		45	240	51.74	27.5	0.215
19		45	240	51.74	27.5	0.215
20		45	240	51.74	27.5	0.215
21	Axial	5	240	51.74	27.5	0.240
22		85	240	51.74	27.5	0.140
23		45	200	51.74	27.5	0.170
24		45	280	51.74	27.5	0.270
25		45	240	41.74	27.5	0.205
26		45	240	61.74	27.5	0.240
27		45	240	51.74	12.5	0.260
28		45	240	51.74	42.5	0.180
29		45	240	51.74	27.5	0.215
30		45	240	51.74	27.5	0.215

4.3 Analysis of variance (ANOVA)

From the ANOVA table as shown in Table 3, the F calculated value is bigger than F tabulated. This condition shows that the mathematical model obtained from regression analysis was significant. The ANOVA also indicated that three from four selected variable parameters give significant effect on the warpage condition.

Table 3. ANOVA of response surface model.

	Sum of Squares	df	Mean Square	F (calculated)	R^2	RA^2	F (tabulated)
SSR	0.0571	7	0.0082	105.2280	0.9710	0.9618	2.46
SSE	0.0017	22	0.0001				
Total	0.0588	29					

The results show that melt temperature was the most significant factor contributed to the warpage condition. This result was inline with previous researchers which found out the same significant factor which influencing the warpage condition [7, 17-21]. Then it follows by cooling temperature and cooling time. Packing pressure was the least significant factor contributed to the warpage condition as shown in Figure 4. This result shows the uneven

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volumetric shrinkage occurred to the poor uniformity of thermal distribution in the mould [22]. According to Subramanian et al. [23] and Huang et al. [24] the temperature difference between upper and lower surfaces in the cavity and core can give effect to the shrinkage condition. This behaviour will cause either warpage or residual stress, depending on the mechanical stiffness of the moulded part design.

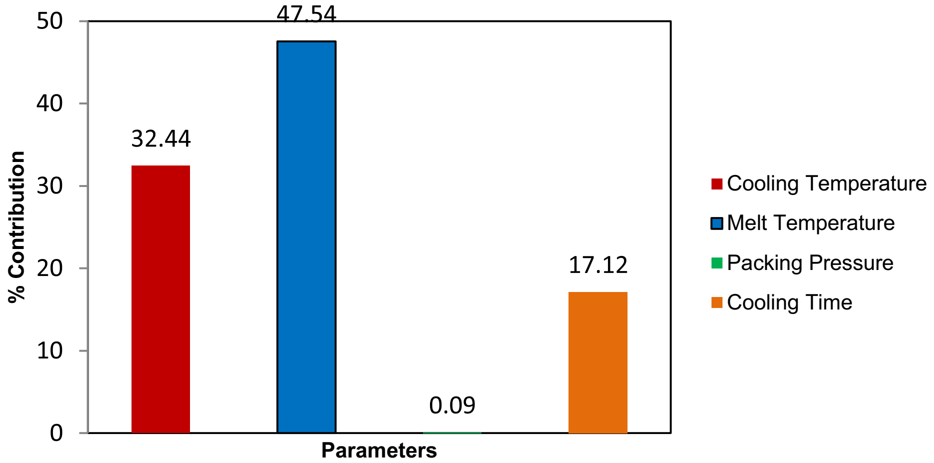

Fig. 4. Contribution for each parameters in percentage.

Equation 5 was applied to calculate the prediction warpage values of the polynomial model and the results is summarised in Figure 5. From the comparison, it shows that the simulation and predicted value are very close to each other which indicated the mathematical response function have given a good prediction value in estimating warpage.

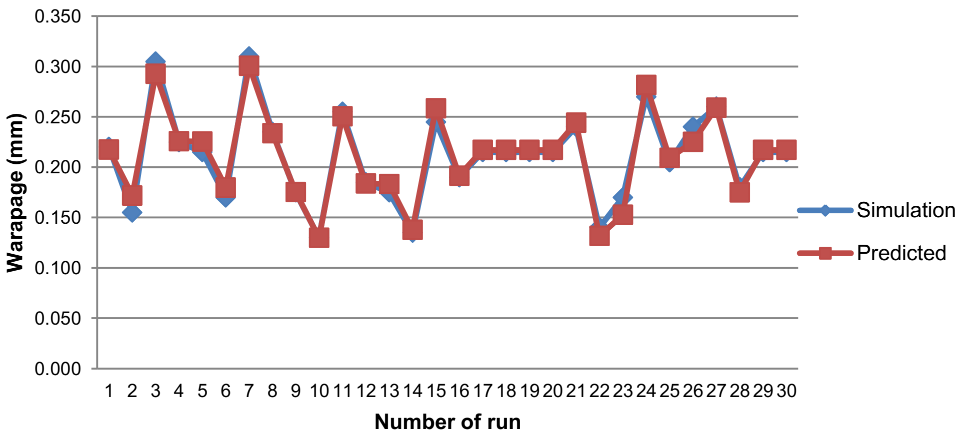

Fig. 5. Simulation and predicted warpage comparison

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4.4 Glowworm swarm optimisation (GSO) analysis

The GSO algorithm has been conducted on injection moulding processing parameters. The algorithm was tested on four selected variable parameters. By using the mathematical model function obtained from RSM, the optimal results were shown in Table 4 and the warpage variation for each glowworm was shown in Figure 6.

Table 4. Recommended simulation results versus GSO Optimised results

Factors	Recommended simulation results	GSO optimised results
Coolant inlet temperature, A (°C)	25	64.27
Melt temperature, B (°C)	240	232.51
Packing pressure, C (MPa)	46.74	52.01
Cooling time, D (s)	30	31.77
Warpage, (mm)	0.2650	0.1614

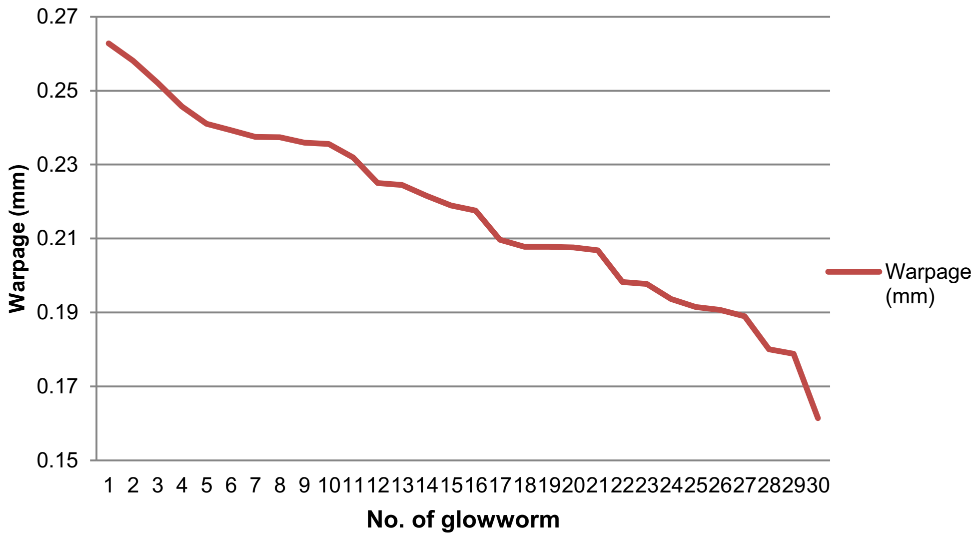

Fig. 6. Warpage variation for each glowworm

5 Conclusion

This study is definitely helpful in enhancing the quality of moulded parts produced where the objective is to optimise warpage of the front panel housing moulded part have been achieved. Based on the results, the warpage has been optimised by using an alternative approach of response surface methodology (RSM) and Glowworm Swarm Optimisation (GSO). The results also show that:

- By using RSM, the significant mathematical model function can be obtained in order to predict warpage value with reasonable accuracy.

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- From the ANOVA results, melt temperature is the most significant factor influencing the warpage condition on the moulded part, follow by coolant temperature and cooling time.
- The optimal processing parameter obtained from GSO has optimised warpage by 39.1% which is from 0.2650mm from the simulation result to 0.1614mm.

In this study, it proved that the proposed optimisation approach has enormous potential in order to obtain better quality of the moulded part.

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